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Computationally Efficient Approach for Evaluating Eco-Approach and Departure for Heavy-Duty Trucks

--Manuscript Draft--

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Computationally Efficient Approach for Evaluating Eco-Approach and Departure for Heavy-Duty Trucks

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ABSTRACT

Prior investigations of the "Eco-Approach and Departure (EAD)" connected vehicle application have shown the potential for energy savings for the vehicle when driving through signalized intersections. These previous works have relied on constructing complex traffic microsimulation models or conducting real-world field tests to estimate energy savings. In this paper, a computationally fast and reasonably accurate methodology to estimate potential energy savings from EAD for trucking applications is presented. The proposed methodology enables corridor- or road network-level energy saving estimates using only road length, speed limit, and travel time at each intersection as inputs. This technique was validated using EAD performance data from traffic microsimulation models of four trucking corridors in Carson, California, and the estimates of energy savings using the proposed methodology were within an average error of -1%. The validated models were subsequently used to estimate potential energy savings from EAD along truck routes in Carson.

INTRODUCTION

Transportation activities, including the movement of people and goods by cars, trucks, trains, and other vehicles, account for 26% of energy consumption in the U.S., with 50-60% from passenger transportation and 40-50% from freight transportation. Consequently, transportation is responsible for 28.2% of the U.S. greenhouse gas (GHG) emissions, the largest share among all the sectors that include electricity, industry, commercial & residential, and agriculture (*1*). As connected and automated vehicle (CAV) technologies rapidly advance, there has been significant interest in using these technologies to help reduce energy consumption and GHG emissions from the transportation sector (*2*). For example, a number of connected eco-driving applications have been developed to improve the energy efficiency of individual vehicles and traffic as a whole via vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I) coordination, including Eco-Approach and Departure (EAD) at Signalized Intersections, Eco-Traffic Signal Timing, Eco-Lanes Management, etc. (*3*). Among them, the EAD at Signalized Intersections application has been widely studied due to its significant energy savings potential (*4-6*). With the EAD application, the equipped vehicle would be able to follow the most energy-efficient trajectory for passing through a signalized intersection that is calculated using the current speed of the vehicle measured by the speedometer, distance to the intersection measured by the Global Positioning System (GPS), Signal Phase and Timing (SPaT) messages from the traffic signal controller, and surrounding traffic information detected by on-board sensors such as radar or camera.

In the last decade, many studies have been conducted to evaluate the energy savings and emissions reduction potential of EAD application under a variety of scenarios—from a simple scenario, such as fixed-time signals without traffic, to a more complex setup that comprises actuated signals in different traffic conditions. As shown in Table 1, these studies used different methods in the evaluation of energy savings and emissions reduction benefits of EAD application, including numerical simulation, traffic microsimulation, or field experiment. Among the three methods, numerical simulation (*4,7-10*) is relatively easy to conduct, but it only simulates the EAD-equipped vehicle without consideration of other vehicles on the road. This limitation can be addressed by using traffic microsimulation (*6, 11-12*) tools where different driving and traffic scenarios can be simulated to replicate real-world conditions. However, the evaluation of EAD application using traffic microsimulation tools is complex and time-consuming, involving the coding, calibration, and validation of the simulation model as well as the implementation of EAD algorithms into the simulation model through Application Programming Interface. Lastly, the evaluation of EAD application through field experiment (*5, 13-14*) is expensive, and thus, is often conducted for a limited number of intersections and corridors. Also, the energy and emissions benefits of EAD heavily depend on intersection and corridor characteristics, such as speed limit and length of the road upstream of the intersection, and thus, the benefits of EAD measured at one intersection or corridor may not be applicable to others.

TABLE 1 Summary of EAD Algorithms and Evaluation Methods from Select Studies

Study Authors and Year	EAD Algorithm	Evaluation Method
Rakha et al. (2011) (7)	Fuel as the optimization objective	Numerical Simulation

Mahler & Vahidi (2012) (*8*)	Signal phase prediction model	Numerical Simulation
Xiang et al. (2015) (*9*)	Driver behavior adapted eco-driving	Numerical Simulation
Kamalanathsharma et al. (2016) (*10*)	Multi-stage dynamic programming	Numerical Simulation
Ye et al. (2019) (*4*)	Neural network based prediction	Numerical Simulation
Xia et al. (2013) (*11*)	Adapted for different congestion levels	Traffic Microsimulation
Li et al. (2016) (*6*)	Drivers make control based on alerts	Traffic Microsimulation
Esaid et al. (2021) (*12*)	Machine learning-based method	Traffic Microsimulation
Muñoz-Organero & Magaña (2014) (*13*)	Design optimal deceleration patterns	Field Experiment
Stahlmann et al. (2017) (*14*)	Green light optimal speed advisory	Field Experiment
Hao et al. (2018) (*5*)	Rule-based method for actuated signals	Field Experiment

The objective of this research is to develop a new methodology that will allow for a computationally fast and reasonably accurate estimation of the energy savings potential of EAD. To achieve the research objective, a lookup table-based method is proposed where the lookup table stores the numerical relationships between vehicle energy consumption and key parameters in EAD operation, such as upstream and downstream link distance. These relationships replace the runtime computation in numerical simulation or traffic microsimulation with a faster array indexing operation. Similar methods (*15*) have been widely used in other research fields due to the vast savings in processing time and the ability to store pre-calculated relationships for use in the execution of a model. Using the proposed method, one can quickly estimate the corridor- or road network-level energy savings potential of the EAD application using only road length, speed limit, and travel time at each intersection as inputs. The estimation results can be used to select intersections for detailed evaluation in traffic microsimulation or prioritize intersections for field implementation.

To develop the estimation method, data generated from an extensive traffic microsimulation of an EAD application for heavy-duty trucks on real-world corridors in Carson, California, were used. First, two lookup tables (one for the baseline scenario and the other for the EAD scenario) were created that compiled upstream distance, downstream distance, average travel time, and energy consumption for the individual intersections. Then, each lookup table was used to build an estimation model, which was later calibrated based on the ratio between the actual and estimated energy consumption. Using the calibrated models, the energy consumption for both the baseline and EAD scenarios at each intersection can be estimated, and subsequently, the energy savings can be calculated.

