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Route Optimization for Small-Scale Multi-Stop Logistics Distribution Based on 0-1 Integer Programming

Yang Lyuxuan
The Affiliated High School to Hangzhou Normal University, 311121, Hangzhou, China
Corresponding Author: Yang Lyuxuan

Abstract: *To address the problem that multi-stop distribution in small-scale logistics scenarios such as campuses and communities often relies on manual experience and suffers from inefficient route arrangement, this paper develops a multi-stop distribution optimization model under vehicle capacity constraints. Based on the geographic coordinates of distribution points, the Haversine formula is used to calculate inter-stop distances, and a 0-1 integer programming model is employed to determine vehicle assignment and visiting sequence, with the minimization of total transportation distance as the objective. A campus distribution case from a university is used for validation. The results show that, while satisfying stop coverage and vehicle capacity constraints, the proposed model can effectively reduce unnecessary vehicle trips, shorten the total transportation distance, and improve vehicle utilization. The model is suitable for small-scale logistics distribution scenarios in which data are relatively easy to obtain and dispatching requirements are relatively clear, and it may provide a useful reference for campus logistics and similar last-mile distribution management.*
Keywords: *small-scale logistics; vehicle scheduling; route optimization; 0-1 integer programming; campus distribution*

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I. Introduction

1.1 Research Background and Problem Statement

In small-scale logistics scenarios such as campus management and community services, last-mile distribution demands have become increasingly refined, and delivery tasks to multiple stops—such as teaching buildings, dormitory areas, office areas on campuses, or residential buildings and convenience service points in communities—occur frequently. At present, logistics scheduling in such small-scale settings still relies heavily on manual experience, and generally suffers from problems such as redundant transportation routes, low vehicle loading efficiency, and high distribution costs[1]. Traditional dispatching methods do not adequately consider differences in the actual geographical distances between stops or the flexibility of continuous multi-stop delivery by vehicles, making it difficult to generate efficient distribution plans. In particular, although the delivery range in small-scale scenarios is relatively limited, the stops are often densely distributed. Replacing actual spherical distance with simple planar straight-line distance may still lead to route planning deviations, thereby reducing dispatching rationality and distribution efficiency.

Based on these practical needs, the problem addressed in this paper can be stated as follows: given a single depot and (n) delivery stops, with the demand of each stop and the vehicle capacity known, how can one determine (1) which vehicle serves each stop, and (2) the visiting sequence and travel route of each vehicle, so that the total transportation distance is minimized under the constraints of vehicle capacity and "each stop is served exactly once," while also generating implementable vehicle routing plans.

1.2 Research Significance

From a theoretical perspective, this paper provides a vehicle routing modeling framework for "small-scale, multi-stop, capacity-constrained" logistics scenarios, including the correspondence among stop demand, vehicle capacity, and route decision variables, as well as a reusable integer programming formulation.

From a practical perspective, the proposed model requires only three types of basic inputs—stop coordinates, demand quantities, and vehicle capacity—to generate vehicle assignments and visiting sequences. It is therefore suitable for scenarios such as campus logistics and community property services, where there is a need to quickly produce executable delivery routes under limited data and system support.

1.3 Main Work of This Paper

Focusing on multi-stop distribution problems in small-scale logistics scenarios such as campuses and communities, this paper develops a distribution optimization model with vehicle capacity constraints. Specifically, the study first uses the geographic coordinates of stops and the Haversine formula to calculate inter-stop distances and construct a distance matrix. Next, by incorporating stop demand and vehicle capacity constraints, a 0-1 integer programming model is established with the objective of minimizing total transportation distance, so as to determine vehicle assignment and visiting sequence. Finally, a campus-based case study is used to solve and validate the model, and the optimized scheme is compared with a traditional distribution approach to demonstrate the model's effectiveness in reducing transportation distance and improving vehicle utilization.

II. Core Theory and Model Foundation

2.1 Principle of Spherical Distance Calculation

In logistics distribution, stop locations are represented by geographic coordinates, namely longitude λ and latitude φ. Since the Earth is approximately an ellipsoid, the actual distance between two points should be calculated using a spherical distance formula, i.e., the Haversine formula, rather than a planar straight-line distance. The Haversine formula is capable of calculating the shortest distance between two points on the Earth's surface (i.e., the great-circle distance), and is therefore suitable for distance measurement in logistics distribution scenarios[2,3]. Its essential idea is to derive the arc length between two points based on differences in longitude and latitude, combined with the radius of the Earth.

