A Hybrid Tour-Based Model for Energy Analysis of Multi-Modal Intra-City Freight: A Case Study of Autonomous Electric Vehicles

Preprint

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Abstract

With the emergence of cutting-edge transportation technologies, such as electric vehicles (EVs), connected and autonomous vehicles, and drones, the adoption of multimodal freight mobility has the potential to improve efficiency and save more energy. This paper proposes a hybrid tour-based model to evaluate the energy impact of multimodal intra-city freight movement for future scenarios. The model is built based on the traveling salesman problem model and clustering techniques. A case study using autonomous electric vehicles for package delivery is evaluated. The study was conducted using data analyzed from the Columbus, Ohio, metropolitan area. The initial results show that multimodal package delivery using autonomous EVs reduced total travel time by 45% and saved total energy use by 19%, but increased total vehicle miles traveled by 15% when compared with the baseline scenario.

Keywords: energy analysis, multimodal, intra-city, freight, autonomous vehicles, electric vehicles

Introduction

Modeling freight movement data and route choice information is crucial to planning; improving current and future transportation infrastructure; locating businesses; improving efforts to streamline goods movement, especially urban goods; and reducing energy use for freight transportation. Also, with increasing demands and changing consumption habits, mobility being offered as a service, and recent advancements in electric vehicle (EVs) and connected and autonomous vehicle technologies, the landscape of freight planning is changing as businesses compete to meet the needs of a growing customer base, while transportation planners aim at meeting these needs by maintaining and updating the transportation infrastructure. There is a growing interest in examining freight movements, and although previous research has been done to look at freight route choice regarding individual trips, there is increasing interest in freight tours.

Consideration of new transportation technologies and the effect that these technologies have on the existing freight network and freight movements are often lacking in the literature. The use of electric and autonomous vehicles for freight movements should be considered, especially for local freight tours. How the increasing use of these vehicle types affects energy use and emissions locally and regionally, determining the location of charging stations, how this affects route choice decisions, and the effects that these vehicle types have on neighborhoods (possibly reducing air and noise pollution levels) should all be considered when developing local-level tour models. Autonomous vehicle use should also be considered, as advancements in autonomous vehicle technology will likely lead to more of these vehicle types being used for deliveries and long-haul freight shipments in the near future, which will have an effect on efficiency and travel times, as autonomous trucks will not have the rest periods that are required for long-haul truck trips.

The lack of an efficient energy analysis tool for freight movement considering adoption of emerging transportation technologies and multimodal shifts motivated this study. Although there are several sources of tour-based freight models that a Metropolitan Planning Organization or other planning entity can refer to when developing a location-specific methodology, these sources are still missing pertinent information regarding changing manufacturing practices, evolving vehicle technologies, and improved delivery systems and technology. Consideration should be given to these issues to better model the existing and quickly changing economic landscape, and to better understand energy use and potential energy-saving strategies for freight transport. The objective of this paper is to fill the gap by developing a hybrid tour-based model for energy analysis of multimodal intra-city freight using the “traveling salesman problem” (TSP) model and clustering techniques. A future scenario where autonomous electric vehicles (AEVs) are used for multimodal package delivery is evaluated using the developed model.

The remainder of the paper is organized as follows: the next section provides a brief review of literature on tour-based freight models; the third section presents the detailed description of methodology for model development; the fourth section presents the data collection process and experimental results of a case study, as well as a sensitivity analysis. The conclusions are presented in the final section.

Literature Review

Tour-based freight modeling, although only recently becoming part of the transportation and freight modeling literature, is crucial to transportation planning and engineering. Whereas trip-based freight models adhered to the traditional four-step travel demand model and were commonly used in modeling passenger vehicle movements, the importance of modeling tours has been realized as a means by which the underlying route decision process is modeled.

