Green Vehicle Routing Problem: The Tradeoff between Travel Distance and Carbon Emissions

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Abstract – Recently, the green vehicle routing problem (GVRP) starts to attract the attention of researchers due to the awareness of the environmental impact of transportation. The GRVP is an extension of the classical VRP by taking minimization of travel distance as well as carbon emissions as the objectives. In this paper, we solved the GVRP by a multiobjective evolutionary algorithm to find the set of Pareto optimal solutions. We found that the tradeoff between travel distance and carbon emissions is small with a load-distance emission model and a parameter setting in the literature. The tradeoff becomes significant only when the emissions of an empty vehicle and of a full-load vehicle differ a lot. Whether the GVRP should be treated as a multiobjective optimization problem (MOP) or not needs more investigation in the future.

<< This paper is included in the Proceedings of the International Conference on Control, Automation, Robotics and Vision (ICARCV), Singapore, Nov. 18-21, 2018. >>

I. Introduction

The vehicle routing problem (VRP) is a classical and important problem in the fields of operations research and transportation science. It deals with the problem of allocating a fleet of vehicles to serve customers under some constraints to optimize concerned objectives. The VRP has many problem variants with different constraints (e.g. capacity, time windows, number of vehicles, etc.) and objectives (e.g. number of vehicles, total travel distance, etc.). In the capacitated vehicle routing problem (CVRP), we are given a fixed number (M) of homogeneous vehicles, and the maximum capacity (Q) is defined for all vehicles. There are N customers i ($1 \leq i \leq N$) in different locations with different load demand q_i. All vehicles should start from a central depot to visit customers to distribute the cargo and go back to the depot. The traditional objective is to minimize the total travel distance of all vehicles without using more than M vehicles.

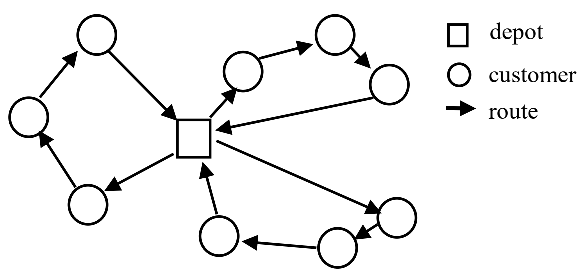


Fig. 1. An illustration of a solution to a VRP with 9 customers and 3 vehicles

Due to the awareness of the global climate change, more and more attention has been paid to the environmental impact of the transportation industry [1][2]. The green vehicle routing problem (GVRP) considers environment-related objectives such as minimization of energy consumption and greenhouse gas (GHG) emissions. In this paper, we model the GVRP based on the CVRP and take total distance (f_1) and carbon emissions (f_2) as the objective functions. The mathematical model is formulated as follows:

Notations:

x_{ijk} is 1 if and only if vehicle k travels from customer i to customer j.

d_{ij} denotes the distance between customers i and j.

e_{ijk} denotes the amount of pollutant emissions produced by vehicle k during traveling from customer i to customer j. It depends on d_{ij} and the current load of the vehicle.

$$f_1\text{: } \min \sum_{i=0}^{N} \sum_{j=0}^{N} \sum_{k=1}^{M} d_{ij} x_{ijk} \tag{1}$$

$$f_2\text{: } \min \sum_{i=0}^{N} \sum_{j=0}^{N} \sum_{k=1}^{M} e_{ijk} x_{ijk} \tag{2}$$

Subject to

$$\sum_{i=1}^{N} x_{i0k} = \sum_{i=1}^{N} x_{0ik} \leq 1, k = 1, 2, \dots, M \tag{3}$$

$$\sum_{k=1}^{M} \sum_{i=1}^{N} x_{0ik} \leq M \tag{4}$$

$$\sum_{i=0}^{N} \sum_{j=0}^{N} q_i x_{ijk} \leq Q, k = 1, 2, \dots, M, \tag{5}$$

$$\sum_{i=0}^{N} x_{iuk} = \sum_{i=0}^{N} x_{uik}, k = 1, 2, \dots, M, u = 1, 2, \dots, N \tag{6}$$

$$\sum_{k=1}^{M} \sum_{i=0}^{N} x_{iuk} = \sum_{k=1}^{M} \sum_{i=0}^{N} x_{uik} = 1, u = 1, 2, \dots, N \tag{7}$$

Eqs. (1) and (2) define the objective functions. Constraints (3) require that each vehicle should go back to the depot if it leaves. Constraint (4) limits the number of vehicles used in a solution. Constraints (5) require that the total load carried by a vehicle cannot exceed the maximum capacity. Constraints (6) require that a vehicle leaves after it visits a customer. Constraints (7) require that each customer should be served by one vehicle exactly once.

