

Evaluating Mixed Electric Vehicle and Conventional Fueled Vehicle Fleets for Last-mile Package Delivery

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16. Abstract The goal of this research project is to evaluate the benefits and disadvantages of electric vehicles (EVs) in delivery vehicle fleets. We assume fleet operators have both EVs and conventionally fueled vehicles (CFVs) at their disposal for delivery services, and that fleet operators select a mix of EVs and CFVs that minimize overall costs. Moreover, we assume EVs offer a per mile cost advantage over CFVs due to the lower costs of electricity compared to gasoline/diesel, and government subsidies. We also assume that EVs have a shorter range than CFVs. We model the fleet operator's decision problem as a mixed vehicle routing problem, wherein the decision levers include the routing of EVs and CFVs to serve all delivery locations at minimum cost. Using the Los Angeles (LA) and Orange counties as the study area with a single depot, we develop computational experiments to evaluate the benefits and disadvantages of EVs in delivery vehicle fleets. The results indicate that with EV range less than 100 miles, it is not possible for EVs to serve all the demand in the region. At a 200-mile EV range, and where the EV cost per mile is approximately 60% of the CFV cost per mile, the optimal fleet mix is all EVs. With EV range less than 200, or a tighter gap between EV and CFV costs, the optimal fleet includes both EVs and CFVs. Mostly importantly, the results indicate that increasing EV range is the most important factor, more so than reducing EV costs, in reducing CFVs in medium-duty delivery vehicle fleets, and reducing total emissions.					
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About the Pacific Southwest Region University Transportation Center

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Abstract

The goal of this research project is to evaluate the benefits and disadvantages of electric vehicles (EVs) in delivery vehicle fleets. We assume fleet operators have both EVs and conventionally fueled vehicles (CFVs) at their disposal for delivery services, and that fleet operators select a mix of EVs and CFVs that minimize overall costs. Moreover, we assume EVs offer a per mile cost advantage over CFVs due to the lower costs of electricity compared to gasoline/diesel, and government subsidies. We also assume that EVs have a shorter range than CFVs. We model the fleet operator's decision problem as a mixed vehicle routing problem, wherein the decision levers include the routing of EVs and CFVs to serve all delivery locations at minimum cost. Using the Los Angeles (LA) and Orange counties as the study area with a single depot, we develop computational experiments to evaluate the benefits and disadvantages of EVs in delivery vehicle fleets. The results indicate that with EV range less than 100 miles, it is not possible for EVs to serve all the demand in the region. At a 200-mile EV range, and where the EV cost per mile is approximately 60% of the CFV cost per mile, the optimal fleet mix is all EVs. With EV range less than 200, or a tighter gap between EV and CFV costs, the optimal fleet includes both EVs and CFVs. Mostly importantly, the results indicate that increasing EV range is the most important factor, more so than reducing EV costs, in reducing CFVs in medium-duty delivery vehicle fleets and reducing total emissions.

Evaluating Mixed Electric Vehicle and Conventional Fueled Vehicle Fleets for Last-mile Package Delivery

Executive Summary

The logistics sector contributes considerably to greenhouse gas (GHG) and local pollutant emissions. Last-mile delivery is a significant part of it. Online shopping has and will only continue to intensify the environmental problems associated with last-mile delivery. To reduce GHGs and local pollutant emissions from last-mile delivery activities, policymakers and logistics companies are making incentivizing and incorporating, respectively, zero-(tailpipe)-emission vehicles, such as electric vehicles (EV), into medium-duty delivery vehicle fleets. The California Air Resource Board (CARB) set the goal to achieve zero-emission for medium- and heavy-duty vehicles by 2045. Logistics companies, such as Amazon Logistics and UPS, have announced purchases of new electric vans to replace conventionally fueled vehicles (CFV). However, in the foreseeable future, delivery services will deploy both EVs and CFVs. We expect a mix not just because it takes a long time to replace the vehicles in a delivery vehicle fleet, but because under current technologies, EVs and CFVs each of their own relative advantages. Specifically, the range of medium-duty CFVs is around 400 miles, whereas the range of medium-duty EVs is closer to 100, for the same vehicle make and model. However, energy from the electric grid in California is cheaper on a per-mile basis than gasoline/diesel fuel, and purchasing EVs is and can continue to be subsidized.

Given the likely mix of medium-duty CFVs and EVs in delivery vehicle fleets for the foreseeable future, understanding the operation of a mixed EV-CFV fleets is meaningful for both policymakers and logistics providers. As such, the main questions to ask for a mixed fleet include the following. First, for the logistics company at the planning level, what is the optimal fleet mix of CFVs and EVs for delivery service? Second, at an operational level, what delivery locations should be assigned to EVs, and what locations should be assigned to CFVs. In making both sets of decisions we assume logistics companies want to minimize total delivery cost. Answering these two questions will also inform policymakers in regards to the importance of regulations and incentives for medium-duty EVs.

To simultaneously answer the operating and planning level questions, we formulate the joint problem as a fleet size and mix vehicle routing problem (FSMVRP). In the FSVRP problem, the input is a set of delivery locations and a set of delivery vehicles. The task is to serve all locations at the minimum cost. However, FSMVRP is an NP hard decision problem; to solve the problem exactly for even medium-size problem instances is extremely time consuming, if not impossible. Therefore, we reduce the complexity of the original problem with over a hundred delivery locations by clustering delivery locations and adding a vehicle load constraint in the problem.

Moreover, this study applies an open-source heuristic solver, Google OR tools, to solve the problem. The script is coded in Python language and details are provided in the data management section. The major factors that impact the fleet mix and route assignment are the relative cost between CFVs and EVs, and EV range, the latter factor depending on battery technology. To quantify the impact of these two factors, we conduct a numerical analysis in the area of Los Angeles (LA) and Orange Counties.

In the numerical study, a logistics company has a single depot. There are hundreds of delivery locations to serve in LA and Orange Counties. These locations are further clustered to 70 nodes. Serving each node requires a pre-specified amount of fuel/energy (converted to traveling distance in miles). The problem then becomes finding the required number of EVs and CFVs to complete all delivery tasks at minimum cost. To assess the impact of the cost ratio between CFVs and EVs, the study varies the CFV:EV cost ratio from 1:1 to 2:1. Similarly to test the impact of EV range, we vary this parameter between 80 and 200 miles.

The results include three parts. The first finding is on the fleet mix. Under the geographical setting of the case study, the results show that when the EV range is 100 miles (roughly the current technology level), full fleet electrification is not possible because some nodes are too far away from the distribution center. In order to achieve full electrification and not significantly increase vehicle fleet sizes, the EV range needs to reach 200 miles. The results section displays the optimal fleet mix for EV ranges between 100 and 200 miles. Interestingly, when EVs are relatively cheap, the optimal mix includes more EVs as EV range increases, but the number of CFVs does not decline at the same rate.

Second, the study also unveils and quantifies the impact of CFV:EV cost ratio on the optimal fleet mix. When the CFV:EV cost ratio is 1:1 for a logistics provider, the optimal fleet mix includes all CFVs because they have a longer range. As the CFV:EV cost ratio increases, the number of EVs in the fleet increases roughly linearly. However, when the cost ratio is 1.6:1, the number of EVs in a fleet will not further increase with higher cost ratios. This finding holds for EV range values of 100 and 160 miles.

Third, the study estimates vehicle miles travelled (VMT) and emissions. As EV range increases and/or the CFV:EV cost ratio increases, naturally the optimal fleet mix includes more EVs. Interestingly, as the number of EVs and ratio of EVs to CVs in the fleet increase, CFV miles decrease but total vehicle miles increase. However, the polluting CFV miles are replaced by zero-tailpipe-emission miles, resulting in a net positive in emissions. When EV range is 100 miles, total emissions can decrease by 20% for the service region compared to the all-CFV case. When the EV range increases to 160 miles, EVs can decrease emissions by nearly 45%.