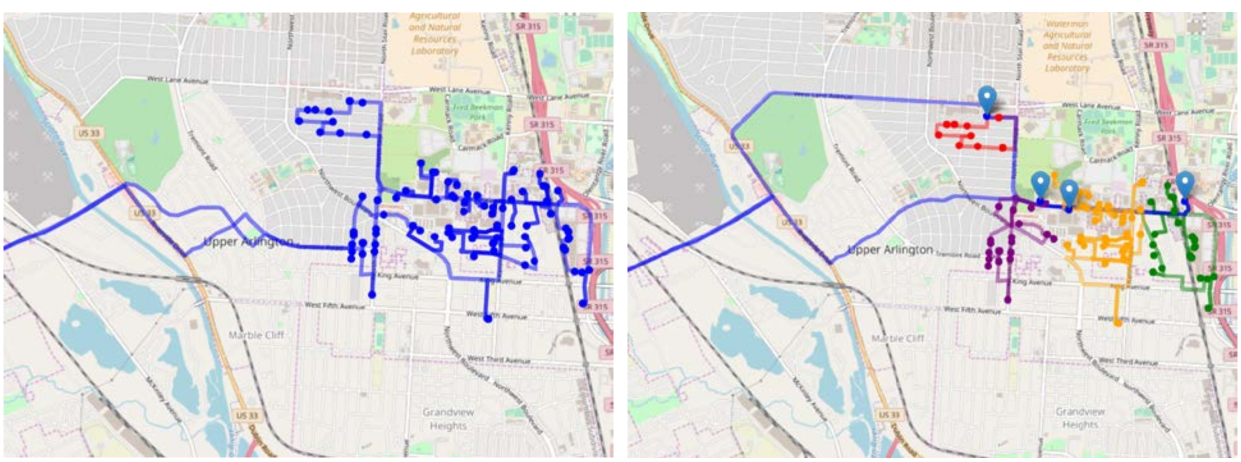
Doustmohammadi et al. (*1*) suggests that tour-based models are more suitable for considering intermediate stops and the effect that these stops have on vehicle miles traveled (VMT), which is an important consideration regarding energy use. Trip-based models fail to include complexities and details, especially prevalent trip-chaining behavior. Although the traditional four-step travel demand model has typically been used to model passenger movement, it fails to capture information regarding the interdependency of multiple trips within tours, and thus is not necessarily suitable for modeling freight tours within an area (*2*).

Global positioning system data (GPS) provide a way to collect very detailed data on freight movements. Although obtaining proprietary shipment data from a parcel delivery service is rare, the American Transportation Research Institute and travel data measurement companies are often the sources of GPS data used in tour-based freight models. Kuppam et al. (*3*) used American Transportation Research Institute GPS travel logs of truck tours from companies collected by the Maricopa Association of Governments and truck GPS data obtained from StreetLight as part of the development of the Mega-Regional Multimodal Agent-Based Behavioral Freight Model. Based on the results from this study, the authors concluded with the recommendation of using GPS data for developing truck tour-based models. Greaves and Figliozzi (*4*) also found that GPS data can be used to complement survey data collected from truck drivers. The methodology presented in this study is in-line with previous methods found throughout the tour-based freight modeling literature.

Methods

Hybrid Tour-Based Model

In an effort to quantify the energy impact via adopting autonomous electric vehicles (AEVs) in multimodal package delivery on an intracity scale, a hybrid tour-based model was developed using the classic operations research model, the traveling salesman problem (TSP), combined with machine learning techniques, such as k-means clustering. Single modal package delivery using a conventional diesel-fueled delivery truck was selected as the baseline for comparison as it is most reflective of current intracity package delivery methods. FIGURE 1(a) shows an example route based on the traditional package delivery method. Blue dots indicate delivery destinations, and the blue lines represent the vehicle path of travel. Under the baseline scenario, all of the packages in a particular area of the city are delivered by only one conventional truck. To examine the opportunity for AEVs in multimodal shifts and associated potential fuel/energy savings, a multimodal scenario with subdepots, where a mode shift would take place, was developed around conventional vehicle delivery. Instead of delivering all packages in a particular area using only one truck, under this scenario the packages are dropped off at a number of distribution centers within the area by conventional trucks and then delivered to final destinations using smaller AEVs responsible for smaller subsections of the area. FIGURE 1(b) shows an example of a multimodal AEV scenario where a conventional diesel-fueled delivery truck drops off packages at four subdepots, which are indicated by the blue markers. The blue route represents the conventional truck trajectory, and the red, purple, orange, and green routes represent the trajectories of four individual AEVs. The dots represent the same delivery destinations as in the baseline scenario; however, in the case of the multimodal AEV scenario, these final deliveries are made by AEVs.



