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Real-World Activity Patterns of Heavy-Duty Battery Electric Trucks from Regional Distribution Fleets in Southern California

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***Abstract*—Heavy-duty trucks are a major source of transportation-related greenhouse gas and criteria pollutant emissions. One approach to reducing the climate and health impacts of these trucks is to transition them to zero-emission technologies such as battery electric trucks (BETs). To date, BETs have been deployed mostly in drayage application. As the performance of BETs has improved in recent years, there is increasing interest in using BETs also in regional haul application. This paper examines real-world activity patterns of 15 heavy-duty BETs in regional haul application using data collected from early deployments of these trucks across eight different fleets in Southern California. The results show that the BETs are typically used on routes (or tours) that are much shorter than their driving ranges. They often make one or two tours per day, and are usually charged at the end of each tour. Due to the variation in the time of day that the BETs are operated, they are charged at different times of day, spreading the charging load throughout the day. In addition, the results indicate that about half of the BET's operations on average occur in or around disadvantaged communities, providing emission reduction benefits to these communities.**

Keywords—Battery electric truck, vehicle activity, energy consumption, charging.

I. Introduction

Medium-duty and heavy-duty trucks are used primarily in freight transportation, which is an important economic driver in the U.S. In 2021, trucking contributed $389.3 billion or 1.7% of the total gross domestic product to the U.S. economy [1]. However, medium-duty and heavy-duty trucks, most of which are powered by diesel engines, are also a major source of greenhouse gas (GHG) emissions, accounting for 23% of GHG emissions from the U.S. transportation sector in 2021 [2]. In the South Coast Air Basin of Southern California, diesel emissions from these trucks accounted for about 23% of oxide of nitrogen and 4% of fine particulate matter emissions in 2018, contributing to the poor air quality in the region [3]. In addition, these diesel emissions are concentrated near freight hubs such as ports, railyards, and warehouses, causing disproportionate burdens on nearby environmental justice or disadvantaged communities.

To address the emission impacts of trucking, efforts have been made to accelerate the development and deployment of zero-emission trucks. For example, California has set aggressive targets for the sales of zero-emission trucks in the state, and has required all medium-duty and heavy-duty trucks operating in the state to be zero-emission by 2045 [4,5]. Based on the current state of zero-emission truck technologies, most zero-emission trucks on the roads today are battery electric trucks (BETs). To date, these trucks have been deployed primarily in drayage application because drayage trucks tend to travel a limited number of miles per day, return to their homebases every night (so that they can be charged at the homebases), and spend a large amount of time creeping and idling (which consume relatively much less energy than driving). Many studies have been conducted on the operation of BETs in drayage application with different focuses, for example, feasibility analysis [6,7], charging infrastructure planning [8,9], en-route charging opportunity assessment [10,11], and charging optimization [12,13].

As the performance of BETs has improved in recent years, it has been argued that BETs could also be deployed in regional haul and even long haul applications [14]. However, studies of BET deployment and operation in regional haul application are limited, and most of them rely on the modeling and analysis of data collected from conventional diesel or natural gas trucks [15,16]. This paper addresses this research gap by examining real-world activity patterns of BETs in regional haul application using data collected from early deployments of these trucks in Southern California. Understanding these real-world activity patterns is important for identifying challenges and opportunities associated with electrifying heavy-duty regional haul trucks. Such information will be useful for developing various intelligent transportation system applications, such as vehicle dispatching [17], eco-routing [18], range estimation [19], and charging reservation [20], to specifically support BET operations.

This paper presents real-world activity patterns of 15 heavy-duty BETs that are part of early deployments across eight different regional distribution fleets in Southern California. Section II describes the vehicle and fleet characteristics as well as the data collection, processing, and analysis procedures. Then, Section III presents the trip characteristics and charging patterns of these BETs. It also examines the environmental justice implications of deploying the BETs. Finally, Section IV provides conclusions and discusses future work.

II. METHODOLOGY

A. Vehicle and Fleet Characteristics

This study examined activity and energy consumption of 15 battery electric trucks (BETs) deployed across eight fleets in Southern California. All 15 BETs are of 2021 model year with 264 kWh nominal battery capacity. Five of them are Class 7 (having gross vehicle weight rating or GVWR of 26,001–33,000 lbs) with an estimated range of 150 miles while the other 10 trucks are Class 8 (having GVWR of 33,001–80,000 lbs) with an estimated range of 120 miles. All the truck fleets run a variety of regional distribution operations within Southern California, such as less-than-truckload, food distribution, beverage distribution, among others.