The GVRP extends the CVRP, which is already known to be an NP-hard problem [3], by considering one more objective. Evolutionary algorithms have been shown to perform well in solving complicated and multiobjective optimization problems. Therefore, we propose to solve the GVRP based on a recent multiobjective evolutionary algorithm, the NSGA-III [4]. We aim to obtain a set of non-dominated solutions, not just a single solution with respect to some aggregated objective function (e.g. the weighted sum of distance and emissions). The rest of this paper is organized as follows: Section II reviews related studies about the GVRP. Section III elaborates the proposed algorithm. Experiments and results are presented in Section IV. Conclusions are made in Section V.

II. Literature Review

A. Algorithms

Metaheuristics are a category of stochastic optimization algorithms and have been applied to solve many classical optimization problems such as scheduling and routing problems. In this subsection, we review the studies applying metaheuristics to the GVRP and briefly explain the algorithms.

Xiao *et al*. [5] proposed a simulated annealing (SA) algorithm. The solution was encoded as a string of integers, in which zero denotes the depot and the substring between two zeroes represents a route. They used three popular neighborhood operators – swap, relocation, and 2-opt, and found that relocation performed the best while 2-opt performed the worst. They further proposed a control method to select one among the three operators based on their success rate (i.e. the rate in which the neighboring solution is accepted). Kwon *et al*. [6] proposed a tabu search (TS) algorithm and used similar route-based encoding scheme as [5]. They generated the initial solution by repeatedly appending the greatest-demand customer to the greatest-load vehicle if the capacity is allowed. Three neighborhood operators – insertion, swap, and hybrid (randomly selecting one of insertion and swap), were adopted. The tabu tenure was uniformly distributed over a pre-specified interval. The algorithm stopped after a certain number of consecutive non-improving iterations. The TS was also used by Úbeda *et al*. [7] to do a real-world case study with the data provided by Eroski, a food company in Spain.

Adiba *et al*. [8] solved the GVRP by the ant colony optimization (ACO) algorithm and the large neighborhood search (LNS). The heuristic values and the amount of deposited pheromone were determined by the amount of carbon emissions of the solution. The best solution found by the ACO algorithm was then improved by the LNS, which re-inserted some random customers into the routes based on a greedy heuristic. Zhang *et al*. [9] proposed an artificial bee colony (ABC) algorithm. They generated the initial solutions by splitting random permutation of customers based on vehicle capacity. Operators swap, reverse, and insertion were used to generate neighboring solutions. A route-based crossover operator was introduced to realize the concept of the movement from one bee to another bee. A local search using 2-opt and 3-opt was applied to every newly generated solution. The method of MirHassani and Mohammadyari [10] was a cluster-first-route-second method. It clustered customers by the Sweep algorithm and sequenced the customers by the gravitational search algorithm (GSA). The random key encoding scheme was used. A local search with 2-opt, relocation, and swap operators was applied to the solution of GSA. The method of Tiwari and Chang [11] has a similar framework to [10]. It clustered customers by a heuristic and then sequenced them by a genetic algorithm (GA). In the GA, a dependent matrix whose role is similar to the pheromone matrix in ACO, was used to generate artificial chromosomes.

B. Emission Models

There are many models of fuel consumption and carbon emissions in the literature. Complex models [12]–[16] may consider driving speed, road angle, frontal surface area, and so on. Although these models could calculate fuel consumption and carbon emissions accurately, the required information might not be easy to obtain.

Úbeda *et al*. [17] estimated carbon emissions of a vehicle k traveling from customer i to customer j by $e_{ijk} = d_{ij} \times \varepsilon(q_j)$, where the emission factor $\varepsilon(q)$ is a function of load. Similar models were used in several studies for calculation of fuel cost and carbon emissions [5][9][10][18]. The typical model is

$$e_{ij} = d_{ij} \cdot (e_0 + (e - e_0) \cdot q_{ij}/Q), \tag{8}$$

where e_0 is the emission coefficient of an empty vehicle, e is the emission coefficient of a full-load vehicle, and q_{ij} is the load during the trip from customer i to j.

