Estimating the Impacts of Automatic Emergency Braking (AEB) Technology on Traffic Energy and Emissions

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A Research Report from the Pacific Southwest Region University Transportation Center

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16. Abstract

As one of the key advances in vehicle safety, Automatic Emergency Braking (AEB) has been introduced in the U.S. and the number of vehicles equipped with this technology has increased significantly in recent years. Most of existing studies have evaluated this technology at the individual vehicle level or focused on its safety performance. In this study, we tried to quantify its effectiveness on the energy consumption and tailpipe emissions. Towards this end, we: 1) performed literature review on AEB technology; 2) built a database including real-world traffic state measurements, traffic accident records, roadway geometry, and weather information; 3) developed a data-driven method to estimate the environmental impacts caused by the accidents that could be mitigated by AEB; and 4) conducted case study to show the efficacy of the proposed method. The results showed that the AEB technology may improve energy economy by up to 34.6% and reduce pollutant emissions (e.g., CO, HC, NOx and PM) by as much as 22.5% if the selected accidents could be avoided.

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About the Pacific Southwest Region University Transportation Center

The Pacific Southwest Region University Transportation Center (UTC) is the Region 9 University Transportation Center funded under the US Department of Transportation's University Transportation Centers Program. Established in 2016, the Pacific Southwest Region UTC (PSR) is led by the University of Southern California and includes seven partners: Long Beach State University; University of California, Davis; University of California, Irvine; University of California, Los Angeles; University of Hawaii; Northern Arizona University; Pima Community College.

The Pacific Southwest Region UTC conducts an integrated, multidisciplinary program of research, education and technology transfer aimed at *improving the mobility of people and goods throughout the region.* Our program is organized around four themes: 1) technology to address transportation problems and improve mobility; 2) improving mobility for vulnerable populations; 3) Improving resilience and protecting the environment; and 4) managing mobility in high growth areas.

U.S. Department of Transportation (USDOT) Disclaimer

Disclosure

Principal Investigator, Co-Principal Investigators, others, conducted this research titled, "Estimating the Impacts of Automatic Emergency Braking (AEB) Technology on Traffic Energy and Emissions" at the Bourn's College of Engineering – Center for Environmental Research and Technology (CE-CERT), University of California at Riverside. The research took place from 07/01/2020 to 06/30/2021 and was funded by a grant from the U.S. Department of Transportation in the amount of $99,995. The research was conducted as part of the Pacific Southwest Region University Transportation Center research program.

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Abstract

As one of the key advances in vehicle safety, Automatic Emergency Braking (AEB) has been introduced in the last several years and the number of vehicles equipped with this technology has been steadily increasing. To date, most of existing studies on AEB systems have been focused on evaluating the safety performance of this technology. In this study, we attempt to quantify the AEB system benefits on environmental sustainability, due to its ability to mitigate accidents and any resulting traffic congestion avoidance. We have developed a data-driven method that analyzing the impact of rear-end accidents that could potentially be avoided due to AEB systems, resulting in improvements to traffic flow. Towards this end, we: 1) performed literature review on AEB technology; 2) built a database including real-world traffic state measurements, traffic accident records, roadway geometry, and weather information; 3) selected the target accident that could be potentially mitigated by AEB systems; 4) developed a data-driven method to estimate the spatial-temporal region caused by the target accident; and 5) estimated the excessive energy consumption and tailpipe emissions that could be potentially avoided due to the deployment of AEB systems. To show the efficacy of the proposed method, we conducted a case study for a real-world scenario along SR-91 in Riverside, California. The results showed that a small penetration of AEB technology could potentially improve energy economy by up to 34.6% and reduce pollutant emissions (e.g., CO, HC, NOx and PM) by as much as 22.5%, if the selected accidents could be avoided.

