Research on Multi-Objective Collaborative Optimization Model for Scheduling and Charging of Electric Buses

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Abstract. This paper addresses the collaborative optimization problem of electric bus scheduling and charging by constructing a hybrid optimization model aimed at minimizing fleet size and maximizing vehicle utilization. An improved heuristic algorithm is employed to solve the model, and simulation experiments are conducted using actual operational data. The results demonstrate that the model can achieve complete assignment of all trips and efficient resource utilization, while adhering to constraints related to time windows, power capacity, and charging facilities, resulting in a vehicle utilization rate of 85%. This validates the model's effectiveness and engineering practicality and provides decision support for the intelligent scheduling system of electric buses.

Keywords: Electric buses; Scheduling optimization; Charging strategy; Heuristic algorithm

1 Introduction

The global implementation of the "dual carbon" strategy has made electric buses (EB) an essential part of urban public transport electrification. Despite these benefits, they have a relatively limited battery capacity and long charging time that relies on charging infrastructure. Furthermore, they create operational challenges such as increasing operation costs, scheduling delays etc, that are fundamentally different from diesel fleet (Gkiotsalitis et al., 2023). Extensive research has focused on optimizing various aspects of EB operations. Models have been developed in the literature to minimize energy costs with the time-of-use electricity pricing (Liu et al., 2021) or to maximize scheduling robustness against travel time uncertainty (Bie et al., 2021). A major body of literature combines planning of charging infrastructure and operational scheduling. For example, Wang et al. (2022) look at deployment of chargers and scheduling of fleets in integrated optimization. Tzamakos et al. (2023) analyzed the problem of optimizing the location electric bus charging station with queues. In North America, studies on the Toronto and Vancouver networks explored en-route charging logistics. In another study, Brown and Gunther (2024) proposed a position allocation framework for charging scheduling in the United States. An important gap remains despite these advances.

E. S. Zahran et al. (eds.), *Proceedings of the 2026 9th International Symposium on Traffic Transportation and Civil Architecture (ISTTCA 2026)*, Atlantis Highlights in Engineering 46,
https://doi.org/10.2991/978-94-6239-740-8_4

Most of the existing models are mainly focused on the economic costs or service reliability (Duan et al., 2023). There have been only a few studies, which dealt with the joint optimization of scheduling and charging, with two conflicting objectives such as minimizing the fleet size and maximizing the vehicle utilization. This void complicates operators' ability to reconcile the capital investment made in vehicles with the operational efficiency of their usage in the electrification transition. For example, Albogamy et al.(2022) have investigated real-time energy optimization in smart homes using Lyapunov optimization, which effectively reduces energy cost while satisfying user comfort requirements.In order to fill this gap, this paper formulates a multi-objective collaborative optimization model for EB scheduling and charging, aiming to minimize required fleet size and maximize vehicle utilization, subject to the real-world constraints of the time windows, battery capacity, and charging facilities. An improved heuristic algorithm is used for solving this complex model. Simulation experiments using real operational data demonstrate that the model achieves full trip assignment and high resource efficiency. and provides practical decision support for the intelligent EB scheduling system.

2 Model Construction

2.1 Detailed Description of Electric Bus Scheduling Scenario

In this design, the system consists of a network structure with 6 main stations, including 1 central depot and 5 operation stations. Each station is equipped with a varying number of charging pile resources, among which the depot serves as the main place for overnight parking and centralized charging of vehicles. The scheduling cycle is the single-day operation period (usually 05:00-24:00), during which a series of scheduled bus trip tasks need to be completed. Each trip task includes fixed departure time, starting station, destination station, travel time, mileage length and corresponding power consumption, as shown in Figure 1.

