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A multi-criteria optimization model for emission-concerned multi-depot vehicle routing problem with heterogeneous fleet

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***Abstract*—Not only greenhouse gases but also other air pollutant emissions from transportation have direct impacts on the environment and human health. The challenge of solving the conflict between profit and environmental consequences in logistics has motivated many studies on the vehicle routing problem. In this paper, a multiobjective mixed integer linear programming model is proposed to minimize transportation expenses and pollutant emissions for the multi-depot heterogeneous vehicle routing problem. A metaheuristic is adapted to obtain the Pareto optimal solutions. After a search procedure, decision makers are able to choose among best transportation plans that balance many objectives at once including economic benefits and environmental impacts. Computational experiments are performed on seven well-known benchmark problem sets. The results demonstrate the existence of greener transportation plans, which are illustrated alongside the best solutions previously reported. The study shows that, in return for a minimal economic tradeoff, a substantial amount of pollution could be avoided.**

***Index Terms*—transportation, multi-depot vehicle routing problem, multi-objective, environmental emissions**

I. Introduction

The awareness of environmental consequences has increased considerably among governments and researchers in various sectors over the last decade. Recent statistics reveal that transportation has left behind electricity production to be the most dominant emitter of carbon dioxide in the US while remaining the second largest contributor of greenhouse gases in EU [11]. Research papers on vehicle routing problem (VRP) in the effort to lower these impacts have shown positive results. An example is the work of [14]. They study the classical VRP with heterogeneous fleet to minimize two objectives of total travel distance and carbon dioxide emissions. Another approach is, instead of travel length, minimizing the fuel consumption which is believed to be proportional to the mass of carbon dioxide emitted (e.g., [14], [16]). On other variants of the classical VRP, [19] minimizes three objectives of CO_2, NO_x, and CO for the open time-dependent VRP. [9] adopted a fuzzy model to minimize the risk for transportation of hazardous materials. However, there has been a lack of works on the multi-depot vehicle routing problem (MDVRP) tackling in detail the minimization of multiple emitted pollutants.

The proposed model considers the case vehicles can be different in type and standard (e.g., capacity, engine, emission factors). This makes the problem more generalized and realistic [22] that in practical logistics, not all working vehicles are normally bought at once. Since homogeneous fleet has been more attentively focused, the shortage of works on VRP with heterogeneous fleet is evident.

This paper focuses on the multi-depot heterogeneous vehicle routing problem (MDHVRP) which is more generalized than MDVRP, with more than one objective. The proposed equation based model considers a multiobjective mixed integer programming problem in which multiple criteria are optimized simultaneously. After a procedure to obtain the set of optimal solutions, decision makers are able to choose among best transportation plans that balance many objectives at once regarding economic benefits and environmental impacts. Mathematical description of the obtained solutions is discussed. Concretely, many computational experiments are presented including tests on seven well-known benchmark instances. The result is reported and compared with the best-known shortest-path solution of each instance.

II. Possibility to achieve greener solutions

Vehicle standards have been continuously updated over the years by the US and EU with increasingly strict barriers, as part of efforts to meet sustainability targets. Table I shows some figures of EU standards for heavy-duty truck extracted from [10]. While most relevant papers are limited to greenhouse gases, the critical necessity of lowering other types of air pollutants has been recently pointed out by [11].

Figure 1 is an example of achieving greener transportation solutions in return for a small sacrifice of economic benefit on MDHVRP. The data set is of instance `p01` described in Section VII using a mixed fleet of different standards taken

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TABLE I
DIFFERENT STANDARDS FOR HEAVY-DUTY DIESEL TRUCKS UNDER 7.5 TONS

Heavy-duty vehicle standards	**Emission factors** (Units: g/km)				
	CO_2	THC-CH_4	CO	Pb	NO_2-e*
HD Euro I	0.486	0.193	0.657	5.43E-6	3.3779
HD Euro II	0.486	0.123	0.537	5.22E-6	3.4969
HD Euro III	0.486	0.115	0.584	5.47E-6	2.6359
HD Euro IV	0.486	0.005	0.047	5.17E-6	1.6489
HD Euro V	0.486	0.005	0.047	5.17E-6	0.9358
HD Euro VI	0.486	0.005	0.047	5.17E-6	0.1828

*NO_2-equivalents: including NO_x, N_2O, and NH_3

from Table I. The inset (a) is the best-known solution by total travel distance [5]. Another plan is presented in the inset (b) where there is a tradeoff between 5.32% longer travel distance and 43.98% CO reduction. It can be partly explained by the numerical presentation of the solution that the number of trucks used is minimized and lower standard trucks are only used when necessary.

