Improved Memetic Algorithm Based on Route Distance Grouping for Multiobjective Large Scale Capacitated Arc Routing Problems

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***Abstract*—The capacitated arc routing problem (CARP) has attracted considerable attention from researchers due to its broad potential for social applications. This paper builds on, and develops beyond, the cooperative coevolutionary algorithm based on route distance grouping (RDG-MAENS), recently proposed by Mei *et al.* Although Mei's method has proved superior to previous algorithms, we discuss several remaining drawbacks and propose solutions to overcome them. First, although RDG is used in searching for potential better solutions, the solution generated from the decomposed problem at each generation is not the best one, and the best solution found so far is not used for solving the current generation. Second, to determine which sub-population the individual belongs to simply according to the distance can lead to an imbalance in the number of the individuals among different sub-populations and the allocation of resources. Third, the method of Mei *et al.* was only used to solve single-objective CARP. To overcome the above issues, this paper proposes improving RDG-MAENS by updating the solutions immediately and applying them to solve the current solution through areas shared, and then according to the magnitude of the vector of the route direction, and a fast and simple allocation scheme is proposed to determine which decomposed problem the route belongs to. Finally, we combine the improved algorithm with an improved decomposition-based memetic algorithm to solve the multiobjective large scale CARP (LSCARP). Experimental results suggest that the proposed improved algorithm can achieve better results on both single-objective LSCARP and multiobjective LSCARP.**

***Index Terms*—Capacitated arc routing problem (CARP), multiobjective optimization, problem decomposition.**

I. Introduction

THE CAPACITATED arc routing problem (CARP) is a classic non-deterministic polynomial (NP)-hard combinatorial optimization problem. CARP has a wide range of applications, such as winter gritting, waste collection, and snow removal [1], [2]. CARP has been deeply researched for several decades. However, most of the previous work only focused on single-objective optimization problems, which are rarely representative of real-practical application [3]. In fact, not only the minimum loop total consumption needs to be found, but also other factors have to be taken into account. In 2006, the optimized model for multiobjective CARP was first proposed by Lacomme *et al.* [4]. In this optimized model, optimizing the loop total consumption is a significant problem. At the same time, it also aims at optimizing the maximum loop total consumption generated by total vehicles. However, these two optimization problems are conflicting and cannot achieve optimal solution simultaneously [5]. Multiobjective CARP is confounded by the need for solving a multiobjective optimization problem [6], [7], and a combinational optimization problem simultaneously [8], which makes it extremely challenging. In 1989, Moscato [9] proposed the memetic algorithm (MA), which is a combination of the global search based on populations and the local heuristic search based on the individual. For an excellent review of work in the field of "adaptive MAs," see [10]. MA also has a wide range of applications in solving NP-hard combinatorial problems [11]. Tang *et al.* [12] proposed an MA [13] with extended neighborhood search (MAENS) which is superior to a number of other state-of-the-art algorithms. MAENS employs a novel local search operator that is capable of large step sizes and thus has the potential to search the solution space more efficiently [14], [15]. However, this algorithm is only intended for solving single-objective CARP. To overcome this shortcoming, D-MAENS, based on problem decomposition, was presented by Mei *et al.* [16] to solve multiobjective CARP. MAENS is incorporated into D-MAENS and its framework is similar to that of a multi-objective evolutionary algorithm based on decomposition. Combined fast nondominated sorting and crowding distance method is adopted in D-MAENS [17]. The performance of D-MAENS is evidently better than multi-objective genetic algorithm which includes a local search procedure, however, there remained room for improvement with respect to the offspring update and allocation mechanisms. Thus, an improved decomposition-based MA (IDMAENS) [18] was presented to further improve D-MAENS. An elitist strategy is adopted in IDMAENS, which

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means that IDMAENS can retain an optimal solution of each decomposed problem according to the direction vector of each sub-problem while seeking solutions and the old solution will be replaced by it at once. When solving each sub-problem, the optimal solution of one sub-problem can provide favorable information to adjacent sub-problems via a neighborhood sharing approach so as to accelerate the convergence.

Meanwhile, CARP usually has a large scale [19], which is called large scale CARP (LSCARP) [20], [21]. Therefore, we should not only study multiobjective CARP, but also LSCARP. In 2008, Brandão and Eglese [22] first considered studying LSCARP with the *EGL-G* test set to evaluate the performance of algorithms used to solve LSCARP. Compared with the usual demand edges from 11 to 190 basis set (*gdb* [23], *val* [24], *egl* [25], and *Beullens* [26]), for all the instances, the number of edges in need of services in *EGL-G* group are more than 300. CARP is an NP-hard problem, which means that the solution space exponentially increases as the size of the problem enlarges. Most algorithms perform well in small-scale and medium-scale, but ignore the scalability problems, which may lead to noncompetitive result or excessive computation time when applied to solve LSCARP [27].

In order to solve LSCARP, a divide-and-conquer strategy can be used to divide the large scale problem into several small-scale sub-problems and then solve each sub-problem, respectively [2]. Pearn [20] and Potter and Jong [28] proposed a genetic algorithm with cooperative coevolution to function optimization. And in 2006, a distributed cooperative CA was proposed by Tan *et al.* [29] for multiobjective optimization. These approaches can not only reduce the scale of solution spaces, but also concentrate effort on searching direction on specific regions restricted by sub-problems. However, optimal decompositions only form a small proportion of the actual decomposition. Thus, solutions of sub-problems have to be updated constantly so as to improve the quality of decomposition along with perfection of solution space information. In the context of evolutionary computation [30], the cooperative coevolutionary (CC) approach realizes the strategy of divide-and-conquer in a natural way which has been applied to solve large-scale function optimization problems successfully [31]–[33].

Mei *et al.* [34] presented random routing grouping (RRG), a simple and effective decomposition scheme. RRG uses the best-so-far routing information to ensure the best-so-far decomposed program improved. RRG incorporates the CC framework and optimizes the sub-problems with MAENS. Evaluations using the *EGL-G* test set, demonstrated the efficacy of CC framework and the RRG decomposition approach. For LSCARP, a CC algorithm based on route distance grouping (RDG-MAENS) was proposed by Mei *et al.* [2]. Experiments show that this algorithm is superior to other existing algorithms with respect to solving LSCARP. However, there is still room to improve it in the turnover of solutions and in solving multiobjective CARP: 1) the solution generated from sub-problems at each generation is not the best one, and the best solution found so far is not used to solve the current generation and 2) to determine which sub-populations the individual belongs to simply according to the distance between them can lead to an imbalance in the number of the individuals among different sub-populations and the allocation of resources.

This paper, attempts to achieve the above two improvements, by proposing and improved RDG-MAENS procedure consisting of two stages.

1) First, problems are decomposed in a CC framework based on the divide and conquer method, and then the decomposed problems are solved from the decomposition solely. In this stage, the best-so-far solution is used in each decomposed problem, updating it immediately and applying it to solving the current solution through shared areas.
2) Second, a fast and simple allocation scheme is proposed to determine which decomposed problem the route belongs to according to the magnitude of the vector of the route direction.

The improved RDG-MAENS is called IRDG-MAENS.

Previously, RDG-MAENS has only been used to solve large-scale single-objective CARP. For solving multiobjective CARP, IDMAENS improves both offspring update mechanism and distribution mechanisms based on D-MAENS. However, IDMAENS still needs to be improved further to solve LSCARP. In order to solve the multiobjective LSCARP effectively, we combine IRDG-MAENS with IDMAENS to give our proposed IRDG-IDMAENS method. Experimental results indicate that IRDG-MAENS not only better meets the constraints of the feasible region compared with RDG-MAENS in solving single-objective LSCARP, but also achieves better results in much shorter time. In addition, for multiobjective LSCARP, experimental results show that IRDG-IDMAENS can find better results in contrast to the IDMANES algorithm. Overall, for large scale tests, it produces better results than the other compared algorithms.

The remainder of this paper is organized as follows. The related work is introduced in Section II. The description of the improved RDG-MAENS is proposed in Section III. Section IV presents results of our experimental studies, which compare the above algorithms using several public benchmark CARP test data sets (small, medium, and large scale). The conclusion is provided in Section V.

II. Related Work

A. Single-Objective CARP Model

In line with [35], CARP can be simply described as follows. Given a directed or undirected connected graph $G = (V, E, A)$, where V, E, and A represent the set of vertices, edge set, and the arc set in the connected graph, respectively. A set of vertices can be expressed as $V = \{v_0, v_1, \ldots, v_n\}$, where v_0 represents the depot. The subsets of E and A are $Z_E \subseteq E$ and $Z_A \subseteq A$, which are also known as service tasks that need to be provided. Every edge e in E has three nonnegative attributes, the service demand $d(e)$, the service consumed $s(e)$, and after consumption of $c(e)$. $E_R = (e \in E|d(e) > 0)$ indicates the task set of the edges. $A_R = (a \in A|d(a) > 0)$ represents a collection of task arcs. There is a vertex of the V designated as the depot, v_0, with the capacity Q for each vehicle,

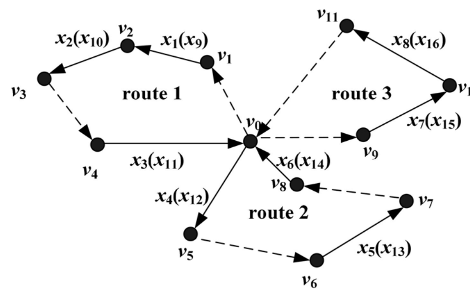

Fig. 1. Simple scheme for CARP.

serving edges, and arcs of G. The problem is to determine a set of reasonable routes, so that all the needs of edges (or arcs) have been serviced and each edge (or arc) is serviced only by one vehicle. Meanwhile, the following constraints should be satisfied: 1) the vehicle must start from the garage, and eventually return back to the garage; 2) all edges and arcs in need of services must be serviced, and can be serviced only once in the connected graph G; and 3) the total demand for vehicle service tasks cannot exceed the capacity Q. The mathematical model of CARP can be summarized as

$$\begin{cases} \min f_1(\boldsymbol{x}) = \sum_{h=1}^{m} \operatorname{cost}(T_h) \\ \text{where} \\ \operatorname{cost}(T_h) = \sum_{i=1}^{|T_h|-1} s\big(v_{h_i}, v_{h_{(i+1)}}\big) \times k_{h_i} \\ \qquad + \; c\big(v_{h_i}, v_{h_{(i+1)}}\big) \times \big(1 - k_{h_i}\big) \\ \big(v_{h_i}, v_{h_{(i+1)}}\big) \in E_R \cup A_R, \quad \forall k_{h_i} = 1, 1 \le h \le m \\ \big(v_h, v_{h_{(i+1)}}\big) \ne \big(v_{t_j}, v_{t_{(j+1)}}\big), \quad \forall k_{h_i} = 0, k_{t_j} = 1, t \ne h \\ \sum_{i=1}^{|T_h|-1} d\big(v_{h_i}, v_{h_{(i+1)}}\big) \times k_{h_i} \le Q, 1 \le h \le m \end{cases} \tag{1}$$

where $T_h = (v_{h1}, v_{h2}, v_{h3}, \ldots, v_{h|T_h|}|k_{h1}, \ldots, k_{h|T_h-1|})$ represents the sequence of the hth route, where $k_{hi} = 1$ denotes the edge $(v_{hi}, v_{h_{(i+1)}})$ serviced by the hth vehicle and $k_{hi} = 0$ denotes that this edge is only traveled but not serviced by the vehicle.