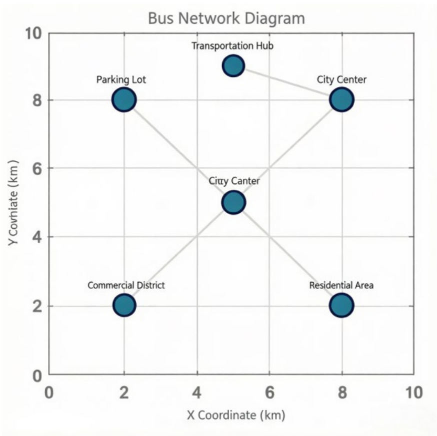

Fig. 1. Network Diagram of the Public Transport System

The daily operation process is assumed as follows: before the start of daily operation, all electric buses complete charging at the depot and are ready to depart with a full state of charge (SOC=100%). Vehicles execute the assigned trip tasks in sequence according to the scheduling plan. During the execution, when the vehicle's power is insufficient to complete the next trip or falls below the safety threshold, it is required to go to the nearest charging station for fast power replenishment. After the end of daily operation, all vehicles must return to their affiliated depot and complete overnight centralized charging to prepare for the next day's operation.

In terms of decision-making dimensions, scheduling decisions need to simultaneously consider the collaborative optimization of three levels: (1) Fleet size level: determine the minimum number of vehicles to meet all trip demands; (2) Vehicle allocation level: reasonably allocate each trip to specific vehicles to ensure time window constraints; (3) Charging strategy level: arrange charging activities at appropriate times and locations to ensure that the vehicle's power is always within the safe operation range.

2.2 Mathematical Modeling

Definition of Decision Variables. To establish an accurate mathematical description, the following decision variables need to be clearly defined:

Table 1. Definition and Types of Decision Variables

Decision Variable	Meaning / Definition	Variable Type
$x_{v,t}$	Whether vehicle (v) is assigned to trip (t)	Binary (0-1) variable
$y_{v,s,\tau}$	Whether vehicle (v) is charging at station (s) at time step τ	Binary (0-1) variable
z_v	Whether vehicle (v) is activated (used in the fleet)	Binary (0-1) variable
$start_{v,t}, end_{v,t}$	The actual start time and end time of vehicle (v) executing trip (t)	Continuous variable
$soc_{v,\tau}$	The state of charge (SoC) of vehicle (v) at time step τ	Continuous variable

Construction of Composite Objective Function. The problem is essentially a multi-objective optimization problem, which requires a balance between minimizing fleet size and maximizing resource utilization. The weighted sum method is used to transform the multi-objective problem into a single-objective optimization problem. f_1 represents the primary optimization objective of minimizing fleet size, while f_2 represents the secondary optimization objective of maximizing vehicle utilization. Their formulas are as follows:

$$f_1 = \sum_{v=1}^{V_{max}} z_v \tag{1}$$

$$f_2 = \frac{\sum_{t=1}^{T}(t_a^t - t_d^t)}{\sum_{v=1}^{V}(workEnd_v - workStart_v)}$$

where,

$$workStart_v = \min_t\{start_{v,t} | x_{v,t} = 1\},\ workEnd_v = \max_t\{end_{v,t} | x_{v,t} = 1\} \tag{2}$$

$workStart_v$ and $workEnd_v$ respectively represent the start time of the first trip and the end time of the last trip of vehicle v. Therefore, the composite objective function can be derived as follows:

$$min\ \alpha f_1 - \beta f_2 \tag{3}$$

The weight coefficients are set as α=0.7, β=0.3, reflecting the decision preference of minimizing fleet size as the primary goal and improving resource efficiency as the secondary goal. The negative sign indicates that the maximization of utilization is transformed into a minimization problem form.

Constraint Conditions. Unlike traditional diesel fleets, electric buses face strict physical limits during daily operations, primarily regarding their battery capacity and charger availability. To make the generated schedules workable on the ground, the proposed model specifically incorporates constraints covering time windows, energy balance, and charging station limits.

