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Strategic bi-objective optimization for electric vehicle fleet replacement leveraging shared charging facilities

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ABSTRACT

Electrification of vehicle fleets has advanced significantly in recent years to achieve net-zero greenhouse gas (GHG) emissions. As a cost-effective strategy, shared charging facilities are increasingly used by public and private sectors. For example, the unoccupied time of a bus charging station can be leveraged to charge other electric vehicles (EVs). This shared usage model presents both opportunities and challenges for organizations considering transitions to electrified mobility. It is especially difficult when considering the variability in daily fleet operations and the availability of charging infrastructures. This paper presents a bi-objective optimization model designed to strategically guide the replacement of vehicle fleets with EV. The model aligns the spatial-temporal dynamics of vehicle routes with the availability of shared charging facilities. It is particularly relevant for organizations managing vehicle fleets that are considering a strategic transition to EVs, with the goals of minimizing GHG emissions from fuel consumption and vehicle idling, and reducing operational delays (e.g. detour and charging time for the EV fleet). We applied this model to the University of Utah campus fleet, utilizing shared charging facilities operated by the Utah Transit Authority. The results demonstrate effective strategies for replacing vehicles with varied operational characteristics, offering detailed plans and schedules that balance GHG emission reductions with operational efficiency. Additionally, we conducted a sensitivity analysis to assess the effects of different battery sizes, station disruptions, and traffic delays on the model's outcomes and a feasibility analysis to prioritize the replacement of high-utility vehicles. Our research provides a foundation for fleet agencies to develop strategic EV replacement plans that consider multiple goals and leverage shared charging infrastructure, ultimately leading to optimized charging facility utilization and reduced maintenance costs. These strategies support more efficient, reliable, and sustainable operations in urban fleet systems.

1. Introduction

With ongoing efforts to reduce greenhouse gas (GHG) emissions and the growing demand for clean energy, the electrification of vehicle fleets is gaining increasing attention from agencies and organizations worldwide. The development of diverse electric vehicle (EV) models facilitates the feasible replacement of vehicle fleets, predominantly composed of trucks, vans and multi-purpose vehicles (MPVs). Many businesses and government agencies have initiated such replacement as part of their strategies to achieve net-zero GHG emissions (He, Liu, Zhang, & Song, 2023; Bragin, Ye, & Yu, 2024). For example, Amazon's delivery fleet has replaced more than 13,500 vans with EVs across the U.S. in 2024, aiming for carbon neutrality by 2040 (Amazon, 2024). However, from the perspectives of agencies and/or organizations, the initial cost associated with transitioning to EVs is still relatively high. New York City plans to invest $420 million in electrification to achieve all-electric fleet in the next five years (Electrive, 2021). A significant portion of the budget is allocated to the development of charging infrastructure (Madina, Zamora, & Zabala, 2016). Given this, a more cost-effective electrification strategy, such as utilizing and sharing existing charging facilities appears to be promising (Ye, Gao, & Yu, 2022, Ye, Yu, Wei, & Liu, 2022). Comparing to constructing and maintaining their own charging infrastructure, fleet operators, especially those managing small-scale fleets, can significantly reduce electrification costs by utilizing existing charging facilities. This sharing mechanism could also enhance the utilization of on-route charging facilities, generating

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additional revenue for agencies that manage these stations.

The growing network of on-route charging stations, installed by many cities to support electric buses at major terminals, presents an opportunity for inter-agency collaboration. These facilities are typically well-distributed across urbanized areas and often have periods of low utilization (Zhou, Liu, Wei, & Golub, 2020). By sharing these charging resources, agencies can maximize the efficiency of existing infrastructure while reducing operational costs. A major challenge in such sharing mechanism is coordinating EV schedules with the availability of charging stations, as fleet schedules could change because of possible travel detour, charging activities, and traffic delay. These dynamic schedules could result in varying charging windows, which requires models to optimize the charging schedules effectively. Existing studies focus on maintaining the original schedule by employing strategies such as stop-skipping and speed adjustments (Wu, Yu, Ma, An, & Zhong, 2022). These strategies are often challenging to be implemented effectively in real-world operations. Some other studies may attempt to reassign vehicle routes to accommodate EV charging. However, unlike personal vehicles, fleet vehicles often follow predefined routes and fixed sequences of stops assigned by the fleet management department, such as in the case of school bus fleets (Jonas, Borlaug, Bruchon, & Wood, 2025). Changing the route solely for charging may be unnecessary and overly restrictive, as the energy consumption of EVs is uncertain, leading to variability in both the timing and location of charging needs. As a result, the optimal charging route may change dynamically in the future. This uncertainty implies that charging routes must remain flexible and may vary over time as operational conditions change. Alternatively, a detour-based strategy offers greater flexibility and aligns better with daily predetermined route assignment. In this approach, vehicles follow their assigned routes but may detour to a nearby charging station if needed, particularly when the route passes close to a facility and the battery level is low. This method avoids unnecessary route changes while accommodating uncertain energy consumption. Furthermore, the traditional electric vehicle routing problem (EVRP) is known to be nondeterministic polynomial-time hard (NP-hard), making it computationally infeasible to solve exactly for large-scale instances. In the context of shared charging infrastructure, even after solving the routing problem, the core challenge lies in coordinating the charging schedule among multiple vehicles and stations. Limited research addresses dynamic scheduling issues under shared charging facility setting for electrification adoption, particularly in optimizing charging schedule to account for additional charging and detour times.

For fleet operators, another challenge they face is managing diverse fleets with multiple vehicle types and routes, each with varying charging requirements and operational complexities. A single fleet agency may operate multiple vehicle models with varying battery capacities and use them for different purposes (Estrada, Mensión, Salicrú, & Badia, 2022). Moreover, each vehicle may follow different routes on different days, depending on the assigned tasks. As a result, a complete understanding of a vehicle's operational pattern may require analysis over multiple days. This complexity makes it difficult for existing models to optimize charging resources effectively and ensure that EVs can consistently meet operational demands. Most existing models focus on single-day optimization, which limits their ability to account for multi-day variability in fleet operations. Campus fleets exemplify these aforementioned features. With growing environmental awareness, many colleges/universities have initiated efforts to electrify their campus fleets (Booth et al., 2022; Juang et al., 2024). For example, Aniegbunem and Kraj (2023) analyzed the electrification potential of the University of Saskatchewan's campus fleet, demonstrating that full electrification could eliminate GHG emissions from the fleet, leading to substantial savings in fuel and operational costs. Institutions like the University of Buffalo (Buffalo, 2025), Temple University (Temple News, 2021), and Harvard Kennedy School (Lee & Clark, 2018) are similarly motivated to replace their campus fleets with EVs. However, these fleets all face similar challenges during electrification: on one hand, they aim to reduce GHG emissions within a limited budget; on the other hand, they seek to minimize the operational impact of EV charging, avoiding significant deviations from original routes and reducing delays associated with charging activities.

In response to these challenges, this research proposes a bi-objective optimization model that addresses both environmental and operational goals in the context of EV fleet replacement. By integrating vehicle detour variability, shared charging infrastructure, and scheduling coordination, the model generates cost-effective and spatially-aware solutions to minimize GHG emissions and operational delays. The first objective is to maximize the replacement of conventional vehicles with EVs, thereby minimizing GHG emissions from the campus fleet. The second objective is to minimize delays due to detours and charging activities. A strategic vehicle replacement plan and a dynamic charging schedule are designed, using a campus fleet as a case study and leveraging existing on-route bus charging facilities. The key contributions of this research are:

- Proposing a dynamic EV scheduling model that integrates shared charging facility availability, detour flexibility, and partial charging feasibility into fleet-level operations;
- Developing a fleet replacement strategy that accounts for multi-day, vehicle-specific route variability and real-time opportunity charging within spatial-temporal constraints; and
- Incorporating idling-related GHG emissions into a bi-objective optimization framework that jointly minimizes emissions and operational delays, enabling more realistic and environmentally grounded electrification planning.

The remainder of this paper is organized as follows. Section 2 reviews the literature on EV fleet optimization, shared charging facilities, and vehicle idling. Section 3 describes the EV fleet replacement problem in detail. Section 4 analyzes the results from detailed replacement plans under different GHG emission reduction targets and shared charging facility occupancy. Finally, Section 5 concludes the study.

2. Literature review

Transportation electrification has been a popular topic in recent years, focusing on exploring the planning, operation, and management of EV fleets. Key areas of emphasis include vehicle routing (Eskenazi, Joshi, Butler, & Ryerson, 2023; Mu & Li, 2024), operational scheduling, and the deployment of charging infrastructure (He, Liu, & Song, 2023; Liu et al., 2023). Our literature review begins with research on GHG emission reduction, particularly studies that assess the impact of vehicle idling on fuel consumption and emissions, an often underemphasized but significant contributor to overall GHG output. Next, we review literature on EV fleet replacement, focusing on optimization models for EV scheduling and the integration of shared charging facilities, both of which are essential for effective electrification. Finally, we examine existing approaches for solving bi-objective optimization problems, which provide the methodological foundation for our proposed model.

Currently, electrification efforts are being pursued across various travel modes, including road freight (Ye, Gao, & Yu, 2022; Ye, Yu, et al., 2022), personal vehicles (Yi et al., 2023), public transit systems (Estrada et al., 2022). A key motivation for transitioning from conventional fuel-powered vehicles to EVs is the reduction of GHG emissions. These emissions are produced not only during vehicle movement but also during periods of idling, which can significantly contribute to overall fuel consumption and environmental impact. Vehicle idling is a prevalent issue in fleet operations, occurring when vehicles remain stationary with the engine running for reasons such as waiting at red lights, experiencing traffic congestion, performing tasks, warming up the engine, or regulating interior temperature. It is an environmental concern worldwide, contributing significantly to traffic-related pollution, including carbon dioxide (CO2), carbon monoxide (CO), particulate matter (PM), and nitrogen oxides (NOx) (Perrot, Constantino, Kim, Hutton, & Hagan, 2004). The emissions produced during idling vary depending on vehicle type and the tasks performed. For instance, passenger vehicle idling accounts for over 93 million metric tons of CO2 and consumes approximately 10.6 billion gallons of gasoline annually (Sharma, Kumar, Dhyani, Ravisekhar, & Ravinder, 2019). Truck fleets, in particular, generate higher emissions and cause significant noise pollution at large truck stops (Perrot et al., 2004; Sharma et al., 2019). Previous research primarily focuses on estimating emissions and fuel wasted during idling. Molari, Mattetti, Lenzini, and Fiorati (2019) discovered that 6 % of fuel consumption occurs during idling. Rahman et al. (2013) found that CO2 emissions can reach as high as 16,500 g/h, with fuel consumption rates reaching 1.85 gal/h during idling. Proposed solutions include stop-start technologies (Molari et al., 2019) and stop electrification (Zhang, Horesh, Kontou, & Zhou, 2023). EV has proven to significantly reduce emissions from idling with the recent technological advancement (Ye, Zhao, & Zhang, 2023). However, few studies have considered the idling time impact of different vehicle types when developing EV replacement plans.

While reducing GHG emissions is the primary motivation, the development of optimization models serves as a key methodological approach to effectively implement fleet electrification. Schedule optimization is a well-studied area for EV fleets, particularly for electric buses. Most existing research focuses on bus fleets with different vehicle types and battery sizes but assumes fixed routes and schedules within a single day (Ye, Gao, & Yu, 2022; Ye, Yu, et al., 2022). This emphasis on a single-day schedule reflects the typically static nature of electric bus operations, where schedules barely change for day-to-day operations. Estrada et al. (2022) optimized the charging schedules for electric bus systems, finding that opportunity charging is more cost-effective than depot charging for small battery EVs, particularly when fast chargers are available at terminal facilities. Yao, Liu, Lu, and Yang (2020) developed an optimized schedule for electric bus fleets, accounting for different vehicle types, driving ranges, recharging durations, and energy consumption rates. A heuristic procedure was developed to solve the optimization model. Their findings indicate that optimal scheduling can significantly reduce operational costs. Other research has focused on optimizing charging schedules from the perspective of charging facilities. Lo Franco et al. (2022) introduced a smart charging scheme designed to enhance facility utilization based on vehicles' state of charge and desired end-of-charge times. Ye, Gao, and Yu (2022), Ye, Yu, et al. (2022) combined optimization models with reinforcement learning to develop an optimal charging schedule aimed at maximizing the profitability of charging facilities (Liu et al., 2024). A spatio-temporal optimization model was developed that incorporates electricity carbon emissions and vehicle-to-grid technology. Much of the research related to passenger EV has also focused on optimizing the charging strategy at charging facilities by considering the spatio-temporal variations in charging demand (e.g. smart charging, vehicle-to-grid (V2G), and dynamic pricing (Qureshi, Ghosh, & Panigrahi, 2024; Tang et al., 2024). In recent years, there is a growing interest in joint schedule optimization (Dai, Liu, Chen, & Ma, 2020), which considers not only EV schedules but also factors like passenger schedules. Wu et al. (2022) explored the alignment of passenger and vehicle schedules for demand-responsive buses, proposing timetable adjustments that incorporate stop-skipping, speed adjustments, and bus holding strategies to minimize operating and passenger waiting costs. Li, Lo, and Xiao (2019) tackled the scheduling problem for multiple vehicle types by considering the time-space flow of buses and passenger detours. Within shared charging facilities or hub strategies, an important consideration is the coordination of charging facility schedules. Effectively aligning the available charging facility schedules with dynamic fleet schedules from different agencies presents a significant challenge. However, few studies on joint schedule optimization focus on this crucial aspect of integrating charging facility schedules with fleet operations.

