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Research Article

Optimal Urban Logistics Facility Location with Consideration of Truck-Related Greenhouse Gas Emissions: A Case Study of Shenzhen City

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The logistics facility location is always involved with great deals of investment. Its construction and operation also bring out a huge amount of the greenhouse gas (GHG) emission due to the consumption of building materials, energy, the running of trucks, and other logistics equipment. Particularly, trucking activities in the urban logistics networks (ULN) are a major source of GHG. This paper aims to formulate an eco-facility location model to minimize both the total cost of ULN construction and operation and the GHG emissions of truck trips. Based on the mathematical relations of GHG emissions rates and several macroscopic factors, which we obtained by multivariate regression analysis on a large set of empirical trucking data in our previous research, the data-driven emissions rates estimation function is acquired. Then, we link the estimation function of each trip purpose by various kinds of logistics facilities through a qualitative analysis. The eco-facility location problem is modeled by integrating the pure facility location model and the GHG emissions function. The problem is first converted to a biobjective mixed-integer program, and the Particle Swarm Optimization algorithm is applied to solve the model. Through experiments with real case, the effectiveness of the models and algorithms is verified. The eco-facility location model for ULN tends to obtain the environment-friendly location decision. Our analytical results also verify the hypothesis that locations of facility do impact the relevant truck-related GHG emissions, especially to transfer transport, as well as inbound and outbound freight.

1. Introduction

The logistics activity in urban areas is responsible for a significant portion of the global greenhouse gas (GHG) emissions [1]. Due to the rapid development of E-commerce, the related GHG emissions share is increasing continuously. Reducing GHG emissions in logistics sector is crucial to sustainable urban development. Since the urban logistics network (ULN) is the backbone for carrying out all the logistics activities and satisfying the logistics demand of the whole city, investigating the emission sources of logistics activity in urban, finding out the relationship of the GHG emissions rate and the corresponding source, and constructing an optimal model considering both economic and environmental factors are necessary to reduce the logistics-related GHG emissions.

On account of the emission source in ULN, first we explore the composition of a typical ULN. Generally, the ULN is involved with nodes and arcs. The node stands for the facility, and the arc refers to the distribution path or flow in each supply-demand pair. Therefore, it is obvious that the GHG emissions in ULN come from the facilities (nodes in ULN) and distribution flows (arcs in ULN), which include

the construction and operation of facilities, the running of trucks, and other freight carriers [2]. Indeed, the construction and operation of the facility bring out a huge amount of GHG emissions due to the consumption of building materials, energy, and so forth. The location of the facility is also involved with great deals of investment and will not be easily relocated after the facility is constructed [3]. For the aspect of truck-related GHG emissions, trucks play a key role in urban freight transport system and ULN [4]. To reduce ULN-related GHG emissions in cities, various strategies may be considered to target to the aforementioned emission sources. With respect to the facility-emission sources, since the relationship between emissions and inside activity of the facility is not hard to estimate, such as the electricity for run the warehouse, the diesel for forklift, or package materials we use in the warehouse, it is obvious that minimizing the number and scale of facilities with satisfying the customer demand as well as improving the energy efficiency can reduce the emissions [5]. On the hand of reducing GHG emissions of trucks, the recent progress is mainly from the operational level [6]. For instance, we have the eco-routing problems and the eco-traffic assignment problem. The former one is to find optimal routes that promise to minimize fuel consumption or GHG emissions [7]. The latter one is to incorporate the GHG emissions into the general traffic assignment models [8–10]. However, due to strict control regulations on truck traffic, the available truck routes in urban areas are often limited once the ULN design is fixed. So, it will be more efficient to optimize the truck routes through the beginning, the design stage of ULN, rather than to optimize the truck routes after the important facility location is fixed *(M. Zhalechian et al., 2016)*. Then, does the location of facility impact the GHG emission of ULN truck flow? What is the interface between "characteristics of location" and truck emissions? The solution of proposed questions may be used to relocate major logistics facilities, which could potentially have far-reaching effects in reducing long-term GHG emissions [11]. However, there is just limited knowledge about this field. Aiming to fill such research gap, we have investigated a large set of empirical truck trajectory data, developed a trip purpose imputation matrix to classify truck-related GHG emissions, and explored how the macroscopic trip would affect overall GHG emissions associated with each type of truck trips *(X. Liu and et al., 2016)*. The mathematical relationships between GHG emissions and various kinds of trip purposes, population density of origin nodes/destination nodes, the Euclidean distance of each trip, and vehicle kerb weight are captured through the multivariate regression analysis. Some managerial insights are drawn from the findings, yet the mathematical representation of GHG emissions has not been applied to optimize the real logistics network in the city.

On the other hand, the facility location problem, as a hot issue in operations research, has been investigated by numerous researchers and practitioners for centuries. In addition, the location of logistics or supply chain facilities is an important composition. With respect to the ECO facility location problem, there are some related literatures about other kinds of facilities, such as manufacturing facility and hydropower location [12]. For the logistics facility location problem considering carbon emissions, Tang et al. investigated the logistics facility location model with consideration of economic costs, services, and CO_2 emissions simultaneously [13]. Wang et al. formulated a multiobjective model for the supply chain design problem, in which the facility location decision is with environmental concerns [14]. Elhedhli and Merrick modelled the relationship between emissions and vehicle weight and merged the emissions into the minimal cost objective by multiplying with the emissions cost [15]. Some of other researchers also focus on traditional network design with multiobjective and environmental aspects [16, 17]. However, the emissions rate is obtained by a macroscopic way. Few of them explore the data-driven emissions function through applying real truck trajectory data or considering the relationship between real truck trip emissions associated with various kinds of facilities. With witness of above analysis, we attempted to propose a hypothesis that reasonable facility location is able to reduce truck-related GHG emissions. First, a group of GHG emissions functions by truck trip is developed through analyzing the regressions results proposed in [18]. Then, we integrated the GHG emissions functions into the logistics network design problem. Similar to the model structure proposed by Wang et al. [14], we constructed a biobjective eco-facility location model, aiming to minimize the total cost of facility location and truck-related GHG emissions simultaneously.

The remainder of this paper is organized as follows. The data-driven emissions rate function, the multiobjective model, and the solution algorithms are addressed in Section 2. In Section 3, we test the models and the algorithms by real-case data. Some managerial insights are drawn from the comparison and analysis of the results in Section 4. The conclusion is given in Section 5.

2. Models and Algorithms

2.1. Classification of Logistics Flow. In our research, since the truck trip purpose is directly linked with diverse kinds of facilities, first we describe the relationship of trip purpose and facility following with the trip purpose classification in previous research [18]. Figure 1 shows a typical logistics network. The trucks are running as a freight carrier on the arcs, linking diverse kinds of facilities or demand nodes together.

The truck trip purpose in a ULN could be classified into 6 groups and 11 types. The trip purposes are strongly related to the properties of origin and destination nodes. Such relationships are described as follows.

Trip Purpose G1. Urban parcel distribution (PD) consists of both personnel parcel and electronic commerce distribution. *Sale distribution* (SD) usually stands for the situation where the seller delivers the goods to final customers. Such trips are related to the third-degree logistics facility and communities (demand nodes).

