World Electric Vehicle Journal

MDPI

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Electric Heterogeneous Fleet Vehicle Routing Optimization for Campus Commuter Services: A Two-Stage Heuristic Approach

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Abstract

The Multi-Destination Vehicle Routing Problem (MD-VRP) with a heterogeneous electric fleet is a critical challenge in optimizing commuter services for large-scale institutions and logistics operations. To address the complexities of electric fleet composition uncertainty and multi-center routing in "micro-city" campus environments, this paper establishes a robust multi-objective programming model. The model aims to simultaneously minimize three conflicting objectives, the total number of vehicles, total driving distance, and total electric energy consumption (kWh), under constraints of flow conservation and vehicle availability. Considering the nondeterministic polynomial-time hard (NP-hard) nature of the problem, a novel two-stage hybrid heuristic algorithm is proposed. In the first stage, a Modified Kruskal's algorithm is employed to aggregate scattered stops into optimized clusters to reduce dimensionality. In the second stage, a State-Compressed Dynamic Programming (SC-DP) algorithm is applied to determine the optimal routing and electric vehicle type selection for each cluster. The methodology is validated using a case study of a large-scale campus network with 100 nodes. The optimization results identify an optimal fleet configuration of 41 campus electric commuter vehicles across three specific types (capacities of 45, 55, and 60), resulting in an annual total energy consumption of 5893.98 kWh. Compared with a global Ant Colony Optimization (ACO) baseline in this case study, the proposed framework reduces the required fleet size by 22.6% and annual energy consumption by 9.2%; however, this comparison should be interpreted as a preliminary case-study benchmark because the proposed method adopts a decomposition-based "Cluster-First, Route-Second" strategy. The results indicate that the approach achieves higher solution efficiency, offering an economically and environmentally friendly scheme for electric vehicle fleet operations.

Keywords: multi-objective optimization; heterogeneous electric vehicle routing problem; electric mobility; Kruskal's algorithm; state-compressed dynamic programming

Check for updates

Academic Editor: Michael Fowler

Received: 8 April 2026
Revised: 12 May 2026
Accepted: 15 May 2026
Published: 17 May 2026

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1. Introduction

Climate change has emerged as the defining challenge of the 21st century, prompting the international community to coalesce around the United Nations Sustainable Development Goals (SDGs), specifically Sustainable Cities and Communities and Climate Action. Within this global framework, the transportation sector stands as a pivotal battleground,

accounting for approximately 24% of direct CO_2 emissions from fuel combustion globally [1–3]. Consequently, the logic of logistics management is undergoing a fundamental paradigm shift: the objective function is no longer solely about minimizing monetary cost or time, but increasingly about minimizing the environmental footprint and energy intensity of operations. This transition has given rise to the concept of "Green Logistics", where operational efficiency has been inextricably linked to carbon reduction [4,5].

Large-scale educational and corporate campuses, functioning as autonomous "micro-cities," play a strategic role in this transition. With populations often exceeding tens of thousands, these enclosed ecosystems serve as ideal testbeds for piloting low-carbon mobility solutions before wider urban deployment [6]. However, current campus transit systems face a critical sustainability bottleneck: the rigidity of fleet composition. Most traditional campus operators rely on a Homogeneous Fleet—typically deploying standardized large buses for all routes. Although the Homogeneous Fleet strategy offers administrative simplicity, it fails to account for the intrinsic spatiotemporal heterogeneity of travel demand. The indiscriminate assignment of high-capacity vehicles to low-density peripheral sectors results in significant 'capacity slack' and elevated per capita energy intensity. Consequently, adhering to global decarbonization mandates necessitates a transition towards a Heterogeneous Fleet model, which optimizes resource allocation by dynamically matching diverse vehicle types to specific route densities [7].

Transitioning to a heterogeneous fleet, however, introduces significant complexity. It transforms the problem from a standard scheduling task into the Heterogeneous Fleet Vehicle Routing Problem (HFVRP), which couples combinatorial routing with resource allocation. While the HFVRP has been studied in urban freight logistics, the campus commuter context remains under-represented in the literature. Unlike freight carriers that prioritize delivery speed, campus systems must adhere to strict service consistency and human-centric constraints (e.g., fixed class schedules and maximum ride times). Furthermore, existing solution methodologies often struggle to balance stability and optimality. Exact algorithms cannot scale to large campus networks, while stochastic meta-heuristics (like Genetic Algorithms) lack the reproducibility required for standardized daily operations.

To address these challenges, this paper proposes a robust multi-objective optimization framework for the Multi-Destination Vehicle Routing Problem with model uncertainty and fleet heterogeneity. The main contributions are summarized as follows.

The primary contributions of this study are threefold.

(I) Integrated fleet composition and route optimization: This study formulates a campus commuter routing problem that simultaneously considers heterogeneous electric fleet selection, passenger capacity constraints, travel distance, and energy consumption. Unlike studies that focus only on fleet sizing or vehicle assignment, the proposed framework explicitly incorporates route construction and vehicle-type selection into a unified optimization process.

(II) Two-stage route optimization framework: A "Cluster-First, Route-Second" heuristic framework is developed to address the computational complexity of the 100-node campus network. In the first stage, a Modified Kruskal's Algorithm is used to generate capacity-feasible and geographically compact traffic zones. In the second stage, State-Compressed Dynamic Programming is applied to optimize intra-zone routes and select suitable electric vehicle types.

(III) Campus commuter application: The proposed method is validated using an anonymized campus commuter case. The results demonstrate how route structure, regional demand density, and vehicle capacity jointly affect fleet configuration and energy-consumption performance.

https://doi.org/10.3390/wevj17050267

The rest of the paper is organized as follows: Section 2 reviews the literature on HFVRP and relevant solution algorithms. Section 3 formulates the multi-objective mathematical model. Section 4 details the dataset description and traffic zoning strategy. Section 5 presents the proposed two-stage hybrid heuristic algorithm and analyzes the empirical results. Finally, Section 6 concludes the study and outlines future research directions.

2. Literature Review

2.1. Heterogeneous Fleet Optimization in Green Logistics

The classical Vehicle Routing Problem (VRP), first formulated by Dantzig and Ramser, typically assumes a homogeneous fleet, where all vehicles possess identical capacities, operating costs, and energy consumption characteristics [8]. However, in practical logistics and commuter transportation scenarios, operators often manage a heterogeneous fleet to flexibly respond to fluctuating demands and operational constraints. The Heterogeneous Fleet Vehicle Routing Problem (HFVRP), first formalized by Gendreau [9,10], extends the classical VRP by introducing fleet composition as a core decision variable. Koç et al. [7] provided a comprehensive review of HFVRP variants, demonstrating that mixed fleets can reduce total operational costs by 15–30% compared to homogeneous fleets by reducing "capacity slack" (unused seats).