B. Multiobjective CARP Model

In single-objective CARP, we need to design only an optimal route scheduling to find a subset of edges which should be served subject to the constraint of vehicle limit under minimum collection, denoted as $f_1(x)$. With the same constraints in the model of single-objective CARP given in Section II-A, the model of multiobjective CARP with two objectives can be defined as

$$\begin{cases} \min f_1(x) = \sum_{h=1}^{m} \operatorname{cost}(T_h) \\ \min f_2(x) = \max_{1 \le h \le m}(\operatorname{cost}(T_h)). \end{cases} \tag{2}$$

It can be seen from (2), for multiobjective CARP, the total cost of the entire program [denoted by $f_1(x)$] and the largest consumption of m vehicles [denoted by $f_2(x)$] should be minimized simultaneously in multiobjective CARP. Furthermore, a simple scheme for CARP is illustrated in Fig. 1.

In Fig. 1, the bold lines represent task edge, the dotted lines indicate the nontask edge, and v_i represents the intersection point between different edges. The depot is denoted by v_0. Meanwhile, we allocate two IDs for each task edge (e.g., ID x_1 from v_1 to v_5, while ID x_6 from v_8 to v_0). In Fig. 1, there are three routes: route 1 $= (0, x_1, x_2, x_3, 0)$, route 2 $= (0, x_4, x_5, x_6, 0)$, and route 3 $= (0, x_7, x_8, 0)$. For single-objective CARP, we should minimize the total cost [min route $= (0, x_1, x_2, x_3, 0, x_4, x_5, x_6, 0, x_4, x_5, x_6, 0)$]. However, in multiobjective CARP, the largest consumption of the circuits (routes 1–3) also should be minimized.

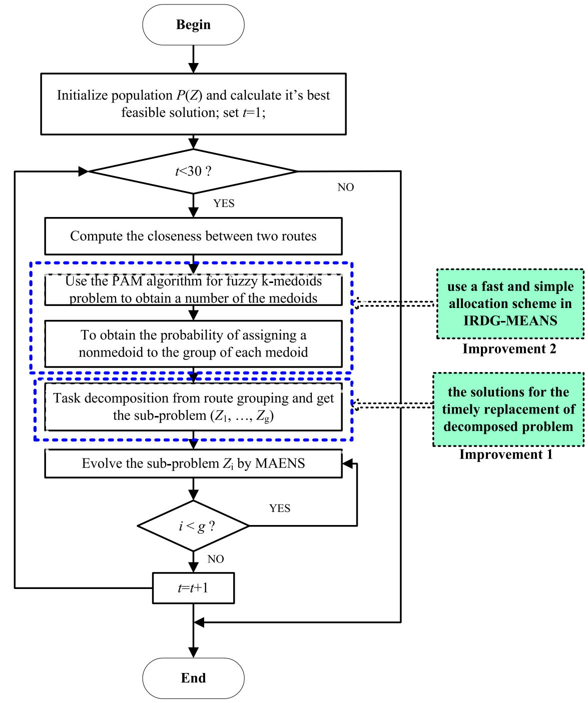

Fig. 2. Flowchart of RDG-MAENS and two improvements of RDG-MAENS in IRDG-MEANS.

C. RDG-MAENS Algorithm

Mei *et al.* [2] proposed RDG-MAENS to solve CARP effectively. For LSCARP, it considers the interaction between variables. The entire evolutionary optimization process is divided into several cycles by using the CC framework. Furthermore, decision variables are partitioned into smaller sub-problems solved separately. In this way, the solution space can be greatly reduced, and the search space can be restricted to an area which is defined only by a sub-assembly [33], [34].

RDG-MAENS uses the routing information of the best solution so far. In other words, in each cycle, the problem is divided into several groups by using a best-so-far decomposition program and updates the best-so-far solution during the search. The flowchart of RDG-MAENS and the two improvements of the proposed IRDG-MEANS are shown in Fig. 2.

Although RDG-MAENS can identify better solutions in the solution space, the solution assigned to each generation of each sub-problem is not the best one. Furthermore, the best-so-far solution does not participate in solving other problems immediately but is retained. The sub-problem solutions are not reallocated dynamically according to the current population information. In contrast, enables timely replacement for the solutions of the decomposed problem (Improvement 1). Second, IRDG-MAENS defines the distance between the two paths based on the route from the sub-division of such a problem, so that those routes which are closer to each other are more likely to be placed in the same sub-problem. However, when solving multiobjective problems, if we simply use proximity to determine which sub-populations the individual belongs to, this distribution may lead to an imbalance in the number of individuals within the various sub-populations and therefore an imbalanced allocation of resources. In order to overcome this problem, we use a fast and simple allocation scheme in IRDG-MAENS (Improvement 2). A detailed description of the two improvements is shown in Section III.

D. IDMAENS Algorithm

For multiobjective CARP, D-MAENS has been demonstrated to be a competitive approach [16]. However, the replacement mechanism and the assignment mechanism of the offspring in D-MAENS remain to be improved. In response to these issues, IDMAENS uses the same framework as DMAENS but improves the replacement mechanism and the assignment mechanism of the offspring [18]. First, it does not replace the generations after all the offspring but replace with the best solution of the current population in a timely fashion. Therefore, the optimum solution can be incorporated into the evolutionary process immediately. Second, elitism is implemented by using an archive to maintain the optimal solution in the allocation mechanisms, and these elite solutions can provide helpful information for solving their neighbor sub-problems by cooperation. Finally, fast nondominated sorting and crowding methods for sorting solutions are used.

The replacement mechanism in IDMAENS keeps the optimal solution for sub-problems on each direction vector after decomposition. For LSCARP, in the proposed IRDG-MAENS, we adopt the policy of divide and conquer. First to do is to decompose a large-scale problem into independent decomposed problems by using RDG scheme, and then decomposed problems are solved, respectively. In this process, timely replacement strategy is adopted to retain their best solutions after solving decomposed problem. According to interactions and interdependence between variables after decomposition of CC framework, the optimal solution takes part in solving adjacent decomposed problem and facilitates the finding of a better solution in an identifiable potential area.

III. Proposed Algorithm

For LSCARP, an improved RDG-MAENS (IRDG-MAENS) is proposed. In IRDG-MAENS, we first decompose a large-scale problem into sub-problems, then solve these sub-problems, respectively. First, the best-so-far routing information is used and the solution to each decomposed problem is reassigned dynamically based on the current population information. The optimal solutions for each decomposed problem are not updated once after all problems have been solved. Instead, a better solution is immediately used in solving the problems as soon as it has been obtained. Second, an improved RDG decomposition program and IDMAENS are combined for solving large-scale multiobjective CARP. In order to make the individuals assigned to each problem equal, to evenly distribute computing resources, a fast and simple path allocation based on the size of the direction vector is used to determine in which the route of decomposed problem to be placed. The above two improvements in IRDG-MAENS are explained in detail in the following sections.

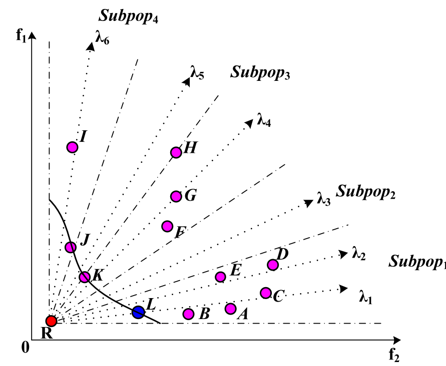

Fig. 3. Timely replacement of solutions.

A. Solutions for the Timely Replacement of IRDG-MAENS

For LSCARP, with a large number of decompositions, the sub-problems are still NP-hard. To solve this problem, Mei *et al.* [2] proposed the RDG decomposition scheme. However, in the RDG decomposition program, the solution for each decomposed problem in the current generation is not the best one, and there is no dynamic reallocation for the solutions of each decomposed problem based on the current population information. Each best-so-far solution is reserved and does not participate in solving the other decomposed problems.

To solve the above problem, we propose the following improvements. We decompose the large-scale problem according to the RDG algorithm, and then solve the respective decomposed problems to obtain the optimal solutions. However, we do not wait until after the completion of all the decomposed problems before updating the optimal solution, but instead we update it immediately and use it to choose a good solution to participate in the current sub-areas by sharing. This improved procedure accelerates the convergence speed of the algorithm to find a better solution in a shorter time, through timely replacement of better solutions of every decomposed problem. This is consistent with the theory of cooperation coevolution, and facilitates areas sharing and finding potentially better solutions. The vivid process of the replacement is shown in Fig. 3.

As shown in Fig. 3, in the process of solving the minimization problem, points $A \sim L$ belong to a series of points in the objective space, the point $R = (\min(f_1(x)), \min(f_2(x)))$ is the reference point for direction vector of all points in the populations. Assuming to produce six evenly distributed weight vectors, the multiobjective CARP is divided into six separate decomposed problems, and then they are solved separately for the optimal solution of the decomposed problem. Before the beginning of evolution, distribution representatives for each decomposed problem solution are: $A, C \rightarrow \lambda_1, E, D \rightarrow \lambda_2, F, G \rightarrow \lambda_4, H \rightarrow \lambda_5$, and $I \rightarrow \lambda_6$. We first solve the decomposed problem by using individual A and the adjacent individual C to evolve to individual B. It is clear that the performance of the individual B is superior to C.

