Tailoring Evolutionary Algorithms to Solve the Multi-Objective Location-Routing Problem for Biomass Waste Collection

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***Abstract*—Location-routing problems widely exist in logistics activities. For the biomass waste collection, there is a recognized need for novel models to locate the collection facilities and plan the vehicle routes. So far most location-routing models fall into the cost-driven-only category. However, comprehensive objectives are required in the specific context, such as time-dependent pollution and speed- and load-related emission. Furthermore, location-routing problems are hierarchical by nature, containing the facility location problems (strategic level) and the vehicle routing problems (tactical level). Existing studies in this field usually adopt computational intelligence methods directly without decomposing the problem. This can be inefficient especially when multiple objectives are applied. Motivated by these, we develop a novel multi-objective optimization model for the location-routing problem for biomass waste collection. To solve this model, we explore the way to tailor evolutionary algorithms to the hierarchical structure. We develop adapted versions of two commonly used evolutionary algorithms: the genetic algorithm and the ant colony optimization algorithm. For the genetic algorithm, we divide the population by the strategic level decisions, so that each subpopulation has a fixed location plan, breaking the location-routing problem down into many multi-depot vehicle routing problems. For the ant colony optimization, we use an additional pheromone vector to track the good decisions on the location level, and segregate the pheromones related to different satellite depots to avoid misleading information. Thus, the problem degenerates into vehicle routing problem. Experimental results show that our proposed methods have better performances on the location routing problem for biomass waste collection.**

***Index Terms*—Location-routing, multi-objective optimization, genetic algorithm, ant colony optimization, multi-population technique.**

I. Introduction

LIVESTOCK and poultry industries are typically the major business in some rural areas of developing countries. As a common feature, they are often conducted by small-scale family farming and near the residential areas. While these industries are earning wealth for the local economy, they also generate wastes (e.g., excreta, feathers and bedding) which will heavily pollute the air, soil, and underground-water. These wastes, usually categorized as a kind of biomass waste, can be collected and transformed into clean energy or fuels through technically feasible ways. To achieve this, an efficient biomass waste collection logistics system is needed, so that the biomass waste would be transferred away from the densely populated areas in a timely manner.

The biomass waste collection logistics system usually contains a biogas plant and several collection facilities. The biomass waste should be first gathered up from family farms to collection facilities for pre-processing and storage. Then it is transferred to the biogas plant. All these entities constitute a two-echelon logistics network, where the locations of collection facilities and routing of the vehicles are the key factors to reach the management goals. Therefore, a location-routing problem (LRP) for biomass waste collection is considered here for the efficiency of the logistics system.

LRPs involve two hard combinatorial optimization problems, i.e., the facility location problem (FLP) to select one or several locations from a finite or infinite set, and the vehicle routing problem (VRP) to determine the sequence of visiting the customers [1]. The location-decision is not implicitly determined by the routing decision, because of the facility-related costs and capacity limitations [2]. The classical LRP is well-defined and widely reviewed in [3]. Among most of the LRP models, cost-related objectives are the most popular used ones [4], [5]. The cost of the routes is mainly determined by the travel distance. Based on this, many variants have extended the basic LRP to new application fields by considering uncertainty [6], [7], flexibility [8], dynamic feature [9]–[11], and so on.

As the environment issues grew into a public concern in the past decades, the concept of green logistics attracts considerable critical attention in that transportation has become one of the major sectors producing green house gas and air pollution [12]. Distance-based objectives of LRPs are insufficient to plan and execute environmental-friendly logistics activities [13]. Though in some cases the travel distance is highly related to some ecological factors such as fossil fuel consumption, it has been argued by literature [14], [15] that the minimization of total distance does not always match the lowest-fuel-consumption solution. They further pointed out that the load of the vehicle is the key factor for reducing fuel consumption, and the speed of the vehicle matters but in a limited way especially when time windows are imposed. Based on these

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work, the fuel consumption measurement is introduced into LRPs with the "green routing" concept [16], [17].

In general, for a comprehensive model of LRP concerning environment impact, the vehicle load, facility locations, and latency are important factors to reduce the undesirability. Hence, in the biomass waste collection LRP, the logistics system should have these features: (i) having a reasonable cost so that it will not be harmful to the economy; (ii) collecting the biomass waste as soon as possible to reduce the time-related pollution; (iii) avoiding producing too much additional pollutant, such as carbon emission caused by the vehicles. These objectives should be considered simultaneously, i.e., it is advantageous to adopt a multi-objective point of view.

Increasing the number of objectives for LRPs makes them more difficult to solve. Although multi-objective evolutionary algorithms (MOEAs) have developed into efficient tools for multi-objective optimization problems in recent years, these problem-independent solvers mainly focus on improving the selection operators. For multi-objective location-routing problems (MOLRPs), tailored variation strategies are needed to overcome the following difficulties. First, MOLRPs are discrete optimization problems so that there is no gradient information to follow. Second, MOLRPs contain location decisions and routing decisions at the same time, resulting in a large decision space. Third, there are many constraints associated with both depots and vehicles. Forth, the information interaction between solutions with different location decisions may lead to a worse or even infeasible solution, because the routing decisions are highly associated with the location decisions.

Based on the above discussion, the main contributions of this paper are summarized as follows.

- We extend the LRP to the application field of biomass waste collection, by establishing a novel multi-objective optimization model.
- We investigate into the drawbacks of solving this problem using generic routing problem methods (i.e., GA and ACO) in their multi-objective versions.
- We tailor two representative evolutionary algorithms (GA and ACO) respectively to fit the hierarchical structure of the MOLRP.

The rest of the paper is organized as follows. We first introduce our MOLRP model in Section II, and also discuss the pitfalls of conventional solvers in dealing with this problem. We propose the specialized versions of GA and ACO in Section III and Section IV, respectively. Section V gives a broad comparison on some standard LRP datasets. Finally, Section VI draws the conclusion.

II. Problem Description

An illustration of the two-echelon logistics network of biomass waste collection is shown in Fig. 1. The network is constituted by the biogas plant (known as the main depot in standard two-echelon LRPs), the collection facilities (known as the satellite depots in standard two-echelon LRPs), and the family farms (known as the customers in standard two-echelon LRPs). We use the standard terms hereafter for clarity.

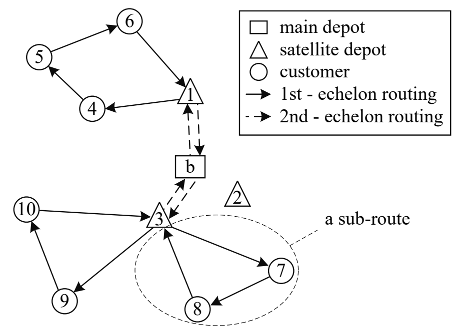

Fig. 1. Illustration of the logistics network.

The positions of the main depot and customers are fixed. For satellite depots, potential positions are given. The decision maker should select a number of them to be opened, then arrange the routing plan accordingly.

The logistics activities take place in the following sequence. In the first echelon, vehicles start from satellite depots, collecting biomass waste generated at customer nodes. Each customer must be visited and can only be visited once. A sub-route is established when a vehicle goes back to its starting depot and discharge. There are sufficient vehicles at satellite depots. Each vehicle is responsible for one sub-route, and the collection at each customer cannot be split. After all the collections have been treated in the satellite depots, they are reloaded into the vehicles for the second echelon transportation. The collections will then be transferred to the main depot. Finally, vehicles return to their own satellite depots with empty load.