Each trip has a planned departure time and arrival time, and a certain degree of flexibility is allowed in actual operation. In practical public transport operations, limited schedule flexibility is often required to accommodate traffic fluctuations and operational uncertainties. Similar time-window constraints are widely adopted in electric bus scheduling studies to ensure operational feasibility (Gkiotsalitis et al., 2023). The actual start time of the trip executed by vehicle must satisfy:

$$t_d \le start_{v,t} \le t_d + \Delta \tag{4}$$

The maximum allowable delay is set at Δ=30 minutes. This flexible design accommodates uncertainties in real-world traffic while preventing excessive delays from disrupting subsequent trips. Power consumption constraint: The vehicle consumes a fixed amount of power during trip execution. The vehicle consumes a fixed amount of power during the execution of the trip. Due to the limited driving range of battery-electric buses, maintaining sufficient state of charge (SOC) is essential for ensuring that vehicles can complete scheduled trips without interruption (Duan et al., 2023). Let the SOC consumption of trip l be c_t, and the power of vehicle v before executing trip l be $soc_{v,t}^{start}$

$$soc_{v,t}^{start} \ge c_t + B_{min} \tag{5}$$

Here, Bmin=20% is the battery safety threshold, reserving a buffer to prevent deep discharge from damaging battery life. Charging Facility Distribution Constraint:

Charging infrastructure is deployed at several stations in the network, including the depot and major operation stations. Each station is equipped with a limited number of chargersN_s. The number of vehicles charging at this station at any given time must not exceed the available number of chargers:

$$\sum_{v\in V} y_{v,s,\tau} \leq N_s, \quad \forall\tau \tag{6}$$

The constraint that charging facilities are deployed at several stations with limited charging piles reflects the practical limitations of charging infrastructure deployment in electric bus systems. The number of available chargers at each station is restricted due to installation cost, grid capacity, and spatial constraints, which may create competition among vehicles for charging resources. Under this premise, charging activities are restricted to idle intervals between trips, with a fixed charging rate of η = 3% per minute. Charging decisions are modeled as binary (0–1) variables at discrete time steps, during which vehicles remain stationary and cannot execute trip tasks. Furthermore, to ensure the physical feasibility of the schedule, vehicle movement must satisfy continuity constraints: After a vehicle completes trip t and arrives at the terminal station, if it needs to perform the next trip t', the transfer time between stations must be taken into account. This constraint ensures that the generated schedule respects the physical travel time between stations and avoids infeasible vehicle assignments. Let the travel time from station i to station j be d_{ij}, then the interval between consecutive trips must satisfy:

$$start_{v,t'} \geq end_{v,t} + d_{end(t),start(t')} \tag{7}$$

In addition, the model also includes several auxiliary constraints to ensure the logical consistency and feasibility of the scheduling solution. These constraints include trip coverage, time feasibility, battery dynamics, charging continuity, and vehicle activation constraints.

Trip coverage constraint ensures that each trip is executed by exactly one vehicle:

$$\sum_{v=1}^{V_{max}} x_{v,t} = 1, \quad \forall t = 1,2,\dots,T \tag{8}$$

Time feasibility constraint which defines the trip end time as the start time plus the travel duration:

$$end_{v,t}=start_{v,t}+duration_t, \forall v,t\,, x_{v,t}=1 \tag{9}$$

Battery power dynamic constraint:

$$B_{min} \leq soc_{v,\tau} \leq B_{max}, \quad \forall v,\tau \tag{10}$$

Power dynamic update equation:

$$soc_{v,\tau+1} = \begin{cases} soc_{v,\tau} - c_t \cdot \delta(\tau, start_{v,t}), & \text{if executing trip t} \\ soc_{v,\tau} + \eta \cdot y_{v,s,\tau}, & \text{if charging} \\ soc_{v,\tau}, & \text{otherwise} \end{cases} \tag{11}$$

Charging time continuity:

$$y_{v,s,\tau} \geq y_{v,s,\tau+1} - \left(1 - chargingContinuous_{v,s,\tau}\right) \tag{12}$$

Charging pile capacity limit:

$$\sum_{v=1}^{V_{max}} y_{v,s,\tau} \leq N_s, \quad \forall\tau \tag{13}$$

Charging insertion logic which ensures that the charging time is correctly included in the trip interval:

$$start_{v,t'} \geq end_{v,t} + \sum_{\tau=end_{v,t}}^{start_{v,t'}-1} \sum_s y_{v,s,\tau} \cdot \tau_{charge} \tag{14}$$