Trip Purpose G2. Multimodal transfer trip (TT) refers to the goods and cargoes that are transferred from one transport

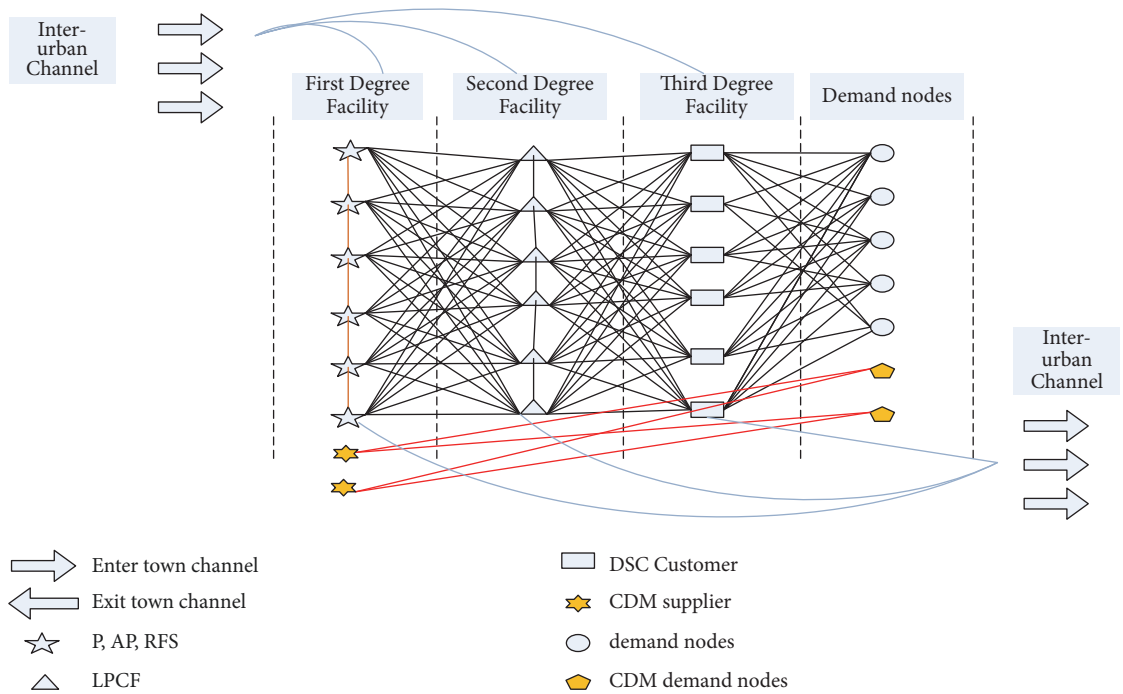


Figure 1: A typical urban logistics network (note: P, AP, and RFS refer to ports, airports, and freight railway stations, resp.; DSC: distribution service center; CDM: chemistry and dangerous materials).

model freight station to another transport model freight station. Such trips are related to first-degree logistics (FDL) facility.

Trip Purpose G3. First-stage distribution (FD) refers to both forward and reverse distributions from FDL nodes to second-degree logistics (SDL) nodes. *The second-stage distribution* (SSD) stands for both forward and reverse distributions from SDL nodes to third-level logistics nodes. In particular, the distribution flow is from the first-level logistics nodes to third level sometimes, which is represented as *direct distribution* (DD). Wholesale distribution (WD) represents the supplier delivering goods to supermarket/other retailers. Such trips are related to trips among first-, second-, and third-degree logistics facilities.

Trip Purpose G4. To meet the economic and social demand, the chemistry and dangerous materials transport in city are inevitable, which is represented as *CDMT*. Such trips are related to CDM supplier and demand nodes.

Trip Purpose G5. In urban logistics, it is common to see the cargo flow from outside the urban boundaries and exit the urban boundaries. We utilize *inbound freight* (IF) and *outbound freight* (OF) to describe the two scenarios, respectively. Such trips are related to interurban corridors.

Trip Purpose G6. RL refers to the residual reverse logistics flow that has not been defined above. Such trips are related to reverse logistics distribution centers and communities (demand nodes).

Then we formulate the eco-facility location model by integrating the pure facility location model and truck trip GHG emissions function.

2.2. Notations. The notations to be used are listed as follows:

Regression Variables

y^{G_1}: GHG emissions rate for single trip by trip purpose PD and SD

y^{G_2}: GHG emissions rate for single trip by trip purpose TT

y^{G_3}: GHG emissions rate for single trip by trip purpose FD, SSD, DD, and WD

y^{G_4}: GHG emissions rate for single trip by trip purpose CDMT

y^{G_5}: GHG emissions rate for single trip by trip purpose IF and OF

y^{G_6}: GHG emissions rate for single trip by trip purpose RL

$X1$: the population density of trip origin node

$X2$: the population density of trip destination node

$X3$: Vehicle kerb weight of trucks

$X4$: Euclidean distance between OD nodes of truck trips

Table 1: Estimated regression analysis output.

Coefficients		(Intercept)	$X1$	$X2$	$X3$	$X4$	Adjusted R-squared
y^{G_1}	Step regression	−1.4023	0.1806*	-	0.8901*	-	0.8063
y^{G_2}	Step regression	14.2980*	1.7167*	-	-	0.4066*	0.8158
y^{G_3}	Step regression	−0.9314	-	-	0.6277*	0.4312*	0.9183
y^{G_4}	Step regression	−12.3164	0.6852*	-	0.5352*	0.6606*	0.9059
y^{G_5}	Step regression	−1.99116*	-	0.04755*	0.22431*	0.50374*	0.8933
y^{G_6}	Step regression	−0.71754	-	−0.05258*	0.12779*	0.44311*	0.8799

Parameters

$b_i, b_j, b_k, b_l, b_{l'}, b_h$: operation costs for each facility, Yuan/kg

$\overline{w}_1, \overline{w}_2, \overline{w}_3, \overline{w}_4, \overline{w}_5, \overline{w}_6$: average trip load of trip purpose $G_1, G_2, G_3, G_4, G_5, G_6$, respectively, ton

D_m, D_m^r: weekly demand of customers and weekly reverse logistics demand of customers, respectively, kg

D_h: weekly demand of CDM demand nodes, kg

$O_i, O_j, O_k, O_l, O_{l'}, O_h$: designed capacity of each facility, kg

$N_i, N_j, N_k, N_l, N_{l'}, N_h$: number of facilities

$d_{ij}, d_{ik}, d_{il}, d_{ji'}, d_{ki'}, d_{li'}$: Euclidean distance between OD pairs $ij, ik, il, ji', ki', li'$, respectively, km

d_{jk}, d_{kl}, d_{lm}: Euclidean distance between OD pairs jk, kl, lm, respectively, km

$d_{hh'}, d_{ml'}$: Euclidean distance between OD pairs hh', ml', respectively, km

Decision Variables

$q_{ij}\ q_{ik}\ q_{il}$: quantity of delivery flow from ET to FLF and SLF and DCs, respectively, kg

$q_{li'}\ q_{ji'}\ q_{ki'}$: quantity of delivery flow from FLF, SLF, and DCs to EXT, respectively, kg

q_{jk}, q_{kl}, q_{lm}: quantity of delivery flow from FLF to SLF, from SLF to DCs, and from DCs to customers, respectively, kg

$q_{jj'}, q_{kk'}$: quantity of transfer delivery flow between FLF and SLF, respectively, kg

$q_{hh'}$: quantity of delivery flow from CDM supplier to CDM demand, respectively, kg

$q_{ml'}$: quantity of delivery flow from customers to reverse logistics service facility, kg

$z_i, z_j, z_k, z_l, z_h, z_{l'}$: =1, when facility is located at potential location nodes; =0 otherwise

2.3. Regression Result and Data-Driven Emission Functions. The objective of this research is to optimize the facility location scheme for minimizing the total costs and GHG emissions of urban logistics activities simultaneously. The classical model for ULN facility location only considers the construction costs and initial distribution costs. In this research, we link the GHG emission and facility location factors by historical data analysis. The regression result [18] shown in Table 1 can be employed and adapted as the data-driven functions.