(a) **(b)**

FIGURE 1 (a) Single modal package delivery (b) Multimodal AEV scenario of package delivery

Starting with initial information of delivery destinations, a hybrid tour-based model was developed and applied to the data to generate optimized routes for the multimodal AEV scenarios. The baseline in this project perfectly fits the TSP paradigm (*5, 6, 7*). TSP asks the classic question: “Given a list of cities and distance between them, what is the shortest route for a traveling salesman to visit each city exactly once and return to the origin city?" Let c_{ij} denote the cost of traveling from destination i to destination j, x_{ij} denotes whether the route between destination i to destination j is in the route, V denotes the set of destinations, and S denotes any subset of V. The route optimization problem in this project can be mathematically formulated as follows:

$$\min \sum_{i=1}^{n} \sum_{j \neq i,\, j=1}^{n} c_{ij} x_{ij}$$

$$\begin{aligned}
s.\,t. \quad & x_{ij} \in \{0,1\} && i,j = 1,\ \dots,\ n \\
& \sum_{i=1,\, i \neq j}^{n} x_{ij} = 1 && j = 1,\ \dots,\ n \\
& \sum_{j=1,\, j \neq i}^{n} x_{ji} = 1 && i = 1,\ \dots,\ n \\
& \sum_{i,j \in S,\, i \neq j}^{n} x_{ji} \leq |S| - 1 && \forall S \subset V,\ S \neq \emptyset
\end{aligned}$$

The first constraint indicates that there are only two states between any two nodes in the network. They are either connected or not. The second and third constraints make sure that there is only one path to enter and leave each node. The fourth constraint prevents the model from resulting in multiple separate independent loops.

In this study, the cost of traveling can be seen as energy consumption. The solution of the TSP can be solved by integer programming and directly applied to the baseline scenario. For the multimodal AEV scenario, a hybrid tour-based model was designed, as illustrated in FIGURE 2. The delivery destinations are first clustered to a few clusters by the k-means clustering algorithm (*8, 9, 10*), of which the essential idea is to assign locations close to each other to the same group. The clustering is to identify how many subdepots should be selected for the scenario, as well as which locations on the map would make the potential subdepots for transfer. Once the k-means cluster algorithm is applied and subdepots are identified, the conventional truck and AEV routes are then optimized separately using the TSP framework.