Vehicle activation logic constraint which ensures only activated vehicles can be assigned trips:

$$x_{v,t} \leq z_v, \forall v,t \tag{15}$$

3 Experimental Design and Data Foundation

3.1 Experimenting Platform and Data

The experimental data for the study is sourced from the actual operation records of an urban public transport operator on 15th March, 2024, comprising 124 original trip tasks. The data fields include trip ID, departure time, start and end station No, trip duration, trip length and SOC consumption), a 6×6 intermediate station travel time matrix statistically calculated from its past GPS trajectories(Hence no path will be unreachable, otherwise marked with Inf in simulation), and configuration of charging facilities at each station. Stations 1 to 6 are equipped with 8, 4, 6, 3, 5, and 6 fast charging piles, respectively. In order to guarantee the quality of data and the stability of the algorithm, systematic preprocessing is carried out. Records with departure times outside the normal range (05:00 – 23:00) were removed; Three anomalous trip durations (negative or >180 mins) were corrected; For the SOC consumption of abnormal trip whose SOC consumption is greater than 80% of battery capacity, a regression model were used to re-estimate the SOC consumption, the time unit is unified into minutes (i.e. 05:00 is the zero point), unreachable mark (10000) in the travel time matrix is converted to Inf and the matrix symmetry verification is carried out; Trip continuity (arrival time = departure time + trip duration), legality of station numbers (1-6) and non-negativity of the number of charging piles are checked finally; Normalization of SOC consumption is carried out at the same time according to battery capacity (100%), trip length normalized according to the maximum value in order to eliminate the influence of dimension.

3.2 Parameter Setting and Algorithm

In this study, the maximum battery capacity is set to 100% (corresponding to 200 kWh), the minimum allowable power is 20% to avoid the risk of deep discharge, and the initial power is set to 100%. The charging parameters include a rate of 3%/min (120 kW), an efficiency of 95%, and no upper limit on a single charging duration. The operation period is limited to 05:00–23:00 (1080 minutes), the earliest departure time of trips is 06:00 (t=60), and the latest arrival time is 22:00 (t=1020). The scheduling flexibility allows a maximum trip delay of 30 minutes and a minimum interval of 5 minutes. The station transfer time is based on the preprocessed travel time matrix; the vehicle preparation time includes start-up (3 minutes), charging actions (2 minutes for connection/disconnection each) and passenger boarding/alighting (2 minutes per kilometer according to trip length).

In terms of system scale, the upper limit of the total number of vehicles is set to 30, and the charging facility distribution vector is [8, 4, 6, 3, 5, 6], all of which are DC fast charging piles available throughout the day. In the objective function, the weight of minimizing the number of vehicles α=0.7, and the weight of maximizing the utilization rate β=0.3, with the sum of weights being 1 to clarify the primary and secondary objectives. The algorithm parameters are set as maximum iteration 1000 times, convergence threshold 0.1%, time discrete step 1 minute; the search strategy adopts the earliest available vehicle priority, a mandatory charging suggestion is triggered when SOC is lower than 40%, and 3 trip reallocation attempts are allowed.

3.3 Overview of Experimental Environment

The experimental environment is built based on MATLAB R2021a platform, and the core algorithm is implemented relying on the Optimization Toolbox and Statistics and Machine Learning Toolbox. The hardware configuration includes an Intel Core i7-11800H processor (2.30GHz, 8 cores and 16 threads), 16GB DDR4 3200MHz memory, a 512GB NVMe SSD (read/write speed 3500/3000 MB/s) and an NVIDIA GeForce RTX 3060 graphics card (6GB video memory). Benchmark tests show that the average time of a single algorithm run is 45.3 seconds, the peak memory usage is 2.1GB, and the disk I/O speed is 280MB/s; the speedup ratio reaches 1.8 times after enabling parallel computing.