Then, the emission function of each trip purpose is as follows:

$$\begin{aligned}
y^{G_1} &= 0.1806x_1(l) + 0.8901x_3(l),\\
y^{G_2} &= 14.2980 + 1.7167x_1(j) + 0.4066x_4(j)\\
y^{G_3} &= -0.9314 + 0.6277x_3(k) + 0.4312x_4(k)\\
y^{G_4} &= -12.3164 + 0.6852x_1(h) + 0.5352x_3(h)\\
&\quad + 0.6606x_4(h)\\
y^{G_5} &= -1.99116 + 0.04755x_2(i', j) + 0.22431x_3(i', j)\\
&\quad + 0.50374x_4(i', j)\\
y^{G_6} &= -0.71754 - 0.05258x_2(l') + 0.12779x_3(l')\\
&\quad + 0.44311x_4(l'),
\end{aligned} \tag{1}$$

where $i, i' \in I, I = 0, 1, \ldots, i$, is the set of interurban channels, $j \in J$, $j = 0, 1, \ldots, j$, is the set of FLF nodes, $k \in K$, $K = 0, 1, \ldots, k$, is the set of SLF nodes, $l \in L$, $L = 0, 1, \ldots, l$, is the set of distribution centers, $h \in H$, $H = 0, 1, \ldots, h$, is the set of CDM supplier nodes, and $l' \in L'$, $L' = 0, 1, \ldots, l'$, is the set of reverse logistics distributions. $x_1(l)$, $x_1(j)$, and $x_1(h)$ are the population densities of nodes l, j, and h when such nodes are the originate nodes, respectively. $x_2(i', j)$, $x_2(l')$, and $x_3(l)$ are the population densities of nodes when they are destination nodes, respectively. $x_3(k)$, $x_3(i', j)$, and $x_3(l')$ are the vehicle kerb weights of trucks of trips, respectively. $x_4(j)$, $x_4(h)$, $x_4(i', j)$, and $x_4(l')$ are the Euclidean distances of trips, respectively.

2.4. Model Formulation. Based on the data-driven emission functions, this section integrates the pure facility location model with the emission functions.

We formulate the eco-facility location problem as a multiobjective model. The first objective is to minimize the total cost of facility location and the primary distribution plan. The second objective is to minimize the total emissions of the urban logistics network.

The objective function is composed of delivery costs, facility construction costs, and the total facilities operation costs.

First Objective

$$\begin{aligned}
\text{minimize } f(a,b,q,c,z) = {} & \sum_{i\in I, j\in J, k\in K, l\in L} \left(q_{ij}a_{ij} + q_{ik}a_{ik} + q_{il}a_{il}\right) + \sum_{j,j'\in J, j\neq j'} q_{jj'}a_{jj'} + \sum_{j\in J, k\in K} q_{jk}a_{jk} \\
& + \sum_{k,k'\in K, k\neq k'} q_{kk'}a_{kk'} + \sum_{k\in K, l\in L} q_{kl}a_{kl} + \sum_{l\in L, m\in M} q_{lm}a_{lm} \\
& + \sum_{m\in M, l'\in L'} q_{ml'}a_{ml'} + \sum_{h\in H, h'\in H'} q_{hh'}a_{hh'} \\
& + \sum_{i'\in I', j\in J, k\in K, l\in L, l'\in L'} \left(q_{ji'}a_{ji'} + q_{ki'}a_{ki'} + q_{li'}a_{li'} + q_{l'i'}a_{l'i'}\right) + \sum_{i\in I} c_i z_i + \sum_{i'\in I'} c_{i'} z_{i'} + \sum_{j\in J} c_j z_j + \sum_{k\in K} c_k z_k \\
& + \sum_{l\in L} c_l z_l + \sum_{l'\in L'} c_{l'} z_{l'} + \sum_{h\in H} c_h z_h + \sum_{j\in J, i'\in I', k\in K} \left(q_{ji'} + q_{jj'} + q_{jk}\right) b_j + \sum_{k\in K, i'\in I', l\in L} \left(q_{ki'} + q_{kl}\right) b_k \\
& + \sum_{i'\in I', l\in L, m\in M} \left(q_{li'} + q_{lm}\right) b_l + \sum_{m\in M, l'\in L'} q_{ml'} b_{l'} + \sum_{h\in H, h'\in H'} q_{hh'} b_h
\end{aligned} \tag{2}$$

The second objective is to minimize the total GHG emissions. However, the estimation functions can only represent the GHG emissions of each single trip. We therefore introduce trip_{G_1}, trip_{G_2}, trip_{G_3}, trip_{G_4}, trip_{G_5}, and trip_{G_6} to stand for number of trips of each trip purpose, respectively. Then the relationship between trip count and flow quantity can be explained as follows:

$$\begin{aligned}
\text{trip}_{G_1} &= q_{lm} \cdot \frac{1}{w_1}, \\
\text{trip}_{G_2} &= q_{jj'} \cdot \frac{1}{w_2}, \\
\text{trip}_{G_3} &= \left(q_{jk} + q_{kl} + q_{kk'} + q_{jk} + q_{jj'}\right) \cdot \frac{1}{w_3}, \\
\text{trip}_{G_4} &= q_{hh'} \cdot \frac{1}{w_4}, \\
\text{trip}_{G_5} &= \left(q_{ij} + q_{ik} + q_{il} + q_{ji'} + q_{ki'} + q_{li'}\right) \cdot \frac{1}{w_5}, \\
\text{trip}_{G_6} &= q_{ml'} \cdot \frac{1}{w_6}.
\end{aligned} \tag{3}$$

Let $x_4(j) = d_{jj'}$, $x_4(k) = (d_{jk}, d_{kk'}, d_{kl})$, $x_4(l) = d_{lm}$, $x_4(l') = d_{ml'}$, $x_4(h) = d_{hh'}$ $x_4(i) = (d_{ij}, d_{ik}, d_{il})$, and $x_4(i') = (d_{ji'}, d_{ki'}, d_{li'})$.

The second objective could be described as follows.

Second Objective

$$\begin{aligned}
\text{minimize} \sum y(G_n) \times \text{trip}_{G_n} = {} & \sum_{l\in L, m\in M} \left[0.1806x_1(l) + 0.8901x_3(l)\right] \text{trip}_{G_1} + \sum_{j,j'\in J, j\neq j'} \left[14.2980 + 1.7167x_1(j) + 0.4066x_4(j)\right] \text{trip}_{G_2} \\
& + \sum_{j\in J, k\in K, l\in L, k\neq k'} \left[-0.9314 + 0.6277x_3(k,l) + 0.4312x_4(k,l)\right] \text{trip}_{G_3} + \sum_{h\in H, h'\in H'} \left[-12.3164 + 0.6852x_1(h) + 0.5352x_3(h) + 0.6606x_4(h)\right] \\
& \cdot \text{trip}_{G_4} + \sum_{i,i'\in I, j\in J, k\in K, l\in L} \left[-1.99116 + 0.04755x_2(i',j) + 0.22431x_3(i',j) + 0.50374x_4(i',j)\right] \text{trip}_{G_5} + \sum_{m\in M, l'\in L'} \left[-0.71754 - 0.05258x_2(l') + 0.12779x_3(l') + 0.44311x_4(l')\right] \text{trip}_{G_6} = \frac{1}{w_1} \sum_{l\in L, m\in M} \left[0.1806x_1(l) + 0.8901w_1\right] q_{lm} + \frac{1}{w_2} \sum_{j,j'\in J, j\neq j'} \left[14.2980 + 1.7167x_1(j) + 0.4066d_{jj'}\right] q_{jj'} \\
& + \frac{1}{w_3} \left\{ \sum_{j\in J, k\in K} \left[-0.9314 + 0.6277w_3 + 0.4312d_{jk}\right] \cdot q_{jk} + \sum_{k\in K, k\neq k'} \left[-0.9314 + 0.6277w_3 + 0.4312d_{kk'}\right] \cdot q_{kk'} + \sum_{k\in K, l\in L} \left[-0.9314 + 0.6277w_3 + 0.4312d_{kl}\right] \cdot q_{kl} \right\} + \frac{1}{w_4} \sum_{h\in H, h'\in H'} \left[-12.3164 + 0.6852x_1(h) + 0.5352w_4 + 0.6606d_{hh'}\right] q_{hh'}
\end{aligned}$$