Estimating the Impacts of Automatic Emergency Braking (AEB) Technology on Traffic Energy and Emissions

Executive Summary

Traffic congestion has brought about a variety of socio-economic issues to our daily lives, which is generally categorized into recurrent congestion and non-recurrent congestion. Specifically, non-recurrent congestion caused by traffic incidents such as accidents, special events and work zones, may be responsible for more than a half of the total travel delays in many urban cities. In particular, traffic accident induced congestion is much more frustrating to the travelers due to its unexpected and undesirable consequence (e.g., late delivery, missed flights, delayed meeting schedule). Even worse, the presence of accidents may also lead to the high risk of secondary accidents.

Over the years, engineers and researchers have proposed and developed numerous solutions to mitigating traffic congestion and improving safety performance on both vehicle technology and traffic operation. As one of the key advances in vehicle safety, Automatic Emergency Braking or Autonomous Emergency Braking (AEB) has been introduced in the U.S. approximately a decade ago and the number of vehicles equipped with this technology has increased significantly. The AEB system can automatically detect an emergency situation and activate the vehicle braking system to decelerate the vehicle with the purpose of avoiding or mitigating a collision. Numerous studies have shown that this technology is capable of reducing the number and/or severity of relevant accidents, thus helping reduce the number of traffic fatalities. However, most of these studies have focused on evaluating this technology at the individual vehicle level and its safety impacts. Relatively few studies have attempted to quantify the traffic level impacts (e.g., congestion mitigation) due to the introduction of AEB, not to mention the effectiveness on the environment.

In this study, we develop an innovative approach to quantifying the environmental benefits of AEB system. Firstly, based on the review of AEB-related literature, we get more in-depth understanding of the accidents that can be prevented by AEB system. Then, we create an integrated database by synchronizing (in both space and time) historical traffic measurements under “accident-free” conditions and with occurrences of accident, roadway geometry, as well as associated weather information. By leveraging the database and machine learning techniques, we: 1) estimate the spatiotemporal extent of traffic accident impact (in terms of the change in speed) using the Otsu’s method and morphological operations; 2) apply the Long Short-Term Memory (LSTM) model to predict the “accident-free” (i.e., “what-if” scenarios) traffic states under the prevailing traffic conditions; and 3) assess the environmental impacts induced by the deployment of AEB technology with the U.S Environmental Protection Agency’s MOtor Vehicular Emission Simulator (MOVES) model.

The case study of two real-world scenarios (one in Riverside, CA and the other in Las Vegas, NV) has showed the efficacy of the proposed methodology. The results indicate that the AEB technology could improve energy consumption by up to 34.6% and reduce pollutant emissions (such as CO, HC, NOx and PM) by as much as 22.5%, if it were adopted in the accident-involved vehicles and could effectively avoid the studied accidents.

Introduction

As one of the key advanced applications in active vehicle safety, Automatic Emergency Braking or Autonomous Emergency Braking (AEB) [1] has been introduced in the U.S. approximately a decade ago and the number of vehicles equipped with this technology has been increasing significantly. Table 1 reports a list of automakers and the percentage of vehicles newly manufactured with AEB capability [2]. Basically, the AEB system can automatically detect an emergency situation and activate the vehicle braking system to decelerate the vehicle with the purpose of avoiding or mitigating a collision. There have been many studies indicating that this technology is capable of reducing the number and/or severity of relevant accidents and has helped reduce the number of traffic fatalities.

Table 1. Summary of Automakers and Their Passenger Vehicles with AEB Capability (adapted from [2])

	Vehicles with AEB produced Sept. 1, 2017, to Aug. 31, 2018, as reported by manufacturer for light-duty vehicles 8,500 lb. or less gross vehicle weight	**2019 models with standard AEB,** as compiled by *Consumer Reports*
Tesla	100%	100%
Mercedes-Benz	96%	89%
Volvo	93%	100%
Toyota/Lexus	90%	90%
Audi	87%	87%
Nissan/Infiniti	78%	54%
Volkswagen	69%	50%
Honda/Acura	61%	59%
Mazda	61%	67%
Subaru	57%	50%
BMW	49%	82%
Maserati/Alfa Romeo	27%	0%
General Motors	24%	0%
Hyundai/Genesis	18%	62%
Kia	13%	27%
Fiat Chrysler	10%	0%
Porsche	8%	17%
Ford/Lincoln	6%	36%
Mitsubishi	6%	0%
Jaguar Land Rover	0%	62%

