Mathematical Modeling and Algorithm Application
ISSN: 3006-0842 | Vol. 8, No. 3, 2026

Research on Urban Distribution Route Optimization Based on Time-Sliced OD Travel Time Matrices

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Abstract: Urban distribution operations are significantly affected by time-varying traffic conditions. If Euclidean distance or static shortest paths are still used as the travel cost between nodes, the actual distribution process under real road network conditions cannot be accurately represented. To address this issue, this study investigates a vehicle routing problem with soft time windows based on time-sliced travel times derived from a real road network. Travel time data between nodes in the core urban area of Zhengzhou are collected through an open map platform, and the service period is divided into multiple consecutive time intervals to construct time-sliced OD travel time matrices with directional and temporal heterogeneity. On this basis, a time-dependent vehicle routing optimization model is established with the objective of minimizing total distribution cost, in which time window deviations are incorporated into the objective function as penalty costs. Considering that local route adjustments may lead to subsequent changes in time states, an improved adaptive large neighborhood search algorithm is designed, together with a local time update mechanism to reduce repeated computations. A distribution network with 69 nodes in an urban area of Zhengzhou is used as the test instance, and the proposed method is compared with a genetic algorithm, ant colony optimization, simulated annealing, tabu search, and adaptive large neighborhood search. The results show that the proposed method can effectively reflect travel cost differences across time periods and achieves a relatively balanced performance in both total distribution cost control and computational efficiency.

Keywords: Urban distribution; Time-sliced OD matrix; Time-dependent vehicle routing problem; Soft time windows; Adaptive large neighborhood search.

1. Introduction

In recent years, the rapid growth of urban distribution services has made the conflict between delivery timeliness and cost control increasingly prominent. Traditional vehicle routing optimization usually treats the travel cost between nodes as a fixed value. Although this assumption may be acceptable in static scenarios, it becomes problematic in urban road networks. Morning and evening peak periods, peak-to-off-peak transitions, localized congestion, and directional traffic flow differences all make the actual travel cost of the same route dependent on the departure time. If route planning is still based on static distance or static travel time, the resulting solution often deviates from actual operations.

A large body of research has been devoted to the vehicle routing problem. Dantzig and Ramser first proposed the basic form of the vehicle routing problem [1], and subsequent studies gradually extended it to more complex settings, such as time windows, multi-depot systems, heterogeneous fleets, and dynamic demand. For situations in which traffic conditions vary over time, Malandraki and Daskin proposed a time-dependent vehicle routing model [2], while Hill and Benton discussed vehicle scheduling under time-varying speeds from the perspective of urban traffic operations [3]. Van Woensel et al. studied route optimization under traffic fluctuations through dynamic travel time modeling [4], and Pan et al. applied hybrid heuristic methods to the time-dependent vehicle routing problem with time windows [5]. Adamo et al. systematically reviewed recent advances in this field and pointed out that real road networks, traffic forecasting, and dynamic re-optimization have become important directions in time-dependent vehicle routing research [6].

Domestic studies have also gradually shifted from static route optimization to distribution decisions under changing traffic conditions. Li and Wei introduced time-varying vehicle speeds into the study of perishable goods distribution [7], Long et al. discussed urban logistics route optimization under time-varying conditions [8], and Tong and Li used navigation data to estimate travel times and studied distribution route optimization under changing traffic conditions [9]. In terms of algorithms, Duan et al. proposed an improved ant colony algorithm for the time-dependent vehicle routing problem [10], and Ge and Zhang investigated vehicle routing optimization in urban traffic networks [11]. Existing studies have shown that changes in traffic conditions directly affect routing decisions, yet two issues still deserve further attention. First, some studies still approximate inter-node costs using Euclidean distance or static shortest paths, making it difficult to reflect directional and temporal differences in real road networks. Second, after a local route adjustment, the time states of subsequent nodes often have to be recalculated along the entire route, leading to high computational overhead.

To address these issues, this paper takes the distribution network in the core urban area of Zhengzhou as the research object. Based on travel time data from a real road network, time-sliced OD travel time matrices are constructed, and a time-dependent vehicle routing model with soft time windows is established. An improved adaptive large neighborhood search algorithm is then designed for solving the problem. The main contributions of this study are threefold. First, time-sliced OD travel time matrices are constructed to describe inter-node travel costs across different time periods and directions. Second, a time-dependent vehicle routing model with soft time windows is built with the objective of minimizing total distribution cost. Third, a local time update mechanism is introduced to reduce repeated computations caused by route adjustments.