In addition to the fleet schedule optimization in transportation electrification, charging infrastructure deployment is also an important area. Yi, Liu, and Wei (2022) optimized the spatial layout of charging stations by maximizing the station utilization. A modified geographical PageRank model and capacitated maximal coverage location problem model is developed. Results revealed that there are mismatches between the existing charging infrastructures and charging demand across different areas. Kuby, Martinez, Kelley, and Tal (2023) investigated planning and modeling methods for the deployment of hydrogen refueling stations, while Luo, Kuby, Honma, Kchaou-Boujelben, and Zhou (2024) optimized station distribution by accounting for dynamic demand and supply conditions. In recent years, the strategy of sharing charging facilities among passenger EVs and different EV fleets is gaining increased attention (Ye, Gao, & Yu, 2022; Ye, Yu, et al., 2022). Research that focuses on the deployment of shared charging facilities is often resorting to either optimization model or simulation method (Zhou et al., 2024). For instance, Ye, Gao, and Yu (2022), Ye, Yu, et al. (2022) investigated the deployment of shared charging facilities between electric buses and passenger cars, with a focus on minimizing GHG emissions. A spatio-temporal optimization model is built by considering the electricity carbon and vehicle-to-grid technology. The findings demonstrate that the shared charging facility strategy can significantly reduce GHG emissions while also meeting the electricity demands of various types of EVs. Su and Kockelman (2024) explored the potential deployment of public-private charging facilities in Austin, Texas. An agent-based simulation, POLARIS model, is used to analyze the EV charging demand and behavior. Similarly, Gong, Tang, Buchmeister, and Zhang (2019) examined the deployment challenges of shared charging facilities for EVs, taking into account factors such as mileage, vehicle types, and passenger distribution. An agent-based model is also used based on Anylogic. Results show that charging frequency can greatly impact the station deployment. The charging frequency of EVs will also impact the charging schedule of shared charging facilities. Research on existing shared charging facilities often emphasizes optimizing their scheduling. Zhang et al. (2023) investigated the scheduling problem of charging hubs for shared chargers within a community, aiming to minimize waiting times. A rule-based heuristic algorithm is proposed to solve random EV arrivals. Their study revealed a trade-off between the total waiting time at the hub and the associated charging costs. Bragin et al. (2024) explored joint routing and charging schedule optimization, by modeling a mixed-integer linear programming problem which is solved by a surrogate level-based lagrangian relaxation method. Results show that battery capacity and charging power can greatly impact the final cost and replacement plan. This study allows EV fleet to adopt alternative routes to better optimize the charging schedule of shared charging facilities. However, in reality, vehicle fleets typically adhere to certain routes and specific schedules that prioritize the shortest possible distance to reach their destination. When EV fleets are introduced, the need to detour for charging at shared facilities can disrupt their planned schedules. Additionally, optimizing charging schedules for EV fleets can affect the utilization of the charging infrastructure itself, creating a complex interdependence. Coordinating fleet schedules with the availability of shared charging facilities to ensure optimal charging times remains a challenge that requires further research. Moreover, when an EV has different destinations and routes on different days, the modeling complexity increases significantly. This is due to the varying shared charging facilities encountered each day, along with a sharp rise in input variables, including the number of routes and time dimensions.

In developing optimization models for fleet electrification, whether focused on scheduling, routing, or station distribution, the choice of objective functions is critical. To reflect real-world needs, it is often necessary to incorporate multiple objectives. For example, Zhou et al. (2020) proposed a bi-objective model that accounts for both environmental equity and replacement costs. Qureshi et al. (2024) developed a multi-objective framework that considers various types of replacement costs, while He, Liu, Zhang, and Song (2023) designed a bi-objective model to balance bus mileage and electrification costs. However, few studies have jointly considered two key concerns in fleet electrification: minimizing GHG emissions, which is the central environmental goal, and minimizing operational delays, which is a major priority for fleet managers aiming to maintain reliable service. To solve bi-objective models, three classical approaches are commonly used. The first is the constraint method, which converts one objective into a constraint with varying thresholds, allowing phased progress toward a target (Zhou et al., 2020). The second is the scalarization method, where multiple objectives are converted into a single objective by expressing them in the same unit (e.g., cost or time) (Qureshi et al., 2024). The third is the Normalized Normal Constraint (NNC) method, which is often used to generate a well-distributed set of Pareto-optimal solutions, providing a complete representation of the solution space (He, Liu, Zhang, & Song, 2023). There is no universal standard for selecting among these methods. And the appropriate approach depends on the specific needs and priorities of the application.

3. Electric vehicle fleet replacement problem

This study addresses the replacement of conventional fuel vehicles with EVs using a campus fleet system as an example. We examine the feasibility of replacing campus fleet with EVs, utilizing existing on-route charging facilities offered by the transit agency to assist with this transition. A generalizable and transferable model framework for this problem is illustrated in Fig. 1. The process consists of three main components: data input, model optimization, and the generation of the final fleet replacement plan. The framework is designed to accommodate a diverse set of charging infrastructure and fleet management scenarios, making it applicable across various regions and operational contexts. The bi-objective optimization model allows for flexible data integration, enabling the use of vehicle trajectory data from a single day to multiple weeks, depending on data availability, to capture a more comprehensive operational profile. It is designed to be adaptable across different fleet compositions and service requirements, such as freight fleet, school bus fleet. It simultaneously minimizes GHG emissions from conventional fuel vehicles and optimizes detour time for newly deployed EVs by choosing when and where to be charged, and charging time. A dynamic schedule cooperation is considered in the model. The resulting fleet replacement plan includes an updated schedule for both the charging facilities and the fleet, followed by sensitivity and feasibility analyses to accommodate various operational scenarios.

3.1. Problem description

Campus fleets at universities across the U.S. share several common characteristics. Vehicles are typically assigned to different departments and serve diverse functions such as goods delivery, student transportation, grounds keeping, and maintenance. The campus fleet consists of various vehicle types, each requiring specific battery capacities to accommodate diverse size and performance needs following their transition to EVs. In terms of operational scope, these vehicles often operates off-campus, and once replaced by EVs, will require on-route charging to maintain operational efficiency and complete tasks. Each vehicle may be tasked with different routes on different days as part of a weekly routine. We designate the campus vehicle as i and represent the day as v, with its associated routes varying across different days. A traditional campus vehicle i^{gas} will be replaced with an EV i^{EV} only if all its routes across operational days are feasible for electric vehicle driving.

Warehouses (triangle in Fig. 2), located off-campus, serve as intermediate stops for campus vehicles along their routes or as final parking locations at the end of the day. At each stop, the fleet either delivers goods to or picks up goods from the designated warehouse. It is assumed that all routes originate from and conclude at a terminal each day. A terminal (rectangle in Fig. 2) could be a designated campus location or a select number of warehouses where vehicles stay overnight. Vehicles may pass through different on-route charging facilities, following varying routes on different days. Once replaced by EVs, they have the flexibility to detour to these facilities for charging as needed. On-route charging facilities consist of existing fast-charging stations that service electric buses. These stations have a charging power of 300 kW and will serve as shared charging facilities, offering a rapid charging solution to support dynamic scheduling needs.

A vehicle's single-day route is used to exemplify the operational scenario of the campus fleet. On a typical day v, a gasoline campus vehicle, denoted by i^{gas}, initiates its journey from a terminal. The vehicle then follows a predefined sequence of warehouses (indexed by m) and/or on-route charging facilities (indexed by j), and finally concludes at a terminal, forming a complete route. This complete route can be divided into sub-segments between two adjacent warehouses or on-route charging facilities. Fig. 2(a) illustrates the origin route of a conventional gasoline vehicle i^{gas} over the course of a day. Fig. 2(b)-(e) illustrate potential routing outcomes under different detour decisions for vehicle i^{EV} after being replaced with an EV. The battery level of vehicle i^{EV} undergoes updates in different sub-segments, indexed by time t. The

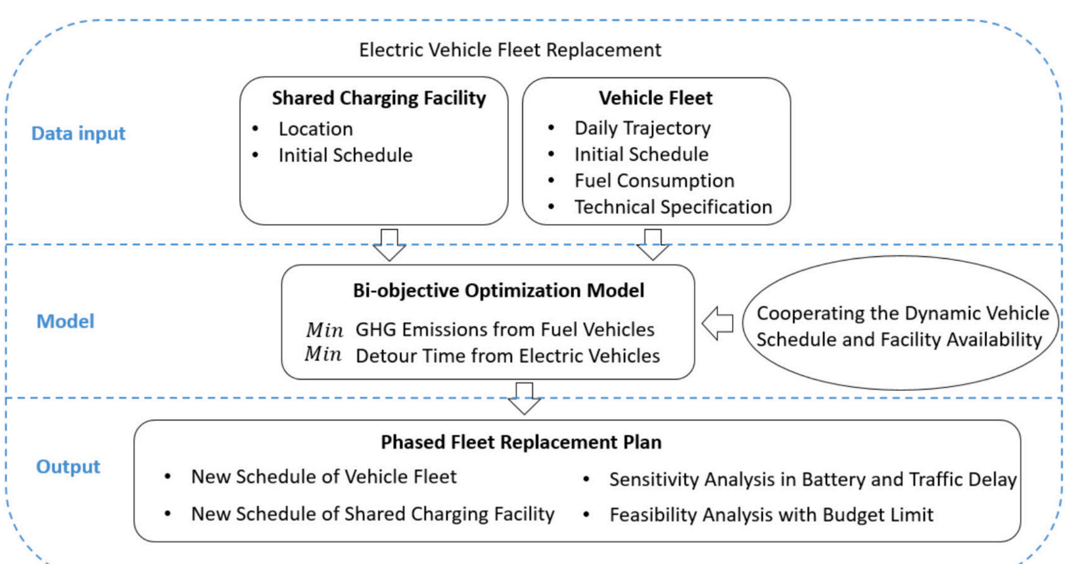


Fig. 1. A generalizable and transferable framework for EV fleet replacement.

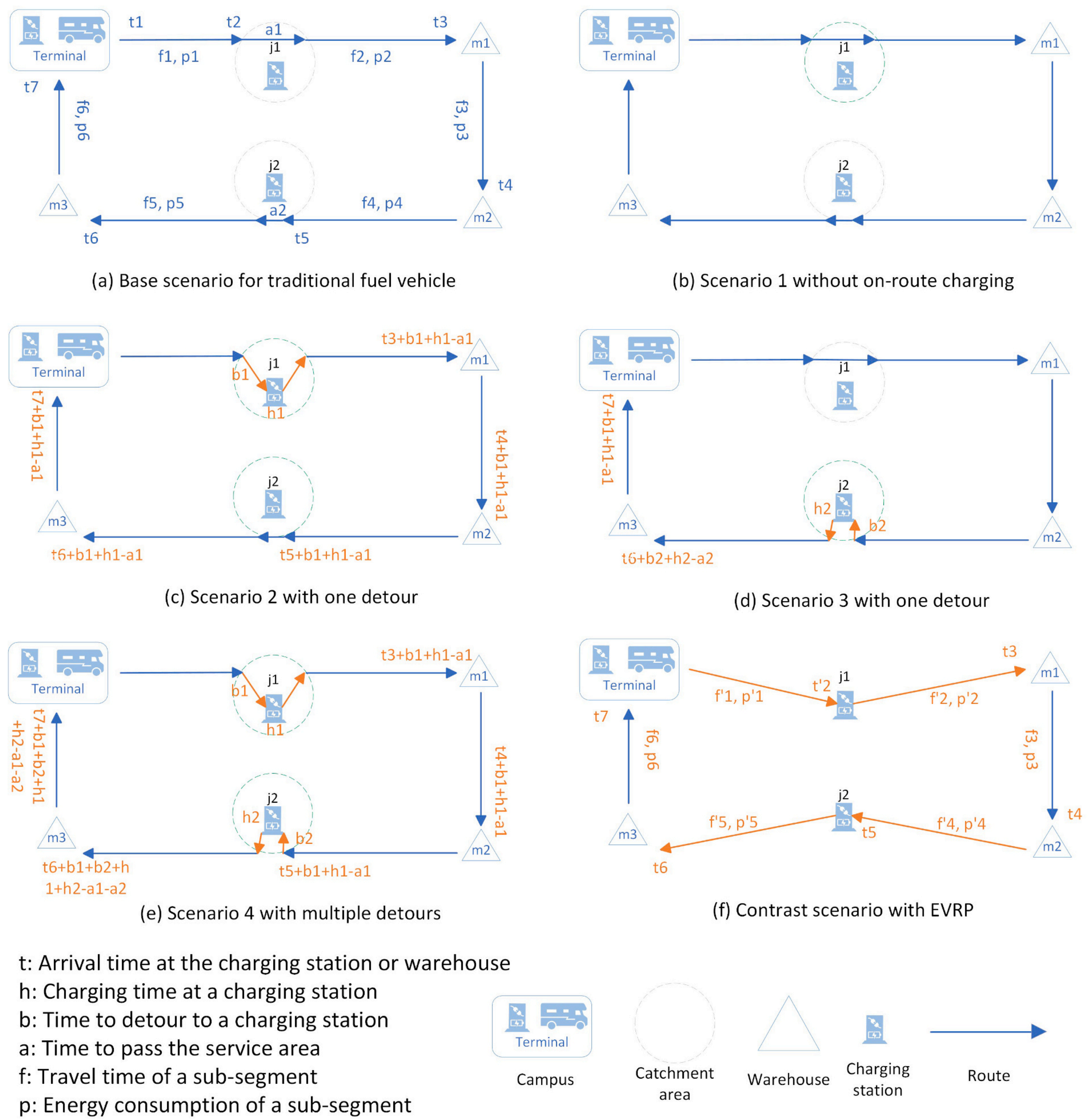


Fig. 2. Operational scenario illustration of EV replacement. Orange lines represent the optimized detour routes from the model, and orange font indicates the updated EV schedule. Green circles denote catchment area charging facilities that are available at the time the EV passes. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

blue lines represent the original routes that vehicles are assigned to follow, while the orange lines indicate the optimized detour routes or modified paths taken for charging. The detour decision considers both the vehicle's battery status and whether its arrival time at the catchment area aligns with the availability of the charging facility. For example, in Fig. 2(c), the EV starts from the terminal with a full battery at t_1. Based on its battery status and the availability of charging facility j_1, vehicle i^{EV} opt to deviate from the origin route to detour to j_1 for charging at t_2. Both the detour time b_1 from the original route to the charging facility and the charging time h_1 are considered in this analysis. After the vehicle rejoins the original route post-charging, the arrival times (shown in orange) at all subsequent locations will be recalculated to account for the detour time b_1 and charging time h_1. When passing charging facility j_2, vehicle i^{EV} decides not to detour, even though the facility is currently available (indicated by the green circle). Notably, j_2 may represent either a second pass of the same facility j_1, highlighting that vehicles can revisit the same charging facility, or a different charging facility. The dynamic schedule changes made along the route is further illustrated in Fig. 3.

Fig. 2(f) illustrates the optimization strategy in a traditional EVRP model, where vehicle routes are directly modified to access charging facilities. In this approach, routing and charging decisions are made jointly. Even when the warehouse visit sequence is fixed, the model still determines whether to insert a charging stop after each warehouse and which route to take for charging. These charging stations are added directly into the vehicle's path, often altering the original travel plan. This tightly integrated structure significantly increases the model's complexity and contributes to the NP-hard nature of the problem, as the solver must continuously explore and evaluate numerous potential routing and charging combinations. Consequently, it becomes more difficult to obtain optimal solutions, especially for large-scale instances (Schneider, Stenger, & Goeke, 2014).