C. *Multiobjective Optimization*

Total distance is the common objective function in the traditional VRP. However, in the GVRP, fuel consumption and carbon emissions should also be considered. Solving an optimization problem with more than one objective is not straightforward. There are many different ways of considering multiple objectives simultaneously.

Figliozzi [12] turned four objectives into cost and summed the total cost. Xiao *et al*. [5] and MirHassani and Mohammadyari [10] used similar methods to calculate the total cost of vehicles and fuel/emissions. To apply this kind of method, we need to define cost functions of each concerned objective. Adiba *et al*. [18] also combined the travel distance and the emissions, but not turning them into the cost. They calculated the weighted sum of normalized objective values. Molina *et al*. [19] used the augmented weighted Tchebycheff method, which is a more complicated aggregation function.

Úbeda *et al*. [7] focused only on the minimization of emissions but also analyzed the increase of distance in the experiments. The results indicated that there is a tradeoff between minimization of the distance and emissions. Zhang *et al*. [9] had the same finding. To resolve the conflict between objectives, the Pareto approach aims to find the set of Pareto optimal solutions. A solution x is said to dominate another solution y if and only if x is not worse than y in all objectives and is better than y in at least one objective. If a solution is not dominated by any other solution, it is Pareto optimal. Pareto approaches do not need the aggregation functions and can provide a set of non-dominated solutions to show the tradeoff relationship between multiple objectives. In recent two decades, many multiobjective evolutionary algorithms (MOEA) have been proposed to solve multiobjective problems in a Pareto way. However, only few studies [20]–[22] utilized MOEAs to solve the GVRP.

III. Proposed Algorithm

A. *Overview*

Our algorithm is based on NSGA-III [4], the newest version of the most well-known NSGA-II [23]. NSGA-III is featured by the reference point-based selection, which will be briefly described in subsection G. Problem-specific operators such as encoding and crossover are described in detail in subsections B-F. Table I gives the pseudo code of the proposed algorithm.

TABLE I Pseudo Code of the Proposed Algorithm

```
Notations
P, R: population; p1, p2, c1, c2: individual
NP: population size
G: maximum number of generations
Pm: mutation rate


Initialize(P, NP)
for t = 1 to G
  R ← ∅
  for i = 1 to NP/2
    {p1, p2} ← RandomSelect(P)
    {c1, c2} ← Crossover(p1, p2)
    for i = 1 to 2
        if rand() < Pm
           LocalRefine(ci)
        Perturb(ci)
    R ← R ∪ {c1, c2}
  P ← EnvironmentalSelect(P ∪ R)
```

B. *Permutation Encoding*

Our algorithm follows the "route-first-cluster-second" method [24] and encodes the permutation of customers in the chromosome. The permutation represents the order of visiting customers in the routes. We use the split method (described in the next subsection) to separate the permutation into several routes. For example, a permutation of six customers [1, 2, 3, 4, 5, 6] could be split into a set of two routes {[0, 1, 2, 3, 0], [0, 4, 5, 6, 0]} or another set of three routes {[0, 1, 2, 0], [0, 3, 4, 5, 0], [0, 6, 0]}, where 0 denotes the depot.

C. Chromosome Decoding

The split method [24] solves the route splitting problem optimally through solving the shortest path problem on an auxiliary graph where the weight of the arc (i, j) is the sum of distance of the route $[0, \pi_i, \pi_{i+1}, \ldots, \pi_j, 0]$ and π_i denotes the i^{th} customer in the encoded permutation. We did two modifications to the split method. First, we consider the number of used vehicles. Whenever it is possible to split the permutation with no more than M vehicles, our method guarantees to split the permutation into a set of routes with the shortest total distance. Sometimes it is not possible to get a feasible solution, we just set a very large total distance to the chromosome so that it will be discarded during environmental selection. The second modification was made to consider both travel distance and emissions. The arc weight (i, j) in the auxiliary graph is the weighted sum $w \cdot d + (1 - w) \cdot e$, where d and e are the travel distance and emissions of the route $[0, \pi_i, \pi_{i+1}, \ldots, \pi_j, 0]$, respectively. In the first generation of our evolutionary algorithm, w is set by one for decoding all individuals. From the second to the last generation, the weight w for decoding an offspring is determined by the performance of its parent. We will describe how to set w in subsection E.