$$+\frac{1}{\overline{w}_5}\left\{\sum_{i\in I,j\in J}\left[-1.99116+0.04755x_2(j)\right.\right.$$
$$\left.+0.22431w_5+0.50374d_{ij}\right]q_{ij}+\sum_{i\in I,k\in K}\left[-1.99116\right.$$
$$\left.+0.04755x_2(k)+0.22431w_5+0.50374d_{ik}\right]q_{ik}$$
$$+\sum_{i\in I,l\in L}\left[-1.99116+0.04755x_2(l)+0.22431w_5\right.$$
$$\left.+0.50374d_{il}\right]q_{il}+\sum_{j\in J,i'\in I}\left[-1.99116\right.$$
$$\left.+0.04755x_2(i')+0.22431w_5+0.50374d_{ji'}\right]q_{ji'}$$
$$+\sum_{k\in K,i'\in I}\left[-1.99116+0.04755x_2(i')+0.22431w_5\right.$$
$$\left.+0.50374d_{ki'}\right]q_{ki'}+\sum_{l\in L,i'\in I}\left[-1.99116\right.$$
$$\left.\left.+0.04755x_2(i')+0.22431w_5+0.50374d_{li'}\right]q_{li'}\right\}$$
$$+\frac{1}{\overline{w}_6}\sum_{m\in M,l'\in L'}\left[-0.71754-0.05258x_2(l')\right.$$
$$\left.+0.12779w_6+0.44311d_{ml'}\right]q_{ml'} \tag{4}$$

subject to

$$D_m=\sum_l q_{lm},\quad l\in L,\ m\in M \tag{5}$$

$$D_m^r=\sum_m q_{ml'},\quad l'\in L',\ m\in M \tag{6}$$

$$D_h=\sum_h q_{hh'},\quad h\in \mathrm{H},\ h'\in H' \tag{7}$$

$$\sum_l q_{kl}+q_{il}=\sum_l q_{lm},\quad \forall l,\ l\in L \tag{8}$$

$$\sum_k q_{ik}+q_{jk}+q_{k'k}=\sum_k q_{kl}+q_{ki'}+q_{kk'},\quad \forall k,\ k\in K,\ k\neq k' \tag{9}$$

$$\sum_j q_{jk}+q_{jj'}+q_{ji'}\le O_j+\sum_j q_{ij},\quad \forall j,\ j\in J,\ j\neq j' \tag{10}$$

$$\sum_{i'}\left(q_{li'}+q_{ji'}+q_{ki'}\right)\le O_{i'},\quad \forall i',\ i'\in I \tag{11}$$

$$z_iO_i\ge\sum_{j,k,l}\left(q_{ij}+q_{ik}+q_{il}\right)\quad \forall i,\ i\in I \tag{12}$$

$$z_jO_j\ge\sum_{k,i'}\left(q_{jk}+q_{ji'}+q_{jj'}\right)\quad \forall j;\ j,j'\in J,\ j\neq j' \tag{13}$$

$$z_kO_k\ge\sum_{l,i'}\left(q_{kl}+q_{ki'}+q_{kk'}\right)\quad \forall k;\ k,k'\in I,\ k\neq k' \tag{14}$$

$$z_lO_l\ge\sum_m q_{lm}\quad \forall l,\ l\in L \tag{15}$$

$$z_{l'}O_{l'}\ge\sum_m q_{ml'}\quad \forall l',\ l'\in L' \tag{16}$$

$$z_hO_h\ge\sum_{h'} q_{hh'}\quad \forall h,\ h\in H \tag{17}$$

$$\begin{aligned}&\sum_i z_i\le N_i,\\&\sum_j z_j\le N_j,\\&\sum_k z_k\le N_k,\\&\sum_l z_l\le N_l,\\&\sum_{l'} z_{l'}\le N_{l'},\\&\sum_h z_h\le N_h\end{aligned} \tag{18}$$

$$q_{ij},q_{ik},q_{il},q_{ji'},q_{ki'},q_{li'},q_{kl},q_{lm},q_{jj'},q_{kk'},q_{ml'},q_{hh'}\ge 0 \tag{19}$$

$$\begin{aligned}&z_i=(1,0),\\&z_j=(1,0),\\&z_k=(1,0),\\&z_l=(1,0),\\&z_{l'}=(1,0),\\&z_h=(1,0)\end{aligned} \tag{20}$$

The constraints are defined as follows: (5), (6), and (7) guarantee that all the customer demands, all the reverse logistics demands, and the CDM demands are served; (8)–(11) are the flow equilibrium constraints; (12)–(14) are the relationship between location variables; flow variables are confined by constraints (15)–(17), which also guarantee that the facility designed capacity cannot be exceeded. Equation (18) limits the facilities numbers. Equation (19) is the nonnegative restriction. Equation (20) is the binary restriction.

2.5. Solution Algorithms. The data-driven function-based facility location model is a biobjective mixed-integer programming problem. If we just take objective (4) and constraints (5)–(11) and (19) into account, the model is a pure integer program problem. However, objective (2) and

constraints (12)–(18) and (20) are involved with fixed costs and binary variable, increasing the complexity of the solving approach. For the small-scale ULN problem, we employed the lexicographic optimization based on the multistage simplex algorithm to solve the model. For the large-scale ULN problem, the heuristic algorithm or intelligent algorithms are suitable for solving the problem.

The approaches are as follows.

Step 0. Establish the initial model, including the two objectives: ideal objective and realistic goal.

Ideal Objective. Objectives (2) and (4).

Realistic Goal

$$\begin{gathered} f(a,b,q,c,z)=0 \\ \sum y(\mathrm{G}_n)\times \mathrm{trip}_{G_n}=0 \end{gathered} \tag{21}$$

Step 1. Identify the expected value of each ideal objective function, introduce η_i and ρ_i as the negative deviation variable and the positive deviation variable (resp.) to realistic goals and constraints, i is number of constraints, and $\eta_i, \rho_i \geq 0$ to change the ideal objective function into realistic objective function.

Step 2. According to the goal deviation factors set in Step 1, adding corresponding variables to the realistic objective function and each constraint, we change the model into objective programming.

