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A Dual-Population Based Co-evolutionary Algorithm for Capacitated Electric Vehicle Routing Problems

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***Abstract*—The capacitated electric vehicle routing problem is a challenging non-deterministic polynomial hard (NP-hard) problem consisting of two interdependent sub-problems, the routing optimization problem and the charging decision problem. The routing optimization for electric vehicles with limited driving range is dependent on the available charging stations, while the charging decision is based on the charging demand that is estimated on the fixed route in return. Taking this coupling relationship into consideration, this paper proposes a dual-population based co-evolutionary algorithm that uses two evolution populations to collaboratively optimize these two sub-problems. In routing population, the charging station is regarded as a kind of customer with no demand, and an improved ant colony optimization algorithm is designed to generate routes that involve the position information of charging stations. In charging population, a binary genetic algorithm is used to generate a population of charging schemes whose qualities are evaluated based on the best ant obtained from the routing population, and then the resultant solution by inserting the best charging scheme is used to update the pheromone for the routing generation. Through the information interaction during the evolution, these two populations collaboratively search for the optimal solution of the problem. Experimental results demonstrate that the proposed algorithm can be able to avoid falling into the local optimum and has a reduction of about 4% in route distance averaged over two test suites. Additionally, it also has a high computational efficiency, which is faster than the advanced ant colony optimization method by about 2 times.**

***Index Terms*—Electric vehicle routing problem, charging decision problem, co-evolution, ant colony optimization, genetic algorithm.**

I. Introduction

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TANSPORTATION has been one of the main sources of greenhouse gas emission over the past decades. Recently, electric vehicles (EVs) have been identified as a promising alternative to traditional fossil fuel-driven vehicles due to the characteristics of energy saving and carbon reduction [1]–[3]. Considering the increasingly serious environmental problems and the goals of carbon peak and carbon neutrality, many logistics companies, such as FedEx, DHL, and UPS, have started using EVs instead of fossil fuel-driven vehicles in their express businesses [4], [5].

Academically speaking, logistics companies usually model the services for customers as the vehicle routing problem (VRP) that is a non-deterministic polynomial hard (NP-hard) problem [6]–[11]. Over the last few decades, a large number of VRP variants have been widely studied for different real scenarios, such as capacitated VRP (CVRP) [12], [13], VRP with time windows [14], VRP with pickup and delivery [15], multi-objective VRP [16], [17], and dynamic VRP [18], [19]. Note that most of these VRPs are formulated based on fossil fuel-driven vehicles, where the refueling problem is usually not considered due to their long driving range and the widely distributed gas stations. However, compared with fuel vehicles, EVs have relatively limited driving range and the number of charging stations is also not enough in the city at present [20]. Thus, when using EVs as the delivery vehicles, not only the order for visiting customers but also the charging scheme of the EVs should be considered.

Due to this extra concern, a new category of VRP variant called electric VRP (EVRP) is proposed in recent years [21]–[25]. Moreover, several EVRP variants have been proposed in the last few years, such as capacitated EVRP (CEVRP) [26], [27], EVRP with time window (EVRPTW) [21], [28] , EVRP with pickup and delivery [29], EVRP with non-linear charging (EVRP-NL) [30], etc. Particularly, CEVRP is the most fundamental variant and is the main concern in this paper. The CEVRP can be described as follows: given a fleet of EVs, the best possible routes need to be found within the capacity and battery power limits of the EVs, starting from the depot and returning to it, to serve a set of customers with

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different demands. Different from the traditional CVRP, the objective of CEVRP is to minimize the total travel distance of vehicles including the visits for not only all the customers but also some charging stations. Each EV cannot be overloaded or run out of electricity during its journey. If a vehicle cannot finish the journey by only using the initial electricity, it needs to visit the charging station to recharge its battery. It is worth noting that there are two aspects should be optimized simultaneously in CEVRP: 1) the routing for visiting the customers and 2) the charging scheme of each EV. These two aspects are highly interdependent with each other, since the routing optimization for EVs with limited driving range is dependent on the available charging stations, while the charging decision scheme of each EV is based on the charging demand that is estimated based on the given driving route in return [31], [32].

Until now, the existing approaches proposed to solve EVRPs mainly include exact algorithms, heuristic algorithms and metaheuristic algorithms [33]–[35]. Exact algorithms always translate the EVRPs into the mixed integer linear programming (MILP) models to address them [36], [37]. They can fast obtain the optimal solution for small-scale test instances, but are inefficient on larger-scale problems with more than 50 customers. Heuristic algorithms are problem-specified programs that improve solutions according to the problem structure, such as Clarke and Wright savings algorithm [2]. Metaheuristic algorithm is a kind of problem-independent heuristic that does not depend on the specific conditions of a problem. It can be divided into individual-based and population-based metaheuristic algorithms. The individual-based ones improve a single solution by the local search strategy, such as simulated annealing (SA) [38], tabu search (TS) [39], variable neighborhood search (VNS) [40], [41], and adaptive large neighborhood search (ALNS) [22], [42]. The population-based ones use multiple solutions to make a collaborative search for finding the optimal solution, such as genetic algorithm (GA) [43]–[46] and ant colony optimization (ACO) [26], [47], [48].

Note that these heuristic and metaheuristic algorithms generally optimize the routing plan and the charging scheme iteratively and in stages, which can tackle the coupling between them to some extent. However, with the increase of the problem scale, the coupling between two subproblems becomes more complicated, this two-stage alternating optimization would make a lot of unpromising searches in the large solution space. Specifically, in the routing stage, only the optimization of the service order for customers is considered, which neglects the influence of the position of charging stations on the routing plan and may cause the EV to take a detour to recharge. While in the charging stage, the optimal charging scheme is excessively sought for a fixed routing plan, once the routing plan is changed in the next generation, the charging scheme needs to be re-optimized. This inconsistency between the optimization of routing and charging causes an unpromising search during the optimization process.

Therefore, how to make a collaborative optimization between routing and charging is important for improving the search efficiency of algorithms. In this study, the idea of co-evolution optimization is adopted for better considering the coupling relationship between the routing optimization and the charging decision, where two subproblems are simultaneously optimized by using two co-evolution populations. Through the information interaction during the evolutionary process, these two populations collaboratively search for the optimal solution of the problem. To sum up, the contributions of this paper are as follows:

1) A dual-population based co-evolutionary algorithm (DPCA) is proposed for solving the CEVRP, where one population is for the routing optimization and another population is for the charging optimization.
2) An improved ACO is designed to generate routes where the charging station is regarded as a kind of customer with no demand, which can consider the influence of the position of charging stations on planning the routes.
3) A binary genetic algorithm is used to generate a population of binary charging schemes, which can provide diverse charging schemes for better matching the optimal routing plan and thus reduce the unpromising search.
4) An interaction strategy is proposed to make two populations co-evolve, where the best ant in the routing population is used to evaluate the charging population and the resultant solution by inserting the best charging scheme is used to update the pheromone information.

The rest of the paper is organized as follows. In Section II, the related work is presented and the motivation for the work is given. In Section III, the formulation of CEVRP is presented. In Section IV, the details of the proposed DPCA for solving the CEVRP are presented. The experimental studies are conducted in Section V. Finally, Section VI makes a conclusion about this paper and points out some future research issues.

II. Related Work and Motivation

This section first introduces existing methods for solving EVRPs, and then summarizes these methods to give the motivation of this work.

A. Existing methods for CEVRP

In this section, the existing methods for solving EVRPs are reviewed, which can be classified into four categories: 1) Exact methods, 2) Heuristic methods, 3) Individual-based metaheuristic methods, and 4) Population-based metaheuristic methods.

Exact methods generally transfer the EVRP into a corresponding mathematical programming model or a linear programming problem and adopt with general exact solvers, such as CPLEX optimizer or other commercial software to solve it. Lin *et al.* [36] described the EVRP considering vehicle loads as an MILP model and used CPLEX to solve the problem. Experimental results showed that CPLEX found the optimal solution for small-scale instances with 13 customers. Xiao *et al.* [49] considered the EVRPTW under nonlinear charging characteristics and transferred it into an MILP model, also using CPLEX to successfully solve the test instance with 25 customers. Recently, Yao *et al.* [50] decomposed the EVRP into two linear programming problems, namely the routing-related problem and the charging-related problem. By iteratively solving these two subproblems in stages, the algorithm can achieve an approximate optimal solution in polynomial time. Even so, the problem scale in the experiment was also small with no more than 50 customers. These studies showed that the exact methods can always find the optimal solution for small-scale instances, but it is not applicable or inefficient when they handle large-scale instances.