D. Initialization

A simple way to generate the initial individuals is by putting random permutation of customers in the chromosomes. However, random permutation usually leads to very long travel distance and/or violates the limit of the number of vehicles. Tiwari and Chang [11] proposed an idea about clustering customers based on the angle and the load demand. Here, we also use the idea of angle. We separate customers into eight groups, [0°, 45°) in the first group, [45°, 90°) in the second group, and so on. We put groups into the permutation sequentially from group 1 to 8. In this way, customers in close positions in chromosomes are also close geographically. It helps the split method to generate feasible solutions. The customer order within each group is randomly shuffled. Fig. 2 illustrates how the initialization procedure works.

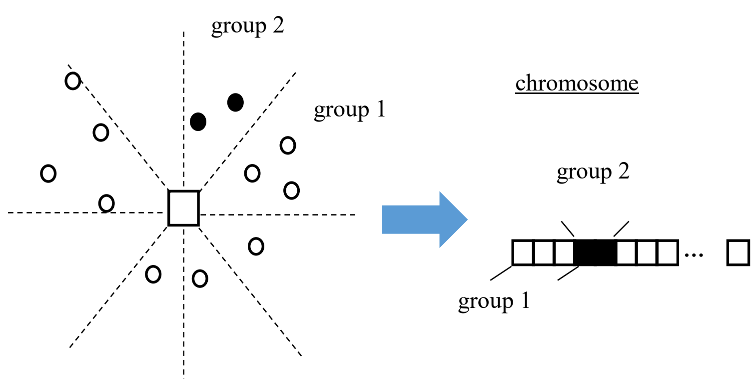


Fig. 2. Illustration of angle-based clustering and initialization

E. Crossover

The crossover operator combines the parents' chromosomes to produce the offspring. We use the linear order crossover (LOX) operator, which is popular for the permutation encoding. The LOX randomly selects two cut points and copies the enclosed section in each parent p_i ($i = 1, 2$) to each offspring c_i, respectively. Then, the remaining positions in the offspring's chromosome are filled by the gene values (i.e. customer indices) in the order in which the values appear in the other parent.

The LOX works at the level of permutation. After the LOX produces the offspring, we decode the offspring by the split method to get the corresponding solutions (i.e. the set of routes). As mentioned in subsection C, a weight w is required during decoding the offspring. The value of w determines the optimization preference over the two objectives (distance and emissions). If w is close to one, we aim to generate a solution with short distance; if w is close to zero, we aim to generate a solution with low emissions. The value of w_i used to decode offspring c_i is set based on how its parent p_i performs:

$$w_i = 1 - (rank(p_i) - 1)/N_{\text{p}}, \tag{9}$$

where $rank()$ returns one for the parent with the shortest distance in the population and returns N_{p} for the parent with the longest distance. In other words, if a parent p_i is good at distance, we set w by a large value to consider more about distance during decoding its offspring c_i.

F. Local Refinement

We do local refinement to the offspring in probability P_{m}. We choose one of three refinement operators, 2-opt [5], nearest neighbor (NN) [11], and NEH [25], randomly. The chosen operator is applied to every route in the solution to reduce the travel distance.

(1) 2-opt: We select every pair of two positions (i, j) with $i < j$ in a route r and reverse the sub-route between i and j, i.e. turning $[\pi_{r,i}, \pi_{r,i+1}, \ldots, \pi_{r,j}]$ to $[\pi_{r,j}, \pi_{r,j-1}, \ldots, \pi_{r,i}]$. If the best route among the new routes has a smaller travel distance than the original route does, change the route to the best route.

(2) NN: We select two positions i and j ($i < j$) randomly in a route r. Then, we remove customers between these two positions and save them in a set U. We connect $\pi_{r,i-1}$ to the nearest customer $\pi_{r,i}^*$ (in terms of geographic distance) in U and remove $\pi_{r,i}^*$ from U. Next, we connect $\pi_{r,i}^*$ to the nearest customer $\pi^*_{r,i+1}$ in U and remove $\pi^*_{r,i+1}$ from U. This step repeats until U becomes empty.