For example, J. Cicchino used the Poisson regression to compare rates of accidents per insured vehicle year in the U.S. from 2010–2014 between passenger vehicle models with AEB system and the same models without this optional technology [*3*]. The results showed that low-speed AEB could reduce front-to-rear crash rates by 43% and front-to-rear injury crash rates by 45%. Based on Gyeonggi province (South Korean) crash data, Jeong and Oh proposed a statistical method using exponential decay functions (EDF) to quantify AEB system effectiveness [*4*]. It was estimated that AEB system could prevent approximately 50% of the total rear-end accidents. In a comparative study, Hellman and Lindman evaluated the crash mitigation effects of AEB technology based on data reported to insurance companies in Sweden [*5*]. They claimed that rear-end frontal collisions were reduced by 27% for cars with AEB, compared to cars without AEB. A meta-analysis method was proposed by Fildes et al. for evaluating AEB system performance across different countries, which showed a 38% overall reduction in real-world rear-end accidents for vehicles due to being equipped with the low-speed AEB system [*6*].

However, most of these studies have focused on evaluating this technology at the individual vehicle level and its safety impacts [*7 – 9*]. Relatively few studies have attempted to quantify the traffic level impacts (e.g., congestion mitigation) due to the introduction of AEB. One of the key challenges in quantifying such effectiveness of AEB technology is to develop reliable algorithm(s) for evaluating the traffic impacts under the "what-if" scenario when the accident can be avoided or mitigated by AEB technology. In addition, the mitigation of traffic accidents can lead to the reduction of excessive energy consumption and tailpipe pollutant emissions. For example, Zhu et al. leveraged macroscopic economics and safety related data to estimate the nationwide equivalent energy costs (including both direct and indirect costs) due to crashes at intersections [*10*]. Nevertheless, to the best of our knowledge, there is no existing attempt to evaluate the effectiveness of AEB technology on the environment.

To address these aforementioned gaps, we develop the following approach in this study: we firstly review literature related to AEB technology, to get more in-depth understanding of how AEB technology can potentially mitigate accidents. Then, based on the archived traffic accident records (e.g., *Highway Safety Information System* [*11*]) and real-time freeway traffic data (e.g., Caltrans Performance Measurement System [*12*]), we create a structured database by synchronizing this information in space and time both under normal conditions and with occurrence of accidents. By leveraging the integrated database and advanced machine learning techniques, we develop a data-driven method which can: 1) estimate the spatiotemporal extent of traffic accident impact (in terms of the change in speed); 2) predict the "accident-free" (i.e., "what-if" scenarios) traffic states under prevailing traffic conditions; and 3) assess the environmental impacts potentially due to the deployment of AEB technology with the state-of-the-art mobile source emissions model.

The rest of this paper is organized as follows: Section 2 discusses some background information on AEB technology, followed by the description of integrated database in Section 3.

The proposed data-driven method is detailed in Section 4, and Section 5 presents the results of case study when applying the method to a real-world example. The last section concludes this paper with discussion of future steps.

Literature Review

Automatic Emergency Braking System

As sensor and control technology advance, the emergence of advanced driving assistance systems (ADAS) allows drivers to identify potential safety risks in different driving scenarios as early as possible, thereby reducing the number of collisions or mitigating their impacts. As one of the promising ADAS, the automatic emergency braking (AEB) system leverages on-board sensors (such as millimeter wave radar or camera) to perceive the surrounding environment (mainly in the front of the equipped vehicle), including vehicles, pedestrians, bicyclists, and other traffic participants or road objects, and automatically triggers the actuator (such as electronic stability program, ESP) to perform braking for collision avoidance or severity mitigation. Different from traditional passive safety technologies, AEB is considered as a preventive active safety technology, which aims to identify the collision risk in advance, and ensures that the people inside and/or outside the car can be well protected.