To sum up, this study proposes and develops an analytical approach to quantify (i) the optimal mix of EVs and CFVs, (ii) VMT by vehicle type, and (iii) total emissions, under changes in (a) the CFV:EV cost ratio and (b) EV range. The study provides both operating and planning details for

mixed vehicle fleets. We expect that logistics companies can benefit from the analytical approach proposed in this paper to make fleet mix decisions. Moreover, we expect policymakers to benefit from the results in this study, namely that without improvements in medium-duty EV range, (even when EVs are subsidized), EVs cannot provide significant benefits in terms of emissions reductions. However, with improvements in EV range up 160-200 miles, EVs are likely to play a significant role in delivery vehicle fleets and in reductions in emissions, even though they will increase VMT.

Future work should evaluate the transferability and generalizability of the results to other study areas of varying service region sizes for depots. The LA and Orange Counties region is quite large spatially, and thus the results might be partially dependent on a single depot needing to serve the whole region. Increasing the number of depots in the region may increase the viability of shorter distance EVs; however, acquiring land in the region is not cheap, as such facility costs will increase even as transportation costs decrease..

Introduction

The demand for package delivery increased dramatically in the past few years, especially during the COVID quarantine era. Package delivery activities contribute considerably to the total carbon footprint of the transportation sector. In order to reduce carbon emissions resulting from logistics activities, both governing entities and business organizations have taken initiatives. The State of California is starting to require the usage of zero-emission vehicles in the logistics sector. The California Air Resource Board (CARB) set a goal for all medium- and heavy-duty vehicles to be zero-emission by 2045 (CA GOV, 2020). On the other hand, logistics companies are gradually electrifying their urban delivery fleets. Amazon, as an example, is expected to have 10,000 electric vans in service by 2022 (Amazon, 2020). During the fleet electrification process, logistics companies are expected to experience a transitional period with a mixed fleet of electric vehicles (EVs) and conventional fuel vehicles (CFVs).

EVs have substantial advantages over CFVs in terms of harmful local pollutants, greenhouse gas emissions and operating cost, depending on what time-of-day the EVs obtain energy from the grid. According to the Department of Energy, national average gasoline cost per gallon is \$4.05, while electricity only costs \$1.54 per gasoline gallon equivalent (U.S. Department of Energy, 2022). These numbers consider the efficiency difference between an electric motor and an internal combustion engine and indicate that the fuel cost of driving a CFV could be 2.6 times the cost of driving an EV. However, in terms of driving distance per vehicle charge or tank of gas, CFVs have an advantage over EVs, as the former vehicle type can travel longer distances without needing to return to the depot, or a charging station, to refuel or recharge. The respective advantages and disadvantages of EVs and CFVs make the operation of a mixed fleet a challenging task for logistics companies. In addition, the vehicle fleet energy/powertrain mix and its impacts on greenhouse gas emissions have a significant impact on social and environmental goals of interest to policymakers.

The main mission of this project is to model and analyze a package delivery system, with a mixed vehicle fleet. The study attempts to answer the following questions related to mixed fleet operations. The first one is at the operational level, what delivery locations/routes should be handled by EVs or CFVs. Additionally, at the tactical planning level, what percentage of fleet vehicles should be electric, given the current range of an EV, in order to minimize costs for the logistics company. Last but not least, what environmental impacts does a mixed fleet have relative to an all-CFV-fleet.

The contribution of this study includes the following. First, the modeling approach supports both tactical and operational planning of logistics companies providing delivery services from distribution centers to customers. More importantly, the analysis in the study provides policymakers and regulators valuable insights into mixed fleet operations. These insights should assist further policy decisions including regulations on the number/percentage of EVs required

in a fleet, possible subsidies to encourage fleet electrification, and the importance of EV range on the optimal fleet mix, VMT, and emissions.

The rest of the report is organized as follows. Section 2 provides further background information and reviews related literature in mixed fleet operations. Section 3 explains the defines the mixed fleet operation problem, provides a mathematical formulation, and presents a solution approach. Section 4 presents a case study in Southern California and compares the results. Section 5 concludes the study and addresses further research questions.

Background and Related Literature

This section provides detailed information on the performance of CFVs and EVs in the logistics industry including a comparison between the two vehicle types. This section also reviews recent studies that focus on deploying EVs for urban delivery. Finally, we review the literature on operating mixed vehicle fleets.

Compared to CFVs, deploying EVs in last-mile package delivery has significant benefits in emission reduction and operational cost savings. On the other hand, EVs have certain disadvantages related to vehicle range and recharging time. To illustrate the difference, we use a widely used cargo van for delivery purposes, the Ford Transit, as an example. Table 1 compares the attributes of an EV Ford Transit vehicle and a CFV Ford Transit vehicle.

Table 1 Comparison between CFV and EV Cargo Vans

	Conventional Fueled Vehicle	Electric Vehicle
Average Fuel Cost ¹	25 ¢/mile	9.7 ¢/mile
CO ₂ Tailpipe Emission ²	19 lbs./gal	0 emission
Range (miles) ³	400	115
Refilling time ⁴	≤ 10 mins	≥ 80 mins
Retail Price ⁵	\$43,455	\$49,575
Figure		


	
<ol style="list-style-type: none"> 1. Average fuel cost is calculated by fuel economy (MPG or MPKw) divided by national average gas/electricity price. Fuel economy source: Ford official website. National average gas price is obtained from USDOE website based on the statistics from Oct 2022. Electricity price is obtained from US Bureau of labor statistics based on the statistics from Dec 2022. 2. Source of CO₂ emission: US energy information administration 3. Range is calculated by averaging the range of 3 models of Ford transit (low, medium and high roof). 4. Refilling time of electric Ford Transit is based on using a DC fast charging stations with an input of 50kw. 5. Retail price was the starting price of each model and retrieved in Jan 2023 from Ford website for postal code 92602. 	

Table 1 shows that the EV Ford Transit has considerable advantages in fuel cost and greenhouse gas emissions. However, range concerns, recharging issues, and higher purchasing prices represent obstacles for the adoption of EVs in the logistics industry. To overcome these obstacles, it is important to understand the typical distance a delivery vehicle travels throughout the day (or half day) and how much a short EV range would limit EV usage for delivery purposes.

According to a study of three cities (Calgary, Denver and Amsterdam) conducted by Figliozzi (2007), a commercial vehicle drives an average of 0.85 hours between depots and 3.95 hours between customers. If the average speed is set to be 30 mph, the total distance to travel for a commercial vehicle in a day is about 144 miles. This number is already larger than the theoretical range of the EV Ford Transit described in Table 1. In addition, the function range of the EV may be lower than 115 miles due to the range anxiety of drivers and fleet managers. (Botsford & Szczepanek, 2009). The range obstacles impact the practice of logistics companies significantly. Quak et al. (2016) and Wikström et al. (2015) suggest that companies should adapt routes based on vehicle ranges that do not require en-route charging. Consequently, more vehicles and delivery personnel may be needed with EVs than CFVs, thereby unavoidably raising logistics costs, unless the fuel cost savings and subsidies are greater than the other cost increases.

To solve the “shorthanded” issue of EVs, researchers suggest en-route charging or battery swapping. In studies that allow recharging for delivery vehicles (Desaulniers et al., 2016; Hiermann et al., 2016; Sassi et al., 2014; Schneider et al., 2014), the vehicles must travel to a designated station and stay at the station for a while. These studies provide different methods of formulating and optimizing the recharging procedure. However, the recharging process is unproductive for short-haul logistics as recharging is time-consuming and wastes the time of both vehicles and drivers during the workday. Hence, several researchers propose battery

swapping. Jie et al. (2019) describe the procedure of battery swapping, which takes less than 10 minutes and is significantly shorter than any type of charging. The disadvantage of battery swapping is the requirement for swapping infrastructure and an inventory of spare batteries. These requirements, unavoidably, raise the cost of operation.

