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A hybrid metaheuristic approach for the capacitated arc routing problem

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ABSTRACT

The capacitated arc routing problem (CARP) is a difficult combinatorial optimization problem that has been intensively studied in the last decades. We present a hybrid metaheuristic approach (HMA) to solve this problem which incorporates an effective local refinement procedure, coupling a randomized tabu thresholding procedure with an infeasible descent procedure, into the memetic framework. Other distinguishing features of HMA include a specially designed route-based crossover operator for solution recombination and a distance-and-quality based replacement criterion for pool updating. Extensive experimental studies show that HMA is highly scalable and is able to quickly identify either the best known results or improved best known results for almost all currently available CARP benchmark instances. In particular, it discovers an improved best known result for 15 benchmark instances (6 classical instances and 9 large-sized instances whose optima are unknown). Furthermore, we analyze some key elements and properties of the HMA-CARP algorithm to better understand its behavior.

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1. Introduction

The capacitated arc routing problem (CARP) has been the subject of a large number of studies during the last decades due to its wide applicability in logistics, such as household waste collection, product distribution, winter gritting and postal deliveries, among others (Dror, 2000). The CARP model can be informally described as follows. We are given a graph with a set of vertices and edges, where each edge has a predefined traversal cost and where a subset of edges, which are required to be serviced by some vehicles, are additionally associated with a service cost and a demand. A fleet of identical vehicles with a limited capacity is based at the depot vertex. The objective of CARP is to find a set of vehicle routes with a minimum cost such that: (1) each required edge is serviced on one of the routes; (2) each route must start and end at the depot vertex; and (3) the total demand serviced on the route of a vehicle must not exceed the vehicle capacity.

From a theoretical point of view, CARP is known to be NP-hard (Golden & Wong, 1981), and hence is not expected to be solved by any exact algorithm in a polynomial time in the general case.

The computational difficulty of solving CARP is also confirmed in practice. Indeed, the best existing exact algorithms are limited to moderate instances with only 140 vertices and 190 edges (Baldacci & Maniezzo, 2006; Bartolini, Cordeau, & Laporte, 2013; Bode & Irnich, 2012). For these reasons, intensive research has been devoted to developing heuristic and metaheuristic methods. Representative heuristic methods include Augment-Merge (Golden & Wong, 1981), Path-Scanning (Golden, DeArmon, & Baker, 1983), the route first-cluster second heuristic (Stern & Dror, 1979) and Ulusoy's Heuristic (Ulusoy, 1985). Among the metaheuristic methods, neighborhood search approaches are popular, e.g., tabu search (Brandão & Eglese, 2008; Hertz, Laporte, & Mittaz, 2000; Mei, Tang, & Yao, 2009), variable neighborhood search (Hertz & Mittaz, 2001; Polacek, Doerner, Hartl, & Maniezzo, 2008), guided local search (Beullens, Muyldermans, Cattrysse, & Van Oudheusden, 2003), GRASP with evolutionary path relinking (Usberti, Paulo, & André, 2013). As another class of popular metaheuristics for tackling CARP, population-based algorithms generally achieve better performances, such as the memetic algorithm (Lacomme, Prins, & Ramdane-Cherif, 2004; Tang, Mei, & Yao, 2009), the ant colony algorithm (Santos, Coutinho-Rodrigues, & Current, 2010) and the cooperative co-evolution algorithm (Mei, Li, & Yao, 2014). Among these methods, two population-based algorithms (MEANS Tang et al., 2009 and Ant-CARP Santos et al., 2010) and one local search algorithm (GLS Beullens et al., 2003) represent the state-of-the-art solution methods for the classical test

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instance set, while RDG-MEANS (Mei et al., 2014) is the current best performing algorithm for the large-scale CARP (LSCARP) instances. Finally, for a thorough and up-to-date discussion of arc routing problems, the reader is referred to the recent book (Corberán & Laporte, 2015) edited by Corberán and Laporte and in particular, chapter 7 by Prins dedicated to heuristic approaches.

In this work, we investigate a new population-based algorithm under the memetic search framework (Moscato, 1989). Memetic algorithms (MAs) have been proved to be very effective for solving a large number of difficult combinatorial optimization problems (Moscato & Cotta, 2003; Neri, Cotta, & Moscato, 2011), including CARP (Lacomme et al., 2004; Tang et al., 2009). The success of a MA highly depends on a careful design of two key search components: the crossover operator and the local refinement procedure (Hao, 2012). Based on our previous experiences on MAs applied to various combinatorial problems, we go one step further by providing innovations for these two key components (crossover and local refinement) with the goal of creating a more effective memetic algorithm able to surpass the current state-of-the-art CARP methods.

The main contributions of our work can be summarized as follows.

- From the algorithmic perspective, the proposed population-based hybrid metaheuristic approach (HMA) combines a powerful local refinement procedure to ensure an effective search intensification with a dedicated crossover operator specially designed for CARP to guarantee a valid search diversification. The local refinement procedure couples a randomized tabu thresholding procedure to locate high-quality feasible solutions, with an infeasible descent procedure to enable tunneling between feasible and infeasible regions. The dedicated crossover operator relies on route information that can be embodied in exchanges of parent solutions to create new promising solutions. Additionally, to maintain a healthy population diversity and to avoid premature convergence, HMA employs a quality-and-distance strategy to manage the pool of solutions using a dedicated distance measure.
- In terms of computational results, extensive experiments carried out on 8 sets of widely used benchmarks show the competitiveness of the proposed method compared to the state-of-the-art CARP algorithms in solution quality and computational efficiency. For the 7 sets of 181 small-sized and medium-sized instances, HMA consistently matches or improves on all the best known results. In particular, HMA discovers a new best known result (new upper bound) for 6 well-studied instances. For the last set of 10 large-sized CARP benchmarks, HMA exhibits an even better performance. It easily dominates the state-of-the-art algorithms, including those specially designed for these CARP instances, by finding 9 new best known solutions, while yielding significantly smaller average gap values, thus demonstrating the outstanding scalability of the proposed method.

The rest of the paper is organized as follows. Section 2 introduces preliminary notation and the solution representation. Sections 3 and 4 are dedicated to the description of the main HMA algorithm. Section 5 presents the computational results. Section 6 investigates some key elements of HMA, followed by the conclusions in Section 7.

2. Notation and solution representation

We are given a graph $G(V, E)$ with a set of vertices (V), a set of edges (E), a set of required edges ($E_R \subset E$) and a fleet of identical vehicles with a capacity of Q that is based at the depot vertex v_d ($v_d \in V$). Each edge $e = (i, j) \in E$ is represented by a pair of arcs $\langle i, j \rangle$ and $\langle j, i \rangle$. A required edge is said to be served if and only

if one of its two arcs is included in one vehicle route of the routing plan. For the sake of simplicity, we use the term *task* to represent a required edge hereafter. Let n be the number of tasks, i.e., $n = |E_R|$. Each arc of a task, say u , is characterized by four elements: the head vertex ($head(u)$), the tail vertex ($tail(u)$), the traversal cost ($tc(u)$) and the demand ($q(u)$).

To represent a CARP solution, we assign to each task (i.e., a required edge) two IDs ($i, i+n$) where i is an integer number in $[1, n]$, i.e., one ID for each arc of the task. We also define a dummy task with 0 as its task ID and both its head and tail vertices being the depot vertex v_d . This dummy task is to be inserted somewhere in the solution as a trip delimiter. Suppose a solution S involves m vehicle routes, S can then be encoded as an order list of $(n+m+1)$ task IDs among which $(m+1)$ are dummy tasks: $S = \{S(1), S(2), \dots, S(n+m+1)\}$, where $S(i)$ denotes a task ID (an arc of the task or a dummy task) in the i th position of S . S can be also written as a set of m routes (one route per vehicle): $S = \{0, R_1, 0, R_2, 0, \dots, 0, R_m, 0\}$, where R_i denotes the i th route composed of $|R_i|$ task IDs (arcs), i.e., $R_i = \{R_i(1), R_i(2), \dots, R_i(|R_i|)\}$, with $R_i(j)$ being the task ID at the j th position of R_i . Let $dist(u, v)$ denote the shortest path distance between the head vertex of arc u ($head(u)$) and the tail vertex of arc v ($tail(v)$), the total cost of a solution S can be calculated as:

$$f(S) = \sum_{i=1}^{n+m} (tc(S(i)) + dist(S(i), S(i+1))) \quad (1)$$

The total load $load(R_i)$ of a route R_i can be calculated as:

$$load(R_i) = \sum_{j=1}^{|R_i|} q(R_i(j)) \quad (2)$$

3. A hybrid metaheuristic algorithm for CARP

In this section, we describe the proposed hybrid metaheuristic algorithm (HMA) for CARP including the main procedure, the procedure for generating initial solutions, the specific route-based crossover as well as the quality-and-distance based pool maintenance procedure. The local refinement procedure of HMA is presented in Section 4.

3.1. Main scheme

Our HMA algorithm can be considered as a hybrid steady-state evolutionary algorithm which updates only one population solution at each generation of the evolution process (Glover & Kochenberger, 2003). Algorithm 1 shows the main scheme of the HMA algorithm. HMA starts with an initial population of solutions (Line 1 of Algorithm 1) which are first generated by a random path scanning heuristic (Section 3.2) and further improved with the local refinement procedure (Section 4). Before entering the main loop, HMA initializes a counter array Cnt (Lines 3 and 4) which is used to record the accumulated number of successful pool updates with the related threshold ratio value in a given set Sr (an external input).

At each generation, HMA randomly selects two parent solutions S^1 and S^2 from the population (Line 6), and performs a route-based crossover (RBX) operation (Line 7, see Section 3.3) to generate an offspring solution S^0 . RBX basically replaces one route of one parent solution with one route from the other parent solution, and repairs, if needed, the resulting solution to ensure the feasibility of S^0 . HMA then applies the local refinement procedure (Line 10, Section 4) to further improve S^0 . The local refinement procedure involves two sub-procedures, namely a randomized tabu thresholding procedure (RTTP) and an infeasible descent procedure (IDP), which can be carried out in two possible orders: RTTP followed by IDP (RTTP \rightarrow IDP) and IDP followed by RTTP (IDP \rightarrow

Algorithm 1: Main Scheme of HMA for CARP.