Heuristic methods solve EVRPs by inductive reasoning from experience and experimental analysis, which start from the initial solution and find a better one in its neighborhood as the current solution, then repeat the process until no better solution can be updated. Heuristic algorithms can be divided into construction heuristics and local improvement heuristics [33], [34]. The construction one starts with "zero" and constructs a solution sequentially. The Clarke and Wright savings (C-W) algorithm is one of construction heuristics commonly used for EVRPs. Erdogan *et al.* [2] used a modified C-W algorithm to solve the routing problem of renewable fuel vehicles. Another widely used construction heuristic is the two-phase heuristic algorithm. Felipe *et al.* [51] used a two-phase heuristic to address an EVRP with limited autonomy. Unlike the construction heuristics, local improvement heuristics start with a complete initial solution and iteratively improve the current solution to obtain a better solution by the heuristic operators. The typical one is the Local Search algorithm, which has been already widely combined with other algorithms in various EVRP studies [52]–[54].

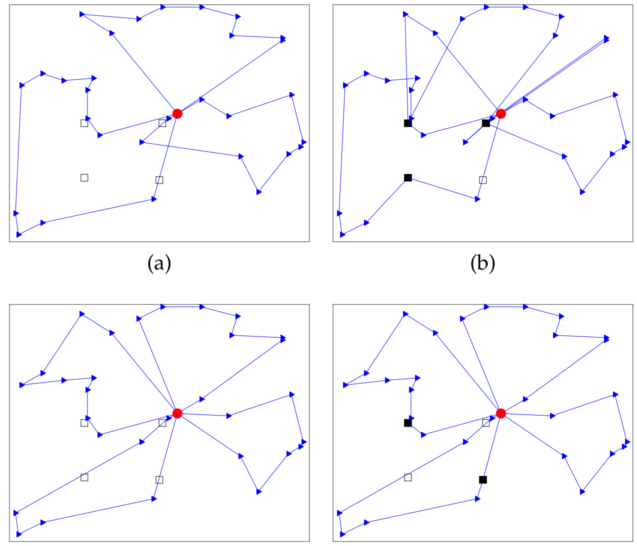
Individual-based metaheuristic methods are mainly based on different local search strategies, which can obtain an approximate optimal solution in a reasonable time for large-scale EVRPs. In 2014, Schneider *et al.* [21] first proposed the EVRPTW model and combined tabu search and variable neighborhood search to solve it. Montoya *et al.* [30] proposed to solve EVRP-NL by using the iterative local search (ILS) algorithm. Yang *et al.* [22] proposed a hybrid heuristic method called SIGALNS to solve the CEVRP, where the routing and charging problems are optimized by ALNS and iterated greedy (IG) heuristic in stages. Along with the ALNS, Hof *et al.* [23] designed a new facility-related neighborhood structure in the shaking step of the ALNS for the fast search for the EV routing plan. Schiffer *et al.* [55] developed a hybrid of an ALNS and dynamic programming using computational parallelization techniques to solve large-scale test instances in a reasonable time. Generally, the effectiveness of these algorithms is commendable but their performance heavily depends on the local search operators that are problem-related. For larger-scale test problems, the choice of an operator can have a great impact on the performance of the algorithm. If the operator is not chosen properly, the algorithm can easily fall into a local optimum.

Population-based metaheuristic algorithms are generally inspired by the natural evolutionary law or behaviors of living organisms and have shown the global search ability for obtaining the optimal solution on a wide range of complex problems. Several scholars have tried to use them to solve EVRPs, such as GA [44], [45] and ACO [26], [47], [48]. At the earliest, Guo *et al.* [44] and Shao *et al.* [45] proposed to use the GA to solve the two subproblems of EVRP simultaneously, by encoding the orders for customers and charging stations together in one evolution population. However, this solution way leads to the search space being huge and also the traditional local search operator like 2-opt is invalid since they cannot handle the customer and station orders at the same time, which eventually makes the proposed GAs ineffective on large-scale EVRPs. Afterward, most studies have turned to the two-stage optimization framework that alternately optimizes the routing plan and the charging scheme in stages. Mavrovouniotis *et al.* [26] adopted a max-min ant system algorithm (MMAS) to optimize the routing without considering the electricity constraint and then used a simple repair method to add charging stations into the obtained routing plan. Jia *et al.* [47] proposed a bi-level ACO (BACO) to solve CEVRP with the idea of bi-level optimization, where ACO is used to optimize the routing plan without considering the electricity constraint in the upper-level CVRP subproblem and the removal heuristic is designed to obtain the charging schemes in the lower level. Recently, for improving the efficiency of the BACO algorithm, Jia *et al.* [48] proposed an improved confidence-based bi-level ant colony optimization algorithm (CBACO), where only promising routing plans were selected for lower-level optimization based on confidence.

B. Motivation

It can be found that most of the existing heuristic and metaheuristic algorithms usually decompose CEVRP into two subproblems, i.e., the routing optimization problem and the charging decision problem, and alternately optimize them in stages. However, this two-stage alternating optimization framework excessively searches the optimal routing plan and the charging scheme in each stage, which easily misses the best matching between them and would make a lot of unpromising searches when the problem scale increases. Specifically, due to the complicated coupling relationship between them, there very likely exists that a suboptimal routing plan but with an appropriate charging scheme can achieve a better result than the combination of the respective optimums in stages. To illustrate this situation, Fig. 1 plots the routing plans without considering charging stations and the final solutions obtained by MMAS [26] and the proposed method on the R-4-C-30 test instance [56]. From Fig. 1(a)(b), it can be found that, although the routing plan and the charging scheme obtained by MMAS are both optimal, the final resultant solution is not optimal. While in Fig. 1(c)(d), although the routing plan is not optimal, but with a well-matched charging scheme, the solution quality can be better. Therefore, in order to make the collaborative optimization of routing and charging, this paper designs a dual-population based co-evolutionary algorithm to collaboratively search for the optimal solution of the problem.

Note that the dual-population co-evolution strategy has been widely used in the continuous optimization field for solving the complex optimization problems [57]–[59]. For example, for tackling multiobjective optimization problems with complicated Pareto-optimal sets, Li *et al.* [57] used two separate and co-evolving populations to deal with convergence and diversity simultaneously. For constrained multiobjective optimization problems, Tian *et al.* [58] proposed to evolve one population to solve the original problem and another population to solve a helper problem without constraints compared to the original problem. By sharing useful information between the two populations, the complex original problem can be solved efficiently. Recently, this co-evolution optimization strategy also has been used for solving combinational optimization problems [60]–[62]. For instance, Wang *et al.* [62] used two populations to collaboratively search the optimal solutions for multi-objective location problems under uncertainty of facilities, where the location population provides the high-quality location schemes for the radius population in evaluating the quality of radii of each location and the radius population equips the proper radii for location population in determining the good location schemes. Therefore, this paper adopts this dual-population co-evolution strategy to solve the CEVRP, where one population is for the routing optimization and another population is for the charging optimization.



(a) (b) (c) (d)

Fig. 1. The routing plans without consider charging stations and the final solutions by MMAS and the proposed method on R-4-C-30 test instance, where ∘, ▷ and □ represent the depot, the customer and the charge station, respectively. (a) Routing plan by MMAS with the travel distance 564.99. (b) Final solution by MMAS with the travel distance 737.62. (c) Routing plan by DPCA with the travel distance 610.01. (d) Final solution by the proposed method with the travel distance 611.26.

III. Problem Formulation

CEVRP can be defined on a fully connected weighted graph $G = (V, E)$, where $V = \{0\} \cup I \cup F'$ is a set of nodes, $E = \{(i,j) \mid i,j \in V, i \neq j\}$ is a set of arcs connecting these nodes. Node 0 denotes the depot. I is the set of n customers, each customer i has a fixed cargo demand c_i. F' denotes an extended set of charging stations that includes δ_i copies of each charging station in $i \in F$, where F is the set of m charging stations that have been built. δ_i is set to $2|I|$ in the worst case and each charging station can be visited once, multiple times or not. Each EV has a maximum capacity of cargo demand C and a maximum battery capacity B. Additionally, an EV has remaining carrying capacity u_i and remaining battery level y_i when it arrives at node $\forall i \in V$. Assume that the charge consumption rate does not change with the load of EVs, the consumed energy is described as $h * d_{ij}$, where d_{ij} denotes the distance from node i to node j and h denotes the constant charge consumption rate.