To sum up, the disadvantages of EVs are mainly caused by current battery and charging technology. With the hope of future advancements in battery technology and charging facilities, the disadvantages may gradually diminish. However, during the transition period, effective planning and management of mixed fleets of CFVs and EVs is critical for delivery providers. Under current battery technologies, an effectively managed mixed fleet may be more cost efficient than a full fleet of short range EVs (and possibly and all CFV fleet), and more environmentally friendly than a full fleet of CFVs.

In the literature, studies that model delivery services with multiple types of vehicles to complete delivery tasks are called mixed vehicle routing problems. Mixed vehicle routing problems typically consider the routing and capacity of vehicles of each type. The vehicles usually differ in cost, size, operating time, and/or capacity. The problem is called the fleet size and mix vehicle routing problem (FSMVRP) in the operations research field.

The FSMVRP was first discussed in Golden et al. (1984). The original problem aimed at minimizing the total acquisition and operating cost when using a set of heterogeneous vehicles to deliver packages. The paper introduces the mathematical formulation of this problem and discusses possible solution algorithms. Due to its NP-hard nature, the problem is usually solved with heuristic algorithms. One common heuristic to solve the FSMVRP is the Clark-Wright (Clarke & Wright, 1964) savings algorithm. Their study suggests using modified saving algorithm to solve the problem. It applies different cost estimation equations compared to the original version of saving algorithm. Desrochers & Verhoog (1991) introduce a matching-based savings algorithm. A matching-based savings algorithm considers the savings associated with all feasible combinations of two distinct routes by using a weighted matching problem. Liu & Shen (1999) introduce an insertion-based savings algorithm. Apart from savings algorithms, other heuristics used in solving FSMVRP include the petal method (Renaud & Boctor, 2002), tabu search (Brandão, 2009), constructive heuristics (Dell'Amico et al., 2007) and genetic algorithms (S. Liu et al., 2009).

In the aforementioned FSMVRP literature, one key assumption is that vehicles are limited by capacity, but not range. In other words, each study assumes that all vehicles have sufficient fuel to deliver all packages, and travel distance (an output) is limited only implicitly by vehicle capacity. Of course, this assumption is not valid in our study; In the mixed fleet of EVs and CFVs case, EVs have a travel distance limitation. Therefore, we formulate and solve a variant of the FSMVRP. We utilize the model and formulation of the original FSMVRP but attempt to implement additional constraints on vehicle range. To efficiently obtain solutions, we use a publicly available commercial solver, Google OR tool, which provides heuristic solutions.

Modeling and Solution Approach

Problem Statement and Notation

A mathematical description of the scenario and problem is as follows.

Consider a logistics company providing distribution center to customer delivery service for a given area. The area is abstracted as a network graph (G) that consists of nodes (N) and arcs (A), $G = (N, A)$. The nodes include the hub (leaving depot as o and returning depot as h) and delivery locations. A node (i) is an aggregation of a group of delivery locations in a sub-area i . A node i may have a latest arrival time, T_i . The arcs are the physical connections between nodes with cost that are a function of link distances. The cost basis (distance) for an arc from node i to j is represented by c_{ij} .

The company has two types of vehicles (EVs and CFVs) to complete the delivery tasks. All vehicles that of the same type are identical. The set notation for the vehicle set, the EV set and the CFV set are V , V^E and V^C respectively. The operating cost coefficients per mile travelled for EVs and CFVs are C^{EV} and C^{CFV} respectively. Each EV has a range of D^{EV} and each CFV has a range of D^{CFV} . Traversing links between nodes consumes energy. In addition, since a node is an aggregation of multiple delivery tasks, each node itself consumes energy. The energy required to serve node i is represented as r_i . All vehicles must return to the depot.

The company aims to complete all delivery tasks at the minimum possible cost. We model the problem as a mix vehicle routing problem (MVRP). The focus of this study is to understand how optimal decisions for the MVRP change under different parameter values. We specifically focus on the relative cost difference between EVs and CFVs, as well as the range of the EVs. Therefore, we solve the MVRP multiple times under various parameter values and compare the results. The formulation and solution method are described in the following section.

Table 2 summarizes all notations in alphabetical order.

Table 2 Summary of Notations

Notation	Description
A	The set of all arcs in the network
C^{CFV}	The cost coefficient of a conventional fueled vehicle
C^{EV}	The cost coefficient of an electric vehicle
c_{ij}	The base cost to transvers an arc (i, j) , it can be distance or time
D^{CFV}	The range of a conventional fueled vehicle
D^{EV}	The range of an electric vehicle
d_i^k	Decision variable represents the cumulative distance that a vehicle k traveled when arriving at node i
G	The network graph

h	The returning depot for all vehicles
(i, j)	The representation of an arc that connects node i and node j
M	A large constant
N	The set of all nodes in the network
o	The leaving depot for all vehicles
r_i	The range needed to complete delivery tasks related to node i
T_i	The latest time that a node i should be visited
t_i^k	Decision variable represents the time that a node i is visited by a vehicle k
V	The set of all vehicles
V^{CFV}	The set of conventional fueled vehicles
V^{EV}	The set of electric vehicles
x_{ij}^k	Binary decision variable, whether a vehicle k transverse the arc (i, j)

Formulation and Solution Method

We formulate the delivery problem as a MVRP. The main decision variable for the problem is x_{ij}^k , a binary decision variable denoting whether vehicle k transverses the arc connecting node n_i to n_j . Additionally, let decision variable t_i^k be the time that a vehicle k completes all tasks at node i , and let d_i^k be vehicle k 's cumulative distance when arriving at node i .

Formulation 1

$$\text{Min } \Theta = C^{EV} \times \sum_{k \in V^E} \sum_{i \in N} \sum_{j \in N} c_{ij} x_{ij}^k + C^{CFV} \times \sum_{k \in V^C} \sum_{i \in N} \sum_{j \in N} c_{ij} x_{ij}^k \quad (1)$$

Subject to

$$\sum_{k \in V} \sum_{j \in N} x_{ij}^k = 1 \quad \forall i \in N \quad (2)$$

$$\sum_{i \in N} x_{ij}^k - \sum_{l \in N} x_{jl}^k = 0 \quad \forall k \in V, \forall j \in N \quad (3)$$

$$\sum_{j \in N} x_{oj}^k - \sum_{i \in N} x_{ih}^k = 0 \quad \forall k \in V \quad (4)$$

$$d_i^k + c_{ij} + r_i \leq d_j^k + (1 - x_{ij}^k) \times M \quad \forall (i, j) \in A, \forall k \in V \quad (5)$$

$$d_h^k \leq D^{EV} \quad \forall k \in V^E \quad (6)$$

$$d_h^k \leq D^{CFV} \quad \forall k \in V^C \quad (7)$$

$$t_i^k + \tau_{ij} \leq t_j^k + (1 - x_{ij}^k) \times M \quad \forall (i, j) \in A \quad (8)$$

$$\forall k \in V$$

$$t_i^k \leq T_i \quad \forall i \in N \quad (9)$$

$$x_{ij}^k \in \{0,1\} \quad \forall (i, j) \in A \quad (10)$$

$$\forall k \in V$$

$$t_i^k, d_i^k \geq 0 \quad \forall k \in V \quad (11)$$

$$\forall j \in N$$

The objective function is to minimize the total delivery cost. Eqn. (2) ensures that a node is only visited once by one vehicle. Eqn. (3) is the flow balance constraint for every node. Eqn. (4) ensures that every vehicle that leaves the depot also returns to the depot. Constraints (5) to (7) capture the range and distance constraints. Constraint (5) records the distance travelled by a vehicle. Constraints (6) and (7) guarantee that both types of vehicles do not travel more miles than their respective ranges. Constraints (8) and (9) are time window constraints that ensure all delivery tasks are completed on time. Constraint (10) and (11) are binary and non-negativity constraints.