Data: P - a CARP instance; $Psize$ - population size; St - a set of tabu timing values; W - the number of non-improving attractors visited; Sr - a set of threshold ratios; LB - the best known lower bound of P

Result: the best solution S^* found

```

// Population initialization, Section 3.2
1 POP ← Pool_Initialization(Psize);
2  $S^* \leftarrow Best(POP)$ ; /*  $S^*$  records the best solution found so far */
3 for  $i = 1$  to  $|Sr|$  do
4    $Cnt(i) = 1$ ; /* Initialize the counter array Cnt */
// Main search procedure
5 while stopping condition not reached do
6   Randomly select two solutions  $S^1$  and  $S^2$  from POP;
7    $S^0 \leftarrow Crossover(S^1, S^2)$ ; /* Route-based crossover, Sect. 3.3 */
8    $Od \leftarrow random\_determine(RTTP \rightarrow IDP, IDP \rightarrow RTTP)$ ;
   /* Determine the order of conducting RTTP and IDP, Sect. 4.4 */
9    $k \leftarrow probabilistic\_select(Cnt)$ ; /* Select a ratio, Sect. 4.2 */
10   $S^0 \leftarrow Local\_refine(P, S^0, St, Sr(k), W, Od)$ ; /* Improve  $S^0$ , Sect. 4 */
11  if  $f(S^0) = LB$  then
12    return  $S^0$ 
13  ( $S^*, POP$ ) ← Pool_Updating( $S^0, POP$ ); /* Pool updating, Sect. 3.4 */
14  if pool updating is successful then
15     $Cnt(k) \leftarrow Cnt(k) + 1$ ;
16 return  $S^*$ 

```

RTTP). The applied order is determined randomly before running the local refinement procedure (Line 8, see Section 4.4). RTTP requires a threshold ratio which is probabilistically chosen among the values of a given set Sr according to the probability formula: $Pr(i) = Cnt(i) / \sum_{i=1}^{|Sr|} Cnt(i)$, where $Pr(i)$ denotes the probability of selecting the i th value of Sr (Line 9).

If the improved solution reaches the lower bound LB , HMA terminates immediately and returns this solution (Lines 11 and 12). Otherwise, HMA ends a generation by updating the recorded best solution and the population with the offspring solution S_c (Line 13, see Section 3.4). If S^0 is successfully inserted into the population, the counter in relation to the threshold ratio used in the current generation is incremented by one (Lines 14 and 15). HMA terminates when a stopping condition is reached, which is typically a lower bound cutoff or a maximum number of generations.

3.2. Population initialization

To generate one initial solution of the population, HMA uses a randomized path-scanning heuristic (RPSH) to construct a solution which is then further improved by the local refinement procedure described in Section 4. RPSH is adapted from the well-known path-scanning heuristic (Golden et al., 1983) by randomizing its five arc selecting rules. Specifically, RPSH builds one route at a time in a step-by-step way, each route starting at the depot vertex. At each step, RPSH identifies a set A of arcs (belonging to a set of unserved tasks) that are closest to the end of the current route and satisfy the vehicle capacity constraint. If A is empty, RPSH completes the current route by following a shortest deadheading path to the depot vertex and starts a new route. Otherwise RPSH randomly se-

lects one arc from A and extends the current route with the selected arc. The selected arc as well as its inverse arc are marked served. This process continues until all tasks are served.

The solution constructed by RPSH is further improved by the local refinement procedure of Section 4. The improved solution is inserted to the population if it is unique in terms of solution cost relative to the existing solutions, or discarded otherwise. The population initialization procedure stops when the population is filled with $Psize$ (population size) different individuals or when a maximum of $3 * Psize$ trials is reached. The latter case helps to fill the population with $Psize$ distinct individuals. If ever only $k < Psize$ distinct solutions are obtained after $3 * Psize$ trials, we set the population size to k .

3.3. Route-based crossover operator for CARP

At each of its generations, HMA applies a crossover operator to create an offspring solution by recombining two parent solutions randomly selected from the population. It has been commonly recognized that the success of memetic algorithms relies greatly on the recombination operator which should be adapted to the problem at hand and be able to transfer meaningful properties (building blocks) from parents to offspring (Hao, 2012). This idea is closely related to the idea of using structured combinations and vocabulary building (Glover & Laguna, 1997).

By considering that the solution of CARP is composed of a set of routes, it is a natural idea to manipulate routes of tasks rather than individual tasks. In this regard, the route-based crossover (RBX) operator used for the vehicle routing problem (VRP) (Potvin & Bengio, 1996) seems attractive for CARP. However, given that CARP is quite different from the VRP, RBX must be properly adapted in our context within HMA. Given two parent solutions $S^1 = \{R_1^1, R_2^1, \dots, R_{m_1}^1\}$ with m_1 routes and $S^2 = \{R_1^2, R_2^2, \dots, R_{m_2}^2\}$ with m_2 routes, our RBX crossover basically copies S^1 to an offspring solution S^0 and replaces a route of S^0 with a route from S^2 , and then repairs S^0 to establish feasibility if needed. The RBX crossover procedure consists of three main steps:

- **Step 1:** Copy S^1 to an offspring solution $S^0 = \{R_1^0, R_2^0, \dots, R_{m_1}^0\}$ and replace a route of S^0 with a route from S^2 . Generate two random integer values a ($a \in [1, m_1]$) and b ($b \in [1, m_2]$); Replace the route R_a^0 of solution S^0 with the route R_b^2 of solution S^2 , and collect the tasks that are not served in S^0 to a set UT ;
- **Step 2:** Remove duplicated tasks by the following rule. Let $S^0(p_i)$ be the task in position p_i , and let $p_i - 1$ be the position before p_i and $p_i + 1$ be the position after p_i . Also let $dist(u, v)$ denote the shortest path distance between vertex $head(u)$ and vertex $tail(v)$. Given a task t_0 which appears twice respectively in position p_1 and p_2 , RBX removes the appearance with the largest value of $s(p_i)$ ($i \in \{1, 2\}$), where $s(p_i) = dist(S^0(p_i - 1), S^0(p_i)) + dist(S^0(p_i), S^0(p_i + 1)) - dist(S^0(p_i - 1), S^0(p_i + 1))$.
- **Step 3:** Insert the unserved tasks of UT in S^0 . Before task insertion, RBX sorts the tasks in set UT in random order. Then for each task t in UT , RBX scans all possible positions of S^0 to insert t . If a position is able to accommodate t while respecting the vehicle capacity, RBX further calculates the saving (change of the total cost) with t inserted. The two arcs of t are both considered for insertion, and the minimum saving is recorded. RBX finally inserts the task to a position which causes the overall least augmentation of the total cost while maintaining the solution feasibility. Ties are broken randomly. This process is repeated until UT becomes empty.

Our proposed RBX operator not only introduces a new route (taken from S^2) into S^0 , but also modifies other existing routes

due to deletion of duplicated tasks and insertion of unserved tasks. Clearly, RBX could lead to an offspring solution which is structurally different from its parent solutions. This is a desirable feature which promotes the overall diversity of HMA. Moreover, the quality of the offspring is not much deteriorated due to the use of greedy heuristics in Steps 2 and 3. As such, when the offspring is used as a seeding solution of local refinement, it helps the search to move into a new promising region. RBX can be realized in $O(n^2)$, where n is the number of tasks.

3.4. Population management

In population-based algorithms, one important goal aims to avoid premature convergence of the population. This can be achieved by adopting a carefully designed strategy for population management. In HMA, we use a quality-and-distance strategy (QNDS) for this purpose. QNDS takes into account not only the solution quality, but also the diversity that the solution contributes to the whole population by resorting to a solution distance measure.

We propose in this work to adapt for the first time the Hamming distance in the context of CARP and use it as our distance measure. Any pair of consecutive tasks $(S(i), S(i+1))$ of a solution S is linked by a shortest path (a path with minimum deadheading cost) between $head(S(i))$ and $tail(S(i+1))$, called *deadheading-link* hereafter. Thus, solution S has $n+m$ deadheading-links where n is the number of tasks and m is the number of routes. Let $V_R \subset V$ be a set of vertices that belong to the required edges, let $V'_R = V_R \cup \{v_d\}$ be a set containing both the vertices of V_R and the depot vertex v_d , let $\Pi = \{(u, v) | u, v \in V'_R\}$ be the set of all possible deadheading-links. Given two solutions S^i with m_i routes and S^j with m_j routes, their Hamming distance $D_{i,j}$ is defined as the number of different deadheading-links between S^i and S^j :

$$D_{i,j} = (n+m) - \sum_{(u,v) \in \Pi} x_{uv} \quad (3)$$

where $m = \min\{m_i, m_j\}$,

$$x_{uv} = \begin{cases} 1, & \text{if } (u, v) \text{ is a deadheading-link of both } S^i \text{ and } S^j \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

Given a population $POP = \{S^1, S^2, \dots, S^{Psize}\}$ of size $Psize$ and the distance $D_{i,j}$ between any two individuals S^i and S^j ($i \neq j \in [1, Psize]$), the average distance between S^i and any other individual in POP is given by:

$$AD_{i,POP} = \left(\sum_{S^j \in POP, j \neq i} D_{i,j} \right) / (Psize - 1) \quad (5)$$

QNDS evaluates each solution in the population using the following quality-and-distance fitness (QDF for short) function:

$$QDF(S^i) = \alpha * OR(f(S^i)) + (1 - \alpha) * DR(AD_{i,POP}) \quad (6)$$

where $OR(f(S^i))$ and $DR(AD_{i,POP})$ represent respectively the rank of solution S^i with respect to its objective value and the average distance to the population (objective value is ranked in ascending order while average distance is ranked in descending order), and α is a parameter. We require the value of α to be higher than 0.5 to ensure that the best individual in terms of objective value will never be removed from the population, which formalizes the elitism property of QNDS.

Given an offspring S^0 (which has undergone both crossover and local refinement), QNDS first inserts S^0 into POP , evaluates the QDF value of each individual and finally removes from POP the solution S^w with the largest QDF value.

4. Local refinement procedure of HMA

The local refinement procedure is another key component of our HMA algorithm and plays an essential role in enforcing intensification which ensures the high performance of HMA. Our local refinement procedure involves two sub-procedures, i.e., a randomized tabu thresholding procedure which explores only the feasible region, and an infeasible descent procedure which visits both feasible and infeasible regions. Both sub-procedures are based on a set of move operators which are explained below. The implementation of the two sub-procedures are also described.

4.1. Move operators

Our local refinement procedure employs six move operators, including five traditional small-step-size operators: inversion, single insertion, double insertion, swap, two-opt; as well as a large-step-size operator called merge-split recently proposed in Tang et al. (2009). These operators are briefly described as follows.

Let u and v be a pair of tasks in the current solution S , tasks x and y be respectively the successor of u and v , $rt(u)$ be the route including task u .

- Inversion (IV): replace the current arc of task u with its reverse arc in S ;
- Single insertion (SI): displace task u after task v (also before task v if v is the first task of $rt(v)$); both arcs of u are considered when inserting u in the target position, and the one yielding the best solution is selected;
- Double insertion (DI): displace a sequence (u, x) after task v (also before task v if v is the first task of $rt(v)$); similar to SI, both directions are considered for each task and the resulting best move is chosen;
- Swap (SW): exchange task u and task v ; similar to SI, both directions are considered for each task to be swapped and the resulting best move is chosen;
- Two-opt (TO): two cases exist for this move operator: 1) if $rt(u) = rt(v)$, reverse the direction of the sequence (x, v) ; 2) if $rt(u) \neq rt(v)$, cut the link between (u, x) and (v, y) , and establish a link between (u, y) and (v, x) ;
- Merge-split (MS): this operator obtains an unordered list of tasks by merging multiple routes of the current solution, and sorts the unordered list with the path scanning heuristic (Golden et al., 1983). It then optimally splits the ordered list into new routes using the Ulusoy's splitting procedure (Ulusoy, 1985). Each application of this operator results in five new solutions and the best one is chosen. Interested readers are referred to Tang et al. (2009) for more details.