A. Mathematical Model

We define the LRP for biomass waste collection on a graph $G(V, A)$. $V = V_1 \cup V_2$ is the set of all first-echelon nodes where V_1 is the set of customers, and V_2 is the set of potential satellite depots. $V_3 \subseteq V_2$ represents the set of satellite depots that are selected to open. A is the set of arcs. K represents the set of vehicles and b is the node of main depot. We tabulate the parameters and variables in Table I, and establish the tri-objective optimization model as in (1) to (18).

The objective functions (1) to (3) represent the cost, pollution and emission, respectively. The cost consists of the fix cost of opened satellite depots, the biomass processing cost at satellite depots, and the transportation cost in the first and the second echelon. These correspond to the four items in (1). Note that in the last item of (1), the number of vehicles is recalculated. This is because vehicles from the first echelon may not be fully-loaded, then after processing and reloading, the second echelon may need fewer vehicles due to the discreteness. For the pollution objective, the longer the biomass waste stays at the customer nodes, the more pollution it will produce. The amount of pollution is also related to the quantity of biomass waste. Hence, we minimize the total waiting time weighted by the quantity of biomass waste of all customer nodes. It is undesirable to reduce the biomass waste pollution while causing another kind of damage to the environment. For this reason, we take the emission as the third

TABLE I
PARAMETERS AND VARIABLES

Parameters:	
f_j	fix cost of opening a satellite depot; $j \in V_2$
m	variable cost per unit of biomass waste for satellite depots;
q_i	amount of biomass generated by customer i; $i \in V_1$
e	unit cost per km of transportation;
$d_{ll'}$	distance on arc(l, l'); $l \in V, l' \in V$
d_{jb}	distance on arc(j, b); $j \in V_2$
s_l	the time when the vehicle leaves node l; $l \in V$
$\gamma_{ll'}$	parameter of weight-related emission on arc(l, l'); $l \in V, l' \in V$
γ_{jb}	parameter of weight-related emission on arc(j, b); $j \in V_2$
δ	parameter of speed-related emission;
w	vehicle net weight;
c_l	load carried when the vehicle leaves node l; $l \in V$
v	average speed for all vehicles;
a_j	capacity of satellite depot j; $j \in V_2$
h	vehicle capacity;
Variables:	
z_j	0-1, if satellite depot j is opened; $j \in V_2$
y_{ij}	0-1, if customer i is served by satellite depot j; $i \in V_1, j \in V_2$
$x^k_{ll'}$	0-1, if l precedes l' in sub-route k; $l \in V, l' \in V, k \in K$

objective. We draw on the idea from [14] that the engine-out emission is mainly related to the weight (the vehicle net weight and the load) and the speed. Thus, in our third objective, the first item is the emission caused by the increasing vehicle weight in the first echelon; The second item denotes the speed-related emission in the first echelon; The third item calculates the two kinds of emission in the second echelon.

For the constraints, (4) ensures that only when $z_j = 1$ can y_{ij} be set to 1, which indicates that customers can only be assigned to opened satellite depots. Together with (5), each customer must and can only be assigned to one opened satellite depot. Constraint (6) means that each customer i must and can only have one subsequent node. This avoids multiple visits of customer nodes. No routing connections between satellite depots are constrained by (7). In (8), if vehicle k visits node l, then it must leave for another node (visit another customer or go to the satellite depot). This guarantees the connections in sub-routes, and with (9) in consideration, each sub-route should only contain one satellite depot. The above constraints set up the basic routing rules of the logistics system. For the other features, the customer waiting time is implied by variable $\mathbf{x}$ within (10) and (11). The timer starts from 0 when the vehicle leaves satellite depot j, and stops at each customer i along the visiting sequence. Likewise, the vehicle load at each node can be obtained by (12) and (13). Equations (14) and (15) represent the capacity constraints of satellite depots and vehicles, respectively. Binary constraints are imposed by (16) to (18).

$$\begin{aligned}\min F_1 = &\sum_{j\in V_2} f_j z_j + m\sum_{j\in V_2}\sum_{i\in V_1} q_i y_{ij} \\ &+ e\sum_{l\in V}\sum_{l'\in V}\sum_{k\in K} d_{ll'} x^k_{ll'} \\ &+ 2e\sum_{j\in V_2}\lceil\frac{(\sum_{i\in V_1} q_i y_{ij})}{h}\rceil d_{jb} z_j\end{aligned} \tag{1}$$

$$\min F_2 = \sum_{i\in V_1} q_i s_i \tag{2}$$

$$\begin{aligned}\min F_3 = &\sum_{l\in V}\sum_{l'\in V}\gamma_{ll'} d_{ll'}\sum_{k\in K}(w + c_l)x^k_{ll'} \\ &+ \sum_{k\in K}\sum_{l\in V}\sum_{l'\in V}\delta x^k_{ll'} d_{ll'} v^2 \\ &+ \sum_{j\in V_2} d_{jb}(\lceil\frac{(\sum_{i\in V_1} q_i y_{ij})}{h}\rceil(\gamma_{jb} + \delta v^2) \\ &+ \gamma_{jb}\sum_{i\in V_1} q_i y_{ij})\end{aligned} \tag{3}$$

s.t.

$$y_{ij} - y_{ij} z_j = 0, i \in V_1, j \in V_2 \tag{4}$$

$$\sum_{j\in V_2} y_{ij} = 1, i \in V_1 \tag{5}$$

$$\sum_{l\in V}\sum_{k\in K} x^k_{il} = 1, i \in V_1 \tag{6}$$

$$\sum_{j'\in V_2}\sum_{k\in K} x^k_{jj'} = 0, j \in V_2 \tag{7}$$

$$\sum_{l'\in V} x^k_{ll'} - \sum_{l'\in V} x^k_{l'l} = 0, l \in V, k \in K \tag{8}$$

$$\sum_{i\in V_1}\sum_{j\in V_2} x^k_{ij} = 1, k \in K \tag{9}$$

$$x^k_{li}(s_l + d_{li}/v - s_i) = 0, l \in V, i \in V_1, k \in K \tag{10}$$

$$s_j = 0, j \in V_2 \tag{11}$$

$$x^k_{li}(c_l + q_i - c_i) = 0, l \in V, i \in V_1, k \in K \tag{12}$$

$$c_j = 0, j \in V_2 \tag{13}$$

$$(\sum_{i\in V_1} q_i y_{ij}) - a_j z_j \le 0, j \in V_2 \tag{14}$$

$$\sum_{i\in V_1}\sum_{l\in V} q_i x^k_{il} \le h, k \in K \tag{15}$$

$$z_j \in \{0, 1\}, j \in V_2 \tag{16}$$

$$y_{ij} \in \{0, 1\}, i \in V_1, j \in V_2 \tag{17}$$

$$x^k_{ll'} \in \{0, 1\}, l \in V, l' \in V, k \in K \tag{18}$$

Compared with the classical LRP [3], the main feature of our model is that we use three conflicting objectives to describe the management goals of biomass waste collection. The first objective in our model is the two-echelon version of the classical LRP's objective. The second and third objectives are inspired by two aspects: (i) The pollution. It is difficult to measure how much pollutant is produced, but we have the basic knowledge that the pollution is positively related to the duration and the amount of biomass at the customer nodes [18]. Therefore, we use the product of them to represent the pollution. This objective is similar to the objective of latency LRP [19]. (ii) The emission. Some pioneer research has pointed out that the fuel consumption is also related to the load of the vehicle [15]. A detailed model to measure the engine-out emission is presented by literature [14]. Based on it, we build our third objective function.