Despite these benefits, HFVRP is inherently more complex than standard VRP because it couples routing with a resource allocation problem (similar to Bin Packing). The operational efficiency of modern commuter logistics is the result of a complex interaction between fleet composition, routing topology, and evolving environmental constraints [11,12]. In response to global sustainability mandates, the focus has shifted to the Green Vehicle Routing Problem (GVRP), which explicitly incorporates fuel consumption and greenhouse gas emissions as primary objective functions. While classical models assume homogenous fleets, recent studies argue that rigid fleet configurations significantly increase the likelihood of operational inefficiencies, specifically "capacity slack" and excessive energy waste in multi-modal networks [13,14]. With the global push for carbon neutrality, determinants such as greenhouse gas emissions [15], battery consumption rates for electric buses [16], and speed-dependent energy models [17] have become the primary drivers in network design. A substantial body of literature has emerged focusing on the electrification of transport fleets, utilizing Mixed-Integer Linear Programming (MILP) to account for complex variables such as battery degradation and charging station location [18,19]. Furthermore, research on Heterogeneous Fleet Green VRP has highlighted that optimizing the fleet mix—replacing large, high-emission vehicles with smaller alternatives—can yield significant energy savings [20]. Recently, there has been a growing interest in tailoring these optimization models specifically for campus commuter systems to enhance sustainability and operational efficiency. For instance, Noor et al. [21] investigated campus shuttle bus route optimization using predictive machine learning models, emphasizing the necessity of minimizing fuel costs and greenhouse gas emissions within university environments. Similarly, Alamatsaz et al. [22] focused on enhancing the efficiency of electric shuttle buses through timetabling and scheduling optimization, highlighting the unique operational dynamics and rigid scheduling constraints of campus transit. While extensive research exists for urban freight logistics, studies specifically addressing HFVRP in campus commuter systems—which require strict adherence to service consistency and passenger capacity—remain limited. This study addresses this gap by optimizing a fleet of three distinct vehicle types to match the spatial heterogeneity of campus demand.

Recent studies on university commuters have shown that campus public transport use is not only affected by aggregate passenger demand, but also by passenger-centered

service-quality factors, such as waiting time, travel satisfaction, comfort, service reliability, and perceived constraints. These findings indicate that demand-oriented routing optimization should be further linked with service-quality considerations [23,24]. However, due to the lack of passenger survey data and detailed timetable information, the present study focuses on aggregate peak-hour demand. Passenger-centered service-quality factors and strict service-time constraints are discussed as important directions for future model extensions rather than being incorporated as active constraints in the current formulation.

2.2. Methodological Evolution

Methodologies for solving the NP-hard HFVRP generally fall into two broad categories: exact algorithms and heuristic approaches [25]. Exact methods, such as Branch-and-Cut-and-Price, provide mathematically optimal solutions but suffer from exponential time complexity. Despite recent advances by Pessoa et al. [26], who successfully solved capacitated VRP instances with up to 275 nodes, these methods remain computationally prohibitive for practical, large-scale heterogeneous fleet applications requiring rapid decision-making. Consequently, the literature has been dominated by meta-heuristic algorithms, including Genetic Algorithms (GA), Ant Colony Optimization (ACO), and Adaptive Large Neighborhood Search (ALNS) [17,27]. While these nature-inspired methods can efficiently explore vast solution spaces, they are inherently stochastic and often lack mechanisms to guarantee local optimality within specific sub-regions. Ferreira et al. [28] noted that in highly constrained scenarios—such as those involving heterogeneous fleets and strict capacity limits—meta-heuristics frequently converge prematurely to local optima. To bridge the gap between the scalability of heuristics and the precision of exact methods, decomposition strategies have gained traction [29]. However, the efficacy of this strategy depends critically on the clustering technique. Traditional geometric clustering ignores road network topology. Conversely, graph-theoretic approaches like Minimum Spanning Trees (MST) capture the structural connectivity of the network but remain under-utilized in VRP contexts [30]. Furthermore, to avoid the "approximation error accumulation" common in pure heuristic frameworks, recent studies advocate for integrating exact algorithms to solve the resulting smaller sub-problems to optimality [31]. Therefore, this study proposes a Two-Stage Hybrid Algorithm that combines the structural advantages of a Modified Kruskal's Algorithm with the precision of State-Compressed Dynamic Programming (SC-DP). This framework ensures topological feasibility during the clustering phase and mathematical optimality during the routing phase, offering a deterministic and robust alternative to traditional stochastic meta-heuristics.

3. Mathematical Model

3.1. Problem Description and Related Assumptions

The problem addresses the optimization of a campus commuter service network, formally defined as a Multi-Destination Vehicle Routing Problem with Fleet Heterogeneity (MD-HFVRP). The network comprises a central depot (unified parking area), a set of distributed pickup stops, and multiple destination nodes (e.g., campus gates or teaching zones). The demand at each pickup stop is deterministic and must be fully serviced. The core decision involves selecting an optimal fleet composition from a candidate pool of heterogeneous vehicles—distinguished by capacity, energy consumption, and cost—and determining the optimal routing plan. The objective is to satisfy all commuting demands while simultaneously minimizing three conflicting goals: total fleet size, total travel distance, and total energy consumption.

To formulate the mathematical model without loss of generality, the following assumptions are established based on operational characteristics:

(I) Network Connectivity: The transportation network is modeled as a complete undirected graph where travel is possible between any pair of nodes.
(II) Service Mandate: All pickup stops must be visited exactly once by exactly one vehicle.
(III) Operation Mode: The model considers a single-trip operation mode (Depot to Pickup Stops to Destination). Return trips to the central depot are excluded from the optimization scope.
(IV) Fleet Constraints: In the baseline scenario, the fleet is limited to no more than three vehicle types to control maintenance, charging, and dispatching complexity.
(V) Capacity Constraints: Vehicles must strictly adhere to maximum passenger capacity limits; overloading is prohibited.
(VI) Energy Linearity: Energy consumption is estimated using route distance and vehicle-type-specific energy-consumption coefficients. This linear formulation is used as an operational-level approximation, while detailed speed- and load-dependent energy dynamics are discussed as limitations.

3.2. Model and Symbol Explanation

The sets, parameters, and decision variables used in the mathematical model are summarized in Table 1.

Table 1. Notation summary.

Symbol	Explanation
Indices	
ij	Indices for all nodes (including pickup stops, depot, and destinations)
$\mathcal{N}$	Set of all nodes, including depot, pickup stops, and destinations
$\mathcal{P}$	Set of pickup stops
$\mathcal{D}$	Set of destination nodes
$\mathcal{K}$	Set of candidate vehicle types
k	Index for candidate vehicle types $k = 1, 2, \ldots 10$
Parameters	
E_k	Energy consumption per 100 km for vehicle type k
w_1, w_2, w_3	Weighting factors for fleet size, distance, and energy objectives, In the baseline scenario, $w_1 = 0.4$, $w_2 = 0.2$, $w_3 = 0.4$
Q_k	Maximum passenger capacity of vehicle type k
d_{ij}	Travel distance from node i to node j
q_i	Number of passengers at pickup stop i
Decision Variables	
y_k	$y_k = \begin{cases} 1, \text{if vehicle type } k \text{ is selected} \\ 0, \text{otherwise} \end{cases}$
x_{ij}^k	$x_{ij}^k = \begin{cases} 1, \text{if vehicle type } k \text{ travels from } i \text{ to } j \\ 0, \text{otherwise} \end{cases}$
u_{ik}	Continuous variable: Cumulative passenger load of vehicle type k upon arriving at node i
$K_{\max}$	Maximum number of vehicle types allowed in the baseline fleet-composition scenario
M	A sufficiently large positive constant used in the MTZ capacity and subtour-elimination constraints

Based on the definitions above, the multi-objective Mixed Integer Linear Programming (MILP) model is formulated as follows.