METHODOLOGY

In this section, we first briefly describe the EAD application for heavy-duty trucks that we previously developed and implemented in traffic microsimulation models of four real-world trucking corridors in Carson, California, to evaluate the energy savings potential of EAD for trucking applications (*16*). After that, we describe the development, calibration, and validation of the energy consumption estimation lookup table using data generated from the traffic microsimulation models.

EAD Simulation

As shown in the system diagram in Figure 1, the EAD application as implemented in traffic microsimulation models has both online components and offline components. The online components are implemented in real time. At each time step, the system first collects required data from multiple sources, including SPaT information, activity data from preceding vehicles, dynamic state of the host vehicle, and infrastructure data such as speed limit, road grade, communication range, etc. If the system does not receive all the required data or the situation is not safe enough to perform speed control (e.g., there is another vehicle right in front of the host vehicle), the EAD application will be turned off and return the control to the default controller in simulation. Otherwise, it will proceed to conduct trajectory planning and speed control for the virtual host vehicle.

As the key component in the EAD application, the trajectory planning algorithm designs the optimal speed profile for the host vehicle to pass through the intersection with minimum energy consumption without compromising safety and mobility. To address the unique vehicle dynamic and powertrain characteristics of trucks in the algorithm, we first train the algorithm using calibrated acceleration and deceleration profiles and power-based cost table. Those data are fed into the graph-based trajectory planning algorithm first to generate a pool of optimal trajectories for all combinations of starting and ending states. Then, a machine learning-based trajectory planning algorithm (MLTPA) is developed and trained to provide a fast and accurate speed recommendation in real time based on the pool of optimal trajectories.

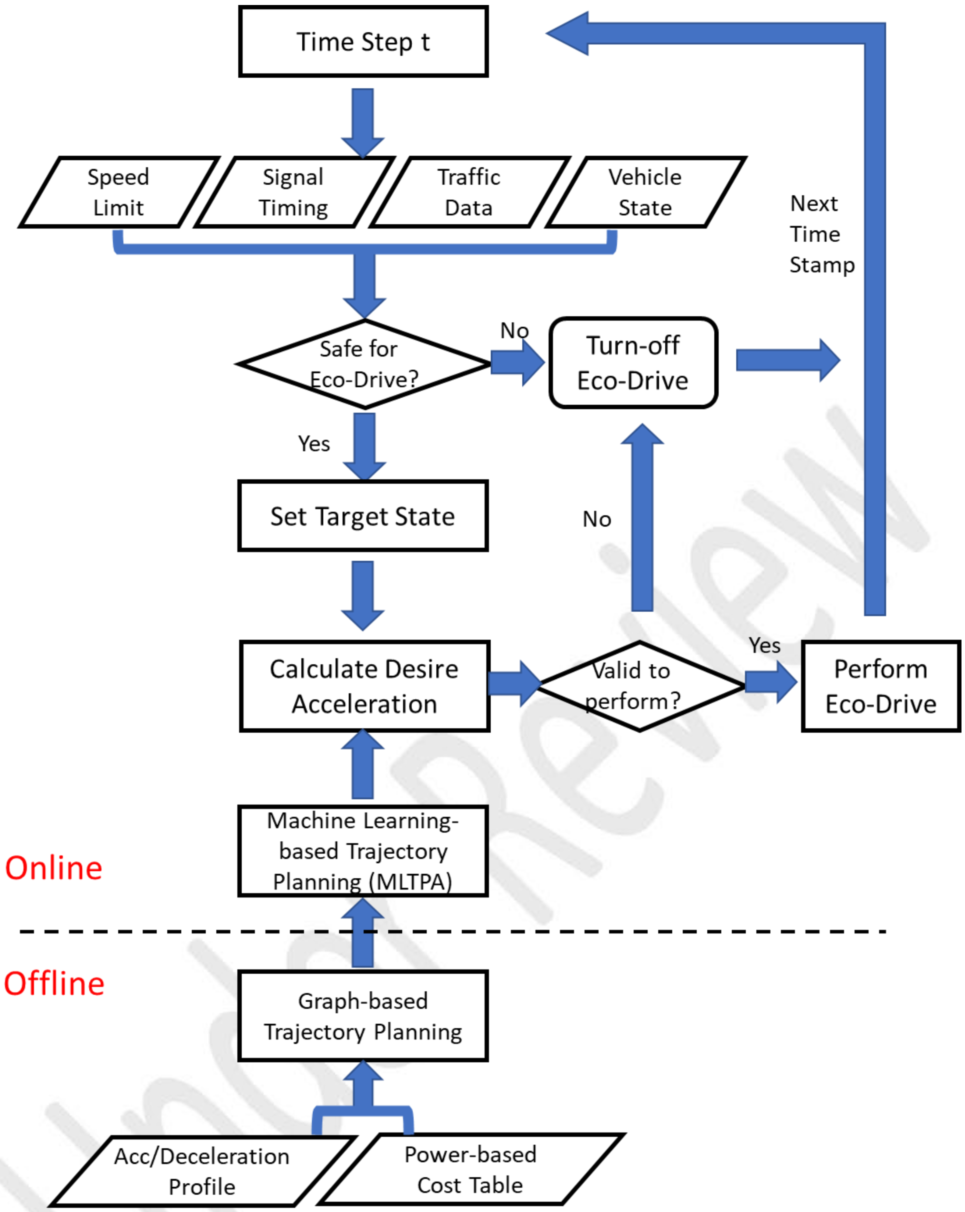

FIGURE 1 System diagram of the EAD application

In the graph-based trajectory planning algorithm, the cost function of the graph is defined as the tractive power of the truck at a certain speed and acceleration rate. When road grade is zero, the coasting acceleration rate is defined as:

$$a_{coast} = -\mu g - \frac{1}{2m} C_D \rho_a A_f v_i^2 \tag{1}$$

where μ, g, m, C_D, ρ_a, A_f, v_i are defined as rolling resistance coefficient, gravity, mass of the truck, drag coefficient, reference area, and speed, respectively.