TABLE I
SOLUTIONS FOR THE TIMELY REPLACEMENT OF DECOMPOSED PROBLEM

Algorithm 1: solutions for the timely replacement of decomposed problem

1: procedure Decompose(Z)
2: for $i = 1 \to g$ do // set i =1 to start a new cycle
3: Use the RDGDecompose($\bar{s}, g, \alpha$) to decompose the task set Z into g subsets $(Z_1, Z_2, \ldots, Z_g)$ and get the subset Z_i.
4: Generate a subpopulation $SP(Z_i)$ and then use an MAENS to evolve the $SP(Z_i)$ to find a solution $S(Z_i)$;
5: Sort the solution $S(Z_i)$ to choose the best feasible solution $\bar{S}(Z_i)$.
6: Evolve the best feasible solution $\bar{S}(Z_i)$ and the subpopulation $SP(Z_i)$ to get a new $\bar{S}^*(Z_i)$;
7: If $T(\bar{S}^*(Z_i)) < T(\bar{S}(Z_i))$ then
8: Update the $\bar{S}(Z_i)$;
9: end if
10: If $i < g$ then go to step 3, using the current information to decompose the task set Z ;
12: end for
13: end procedure;

Z is the task set, $S(Z_i)$ is the feasible solution and $T(\bar{S}(Z_i))$ is the total cost of $S(Z_i)$.

Followed by the decomposed problem λ_2, we get L by combining the individuals E, D, and B. Then, we replace the solution and use it to participate in solving the adjacent problems in a timely fashion. In IRDG-MAENS, the replacement mechanism is also used in the decomposition scheme. In contrast to the replacement method of direction vector solutions in the IDMAENS, the optimal solution for the single objective problem is retained in the IRDG-MAENS, and the framework of CC is utilized by combining with the decomposition method of the RDG. Finally, the solutions of current problems are replaced immediately by the means of sharing areas. The timely replacement mechanism of offspring solutions in IRDG-MAENS is shown in Table I.

B. Determine the Regions Which Individuals Belong to

The RDG-MAENS approach with the RDG decomposition scheme can identify promising decompositions without using geographic information [2]. In this algorithm, RDG decomposition strategy is used to define the distance between two paths, so that routes which are closer to each other are more likely to be placed into the same decomposed sub-problem. This approach has been proven superior to other existing algorithms for solving large-scale single-objective CARP, however, its performance in solving large-scale multiobjective problems is still inadequate.

For each decomposed problem, we calculate the distance between the paths based on the RDG decomposition scheme, and then determine the route in which the individual is to be placed according to the size of the distance. However, under this distribution, a phenomenon can arise in which some individuals become assigned to the same decomposed problem, while some parts of the problem are not allocated any sub-instance. In order to ensure that each decomposed problem has the same number of individuals (i.e., ensuring even allocation of computing resources), we propose a fast and simple distribution method based on the size of the direction vector of the path. The vivid process of the distribution is shown in Fig. 4.

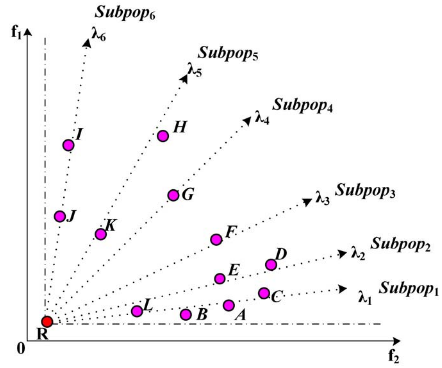

Fig. 4. Determine the regions which individuals belong to.

TABLE II
IMPROVED ROUTE DISTANCE GROUPING DECOMPOSITION FOR MULTIOBJECTIVE LSCARP

Algorithm 2: An improved route distance grouping decomposition for multi-objective LSCARP

1: Procedure IRDG Decompose ($\bar{s}, g, \alpha$)
2: Compute $(\hat{\Delta}_{route}(\bar{s}_{k1}, \bar{s}_{k2}))_{m\times m}$ by Eqs.(5)-(7);
3: In the entire set of routes s, randomly choose $c \in s$, in which $c = \{c_1, \ldots, c_g\}$ is the medoid which represents the group in CARP, and g is the predefined number of groups;
4: for $j = 1 \to g$ do
5: for $s_i \in s \setminus c$ do // $s\backslash c$: Removal of c from the whole route s
6: $c_j^{'} \leftarrow c_j$;
7: If $\dfrac{f_1(c_j^{'}) - f_{1_{\min}}}{\sqrt{(f_1(c_j^{'}) - f_{1_{\min}})^2 + (f_2(c_j^{'}) - f_{2_{\min}})^2}} > \dfrac{f_1(s_i) - f_{1_{\min}}}{\sqrt{(f_1(s_i) - f_{1_{\min}})^2 + (f_2(s_i) - f_{2_{\min}})^2}}$
8: Then swap $c_j^{'}$ and s_i. In this process, $s_i \in s \setminus c$ are evaluated in terms of the new objective value (the minimal one) and use it to conduct on c;
9: end if
10: end for
11: end for
12: for $i = 1 \to g$ do
12: $\zeta_i = \{c_i\}$
13: Using the membership of s_i to c_i to obtain the fuzzy distance and updating the value. After that, assign all the non-medoid routes to the groups and then obtain a route ζ_i (the vivid algorithm is in Mei's Algorithm3);
14: The decomposition of the task set Z can be obtained directly from the grouping of the routes Z_i={} ;
15: for $s_k \in \zeta_i$ do // a task is in a route of ζ_i
16: for $z \in s_k$ do
17: Replace solution Z_i and use it solve adjacent decomposed problems, $Z_i \leftarrow Z_i^* \cup z$;
18: end for
19: end for
20: end for
21: return $(Z_1, \ldots, Z_g)$;
22: end procedure

In RDG-MAENS, RDG defines the distance between two paths, so that those routes closest to each other are more likely to be placed in the same sub-problem. We determine the sub-population to which the individuals belong according to how close those individuals are, so that in Fig. 4, individuals $A, B, C, D, E,$ and L belong to $Subpop_1$, individuals $F, G, H, K,$ and J belong to $Subpop_3$, individual I belongs to $Subpop_4$, and there are no individual in $Subpop_2$. The distribution of the currently best solutions could be affected

TABLE III
IMPROVED RDG-MAENS COMBINED WITH IDMAENS FOR MULTIOBJECTIVE LSCARP

Algorithm 3: An improved RDG-MAENS combined with IDMAENS for multi-objective LSCARP

Begin
Initialize population $P(Z)$;
$\overline{s}(Z) = \arg\min_{s(z)\in p(z)}(tc(s(Z)))$;
$t \leftarrow 1$
repeat
$(Z_1,\ldots,Z_g) = Decompose(Z)$; // the step of IRDG
for $i = 1 \rightarrow g$ do // begin the IDMAENS process
  $P(Z_i) = Pop2subpop(P(Z), Z_i)$;
  Generate N evenly distributed weight vectors $\boldsymbol{\lambda}_1,\ldots,\boldsymbol{\lambda}_N$ randomly.
  Find T weight vectors which are closest to $\boldsymbol{\lambda}_i$ according to the Euclidean distance between each pair of weight vectors;
  According to the $\boldsymbol{\lambda}_1,\ldots,\boldsymbol{\lambda}_N$, decompose the multi-objective CARP into N single-objective CARPs ($g_1,\ldots,g_N$);
  for (i=1 to N; i++) do
    $\overline{s}_g(g_i) = \arg\min_{s_g(g_i)\in p(z_i)}(T(s_g(g_i)))$;
    Choose the optimal solution of i decomposed problem, replace solution and use it to solve adjacent decomposed problems;
    $((\overline{s}_g(g_i), P(g_i)) = Evolve((\overline{s}_g(g_i), P(g_i))$;
  end for
  $P(Z) = subpop2Pop(P(Z_1),\ldots,P(Z_g))$;
  $\overline{s}^{(t)}(Z) = \{\overline{s}(Z_1),\cdots\overline{s}(Z_g)\}$;
  Use fast non-dominated sorting and crowding method for Z sort, select solution to save;
end for
$t \leftarrow t+1$;
until t reaches to a predefined upper bound;
return $\overline{s}(Z)$;
end

when solving multiobjective CARP in this way. Therefore, we propose a fast and simple allocation scheme. We design the algorithm to sort the individuals based on the angles between the individuals and the axis f_1 as shown in Fig. 4. In Fig. 4, the population includes 12 individuals $A \sim L$. The distribution of solutions in IRDG-MAENS is as follows: A, B, C, D, and L belong to $Subpop_1$, individuals E and D belong to $Subpop_2$, individual F belongs to $Subpop_3$, individual G belongs to $Subpop_4$, individuals K and H belong to $Subpop_5$, and individuals I and J belong to $Subpop_6$. We seek to ensure that the number of the individuals assigned to each population is the same, thereby ensuring even distribution of computing resources. This distribution method is shown in Table II.

C. IRDG-MAENS for Multiobjective LSCARP

IDMAENS has been proven superior to other algorithms in solving multiobjective CARP [18]. However, referring to LSCARP, IDMAENS has some limitations. For multiobjective LSCARP, it is unable to perform the decomposition under the direction vector directly. The size of space to be searched doubles with the scale of problem increasing, which makes it more difficult to find potential solutions in such a large solution space. Previous algorithms predominantly ignore the problem of scalability.

From the description of two improvements in IRDG-MAENS, we can see that IRDG-MAENS can: increase convergence speed, update better solutions immediately to participate in solving the current cycle and other sub-problems; and is consistent with the theory of coevolution. This approach enhances area sharing and searching potentially better solutions, and also helps to maintain the diversity of populations. Therefore, IRDG-MAENS combines IDMAENS to solve multiobjective LSCARP. The details of the proposed algorithm are shown in Table III.

IV. SIMULATION RESULTS AND ANALYSIS

A. Experimental Procedure

The performance of CC framework combined with RDG decomposition strategy in RDG-MAENS mainly depends on two parameters g and α for solving LSCARP. In order to choose a good parameter to get good results, the parameters are set as $g = 2, 3$ and $\alpha = 1, 5, 10$. In IRDG-MAENS and the combination of it with IDMAENS to solve LSCARP, the parameters are set as $g = 2, \alpha = 5$. For fair comparison, we set the same parameters: the maximum number of iterations $G_{\max} = 500$, population size $p_{\text{size}} = 30$, the probability of local search $p_{\text{ls}} = 0.2$, and the number of cycles $= 50$. We have performed two kinds of experiments, as follows.

B. Test Problems

The performance of IRDG-MAENS versus RDG-MAENS is tested in the first experiment. This experiment contains three sets of test problems *Beullens*, *egl*, and *EGL-G*. The test set of *Beullens* consists of data of the Belgian Flanders intercity road network, including four sets of data containing 28–121 tasks under 25 different situations. *D* and *F* and *C* and *E* in *Beullens* from the same network diagram, but these problems have a larger capacity. The test set of *egl* is collected from the applications of winter friction routing in U.K. contains two maps and 24 test instances. Each different instance is generated by setting a different set of tasks with different vehicle capacity. The test set of *EGL-G* is based on the U.K.s road network, which includes ten LSCARP instances with 347–375 tasks. In summary, all test sets are instances of large CARP, but have differing sizes. In order to verify the effectiveness of the proposed algorithm, we make a comparison between IRDG-MAENS and RDG-MAENS.