2. Problem Description and Model Formulation

2.1. Problem Description

This study considers a time-dependent vehicle routing problem with soft time windows. Let the distribution network be represented by a directed graph: $G=(V,A)$

Where $V=\{0,1,2,...,n\}$ denotes the set of nodes, node 0 represents the depot, and the remaining nodes represent customers; A is the set of arcs; and $K=\{1,2,...,m\}$ is the set of available vehicles.

Each customer node i has a known demand q_i ,service time s_i ,and service time window $[a_i,b_i]$ .Vehicles depart from the depot, serve a sequence of customers, and eventually return to the depot. Unlike the static vehicle routing problem, the travel time from node i to node j is no longer a fixed constant; instead, it depends on the time interval to which the departure time from node i belongs.

In this paper, customer time windows are treated as soft constraints. Vehicles are allowed to arrive before the lower bound of the time window and wait, or arrive after the upper bound, but such deviations incur penalty costs. The objective is to minimize total distribution cost while satisfying vehicle capacity and route feasibility constraints.

2.2. Time-Sliced OD Travel Time Matrices

To capture the time-varying nature of inter-node travel times under dynamic traffic conditions, the service period $[T_s,T_e]$ is divided into consecutive time intervals of length Δt .The resulting set of time slices is denoted by $\Theta=\{0,1,2,...,H-1\}$,where H is the total number of time slices. For each time slice $\theta\in\Theta$,an OD travel time matrix is constructed as $T^{\theta}=\left[t_{ij}^{\theta}\right]$,where t_{ij}^{θ} denotes the estimated travel time from node i to node j when departing in time slice θ ,when $i=j$, $t_{ii}=0$.

During route execution, if the departure time from node i is d_i ,the corresponding entry $t_{ij}^{\theta(d_i)}$ is retrieved from the matrix associated with the time slice containing d_i ,and subsequent time propagation is performed accordingly. In this way, time-varying traffic information from the real road network is transformed into structured input that can be directly incorporated into the optimization model.

2.3. Objective Function

The objective of this study is to minimize total distribution cost, which consists of travel cost and penalty cost due to time window deviations:

$$\min Z=\sum_{k\in K}\sum_{i\in V}\sum_{\substack{j\in V\\ j\neq i}}c_t t_{ij}^{\theta(d_i)}x_{ijk}+\gamma\sum_{i\in V\setminus\{0\}}Penalty(\tau_i) \tag{1}$$

Where c_t is the unit travel-time cost, x_{ijk} is a binary decision variable taking value 1 if vehicle k travels from node i to node j ,and 0 otherwise; τ_i is the arrival time at node i ;and γ is the penalty weight for time window violations.

To reduce the abrupt change caused by traditional piecewise linear penalties around the time window boundaries, a smooth penalty function is used to describe early and late arrival costs:

$$Penalty(\tau_i)=\begin{cases}\dfrac{\beta_e(a_i-\tau_i)}{1+\exp\{-(a_i-\tau_i+\delta_e)\}}, & \tau_i<a_i,\\ 0, & a_i\le\tau_i\le b_i,\\ \dfrac{\beta_l(\tau_i-b_i)}{1+\exp\{-(\tau_i-b_i-\delta_l)\}}, & \tau_i>b_i.\end{cases} \tag{2}$$

where β_e and β_l are the penalty coefficients for early and late arrivals, respectively, δ_e and δ_l control the smoothness near the time window boundaries.

2.4. Constraints

(1) Unique service constraint

$$\sum_{k\in K}\sum_{j\in V}x_{ijk}=1,\quad \forall i\in V\setminus\{0\} \tag{3}$$

This constraint ensures that each customer is served exactly once.

(2) Departure and return constraints for vehicles

$$\sum_{j\in V\setminus\{0\}}x_{0jk}=y_k,\ \sum_{i\in V\setminus\{0\}}x_{i0k}=y_k,\quad \forall k\in K \tag{4}$$

where y_k indicates whether vehicle k is used. These constraints ensure that each utilized vehicle departs from the depot and returns to the depot after completing service.

(3) Flow balance constraint

$$\sum_{\substack{i\in V\\ i\neq h}}x_{ijk}=\sum_{\substack{j\in V\\ j\neq h}}x_{ijk},\forall h\in V\setminus\{0\},\forall k\in K \tag{5}$$

This constraint guarantees flow conservation at each customer node for every vehicle.