When the truck is in a coasting or braking mode, i.e. $a \leq a_{coast}$, the tractive power is equal to 0. Otherwise, the truck is in traction mode ($a > a_{coast}$), and the tractive power is calculated as:

$$P = \left(ma + \mu mg + \frac{1}{2} C_D \rho_a A_f v_i^2\right) v \tag{2}$$

Using the single intersection microsimulation models and the online EAD model, the single intersection trajectory datasets are generated and fed into the energy benefit estimation model, as discussed in the next section.

Energy Benefit Estimation Model

Unit Intersection Lookup Table

Many parameters are related to energy consumption in the proposed EAD model, e.g. starting and ending location with respect to the intersection, the SPaT information, the speed limit, and the traffic condition, etc. The upstream distance (l_u) determines the maximum distance of which the eco-driving could be initiated. If l_u is smaller than the communication range of the connected signal, the host vehicle will start eco-driving as soon as it enters the intersection. Otherwise, the host vehicle will drive unconnectedly until it enters the communication range. The second parameter that is important in the EAD model is the downstream distance (l_d), which describes how far the vehicle could drive after passing the intersection. l_d constraints the target speed the vehicle could reach at the end of the network, therefore impacts the energy consumption of the model. Both distance measures are critical in EAD model and are convenient to acquire from the geographic database. The speed and time-related parameters are also significant in the EAD process. For example, when the traffic is congested, the eco-driving will not be able to be effectively performed due to the close gap between the host vehicle and the leading vehicle. When the traffic signal has a longer red-light phase, the host vehicle will be more likely to slow down due to the signal and queue. When the city engineers are estimating potential energy benefits by enabling certain connected signals, we would like the process to be fast and relatively accurate. Although all these parameters are important in estimating the energy consumption, we only choose the travel times along with upstream/downstream distances in the lookup table as they are easier to be measured and obtained, other parameters, such as the traffic signal timing and traffic condition, are difficult to acquire or estimate in a real-time manner.

We create two lookup tables (one for baseline, and one for eco-driving) where the Energy consumption (E) for each (t, l_u, l_d) combination in the single-intersection simulation was listed. The two lookup tables can be summarized as two functions below:

$$E = E_e(t_e, l_u, l_d) \text{ for eco-driving case,} \tag{3}$$

$$E = E_b(t_b, l_u, l_d) \text{ for baseline case.}$$

The single-intersection simulation provides the simplest EAD scenario, from which different (t, l_u, l_d) combinations could be extracted from. Later, the corridor with multiple intersections could be split into single intersections, calculated separately, and added together for total energy consumption and benefit estimation.

Lookup Table Calibration

The lookup table in the previous step is obtained by running microsimulations of a single intersection network. The network is designed to have large enough l_u and l_d (both 1500m) so that the lookup table could cover all conditions of the real-world intersections. However, such a lookup table might not work when the network is extended to corridors of multiple intersections with different lengths of l_u and l_d, especially when the intersections are closely spaced. When the l_u or l_d is small, vehicles usually prepare to decelerate before they reach the desired speed, causing a smaller average speed and longer travel time. The actual energy consumption is usually less than the estimated value from E_e or E_b.

To calibrate the adjustment factor R (defined as the ratio between the actual energy and the estimation), we first used corridor simulation data from two corridors as training sets and collected actual energy consumption data for each link. We then estimate the energy consumption at corresponding links from the single-intersection simulation dataset. According to the link distance (short or long) and driving mode (eco-drive or baseline), data were categorized into four groups. Here short links are defined as links in which $l_u \leq 100m$, and long upstream links are defined as links in which $l_u > 100m$. The adjustment factor R between actual and estimation for certain link length type and driving mode is then calculated as below:

$$R = \frac{\sum_{i=1}^{k} E_{actual_i}}{\sum_{i=1}^{k} E_{estimation_i}} \tag{4}$$

where k is defined as the number of signals with the same link length type and driving mode.

Scenario and Input Identification

For a real-world corridor, divide it into links. We define the link length d_{ij} as the distance between the stop line of the upstream intersection i and downstream intersection j, downstream distance of intersection i (defined as l_{di}) and upstream distance of intersection i (defined as l_{uj}) are then defined below:

$$\begin{aligned} &\text{if } d_{ij} \geq 1300\text{: } l_{di} = 900;\ l_{uj} = d_{ij} - l_{di};\\ &\text{else if } d_{ij} \geq 400\text{: } l_{di} = 425;\ l_{uj} = d_{ij} - l_{di};\\ &\text{else: } l_{di} = d_{ij} - 25;\ l_{uj} = 25; \end{aligned}$$

The baseline travel time for each link can be either derived from sample truck trajectory data, estimated by the equations in Highway Capacity Manual (HCM) or looked up from the historical travel time in Google Map Application Programming Interface (API). Since the link travel times for eco-drive scenarios are similar to corresponding baseline cases, we used the same travel time for both baseline and eco-driving on the same network. For baseline scenarios, all the intersections are non-connected. For eco-drive scenarios, intersections can be connected or non-connected, according to the implementation plan.

Energy Benefit Estimation

For each link in the real-world corridor, the estimated energy consumption under the baseline scenario is

$$E_{i,b} = \begin{cases} R_{short,baseline} \times E_b(\mathrm{t_i}, l_{ui}, l_{dj}) & if\ l_{ui} \le 100m \\ R_{long,baseline} \times E_b(\mathrm{t_i}, l_{ui}, l_{dj}) & if\ l_{ui} > 100m \end{cases} \tag{5}$$

where R is calculated from Step 2 using the grouped training data. The equations above are also applicable to the links with non-connected signals for eco-drive scenarios. For links with connected signals, the estimated energy consumption under the eco-drive scenario is

$$E_{i,e} = \begin{cases} R_{short,eco} \times E_e(\mathrm{t_i}, l_{ui}, l_{dj}) & if\ l_{ui} \le 100m \\ R_{long,eco} \times E_e(\mathrm{t_i}, l_{ui}, l_{dj}) & if\ l_{ui} > 100m \end{cases} \tag{6}$$

After calculating the energy consumption of single intersections of a corridor, the total baseline energy consumption is the summation of all the calibrated energy values and the energy benefit is then calculated correspondingly.

$$E_{total} = \sum_{i=1}^{n} E_i \tag{7}$$

$$E_{saving} = 1 - \frac{E_{total,e}}{E_{total,b}} \tag{8}$$

RESULT

In this section, we first show the results of unit intersection simulation. Then, we validated the proposed estimation method using the traffic microsimulation-generated data from four real-world corridors in Carson, California. Lastly, the validated models were applied to estimate the potential energy savings from the EAD application for the entire truck route network in the city of Carson.

