# EVALUATION OF BATTERY ELECTRIC TRUCKS AND CONNECTED VEHICLE TECHNOLOGIES FOR DRAYAGE APPLICATION

October 2021

Center for Advancing Research in
**Transportation Emissions, Energy, and Health**
A USDOT University Transportation Center

## Disclaimer

# TECHNICAL REPORT DOCUMENTATION PAGE

| 1. Report No. | 2. Government Accession No. | 3. Recipient's Catalog No. |
|---|---|---|
| 4. Title and Subtitle<br>Evaluation of Battery Electric Trucks and Connected Vehicle Technologies for Drayage Application | | 5. Report Date<br>October 2021<br>6. Performing Organization Code |
| 7. Author(s)<br>Peng Hao, Shams Tanvir, Abdullah Fuad Un-Noor, Zhensong Wei, and Kanok Boriboonsomsin | | 8. Performing Organization Report No.<br>CARTEEH project # UCR-05 |
| 9. Performing Organization Name and Address:<br>CARTEEH UTC<br>College of Engineering—Center for Environmental Technology and Research, University of California, Riverside<br>1084 Columbia Avenue, Riverside, CA 92507 | | 10. Work Unit No.<br>11. Contract or Grant No.<br>69A3551747128 |
| 12. Sponsoring Agency Name and Address<br>Office of the Secretary of Transportation (OST)<br>U.S. Department of Transportation (USDOT) | | 13. Type of Report and Period<br>Final<br>May 1, 2017–October 31, 2019<br>14. Sponsoring Agency Code |

15. Supplementary Notes

This project was funded by the Center for Advancing Research in Transportation Emissions, Energy, and Health University Transportation Center, a grant from the U.S. Department of Transportation Office of the Assistant Secretary for Research and Technology, University Transportation Centers Program. The project was also partially funded by the California Energy Commission, the California Air Resources Board, and the South Coast Air Quality Management District.

16. Abstract

In recent years, battery electric trucks have emerged as an increasingly viable solution for reducing energy consumption and environmental impacts. This study evaluated whether these trucks would be capable of meeting the needs of drayage operation at the fleet level using second-by-second activity data collected from 20 trucks of a drayage operator in Southern California in conjunction with a microscopic electric energy consumption model. It was found that 11 percent of the truck tours had a tour distance longer than the range of the modeled electric truck. Considering the sequence of tours and their start times in the itinerary, 55 percent of all the tours could be served by electric trucks. That number would increase to 75 percent if allowing for opportunity charging at the home base during the time gap between two consecutive tours. These results imply that it would not yet be operationally feasible for this drayage operator to fully transition to a 100 percent electric truck fleet. In addition, this study evaluated the potential for a connected vehicle application called eco-approach and departure (EAD) at signalized intersections to provide energy savings, and consequently increase the driving range, for electric trucks. An algorithm was developed based on the microscopic electric energy consumption model and advanced optimization methods, and then applied in a traffic microsimulation environment to evaluate the energy and emission impacts on both the EAD-equipped electric trucks and traffic as a whole. A sensitivity analysis of those impacts with respect to traffic volumes and market penetration rates was also performed. The results showed that the EAD application could achieve up to 8 percent energy savings for the electric trucks in light traffic, but the EAD application became less effective as traffic congestion increased. If the energy savings benefit that the EAD application provides can help increase the market adoption of electric trucks, then there will be substantial benefits in terms of traffic emission reductions from the turnover of diesel trucks to electric trucks as well.

| 17. Key Words<br>Electric truck, drayage operation, energy efficiency, emissions, connected vehicle, traffic signal, vehicle trajectory | | 18. Distribution Statement<br>No restrictions. This document is available to the public through the CARTEEH UTC website.<br>http://carteeh.org | |
|---|---|---|---|
| 19. Security Classif. (of this report)<br>Unclassified | 20. Security Classif. (of this page)<br>Unclassified | 21. No. of Pages<br>32 | 22. Price<br>$0.00 |

**Form DOT F 1700.7 (8-72)** Reproduction of completed page authorized

## Executive Summary

Heavy-duty trucks account for the second largest share of the total energy consumed by the transportation sector, and their share is projected to grow larger as a result of increasing e-commerce activity. In addition, these trucks also produce a significant amount of greenhouse gas and criteria pollutant emissions. In recent years, the electrification of heavy-duty trucks has emerged as an increasingly viable solution for reducing energy consumption and environmental impacts. In particular, heavy-duty trucks that operate in drayage application are well suited for electrification because they generally have limited daily mileage, return to a home base every night, and spend a large amount of time creeping and idling. These conditions provide opportunities for adopting battery electric trucks that can be charged at the home base and do not waste energy when idling. The technical feasibility of operating battery electric trucks in drayage application has been demonstrated at the vehicle level. However, due to the range limitation of current battery electric trucks in the market, questions remain regarding whether these trucks will be capable of meeting the broader needs of drayage operation at the fleet level and whether drayage operators aiming to transition to electric trucks will need to maintain some conventional diesel trucks or other forms of alternative fuel trucks in their fleets.

One way to help mitigate the concern around the range limitation of current battery electric trucks is to improve the energy efficiency of these trucks during their operation. Improving the energy efficiency will, in turn, increase the maximum range of the trucks and operational coverage of the fleets. Over the past decade, connected vehicles have emerged as a promising technology that can help reduce vehicle energy consumption and emissions via information sharing among vehicles or between vehicles and infrastructure. Among several connected vehicle applications, eco-approach and departure (EAD) has shown great potential for energy savings around signalized intersections. Through connected vehicle technology, a traffic signal can broadcast its current signal phase and timing to approaching vehicles, which the EAD application can use in conjunction with other information to calculate an energy-efficient speed profile for the vehicle to follow until the vehicle passes through the intersection. Since drayage trucks are operated mostly on surface streets with a lot of traffic signals, the trucks are well positioned to take advantage of the energy savings benefit offered by the EAD application. However, the energy savings potential from applying EAD to electric trucks is unknown and needs to be evaluated.

This project's purpose was to answer questions related to the feasibility of heavy-duty truck fleet electrification by analyzing real-world operation data of a typical drayage operator. To achieve this project objective, second-by-second activity data collected from 20 trucks of a drayage operator in Southern California were used to estimate the corresponding electric energy consumption and the state of charge of the battery using a microscopic electric energy consumption model. An algorithm for generating tours of drayage activity from the collected data was developed and implemented. Multiple scenarios with different battery charging and truck scheduling assumptions were analyzed. The results showed that 11 percent of the tours had a tour distance that was longer than the range of the modeled electric truck. The presence of these infeasible tours means that it is not operationally feasible for this drayage operator to fully transition to a 100 percent electric truck fleet. The operator still needs to maintain a few conventional diesel trucks to serve those long tours on an occasional basis. Managing this duality in technology may translate to an increase in operational overheads (e.g., refueling infrastructure, maintenance service) for the drayage operator.

Considering the sequence of tours and their start times in the itinerary, only 62 percent of the feasible tours (or 55 percent of all the tours) could be served by electric trucks. The number of fulfilled feasible tours would increase to 85 percent (or 75 percent of all the tours) if allowing for opportunity charging at the home base during the time gap between two consecutive tours. Such opportunity charging events may coincide with the peak load period for the grid. Thus, the fleet will need to manage these events carefully. Moreover, charging multiple electric trucks at the same time can put an excessive load on the electrical grid, which could require the power transmission lines to be upgraded. The fleet may consider using an energy storage system to help manage the load. In addition, the

operational feasibility of electric truck fleets can be improved through enhanced truck scheduling and routing, which considers the driving range limitations and the charging time requirements of electric trucks. Advanced telematics and real-time monitoring of electric trucks and charging stations would allow for the implementation of such enhanced scheduling and routing technology in the future.

Another objective of this project was to evaluate the potential for the EAD application to provide energy savings, and consequently increase the driving range, for electric trucks. To meet this objective, an electric truck eco-approach and departure (ETEAD) algorithm was developed based on the microscopic electric energy consumption model and advanced optimization methods and then applied in a traffic microsimulation environment to evaluate the energy and emission impacts on both the EAD-equipped electric trucks and traffic as a whole. A sensitivity analysis of those impacts with respect to traffic volumes and technology penetration rates was also performed. It was found that the machine-learning-based ETEAD algorithm can design an energy-efficient trajectory for electric trucks in real time. The results from the traffic microsimulation showed that the EAD application could achieve up to 8 percent energy savings for the electric trucks in light traffic. However, the application became less effective as traffic congestion increased due to fewer opportunities for electric trucks to engage in energy-efficient driving.

The results from the traffic microsimulation also showed that the EAD application caused up to 2 percent increases in emissions from the overall traffic. These increases in emissions were partly due to the non-cooperative nature of the current ETEAD algorithm, where the algorithm optimized the speed profiles of the individual electric trucks without considering how their driving behaviors may impact the surrounding vehicles in traffic. However, these emission increases were very small compared to the 48 percent, 54 percent, 94 percent, and 51 percent reductions in carbon dioxide, hydrocarbons, nitrogen oxides, and fine particulate matter emissions, respectively, that were brought about by the turnover of diesel trucks to electric trucks. If the energy savings (and driving range extension) benefit that the EAD application provides to electric trucks can help increase the market adoption of these trucks, then the net impact on the overall traffic emissions will be highly positive. Therefore, the EAD application can be used as one of the tools for mitigating the range limitation of the current electric trucks in the market to help accelerate their adoption.

## Acknowledgments

The authors acknowledge the funding support from the U.S. Department of Transportation Office of the Assistant Secretary for Research and Technology through the Center for Advancing Research in Transportation Emissions, Energy, and Health. They also acknowledge the co-funding from the California Energy Commission, the California Air Resources Board, and the South Coast Air Quality Management District.

The authors would like to thank Dr. Zhiming Gao of Oak Ridge National Laboratory for collaboration on the vehicle energy consumption model. They also thank the anonymous drayage operator for accommodating the collection of truck activity data used in this project.

# Table of Contents

## List of Figures



## List of Tables

# Introduction

## Background

Transportation is the largest consumer of petroleum in the United States. In 2017, the transportation sector consumed 71 percent of the total U.S. petroleum consumption, at 14 million barrels per day [1]. The combustion of petroleum products is also responsible for 45 percent of anthropogenic emissions of greenhouse gases (GHGs) in the United States [2]. Within the transportation sector, heavy-duty vehicles account for the second largest share of the total energy consumed, and their share is projected to grow larger as a result of increasing e-commerce activity. In addition, these vehicles also produce a significant amount of GHG and criteria pollutant emissions. For example, in California, heavy-duty vehicles account for 7 percent of total GHG emissions, but the vehicles are the single largest source of nitrogen oxide emissions, accounting for 33 percent of the total [3].

In recent years, the electrification of heavy-duty trucks has emerged as an increasingly viable solution for reducing energy consumption and environmental impacts. Electric trucks have no tailpipe emissions, and the total life-cycle emissions from battery electric trucks is minimal if renewable energy sources are used to generate electricity that charges the battery. In particular, heavy-duty trucks that operate in drayage application are suitable candidates for electrification because of their limited daily mileage. In addition, these drayage trucks return to the home base at least once per day during the operation and spend a significant portion of their operation in creeping and transient modes. These conditions provide opportunities for adopting electric trucks that can be charged at the home base and do not waste energy when idling.

Drayage trucks in the Southern California region are used mostly in port operations, carrying cargo containers to and from ports, railyards, or warehouses. In most cases, these trucking activities occur in close proximity to low-income and minority communities, which raises environmental justice concerns [4]. In November 2017, the Port of Los Angeles and the Port of Long Beach updated the San Pedro Bay Ports Clean Air Action Plan, which called for an accelerated timeline to transition the ports’ drayage fleet to zero or near-zero emissions trucks [5]. Considering the policy impetus, adoption of electric trucks in drayage fleets is an issue of technical, operational, and economic feasibility. With the diminishing battery and charging infrastructure costs, electric trucks are getting more affordable for trucking operators. Multiple vehicle manufacturers have already demonstrated the technical feasibility of operating battery electric drayage trucks at the vehicle level [6]. However, due to the range limitation of current battery electric trucks in the market, questions remain regarding whether these trucks will be capable of meeting the broader needs of drayage operation at the fleet level and whether drayage operators aiming to transition to electric trucks will need to maintain some conventional diesel trucks or other forms of alternative fuel trucks in their fleets.

One way to help mitigate the concern around the range limitation of current battery electric trucks is to improve the energy efficiency of these trucks during their operation. Improving the energy efficiency will, in turn, increase the maximum range of the trucks and operational coverage of the fleets. Over the past decade, connected vehicles (CVs) have emerged as a promising technology that can help reduce vehicle energy consumption and emissions via information sharing among vehicles or between vehicles and infrastructure. The Applications for the Environment: Real-Time Information Synthesis research program sponsored by the U.S. Department of Transportation defined and evaluated multiple eco-friendly CV applications, such as eco-cooperative adaptive cruise control, eco-ramp metering, eco-lane change, eco-signal priority, etc. [7]. Among these CV applications, eco-approach and departure (EAD) has shown great potential for energy savings around signalized intersections. Through vehicle-to-infrastructure communication enabled by CV technology, the traffic signal can broadcast its current signal phase and timing (SPaT) to approaching vehicles. Using the SPaT and other information, the EAD application can calculate an energy-efficient speed profile for the vehicle to follow until the vehicle passes through the intersection. Since drayage trucks are operated mostly on surface streets with a lot of traffic signals, these trucks are well positioned to take advantage of the energy savings benefit offered by the EAD application.

## Objectives

This project's purpose was to answer questions related to the feasibility of heavy-duty truck fleet electrification by analyzing real-world operation data of a typical drayage operator in Southern California. To achieve this project objective, a microscopic electric energy consumption model was applied to estimate electricity consumption and state of charge (SOC) of electric trucks based on real-world, second-by-second activity data collected from the existing conventional diesel trucks of the drayage operator. An algorithm was also developed for generating tours of drayage truck activity from the collected data. Based on the SOC profile for each truck tour, the research team then evaluated the feasibility of operating an electric truck fleet in drayage application.