In the following two subsections, we explain how these operators are used in our two local refinement sub-procedures.

4.2. Randomized tabu thresholding procedure

The proposed randomized tabu thresholding procedure (RTTP) follows the general principle of the Tabu Thresholding (TT) method whose basis was first proposed in Glover (1995). A main ingredient of TT is the candidate list strategy (CLS) which is dedicated to reduce the number of moves to be considered in order to accelerate the neighborhood examination. CLS subdivides the possible moves of the current solution into subsets and executes one move for each subset rather than for the whole neighborhood. CLS, along with the elements of probabilistic tabu search, simulates the tabu mechanism with memory structure. RTTP is a randomized procedure in the sense that it explores multiple neighborhoods in a random order.

4.2.1. Outline of the randomized tabu thresholding procedure

The randomized tabu thresholding procedure basically alternates between a *Mixed phase* and an *Improving phase* where for both phases, five traditional move operators are employed: inversion, single insertion, double insertion, swap and two-opt. Algorithm 2 sketches the outline of the RTTP procedure for CARP.

Algorithm 2: Outline of the RTTP for CARP.

Data: P - a CARP instance, St - a set of tabu timing values, r - threshold ratio, W - the number of non-improving attractors visited, S_0 - an initial solution;

Result: the best solution S^* found so far;

```

1  $O \leftarrow \{IV, SI, DI, SW, TO\}$ ; /*  $O$  contains five move operators */
2  $S^* \leftarrow S_0$ ; /*  $S^*$  records the global best solution */
3  $S \leftarrow S_0$ ; /*  $S$  records the current solution */
4  $f_p \leftarrow f(S^*)$ ; /*  $f_p$  records the best local optimum objective value */
5  $w \leftarrow 0$ ; /* set counter for consecutive non-improving local optima */
6 while  $w < W$  do
7    $T \leftarrow \text{random\_select}(St)$ ;
8   // Mixed Phase
9   for  $k \leftarrow 1$  to  $T$  do
10    Randomly shuffle all operators in  $O$ ;
11    for each  $o \in O$  do
12      Randomly shuffle tasks of  $S$  in  $M$ ;
13      for each  $i \in M$  do
14         $(S, S^*) \leftarrow$  Apply operator  $o$  to task  $i$  by searching  $\text{MOVE\_CL}(i, S, o)$  and accepting a move according to the quality threshold;
15      // Improving Phase
16      while Improving moves can be found do
17        Randomly shuffle all operators in  $O$ ;
18        for each  $o \in O$  do
19          Randomly shuffle tasks of  $S$  in  $M$ ;
20          for each  $i \in M$  do
21             $(S, S^*) \leftarrow$  Apply operator  $o$  to task  $i$  by searching  $\text{MOVE\_CL}(i, S, o)$  and accepting the first met improving move;
22          if  $f(S) < f_p$  then
23             $f_p \leftarrow f(S)$ ;  $w \leftarrow 0$ ;
24          else
25             $w \leftarrow w + 1$ ;

```

RTTP starts by initializing a set of global variables with an initial solution S_0 taken from an external input. RTTP then enters the main loop where *Mixed phase* and *Improving phase* alternate.

In the *Mixed phase*, for any move operator o and for a given task i , RTTP examines the candidate list $\text{MOVE_CL}(i, S, o)$ in random order and accepts the first improving feasible move if any, or the best admissible feasible move otherwise. The admissible feasible move satisfies a quality threshold TV , i.e., $f(S') \leq TV$ where S' is the neighboring solution generated by the accepted move. TV is calculated as: $TV = (1 + r) * f_p$, where f_p is the current best local optimum objective value, and r is a threshold ratio. With this quality threshold, deteriorating solutions are allowed in order to diversify the search. Solution cycling is prevented through the complete reshuffling of the order in which candidate lists are examined before each neighborhood examination. An iteration of the *Mixed phase* is based on the examination of the complete neighborhoods of all move operators. The *Mixed phase* is repeated for T iterations.

T is called a tabu timing parameter, which is analogous to the tabu tenure when an explicit tabu list is used. T is randomly selected among the values of a given set St .

In the *Improving phase*, RTTP always seeks an improving move among the feasible moves within each candidate list $\text{MOVE_CL}(i, S, o)$. If no improving move is found in a given candidate list, RTTP skips to the next candidate list. This phase is iterated until no improving move can be found in any candidate list.

If the local optimum reached in the *Improving phase* has a better objective value than the recorded best objective value f_p , the algorithm updates f_p and resumes a new round of *Mixed – Improving* phases. RTTP terminates when f_p has not been updated for a consecutive W *Mixed – Improving* phases.

4.2.2. Construct candidate list

When using the five traditional move operators, neighborhoods of the current solution can always be obtained by operating on two distinct tasks. For instance, *insertion* is to insert one task after or before another task; *swap* is to swap one task with another task; *two-opt* is to exchange the subsequent part of a task with that of another one. As such, given a move operator o , a natural choice for the subsets to be used in the candidate list strategy is to define one subset $\text{MOVE_SUBSET}(i, S, o)$ for each task i . In order to speed up neighborhood examination, we further use an estimation criterion to discard moves from $\text{MOVE_SUBSET}(i, S, o)$ that are unlikely to lead to a promising solution. This estimation criterion is based on a distance measure between two tasks t_1, t_2 which is defined as:

$$D_{\text{task}}(t_1, t_2) = \left(\sum_{a=1}^2 \sum_{b=1}^2 D(v_a(t_1), v_b(t_2)) \right) / 4 \quad (7)$$

where $D(v_a(t_1), v_b(t_2))$ is the traversing distance between t_1 's a th end node $v_a(t_1)$ and t_2 's b th end node $v_b(t_2)$. (This distance measure was first used in Mei et al. (2014) to define the distance between two routes.) The candidate move list associated to task i ($\text{MOVE_CL}(i, S, o)$) is restricted to contain $Csize$ most promising moves such that for each move which is associated with two tasks (i, t) , t is a member of i 's $Csize$ closest neighboring tasks according to the distance measure of formula (7).

4.3. Infeasible descent procedure

For a constrained optimization problem like CARP, it is known that allowing a controlled exploration of infeasible solutions may facilitate transitions between structurally different solutions and help discover high-quality solutions that are difficult to locate if the search is limited to the feasible region. This observation is highlighted by discoveries made with the strategic oscillation approach (see, e.g., Glover & Hao, 2011) which alternates between phases of infeasible descent and phases of improving feasible search. To further intensify the search, we employ in our local refinement procedure, as a complement to RTTP, an infeasible descent procedure (IDP) which allows visiting infeasible solutions. IDP is a best-improvement descent procedure based on three traditional move operators, i.e., single insertion, double insertion, swap, as well as a large-step-size merge-split operator that was recently proposed and proved to be effective for CARP (Tang et al., 2009). We use the merge-split operator in the way as suggested in Tang et al. (2009). IDP basically involves two different stages. In the first stage, IDP examines the complete neighborhoods induced by the SI, DI and SW operators and chooses the best move to perform if it improves the current solution. When no improvement can be found in the first stage, IDP switches to the second stage where it examines the neighboring solutions generated by the MS operator. Since MS is computationally expensive, IDP restricts the examination to a maximum of 100 neighboring solutions which are

randomly sampled from the C_m^2 possibilities where m is the number of routes. If $C_m^2 \leq 100$, all neighboring solutions will be examined. Still, the best improving move is performed until no improvement is reported in this stage. If any improvement is found in the second stage, IDP switches back to the first stage to explore the new local region and terminates the algorithm when this stage is finished; otherwise, IDP terminates at the end of the second stage. As in many previous CARP algorithms which allow intermediate infeasible solutions (Beullens et al., 2003; Brandão & Eglese, 2008; Hertz et al., 2000; Tang et al., 2009), we evaluate the solution quality generated in the search process of IDP by adding a penalty item to the original cost:

$$\phi(S) = f(S) + \beta * EX(S) \quad (8)$$

where $EX(S)$ is the total excess demand of S and β is a self-adjusting penalty parameter. β is halved (doubled) if feasible (infeasible) solutions have been achieved for five consecutive iterations, and its initiating value is set to:

$$\beta = f(S) / (2 * Q) \quad (9)$$

where Q is the vehicle capacity. One notices that we don't consider the violation of S in Eq. 9. This is because we always ensure that IDP starts the search from a feasible solution.

4.4. Combination of RTTP and IDP

After presenting the implementation of RTTP and IDP, the order of combining them in the local refinement procedure remains an issue to be addressed. RTTP is the most important component of our HMA algorithm which compared to IDP, makes more contribution to the high performance of HMA, but also consumes more computing time (see the analysis in Section 6.1). IDP is a very simple descent procedure which, when used alone, is not expected to identify very high quality solutions (see the analysis in Section 6.1). However, the search ability of RTTP and IDP can be mutually strengthened when they are combined. Indeed, it is beneficial to put IDP either before or after RTTP. When IDP is placed before RTTP, the best feasible solution found by IDP can be considered as a good starting point for RTTP. This is because the performance of neighborhood search algorithms may highly depend on the initial solution and a high-quality initial solution could help discover still better solutions. When IDP is put after RTTP, the property of tunneling through infeasible regions and the large-step-size MS operator of IDP may help to further improve the high quality solution provided by RTTP. For the above reasons, both orders (i.e., RTTP \rightarrow IDP and IDP \rightarrow RTTP) are allowed in our HMA algorithm. The order is randomly determined before the local refinement procedure is carried out.

5. Computational experiments

To evaluate the efficacy of the proposed HMA algorithm, we carry out extensive experiments on a large number of well-known CARP benchmark instances, and compare the results¹ with those of the state-of-the-art algorithms as well as the best known solutions ever reported in the literature.

HMA was coded in C++ and compiled by GNU g++ 4.1.2 with the '-O3' option. The experiments were conducted on a computer with an AMD Opteron 4184 processor (2.8 gigahertz and 2 gigabytes RAM) running Ubuntu 12.04. When solving the DIMACS machine benchmarks² without compilation optimization flag, the run time on our machine is 0.40, 2.50 and 9.55 seconds respectively for instances r300.5, r400.5 and r500.5.