The whole working process of AEB system can be divided into the following four stages (as shown in Figure 1):

1) *Normal Stage*: At this stage, the system continuously monitors its surrounding environment for risk assessment, and determines that the equipped vehicle would not collide with other road users (e.g., vehicles, pedestrians, and bicyclists) or obstacles in front. Towards this end, the AEB system will not intervene the driver's driving maneuvers.
2) *Warning Stage*: If the system judges that there is a potential collision risk, but the driver can take some actions (e.g., decelerating or changing the lane) in time to avoid the collision, then the system will alert the driver by triggering warning signals via visual, audial or haptic human-machine interfaces (HMI).
3) *Braking Stage*: When the system judges that the collision risk is imminent and an accident will occur immediately if no action is taken, then the system will use a single-stage (directly applying the maximum braking pressure) or multi-stage braking strategy (gradually increase the braking pressure) to stop the equipped vehicle;
4) *Collision Stage*: In some extreme cases (for example, a pedestrian crossing the road suddenly appears in front of the vehicle), even though the vehicle immediately uses the maximum braking capacity to slow down, the collision cannot be avoided. The system will take over the driver’s brake control to minimize the severity of the collision and reduce casualties and property losses.

Figure 1. AEB System Working Principle Diagram

As aforementioned, many studies indicate that AEB technology is capable of reducing the number and/or severity of rear-end accident in the range of 25 – 50%. The effectiveness may vary with different factors, including external environment (such as road surfaces, weather and lighting conditions), equipped vehicle's features (e.g., perception modules, decision control strategies, and actuation functions), and even drivers' characteristics. For example, road grade and pavement adhesion coefficient may affect the braking distance, so adaptive AEB system is needed to effectively operate under different road conditions [*7*]. On-board sensor settings (e.g., the field of view), combined with weather and lighting conditions, have significant impacts on the perception capability, thus influencing the reliability and accuracy of AEB system [*14*]. Many researchers have proposed a variety of AEB systems that are suitable for different types of equipped vehicles (e.g., motorcycles [*15*], electric vehicles [*16*], and buses [*17*]) and target objects such as pedestrians [*18*] and cyclists [*19*]. To improve the system acceptance, personalized AEB systems that leverage emerging technologies such as machine learning [*20*] and V2V communications [*21*] have been developed for differentiating driver's preference and driving styles in the past few years [*22*]. In this study, we mainly consider those rear-end accidents that can be potentially avoided by AEB systems and quantify the effectiveness of AEB systems in terms of traffic impact of accident avoidance or mitigation.

Impact of Traffic Accident

AEB can reduce traffic accidents rate, and hence indirectly reduce traffic congestion and energy consumption. To estimate the effectiveness of AEB, the impact of traffic accident needs to be quantified. From the traffic operation perspective, estimation of traffic accident impact and development of countermeasures (e.g., traffic incident management or TIM strategies) to mitigate such impact have gained much attention by researchers and public agencies [*23*]. Some fundamental questions associated with the traffic accident and TIM strategies are: a) how to predict the traffic states if the accidents do not occur; and b) how to predict the evolution of traffic flows when certain type of countermeasures are deployed. Numerous methodologies have been introduced over the years to address these concerns. Early studies have put significant emphases on analytical approaches based on the queuing theory [*24*] and shockwave analysis [*25*]. Although these approaches may address a few interesting phenomena (e.g., "rubbernecking" effects [*26*]), for the most part they can be only applied to very limited scenarios. With the advent of traffic simulation software, especially microscopic simulation tools (e.g., PTV VISSIM), some researchers have proposed to use them to model and analyze the impact of traffic incidents as well as to evaluate the effectiveness of TIM applications [*27*, *28*]. Although a traffic simulation environment may provide the ability to conduct "before-and-after" studies and to model a variety of "what-if" scenarios, real-world validation of more realistic driving behaviors during accidents is critical. Further, most existing incident management impact studies have been focused on quantifying safety and mobility effects of traffic accidents, while very few have considered environmental impacts [*29 – 31*].