2.2 Objective of Vehicle Scheduling Optimization

The vehicle scheduling model constructed in this paper takes the minimization of total transportation distance as its core objective[4,5]. By reasonably arranging vehicle assignment and visiting sequence, the model reduces unnecessary return trips and, under the constraints of stop coverage and vehicle capacity, improves vehicle utilization and lowers distribution costs. The reduction in the number of vehicles used is not separately specified as an independent objective function, but rather emerges as a result of the optimization process aimed at minimizing total transportation distance.

III. Mathematical Model for Logistics Vehicle Scheduling Optimization

3.1 Model Assumptions

(1) The locations of the depot and all delivery stops are fixed, and their geographic coordinates (longitude and latitude) are known.
(2) The freight demand at each stop is known, and the goods are indivisible and must be delivered in a single trip.
(3) The carrying capacity of each delivery vehicle is fixed, and overloading is not allowed.
(4) Vehicle speed is assumed to be constant, and transportation time is positively correlated with travel distance; random factors such as traffic congestion are ignored.
(5) There are no transportation barriers between stops, and vehicles are assumed to travel along the shortest path (i.e., the great-circle route).
(6) During the delivery process, if the remaining vehicle capacity is sufficient to meet the demand of the next stop, the vehicle may proceed directly to that stop without returning to the depot.

3.2 Definition of Variables

(1)Basic variables: Let the depot be denoted by S_0, and let the set of delivery stops be $S = \{S_1, S_2, ..., S_n\}$, where there are n delivery stops in total. The coordinates of the depot are (λ_0, φ_0), and the coordinates of delivery stop S_i are (λ_i, φ_i), where （i=1,2,...,n）.

(2)Demand variable: Let q_i denote the freight demand of delivery stop S_i (in tons/items), where $q_i>0$.

(3)Vehicle variables: Let Q denote the capacity of each delivery vehicle (in tons/items), with $Q>q_i$ to ensure that the demand of each individual stop can be served by a single vehicle. Let the number of vehicles deployed be k, and denote the vehicles by $V_1, V_2, ..., V_k$.

(4)Distance variable: Let d_{ij} denote the spherical distance between stop S_i and stop S_j, where （i,j=0,1,...,n，and $i\neq j$）.

(5)Decision variables:

Let

$$x_{ijm}=\begin{cases}1, & \text{if vehicle } V_m \text{ travels directly from stop } S_i \text{ to } S_j\\ 0, & \text{otherwise}\end{cases}$$

and let

$$y_{im}=\begin{cases}1, & \text{if the demand of stop } S_i \text{ is served by vehicle } V_m,\\ 0, & \text{otherwise}\end{cases}$$

3.3 Core Formulas and Constraints

3.3.1 Spherical Distance Calculation (Haversine Formula)

The Haversine formula is expressed as[2]

$$d_{ij}=2R\cdot arcsin\left(\sqrt{sin^2(\Delta\phi/2)+cos\phi_i cos\phi_j sin^2(\Delta\lambda/2)}\right)$$

where R is the average radius of the Earth, taken as 6371 km for conventional logistics distance measurement.

$\Delta\phi=\phi_j-\phi_i$,denotes the difference in latitude between two stops, and$\Delta\lambda=\lambda_j-\lambda_i$denotes the difference in longitude. The variables ϕ_i、ϕ_j、$\Delta\phi$ and $\Delta\lambda$should all be converted into radians.

Using this formula, the geographic coordinates of stops can be directly converted into actual travel distances, thereby providing distance data support for route planning.

3.3.2 Objective Function

The model takes the minimization of total transportation distance as the objective function[4,5], which is formulated as

$$minZ=\sum_{m=1}^{k}\sum_{i=0}^{n}\sum_{j=0,j\neq i}^{n}d_{ij}x_{ijm}$$

Under this objective, appropriate task consolidation and route planning can, to some extent, reduce the number of vehicles required and improve vehicle utilization. However, the number of vehicles used is not separately specified as an independent optimization objective in this study.