The objective function minimizes the weighted sum of the total fleet size, total travel distance, and total energy consumption. To improve the interpretability and reproducibility of the multi-objective model, the three objective terms were normalized before weighted

aggregation. In the baseline scenario, the weighting factors were set as $w_1 = 0.4$, $w_2 = 0.2$, and $w_3 = 0.4$, corresponding to fleet size, total travel distance, and energy consumption, respectively. Fleet size was assigned a slightly higher weight because it directly affects vehicle purchase, depot parking, charging management, and driver scheduling in campus commuter operations. Travel distance and energy consumption were assigned equal weights because they jointly represent operational efficiency and environmental performance in campus commuter operations. Since the weighting factors directly reflect the decision-maker's operational preference, different weight settings may lead to different trade-offs among fleet size, route length, and energy consumption. A larger w_1 tends to reduce the number of dispatched vehicles, while a larger w_3 gives higher priority to energy saving. In this study, the selected weights reflect the practical priority of reducing fleet size while maintaining distance and energy efficiency. A full quantitative sensitivity analysis of weighting factors will be further examined in future research.

$$\min Z = w_1 \frac{N_v}{N_v^{\max}} + w_2 \frac{D}{D^{\max}} + w_3 \frac{E}{E^{\max}} \tag{1}$$

where

$$N_v = \sum_{k \in K} \sum_{j \in P} x_{0j}^k \tag{2}$$

$$D = \sum_{k \in K} \sum_{i \in N} \sum_{j \in N} d_{ij} x_{ij}^k \tag{3}$$

$$E = \sum_{k \in K} \sum_{i \in N} \sum_{j \in N} e_k d_{ij} x_{ij}^k \tag{4}$$

Equation (4) is used as a linear operational-level energy estimate based on route distance and vehicle-type-specific energy-consumption coefficients. Detailed speed- and load-dependent EV energy dynamics are not explicitly modeled in this study and are discussed as limitations in Section 6.

Subject to:

(i) Flow Conservation: Each pickup stop j must be serviced exactly once by exactly one vehicle.

$$\sum_{k \in \mathcal{K}} \sum_{i \in \mathcal{N}, i \neq j} x_{ij}^k = 1, \ \forall j \in \mathcal{P} \tag{5}$$

(ii) Flow Balance: For any intermediate node (pickup stop), the number of incoming vehicles must equal the number of outgoing vehicles.

$$\sum_{i \in \mathcal{N}} x_{ij}^k - \sum_{l \in \mathcal{N}} x_{jl}^k = 0, \ \forall j \in \mathcal{P}, \forall k \in \mathcal{K} \tag{6}$$

(iii) Depot and Destination Constraints: Every vehicle leaving the depot must eventually arrive at a destination to complete the service.

$$\sum_{j \in \mathcal{P}} x_{0j}^k = \sum_{i \in \mathcal{P}} \sum_{d \in \mathcal{D}} x_{id}^k, \ \forall k \in \mathcal{K} \tag{7}$$

(iv) Capacity Constraints (Miller-Tucker-Zemlin (MTZ) Formulation): These constraints ensure that the vehicle load does not exceed capacity and simultaneously eliminate subtours.

$$u_{jk} \geq u_{ik} + q_j - M(1 - x_{ij}^k) + M(1 - y_k), \ \forall i, j \in \mathcal{P}, \forall k \in \mathcal{K} \tag{8}$$

$$q_i \leq u_{ik} \leq Q_k, \ \forall i \in \mathcal{P}, \forall k \in \mathcal{K} \tag{9}$$

(v) Fleet Composition Constraints: In the baseline scenario, the number of selected vehicle types is limited to no more than $K_{\max}$. In this study, $K_{\max} = 3$ is adopted to control maintenance, charging management, and dispatching complexity.

$$\sum_{k \in \mathcal{K}} y_k \leq K_{\max} \tag{10}$$

(vi) Logical Constraints: A vehicle type k can only perform trips if it is selected in the fleet composition.

$$x_{ij}^k \leq M \cdot y_k, \ \forall i, j \in \mathcal{N}, \forall k \in \mathcal{K} \tag{11}$$

(vii) Variable Domains:

$$x_{ij}^k, y_k \in \{0, 1\}, \ u_{ik} \geq 0 \tag{12}$$

4. Case Study and Data Preprocessing

4.1. Case Description and Network Configuration

The case study is based on an anonymized campus commuter network. The studied network contains 100 nodes, including one central depot, three destination nodes, and 96 pickup stops. The passenger-demand dataset contains 288 observation records collected from the 96 pickup stops. The demand value of each pickup stop is represented by observed aggregate passenger demand. The original geographic coordinates are anonymized and normalized for privacy protection, while the relative spatial structure and travel-distance relationships are retained for model validation. The edge weights between nodes represent travel distances, which are used for route optimization and energy-consumption estimation.

The empirical validation of the proposed MD-HFVRP model is conducted using a real-world dataset derived from a large-scale comprehensive educational campus. This campus integrates elementary, middle, and high school zones, serving a total population of approximately 10,000 students and staff. Due to institutional data-management and privacy requirements, the exact campus name and original geographic coordinates are anonymized. However, the network structure and demand information are preserved for model validation. The studied commuter network consists of one central depot, three destination nodes, and 96 pickup stops. The node coordinates used in the experiment are normalized representations of the campus network rather than purely synthetic data. The edge weights represent travel distances between nodes, and the demand at each pickup stop is derived from observed peak-hour commuter passenger flows. The internal transportation network is modeled as a weighted undirected graph comprising 100 discrete nodes, indexed from 0 to 99. The node set is categorized as follows:

Central Depot (Node ID 5): A single unified facility responsible for vehicle parking, maintenance, and dispatching. All routes originate from this node.

Destinations (Node IDs 10, 30, and 80): These nodes represent key drop-off locations, such as main campus gates or primary teaching building clusters, which serve as the sinks for the commuter flow.

Pickup Stops (96 Nodes): The remaining 96 nodes represent distributed pickup locations scattered across residential dormitories and functional areas.

To address the highly fluctuating and diverse commuting demands, this study employs a heterogeneous fleet strategy rather than a homogeneous one. The candidate pool consists of 10 distinct vehicle types. As detailed in Table 2, these vehicles exhibit significant variations in operational parameters: the maximum passenger capacity (Q_k) ranges from 15 to 60 persons, while the energy consumption rate (E_k) varies linearly from 22 to 40 kWh per 100 km. This fleet diversity is critical, as it allows the optimization algorithm to flexibly

match vehicle types to specific route densities—assigning larger vehicles to high-demand clusters and smaller vehicles to sparse areas—thereby balancing capacity utilization with energy efficiency.