(4) Time propagation constraint

The departure time from node i satisfies

$$d_i = \max\{\tau_i, a_i\} + s_i \tag{6}$$

If vehicle k travels from node i to node j ,then

$$\tau_j \geq d_i + t_{ij}^{\theta(d_i)} - M(1 - x_{ijk}) \tag{7}$$

where M is a sufficiently large constant. These constraints describe the arrival and departure process under time-dependent travel times.

(5) Capacity constraint

$$u_j \leq u_i - q_j + Q\left(1 - x_{ijk}\right), u_j \geq u_i - q_j - Q\left(1 - x_{ijk}\right) \tag{8}$$

Where u_i denotes the remaining load of the vehicle after leaving node i ,and Q is the vehicle capacity. These constraints ensure that the delivered quantity on each route does not exceed the vehicle capacity.

Through the above objective function and constraints, the time-sliced OD travel time matrices, soft time window penalties, and vehicle capacity limitations are integrated into a unified optimization framework.

3. Solution Algorithm Design

3.1. Overall Algorithmic Framework

The problem studied in this paper is jointly affected by time-dependent travel times, soft time window penalties, and vehicle capacity constraints. As the problem size increases, exact algorithms become difficult to apply within acceptable computational time. Therefore, an adaptive large neighborhood search framework is adopted.

The overall procedure consists of five stages: initial solution construction, customer removal, time-state updating, customer reinsertion, and solution acceptance. First, an initial route set satisfying capacity and time window requirements is generated. Then, a subset of customer nodes is removed from the current solution to form a partial solution and an unserved customer set. Next, according to the impact of insertion operations on route time states, local time propagation is performed on the affected route segments. The unserved customers are then reinserted into the current routes to generate a new candidate solution. Finally, an acceptance criterion is applied to determine whether the current solution and the best solution should be updated.

3.2. Local Time Update Mechanism

In the time-dependent vehicle routing problem, a change in the insertion position of one customer affects not only the travel time of the current arc but also the arrival times, departure times, and corresponding travel time values of subsequent nodes. If the entire route time state is recalculated after each local operation, the computational burden increases substantially.

To address this issue, a local time update mechanism is used during the repair stage. Specifically, when a node is inserted or removed, time propagation starts only from the first affected node and proceeds forward along the route. The time states of the unaffected prefix of the route remain unchanged and are not recomputed. In this way, the consistency of time propagation is preserved while unnecessary repeated calculations are reduced.

Suppose customer j is inserted between nodes i and l on a route. The resulting increment in the objective function can be expressed as

$$\Delta Z_{i,j,l} = c_t\left(t_{ij}^{\theta(d_i)} + t_{jl}^{\theta(d_j')} - t_{il}^{\theta(d_i)}\right) + \gamma \Delta P_{i,j,l} \tag{9}$$

Where $\Delta P_{i,j,l}$ denotes the variation in time window penalties for the affected nodes after insertion. The algorithm compares the incremental costs of different insertion positions and selects the one with the minimum cost.

3.3. Removal, Repair, and Acceptance Strategies

During the destroy phase, customer nodes are not removed purely at random. Instead, the algorithm adaptively selects nodes for removal by considering their spatial positions in the current route, their service-time states, and the operational variability of the related road segments. This helps identify route segments that are more worthwhile to rearrange.

During the repair phase, all feasible insertion positions for each unserved customer are evaluated, and the corresponding incremental costs are computed. If an insertion position leads to capacity infeasibility or significant deterioration in time states, it is regarded as infeasible. Among the feasible positions, the one with the smallest incremental cost is selected.

To avoid premature convergence to local optima, the algorithm preserves a certain degree of perturbation and non-improving solution acceptance. If the candidate solution is better than the current solution, it is accepted directly. If it is slightly worse, it may still be accepted with a certain probability to maintain search diversity. Overall, the proposed method retains the basic framework of adaptive large neighborhood search, while introducing targeted treatments for node removal and time-state updating under time-dependent travel costs, making it more suitable for urban distribution route optimization on real road networks.

4. Experimental Analysis

4.1. Experimental Data and Settings

A district of Zhengzhou is selected as the empirical study area.The region is characterized by concentrated commercial and residential locations and a relatively complex road network, making it representative of urban distribution scenarios. The dataset contains one depot and 68 customer nodes, for a total of 69 nodes. Customer demands range from 35 to 150 kg, service times range from 5 to 10 minutes, and the service period is set from 08:00 to 12:00. The customer time windows exhibit some heterogeneity, with a relatively large proportion of customers concentrated after 10:00, which reflects the coexistence of uneven customer distribution and time-sensitive requirements in urban distribution.