Unit Intersection Simulation

As mentioned in the methodology section, a single-intersection simulation network with 1500m l_u and l_d was built in VISSIM to create the lookup table of the energy consumption correspondence. To understand the impact of each parameter on the performance of the EAD algorithm, we plot the energy consumption v.s. l_u and l_d when travel time is set to be 100 sec, as shown in Figure 2. As can be seen from Figure 2(b), when l_d and t is constant, the total energy consumption decreases as l_u increases. This is because the vehicle tends to slow down before the intersection and accelerate after passing the intersection when l_u is small, causing extra energy consumption in the acceleration process. We can also see that when l_u and t is constant, the total energy consumption increases as l_d increases. This is because the host vehicle spends more time accelerating to coasting speed when l_d increases. As for energy benefit, E_{saving} ranges from 0% to 30%, increases as l_u increases and decreases as l_d increases. To explain this phenomenon, we can interpret E_{saving} using the formula below:

$$E_{saving} = \frac{E_{total,b,u} + E_{total,b,d} - E_{total,e,u} - E_{total,e,d}}{E_{total,b,u} + E_{total,b,d}} \tag{9}$$

where $E_{total,b,u}$ represents the total energy consumption for baseline in the upstream driving. When l_u increases, the host vehicle can start eco-driving at an earlier stage, causing $E_{total,b,u} - E_{total,e,u}$ to increase while keeping $E_{total,b,d} - E_{total,e,d}$ consistent, therefore E_{saving} increases. Once the vehicle passes the intersection, the V2I communication will terminate and the connected vehicle will perform the same as the baseline vehicle. When l_d increases, the numerator of formula 9 remain unchanged while $E_{total,b,d}$ increases, therefore E_{saving} decreases.

Next, we plot the energy consumption v.s. l_u and t when l_d is set to be 500m, in Figure 3. As can be seen form Figure 3a and 3b, when l_d and t is constant, $E_{total,e}$ decreases as l_u increases, which is similar to Figure 2. When l_d and l_u is constant, as t increases, $E_{total,e}$ increases to a certain threshold before reaching constant. This is because when t is smaller than the threshold, the vehicle will spend less time decelerating and accelerating. When t is larger than the threshold, all the vehicles will have to stop at the intersection, therefore costing same $E_{total,e}$ for proceeding the similar speed profile in downstream.

Corridor Energy Benefit Estimation

In the simulation scenario, we created a dataset for the single intersection simulation and estimated the raw energy consumption for each link in the four corridors, namely Wilmington North (WN), Wilmington South (WS), Alameda North (AN), and Alameda South (AS), as shown in Figure 4. The four corridors are located right next to the Port of Los Angeles and Port of Long Beach, the two busiest container ports in the United States. There are 11 and 8 signals in the Wilmington S/N and Alameda S/N corridors respectively, and each corridor has 5 connected signals as labeled in the figure. We adapted the signal timing and traffic condition from the real world and created a simulation environment in VISSIM. The baseline is controlled by VISSIM using the default driver model, and the eco-driving data is created using the EAD model mentioned in the background section. We employed an exhaustive cross-validation technique called leave-p-out cross-validation with p = 2. This involved using data from two corridors as the training set and validating the trained model against data from the remaining two corridors. The validation was repeated for all possible ways of splitting the training versus validation set. The result is shown in Table 2.