When establishing catchment areas (represented by the grey circle in

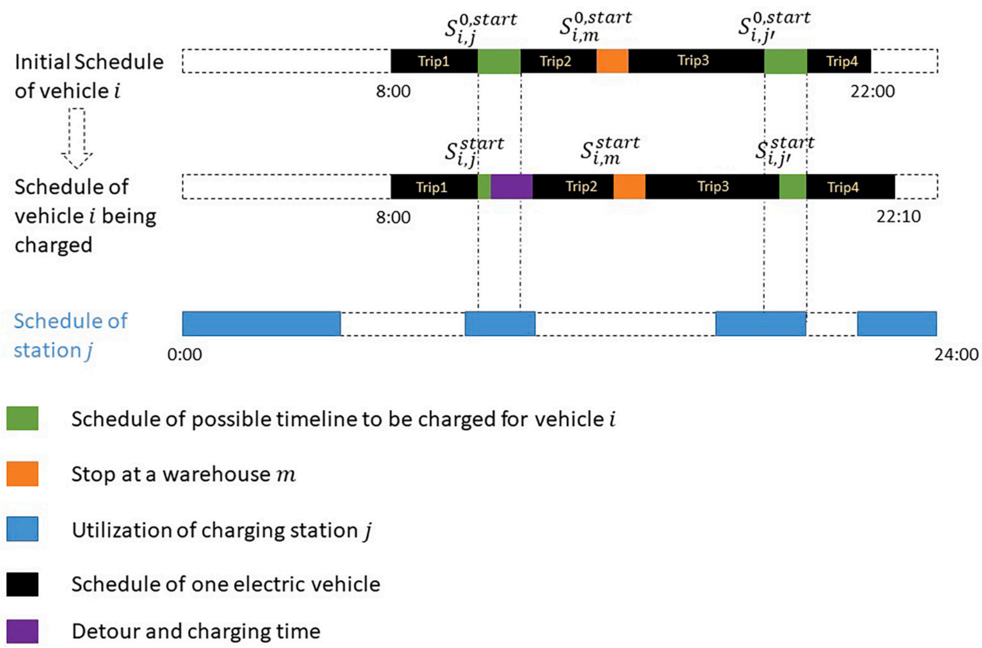


Fig. 3. Dynamic time schedule of replaced EVs. The green area represents the time duration from when vehicle i is traveling within the catchment area of station j. Once replaced by an EV, the vehicle will determine whether to detour to station j and how long it will charge at any point within this duration. The start of the purple area indicates the moment the vehicle decides to detour to the station and perform charging. The purple area captures the total detour time, including the time spent traveling to facility j and the time required to return to its original route, and the charging duration. The end of the purple area extends beyond the end of the green area due to the charging activity, reflecting the delay caused by the detour and charging process. The orange area represents the duration at a warehouse, during which vehicle idling may occur. The blue area represents the available time window at the shared charging facility that the EV fleet can utilize. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 2) for shared charging facilities, a one-mile radius is set as the maximum allowable deviation distance for the campus fleet to access these facilities for charging. The determination of this one-mile radius is supported by previous studies indicating that optimal accessibility to charging facilities ranges from 1000 to 2000 m (Oluwajana, Chowdhury, Wang, & Oluwajana, 2023). Accordingly, a one-mile radius corresponds to the distance a campus vehicle can cover in approximately 2 min at a speed of 30 miles per hour, which is a typical speed limit on urban roads in the Wasatch Front of Utah. Therefore, this radius ensures that the detouring time for a campus vehicle to access a charging facility and return to its original route remains within 4 min which would not induce too much operational delay.

Once a vehicle is replaced with an EV, its schedule may be adjusted to account for the extra time required for detours and charging, potentially altering both the vehicle's overall schedule and available charging windows. The proposed bi-objective optimization model addresses this dynamic scheduling problem by considering all relevant EV operations and charging facility constraints. Using a specific vehicle as an example, Fig. 3 demonstrates how the dynamic EV schedule aligns with the availability of on-route charging facilities, implementing a shared charging strategy within the framework of the optimization model. The optimization process is illustrated in the following steps:

- First, the initial schedule of vehicle i is provided as an input to the optimization model. The variables $S_{i,j}^{0,start}$, $S_{i,m}^{0,start}$, and $S_{i,j'}^{0,start}$ represent the times at which vehicle i first arrives within the catchment area of charging facility j, then at warehouse m, and finally within the catchment area of charging facility j'. Together with the initial schedule, the model incorporates related charging facility schedules, idling time, and battery constraints. The optimization model then determines whether vehicle i can be replaced by an EV and, if replaced, whether it requires on-route charging, considering two objectives: minimizing GHG emissions and operational delays, alongside factors like vehicle schedules, battery states, and charging facility availability.
- If the model determines that vehicle i either cannot be replaced by an EV or can be replaced and does not require on-route charging, the process concludes at this stage. In such case, the vehicle's final schedule remains unchanged, and the optimization outputs the replacement decision and unchanged schedule.
- If the model determines that vehicle i is to be replaced by an EV and requires on-route charging to complete its route, the process continues to determine the optimal charging strategy, including the selection of charging facilities and the allocation of charging time. This process is based on an opportunity charging strategy, which evaluates whether the vehicle has sufficient battery capacity to complete its route, whether an available charging window exists at the facility, and whether there are charging opportunities at subsequent stations. For example, the model identifies a suitable charging facility (e.g., j) during its first charging opportunity encounter. By comparing the utilization of charging facility j (represented by the blue area in Fig. 3) against the initial schedule of vehicle i, the potential time window for charging (represented in the green area) can be determined. It is important to note that the utilization of charging facility j may also be influenced by the charging activities and schedule adjustments of other EVs. The charging rule follows a first-come, first-served principle, where the first EV is prioritized for charging. Subsequent EVs will make charging decisions based on the updated and most recent utilization status of station j. Once the current charging instance is completed, a new schedule for EV i will then be updated. The subsequent schedule of vehicle i will be adjusted, resulting in $S_{i,m}^{0,start}$ changing to $S_{i,m}^{start}$, and $S_{i,j'}^{0,start}$ changing to $S_{i,j'}^{start}$. Based on this new schedule of vehicle i, a new available time window for charging at the next encounter with a charging facility is established. For instance, if vehicle i visits facility j for a second time, the model reassesses whether additional charging is necessary. This scenario also applies to cases where the vehicle encounters multiple facilities

or revisits the same facility multiple times. Each subsequent charging decision updates the schedule dynamically, guiding the vehicle to its final destination.

- Finally, the optimization process concludes with a comprehensive output, including the final schedules of all vehicles, charging plans, and the replacement plan for transitioning to EVs.

The notation that this bi-objective model considers is summarized in Table 1.

Binary decision variable Y_i^v represent whether vehicle i at day v is replaced with an EV. $D_{k,\alpha}^{i,v}$ are also binary decision variables which indicate whether vehicle i at day v is charged in charging facility k, during its α-th visit. $Z_t^{i,v,j,\alpha}$ denote the same value but add a temporal dimension to specify the exact charging time in order to match the arrival time of vehicle i and available time of charging facility j of α-th visit. The actual charging time is given by integer variable $H_{i,v}^{k,\alpha}$. Integer decision variable $B_{k,\alpha}^{i,v}$ represent the remaining battery of vehicle i at day v at facility k, during its α-th visit.

3.2. Fleet operations

To accurately reflect the charging activities, and prioritization within the shared charging facility context, this model also incorporates the following characteristics of the campus fleet system and shared on-route charging facilities.

Table 1
Summary of notations for sets, parameters, and variables.

Sets	Description
$\boldsymbol{I}$	Set of campus fleet, indexed by i
$\boldsymbol{V}_i$	Set of operation days of vehicle i, indexed by v
$\boldsymbol{J}_{i,v}$	Set of charging facilities that vehicle i day v will go through, indexed by j
$\boldsymbol{M}_{i,v}$	Set of warehouse that vehicle i day v will go through, indexed by m
$\boldsymbol{K}_{i,v}$	Set of warehouse or charging facilities that vehicle i at day v will go through, indexed by k. $\boldsymbol{J}_{i,v} \cup \boldsymbol{M}_{i,v} = \boldsymbol{K}_{i,v}$
$\boldsymbol{T}_{j,\alpha}^{i,v}$	Set of time sequence for vehicle i at day v at facility j during its α-th visit, indexed by t
$\boldsymbol{\alpha}_k^{i,v}$	Set of visit indices for vehicle i day v to warehouse or charging facility j, indexed by α
l	Integer counter for previously visited locations in summation constraints

Parameters	Description
R_t^j	Available charging time for on-route charging facility j at time t. Detour time will be 0 if k represents a warehouse
N_t^j	Number of vehicles that one on-route charging facility j can charge simultaneously at time t
λ_i	Full battery capacity with the type of vehicle i
$\sigma_{k,\alpha}^{i,v}$	Idle time of vehicle i at day v in a warehouse or charging facility k, during its α-th visit
$C_{i,v}$	Fuel consumption of vehicle i at day v
β_i^k	Detour time of vehicle i from going to charging facility k and going back to origin route. It is calculated by average speed and shortest path from ArcGIS. Detour time will be 0 if k represents a warehouse
θ_k^i	Acceptable waiting time threshold for vehicle i to be charged at charging facility k when i arrive at facility k and there is no available charging facilities. It will be 0 if k represents a warehouse
τ_k^i	Available charging time window for vehicle i from entering the catchment area to leave the catchment area of charging facility k. Time window will be 0 if k represents a warehouse
E_i	Idle fuel consumption rate of vehicle i (liters per minute)
ρ_{fuel}	Emission factors for fuel consumption (kg CO_2 per liter of fuel)
ρ_{idle}	Emission factors for idling (kg CO_2 per liter of fuel)
Q	Charging power on electric vehicles (kwh per minute)
P_i	Power consumption rate of electric vehicle i
$S_{i,v,k,\alpha}^{0,start}$	Initial starting time for vehicle i at day v to enter the catchment area of charging facility or warehouse k, during its α-th visit
$\varphi_{k-1,k,\alpha}^{i,v}$	Driving time in a sub- segment from facility or warehouse $k-1$ to facility or warehouse k during its α-th visit for vehicle i at day v
W	GHG emissions from traditional gas vehicles
ϵ	Tolerance level in the GHG emission reduction target
ϑ_e	Charging rate for a day in shared charging facilities
ϑ_f	Fuel price (dollar per liter of fuel)

Decision variables	Description
$B_{k,\alpha}^{i,v}$	Battery level of vehicle i at day v at warehouse or on-route bus charging facilities k, during its α-th visit
$H_{i,v}^{k,\alpha}$	Charging time of vehicle i at day v at facility k, during its α-th visit
$A_{i,v}^{k,\alpha}$	Starting time for vehicle i at day v to be charged at charging facility k, during its α-th visit
X_i	$X_i = 1$ indicates vehicle i is replaced with EV. Otherwise, $X_i = 0$
$D_{k,\alpha}^{i,v}$	$D_k^{i,v} = 1$ indicates vehicle i at day v is charged at facility k, during its α-th visit. Otherwise, $D_k^{i,v} = 0$

Auxiliary variables	Description
$S_{i,v,k,\alpha}^{start}$	Starting time for vehicle i at day v to enter the catchment area of charging facility k, during its α-th visit
$F_{i,v,k,\alpha}^{start}$	Starting time for vehicle i at day v to decide to go to the charging facility k during its α-th visit in the catchment area
$Z_t^{i,v,j,\alpha}$	$Z_t^{i,v,j,\alpha} = 1$ indicates vehicle i at day v is charged at facility j during its α-th visit at time t. Otherwise, $Z_t^{i,v,j,\alpha} = 0$
Y_i^v	$Y_i^v = 1$ indicates vehicle i at day v can be replaced with EV. Otherwise, $Y_i^v = 0$
U_t^j	$U_t^j = 1$ indicates facility j is occupied at time t. Otherwise, $U_t^j = 0$

- The charging activities of electric buses are prioritized to ensure their normal operation, meaning the initial schedule of charging facilities remains fixed and unaltered. Consequently, the initial availability of these on-route facilities for charging the campus fleet will follow a predetermined schedule.
- EVs in the campus fleet can undergo partial and multiple charging sessions at the shared on-route charging facilities throughout the day as needed. Considering the time constraints at intermediate stops and the need for vehicles to conduct essential loading and unloading operations, EVs cannot be charged at intermediate stops (warehouse). Terminals will provide overnight charging to ensure that each vehicle starts the day with a full battery.
- Vehicle fleet, once replaced by EVs, operate on a flexible schedule. A flexible schedule allows each EV to arrive at its designated warehouse within an acceptable range beyond the pre-determined time. This flexibility ensures that EVs can accommodate detours and necessary charging stops while minimizing delays to their overall schedules.

3.3. Problem formulation

3.3.1. Objective function

Considering the GHG emissions arising from both fuel consumption and idling in the campus fleet, alongside the objective to minimize detour time and charging time, the Electric Vehicle Fleet Replacement Problem (EVFRP) is formulated as a bi-objective optimization model as follows:

$$min\sum_{i\in \boldsymbol{I}}\sum_{v\in \boldsymbol{V}_i}\left[E_i\sum_{k\in \boldsymbol{K}_{i,v}}\sum_{\alpha\in\boldsymbol{\alpha}_k^{i,v}}\sigma_{k,\alpha}^{i,v}\rho_{idle}+\left(C_{i,v}-E_i\sum_{k\in \boldsymbol{K}_{i,v}}\sum_{\alpha\in\boldsymbol{\alpha}_k^{i,v}}\sigma_{k,\alpha}^{i,v}\right)\rho_{fuel}\right](1-X_i) \tag{1}$$

$$min\sum_{i\in \boldsymbol{I}}\sum_{v\in \boldsymbol{V}_i}\sum_{k\in \boldsymbol{K}_{i,v}}\sum_{\alpha\in\boldsymbol{\alpha}_k^{i,v}}\left(\beta_i^k D_{k,\alpha}^{i,v}+H_{i,v}^{k,\alpha}\right) \tag{2}$$

Objective (1) is to minimize the GHG emissions from traditional campus fleet considering vehicle idling. $E_i\sum_{k\in \boldsymbol{K}_{i,v}}\sum_{\alpha\in\boldsymbol{\alpha}_k^{i,v}}\sigma_{k,\alpha}^{i,v}\rho_{idle}$ represent the GHG emissions due to vehicle idling, while $\left(C_{i,v}-E_i\sum_{k\in \boldsymbol{K}_{i,v}}\sum_{\alpha\in\boldsymbol{\alpha}_k^{i,v}}\sigma_{k,\alpha}^{i,v}\right)\rho_{fuel}$ represent the GHG emissions from fuel consumption. $(1-X_i)$ indicate that the GHG emissions from vehicle i will be zero once it is replaced by an EV. Objective (2) is to minimize the total detour time $\beta_i^k D_{k,\alpha}^{i,v}$ and charging time $H_{i,v}^{k,\alpha}$ of the EV i at location k during its α-th visit on day v.