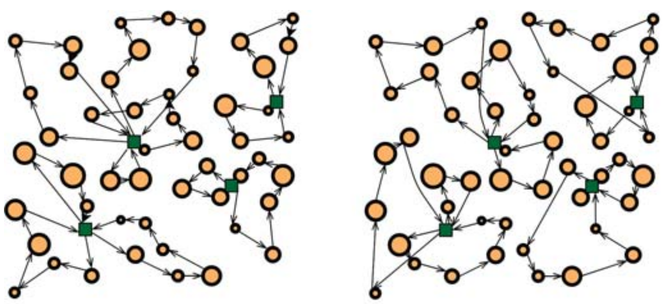

Fig. 1. Different solution plans for a MDHVRP. Yellow circles denote customers (waste resources); green squares denote the waste depots. The radius of circles linearly indicates customer demand. (a) is the optimal solution by total travel distance reported for the given problem while (b) is another feasible solution.

III. A REVIEW ON RECENT LITERATURE ON MDVRP

Some related papers on MDVRP and its variants are summarized in Table II. As shown, similarly to other variants of VRP, research works on MDVRP are drastically diverse in optimization objectives and computational methods. Although the usual desire of logistic enterprises is to optimize several criteria at once, according to [18] (2015), nearly ninety percent of research papers were conducted on single objective optimization models. In general, only a few works on VRP involve multiple objectives, some working on two (e.g., [8], [13]); very few working with three and more (e.g., [17], [19]). Exact methods to solve those problems are outnumbered by metaheuristics, due to the modern availability of computational power [18], including ant colony, tabu search, evolutionary, and genetic algorithms (see [1], [2], [3], [4], [16], [20], [25]). Though there is no best algorithm to solve MDVRPs. Such a choice of solution method is problem-related. Recently, [16] assesses in detail the involvement of shared depot resources in MDVRP. Taking advantage from the relaxed feasible domain of decision, the overall benefit is apparent in many cases. However, experiments on popular benchmark problem sets were not reported. As also stated above, there is still a lack of literature on MDVRP working with heterogeneous fleet.

TABLE II
A REVIEW ON RECENT LITERATURE ON MDVRP AND VARIANTS

Year	*Article*	*Objective(s)*	*Solution method**
2015	Chavez et al. [3]	total distance[a]	M
2015	Rahimi et al. [21]	fleet size	H
2016	Bae and Moon [1]	transportation, installation	H, GA
2016	Chavez et al. [4]	total distance, time, fuel[a]	ACO
2016	Oliveira et al. [20]	total distance	E
2016	Wang et al. [28]	longest route time	H
2017	Du et al. [9]	transportation risk	H
2017	Soto et al. [25]	total distance	hybrid M
2017	Ucar et al. [27]	recovery planning	H
2018	Bezerra et al. [2]	total distance	M
2018	Li et al. [16]	fuel[b]	GA

*ACO: Ant colony optimization algorithm
M: Metaheuristic algorithm
H: Heuristic algorithm
E: Evolutionary algorithm
GA: Genetic algorithm
[a]Considering MDVRP with backhauls
[b]Considering MDVRP with shared depot resources

Readers are referred to [18] for a comprehensive review on related research papers before 2015.

IV. MULTIOBJECTIVE PROGRAMMING AND THE PARETO SURFACE

A multiobjective programming problem is usually given in the form of

$$\begin{aligned} &\text{Vmin} \;\; G = (g_1(x), g_2(x), \ldots, g_{\mathcal{Q}}(x))^T \qquad \text{(MOP)} \\ &\text{subject to} \;\; x \in \mathcal{X}, \end{aligned}$$