(3) NEH: The NEH heuristic is popular in the field of permutation flow shop scheduling. Simply speaking, it repeats greedy re-insertion. We select two positions i and j ($i < j$) randomly in a route. Then, we remove customers between these two positions and save them in a set U. We re-insert the customers in U one by one into the best position in the partial route. The best position refers to the position resulting in the smallest travel distance of the partial route.

G. *Perturb (for Duplicate Elimination)*

Population diversity strongly affects the search ability of a GA. Thus, we want to avoid the existence of duplicate individuals in the population. In our algorithm, when we find that an offspring has the same objective vector as any parent does, we choose one of the following two operators randomly and repeat applying the operator to the offspring until the offspring does not have the same objective vector as any parent does.

(1) Swap: the swap operator selects one route randomly and exchanges two random customers in the route.

(2) Greedy relocation: this operator selects one route randomly and re-inserts a random customer into the best position in the route.

H. *Environmental Selection*

Selection is the key step in an evolutionary algorithm, especially in an MOEA. When more than one objective is considered, judging which individual is better is not always straightforward. A solution can be better than the other in one objective but worse in another objective. NSGA-II [23], which was cited by about 25,000 times in the google scholar database, could be the most famous MOEA. It uses a non-dominated sorting procedure to rank individuals. The set of individuals not dominated by any other are assigned rank 1. Then, the set of individuals dominated only by those ranked individuals are assigned ranks 2, 3, and so on. In our algorithm, we use the selection procedures of NSGA-III, the latest version of NSGA-II. NSGA-III also ranks individuals by the non-dominated sorting procedure. To select the individuals from the last acceptable rank, NSGA-III generates a set of evenly distributed reference points on a hypothesized hyperplane in the objective space. The perpendicular distance from each individual to each reference line connecting the origin and the reference point is calculated. Each individual is associated with the reference point with the shortest distance. Finally, individuals whose associated reference points have fewer individuals (i.e. less crowded) are preferred in the selection process. Due to the limit of space, we cannot describe the whole procedure in detail. Readers who are interested in the details of NSGA-III may refer to [4].

IV. EXPERIMENTS AND RESULTS

A. *Problem Instances*

We tested our algorithm by a set of public data instances from CVRPLIB [26]. These instances were widely used in the literature. The tested instances have different problem scales (31-300 customers and 5-28 vehicles), different relative positions of the depot (at the center or at the border), and different location distributions of customers (uniform or clustered).

These instances do not include the information about emissions calculation. In our paper, we use the same emission model as [5][9][10][17][18] did. The equation to calculate emissions is listed in (8) in Section II. The values of emission coefficients (in *kg*/*liter*) e_0 (of an empty vehicle) and e (of a full-load vehicle) depend on the types of vehicles and fuels. The values of (e_0, e) are (1, 2) in [5], (0.296, 0.390) in [7][9][17], and (0.772, 1.096) in [18]. In our experiments, we followed the setting in [7], which was derived from real-world company data. The fuel consumption rate is 2.61 (*liter*/*km*).

B. *Algorithm Setting*

The population size (N_p in Table I) of our algorithm was set by 100, and the generation number (G) was set by 100. The value of P_m, i.e., the probability to do one of the three local refinement operators, was set by 2%.

C. *Experiment 1: Is GVRP an MOP?*

In the experiment, we applied NSGA-III, a multiobjective evolutionary algorithm, to solve the GVRP, a VRP variant with two objective functions – travel distance and emissions. We solved each problem instance by ten times. The net set of the non-dominated solutions was collected for each problem instance.

According to our experience on solving biobjective minimization problems, we expected to obtain a set of non-dominated solutions scattered from the top-left corner to the bottom-right corner in the objective space. However, the results were surprising. The number of non-dominated solutions was quite small. We even found only a single solution when solving four problem instances (B-n35-k5, E-n51-k5, E-n101-k8, and E-n301-k28). The two extreme solutions (i.e. the solutions with the minimal distance or the minimal emissions) in the net set of non-dominated solutions are listed in Table II. Although there is indeed a tradeoff between minimization of distance and minimization of emissions, the difference is small. For example, we can reduce emissions by 0.34% with 0.17% extra distance for instance A-n32-k5. We checked the numerical results in [7] and [9], and the tradeoff was also small in most test cases.