3.3.2. Constraints

3.3.2.1. Battery transition

$$B_{k,\alpha}^{i,v}=B_{k-1,\alpha}^{i,v}+\left(QH_{i,v}^{k-1,\alpha}-\varphi_{k-1,k,\alpha}^{i,v}P_i\right)Y_i^v-\beta_{k-1,\alpha}^{i,v}P_iD_{k-1,\alpha}^{i,v},\forall i\in \boldsymbol{I},\forall v\in \boldsymbol{V}_i,\forall k\in \boldsymbol{K}_{i,v},\forall\alpha\in\boldsymbol{\alpha}_k^{i,v},\forall k\geq 2 \tag{3}$$

$$0.2\lambda_i<B_{k,\alpha}^{i,v}\leq\lambda_i,\forall i\in \boldsymbol{I},\forall v\in \boldsymbol{V}_i,\forall k\in \boldsymbol{K}_{i,v} \tag{4}$$

$$B_{k=1,\alpha=1}^{i,v}=\lambda_i,\forall i\in \boldsymbol{I},\forall v\in \boldsymbol{V}_i \tag{5}$$

Constraints (3) describe the battery energy transition of the vehicle i at day v between k and $k-1$, where k represents a warehouse or charging facility that the vehiclewill stop at or pass through.The term $\beta_{k-1,\alpha}^{i,v}PD_{k-1,\alpha}^{i,v}$ calculate the power consumption for the detour, while $QH_{i,v}^{k-1,\alpha}$ represent the potential power obtained from the last facility at $k-1$. $\varphi_{k-1,k,\alpha}^{i,v}P$ account for the power consumption from k to $k-1$.

Constraints (4) specify the range of the vehicle's energy level, ensuring that each vehicle has sufficient power to complete its entire route. To maintain a safe battery reserve, the vehicle's battery power level is kept above 20 % of its capacity (Davies et al., 2019). Constraints (5) ensure that the initial battery energy for different types of vehicles is fully charged before departure in each day.

3.3.2.2. Charging time and cost

$$H_{i,v}^{j,\alpha}\leq D_{j,\alpha}^{i,v}\sum_{t\in\boldsymbol{T}_{j,\alpha}^{i,v}}\left(R_t^jZ_t^{i,v,j,\alpha}\right),\forall i\in \boldsymbol{I},\forall v\in \boldsymbol{V}_i,\forall j\in \boldsymbol{J}_{i,v},\forall\alpha\in\boldsymbol{\alpha}_j^{i,v} \tag{6}$$

$$D_{j,\alpha}^{i,v}\leq Y_i^v,\forall i\in \boldsymbol{I},\forall v\in \boldsymbol{V}_i,\forall j\in \boldsymbol{J}_{i,v},\forall\alpha\in\boldsymbol{\alpha}_j^{i,v} \tag{7}$$

$$\sum_{t\in\boldsymbol{T}_{j,\alpha}^{i,v}}Z_t^{i,v,j,\alpha}=D_{j,\alpha}^{i,v},\forall i\in \boldsymbol{I},\forall v\in \boldsymbol{V}_i,\forall j\in \boldsymbol{J}_{i,v},\forall\alpha\in\boldsymbol{\alpha}_j^{i,v} \tag{8}$$

$$D_{j,\alpha}^{i,v}\leq H_{i,v}^{j,\alpha},\forall i\in \boldsymbol{I},\forall v\in \boldsymbol{V}_i,\forall j\in \boldsymbol{J}_{i,v},\forall\alpha\in\boldsymbol{\alpha}_j^{i,v} \tag{9}$$

$$H_{i,v}^{m,\alpha}+D_{m,\alpha}^{i,v}=0,\forall i\in \boldsymbol{I},\forall v\in \boldsymbol{V}_i,\forall m\in \boldsymbol{M}_{i,v},\forall\alpha\in\boldsymbol{\alpha}_m^{i,v} \tag{10}$$

$$Z_t^{i,v,j,\alpha}Q\vartheta_e\leq 0.3C_{i,v}Y_i^v\vartheta_f \tag{11}$$

Constraints (6) ensure that the charging time for vehicle i on day v does not exceed the available time window at charging facility j. Constraint (7) stipulates that only vehicles replaced by EVs can utilize the charging facilities. Constraint (8) ensures that a vehicle can only select a single time slot for charging. Constraints (9) mandate that when a vehicle detours to a charging facility and initiates charging, it must charge for a minimum of 1 min. Lastly, Constraint (10) ensures that warehouses as intermediate stops do not provide on-route charging services. According to the U.S. Department of Energy and the National Renewable Energy Laboratory (NREL), electric vehicles can achieve fuel cost savings of approximately 30–60 % compared to gasoline vehicles, depending on electricity rates and vehicle efficiency (NREL, 2024; AFDC Calculator). Accordingly, Constraint (11) ensures that the charging cost for each vehicle does not exceed 30 % of the corresponding fuel cost for a given trip.

3.3.2.3. Available charging status

$$S_{i,v,k,\alpha}^{start}=S_{i,v,k,\alpha}^{0,start}+\sum_{l=1}^{k-1}\left(D_{k-l,\alpha}^{i,v}\beta_i^{k-l}+H_{i,v}^{k-l,\alpha}\right),\forall i\in \boldsymbol{I},\forall v\in \boldsymbol{V}_i,\forall k\in \boldsymbol{K}_{i,v},\forall\alpha\in\boldsymbol{\alpha}_k^{i,v},l\in Integer,\forall k\geq 2 \tag{12}$$

$$F_{i,v,k,\alpha}^{start}\geq S_{i,v,k,\alpha}^{start},\forall i\in \boldsymbol{I},\forall v\in \boldsymbol{V}_i,\forall k\in \boldsymbol{K}_{i,v},\forall\alpha\in\boldsymbol{\alpha}_k^{i,v} \tag{13}$$

$$F_{i,v,k,\alpha}^{start}\leq S_{i,v,k,\alpha}^{start}+\tau_k^i,\forall i\in \boldsymbol{I},\forall v\in \boldsymbol{V}_i,\forall k\in \boldsymbol{K}_{i,v},\forall\alpha\in\boldsymbol{\alpha}_k^{i,v} \tag{14}$$

$$A_{i,v}^{k,\alpha}\geq F_{i,v,k,\alpha}^{start}+\frac{1}{2}\beta_i^k,\forall i\in \boldsymbol{I},\forall v\in \boldsymbol{V}_i,\forall k\in \boldsymbol{K}_{i,v},\forall\alpha\in\boldsymbol{\alpha}_k^{i,v} \tag{15}$$

$$A_{i,v}^{k,\alpha}\leq F_{i,v,k,\alpha}^{start}+\frac{1}{2}\beta_i^k+\theta_k^i,\forall i\in \boldsymbol{I},\forall v\in \boldsymbol{V}_i,\forall k\in \boldsymbol{K}_{i,v},\forall\alpha\in\boldsymbol{\alpha}_k^{i,v} \tag{16}$$

$$S_{i,v,1,1}^{start}=S_{i,v,1,1}^{0,start},\forall i\in \boldsymbol{I},\forall v\in \boldsymbol{V}_i \tag{17}$$

$$U_t^j=1,\forall i\in \boldsymbol{I},\forall v\in \boldsymbol{V}_i,\forall j\in \boldsymbol{J}_{i,v},\forall t\in\left[A_{i,v}^{j,\alpha},A_{i,v}^{j,\alpha}+H_{i,v}^{j,\alpha}\right],\forall\alpha\in\boldsymbol{\alpha}_k^{i,v} \tag{18}$$

Once vehicle i is replaced by an EV, it firstly adheres to an initial schedule that dictates the timeline for passing through charging facilities and warehouses. Since detour time and charging time are significant factors, if vehicle i opts to detour to a charging facility, its subsequent schedule for reaching other potential charging facilities will be altered. Therefore, a dynamic schedule for each vehicle is required to compare with the availability schedule of charging facilities to determine if vehicle i can be charged. Consequently, Constraint (12) is established to determine the earliest time vehicle i can arrive at the catchment area of charging facility or a warehouse k during its α-th visit, based on all previously visited facilities or warehouses $k-l$. Constraints (13) and (14) collectively define the time windows during which the vehicle can choose to detour to charging facility k, during its α-th visit. If k represents a warehouse, then $\tau_k^i = 0$, ensuring that the warehouse does not provide charging services or a charging window. Constraints (15) and (16) specify a time window during which vehicle i arrives at a facility and may wait for θ_k^i minutes to be charged if the facility is occupied. Similar, if k is a warehouse, then $\frac{1}{2}\beta_i^k + \theta_k^i = 0$. Constraint (17) defines the arrival time of vehicle i at the first facility or warehouse. Lastly, Constraint (18) introduces a decision variable to indicate whether facility j is occupied during a given time.

3.3.2.4. Interaction of charging facility and vehicle

$$Z_{t=A_{i,v}^{j,\alpha}}^{i,v,j,\alpha} = 1, \forall i \in \boldsymbol{I}, \forall v \in \boldsymbol{V}_i, \forall j \in \boldsymbol{J}_{i,v}, \forall \alpha \in \boldsymbol{\alpha}_j^{i,v} \tag{19}$$

$$\sum_{i \in \boldsymbol{I}} \sum_{v \in \boldsymbol{V}_i} Z_t^{i,v,j,\alpha} \le N_t^j, \forall j \in \boldsymbol{J}_{i,v}, \forall t \in \boldsymbol{T}, \forall \alpha \in \boldsymbol{\alpha}_j^{i,v} \tag{20}$$

$$\sum_{j \in \boldsymbol{J}_i} \sum_{\alpha \in \boldsymbol{\alpha}_j^{i,v}} Z_t^{i,v,j,\alpha} \le 1, \forall i \in \boldsymbol{I}, \forall v \in \boldsymbol{V}_i, \forall t \in \boldsymbol{T} \tag{21}$$

$$U_t^j + Z_t^{i,v,j,\alpha} \le 1, \forall i \in \boldsymbol{I}, \forall v \in \boldsymbol{V}_i, \forall j \in \boldsymbol{J}_{i,v}, \forall t \in \boldsymbol{T}_{j,\alpha}^{i,v}, \forall \alpha \in \boldsymbol{\alpha}_j^{i,v} \tag{22}$$

$$X_i \le Y_i^v, \forall i \in \boldsymbol{I}, \forall v \in \boldsymbol{V}_i \tag{23}$$

Constraint (19) introduces a decision variable to indicate whether vehicle i will be charged at facility j during its α-th visit and time t. The index α is used to distinguish multiple visits to the same station by the same vehicle on the same day, while t captures the dynamic charging schedule over discrete time intervals. Constraint (20) ensures that the number of vehicles being charged at any given time does not exceed the available charging facilities. Constraint (21) stipulates that each vehicle can only be charged at one charging facility at a time. Constraint (22) guarantees that if a charging facility is occupied, no other vehicles can be charged at that facility. Finally, Constraint (23) ensures that all operational routes on different days for a single vehicle are serviced by EVs, thereby permitting the replacement of the vehicle with an EV.

In summary, these constraints collectively ensure that eligible vehicles can be replaced with EVs based on the shared on-route charging facilities.

3.4. Reformulation

To solve the bi-objective EVFRP model, we adopt the classical constraint method, where the first objective (GHG emissions from traditional campus vehicles) is transformed into a constraint (see Constraints (24) and (25)). By setting various GHG emission reduction targets ϵ, the model generates corresponding fleet replacement and scheduling plans. This approach allows us to obtain optimal solutions under specific, policy-relevant emission targets rather than solving for the entire Pareto frontier. It reflects the practical decision-making context in which agencies set phased sustainability goals and require targeted operational strategies that meet those targets.

$$\sum_{i \in \boldsymbol{I}} \sum_{v \in \boldsymbol{V}_i} \left[E_i \sum_{k \in \boldsymbol{K}_{i,v}} \sum_{\alpha \in \boldsymbol{\alpha}_k^{i,v}} \sigma_{k,\alpha}^{i,v} \rho_{idle} + \left(C_{i,v} - E_i \sum_{k \in \boldsymbol{K}_{i,v}} \sum_{\alpha \in \boldsymbol{\alpha}_k^{i,v}} \sigma_{k,\alpha}^{i,v} \right) \rho_{fuel} \right] (1 - X_i) \ge W(1-\epsilon) \tag{24}$$

$$\sum_{i \in \boldsymbol{I}} \sum_{v \in \boldsymbol{V}_i} \left[E_i \sum_{k \in \boldsymbol{K}_{i,v}} \sum_{\alpha \in \boldsymbol{\alpha}_k^{i,v}} \sigma_{k,\alpha}^{i,v} \rho_{idle} + \left(C_{i,v} - E_i \sum_{k \in \boldsymbol{K}_{i,v}} \sum_{\alpha \in \boldsymbol{\alpha}_k^{i,v}} \sigma_{k,\alpha}^{i,v} \right) \rho_{fuel} \right] (1 - X_i) < W[1-\epsilon+0.01] \tag{25}$$

To integrate the dynamic schedules of EVs with the availability schedules of shared charging facilities, several key constraints were established, including Constraint (6) related to charging time, Constraint (18) concerning the available charging status, and Constraint (19) regarding the combination of facility and vehicle. Notably, Constraints (18) and (19) involve decision variables that continuously assess the availability of shared charging facilities and whether EVs with dynamic schedules can utilize them. A significant challenge arises from variable-dependent indexing in these constraints, particularly in Constraint (18), where the facility occupancy variable U_t^j is defined over a time range determined by other decision variables: $t \in \left[A_{i,v}^{j,\alpha}, A_{i,v}^{j,\alpha} + H_{i,v}^{j,\alpha}\right]$. Similarly, Constraint (19) involves a condition where the charging decision variable Z depends on the dynamically determined charging start time $A_{i,v}^{j,\alpha}$. These formulations introduce implicit dependencies that solvers cannot directly handle, leading to nonlinearity and computational inefficiencies. To address this, a Big-M method was employed to transform these constraints into a linear form. As a result, the EVFRP model remains computationally tractable while accurately capturing the scheduling dependencies. Assuming ℶ represents an infinitely large positive value, Constraint (18) is reformulated as follows:

$$U_t^j \le \frac{\left(t - A_{i,v}^{j,\alpha} + \beth\right)}{\beth}, \forall i \in \boldsymbol{I}, \forall v \in \boldsymbol{V}_i, \forall j \in \boldsymbol{J}_{i,v}, \forall t \in \boldsymbol{T}_j^{i,v}, \forall \alpha \in \boldsymbol{\alpha}_j^{i,v} \tag{26}$$

$$U_t^j \le \frac{\left(A_{i,v}^{j,\alpha} + H_{i,v}^{j,\alpha} - t + \beth\right)}{\beth}, \forall i \in \boldsymbol{I}, \forall v \in \boldsymbol{V}_i, \forall j \in \boldsymbol{J}_{i,v}, \forall t \in \boldsymbol{T}_j^{i,v}, \forall \alpha \in \boldsymbol{\alpha}_j^{i,v} \tag{27}$$

Constraint (18) is thus reformulated as following constraints:

$$Z_t^{i,v,j,\alpha} \le \frac{\left(t - A_{i,v}^{j,\alpha} + \beth\right)}{\beth}, \forall i \in \boldsymbol{I}, \forall v \in \boldsymbol{V}_i, \forall j \in \boldsymbol{J}_{i,v}, \forall t \in \boldsymbol{T}_j^{i,v}, \forall \alpha \in \boldsymbol{\alpha}_j^{i,v} \tag{28}$$

$$Z_t^{i,v,j,\alpha} \le \frac{\left(A_{i,v}^{j,\alpha} - t + \beth\right)}{\beth}, \forall i \in \boldsymbol{I}, \forall v \in \boldsymbol{V}_i, \forall j \in \boldsymbol{J}_{i,v}, \forall t \in \boldsymbol{T}_j^{i,v}, \forall \alpha \in \boldsymbol{\alpha}_j^{i,v} \tag{29}$$

New constraints, Eqs. (26)–(29), could enforce time-dependent conditions on charging and facility occupancy. This ensures that an EV is only charged or occupying a facility within its available time window.