where the *domain of decision* $\mathcal{X}$ is a nonempty subset of $\mathbb{R}^{\mathcal{P}}$ and $g_i : \mathbb{R}^{\mathcal{P}} \to \mathbb{R}, i = 1, \ldots, \mathcal{Q}$. It is clear that $G : \mathbb{R}^{\mathcal{P}} \to \mathbb{R}^{\mathcal{Q}}$. We then call $\mathbb{R}^{\mathcal{P}}, \mathbb{R}^{\mathcal{Q}}$ the *decision space* and the *image space*, respectively. Unlike the single objective case (i.e., $\mathcal{Q} = 1$), $\mathbb{R}^{\mathcal{Q}}$ for $\mathcal{Q} \geq 2$ is not a totally ordered space under elementwise relation (i.e., $a \leq b \Leftrightarrow a_i \leq b_i, i = 1, \ldots, \mathcal{Q}$ for $a, b \in \mathbb{R}^{\mathcal{Q}}$). Namely, given $y_1, y_2 \in \mathbb{R}^{\mathcal{Q}}$, possibly neither $y_1 \leq y_2$ nor $y_2 \leq y_1$. The solution of (MOP) is thus seen under Pareto optimality whence the vector objective function is often placed after notation "Vmin" instead of the usually seen "min". A solution $x^* \in \mathcal{X}$ is *weakly Pareto optimal* if and only if $\{x \in \mathcal{X} \mid G(x) < G(x^*)\} = \emptyset$. $G(x^*)$ is then called a *weakly nondominated point* in the image space. The set of all such weakly nondominated points is known as the *Pareto surface* (or *Pareto curve* in case $\mathcal{Q} = 2$). It is easy to prove that for any $x \in \mathcal{X}$, there exists $x' \in \mathcal{X}, G(x')$ lying on the Pareto surface such that x' results in better outcome or at least not any worse for all considering objectives. Therefore, presentation of the

Pareto surface is immensely meaningful in the case of having multiple objective functions.

Multiobjective mixed integer linear programming (MOMILP) is a special case of (MOP) in which $g_i, i = 1, \ldots, \mathcal{Q}$ are linear and some elements of the decision variable are restricted to integer values.

V. Model formulation

This section proposes the MOMILP model. In general, a multi-depot VRP is normally defined on an undirected graph $G = (V, E)$ where the set of vertices $V = \{c_1, c_2, \ldots, c_N, D_1, D_2, \ldots, D_M\}$ contains N collection centres/customers $c_i, i = 1, \ldots, N$ and M waste depots $D_i, i = 1, \ldots, M$; the set of edges E represents the paths connecting each pair of collection centres. Since they are normally considered as geographical connections, G is a complete graph, i.e., $E = \{(v_i, v_j) \mid v_i, v_j \in V, v_i \neq v_j\}$. There is a schedule of waste in each collection centre, denoted by a positive $q_i, i = 1, \ldots, N$ that needs to be fully transported to the waste depots by the collecting vehicles, each starting and ending at its assigned depot. Additional constraints are: each vehicle collects the full demand of each centre it visits; the total load of any route does not exceed the capacity of its assigned vehicle. The known NP-hard problem is to determine a routing plan that minimizes the cost function with weight matrix $C = (c_{ij})$, where c_{ij} corresponds to the cost to travel from v_i to v_j, with some $v_i, v_j \in V$. The most straightforward choice of matrix C is letting $C \equiv D = (d_{ij})$ where d_{ij} is the length of (v_i, v_j).

A. The constraint set

This constraint set is extended from the earlier formulation of single-depot VRP [15] combined with some suggestions from a recent work of [22]. Let K be the set of all vehicles, $x_{ijk} \in \{0, 1\}$ for $i, j \in \{1, \ldots, M + N\}, k \in K$ be the decision variable whether vehicle k travels from v_i to v_j. Let Q_k be the capacity of vehicle k. The mathematical constraint set can be formed as follows.

$$\sum_{i=1}^{M+N} \sum_{k \in K} x_{ijk} = 1 \quad j = 1, \ldots, N \tag{1}$$

$$\sum_{j=1}^{M+N} \sum_{k \in K} x_{ijk} = 1 \quad i = 1, \ldots, N \tag{2}$$

$$\sum_{i=1}^{M+N} x_{ihk} = \sum_{j=1}^{M+N} x_{hjk} \quad k \in K, h = 1, \ldots, M + N \tag{3}$$

$$\sum_{i=1}^{M+N} q_i \sum_{j=1}^{M+N} x_{ijk} \leq Q_k \quad k \in K \tag{4}$$

$$\sum_{i=1}^{M+N} \sum_{j=1}^{M+N} d_{ij} x_{ijk} \leq T_k \quad k \in K \tag{5}$$