Table 2. Candidate campus electric commuter vehicle types and nominal operating parameters.

Carrying capacity (unit: people)	60	55	50	45	40	35	30	25	20	15
Energy consumption (unit: kWh)	40	38	36	34	32	30	28	26	24	22

Note: The energy-consumption coefficients in this table represent nominal vehicle-type-specific parameters. They are not intended to imply that passenger capacity alone determines energy consumption. In actual operations, EV energy use may also be affected by route characteristics, passenger load, speed variation, and driving conditions.

4.2. Data Preprocessing and Outlier Analysis

Data quality is a prerequisite for the effective operation of the optimization model. A rigorous data cleaning process was applied to the raw passenger demand data collected from the 96 pickup stops. The dataset comprises 288 observation points representing peak-hour passenger flows. To ensure robustness against statistical anomalies, a Box Plot analysis was employed to examine the data distribution and identify potential outliers that could skew the model results. Descriptive statistics of the raw dataset indicate that the demand distribution is relatively concentrated, with the first quartile (Q_1) at 3.75 and the third quartile (Q_3) at 11.00. This results in an Interquartile Range (IQR) of 7.25, which reflects the spread of the middle 50% of the data. Based on the standard outlier detection criteria (Tukey's fences), the validity range is defined by the following lower and upper bounds:

$$LB = Q_1 - 1.5 \times IQR = 3.75 - 1.5 \times 7.25 = -7.125 \quad (13)$$

$$UB = Q_3 + 1.5 \times IQR = 11.00 + 1.5 \times 7.25 = 21.875 \quad (14)$$

The analysis confirmed that all 288 observation points fall strictly within the range of $(-\infty, 21.875]$. Since no data points exceed the upper bound, the dataset is deemed statistically valid and free of significant outliers. Consequently, the original data preserves its integrity and is suitable for direct application in the optimization model without further truncation or modification.

Figure 1 graphically verifies the data integrity. The upper and lower validity bounds, calculated via the IQR method (Equations (10) and (11)), are marked by the red and green dashed lines, respectively. It is evident that all 288 observation points (represented by blue dots) fall strictly within these thresholds, confirming that the dataset is free from statistical anomalies or extreme outliers that could distort the optimization results.

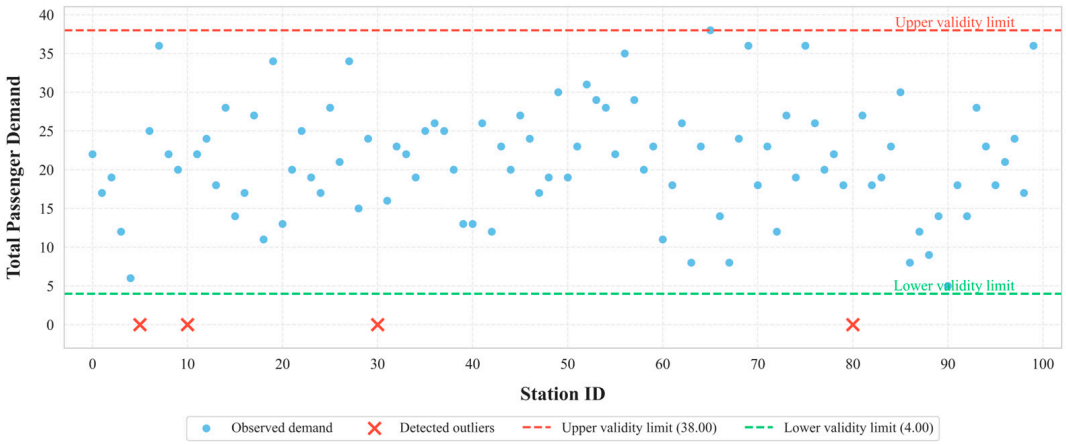


Figure 1. Outlier detection for observed passenger demand with lower and upper validity limits.

As illustrated in Figure 2, the spatial distribution of commuting demand is highly uneven. The visualization reveals distinct "hotspots" (indicated by larger, brighter nodes) primarily concentrated in the northeast sector, contrasting with the scattered, low-density demand in the southwest. This spatial heterogeneity necessitates the proposed traffic zoning strategy and justifies the deployment of a heterogeneous fleet to match capacity with local density. The 11-zone division is used as a case-specific decomposition strategy rather than a universal optimal zoning number. The zoning process considers geographic adjacency, passenger-demand distribution, and capacity-feasible clustering. Its purpose is to reduce the computational complexity of the subsequent routing optimization while preserving the spatial continuity of campus commuter demand.

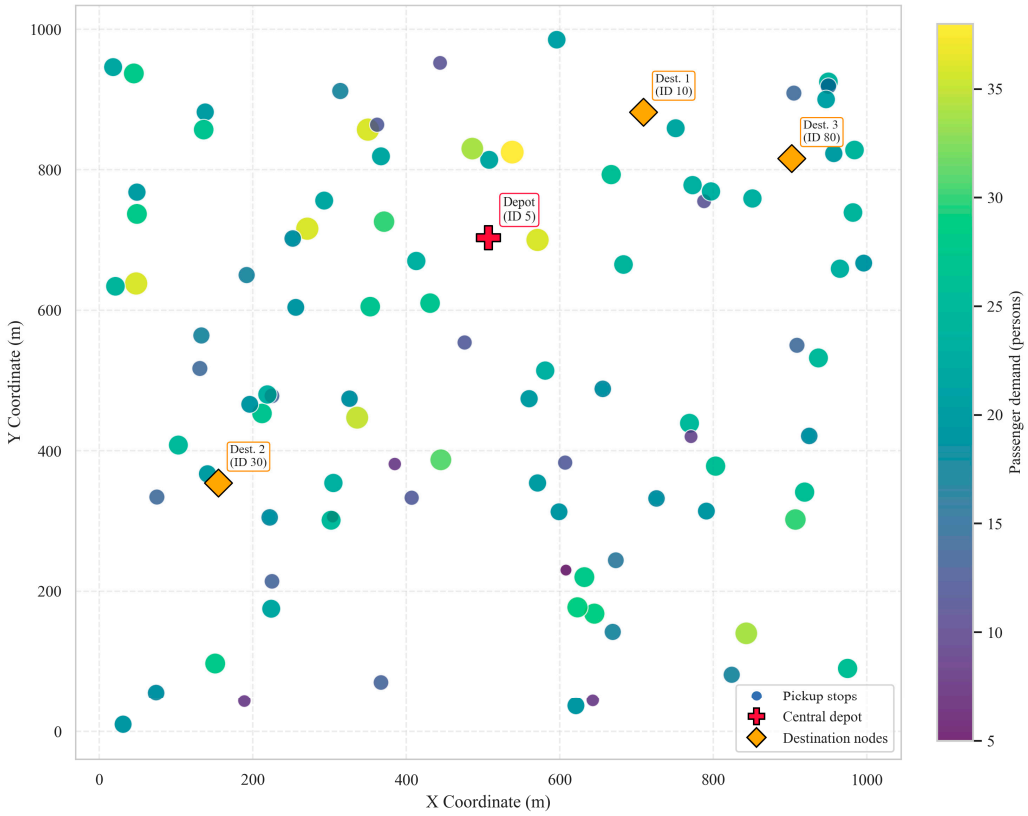


Figure 2. Passenger demand distribution, depot, and destination nodes in the campus commuter network.