4. Data description

We use University of Utah (UU) campus fleet and its strategic initiative to transition a portion of its fleet to EVs as a case study. The fleet comprises 88 gasoline vehicles serving 43 departments for various transportation tasks, many of which involve multiple routes within a week. The campus fleet is categorized into three vehicle types: trucks, multipurpose vehicles (MPVs), and passenger cars. To align with the original vehicle classifications, three similar EV types are considered candidates for replacement: Nissan e-NV200 and Nissan Leaf, each equipped with 40 kWh batteries, will replace the MPVs and passenger cars, respectively, while Ford *E*-Transit, with a 68 kWh battery, will replace the trucks.

Existing on-route bus charging facilities will be leveraged to provide fast charging services when the campus fleet operates off-campus. These charging facilities, constructed by the Utah Transit Authority (UTA), represent a critical infrastructure element in the Wasatch Front region. UTA, providing public transportation services in this region, currently operates 34 battery-electric buses, supported by on-route and in-depot charging facilities (Utah Transit Authority, n.d.). This study utilizes vehicle operation data from the UU campus fleet for the week of February 13, 2023 (Monday) to February 18, 2023 (Saturday), and incorporates charging schedule from 11 UTA on-route charging facilities to conduct a comprehensive analysis. There was a total of 268 operational routes over the six-day period.

Five datasets were used in this study: trajectory, warehouse, fuel consumption, vehicle data, and on-route charging facility data. Trajectory data captures the GPS movements of each vehicle across different days, providing the basis for deriving initial schedule for each vehicle. This schedule outlines the expected arrival times at various warehouses along the vehicle's route and offers a detailed timeline of daily operations. Warehouse data details the locations and service times, including idling periods, for the vehicles. Fuel consumption data provides insights into the fuel usage for each vehicle over a complete daily route. Vehicle data includes comprehensive information about each vehicle, such as make, model, vehicle type, and the department it serves. On-route charging facility data encompasses the locations and charging schedules of existing charging facilities. By analyzing trajectory data alongside on-route charging facility data, a set of charging facilities that the campus fleet can access is identified. Furthermore, the charging schedules are used to determine when these facilities are not occupied by electric buses, allowing us to convert this information into available charging window that the campus fleet can utilize.

Fig. 4 presents the trajectories of the campus fleet over the study period and the locations of on-route charging facilities with catchment areas. The blue area represents the University of Utah campus in Salt Lake City, while the green lines depict the trajectories of all 88 campus fleet vehicles over a week. These routes span the entire state of Utah, with most activity concentrated in the Salt Lake City area.

5. Results

Data preprocessing and EVFRP modeling were performed using Python. The EVFRP model includes 1,231,460 continuous variables, 6,432,500 integer variables, and 6391 quadratic constraints. The model was solved using Gurobi, a commercial optimization solver, on a computer with an Intel i5 8400 processor running Windows 10 at 2.80 GHz and 16 GB of RAM. The dual simplex method was applied, with a computational time of 409.29 s for achieving the maximum GHG emission reduction target, resulting in a relative optimality gap of less than 0.00001 %. The results are organized to highlight both the technical performance and practical value of the proposed model. First, we present a phased fleet replacement plan under varying GHG emission reduction targets, offering realistic guidance for gradual EV adoption. We then analyze the spatial and temporal distribution of EV charging across shared facilities, demonstrating efficient station usage and off-peak charging behavior. Sensitivity analyses are conducted on battery capacities and short-term traffic delays to assess model robustness under real-world conditions. Finally, a feasibility analysis identifies high-priority vehicles for replacement based on operational characteristics, supporting practical decision-making for fleet managers.

5.1. Replacement of campus fleet

We present multiple EV replacement scenarios, detailing the number of campus fleet vehicles to be replaced by EVs, the vehicles requiring shared on-route charging facilities, and the associated delays due to detours and charging. Total GHG emission from the current campus fleet, W, amount to 2131 kgCO_2, as calculated using Eq. (24) and (25). The EVFRP model was found to be infeasible when $\epsilon > 0.77$, which corresponds to a 77 % reduction target in total GHG emissions. It was noted that 81 campus fleet vehicles could be eventually replaced by EVs when target is set at 77 %. We therefore analyze the replacement plans described as GHG emission reduction targets ranging from 0 % to 70 % at 10 % intervals to reflect the transition process. This means we run the mode total 8 times for each target and one time for the maximum 77 % reduction target. Fig. 5 presents the tradeoff curve between different GHG emission reduction targets and the corresponding fleet replacement plans.

A clear positive correlation was observed between reduced GHG emissions and the number of replaced vehicles. In contrast, the trends for charged vehicles, charged routes, and charging sessions vary under

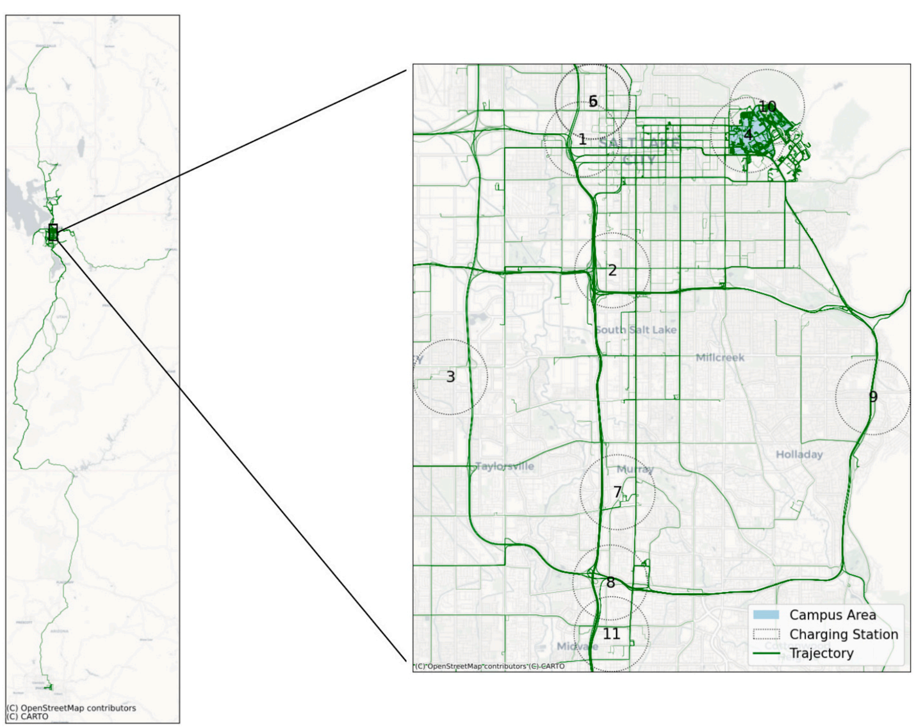


Fig. 4. Study area and trajectory of campus fleet.

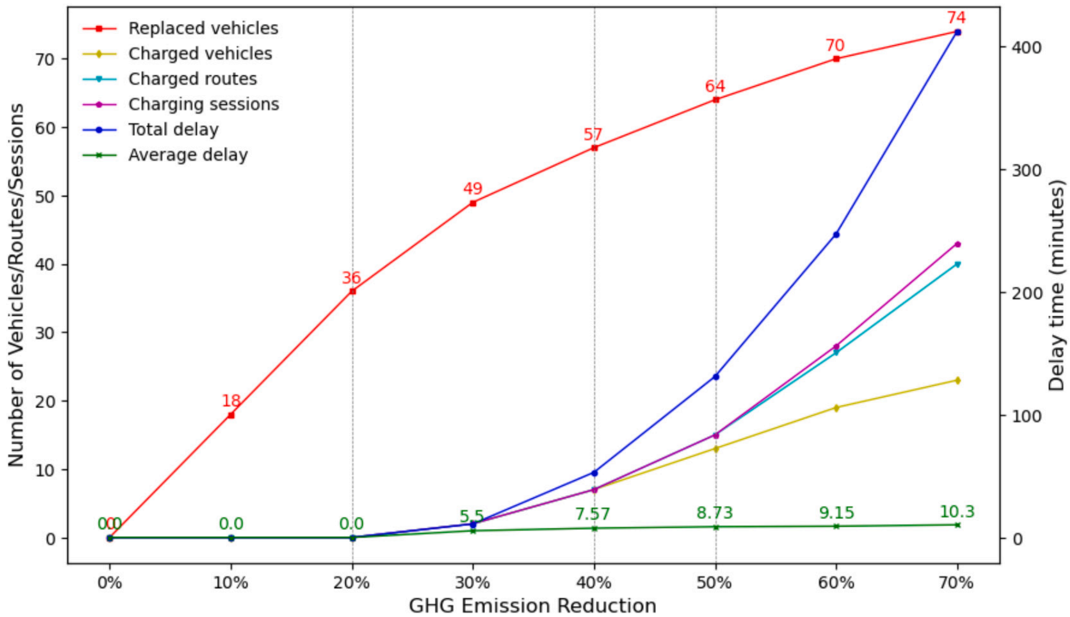


Fig. 5. Campus fleet replacement plan under different GHG emission reduction targets. Replaced vehicles refer to the number of campus fleet vehicles being replaced by EVs. Charged vehicles indicate the vehicles that require shared on-route charging facilities. Charged routes represent the number of routes operated by charged vehicles within the study period. Charging sessions refer to the number of times vehicles are charged along these routes. Total delay is the sum of detour time and charging time from the charged routes, while average delay is calculated by dividing the total delay by the number of charged vehicles per day.

different GHG reduction scenarios. Based on the operational conditions of the replaced vehicles and on-route charging activities, the replacement scenario is categorized into four phases:

- Phase 1 (0–20 % GHG reduction): This is the most cost-effective phase. Up to 36 vehicles are replaced without requiring any on-route charging, thereby incurring no operational delays.
- Phase 2 (20–40 % GHG reduction): This phase introduces minor delays as on-route charging begins. A key feature of this phase is that the number of charged vehicles, charged routes, and charging sessions increased at the same rate, meaning each vehicle required only a single on-route charging session in one route over the entire week. Delays remain minimal (e.g., 53 total minutes at 40 % reduction), with average per-route delays rising gradually to 5.5 min. The number of replaced vehicles nearly triples from 21 to 57, suggesting an efficient expansion of electrification with minimal disruption.
- Phase 3 (40–50 % GHG reduction): The number of charged routes and charging sessions started to increase at a faster rate than the number of charged vehicles, showing a diverging growth trend. In this phase, more replaced vehicles required on-route charging, leading to longer operational delays (up to 131 min total). Some vehicles required on-route charging on multiple routes across different days, causing average delays to gradually rise from 7.57 to 8.73 min and slowing the rate of vehicle replacement.
- Phase 4 (50–70 % GHG reduction): The number of charging sessions began to increase at a faster rate than the number of charged routes, often requiring multiple charges in a single day. Delays grow substantially (up to 412 min). The number of replaced vehicles plateaus at approximately 74, with only a marginal increase of 11 %. All additional vehicles replaced in this phase required on-route charging facilities.

The phased replacement plan provides fleet operators with flexible strategies aligned with their operational priorities. Phase 1 is recommended for maintaining minimal operational delays and ensuring timely warehouse arrivals, making it ideal for operations where punctuality is critical. Phase 2 offers a balanced approach, achieving a moderate reduction in delays while significantly increasing the number of EVs. Phase 3 is suitable for scenarios where vehicles can accommodate charging delays associated with diverse delivery schedules, allowing for extended driving distances and the ability to serve more warehouses. Phase 4 achieves the maximum fleet replacement but comes with considerable delays, making it appropriate only when the highest level of GHG emission reduction is prioritized over operational efficiency.

To verify the advantages of our model, which incorporates a detour-based strategy rather than full route optimization, we conducted a comparative analysis between our EVFRP model and a traditional EVRP model. Given the NP-hard nature of the EVRP in large instances, we employed a heuristic algorithm proposed by He, Yang, Tang, and Huang (2018) to obtain feasible solutions. As shown in Fig. 6, our EVFRP model consistently results in lower operational delays across all GHG emission reduction targets.

We further examined other operational characteristics of vehicles being replaced by EVs in an effort to elucidate the benefits. Fig. 7 provides scenario-based insights into travel distance, travel time, operation frequency, GHG emissions before being replaced by EVs, idling time, and the number of warehouses served. The total replaced vehicles are represented by the blue line, while the charged vehicles, a subset of the replaced vehicles, are depicted by the orange dotted line. Two key patterns emerged. First, up to the 20 % GHG reduction target, the model prioritizes replacing short-distance, high-idling vehicles that do not require on-route charging. This aligns with the model's objective to minimize delay, as these vehicles impose minimal disruption on the schedule. After 20 %, the replacements shift toward longer-distance and higher-utilization vehicles, including those requiring charging, demonstrating that the model adaptively balances GHG reduction and operational efficiency. If we focus only on the replaced vehicles requiring on-route charging, additional patterns emerge. As depicted by the orange dotted line in Fig. 7, an inflection point emerged at the 40 % emission reduction target, marking a shift in replacement patterns. Prior to this threshold, all six operational metrics steadily increase, suggesting that the model prioritizes high-impact replacements with substantial operational coverage and emission reduction potential. However, beyond the 40 % target, travel distance, emissions, and operational days begin to decline. This trend implies that after 40 %, the model begins to replace

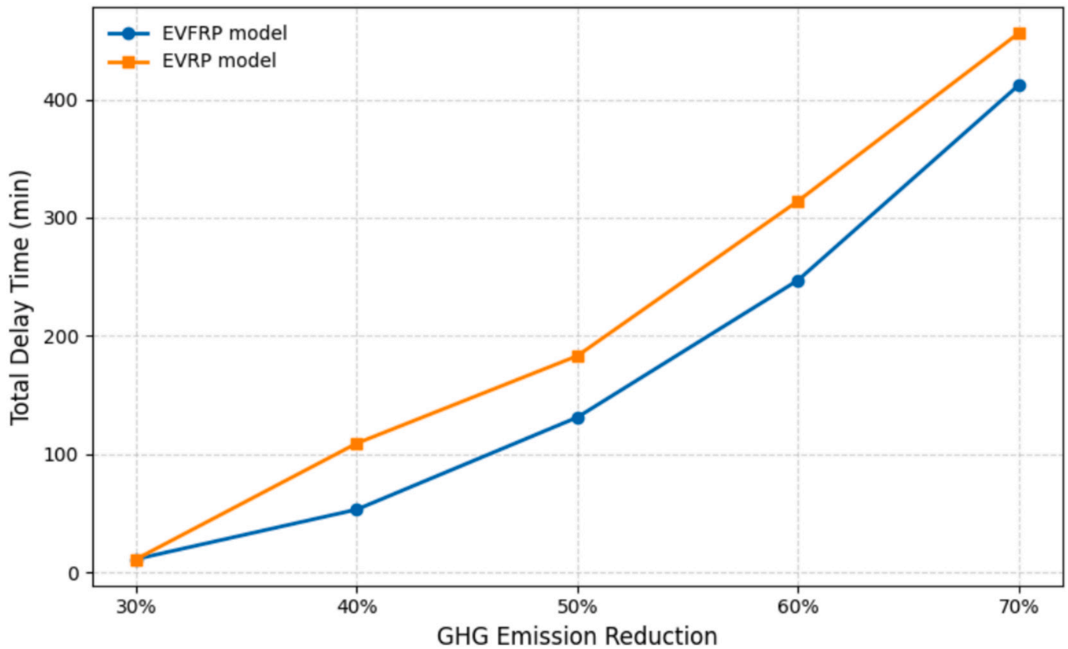


Fig. 6. Comparative analysis of operational delay between the proposed EVFRP model and the traditional EVRP model.