According to existing studies [33]–[35], the basic assumptions for the CEVRP are as follows:

1) EVs start from the depot and finally return to the depot.
2) Each customer node is to be serviced by exactly one electric vehicle.
3) Electric vehicle can visit a charging station for recharging the battery between any two customers.
4) Each charging station can be visited by more than one electric vehicle.
5) The locations of the depot, customers and charging stations and the traveling distance from any node to any charging station are known.
6) The battery level of an EV must always be between 0 and its battery capacity.
7) The total demand of customers in a route cannot exceed the maximum capacity of an EV.
8) The battery of an EV is fully charged when leaving the depot and charging stations.

Formally, the CEVRP can be formulated as follows:

$$\min \sum_{i \in V, j \in V, i \neq j} d_{ij} x_{ij} \tag{1}$$

s.t.

$$\sum_{j \in V, i \neq j} x_{ij} = 1, \forall i \in I, \tag{2}$$

$$\sum_{j \in V, i \neq j} x_{ij} \leq 1, \forall i \in F', \tag{3}$$

$$\sum_{j \in V, i \neq j} x_{ij} - \sum_{j \in V, i \neq j} x_{ji} = 0, \forall i \in V, \tag{4}$$

$$0 \leq u_i \leq C, \forall i \in V, \tag{5}$$

$$u_j \leq u_i - c_i x_{ij} + C\left(1 - x_{ij}\right), \forall i \in V, \forall j \in V, i \neq j, \tag{6}$$

$$0 \leq y_i \leq B, \forall i \in V, \tag{7}$$

$$y_j \leq B - h d_{ij} x_{ij}, \forall i \in F' \cup \{0\}, \forall j \in V, i \neq j, \tag{8}$$

$$y_j \leq y_i - h d_{ij} x_{ij} + B\left(1 - x_{ij}\right), \forall i \in I, \forall j \in V, i \neq j, \tag{9}$$

$$x_{ij} \in \{0, 1\}, \forall i \in V, \forall j \in V, i \neq j, \tag{10}$$

Objective (1) is to minimize the total driving distance of all EVs. Constraint (2) ensures that each customer is visited by one EV. Constraint (3) guarantees that a charging station can be visited multiple times. Constraint (4) establishes the flow conservation by guaranteeing that at each node, the number of incoming arcs is equal to the number of outgoing arcs. Constraints (5)-(6) are related to the EV loadings, which are called "capacity constraints". Constraint (5) requires that the load of the EV is non-negative and cannot exceed the maximum value when it reaches any node. Constraint (6) guarantees that the cargo demand of all customers is satisfied. Constraints (7)-(9) are related to the battery level of EVs, which are called "electricity constraints". Constraint (7) requires that the remaining battery capacity of the EV is non-negative and cannot exceed the maximum battery capacity when it reaches any node. Constraint (8) assumes that EVs are always fully charged in charging stations or the depot. Constraint (9) links the amount of energy available at node j to the amount of energy available at node i. The quantity of electricity at node j decreases with the consumption of the arc (i, j). In constraint (10), x_{ij} is a binary variable that indicates whether arc (i, j) is traveled or not.

As an extension of the well-known CVRP, CEVRP needs to determine not only the customer orders but also the charging station visits in a route. Since the number of visits to charging stations is not restricted for a route, an EV can make none, one or more visits to charging stations, which poses a challenge for the charging optimization. Fig. 2 presents an illustrative example of a solution to the CEVRP involving ten customers (C1,...,C10), four charging stations (S1,...,S4), and the depot that can be also used as a charging station. It can be found that one EV visits the charging station twice during its journey, one EV visits once and another EV does not visit any charging station. Moreover, the charging decision for the EV is also a complex optimization problem. It needs to determine the appropriate position for the EV visiting the charging stations, meeting the electricity constraints and avoiding the detour. For example, for the routes C7-C8-S3-C9-C10 and C7-C8-S4-C9-C10 in Fig. 2, though both two routes are electricity-feasible, the former can achieve the better total distance than the later as it effectively avoids the detour. In other words, when an EV needs to recharge, the choice to the nearest charging station is not always optimal as it is greatly influenced by the routing plan. Therefore, the optimizations for the routing plan and the charging scheme should be considered at the same time for better dealing with the coupling relationship between them.

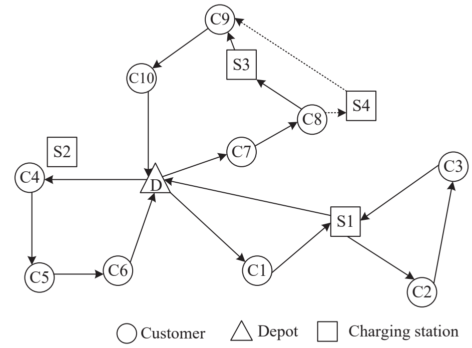


Fig. 2. An illustrative example for the CEVRP.

Algorithm 1: Framework of the Proposed DPCA

Input: I (The set of customers), F' (The set of charging stations), N (Population size)
Output: **s** (Final solution)
$P \leftarrow Initialization(N)$;
$Q \leftarrow Initialization(N)$;
Initialize the best solution **s** and the pheromone matrix Φ;
while *the termination criterion is not met* **do**
  $[P^{best}, l_s] \leftarrow RoutingOptimization(\Phi, I, F', N)$;
  $O \leftarrow ChargingOptimization(Q, l_s)$;
  $[Q, \Phi, \mathbf{s}] \leftarrow Interaction(Q, O, P^{best}, \mathbf{s})$;
Adjust the charging scheme of **s** by the iterated greedy (IG) algorithm;
return s;

IV. Solution Approach and Algorithm

In this section, the framework of the proposed algorithm is first given. Then, the detailed evolution procedures for the routing population and the charging population are presented. Finally, the information interaction method between two populations is detailed, which is the main component of the proposed DPCA.

A. Framework of the Proposed DPCA

The framework of the proposed DPCA is summarized in Algorithm 1. A population P is used for routing optimization and each individual (ant) uses the integer encoding. Specifically, an ant $\mathbf{x} = (x_1, x_2, ..., x_{n+m})$ denotes the routing plan including orders for visiting customers $(1, 2, ..., n)$ and charging stations $(n+1, ..., n+m)$. Another population Q is used for the charging optimization and each individual uses the binary encoding. Consider an individual $\mathbf{y} = (y_1, y_2, ..., y_n)$, the binary 1 in the ith bit denotes that the EV needs charging after visiting the ith customer in the given routing plan and the binary 0 otherwise. First of all, these two populations P and Q with the size of N, the best solution $\mathbf{s}$ and the pheromone matrix Φ (lines 1-3) are initialized. Afterward, at each generation, the two populations are first evolved separately, where the population P uses an improved max-min ant system to optimize the routing plan (line 5) and the population Q uses a binary genetic algorithm to optimize the charging scheme (line 6). Then, the interaction between them is implemented to exchange the useful information to further improve the solution quality (line 7). These two processes are alternately implemented and terminated when the termination criterion is met. At the end of the evolution, the charging scheme in the final solution of CEVRP is finally improved by the iterated greedy (IG) algorithm [22] (line 8).

B. Routing Optimization Based on Improved ACO

Ant colony optimization (ACO) algorithm [63] is a population-based metaheuristic algorithm that simulates the real ant colony cooperation process based on the study of the collective foraging behavior of real ant colonies in nature. ACO does not depend on a specific local search operator and has a good global search ability, which has been widely used to solve EVRPs in recent years [26], [47], [48], [63]–[65]. Among several ACO variants, the max-min ant system (MMAS) is the most studied one and has proven its good performance in CEVRPs [26], [47], [48]. Hence, MMAS is also used to optimize the EV routes in this study. Different from the existing methods only considering the service order of customers, this paper considers the influence of the position of charging stations on planning the route and pre-places the charging stations into the route construction, where the charging station is regarded as a king of customer with no demand. Since both the customers and the charging stations are considered, the size of the pheromone matrix Φ is $n' * n'$, where $n' = n + m + 1$ and each element $\varphi_{ij} \in \Phi$ represents the pheromone value of traveling from i to j. Besides, the boundaries of pheromone values $\varphi_{\max}$ and $\varphi_{\min}$ are calculated as suggested by [26]:

$$\varphi_{\max} = \frac{1}{(1-\rho) \cdot C^{bs}} \tag{11}$$

$$\varphi_{\min} = \frac{\varphi_{\max}(1 - \sqrt[n']{0.05})}{(n'/2 - 1)\sqrt[n']{0.05}} \tag{12}$$

where ρ is the evaporation rate and C^{bs} is the driving distance of the best-so-far ant.