A number of studies have begun to design multi-objective optimization models for eco-friendly LRPs. The cost objective function in classical LRP is always involved in these studies. Additional objectives are investigated, such as the distance between depots and customers [20], risk of hazardous material exposure [21], [22], customer satisfaction [21] and fuel consumption [23], [24]. Some of these objectives are similar to those of our MOLRP. However, none of the model covers the whole management goals as discussed in Section I. Moreover, these researches focus on the classic delivery task, while our model studies the collection activity. This means that, in our model, the load of a vehicle increases as it visit more customers. Then, trade-off decisions should be made to give priority to either customers with low stock (good for reducing emission) or customers with high stock (good for reducing pollution). Adding to the confliction with cost-reducing pursuit, our model will generate comprehensive trade-off solutions for decision makers.

B. Model Analysis

The proposed MOLRP for biomass waste collection contains three kinds of variables, i.e., $\mathbf{z}$ for the location-related variable, $\mathbf{y}$ for the customer allocation-related variable, and $\mathbf{x}$ for the routing-related variable. The description of the MOLRP model can be simplified as:

$$\begin{aligned} &\min \mathbf{F}(\mathbf{z},\mathbf{y},\mathbf{x}) \\ &\text{s.t. } (\mathbf{z},\mathbf{y},\mathbf{x}) \in \Omega, \end{aligned} \tag{19}$$

where Ω is the feasible region of MOLRP. The MOLRP degenerates into a multi-objective multi-depot VRP [25] when $\mathbf{z}$ is given:

$$\begin{aligned} &\min \mathbf{F}(\mathbf{y},\mathbf{x} \mid \mathbf{z}=\mathbf{z}^{'} \in \Omega^{z}) \\ &\text{s.t. } (\mathbf{z}^{'},\mathbf{y},\mathbf{x}) \in \Omega^{'} \subseteq \Omega, \end{aligned} \tag{20}$$

where Ω^z is the feasible region of location-related constraints. Furthermore, if $\mathbf{y}$ is fixed, it will be decomposed into several independent multi-objective VRPs [26]:

$$\begin{aligned} &\min \mathbf{F}(\mathbf{x} \mid \mathbf{z}=\mathbf{z}^{'} \in \Omega^{z}, \mathbf{y}=\mathbf{y}^{'} \in \Omega^{y}) \\ &\text{s.t. } (\mathbf{z}^{'},\mathbf{y}^{'},\mathbf{x}) \in \Omega^{''} \subseteq \Omega^{'}, \end{aligned} \tag{21}$$

where Ω^y is the feasible region of $\mathbf{y}$. If we define Ω^x as the feasible region of $\mathbf{x}$, we will see the relationship between the decision spaces:

$$\Omega^{''} \subseteq \Omega^{'} \subseteq \Omega \subseteq (\Omega^{z} \times \Omega^{y} \times \Omega^{x}). \tag{22}$$

Since the vehicle routing problem is NP-hard [27], it will be a challenging task to solve the more complex MOLRP.

Due to the hierarchical structure of MOLRP, it is naturally to attempt an ordered method to solve it. A common way is to group the customers by distance-based clustering algorithms to obtain $\mathbf{z}^{'} \in \Omega^z$ and $\mathbf{y}^{'} \in \Omega^y$ at strategic level, where Ω^z and Ω^y represent the feasible regions, and then solve the rest VRPs at tactical level to find [28]:

$$\mathbf{x}^{*} = \arg\min_{\mathbf{x}} \mathbf{F}(\mathbf{x} \mid \mathbf{z}=\mathbf{z}^{'} \in \Omega^{z}, \mathbf{y}=\mathbf{y}^{'} \in \Omega^{y}). \tag{23}$$

However, it is reported that the sequential method is likely to result in suboptimal solutions [29], because the optimal location decision is highly related to the routing decisions and thus cannot be made in a once-for-all way. There is no evidence that the $\mathbf{z}^{'}$ and $\mathbf{y}^{'}$ by any clustering algorithm would be the $\mathbf{z}^*$ and $\mathbf{y}^*$ for the entire LRP, because $(\mathbf{z}^*,\mathbf{y}^*,\mathbf{x}^*)$ may lie in $\Omega \setminus \Omega^{''}$. Not to mention that the multi-objective nature makes it more likely to hold diverse location decisions. Therefore, it is also important to explore the location-related decision space while trying to decompose the problem.

C. Pitfalls of Conventional Solvers on MOLRPs

There are many approaches for solving LRP-related problems. They can be mainly grouped into three categories: exact algorithms, integrated methods, and evolutionary algorithms.

Exact methods, such as column generation [30], branch and price [31], have proved their success in single-objective LRPs. However, these methods are not able to track multiple non-dominant solutions at the same time. Some researchers have attempted to adapt exact methods to MOLRP using the augmented ϵ-constraint method [32], [33]. This method takes one of the objectives as the main objective, and put the others in the constraints to convert the multi-objective optimization problem into a single-objective optimization problem. The limitation of this method is that it is difficult to choose the perfect ϵ vector.

For integrated methods, they usually solve the MOLRP by two steps. First, they obtain a location decision by some one-off techniques. The most widely-used one is the clustering algorithm. There are other heuristic methods designed for the first step. For example, literature [34] sets the lower bound and upper bound of the number of depots to be opened, and then try all possible combinations of the opened depots as the location decision. Then, in the second step, given a fixed location plan, the problem degenerates into a multi-depot VRP, which can be solved by evolutionary algorithms, such as GA [35], ACO [9], [36], tabu serach [37], particle swarm optimization [20], and so on. The integrated method divides the MOLRP into two separated problems and try to solve them independently. However, although in the first step they can get a promising location solution, the strategic level problem is not well solved because they have not received any feedback of the second step. And premature location decisions can impact the diversity of the solutions.

Many evolutionary algorithms are developed to solve LRP-related problems directly. GA and ACO are popular ones that are proved to exhibit good performances and are widely used in real-world applications [38]–[45]. However, when it comes to the field of MOLRP, the multi-objective versions of GA and ACO are likely to hold pitfalls if no specialized modification is made. The major limitation of these methods is that they operate by making use of the information of other good solutions, however, it is likely to confuse information provided by solutions with different structures (e.g., different location decisions, different assignments of the customers), especially when multiple location decisions are able to form non-dominant solutions. Hence, deposition strategies on the decision space should be considered to make them valid for MOLRPs. More discussion on the pitfalls of GA and ACO can be found in the **Supplementary Material**.