Step 3. Based on the proper degree of objectives, we apply the lexicographic optimization technique technique to obtain the single objective standard lexicographic function. In the problem, constraints (5)–(9) are hard constraints, and the proper degree is first degree. The proper degree of other constraints is second degree. The single objective lexicographic function is

$$\begin{aligned} \text{lex min } a = \{&(\eta_1+\eta_2+\eta_3+\eta_4+\eta_5+\rho_1+\rho_2+\rho_3 \\ &+\rho_4+\rho_5), \rho_6,\rho_7,\eta_8,\eta_9,\eta_{10},\eta_{11},\eta_{12},\eta_{13},\eta_{14}+\rho_{14},\eta_{15} \\ &+\rho_{15}\} \end{aligned} \tag{22}$$

subject to

$$D_m-\sum_l q_{lm}+\eta_1-\rho_1=0,\quad l\in L,\ m\in M$$

$$D_m^r-\sum_m q_{ml'}+\eta_2-\rho_2=0,\quad l'\in L',\ m\in M$$

$$D_h-\sum_h q_{hh'}+\eta_3-\rho_3=0,\quad h\in H,\ h'\in H'$$

$$\sum_l q_{kl}+q_{il}-\sum_l q_{lm}+\eta_4-\rho_4=0,\quad \forall l,\ l\in L$$

$$\sum_k (q_{ik}+q_{jk}+q_{k'k})-\sum_k (q_{kl}+q_{kl'}+q_{kk'})+\eta_5-\rho_5 = 0,\quad \forall k,\ k\in K,\ k\neq k'$$

$$\sum_j q_{jk}+q_{jj'}+q_{ji'}-O_j-\sum_j q_{ij}+\eta_6-\rho_6=0,\quad \forall j,\ j\in J,\ j\neq j'$$

$$\sum_{i'}(q_{li'}+q_{ji'}+q_{ki'})-O_{i'}+\eta_7-\rho_7=0,\quad \forall i',\ i'\in I$$

$$z_iO_i-\sum_{j,k,l}(q_{ij}+q_{ik}+q_{il})+\eta_8-\rho_8=0,\quad \forall i,\ i\in I$$

$$z_jO_j-\sum_{k,i'}(q_{jk}+q_{ji'}+q_{jj'})+\eta_9-\rho_9=0,\quad \forall j;\ j,j'\in J,\ j\neq j'$$

$$z_kO_k-\sum_{l,i'}(q_{kl}+q_{ki'}+q_{kk'})+\eta_{10}-\rho_{10}=0,\quad \forall k;\ k,k'\in I,\ k\neq k'$$

$$z_lO_l-\sum_m q_{lm}+\eta_{11}-\rho_{11}=0,\quad \forall l,\ l\in L$$

$$z_{l'}O_{l'}-\sum_m q_{ml'}+\eta_{12}-\rho_{12}=0,\quad \forall l',\ l'\in L'$$

$$z_hO_h-\sum_{h'} q_{hh'}+\eta_{13}-\rho_{13}=0,\quad \forall h,\ h\in H$$

$$f(a,b,q,c,z)+\eta_{14}-\rho_{14}=0$$

$$\sum y(G_n)\times \mathrm{trip}_{G_n}+\eta_{15}-\rho_{15}=0$$

$$\sum_i Z_i\leq N_i,$$

$$\sum_j Z_j\leq N_j,$$

$$\sum_k Z_k\leq N_k,$$

$$\sum_l Z_l\leq N_l,$$

$$\sum_{l'} Z_{l'}\leq N_{l'},$$

$$\sum_h Z_h\leq N_h$$

$$q_{ij},q_{ik},q_{il},q_{ji'},q_{ki'},q_{kl},q_{lm},q_{jj'},q_{kk'},q_{ml'},q_{hh'}\geq 0$$

$$z_i=(1,0),$$

$$z_j=(1,0),$$

$$z_k=(1,0),$$

$$z_l=(1,0),$$

$$z_{l'}=(1,0),$$

$$z_h=(1,0)$$

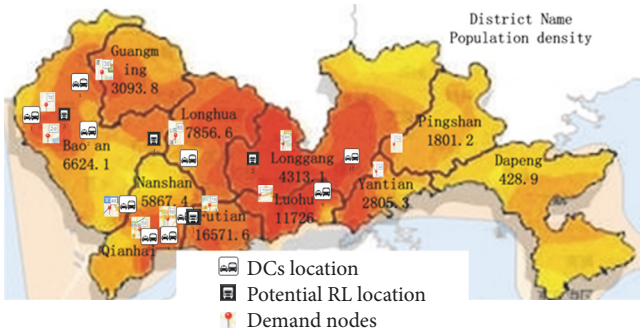


Figure 2: Distribution of DCs, RL facilities, demand nodes, and population density by district of Shenzhen city.

$$\eta_1, \eta_2, \eta_3, \eta_4, \eta_5, \rho_1, \rho_2, \rho_3, \rho_4, \rho_5, \rho_6, \rho_7, \eta_8, \eta_9, \eta_{10}, \eta_{11}, \eta_{12}, \eta_{13}, \eta_{14}, \rho_{14}, \eta_{15}, \rho_{15} \geq 0 \tag{23}$$

Step 4. The above model is also a mixed-integer programming problem. Since the problem scale is increased by adding variables, we employ the Particle Swarm Optimization algorithm and apply the PSO toolbox developed by George Evers [19] with Matlab R2015b to solve the model. PSO algorithm, first proposed by Eberhart and Kennedy [20], an optimal algorithm based on the social behavior of bird flocking, has recently proven its high effectiveness and robustness in solving multiobjective problems.

3. Numerical Experiments and Analysis

In this section, we conduct the numerical experiments for the aforementioned model and algorithms. The data we applied are real data collected in Shenzhen city in the year 2011, contemporaneous with the truck trajectory data.

3.1. Numerical Experiments Description. The logistics network of Shenzhen comprises fourth-echelon network from the first-degree logistics centers to final customers. The locations of the first-degree logistics facilities are airports, the main railway station, the north railway station, the Qianhai ports, and Yantian ports, which are numbered from 1 to 5. Similarly, the logistics parks (LP) are Jinpeng LP, Yantian ports LP, Qianhai Ports LP, Songgang LP, Airport LP, Longhua LP, and Pinghu LP, with corresponding numbers from 1 to 7 as the second-degree logistics facilities. The third-degree facilities mainly include distribution service centers (DSCs). In our experiments, we group the 460 DCs into 10 accumulation areas to simplify the network. The commercial and residential areas are preprocessed into 12 zones in accordance with city main center and secondary centers. The highway tunnels of enter and exit town of Shenzhen city are clustered into 5 main corridors by direction. The main supplier of CDM is grouped to 4 nodes, so does the CDM demand nodes. Figure 2 shows the DCs location, demand zones, potential reverse logistics facility location, and population density distribution of each district of Shenzhen city.

The capacity limit of first-degree facilities 1, 2, and 3, all of the second-degree facilities, and the DCs is 30,000 kg. The capacity limit of the harbor ports such as first-degree facilities 4 and 5 is unlimited. The capacity limit to CDM supplier and RL facility is 4,000 kg. The rest of related parameters are presented in Tables 2, 3, 4, and 5. Table 2 gives the weekly depreciation charge of construction fixed costs and unit operation costs of each facility. Table 3 describes the Euclidean distance in each OD pair. Table 4 shows the market cargo transport costs per unit per Euclidean distance. The average vehicle net weight is obtained from the truck data and is shown in Table 5. Table 6 presents the demand of final customer and CDM demand node.

3.2. Results. The optimal goal is to minimize the total ULN costs as well as the GHG emissions simultaneously with satisfying the logistics demand of the whole city. We input the data, apply the proposed model, utilize the PSO toolbox merged in Matlab R2015b, and conduct the experiments by a PC with Intel core i7 processor to solve the problem. The solver iterations are 50, and the elapsed runtime seconds are 0.10 s. As can be seen in Figure 3, the optimal results of corridors selection, location of each tier facilities, and primary distribution plan are displayed.