The second experiment is to combine the improve RDG-MAENS with IDMAENS which is denoted as IRDG-IDMAENS to solve multiobjective LSCARP. Experimental test cases include *gdb* (small scale), *val* (mid-scale), *egl* and *EGL-G* (large scale). In order to set a fair comparison, we use the same parameter values in both experiments.

C. Wilcoxon Signed Rank Test

For comparing the performance among different algorithms on CARP, the Wilcoxon signed rank test is used to estimate the performance on each data set to verify the effectiveness of the proposed method [36]. This method is appropriate for paired comparison in T-test and does not rely on the distribution of differences between paired data. Hence, normal distribution is not required, and a symmetrical distribution is enough to meet the requirements of the test. The difference of paired observations needs to be tested to see whether they belong to

TABLE IV
SIMULATION RESULTS OF TWO ALGORITHMS ON *Beullens'C*, *D*

Name(|V|,|E|,|T|,τ)	RDG-MAENS	IRDG-MAENS	*p*	*h*	winner
C01(69,98,79,9)	**3232.8**	3234.3	0.2500	0	RDG-MAENS
C02(48,66,53,7)	**2528.5**	2529.7	0.1484	0	RDG-MAENS
C03(46,64,51,6)	2082.5	**2082.0**	1	0	IRDG-MAENS
C04(60,84,72,8)	**2786.3**	2802.5	0.2500	0	RDG-MAENS
C05(56,79,65,10)	3949.7	**3943.3**	0.0325	1	IRDG-MAENS
C06(38,55,51,6)	2171.0	**2167.0**	0.1816	0	IRDG-MAENS
C07(54,70,52,8)	**3152.3**	3162.3	0.0059	1	RDG-MAENS
C08(66,88,63,8)	**3070.5**	3080.3	0.0012	1	RDG-MAENS
C09(76,117,97,12)	**4127.8**	4130.7	0.0325	1	RDG-MAENS
C10(60,82,55,9)	3352.3	**3351.7**	1	0	IRDG-MAENS
C11(83,118,94,10)	3767.8	**3763.5**	0.0001	1	IRDG-MAENS
C12(62,88,72,9)	**3327.2**	3330.2	0.7813	0	RDG-MAENS
C13(40,60,52,7)	2539.3	**2537.0**	0.0156	1	IRDG-MAENS
C14(58,79,57,8)	3295.0	**3290.7**	0.2500	0	IRDG-MAENS
C15(97,140,107,11)	**4001.5**	4012.0	0.1563	0	RDG-MAENS
C16(32,42,32,3)	1278.5	**1266.3**	0.00006	1	IRDG-MAENS
C17(43,56,42,7)	**2620.0**	**2620.0**	1	0	Both
C18(93,133,121,11)	4194.2	**4194.0**	1	0	IRDG-MAENS
C19(62,84,61,6)	2410.0	**2404.2**	0.00097	1	IRDG-MAENS
C20(45,64,53,5)	**1905.5**	1918.7	0.0049	1	RDG-MAENS
C21(60,84,76,8)	**3097.5**	3099.7	1	0	RDG-MAENS
C22(56,76,43,4)	1938.7	**1924.2**	0.00047	1	IRDG-MAENS
C23(78,109,92,8)	**3148.0**	3153.2	0.00015	1	RDG-MAENS
C24(77,115,84,7)	**2738.3**	2744.5	0.00097	1	RDG-MAENS
C25(37,50,38,5)	**1823.7**	1825.7	0.2344	0	RDG-MAENS
D01(69,98,79,5)	**3242.0**	3244.0	0.5000	0	RDG-MAENS
D02(48,66,53,4)	2537.2	**2534.0**	0.4375	0	IRDG-MAENS
D03(46,64,51,3)	2080.3	**2073.5**	0.0175	1	IRDG-MAENS
D04(60,84,72,4)	**2785.0**	**2785.0**	1	0	Both
D05(56,79,65,5)	3945.0	**3942.0**	0.5000	0	IRDG-MAENS
D06(38,55,51,3)	2170.3	**2168.2**	0.5632	0	IRDG-MAENS
D07(54,70,52,4)	3171.3	**3164.3**	0.3906	0	IRDG-MAENS
D08(66,88,63,4)	3079.2	**3076.2**	0.1875	0	IRDG-MAENS
D09(76,117,97,6)	**4126.3**	4137.2	0.5000	0	RDG-MAENS
D10(60,82,55,5)	**3349.0**	3363.7	0.0020	1	RDG-MAENS
D11(83,118,94,5)	**3767.2**	3773.0	0.0050	1	RDG-MAENS
D12(62,88,72,5)	**3329.2**	3331.3	0.3125	0	RDG-MAENS
D13(40,60,52,4)	**2540.2**	2541.0	0.00001	1	RDG-MAENS
D14(58,79,57,4)	**3290.0**	3293.3	0.0225	1	RDG-MAENS
D15(97,140,107,6)	4011.0	**4007.7**	0.8281	0	IRDG-MAENS
D16(32,42,32,2)	**1272.0**	1274.7	0.0313	1	RDG-MAENS
D17(43,56,42,4)	2626.3	**2620.0**	0.5000	0	IRDG-MAENS
D18(93,133,121,6)	4189.0	**4183.8**	0.0078	1	IRDG-MAENS
D19(62,84,61,3)	2406.2	**2402.7**	0.0078	1	IRDG-MAENS
D20(45,64,53,3)	1944.0	**1935.5**	0.1801	0	IRDG-MAENS
D21(60,84,76,4)	3098.8	**3098.7**	0.9795	0	IRDG-MAENS
D22(56,76,43,2)	1932.3	**1931.8**	0.7178	0	IRDG-MAENS
D23(78,109,92,4)	3158.2	**3150.3**	0.0314	1	IRDG-MAENS
D24(77,115,84,4)	**2740.3**	2740.8	0.8242	0	RDG-MAENS
D25(37,50,38,3)	1840.3	**1834.3**	0.0050	1	IRDG-MAENS

TABLE V
SIMULATION RESULTS OF TWO ALGORITHMS ON *Beullens'E*, *F*

Name(|V|,|E|,|T|,τ)	RDG-MAENS	IRDG-MAES	*p*	*h*	winner
E01(73,105,85,10)	**4064.0**	4073.0	0.0032	1	RDG-MAENS
E02(58,81,58,8)	3321.5	**3320.3**	0.7813	0	IRDG-MAENS
E03(46,61,47,5)	1686.5	**1682.2**	0.0313	1	IRDG-MAENS
E04(70,99,77,9)	3508.0	**3504.2**	0.8438	0	IRDG-MAENS
E05(68,94,61,9)	**3608.8**	3612.3	0.1250	0	RDG-MAENS
E06(49,66,43,5)	**1886.0**	1890.3	0.1250	0	RDG-MAENS
E07(73,94,50,8)	3393.2	**3380.0**	0.00049	1	IRDG-MAENS
E08(74,98,59,9)	3712.7	**3711.8**	0.3750	0	IRDG-MAENS
E09(91,141,103,12)	4796.0	**4794.7**	0.3867	0	IRDG-MAENS
E10(56,76,49,7)	2940.0	**2935.7**	1	0	IRDG-MAENS
E11(80,113,94,10)	3870.2	**3866.7**	0.0225	1	IRDG-MAENS
E12(74,103,67,9)	**3454.3**	3457.7	0.1548	0	RDG-MAENS
E13(49,73,52,7)	**2860.3**	2865.3	0.0625	0	RDG-MAENS
E14(53,72,55,8)	**3383.5**	3383.5	1	0	Both
E15(85,126,107,9)	4228.0	**3572.5**	0.000001	1	IRDG-MAENS
E16(60,80,54,7)	**2738.3**	2746.3	0.1328	0	RDG-MAENS
E17(38,50,36,5)	**2055.0**	**2055.0**	1	0	Both
E18(78,110,88,8)	3844.8	**3125.2**	0.000001	1	IRDG-MAENS
E19(77,103,66,6)	**2526.7**	2527.2	1	0	RDG-MAENS
E20(56,80,63,7)	2460.0	**2458.0**	0.8789	0	IRDG-MAENS
E21(57,82,72,7)	3797.3	**2949.8**	0.000002	1	IRDG-MAENS
E22(54,73,44,5)	**2079.0**	2080.2	0.0313	1	RDG-MAENS
E23(93,130,89,8)	3747.2	**3016.7**	0.000002	1	IRDG-MAENS
E24(97,142,86,8)	4075.5	**3253.3**	0.000001	1	IRDG-MAENS
E25(26,35,28,4)	1652.0	**1527.3**	0.00002	1	IRDG-MAENS
F01(73,105,85,5)	**4060.5**	4068.5	0.0034	1	RDG-MAENS
F02(58,81,58,4)	**3311.3**	3318.5	0.0078	1	RDG-MAENS
F03(46,61,47,3)	1696.2	**1693.7**	0.6797	0	IRDG-MAENS
F04(70,99,77,5)	3507.5	**3507.2**	0.0337	1	IRDG-MAENS
F05(68,94,61,5)	**3605.3**	3616.3	0.0068	1	RDG-MAENS
F06(49,66,43,3)	1909.8	**1882.7**	0.0088	1	IRDG-MAENS
F07(73,94,50,4)	3393.5	**3386.8**	0.0381	1	IRDG-MAENS
F08(74,98,59,5)	**3712.3**	3718.0	0.0313	1	RDG-MAENS
F09(91,141,103,6)	4801.8	**4797.5**	0.1846	0	IRDG-MAENS
F10(56,76,49,4)	**2936.5**	2944.0	0.1250	0	RDG-MAENS
F11(80,113,94,5)	**3864.8**	3867.5	0.2132	0	RDG-MAENS
F12(74,103,67,5)	**3462.3**	**3462.3**	0.9668	0	Both
F13(49,73,52,4)	**2860.0**	2860.2	0.8960	0	RDG-MAENS
F14(53,72,55,4)	3398.8	**3384.8**	0.0213	1	IRDG-MAENS
F15(85,126,107,5)	3575.7	**3575.5**	0.8398	0	IRDG-MAENS
F16(60,80,54,4)	**2741.7**	2759.0	0.0625	0	RDG-MAENS
F17(38,50,36,3)	2058.0	**2055.0**	1	0	IRDG-MAENS
F18(78,110,88,4)	3126.3	**3124.0**	1	0	IRDG-MAENS
F19(77,103,66,3)	2527.0	**2525.3**	0.2500	0	IRDG-MAENS
F20(56,80,63,4)	**2450.3**	2452.8	0.0156	1	RDG-MAENS
F21(57,82,72,4)	**2943.3**	2952.3	0.0078	1	RDG-MAENS
F22(54,73,44,3)	**2077.8**	2078.0	1	0	RDG-MAENS
F23(93,130,89,4)	3015.7	**3015.0**	0.0679	0	IRDG-MAENS
F24(97,142,86,4)	3253.5	**3251.5**	0.0474	1	IRDG-MAENS
F25(26,35,28,2)	1510.2	**1485.7**	0.0002	1	IRDG-MAENS

the totality with zero-mean [37]. In the experiment, we use the Wilcoxon signed rank test with a significance level 0.05.