B. Data Collection and Processing

Data were collected from the BETs using a commercial telematics service between April 2021 and September 2023. However, the start and end dates of the data collection period for each BET varied. The raw data collected from each BET include timestamp, vehicle location (latitude and longitude), vehicle speed, key on/off status, odometer, energy out (total energy flowing out of the battery while driving), energy in (total energy flowing into the battery while driving), and battery state of charge (SOC). All data items have 3-minute interval except for energy out and energy in, which have 1-day interval. By subtracting energy in from energy out, the net energy consumption during each interval can be calculated.

Since the data fields were logged at different frequencies, they were first synchronized and some of them were interpolated to fill the data gaps. Specifically, the timestamp of vehicle location was used as the basis for vehicle activity. Then, vehicle speed and odometer were interpolated based on time. Subsequently, energy out and energy in were interpolated based on odometer, after which net energy consumption was calculated. Finally, SOC was interpolated based on net energy consumption.

Additionally, the vehicle location data were analyzed to determine whether the BET was traveling inside or outside disadvantaged communities (DACs). DACs are based on census tracts and represented as polygons on maps. To perform this spatial analysis, first a buffer of 40 m was created along the boundary of each DAC to account for the potential inaccuracy of vehicle location data obtained via GPS. Then, each vehicle location was placed on the map of DACs with the buffer according to its latitude and longitude. A BET would be deemed to be traveling inside DAC if its location was matched to DAC polygon(s) only. It would be deemed to be traveling outside DAC if its location was matched to non-DAC polygon(s) only. Lastly, the BET would be considered to be traveling around DAC (i.e., along the border between DAC and non-DAC) if its location was matched to both DAC and non-DAC polygons.

C. Data Aggregation and Analysis

Using the processed data, four types of activity event below were identified and stored in an *Activity Event* table chronologically. Moving, Idling, and Stopped are mutually exclusive. However, Charging is a subet of Stopped.

- Moving – key on and vehicle speed ≥ 3 kph
- Idling – key on and vehicle speed < 3 kph
- Stopped – key off
- Charging – key off and ending SOC > starting SOC

Then, the *Activity Event* table was used to determine trips accordingly to the trip definition in Fig. 1, which were then stored in a *Trip* table chronologically. After that, the start and end locations of each trip were indexed as either homebase or non-homebase. Finally, the *Trip* table was used to identify tours. A tour consists of a series of consecutive trips that starts with an outbound trip (starting from homebase and ending outside), optionally one or more trips with start and end locations outside of homebase, and finally an inbound trip (starting from outside of homebase and ending inside). The identified tours were stored in a *Tour* table chronologically.

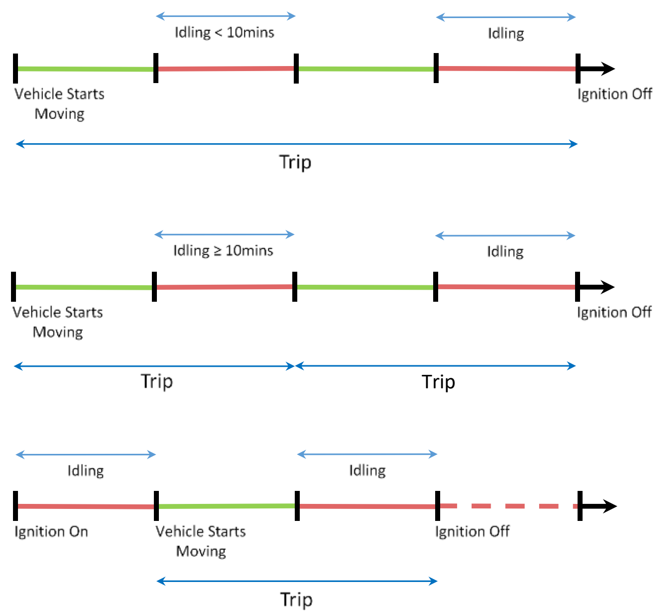

Figure 1. Illustration of trip definition.