Another objective of this project was to evaluate the potential for the EAD application to provide energy savings, and consequently increase the driving range, for electric drayage trucks. To meet this objective, the research team developed an electric truck eco-approach and departure (ETEAD) algorithm based on machine learning techniques and applied the algorithm to evaluate the energy and emission impacts of EAD on both the equipped electric trucks and traffic as a whole in a traffic microsimulation environment. A sensitivity analysis of those impacts was also conducted with respect to different traffic volumes and technology penetration rates.

## Report Organization

This report is organized as follows. Section 2 describes the evaluation of the feasibility of operating a heavy-duty battery electric truck fleet in drayage application. Thereafter, Section 3 presents the details of the ETEAD algorithm, the simulation of the algorithm under a number of scenarios, and the simulation results. Finally, Section 4 offers conclusions from the research results and a discussion of future work.

## Feasibility of Operating a Battery Electric Truck Fleet in Drayage Application

This section presents the feasibility analysis of operating a heavy-duty battery electric truck fleet in drayage application. The section begins with a discussion of the literature review and research gaps, followed by the data collection, assumptions, and models used in the analysis. The section concludes with a discussion of the analysis results.

### Literature Review

Several researchers have studied the activity patterns of drayage trucks and electrification of drayage fleets. Scora et al. analyzed real-world activity patterns of heavy-duty vehicles in various vocations and found that drayage trucks were among those with the shortest average trip distance and lowest average trip speed [8]. Ambrose and Jaller analyzed the drayage trips at the ports of Los Angeles and Long Beach and found that less than 1 percent of the drayage trucks completed more than five trips per shift, and on average, a truck completed 12 round trips per day [9]. During these near-dock services, the trucks only traveled the total distance of 60 mi per day due to time spent in navigating the port and dealing with cargo retrieval logistics.

Gao et al. used the Fleet DNA composite statistics on real-world driving behavior of 10 representative Classes 3–8 commercial trucks to estimate the energy consumption for the electric trucks and made charging-related assumptions [10]. Fleet DNA is a clearinghouse of commercial fleet operating data. This particular study used service coverage levels of typical operation of different trucks to determine battery capacity requirements. Consequently, an investment payback period was estimated to quantify the suitability for electrification. The authors concluded that Classes 3–6 medium-duty trucks and Class 8 port drayage tractors were the most suitable for electrification.

These previous studies did not consider the fleet management perspective while analyzing the possibility of electrifying drayage truck operation. Usually, a drayage operator has a number of orders (i.e., container moves) in a day, and the drayage operator dispatches trucks in the fleet to fulfill those orders through some form of scheduling and routing. While port truck scheduling and routing has been studied previously [11–14], these studies were mostly focused on minimizing travel time and distance. The fleet management perspective in operating an electric truck fleet was not previously considered.

Energy consumption models for conventional diesel trucks are already well established [15, 16]. However, a limited number of studies have devised methods to estimate energy consumption for electric trucks [17–19]. Gao et al. developed a simulation tool for estimating electric truck tractive energy considering second-by-second vehicle speed and component efficiency [20]. They found that both the battery electric and plug-in hybrid electric trucks were more energy efficient than conventional diesel trucks. Moreover, the large battery size did not cause payload problems in Class 8 utility bucket trucks.

For electric truck operation in drayage application, a distinct advantage appears when considering the placement of charging stations. Rather than having to set up a large charging network similar to that for passenger vehicles, it may be possible to solely rely on charging infrastructure at the home base because the electric trucks in the fleet can be assigned activity tours that will allow them to retain sufficient SOC to come back to the home base. However, charging a Class 8 electric truck can take a number of hours even with DC fast chargers. This time requirement poses limitations on when the electric truck can begin the next tour and how long of a tour the truck can serve. To the best of the researchers' knowledge, no previous study has analyzed the tour formation of electric drayage trucks in terms of battery charging constraints.

Based on the gaps identified in the literature, part of the project was aimed at addressing the following research questions:

- Can a typical drayage operator transition its truck fleet entirely from conventional diesel to battery electric?
- Are the tour formations of drayage trucking operations compatible with electric trucks?
- What is the effect of home base 240 kW charging on turn time of drayage trucking operations? And how much can improved scheduling enhance the productivity of drayage operation?

## Methodology

### Data Collection

Vehicle and engine activity data were collected from 38 Class 8 trucks of a drayage operator in Southern California. The home base of the truck fleet was located about 1 mi away from the Port of Los Angeles. This fleet primarily serviced the San Pedro Bay port complex comprising the ports of Los Angeles and Long Beach, as well as several other locations in the Greater Los Angeles metropolitan area and the Inland Empire area. The fleet also occasionally serviced locations in the Central Valley and the inland part of Northern California. A 2013 survey on drayage truck operations in the area [21] reported that 85 percent of the respondents maintained a home base in the Los Angeles basin, and approximately 60 percent of the tours were less than 40 mi. The drayage operator whose truck activity data were used in this study did not maintain a warehouse facility at the home base. Therefore, each tour comprised at least one pick-up and one drop-off outside of the home base.

Data were collected from each truck for a period of 1–2 months, depending on the availability of the trucks for installation and retrieval of data loggers. In total, the data collection effort resulted in over 130,000 mi and more than 15,000 hours of real-world operation data. The data were collected using combined global positioning system (GPS) and engine control unit (ECU) data loggers, which were configured to log GPS data (e.g., timestamp, latitude, longitude, speed) along with more than 170 ECU parameters at the frequency of 1 Hz. The collected data went through multiple steps of processing including format conversion (from binary to text), quality assurance (to identify and, if possible, correct erroneous data), trip identification (to segregate trips from strings of data), and trip origin and destination cloaking (to protect confidentiality of the fleet) [8].

### Tour Generation Algorithm

In this research, a tour was a contiguous sequence of trips starting from the home base location and ending at the home base location. The pseudocode for tour generation is given in **Error! Reference source not found.**. The tour g eneration algorithm assumed that any trip that ended within 1 mi of the home base (Base_Pos) was a home-based trip. The assumption was based on the higher level of positional inaccuracies in the GPS data at the beginning of the trip due to the time required to initialize satellite communication. It was also assumed that any trip that started and ended at home base (“Home”) but was longer than 4 mi was a combination of two trips—one from Home to Out and the other from Out to Home.

The stop information was extracted from the trip database by sequencing the trips by the corresponding trip start time. The duration between the end time of the previous trip and the start time of the next trip was taken as the time spent at the stop location or node. A node was classified as Home if the end location (End_Loc) of the last trip was Home. Therefore, a trip chain was formed using the node table. The number of nodes in a trip chain was essentially one more than the number of trips for the truck. Tours were considered complete when a trip sequence that started at Home returned to Home. The algorithm automatically detected the end of a tour and assigned a tour start indicator (Tour_StartIndicator) to the corresponding node. Once the tour index (Tour_ID) was populated for the entire trip table, all the trip-based and node-based information could be summarized into tour-based information, including total distance traveled, total duration, and total stop time in a tour.

**Data: trip table for trips $i \in I$ for trucks $k \in K$; node table for nodes *(1,2,3, . . . , I+1)***
**Result: tour table for tours $p \in P$**

```
FOR each trip i
    IF (Distance(Start_Pos_i, Base_Pos) < 1 mile) THEN
        Start_Loc_i = 'Home'
    ELSE
        Start_Loc_i = 'Out'
    ENDIF
    IF (Distance(End_Pos_i, Base_Pos) < 1 mile) THEN
        End_Loc_i = 'Home'
    ELSE
        End_Loc_i = 'Out'
    ENDIF
    IF (Start_Loc_i = 'Home' & End_Loc_i = 'Home' & Distance_Traveled > 4 miles) THEN
        SPLIT trip i into ('Home' to 'Out') and ('Out' to 'Home') segments
    ENDIF
    INIT Tour_StartIndicator_1 = 1
    Node_Loc_i = End_Loc_i-1
    IF (Node_Loc_i-1 = 'Out' & Node_Loc_i = 'Home') THEN
        Tour_StartIndicator_i = 1
    ENDIF
    Tour_ID_i = Tour_ID_i-1 + Tour_StartIndicator_i
ENDFOR
// Summarizing trip table by Tour_ID
FOR every Tour_ID
    Total_Distance_Traveled_p = ∑ Distance_Traveled_i, where Tour_ID_i = p
ENDFOR
```

**Figure 1. Pseudocode for tour generation algorithm using trip database.**

## Electric Truck Energy Consumption and Charging Models

The parameters for electric truck and charging infrastructure required for modeling electric energy consumption and calculating the remaining SOCs were chosen [22, 23]. The assumed values of these parameters are listed in Table 1.

The second-by-second activity data were collected from conventional diesel trucks. In order to emulate the operation of electric trucks, vehicle mass and drivetrain efficiencies were converted to electric truck equivalents. Therefore, the values of mass and efficiency for diesel truck components were used alongside the values for electric trucks. For each time instance, $t$, the tractive power $P(t)$ was calculated as:

$$P(t) = m_{ev} v_t a_t + 0.5 \rho C_d A v_t^3 + C_{rr} g m_{ev} v_t \tag{1}$$

where $v$ is truck velocity; $a$ is acceleration; and $m_{ev}$ is the mass of the electric truck, defined as:

$$m_{ev} = m_v - m_e - m_{gb} + \frac{E_{battery}}{U} + m_m \tag{2}$$

**Table 1. Parameters Used for Electric Truck Simulation**

| | Parameter | Symbol | Value |
|---|---|---|---|
| Vehicle | Coefficient of drag | $C_d$ | 0.65 |
| | Coefficient of rolling resistance | $C_{rr}$ | 0.008 |
| | Front area ($m^2$) | $A$ | 8.5 |
| | Accessory efficiency | $\eta_a$ | 0.94 |
| | Clutch and torque converter efficiency | $\eta_{tc}$ | 0.86 |
| | Gearbox efficiency | $\eta_{gb}$ | 0.92 |
| | Final drive efficiency | $\eta_d$ | 0.98 |
| | Wheel efficiency | $\eta_w$ | 0.99 |
| | Motor efficiency | $\eta_m$ | 0.88 |
| | Battery efficiency | $\eta_b$ | 0.98 |
| | Loaded vehicle mass (kg) | $m_v$ | 34,545 |
| | Maximum road grade | $grade$ | 0.25 |
| | Accessory load for electric vehicle (kW) | $AL_{ev}$ | 2.8 |
| | Engine mass (kg) | $m_e$ | 558 |
| | Gearbox mass (kg) | $m_{gb}$ | 180 |
| | Motor mass (kg) | $m_m$ | 432 |
| Atmosphere | Air density ($kgm^{-3}$) | $\rho$ | 1.161 |
| | Gravity ($ms^{-2}$) | $g$ | 9.8 |
| Battery | Battery size (kWh) | $E_{battery}$ | 250 |
| | Energy density (kWh/kg) | $U$ | 0.15 |
| Charger | Charging power (kW) | $P$ | 240 |
| | Charger efficiency | $\eta_c$ | 0.85 |

The algorithm designed for this analysis could consider the change in loaded vehicle mass, $m_v$, with each trip as the truck loads and unloads. However, the data used in this research did not contain weight or mass information on a trip-by-trip basis. Therefore, a static $m_v$ of 34,545 kg (76,000 lb) was assumed for all the trips. Given that the legal weight limit of Class 8 heavy-duty vehicles was 80,000 lb, this assumption implied that the electric truck was almost fully loaded all the time. This was a conservative assumption from the energy consumption perspective because it indicated a fully loaded truck consumed much more energy than a truck with an empty container and a bobtail truck. In reality, it was more likely that the truck would not be fully loaded all the time. Thus, its energy consumption would be overestimated for most of the tours. This meant that the number of tours that would not be possible for electric trucks to make would also be overestimated. With range anxiety being a major concern for electric vehicles, using this conservative assumption was reasonable.

The amount of battery discharge to meet the required $Tractivepower$ was calculated according to:

$$Discharge = \frac{Tractivepower}{\eta_m \times \eta_b \times \eta_w \times \eta_d} \tag{3}$$

The electricity regeneration from regenerative braking was calculated as:

$$Regeneration = (Tractivepower < 0) \times \eta_m \times \eta_b \times \eta_w \times \eta_d \tag{4}$$

Next, the consumed energy over the entire operating period, $E_{consumed}$ , was calculated as:

$$E_{consumed} = \int (Discharge + Regeneration + AL_{ev})dt \tag{5}$$

This led to the SOC calculation for each time instance, $t$ :

$$SOC(t) = SOC(t-1) - \frac{E_{consumed}(t)}{E_{battery}} \tag{6}$$

Velocity was at the core of the SOC calculation because each time the truck moved, the battery depleted to provide the tractive power. Because calculating the SOC levels was the focus of this study, every reading instance having a velocity value was used for the calculation whether those readings had GPS coordinates or not—thus emulating the real-world scenario as closely as possible from the available data. This way, the analysis perfectly reflected the distance traveled by the trucks in addition to the shortest path between two end points, which contributed to a decrease in battery charge. However, battery discharge for accessory load was not calculated for the time instances when the trucks were stationary, but this omission was a minor relaxation that did not affect the analysis because the battery discharge for accessory load was very small compared to the battery size.

The trucks used for this data collection moved within the home base from time to time and stayed at different locations inside the home base for different time periods. These movements can safely be assumed as activities such as parking, loading/unloading, refueling, and maintenance. To obtain a safe estimate for the time available for electric trucks to get charged at the home base, the maximum parked time among these parking events was taken as the charging time. This time may not necessarily be the time the trucks were parked, but when electric trucks will be employed, the freight operator will most certainly manage the time within the home base in a way that allows for maximum time for charging. The increase in SOC for charging can be obtained from:

$$SOC_{increase} = \frac{P \times \text{charging time} \times \eta_c}{E_{battery}} \tag{7}$$

Having the charging facility at the home base allowed the operator to have full control over the facility and maximize its use. Because of this, it was feasible to consider a comparatively fast charging system to be installed at the home base since it would facilitate lower downtime for the electric trucks. In this study, a 240 kW charger was considered, which was realistic considering 350 kW chargers are already being employed [22].