$$\sum_{i=N+1}^{N+M} \sum_{j=1}^{N} x_{ijk} \leq 1 \quad k \in K \tag{6}$$

$$\sum_{j=N+1}^{N+M} \sum_{i=1}^{N} x_{ijk} \leq 1 \quad k \in K \tag{7}$$

$$y_i - y_j + (M + N) x_{ijk} \leq M + N - 1 \tag{8}$$
$$\forall 1 \leq i \neq j \leq N, k \in K$$

$$x_{ijk} = 0 \quad i, j = N + 1, \ldots, N + M, k \in K \tag{9}$$

$$x_{ii} = 0 \quad i = 1, \ldots, M + N, k \in K \tag{10}$$

$$\sum_{k \in K} \sum_{j=1}^{N} x_{ijk} \leq K_i \quad i = N + 1, \ldots, N + M \tag{11}$$

$$x_{ijk} \in \{0, 1\}, \forall i, j, k \tag{12}$$

Classical restrictions (1), (2) ensure each collection centre is served exactly once. Constraints (3) balance the inflow and outflow in each vertex of the graph. They also guarantee that any vehicle finishes its route at starting depot. Vehicle capacity and maximum total route length T_k (fuel capacity, optional) for vehicle k is confined in Constraints (4) and (5). Constraints (6), (7) ensure that each vehicle is assigned to at most one depot. Constraints (8) are for subtour elimination transformed from the capacity cut constraints [7]. Notice that the variables $y_i, i = 1, \ldots, N$ are introduced only to serve these equations. The tightened conditions to avoid traveling from depot to depot and self returns are respectively included in Constraints (9) and (10). Constraints (11) are applicable only if K_i the number of vehicles at depot v_i is given. Constraints (12) present a natural property of the model variables.

B. The objective functions

The proposed model is defined on the domain of decision $\mathcal{X}$ constructed in Section V-A. For presentation, we consider a function vector $\mathcal{F}$ of which each element is some concerned objective function mapping from the decision space to the space of real numbers. Among options, total travel distance (13) is the most popular objective in previous studies.

$$f_d = \sum_{i=1}^{M+N} \sum_{j=1}^{M+N} \sum_{k \in K} d_{ij} x_{ijk}. \tag{13}$$

Some additional model parameters are introduced:

- I_i – fixed cost of running depot D_i;
- J_k – fixed cost of maintenance/depreciation for vehicle k;
- P – fuel price per litre;
- V – fuel consumption (litre);
- ξ_k – consumption rate of vehicle k.

The total expense of transportation can then be written as

$$f_e = \sum_{i=N+1}^{N+M} I_i + \sum_{i=N+1}^{N+M} \sum_{j=1}^{N} \sum_{k\in K} J_k x_{ijk}$$

$$+PV \sum_{i=1}^{M+N} \sum_{j=1}^{M+N} \sum_{k\in K} \xi_k d_{ij} x_{ijk} = \sum_{i=N+1}^{N+M} I_i + \langle \eta, x\rangle. \quad (14)$$

Let $m_{ijk}^{(\ell)}, \ell = 1,\ldots,L$ be the emission amount (g) of the ℓ^{th} pollutant by vehicle k when traversing edge (v_i, v_j) and ε_k^ℓ be the emission factor (g/km) of the ℓ^{th} pollutant by vehicle k. The minimization objectives of emissions are constructed as follows.

$$f_\ell = \sum_{i=1}^{M+N} \sum_{j=1}^{M+N} \sum_{k\in K} m_{ijk}^{(\ell)} x_{ijk} \qquad \ell = 1,\ldots,L, \qquad (15)$$

where the mass of emission on each edge, as per standards those in Table I, is considered to be proportional to the length of travel, namely $m_{ijk}^{(\ell)} = \varepsilon_k^\ell d_{ij}$. The desired MOMILP model is finally formed.