The routing optimization process is shown in Algorithm 2. First, the routing $\mathbf{r}$ is constructed by selecting nodes from the candidate nodes according to the roulette wheel selection strategy (lines 4-12). In each step, the probability of going to node j from the current node i is calculated by:

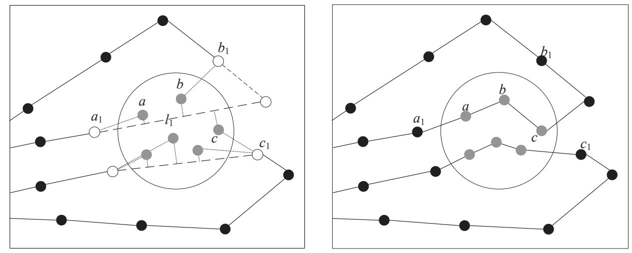


Fig. 3. Illustration of the process of inserting nodes by using the proposed insertion operator.

$$p_{ij} = \frac{\varphi_{ij}^{\alpha}/d_{ij}^{\beta}}{\sum_{k \in I_s} \varphi_{ik}^{\alpha}/d_{ik}^{\beta}} \tag{13}$$

where α, β are two parameters to adjust the weights of the pheromone value and the distance value and I_s is a set of candidate nodes.

Then, the routing plan $\mathbf{r}$ is split into several capacity-feasible routes by using the split algorithm proposed in [66] (line 13). Afterward, the 2-opt local search operator is used to further improve the routing quality (line 14). After obtaining a population of routing plans denoted by ants, the best ant in P is found, denoted as P^{best} and then improved by the proposed local search operator (lines 17-18). Besides, the associated charging scheme in P^{best}, denoted as l_s, is extracted for guiding the evolution of the charging population (line 19).

When conducting the local search on the P^{best}, in order to better match the charging scheme to finally make up the high-quality solution, a new associative insertion operator is proposed to generate the routing plan with better stability, where the nodes are still removed from the routing plan by using the continuous string removal operator [67]. First, find all the associated nodes and associated edges to the nodes that have been removed. For example, in Fig. 3, for the node a to be inserted, its associated node a_1 is the node closest to a that has not been removed, l_1 is the associated edge of the node a since it is closest to a among all the edges in the routing after removing some nodes. c_1 and l_1 are the associated node and the associated edge of node c, respectively. Then, the nodes will be inserted in sequence according to the following rules: If the associated node and the associated edge belong to the same route (e.g., node a), the node will be inserted into the route first without violating the capacity constraint; If not (e.g., node c), the node will be inserted into each of the two routes and one with the shorter driving distance will be selected. If the node violates the capacity constraint in both of the above cases, a greedy insertion is attempted in all routes. If there is no route to be inserted, a new route is opened.

Algorithm 2: $RoutingOptimization(\Phi, I, F', N)$

Input: I (Set of customers), F' (Set of charging stations), Φ (Pheromone matrix), N (Population size)
Output: P^{best} (Best ant in P), l_s (Charging scheme in P^{best})

$\hat{I} = \{0\} \cup I \cup F'$;
$k \leftarrow 1$;
while $k \leq N$ **do**
  Initialize **r** empty;
  Randomly select a node i in $\hat{I}$;
  Append i to **r**;
  Remove i from $\hat{I}$;
  while $\hat{I}$ *is no empty* **do**
    Find the last node i in **r**;
    $j \leftarrow RouletteWheelSelection(\hat{I}, i)$;
    Append j to **r**;
    Remove j from $\hat{I}$;
  $\mathbf{x} \leftarrow Split(\mathbf{r})$;
  Do 2-opt local search on **x**;
  Add **x** into P;
  $k \leftarrow k + 1$;
$P^{best} \leftarrow$ Find the best ant in P;
Improved P^{best} by the proposed local search operator;
$l_s \leftarrow$ Extract the charging scheme in P^{best};
return P^{best}, l_s;

C. Charging Optimization Based on Binary GA

For the charging optimization, a binary GA is used to generate a population of charging schemes for providing the diverse charging schemes for the routing population. First, an initialization method is proposed to produce the initial charging schemes. To be specific, each customer is assigned to its nearest charging station based on the Euclidean distance. Suppose that the ith customer is assigned to the jth charging station S_j, the probability of going to S_j after visiting the ith customer is calculated by:

$$p_{i,j} = \frac{d_{\max} - d_{i,j}}{(d_{\max} + \xi) - d_{\min}} \tag{14}$$

where $d_{i,j}$ is the distance from the ith customer to S_j, $d_{\max}$ ($d_{\min}$) is the distance between S_j and the farthest (closest) customer assigned to S_j. The constant ξ is added to avoid the denominator being 0, which is set to 1. For the ith bit of each individual in the population, it is calculated as follows:

$$y_i = \begin{cases} 1, & \text{if rand()} \leq p_i \\ 0, & \text{otherwise} \end{cases}$$

Then, the offspring population Q is generated by using the common uniform crossover and the bit-flip mutation proposed in [68]. The difference is that the binary charging scheme l_s contained by the best ant P^{best} in the routing population is used as the parent, which aims to guide the evolution of the charging population by the elite information from the routing population. Through the population-based search, the charging population can always maintain a number of diverse charging schemes that can well match the iteratively varying routing plans.

D. Interaction Between Two Populations

In order to better take into account the coupling between the subproblems in CEVRP, the interaction during the evolution of two populations is implemented for collaboratively searching for the optimal solution of the problem. Algorithm 3 describes the detailed steps of the interaction between the routing population P and the charging population Q. First, the customer service sequence $\mathbf{r}_c$ in the best ant P^{best} is taken as a basic routing plan to match each charging scheme in $Q \cup O$ and thus the quality of each charging scheme can be evaluated (line 1). Then, the best charging scheme Q^{best} can be determined and the first N best charging schemes in $Q \cup O$ can be survived for the next generation (lines 2-3). Afterward, a new solution $\mathbf{s}'$ can be constructed by combining $\mathbf{r}_c$ and Q^{best} (line 4). If the solution $\mathbf{s}'$ is electricity-feasible and its quality is better than the current best solution $\mathbf{s}$, $\mathbf{s}$ is updated by $\mathbf{s}'$ and the pheromone matric Φ is updated by $\mathbf{s}'$ (lines 5-7); Otherwise, the pheromone matric Φ is updated by P^{best} (lines 8-9). Specifically, the pheromone matrix is updated as follows:

$$\tau_{ij} \leftarrow \varphi_{ij} + \Delta\varphi_{ij}^{best}, \forall (i,j) \in \mathbf{s} \text{ or } P^{best} \tag{15}$$

where $\Delta\varphi_{ij}^{best} = 1/C^{best}$ and C^{best} is the quality of the best solution $\mathbf{s}$ or P^{best}.

For better understanding the interaction process, Fig. 4 illustrates the information exchange between two populations in each generation. Assume that there exist four customers and one charging station, the number of customers is 1∼4 and the number of the charging station is 5. First, the best ant $P^{best} = (1, 5, 2, 3, 4)$ in the routing population is found and used to guide the evolution of the charging population. The function of the best ant mainly includes the following two aspects: 1) The customer service sequence $\mathbf{r}_c = (1, 2, 3, 4)$ is taken as a basic routing to evaluate the quality of charging schemes, 2) The binary charging scheme $l_s = (1, 0, 0, 0)$ contained by P^{best} is used as the parent to generate the offspring charging schemes. In this way, the charging population can well match the best routing plan with some diversity, which is helpful for preventing the solution from the local optimum. Then, the best charging scheme $Q^{best} = (0, 1, 0, 0)$ can be determined to match $\mathbf{r}_c = (1, 2, 3, 4)$ and thus a new solution $(1, 2, 5, 3, 4)$ can be obtained by combining them. In return, this new solution is used to update the pheromone matrix Φ for the routing generation. Through the information interaction during evolution, these two populations can collaboratively search for the optimal solution of the problem.