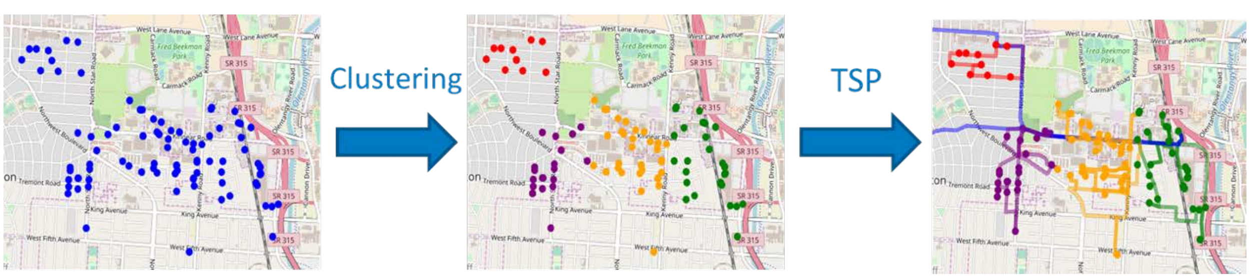


FIGURE 2 Hybrid tour-based model for multimodal AEV scenario

Case Study

In order to provide estimated delivery scenarios for the modeling framework to function, a sample case study was created to simulate typical package delivery services in Columbus, Ohio. The framework and the logic of the case study are presented in FIGURE 3. Sample delivery truck trajectory data from the NREL Fleet DNA database *(11)* is used to estimate package delivery destinations. Then, an energy consumption matrix describing energy consumption for traveling between any two delivery destinations by the same truck is estimated for each truck based on travel distances between delivery destinations and the energy consumption rate. For the baseline scenario, TSP is directly applied to the energy consumption matrix to obtain the optimum routes and energy estimates. For the multimodal AEV scenario, the hybrid tour-based model looks at both delivery destinations and the energy consumption matrix and outputs the optimum routes and total energy consumption. Energy impacts of adopting AEVs in multimodal shifts are quantified by comparing with baseline results.

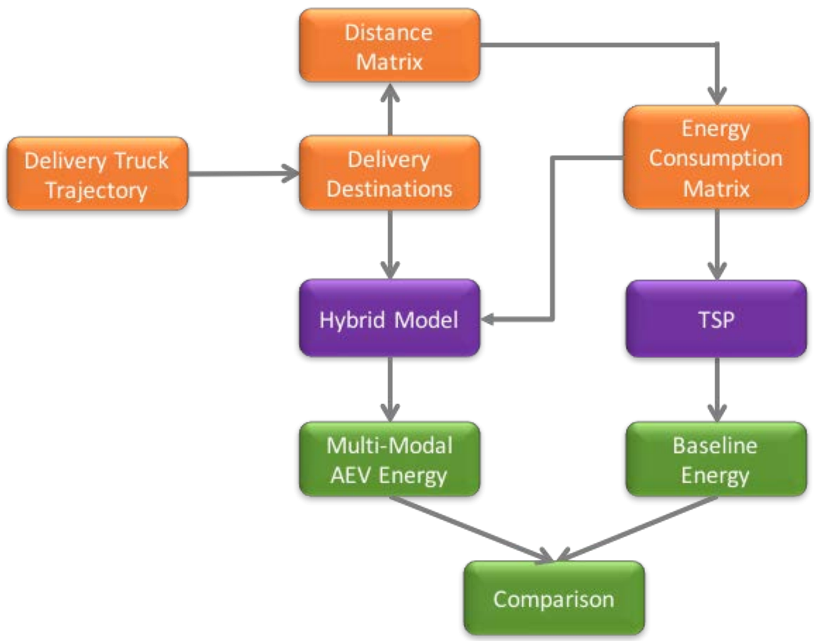


FIGURE 3 Case study framework and logic

Estimation of Routes and Destinations

A total of 18 parcel delivery vehicles were simulated along routes and for destinations created using sampled data from the National Renewable Energy Laboratory's Fleet DNA database. Data sampled from the Fleet DNA database included vehicle location, vehicle speed, engine coolant temperature and engine speed at a one Hertz sampling rate. Data from the engine coolant temperature signal was used to identify "key-on" ignition conditions, which was then used to estimate package delivery destinations along the routes.

To accurately quantify the energy benefits of shifting to multimodal AEV package delivery within cities, delivery destinations needed to be identified for use as inputs into the hybrid model. Since the number of total delivery destinations does not vary too much, randomly selected weekday delivery data for all trucks were used for analysis to quantify the energy impact. Using the coolant temperature signal, a method to create package delivery "destinations" was created and, based on this method, a total of 1,996 destinations were identified for the 18 delivery trucks in an average day's delivery, as shown in FIGURE 4. The marker indicates a distribution center (origin) from which all the trucks depart. All the colored dots represent estimated delivery destinations of each individual truck that were used for the modeling and analysis. The number of destinations for each truck ranges from 37 to 163, with an average of 111.

FIGURE 4 Estimated delivery destinations for 18 delivery trucks in Columbus, Ohio

Once the delivery destinations were estimated from the truck trajectory data, a distance matrix that describes the travel distance between any two delivery destinations of the same truck was obtained for each truck by querying the shortest route using the MapQuest direction application programming interface. Multiplying the travel distance by the average fuel consumption rate derived from Fleet DNA delivery truck data, a fuel consumption matrix was estimated for each truck. In this study, the average fuel consumption rate of a conventional diesel fueled delivery truck was estimated to be 11.54 gallons per 100 miles.