The MVRP is NP-hard in nature, therefore pursuing exact solutions is extremely computationally intensive. In this project, we use Google OR tools to solve the MVRP, for two reasons. First, Google OR tools apply heuristic algorithms that obtain solutions to large scale MVRP instances quickly, and the solutions appear reasonable under a wide range of input parameters. The heuristic approach is much faster than exact solution methods, such as branch-and-bound or branch-and-cut. Second, the Google OR tools are publicly available for free. Given that we will make our code and input data available, our results are fully replicable. Please see the “Data Management Plan” section for details on code availability.

In the numerical case study section, we use a set of delivery locations as the input. We calculate the distance matrix among the delivery locations, set the relative cost between EV and CFV, and set the range of different vehicles. Given these as input, the solver outputs the vehicle routes for each vehicle type and the total costs. We then obtain results for different ratios of CFV:EV cost and EV range and compare the routes and total operating cost changes.

Illustrative Example

This subsection provides an example to illustrate the problem and help visualize what the solutions look like.

This example uses part of the network in the City of Los Angeles. Node 4191 (the blue triangle) is the depot. The total number of vehicles is five, of which three are EVs. The CFV:EV operational cost ratio is 3:1. The CFV range is 400 miles. Figure 1 displays the routes for a 2

CFVs and 3 EVs, when the EV range is 80 miles (range ratio CFV/EV = 5). Figure 2 displays the routes when the EV range is 120 (range ratio CFV/EV = 3.33).

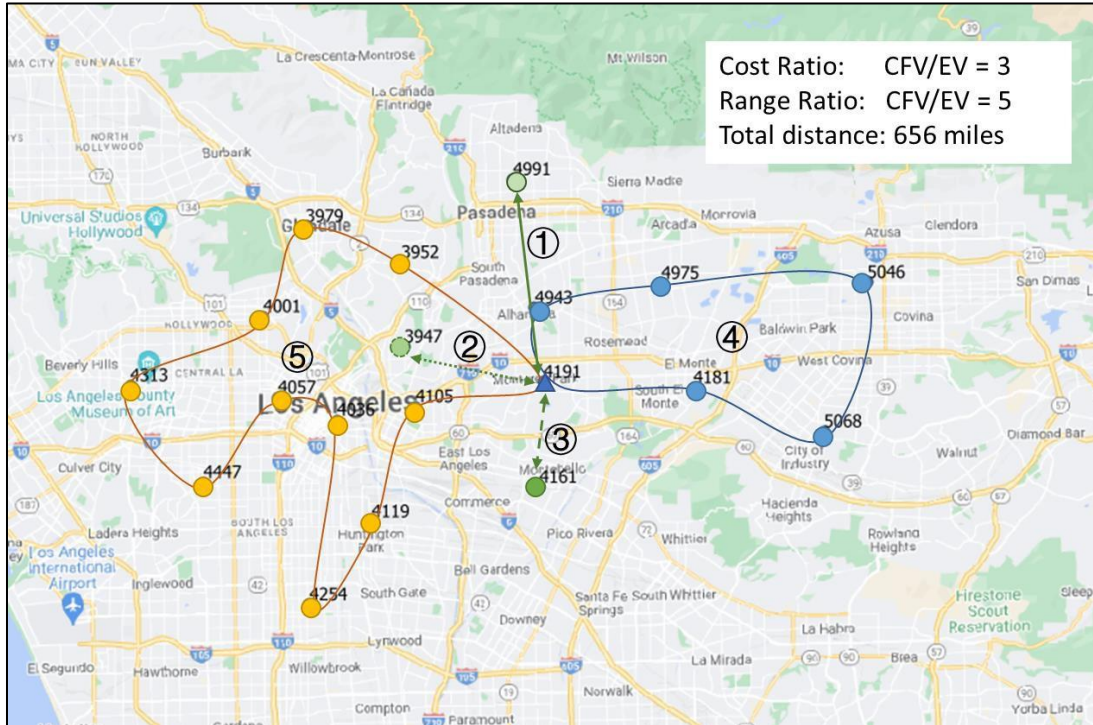


Figure 1 Illustrative Example 1

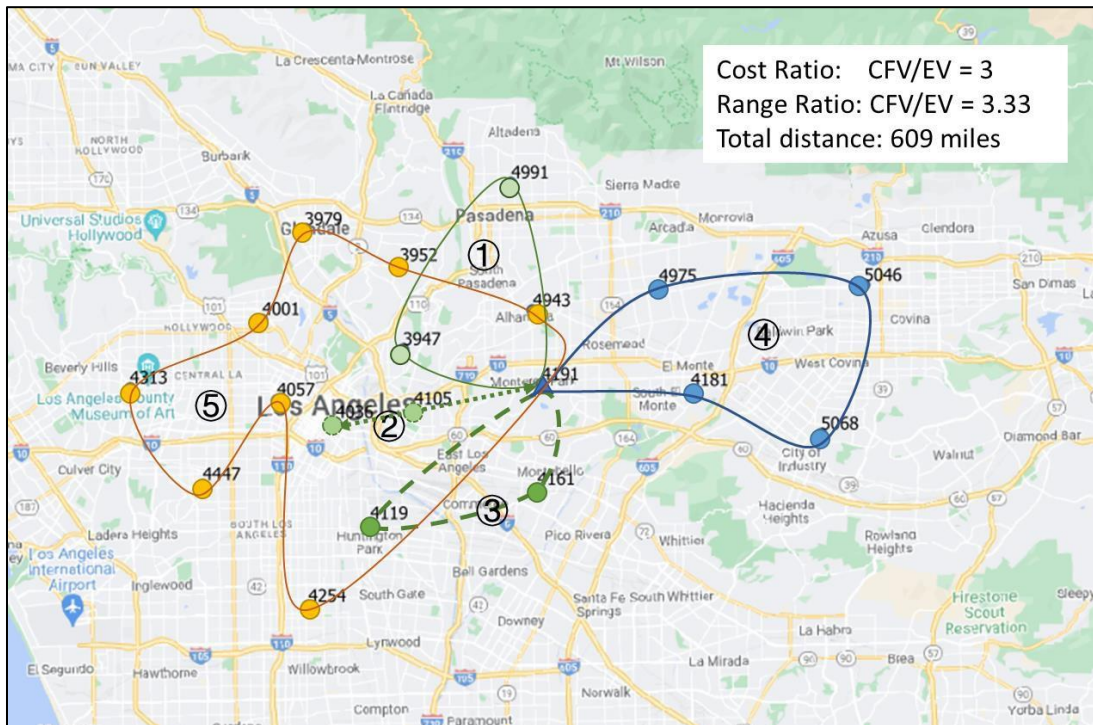


Figure 2 Illustrative Example 2

Comparing the two figures, we observe that when EV range increases from 80 to 120 miles, the routes fundamentally change and the total cost decreases, as the three EVs can serve more demands. When the EV range is 80, EV1 can only serve Node 4991 (Route 1 in Figure 1), and EV2 can only serve Node 3947 (Route 2 in Figure 1). However, when the EV range increases to 120 miles, the two routes merge and form a new route served by EV1 (Route 1 in Figure 2). As a result, EV2 can serve other locations (Node 4105 and 4036), previously served by CFVs in Figure 1. Additionally, locations that are closer to the depot are more likely to be served by an EV. For example, with Node 5068 that is far from the depot, the EV range would need to reach 160 miles for it an EV to feasibly serve it.

Numerical Case Study

Case Study Settings

To provide insights into the importance of EV range and EV cost on the deployment of EVs in delivery vehicle fleets, we set up a numerical case study in the Los Angeles and Orange Counties of California.