V. Experimental Results and Analysis

This section first gives the related experimental settings. Then, the performance of DPCA is compared with

Algorithm 3: $Interaction(Q, O, P^{best}, \mathbf{s})$

Input: Q (Charging population), O (Charging offspring population), P^{best} (The best ant in P), $\mathbf{s}$ (The best solution)
Output: Q, Φ, $\mathbf{s}$

```
Evaluate each charging scheme in Q ∪ O based on the basic routing r_c;
Q ← Select first N charging schemes in Q ∪ O;
Q^best ← Determine the best charging scheme in Q;
s' ← Construct a new solution by combining r_c and Q^best;
if s' is electricity-feasible and better than s then
    s ← s';
    Update pheromone matric Φ by s;
else
    Update pheromone matric Φ by P^best;
return Q, Φ, s;
```

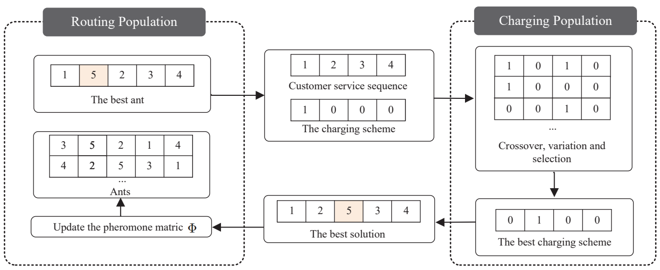


Fig. 4. Illustration of the interaction process between two populations.

four state-of-the-art algorithms in the solution quality and the time efficiency. Afterward, the effectiveness of the dual-population coevolution strategy is verified by comparing DPCA with its three variants. Finally, the effectiveness of the proposed associative insertion operator in improving the quality of routes is validated.

A. Experimental Setup

1) Algorithms: The performance of the proposed DPCA is verified by comparing it with four state-of-the-art algorithms, namely, the hybrid ALNS heuristic algorithm (SIGALNS) [22], the max-min ant system (MMAS) [26], the bi-level ant colony optimization algorithm (BACO) [47] and the confidence-based BACO (CBACO) [48]. Note that SIGALNS is an individual-based metaheuristic algorithm while MMAS, BACO and CBACO are population-based metaheuristic algorithms.

2) Test Problems: Two well-known test suites, namely the R-C test suite [56] and the E-X test suite [26], are chosen for the performance comparison of algorithms. R-C test suite takes into account the impact of uncertainties in actual logistics distribution by randomly scattering the locations of customers and charging stations on a 100×100 grid. It includes 34 test instances with the number of customers varying from 30 to 200. The demand of each customer is set as 5, 10, and 15, and the numbers of charging stations are set to 2, 4, 6, and 8 in these instances. The maximum capacity of the EV is set to 100 and the maximum battery capacity of the EV is set to 150. E-X test suite [26] is recently proposed by Mavrovouniotis *et al.*, which covers a large number of different scenarios concerning the characteristics of the real problem, such as the distribution of consumers and their demands, the number and distribution of charging stations, the freight and battery capacities of vehicles. Table-I in the supplementary file gives the detailed information of the E-X test instances.

3) Parameter Settings: Experiments are conducted on a workstation computer with an Intel Core i7 3.4GHz CPU with 64GB of memory. Each test instance performs 20 independent runs and the maximum number of generations is set to 5,000. For fair comparisons, all the parameters are set to the same as suggested in the original studies. Regarding the settings of DPCA, the used MMAS follows the recommended setting as suggested by Mavrovouniotis *et al.* [26], where the information evaporation rate ρ is set to 0.98, α and β are set to 1, and 2, respectively. The population size is set to the number of customers as suggested by Jia *et al.* [48].

B. Performance of the Proposed DPCA

To verify the performance of the proposed algorithm in solving CEVRP, it is compared with the four state-of-the-art algorithms on both R-C and E-X test suites. The performance of DPCA is analyzed from the following aspects.

1) Total Driving Distance Comparison: The min and mean objective values obtained by MMAS, SIGALNS, BACO, CBACO and DPCA in 20 independent runs are compared, and the comparison results are given in Table II and Table III in the supplementary file, where the number in parentheses denotes the number of vehicles used. The "w/t/l" denotes how many instances DPCA wins, ties or loses to the other algorithms and the "rank" row shows the overall rank of each algorithm according to the Friedman test. For the R-C test suite [56], DPCA obtains 12 best min objective values among 14 test instances with fewer charging stations (2 and 4). BACO achieves 4 best min objective values among these instances while the other two algorithms fail to achieve the best value. For the test instances with fewer charging stations, the coupling between the routing optimization and the charging decision is stronger. SIGALNS, MMAS, BACO, and CBACO optimize two subproblems in stages, which cannot handle this strong coupling relationship well during the optimization process, resulting in the poor performance. Specifically, for the "R-2-C-90", MMAS even cannot find a feasible solution since the electricity constraint is hard to be met when the number of charging stations is less. For the 20 test instances with more charging stations (6 and 8), DPCA achieves a comparable performance in comparison to BACO in terms of the mean value. In terms of the min value, DPCA obtains 12 best results among these instances, while BACO obtains 7 and the other algorithms achieve only one or none. This indicates that DPCA is comparable in solving CEVRP even when the coupling between the routing optimization and the charging decision is weak. Overall, on the R-C test suite, DPCA has a reduction of 3.34%, 6.79%, 2.74% and 3.30% compared to SIGALNS, MMAS, BACO, and CBACO, respectively. For the E-X test suite [26], due to the complex distribution of customers and stations, the coupling between the routing optimization and the charging decision becomes more complicated. DPCA is clearly superior to other algorithms due to the effectiveness of the dual-population co-evolution strategy for this coupling problem. Specifically, it has a reduction of 5.37%, 5.73%, 0.75% and 1.94% compared to SIGALNS, MMAS, BACO, and CBACO, respectively.

2) Effectiveness of Route Adjustment During Iteration: Fig. 5 shows the routes obtained by MMAS, BACO and DPCA at different stages of the evolutionary process on the "R-2-C-40" test instance, respectively. The routes denoted by the dashed lines are obtained by ignoring the charging stations and regarding the problem as a CVRP. It can be found that, at the 200-*th* generation, the initial routes obtained by MMAS, BACO and DPCA almost overlap with those in the case that is solved as a CVRP. At the 400-*th* or 600-*th* generation, the routes obtained by MMAS, BACO and DPCA change under the action of the pheromone. Among them, DPCA has an obvious change. The reason is that, with the new pheromone update rule, DPCA takes into account the influence of the position of charging stations, and thus the routing plan is gradually closer to the charging stations. Meanwhile, the driving distance of going to the charging station is gradually reduced. Finally, at the 800-*th* generation, the routing plan obtained by DPCA has little overlap with the case of CVRP. It is worth noting that it is not the best routing plan for CVRP but for CEVRP, which indicates the necessity of the collaborative optimization of routing and charging.

3) Solution Comparison: Fig. 6 shows the final solutions obtained by SIGALNS, MMAS, BACO and DPCA on the "R-8-C-30" test instance. This run corresponds to the result with the min objective value. As shown in Fig. 6(a), EVs visit charging stations between customers 18 and 16, 28 and 29, even the nearest charging station is far from the customer. The reason is that MMAS only allows EVs to visit the charging station when the electricity is not satisfied to reach the next customer. Making a detour to the charging stations inevitably increases the driving distance. As shown in Fig. 6(b), the route repair method used by SIGALNS has some improvements on the detour compared to MMAS. When encountering insufficient electricity to reach the next customer, there are more options for the position of the charging station to be inserted in SIGALNS. However, the previously inserted charging station in the routing will affect the decision of the following charging stations, and when the electricity is insufficient again, the best position of the next charging station may also cause the detour, leading to an increase in the total driving distance. As shown in Fig. 6(c), BACO uses a removal heuristic approach to optimize the charging scheme that is effective to avoid the detour of EVs, but the optimization process is very time-consuming as it needs to optimize the charging scheme for each routing plan in the population. As shown in Fig. 6(d), DPCA can obtain an appropriate charging scheme to match the routing plan and thus can effectively avoid the increase in the total driving distance.