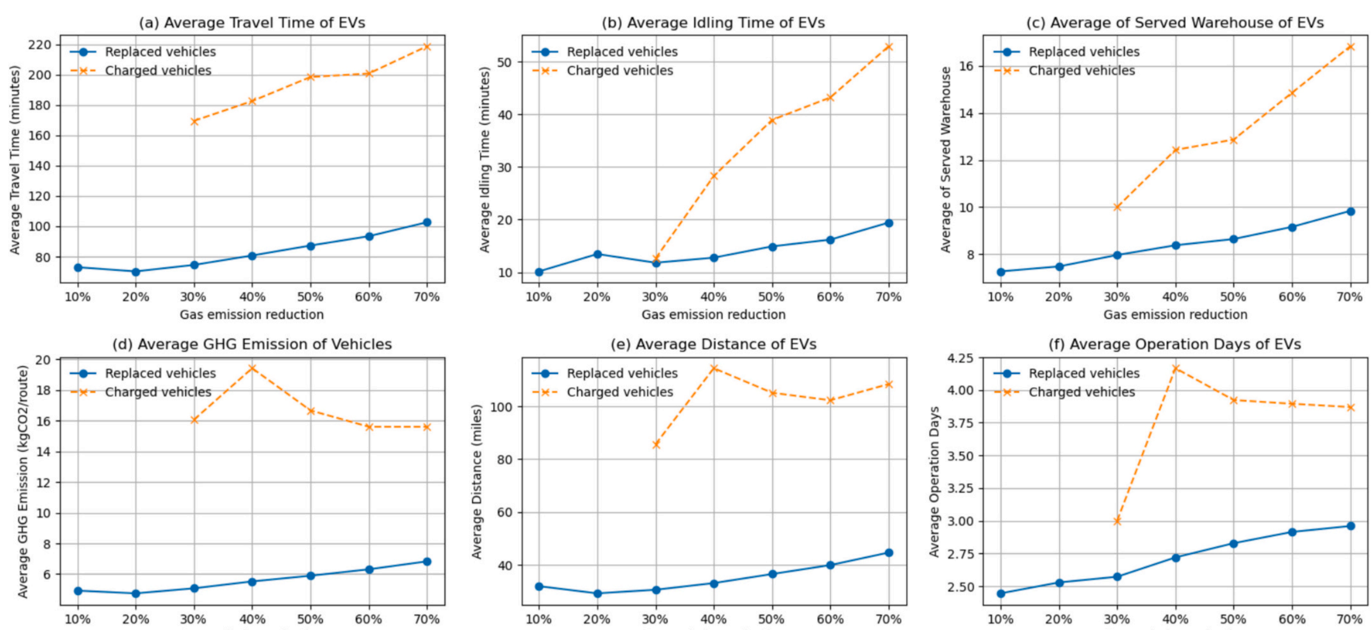


Fig. 7. Scenario-based pattern of EV fleet operation conditions.

vehicles that are less operationally intensive but still logistically complex, characterized by shorter routes and lower emissions but higher time demands. These findings indicate that the 40 % target represents a strategic threshold for effective on-route charging deployment, beyond which the marginal benefits of replacement may diminish.

Although vehicles requiring on-route charging make up a smaller share of the replaced fleet (Fig. 5), they represent a disproportionately high operational utility (Fig. 7), with longer travel times and distances, more operational days, and higher GHG emissions. These high-utility vehicles are crucial to achieving deeper emission reductions. However, they are not prioritized in early replacement phases due to their charging needs and associated delays. This insight highlights a critical trade-off: prioritizing low-impact, easy-to-replace vehicles early on may miss the opportunity to address the largest emitters. By strategically leveraging shared charging infrastructure, agencies can cost-effectively integrate these high-impact vehicles into the electrification plan, especially in later phases, thus maximizing environmental benefits without incurring excessive infrastructure costs.

To better understand the operational implications of on-route charging, we analyzed the spatial distribution of routes requiring charging across varying GHG emission reduction targets. As illustrated in Fig. 8, the service area of charged vehicles expanded progressively with more ambitious targets. At the 30 % target, only two charged routes appeared, concentrated around Salt Lake City and its northern vicinity. By 40 %, the coverage extended to southern Utah; by 50 %, to eastern regions; and by 70 %, charged routes reached into western Utah. In

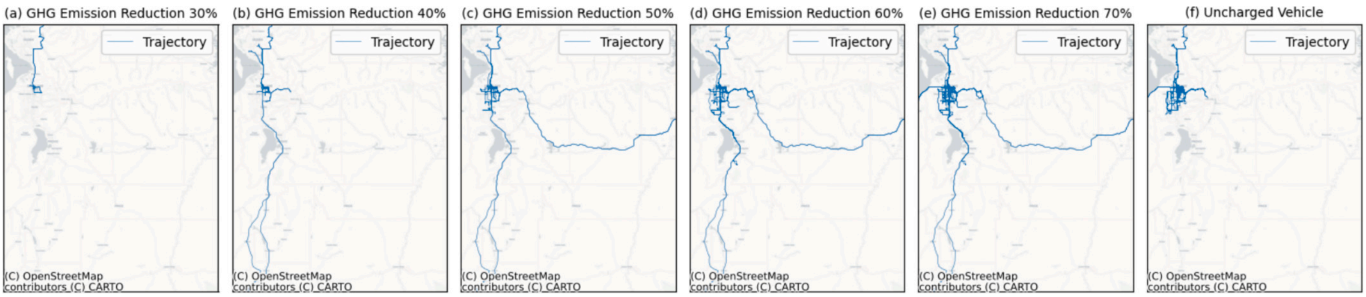


Fig. 8. Spatial distribution of replaced vehicles under different GHG emission reduction targets. (a)-(e) represent the coverage of charged vehicles under different targets. (f) represents vehicles that have been replaced by EVs but don't require on-route charging.

contrast, vehicles not requiring on-route charging, though more numerous, remained largely concentrated within the Salt Lake City area (Fig. 8f). This finding underscores the broader spatial reach and operational importance of charged vehicles in achieving deeper emission reductions.

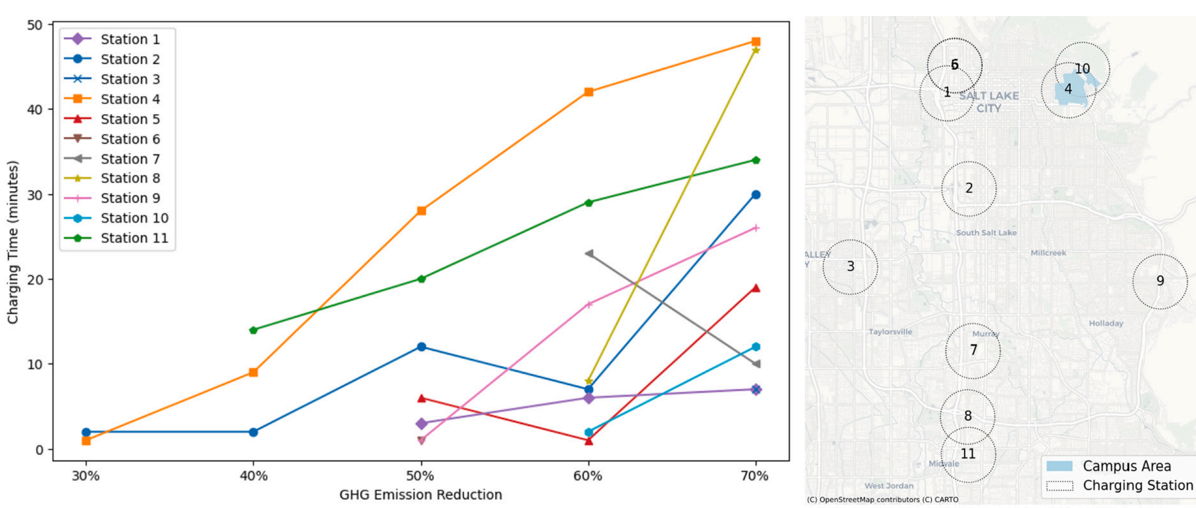
5.2. *Shared charging facility*

Integrating campus fleet replacement with existing bus charging facilities improves charger utilization across all emission reduction targets. As shown in Fig. 9(a), 11 on-route facilities are shared by the replaced EV fleet, with total charging time reflecting each facility's usage. The spatial distribution of these charging facilities is depicted in Fig. 9(b), where blue areas is the campus area that represent the primary terminals of campus fleets, and each circle denotes the catchment area of a shared charging facility labeled by station numbers. Different facilities exhibit varying levels of utilization depending on the geographical location and emission reduction targets. Major charging activities are concentrated at station 4 near the campus, with some also occurring in more distant locations, such as Stations 8 and 11. Most shared charging facilities, such as Stations 1, 4, 8, 9, 10, and 11, experience increased utilization as the emission reduction target rises. A few stations, however, exhibit a decline in utilization, such as Station 7 in 60 % to 70 % emission reduction. This shows special demand shift phenomenon because of opportunity charging and dynamic schedule. This cause Station 7's partial demand shift to the close Station 8. Similarly, Stations 2 and 5 show a decrease in demand from the 50 % to 60 % emission reduction targets, followed by an increase after 60 %. Some stations have less utility, such as Stations 3 and 6, are only utilized at specific targets.

We further analyzed the utilization patterns of shared charging facilities by the campus fleet throughout the day. For each emission reduction target, we aggregated the total utilization durations across all charging stations over the entire study period, as illustrated by the blue-shaded area in Fig. 10 (a). Charging demand is distributed throughout the day, peaking between 8 AM and 2 PM. This distribution aligns favorably with time-of-use electricity rates, shown in Fig. 10(b), which reflect local pricing for company-managed EV charging stations (Rocky Mountain Power, n.d.). Notably, most charging activities occur before 3 PM, helping to avoid late-afternoon peak electricity prices and grid stress (Ye, Gao, & Yu, 2022; Ye, Yu, et al., 2022). Given that the campus EV fleet utilize shared charging facilities and incur associated fees, this charging pattern can significantly reduce the overall charging costs. The model's ability to shift demand away from high-cost periods illustrates the strategic value of coordinated charging in shared facility settings.

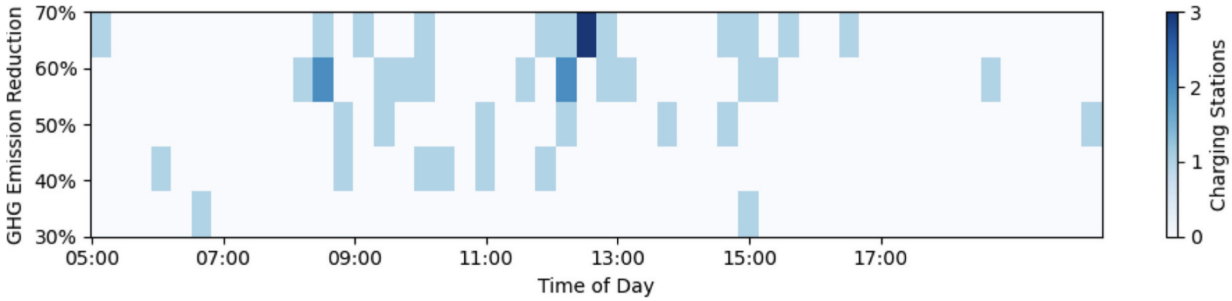
5.3. *Sensitivity analysis*

To evaluate the robustness of the proposed model, sensitivity analyses were conducted across three key dimensions: battery capacity, charging station disruption, and short-term traffic delay. For each scenario, the model was run multiple times under different GHG emission reduction targets (from 0 % to 70 % at 10 % intervals). These analyses help assess how changes in vehicle range, infrastructure availability, and

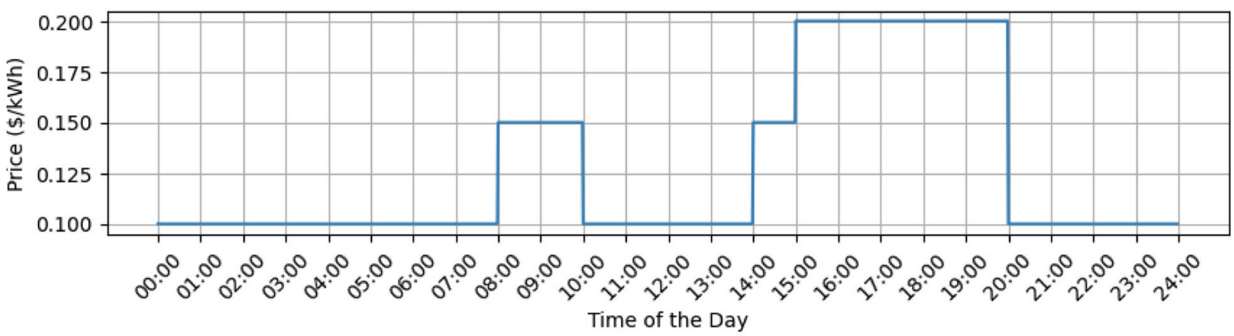


(a) Charging time allocated by on-route charging facilities (b) Spatial distribution of charging facilities

Fig. 9. Charging time and spatial distribution of shared charging facility.