Results

Other than total energy consumption, the performance metrics, including total delivery time and total vehicle miles traveled (VMT), were also evaluated. The performance metrics are defined as follows:

- Total energy consumption: the total energy consumed, in gallons of gasoline, for delivering all packages to their destinations in a one-day analysis.
- Total delivery time: the total time for all vehicles to finish delivering all packages to their destinations and travel back to departure origins in a one-day analysis. It includes both vehicle travel time and vehicle stopping time for package delivery. Estimated from the trajectory data, the average vehicle stopping time for a package delivery is 130.9 seconds. The unit is vehicles per hour.
- Total VMT: the total miles traveled by all vehicles during the process of delivering all packages to their destinations.

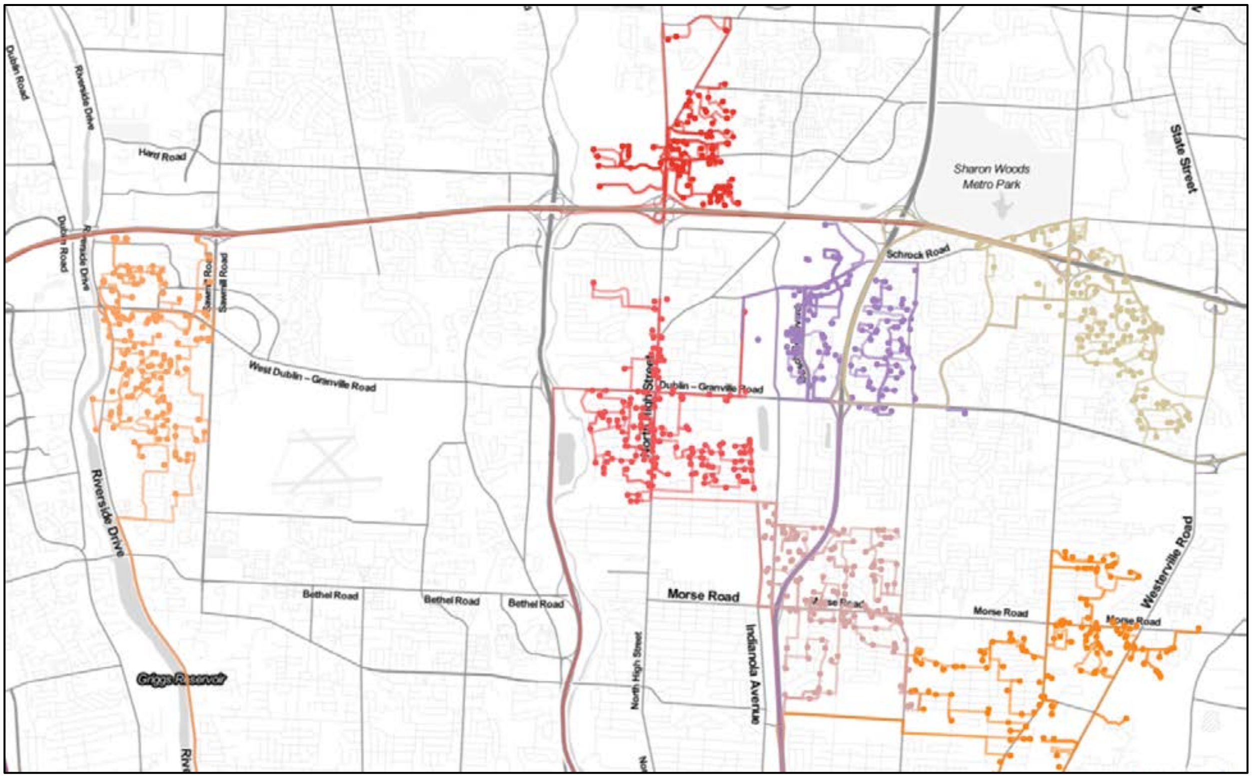
The TSP in both the baseline and multimodal AEV scenarios was solved by a solver in the R software package called "TSP" (*12, 13*). For the baseline scenario, TSP was directly applied to each delivery truck separately. For the multimodal AEV scenario, a number of assumptions need to be made before applying the hybrid model. They are as follows:

1. Each conventional delivery truck is responsible for the same packages that need to be delivered to the same destinations as the baseline scenario. Instead of delivering all the packages to the destinations, each truck drops off the packages at several subdepots. AEVs deliver the packages from subdepots to the final destinations.
2. For the i^{th} conventional delivery truck, to determine the number of subdepots, N_i, the average delivery capacity of AEV, C_i, needs to be assumed. The number of subdepots is calculated as:

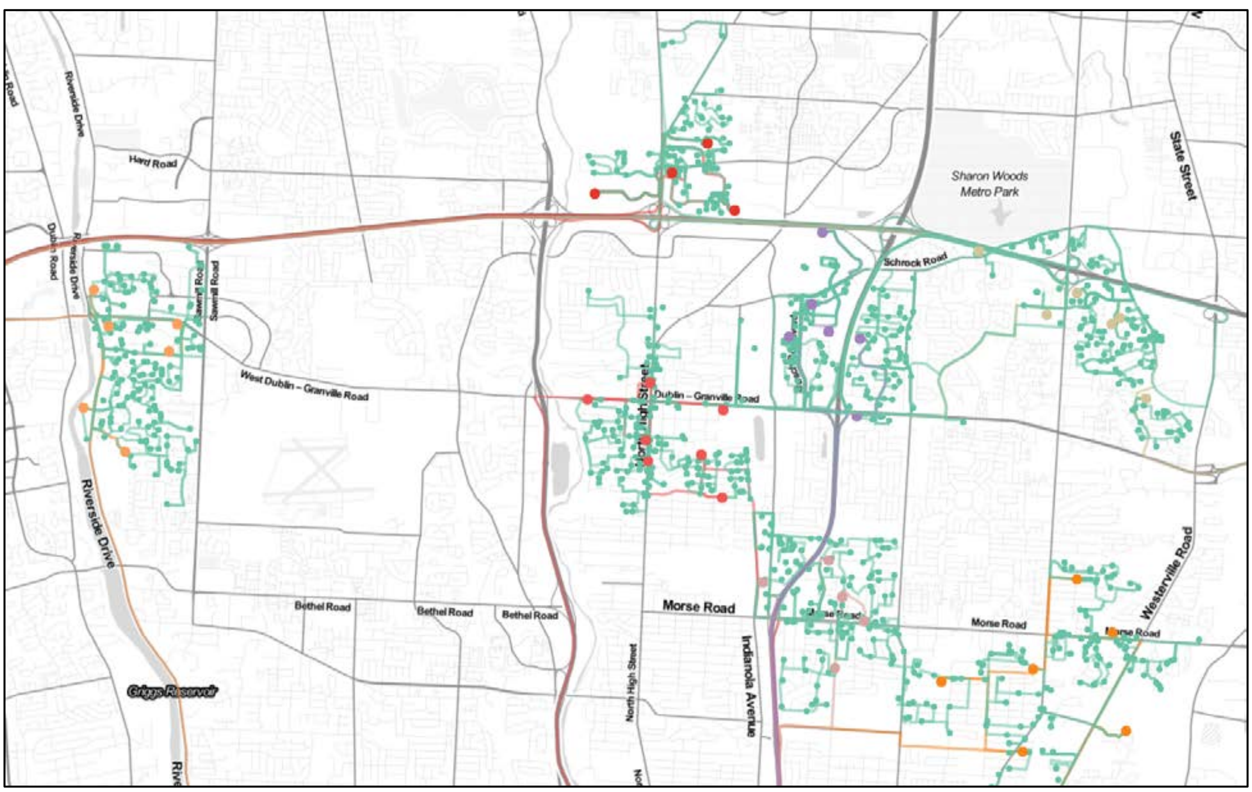
$$N_i = ceil\left(\frac{M_i}{C_i}\right),$$

   where M_i is the number of packages the i^{th} conventional delivery truck carries. In this analysis, the average delivery capacity of the AEVs is assumed to be 50 packages/vehicle.
3. For the i^{th} conventional delivery truck, after clustering destinations to N_i destination clusters, the locations of subdepots are randomly selected within the cluster areas.
4. The AEVs are assumed to have the same vehicle size as a conventional delivery trucks and to consume one-third of the energy of a conventional delivery truck.