III. Multi-Population-based Genetic Algorithm

A. Framework of MPGA

We propose a new version of GA to fit in with our MOLRP, namely Multi-Population-based Genetic Algorithm (MPGA). The framework of our MPGA is shown in **Algorithm 1**. We first use our proposed initialization method to make sure that all the initial solutions are feasible. Then, we divide the population according to the location decision $\mathbf{z}$, so that solutions of a subpopulation share the same location plan. Therefore, for each subpopulation, we need to solve a multi-objective multi-depot VRP which is less complex than the MOLRP. Crossover and mutation are only operated within the same subpopulation. Note that in this step, a new solution from a subpopulation has a chance to get a different location decision, which means that it will be assigned to another subpopulation or create a new subpopulation. Afterwards, we gather all subpopulations for environmental selection. All solutions compete together so that subpopulations with unpromising location decisions will gradually be eliminated, and then we can focus on a reduced decision space. Since the main purpose of our work is to design a specified scheme to be adapted for our MOLRP, we directly use the selection operator of NSGA-II [46] as a baseline.

Algorithm 1 Framework of MPGA

$Population \leftarrow$ initialization
while termination condition is not met **do**
  $Subpopulations \leftarrow \text{partition}(Population)$
  $Offspring \leftarrow \emptyset$
  for each $Subpopulation$ **do**
    $Suboffspring \leftarrow \text{crossover}(Subpopulation)$
    $Suboffspring \leftarrow \text{mutation}(Suboffspring)$
    $Offspring \leftarrow Offspring \cup Suboffspring$
  end for
  $Population \leftarrow \text{selection}(Population \cup Offspring)$
end while

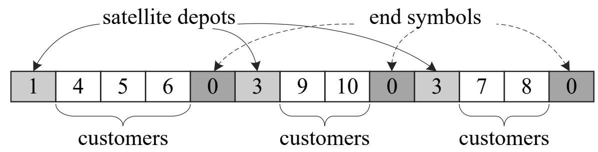

Fig. 2. The encoding method.

Algorithm 2 Initialization

$Population \leftarrow \emptyset$
while $|Population| < popSize$ **do**
  while $\sum_j a_j z_j < \sum_i q_i, i \in V_1, j \in V_2$ **do**
    $\mathbf{z} \leftarrow$ preInitializeZ
  end while
  $mem_{ij} \leftarrow \text{calcMem}(\mathbf{z}, d_{ij}), i \in V_1, j \in V_3$
  $maxMem_i \leftarrow \max_j\{mem_{ij}\}, i \in V_1, j \in V_3$
  $y_{ij} \leftarrow 0, i \in V_1, j \in V_3$
  while $\text{any}(\sum_j y_{ij} = 0), i \in V_1, j \in V_3$ **do**
    if $\text{any}(\sum_j mem_{ij} = 0), i \in V_1, j \in V_3$ **then**
      $\mathbf{z} \leftarrow \text{addSatelliteDepot}(\mathbf{z})$
      $mem_{ij} \leftarrow \text{calcMem}(\mathbf{z}, d_{ij}), i \in V_1, j \in V_3$
      $y_{ij} \leftarrow 0, i \in V_1, j \in V_3$
      continue
    end if
    $i^{'} \leftarrow \text{rouletteSelection}(maxMem_i)$
    $j^{'} \leftarrow \arg\max_j\{mem_{i'j}\}$
    if $load^{depot}_{j'} + q_{i'} \leq a_{j'}$ **then**
      $y_{i'j'} \leftarrow 1$
      $depotLoad_{j'} \leftarrow load^{depot}_{j'} + q_{i'}$
      $maxMem_{i'} \leftarrow 0$
    else
      $mem_{i'j'} \leftarrow 0$
      $maxMem_{i'} \leftarrow \max_j\{mem_{i'j}\}, j \in V_3$
    end if
  end while
  $\mathbf{x} \leftarrow \text{initializeX}(\mathbf{z}, \mathbf{y})$
  $Individual \leftarrow \text{encode}(\mathbf{z}, \mathbf{y}, \mathbf{x})$
  $Population \leftarrow Population \cup Individual$
end while

B. Initialization

We encode the variables in a chromosome in a way shown in Fig. 2. In it, we illustrate the encoding of the location-routing example in Fig. 1. The chromosome is constituted of several sub-routes. Each sub-route begins with a satellite depot, which is numbered by $1, \ldots, |V_2|$. Customer nodes, numbered by $|V_2|+1, \ldots, |V|$, follow and are sorted in the visiting sequence. Item 0 means the end of the sub-route, that is, the vehicle has finished its service and returns to the satellite depot where it sets off. The satellite depot indexes that do not appear in the chromosome indicate these satellite depots will not be opened. Therefore, all the information of solution $(\mathbf{z}, \mathbf{y}, \mathbf{x})$ can be represented by this chromosome. And if we ensure that all the customer nodes are included and only appear once, we will satisfy all the constraints except for capacity constraints (14) and (15).

Our initialization procedure is presented in **Algorithm 2**. We initialize the individuals one by one. To begin with, we randomly pick some satellite depots to be opened, under the condition that the total capacity of the opened satellite depots must be not less than the total stock of customers. Then we calculate the membership of customers to the opened satellite depots according to

$$mem_{ij} = \frac{1}{\sum_{j' \in V_3}(\frac{d_{ij}}{d_{ij'}})^2}, i \in V_1, j \in V_3, \tag{24}$$

and record their maximum membership $maxMem_i$. According to which, we use the roulette selection to pick a customer and assign it to its nearest satellite depot if depot capacity constraint holds. And if not, we replace the $maxMem_i$ with its second-largest membership value and start another round of roulette selection, until all customers are assigned. This allows the customer with a large $maxMem_i$ to have a better chance to be assigned first to its ideal depot by distance, since the distance is universally important for every objective. During

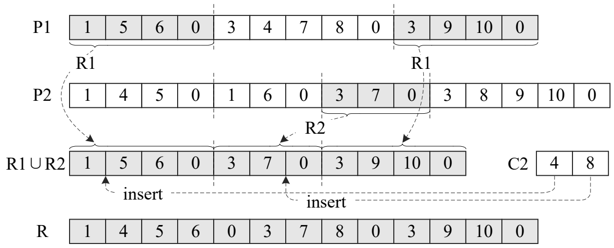

Fig. 3. Illustration of the crossover operation.

Algorithm 3 Route-based crossover

$matingPool \leftarrow$ tournamentSelection($Subpopulation$)
for each pair of $\{P_1, P_2\}$ in $matingPool$ **do**
  $R_1 \leftarrow$ selectSubRoutes(P_1)
  $(C_2, R_2) \leftarrow$ knockOffSubRoutes(P_2, R_1)
  $R \leftarrow R_1 \cup R_2$
  for $i \in C_2$ **do**
    $D^{avail} \leftarrow \{j \mid load_j^{depot} + q_i \leq a_j\}, j \in V_3$
    $S^{avail} \leftarrow \{k \mid load_k^{vehicle} + q_i \leq h\}, k \in K$
    if $D^{avail} = \emptyset$ **then**
      $R \leftarrow$ addDepot(R)
      continue
    else if $S^{avail} = \emptyset$ **then**
      $R \leftarrow$ addSubRoute(R)
      continue
    end if
    $R \leftarrow$ minAddDisInsert($R, i, D^{avail}, S^{avail}$)
  end for
  $Suboffspring \leftarrow Suboffspring \cup \{R\}$
end for

these steps, it may occur that some customer's stock cannot be covered by any one of the opened satellite depot. Even if we have ensured the total depot capacity is greater than the customer stock, this can still happen because stock cannot be split. In this situation, we will randomly open a new depot to keep the satisfaction of constraint (14). Afterwards, for each depot, we randomly split the assigned customers by the vehicle capacity to satisfy constraint (15). Therefore, we can get a feasible population with diverse location decisions.