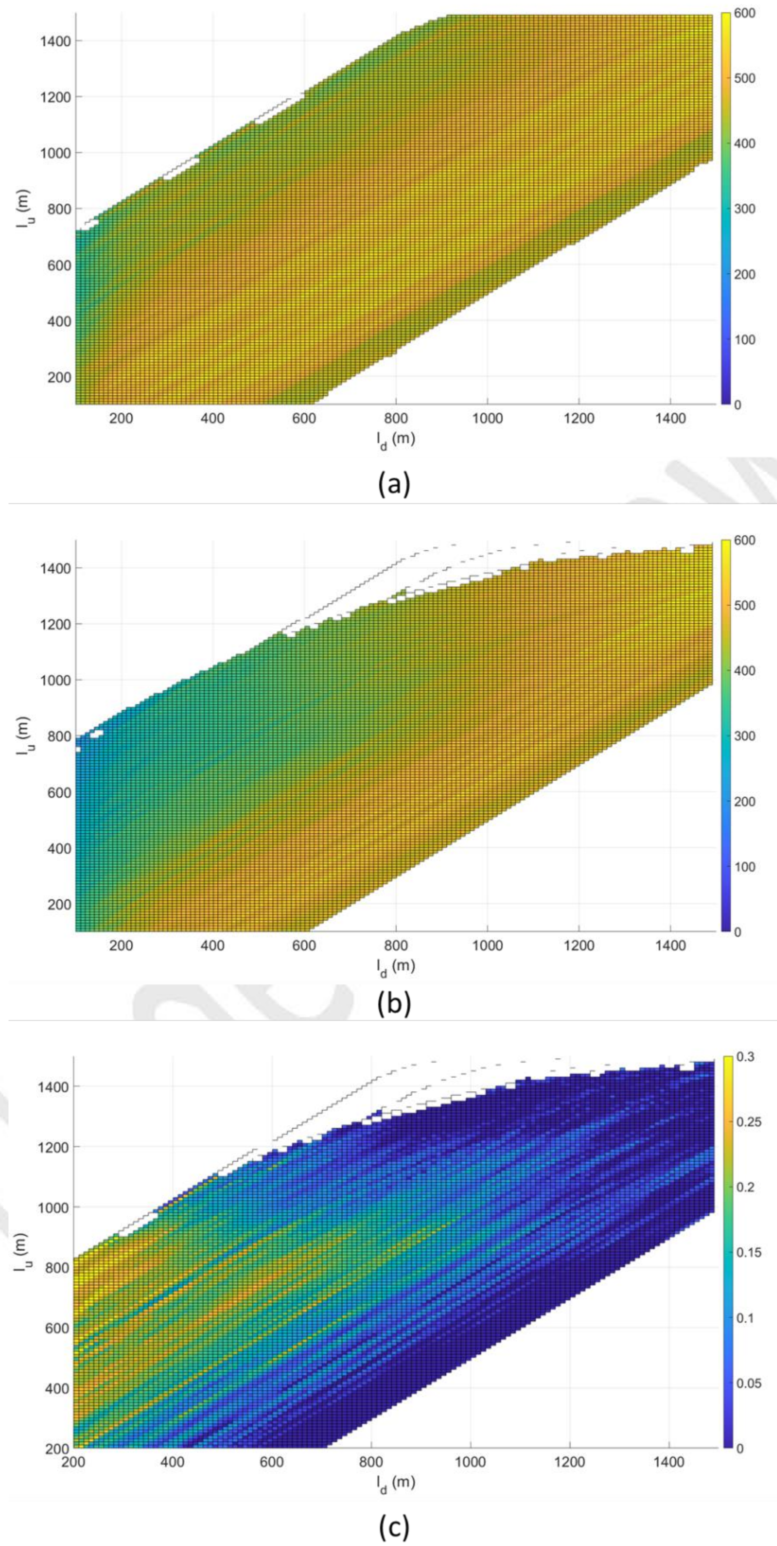

FIGURE 2 Energy Consumption and Energy Benefit for t = 100 sec. (a) Energy consumption for baseline. (b) Energy consumption for EAD. (c) Energy savings benefit ((energy for baseline – energy for EAD) / energy for baseline)

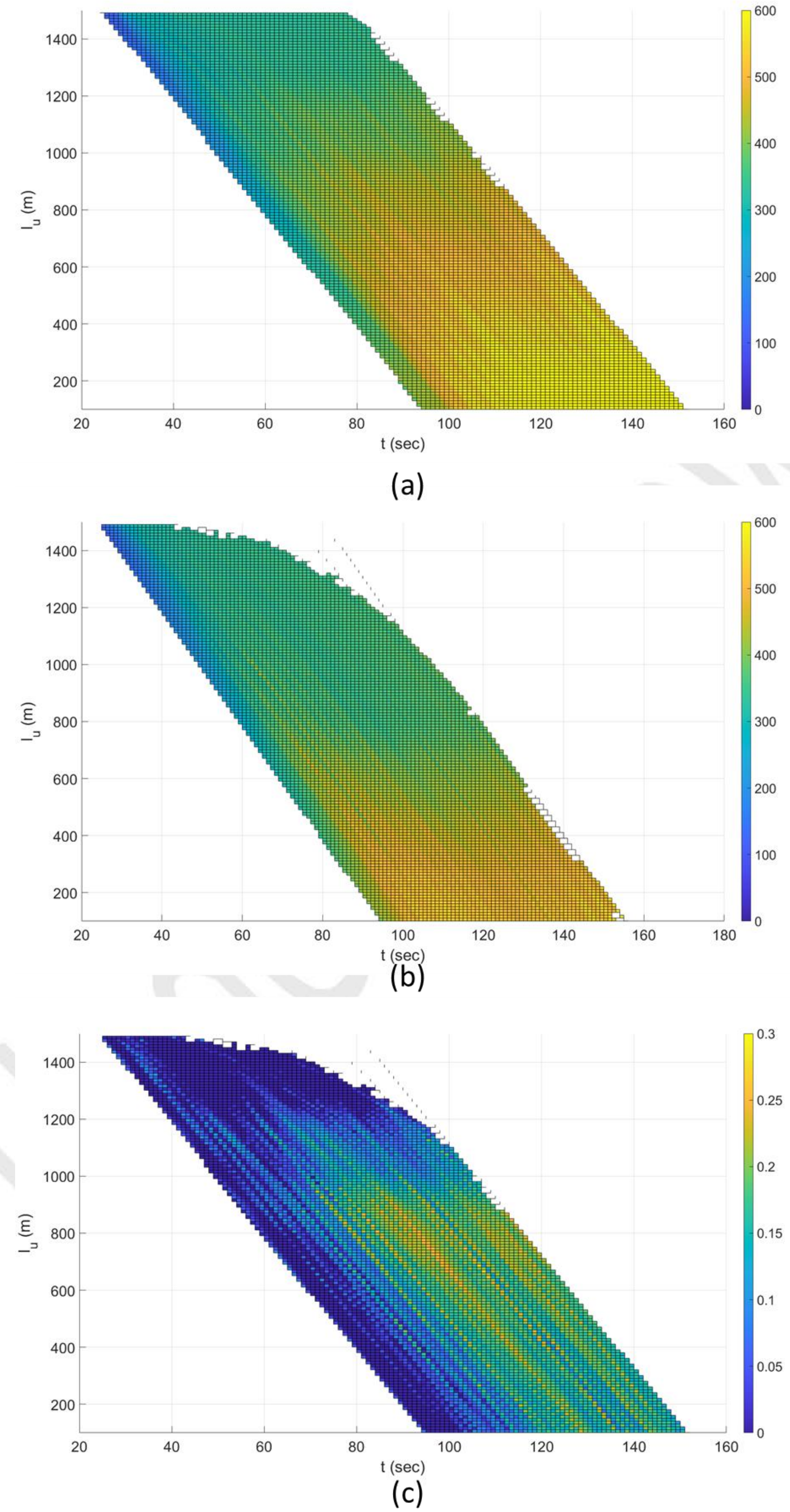

FIGURE 3 Energy Consumption and Energy Benefit for l_d = 500 meters. (a) Energy consumption for baseline. (b) Energy consumption for EAD. (c) Energy savings benefit ((energy for baseline – energy for EAD) / energy for baseline)