Fig. 7 plots one route in the final solution obtained by the proposed method on R-6-C-40, involving nine customers (C1,…,C9), six charging stations (S1,…,S6), and the depot (D) that can be also used for recharging, and at the same time records the remaining load and battery level of the EV before and after the EV visits each node (depot, charging station, or customer) during its journey. The first item in bracket denotes the the remaining load and the second is the remaining battery level, and the value along the arc means the consumed battery power of the EV. The cargo demands of C3 and C4 are 5, the demands of C6, C7 and C8 are 10, and the demands of C1, C2 and C9 are 15. EV starts from the depot (D) with the remaining load 100 and the remaining battery level 150. When the EV arrives at customer C1, it consumes the battery power 9, and after visiting C1, the remaining load of the EV is 85. When leaving C3, EV chooses to go to S5 to recharge and then visit C4, even though the EV still has enough energy to go from C3 to C4. The reason is that there exists no charging station available on the subsequent journey. When EV returns to the depot, the remaining battery level is 2 and the remaining load is 0. By recording the changes on the remaining battery level and load of the EV, it can be found that the proposed method makes the best use of the available charging stations and embeds the routing plan with the appropriate charging scheme, resulting in a shorter driving distance.

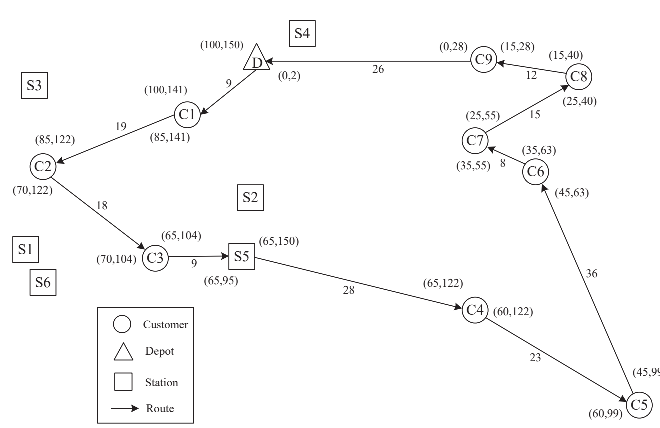
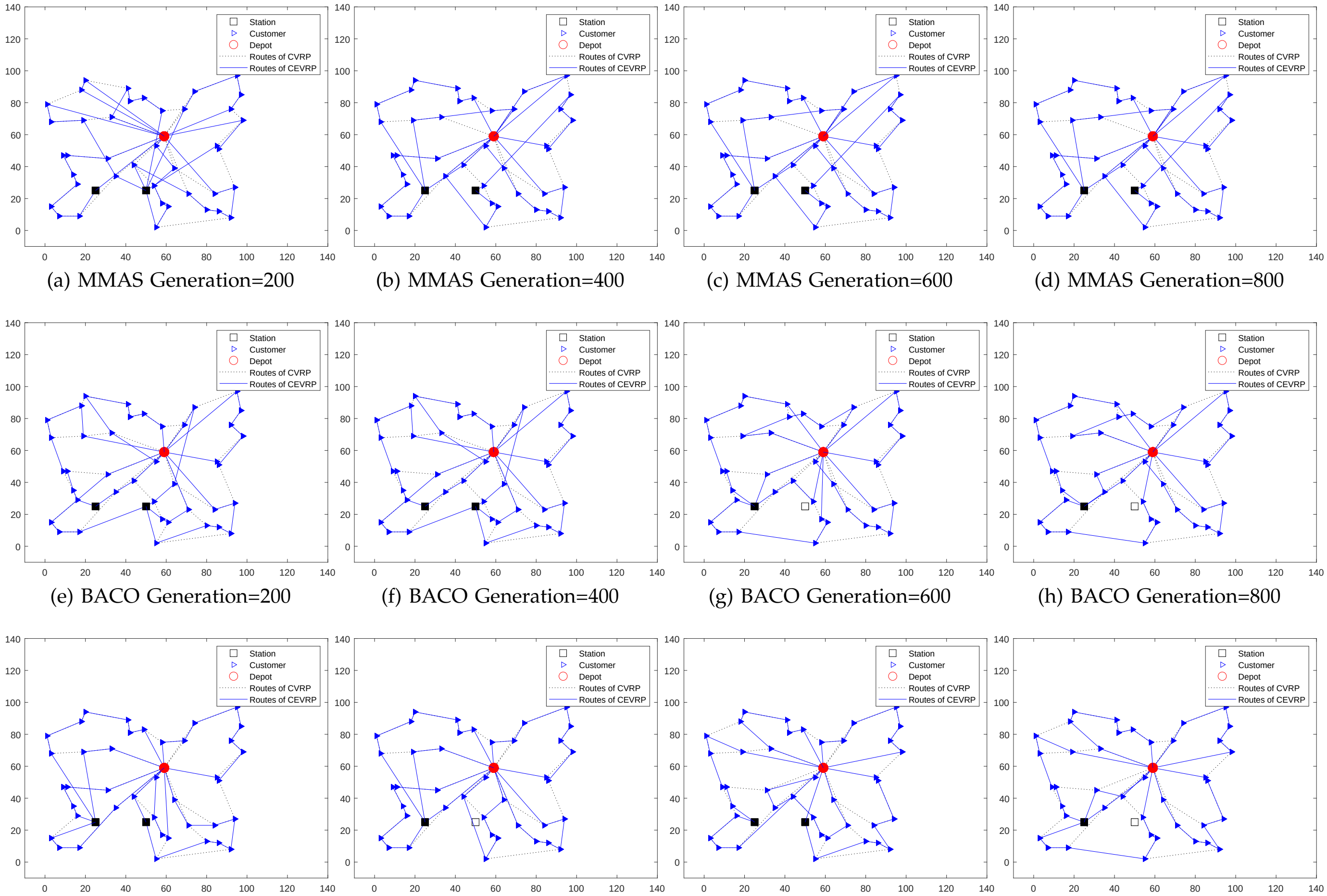


Fig. 7. Changes in the battery level and the load of the EV during journey.

4) Convergence Speed: In order to analyse the convergence ability of each algorithm, the objective value is

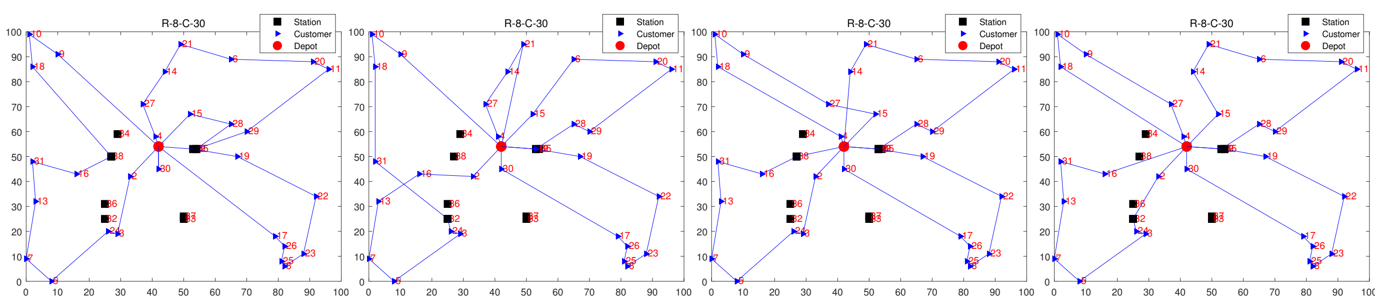


(a) MMAS Generation=200 (b) MMAS Generation=400 (c) MMAS Generation=600 (d) MMAS Generation=800

(e) BACO Generation=200 (f) BACO Generation=400 (g) BACO Generation=600 (h) BACO Generation=800

(i) DPCA Generation=200 (j) DPCA Generation=400 (k) DPCA Generation=600 (l) DPCA Generation=800

Fig. 5. Illustration of solutions generated by MMAS, BACO and DPCA on "R-2-C-40" instance during the evolutionary process.



(a) MMAS (b) SIGALNS (c) BACO (d) DPCA

Fig. 6. Illustration of final solutions obtained by MMAS, SIGALNS, BACO and DPCA on the "R-8-C-30" test instance.