C. Route-based Crossover

The procedure of our route-based crossover operator is presented in **Algorithm 3**. First, we create a mating pool by tournament selection according to the fitness, which, to be consistent with NSGA-II, refers to the number of non-dominant front layer and the crowding distance. Then, for a pair of parent solutions P_1 and P_2, we use the sub-routes as the basic units to implement crossover. As shown in Fig. 3, the chromosomes can be divided into many gene parts by the end symbol "0". Each gene part represents a sub-route. We try not to break the sub-route because the random crossover can easily break the capacity constraints of the vehicle. Therefore, we randomly select several sub-routes R_1 from P_1 to offer to the offspring, as shown by those shaded gene parts of P_1 in Fig. 3. Afterwards, the customers "5, 6, 9, 10" in R_1 will be added in the routing plan. Any sub-route in P_2 that contains these repeated customers will be knocked off to avoid conflict. The rest sub-route "3-7-0" will be provided as R_2 if it will not break the depot capacity constraint. Finally, for each unassigned customer $i \in C_2$, we check the capacity constraints to find the available satellite depots D^{avail} and available vehicles S^{avail} to serve it. And we insert i into R between $(l, l^{'})$ where it causes minimum extra distance:

$$(l, l^{'}) = \arg\min_{(l,l')}(d_{li} + d_{il'} - d_{ll'}) \tag{25}$$

$$\text{s.t.} \quad x_{ll'}^k = 1, k \in S^{avail}, l, l^{'} \in V_1 \cup D^{avail} \tag{26}$$

$$i \in C_2. \tag{27}$$

During this process, if there is no available satellite depot or vehicle to cover the stock of the customer in C_2, then we add a new one to R so that the offspring can remain feasible.

D. Mutation

We design three mutation operators for MPGA, namely "insert", "swap" and "reverse". The operations are shown in Fig. 4. For the "insert" operator, we randomly select a customer, and then insert it into a position where the newly added visit causes the minimal extra travel distance. For the "swap" operator, we choose two customers and swap their positions in the chromosome. For the "reverse" operator, we select one sub-route and change the visiting sequence of it. Note that during these operations, the structure of the chromosome is not broken. Therefore, all constraints except for the capacity constraints are not violated. We check if the operation will violate the capacity constraints in advance so that infeasible positions are not considered applying these operations. The detailed descriptions of these mutation operators can be found in the **Supplementary Material**, where we also compare the efficiency of the three operators.

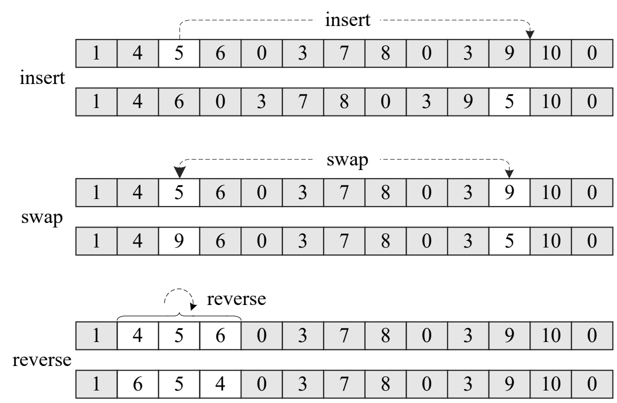

Fig. 4. Illustration of the mutation operations.

IV. Segregated Pheromone Ant Colony Optimization

A. Framework of SPACO

We propose an adapted version of ACO, named Segregated Pheromone ACO (SPACO), for the MOLRP. The main idea

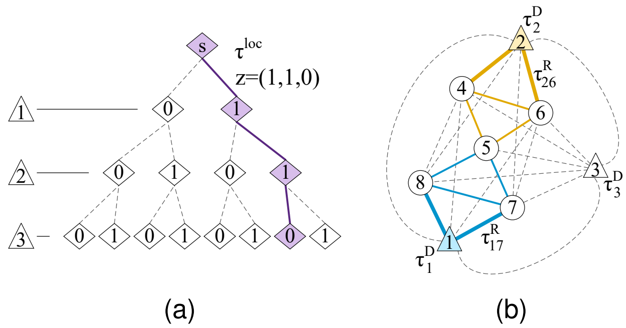

Fig. 5. Different pheromones in SPACO. (a) τ^{loc}. (b) τ^D and τ^R.

is to decompose the MOLRP at both strategic and tactical levels by segregating the pheromone to avoid interference. We achieve this by using three kinds of pheromone τ^{loc}, τ^D and τ^R to guide an ant to complete the location and routing tasks. An illustration of these different pheromones are shown in Fig. 5. Before traveling on the logistics network, an ant should travel on the logical network to get a location decision as in Fig. 5(a). The example here shows that there are three satellite depots $\{1,2,3\}$. The route travels through the logical decision $\mathbf{z} = (1, 1, 0)$, so this ant will ignore the satellite depot 3 afterwards. The pheromone τ^{loc} will be left on the logical route to record the performance. At tactical level, the ant will travel on the real logistics network to form and optimize sub-routes, as shown in Fig. 5(b). The ant will start from a satellite depot, visits some customers and returns to form a sub-route, and then it will travel to other satellite depots to create more sub-routes. During this procedure, two kinds of information should be record: (i) τ^D, the pheromone on the satellite depots, which only works when an ant finishes a sub-route and heads to another satellite depot; (ii) τ^R, the pheromone on the routes. Note that to avoid confusing the information between different sub-routes, we set segregated routing pheromone τ_j^R for each satellite depot j. Then, for each ant at a satellite depot, the problem degenerates into VRPs.

The framework of SPACO is presented in **Algorithm 4**. We use the same encoding and initialization method described in Section III-B to obtain an initial colony. The colony consists of solutions with different $\mathbf{z}$ to determine the initial τ^{loc}. τ^R and τ^D are initialized with the value 1 for all arcs and satellite depot nodes. Then, for each ant, it will be randomly assigned a location strategy π^D and a routing strategy π^R. There are two kinds of location strategies: (i) taking a roulette selection by τ^{loc} to get a fixed location plan $\mathbf{z}$, then it will not visit the other satellite depots; (ii) Being able to visit all satellite depots for a better exploration on location decisions. The routing strategies are presented by the heuristic information

$$\eta_{li} = \frac{1}{d_{li}}, i \in C^u, \tag{28}$$

$$\eta_{li} = q_i , i \in C^u, \tag{29}$$

$$\eta_{li} = \frac{q_i}{d_{li}}, i \in C^u, \tag{30}$$

namely distance-first, stock-first and integrated strategies, respectively. The ant will select the next node to visit according

Algorithm 4 Framework of SPACO

```
(Colony_0, τ^D, τ^R, τ^loc) ← initialization
while termination condition is not met do
    for each ant in Colony_t do
        ant ← ∅
        (π^D, π^R) ← getStrategy(ant, τ^loc)
        C^u = V_1
        while C^u ≠ ∅ do
            p_ij ← calcP(π^D, π^R, τ^D, τ^R)
            ant ← selectRoute(p_ij)
            C^u = C^u \ ant
        end while
        ant ← perturbation(ant)
    end for
    Colony_t ← selection(Colony_t, Colony_{t−1})
    (τ^D, τ^R, τ^loc) ← updatePheromone(Colony_t)
end while
```

to its heuristic information and the pheromones until all customers are served. After that, the perturbation operator will randomly select several sub-routes to reverse the visiting sequences. When all the ants in the colony have finished their routing, we apply the selection operator of NSGA-II [46] to get a non-dominant colony, so that we can update the pheromones accordingly. We present the details of the route selection and pheromone update in the next subsections.