$$\begin{aligned} \text{Vmin } \; & \mathcal{F} = \sum_{k\in K} \mathcal{C}_k x \\ \text{subject to } \; & x, y \in \mathcal{X}, \end{aligned} \qquad \text{(MOMDHVRP)}$$

where

$$\mathcal{C}_k = \begin{bmatrix} \eta_{11k} & \eta_{12k} & \eta_{13k} & \cdots & \eta_{M+N,M+N,k} \\ m_{11k}^{(1)} & m_{12k}^{(1)} & m_{13k}^{(1)} & \cdots & m_{M+N,M+N,k}^{(1)} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ m_{11k}^{(L)} & m_{12k}^{(L)} & m_{13k}^{(L)} & \cdots & m_{M+N,M+N,k}^{(L)} \end{bmatrix}.$$

Although the vector $\mathcal{F}$ contains only linear functions, solving (MOMDHVRP) is, in general, difficult since the complicated structure of the constraint set (e.g., the domain of decision is not even connected) excludes many useful properties of the solution set or the set of nondominated points that are normally utilized to build robust solution methods. Hence, for generating the Pareto surface in this case, it is suitable to use basic tools of multiobjective programming such as the weighted sum or ε-constraint method. This view is shared by researchers when dealing with the same situation on other problems (e.g., multiobjective environmental/economic dispatch problem [26]). It also makes the problem solvable using some metaheuristic algorithm.

VI. Solution method

Due to the increased difficulty of the problem, most exact methods on single depot VRP fail to adapt for solving MDVRP [18]. In the case of having sequence decision variable and a complicated discontinuous domain of decision, metaheuristics are often the method of choice. They are known for their short execution time and sufficient accuracy. So far, almost all best-known solutions for popular benchmark data sets can be achieved by metaheuristic algorithms [16].

A. The adapted metaheuristic

An example of a state of the art but easy to explain metaheuristic on VRP that we will use in the solution procedure is the work of [24]. A possible implementation of this algorithm is: (i) start with a feasible solution; (ii) choose a small area of some reasonable radius and remove all the collection centres within from their existing routes; (iii) recreate the routes in some way so that they do not violate the constraints; (iv) accept the new solution if it is good enough, otherwise continue with the current one; (v) go back to step (ii) and repeat the process for a fixed number of iterations. Moreover, it is possible to extend the algorithm, by replacing the evaluation function in step (iv), to carry different weighted distances for each type of vehicle on MDVRP, which can be utilized to solve our problem of (MOMDHVRP). The detail on how will be described in Section VI-B.

B. Generation of the Pareto surface

Procedure *GenerateNondominatedPoints* (*GNP*) shows the way to generate the surface containing weakly nondominated points in the image space for (MOMDHVRP).

Procedure: *GenerateNondominatedPoints*

Input: Data of the collection centres, depots, vehicle fleet, and other model parameters

Output: Γ the set of weakly nondominated points and corresponding weakly Pareto optimal solutions

1 Calculate the objective matrix $\mathcal{C} \longleftarrow \sum_{k\in K} \mathcal{C}_k$ and merge the ones with proportional relation;
2 Set $\mathcal{N}$ the number of attempt points in the image space;
3 $\Gamma \longleftarrow \emptyset$;
4 **for** $i \longleftarrow 1$ **to** $\mathcal{N}$ **do**
5   Randomly generate weight vector $\bar{w} = (w_1, w_2, \ldots, w_{L+1})$ such that $\sum_{j=1}^{L+1} w_j = 1$;
6   Solve the single objective problem $\min\langle \sum_{j=1}^{L+1} w_j \mathcal{C}^{(j)}, x\rangle$ subject to $x, y \in \mathcal{X}$ using the metaheuristic algorithm;
7     $\Gamma \longleftarrow (\mathcal{F}(x^*), x^*)$ where x^* is the newly found optimal solution;
8 **end**
9 **foreach** $(\mathcal{F}(x), x) \in \Gamma$ **do**
10   **if** *there exists* $(\mathcal{F}(x'), x') \in \Gamma$ *such that* $\mathcal{F}_j(x') < \mathcal{F}_j(x), \forall j \in \{1,\ldots,L+1\}$ **then**
11   Remove $(\mathcal{F}(x), x)$ from Γ;
12   **end**
13 **end**

The following proposition points out essential properties of procedure *GNP*.