Given the spatial complexity and high density of the 96 pickup stops, solving the routing problem globally without decomposition would lead to excessive computational complexity. Therefore, a traffic zoning strategy was implemented to facilitate the initial solution generation and improve the efficiency of the subsequent heuristic algorithm. This "divide and conquer" approach partitions the study area based on geographic coordinates, relative Euclidean distances, and passenger demand density. As illustrated in Figure 3, the campus was spatially divided into 11 distinct traffic zones. Each zone covers an average area of approximately 0.05 km^2 and contains an average of 9 geographically proximal pickup stops. This zoning visualization confirms that the partition respects the geographical clustering of stops, ensuring that stops within the same zone can be efficiently serviced by a single route or a cluster of routes, thereby significantly reducing the dimensionality of the problem.

Furthermore, analysis of the traffic expectation lines (as visualized in Figure 4) reveals significant spatial heterogeneity in commuting demand. The thickness of the lines in Figure 4 directly corresponds to the traffic flow intensity. It is evident that the lines

connecting the northeast region are notably thicker and denser, indicating a strong requirement for high-capacity vehicles. In contrast, the lines in the southwest region are relatively sparse and thin. This spatial insight provides a structural basis for the algorithm to apply differentiated fleet assignment strategies across different zones.

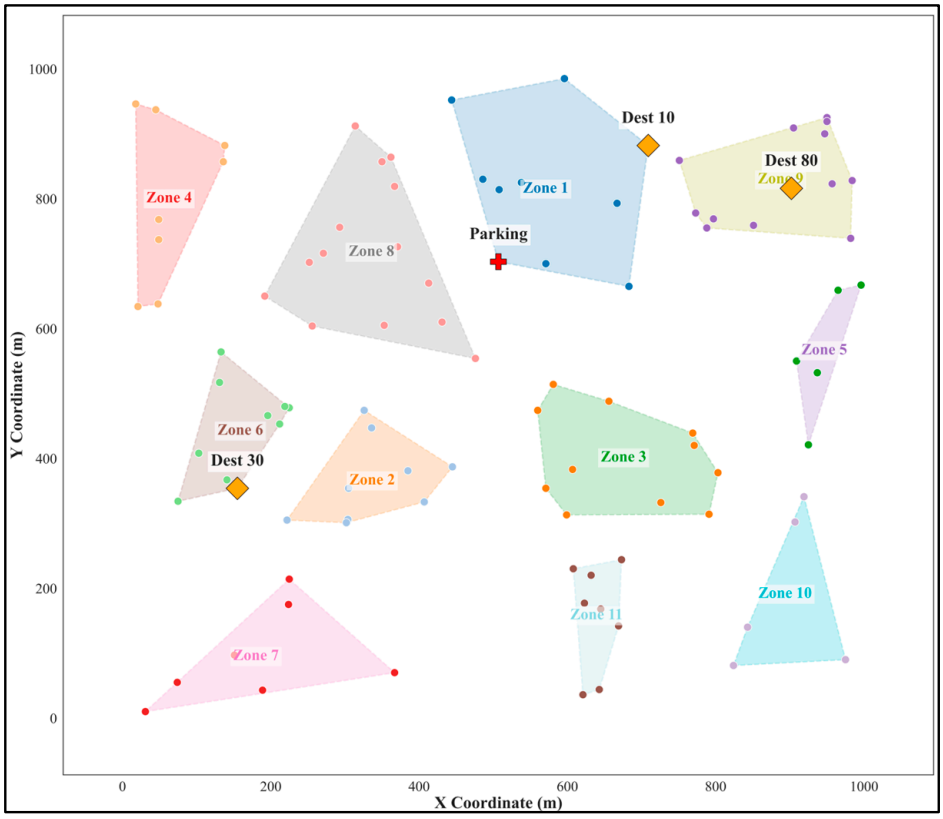


Figure 3. Traffic community zones.

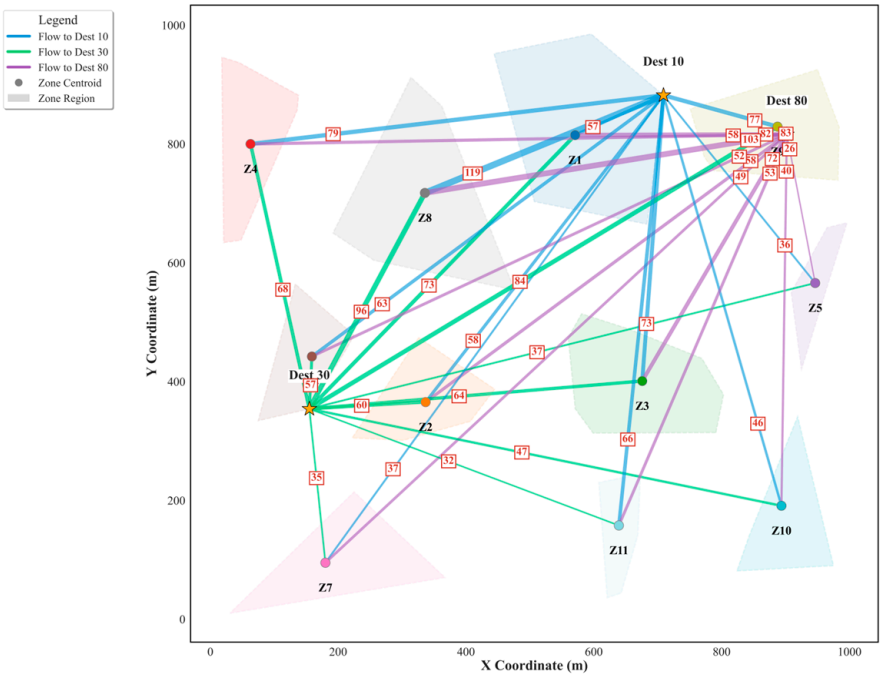


Figure 4. Expectation line diagram of campus commuter demand. Line thickness represents traffic-flow intensity, and star symbols indicate the destination nodes.

5. Solution Algorithm and Empirical Results

The MD-HFVRP model constructed in Section 3 belongs to the class of NP-hard problems, and given the network scale of 100 nodes, applying exact algorithms directly is computationally prohibitive. Consequently, this study adopts a "Cluster-First, Route-Second" strategy, implemented via a two-stage hybrid heuristic algorithm to decompose the global optimization problem into manageable sub-problems.