B. Route Selection

The route selection of an ant depends on the situation of the ant. If the latest sequence code does not equal to the end symbol "0", it means that now the ant is still on its routing. Otherwise, it indicates that the ant has just finished its service and returned to the satellite depot. For the former situation, the heuristic information is calculated according to Equations (28)–(30). The probability of visiting the next nodes will be:

$$p_{ll'} = \begin{cases} \frac{(\tau_{ll'}^R)^\alpha(\eta_{ll'})^\beta}{\sum_{l''}(\tau_{ll''}^R)^\alpha(\eta_{ll''})^\beta} & , (l, l') \text{ satisfies (14)(15)} \\ 0 & , \text{others} \end{cases}. \tag{31}$$

Note that $\tau_{ll'}^R$ is the routing pheromone associated to the current depot of the ant. If no available node exists (i.e., $\sum_{l'} p_{ll'} = 0$), the ant will return its current depot and add the end symbol "0" to the sequence code. For the latter situation, the heuristic information of choosing a new depot is calculated by

$$\eta_j = \sum_i mem_{ij}, i \in C^u, j \in V_3. \tag{32}$$

Then, we can get the possibility of which satellite depot to start a new sub-route at

$$p_j = \begin{cases} \frac{(\tau_j^D)^\alpha(\eta_j)^\beta}{\sum_j(\tau_j^R)^\alpha(\eta_j)^\beta} & , j \in V_3' \\ 0 & , \text{others} \end{cases}, \tag{33}$$

where V_3' is the set constrained by the location strategy π^D. When a satellite depot has filled up its capacity, we eliminate this satellite depot from V_3' to avoid creating empty sub-routes with no customers.

C. Pheromone Update

The pheromone update is followed by the selection operator, so that the ants with better performances will leave a large amount of pheromone. All kinds of pheromones are updated by an evaporation of the existing pheromone and an addition of new pheromone:

$$\tau_t = (1-\rho)\tau_{t-1} + \Delta\tau_t, \tau_t \in \{\tau^R, \tau^D, \tau^{loc}\}. \quad (34)$$

We update different pheromones in various ways. For $\Delta\tau^R$, we use Equation (35) if the colony in this generation lies in different layers of non-dominant fronts:

$$\Delta\tau^R_{ll'} = \frac{Q}{N\sum_{l,l'\in S_k} d_{ll'}}, S_k = \{(l,l^{'}) \mid x^k_{l,l'} = 1\}, \quad (35)$$

where N is the front number of the ant, Q is the standard amount of pheromone that an ant carries. If the colony has only one layer, then we use the crowding distance [46] to control the amount of pheromone:

$$\Delta\tau^R_{ll'} = \frac{Q * crowdDis}{\sum_{l,l'\in S} d_{ll'}}, S_k = \{(l,l^{'}) \mid x^k_{l,l'} = 1\}. \quad (36)$$

For $\Delta\tau^D$, as it is the pheromone on the nodes rather than the arcs, we aggregate the pheromones on arc $(i,i^{'})$ as the pheromone on satellite depot j, if i and $i^{'}$ are served by it:

$$\Delta\tau^D_j = \sum_{(i,i')\in S'} \Delta\tau^R_{ii'}, S^{'}_k = \{(i,i^{'}) \mid x^k_{ii'} = 1, y_{ij} = 1\}. \quad (37)$$

For $\Delta\tau^{loc}$, an average of the pheromones on the satellite depots will be given to the nth location decision:

$$\Delta\tau^{loc}_n = \frac{\sum_j \Delta\tau^D_j}{\sum_j z_j}. \quad (38)$$

V. Experimental Study

A. Experiment Settings

We conduct experiments on the performance of our MPGA and SPACO by comparing with other conventional solvers: MCACO [47], MPACO [48], and FR-NSGA-II which is based on NSGA-II [46] with feasible rules [49] as the constraint handling method and applies the ordered crossover [38]. Also, we take the integrated method M-NSGA-II [28] as another comparing algorithm, which first uses a clustering algorithm to get the location decision and then optimize the routing problem by NSGA-II accordingly. The parameters of these algorithms are set as follows: For the ACO-based algorithms (i.e., MCACO, MPACO and SPACO), we set the colony size as 100; the maximum number of iteration is 200; we set $\rho = 0.05$, $\alpha = 2$ and $\beta = 2$; we set Q by the average distance between two nodes. For the GA-based algorithms (i.e., FR-NSGA-II, M-NSGA-II and MPGA), we set the population size as 100, and the maximum number of iteration is 200.

The experiments are carried out on three well-know LRP benchmarks, namely Barreto's instances [50], Prodhon's instances [51], and Tuzun's instances [52]. The Barreto's instance set covers a range of 50 to 150 nodes; The Prodhon's instance set ranges from 20 to 200 nodes; The scale of Tuzun's instance set is within 110 to 220 nodes. Note that these datasets are for one-echelon cost-driven LRPs, therefore we include the main depot at the coordinates $(0,0)$ for every instance, and customize them for our proposed model by setting the additional parameters as follows: We set the satellite depot variable cost $m = 50$, and the unit cost of transportation $e = 1$ according to [37]. We assume the vehicle weight w equals the vehicle capacity h which is given by the instances. We set $v = 70$ as the economic speed of the truck generally falls in $[30, 70]$ [53]. The values of $\gamma_{ll'}$ and δ are calculated by the comprehensive emission model [54]:

$$\gamma_{ll'} = g\sin(\theta_{ll'}) + gC_r\cos(\theta_{ll'}), \quad (39)$$

$$\delta = 0.5C_d A\sigma, \quad (40)$$

where $g = 9.81$ is the gravitational constant; $C_r = 0.01$ is the coefficient of rolling resistance; $\theta_{ll'} = 0^\circ$ is the road angle between $(l,l^{'})$; $C_d = 0.7$ is the coefficient of aerodynamic drag; $A = 5.0$ is the frontal surface area; $\sigma = 1.2$ is the air density.

We illustrate the overall performance of the proposed MPGA and SPACO, and discuss the effectiveness of our MOLRP model in obtaining the trade-off solutions in the following subsections. Detailed experiment results and further investigations can be found in the **Supplementary Material**.