For each of the *Activity Event*, *Trip*, and *Tour* tables, descriptive statistics of travel distance, travel time, and energy consumption were calculated. These descriptive statistics were also differentiated between inside, around, and outside DACs. Also, other metrics such as idle fraction and energy efficiency (kWh per mile) were derived.

III. RESULTS AND DISCUSSION

Table 1 provides summary statistics of the collected data. The rows are color-coded by fleet. They are also split into two groups. The first five rows (EV01 to EV05) are for Class 7 BETs and the remaining rows (EV06 to EV15) are for Class 8 BETs. For most of the BETs, data were collected for about two years. Cumulatively, the data represent almost 300,000 miles of driving and over 25,000 hours of operation.

The Class 7 and Class 8 BETs have a sample average energy efficiency of 1.5 kWh and 1.7 kWh per mile, respectively. Assuming a usable battery capacity to be 80% of the nominal battery capacity, or 0.8*264 = 211 kWh, then the average real-world range of the Class 7 BETs is 141 miles, which is slightly lower than the manufacturer-estimated range of 150 miles. On the other hand, the average real-world range

TABLE 1. SUMMARY STATISTICS OF COLLECTED DATA

Truck ID	Fleet ID	Days Total	Days Driven	Total Miles	Operating Hrs	Driven Hrs	Idle Fraction	Total Energy (kWh)	kWh per Mile
EV01	FL01	631	309	23,859	1,333	913	32%	39,427	1.7
EV02	FL02	763	372	29,620	1,357	1,065	22%	41,541	1.4
EV03	FL03	760	394	15,936	2,957	1,164	61%	27,045	1.7
EV04	FL03	757	326	13,349	3,257	1,060	67%	21,998	1.6
EV05	FL03	426	126	5,636	742	353	52%	6,626	1.2
EV06	FL04	734	194	13,246	996	482	52%	22,367	1.7
EV07	FL04	729	223	15,997	686	574	16%	27,980	1.7
EV08	FL05	763	378	24,380	1,573	1,082	31%	34,284	1.4
EV09	FL05	763	406	27,095	1,671	1,150	31%	39,609	1.5
EV10	FL06	734	401	25,844	3,553	1,573	56%	37,260	1.4
EV11	FL06	734	417	39,047	3,076	2,093	32%	67,917	1.7
EV12	FL06	371	59	4,316	377	208	45%	7,736	1.8
EV13	FL07	722	181	11,541	849	610	28%	21,514	1.9
EV14	FL07	751	178	8,953	505	361	29%	13,572	1.5
EV15	FL08	779	721	37,598	2,465	1,802	27%	77,249	2.1

Days Total: Total number of days between first and last data dates
Day Driven: Total number of days with at least 1 miles of distance traveled
Total Miles: Total number of miles traveled
Operating Hrs: Total number of hours when the vehicle was on
Driven Hrs: Total number of hours when the vehicle speed ≥ 3 kph
Idle Fraction: Fraction of operating hours when the vehicle was idled
Total Energy: Total energy consumption (kWh)
kWh per Mile: Average vehicle energy efficiency

of the Class 8 BETs is 124 miles, which is slightly higher than the manufacturer-estimated range of 120 miles.

The idle fraction of the BETs in this study ranges from 16% to 67%, with a sample average of 43%. This is in line with what was reported in [21] for conventional diesel trucks in California. Idling emissions from heavy-duty diesel trucks have long been a subject of air quality and public health concerns, especially in environmental justice communities near freight hubs where there usually is a high concentration of idling trucks. Since BETs have no tailpipe emissions, they can help abate some of these concerns. The following subsections explore the different aspects of the real-world operation of the BETs in this study.

A. *Trip and Tour Characteristics*

Table 2 provides statistics related to trips and tours. The average number of trips per tour ranged from two (i.e., making only one stop) to 14. The majority of the BETs made one or two tours per day with the average tour distances of 35-80 miles. Most of the BETs were charged about once after each tour, having an average charging per tour of 0.9-1.1. However, some BETs had an average charging per tour of 0.7, indicating that they occasionally completed two or more tours before needing to be charged. All the BETs were charged mostly at their homebases, with only a small fraction of their charging sessions occurring outside of their homebases. This is not surprising given the current lack of charging infrastructure for heavy-duty BETs. One exception was EV12, which had 23% of its charging sessions off-site. However, this was a special case where the BET was frequently charged at a dealership nearby its homebase.