## Results

This section describes (a) an analysis of activities in a drayage operation, and (b) different scenarios of drayage truck electrification regarding charging, infrastructure, and scheduling.

### Activities in Typical Drayage Operations

The collected data were reduced at the trip level to analyze typical drayage activity. Figure 2 shows the location of trip end points. Most of the trips ended near the home base, including some of the trips that ended at the home base. There were a few instances of the trucks visiting far from the home base; however, most of the time, the same remote locations were visited multiple times.

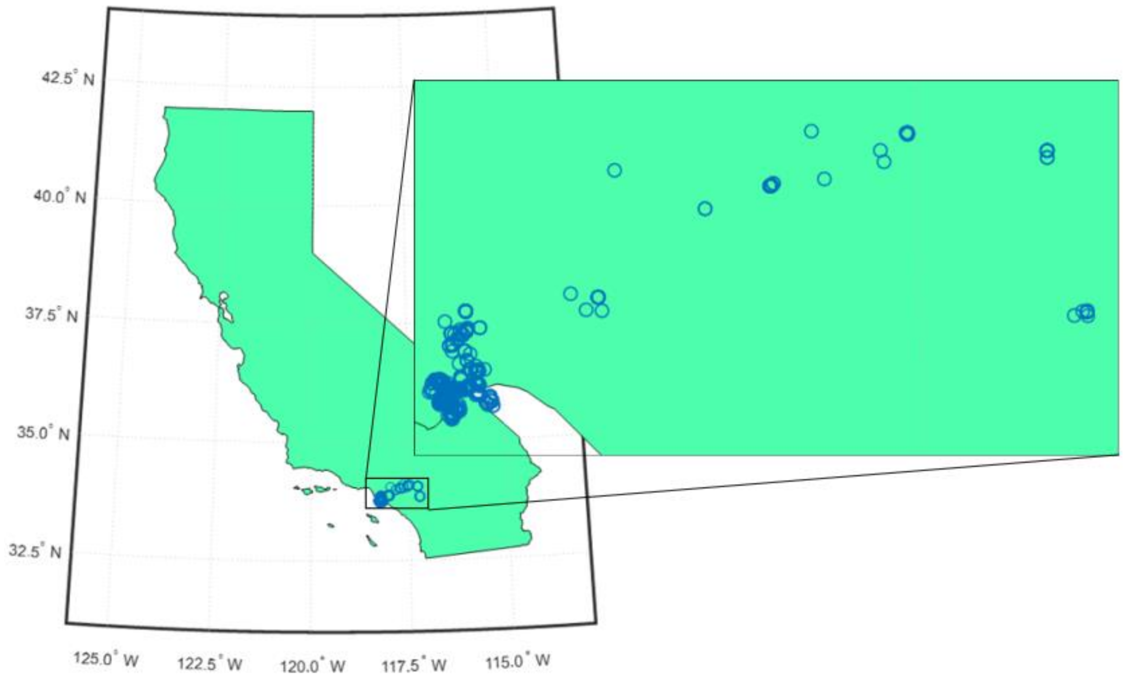



**Figure 2. Locations of trip end points.**

Since new trucks were instrumented during the course of the study, the research team wanted to capture a week with the maximum activity. Figure 3 shows that total number of unique trucks that reached 20 during the first 6 weeks of 2017, with approximately 2,500 trips per day on average (125 trips/day/truck). However, the total distance traveled by the trucks was at maximum in the fourth week of January 2017 (January 22–28, 2017), at 11,271 mi. In this project, trips from the fourth week of January were used to generate the electrification scenarios.

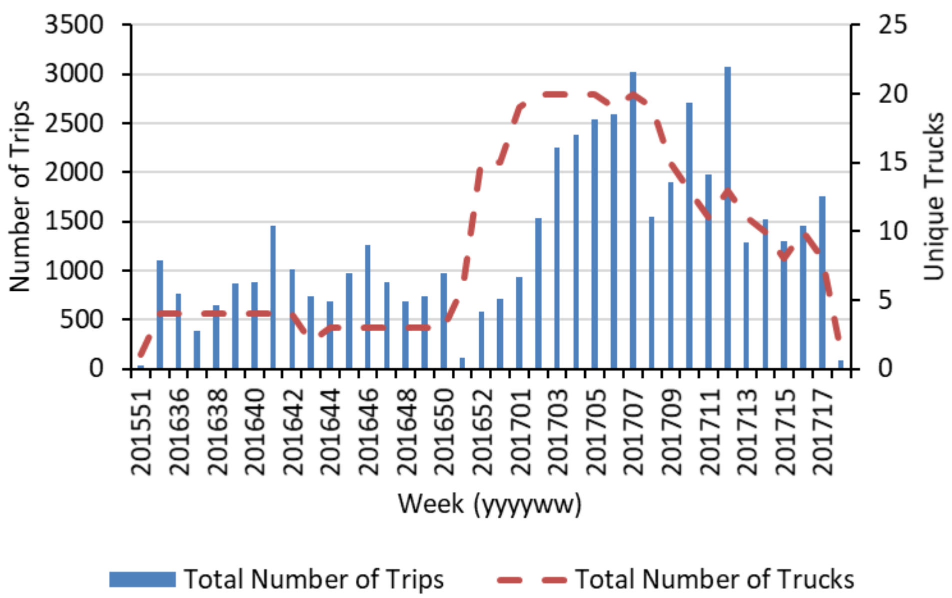



**Figure 3. Number of trips and trucks across the entire study period.**

Table 2 summarizes the trip database for each truck trip. The values were averaged for each truck. On average, this drayage facility operated trucks over a short distance. A large portion of the trips was spent in the idling mode where speed was close to zero. Average trip speed was calculated by dividing the trip distance by the trip duration, which included the idling period. Since most drayage trucks spent a significant proportion of time waiting for pick-up and drop-off, the average speed was less than 9 mph for all the trucks. Moreover, a large proportion of the time was spent in braking, which made these trips ideal candidates for regeneration of power from braking.

**Table 2. Summary Statistics of the Trip Database Averaged for Each Truck**

| Variables per Truck | Average | Range |
|---|---|---|
| Average Trip Distance (mi) | 3.6 | 0.6–8.0 |
| Average Trip Duration (minutes) | 21.0 | 5.0–42.8 |
| Average Trip Speed (mph) | 5.6 | 1.8–8.4 |
| Average Percent Time Spent Idle (%) | 63.6% | 43.7%–88.9% |
| Average Percent Time Spent Braking (%) | 36.2% | 10.9%–56.3% |

Table 3 shows the statistics of the tours. On average, there were 6.4 trips included in one tour. The trucks completed 2.2 tours per day and traveled less than 60 mi per day on average, which was in the expected range, as mentioned in Ambrose and Jaller [9]. The average running time in a tour was approximately 4 hours; however, some trucks exceeded 6 hours of running time. The trucks spent only 21 minutes on average at the home base, which was adequate time to replenish only 29 percent of the battery SOC under current assumptions of the battery and charger.

**Table 3. Tour Statistics of Drayage Trucks**

| Variables per Truck | Average | Range |
|---|---|---|
| Average Number of Tours per Day | 2.2 | 1–7 |
| Average Tour Distance (mi) | 58.9 | 5.7–122.5 |
| Average Running Time (minutes) | 244.3 | 43.6–401.9 |
| Average Time Spent at Home Base (minutes) | 21.1 | 0–44.9 |
| Average Time Spent at Outside Stops (minutes) | 262.8 | 0–490.6 |
| Average Tour Battery Consumption (%) | 39.2% | 5.5%–76.0% |

A 2013 study by Papson and Ippoliti reported that the average daily mileage for drayage trucks operating at the ports of Los Angeles and Long Beach was about 200 mi, and the average distance per tour was about 40 mi [21]. Additionally, the same report found that the average speed for local and near-dock operations of these trucks was 6.8 mph and 6.6 mph, respectively. The drayage truck activity data used in this research showed the average daily mileage of 185 mi, the average tour distance of approximately 60 mi, and the average trip speed of 5.6 mph, all of which were comparable to reported statistics [21].

Total time spent at the outside stops such as the ports, container terminals, railyards, and warehouses was significantly longer than the time spent at the home base. The average tour battery consumption (39 percent) was found to be larger than the average tour battery replenishment capacity (29 percent). Since some stops within the home base may be made to perform loading/unloading, logistical, and maintenance activities, the stop times during those activities may be unsuitable for a stationary charging operation. Total stop time at the home base included the times when these activities were performed. In contrast, maximum stop time referred to the longest stretch of time the truck was resting at the home base. The electrification scenarios, as described in the following section, considered maximum stop time at the home base as the time available for the trucks to be recharged. This assumption was intended for the analysis to be conservative. Figure 4 shows the difference in the distributions between total stop time and maximum stop time at the home base.

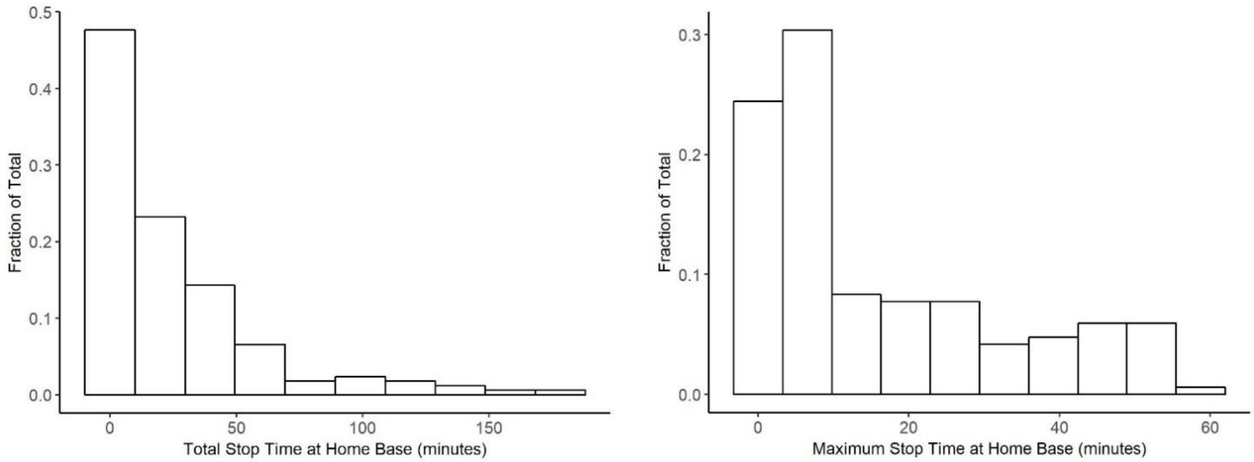



**Figure 4. Distributions of total stop time and maximum stop time at the home base.**

Figure 4 shows that the maximum stop time was more evenly distributed than the total stop time. Although more than 80 percent of the tours had a total stop time of less than 50 minutes, some of the tours had long stop times at the home base, sometimes more than 150 minutes. A possible reason for longer stop periods was day breaks. However, the dataset was selected to exclude the Saturday to Monday transition periods since the selected drayage facility did not operate on Sundays.

## Truck Fleet Electrification Scenarios

Four scenarios regarding drayage truck fleet electrification were analyzed. These scenarios represented different operational and infrastructure decisions of the drayage operator. The scenarios were as follows:

- *S-1: All tours started with 100 percent SOC*. This scenario represented a hypothetical condition in which the length of charging time available did not restrict trucks to replenish at the full battery level. In reality, this scenario was only possible if the drayage operator had no limits on the number of electric trucks available.
- *S-2: Tours started at 100 percent SOC at the beginning of the week, without opportunity charging*. The trucks continued to serve the tours until the remaining charge was not sufficient to complete the next tour. S-2 was a scenario for drayage operators that ran both day and night shifts, so the trucks could not be charged overnight. In S-2, it was assumed that the trucks would only be charged on the rest day (in this case, on Sunday).
- *S-3: Tours started at 100 percent SOC at the beginning of the week, with opportunity charging*. In addition to being charged to a full charge on the rest day, in this scenario, the trucks could also use opportunity charging throughout the work days to replenish the battery during the time gap before the next tour. S-3 was a practical scenario for drayage operators with dedicated charging facilities at the home base.
- *S-4: Trucks were reassigned to facilitate efficiency gain*. This scenario was based on the conditions in S-3. The difference was that when a truck did not have enough SOC to complete the next tour, the tour was reassigned to another available truck with sufficient SOC. In practice, this scenario entailed maintaining a queue of tours made up of pick-up and drop-off orders and matching those tours with electric trucks that had enough SOC to complete tours. The most recent tour request was assigned to the truck with the highest level of SOC.

### *S-1: All Tours Started with 100 Percent SOC*

Scenario S-1 represented a condition where there was no restriction of charging time imposed on the trucks. The only limiting factor in this scenario was the range of the electric trucks. Since the analysis was conducted using real-world second-by-second data, the estimated energy consumption of the electric trucks for any given tour would depend on a number of factors, such as the speed profile during the tour, time spent idling and braking, and vertical grade of the roads that these trucks traveled on. Thus, the energy consumption of the electric trucks could vary from one tour to another. Even for the same tour, the energy consumption could vary from one time to another. Approximately 60 percent of the trucks would be able to complete all the tours. For the rest of the trucks, about 20 percent of the tours would not be completed because of the range limitation.

The relationship between the tour distance and the fraction of battery charge depletion (compared to the battery capacity) is shown in Figure 5. The horizontal line drawn at the fraction of 1 represented the boundary between feasible and infeasible tours. With no charging available during the tours, 88.9 percent of the tours could be completed. The remaining 11.1 percent of the tours were longer than the range of the modeled electric trucks. The linear fit using the data points provided a good fit ($R^2$ = 0.94). This finding suggested that for every 10 mi traveled, 6.6 percent of the battery was depleted on average. Moreover, the fitted tour distance at 100 percent battery depletion suggested an approximate range of 150 mi for the modeled electric truck. This number was in line with the manufacturer-claimed ranges of commercially available Class 8 electric trucks in the market [23]. The actual range of electric trucks varied significantly from the manufacturer-claimed ranges, which were often overestimated.