5.1. Experimental setup

Our HMA algorithm was evaluated on a total of 191 benchmark graphs with 7–255 vertices and 11–375 edges. These instances are very popular and widely used in the CARP literature. They cover both random instances and real-life applications, and are typically classified into eight sets:

- **gdb**: 23 instances randomly generated by DeArmon (DeArmon, 1981), with 7–27 nodes and 11–55 required edges.
- **val**: 34 instances derived from 10 randomly generated graphs proposed by Benavent, Campos, Corberan, and Mota (1992), with 25–50 nodes and 34–97 required edges.
- **egl**: 24 instances proposed by Eglese (1994), which originate from the data of a winter gritting application in Lancashire (UK), with 77–140 nodes and 98–190 edges that include 51–190 required edges.
- **C**: 25 instances generated by Beullens et al. (2003) based on the intercity road network in Flanders, with 32–97 nodes and 42–140 edges that include 32–107 required edges.
- **D**: 25 instances modified from the instances of set C by doubling the vehicle capacity for each instance.
- **E**: 25 instances, also generated by Beullens et al. (2003) based on the intercity road network in Flanders, with 26–97 nodes and 35–142 edges that include 28–107 required edges.
- **F**: 25 instances modified from the instances of set E by doubling the vehicle capacity for each instance.
- **EGL-G**: 10 large-sized CARP instances, which like the set *egl*, were also generated based on the road network of Lancashire (UK) (Brandão & Eglese, 2008), each having 255 nodes and 375 edges with 374 to 375 required edges.

Following the common practice in the literature, we compare the results produced by our HMA algorithm on these benchmarks to those of the following eight state-of-the-art algorithms:

1. A guided local search (GLS) algorithm proposed by Beullens et al. (2003), who reported results on the instance set *gdb*, *val* and C-F.
2. A deterministic tabu search algorithm (TSA) proposed by Brandão and Eglese (2008), who reported results on all eight instance sets. Two sets of results ("TSA1" and "TSA2") were reported, and the one ("TSA2") yielding better performance will be considered for comparative study for all instance sets except for EGL-G where only results of "TSA1" were reported.
3. A variable neighborhood search (VNS) algorithm proposed by Polacek et al. (2008), who reported results on set *val* and *egl*. Two sets of results ("993 megahertz" and "3.6 gigahertz") were reported, and the one ("3.6 gigahertz") yielding better performance will be considered for comparative study.
4. A memetic algorithm with extended neighborhood search (MAENS) proposed by Tang et al. (2009), who reported results on set *gdb*, *val*, *egl* and C-F.
5. An improved ant colony optimization based algorithm (Ant-CARP) proposed by Santos et al. (2010), who reported results on set *gdb*, *val*, *egl* and C-F. Two sets of results ("Ant-CARP_6" and "Ant-CARP_12") were reported, and the one ("Ant-CARP_12") yielding overall better performance will be considered for comparative study. Hereafter, we use "Ant_12" to represent "Ant-CARP_12", and use its median results for comparison when we study the average performance of the reference algorithms since their average results are not available.
6. A GRASP with evolutionary path relinking (GRASP) proposed by Usberti et al. (2013), who reported results on the set *gdb*, *val* and *egl*.

¹ Our best solution certificates are available at: <http://www.info.univ-angers.fr/pub/hao/CARPResults.zip>.

² dfmax: <ftp://dimacs.rutgers.edu/pub/dsj/cliquote/>.

Table 1

Scaling factors for computers used in the reference algorithms. Our computer (AMD Opteron 4184) is used as the basis.

Algorithm	Reference	Processor type	Frequency (gigahertz)	Factor
HMA	–	AMD Opteron 4184	2.8	1.0
GLS	(Beullens et al., 2003)	Pentium II	0.5	0.18
VNS	(Polacek et al., 2008)	Pentium IV	3.6	1.29
TSA2	(Brandão & Eglese, 2008)	Pentium Mobile	1.4	0.50
MAENS	(Tang et al., 2009)	Intel Xeon E5335	2.0	0.71
Ant_12	(Santos et al., 2010)	Pentium III	1.0	0.36
GRASP	(Usberti et al., 2013)	Intel Core 2	3.0	1.07
ILS-RVNS	(Martinelli et al., 2013)	Intel Core i5	3.2	1.14
RDG-MAENS	(Mei et al., 2014)	Intel Core i7-2600	3.4	1.21

Table 2

Parameter tuning results.

Parameter	Description	Range	Final value
Psize	Population size	[6,16]	10
α	Parameter of QDF in pool updating	[0.51,0.90]	0.60
St	Tabu timing parameter values in RTTP	[28,33]	–
W	Maximum number of attractors in RTTP	[5,20]	10
Sr	Threshold ratios in RTTP for classical sets	{0.003,0.004,0.005,0.006}	–
	for EGL-G set	{0.0001,0.0005,0.0010,0.0015}	
Csize	Candidate list size	[6,20]	12

7. An iterated variable neighborhood descent algorithm (ILS-RVND) proposed by Martinelli, Poggi, and Subramanian (2013). We reference their reported results of set *EGL-G*.
8. A cooperative co-evolution algorithm with route distance grouping (RDG-MAENS) proposed by Mei et al. (2014). RDG-MAENS was specifically designed for large-sized CARP instances, and thus we reference their results on set *EGL-G*.

These reference algorithms were tested on different computers with a CPU frequency ranging from 500 megahertz to 3.6 gigahertz. To make a relatively fair comparison of the runtime, all CPU times reported in the reference papers are scaled here into the equivalent AMD Opteron 4184 2.8 gigahertz run times. Like in previous CARP literature (Martinelli et al., 2013; Mei et al., 2014; Santos et al., 2010; Tang et al., 2009), our time conversion is based on the assumption that the CPU speed is approximately linearly proportional to the CPU frequency. We provide in Table 1 the CPU type and its frequency of each reference algorithm, as well as its resulting scaling factors. This time conversion is only made for indicative purposes, since the computing time of each algorithm is not only influenced by the processor, but also by some inaccessible factors such as the operating systems, compilers and coding skills of the programmer. Nevertheless, we show in the following experiments, the outcomes provide interesting information about the performance of the proposed algorithm relative to the best performing algorithms.

5.2. Parameter tuning

The HMA algorithm relies on a set of correlated parameters. To achieve a reasonable tuning of the parameters, we adopt the Iterated F-race (IFR) method (Birattari, Yuan, Balaprakash, & Stützle, 2010), which allows an automatic parameter configuration, using the IFR algorithm that is implemented and integrated in the irace package (López-Ibáñez, Dubois-Lacoste, Stützle, & Birattari, 2011). Table 2 summarizes the parameters of our HMA algorithm, along with the range of values that were determined by preliminary experiments. Among these parameters, four of them (Psize, α , W, Csize) need to be tuned and the other two parameters (threshold ratio r and tabu timing parameter T) are adaptively or randomly chosen among the values in the given sets (Sr and St) during the search process. We set the tuning budget to 1000 runs of HMA and

each run is given 100 generations. We restrict the training set to contain 8 challenging instances taken from *val*, *egl*, *C*, *E* and *EGL-G* sets: *val*-10D, *egl*-e3-B, *egl*-s3-C, C11, E12, E15, *EGL-G*-1-B, *EGL-G*-2-B. The final choices of the parameter values are presented in Table 2 and they are used in all experiments in the following sections unless otherwise mentioned.

5.3. Comparative results on 7 classical instance sets

We first assess HMA on the 7 most commonly used instance sets (181 instances): *gdb*, *val*, *egl*, *C*, *D*, *E*, *F*. It is compared to 5 current state-of-the-art algorithms: GLS (Beullens et al., 2003), TSA2 (Brandão & Eglese, 2008), VNS (Polacek et al., 2008), Ant-CARP (Santos et al., 2010), GRASP (Usberti et al., 2013), and MAENS (Tang et al., 2009). To give a general picture of the performance of each compared algorithm, we summarize in Table 3, for each instance set and for each algorithm, the number of best results that match or improve on the best known results (#Best), the number of average results that match or improve on the best known results (#BestAvg), the average gap between the average results and the best known results in percentage (AvgGap, the gap is calculated as $(f_{avg} - f_{bk}) \times 100 / f_{bk}$ where f_{avg} is the average solution value obtained by the algorithm and f_{bk} is the best known solution value reported in the literature), and the average of the instance computing time in seconds (AvgTime). When we count #Best, we refer to the current best known results (BKR) which are compiled from the “best results” reported in all previous CARP literature. These “best results” could be those obtained by a single algorithm with various parameter settings (e.g., Lacomme et al., 2004; Polacek et al., 2008; Santos et al., 2010) or even with a specific setting tuned for each instance (e.g., TSA_{best} in Brandão & Eglese, 2008). Finally, to complement these summarized results, Appendix A (Tables A.1–A.7) reports, for each of the 181 CARP instance, the detailed results of our HMA algorithm as well as the average results of the reference algorithms. These tables permit a thorough assessment of all compared algorithms.

Note that some results were obtained from a single run of the algorithms (GLS and TSA) whereas other results came from multiple runs (VNS, GRASP, Ant-CARP, MAENS, HMA1 and HMA2). Clearly, #Best favors multiple-run results. To make a fair comparison, we refer to average statistics (#BestAvg, AvgGap, AvgTime) when we compare single-run results with multiple-run results.

Table 3

Comparative statistical results on the 7 classical instance sets: gdb, val, egl, C-F. The best result of each row is indicated in bold. The results of HMA₂ are starred if they improve on the results of HMA₁.

		GLS 1 run	TSA2 1 run	VNS 10 runs	GRASP 15 runs	Ant_12 10 runs	MAENS 30 runs	HMA ₁ 30 runs	HMA ₂ 30 runs
gdb	#Best	23	21	-	23	22	23	23	23
	#BestAvg	23	21	-	19	21	22	23	23
	AvgGap	0.00	0.07	-	0.11	0.10	0.01	0.00	0.00
	AvgTime	0.32	1.23	-	5.47	1.21	4.47	1.19	1.19
val	#Best	30	29	32	30	29	31	32	34*
	#BestAvg	30	29	26	0	26	0	29	30
	AvgGap	0.05	0.14	0.09	0.12	0.17	0.18	0.03	0.02*
	AvgTime	14.64	10.09	56.70	65.85	9.11	48.35	11.23	26.71
egl	#Best	-	4	11	12	11	12	15	23*
	#BestAvg	-	4	4	3	9	2	9	14*
	AvgGap	-	0.75	0.56	0.50	0.58	0.59	0.13	0.07*
	AvgTime	-	145.68	649.17	854.48	181.09	498.49	198.83	646.03
C	#Best	20	18	-	-	22	23	24	25*
	#BestAvg	20	18	-	-	16	3	18	23
	AvgGap	0.12	0.14	-	-	0.52	0.98	0.06	0.02*
	AvgTime	42.49	42.92	-	-	40.76	165.50	36.88	54.22
D	#Best	24	17	-	-	23	23	25	25
	#BestAvg	24	17	-	-	20	10	20	23
	AvgGap	0.04	0.66	-	-	0.34	0.79	0.17	0.10
	AvgTime	17.36	19.20	-	-	51.88	219.53	14.65	35.13
E	#Best	19	17	-	-	20	20	23	25*
	#BestAvg	19	17	-	-	16	5	16	20
	AvgGap	0.20	0.39	-	-	0.83	1.44	0.19	0.08*
	AvgTime	40.65	46.00	-	-	40.54	160.89	42.62	116.54
F	#Best	25	15	-	-	22	25	25	25
	#BestAvg	25	15	-	-	20	12	25	25
	AvgGap	0.00	0.90	-	-	0.77	1.01	0.00	0.00
	AvgTime	10.67	21.09	-	-	52.17	166.85	8.44	8.44

For each instance, our HMA algorithm was run 30 times under two different stop criteria: 500 generations and 2000 generations. To ease presentation, we denote HMA with 500 generations as HMA₁, and HMA with 2000 generations as HMA₂. Studying the outcomes of these two termination criteria affords insights into how HMA behaves when more computing time is available.