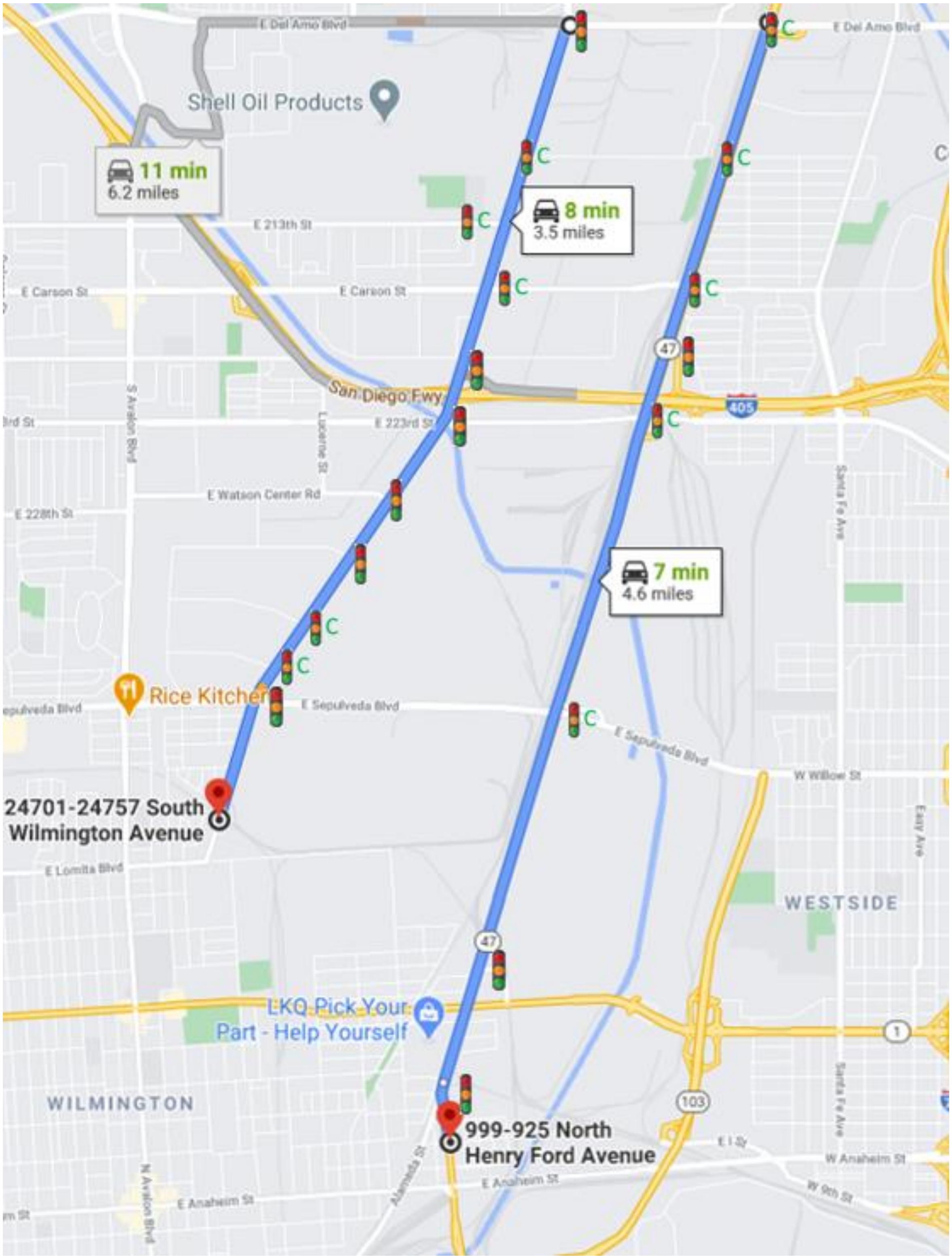

FIGURE 4 Location of 4 corridors applied in the simulation

TABLE 2 Cross-validation result for the 4 corridors

Training Set	Test Set	Real Benefit in %	Benefit in % before Calibration (Error)	Benefit in % after Calibration (Error)
AN + AS	WN	17.2	1.8 (-15.5)	11.1 (-6.2)
	WS	12.0	4.8 (-7.2)	11.7 (-0.3)
AN + WN	AS	7.6	11.1 (3.5)	10.5 (2.8)
	WS	12	4.8 (-7.2)	7.6 (-4.4)
AN + WS	AS	7.6	11.1 (3.5)	13.0 (5.3)
	WN	17.2	1.8 (-15.5)	7.2 (-10.0)
AS + WN	AN	6.2	6.4 (0.2)	5.3 (-0.8)
	WS	12.0	4.8 (-7.2)	6.4 (-5.6)
AS + WS	AN	6.2	6.4 (0.2)	8.4 (2.2)
	WN	17.2	1.8 (-15.5)	6.9 (-10.3)
WN + WS	AN	6.2	6.4 (0.2)	8.7 (2.5)
	AS	7.6	11.1 (3.5)	12.8 (5.2)

The validation results show that the estimation error ranges from -10% to +5% with an average error of -1%. 5 out of 6 validation trials show a significantly better estimation result after the calibration factor is applied. The raw estimated energy turns out to be an overestimation for all dataset, which might be caused by the less traffic and higher average speed in the corridor simulation compared with the single intersection simulation. The proposed method can also make an accurate estimation for the energy consumption in both baseline and eco-driving with less than 10% estimation error. Since the computation is based on several lookup tables, the computational time is less than 1 sec for each corridor and is fast enough for real-time applications.