TABLE II THE EXTREME SOLUTIONS IN THE NET SET OF NON-DOMINATED SOLUTIONS (VALUES OF E_0 AND E: 0.296 AND 0.390)

	Min. distance		Min. emissions	
Instance	distance	emissions	distance	emissions
A-n32-k5	789.061	687.385	790.435 (+0.17%)	685.053 (-0.34%)
A-n36-k5	880.670	771.001	890.737 (+1.14%)	768.233 (-0.36%)
A-n37-k5	699.216	619.785	704.047 (+0.69%)	611.98 (-1.26%)
A-n38-k5	736.538	649.042	739.534 (+0.41%)	648.542 (-0.08%)
A-n48-k7	1153.43	1007.83	1153.7 (+0.02%)	1005.91 (-0.19%)
B-n35-k5	983.501	858.902	983.501	858.902
B-n44-k7	948.231	841.996	949.515 (+0.14%)	839.131 (-0.34%)
E-n51-k5	546.791	483.8	546.791	483.8
E-n101-k8	894.422	784.835	894.422	784.835
E-n301-k28	1334.22	1178.84	1334.22	1178.84

The results implied that the travel distance and carbon emissions are very positively correlated. We generated one million random solutions without duplicate objective vectors and calculated the correlation coefficient of distance and emissions. Table III lists the results, which confirmed that the correlation is very high for all problem instances.

TABLE III CORRELATION COEFFICIENTS OF DISTANCE AND EMISSIONS OF ONE MILLION RANDOM SOLUTIONS

Instance	Correlation	Instance	Correlation
A-n32-k5	0.992	B-n35-k5	0.986
A-n36-k5	0.986	B-n44-k7	0.993
A-n37-k5	0.989	E-n51-k5	0.986
A-n38-k5	0.987	E-n101-k8	0.988
A-n48-k7	0.989	E-n301-k28	0.985

D. *Experiment 2: Effect of Emission Coefficients*

The emission model we chose from the literature calculates the emissions by distance, load, and emission coefficients. Since the tested instances in our experiments already cover different problem characteristics, we conjectured that the tradeoff between distance and emissions is affected by the values of the emission coefficients e_0 and e. We adjusted the value of e (emissions of a full-load vehicle) by 3, 5, 7, and 10 times, and repeated the experiment on correlation. We show the curves of correlation coefficient of four problem instances in Fig. 3. The correlation decreases as the value of e increases, which means that the tradeoff between distance and emissions becomes significant when the emission levels differ significantly with different load levels. The correlation is smaller for larger-scale problem instances.

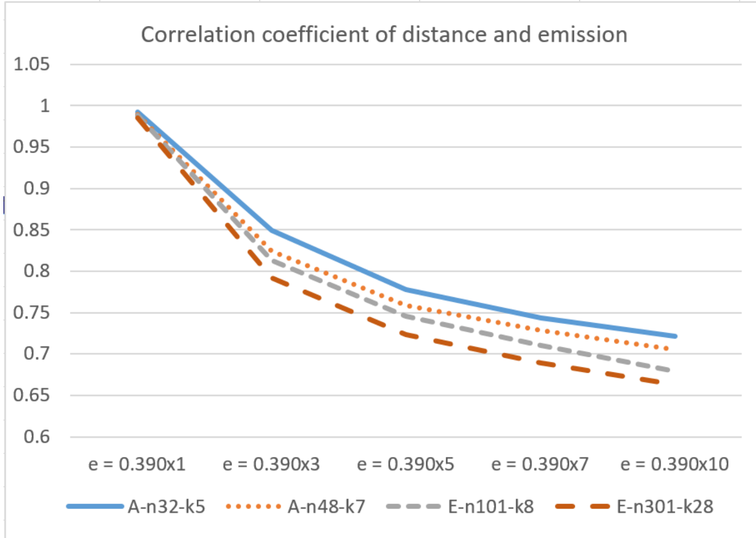


Fig. 3. Correlation coefficient of distance and emissions of solutions for different problem instances under different values of emission coefficient (e)

We solved the ten problem instances again with e_0 as 0.296 and e as 3.9. Table IV presents the results. This time we did find the obvious tradeoff between distance and emissions. For example, we can reduce 27.69% emissions by 11.59% extra distance for instance A-n36-k5. Fig. 4 shows the obtained solutions in the objective space for two problem instances. Fig. 4(a) shows the possibility of a large reduction of emissions at the cost of a slight increase of travel distance.