B. Overall Performance

We run every algorithm on the instances for 30 times. For each instance, we obtain the approximate Pareto front by combining all test results. Then we calculate the Inverted Generational Distance (IGD) and Hypervolume (HV) [55] to evaluate their performance, where

$$IGD = \frac{1}{|PF|}\sum_{s^2\in PF}\min_{s^1\in S^a}\left\|s^1 - s^2\right\|, \quad (41)$$

and

$$HV = \lambda_m(\cup_{s\in S^a}[s,r]). \quad (42)$$

In the equations, PF represents the set of solutions in the Pareto front; S^a is the set of solutions obtained by algorithm a; r is the reference point which we use the nadir point of the Pareto front; and λ_m is the m-dimensional Lebesgue measure. These two metrics measure the overall performance on both convergence and diversity. The mean value and standard deviation of IGD and HV values for each individual instance are tabulated in the **Supplementary Material**. Here we display the scores of winning times in the pairwise comparison of every instance set in Fig. 6.

The major observations of the experimental results are detailed as follows. For Barreto's instances, GA-based algorithms (FR-NSGA-II, M-NSGA-II and MPGA) have better performance over the ACO-based ones under both IGD and HV metrics. Overall, MPGA has the best performance, winning 61 out of 70 comparisons under IGD and 63 out of 70 under HV. For Prodhon's instances and Tuzun's instances, SPACO, FR-NSGA-II and MPGA rank the top three positions, but the sequences are different between IGD and HV results. Under IGD, SPACO ranks the first (88 out of 150 for Prodhon's instances and 154 out of 180 for Tuzun's instances). However,

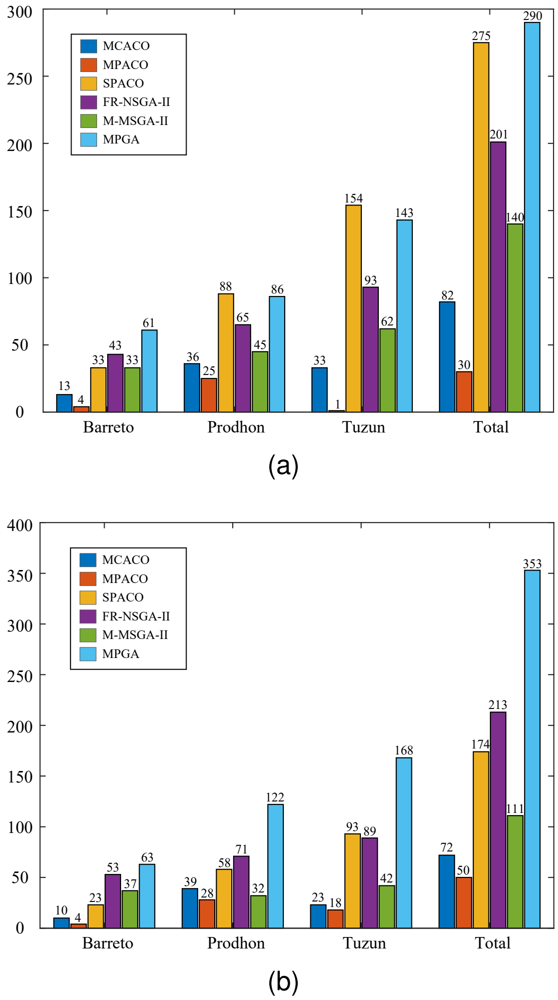

Fig. 6. Winning times in pairwise comparisons on Barreto's, Prodhon's and Tuzun's instances, obtained by the Wilcoxon signed rank test [56] at a 0.05 significant level: (a) Measured by IGD; (b) Measured by HV. More detailed results are given in the **Supplementary Material**.

when it comes to the HV metric, MPGA turns out to be the best (122 out of 150 for Prodhon's instances and 168 out of 180 for Tuzun's instances). The total results show that MPGA ranks the first under both metrics, and SPACO is only comparable with MPGA under IGD. The reasons for the difference ranking under IGD and HV are many, such as the bias towards the emphasis on convergence or diversity, the shape of the Pareto front and the position of the reference point. A further investigation is taken in the next subsection. In total, our SPACO and MPGA rank the top two positions under IGD, and SPACO is close to the second place under HV, demonstrating their overall efficiency on the proposed MOLRP. SPACO and MPGA perform better in their respective kind of evolutionary algorithm. This indicates that our strategies to tailor the ACO and GA to the MOLRP take effect. FR-NSGA-II has good performances on some instances. M-NSGA-II ranks the middle position. MCACO and MPACO fail to obtain desirable results, verifying the pitfalls in solving the MOLRP. Comparing between MCACO and MPACO, MCACO outperforms MPACO on all three instance sets and two metrics. This indicates that, on our MOLRP, using different pheromones independently is better than multiplying them together. However, MCACO segregates the pheromones for different objectives, failing to decompose the problem according to the problem structure, therefore it still has drawbacks when the logistics network is complex.

C. Performance on Obtaining Diverse Location Decisions

For a better understanding of why there are different performances over the instances and metrics, we take an investigation on the Pareto front of them. Some representative instances are shown in Fig. 7. The different colors of the solutions indicate that they have different location decision $\mathbf{z}$. For Barreto10 in Fig. 7(a), we can see that the Pareto front contains solutions of six different location decisions. The location decisions have an overall impact on the distribution of solutions in the objective space: solutions are clustered according to different location decisions. For Prodhon10 in Fig. 7(b), the Pareto front is constituted by almost the solutions of the same location decision. This means that the location decision dominates almost all the others. For Tuzun22 in Fig. 7(c), solutions with multiple diverse location decisions overlap in neighboring regions of the objective space, exhibiting a multi-modal nature. In this case, many alternative location decisions are able to form a well-distributed Pareto front. In summary, the importance of the diversity on location decisions varies from different instances. However, in real-world logistics application, not only the diversity on the objective space, but also abundant choices on the decision space are desired, especially on the location decisions. This is because facility location is about a long-term strategy. Decision makers may have an unquantifiable preference on different location decisions, which is not reflected in the mathematical model. Hence, as a complement of IGD and HV, we need to further evaluate the performance over the diversity of the location decisions.

We propose another metric to evaluate the diversity of location decisions. Let PF be the set of solutions in the Pareto front, S be a solution set. $P(S) = \{S_1, S_2, ..., S_n\}$ is the partition of S, that $\mathbf{z}_i \neq \mathbf{z}_j, \forall(\mathbf{z}_i, \mathbf{y}_i, \mathbf{x}_i) \in S_i, (\mathbf{z}_j, \mathbf{y}_j, \mathbf{x}_j) \in S_j$. Then for the solution set S^a obtained by algorithm a, we calculate

$$D^{loc} = \frac{|P(S^a \cap PF)|}{|P(PF)|}, \tag{43}$$

as the rate of non-dominant location decisions that the algorithm has discovered. We illustrate the mean value of D^{loc} for each instance set in Fig. 8. We can see that MPGA ranks at the first place for all instance sets. SPACO is competitive on Prodhon's instances and Tuzun's instances, but undesirable on Barreto's instances. Compared with the IGD result, it suggests that the strategy of our MPGA is efficient for obtaining diverse non-dominant location decisions. Though our SPACO has improved the diversity compared with conventional ACOs, the node-to-node nature of ACO restricts the exploration to a narrower range of the multi-population method. However, when it comes to the problem where the location decision is not a determining factor, SPACO will show good performance since it is efficient in routing.