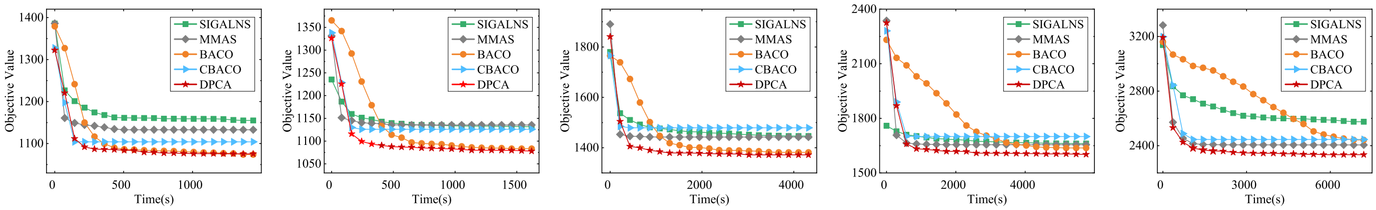
calculated by running each algorithm at a fixed CPU time T, which can be determined as follows:

$$T = \vartheta \times \frac{|I|}{100}(\text{hr}) \tag{16}$$

where $|I|$ is the total number of customers. For test instances with less than 100 customers, ϑ is set to 0.5, and for test instances with 100∼200 customers, ϑ is set to 1.

Fig. 8 plots the convergence curves of the five algorithms on different scales of test instances. It can be found that, in terms of the final total driving distance, DPCA can achieve a comparable performance to BACO on "R-6-C-80", and perform better on both "R-6-C-90" and "R-6-C-120". Also, DPCA has an obvious advantage on large-scale test instances, such as "R-6-C-200". Additionally, in terms of convergence speed, DPCA converges faster than the other three algorithms on most of the test instances.

5) Time Efficiency: Fig. 9 shows the CPU time consumed by these five algorithms on the 34 test instances from the R-C test suite. It can be found that the CPU



(a) R-6-C-80 (b) R-6-C-90 (c) R-6-C-120 (d) R-6-C-160 (e) R-6-C-200

Fig. 8. Convergence curves of SIGALNS, MMAS, BACO, CBACO and DPCA on the five test instances with different scales.

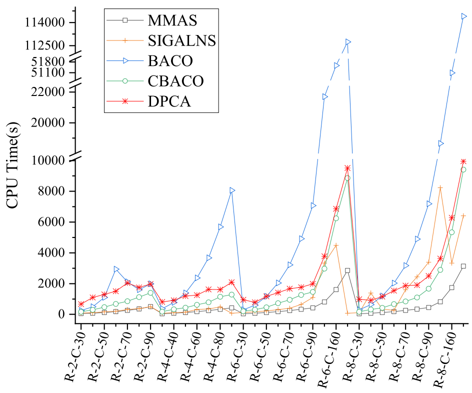


Fig. 9. CPU time consumed by MMAS, SIGALNS, BACO, CBACO and DPCA on the R-C test suite.

time consumed by DPCA is significantly less than that consumed by BACO. Specifically, DPCA is faster than BACO by about 2 times, even reaching 10 times on some large-scale instance. For BACO, the lower-level charging optimization for all ants consumes much time, while DPCA only needs to optimize the charging scheme for the best ant that can greatly save time. For CBACO, it only selects some promising ants to execute the charging optimization that can also reduce the CPU time, while DPCA has a comparable computational efficiency to it. For MMAS, it directly inserts the closest charging station to make the solution electricity-feasible that has the lowest computation complexity, but there is a significant increase in the total driving distance. Overall, the proposed DPCA maintains an acceptable and comparable computational efficiency compared to other algorithms.

C. *Effectiveness of the Dual-Population Co-evolution Strategy*

To verify the effectiveness of the adopted dual-population coevolution strategy, DPCA is compared with its three variants on the R-C test suite. In Variant-I, the charging scheme contained by the best ant is not used to guide the evolution of the charging population, i.e., two individuals in the charging population are randomly selected as the parents to generated the offspring, which mainly verifies the effectiveness of the interaction from the routing population to the charging population. In Variant-II, GA is not used to generate a population of charging schemes for the best ant, but using the IG heuristic algorithm [22] to optimize the charging scheme for each ant, which aims to verify the effectiveness of maintaining the diverse charging schemes for jumping out the local optimum. In Variant-III, charging stations are not considered when planning the routing and only the service order for customers is optimized, which mainly verifies the effectiveness of pre-placing the charging stations into the routing plan for avoiding the detour of EVs.

Table I shows the min objective values among 20 independent runs obtained by DPAC and its three variants on the R-C test suite. Fig. 10 shows the convergence curves of DPCA and the three variants on ten R-C test instances with six charging stations. The following observations can be obtained from the results in Table I:

1) Compared with Variant-I, DPCA can perform better on 20 out of 34 test instances. Moreover, from Fig. 10, it can be found that the convergence performance of DPCA is better than that of Variant-I on all instances. This indicates that, when the charging scheme contained by the best ant is crossed with individuals in the charging population, some charging stations that are far away from customers can be quickly removed and thus the solution quality can be greatly improved.
2) Compared with Variant-II, DPCA can obtain the better results on 22 out of 34 test instances. Also in Fig. 10, DPCA can perform better convergence ability than Variant-II on most of test instances. The reason is that the dual-population coevolution strategy can generate a suitable charging scheme for the best routing plan to escape from the local optimum. The IG algorithm focuses on providing the optimal charging scheme for the fixed routing plan. However, the combination of the respective optimums in stages is not always the optimal solution for the CEVRP, IG very likely makes the solution fall into the local optimum.
3) Compared with Variant-III, DPCA can achieve better results on 31 out of 34 test instances. The reason is that pre-placing the charging stations into the routing plan can better balance the objective minimization and the electricity-constraint satisfaction, avoiding that excessively seeking the minimization of the driving distance among customers leads to the detour of EVs to recharge. As shown in Fig. 10, DPCA shows better convergence ability

TABLE I
OBJECTIVE VALUES OBTAINED BY DPCA AND THREE VARIANTS ON R-C TEST SUITE. BEST RESULT IN EACH INSTANCE IS HIGHLIGHTED.

	Variant-I	Variant-II	Variant-III	DPCA		Variant-I	Variant-II	Variant-III	DPCA
R-2-C-30	**596.45(4)**	**596.45(4)**	**596.45(4)**	**596.45(4)**	R-4-C-30	623.17(4)	634.29(4)	639.37(4)	**611.26(4)**
R-2-C-40	784.66(5)	**766.31(5)**	817.75(5)	769.05(5)	R-4-C-40	738.91(5)	729.31(4)	779.97(4)	**723.68(4)**
R-2-C-50	817.00(5)	**808.26(5)**	844.06(5)	811.83(5)	R-4-C-50	785.83(6)	785.83(6)	787.27(6)	**785.45(6)**
R-2-C-60	**978.88(7)**	**978.88(7)**	**978.88(7)**	**978.88(7)**	R-4-C-60	900.84(7)	**899.80(7)**	933.69(7)	899.92(7)
R-2-C-70	**1038.86(8)**	1048.91(8)	1053.12(8)	1049.22(8)	R-4-C-70	1115.47(8)	1114.23(8)	1130.73(8)	**1113.84(8)**
R-2-C-80	1206.36(9)	1154.14(9)	1165.30(9)	**1152.13(9)**	R-4-C-80	**1144.34(10)**	1146.90(9)	1149.24(9)	1146.39(9)
R-2-C-90	**1178.62(10)**	1183.53(10)	1237.33(10)	1182.21(10)	R-4-C-90	1182.79(10)	1182.79(10)	1241.42(10)	**1181.84(10)**
R-6-C-30	**526.68(3)**	**526.68(3)**	**526.68(3)**	**526.68(3)**	R-8-C-30	613.70(4)	611.77(4)	617.50(4)	**611.48(4)**
R-6-C-40	**688.14(5)**	691.05(5)	710.16(5)	**688.14(5)**	R-8-C-40	**648.23(5)**	**648.23(5)**	666.54(5)	**648.23(5)**
R-6-C-50	867.22(6)	883.57(6)	909.23(6)	**863.18(6)**	R-8-C-50	801.07(6)	**798.12(6)**	808.23(6)	**798.12(6)**
R-6-C-60	979.11(6)	**964.67(7)**	979.11(6)	978.85(6)	R-8-C-60	**862.02(7)**	874.91(6)	868.80(6)	864.65(6)
R-6-C-70	**938.57(7)**	941.36(7)	949.08(7)	941.07(7)	R-8-C-70	**1120.87(8)**	1099.84(8)	1130.99(8)	1128.51(8)
R-6-C-80	1063.80(8)	1059.78(8)	1084.23(9)	**1059.61(8)**	R-8-C-80	1108.55(9)	1114.06(9)	1122.55(9)	**1108.55(9)**
R-6-C-90	**1052.72(11)**	1071.03(11)	1069.07(10)	1063.72(10)	R-8-C-90	1221.12(11)	1197.09(9)	1286.70(9)	**1189.66(9)**
R-6-C-120	1350.82(13)	1348.22(13)	1370.13(13)	**1344.67(13)**	R-8-C-120	1597.80(13)	**1576.42(13)**	1601.73(12)	1590.36(12)
R-6-C-160	1572.04(17)	1561.81(17)	1593.35(17)	**1553.89(16)**	R-8-C-160	1569.85(18)	1571.97(17)	1568.97(18)	**1568.29(18)**
R-6-C-200	**2267.41(23)**	2274.15(22)	2313.30(24)	2271.14(23)	R-8-C-200	2034.83(23)	2021.17(22)	2067.77(23)	**2015.33(23)**