(a) Utilized charging facilities over time under different GHG emission reduction targets



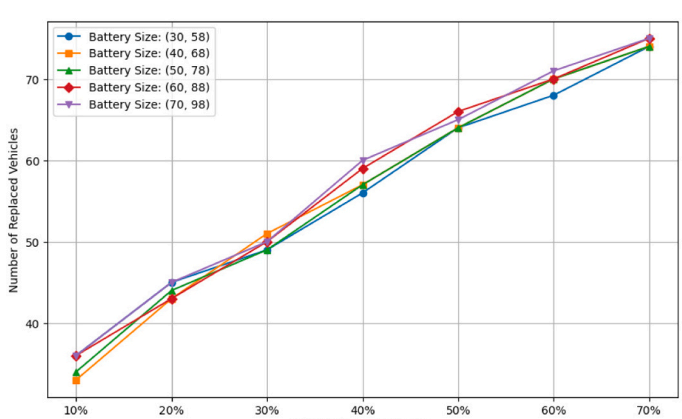
(b) Time-of-use electricity rates for company-operated EV charging stations

Fig. 10. Shared charging schedule and corresponding dynamic electricity rates.

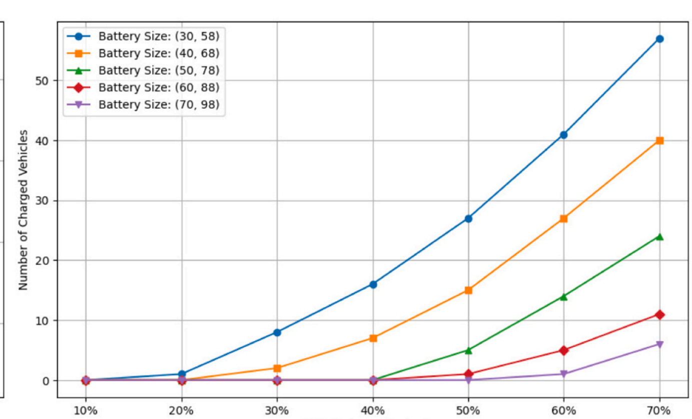
operational delays influence fleet replacement decisions and charging schedules.

Fig. 11 presents the analysis of the number of replaced and charged vehicles across different battery sizes for three types of EVs. The battery sizes for MPVs and passenger cars range from 30 to 70 kWh, incremented by 10 kWh, while the battery sizes for trucks range from 58 to 98 kWh. These battery sizes are grouped by vehicle type (MPVs/passenger cars, trucks) and used as an input to the EVFRP model. To reflect realistic replacement plan, their battery sizes are increased synchronously. As a result, five battery groups are established, as shown in Fig. 11. The model then outputs the replacement plan including the number of replaced vehicles (Fig. 11(a)) and charged vehicles (Fig. 11(b)). Generally, increasing battery size has a minimal impact on the number of replaced campus fleet vehicles but significantly affects the number of vehicles requiring on-route charging. This disparity becomes more pronounced with greater reductions in GHG emissions. Specifically, for the number of replaced vehicles, as shown in Fig. 11(a), larger battery sizes do not consistently result in a higher number of replaced vehicles across different emission reduction targets, such as the battery size group (70 kWh for MPVs or passenger cars, 98 kWh for trucks) in purple line. This counterintuitive trend suggests that simply increasing battery capacity does not guarantee greater replacement feasibility. Other factors, such as route compatibility and detour constraints, also play critical roles.

For the number of charged vehicles, as shown in Fig. 11(b), larger battery sizes delay the need for on-route charging among replaced



(a) Number of replaced vehicles



(b) Number of charged vehicles

Fig. 11. Number of replaced and charged vehicles under different battery sizes.

vehicles and also reduce their overall numbers. For example, the smallest battery size group (30, 58) sees 57 vehicles needing on-route charging by the 70 % target, while the largest battery size group (70, 98) only reaches 6 vehicles and only after the 50 % target. Additionally, as battery size increases for a given emission reduction target, the decline in the number of EVs requiring on-route charging occurs at a diminishing rate, highlighting the reduced marginal benefit of further increasing battery capacity. Fleet management should adopt a comprehensive strategy that balances suitable GHG emission reduction targets, actual operational needs, and EV models to optimize both cost-effectiveness and operational efficiency.

Given that schedule coordination in shared charging facilities is highly sensitive to both facility availability and vehicle arrival times, we analyzed the impact of disruptions under two scenarios: single-facility failure and multiple-facility failure, as well as short-term traffic delays, on the performance of the EVFRP model.

For the single-facility disruption analysis, we sequentially disabled each charging station and ran the model under various GHG emission reduction targets. As shown in Fig. 12(a) and (b), the y-axis represents the ID of the disabled station, while the heatmaps illustrate the number of vehicles replaced and charged under each emission reduction target and disruption scenario. The variation in colour across cells reflects the sensitivity of the model to different disruptions. The results indicate that the disruption of a single station generally has limited impact on the number of vehicles replaced, demonstrating the robustness of the EVFRP model. However, certain stations, e.g. Station 4, have a greater influence, resulting in fewer vehicles being replaced when disabled. Furthermore, the effect of a station's disruption can vary depending on the emission reduction target level. We then analyzed the impact of simultaneous multi-station disruptions. As shown in Fig. 12(c) and (d), concurrent failures of multiple charging facilities significantly affect the number of vehicles that can be replaced and, more notably, the number of vehicles that can be charged. These results highlight the increased vulnerability of the system under compound disruptions and emphasize the importance of redundancy and coordination in shared charging infrastructure.

Short-term traffic congestion can affect the arrival time of EVs at charging facilities, potentially disrupting coordinated charging

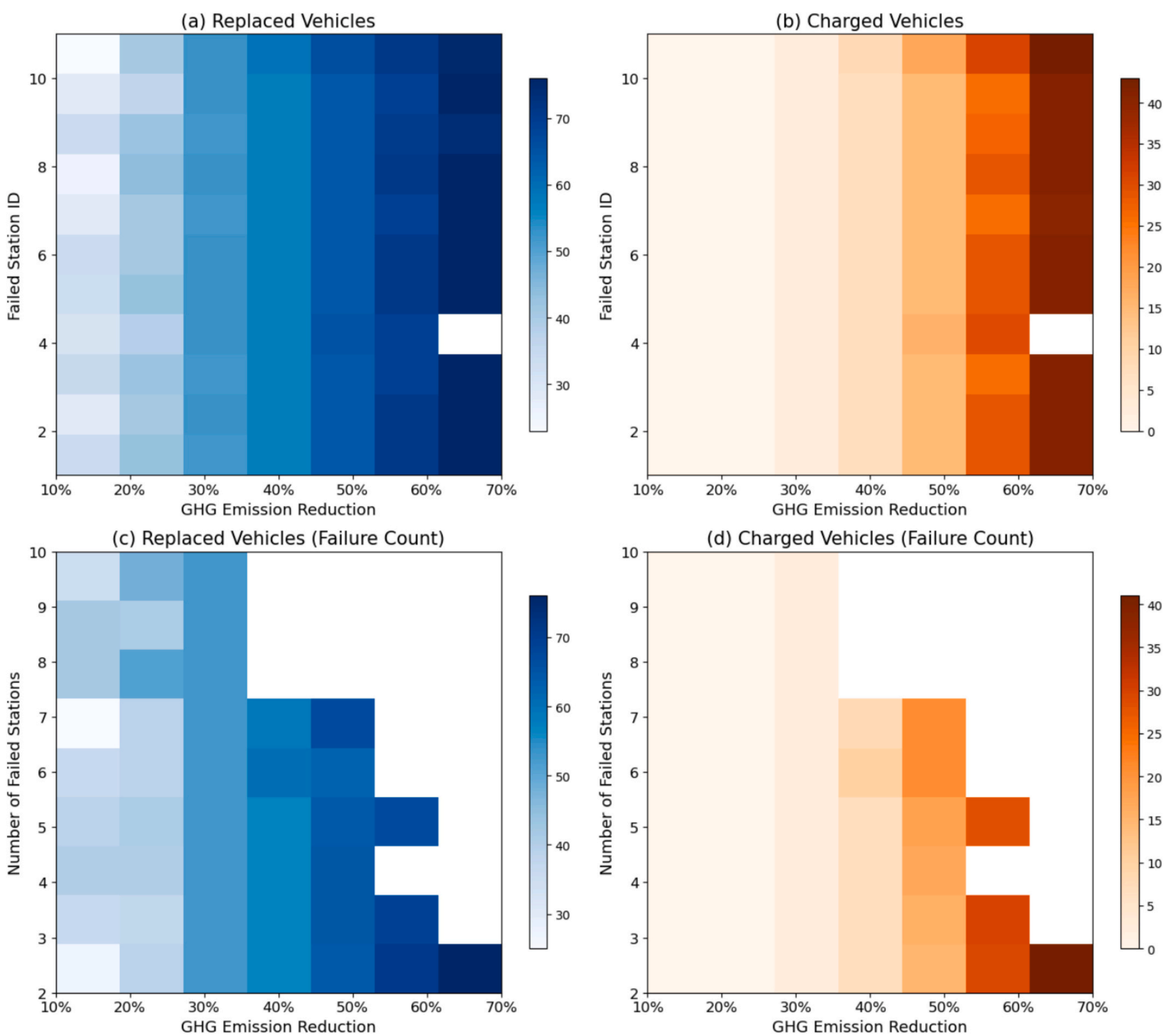


Fig. 12. Impact of shared charging facility failure.

schedules. To assess this impact, we introduced traffic delays of 5, 10, 15, 20, 25, and 30 min and analyzed their effects on the vehicle replacement and charging activity. We defined two peak periods: a one-hour morning peak (7:30–8:30 AM) and a one-hour evening peak (4:30–5:30 PM). Vehicles operating within these time windows were subjected to the corresponding delay durations. As shown in Fig. 13, the impact of delay time on EV replacement and charging behavior under the shared charging strategy is not linear. A threshold effect is evident in system performance. Specifically, the morning peak line in Fig. 13(a) shows that a 15-min delay during the morning peak leads to a sharp decline in the number of vehicle replacements, accompanied by increased charging and detour time (Fig. 13b). Conversely, the evening peak shows a more resilient pattern: a 20-min delay leads to a noticeable increase in vehicle replacements without additional charging or detour time. This suggests that the EVFRP model, when subjected to delay pressure, may strategically favor replacing vehicles that do not require on-route charging, thus preserving operational efficiency while still achieving emission goals.

5.4. Feasibility analysis

Given the budget constraints associated with transitioning the campus fleet to EVs, it is crucial to prioritize which vehicles should be replaced first. In the EVFRP model, the primary objective is to minimize charging and detour times, which means that vehicles not requiring on-route charging are prioritized for replacement. However, these vehicles typically have shorter travel time (see Fig. A3). From the perspective of the UU Campus Fleet, prioritizing the replacement of high-utility vehicles, those that maximize the use of EVs, is essential. To address this, we further conducted a feasibility analysis of high-utility vehicles across different phases, taking into account factors such as travel time, operating days, and the number of served warehouses. As depicted in Fig. 14, a positive correlation exists between these three factors: vehicles with longer travel times tend to operate more frequently and serve more warehouses. We therefore identified the top five vehicles with the highest utility based on travel time. As shown in Table 2, as the EV transition progresses from Phase 1 to Phase 4, the travel time, operating days, and warehouse coverage of the replaced vehicles exhibit a consistent increasing trend. In the final two phases, all the top most utilized EVs require on-route charging to complete their routes. Notably, vehicles 78, 43, and 79, highlighted in the bold row, consistently rank among the highest-utilized across multiple phases.

The spatial distribution of high-utility vehicles across the four phases also illustrates varying coverage patterns. As depicted in Fig. 15, these vehicles primarily operate within the urban area of Salt Lake City, where ample shared charging facilities provide reliable on-route charging once these high-utility vehicles are replaced by EVs. Only a few vehicles extend their operations northward in Phase 2, eastward in Phase 3, and westward in Phase 4.

6. Conclusion

This paper developed a spatially- and temporally-informed bi-objective EVFRP model to determine the optimal EV replacement strategy and charging schedule by leveraging shared charging facilities. The two objectives encompassed the entire electrification process: minimizing GHG emissions from the traditional fuel vehicle fleet and minimizing charging and detour times after EV replacement. By converting the GHG emission reduction target into a constraint and linearizing the model, the bi-objective problem was transformed into a single-objective integer linear problem, which could be efficiently solved using commercial optimization solvers. A key highlight of the EVFRP model is its ability to dynamically manage EV schedules while accounting for charging delays at shared facilities. The model identified which vehicles should be electrified, when they should utilize shared charging facilities, and how their charging schedules should be coordinated. Additionally, since vehicle fleets often operate different routes on different days, on-route charging demand can be uncertain. To address this, the model incorporated a time-based approach that considered multiple operating days, ensuring comprehensive coverage of various routes before determining replacement feasibility. The EVRFP model is adaptable and can be applied to fleets of different scales, enabling cost-effective electrification planning. Another key contribution is the consideration of vehicle idling as a significant source of GHG emissions, which has received limited attention in previous studies. The model prioritizes replacing high-idling vehicles to optimize fleet electrification.

To validate the model's effectiveness, we applied it to the UU campus fleet. A comprehensive analysis was conducted, yielding a detailed vehicle replacement plan and charging schedule. Specifically, the results segmented the replacement plan into four distinct phases, based on the trade-off between GHG emission reduction and charging-related factors. The asynchronous variations in the number of charged vehicles, charging time, and charging routes across phases highlighted the characteristics of each stage. In Phase 1, 36 vehicles were replaced, none of which required on-route charging. Delays began to appear in Phase 2, and by Phase 3, some vehicles required charging on multiple routes across different days. In Phase 4, vehicles required multiple charges within a single day, with delay times increasing nonlinearly as the phases progressed. Fleet managers can utilize these phase-based insights to implement electrification strategies based on their priorities and constraints. For the replaced vehicles, further scenario-based analyses were conducted, evaluating travel distance, travel time, operational

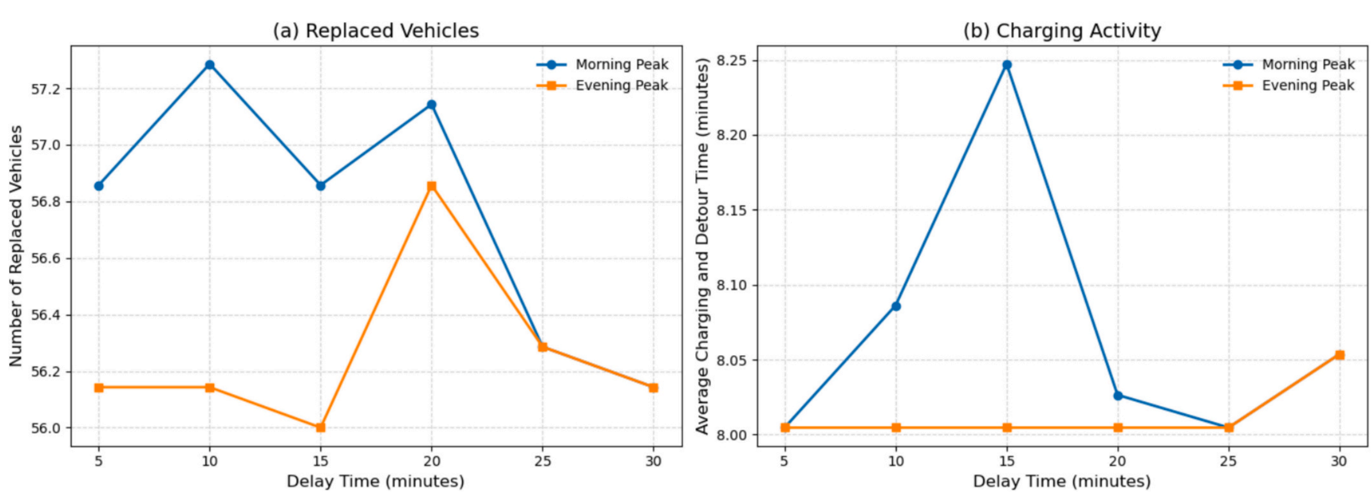


Fig. 13. Impact of short-term traffic delay in morning and evening peaks.