TABLE 2. TRIP, TOUR, AND CHARGING STATISTICS

Truck ID	Fleet ID	Total Trips	Total Tours	Trips per Tour	Tours per Day	Miles per Tour	Charging Sessions	Charging per Tour	Charging off-site
EV01	FL01	1,656	618	3	2.0	39	457	0.7	1%
EV02	FL02	1,970	369	5	1.0	80	390	1.1	6%
EV03	FL03	3,741	409	9	1.0	39	389	1.0	2%
EV04	FL03	3,217	324	10	1.0	41	332	1.0	2%
EV05	FL03	935	126	7	1.0	45	125	1.0	5%
EV06	FL04	655	178	4	0.9	74	172	1.0	6%
EV07	FL04	752	217	3	1.0	74	204	0.9	4%
EV08	FL05	1,284	689	2	1.8	35	512	0.7	2%
EV09	FL05	1,362	735	2	1.8	37	529	0.7	4%
EV10	FL06	4,084	591	7	1.5	44	446	0.8	2%
EV11	FL06	3,832	798	5	1.9	49	717	0.9	3%
EV12	FL06	357	55	6	0.9	78	47	0.9	23%
EV13	FL07	779	191	4	1.1	60	213	1.1	4%
EV14	FL07	667	132	5	0.7	68	151	1.1	5%
EV15	FL08	8,893	655	14	0.9	57	734	1.1	7%

While the average tour distances made by the BETs were well below the manufacturer-estimated ranges of 150 miles and 120 miles for Class 7 and Class 8 BETs, respectively, some of the tours were longer than those ranges. Fig. 2 shows the longest tour made by each BET. It can be seen that the longest tour made by EV07 and EV12 exceeded the manufacturer-estimated range by a wide margin. These tours were possible due to off-site charging. This is illustrated in Fig. 3 for EV07. The BET started the tour with 98% SOC. It made two stops, after which the SOC dropped to about 26%, which would not be sufficient for it to return to the homebase. Thus, it made a trip to a charging station instead. When it arrived at the charging station, the SOC was only 11%. There, the BET was charged for about 1.5 hours, which increased its SOC from 11% to 96%. After that, the BET traveled back to its homebase, arriving at the homebase with an SOC of 58%. Out of the 156 miles of this tour, 52 miles or about one-third were deadhead miles for the BET to travel to and from the off-site charging station. These deadhead miles would not have been necessary if the BET had a longer range, or if there was a charging station at either Stop #1 or Stop #2 for the BET to be charged while there.

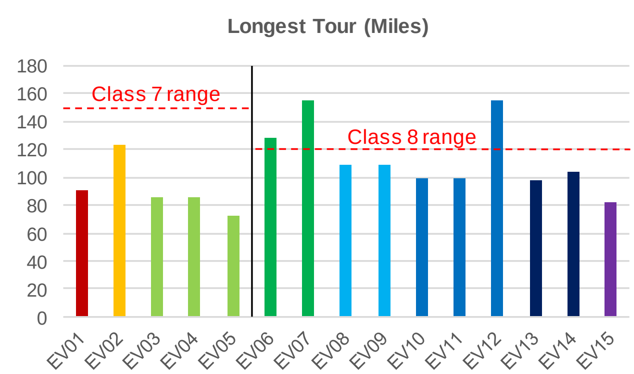

Figure 2. Longest tour traveled by each BET

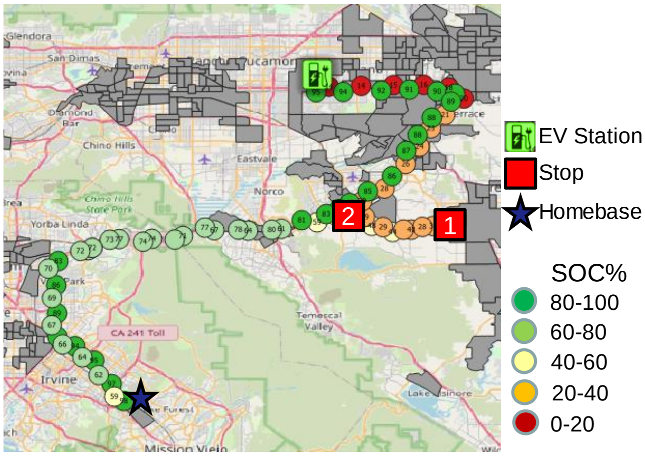

Figure 3. Longest tour of EV07 (156 miles)