Subsets of the optimized routes for both the baseline and multimodal AEV scenarios are displayed in FIGURE 5. The colored lines and dots in FIGURE 5(a) represent routes and delivery destinations for each conventional delivery truck. In FIGURE 5(b), the light green lines represent AEV routes, while other colored lines represent conventional delivery truck routes. The small light green dots represent delivery destinations, while the large colored dots represent subdepots of each conventional delivery truck.



(a)



(b)

FIGURE 5 Subset of optimized routes (a) Baseline scenario, (b) Multimodal AEV scenario

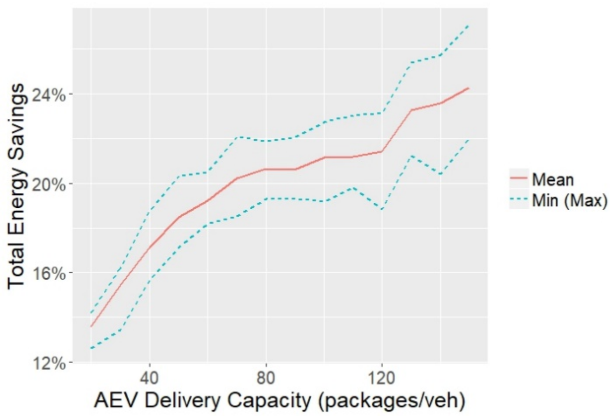
The total energy consumption, along with the other two performance metrics, of both scenarios are compared in TABLE 1. In the "Savings" column, "-" indicates the reduction of performance metrics after adopting AEVs in the multimodal shift when compared with the baseline, and "+" indicates an increase. The benefits are shown in green, while the negative impacts are shown in red. Although the total VMT increased by 14.9% after adopting the AEVs, there were 19.4% savings on total energy consumption, as well as 44.9% of savings on total delivery time. This means that the energy savings are solely attributable to the improvement of EV powertrain technology.

TABLE 1 Performance Metrics Comparison

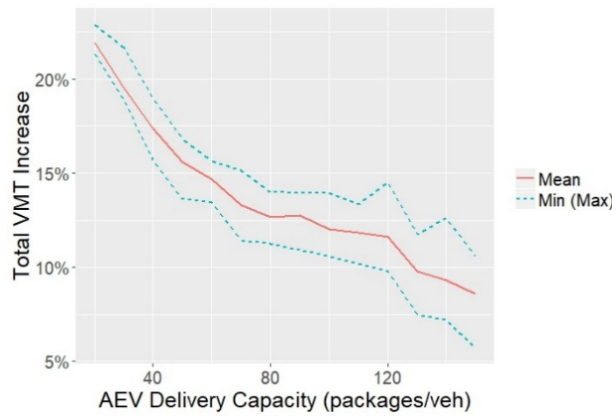
	Baseline	Autonomous EV	Savings
Total Energy Consumption (gal)	85.3	68.8	-19.4%
Total Delivery Time (veh×hour)	4.5	2.5	-44.9%
Total VMT (mile)	739.2	849.3	+14.9%