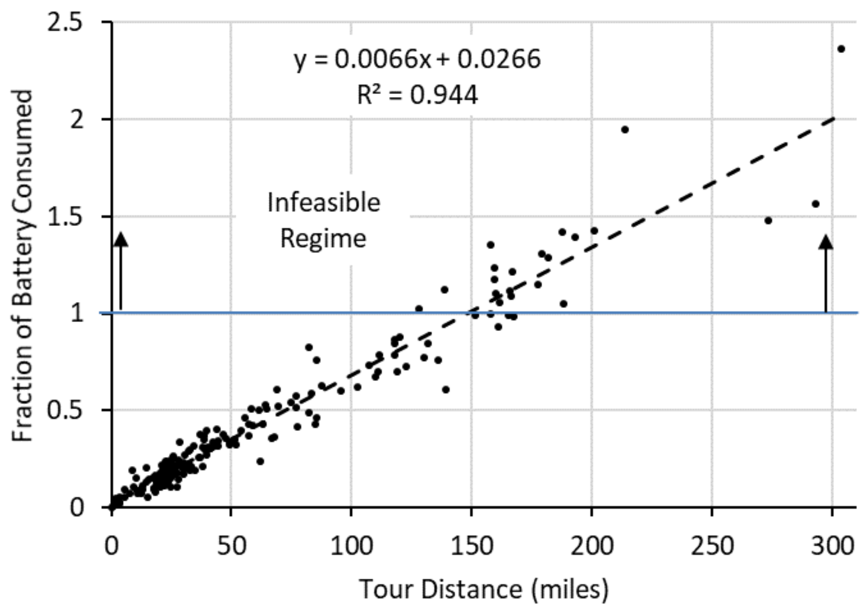



**Figure 5. Fraction of battery consumed by total distance traveled in a tour.**

### *S-2 versus S-3: Without versus With Opportunity Charging at Home Base*

Scenarios S-2 and S-3 were based on a similar operational concept except that in S-2, there was no opportunity charging when the trucks were parked at the home base. That meant the trucks could only complete the next feasible tour on the itinerary with the remaining battery from the previous tour. On the other hand, in S-3, the trucks could be charged when they were parked at the home base during the time gap between consecutive tours.

As stated earlier, with the 100 percent SOC requirement at the beginning of each tour, as in scenario S-1, 11.1 percent of the tours would be beyond the range of the modeled electric trucks. Of the 88.9 percent feasible tours, only 61.9 percent would be served if the 100 percent SOC requirement before each tour were relaxed (scenario S-2). That number would increase to 84.6 percent in scenario S-3 where charging was allowed between the end of one tour and the beginning of the next tour. The average number of tours that could be completed before charging was needed in scenario S-2 was 2.6, but in scenario S-3, 3.6 tours could be completed before charging was needed. In both of these scenarios, about 22–26 percent SOC would still remain in the batteries before charging would be required to serve the next tour.

### *S-4: Trucks Were Reassigned to Facilitate Efficiency Gain*

With the opportunity charging during the time gap between consecutive tours, the percentage of infeasible tours was 15.4 percent if each truck was assigned tours according to the existing itinerary. In scenario S-4, the research team investigated the potential of recreating itineraries for reassigning the trucks according to the demands set by the fixed itinerary of the tour tasks. The tours were assigned to any available trucks at the home base. It was assumed that there would be at least one truck waiting at the home base and fully charged to complete the next feasible tour (i.e., a tour with required battery consumption less than the fixed battery capacity). Table 4 shows the percentage of unserved tours as a function of the number of available trucks.

**Table 4. Fleet Size Effect on Service Coverage Considering Scheduling (Scenario S-4)**

| Available Number of Trucks | Percentage of Unserved Tours |
|---|---|
| 1 | 98% |
| 2 | 96% |
| 3 | 90% |
| 4 | 82% |
| 5 | 75% |
| 6 | 65% |
| 7 | 57% |
| 8 | 46% |
| 9 | 36% |
| 10 | 26% |
| 11 | 21% |
| 12 | 14% |
| 13 | 5% |
| 14 | 0% |

Table 4 suggests that with 12 trucks, the number of unserved tours could be reduced to less than the number of unserved tours with no reassigning of trucks. It should be noted that the existing fleet size was 20. Such scheduling of tours in effect could cause 40 percent reduction of fleet size. With just 14 trucks (i.e., 70 percent of the original fleet size), 100 percent of the tours could be served for the given drayage facility.

Most drayage operators cannot predict how many pick-up and drop-off orders they will get at certain times in the future. In addition, maintenance and repair is a critical issue, especially for older model year trucks. Considering these issues, drayage operators usually decide a fleet size ahead of time. In most cases, some trucks in the fleet stay idle at the home base. The enhanced scheduling approach considered in S-4 did not include these practical issues and used a comparatively fast charger (240 kW). As an effect, the drayage operator could perform the same tasks with 14 electric trucks, which actually took 20 diesel-operated tractors. The operational improvement in S-4 was completely due to an improved scheduling process, which was applicable even to the existing diesel-operated system. Table 5 shows the percentage of infeasible tours for different scenarios.

**Table 5. Infeasible Tours under Different Electric Truck Operational Scenarios**

| Scenarios | % Infeasible Tours | Number of Trucks Used |
|---|---|---|
| S-1 | 11.1 | 20 |
| S-2 | 45.0 | 20 |
| S-3 | 24.8 | 20 |
| S-4 | 11.1 | 14 |

## Sensitivity Analysis for Different Battery Sizes

To test the sensitivity of estimated drayage truck electrification feasibility with respect to future electrification technologies, four different battery sizes—250 kWh, 300 kWh, 400 kWh, and 500 kWh—were used to re-run the truck activity analysis. Figure 6 shows that the fraction of infeasible tours per truck was reduced as the battery size increased. The width of the violin plots in the figure represent the relative density of points at the different levels of infeasibility. Each data point (black dot) in this figure represents a single truck. Nineteen out of 20 trucks at 400 kWh and 500 kWh battery size could complete all the assigned tours. Therefore, no marginal benefit was gained by increasing the battery size beyond 400 kWh.

Figure 7 shows the sensitivity of estimated ranges of the different battery sizes. Each data point in this figure represents a tour. As represented by the regression lines, similar to Figure 5, the greater the tour distance, the higher the fraction of battery consumed. The red dotted horizontal line represents the 100 percent battery consumption line. Ranges for the different battery sizes were derived by finding the tour distance at the intersection of the 100 percent battery consumption line and the regression lines. The derived ranges for 250 kWh, 300 kWh, 400 kWh, and 500 kWh battery sizes were 150 mi, 190 mi, 250 mi, and 300 mi, respectively.

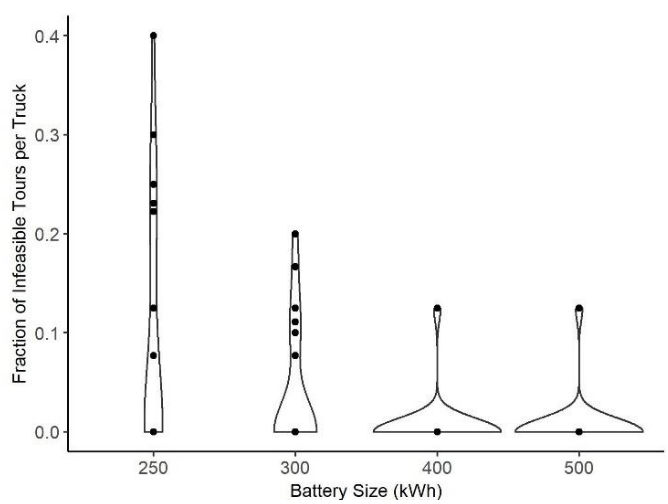



**Figure 6. Sensitivity of fraction of infeasible tours per truck for different battery sizes.**

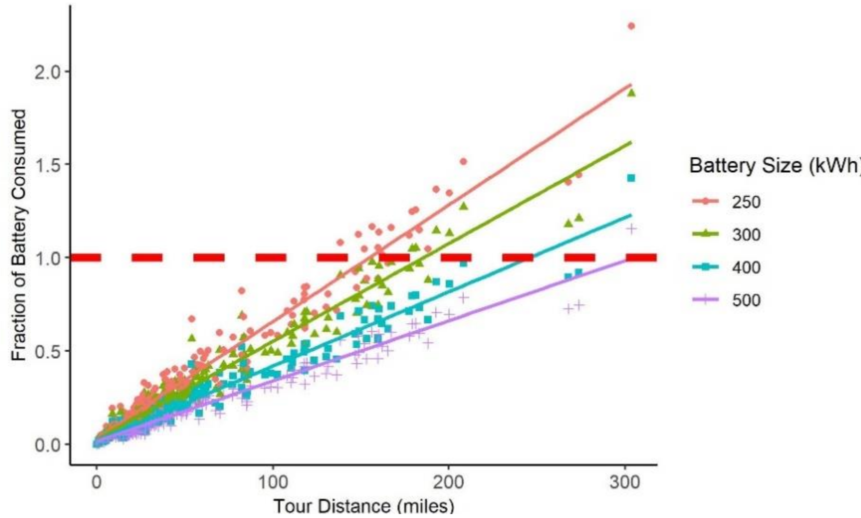



**Figure 7. Sensitivity of estimated electric truck ranges for different battery sizes.**

## Improving Electric Truck Efficiency with Connected Vehicle Technology

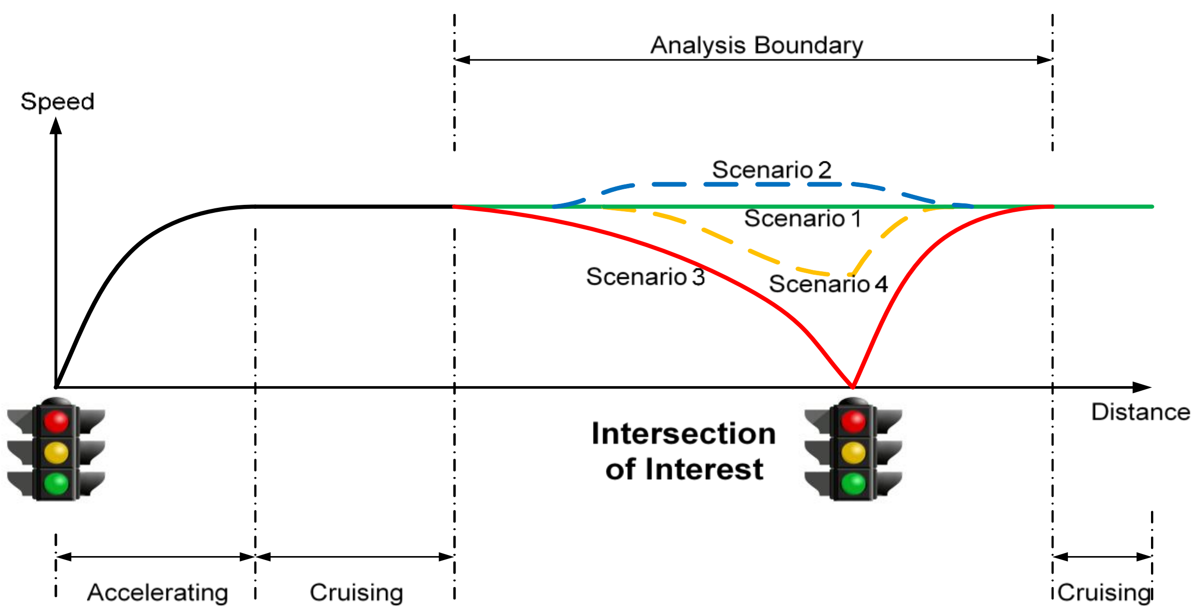
This section describes an evaluation of the potential for the EAD application to provide energy savings, and consequently increase the driving range, for electric trucks. The section begins with a discussion of the literature review and research gaps, followed by a description of the ETEAD algorithm. Finally, the section presents an application of the ETEAD algorithm to a case study intersection in a traffic microsimulation and discusses the energy and emission results.

### Literature Review

An EAD application uses SPaT information from the upcoming traffic signal along with the information about the current state of the equipped vehicle and the preceding traffic to determine the most energy-efficient speed profile for the vehicle to follow until the vehicle passes through the intersection. There are four general driving scenarios when an EAD-equipped vehicle approaches a connected signalized intersection, as shown in Source: [24].

Figure 8 [24]:

- *Scenario 1*: Approaching the intersection while the traffic signal is green and there is plenty of green time left. In this scenario, the EAD application will advise the driver to simply cruise through the intersection at a constant speed.
- *Scenario 2*: Approaching the intersection while the traffic signal is green but the green phase is about to end. In this scenario, the EAD application will advise the driver to speed up in order to pass through the intersection before the signal turns red, if it is possible to do so without exceeding the speed limit.
- *Scenario 3*: Approaching the intersection while the traffic signal is red and there is still a lot of red time remaining. In this scenario, the EAD application will advise the driver to coast to a stop at the intersection since stopping is unavoidable.
- *Scenario 4:* Approaching the intersection while the traffic signal is red but about to turn green. In this scenario, the EAD application will advise the driver to slow down in advance so that the vehicle reaches the intersection just when the signal turns green.




Source: [24].

**Figure 8. Four general scenarios for passing through a signalized intersection.**

Most of the EAD studies to date have focused primarily on internal combustion engine (ICE) vehicles, especially gasoline-powered passenger cars. For example, Hao et al. developed an EAD application traveling through actuated traffic signals. They tested the application in the real world, achieving 6 percent fuel savings when the test vehicle was within the range of communication with traffic signals [25]. Ye et al. developed a prediction-based EAD model to predict the state of the preceding vehicle for calculating the optimal speed profile for the host vehicle [26]. Asadi et al. proposed a rule-based control algorithm to schedule an optimum speed trajectory for the vehicle using the short-range radar and traffic signal information [27]. In recent years, some studies have applied EAD to electric vehicles, which, unlike ICE vehicles, can recoup some energy from braking through regeneration. For instance, Lu et al. used linear programming to calculate the optimal speed trajectory for electric vehicles with consideration of their regenerative braking capability [28]. Qi et al. designed an EAD system for electric vehicles based on real-world driving data and found that around 15 percent energy savings can be achieved with the system [29].