From Table 3, we can see that HMA₁ shows a remarkable performance on all 7 tested instance sets compared to the multiple-run reference algorithms. Indeed, it attains the largest number of best known results for all 7 data sets and the lowest average gap to the best known results for 6 out of 7 sets. Compared to Ant_12 and MAENS which, like HMA₁, are both population-based algorithms, HMA₁ clearly shows its dominance in terms of both best results and average results. For set D, HMA₁ is the only algorithm which is able to find all BKR. Additionally, HMA₁ obtains improved best known results on three well-studied instances from set egl. By increasing the HMA₁ termination criterion of 500 to 2000 generations, HMA₂ achieves a still better performance, always obtaining equal or better results in terms of both #Best and AvgGap. In particular, for set egl, HMA₂ discovers 6 new BKR and matches 6 more BKR, leading to #Best = 23 which is significantly larger than those obtained by the reference algorithms. HMA₂ is able to achieve overall 180 current or new BKR out of 181 instances with one standard parameter setting, while the previous BKR are compiled from many previous articles, among which some were obtained with parameters specifically tuned for individual instance.

Now we turn to compare our HMA algorithm to the single-run reference algorithms. As mentioned before, we should look at average statistics when comparing multiple-run algorithms to single-run algorithms. According to two average indicators, namely #BestAvg and AvgGap, GLS is clearly the best performing single-run algorithm among all 6 reference algorithms (including single-run algorithms and multiple-run ones). Still, compared to GLS, our HMA algorithm remains competitive on 6 instance sets (i.e., gdb,

val and C-F). Indeed, when the short time limit (500 generations) is applied, HMA₁ performs better in items of AvgGap (by achieving an equal or lower AvgGap for more instance sets: 5 vs. 3), but worse in terms of #BestAvg (by attaining an equal or higher #BestAvg for less instance sets: 2 vs. 6). On set D, both HMA₁ and HMA₂ are dominated by GLS in terms of both indicators. Finally, one observes that when given more computing time, HMA₂ is able to further improve its results.

To validate the above observations, we apply a Wilcoxon test with a significance factor of 0.05 for a pairwise comparison of the average performance between HMA₁ and TSA2, Ant_12 as well as MAENS, which are three approaches that have been tested on all 181 instances. The resulting p-values of 2.15E-10, 9.31E-10 and 2.20E-16 confirm that the results of HMA₁ are significantly better than those of these current best performing algorithms. This conclusion remains valid for HMA₂ since it always performs better than HMA₁.

When it comes to computational time ('AvgTime' in Table 3), our HMA algorithm also remains competitive. Recall that the indicated time for the reference algorithms are scaled according to our computer and the average time of a multiple-run algorithm can be compared to the time of a single-run algorithm. Table 3 shows that HMA₁ is in overall not slower than any of the reference algorithms. Compared to the fast GLS, TSA2 and Ant_12 algorithms, HMA₁ generally requires comparable computing time. Compared to the remaining reference algorithms (i.e., VNS, GRASP and MAENS), HMA₁ is clearly more efficient. By extending the stop condition to 2000 generations, HMA₂, which finds improved solutions, consumes more computing time than HMA₁ as expected.

Finally, the "best results" reported by previous CARP studies were often achieved by executing tests involving multiple parameter settings to show the extreme performance of the associated algorithms. Following this practice, we report in Appendix A some new best known results discovered by our HMA algorithm with

5.4. Comparative results on the EGL-G set

As before, HMA was executed 30 runs to solve each instance under two termination criteria: 500 generations (HMA_1) and 2000 generations (HMA_2). We also report the results obtained by HMA with various other parameter settings (HMA^*). Table 4 summarizes our results on the EGL-G set, along with those of the current best performing algorithms: TSA1, ILS, MAENS, RDG-MAENS. In Mei et al. (2014), the authors report the results of RDG-MAENS for 6 parameter combinations of (g, α) where $g = 2$ and 3, $\alpha = 1, 5$ and 10. We include the results of the best version ($g = 2, \alpha = 10$) for our comparative study. Table 4 lists the average results of each algorithm, the solution time of HMA, the best lower bounds (LB), the best known results (BKR), and the best results of HMA. The last two rows show, for each algorithm, the average of the average gaps to the BKR ($AvgGap$), and the “scaled” average of the average solution time ($AvgTime$).

A Wilcoxon test is finally applied to a pairwise comparison of the average performance between HMA₁ and each of the four reference methods, which always results in a p-value of 0.001953 (<0.05) for all tested pairs, indicating the superiority of our method relative to the compared approaches.

Table 4
Comparative results of our HMA algorithm with 4 state-of-the-art algorithms on the 10 instances of EGL-G set. The best average results and best results are in bold. The best result of HMA* is starred if it improves on the BKR.

INST	(N ₁ , E _K)	Average results					Best results							
		TSA1 1 run	ILS 10 runs	MAENS 30 runs	RDG 30 runs	HMA ₁ 30 runs	Time	HMA ₂ 30 runs	Time	LB	BKR	HMA ₁	HMA ₂	HMA*
G1-A	(255,347)	1049708	1010937.40	1009302	1007619	992823.00	1221.45	992300.33	3209.16	976907	998777	992337	992045	992045*
G1-B	(255,347)	1140692	1137141.50	1128114	1122863	1117198.77	1354.57	1114992.53	3961.81	1093884	1111971	1114125	1112245	1112245
G1-C	(255,347)	1282270	1266576.80	1255709	1250174	1240200.13	1453.32	1237543.93	4288.60	1212151	1241762	1235062	1233536	1231335*
G1-D	(255,347)	1420126	1406929.20	1390034	1386120	1374555.27	1411.71	1371488.53	3768.35	1341918	1371443	1370331	1365259*	1365259*
G1-E	(255,347)	1581333	1554229.20	1535511	1525629	1516790.63	1338.02	1513731.10	3496.35	1482176	1512584	1511684	1506179	1503871*
G2-A	(255,375)	1129229	1118363.00	1109376	1104944	1095027.80	1816.93	1091999.37	4566.27	1069536	1094912	1090595	1088040	1088040*
G2-B	(255,375)	1255907	1233720.50	1225361	1221429	1206313.77	1749.72	1201944.50	4972.88	1185221	1208326	120817	1199272*	1199272*
G2-C	(255,375)	1418145	1374479.70	1358398	1355548	1338918.87	1646.83	1337615.83	3913.69	1311339	1341519	1334130	1332791	1331646*
G2-D	(255,375)	1516103	1515119.30	1500415	1492063	1480175.70	1580.93	1477007.10	4464.64	1446680	1481181	1473099	1471107	1470059*
G2-E	(255,375)	1701681	1658378.10	1641260	1629002	1618924.97	1655.15	1615848.83	4407.06	1581459	1618899	1611364	1606807	1606079*
AvgCap		3.94	2.22	1.32	0.89	-0.02		-0.22		-	-	-	-	-
AvgTime		510.55	1163.71	2437.30	1633.86	1522.86		4104.88		-	-	-	-	-

Table 5

Analysis of the components of the local refinement procedure using a single solution approach.

	IDP	TTP	RTTP	I+R	RST	HMA ₁
BestGap	4.63	0.69	0.65	0.55	0.14	0.01
AvgGap	9.30	1.80	1.79	1.80	0.29	0.13
AvgTime	0.07	0.98	0.98	0.99	213.02	198.83

6. Analysis

In this section, we present additional experimental results to analyze the performance of each algorithmic component of the proposed HMA algorithm, in order to understand their contribution to the overall performance of HMA and how they should be combined in the proposed algorithm. These experiments were performed on the *egl* set which contains a number of challenging instances of medium size, and helps to better distinguish the performance of the algorithm variants to be considered.

6.1. Analysis of algorithmic components

To provide insight of the performance of the local refinement procedure and the crossover operator, we test in this experiment several algorithm variants based on a single solution rather than a population of solutions. The “IDP” version is a very simple algorithm having only solution initialization (random path scanning) and IDP as its two components. Similar to “IDP”, the “RTTP” version includes only the solution initialization and the RTTP procedure. The “TTP” version is exactly the same as “RTTP” except that the move operators are used in a fixed order as they are presented in Section 4.1. The “I+R” version combines IDP and RTTP in random order. The “RST” version is a random restart algorithm that simply starts “I+R” for 500 times. We also include the results of HMA₁ (500 generations) for comparative purposes. For each algorithm variant, we report in Table 5 the average of the best gap to the BKR in percentage (BestGap), and the average of the average gap to the BKR in percentage (AvgGap), as well as the average computing time in seconds (AvgTime).

Table 5 shows that TTP performs much better than IDP. RTTP further improves on TTP which shows the effectiveness of the random use of move operators. The results of “I+R” indicates that though RTTP is a very crucial component, its performance can be still ameliorated by a random collaboration with IDP. The comparative results of RST and HMA₁ clearly shows the relevance of the crossover operator and the population-based framework.

6.2. Analysis under the population-based framework

Given that both the local refinement procedures and the crossover operator are effective, this part of analysis investigates how they should be combined to achieve the best performance. For this purpose, we propose another set of algorithm variants based on a population of solutions. The “XO+I” version is obtained by removing the RTTP procedure from HMA, “XO+R” version by removing IDP from HMA. “XO+I → R” version works all the same as HMA, except that the order of using IDP and RTTP is fixed to I → R. Similarly, “XO+R → I” uses the order R → I. Table 6 summarizes the results of these algorithm variants, along with those of HMA₁. Without surprise, using only IDP in the local refinement procedure shows a rather poor performance, while employing RTTP in the local refinement procedure leads to a much better performance. Compared to “XO+R”, including an additional IDP in the local refinement procedure never leads to a definitely better performance if the order of using IDP and RTTP is fixed. However, if IDP and

Table 6

Analysis of different combinations of the crossover operator and the local refinement procedure using a population of solutions.