5.1. Clustering via Modified Kruskal's Algorithm

To simplify the solution space, the first phase focuses on merging dispersed pickup stops into feasible route groups using a clustering strategy. We utilize a Modified Kruskal's Algorithm, which extends the classic Minimum Spanning Tree (MST) approach by integrating specific capacity constraints. Let $G = (V, E)$ be the weighted undirected graph of a traffic zone. The algorithm initializes each pickup stop as an independent connected component and iterates through all edges in ascending order of their generalized cost, which combines both spatial distance and energy consumption. For each selected edge (u, v), if vertices u and v belong to different components, the algorithm attempts to merge them. A critical modification here is the capacity constraint check: a merge is considered valid if and only if the total accumulated demand of the newly formed component does not exceed the maximum capacity of the largest available vehicle type ($Q_{\max} = 60$). This process repeats until no further edges can be added without violating capacity or acyclic constraints, resulting in connected components that form the initial route clusters.

To clarify the clustering criterion used in the Modified Kruskal's Algorithm, the generalized edge cost between node i and node j is defined as a normalized weighted sum of spatial distance and estimated energy consumption:

$$C_{ij}^{K} = \gamma\left(\frac{d_{ij}}{d_{\max}}\right) + (1-\gamma)\left(\frac{\overline{E}_{ij}}{\overline{E}_{\max}}\right) \tag{15}$$

where C_{ij}^{K} denotes the generalized edge cost between nodes i and j, d_{ij} is the travel distance between the two nodes, and $\overline{E}_{ij}$ represents the estimated average energy consumption across the candidate vehicle pool. The denominators $d_{\max}$ and $\overline{E}_{\max}$ are the maximum values in the network and are used for normalization to avoid scale dominance. The parameter $\gamma \in [0, 1]$ is a balancing coefficient between spatial proximity and energy cost. In the baseline case, $\gamma = 0.5$ is adopted to give equal consideration to travel distance and estimated energy consumption during the clustering stage.

To improve the readability and reproducibility of the proposed method, Figure 5 provides an algorithmic flowchart of the two-stage heuristic framework. In the first stage, the campus network, node coordinates, observed passenger demand, depot, destination nodes, and candidate vehicle types are used to construct a weighted network and generate capacity-feasible traffic zones through Modified Kruskal-based clustering. In the second stage, State-Compressed Dynamic Programming is applied within each zone to optimize the visiting sequence, evaluate route distance and energy consumption, and select the appropriate vehicle type under passenger-capacity constraints. The final outputs include optimized routes, assigned vehicle types, fleet configuration, total travel distance, and total energy consumption.

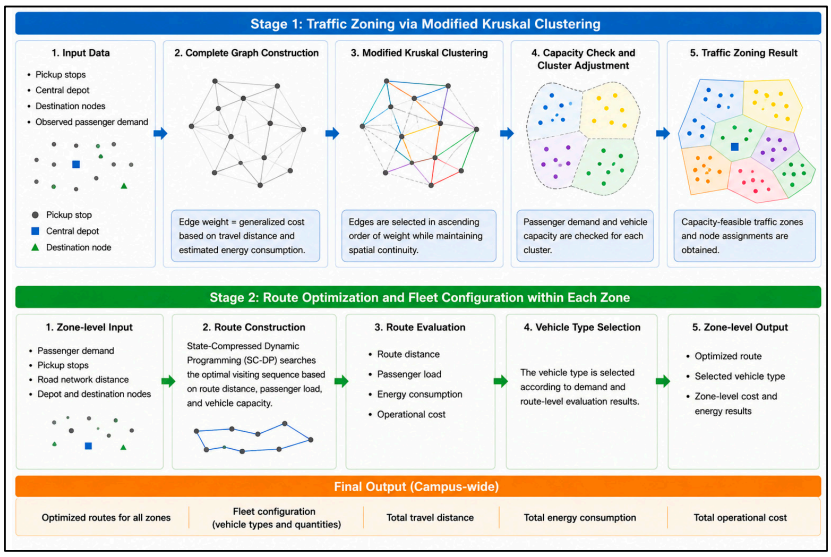


Figure 5. Flowchart of the proposed two-stage heuristic algorithm.

5.2. Intra-Route Optimization via State Compression DP

Dynamic Programming (DP) is a mathematical optimization method designed for solving multi-stage decision processes. Among its variants, SC-DP is a highly efficient algorithm specifically tailored for problems with exponential state spaces. By encoding a complex state into a binary number (bitmask), this approach not only reduces time complexity and computational duration but also optimizes memory usage. In a multi-stage decision process, the DP method decomposes the problem into interconnected stages, selects state and decision variables and defines an optimal value function. This transformation converts the original problem into a sequence of homologous sub-problems, which are solved sequentially. The optimal solution of the final sub-problem constitutes the optimal solution for the entire problem.

Once the feasible clusters are formed, the problem transforms into finding the optimal Hamiltonian path within each cluster. Since the number of nodes per cluster is relatively small (controlled by the zoning strategy described in Section 4), State-Compressed Dynamic Programming (SC-DP) is employed to obtain the exact optimal sequence efficiently. We define the state $dp[mask][i]$ as the minimum cost to visit the subset of nodes represented by the binary bitmask mask, ending at node i, The core transition equation is defined as

$$dp[mask \mid (1 \ll j)][j] = \min\{dp[mask][i] + c_{ij}\} \tag{16}$$

where node j is the next node to visit, $mask \mid (1 \ll j)$ represents the new state after visiting the j, c_{ij} represents the travel cost from i to j. The algorithm iterates until all nodes in the cluster are visited, finally connecting the last node to the optimal destination (Node 10, 30, or 80). For each optimized path, the algorithm calculates the total required capacity and compares the energy consumption across all 10 candidate vehicle types, ultimately selecting the specific vehicle k that minimizes the weighted objective function Z while satisfying the condition $Q_k \geq \sum_{v \in S} q_v$.

5.3. Empirical Results Analysis

The proposed two-stage heuristic algorithm was executed on the preprocessed dataset to validate the model's efficacy. The global optimal solution successfully dispatched a heterogeneous fleet of 41 vehicles to fully service the demand of all 96 pickup stops. In terms of operational compliance, the solution strictly adheres to all constraints; specifi-

cally, the passenger load of every route remains within the rated capacity of the assigned vehicle ($q_{route} \leq Q_k$), and the flow conservation constraints ensure that every stop is visited exactly once. Regarding energy efficiency, the aggregate results derived from the optimization model, as detailed in Table 3, indicate that the total energy consumption within the defined service-trip scope is 19.65 kWh, with the fleet covering a total travel distance of 52,206.45 m. The annual energy consumption is estimated as 5893.98 kWh based on 300 operating cycles, corresponding to approximately 150 school days and two commuter service cycles per school day. By utilizing a mix of vehicle capacities rather than a uniform fleet, the algorithm improves the average load factor and reduces the capacity slack and energy waste that may occur when low-demand zones are served by oversized vehicles. It should be noted that post-service return trips to the depot are not optimized in the current framework and will be incorporated in future closed-loop vehicle circulation modeling.