D. Comparison Between IRDG-MAENS and RDG-MAENS for Solving Single-Objective LSCARP

The results of IRDG-MAENS and RDG-MAENS for simple objective LSCARP are listed in the following tables, which also include the significant difference test values between the two algorithms. In the tables: $|V|$, $|E|$, $|T|$, and τ represent the number of nodes, total number of edges, number of tasks, and minimum number of vehicles required to serve for total tasks, respectively; p denotes the probability of equal value number between two instances; h represents test results, where the difference between two instances is not significant if $h = 0$, and the difference between two instances is obvious if $h = 1$. In terms of an evaluation index to rank various algorithms, one algorithm will be called the winner if its mean value is the minimum. Results in bold represent the best performance.

In Table IV, ten better solutions can be found by IRDG-MAENS and only one solution is equal to that obtained by RDG-MAENS when testing 25 instances of *Beullens*'*C*. As for another 25 instances of *Beullens*'*D*, IRDG-MAENS yields 15 better solutions in contrast with RDG-MAENS, and one solution is the same as that of RDG-MAENS. From Table IV, it can be clearly demonstrated that better solutions could be found by our proposed method, as compared with the original algorithm. For Wilcoxon signed rank test, instances *C*05, *C*09, *C*11, *C*13, *C*16, *C*19, *C*22, *D*03, *D*17, *D*18, *D*19, *D*23, and *D*25 get $h = 1$, which indicates that the results obtained by IRDG-MAENS are significantly better than those of RDG-MAENS.

Table V shows the simulation results of IRDG-MAENS and RDG-MAENS on *Beullens*'*E*, *F* data sets. Compared with RDG-MAENS, 15 better solutions were generated by IRDG-MAENS, and two solutions equal to those of RDG-MAENS, when testing 25 instances of *Beullens*'*E*. For 25 instances of *Beullens*'*F*, IRDG-MAENS yields 13 better solutions in contrast with RDG-MAENS. For the Wilcoxon signed rank test, instances *E*03, *E*07, *E*11, *E*15, *E*18, *E*21, *E*23, *E*24, *E*25, *F*04, *F*06, *F*07, *F*14, *F*23, *F*24, and *F25*

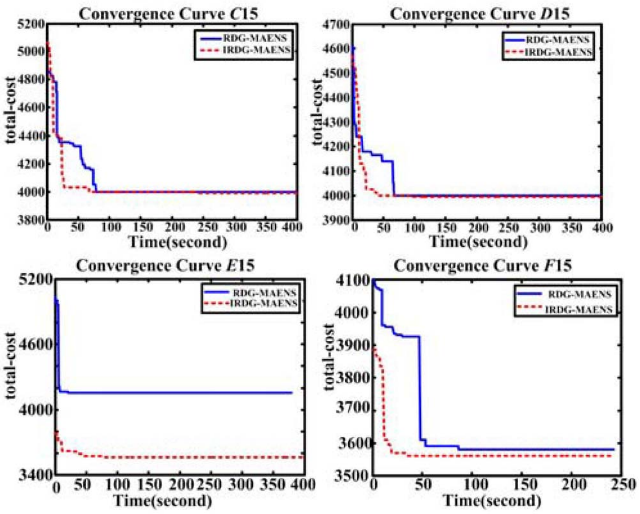

Fig. 5. Convergence curves on *Beullens*.

get $h = 1$, which shows that IRDG-MAENS improves the results significantly on these instances.

For a more detailed description of the test results of IRDG-MAENS, Fig. 5 shows the convergence curve on *Beullens* instances. In the figures, the x-axis indicates the computational time in seconds and the y-axis represents the average total cost of the best-so-far solutions over 30 independent runs.

In Fig. 5, the curves of IRDG-MAENS converge significantly faster and it finds better solutions in a shorter time on four test instances. The curve of IRDG-MAENS on $D15$ converges faster than on $C15$, and a better lower bound is obtained. The performance of IRDG-MAENS on $D15$ and $F15$ is significantly better than on $C15$ and $E15$, and this is due to the capacity of vehicles in D and F being twice that in C and E.

Table VI presents the test results of IRDG-MAENS and RDG-MAENS on the *egl* test set. Compared with RDG-MAENS, 18 better solutions are obtained by using IRDG-MAENS when testing 24 instances of *egl*. The Wilcoxon signed rank test shows 11 out of the 18 best solutions also show $h = 1$, which confirms their significance. It explains that IRDG-MAENS can achieve better solutions than RDG-MAENS on most large scale *egl* instances.

For a more detailed description of the test results of IRDG-MAENS, Fig. 6 shows the convergence curve of *egl-e4-C*, *egl-s2-B*, *egl-e4-A*, and *egl-s3-B* over 30 independent runs.

Fig. 6 shows IRDG-MAENS can find a better solution at a faster speed than RDG-MAENS on instances *egl-e4-C* and *egl-s2-B*. However, IRDG-MAENS performs better on the *egl-s2-B* instance than on the *egl-e4-C* instance. This is because *egl-s2-B* has a larger number of tasks compared with *egl-e4-C*. A similar result is apparent for *egl-e4-A* and *egl-s3-B*.

In summary, IRDG-MAENS can find a better solution for large scale single-objective CARP than RDG-MAENS with a faster convergence rate, for the majority of tested instances.

TABLE VI
SIMULATION RESULTS OF TWO ALGORITHMS ON *egl*

Name(|V|,|E|,|T|,τ)	RDG-MAENS	IRDG-MAENS	p	h	winner
e1-A (77,98,51,5)	3556.7	**3552.0**	0.5000	0	IRDG-MAENS
e1-B (77,98,51,7)	4530.7	**4530.4**	0.5625	0	IRDG-MAENS
e1-C (77,98,51,10)	5621.4	**5617.8**	0.0005	1	IRDG-MAENS
e2-A (77,98,72,7)	5026.8	**5022.2**	0.2500	0	IRDG-MAENS
e2-B (77,98,72,10)	6344.7	**6340.5**	0.0021	1	IRDG-MAENS
e2-C (77,98,72,14)	**8358.1**	8358.8	0.5703	0	RDG-MAENS
e3-A (77,98,87,8)	5913.5	**5910.4**	0.000001	1	IRDG-MAENS
e3-B (77,98,87,12)	7817.8	**7814.4**	0.0877	0	IRDG-MAENS
e3-C (77,98,87,17)	10327.9	**10322.6**	0.0125	1	IRDG-MAENS
e4-A (77,98,98,9)	6479.8	**6470.2**	0.000002	1	IRDG-MAENS
e4-B (77,98,98,14)	**9028.4**	9029.1	0.0409	1	RDG-MAENS
e4-C (77,98,98,19)	11654.5	**11648.6**	0.1528	0	IRDG-MAENS
s1-A (140,190,75,7)	5059.5	**5048.8**	0.00097	1	IRDG-MAENS
s1-B (140,190,75,10)	**6424.5**	6428.0	0.7803	0	RDG-MAENS
s1-C (140,190,75,14)	8541.9	**8533.4**	0.00024	1	IRDG-MAENS
s2-A (140,190,147,14)	10000.9	**9987.9**	0.0324	1	IRDG-MAENS
s2-B (140,190,147,20)	13203.5	**13200.5**	0.6883	0	IRDG-MAENS
s2-C (140,190,147,27)	**16488.6**	16490.0	0.3806	0	RDG-MAENS
s3-A (140,190,159,15)	**10288.5**	10292.3	0.0113	1	RDG-MAENS
s3-B (140,190,159,22)	13814.1	**13797.2**	0.0194	1	IRDG-MAENS
s3-C (140,190,159,29)	17288.7	**17287.7**	0.3279	0	IRDG-MAENS
s4-A (140,190,190,19)	**12388.6**	12396.5	0.0010	1	RDG-MAENS
s4-B (140,190,190,27)	16407.7	**16394.8**	0.0014	1	IRDG-MAENS
s4-C (140,190,190,35)	20672.1	**20661.5**	0.0098	1	IRDG-MAENS

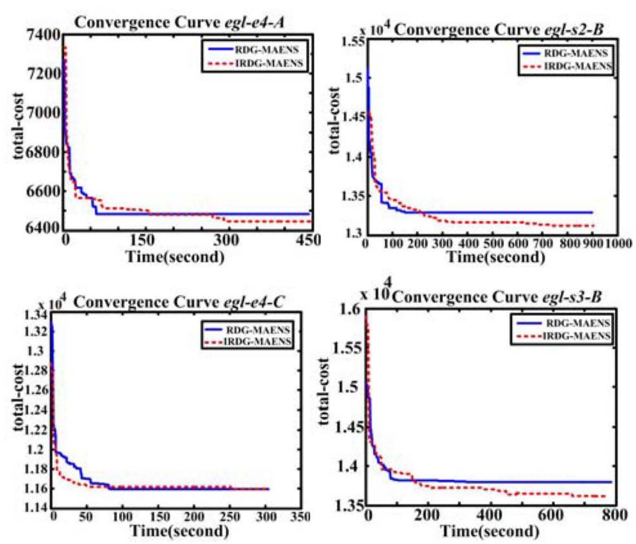

Fig. 6. Convergence curves on *egl* set.

Table VII shows the results of IRDG-MAENS and RDG-MAENS on *EGL-G* test data. Compared with RDG-MAENS, seven better solutions can be found by IRDG-MAENS, when testing ten instances of *EGL-G*. The Wilcoxon signed rank test shows that for five out of the seven instances of IRDG-MAENS gives the best solution, "$h = 1$." IRDG-MAENS has significantly improved the test results on most of the very large scale *EGL-G* instances, which shows the effectiveness of IRDG-MAENS in solving single-objective LSCARP.

For a more detailed description of test results of IRDG-MAENS and RDG-MAENS on *EGL-G* instances, Fig. 7 gives the convergence curves for *EGL-G*. Fig. 7 shows that IRDG-MAENS can converge faster than RDG-MAENS and converge on better solutions. In all four cases, our proposed method converges on a better or as good end result. On two out of four instance, the convergence rate is obviously faster, on one it is similar, and on one slightly slower.