	XO+I	XO+R	XO+I → R	XO+R → I	HMA ₁
BestGap	0.72	0.02	0.02	0.04	0.01
AvgGap	1.59	0.16	0.16	0.15	0.13
AvgTime	6.77	254.11	158.37	244.20	198.83

Table 7

Analysis of the quality-and-distance pool updating strategy.

	HMA _{PW1}	HMA ₁	HMA _{PW2}	HMA ₂
BestGap	0.02	0.01	0.00	-0.04
AvgGap	0.15	0.13	0.10	0.07
AvgTime	188.15	198.83	437.34	646.03

RTTP are used in a random order as in HMA, a better performance can be observed in terms of both BestGap and AvgGap.

6.3. Analysis on the pool updating strategy

The third part of the analysis investigates the effectiveness of our pool updating strategy, which uses the hamming distance to control the diversity of the population. We therefore compare the adopted strategy to a traditional “pool worst” strategy which simply replaces the worst solution in terms of fitness in the population, leading to an algorithm variant denoted as HMA_{PW}. HMA_{PW} was tested under two termination criteria: 500 generations (HMA_{PW1}) and 2000 generations (HMA_{PW2}), and the outcomes are compared to those of HMA₁ and HMA₂. The computational results are summarized in Table 7, from which we can clearly see that HMA₁ performs better than HMA_{PW1}, and the superiority of HMA₂ relative to HMA_{PW2} enlarges when more computing time is allowed. This experiment confirms the usefulness of the diversity control mechanism used in our HMA.

7. Conclusions

The capacitated arc routing problem (CARP) is of great practical interest and represents a significant computational challenge due to its NP-hardness. We developed a new hybrid metaheuristic approach (HMA) for effectively solving CARP, which employs a randomized tabu thresholding procedure (RTTP) coupled with an infeasible descent procedure to explore both feasible and infeasible regions. HMA relies on a specialized route-based crossover operator to generate diversified and promising new solutions. Thanks to its quality-and-distance based pool updating strategy, HMA prevents the search process from premature convergence.

The proposed approach demonstrates an excellent performance over the eight sets of 191 popular CARP benchmarks. Specifically, on the 7 sets of 181 classical instances, HMA with a standard parameter setting outperforms the current best performing algorithms, in terms of both solution quality and computational efficiency. HMA further improves its own performance when more computing time is available (to run 2000 generations), attaining the best known results for all 181 cases including 6 improved new best results. HMA also proves to be scalable to handle the last set of 10 large-sized instances, by obtaining 9 new best results, dominating the current state-of-the-art algorithms including the approaches which were specially designed for the large-sized CARP instances. We additionally conducted experiments to analyze the contribution of the two sub-procedures for local refinement, the relevance of the route-based crossover operator (and thus the population-based framework), the strategy for combining crossover

with the local optimization procedure, as well as the quality-and-distance pool updating strategy.

Finally, we observe that the proposed method can be adapted to handle other CARP variants with slight modifications of the route-based crossover operator and of the local refinement procedure to accommodate additional constraints.

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Appendix A

This appendix shows the detailed results of our HMA algorithm on the 181 conventional CARP instances (Tables A.1–A.7). We also include in Table A.3 the new best known results (BKR) discovered by HMA on *egl* instances with various parameter settings (indicated by HMA*) other than the standard setting given in Table 2.

Table A.1

Detailed comparative results of HMA algorithm with five state-of-the-art algorithms on the 23 instances of Set gdb. The average results of all algorithms and the best results of HMA₁ (500 generations) are highlighted in bold if they match the BKR. The optimal BKR are underlined.

INST	(N , E)	Average (median) results							Best results	
		GLS 1 run	TSA2 1 run	Ant_12 10 runs	GRASP 15 runs	MAENS 30 runs	HMA ₁ 30 runs	Time	BKR	HMA ₁
1	(12,22)	316	316	316	316.00	316.00	316.00	0.09	<u>316</u>	316
2	(12,26)	339	339	339	339.00	339.00	339.00	0.16	<u>339</u>	339
3	(12,22)	275	275	275	275.00	275.00	275.00	0.09	<u>275</u>	275
4	(11,19)	287	287	287	287.00	287.00	287.00	0.08	<u>287</u>	287
5	(13,26)	377	377	377	377.00	377.00	377.00	0.13	<u>377</u>	377
6	(12,22)	298	298	298	298.00	298.00	298.00	0.13	<u>298</u>	298
7	(12,22)	325	325	325	325.00	325.00	325.00	0.09	<u>325</u>	325
8	(27,46)	348	348	348	349.50	348.70	348.00	14.01	<u>348</u>	348
9	(27,51)	303	303	303	303.60	303.00	303.00	3.20	<u>303</u>	303
10	(12,25)	275	275	275	275.00	275.00	275.00	0.12	<u>275</u>	275
11	(22,45)	395	395	395	395.00	395.00	395.00	0.34	<u>395</u>	395
12	(13,23)	458	458	458	458.00	458.00	458.00	0.24	<u>458</u>	458
13	(10,28)	536	540	544	542.60	536.00	536.00	6.59	<u>536</u>	536
14	(7,21)	100	100	100	100.00	100.00	100.00	0.11	<u>100</u>	100
15	(7,21)	58	58	58	58.00	58.00	58.00	0.10	<u>58</u>	58
16	(8,28)	127	127	127	127.00	127.00	127.00	0.14	<u>127</u>	127
17	(8,28)	91	91	91	91.00	91.00	91.00	0.13	<u>91</u>	91
18	(9,36)	164	164	164	164.00	164.00	164.00	0.16	<u>164</u>	164
19	(8,11)	55	55	55	55.00	55.00	55.00	0.05	<u>55</u>	55
20	(11,22)	121	121	121	121.00	121.00	121.00	0.12	<u>121</u>	121
21	(11,33)	156	156	156	156.00	156.00	156.00	0.19	<u>156</u>	156
22	(11,44)	200	200	200	200.00	200.00	200.00	0.33	<u>200</u>	200
23	(11,55)	233	235	235	234.70	233.00	233.00	0.71	<u>233</u>	233
AvgGap		0.00	0.07	0.10	0.11	0.01	0.00		-	-
AvgTime (scaled)		0.32	1.23	1.21	5.47	4.47	1.19		-	-

Table A.2

Detailed comparative results of HMA algorithm with 6 state-of-the-art algorithms on the 34 instances of Set val. The average results of all algorithms and the best results of HMA₁ (500 generations) and HMA₂ (2000 generations) are highlighted in bold if they match the BKR. The optimal BKR are underlined.

INST	(N , E)	Average (median) results										Best results		
		GLS 1 run	TSA2 1 run	VNS 10 runs	Ant_12 10 runs	GRASP 15 runs	MAENS 30 runs	HMA ₁ 30 runs	Time	HMA ₂ 30 runs	Time	BKR	HMA ₁	HMA ₂
1A	(24,39)	173	173	173.00	173	173.00	173.00	173.00	0.28	173.00	0.28	<u>173</u>	173	173
1B	(24,39)	173	173	173.00	173	173.00	173.00	173.00	0.33	173.00	0.33	<u>173</u>	173	173
1C	(24,39)	245	245	245.00	245	245.00	245.00	245.00	0.43	245.00	0.43	<u>245</u>	245	245
2A	(24,34)	227	227	227.00	227	227.00	227.00	227.00	0.16	227.00	0.16	<u>227</u>	227	227
2B	(24,34)	259	259	259.00	259	259.00	259.00	259.00	6.37	259.00	6.37	<u>259</u>	259	259
2C	(24,34)	457	457	457.00	457	457.30	457.20	457.17	10.18	457.00	12.90	<u>457</u>	457	457
3A	(24,35)	81	81	81.00	81	81.00	81.00	81.00	0.17	81.00	0.17	<u>81</u>	81	81
3B	(24,35)	87	87	87.00	87	87.00	87.00	87.00	0.25	87.00	0.25	<u>87</u>	87	87
3C	(24,35)	138	138	138.00	138	138.00	138.00	138.00	0.31	138.00	0.31	<u>138</u>	138	138
4A	(41,69)	400	400	400.00	400	400.00	400.00	400.00	0.43	400.00	0.43	<u>400</u>	400	400
4B	(41,69)	412	412	412.00	412	412.00	412.00	412.00	0.44	412.00	0.44	<u>412</u>	412	412
4C	(41,69)	428	428	428.00	428	430.30	431.10	428.00	1.22	428.00	1.22	<u>428</u>	428	428
4D	(41,69)	530	530	531.20	530	531.00	532.90	530.00	6.39	529.87	17.57	<u>528</u>	530	528
5A	(34,65)	423	423	423.00	423	423.00	423.00	423.00	0.49	423.00	0.49	<u>423</u>	423	423
5B	(34,65)	446	446	446.00	446	446.00	446.00	446.00	0.41	446.00	0.41	<u>446</u>	446	446
5C	(34,65)	474	474	474.00	474	474.00	474.00	474.00	0.48	474.00	0.48	<u>474</u>	474	474
5D	(34,65)	579	583	579.80	583	584.50	582.90	576.33	59.65	575.60	210.21	<u>575</u>	575	575
6A	(31,50)	223	223	223.00	223	223.00	223.00	223.00	0.25	223.00	0.25	<u>223</u>	223	223
6B	(31,50)	233	233	233.00	233	233.00	233.00	233.00	0.82	233.00	0.82	<u>233</u>	233	233

(continued on next page)

Table A.2 (continued)

INST	(N , E)	Average (median) results										Best results		
		GLS 1 run	TSA2 1 run	VNS 10 runs	Ant_12 10 runs	GRASP 15 runs	MAENS 30 runs	HMA ₁ 30 runs	Time	HMA ₂ 30 runs	Time	BKR	HMA ₁	HMA ₂
6C	(31,50)	317	317	317.00	317	317.00	317.00	317.00	0.54	317.00	0.54	<u>317</u>	317	317
7A	(40,66)	279	279	279.00	279	279.00	279.00	279.00	0.41	279.00	0.41	<u>279</u>	279	279
7B	(40,66)	283	283	283.00	283	283.00	283.00	283.00	0.37	283.00	0.37	<u>283</u>	283	283
7C	(40,66)	334	334	334.00	334	334.00	334.00	334.00	0.48	334.00	0.48	<u>334</u>	334	334
8A	(30,63)	386	386	386.00	386	386.00	386.00	386.00	0.39	386.00	0.39	<u>386</u>	386	386
8B	(30,63)	395	395	395.00	395	395.00	395.00	395.00	0.43	395.00	0.43	<u>395</u>	395	395
8C	(30,63)	521	529	522.00	527	526.50	525.90	521.00	58.00	521.00	58.00	<u>521</u>	521	521
9A	(50,92)	323	323	323.00	323	323.00	323.00	323.00	1.09	323.00	1.09	<u>323</u>	323	323
9B	(50,92)	326	326	326.00	326	326.00	326.00	326.00	0.83	326.00	0.83	<u>326</u>	326	326
9C	(50,92)	332	332	332.00	332	332.00	332.00	332.00	0.88	332.00	0.88	<u>332</u>	332	332
9D	(50,92)	391	391	390.80	391	392.10	391.00	390.03	112.24	389.50	391.30	<u>389</u>	389	389
10A	(50,97)	428	428	428.40	428	428.00	428.00	428.00	1.52	428.00	1.52	<u>428</u>	428	428
10B	(50,97)	436	436	436.60	436	436.00	436.00	436.00	2.45	436.00	2.45	<u>436</u>	436	436
10C	(50,97)	446	446	447.00	446	446.20	446.00	446.00	1.78	446.00	1.78	<u>446</u>	446	446
10D	(50,97)	526	530	526.90	528	530.60	533.60	526.37	111.37	526.00	194.26	<u>525</u>	526	525
AvgGap		0.05	0.14	0.09	0.12	0.17	0.18	0.03		0.02		-	-	-
AvgTime (scaled)		14.64	10.09	56.70	9.11	65.85	48.35	11.23		26.71		-	-	-

Table A.3

Detailed comparative results of HMA algorithm with five state-of-the-art algorithms on the 24 instances of Set egl. The average results of all algorithms and the best results of HMA₁ (500 generations) and HMA₂ (2000 generations) are highlighted in bold if they match the BKR. The best results of HMA* are starred if they are new BKR. The optimal BKR are underlined.