Travel time data are obtained from an open map platform. The service period from 08:00 to 12:00 is divided into 16 consecutive time slices of 15 minutes each, based on which 16 time-sliced OD travel time matrices of size 69×69 are constructed. These matrices exhibit both directional and temporal heterogeneity and capture traffic variations during the transition from morning peak to off-peak periods. All algorithms are implemented under the same experimental environment and use the same customer data and time-sliced OD matrices.

To verify the effectiveness of the proposed method, the genetic algorithm, ant colony optimization, simulated annealing, tabu search, and adaptive large neighborhood search are selected as comparison methods. The evaluation metrics include total distribution cost, number of vehicles used, average computation time, and number of time window violations.

4.2. Comprehensive Performance Comparison

The comprehensive performance comparison of all algorithms is shown in Table 1.

Table 1 Comprehensive performance comparison of different algorithms

Algorithm	Number of Vehicles	Average Runtime (s)	Time Window Violations	Total Distribution Cost (CNY)
STA-LNS	8	48.3	12	1382
Genetic Algorithm	8	35.7	21	1831
Ant Colony Optimization	8	67.2	30	2393
Simulated Annealing	10	42.8	8	1488
Tabu Search	10	52.4	11	1633
Adaptive Large Neighborhood Search	10	45.6	10	1596

As shown in Table 1, the proposed method performs best in terms of total distribution cost, with a cost of 1382 CNY. Compared with the genetic algorithm, ant colony optimization, simulated annealing, tabu search, and adaptive large neighborhood search, the total cost is reduced by 24.5%, 42.2%, 7.1%, 15.4%, and 13.4%, respectively. In terms of fleet size, the proposed method completes the distribution task using only 8 vehicles, whereas simulated annealing, tabu search, and adaptive large neighborhood search all require 10 vehicles, indicating that the proposed method achieves better route integration and vehicle utilization.

Regarding runtime, STA-LNS requires 48.3 seconds on average. Although it is not the fastest algorithm, its runtime remains within an acceptable range. The genetic algorithm runs fastest, but both its total cost and the number of time window violations are significantly worse than those of the proposed method. Ant colony optimization has the longest runtime and also the highest total cost. In contrast, the proposed method achieves a relatively balanced trade-off between computational efficiency and solution quality.

In terms of time window violation control, STA-LNS results in 12 violating customers, which is lower than the genetic algorithm and ant colony optimization, but slightly higher than simulated annealing, tabu search, and adaptive large neighborhood search. This indicates that the proposed method does not outperform all comparison methods on every single metric, but maintains a favorable balance among cost, fleet size, and service timeliness.

4.3. Discussion of Results

The experimental results show that the time-sliced OD travel time matrices can effectively capture the time-varying characteristics of inter-node travel costs under dynamic traffic conditions. As a result, route evaluation no longer relies on the accumulation of static edge weights, but instead dynamically retrieves travel times according to the actual departure times of vehicles. At the same time, the local time update mechanism reduces repeated computations in time-dependent route evaluation, allowing the large neighborhood search process to maintain good computational efficiency when handling local changes under time-varying travel costs.

From the route plots, the solutions generated by the proposed method are relatively compact, with fewer large cross-regional detours and clearer vehicle task allocations. This is closely related to the use of time-dependent cost representation in the model and the timely updating of local time states during the solution process.

5. Conclusion

This paper investigates the route optimization problem arising from time-varying traffic conditions in urban distribution. A time-sliced OD travel time matrix is constructed from a real road network, and on this basis a time-dependent vehicle routing model with soft time windows is established. To address the repeated propagation of time states after local route adjustments, an improved adaptive large neighborhood search algorithm is proposed together with a local time update mechanism.

Using a distribution network in an urban area of Zhengzhou as the test instance, the experimental results show that the proposed method can effectively reflect travel cost differences across time periods. It outperforms several comparison algorithms in total distribution cost while also achieving relatively balanced performance in fleet size and runtime. These findings indicate that incorporating time-sliced OD travel time matrices into urban distribution route optimization can improve the model’s ability to describe the operational characteristics of real road networks, and that the corresponding improved solution method provides a practical approach for route optimization under time-varying traffic conditions.

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