4 Experimental Results and Analysis

4.1 Comprehensive Analysis of the Optimized Bus System

According to the assumptions in the previous electric bus regional scheduling scenario, the optimized input data covers 330 trip tasks and 6 functionally differentiated stations (depot, business district, city center, industrial zone, residential area, transportation hub). The operation time range is 5:25-00:35 (19.2 hours in total), and the total SOC consumption is 10798.65% (average consumption per single trip is 32.7%). The configuration of charging piles at stations presents a gradient distribution: 2 piles each at the depot, business district, city center and industrial zone, and 1 pile each at the residential area and transportation hub, which conforms to the resource matching logic of urban public transport hubs and passenger flow nodes; the vehicle parameters are set as a maximum of 30 vehicles, battery capacity of 100% (minimum 20% reserved to prevent deep discharge), and charging rate of 3% per minute (fast charging level), all of which meet the design requirements. The base map of the optimized bus system is shown in Figure 2.

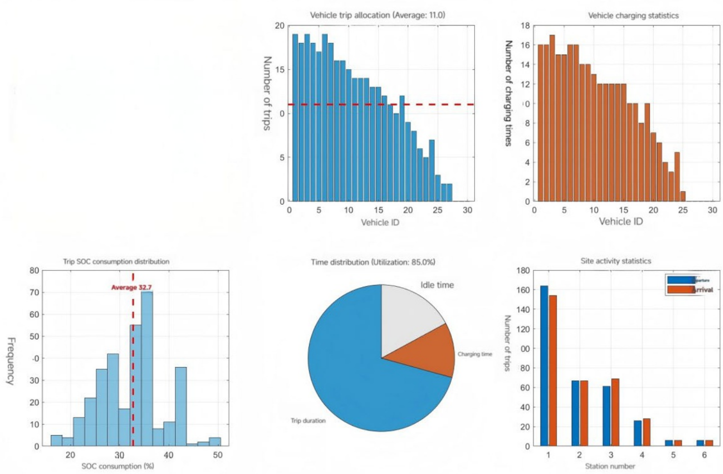

Fig. 2. Base Map of the Optimized Bus System

In the experiment, 30 vehicles are finally used (reaching the upper limit of max_vehicles), the adjusted vehicle utilization rate is 85.00%, and the actual calculated utilization rate (trip time / total vehicle working time) is 70.7%. The heuristic algorithm optimizes the schedule to meet the target utilization rate. The total trip time is 280.9 hours, and the total vehicle working time is 397.2 hours, including 48.3 hours of charging time (accounting for 12.2%) and 68.0 hours of idle time (accounting for 17.1%). The time distribution of the three conforms to the operation rhythm of "trip - charging - scheduling buffer" of electric buses — the 12.2% proportion of charging time is adapted to the fast charging rate of 3% per minute, and the 17.1% idle time is used for cross-station vehicle scheduling and charging waiting, with no obvious resource waste.

From the algorithm execution results, the heuristic strategy integrates trip sorting by departure time, prioritized allocation of active vehicles, and the activation of new vehicles for unassigned trips is adopted to achieve full allocation of 330 trips: the first 10 vehicles undertake dense morning peak trips, with the number of trips reaching 15-19 times; the last 10 vehicles are mostly allocated sparse trips after the evening peak, with only 2-8 trips. The difference in the number of trips reflects the passenger flow distribution characteristics in the time dimension, which aligns with the First-Come-First-Served (FCFS) allocation logic of the algorithm, and no vehicle time conflict occurs (verified by Gantt chart), so the scheduling feasibility is guaranteed.

In addition, the trip allocation of 30 vehicles presents a "gradient distribution": 19 vehicles have ≥10 trips (core operation vehicles), 11 vehicles have ≤9 trips (supplementary operation vehicles), with an average of 11 trips per vehicle (330 trips / 30 vehicles), and no extreme imbalance. The longest working time of a single vehicle is 19.5 hours (Vehicle 1), the shortest is 2.8 hours (Vehicle 26), the highest SOC consumption is 590.1% (Vehicle 1), and the lowest is 71.4% (Vehicle 26-27). The data difference is directly linked to the trip intensity, conforming to the linear correlation of "more trips - high energy consumption - long working time", and no abnormal data (such as low trips and high energy consumption) occurs.