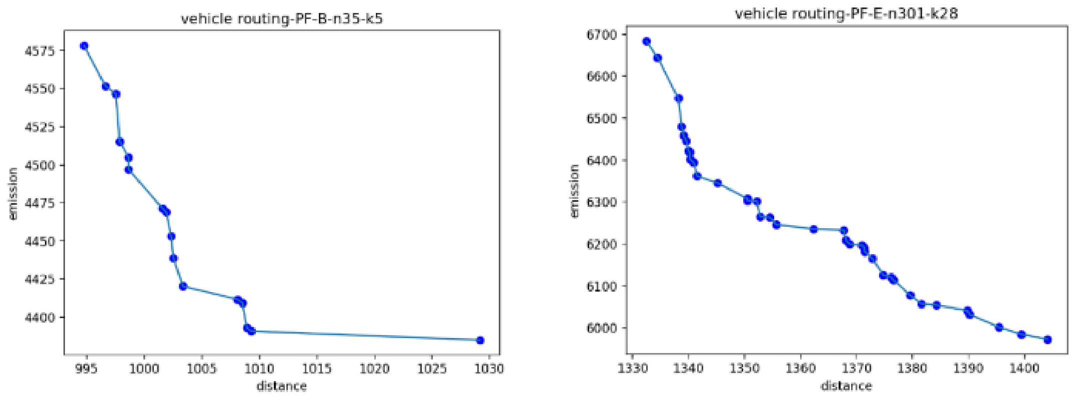
TABLE IV THE EXTREME SOLUTIONS IN THE NET SET OF NON-DOMINATED SOLUTIONS (VALUES OF E_0 AND E: 0.296 AND 3.9)

	Min. distance		Min. emissions	
Instance	distance	emissions	distance	emissions
A-n32-k5	789.168	3541.36	861.739 (+9.20%)	3377.16 (-4.64%)
A-n36-k5	880.742	4524.74	982.791 (+11.59%)	3271.62 (-27.69%)
A-n37-k5	722.848	2961.97	760.422 (+8.54%)	2692.44 (-25.13%)
A-n38-k5	739.293	3546.47	788.935 (+6.71%)	3252.36 (-8.29%)
A-n48-k7	1116.99	5854.32	1198.44 (+7.29%)	4868.27 (-16.84%)
B-n35-k5	993.299	4590.97	1009.3 (+1.61%)	4390.86 (-4.36%)
B-n44-k7	948.737	4645.99	951.837 (+0.33%)	4448.38 (-4.25%)
E-n51-k5	546.791	2891.9	586.194 (+7.21%)	2510.96 (-13.17%)
E-n101-k8	885.184	4407.94	912.41 (+3.08%)	3688.85 (-16.31%)
E-n301-k28	1332.06	6683.77	1404.05 (+5.40%)	5973.16 (-10.63%)

V. CONCLUSIONS

The GVRP extends the VRP by taking both minimization of travel distance and carbon emissions as two objectives to consider economic cost and environmental impact simultaneously. In this paper, we solved the GVRP as a bi-objective problem. Our algorithm is based on a multiobjective evolutionary algorithm. It aims to find the set of non-dominated solutions for decision making without the need of a prior aggregation function of the objectives. Based on our experimental results, we found that the tradeoff between distance and emissions is heavily influenced by the difference between the emission levels of an empty vehicle and of a full-load vehicle. When the difference is small, the tradeoff is also small and the GVRP can be solved as a single-objective optimization problem; when the difference gets large, the tradeoff rises and multiobjective optimization methods become useful.

In this study we took an emission model that calculates emissions based on travel distance and vehicle load. In the literature there are other models that considered more factors such as road angle and driving speed. In the future we will investigate how these models affect the problem nature (multiobjective or not) of the GVRP. After confirming the problem nature, we will keep on designing good algorithms to solve the GVRP and applying our algorithms to real-world problems.



(a) (b)

Fig. 4. The set of non-dominated solutions found for (a) B-n35-k5 and (b) B-n301-k28 instances (e_0: 0.296, e: 3.9)

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