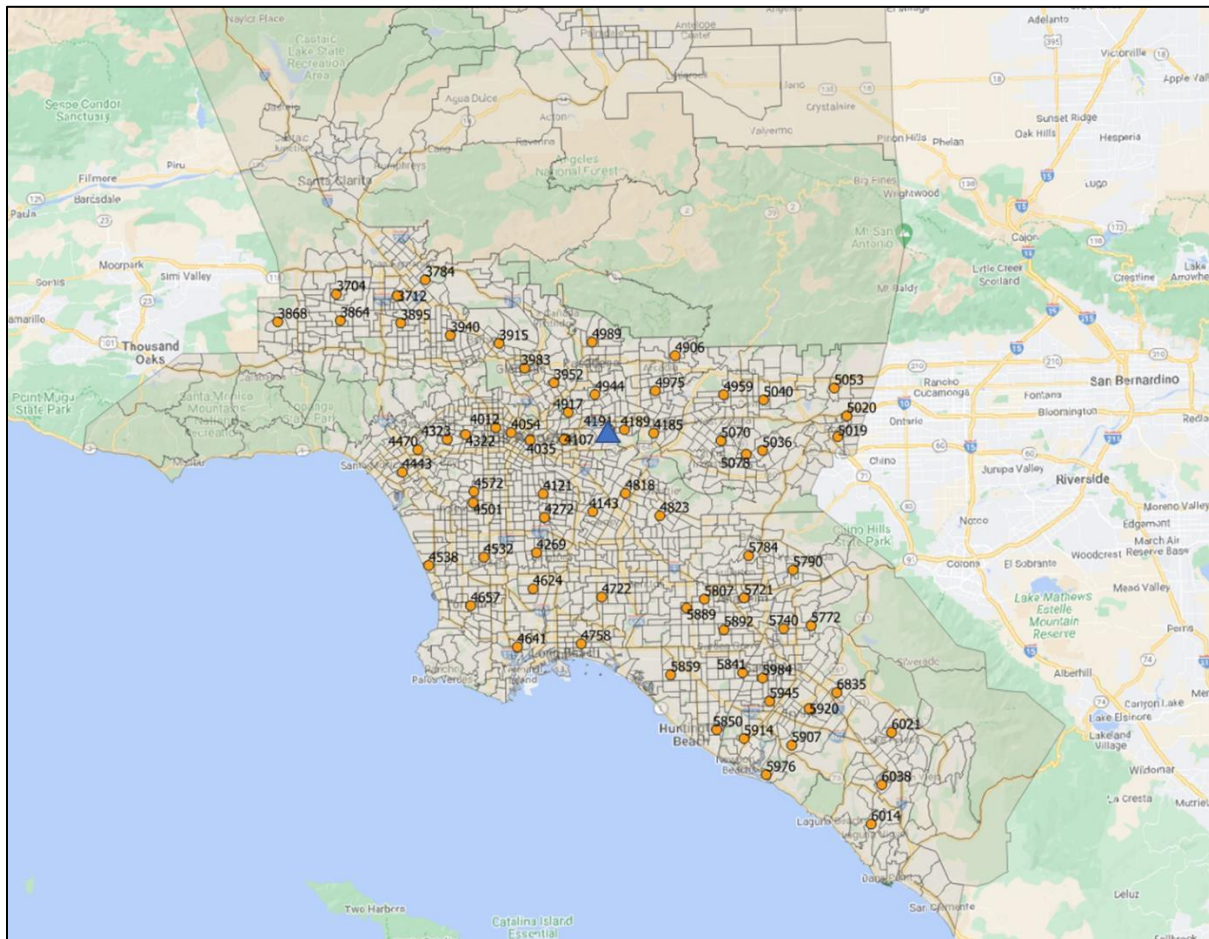


Figure 3 Delivery Locations in LA/Orange County Area

We use the CSTDM (California Statewide Travel Demand Model) network as the base network. We randomly chose 70 nodes in the area to represent package delivery nodes, where each node represents several final delivery locations. A single depot is in East Los Angeles (Node 4194—the blue triangle in Figure 3). We calculate the travel distance between node pairs using geographical XY coordinates. To serve a target node, a vehicle needs to have sufficient fuel/charge to travel from their previous node to the target node, to complete all tasks at the target node, and return to the depot. We convert the required fuel/charge to serve the package delivery locations at each node to travel distances; we randomly generate the required distance to serve the delivery locations at each node from the uniform distribution $U \sim [20, 30]$. In the benchmark case, we assume the cost coefficients for CFV and EV (C^{CFV} , C^{EV}) are both 1, i.e., the CFV costs the same as EV per mile. The cost per mile includes vehicle depreciation, fuel cost, and maintenance cost. We fix the maximize fleet size to 20 vehicles for the study area in each scenario.

To analyze the impact of EV per-mile costs on total fleet cost, fleet mix, vehicle miles traveled, and vehicle emissions, we vary the CFV:EV cost ratio between 1 and 2. Similarly, to analyze the impacts of EV range, we vary this parameter between 80 and 200 miles. Based on current battery technology, we set the base EV range at 100 miles. Table 3 provides a summary of key parameters.

Table 3 Parameter Values

Parameter	Value	Units
N	70	Delivery Nodes
C^{CFV}	(1, 2), Baseline of 1	Monetary
C^{EV}	1	Monetary
r_i	$U \sim [20, 30]$	Delivery Locations
D^{CFV}	400	Miles
D^{EV}	80-200, Baseline of 100	Miles
V	20	Vehicles

Given a maximize fleet size of 20, to determine the optimal fleet mix in each scenario, we solve the MVRP for two vehicles, three vehicles, four vehicles, etc. After solving the problem each time, we retain the fleet mix, VMT, and total cost. Then after solving the problem for various fleet sizes, we select the one with the lowest total cost as the optimal fleet mix.

Results

Fleet Mix

This section analyzes the optimal fleet mix under varying EV ranges. We assume that using an EV is always cheaper per mile than using a CFV; we set the cost coefficient of CFV (C^{CFV}) as 3, resulting in a 3:1 CFV:EV cost ratio. We vary EV range to analyze how this parameter impacts the final fleet mix. Figure 4 presents the results.

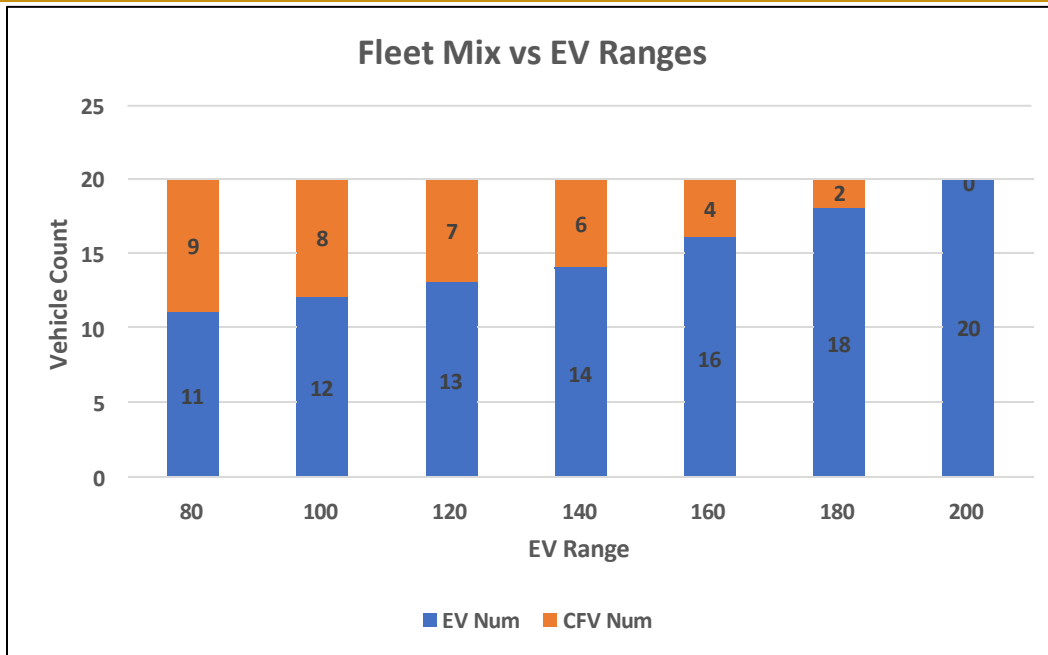


Figure 4 Fleet Mix vs EV Ranges

Figure 4 indicates that the number of EVs in the optimal fleet mix grows roughly linearly with the EV range. Two interesting data points are the number of EVs when the EV ranges are 100 miles and 200 miles, respectively. With an EV range of 100 miles (current technology) and a 3:1 CFV:EV cost ratio, the optimal fleet mix for the study area is 60% electric. This suggests that in cases where (i) electricity from the grid is much cheaper than diesel/gasoline fuel and EV and CFV purchasing costs are competitive and/or (ii) EVs are heavily subsidized by the government, it would make sense for logistics providers to incorporate a substantial portion of EVs in their fleet.