City of Carson Truck Route Energy Benefit Estimation

We then applied the energy benefit estimation model to the truck route network in the city of Carson and estimated the potential energy savings using the EAD application. Below Figure. 5 is the truck routes and parking map in Carson, California, where 14 east-west and 10 north-south corridors are colored in yellow. To estimate the energy consumption and benefit for the corridors, we need to divide each corridor into links based on the traffic signals and calculate the travel time and upstream/downstream length for each link. Using Google Earth (Figure. 6), we locate all the traffic signals with their length on the corridor and note down the longitude and latitude of the beginning and end of each corridor. Then using Google Map Distance Matrix API, we collect the real time travel time data of the entire corridor using the longitude and latitude coordinates of the corridor. To adapt to the uncertain traffic conditions on the corridors, travel time data is collected every 15 mins for 7 days and then averaged into hourly data. Finally, the link travel time t_{L_i} is calculated using the corridor travel time t_c based on the speed limit v_{L_i} and the distance of each link d_i, shown as below:

$$t_{L_i} = t_c \times \frac{\frac{d_i}{v_{L_i}}}{\sum_{j=1}^{n} \sum \frac{d_j}{v_{L_j}}} \tag{9}$$

With the travel time, distance, and the calibration factor calculated from the simulation study, the estimated energy consumption and EAD estimation are listed in Table 3 below. Note that some corridors with no traffic signal have been removed from the table.

TABLE 3 Truck Route Energy Consumption and Saving

Horizonta	Name	Corridor Length (mi)	# Signals	Baseline Energy (kWh)	Eco-driving Energy (kWh)	Energy Savings (%)
1	Alondra Blvd	1.2	8	3.6	2.9	-19%
3	E Walnut St	1.0	4	2.2	1.7	-25%
5	Albertoni St	1.1	10	3.6	3.3	-9%
6	E Victoria St	0.7	4	1.6	1.3	-20%
7	W Victoria St	0.4	4	1.5	1.5	-1%
8	Del Amo Blvd	4.5	21	9.6	9.2	-4%
9	W Torrence Blvd	0.3	4	1.2	1.2	-5%
10	E Carson St	1.9	10	5.1	4.2	-17%
11	223rd St	4.8	30	14.2	12.5	-12%
12	Sepulveda Blvd	3.7	28	8.8	8.0	-9%
13	Lomita Blvd	1.3	6	4.0	3.5	-11%
Vertical	**Name**	**Corridor Length (mi)**	**# Signals**	**Baseline Energy (kWh)**	**Eco-driving Energy (kWh)**	**Energy Savings (%)**
1	S Figueroa St	6.1	32	15.6	13.5	-14%
2	S Broadway	3.0	14	8.4	6.7	-20%
3	S Main St (north)	1.4	8	3.9	3.1	-20%
5	S Avalon Blvd (no	1.0	10	3.5	2.9	-16%
6	S Avalon Blvd (sou	1.4	11	4.1	3.5	-17%
7	S Central Ave	0.7	11	3.1	2.6	-16%
8	S Wilmington Ave	5.1	31	15.6	13.6	-13%
9	Alameda St	3.4	11	8.4	7.0	-17%
10	Santa Fe Ave	1.5	12	4.5	3.5	-23%

The results show that the potential energy savings vary by the corridor, ranging from 1% to 25% with an average of 14%. The longest corridor, which is South Figueroa St, reaches an average 14% energy savings and 13.5 kWh/signal in 16 connected signals. The amount of savings is in accord with the number we calculated in the 4 simulated corridors, which proves that the proposed methodology is applicable to real world traffic scenarios.