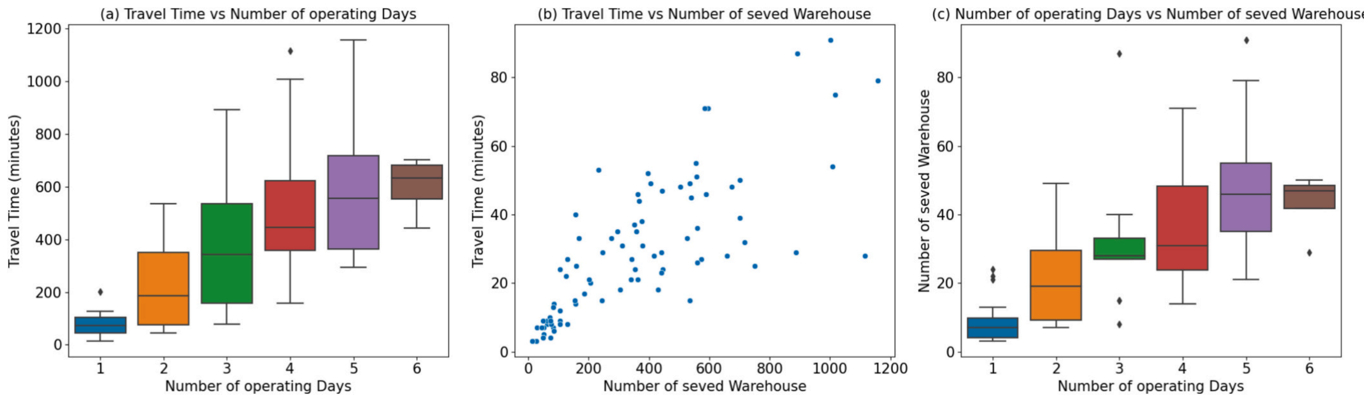


Fig. 14. Relationship between travel time, operating days and served warehouse for replaced vehicles.

Table 2
Top 5 high-utility EVs in different phases.

Phases	Vehicle ID	Whether charged	Travel time	Operating days	Served warehouse
1	106	No	504	5	48
	6	No	446	4	24
	114	No	442	6	29
	104	No	442	4	23
	1	No	364	5	46
2	**78**	**Yes**	**701**	**6**	**50**
	43	**Yes**	**595**	**4**	**71**
	79	**Yes**	**559**	**4**	**36**
	62	No	555	5	55
	23	No	539	5	45
3	**78**	**Yes**	**701**	**6**	**50**
	43	**Yes**	**595**	**4**	**71**
	116	Yes	590	6	46
	30	Yes	574	3	27
	79	**Yes**	**559**	**4**	**36**
4	3	Yes	1157	5	79
	107	Yes	1017	5	75
	110	Yes	1001	5	91
	113	Yes	891	3	87
	78	**Yes**	**701**	**6**	**50**

frequency, GHG emissions, idling time, and the number of warehouses served. The results indicated that Phase 2, corresponding to a 30 %–40 % GHG emission reduction target, provided the optimal balance between vehicle replacement and on-route charging, maximizing both cost-effectiveness and operational efficiency. Additionally, the spatial distribution of replaced vehicles varied across different GHG emission reduction targets, ensuring comprehensive service area coverage. The spatial-temporal analysis of shared charging facilities demonstrated significant improvements in utilization, with facility usage influenced by geographic location and emission reduction targets. Charging activities were primarily concentrated near the campus and in remote urban areas, occurring predominantly during off-peak periods to reduce costs and minimize power system strain.

We also conduct a sensitivity analysis to assess the impact of different battery sizes, facility failure, and traffic delay on model outcomes. While increasing battery size has minimal impact on the number of replaced vehicles, it significantly influences the number of vehicles requiring on-route charging. Larger batteries delay the need for on-route charging at higher GHG emission reduction targets. Single station failures have minimal impact on vehicle replacement outcomes, indicating the robustness of the model. However, simultaneous failures of multiple stations significantly reduce the number of vehicles that can be replaced, particularly those requiring charging. Short-term traffic delays affect overall model performance non-linearly and delays during the morning peak period tend to have a greater impact than those during the evening peak. The feasibility analysis offers a replacement priority framework considering the utility of vehicles and investment constraint. Vehicles with higher utility, characterized by longer travel times, more frequent operations, and service to a greater number of warehouses, consistently require on-route charging from phase 1 to phase 4. These vehicles primarily operated in urban areas, where they could reliably utilize shared charging facilities upon electrification.

It is worthwhile to mention some limitations of this research. The campus fleet excludes emergency vehicles, such as those required for critical patient transportation. GHG emissions from grid electricity are not considered in this model. The primary objective is to replace traditional fuel vehicles, which produce higher GHG emissions, with EVs. Including GHG emissions from grid electricity would not significantly impact the vehicle replacement plan in this context. Looking ahead, future work involves considering multiple charging ports per shared charging facility to better manage complex scheduling and real-time demands. Furthermore, analyzing other types of vehicle fleets, such as delivery or drayage trucks, could provide new insights when relevant data becomes available.

CRediT authorship contribution statement

Shouzheng Pan: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Ran Wei:** Validation, Formal analysis, Investigation, Writing – review & editing, Visualization. **Xiaoyue Cathy Liu:** Conceptualization, Methodology, Data curation, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Jeff Phillips:** Methodology, Resources, Writing – review & editing. **Bei Wang:** Methodology, Resources, Data curation.

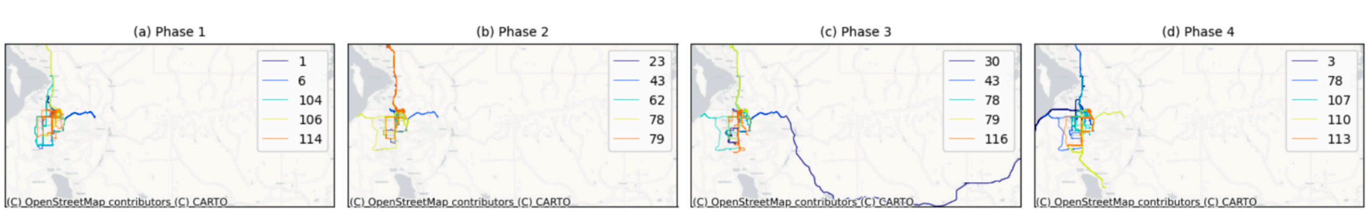


Fig. 15. Trajectory of top 5 replaced vehicles at different phases.

Declaration of competing interest

None.

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Appendix A. Operational features of UU campus fleet

Fig. A1 illustrates the temporal distribution of operating vehicles across different times of the day over the one-week period. The campus fleet operates near-continuously throughout the day, with peak activity observed during the morning hours between 5:00 AM to 12:00 PM. Vehicle activity significantly declines during weekends.

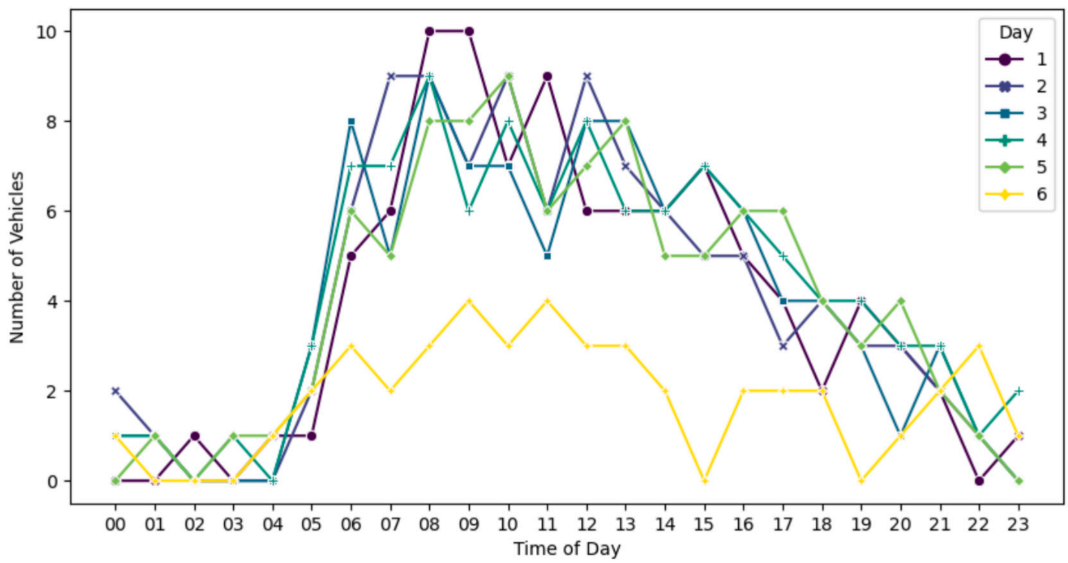

Fig. A1. Number of operating vehicles on different time-of-day.

Fig. A2 shows the distribution of operating vehicles across different days of the week and their operation frequency. In Fig. A2(a), the number of active vehicles is notably higher on weekdays, fluctuating around 50, with a significant reduction on weekends. Day 2 (Tuesday) and Day 4 (Thursday) have the highest vehicle activity. Fig. A2(b) displays vehicle operating frequency throughout the week, showing that most vehicles operate intermittently rather than daily, predominantly for 1, 2, 4, or 5 days. Overall, the active vehicles on weekdays constitute a substantial proportion of the total fleet, providing sufficient operational records for EVFRP model inputs.

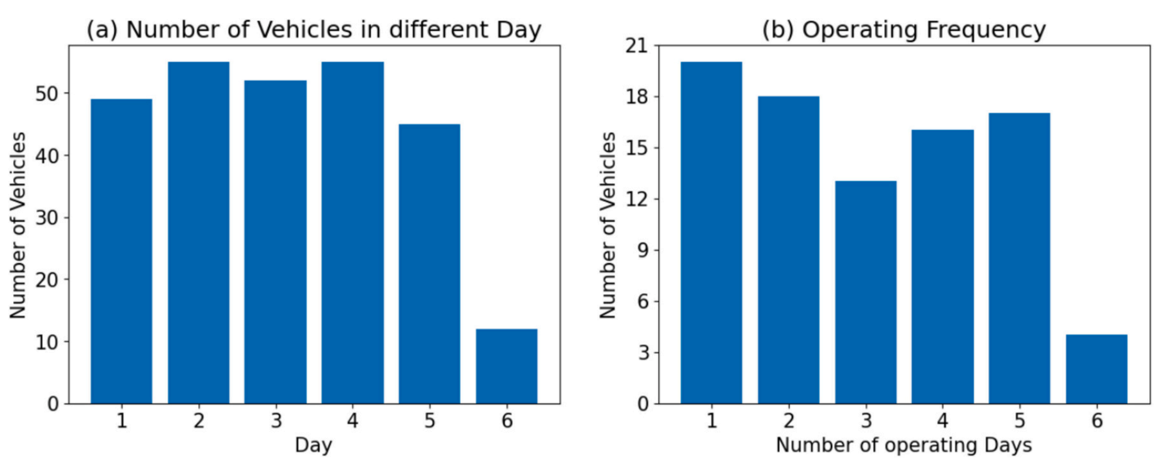

Fig. A2. Statistics of operating vehicles and days.

Fig. A3 illustrates the distribution of travel time and idling time for all routes. As depicted in Fig. A3(a), the highest bar indicates that 43 routes, which account for 16 % of the total routes, fall within the range of 48 to 72 min. Additionally, 96 % of routes are completed in less than 5 h. Fig. 7(b) presents the idling time distribution, derived from warehouse data, revealing that 30 % of routes experience long idling times exceeding 15 min, while 8 % of routes have extremely long idling times of more than 1 h. To effectively reduce GHG emissions during the transition to EVs, it is crucial to prioritize the replacement of those vehicles with long idling times.

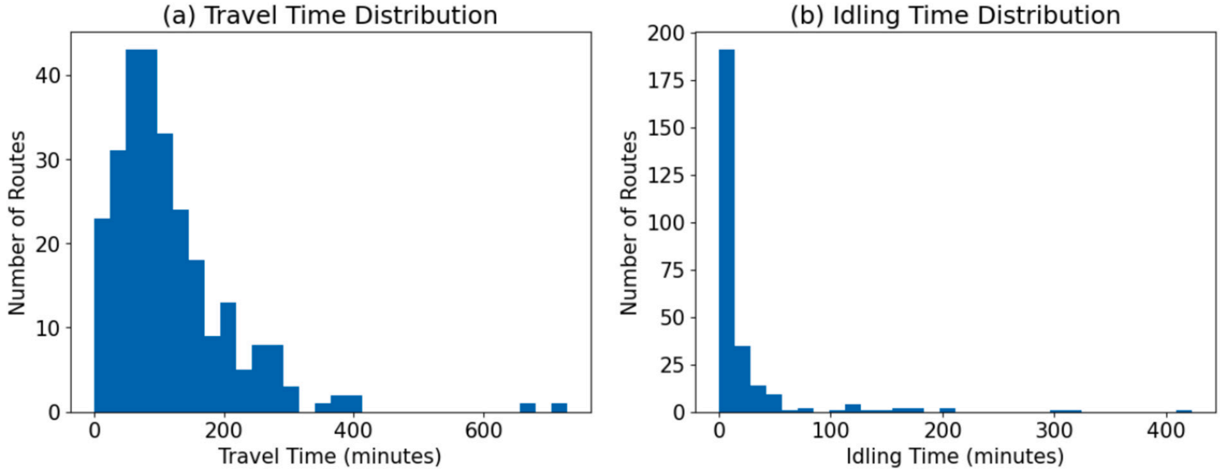

Fig. A3. Distribution of route travel time and idling time.

Data availability

Data will be made available on request.

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