INST	(N , E)	Average (median) results										Best results				
		TSA2 1 run	VNS 10 runs	Ant_12 10 runs	GRASP 15 runs	MAENS 30 runs	HMA ₁ 30 runs	Time	HMA ₂ 30 runs	Time		LB	BKR	HMA ₁	HMA ₂	HMA*
E1-A	(77,98)	3548	3548.00	3548	3548.00	3548.00	3548.00	0.58	3548.00	0.58	3548	<u>3548</u>	3548	3548	3548	3548
E1-B	(77,98)	4533	4522.20	4539	4508.60	4516.50	4498.00	9.62	4498.00	9.62	4498	<u>4498</u>	4498	4498	4498	<u>4498</u>
E1-C	(77,98)	5595	5608.00	5595	5615.30	5601.60	5595.00	8.71	5595.00	8.71	5595	<u>5595</u>	5595	5595	5595	<u>5595</u>
E2-A	(77,98)	5018	5023.80	5018	5018.00	5018.00	5018.00	24.08	5018.00	24.08	5018	<u>5018</u>	5018	5018	5018	5018
E2-B	(77,98)	6343	6335.40	6344	6330.70	6341.40	6319.77	44.29	6317.00	104.93	6317	<u>6317</u>	6317	6317	6317	<u>6317</u>
E2-C	(77,98)	8347	8355.90	8335	8335.80	8355.70	8335.00	28.12	8335.00	28.12	8335	<u>8335</u>	8335	8335	8335	8335
E3-A	(77,98)	5902	5898.00	5898	5898.00	5898.80	5898.00	5.35	5898.00	5.35	5898	<u>5898</u>	5898	5898	5898	<u>5898</u>
E3-B	(77,98)	7816	7806.40	7787	7787.30	7802.90	7777.00	76.19	7776.93	98.19	7744	7775	7777	7775	7775	7775
E3-C	(77,98)	10309	10322.30	10292	10296.50	10321.90	10294.43	133.00	10292.00	177.41	10244	10292	10292	10292	10292	10292
E4-A	(77,98)	6473	6459.40	6464	6461.10	6475.20	6461.17	82.61	6450.57	675.30	6408	6444	6446	6444	6444	6444
E4-B	(77,98)	9063	9016.30	9047	9037.10	9023.00	8991.50	143.63	8987.00	454.17	8935	8961	8972	8961	8961	8961
E4-C	(77,98)	11627	11750.10	11645	11670.00	11645.80	11582.40	203.43	11563.97	511.24	11512	11529	11545	11529	11529	11529
S1-A	(140,190)	5072	5018.00	5018	5038.90	5039.80	5018.00	11.98	5018.00	11.98	5018	5018	5018	5018	5018	5018
S1-B	(140,190)	6388	6388.00	6388	6388.40	6433.40	6388.00	36.29	6388.00	36.29	6388	<u>6388</u>	6388	6388	6388	<u>6388</u>
S1-C	(140,190)	8535	8518.20	8518	8521.50	8518.30	8518.00	21.59	8518.00	21.59	8518	<u>8518</u>	8518	8518	8518	8518
S2-A	(140,190)	10038	9997.90	9974	9980.50	9959.20	9907.23	390.84	9891.33	1887.59	9825	9884	9888	9874	9874	9874*
S2-B	(140,190)	13178	13176.00	13283	13240.60	13231.60	13149.97	361.66	13153.70	597.74	13017	13099	13111	13078	13078	13078*
S2-C	(140,190)	16505	16551.60	16558	16539.90	16509.80	16465.30	294.90	16439.67	1002.06	16425	<u>16425</u>	16430	16425	16425	16425
S3-A	(140,190)	10451	10291.20	10306	10276.10	10312.70	10228.10	463.81	10217.83	1719.03	10165	10220	10220	10201	10201	10201*
S3-B	(140,190)	13981	13829.20	13890	13860.70	13876.60	13739.10	466.39	13705.67	1397.05	13648	13682	13688	13682	13682	13682
S3-C	(140,190)	17346	17327.90	17304	17277.70	17305.80	17248.60	345.12	17217.63	1338.38	17188	<u>17188</u>	17196	17189	<u>17188</u>	17188
S4-A	(140,190)	12462	12440.40	12439	12406.50	12419.20	12269.73	603.98	12258.30	2035.96	12153	12268	12254	12244	12244	12216*
S4-B	(140,190)	16490	16410.30	16502	16432.00	16441.20	16264.70	611.16	16243.70	1663.58	16113	16260	16222	16216	16216	16201*
S4-C	(140,190)	20733	20731.50	20731	20660.50	20767.20	20545.53	404.61	20518.37	1695.86	20430	20481	20479	20476	20476	20476*
AvgGap		0.75	0.56	0.58	0.50	0.59	0.13		0.07		-	-	-	-	-	-
AvgTime (scaled)		145.68	649.17	181.09	854.48	498.49	198.83		646.03		-	-	-	-	-	-

Table A.4

Detailed comparative results of HMA algorithm with 4 state-of-the-art algorithms on the 25 instances of Set C. The average results of all algorithms and the best results of HMA₁ (500 generations) and HMA₂ (2000 generations) are highlighted in bold if they match the BKR. The optimal BKR is underlined.

INST	(N , E)	Average (median) results								Best results			
		GLS 1 run	TSA2 1 run	Ant_12 10 runs	MAENS 30 runs	HMA ₁ 30 runs	Time	HMA ₂ 30 runs	Time	LB	BKR	HMA ₁	HMA ₂
C1	(69,98)	1660	1660	1705	1707.00	1661.00	117.04	1660.00	160.51	1660	<u>1660</u>	1660	1660
C2	(48,66)	1095	1095	1095	1095.70	1095.00	9.10	1095.00	9.10	1095	<u>1095</u>	1095	1095
C3	(46,64)	925	925	925	927.80	930.33	30.94	926.33	163.67	925	<u>925</u>	925	925
C4	(60,84)	1340	1340	1340	1342.70	1340.00	5.20	1340.00	5.20	1340	<u>1340</u>	1340	1340
C5	(56,79)	2475	2470	2540	2522.30	2470.33	67.19	2470.00	84.00	2470	<u>2470</u>	2470	2470
C6	(38,55)	895	895	895	907.50	895.00	13.78	895.00	13.78	895	<u>895</u>	895	895
C7	(54,70)	1795	1795	1795	1795.00	1795.00	0.61	1795.00	0.61	1795	<u>1795</u>	1795	1795
C8	(66,88)	1730	1730	1730	1732.30	1730.00	14.20	1730.00	14.20	1730	<u>1730</u>	1730	1730
C9	(76,117)	1825	1830	1860	1852.80	1820.00	74.70	1820.00	74.70	1805	1820	1820	1820
C10	(60,82)	2290	2270	2305	2317.80	2270.00	24.17	2270.00	24.17	2270	<u>2270</u>	2270	2270
C11	(83,118)	1815	1815	1820	1853.70	1815.00	37.19	1813.67	121.19	1790	1805	1815	1805
C12	(62,88)	1610	1610	1610	1610.00	1610.00	1.30	1610.00	1.30	1605	<u>1610</u>	1610	1610
C13	(40,60)	1110	1110	1110	1122.00	1110.00	8.20	1110.00	8.20	1110	<u>1110</u>	1110	1110
C14	(58,79)	1680	1680	1680	1687.30	1680.00	15.88	1680.00	15.88	1680	<u>1680</u>	1680	1680
C15	(97,140)	1860	1865	1880	1896.50	1860.00	82.70	1860.00	82.70	1840	1860	1860	1860
C16	(32,42)	585	585	585	585.20	585.00	9.56	585.00	9.56	585	<u>585</u>	585	585
C17	(43,56)	1610	1610	1610	1618.30	1610.00	5.00	1610.00	5.00	1610	<u>1610</u>	1610	1610
C18	(93,133)	2410	2415	2390	2411.70	2385.00	160.09	2385.00	160.09	2345	2385	2385	2385
C19	(62,84)	1395	1400	1400	1425.70	1396.33	53.91	1395.00	115.09	1395	<u>1395</u>	1395	1395
C20	(45,64)	665	665	665	668.50	665.00	0.64	665.00	0.64	665	<u>665</u>	665	665
C21	(60,84)	1725	1725	1725	1725.20	1725.00	1.52	1725.00	1.52	1725	<u>1725</u>	1725	1725
C22	(56,76)	1070	1070	1070	1070.00	1070.00	0.30	1070.00	0.30	1070	<u>1070</u>	1070	1070
C23	(78,109)	1690	1700	1710	1724.30	1690.33	66.86	1690.00	76.30	1680	1690	1690	1690
C24	(77,115)	1360	1360	1360	1368.50	1361.00	104.42	1360.00	190.24	1360	<u>1360</u>	1360	1360
C25	(37,50)	905	905	905	907.00	905.00	17.47	905.00	17.47	905	<u>905</u>	905	905
AvgGap		0.12	0.14	0.52	0.98	0.06		0.02		-	-	-	-
AvgTime (scaled)		42.49	42.92	40.76	165.50	36.88		54.22		-	-	-	-

Table A.5

Detailed comparative results of HMA algorithm with 4 state-of-the-art algorithms on the 25 instances of Set D. The average results of all algorithms and the best results of HMA₁ (500 generations) and HMA₂ (2000 generations) are highlighted in bold if they match the BKR. The optimal BKR is underlined.