B. *Charging Patterns*

In addition to understanding how often and where the BETs were charged, it is also important to examine when they were charged. Traditionally, with a fleet of diesel trucks, the fleet operator only has to worry about optimizing the routes and schedules of its trucks to serve its customers. However, with a BET fleet, the fleet operator will also have to optimize the charging of the BETs, taking into account the operation schedule of the BETs, time-of-use electricity rates, the BET-to-charging station ratio, and other factors.

Fig. 4 shows the frequency distribution of charging by time of day for each of the BETs. It is interesting to see that the charging patterns vary greatly where some BETs were charged predominantly at night while other BETs were charged mostly during the day. This finding is contrary to the belief that most heavy-duty trucks, once transitioned to BETs, would be charged at night, creating a large amount of charging load during those hours. However, as shown here in this study as well as in [22], heavy-duty trucks are quite diverse in their operations and many of them operate in the nighttime. In California, BETs that operate at night and are charged during the day can take advantage of solar energy, whose production peaks in the daytime. Therefore, a large deployment of these BETs can help reduce the amount of curtailed solar energy, which has been increasing in the last several years [23].

Truck ID	EV01	EV02	EV03	EV04	EV05	EV06	EV07	EV08	EV09	EV10	EV11	EV12	EV13	EV14	EV15
# of Hours	2.73	5.41	7.34	5.17	1.05	3.46	3.37	1.36	1.41	3.71	1.06	1.66	2.74	1.44	2.84
Time of Day															
0	0.50	11.96	8.24	7.65	6.34	3.32	3.64	3.79	3.99	8.94	2.96	0.15	5.46	2.34	3.42
1	0.17	10.92	8.78	10.13	5.14	3.44	3.47	2.99	3.74	8.98	3.66	0.00	6.70	1.72	4.01
2	0.03	8.81	9.19	11.03	3.85	4.18	3.63	2.91	3.63	9.03	4.77	0.00	5.93	1.34	4.00
3	0.83	1.69	9.50	11.45	5.88	4.12	3.57	5.33	4.70	9.03	6.28	0.05	4.67	1.34	3.89
4	1.06	0.57	10.14	11.44	6.79	4.46	3.83	5.77	5.16	9.06	7.90	0.00	4.29	1.69	6.18
5	0.99	0.58	10.76	11.82	2.82	4.59	3.82	5.29	4.48	8.76	8.90	0.23	3.42	3.43	8.62
6	5.36	0.39	10.78	11.92	4.60	4.72	3.18	5.13	3.63	5.28	9.26	2.90	2.70	5.28	9.35
7	7.16	0.36	9.96	8.71	4.58	3.82	2.43	5.21	3.64	0.79	9.34	3.14	2.10	4.27	8.17
8	8.92	0.31	3.50	1.37	5.92	3.47	2.57	5.68	3.52	0.35	8.64	3.89	2.89	3.24	5.51
9	6.46	0.34	0.54	0.25	2.78	1.65	2.85	4.57	3.42	0.32	2.68	3.39	3.29	2.83	4.23
10	7.19	0.29	0.17	0.42	0.41	1.62	4.82	3.13	2.88	0.30	0.98	5.20	3.24	2.74	4.33
11	8.40	0.24	0.09	0.33	0.00	1.54	4.58	3.60	2.85	0.18	0.88	4.77	3.87	3.25	5.18
12	7.89	0.34	0.06	0.06	0.00	2.23	5.45	2.98	3.17	0.10	0.76	3.75	5.34	5.63	5.95
13	7.67	0.32	0.09	0.09	0.51	5.33	4.72	4.46	4.52	0.09	0.62	3.59	6.62	7.58	6.95
14	7.51	0.36	0.05	0.20	0.04	7.74	4.79	4.34	4.60	0.14	0.92	3.26	7.79	12.84	8.09
15	7.46	0.55	0.12	0.24	0.37	7.81	4.92	4.97	5.84	0.41	1.04	3.94	7.69	13.55	6.79
16	4.04	0.84	0.43	0.22	0.77	8.26	4.69	4.76	5.97	1.09	2.45	3.39	7.38	8.32	1.95
17	1.38	3.00	1.49	0.20	2.56	6.99	4.76	4.57	6.47	1.23	6.94	3.77	4.87	4.56	0.50
18	0.40	5.82	1.52	0.59	5.75	5.14	4.79	4.56	6.69	2.18	8.94	6.79	1.69	2.09	0.22
19	1.52	7.68	1.03	0.81	7.06	3.47	4.26	3.83	4.31	3.77	3.75	14.95	0.99	2.27	0.06
20	5.12	9.07	1.16	1.18	8.41	3.09	4.44	2.60	2.94	5.73	1.53	16.28	1.47	3.00	0.05
21	5.73	10.54	2.03	2.08	8.23	3.28	5.14	2.78	2.98	7.32	2.36	11.15	1.73	2.06	0.07
22	3.36	12.09	3.84	3.01	8.57	2.92	5.47	3.34	3.51	8.22	2.20	4.80	2.45	2.63	0.37
23	0.84	12.94	6.54	4.78	8.62	2.78	4.21	3.41	3.37	8.70	2.25	0.63	3.42	2.01	2.11