Table 3 presents the detailed routing schedule, enumerating the route sequence, passenger load, vehicle capacity, and energy consumption for each dispatched vehicle. A critical analysis of this data reveals the algorithm's precision in matching vehicle types (Q_k) with specific route demands. For routes serving the high-density northeast zones, such as Route 3 (Load: 58, Capacity: 60) and Route 34 (Load: 58, Capacity: 60), the algorithm assigns high-capacity vehicles. In these instances, the vehicle capacity utilization rate reaches approximately 96.7%, demonstrating that although these vehicles have a higher energy rate ($E_k = 40$), the high passenger throughput justifies the deployment. Conversely, for routes serving peripheral or scattered zones, such as Route 1 (Load: 33, Capacity: 45) and Route 4 (Load: 34, Capacity: 45), the model intelligently assigns smaller, more energy-efficient vehicles ($E_k = 34$). Had a standard 60-seat bus been assigned to these routes, it would have resulted in significant capacity redundancy and unnecessary energy expenditure. The simultaneous deployment of 45-seat, 55-seat, and 60-seat vehicles confirms the necessity of a heterogeneous fleet, allowing the system to flexibly adapt to the spatial heterogeneity of demand and achieve a balance between service quality and energy conservation.

The final routing plan is visualized in Figure 6, where trajectories are color-coded to distinguish between different vehicle assignments. The visualization exhibits clear clustering patterns that align with the traffic zones defined in Figure 4, confirming the effectiveness of the "Cluster-First" strategy in reducing problem complexity without sacrificing solution quality. Spatially, the routes demonstrate distinct characteristics based on regional demand: routes in the high-demand northeast regions are characterized by short, compact segments that efficiently connect neighboring stops. In contrast, routes in the low-demand southwest regions are more elongated and cover larger geographic distances to aggregate dispersed passengers. This visual evidence corroborates the numerical results, demonstrating that the model successfully optimizes the trade-off between minimizing travel distance and maximizing vehicle load factors across the entire campus network.

Table 3. Model solving results.

Route ID	Distance (m)	Route Sequence	Passenger Load (Passengers)	Capacity (Passenger/veh)	Energy Rate (kWh/100 km)	Energy Consumption (kWh)
1	368.13	5-27-0-65-10	33	45	34	0.1252
2	1203.21	5-39-64-45-50-89-1-10	42	45	34	0.4091
3	1742.86	5-13-19-98-62-2-36-88-35-10	58	60	40	0.6971
4	832.91	5-3-81-17-43-49-10	34	45	34	0.2832
5	1381.17	5-61-56-59-79-22-4-72-67-52-10	58	60	40	0.5525
6	2340.35	5-6-44-15-20-8-14-70-83-86-40-10	58	60	40	0.9361
7	1298.39	5-7-46-25-21-10	35	45	34	0.4415
8	1257.00	5-73-33-93-9-10	44	45	34	0.4274
9	749.67	5-11-75-87-47-60-26-10	41	45	34	0.2549
10	1030.45	5-71-48-68-97-58-96-28-12-66-10	53	55	38	0.3916

Table 3. *Cont.*

Route ID	Distance (m)	Route Sequence	Passenger Load (Passengers)	Capacity (Passenger/veh)	Energy Rate (kWh/100 km)	Energy Consumption (kWh)
11	931.95	5-74-16-95-69-55-10	51	55	38	0.3541
12	705.79	5-99-29-41-51-18-94-84-78-10	54	55	38	0.2682
13	1570.42	5-32-38-77-23-63-34-42-91-10	54	55	38	0.5968
14	1353.84	5-90-54-57-53-24-31-10	53	55	38	0.5145
15	1219.94	5-85-76-82-37-92-10	43	45	34	0.4148
16	1322.14	5-99-29-26-65-0-27-30	59	60	40	0.5289
17	863.69	5-39-64-45-50-1-89-6-15-44-30	57	60	40	0.3455
18	1797.57	5-35-88-36-13-2-19-62-98-30	52	55	38	0.6831
19	1141.87	5-32-91-38-3-81-43-49-17-30	60	60	40	0.4567
20	849.86	5-61-56-67-52-72-59-4-22-79-30	60	60	40	0.3399
21	930.30	5-21-25-7-46-30	40	45	34	0.3163
22	2214.85	5-68-48-71-40-86-83-70-14-8-20-30	58	60	40	0.8859
23	1170.92	5-73-9-93-33-30	28	45	34	0.3981
24	1110.55	5-60-47-87-75-11-55-69-95-16-74-30	60	60	40	0.4442
25	1558.62	5-66-12-28-96-97-58-30	47	55	38	0.5923
26	1267.34	5-41-78-51-94-84-18-30	43	45	34	0.4309
27	1409.02	5-42-77-34-31-54-90-57-53-24-63-23-30	51	55	38	0.5354
28	1449.89	5-92-37-82-76-85-30	38	45	34	0.4930
29	937.87	5-0-27-60-65-99-29-80	54	55	38	0.3564
30	1633.56	5-1-89-6-15-44-45-50-64-39-80	52	55	38	0.6208
31	1120.39	5-32-38-91-13-2-36-88-35-80	58	60	40	0.4482
32	942.08	5-43-49-17-81-3-80	43	45	34	0.3203
33	1446.98	5-61-56-59-79-22-4-72-67-52-80	58	60	40	0.5788
34	1737.97	5-7-46-25-21-33-93-9-73-80	58	60	40	0.6952
35	2119.74	5-20-8-14-70-83-86-40-80	49	55	38	0.8055
36	1311.84	5-74-16-95-69-55-11-75-47-87-80	60	60	40	0.5247
37	685.00	5-66-12-28-96-97-58-80	39	45	34	0.2329
38	847.48	5-41-26-78-51-18-94-84-80	58	60	40	0.3390
39	1817.62	5-23-63-98-19-62-80	34	45	34	0.6180
40	1361.92	5-42-77-34-90-54-57-53-24-31-80	59	60	40	0.5448
41	1171.30	5-85-76-82-37-92-71-48-68-80	54	55	38	0.4451
total	52,206.45		2040			19.6466

Note: Annual energy consumption is calculated based on 300 operating cycles per year.