Construction of Integrated Database

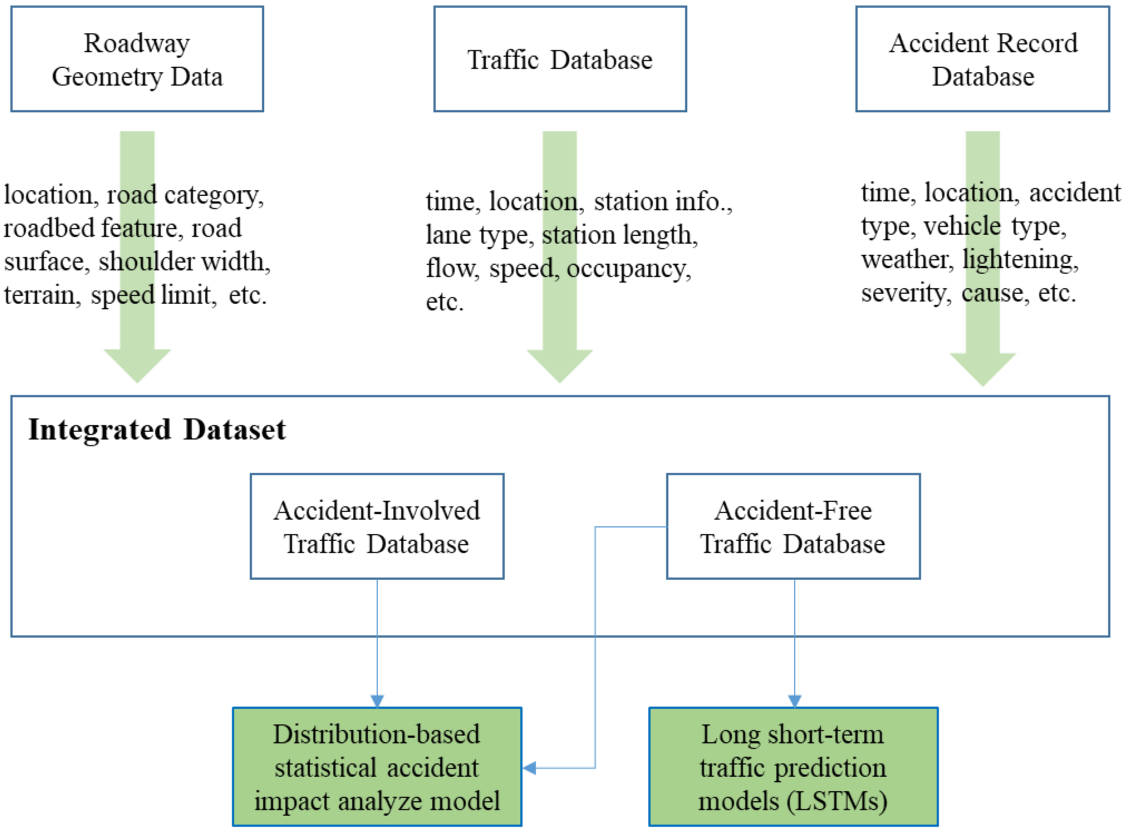
In this research, several data sources are utilized to assess the accident-induced environmental impact. As shown in Figure 2, key information includes: real-world traffic states, historical accident records, roadway geometry logs, and meteorological conditions (optional). Regarding traffic conditions, we mainly take advantage of the Caltrans Performance Measurement System (PeMS) [*12*], which receives real-time 30-second measurements of traffic count and occupancy from every loop detector throughout the California freeway system, detects the invalid or missing data, and rectifies them or fills those "holes". Based on the flow and occupancy data for each lane, speed is estimated using the well-known g-factor algorithm for single loop detector [*32*]. In addition, all these raw data are aggregated at various temporal levels, e.g., 5 minutes, for different purposes of analysis [*12*].