TABLE VII
SIMULATION RESULTS OF TWO ALGORITHMS ON *EGL-G*

Name (|V|,|E|,|T|,τ)	RDG-MAENS	IRDG-MAENS	p	h	winner
G1-A (255,375,347,20)	1008717.5	**1007977.1**	0.0016	1	IRDG-MAENS
G1-B (255,375,347,25)	1126652.7	**1125763.6**	0.0009	1	IRDG-MAENS
G1-C (255,375,347,30)	**1254743.4**	1255674.1	0.0003	1	RDG-MAENS
G1-D (255,375,347,35)	1388719.2	**1388277.5**	0.5170	0	IRDG-MAENS
G1-E (255,375,347,40)	1533089.5	**1528397.0**	0.0000	1	IRDG-MAENS
G2-A (255,375,375,22)	**1108472.7**	1108959.5	0.2536	0	RDG-MAENS
G2-B (255,375,375,27)	1223670.2	**1223541.5**	0.9426	0	IRDG-MAENS
G2-C (255,375,375,32)	1354538.8	**1353653.7**	0.0333	1	IRDG-MAENS
G2-D (255,375,375,37)	**1493660.2**	1495822.2	0.9590	0	RDG-MAENS
G2-E (255,375,375,42)	1637388.9	**1636473.4**	0.0256	1	IRDG-MAENS

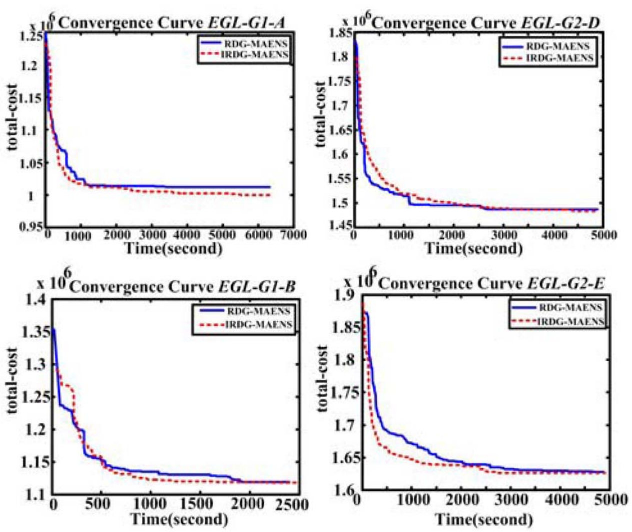

Fig. 7. Convergence curves on *EGL-G*.

Overall, IRDG-MAENS appears beneficial for finding better solution, especially on large-scale problems.

In summary, with the increasing of tasks, the improvement of IRDG-MAENS becomes increasingly obvious, suggesting that IRDG-MAENS is a suitable method for solving single-objective LSCARP.

E. Results of IRDG-IDMAENS in Solving the MOLSCARP

The following tables show experimental results of IRDG-IDMAENS, which combines IRDG-MAENS and IDMAENS, for solving multiobjective LSCARP. In the tables, f_1 represents the optimal "total-cost" on each instance obtained by the algorithm and f_2 denotes the optimization of maximum loop total consumption (makespan). To evaluate the performance of IRDG-IDMAENS, we use three metrics. First, I_D indicates the distance between the true front and the obtained nondominated set [38]. Smaller values indicate better convergence. Second, purity also represents the convergence of the algorithm, and a higher purity indicates a better convergence [39]. Third, hypervolume (HV) is used to evaluate the diversity and broadness of the solutions [40]. Table VIII lists the results of IRDG-IDMAENS on *gdb* which is a small-scale data set. Table VIII shows that IRDG-IDMAENS generates 17 solutions with better results than IDMAENS on 23 sets of data, and the remaining six solutions are almost as good as IDMAENS.

In order to show the distribution of the nondominated solutions in the objective space, Fig. 8 graphs the results of IRDG-IDMAENS and IDMAENS on four test problems. The horizontal axis represents the total consumption of the circuit, and the vertical axis denotes the maximum consumption of a single circuit. The symbol "o" indicates IDMAENS, and "*" represents IRDG-IDMAENS.

Fig. 8 shows that IRDG-IDMAENS has better convergence on the *gdb5* and *gdb10* instances than IDMAENS which are consistent with the value of purity according to its definition. However, because the scale of the *gdb* test set is small, the superiority of IRDG-IDMAENS for solving multiobjective CARP is not obvious. The performance of the two algorithms on this test set is similar.

Table IX shows the experimental results of testing IRDG-IDMAENS on the *val* test set. Because *val* is a medium-scale test set, the number of nondominated solutions for each instance is relatively large.

Table IX shows that IRDG-IDMAENS finds 27 better solutions than IDMAENS on *val*, and the other solutions are approximately equal. Comparing values of I_D, Table IX shows that IRDG-IDMAENS obtains a better result than IDMAENS on 21 instances. Meanwhile, the purity of IRDG-IDMAENS is far superior to IDMAENS. This suggests that IRDG-IDMAENS produces better convergence.

The distribution of the nondominated solutions obtained by IRDG-IDMAENS and IDMAENS testing on *val1B*, *val4A*, *val5A*, and *val7A* are shown in Fig. 9.

It can be seen from Fig. 9 that the ability of IRDG-IDMAENS to find the optimum solution, and the convergence rates of IRDG-IDMAENS, are visibly better than those of IDMAENS. IRDG-IDMAENS can find more nondominated solutions than IDMAENS, which demonstrates that the ability of IRDG-IDMAENS in searching for solutions is stronger than that of IDMAENS. Using adjacent shared areas, not only can accelerate the convergence rate but also can increase the diversity of solutions. For the medium-sized data set *val*, the advantages of IRDG-IDMAENS are significantly greater than IDMAENS compared with the results generated on a small-scale data set.

Table X shows the results of IRDG-IDMAENS on a large-scale CARP data set *egl*. Each instance has a greater number of nondominated solutions relative to the small-scale *gdb* and medium-scale *val* data sets.

Table X shows that IRDG-IDMAENS generates 16 solutions which significantly dominate those of IDMAENS, and the other solutions do not show significant dominance by one algorithm or the other. This suggests that IRDG-IDMAENS can obtain better results than IDMAENS whether optimizing the total circuit consumption or the maximum total circuit consumption on large-scale data sets. For the metric HV, IRDG-IDMAENS obtains a better solution on 18 out of 24 *egl* instances than IDMAENS. The performance with respect to

TABLE VIII
RESULTS OF IRDG-IDMAENS AND IDMAENS ON *gdb*

name	IDMAENS					IRDG-IDMAENS					*winner*
	f_1	f_2	I_D	*Purity*	*HV*	f_1	f_2	I_D	*Purity*	*HV*	
gdb1	316	74	7.6158	0.0000	112	**316**	**63**	**0.0000**	**1.0000**	**231**	IRDG-IDMAENS
gdb2	**339**	**69**	**0.0000**	**1.0000**	**508**	**339**	**69**	**0.0000**	**1.0000**	**508**	Both
gdb3	275	65	2.5000	0.2500	262	**275**	**60**	**0.0000**	**1.0000**	**320**	IRDG-IDMAENS
gdb4	**287**	**74**	**0.0000**	**1.0000**	**453**	287	77	1.0000	0.6667	363	IDMAENS
gdb5	377	78	0.4000	0.6667	1006	**377**	**76**	**0.0000**	**1.0000**	**1016**	IRDG-IDMAENS
gdb6	298	75	**0.0000**	**1.0000**	272	**298**	**74**	**0.0000**	**1.0000**	**273**	IRDG-IDMAENS
gdb7	**325**	**68**	**0.0000**	**1.0000**	**420**	**325**	**68**	**0.0000**	**1.0000**	**420**	Both
gdb8	350	44	**1.0472**	0.3333	338	**348**	**44**	1.8325	**0.6000**	**340**	IRDG-IDMAENS
gdb9	**303**	**43**	0.2500	0.7500	357	**303**	**43**	**0.0000**	**1.0000**	**368**	IRDG-IDMAENS
gdb10	275	70	1.7310	0.7500	3355	**275**	**69**	**0.0000**	**1.0000**	**3434**	IRDG-IDMAENS
gdb11	395	81	10.3086	0.0833	5560	**395**	**69**	**0.0714**	**0.9286**	**5949**	IRDG-IDMAENS
gdb12	458	97	0.6667	0.5000	119	**458**	**95**	**0.0000**	**1.0000**	**228**	IRDG-IDMAENS
gdb13	536	151	8.0000	0.0000	0	**536**	**128**	**0.0000**	**1.0000**	**184**	IRDG-IDMAENS
gdb14	100	21	0.4000	0.8000	144	**100**	**18**	**0.0000**	**1.0000**	**152**	IRDG-IDMAENS
gdb15	58	15	0.3333	0.8333	36	**58**	**13**	**0.0000**	**1.0000**	**40**	IRDG-IDMAENS
gdb16	**127**	**26**	**0.0000**	**1.0000**	**504**	**127**	**26**	**0.0000**	**1.0000**	**504**	Both
gdb17	**91**	**13**	0.4000	0.8000	34	**91**	**13**	**0.0000**	**1.0000**	**36**	IRDG-IDMAENS
gdb18	164	33	0.4286	0.5714	382	**164**	**30**	**0.0000**	**1.0000**	**406**	IRDG-IDMAENS
gdb19	55	21	1.5000	0.5000	**0**	**55**	**18**	**0.0000**	**1.0000**	24	IRDG-IDMAENS
gdb20	121	34	10.4836	**1.0000**	80	**121**	**29**	**0.2828**	0.6667	**169**	IRDG-IDMAENS
gdb21	**156**	**27**	**0.0000**	**1.0000**	**348**	**156**	**27**	**0.0000**	**1.0000**	**348**	Both
gdb22	**200**	**26**	1.4117	**1.0000**	**36**	200	28	**0.1429**	0.7500	37	IDMAENS
gdb23	233	25	2.5508	0.0000	115	**233**	**22**	**0.0000**	**1.0000**	**130**	IRDG-IDMAENS

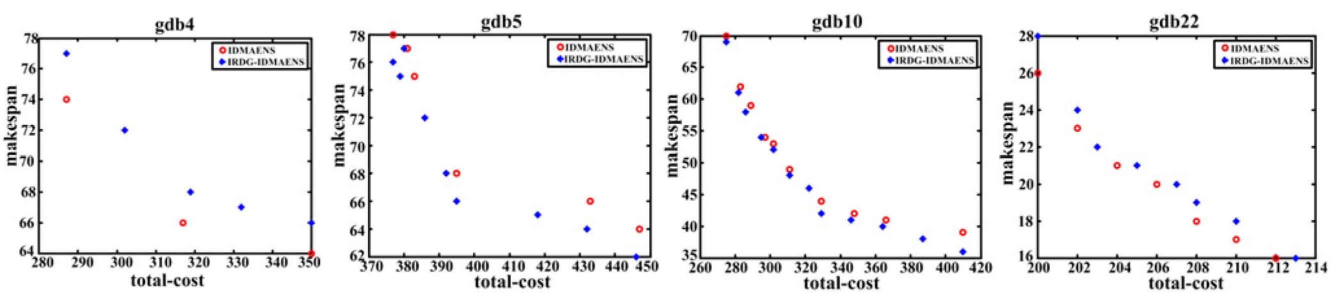

Fig. 8. Solutions obtained by two algorithms for the *gdb* set.