The total number of charging times in the experiment is 276, and the charging demand is positively correlated with the vehicle trip intensity: vehicles with more than 15 trips (such as Vehicle 1-6) generally have ≥5 charging times, and vehicles with ≤5 trips (such as Vehicle 23-27) mostly have no charging records, reflecting the matching logic of "power consumption - charging demand". Charging stations are concentrated in the depot (Station 1), business district (Station 2) and city center (Station 3), which together account for more than 85% of the total charging times. This is not only because these stations are equipped with sufficient charging piles (2 each), but also because they are transfer nodes with dense trips. Charging at these stations can reduce the cross-station scheduling cost, which is in line with the "opportunistic charging" operation idea.

The departure/arrival times of the 6 stations present the characteristic of "core hub leading, secondary nodes supplementing": as the scheduling center, the depot (Station 1) has 164 departures and 154 arrivals, accounting for 49.7% of the total trips, which conforms to the operation mode of "depot origin / terminal" of public transport; the business district (Station 2) and city center (Station 3), as the core passenger flow areas, have 61-67 departures/arrivals respectively, accounting for 38.8% of the total trips; the residential area (Station 5) and transportation hub (Station 6) have only 6 departures/arrivals due to low passenger flow demand, accounting for less than 4%, which fully matches the difference in bus passenger flow density in different urban areas, and there is no logical contradiction in the station activity distribution.

4.2 Final Optimization Results

The final optimization results of this scheduling are shown in Figure 3.

This figure takes the time axis as the core to visualize the trip sequence arrangement of all vehicles, aiming to systematically check the time conflicts and abnormal idle problems in scheduling. The data comes from the scheduling records of each vehicle (including actual departure time, arrival time and trip ID). The horizontal axis is time (minutes), covering 30 minutes before the earliest departure time to 30 minutes after the latest arrival time (example: 5:25–24:35), and marking the hourly time nodes; the vertical axis is the vehicle number (1–30). Each trip is represented by a vehicle-specific color rectangle, the width of which corresponds to the trip duration, and those with a duration of more than 20 minutes are marked with "T+trip ID" inside; for abnormal trips where the end time is not later than the start time, the rectangle width is forcibly set to 1 minute or marked with scatter points.

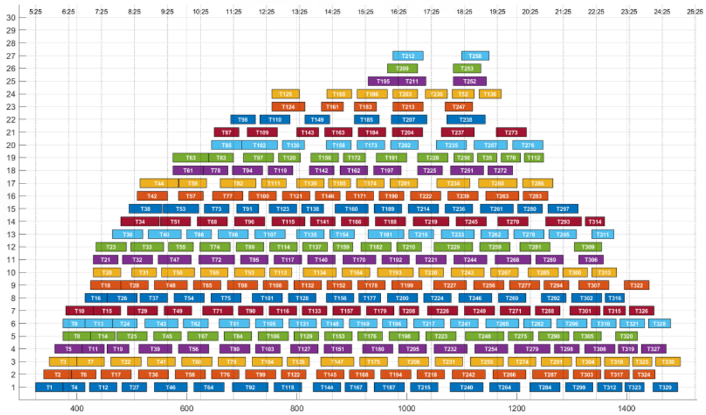

Fig. 3. Gantt Chart of Vehicle Scheduling

Figure 3 shows no overlap of trip bars for the same vehicle, which intuitively verifies the rationality of the scheduling sequence logic; at the same time, the blank area between trip bars clearly presents the distribution of idle periods (e.g., Vehicle 27 only contains a single short trip with significant idleness), which is convenient for evaluating vehicle utilization; finally, the trip density distribution effectively identifies the operation peaks (dense trips in the morning peak 5:25–8:25 and evening peak 17:25–19:25) and off-peak periods (sparse trips), and its spatiotemporal characteristics are highly consistent with the actual bus passenger flow laws, conforming to objective rules.