Regarding traffic accident records, the *Highway Safety Information System* (HSIS) is considered in this study. HSIS is a multi-state (including California) database which documents safety-related information for highways [*11*]. It provides not only accident inventory but also detailed information about the geometrics and other characteristics of roadways, interchange ramps, and intersections, such as the number of lanes, roadway width, design speed, ramp's location, and horizontal and vertical alignment, as well as weather and lighting conditions (e.g., sunny vs. cloudy). Therefore, we also use HSIS as another major data source of geometric characteristics of the freeways and weather information, in addition to PeMS and other meteorological database (or remote automatic weather stations, RAWS). In particular, HSIS may provide detailed information on traffic accidents such as the accident's lane-level location (in terms of post-mile and lane index), start time, duration, type (e.g., rear-end, head-on, angle, and sideswipe) and severity (e.g., property damage only, numbers of injuries). This information can be used to select those accidents that can be potentially prevented by AEB technology.

With the availability of all these data sources, we make significant effort to preprocess them (e.g., inconsistency check across different sources) and develop a structured database by fusing various datasets based on the time stamp and location tags. Associated with each accident record, there are two sub-sets of traffic data: one includes normal traffic conditions (of multiple historical days) which are used to construct the model for predicting the "accident-free" traffic states. The other is for the actual traffic condition directly related to the occurrence of accident, i.e., the actual traffic condition after the accident. It is noted that in this study we extend our scope beyond California dataset and work with Waycare Technologies, Inc.

(https://waycaretech.com/) on a comprehensive cloud-based traffic incident management data platform. This dataset fuses various real-world traffic data such as roadway network geometry, traffic flow/density/speed information from loop detectors, probe vehicle data (i.e., from smartphone apps), and road weather information, and provides updates (up to) every 1 minute.

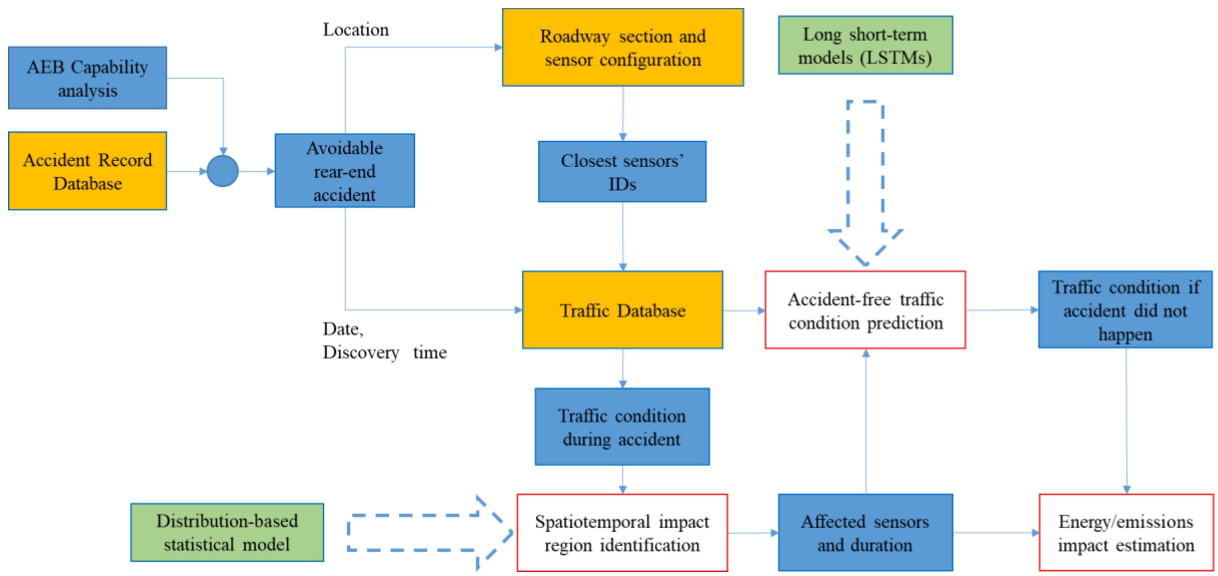
Figure 2. Integrated Database and Work Flow