The result shows that the main corridors for entering and exiting city should be tunnels 1, 2, and 3. The LP 1, 2, 3, 4, 5, 6; DCs 2, 4, 6, 8, 9, and 10, RL facilities 2, 3, and 4, and CDM suppliers 3 and 4 are the optimal locations of ULN. The designed capacity of airport, main railway station, north railway station, and Qianhai ports is no less than 30000, 15000, 15000, and 15000, respectively. The Yantian ports undertake the major parts of urban freight, of which capacity is 51680. The capacity of LP 1, 2, 3, 4, 5, and 6 is 45080, 30000, 30000, 30000, 28500, and 8400, respectively. For DCs 2, 4, 6, 8, 9, and 10, the corresponding capacity is 28500, 30000, 8400, 26180, 30000, and 12000, respectively. For RL facilities 2, 3, and 4, the corresponding capacity is 5844, 3455, and 5738, respectively. For CDM supplier, the capacity of node 3 is 6920, and the capacity of node 4 is 7000. The initial distribution plan is also demonstrated clearly in the figure. The arrow and text show the plan and volume. The logistics flow generally from upstream to downstream nodes in the network. Particularly, the transfer transportation exists in second-degree facility. The distribution plan is 10500 from LP1 to LP5, 8400 from LP1 to LP6, and 18000 from LP2 to LP5.

4. Discussion and Managerial Insights

After optimization, the total facilities of the city decrease from 29 to 25. The number of truck trips of the city also decreases from 90269 to 68117. Furthermore, Figure 4(a) demonstrates the relationship between number of facilities, trips, and costs. The arrow shows the increasing trend of various kinds of costs by trips and facilities.

The comparison of GHG emissions rates (GHGE) of each trip purpose with original scenario against optimal scenario is displayed in Figure 4(b). The GHG emissions for trip purposes G1, G2, G4, G5, and G6 are reduced remarkably.

Table 2: Fixed costs and unit (kg) operation costs of facilities.

Enter and Exit town tunnel			P, AP, RFS			LPCF		
i	Fixed costs	Unit operation costs	j	Fixed costs	Unit operation costs	k	Fixed costs	Unit operation costs
1	1850	0.5	1	28100	0.518	1	3300	0.21
2	2200	0.5	2	17500	0.321	2	1210	0.32
3	2100	0.5	3	12100	0.254	3	4320	0.15
4	2150	0.5	4	18950	0.178	4	5000	0.19
5	1950	0.5	5	21000	0.109	5	4300	0.17
						6	3800	0.22
						7	3120	0.18
DSC			RDSC			CDM		
l	Fixed costs	Unit operation costs	l'	Fixed costs	Unit operation costs	h	Fixed costs	Unit operation costs
1	700	0.15	1	1300	0.13	1	13000	0.35
2	890	0.28	2	1250	0.16	2	12100	0.29
3	850	0.16	3	1150	0.15	3	8000	0.28
4	950	0.22	4	1280	0.21	4	15000	0.33
5	1000	0.21						
6	920	0.13						
7	880	0.12						
8	750	0.15						
9	690	0.31						
10	830	0.12						

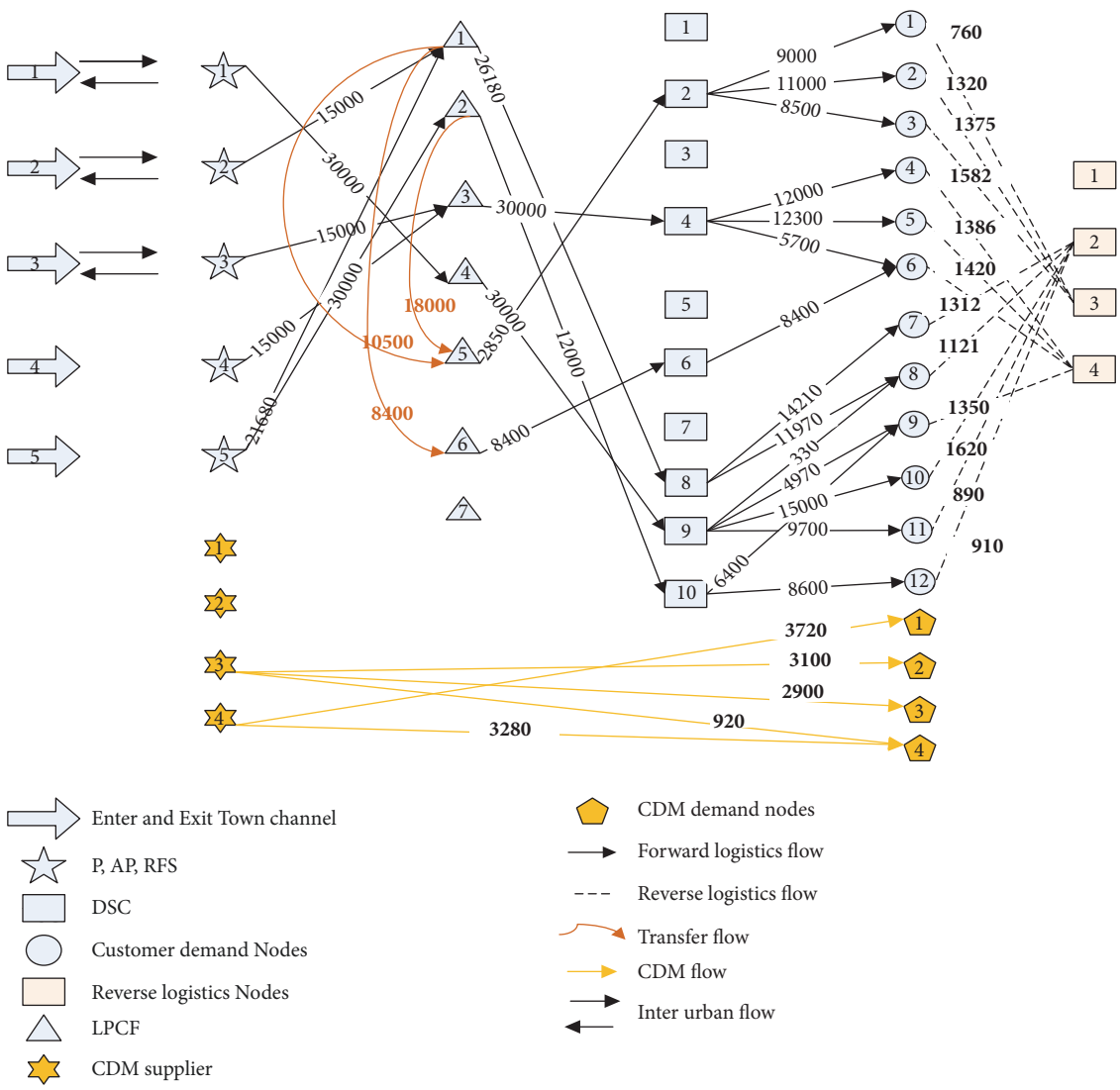


Figure 3: ULN optimal solutions.

Table 3: Transportation Euclidean distances in each stage of ULN.