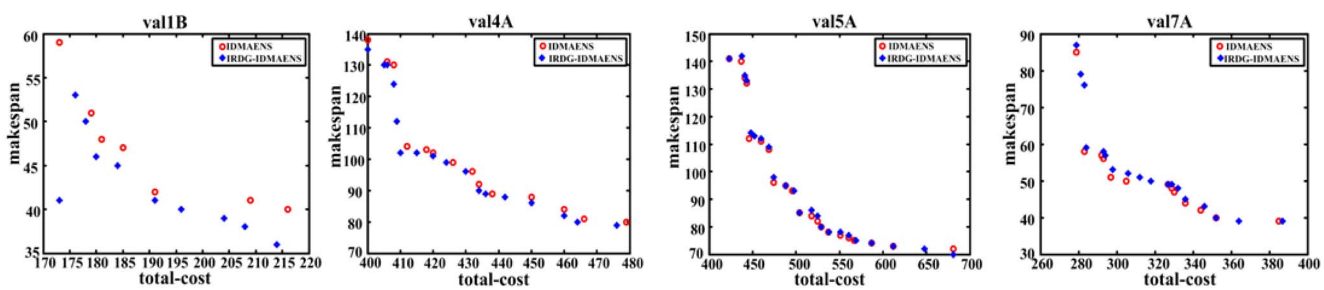

Fig. 9. Solutions obtained by two algorithms for the *val* set.

the I_D metric is also more significant in IRDG-IDMAENS. Furthermore, for purity, IRDG-IDMAENS finds the optimal value "1" on ten out of the total 24 instances. These results suggest that the proposed algorithm is effective for solving multiobjective problems.

In order to see the distribution of the nondominated solutions more clearly, Fig. 10 graphs the results of the two algorithms on the test set *egl*. It can be seen from Fig. 10 that the ability to find a better solution and the convergence of IRDG-IDMAENS are both stronger than IDMAENS. IRDG-IDMAENS performs well both on finding better solutions in the middle region and on finding the front of the multiobjective problem. IRDG-IDMAENS can find more nondominated solutions than IDMAENS. The front found by IRDG-IDMAENS is significantly better than that of IDMAENS. IRDG-IDMAENS is effective in searching solutions, and it is suitable for solving multiobjective LSCARP.

Table XI shows the values of I_D, purity, and HV on a large scale data set *EGL-G*. It can be seen from Table XI that, for three metrics I_D, purity, and HV, IRDG-IDMAENS obtains nine solutions which significantly dominate those of IDMAENS on *EGL-G*, again suggesting that IRDG-IDMAENS outperforms IDMAENS for solving multiobjective LSCARP.

In order to show the distribution of the nondominated solutions in the objective space, the results generated by both algorithms on *EGL-G* are shown in Fig. 11. Fig. 11 shows that IRDG-IDMAENS can find better optimal solutions,

TABLE IX
RESULTS OF IRDG-IDMAENS AND IDMAENS ON *val* SET

name	IDMAENS					IRDG-IDMAENS					*winner*
	f_1	f_2	I_D	*Purity*	*HV*	f_1	f_2	I_D	*Purity*	*HV*	
1A	**173**	**58**	**0**	**1.0000**	**597**	**173**	**58**	1.2975	0.8333	590	IDMAENS
1B	173	59	5.3151	0.1429	1295	**173**	**41**	**0.0000**	**1.0000**	**1505**	IRDG-IDMAENS
1C	245	41	5.0000	0.0000	0	**245**	**36**	**0.0000**	**1.0000**	**15**	IRDG-IDMAENS
2A	227	114	**0.2308**	0.8571	4511	**227**	**111**	1.4319	**1.0000**	**4576**	IRDG-IDMAENS
2B	259	108	6.1192	0.1667	3665	**259**	**75**	**0.0000**	**1.0000**	**4558**	IRDG-IDMAENS
2C	**457**	**71**	5.2202	**1.0000**	**24**	457	77	**3.0000**	0.5000	6	IDMAENS
3A	**81**	**41**	**0.1667**	**0.8333**	241	82	39	**0.1667**	**0.8333**	**242**	IRDG-IDMAENS
3B	87	32	1.5811	0.2500	37	**87**	**28**	**0.0000**	**1.0000**	**77**	IRDG-IDMAENS
3C	138	27	**0.5000**	0.5000	0	**138**	**26**	0.7071	**1.0000**	**1**	IRDG-IDMAENS
4A	400	138	**2.2527**	0.3333	2882	**400**	**135**	10.2275	**1.0000**	**3000**	IRDG-IDMAENS
4B	412	106	**0.8047**	0.6364	**5409**	**412**	**99**	2.0710	**0.6923**	5495	IRDG-IDMAENS
4C	434	96	15.9923	0.3333	1716	**434**	**91**	**0.9220**	**1.0000**	**2661**	IRDG-IDMAENS
4D	**536**	**82**	**0.4714**	**0.6667**	**349**	536	88	**2.3570**	0.6667	344	IDMAENS
5A	**423**	**141**	**0.6842**	0.7000	**20509**	423	143	6.2286	**0.7273**	20340	IDMAENS
5B	446	112	**0.6667**	0.7059	10374	**446**	**105**	4.8376	**0.7692**	**10427**	IRDG-IDMAENS
5C	474	96	7.2720	0.0000	3700	**474**	**92**	**0.0000**	**1.0000**	**4244**	IRDG-IDMAENS
5D	586	83	**1.6214**	0.4286	1573	**579**	**81**	2.5165	**0.8000**	**1604**	IRDG-IDMAENS
6A	223	75	0.5000	0.7692	1778	**223**	**69**	**0.3190**	**0.8182**	**1783**	IRDG-IDMAENS
6B	245	54	0.2012	0.9091	1384	**233**	**51**	**0.1179**	**0.9167**	**1389**	IRDG-IDMAENS
6C	317	54	0.7500	0.6667	134	**317**	**51**	**0.0000**	**1.0000**	**144**	IRDG-IDMAENS
7A	**279**	**85**	**0.3636**	0.6154	**5489**	279	87	1.9238	**0.9000**	5474	IDMAENS
7B	283	58	1.0000	0.5000	2327	**283**	**51**	**0.4268**	**0.8571**	**2410**	IRDG-IDMAENS
7C	**334**	**50**	0.6009	**1.0000**	**598**	**334**	**50**	**0.3727**	0.8333	598	Both
8A	386	129	6.4729	0.0000	13293	**386**	**117**	**0.0000**	**1.0000**	**14003**	IRDG-IDMAENS
8B	395	99	6.6020	0.0769	5701	**395**	**94**	**0.0000**	**1.0000**	**6187**	IRDG-IDMAENS
8C	523	82	**0.9261**	0.6000	2370	**527**	**78**	2.4755	**0.7143**	**2377**	IRDG-IDMAENS
9A	323	108	10.4325	0.0667	7206	**325**	**107**	**2.0897**	**1.0000**	**7978**	IRDG-IDMAENS
9B	326	84	7.5086	0.0000	3166	**326**	**75**	**0.0000**	**1.0000**	**3764**	IRDG-IDMAENS
9C	332	67	9.2762	0.0000	2601	**332**	**65**	**0.0000**	**1.0000**	**3052**	IRDG-IDMAENS
9D	391	49	1.0000	**0.6000**	202	**391**	**41**	**0.4000**	0.5000	**207**	IRDG-IDMAENS
10A	429	146	10.3730	0.5000	29752	**430**	**139**	**1.6507**	**0.7059**	**30213**	IRDG-IDMAENS
10B	437	116	**0.8855**	0.4800	16223	**437**	**97**	3.9967	**0.6667**	**16282**	IRDG-IDMAENS
10C	446	90	6.0243	0.0000	4760	**447**	**89**	**0.0000**	**1.0000**	**5435**	IRDG-IDMAENS
10D	533	66	1.6524	0.4000	3842	**535**	**60**	**2.2756**	**0.5455**	**3879**	IRDG-IDMAENS