Sensitivity Analysis

A sensitivity analysis was performed to understand how AEV delivery capacity and subdepot location choice affect the energy impact. The AEV capacity was set to be from 20 to 150 packages per vehicle with an increment of 10 packages per vehicle. For each AEV capacity value, the hybrid tour-based model ran for 20 different random seeds with subdepot locations being randomly chosen within the cluster area. The changes in performance metrics are shown in FIGURE 6. The solid red line is the mean value, while the green dashes are the maximum and minimum bounds. FIGURE 6 demonstrates that adopting AEVs in multimodal package delivery, on average, saved 13.6% to 24.3% of energy usage, and 8.0% to 57.3% of delivery time, whereas it increased 8.6% to 21.9% of VMT. The higher AEV delivery capacity resulted in more energy savings and fewer VMT, but also less delivery time savings. With the increase in AEV delivery capacity, package delivery required fewer subdepots, which resulted in fewer miles traveled for trucks to drop off packages at subdepots, as well as fewer miles traveled for AEVs to travel between subdepots and destinations at the beginning and end of delivery. Therefore, less energy was consumed. At the same time, more delivery time was needed with fewer AEVs delivering simultaneously. In addition, FIGURE 6 indicates that subdepot location choice had a more significant effect on the energy consumption and VMT as AEV delivery capacity increased. The higher delivery capacity enabled AEVs to deliver packages to more destinations in a larger cluster area, leading to a larger variation in subdepot location choice and route optimization results.



(a)



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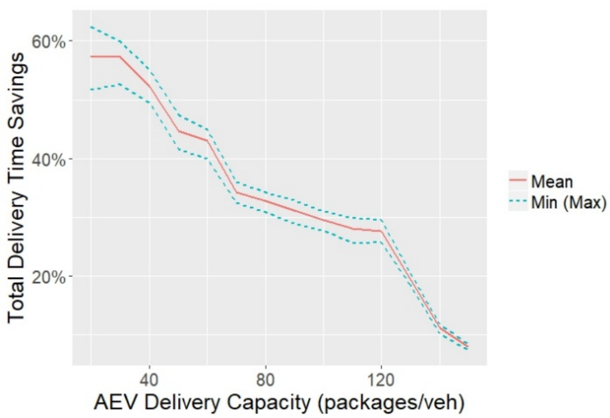

(c)

FIGURE 6 Performance metrics of changes with different AEV delivery capacity assumptions (a) Total energy savings, (b) Total VMT increase, (c) Total delivery time savings

Conclusions

Using a TSP framework combined with k-means clustering, a hybrid tour-based model was developed for multimodal intracity package delivery via adopting AEVs. The hybrid model was then applied to a case study in Columbus, Ohio, where conventional delivery truck trajectory data were analyzed. Based on a number of reasonable assumptions, the analysis results revealed that adopting AEVs in multimodal intracity package delivery was able to save 19.4% of energy usage and 44.9% of delivery time whereas it increased total VMT by 14.9%. In addition, a sensitivity analysis was performed to quantify the effect of AEV delivery capacity and subdepot location choice on the performance metrics. It was found that higher AEV capacity resulted in more energy savings and less VMT, but also less delivery time savings. AEV capacity ranging from 20 to 150 packages per vehicle on average resulted in 13.6% to 24.3% of energy savings and 8.0% to 57.3% of delivery time savings whereas VMT increased by 8.6% to 21.9%. Subdepot location choice had a more significant effect on energy usage and VMT as AEV capacity went up.

In this study, the energy savings estimation was conservative since AEVs were assumed to have the same capacity as conventional delivery trucks. But in real-world applications, the AEV vehicle size could be smaller since it carries only a subset of packages than conventional delivery trucks. In future studies, detailed vehicle size and package weight information will be included. Instead of assuming average AEV delivery capacity, more realistic metrics, such as AEV maximum delivery capacity and charging distance, will be considered. A more comprehensive model that simultaneously optimizes both routes and subdepot location choice will be developed.

The methodology presented in this paper is location-agnostic. It can be applied to evaluate the energy impacts of adopting AEVs in multimodal shifts in any city, given the package delivery destinations. The location-agnostic methodology to evaluate and quantify the energy impacts of other multimodal intra-city package delivery scenarios, such as drone delivery, Uber-style delivery, and the use of centralized package lockers will be also developed in the future.

Author Contribution Statement

The authors confirm contribution to the paper as follows. Study conception and design: Adam Duran, Yi Hou, and Amy Moore; Data collection: Adam Duran; Analysis and interpretation of results: Yi Hou and Amy Moore; Draft manuscript preparation: Yi Hou, Amy Moore, Adam Duran, Kevin Walkowicz, and David Smith. All authors reviewed the results and approved the final version of the manuscript.

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