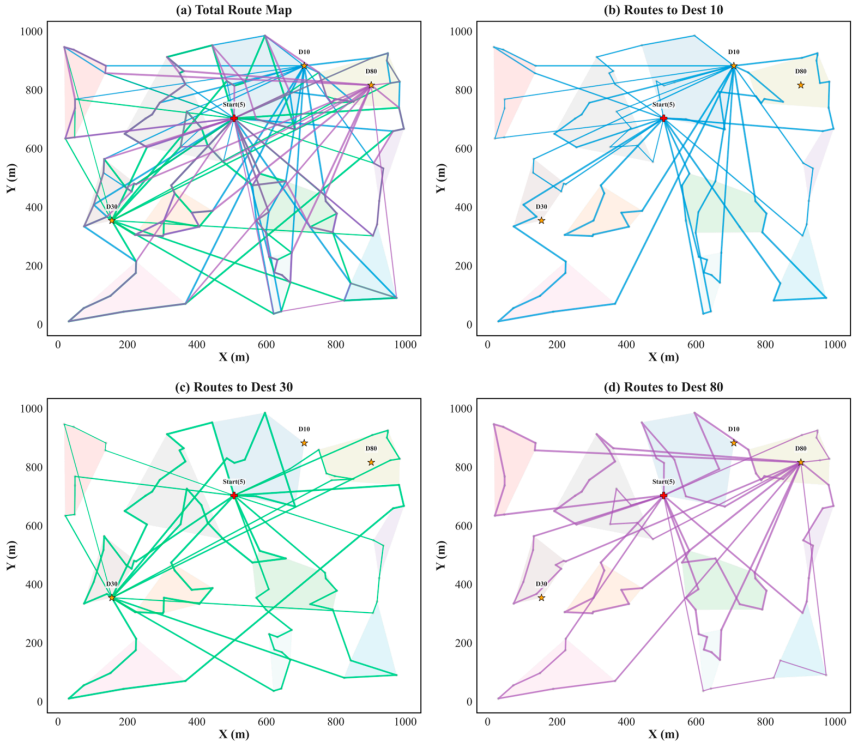


Figure 6. Commuter route map. Colored lines represent optimized commuter routes assigned to different vehicles, and shaded areas indicate the corresponding traffic zones.

5.4. Preliminary Comparison with ACO

To provide a preliminary benchmark for the proposed "Cluster-First, Route-Second" SC-DP methodology, a comparison with a classical Ant Colony Optimization (ACO) algorithm was conducted.

The ACO algorithm was configured to solve the global routing problem without prior traffic zoning. Based on standard parameter tuning, the algorithm was initialized with 30 ants and a maximum of 100 iterations. The information heuristic factor (α) was set to 1, the path visibility factor (β) was set to 5, and the pheromone evaporation coefficient (ρ) was specified as 0.8. The algorithm was allowed to select from the same candidate pool of 10 heterogeneous vehicle types to satisfy the passenger demand across all pickup stops.

The comparative performance metrics between the traditional ACO and the proposed two-stage hybrid approach are summarized in Table 4.

Table 4. Performance comparison.

Optimization Metric	Traditional ACO	SC-DP	Improvement
Total Fleet Size (Vehicles)	53	41	−22.6%
Annual Energy Consumption (kWh)	6492.00	5893.98	−9.2% (−598.02 kWh)

In the studied case, the global ACO baseline generated a more fragmented fleet configuration, dispatching 53 vehicles across 10 candidate vehicle types. In contrast, under the baseline fleet-management constraint of $K_{\max} = 3$, the proposed "Cluster-First, Route-Second" SC-DP framework generated a more compact fleet configuration with 41 vehicles. This result suggests that the decomposition-based strategy can improve the matching between regional demand and vehicle capacity in the studied campus scenario. In terms of energy consumption, the global ACO baseline produced an annual energy consumption of 6492 kWh, while the proposed framework achieved 5893.98 kWh under the same case setting, corresponding to a 9.2% reduction. This improvement may be partly attributed to the traffic-zoning decomposition and the exact route optimization within each cluster. However, it should be noted that the ACO baseline was implemented as a global benchmark, whereas the proposed method adopts a decomposition-based strategy. Therefore, this comparison should be interpreted as a preliminary case-study benchmark rather than a complete proof of general algorithmic superiority. More systematic comparisons using zoned ACO, repeated stochastic runs, computational runtime statistics, and standard VRP benchmark instances will be conducted in future research.

6. Conclusions

This study formulated a Multi-Destination Heterogeneous Fleet Vehicle Routing Problem (MD-HFVRP) for campus commuter service optimization and developed a two-stage "Cluster-First, Route-Second" heuristic framework. The proposed method combines Modified Kruskal-based traffic zoning with State-Compressed Dynamic Programming (SC-DP) to address the computational complexity caused by large-scale networks and spatially heterogeneous passenger demand. The empirical results from an anonymized campus case show that the proposed method decomposes 96 pickup stops into 11 traffic zones and generates capacity-feasible routes with appropriate vehicle-type assignments. The optimized solution dispatches a mixed fleet of 41 vehicles with capacities of 45, 55, and 60 passengers. High-capacity vehicles are mainly assigned to dense-demand zones, while smaller vehicles serve relatively scattered demand areas, helping reduce capacity slack and improve vehicle–capacity matching. The optimized system consumes 19.65 kWh per operating cycle, corresponding to an estimated annual energy consumption of 5893.98 kWh under the assumption of 300 operating cycles. Compared with a global ACO baseline in this case

study, the proposed framework reduces the fleet size by 22.6% and annual energy consumption by 9.2%. However, this comparison should be interpreted as a preliminary case-study benchmark rather than a complete proof of general algorithmic superiority, because the proposed method adopts a decomposition-based optimization strategy.

Several limitations remain. Battery-feasibility constraints, SOC evolution, en-route charging decisions, and service-time constraints are not included as active constraints in the current formulation because the required case-specific parameters are unavailable; these elements are therefore restated as future modeling intentions rather than active constraints. In addition, the current energy-consumption model is an operational-level approximation based on route distance and vehicle-type-specific energy-consumption coefficients, and the empirical validation is limited to one anonymized campus and peak-hour demand. Future research will incorporate battery-capacity constraints, SOC evolution, charging scheduling, service-time estimation, stochastic demand, dynamic traffic conditions, service-quality indicators, and broader benchmark instances to improve the operational realism and generalizability of the framework [32].

Author Contributions: The authors confirm contribution to the paper as follows: X.Y.: Writing—original draft, Investigation. L.W.: Conceptualization, Writing—review & editing, Supervision. X.Z.: Methodology, Data curation. M.Y.: Formal Analysis. L.H.: Software, Visualization. Q.C.: Validation. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the National Key Research and Development Program of China (2020YFB1600500).

Data Availability Statement: The data supporting the findings of this study are not publicly available due to institutional data-management requirements and privacy restrictions related to the anonymized campus commuter case. The data are available from the corresponding author upon reasonable request and with permission from the relevant institution.

Conflicts of Interest: Ming Yang is an employee of Nanjing Institute of City & Transport Planning Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ACO	Ant Colony Optimization
ALNS	Adaptive Large Neighborhood Search
DP	Dynamic Programming
GAs	Genetic Algorithms
GVRP	Green Vehicle Routing Problem
HFVRP	Heterogeneous Fleet Vehicle Routing Problem
IQR	Interquartile Range
MD-HFVRP	Multi-Destination Vehicle Routing Problem with Fleet Heterogeneity
MD-VRP	Multi-Destination Vehicle Routing Problem
MILP	Mixed-Integer Linear Programming
MST	Minimum Spanning Tree
MTZ	Miller–Tucker–Zemlin
SC-DP	State-Compressed Dynamic Programming
SDGs	Sustainable Development Goals
VRP	Vehicle Routing Problem

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