Recently, an increasing number of studies have applied EAD to heavy-duty vehicles. In an eCoMove project [30], the project team found that driver behavior could affect fuel consumption of commercial trucks by 10–15 percent based on simulator and on-road experiments [31]. Hao et al. designed a truck EAD application that used SPaT messages from traffic signal controller and road grade information along the path [32]. Numerical experiments were conducted using a hypothetical pretimed signalized intersection with varying entry times and speeds. The average energy savings compared with a baseline trigonometric EAD algorithm was 11 percent for level terrain, 6 percent for uphill, and 20 percent for downhill. Rodriguez and Fathy developed a dynamic-programming-based model to explore the fuel saving benefits of heavy-duty truck trajectory optimization given advanced traffic signal information [33]. Numerical simulations were conducted to evaluate the performance of the proposed method for different arterial corridor configurations, and the results showed 32–72 percent fuel savings. Wang et al. developed a connected eco-driving system and implemented the system on a heavy-duty diesel truck using cellular communications. The system was demonstrated in Carson, California, showing the system's efficacy in real-world traffic [34].

According to the literature review, there has not been a study that evaluated the potential energy savings of EAD for electric trucks. Meanwhile, because most studies have mainly focused on the energy impact for a single EAD-equipped vehicle, the discussion about the impacts when multiple vehicles are equipped with EAD as well as the impacts on unequipped vehicles is limited. Based on the gaps identified in the literature, the part of the project discussed in this section was aimed at addressing the following research questions:

- How much energy savings can an electric truck gain from utilizing the EAD application?
- What is the energy savings potential for electric trucks from utilizing the EAD application under different levels of traffic congestion?
- What are the impacts of a large-scale adoption of EAD application on the total energy and emissions of the overall traffic?

## Methodology

### Inputs

Seven types of information are required for the ETEAD algorithm to calculate an optimal speed profile for an EAD-equipped electric truck to pass through a signalized intersection in a safe and energy-efficient manner:

- *Distance to Intersection (D)*: The longitudinal distance from the current location of the vehicle to the upcoming intersection. This information can be derived from the GPS coordinates of the vehicle in relation to the base map.
- *Time (t)*: The current timestamp.

- *Vehicle Speed (V)*: The instantaneous speed of the vehicle at the current timestamp. This information can be obtained from the vehicle's onboard diagnostics, a GPS device, or a combination of the two for a more accurate measurement.
- *Communication Range (C)*: The range in which the vehicle is able to communicate in real time with the upcoming traffic signal through CV technology such as cellular vehicle-to-everything (C-V2X) or dedicated short-range communications. This communication range determines how far ahead of the intersection the EAD application can function (i.e., $C \geq D$).
- *SPaT (W)*: Data messages containing SPaT information, which are needed to define a time window during which the vehicle can pass through the intersection.
- *Presence of Preceding Vehicle (R)*: Information about the state (relative distance and speed) of the preceding vehicle, if any, which can be obtained through onboard sensors such as radar or a camera. This information is required for both safety and energy efficiency reasons. The optimal speed profile designed by the EAD application must ensure that the equipped vehicle will not crash into the preceding vehicle. If the preceding vehicle is detected to be queuing at the intersection, the length of the queue can be calculated, and the time window for passing through the intersection will be adjusted accordingly to account for the extra time needed for the queue to dissipate.
- *Vehicle Characteristics*: Information about the equipped vehicle such as its maximum speed, acceleration, and deceleration as well as energy consumption rates under different operating conditions.

This information is used by different modules of the ETEAD algorithm to calculate the most energy-efficient speed profile for the vehicle to pass through the intersection under safety constraints. The next subsection explains the energy consumption model used in the algorithm. Then, the subsection discusses the graph-based optimization method for optimal speed profile calculation and the random forest–based optimization method for reducing computation time. Finally, the subsection describes the system workflow of how the different modules work together.

### Energy Consumption Model

Section 2.2.3 presented a microscopic electric truck energy consumption model that estimates energy consumption of an electric truck on a second-by-second basis based on a number of data inputs and model parameters. In this portion of the project, the research team used the same electric truck energy consumption model and the same value of model parameters as listed in Table 1. For each time instance, $t$, the tractive power $P(t)$ was calculated as:

$$P(t) = m_{ev} v_t a_t + 0.5 \rho C_d A v_t^3 + C_{rr} g m_{ev} v_t \tag{8}$$

where $v$ is truck velocity; $a$ is acceleration; and $m_{ev}$ is the mass of the electric truck, defined as:

$$m_{ev} = m_v - m_e - m_{gb} + \frac{E_{battery}}{U} + m_m \tag{9}$$

The amount of battery discharge to meet the required $Tractivepower$ was calculated according to:

$$Discharge = \frac{Tractivepower}{\eta_m \times \eta_b \times \eta_w \times \eta_d} \tag{10}$$

The electricity regeneration from regenerative braking was calculated as:

$$Regeneration = (Tractivepower < 0) \times \eta_m \times \eta_b \times \eta_w \times \eta_d \tag{11}$$

Next, the net energy consumed per second was calculated as:

$$E_{consumed} = Discharge + Regeneration + AL_{ev} \tag{12}$$

where $AL_{ev}$ represents electricity consumption by accessory load, such as powertrain support systems, climate control systems, and driver comfort features.

Instead of calculating the total energy consumption of the electric truck over the course of a trip, this portion of the project aimed to characterize the energy consumption per second of the electric truck as a function of instantaneous speed and acceleration, which were the variables that defined the speed profile of the truck. To develop this model, the research team first compiled the previously estimated second-by-second energy consumption data of the electric truck from all the trips, along with the corresponding instantaneous speed and acceleration values. These data were then turned into a two-dimensional lookup table where speed and acceleration jointly defined cells of the table and each cell stored the mean value of electric truck energy consumption for the corresponding speed and acceleration values. This lookup table was then used to create a surface plot, similar to the one in Figure 9. The resulting surface plot was not smooth and had some spikes, which were caused by the high variability in the energy consumption value, especially for cells with a limited amount of data. Therefore, the thin-plate splines smoothing technique [35] was applied to smooth out the surface plot. The final surface plot is shown in Figure 9. There were some cells where the energy consumption value was negative. These cells had a negative value of acceleration, which meant the electric truck was slowing down and its motor was in the regeneration mode. Thus, the energy consumption value was negative because energy was actually being generated under those circumstances.

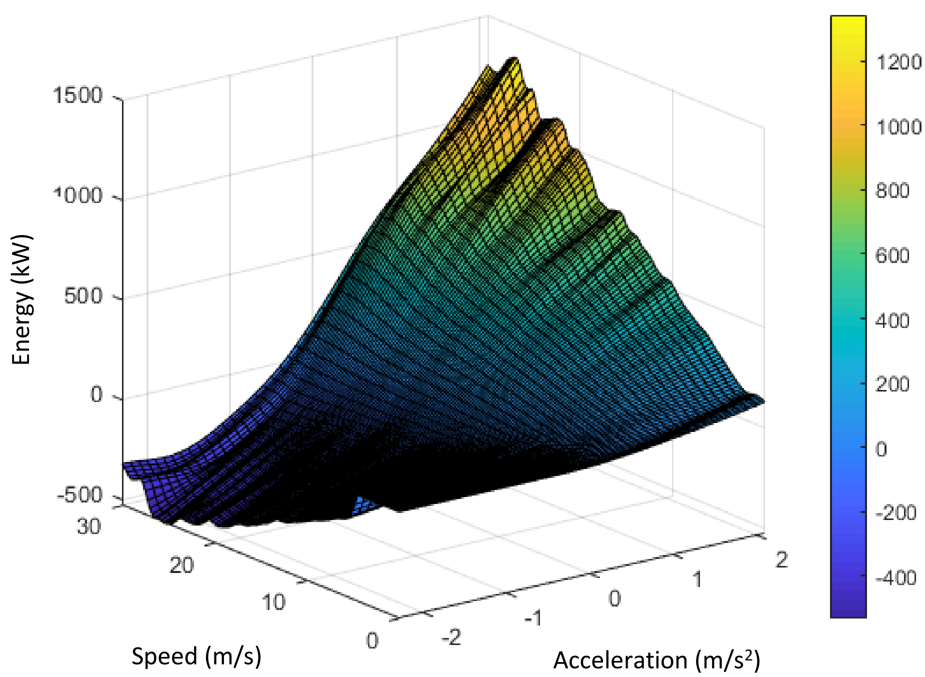



**Figure 9. Energy consumption model used in the calculation.**

## Graph-Based and Random Forest–Based Optimization Methods

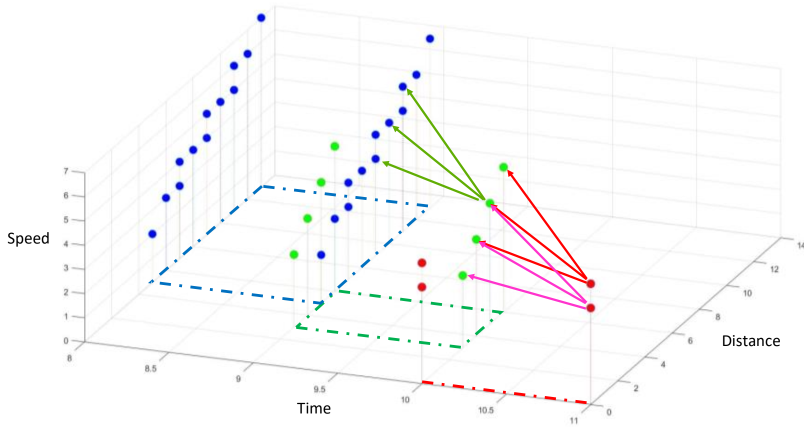
The research team used a lookup table of electric truck energy consumption as a function of instantaneous speed and acceleration to design an optimal speed profile or trajectory for the truck. Two optimization methods were used—a graph-based method and a random forest-based method.

The graph-based trajectory planning algorithm was based on the authors' previous work [36]. In this method, three-dimensional (3-D) dynamic vehicle states, time-distance-speed (*t-D-V*), were used to represent nodes in the graph, and the energy consumption required for the vehicle to transition from its current state to another state was used to represent the weight of the directed edge. Discretized time, distance, and speed spaces formed the graph model, and the energy consumption minimization problem was then converted into a shortest path problem where the objective was to find the shortest (or least energy consumption) path from the source node $V_s$ (*t*, *D*, *V*) to the destination node $V_d$ (*T*, *0*, *V'*) in the directed graph. *T* was the target time for the vehicle to reach the stop line on the approach leg of the intersection. In the scenario where the vehicle started the trajectory planning when the traffic signal was green (referred to as green phase arrival scenario), *T* was the minimum number such that the shortest path problem was feasible. In other words, the algorithm aimed for the vehicle to reach the stop line at the earliest time possible within the current green phase and found the most energy-efficient trajectory given that time target. In the red phase arrival scenario, *T* could be defined as the start of the upcoming green phase plus a buffer time to account for the amount of time needed for the queueing vehicles to cross the stop line (i.e., $T = T_g + \tau_b$). This shortest path problem with the size of $\theta((|V| + |E|)log|V|)$, where $|V|$ was the number of nodes and $|E|$ was the number of edges, could be solved using the classical Dijkstra's algorithm [37].

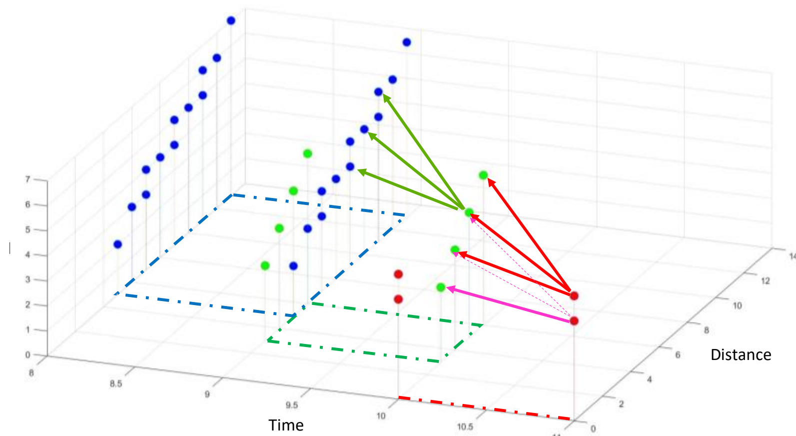
An example illustration of the graph-based trajectory planning algorithm is shown in Figure 10. The dots with different colors (red, green, and blue) represent the states of the vehicle in consecutive timestamps. Figure 10(a) shows the process of finding all the possible child nodes, which were within certain speed, time, and distance ranges of the parent node. Figure 10(b) shows that the optimal valid actions were chosen based on the minimum edge weight between the parent node and the child node. Figure 10(c) illustrates all the optimal valid actions for the red and green states tracing through all the *t-D-V* combinations.

The graph-based trajectory planning algorithm showed good performance in optimizing the vehicle energy efficiency. However, the computation time for creating the graph and solving the shortest path problem was long, which made that method unsuitable for real-time application. As the computation time required by the Dijkstra's algorithm grew with the size of the graph, it made real-time computation very challenging, especially when the EAD application must also deal with other data that the application collected, such as those from GPS and radar. In addition, an increase in communication range enabled by C-V2X that allowed the EAD application to start planning vehicle trajectory far ahead of the intersection also increased the size of the graph, which rendered real-time computation almost impossible. To accommodate the long computation time, the EAD application will have to increase the size of the time step $\Delta t$ to be larger than the computation time required, which might reduce the energy savings that the EAD application can provide.