INST	(N , E)	Average (median) results								Best results			
		GLS 1 run	TSA2 1 run	Ant_12 10 runs	MAENS 30 runs	HMA ₁ 30 runs	Time	HMA ₂ 30 runs	Time	LB	BKR	HMA ₁	HMA ₂
D1	(69,98)	725	740	745	745.00	743.83	14.09	738.83	145.70	725	<u>725</u>	725	725
D2	(48,66)	480	480	480	480.00	480.00	0.34	480.00	0.34	480	<u>480</u>	480	480
D3	(46,64)	415	415	415	415.20	415.00	0.24	415.00	0.24	415	<u>415</u>	415	415
D4	(60,84)	615	615	615	616.00	615.00	1.25	615.00	1.25	615	<u>615</u>	615	615
D5	(56,79)	1040	1040	1040	1040.00	1040.00	0.76	1040.00	0.76	1040	<u>1040</u>	1040	1040
D6	(38,55)	485	485	485	493.00	485.00	0.43	485.00	0.43	485	<u>485</u>	485	485
D7	(54,70)	835	835	855	847.30	838.67	53.72	835.00	145.24	835	<u>835</u>	835	835
D8	(66,88)	685	685	685	704.20	685.00	6.98	685.00	6.98	685	<u>685</u>	685	685
D9	(76,117)	680	680	680	680.00	680.00	0.84	680.00	0.84	680	<u>680</u>	680	680
D10	(60,82)	910	910	910	910.00	910.00	0.26	910.00	0.26	910	<u>910</u>	910	910
D11	(83,118)	930	960	935	935.20	930.00	38.38	925.33	286.78	920	<u>920</u>	920	920
D12	(62,88)	680	680	680	680.00	680.00	4.94	680.00	4.94	680	<u>680</u>	680	680
D13	(40,60)	690	695	690	691.00	690.00	6.70	690.00	6.70	690	<u>690</u>	690	690
D14	(58,79)	930	940	930	931.00	930.00	0.40	930.00	0.40	930	<u>930</u>	930	930
D15	(97,140)	910	950	920	919.00	910.50	115.49	910.00	141.87	910	<u>910</u>	910	910
D16	(32,42)	170	170	170	170.00	170.00	0.13	170.00	0.13	170	<u>170</u>	170	170
D17	(43,56)	675	675	675	675.00	675.00	0.17	675.00	0.17	675	<u>675</u>	675	675
D18	(93,133)	930	930	930	934.20	930.00	3.69	930.00	3.69	930	<u>930</u>	930	930
D19	(62,84)	680	690	680	680.00	680.00	0.64	680.00	0.64	680	<u>680</u>	680	680
D20	(45,64)	415	415	415	415.20	415.00	0.32	415.00	0.32	415	<u>415</u>	415	415
D21	(60,84)	805	825	810	834.20	805.17	79.37	805.00	93.50	760	805	805	805
D22	(56,76)	690	690	690	690.00	690.00	0.24	690.00	0.24	690	<u>690</u>	690	690
D23	(78,109)	735	735	735	748.20	735.00	33.69	735.00	33.69	735	<u>735</u>	735	735
D24	(77,115)	670	670	670	683.50	670.00	2.88	670.00	2.88	665	<u>670</u>	670	670
D25	(37,50)	410	410	410	410.00	410.00	0.19	410.00	0.19	410	<u>410</u>	410	410
AvgGap		0.04	0.66	0.34	0.79	0.17		0.10		-	-	-	-
AvgTime (scaled)		17.36	19.20	51.88	219.53	14.65		35.13		-	-	-	-

Table A.6

Detailed comparative results of HMA algorithm with 4 state-of-the-art algorithms on the 25 instances of Set E. The average results of all algorithms and the best results of HMA₁ (500 generations) and HMA₂ (2000 generations) are highlighted in bold if they match the BKR. The optimal BKR. are underlined.

INST	(N , E)	Average (median) results								Best results			
		GLS 1 run	TSA2 1 run	Ant_12 10 runs	MAENS 30 runs	HMA ₁ 30 runs	Time	HMA ₂ 30 runs	Time	LB	BKR	HMA ₁	HMA ₂
E1	(73,105)	1940	1935	1945	1967.80	1936.83	102.65	1935.00	160.72	1925	1935	1935	1935
E2	(58,81)	1610	1610	1610	1615.50	1610.00	11.38	1610.00	11.38	1610	<u>1610</u>	1610	1610
E3	(46,61)	750	750	750	752.00	750.00	1.33	750.00	1.33	750	<u>750</u>	750	750
E4	(70,99)	1610	1615	1675	1684.30	1610.00	23.60	1610.00	23.60	1610	<u>1610</u>	1610	1610
E5	(68,94)	2170	2160	2220	2228.70	2162.33	85.64	2160.00	132.12	2160	<u>2160</u>	2160	2160
E6	(49,66)	670	670	670	670.00	670.00	0.24	670.00	0.24	670	<u>670</u>	670	670
E7	(73,94)	1900	1900	1900	1900.00	1900.00	0.63	1900.00	0.63	1900	<u>1900</u>	1900	1900
E8	(74,98)	2150	2155	2150	2150.50	2150.00	2.11	2150.00	2.11	2150	<u>2150</u>	2150	2150
E9	(93,141)	2250	2300	2295	2327.70	2247.50	170.23	2228.67	498.99	2220	2225	2225	2225
E10	(56,76)	1690	1690	1690	1691.50	1690.00	1.44	1690.00	1.44	1690	<u>1690</u>	1690	1690
E11	(80,113)	1850	1855	1860	1932.00	1846.67	96.44	1840.00	460.01	1830	<u>1830</u>	1830	1830
E12	(74,103)	1710	1730	1760	1764.30	1723.83	124.02	1707.00	341.32	1695	<u>1695</u>	1700	1695
E13	(49,73)	1325	1325	1325	1335.30	1325.00	7.97	1325.00	7.97	1325	<u>1325</u>	1325	1325
E14	(53,72)	1810	1810	1810	1817.00	1810.67	46.57	1810.00	51.25	1810	<u>1810</u>	1810	1810
E15	(85,126)	1610	1610	1610	1617.80	1601.00	149.37	1599.00	723.39	1590	<u>1590</u>	1600	1590
E16	(60,80)	1825	1825	1825	1825.00	1825.00	39.74	1825.00	39.74	1825	<u>1825</u>	1825	1825
E17	(38,50)	1290	1290	1290	1294.30	1291.00	18.71	1290.00	26.35	1290	<u>1290</u>	1290	1290
E18	(78,110)	1610	1610	1610	1612.30	1610.00	1.41	1610.00	1.41	1610	<u>1610</u>	1610	1610
E19	(77,103)	1435	1435	1435	1437.00	1435.00	3.54	1435.00	3.54	1435	<u>1435</u>	1435	1435
E20	(56,80)	990	990	990	990.00	990.00	0.64	990.00	0.64	990	<u>990</u>	990	990
E21	(57,82)	1705	1705	1760	1755.50	1705.00	51.59	1705.00	51.59	1705	<u>1705</u>	1705	1705
E22	(54,73)	1185	1185	1185	1187.50	1185.00	1.42	1185.00	1.42	1185	<u>1185</u>	1185	1185
E23	(93,130)	1430	1445	1435	1469.00	1432.33	88.98	1430.33	336.54	1430	<u>1430</u>	1430	1430
E24	(97,142)	1785	1785	1785	1822.20	1785.00	35.38	1785.00	35.38	1785	<u>1785</u>	1785	1785
E25	(26,35)	655	655	655	655.00	655.00	0.45	655.00	0.45	655	<u>655</u>	655	655
AvgGap		0.20	0.39	0.83	1.44	0.19		0.08		-	-	-	-
AvgTime (scaled)		40.65	46.00	40.54	160.89	42.62		116.54		-	-	-	-

Table A.7

Detailed comparative results of HMA algorithm with 4 state-of-the-art algorithms on the 25 instances of Set F. The average results of all algorithms and the best results of HMA₁ (500 generations) are highlighted in bold if they match the BKR. The optimal BKR. are underlined.

INST	(N , E)	Average (median) results						Best results		
		GLS 1 run	TSA2 1 run	Ant_12 10 runs	MAENS 30 runs	HMA ₁ 30 runs	Time	LB	BKR	HMA ₁
F1	(73,105)	1065	1085	1065	1071.00	1065.00	43.29	1065	<u>1065</u>	1065
F2	(58,81)	920	920	920	920.00	920.00	0.67	920	<u>920</u>	920
F3	(46,61)	400	400	400	400.00	400.00	0.25	400	<u>400</u>	400
F4	(70,99)	940	960	955	963.50	940.00	22.54	940	<u>940</u>	940
F5	(68,94)	1180	1180	1180	1180.30	1180.00	3.86	1180	<u>1180</u>	1180
F6	(49,66)	490	490	490	490.00	490.00	0.22	490	<u>490</u>	490
F7	(73,94)	1080	1080	1080	1090.70	1080.00	3.00	1080	<u>1080</u>	1080
F8	(74,98)	1145	1145	1145	1145.00	1145.00	0.41	1145	<u>1145</u>	1145
F9	(93,141)	1145	1170	1225	1197.80	1145.00	11.24	1145	<u>1145</u>	1145
F10	(56,76)	1010	1010	1010	1010.00	1010.00	0.23	1010	<u>1010</u>	1010
F11	(80,113)	1015	1015	1045	1037.50	1015.00	6.56	1015	<u>1015</u>	1015
F12	(74,103)	910	910	975	939.50	910.00	10.40	910	<u>910</u>	910
F13	(49,73)	835	835	835	835.00	835.00	0.63	835	<u>835</u>	835
F14	(53,72)	1025	1035	1025	1065.50	1025.00	9.62	1025	<u>1025</u>	1025
F15	(85,126)	945	990	945	951.70	945.00	2.41	945	<u>945</u>	945
F16	(60,80)	775	775	775	775.00	775.00	0.45	775	<u>775</u>	775
F17	(38,50)	605	630	605	605.00	605.00	0.15	605	<u>605</u>	605
F18	(78,110)	850	850	850	861.20	850.00	0.85	840	850	850
F19	(77,103)	725	740	725	725.00	725.00	3.21	715	725	725
F20	(56,80)	610	610	610	614.80	610.00	6.38	610	<u>610</u>	610
F21	(57,82)	905	905	905	905.00	905.00	2.43	905	<u>905</u>	905
F22	(54,73)	790	790	790	790.00	790.00	0.85	790	<u>790</u>	790
F23	(93,130)	725	730	730	736.30	725.00	27.86	725	<u>725</u>	725
F24	(97,142)	975	1010	975	1001.30	975.00	53.28	975	<u>975</u>	975
F25	(26,35)	430	430	430	430.00	430.00	0.12	430	<u>430</u>	430
AvgGap		0.00	0.90	0.77	1.01	0.00		-	-	-
AvgTime (scaled)		10.67	21.09	52.17	166.85	8.44		-	-	-

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