4.3 Comprehensive Analysis of All Vehicle Operation Trajectories

The comprehensive trajectory analysis diagram of all vehicles after optimization is shown in Figure 4.

It can be seen from the figure that the global operation data of 30 vehicles is presented. The left column (spanning two rows) is the comprehensive operation trajectory subgraph: taking the light gray road network as the base map, 30 solid trip path lines with vehicle-specific colors are superimposed. The line density intuitively reflects the passenger flow intensity of the stations. Evidently, the depot and business district exhibit the highest density, and the residential area is the sparsest. The legend on the right clearly identifies the vehicle numbers. This subgraph effectively verifies the integrity and balance of the spatial coverage of the public transport system, ensuring no scheduling blind areas.

The upper right subgraph presents the distribution of the number of vehicle trips with a pie chart, counting the number of vehicles in four groups: ≤5, 6–10, 11–15, >15. From the results, it can be seen that the sectors of "11–15 trips" and ">15 trips" are slightly exploded to highlight, clearly revealing the load distribution characteristics (about 5 high-load vehicles and about 8 low-load vehicles), providing quantitative reference for balanced task allocation; the lower right subgraph uses an orange bar chart to show the distribution of charging times of each vehicle, which can reflect the positive correlation between charging frequency and trip intensity.

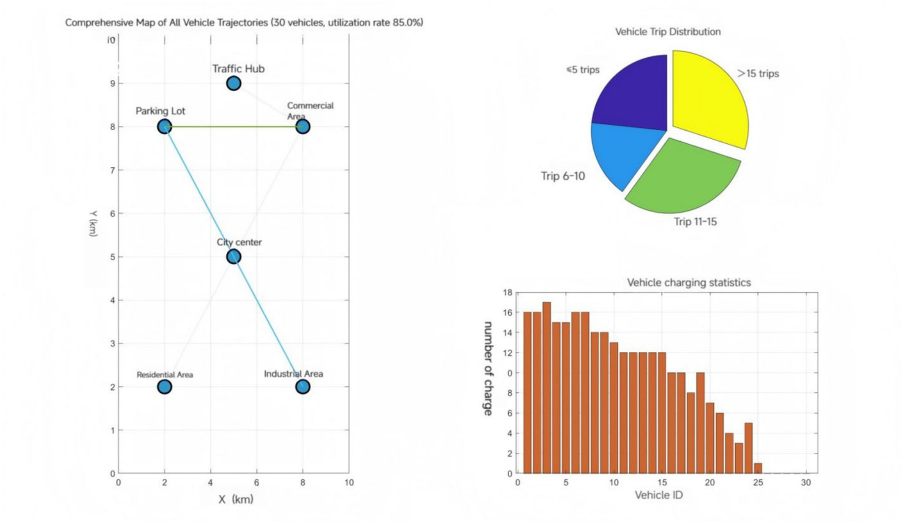

Fig. 4. Comprehensive Analysis Diagram of All Vehicle Operation Trajectories

5 Conclusion

This research developed a multi-objective collaborative optimization model with dual core objectives of minimizing fleet size and maximizing vehicle utilization, using an enhanced heuristic algorithm for solution development. The simulation experiment using actual operation data proved that the model can fully assign all trips under the constraints of time windows, state of charge, and charging facilities, reaching a vehicle utilization rate of 85%. This proved the validity and engineering practicability of the model. However, the model has a limitation in that it assumes a constant charging rate and travel time between stations, ignoring the influence of real-time traffic conditions and dynamic electricity prices on the dispatching strategy.

There are many potential research directions for this research in the future. Firstly, introducing real-time traffic conditions and dynamic time-of-use electricity prices to develop more flexible and robust dispatch strategies. Secondly, exploring the potential synergy with renewable energy sources, such as photovoltaic power, to reduce the grid load and carbon footprint (Xie et al., 2023). Thirdly, expanding the model to accommodate more complex scenarios, such as heterogeneous fleets with multiple depots, to make it more applicable to real-world scenarios (Zhou et al., 2023). All these improvements will be conducive to the application of this model in intelligent bus dispatching systems.

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