(a)

P, AP, RFS			P, AP, RFS		
$a_{jj'}, d_{jj'}$	1	2	3	4	5
1	0	37	14.5	33.9	49.1
2	37	0	28.2	30.7	17.8
3	14.5	28.2	0	5	40
4	33.9	30.7	5	0	38
5	49.1	17.8	40	38	0

(b)

P, AP, RFS				LPCF			
a_{jk}, d_{jk}	1	2	3	4	5	6	7
1	49	49.1	33.9	22	0	24.3	41.4
2	14.6	17.8	30.7	52	37	33.2	21
3	35.1	40	5	30	14.5	29.4	37.4
4	36.9	38	0	38.3	33.9	31.2	39.2
5	20.7	0	38	62	49.1	38.6	21.7

(c)

P, AP, RFS			Enter/exit		
$a_{ij}, d_{ij}/a_{ji'}, d_{ji'}$	1	2	3	4	5
1	7.5	23.7	48.5	29.8	38
2	48.7	32.6	26	21.7	8.4
3	23.8	28.8	44.9	10	22.8
4	24.4	30.6	47	8.8	22.6
5	55	30.6	16.9	35.5	24.9

(d)

LPCF				LPCF			
$a_{kk'}, d_{kk'}$	1	2	3	4	5	6	7
1	0	33.9	36.9	17.9	49	17	15.5
2	33.9	0	38	62	49.1	18.2	13.3
3	36.9	38	0	38.3	33.9	29.3	31.6
4	17.9	62	38.3	0	22	14	11
5	7.5	49.1	49.1	22	0	24.3	41.4
6	17	18.2	29.3	14	24.3	0	16.2
7	15.5	13.3	31.6	11	41.4	16.2	0

(e)

LPCF			Enter/exit		
a_{jk}, d_{jk}	1	2	3	4	5
1	51.5	18	8	18	21.3
2	55	30.6	16.9	35.5	24.9
3	24.4	28.8	26	8.8	22.6
4	15.3	22	43	41.4	51
5	7.5	23.7	48.5	29.8	38
6	40	8.9	24	28	21.2
7	47	23	16	25.2	18

(f)

LPCF						DSC				
a_{kl}, d_{kl}	1	2	3	4	5	6	7	8	9	10
1	38.7	39.5	32	30.8	26.2	18.7	15.9	5.2	6.4	9.7
2	48	47.2	42	34.5	30	20.9	24.2	17.5	15	5
3	23.8	20.7	30.5	6.8	11	17.6	23.1	34.4	30	39.5

(f) Continued.

LPCF						DSC				
4	35	33.7	32.9	19.8	14	6	14.3	16.9	1	16.2
5	10	6.5	19.7	12.1	19.2	25.1	23	35.6	33.3	45.2
6	27.4	26.8	24.3	15.5	12.5	5.7	7.8	13.3	9.1	20.3
7	35	31.7	28.2	22	19.8	10.3	8.5	8.8	4	14.7

(g)

DSC	Enter/exit				
a_{jk}, d_{jk}	1	2	3	4	5
1	5.3	16.4	37.7	28.4	34
2	16	17.1	36	25.6	32.6
3	15.7	11.6	31.4	30.8	33.8
4	18.7	15.6	29.6	9	17.5
5	25	20.4	28	4.2	13.7
6	31.1	17.6	25.1	10.6	8
7	26.6	7.8	18.1	20.4	15.8
8	37	18.6	14.4	29.9	21
9	38.1	21	11.5	40.4	30
10	50.3	30.7	13.2	32.8	19

(h)

DSC	Demand nodes											
a_{lm}, d_{lm}	1	2	3	4	5	6	7	8	9	10	11	12
1	1	3	11	19.1	22.5	21	18.8	35	45.2	34.6	33.1	46.8
2	2.2	1.2	8	22.1	22.7	23.2	17.8	33.2	46.3	34.2	32	46.4
3	2.5	3.5	4.7	19.8	33	27	22.1	34	39.9	31.1	34	43.5
4	18.4	20.1	19	2.1	4.7	8	18.3	26.1	39.7	25.1	23.5	35
5	23	25	28	6.7	4.5	7	16.9	25.2	40.5	23.8	22.1	33.6
6	27	28.1	31	7.5	4.9	2.1	17.2	23.4	35.7	20	18	29.4
7	29.9	31	33	19.9	15	5.2	18	25	29.3	17	15.3	21.8
8	17	19	22	21	19	16.5	1.1	1.6	23.9	15.6	7.6	24.3
9	25	28	24	28	28.2	33	19.2	11	11.2	3	4.5	16.8
10	38.2	40	39	35.2	30.3	25.2	23	15	14.9	16.6	13	1.3

(i)

RDSC	Demand nodes											
$a_{ml'}, d_{ml'}$	1	2	3	4	5	6	7	8	9	10	11	12
1	32.4	31.4	30.5	16.4	13.5	9.8	3.3	14.5	19.2	29.1	21.2	20.2
2	16.5	19.3	21.2	23	19.3	16.5	17	32.5	1.5	1.9	7.2	22.1
3	1.8	1.6	7.2	19.8	21.7	22.8	16.8	8.9	43.3	15.6	31.7	47
4	18.1	17.2	18.8	7.8	9.2	4.9	7		20.2	35.3	30.3	27.5
										16.1		

(j)

CDMS	CDMD			
$a_{hh'}, d_{hh'}$	1	2	3	4
1	48.1	25.9	24.5	47.3
2	28.9	35.8	24.6	32.7
3	28.4	29.2	15.1	24.2
4	15.5	42.6	26.3	14

Table 4: Costs of unit freight per distance.

Origin node	i	j	k	l	l'	h
Costs	(0.05, 0.05, 0.05, 0.12, 0.23)	(0.05, 0.035, 0.045, 0.055, 0.061)	(0.065, 0.053, 0.055, 0.055, 0.053, 0.052, 0.049)	(0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075)	(0.021, 0.022, 0.018, 0.032)	(0.064, 0.071, 0.063, 0.059)

Table 5: Weight of trucks.

$x_3^{G_n}$	1	2	3	4	5	6
Average kerb weight	3.988	11.23	8.95	9.29	9.88	7.55
$\overline{w}_{G_n}$	1	2	3	4	5	6
Average loading weight	1.85	5.17	4.12	4.21	4.42	3.55

Table 6: The weekly demand amount of customers/market (kg).

D_m	D_1	D_2	D_3	D_4	D_5	D_6
Demand	9000	11000	8500	12000	12300	14100
D_m	D_7	D_8	D_9	D_{10}	D_{11}	D_{12}
Demand	14210	12300	11370	15000	9700	8600
D_m^r	D_1^r	D_2^r	D_3^r	D_4^r	D_5^r	D_6^r
Demand	760	1320	1375	1582	1386	1420
D_m^r	D_7^r	D_8^r	D_9^r	D_{10}^r	D_{11}^r	D_{12}^r
Demand	1312	1121	1350	1620	890	901
D_h	1	2	3	4	5	6
Demand	3720	3100	2900	4200	128	600

However, there is just a minor reduction of GHG emissions of trip purpose G3.