TABLE X
RESULTS OF IRDG-IDMAENS AND IDMAENS ON *egl* SET

name	IDMAENS					IRDG-IDMAENS					*winner*
	f_1	f_2	I_D	*Purity*	*HV*	f_1	f_2	I_D	*Purity*	*HV*	
E1-A	3548	943	**2.2000**	0.8000	26472	**3548**	**932**	4.2521	**1.0000**	**26650**	IRDG-IDMAENS
E1-B	4525	839	1.5000	0.3333	1590	**4525**	**836**	**0.0000**	**1.0000**	**1632**	IRDG-IDMAENS
E1-C	**5595**	**836**	**0.0000**	**1.0000**	**2107**	5595	838	6.8000	0.0000	1597	IDMAENS
E2-A	5018	953	**14.5543**	0.1111	114176	**5018**	**928**	15.5289	**1.0000**	**121038**	IRDG-IDMAENS
E2-B	6340	864	56.5802	0.0000	29024	**6317**	**852**	**0.0000**	**1.0000**	**38672**	IRDG-IDMAENS
E2-C	8414	854	25.3199	0.2500	4108	**8343**	**854**	**2.1260**	**1.0000**	**4714**	IRDG-IDMAENS
E3-A	5898	929	31.3282	0.4167	199276	**5898**	**916**	**11.6548**	**0.6923**	**200420**	IRDG-IDMAENS
E3-B	**7789**	**872**	**8.0000**	**0.8571**	**13048**	7801	872	37.6454	0.1429	6809	IDMAENS
E3-C	10307	875	49.1875	0.0000	12192	**10305**	**864**	**2.6784**	**1.0000**	**15137**	IRDG-IDMAENS
E4-A	6472	930	36.8372	0.0000	25917	**6464**	**914**	**0.0000**	**1.0000**	**30343**	IRDG-IDMAENS
E4-B	**9004**	**918**	16.6385	**1.0000**	**20755**	9037	843	**15.9998**	0.3333	16694	IDMAENS
E4-C	**11618**	**820**	6.9642	**1.0000**	**230**	**11618**	**820**	**0**	0.5714	**230**	Both
S1-A	**5018**	**1023**	4.5586	0.4444	182251	**5018**	**1032**	**4.5636**	**0.7692**	**188225**	IRDG-IDMAENS
S1-B	6422	984	38.9480	0.4000	52740	**6422**	**981**	**3.5201**	**0.7500**	**63430**	IRDG-IDMAENS
S1-C	8518	1018	31.3683	0.1667	48371	**8518**	**966**	**0.3194**	**0.8571**	**55054**	IRDG-IDMAENS
S2-A	10122	1063	80.3415	0.0769	150698	**10122**	**1023**	**4.6373**	**1.0000**	**177807**	IRDG-IDMAENS
S2-B	13345	1040	45.5230	**0.6000**	27728	**13331**	**1040**	**36.6918**	**0.6000**	**38325**	IRDG-IDMAENS
S2-C	16682	1040	36.1644	0.2000	40210	**16674**	**1040**	**7.5664**	**0.7500**	**44805**	IRDG-IDMAENS
S3-A	**10347**	**1070**	**4.1123**	**0.7143**	**328700**	10436	1063	9.2376	0.3333	323502	IDMAENS
S3-B	**13918**	**1060**	34.0083	**0.6500**	151319	14020	998	**26.8775**	0.5556	**156366**	IRDG-IDMAENS
S3-C	17363	1086	26.2627	0.5000	66763	**17342**	**1040**	**12.8409**	**0.5000**	**68391**	IRDG-IDMAENS
S4-A	**12442**	**1058**	25.0801	0.5000	**76321**	12654	994	**4.1243**	**0.7500**	75397	IRDG-IDMAENS
S4-B	16443	1027	1.0000	0.0000	506	**16600**	**1023**	**0.0000**	**1.0000**	**508**	IRDG-IDMAENS
S4-C	21195	1027	203.3043	0.0000	12640	**20933**	**1027**	**0.0000**	**1.0000**	**15776**	IRDG-IDMAENS

which have better convergence to the true front than IDMAENS. In summary, IRDG-IDMAENS can find a significantly better front than IDMAENS in handling multi-objective LSCARP. The convergence of IRDG-IDMAENS is significantly better than IDMAENS, and the diversity of IRDG-IDMAENS is also better in most instances which is consistent with the values of the three metrics in Table XI.

As the scale of the data grows, the advantages of IRDG-IDMAENS become increasingly apparent, as seen when comparing the results on different sizes of (small, medium, and large scale) test data. This is because IRDG-IDMAENS uses the RDG decomposition program to solve large scale problems, and dynamically allocates the solutions for each decomposed problem on the basis of the current population information. In addition, it performs timely updates of the optimal solutions of decomposed problem and enables the replaced solution to participate in the solution of the circulation problem. IRDG-IDMAENS not only retains the characteristics

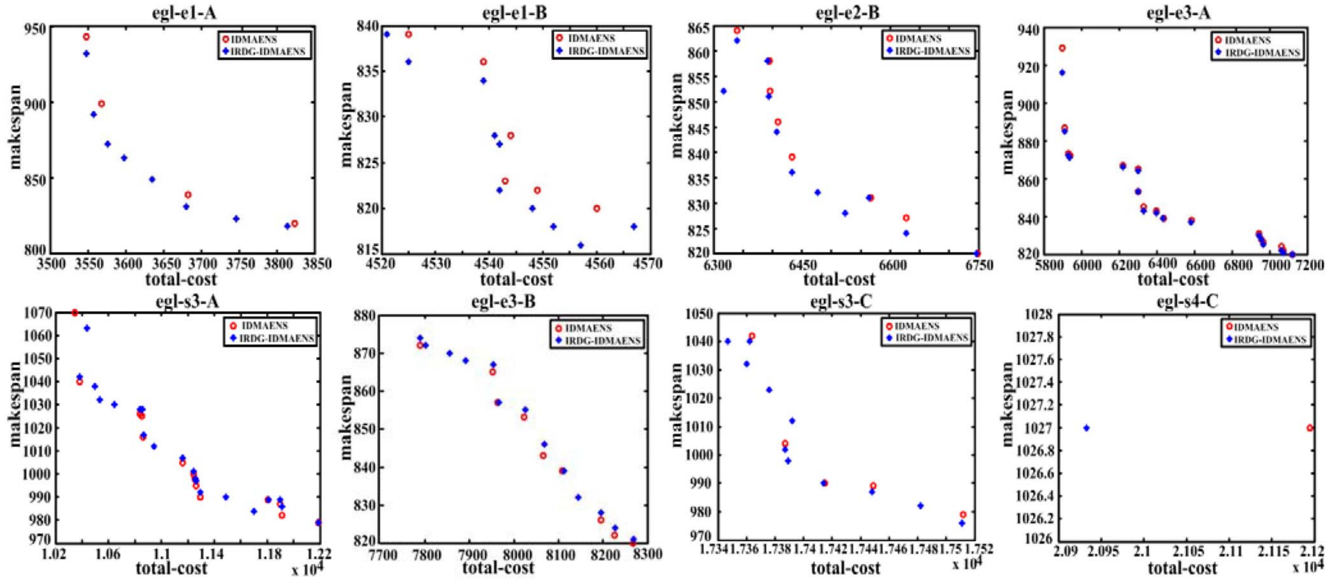

Fig. 10. Solutions obtained by two algorithms for the *egl* set.

TABLE XI
RESULTS OF IRDG-IDMAENS AND IDMAENS ON *EGL-G* SET

name	IDMAENS					IRDG-IDMAENS					*winner*
	f_1	f_2	I_D	*Purity*	*HV*	f_1	f_2	I_D	*Purity*	*HV*	
G1-A	1044613	66055	1.0476e+004	0.00	305201187	**1027498**	**65367**	**0.0476e+004**	**1.00**	**365845252**	IRDG-IDMAENS
G1-B	**1167692**	**66937**	**2.2102e+003**	**1**	**182680575**	1174216	65752	1.0589e+004	0.50	174758640	IDMAENS
G1-C	1337941	67327	4.8302e+004	0.12	948050679	**1289544**	**63833**	**1.0067e+004**	**0.85**	**1.6828e+009**	IRDG-IDMAENS
G1-D	1488721	65050	2.2866e+004	0.00	19533542	**1441236**	**64473**	**0.0000**	**1.00**	**47676195**	IRDG-IDMAENS
G1-E	1644639	65050	4.3243e+004	0.00	96329800	**1587913**	**63365**	**0.0000**	**1.00**	**343156072**	IRDG-IDMAENS
G2-A	1166119	67955	5.6263e+003	0.00	377063909	**1137134**	**65050**	**0.0000**	**1.00**	**403557012**	IRDG-IDMAENS
G2-B	1271041	66937	2.2806e+004	0.06	196218809	**1256059**	**67738**	**1.2406e+004**	**0.96**	**428722279**	IRDG-IDMAENS
G2-C	1476213	67327	2.6482e+004	0.00	68078980	**1428880**	**67296**	**0.0000**	**1.00**	**193795680**	IRDG-IDMAENS
G2-D	1604230	64602	1.6353e+004	0.04	3473394	**1568942**	**64602**	**0.2353e+004**	**0.97**	**15600133**	IRDG-IDMAENS
G2-E	1755482	65050	5.3422e+004	0.00	0	**1687900**	**64602**	**0.0000**	**1.00**	**31756480**	IRDG-IDMAENS

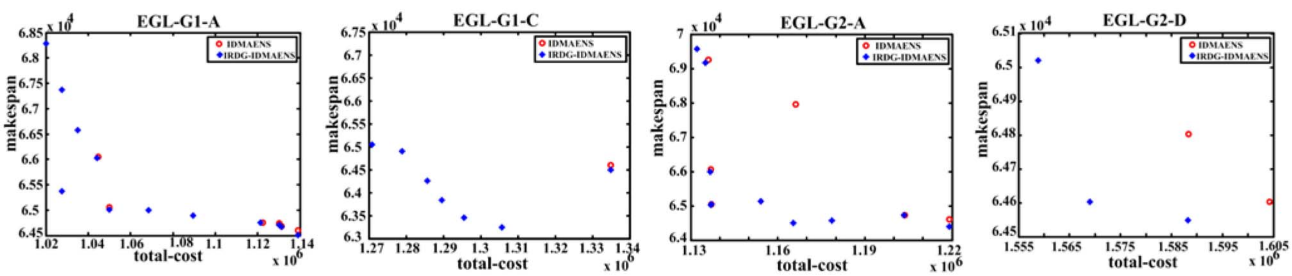

Fig. 11. Solutions obtained by two algorithms for the *EGL-G* set.

of RDG-MAENS, but also retains the optimal solution for each decomposed problem. Therefore, IRDG-IDMAENS presents a fast and simple allocation scheme according to the magnitude of the vector of the route direction, thereby evenly distributing computing resources. Overall, the results suggest that IRDG-IDMAENS is effective for solving multiobjective LSCARP.

V. CONCLUSION

This paper has analyzed, and proposed improvements to, the RDG-MAENS algorithm which has previously been used for solving single-objective LSCARP.

Better solutions were generated when solving single-objective LSCARP by using our proposed IRDG-MAENS algorithm, than by RDG-MAENS. This is due to the proposed algorithm using the RDG decomposition program to solve large-scale problems, and dynamically allocating the solution for each decomposed problem based on the current population information. Our method benefits from updating the optimal solution of decomposed problem and enabling them to participate in solving circulation problems. The improved algorithm not only retains the advantages of RDG-MAENS but also retains the optimal solution for each decomposed problem. Experimental results show that the performance of IRDG-MAENS outperform RDG-MAENS on most test data examples.

However, many real-world applications require the optimization of multiple objectives simultaneously. We often need to optimize more than two conflicting objectives and generate a set of good tradeoff solutions for different objectives. For multiobjective problems, the performance of IDMAENS has been verified as better than the other existing algorithms for solving multiobjective CARP. Second, ensures that the number of individuals of each decomposed sub-problem is similar, and thus helps to equally distribute computing resources. A fast and simple path allocation based on the size of the direction is used to determine which decomposed problem the route is placed in. Finally, we combine IRDG-MAENS algorithm with IDMAENS to solve multiobjective LSCARP. Experimental results suggest that IRDG-IDMAENS can find better solutions than IDMAENS.

In order to make the model closer to practical applications of arc routing problem, we also need to consider other factors and the attendant increase of the complexity of the algorithm. In future research, will investigate more complex formulations of the arc routing problem, and will investigate ways of reducing the complexity of the algorithms needed for their solution.

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