However, it is not until the EV range reaches 200 miles, does the optimal fleet mix include all EVs, even with the 3:1 cost ratio. This suggests that incremental improvements in battery technology alongside cheap EV purchasing, and energy costs are unlikely to shift delivery fleets to 100% electric vehicles alone. To move to 100% electric fleets, logistics companies would also need to reconfigure their supply chains to include more distribution centers and spread these distribution centers throughout the region, in order for vehicle routes to be shorter for EVs. However, this would increase facilities costs for the firm, as land and real-estate in the Southern California is quite expensive.

We want to remind the reader that these results apply to the Southern California region, which is a mix of urban and suburban areas sprawling across a large spatial area, with only one distribution center in the East LA area. Adding more distribution centers and/or using a denser and smaller study area would alter some numerical values in Figure 4. If delivery locations are more densely clustered in an urban core, the EV range requirement for a 100% EV optimal max may be significantly reduced. On the other hand, for a more rural area with low density and

sparse delivery locations, the required EV range for the optimal fleet mix to be all electric may easily exceed 200 miles.

Another way to assess the requirements for a fully electric delivery fleet is to ask the question, given an EV range, how many EVs are required to serve all delivery nodes? To determine the minimum number of EVs to serve all demand for a given EV range, we solve a vehicle routing problem with one vehicle, then two vehicles, then three vehicles, etc. until the solution algorithm finds a feasible solution to the problem. Figure 5 presents the results.

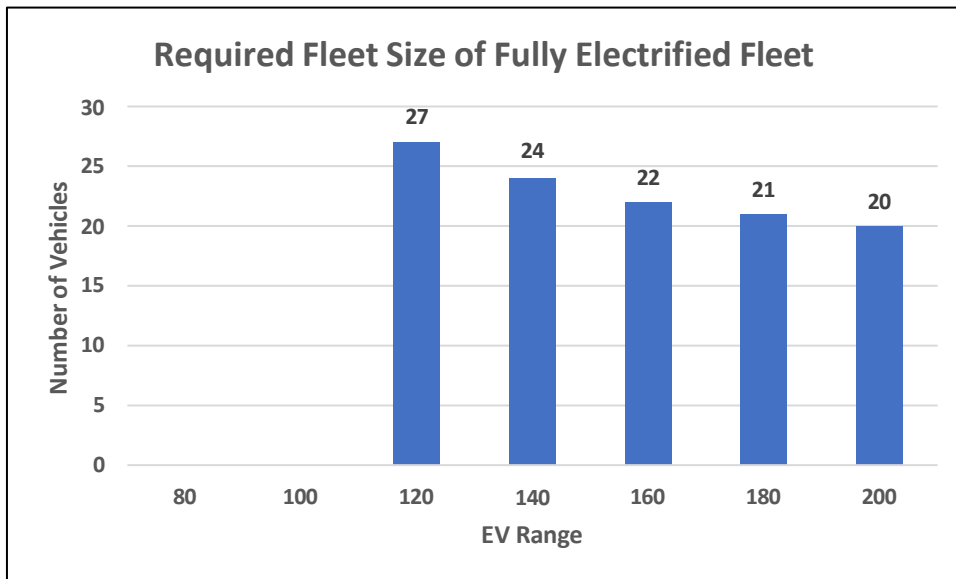


Figure 5 Required Fleet Size of Fully Electrified Fleet

Figure 5 shows that when the EV range is 100 miles or less, a fully EV fleet cannot serve the demand. When the range increases from 120 to 200 miles, the required EV fleet size decreases from 27 to 20 vehicles. Given that a mixed fleet of EVs and CFVs, where the EVs have a range of 120, can easily handle all demand with 20 total vehicles, requiring logistics providers to use only EVs under current battery technology would certainly increase overall transportation costs.

Impact of EV-CFV Cost Ratio

This section analyzes the impact of the CFV:EV cost ratio on the optimal fleet mix. In the previous section, we set the CFV:EV ratio to 3:1, a value that is highly favorable to EVs. Currently, without subsidies, EVs are likely more expensive per mile than CFVs for medium-duty vehicles. Going forward, the CFV:EV ratio for logistics providers is highly uncertain, as it depends on subsidies for EVs, gasoline/diesel prices, electric grid prices, and improvements in vehicle technologies. To understand the impact of the CFV:EV cost ratio on optimal fleet mix, we perform a sensitivity analysis.

Figure 6 (Figure 7) shows the optimal fleet under cost ratios varying between 1:1 and 2:1 for an EV with a 100 mile (160 mile) range. In each figure, we once again assume a fleet size of 20 total vehicles.

The results in Figure 6 show that at a CFV:EV cost ratio of 1:1, the optimal fleet mix includes 11 CFVs and 0 EVs. This makes sense as the EV provides zero advantage over CFVs in this case. As the cost ratio gradually increases, the number of EVs in the fleet increases. At a 1.4:1 cost ratio, the optimal fleet mix includes 9 CFVs and 5 EVs. Interestingly, this is considerably more total vehicles than the 1:1 cost ratio case where the optimal fleet mix includes 11 total vehicles. Finally, Figure 6 shows that as the cost ratio hits 1.6 the optimal fleet mix includes 10 EVs and 8 CFVs. This set of EVs and CFVs in the optimal fleet mix remains the same for a cost ratio up to 2:1. Interestingly, despite the significant increase in EVs in the fleet between a 1:1 and a 2:1 cost ratio, the number of CFVs only decreases from 11 to 8 vehicles.

These results provide insights for both logistics companies and policymakers. For companies, the graph provides insights into the optimal fleet mix under various CFV:EV cost ratios, to inform strategic and tactical planning. For policymakers interested in encouraging the penetration of current technology EVs in private sector fleets, strong economic incentives are currently necessary for EVs to become a substantial portion of the fleet. For a fleet mix of 10 EVs and 8 CFVs, EV per mile costs must be 63% of CFV per mile costs. Otherwise, the fleet mix will be dominated by CFVs, in this study area.