Figure 4. Charging activity of each BET by time of day

C. *Environmental Justice Implications*

As noted earlier, the deployment of BETs can bring about emission reduction and other environmental benefits to environmental justice communities that have been heavily impacted by truck traffic. The level of benefits will vary depending on the extent to which the conventional diesel trucks that the BETs replace travel in or around these communities. Fig. 5 shows the fraction of vehicle operation, in terms of both vehicle miles traveled (VMT) and vehicles hours traveled (VHT), in or around DACs for each BET in this study. The fraction varies considerably, ranging from 23% to 85% (with a weighted average of 54%) for VMT and from 12% to 88% (with a weighted average of 47%) for VHT. The variation is apparent across BETs from different fleets, but there is variation among BETs from the same fleets as well, albiet to a lesser degree.

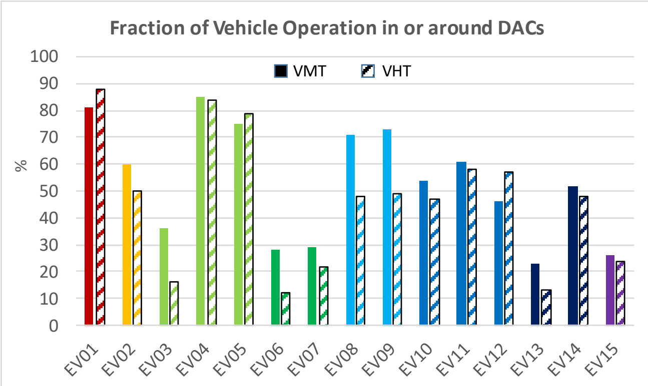

Figure 5. Fraction of vehicle miles traveled (VMT) and vehicle hours traveled (VHT) in or around DACs for each BET in this study.

The extent to which a BET operates in or around DACs depends on a few factors including whether or not its homebase is located inside a DAC, the locations of its trip destinations (e.g., customer locations), and the travel routes it takes when making the trips. Fig. 6 shows the operation footprints of the BETs EV01 and EV15 as examples. The homebase of EV01 is located inside a DAC, and this BET operates mostly within 25 miles from its homebase. During the data collection period, 81% of the total VMT and 88% of the total VHT for this BET were in or around DACs, thus significantly reducing diesel emissions that woud have otherwise been released into these communities. While the homebase of EV15 is located inside a DAC and this BET also operates mostly within 25 miles from its homebase, it often travels on freeway corridors that do not pass through DACs. Therefore, only 26% of its total VMT and 24% of its total VHT during the data collection period were in or around DACs. These examples illustrate the fact that the emission reduction benefit to DACs as a result of replacing conventional diesel trucks with BETs can vary greatly depending on the travel patterns of those trucks.