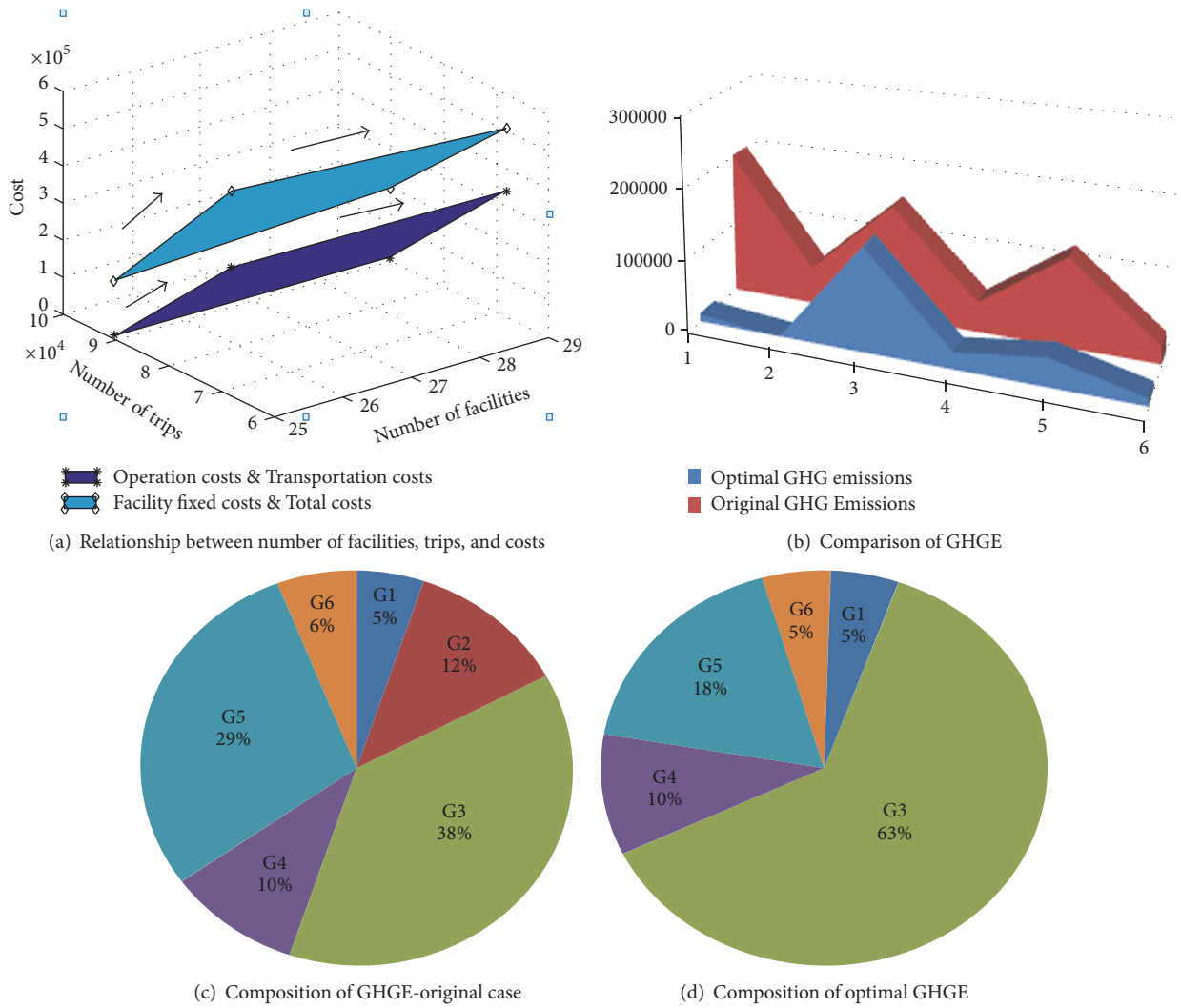
Figures 4(c) and 4(d) give out the composition of GHG emissions of the original real case and optimal location scheme, respectively. Compared with the two GHG emissions sharnig pie charts, the most prominent change is that the GHG emissions of trip purpose 2 have been eliminated from 20% to 0. It is also worth noting that the share of trip purpose 3 increases from 38% to 63%, yet the share of trip purpose 5 decreases from 29% to 18%. The distributions of GHG emissions share of other trip purposes are similar.

Several managerial implications are generated from the optimal result. First, it is observed that the optimal result reduces the numbers of facilities and trips in the meantime. This means that the capacity of original ULN facility is enough for satisfying the demands of entire city. However, the previous location, distribution plan, and trips are not reasonable. There are a lot of redundant truck trips between the facilities in Shenzhen city.

Moreover, in general, the tradeoff between the facility location cost and the transportation cost is typical in logistics system optimization. Our research shows that the reasonable location can save transportation costs and reduce GHG emissions by avoiding unnecessary trips, which is eco-friendly and more meaningful than just adding numbers of facility.

Second, some interesting findings are brought from the eco-facility location decisions. It is coincidence that the decision results correspond to the discussion based on regression analysis in our previous research (18). In addition, the decision for corridors location suggests a managerial insight that it is better to organize the freight flow entering and exiting the city from the north bound highway. For the freight flow from or to the south part outside the city, a ring freeway road around the city of a viaduct highway crossover the city should be applied to avoid the truck flow entering the city directly. Considering the location decision of FDL facility and SDL facility as well as the distribution plan revealed, it is necessary to avoid transfer trip between FDL facilities, yet the transfer trip demand could be passed from FDL facility to SDL facility.

Third, when comparing the GHG emissions distribution result associated with the original scenario and optimal one, it seems that the GHG emissions distribution structure is almost stable; the dominant emissions sources of truck in Shenzhen city are associated with first-stage, second-stage, direct, and wholesale distribution, as well as inbound and outbound freight transportation. Furthermore, the distinct decreasing of emissions share shows the facility location and flow organization optimization with transfer transport, and inbound and outbound freight flow is significant.



(a) Relationship between number of facilities, trips, and costs

(b) Comparison of GHGE

(c) Composition of GHGE-original case

(d) Composition of optimal GHGE

Figure 4: Numerical results.

The results and insights proposed in this section highlight the fact that the analysis of the source and effect factors of truck GHG emissions supports the government's decision to put forward more efficient, well-directed emissions-cut policy by the truck trip purpose. Furthermore, the data-based biobjective facility location model tends to optimize the location and trip organization in the meantime so as to reach equilibrium number of facilities and trips. Thus, the total cost will be reduced with the depletion of facility numbers and trips numbers, while the emissions can also be reduced by cutting down trips.

5. Conclusions

To reduce the ULN-related GHG emissions is a crucial long-term objective of cities around the world. We try to develop a new horizon to cut down the GHG emissions in ULN by optimizing the facility location decisions. In this paper, we first developed a truck trip purpose imputation matrix approach to classify the truck data based on truck trip purposes. Then, the various truck trip distribution and impact of various truck trip characteristics on GHG emissions were investigated. We conducted a multivariate regression analysis to explore the impact of OD nodes population density, Euclidean distance between OD nodes, and vehicle kerb weight on GHG emissions by each trip purpose. Based on the analysis above, the eco-facility location model was constructed. Last but not least, some managerial insight has been obtained through result analysis.

The main findings from the numerical analysis are summarized as follows:

(1) The dominant emissions sources of trucks in Shenzhen city are associated with first-stage, second-stage, direct, and wholesale distribution, as well as inbound and outbound freight transportation, the sum of which accounts for more than 60%. Even after optimization, the share of emissions associated with first-stage, second-stage, direct, and wholesale distribution still holds at 63%, whereas the share of

emissions of inbound and outbound freight transportation reduced from 29% to 18%.

(2) There are a lot of redundant truck trips between the facilities. Reasonable locations can save transportation costs and reduce GHG emissions by avoiding unnecessary trips, which is eco-friendly and more meaningful than just adding numbers of facility.

(3) It is better to organize the freight flow entering and exiting the city from the north bound highway. For the freight flow from or to the south part outside the city, a ring freeway road around the city of a viaduct highway crossover the city should be applied. It is also necessary to avoid transfer trip between first-degree logistics facilities such as airport, railway, and ports, yet the transfer trip demand could be passed to logistics parks.

The above findings offer useful decision-support insights to policy makers on efficient truck utilization, ULN design, and environment-friendly freight transport regulations. The future study may include but will not be limited to using more detailed trajectory data for emission estimation, considering land use type, employment, or establishment type and commodity type as the independent variables, and applying more sophisticated statistical tools in the analysis.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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