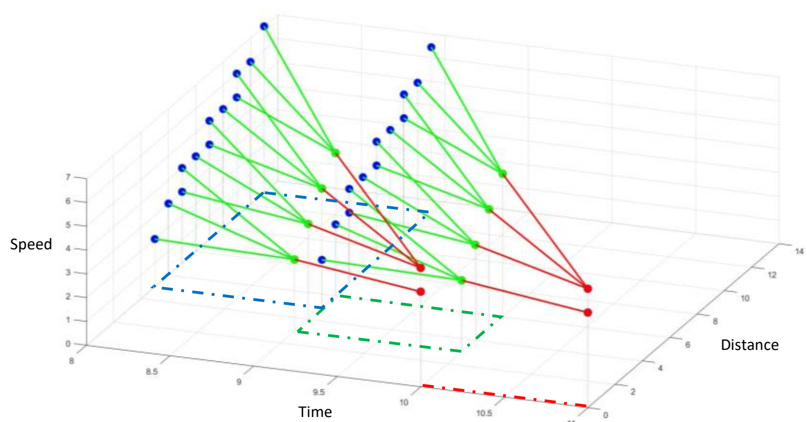
To help increase the computational efficiency of the EAD application, the research team employed a machine learning technique to learn the patterns of the solutions from the graph-based algorithm. A random forest model was trained using the data created by the graph-based algorithm. The input of the random forest model was the 3-D vehicle states (*t-D-V*), and the output was the optimal speed for the next time step. The random forest model consisted of multiple decision trees, with each tree trained with a random subset of the created data. The predicted output of the random forest model was the average of the predictions from all the decision trees. As shown in Figure 11, the computation time of the random forest model was not affected by the size of the graph and performed on the order of magnitudes faster than the graph-based method.




(a) Valid parent states searching




(b) Optimal valid actions identification




(c) All optimal valid actions

**Figure 10. Illustrations of the graph-based optimization.**

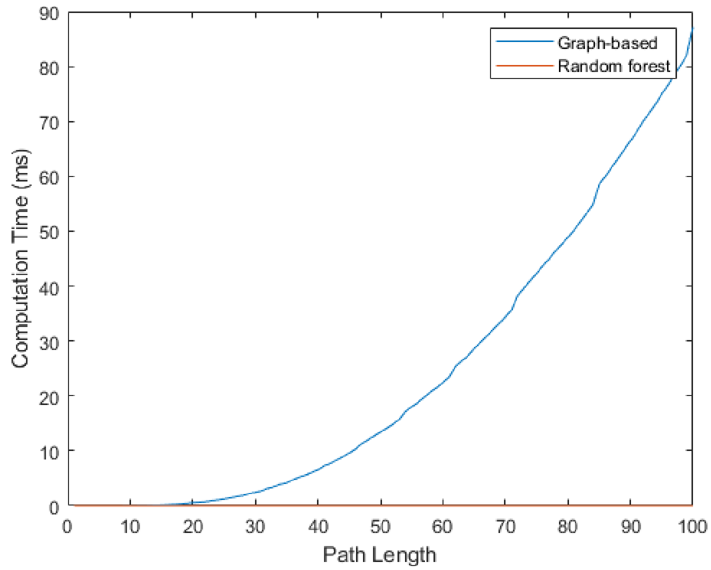



**Figure 11. Computational time comparison between graph-based and random forest–based methods.**

## System Workflow

The ETEAD system consisted of two parts, offline and online. The offline part trained a random forest model using the output of the graph-based model. The online part was the one running in real time on the electric truck that determined the optimal speed profile for passing through the intersection. As shown in Figure 12, the 3-D vehicle states (*t-D-V*) collected by the equipped vehicle were used in conjunction with vehicle dynamics information, which included the energy consumption model, to create the graph-based model. Using the energy consumption model for the electric truck, the optimal speed profile cab was calculated using Dijkstra's algorithm (i.e., $v_{t+1} = G(t, D_t, v_t)$). The input-output pairs from the graph-based model were recorded and later used as data to train the random forest model. Finally, the trained random forest model was used in the online part of the ETEAD system for real-time computation of the optimal speed profile for the electric truck.

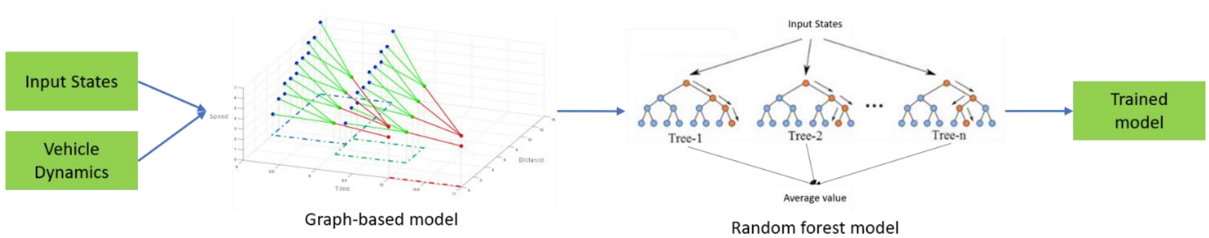



**Figure 12. Offline process for developing the random forest model for use in the online ETEAD algorithm.**

Figure 13 shows the workflow of the online part of the ETEAD system. Once the electric truck was within the communication range of the connected signalized intersection, real-time information about vehicle states (*t-D-V*) was collected by the system. Using data from an onboard radar or camera, the system determined whether there was a preceding vehicle. If the preceding vehicle was too close, the system did not start the trajectory planning because it may not have been safe to do so. Otherwise, kinematic equations were used to determine whether the remaining green time was enough for the vehicle to pass through the intersection from the current vehicle position. For example, if the traffic signal was in red phase, the system determined whether the vehicle could stop before reaching the intersection based on the information about the current vehicle speed, the remaining red time, and the maximum deceleration rate of the vehicle. If the traffic signal was in green phase, the system decided whether the vehicle would be able to pass through the intersection based on the information about the current vehicle speed, the remaining green time, and the maximum acceleration rate of the vehicle. If any part of these two checks was not satisfied, the system stopped the eco-driving trajectory planning and let the human driver determine the best course of action. On the other hand, if any part of the two checks was satisfied, the real-time vehicle states information was provided to the trained random forest model to determine the optimal speed at time *t*, after which the system started the process for the next time step *t+1*.

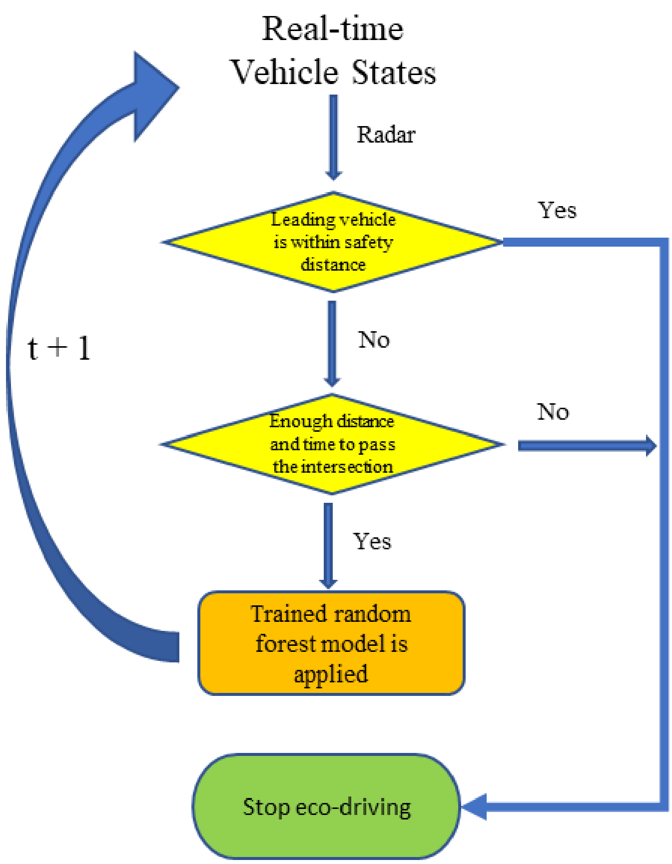



**Figure 13. Online process of the ETEAD algorithm.**

## Case Study and Results

PTV Vissim [38], a microscopic multimodal traffic simulator, was used to evaluate the ETEAD algorithm in a simulation environment. A dynamic-link library interface was developed to communicate between the Vissim simulation environment and the ETEAD algorithm so that the equipped vehicles that were simulated in Vissim could follow the optimal speed profile generated by the ETEAD algorithm. As shown in Figure 14, a simple simulation network representing an approach leg of a signalized intersection with three lanes was created. The upstream and downstream distances of the approach leg were 800 m and 360 m from the stop line, respectively. The timing of the traffic signal in the simulation was adapted from that of a real-world traffic signal in Carson, California.

In this project, the research team only simulated one approach leg because the way vehicles went through a signalized intersection was largely the same for all the approach legs. Also, only through movement was simulated because it was usually the most common movement at signalized intersections. Turning movements at some signalized intersections have dedicated lanes (e.g., left turn lane) and dedicated signal phases (e.g., protected left turn phase). Thus, the EAD application can be extended to accommodate vehicles making turning movements at signalized intersections as well. Expanding the EAD application will be addressed in future work.

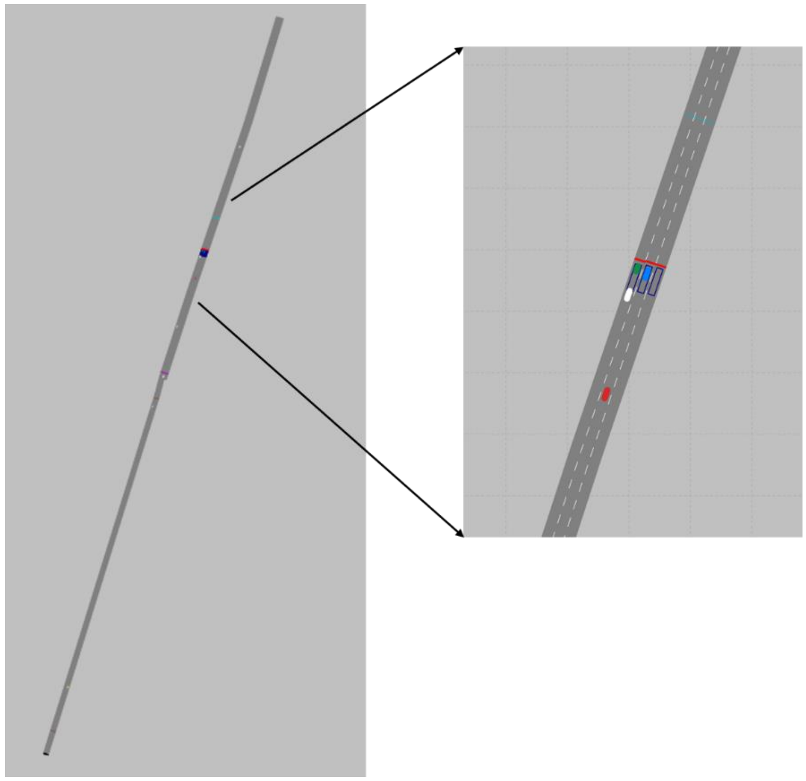


**Figure 14. Microscopic simulation environment for the baseline and ETEAD cases.**

The simulation settings are listed in Table 6. *V* was traffic volume (vehicles/hour), and *p* was the market penetration rate of the electric truck (i.e., the number of electric trucks out of all the trucks). It was assumed that trucks accounted for 20 percent of all of the traffic, a situation that can be found on arterial freight corridors, especially near freight hubs such as ports, railyards, and warehouses. Using these simulation settings, different combinations of traffic volume (representing the level of traffic congestion) and market penetration rate of the electric truck were simulated. It was assumed that all the electric trucks were equipped with the EAD application to help save energy and extend their driving range. For each combination, the corresponding baseline case where no electric truck was equipped with the EAD application was also simulated so that the research team could evaluate the energy and emission impacts of the EAD application on both the EAD-equipped vehicles and traffic as a whole. In total, 32 scenarios were simulated, which included 2 technology cases × 4 levels of traffic volume × 4 market penetration rates as follows:

- *Technology*—Baseline, ETEAD.
- *Traffic volume (vehicles/hour)*—300, 600, 900, and 1,200.
- *Market penetration rate (percent)*—0 percent, 10 percent, 20 percent, and 100 percent.

During the simulation runs, vehicles that were not actively engaged in EAD (i.e., non-EAD-equipped vehicles and EAD-equipped vehicles outside of the range of communication with connected traffic signals) were controlled by the default vehicle controller in Vissim, which used the Wiedemann car-following model for longitudinal vehicle control. The speed profiles of all the vehicles in the simulation were recorded and used for energy and emissions estimation. The electric truck energy consumption model described in Section 2.2.3 was used to estimate the electric energy consumption for the electric trucks. The Motor Vehicle Emission Simulator (MOVES) model [39] developed by the U.S. Environmental Protection Agency was used to estimate the carbon dioxide ($CO_2$), carbon monoxide (CO), hydrocarbon (HC), nitrogen oxide ($NO_x$), and fine particulate matter ($PM_{2.5}$) emissions produced by the ICE vehicles (i.e., all cars and diesel trucks).

**Table 6. Settings in the Traffic Microsimulation**

| Parameter | Value |
|---|---|
| Speed Limit (m/s) | 20 |
| Look Ahead Distance (for EAD-Equipped Vehicles) (m) | 750 |
| Look Ahead Distance (for Unequipped Vehicles) (m) | 250 |
| Maximum Acceleration and Deceleration (for EAD-Equipped Vehicles) (m/s$^2$) | ±1 |
| Extra Time for ETEAD Algorithm (s) | 30 |
| Extra Distance for ETEAD Algorithm (m) | 400 |
| Duration of Simulation (min) | 40 |
| Number of Cars | $0.8V\times\frac{2}{3}$ |
| Number of Trucks | $0.2V\times\frac{2}{3}$ |
| Number of Electric Trucks | $0.2pV\times\frac{2}{3}$ |
| Number of Diesel Trucks | $0.2(1-p)V\times\frac{2}{3}$ |

Due to the stochastic nature of the traffic microsimulation, 30 runs were made with different seed numbers for each of the 32 scenarios. For each run, the total travel time, energy, and emissions for all vehicles were calculated, and the average values of the 30 runs in each scenario are summarized in Table 7. For the scenarios with 0 percent market penetration of the electric truck, the electric energy consumption was zero. Also, since it was assumed that all and only the electric trucks were equipped with the EAD application, at a certain level of traffic volume, the results for the baseline case with 0 percent market penetration of the electric truck and the ETEAD case with 0 percent market penetration of the electric truck were essentially the same.