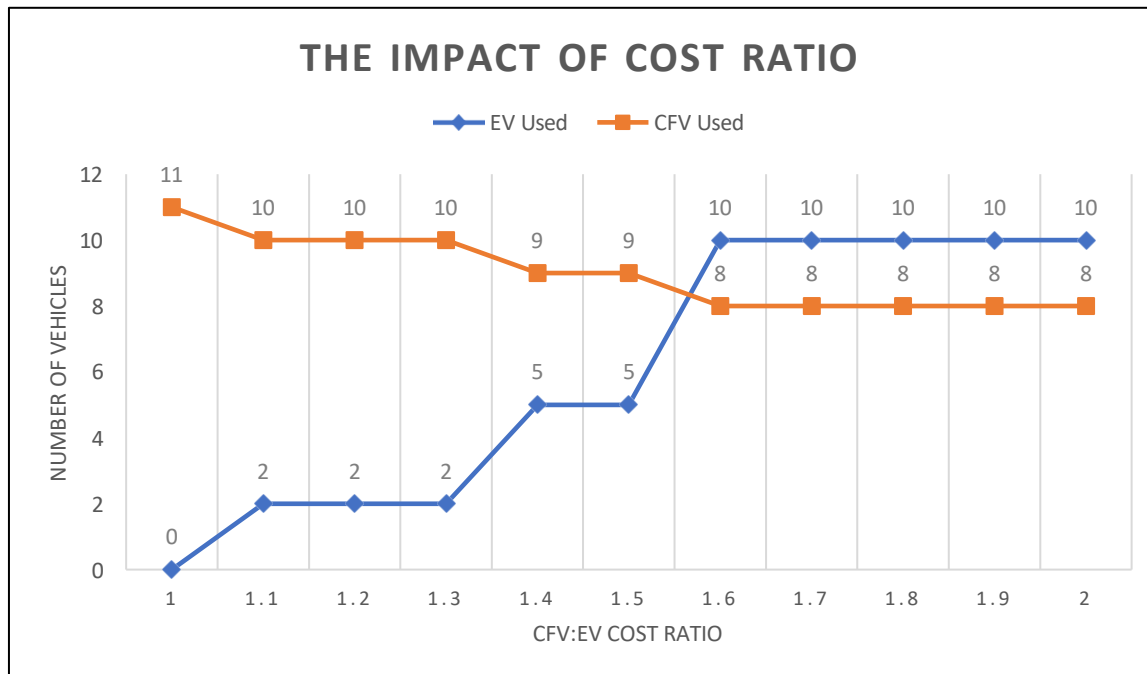


Figure 6 Vehicle Usage vs Cost Ratio (EV Range = 100 miles)

Figure 7 parallels Figure 6, except the EV range is 160 miles. While the trends are the same in both figures, a comparison between the two figures indicates that EV range has a significant impact on the number of CFVs (and EVs) in the optimal fleet mix. When the cost ratio reaches 1.6 in Figure 7, the optimal fleet mix includes only 5 CFVs (and 12 EVs) compared to 8 CFVs in Figure 6. This is a significant difference that illustrates the significant benefits of improved

battery technology for reducing CFVs in logistics fleets, and thereby greenhouse gas emissions in California.

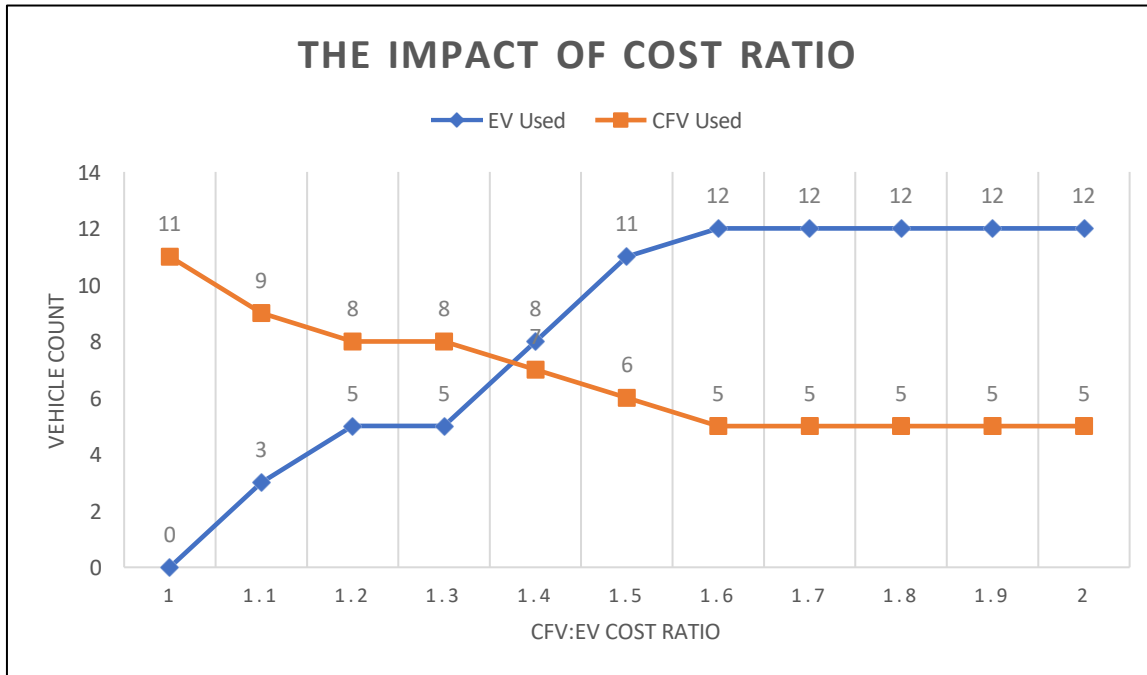


Figure 7 Vehicle Usage vs Cost Ratio (EV Range = 160 miles)

Together, Figure 6 and Figure 7 indicate that for the case study region, improving EV range is the most important factor for both medium-duty EV manufacturers and policymakers interested in the reduction of medium-duty CFVs. Subsidizing the purchasing and fuel costs for vehicles with a 100 mile range is likely to provide significantly fewer benefits than incentivizing improvements in battery technology to extend the range of medium-duty EVs.

Vehicle Miles Travelled and Emissions

Another metric that is important for transportation analysis, particularly in California, is vehicle miles travelled (VMT). To analyze VMT, we once again vary the cost ratio for two different EV ranges. The results are in Figure 8 (EV range 100 miles) and Figure 9 (EV range 160 miles).