than Variant-III on almost of test instances.

D. Effectiveness of the Proposed Insertion Operator

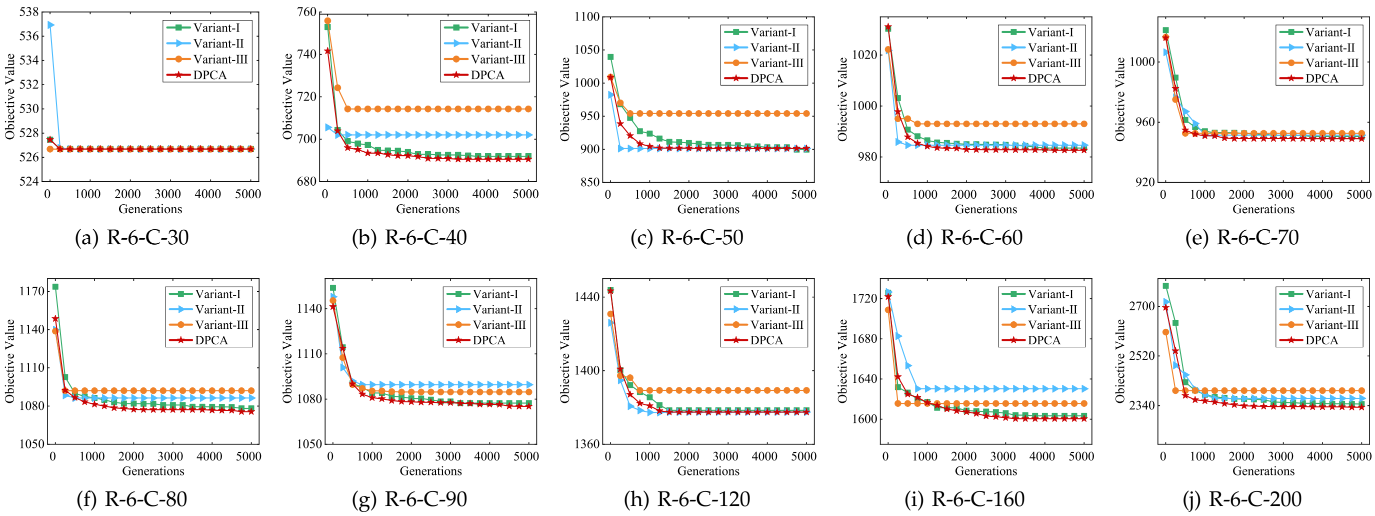
To verify the effectiveness of the proposed insertion operator in the routing optimization, it is compared with the basic greedy insertion operator (BGI) and the regret-2 insertion operator (Regret-2I) [69], while the string-based removal operator [67] is still used to remove nodes in the routing plan. Table II shows the min and mean objective values on 10 R-C test instances with different scales, where "Associate-I" denotes the proposed associative insertion operator. It can be found that Associate-I performs well on most of the test instances compared to the BGI method and the Regret-2I method. Although these two methods have been verified to be effective for the vehicle routing optimization, they seem to be unsuitable for the routing optimization with charging stations in CEVRP. This is because CEVRP is not only limited by the capacity constraint, but also the electricity constraint. Without considering the electricity constraint, the greedy selection of the least-cost insertion may not be effective for generating the optimal solution for CEVRP, even if the optimal routing plan is found. The proposed Associate-I refers to the associated customers and the associated edges. It first inserts customers belonging to the same route, and then considers the best insertion position for customers belonging to multiple routes. Compared with the greedy or regret insertion, the proposed operator can find a more suitable position to insert nodes for CEVRP.

TABLE II
OBJECTIVE VALUES OBTAINED BY APPLYING THREE INSERTION OPERATORS ON THE R-C TEST INSTANCES WITH DIFFERENT SCALES.

Instance		Associate-I	BGI	Regret-2I
R-6-C-30	min	**526.68(3)**	**526.68(3)**	**526.68(3)**
	mean	**526.68**	**526.68**	**526.68**
R-6-C-40	min	**688.03(5)**	688.14(5)	688.14(5)
	mean	**688.84**	689.70	691.76
R-6-C-50	min	**863.18(6)**	891.38(6)	894.09(6)
	mean	**888.31**	897.38	897.09
R-6-C-60	min	978.85(6)	978.85(6)	**969.40(7)**
	mean	979.19	980.23	**977.05**
R-6-C-70	min	941.07(7)	**937.51(7)**	941.29(7)
	mean	948.28	**946.17**	947.66
R-6-C-80	min	**1059.61(8)**	1066.79(8)	1066.34(8)
	mean	**1066.23**	1069.33	1071.39
R-6-C-90	min	1063.72(10)	**1062.69(10)**	1063.72(10)
	mean	1071.26	**1071.04**	1073.12
R-6-C-120	min	**1344.67(13)**	1346.18(13)	1353.99(13)
	mean	**1354.64**	1360.39	1363.99
R-6-C-160	min	**1553.89(16)**	1571.99(16)	1564.29(17)
	mean	**1581.02**	1586.33	1584.43
R-6-C-200	min	**2271.14(23)**	2287.56(22)	2290.04(23)
	mean	**2296.77**	2300.86	2306.14

VI. CONCLUSIONS

In this paper, a dual-population based co-evolutionary algorithm (DPCA) was proposed to solve the CEVRP. The proposed algorithm considered the coupling between the routing optimization and the charging decision by running two co-evolution populations. In the routing population, an improved ant colony optimization algorithm was designed to generate high-quality routing plans that can include the position information of charging stations in advance. In the charging population, a binary genetic algorithm was used to generate a population of charging schemes whose qualities are evaluated based on the best ant obtained from the routing population. Through the information interaction during the evolution, these two populations can collaboratively search for the optimal solution of the problem. Based on the experiment, it is found that DPCA can outperform four widely used metaheuristics in terms of the total



(a) R-6-C-30 (b) R-6-C-40 (c) R-6-C-50 (d) R-6-C-60 (e) R-6-C-70

(f) R-6-C-80 (g) R-6-C-90 (h) R-6-C-120 (i) R-6-C-160 (j) R-6-C-200

Fig. 10. Convergence curves of DPCA and its three variants on test instances with different scales.

driving distance, which has a reduction of 3.82%, 5.83%, 1.62% and 2.57% compared to SIGALNS, MMAS, BACO, and CBACO averaged over two test suites. Through the observation on the route change during iteration, it can be found that DPCA can effectively avoid falling into the local optimum by matching the routing plan with the appropriate charging scheme. In terms of the time efficiency, DPCA has an obvious advantage over the advanced BACO with twice the speed and a comparable performance compared to SIGALNS.

In the future research, it will be interesting to develop the dual-population based co-evolution framework for more complex EVRP variants, such as EVRP with time windows [21], [28] and EVRP with non-linear charging (EVRP-NL) [30].

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