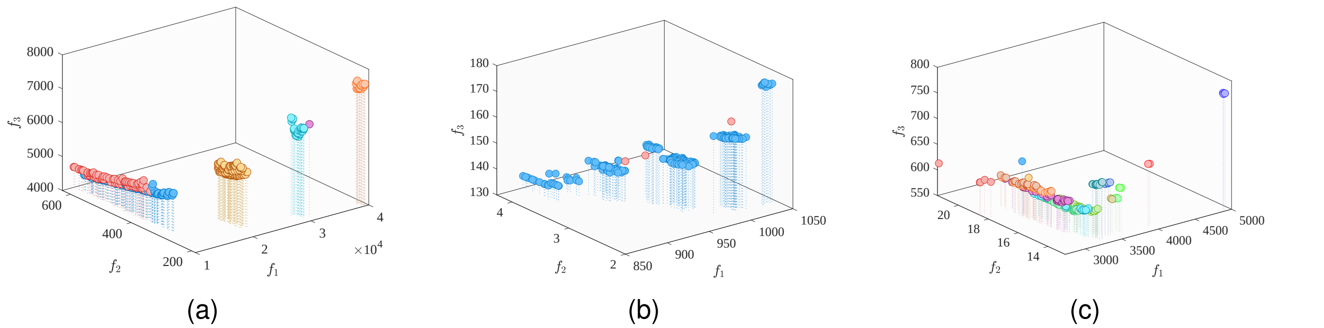

Fig. 7. The Pareto fronts composed of heterogeneous solutions on some example instances. Solutions with different location decision $\mathbf{z}$ are distinguished by different colors. (a) Barreto10. (b) Prodhon10. (c) Tuzun22.

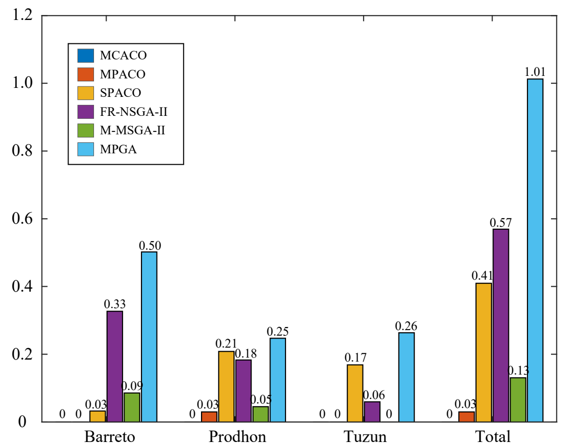

Fig. 8. Diversity measure of the location decisions on Barreto's, Prodhon's and Tuzun's instances.

D. Study on the Effectiveness of the MOLRP Model

To investigate the effectiveness of our MOLRP model in finding trade-off solutions, we compare it with the results obtained from the cost-driven single-objective LRP model. We eliminate the second and third objectives from our MOLRP to establish the Single-Objective LRP (SOLRP). The results are illustrated in Fig. 9. Fig. 9(a) shows the objective space, where the Pareto front is obtained by our MOLRP. We only obtained solution A from the SOLRP. Solutions A, B and C are selected to show the differences of location-routing decisions in Fig. 9(b)-(d).

First, we can see that there exist trade-offs decisions among the three objectives. Second, solutions A and B have the same objective value for f_1 (cost), but they have different values for f_2 and f_3. This is because in the decision level, the vehicles travel the same route, but the visiting sequences can be different (illustrated by sub-route1 and sub-route2 in Fig. 9(b) and Fig. 9(c), respectively). This also indicates that the SOLRP is a multi-modal problem. We can not distinguish solutions A and B in the objective space if only applying the cost objective. Third, solution C provides solution that holds different location decisions. It represents a completely different plan to build the logistics network. Our MOLRP can help to find these heterogeneous solutions for decision makers to choose. We also illustrate this with a small-scale example in the **Supplementary Material**.

VI. Conclusion

This study sets out to develop a model for the LRP in the context of biomass waste collection. Different from standard cost-driven LRPs, we also consider the weighted waiting time and emission affected by the vehicle speed and load. To solve this problem, we analyze the pitfalls of conventional ACO and GA solvers. A common reason is that LRPs are hierarchical by nature. A solution can not get useful information from another one which has a different strategic level decision. Furthermore, our LRP model pursues multiple objectives at the same time. We can not determine fixed decisions level-by-level since this will harm the diversity of solutions. Hence, a good way is to decompose the problem according to its structure, and solve all the sub-problems together. Inspired by this, we design decomposition strategies for ACO and GA respectively to be applicable to our model. Our experiments find that our strategies improve the performance on both ACO and GA. The proposed MPGA is capable of obtaining diverse solutions with different location decisions, while SPACO performs better when the location decision determines less than the routing decision.

By providing an MOLRP model, this work offers a novel extension of the vehicle routing based problems. It can be applied to similar applications elsewhere in the world, such as hazardous material collection and green VRPs. The methods used for this problem highlight the potential usefulness of decomposing specific problems with the framework of ACO and GA. A further study could focus on the extension in a dynamic environment, where the stock of customer nodes changes over time. And more investigations on the decomposition strategies of other evolutionary algorithms would be of great help in solving similar MOLRPs.

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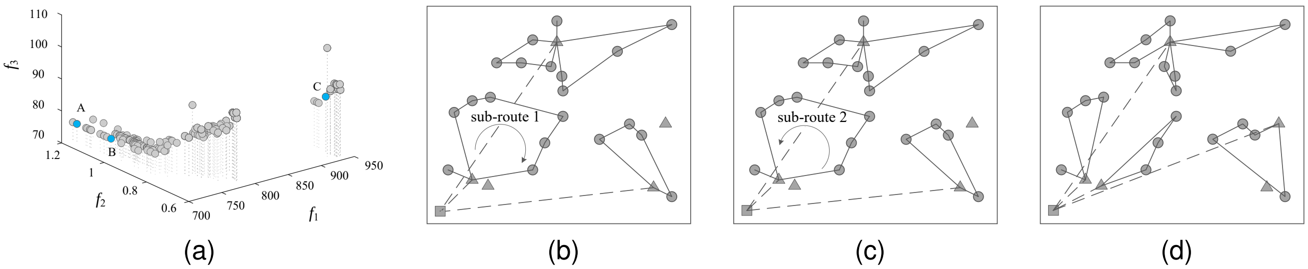

Fig. 9. Comparison between results of SOLRP and MOLRP models. The Pareto front is obtained by the MOLRP model. Three example solutions A, B and C are illustrated in the routing maps. Solution A is obtained by the SOLRP model. (a) The objective space (b) Solution A (c) Solution B (d) Solution C.

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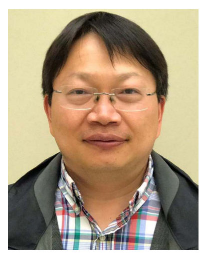

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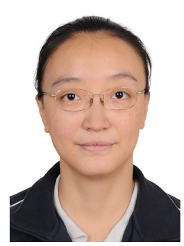

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