Methodology

Figure 3 illustrates the flowchart of our proposed approach to estimating the effectiveness of AEB technology on environmental sustainability. The orange blocks represent input data sources (from the integrated database) that enable the analysis. We firstly perform data fusion based on the time stamp and location tags of accidents. By associating with each crash record, we obtain two sets of traffic data: 1) a representation of normal traffic conditions without accident occurrence, which helps construct a deep learning model for predicting the "accident-free" traffic states; and 2) the actual traffic conditions with the occurrence of accident, across a spatiotemporal region large enough to cover all of the potential impacts. Enlightened by the image processing, we develop a data-driven algorithm to determine the accident-impacted area in both space and time. After identifying the impact region and predicting the traffic conditions under a "what-if" scenario (i.e., no accident), we apply the U.S. Environmental Protection Agency's Motor Vehicular Emissions Simulator (MOVES) model [*33*] to conduct energy/emissions analysis. In the following, we elaborate on three key modules (see red boxes in Figure 3) as well as the associated models (i.e., green blocks) in the overall workflow. These modules are: *spatiotemporal impact region identification*, *accident-free traffic condition prediction*, and *energy/emissions impact estimation*.

Figure 3. Overall Flowchart of Our Proposed Methodology



Spatiotemporal Impact Region Identification

The purpose of this module is to identify the impacted area of the incident (that can be potentially avoided by AEB technology) in both space and time, so that the following energy/emissions analysis can capture the full effect. To achieve this goal, we first construct a "baseline" spatiotemporal speed table based on available resolutions from the data. Figure 4 presents an example of such table where the *i*-th row represents the *i*-th road segment covered by the infrastructure-based sensor, and the *j*-th column represents the data collection duration at the *j*-th time stamp. For each cell in the baseline speed table, the value is determined as the *p*-th percentile of all speed data samples collected within that segment over multiple historical days (when no traffic accidents occur). More specifically, the *p*-th percentile speed over *D* days at the *i*-th road segment (or loop detector station) during the *j*-th discrete time interval (e.g. 5 minutes), denoted by $v^p(i,j)$, can be defined as:

$$P\left(v_d(i,j) \leq v^p(i,j)\right) \geq p \quad \forall d = 1, 2, \cdots, D$$

where $\mathrm{P}(\cdot)$ represents the probability and $\mathrm{v_d(i,j)}$ is the speed at road segment *i* at time window *j* on the *d*-th day. In this study, we choose the median (or the 50th percentile) of all speed data samples across one month (when no traffic accidents occur) to represent the baseline value. This assumes that the median of speed distributions over a period of time (if long enough) can be representative of recurring traffic states, and non-recurrent effects (if any) can be mitigated.

By comparing the spatiotemporal speed table on the crash day (as shown in Figure 4(b)) with the baseline table (as shown in Figure 4(a)), we may flag those cells (in red) whose speeds are lower than the baseline value by certain threshold [*34*], i.e.,

$$flag(i,j) = \begin{cases} 1, & v^{Acc}(i,j) \leq v^{Base}(i,j) - c(i,j) \\ 0, & \text{otherwise} \end{cases}$$

where $v^{Acc}(i,j)$ represents the speed of $cell(i,j)$ (i.e., at the *i*-th road segment within time window *j*) when the accident occurs; $v^{Base}(i,j)$ is the baseline speed; and $c(i,j)$ denotes the threshold value for $cell(i,j)$. In this study, we apply the *Otsu*'s method to determining the threshold that can maximize inter-class variance [*35*].