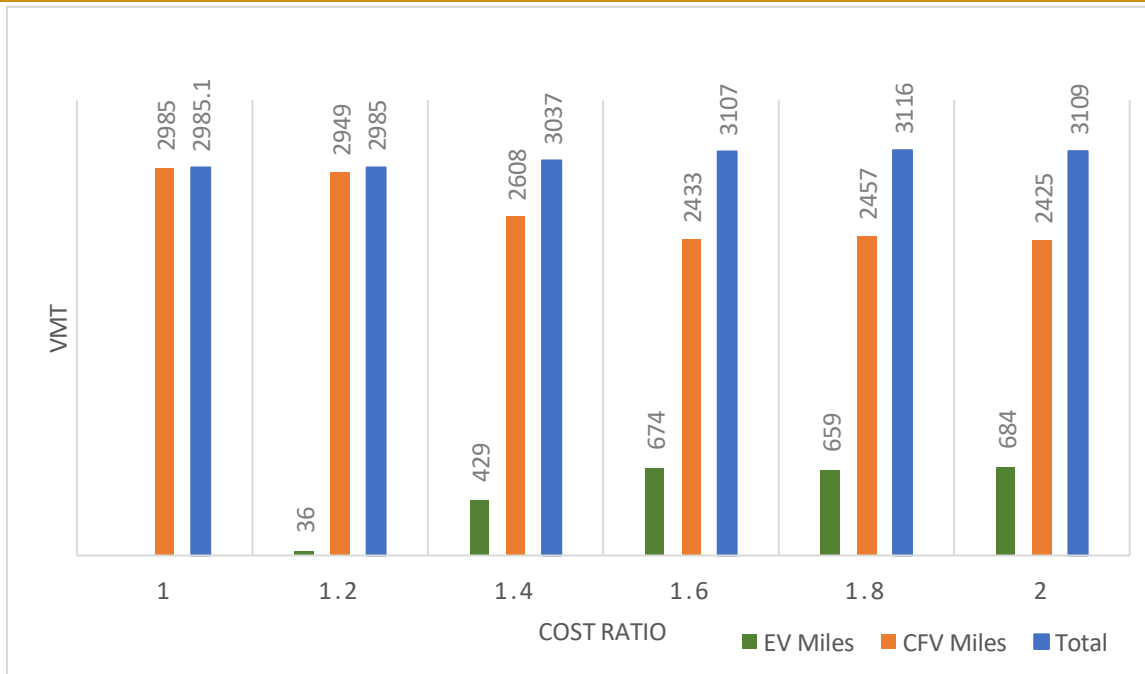


Figure 8 VMT for the Case of EV Range Equals 100 Miles

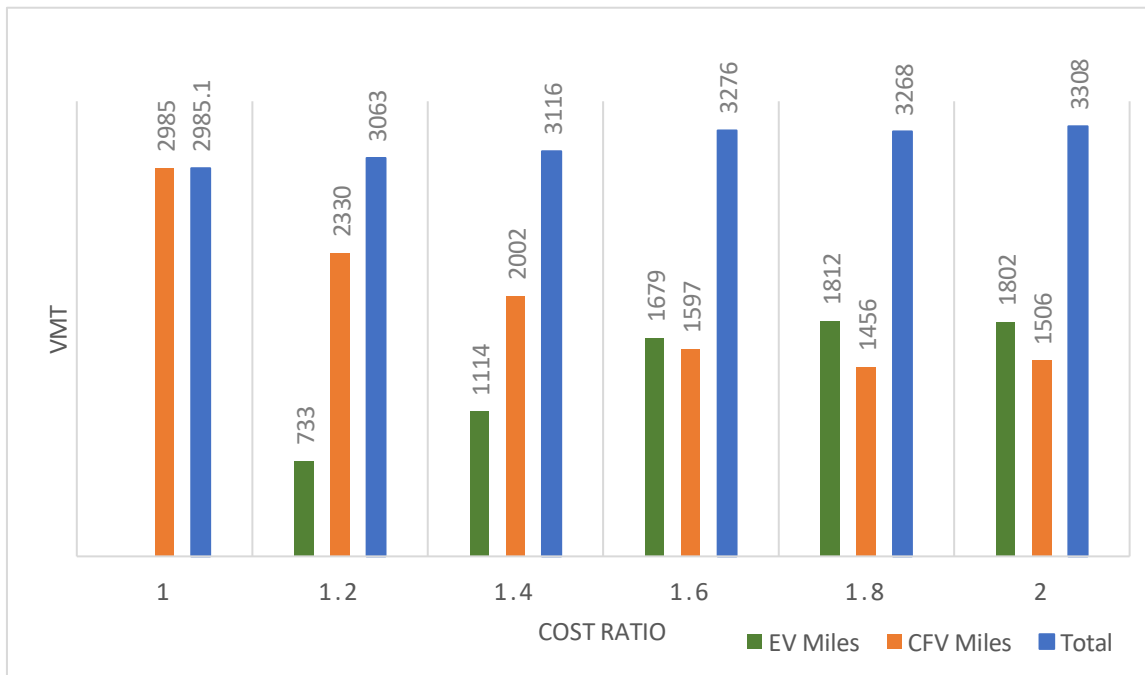


Figure 9 VMT for the Case of EV Range Equals 160 miles

The two figures demonstrate similar trends in VMT changes. As the cost ratio increases, there are more EVs in the fleet, and EVs serve more delivery nodes and final delivery locations, which increases EV VMT. Correspondingly, CFV VMT decreases, but the total VMT increases slightly. The increase in total VMT is due to the range limitation of EVs that requires more vehicle routes and more trips and miles from the depot to the first package locations in the vehicle routes.

Given that EVs increase VMT compared to CFVs, we next analyze whether this downside of EVs outweighs the local pollutant emissions per mile benefits of EVs. Table 4 includes projections for several pollutants as a function of the cost ratio and EV range. The projection is based on statistics published by the Bureau of Transportation Statistics (U.S. Department of Transportation, 2021). The unit is in grams. Since the case with a cost ratio of 1:1 only includes CFVs, we can treat this as the baseline case.

Table 4 Estimated Emissions

		Emissions (in grams)					
Emission Types (Range 100)	Cost Ratio	1	1.2	1.4	1.6	1.8	2
	HC	946	935	827	771	779	769
	CO	15,062	14,881	13,160	12,277	12,398	12,237
	NOx	997	985	871	813	821	810
	PM2.5	18	18	16	15	15	15
Emission Types (Range 160)	Cost Ratio	1	1.2	1.4	1.6	1.8	2
	HC	946	739	635	506	462	477
	CO	15,062	11,757	10,102	8,058	7,347	7,599
	NOx	997	778	669	533	486	503
	PM2.5	18	14	12	10	9	9

Overall, emissions have a linear relation with the VMT of CFVs. Comparing the all-CFV fleet case with the case where the cost ratio equals 1.6 (10 EVs and 8 CFVs), the latter case has 20% fewer emissions than the all-CFV case, under the baseline assumption of 100 mile EV range. When the EV range increases to 160 miles, the emissions reduction is nearly 45% percent. This further illustrates the importance of battery technology.

Discussions and Conclusions

From the case study, we could summarize the following findings. When the fleet size is fixed at 20 for the current service area, with the current battery technology for EV cargo vans, the maximum number of EVs in the fleet is 12, which is about 60% of the vehicles. When EV range increases, the percentage of EVs in the fleet increases approximately linearly. When EV range reaches 200 miles, the delivery fleet can be fully electrified. The case study also shows that under current medium-duty EV range, it is not feasible to fully electrify vehicle fleets. The calculations and estimations are based on the geographical and demographic distribution of Southern California, which has an urban-suburban setting. If the density of delivery locations increases, the required EV range will reduce. On the contrary, if the delivery region changes to a

more rural area, the EV range to fully electrify the vehicle fleet will increase. Importantly, the analytical approach utilized in this study can directly be applied to analyze those cases.

This study introduces a parameter, CFV:EV cost ratio, that represents the relative cost of the two types of vehicles. When the cost ratio increases, naturally EVs becomes more favorable. Interestingly, under current EV technology (range of 100 miles), the percentage of EVs in a fleet will not increase further after the cost ratio reaches 1.6. A similar pattern could be found for the 160-mile range case. This finding indicates that if any subsidizing EVs beyond a 1.6:1 CFV-EV cost ratio will not provide additional benefits in terms of EV penetration and emissions reductions. Indirectly, our findings indicates that if the logistics company want to fully electrify their fleets, they need to have smaller service areas than the one in the case study.

This study also analyzes VMT and emissions. When EVs are introduced to a fleet, CFV VMT decreases but total VMT increases. However, since EVs produce lower pollutants per mile, under current battery technology (that produces a fleet with 60% EVs), total emissions decreases 20%. When the EV range increases to 160 miles, total emissions decreases by 44%.

In summary, this study focuses on the fleet sizing and routing of a mixed fleet of EVs and CFVs. It provides insights about both the operational and planning level details of a delivery fleet. The two major factors that impact the electrification of the delivery fleet are EV range and the cost ratio between CFV and EV. Although the case study is for the region of Southern California, the proposed analytical approach applies to other regions with different demographics as well. The main contribution of this study is to provide insights on vehicle usage by vehicle type, vehicle miles, and coarse emissions projections to both logistics companies and policymakers. For practitioners, the propose analytical approach represents a valuable tool to help make fleet mix decisions. For policymakers, the results provide insights for incentivizing electrification of delivery vehicle fleets in the future.

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Data Management Plan

Products of Research

The data used for this study is mainly for the case study.

Data input:

- A set of delivery locations in the study region. Randomly generated by using the shape file. (CSTDM_original.csv, LargeNodeSet.csv and SmallNodeSet.csv)

Output:

- Routes of EVs and CFVs under different conditions (Output.rar)

Other products:

- A script coded in Python language for computing the vehicle routes. (main.py and Input_node.py)

Data Format and Content

The input folder:

- The delivery locations in comma separated value format (.csv)

The output folder:

- The results are in window notepad file format (.txt)
- A summary of results (figures and tables of the case study) in (.xlsx)

The code folder:

- The script coded in Python language.

Data Access and Sharing

There is no limitation of access. The general public can access the data according to the requirements of PSR.

Reuse and Redistribution

The data is available at

https://datadryad.org/stash/share/_jHIX7Jx8uKzNrmHmUDlyw4Zle2nXA3OL_vtpfXykWo