Since the dispersion of vehicular emissions is primarily within 500 meters from roadways [24], the contribution to near-road air quality improvements would be higher for BETs that travel through populated areas more frequently, and those improvements in near-road air quality will be espeically beneficial for environmental justice populations. At the same time, the deployment of BETs in place of conventional trucks that consume fossil fuel, irrespective of their local travel patterns, can also help improve regional air quality and reduce greenhouse gas emissions from freight transportation.

In addition to emission reduction, BETs are also reported to generate lower levels of noise than their diesel counterparts [25]. This can reduce the level of noise pollution experienced by the truck drivers as well as the communities where BETs travel through, especially during nighttime. As an example, the data for EV01 in Fig. 4 implies that this BET operated mostly between 4 p.m. and 6 a.m. Given that 81% of this BET's VMT were in or around DACs, the deployment of this BET not only provided emission reduction benefit but also reduced noise pollution for these DACs.

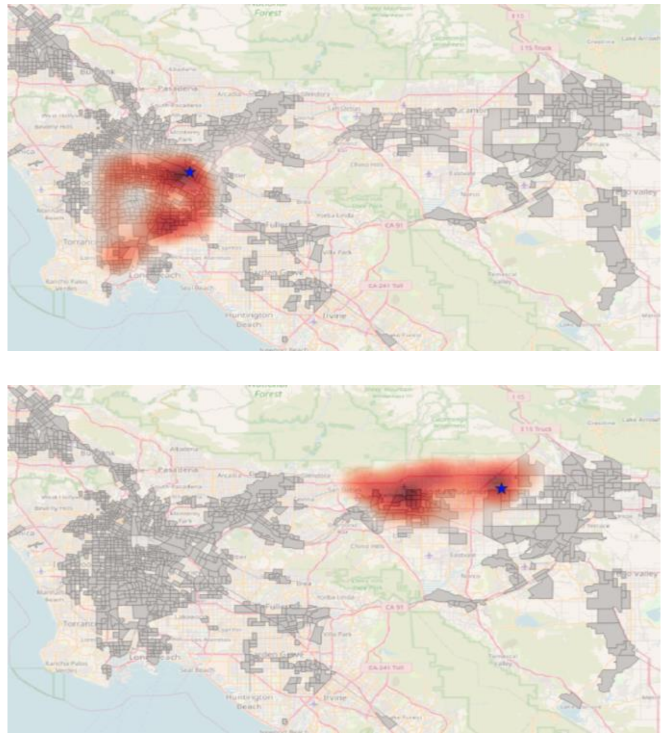

Figure 6. Operation footprints of EV01 (top) and EV15 (bottom) displayed as red shades. Darker red indicates higher density of VMT. Blue stars represent the locations of the BETs' homebases. Grey polygons represent the census tracts designated as DACs.

IV. Conclusions and Future Work

This paper presents real-world activity patterns of 15 heavy-duty BETs that are part of early deployments across eight different regional distribution fleets in Southern California. The results show that the BETs are typically used on routes (or tours) that are much shorter than their driving ranges. They often make one or two tours per day, and are usually charged at the end of each tour. Due to the variation in the time of day that the BETs are operated, they are charged at different times of day, spreading the charging load throughout the day. In addition, the results indicate that about half of the BET's operations on average occur in or around disadvantaged communities, providing emission reduction benefits to these communities. While BETs are being promoted primarily as a way to decarbonize freight transportation, they can bring about several air quality and public health co-benefits due to the fact that they have no tailpipe emissions. This is especially important for urban freight transportation where trucks usually travel in highly populated urban areas.

On the other hand, there are still many barriers to the adoption of BETs such as the lack of charging infrastructure to support the future demand of heavy-duty BET charging. In addition, there could be unintended consequences that should be proactively considered in the efforts to electrify heavy-duty trucks. For example, the development of charging infrastructure network should consider the potential increase in truck VMT due to BETs having to make deadhead trips to and from charging stations. One area of future work is thus the design of charging infrastructure network that minimizes such trips. In addition, the development of charging stations should also consider the traffic congestion and safety impacts of heavy-duty truck traffic that the charging stations will attract. Stakeholders and communities should be engaged during the process so that their inputs can be taken into account in the siting, design, and construction of the charging stations.

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