Proposition. *Assuming the metaheuristic in procedure GNP produces only exact solutions, then any pair* $(\mathcal{F}(x), x) \in \Gamma$ *contains a weakly nondominated point and its corresponding weakly Pareto optimal solution. Moreover, under this assumption, no pairs are removed by the procedure (Line 9–13).*

The first part of the proposition is straightforward, following from properties of the weighted sum method. This statement implies that an approximation of the Pareto surface can be obtained with the use of an adequate metaheuristic. The second part suggests that the procedure part to remove image space points from the nondominated set is only added because the metaheuristic is an inexact algorithm.

VII. Computational experiments

We perform some experiments on the proposed model in this section. For the purpose of reproducibility, the tests are done on the classical benchmark instances `p01`, `p02`, ..., `p07` introduced by [6]. Each instance corresponds to a MDVRP containing 50–100 collection centres, 2–5 depots, and 2–8 vehicles (see [6] for more detail). For the metaheuristic, the code implementation uses some functions of [23], a Java library for VRP problems.

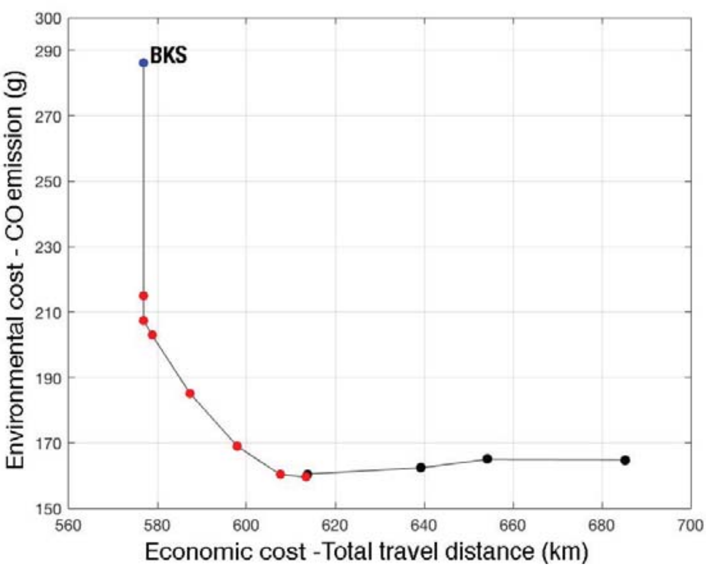

Fig. 2. The approximate Pareto curve generated by random choices of $\bar{w}$. The red dots present nondominated points constructing the optimal curve. The black dots indicate the points removed by procedure *GNP*. The topmost blue dot corresponds to the previously reported best-known solution by the meaning of shortest path (also a nondominated point itself).

The approximate Pareto curve generated by procedure *GNP* on two objectives of travel distance and CO emission for instance `p01` is shown in Figure 2. A mixed fleet is taken from Table I. Here we use the same truck capacity as stated in [6] only to make a relevant comparison with the previously reported results. The model and solution procedure remain the same for a fleet with varying capacity classes. The figure shows a clear conflict between the two minimization desires. The best-known solution (BKS) by shortest path (reported by [5], [16] and also obtained by *GNP* by putting zero weights on emission objectives) is compared. Some obvious alternative solutions with significantly lower amounts of emission and small differences in travel length can be observed.

Figure 3 shows the approximate Pareto surface generated by procedure *GNP* for instance `p01` on three objectives of travel distance, CO, and NO_2-equivalents. The same kind of conflict can be observed in the case of a three-dimensional image space. Note that the convex hull in Figure 3 is presented solely for ease of perception.

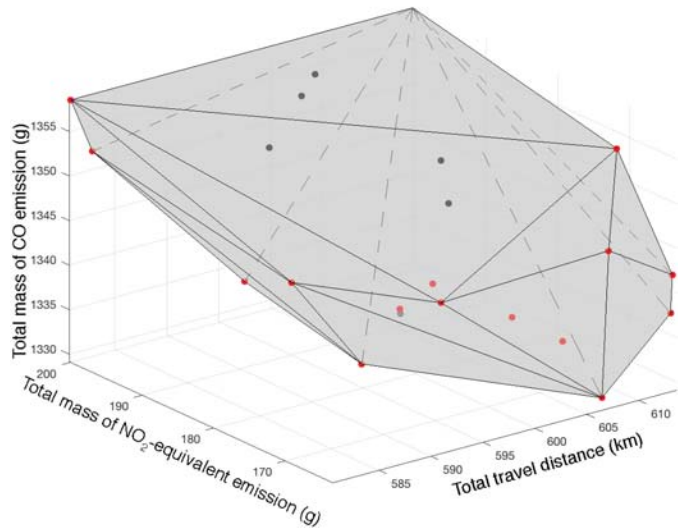

Fig. 3. The approximate Pareto surface generated by random choices of $\bar{w}$. The red dots represent nondominated points constructing the optimal surface. The black dots indicate the points removed by procedure *GNP*.