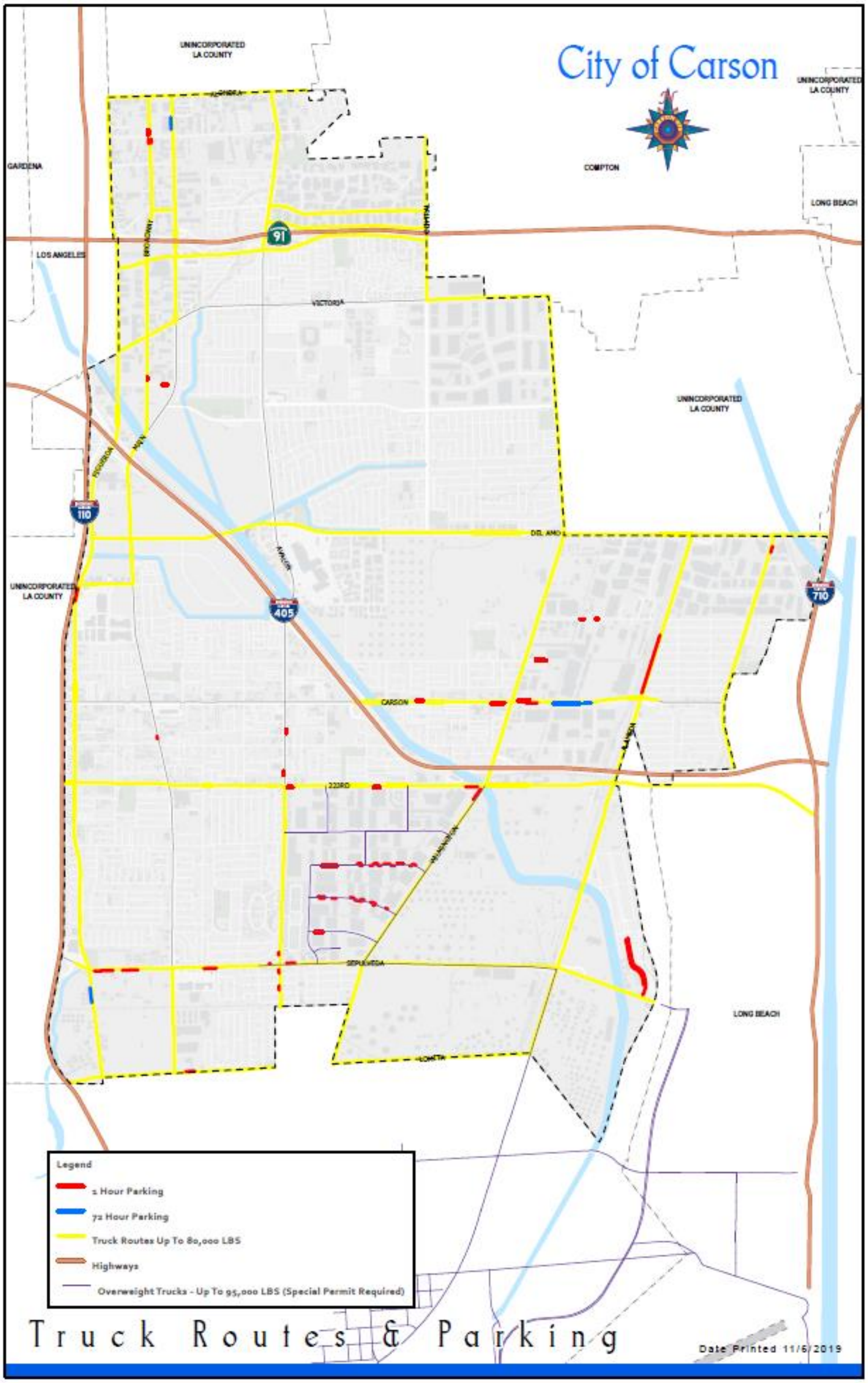

FIGURE 5 Truck Route and Parking Map in City of Carson

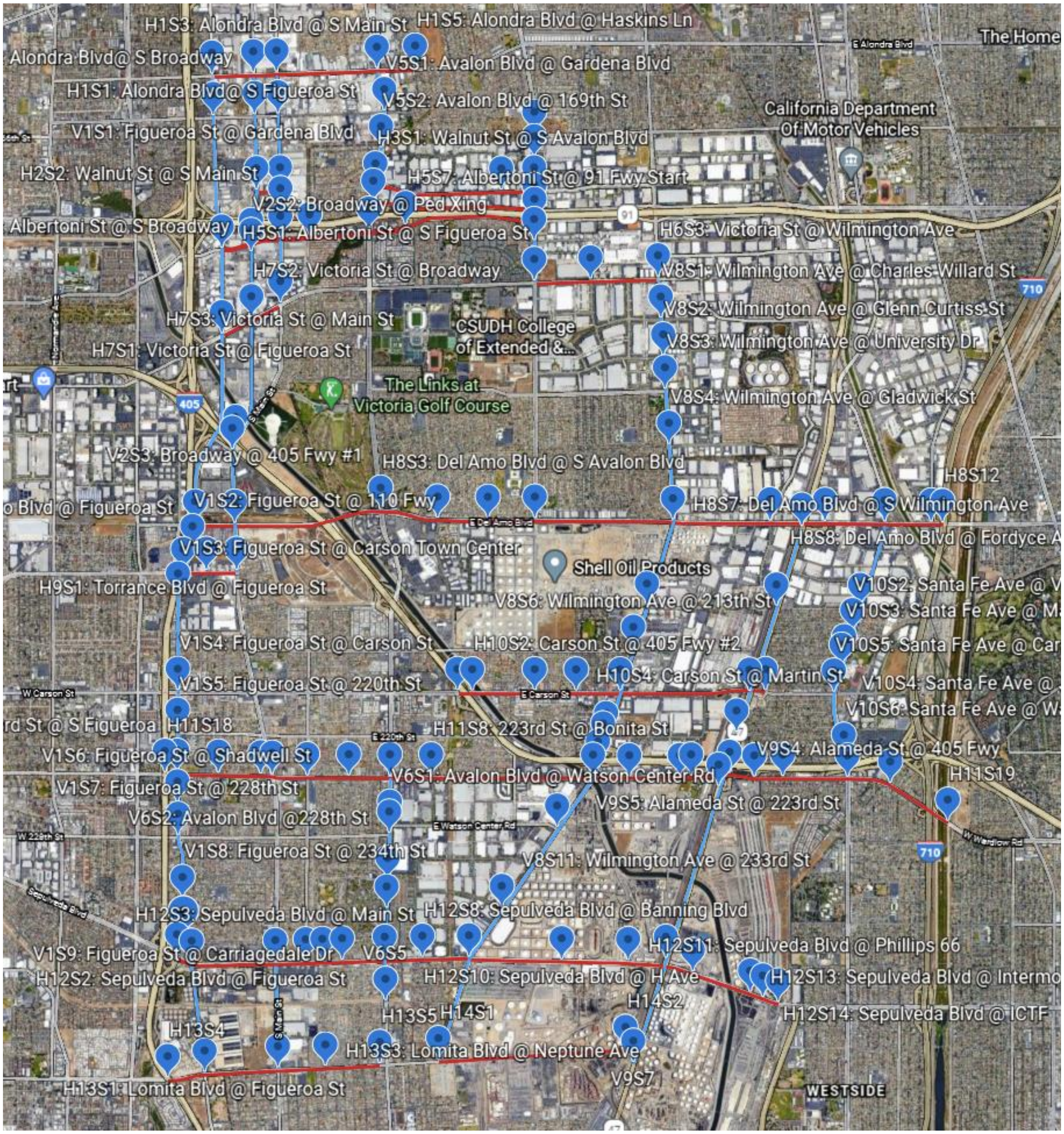

FIGURE 6 East-west (red) and north-south (blue) corridors in City of Carson from Google Earth

CONCLUSION

This paper presents a computationally efficient and accurate methodology for evaluating and estimating potential energy savings of using EAD along trucking corridors within cities. Using the road length, travel time, and speed limit at each intersection in the corridor, one can quickly estimate the corridor-level energy savings with customized connected or non-connected signal combinations. We validated the proposed estimation method using the traffic microsimulation-generated data from four real-world corridors in Carson, California. The proposed method made an accurate estimation of the energy consumption in both the baseline and eco-driving cases with less than 10% estimation error, and the cross-validation results showed that the benefit estimation error ranges from -10% to +5% with an average error of -1%. This method could be used by city planners and engineers to estimate potential energy benefit when enabling certain connected signals and to decide which signals to prioritize for enabling connectivity.

In our future work, we plan to apply the proposed methodology to different types of vehicles and roadway networks. Additional simulations will be performed to estimate energy savings benefit under different connected vehicle penetration rates. Real-world field tests will also be conducted to verify and improve the proposed algorithm.

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AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: K. B., P. H., A. K., P. A., M. B.; data collection: Z.W., K. P., L. L., S. O.; analysis and interpretation of results: Z. W., P. H., K. B.; draft manuscript preparation: Z. W, P. H., K. B, A. K..

All authors reviewed the results and approved the final version of the manuscript.

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