Based on the results in Table 7, Table 8 shows the percentage differences in travel time, energy, and emissions for all vehicles combined between the baseline case and the ETEAD case under the same traffic volume and market penetration rate of the electric truck. The increases are colored red, while the decreases are colored green. The scenarios with 0 percent market penetration of the electric truck are not shown since the baseline and ETEAD cases were the same for those scenarios.

According to the last column in Table 8, the electric energy savings of ETEAD can be as much as 8 percent for the scenario with a traffic volume of 300 vehicles per hour (veh/h) and 10 percent market penetration of EAD-equipped electric trucks. However, the electric energy savings of ETEAD decreased as traffic volume increased. The reason for this trend was that as the traffic became more congested, it was more likely that other vehicles would be within the safety distance of the EAD-equipped electric trucks. In those situations, the EAD application was deactivated, resulting in fewer opportunities for the electric trucks to engage in energy-efficient driving.

Table 8 also shows that ETEAD resulted in slight increases in emissions from traffic as a whole for $CO_2$, CO, HC, $NO_x$, and $PM_{2.5}$ by up to 1 percent, 1 percent, 2 percent, 2 percent, and 1 percent, respectively, for the scenario with a traffic volume of 1,200 veh/h at 100 percent market penetration of EAD-equipped electric trucks. For any market penetration rate of EAD-equipped electric trucks, the increases in emissions were larger for a higher level of traffic volume. Moreover, for any level of traffic volume, the increases in emissions were larger for a higher market penetration rate of EAD-equipped electric trucks. These changes were partly caused by the non-cooperative nature of the current ETEAD algorithm (i.e., the algorithm optimized the speed profiles of the individual electric trucks without considering how their driving behaviors may impact the surrounding vehicles in the traffic stream). For instance, the ETEAD algorithm may recommend that an electric truck slow down far ahead of a red light, which can create a gap in front of the truck. This in turn may encourage the following vehicle or a nearby vehicle to accelerate and cut in, resulting in unnecessary acceleration, and thus increased emissions.

**Table 7. Total Travel Time, Energy, and Emissions for All Vehicles Combined**

| Traffic Volume (veh/h) | ETEAD /Baseline (B) | Penetration Rate % | Time (s) | MOVES_ HC (kg) | MOVES_ CO (kg) | MOVES_ NOx (kg) | MOVES_ CO2 (kg) | MOVES_ PM2.5 (kg) | Electric Energy (kJ) |
|---|---|---|---|---|---|---|---|---|---|
| 300 | B | 0 | 15401 | 0.14 | 8.04 | 4.36 | 2453 | 0.011 | 0 |
| | | 10 | 15417 | 0.13 | 8.01 | 3.97 | 2340 | 0.011 | 30643 |
| | | 20 | 15432 | 0.12 | 7.98 | 3.58 | 2231 | 0.010 | 60671 |
| | | 100 | 15423 | 0.06 | 7.73 | 0.28 | 1274 | 0.006 | 300051 |
| | ETEAD | 0 | 15401 | 0.14 | 8.04 | 4.36 | 2453 | 0.011 | 0 |
| | | 10 | 15414 | 0.13 | 8.01 | 3.97 | 2340 | 0.011 | 28250 |
| | | 20 | 15432 | 0.12 | 7.98 | 3.59 | 2233 | 0.010 | 57024 |
| | | 100 | 15410 | 0.06 | 7.75 | 0.28 | 1277 | 0.006 | 280759 |
| 600 | B | 0 | 31753 | 0.28 | 16.26 | 8.87 | 4991 | 0.024 | 0 |
| | | 10 | 31757 | 0.27 | 16.20 | 8.06 | 4758 | 0.022 | 60704 |
| | | 20 | 31747 | 0.25 | 16.13 | 7.21 | 4512 | 0.021 | 121086 |
| | | 100 | 31754 | 0.13 | 15.61 | 0.57 | 2588 | 0.012 | 605799 |
| | ETEAD | 0 | 31753 | 0.28 | 16.26 | 8.87 | 4991 | 0.024 | 0 |
| | | 10 | 31758 | 0.27 | 16.21 | 8.06 | 4759 | 0.022 | 57787 |
| | | 20 | 31752 | 0.25 | 16.16 | 7.22 | 4518 | 0.021 | 115579 |
| | | 100 | 31751 | 0.13 | 15.72 | 0.57 | 2601 | 0.012 | 579435 |
| 900 | B | 0 | 48678 | 0.43 | 24.59 | 13.46 | 7584 | 0.036 | 0 |
| | | 10 | 48653 | 0.41 | 24.48 | 12.20 | 7213 | 0.034 | 91206 |
| | | 20 | 48677 | 0.38 | 24.39 | 10.96 | 6860 | 0.032 | 182672 |
| | | 100 | 48677 | 0.20 | 23.59 | 0.86 | 3925 | 0.018 | 910162 |
| | ETEAD | 0 | 48678 | 0.43 | 24.59 | 13.46 | 7584 | 0.036 | 0 |
| | | 10 | 48662 | 0.41 | 24.51 | 12.20 | 7220 | 0.034 | 88321 |
| | | 20 | 48725 | 0.39 | 24.46 | 10.99 | 6881 | 0.032 | 176218 |
| | | 100 | 48769 | 0.20 | 23.84 | 0.87 | 3957 | 0.018 | 888612 |
| 1200 | B | 0 | 66725 | 0.59 | 33.18 | 18.29 | 10309 | 0.049 | 0 |
| | | 10 | 66697 | 0.56 | 33.03 | 16.57 | 9809 | 0.047 | 122460 |
| | | 20 | 66629 | 0.52 | 32.87 | 14.82 | 9288 | 0.044 | 242897 |
| | | 100 | 66627 | 0.27 | 31.78 | 1.16 | 5314 | 0.024 | 1222713 |
| | ETEAD | 0 | 66725 | 0.59 | 33.18 | 18.29 | 10309 | 0.049 | 0 |
| | | 10 | 66719 | 0.56 | 33.06 | 16.59 | 9823 | 0.047 | 119288 |
| | | 20 | 66787 | 0.53 | 32.99 | 14.87 | 9328 | 0.044 | 241344 |
| | | 100 | 67092 | 0.27 | 32.24 | 1.18 | 5381 | 0.024 | 1224930 |

**Table 8. Differences in Total Travel Time, Energy, and Emissions between ETEAD and Baseline Scenarios**

| Traffic Volume (veh/h) | Penetration Rate % | Time (s) | MOVES_ HC (kg) | MOVES_ CO (kg) | MOVES_ NOx (kg) | MOVES_ CO2 (kg) | MOVES_ PM2.5 (kg) | Electric Energy (kJ) |
|---|---|---|---|---|---|---|---|---|
| 300 | 10 | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | -7.8% |
| | 20 | 0.0% | 0.1% | 0.1% | 0.1% | 0.1% | 0.0% | -6.0% |
| | 100 | -0.1% | 0.5% | 0.3% | 0.4% | 0.2% | 0.0% | -6.4% |
| 600 | 10 | 0.0% | 0.1% | 0.1% | 0.0% | 0.0% | 0.0% | -4.8% |
| | 20 | 0.0% | 0.2% | 0.2% | 0.1% | 0.1% | 0.0% | -4.5% |
| | 100 | 0.0% | 1.1% | 0.7% | 0.8% | 0.5% | 0.1% | -4.4% |
| 900 | 10 | 0.0% | 0.1% | 0.1% | 0.0% | 0.1% | 0.0% | -3.2% |
| | 20 | 0.1% | 0.4% | 0.3% | 0.2% | 0.3% | 0.1% | -3.5% |
| | 100 | 0.2% | 1.7% | 1.1% | 1.2% | 0.8% | 0.2% | -2.4% |
| 1200 | 10 | 0.0% | 0.2% | 0.1% | 0.1% | 0.1% | 0.0% | -2.6% |
| | 20 | 0.2% | 0.5% | 0.4% | 0.3% | 0.4% | 0.2% | -0.6% |
| | 100 | 0.7% | 2.3% | 1.4% | 1.6% | 1.3% | 0.8% | 0.2% |

While Table 8 shows that ETEAD resulted in slight increases in emissions from traffic as a whole, those emission increases were very small compared to the decreases in emissions brought about by the adoption of electric trucks. To illustrate this point, Table 9 shows the percent differences in total travel time and emissions for traffic as a whole between scenarios without and with electric trucks (all of which were equipped with the EAD application). In other words, the baseline scenario for any level of traffic volume was one in which there was no electric truck (i.e., 0 percent market penetration rate). As can be seen in the table, for any level of traffic volume, the decreases in emissions were larger for a higher market penetration rate of EAD-equipped electric trucks. For the scenario with a traffic volume of 1,200 veh/h at 100 percent market penetration of EAD-equipped electric trucks, the decreases in emissions were 48 percent, 3 percent, 54 percent, 94 percent, and 51 percent for $CO_2$, CO, HC, $NO_x$, and $PM_{2.5}$, respectively. These results emphasize the contribution of emissions from diesel trucks to the overall traffic emissions, especially in areas with a high fraction of truck traffic. The diesel trucks in the simulation, which accounted for 20 percent of the total traffic volume, contributed approximately half of $CO_2$, HC, and $PM_{2.5}$ emissions and more than 90 percent of $NO_x$ emissions from the overall traffic.

**Table 9. Differences in Total Travel Time and Emissions between Scenarios Without and With EAD-Equipped Electric Trucks**

| Traffic Volume (veh/h) | Penetration Rate % | Time (s) | MOVES_ HC (kg) | MOVES_ CO (kg) | MOVES_ NOx (kg) | MOVES_ CO2 (kg) | MOVES_ PM2.5 (kg) |
|---|---|---|---|---|---|---|---|
| **300** | **0** | baseline | baseline | baseline | baseline | baseline | baseline |
| | **10** | 0.1% | -5.3% | -0.3% | -9.1% | -4.6% | -4.9% |
| | **20** | 0.2% | -10.4% | -0.7% | -17.8% | -9.0% | -9.7% |
| | **100** | 0.1% | -53.3% | -3.6% | -93.5% | -47.9% | -50.6% |
| **600** | **0** | baseline | baseline | baseline | baseline | baseline | baseline |
| | **10** | 0.0% | -5.4% | -0.3% | -9.2% | -4.6% | -5.1% |
| | **20** | 0.0% | -10.7% | -0.6% | -18.6% | -9.5% | -10.2% |
| | **100** | 0.0% | -53.5% | -3.3% | -93.5% | -47.9% | -50.7% |
| **900** | **0** | baseline | baseline | baseline | baseline | baseline | baseline |
| | **10** | 0.0% | -5.4% | -0.3% | -9.4% | -4.8% | -5.2% |
| | **20** | 0.1% | -10.6% | -0.5% | -18.4% | -9.3% | -10.1% |
| | **100** | 0.2% | -53.6% | -3.1% | -93.5% | -47.8% | -50.7% |
| **1200** | **0** | baseline | baseline | baseline | baseline | baseline | baseline |
| | **10** | 0.0% | -5.4% | -0.4% | -9.3% | -4.7% | -5.1% |
| | **20** | 0.1% | -10.7% | -0.6% | -18.7% | -9.5% | -10.1% |
| | **100** | 0.5% | -53.7% | -2.8% | -93.6% | -47.8% | -50.6% |

Except for CO, which is produced mostly by gasoline cars, the levels of emission reductions in Table 9 were much larger than the levels of emission increases seen in Table 8. This finding implies that there are significant emission reduction benefits to be gained from the turnover of diesel trucks to electric trucks. While the EAD application may unintentionally lead to emission increases in unequipped vehicles, if the energy savings benefit that the application provides to equipped vehicles can help increase the market adoption of electric trucks, then the net impact on traffic emissions will be highly positive.

## Conclusions and Recommendations

In this project, the research team conducted a feasibility analysis of operating an electric truck fleet in drayage application. Real-world, second-by-second activity data collected from 20 trucks of a drayage operator in Southern California were used to estimate the corresponding electric energy consumption and the SOC of the battery using a microscopic electric energy consumption model. An algorithm for generating tours of drayage activity from the collected data was developed and implemented. Multiple scenarios with different battery charging and truck scheduling assumptions were analyzed. The results showed that 11 percent of the tours had a tour distance that was longer than the range of the modeled electric truck. The presence of these infeasible tours means that it is not operationally feasible for this drayage operator to fully transition to a 100 percent electric truck fleet. The operator still needs to maintain a few conventional diesel trucks to serve those long tours on an occasional basis. Managing this duality in technology may translate to an increase in operational overheads (e.g., refueling infrastructure, maintenance service) for the drayage operator.

Considering the sequence of tours and their start times in the itinerary, only 62 percent of the feasible tours (or 55 percent of all the tours) could be served by electric trucks. The number of fulfilled feasible tours would increase to 85 percent (or 75 percent of all the tours) if allowing for opportunity charging at the home base during the time gap between two consecutive tours. Such opportunity charging events may coincide with the peak load period for the grid. Thus, the fleet will need to manage these events carefully. Moreover, charging multiple electric trucks at the same time can put an excessive load on the electrical grid, which could require the power transmission lines to be upgraded. The fleet may consider using an energy storage system to help manage the load. In addition, the operational feasibility of electric truck fleets can be improved through enhanced truck scheduling and routing, which considers the driving range limitations and the charging time requirements of electric trucks. Advanced telematics and real-time monitoring of electric trucks and charging stations would allow for the implementation of such enhanced scheduling and routing technology in the future.