Computational results on other instances can be found in Table III. For each instance, four objectives of travel distance, CO, NO_2, and Pb emissions are considered. Each vehicle fleet contains random types of vehicles in which emission factors are taken from Table I. The greener solution is determined by putting equal weights on objectives after constant terms are multiplied to normalize their magnitude. The best-known solution by conventional meaning (*BKS*), solution generated with zero weights on emission objectives (*GNP0*), and with equal weighted objectives (*GNP*) are respectively presented for each instance. The tradeoff and cutdown are calculated on the two latter solutions. For each instance, although only one alternative is shown among many eco-friendly plans achievable by *GNP*, the overall benefit can be seen.

VIII. Conclusion and discussion

Climate change and contemporary environmental issues establish an urgent necessity of lowering pollutants induced by human activities including transportation. This paper studies a multiobjective mixed integer linear programming model to simultaneously minimize transportation expenses and pollutant emissions for the multi-depot heterogeneous vehicle routing problem. The authors try to formulate a general framework to study the global optimization problem with multiple objectives for a class of VRP since there has been no similar works. The proposed solution method provides a simple and fast way to obtain an adequate solution set. The weakness is the accuracy

TABLE III
ALTERNATIVE GREENER SOLUTIONS ON INSTANCES OF [6]

#	**Total travel distance (Units: km)**				**Emissions (CO, NO_2, Pb) (Units: g)**		
	BKS	***GNP0***	***GNP***	Trade -off	***GNP0***	***GNP***	Cut-down
p01	576.86	576.86	603.07	4.5%	(288.46,	(170.61,	40.9%
					1775.57,	1334.17,	24.9%
					3.32E-3)	3.18E-3)	4.2%
p02	473.53	473.53	475.86	0.0%	(287.45,	(254.29	11.5%
					1623.02,	1655.90,	-2.0%
					2.53E-3)	2.47E-3)	2.4%
p03	640.65	647.12	649.54	0.4%	(388.11,	(366.97,	5.4%
					2062.27,	1938.61,	6.0%
					3.48E-3)	3.48E-3)	0.0%
p04	999.21	1015.62	1032.16	1.6%	(564.37,	(360.67,	36.1%
					3049.52,	2389.58,	21.6%
					5.46E-3)	5.49E-3)	-0.5%
p05	750.03	753.88	758.26	0.6%	(368.56,	(248.39,	32.6%
					2142.91,	1809.32,	15.6%
					4.03E-3)	4.01E-3)	0.5%
p06	876.50	877.58	883.59	0.7%	(462.02,	(355.41,	23.1%
					2752.41,	2380.65,	13.5%
					4.66E-3)	4.66E-3)	0.0%
p07	881.97	889.35	901.87	1.4%	(439.46,	(303.30,	31.0%
					2487.43,	2345.76,	5.7%
					4.77E-3)	4.73E-3)	0.8%

Note: *BKS* – Best-known solution [16]; *GNP0* – solution generated solely by the metaheuristic (zero weight on emission objectives); *GNP* – solution generated by procedure *GNP* with equal weighted objectives.

of the metaheuristic (for large problems), and the distribution of the weakly nondominated points in the outcome space. The contribution of this paper can be summarized as:

(i) giving a short review on recent papers studying MDVRP;
(ii) proposing a MOMILP model for the mentioned purpose;
(iii) developing a procedure using a metaheuristic to obtain the set of weakly Pareto optimal solutions which allows the decision maker to choose from the best possible plans;
(iv) analyzing and comparing the computational results on popular data sets.

Future works may consider more generalized classes of objective functions that can describe complex sustainability issues. On the other hand, it is challenging to involve environmental and social metrics in rich variants of VRP which are closer to reality such as those with fuzzy travel time or stochastic demands. An improved method to solve (MOP) can be used to obtain a better distribution of the weakly nondominated set.

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