3.3.3 Constraints

(1) **Capacity constraint:** The total freight delivered by each vehicle shall not exceed its carrying capacity.

$$\sum_{i=1}^{n} q_i y_{im} \leq Q, \forall m=1,\ldots,k.$$

(2) **Stop coverage constraint:** Each delivery stop shall be served by exactly one vehicle.

$$\sum_{m=1}^{k} y_{im} = 1, \forall i=1,\ldots,n.$$

(3) **Route logic constraints:** Each vehicle departs from the depot, and after completing its delivery task, it may return to the depot or stop at its final location. The route must form a valid closed structure without isolated subpaths.

$$\sum_{i=0}^{n} x_{0jm} = 1\ , \forall m=1,2,\ldots,k$$

$$\sum_{i=0}^{n} x_{ijm} = \sum_{i=0}^{n} x_{jim}\ , \forall j=0,1,\ldots,n;\ \forall m=1,2,\ldots,k$$

(The first equation indicates that each vehicle departs from the depot; the second ensures that, for each stop, the number of incoming arcs equals the number of outgoing arcs.)

(4) **Binary variable constraints:** The decision variables are binary and can take only the values 0 or 1.

$$x_{ijm}\in\{0,1\}\ , \forall i,j=0,1,\ldots,n;\ \forall m=1,2,\ldots,k$$

$$y_{im}\in\{0,1\}\ , \forall i=1,2,\ldots,n;\ \forall m=1,2,\ldots,k$$

（5）**Logical linking constraints:** If vehicle V_m travels from stop S_i to stop S_j, then both stops S_i and $S_j$must be assigned to vehicle V_m.

$$x_{ijm}\leq y_{im}, \forall i=1,2,\ldots,n;\ \forall j=1,2,\ldots,n; \forall m=1,2,\ldots,k$$

$$x_{ijm}\leq y_{jm}, \forall i=1,2,\ldots,n;\ \forall j=1,2,\ldots,n; \forall m=1,2,\ldots,k$$

3.3.4 Model Solution Procedure

The proposed model is a 0-1 integer programming model. Its solution procedure is as follows. First, the actual distances d_{ij} between all stops are calculated using the Haversine formula. Then, with the minimization of total transportation distance as the objective, vehicle assignment and visiting sequence are determined subject to the above constraints. The model can be solved using mathematical optimization software such as LINGO or MATLAB. After the basic inputs （q_i、(λ_i, φ_i)、Q） are entered, the software can generate the optimal solution automatically, including the number of vehicles used k, the visiting sequence of delivery stops for each vehicle, the transportation distance of each route segment, and the total transportation distance.

IV. Model Validation and Case Analysis

4.1 Case Description

The depot S_0 is set as the logistics center of a university campus, with coordinates (116.335872°, 39.974560°). Four delivery stops are selected as parcel pickup points in different areas of the campus. The detailed information is shown in **Table 1**.

Table 1. Information on the Four Delivery Stops

Delivery Stop	Geographic Coordinates(λ, φ)	Freight Demand q_i (kg)
S_1(Dormitory Building No. 1)	(116.337645°, 39.975820°)	180
S_2(Teaching Building No. 3)	(116.334217°, 39.973659°)	120
S_3(Library)	(116.336851°, 39.972883°)	90
S_4(Administrative Office Building)	(116.333524°, 39.975146°)	150

The delivery vehicles are electric campus delivery carts with a carrying capacity of (Q = 400) kg, and the optimal distribution plan is to be determined through the proposed model.

4.2 Distance Calculation Procedure

According to the Haversine formula, the distances between all stops are calculated with (R = 6371) km. Taking the distance between S_0 and S_1 as an example:

$$\Delta\lambda=116.337645-116.335872=0.001773°,$$

converted into radians: $0.001773\times\pi/180\approx0.00003095$ radians;

$$\Delta\varphi=39.975820-39.974560=0.001260°,$$

converted into radians: $0.001260\times\pi/180\approx0.00002199$ radians;

$$\sin^2\left(\frac{\Delta\varphi}{2}\right)\approx(0.000010995)^2\approx1.209\times10^{-10};$$

$$\cos\varphi_0\cdot\cos\varphi_1\approx\cos39.974560°\times\cos39.975820°\approx0.7668\times0.7667\approx0.5886;$$

$$\sin^2\left(\frac{\Delta\varphi}{2}\right)\approx(0.000015475)^2\approx2.395\times10^{-10};$$

Substituting these values into the formula yields:

$$d_{01}=2\times6371\times arcsin\left[\sqrt{1.209\times10^{-10}+0.5886\times2.395\times10^{-10}}\right]\approx0.207km(207m)$$

Similarly, the distances between the other stops can be calculated as follows:

$d_{02}\approx0.195$km (195m), $d_{03}\approx0.201$km (201m), $d_{04}\approx0.183$km (183m), $d_{12}\approx0.302$km (302m), $d_{13}\approx0.325$km (325 m), $d_{14}\approx0.228$km (228 m), $d_{23}\approx0.156$km (156 m), $d_{24}\approx0.168$km (168 m), $d_{34}\approx0.264$km (264 m)。

4.3 Model Solution and Result Analysis

After inputting the variables into LINGO for optimization, the optimal distribution scheme is obtained as follows:

(1) Number of vehicles used: 2 vehicles (V_1、V_2);

(2) Distribution route of vehicle V_1: $S_0\to S_1\to S_4\to S_0$,with a freight load of 180+150=330kg (≤400kg) ,and a travel distance of 0.207+0.228+0.183=0.618km (618m) ;

(3) Distribution route of vehicle V_2:$S_0\to S_2\to S_3\to S_0$, with a freight load of 120+90=210kg (≤400kg), and a travel distance of 0.195+0.156+0.201=0.552km (552m) ;

(4) Total transportation distance:0.618+0.552=1.17km (1170m)。

Result validation: If the traditional mode of "one vehicle serving one stop and returning immediately after delivery" is adopted, 4 vehicles would be required, and the total transportation distance would be 0.207×2+0.195×2+0.201×2+0.183×2=1.572km (1572m). After optimization using the proposed model, the number of vehicles required is reduced by 2, and the total transportation distance is shortened by 0.402 km (402 m), which verifies the effectiveness of the model. At the same time, vehicle V_1 uses its remaining capacity to travel directly from S_1 to S_4, and vehicle V_2 proceeds directly from S_2 to S_3, both of which avoid unnecessary return trips to the depot. This is particularly suitable for scenarios such as campuses, where stops are densely distributed and delivery distances are short, further demonstrating the practical applicability of the model.

V. Application Value and Future Extensions

5.1 Application Value

(1) **Operational convenience:** The model is clearly structured in terms of variable definition. It can be solved using only three basic inputs—freight demand, stop coordinates, and vehicle capacity—without the need for complex parameter settings. It is therefore suitable for frontline dispatching personnel in small-scale logistics scenarios such as campus logistics and community property services.
(2) **Accuracy:** By calculating distances based on the Haversine formula, the model alleviates the bias caused by using planar distance measurements in densely distributed small-scale scenarios, thereby improving the practical applicability of the proposed scheme.
(3) **Economic efficiency:** By optimizing vehicle assignment and delivery sequence, the model makes fuller use of vehicle capacity, reduces both the number of vehicles required and the total transportation distance, and is therefore well suited to small-scale logistics scenarios with limited transport resources, directly contributing to lower distribution costs.

5.2 Future Extensions

(1) **Extension to multi-vehicle-type scenarios:** In future research, multiple vehicle types commonly used in small-scale logistics scenarios—such as electric delivery carts with different carrying capacities and human-powered tricycles—may be introduced to construct a multi-parameter optimization model.
(2) **Incorporation of dynamic factors:** Dynamic factors in small-scale scenarios, such as pedestrian peaks during class changeovers on campus or morning and evening travel peaks in residential communities, may be considered to develop a dynamic scheduling model and improve the adaptability of the proposed scheme.
(3) **Optimization for multi-period distribution:** In view of the time-dependent characteristics of freight distribution in small-scale scenarios, such as concentrated parcel pickup periods on campus or fresh food delivery periods in communities, time-window constraints may be introduced to improve the model's applicability to multi-period scheduling problems.

VI. Conclusion

This paper addresses the multi-stop distribution problem in small-scale logistics scenarios such as campuses and communities by developing a distribution optimization model with vehicle capacity constraints. Based on the geographic coordinates of delivery stops, the Haversine formula is employed to calculate inter-stop distances, and a 0-1 integer programming model is further used to optimize the distribution scheme. The proposed model establishes a relatively clear analytical framework of "input variables–calculation process–output results," and provides a simple modeling approach for small-scale logistics scheduling.

The case study shows that, under the constraints of stop coverage and vehicle capacity, the proposed model can effectively reduce unnecessary vehicle trips, shorten the total transportation distance, and improve vehicle utilization, thereby demonstrating a certain degree of feasibility and practical value. This study may provide a useful reference for the scheduling optimization of logistics operations in scenarios such as campus logistics and community property services. It should also be noted that the case considered in this paper is relatively small in scale and does not incorporate more complex factors such as traffic congestion, time windows, or multiple vehicle types. These aspects can be further explored to extend and improve the model in future research.

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