In this project, the research team also evaluated the potential for the EAD application to provide energy savings, and consequently increase the driving range, for electric trucks. The ETEAD algorithm was developed based on the microscopic electric energy consumption model and advanced optimization methods and then applied in a traffic microsimulation environment to evaluate the energy and emission impacts on both the EAD-equipped electric trucks and traffic as a whole. A sensitivity analysis of those impacts with respect to traffic volumes and technology penetration rates was also performed. It was found that the machine-learning-based ETEAD algorithm can design an energy-efficient trajectory for electric trucks in real time. The results from the traffic microsimulation showed that the EAD application could achieve up to 8 percent energy savings for the electric trucks in light traffic. However, the application became less effective as traffic congestion increased due to having fewer opportunities for the electric trucks to engage in energy-efficient driving.

The results from the traffic microsimulation also showed that the EAD application caused up to 2 percent increases in emissions from the overall traffic. This was partly due to the non-cooperative nature of the current ETEAD algorithm where the application optimized the speed profiles of the individual electric trucks without considering how their driving behaviors may impact the surrounding vehicles in traffic. However, these emission increases were very small compared to the 48 percent, 54 percent, 94 percent, and 51 percent reductions in $CO_2$, HC, $NO_x$, and $PM_{2.5}$ emissions, respectively, that were brought about by the turnover of diesel trucks to electric trucks. If the energy savings (and driving range extension) benefit that the EAD application provides to electric trucks can help increase the market adoption of these trucks, then the net impact on the overall traffic emissions will be highly positive. Therefore, the EAD application can be used as one of the tools for mitigating the range limitation of the current electric trucks in the market to help accelerate their adoption.

Finally, with proper calibration, the EAD application can also be used by other types of vehicles. In fact, the concept was first developed and tested in passenger cars. Thus, if all types of vehicles in the traffic follow efficient driving speed profiles determined by the EAD application, then its energy and emissions impacts are likely to be more positive. Nevertheless, more research is needed to calibrate or customize EAD algorithms for the different types of vehicles, and to ensure that these new algorithms take the driving behaviors of other vehicles in the traffic stream into account in a coordinated fashion.

# Outputs, Outcomes, and Impacts

## Research Outputs, Outcomes, and Impacts

This research has resulted in the following publications and presentations to date. Additional publications and presentations are expected:

- Tanvir, S., Un-Noor, F., Boriboonsomsin, K., and Gao, Z. 2021. “Feasibility of Operating Heavy-Duty Battery Electric Truck Fleet in Drayage Application.” *Transportation Research Record*, *2675*(1), 258–268, https://doi.org/10.1177/0361198120957325.
- Tanvir, S., Un-Noor, F., Boriboonsomsin, K., and Gao, Z. 2020. “Feasibility of Operating Heavy-Duty Battery Electric Truck Fleet in Drayage Application.” Presented at the 99th Annual Meeting of the Transportation Research Board, Washington, D.C., January 12–16, 2020.
- Wang, C., Hao, P., Boriboonsomsin, K., Gao, Z., and Barth, M. 2019. “Developing a Mesoscopic Energy Consumption Model for Battery Electric Trucks Based on Real-World Driving Data.” First Transportation, Air Quality, and Health Symposium, Austin, TX, February 18–20, 2020.

This research also offers new insights on the operational challenges that will be faced by drayage truck fleets in transitioning to a 100 percent electric fleet. These insights point to the need for electric trucks with a longer driving range and new technologies that support the operation of electric trucks at the fleet level, such as smart charging, SOC monitoring, and electric truck scheduling and routing.

## Technology Transfer Outputs, Outcomes, and Impacts

In addition to the research outputs previously discussed, the research team has presented the results from this research to several entities that take part in the concerted effort to transition the heavy-duty vehicle sector in California toward zero-emission technologies. These entities include the California Air Resources Board, the Port of Los Angeles, the Port of Long Beach, and the Transportation Electrification Partnership.

## Education and Workforce Development Outputs, Outcomes, and Impacts

Three PhD students and one postdoctoral scholar were involved in this research:

- Dr. Shams Tanvir worked on the feasibility analysis of operating electric drayage truck fleet during his postdoctoral training at the College of Engineering—Center for Environmental Research and Technology, University of California at Riverside. After completing his training, he accepted an assistant professor position in the Department of Civil and Environmental Engineering at the California Polytechnic State University, San Luis Obispo.
- Mr. Abdullah Fuad Un-Noor also worked on the feasibility analysis of operating an electric drayage truck fleet. He was a third-year PhD student in the Department of Electrical and Computer Engineering at the University of California at Riverside.
- Mr. Chao Wang worked on the microscopic electric energy consumption model while he was a PhD student in the Department of Electrical and Computer Engineering at the University of California at Riverside. He joined Google Inc. after his graduation.
- Mr. Zhensong Wei worked on the evaluation of the EAD application for electric trucks. He was a third-year PhD student in the Department of Electrical and Computer Engineering at the University of California at Riverside.

## References


1. U.S. Energy Information Administration. 2018. Oil and Petroleum Products Explained: Use of Oil. https://www.eia.gov/energyexplained/index.php?page=oil_use. Accessed July 28, 2019.

2. U.S. Energy Information Administration. 2018. Energy and the Environment Explained: Where Greenhouse Gases Come From. https://www.eia.gov/energyexplained/index.php?page=environment_where_ghg_come_from. Accessed July 28, 2019.

3. Chandler, S., Espino, J., and O'Dea, J. 2017. *Delivering Opportunity: How Electric Buses and Trucks Can Create Jobs and Improve Public Health in California*. A Report by the Union of Concerned Scientists and Greenlining Institute.

4. Houston, D., Krudysz, M., and Winer, A. 2008. Diesel Truck Traffic in Low-Income and Minority Communities Adjacent to Ports: Environmental Justice Implications of Near-Roadway Land Use Conflicts. *Transportation Research Record*, 2067(1), 38-46.

5. San Pedro Bay Ports. 2017. Clean Air Action Plan Update, November 2017. https://cleanairactionplan.org/2017-clean-air-action-plan-update/. Accessed July 28, 2019.

6. California Climate Investment. 2018. California Collaborative Advanced Technology Drayage Truck Demonstration Project. http://www.caclimateinvestments.ca.gov/2018-profiles/2018/3/15/california-collaborative-advanced-technology-drayage-truck-demonstration-project. Accessed August 1, 2019.

7. Pindilli, E. 2012. *Applications for the Environment: Real-Time Information Synthesis (AERIS)—Benefit-Cost Analysis*. Federal Highway Administration, U.S. Department of Transportation, Washington, D.C.

8. Scora, G., Boriboonsomsin, K., Durbin, T., Johnson, K., Yoon, S., Collins, J., and Dai, Z. 2019. Variability in Real-World Activity Patterns of Heavy-Duty Vehicles by Vocation. *Transportation Research Record*, 2673(9), 51-61.

9. Ambrose, H., and Jaller, M. 2016. Electrification of Drayage Trucks: On Track for a Sustainable Freight Path. *Proceedings of the Transportation Research Board 95th Annual Meeting*, Washington, DC, January 10-14.

10. Gao, Z., Lin, Z., Davis, S. C., and Birky, A. K. 2018. Quantitative Evaluation of MD/HD Vehicle Electrification Using Statistical Data. *Transportation Research Record*, 2672(24), 109-121.

11. Erera, A. L., and Smilowitz, K. R. 2008. Intermodal Drayage Routing and Scheduling. In *Intelligent Freight Transportation*, edited by P. A. Ioannou, CRC Press, 344 pp.

12. Zhang, R., Yun, W. Y., and Kopfer, H. 2010. Heuristic-Based Truck Scheduling for Inland Container Transportation. *OR Spectrum*, 32(3), 787-808.

13. Namboothiri, R., and Erera, A. L. 2008. Planning Local Container Drayage Operations Given a Port Access Appointment System. *Transportation Research Part E: Logistics and Transportation Review*, 44(2), 185-202.

14. Schulte, F., González, R. G., and Voss, S. 2015, September. Reducing Port-Related Truck Emissions: Coordinated Truck Appointments to Reduce Empty Truck Trips. In *International Conference on Computational Logistics* (pp. 495–509). Springer, Cham.

15. Barth, M., Younglove, T., and Scora, G. 2005. *Development of a Heavy-Duty Diesel Modal Emissions and Fuel Consumption Model*. California PATH Research Report UCB-ITS-PRR-2005-1.

16. Demir, E., Bektaş, T., and Laporte, G. 2011. A Comparative Analysis of Several Vehicle Emission Models for Road Freight Transportation. *Transportation Research Part D: Transport and Environment*, 16(5), 347-357.

17. Butler, K. L., Ehsani, M., and Kamath, P. 1999. A Matlab-Based Modeling and Simulation Package for Electric and Hybrid Electric Vehicle Design. *IEEE Transactions on Vehicular Technology*, 48(6), 1770-1778.

18. Chan, C. C., Bouscayrol, A., and Chen, K. 2010. Electric, Hybrid, and Fuel-Cell Vehicles: Architectures and Modeling. *IEEE Transactions on Vehicular Technology*, 59(2), 589-598.

19. Richardson, D. B. 2013. Electric Vehicles and the Electric Grid: A Review of Modeling Approaches, Impacts, and Renewable Energy Integration. *Renewable and Sustainable Energy Reviews*, 19, 247-254.

20. Gao, Z., Lin, Z., and Franzese, O. 2017. Energy Consumption and Cost Savings of Truck Electrification for Heavy-Duty Vehicle Applications. *Transportation Research Record: Journal of the Transportation Research Board*, 2628, 99-109.

21. Papson, A., and Ippoliti, M. 2013. Key Performance Parameters for Drayage Trucks Operating at the Ports of Los Angeles and Long Beach. https://calstart.org/wp-content/uploads/2018/10/I-710-Project_Key-Performance-Parameters-for-Drayage-Trucks.pdf. Accessed June 12, 2020.

22. Srdic, S., and Lukic, S. 2019. Toward Extreme Fast Charging: Challenges and Opportunities in Directly Connecting to Medium-Voltage Line. *IEEE Electrification Magazine*, 7(1), 22-31.

23. BYD. 2019. Brochure for Long-Range 100% Battery Electric Trucks Class 8—105,000 lbs GCWR. https://en.byd.com/wp-content/uploads/2018/07/8tt_redesign6-23-18.pdf. Accessed August 1, 2019.

24. Wu, G., Xia, H., Boriboonsomsin, K., and Barth, M. 2014. Supplementary Benefits from Partial Vehicle Automation in an Eco-approach/Departure Application at Signalized Intersections. *Transportation Research Record*, 2424, 66-75.

25. Hao, P., Wu, G., Boriboonsomsin, K., and Barth, M. J. 2018, March. Eco-approach and Departure (EAD) Application for Actuated Signals in Real-World Traffic. *IEEE Transactions on Intelligent Transportation Systems*, 20(1), 30-40.

26. Ye, F., Hao, P., Qi, X., Wu, G., Boriboonsomsin, K., and Barth, M. J. 2018, September. Prediction-Based Eco-approach and Departure at Signalized Intersections with Speed Forecasting on Preceding Vehicles. *IEEE Transactions on Intelligent Transportation Systems*, 20(4), 1378-1389.

27. Asadi, B., and Vahidi, A. 2009, January. Predictive Use of Traffic Signal State for Fuel Saving. *IFAC Proceedings Volumes*, 42(15), 484-489.

28. Lu, S., Xue, F., Ting, T. O., and Du, Y. 2016. Speed Trajectory Optimisation for Electric Vehicles in Eco-approach and Departure Using Linear Programming. *Proceedings of the 2016 IET International Conference on Intelligent and Connected Vehicles*, Chongqing, China, September 22-23.

29. Qi, X., Barth, M. J., Wu, G., Boriboonsomsin, K., and Wang, P. 2018. Energy Impact of Connected Eco-driving on Electric Vehicles. In *Road Vehicle Automation 4* (pp. 97–111). Springer, Cham.

30. European Commission. 2021, January. eCoMove—Cooperative Mobility Systems and Services for Energy Efficiency. http://www.ecomove-project.eu/. Accessed August 1, 2019.

31. Lesage, J. 2021, February. Volvo Finds Eco-Driving Improves Fuel Economy 10–15% in Trucks. https://www.autoblog.com/2013/12/16/volvo-finds-eco-driving-improves-fuel-economy-10-15-percent-trucks/. Accessed August 1, 2019.

32. Hao, P., Boriboonsomsin, K., Wang, C., Wu, G., and Barth, M. 2021. Connected Eco-approach and Departure (EAD) System for Diesel Trucks. *SAE International Journal of Commercial Vehicles*, *2*(14).

33. Rodriguez, M. A., and Fathy, H. K. 2018. Speed Trajectory Optimization for a Heavy-Duty Truck Traversing Multiple Signalized Intersections: A Dynamic Programming Study. 2018 IEEE Conference on Control Technology and Applications.

34. Wang, Z., Hsu, Y.-P., Vu, A., Caballero, F., Hao, P., Wu, G., Boriboonsomsin, K., Barth, M., Kailas, A., Amar, P., Garmon, E., and Tangula, S. 2019. Early Findings from Field Trials of Heavy-Duty Truck Connected Eco-Driving System. 2019. *Proceedings of the 2019 IEEE Intelligent Transportation Systems Conference*, Auckland, New Zealand, October 27-30.

35. Wood, S. N. 2003. Thin Plate Regression Splines. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, *65*(1), 95–114.

36. Hao, P., Boriboonsomsin, K., Wang, C., Wu, G., and Barth, M. 2018. Connected Eco-approach and Departure (EAD) System for Diesel Trucks. Proceedings of the 97th Annual Meeting of Transportation Research Board, Washington, D.C.

37. Dijkstra, E. W. 1959. A Note on Two Problems in Connexion with Graphs. *Numerische Mathematik*, *1*, 269–271.

38. PTV Vissim Group. Products. https://www.ptvgroup.com/en/solutions/products/ptv-vissim. Accessed August 1, 2019.

39. U.S. Environmental Protection Agency. Motor Vehicle Emission Simulator. https://www.epa.gov/moves/latest-version-motor-vehicle-emission-simulator-moves. Accessed August 1, 2020.