Figure 4. An Example of Spatiotemporal Speed Tables for Both Baseline and Incident Day

Time →

Traffic Direction ↑

Speed(mph)	00:00	00:05	00:10	00:15	…	23:50	23:55
N	72	72	73	71	…	68	70
N-1	70	74	70	75	…	67	65
N-2	72	75	71	68	…	64	66
….	…	…	…	…	…	…	…
2	…	…	…	…	…	…	…
1	…	…	…	…	…	…	…

(a) Baseline ("incident-free") case

Time →

Traffic Direction ↑

Speed(mph)	00:00	00:05	00:10	00:15	…	23:50	23:55
N	71	69	73	72	…	66	72
N-1	72	60	40	45	…	70	69
N-2	71	70	55	40	…	68	68
….	…	…	…	…	…	…	…
2	…	…	…	…	…	…	…
1	…	…	…	…	…	…	…

(b) Case with incident occurrence

Threshold determination

In this study, the first step of Otsu's method is to generate a table of the speed difference between baseline speed and accident speed, which is calculated by

$$\Delta v(i,j) = v^{Acc}(i,j) - v^{Base}(i,j)$$

Then we can have a histogram for L sections of speed difference, and the frequency of i-th section can be computed as

$$p_i = f_i / N$$

where f_i is the number of cells within section i, and N is the total number of cells in the table.

Since there are two classes in the study region, the affected (C_1) area and non-affected area (C_2), we can find a threshold to distinguish the affected area from the study region by maximizing the inter-class variance σ_B^2. The problem can be described as:

$$\max_t \sigma_B^2 = w_1(\mu_1 - \mu_T)^2 + w_2(\mu_2 - \mu_T)^2$$

where the weights for each class are:

$$w_1 = \sum_{i=1}^{t} p_i$$

and

$$w_2 = \sum_{i=t+1}^{L} p_i$$

and t is the threshold to separate two classes, the mean value for each class:

$$\mu_1 = \frac{1}{w_1} \sum_{i=1}^{t} ip_i$$

and

$$\mu_2 = \frac{1}{w_2} \sum_{i=t+1}^{L} ip_i$$

and the mean value for the whole table:

$$\mu_T = w_1\mu_1 + w_2\mu_2$$

Impact boundary determination

However, this threshold-based method when applied to real-world data may result in disconnected cells. Considering that progression of an accident shockwave should be (theoretically) uninterrupted, a three-layer filtering algorithm is performed on the flagged (binary) spatiotemporal speed table to guarantee continuity of the impact region. As explained in Algorithm 1, the filter consists of noise reduction layer [*36*], morphological closing operation layer, and morphological opening operation layer [*37*], processing the information in such an order. Considering the temporal characteristics of the shockwave, a morphological structuring element (M_t), is adopted to keep the shockwave continuous in time. For example, if the resolution of the data is 5-min, $M_t = [1 \quad 1 \quad 1]$ assumes the accident lasts at least for 15 minutes (3 consecutive cells in time). Similar to the design of M_t, a structuring element (M_s) is chosen to maintain the spatial continuity. Provided that the traffic congestion or shockwave should propagate upstream along the road segment at certain (bounded) speed, we can define M_s as an upper triangular block matrix to filter out those unreasonable noises with respect to the shockwave propagation direction. For example, in this study, we apply

$$M_s = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix}$$

to trim the congested cells along the backward forming shockwave. It is noted that regarding the forward recovery shockwave, we do not apply any morphological operation, as real-world situations (e.g., re-routing of traffic) may complicate the evolution of recovery shockwave. Figure 5 illustrates how the affected areas keep updating after applying each filter layer.

Algorithm 1: Impact boundary determination

Input: 1) The raw-labelled impacted area table (T). 2) A threshold (P) of defining noise 3) A morphological structuring element (M_t) for temporal characteristic. 4) Morphological structuring element (M_s) for spatial characteristic.

Output: The ultimate impacted area table (T_{ult})

-Noise reduction layer-

1： Remove all connected components (objects) that have fewer than P cells from the binary T;

-Morphological closing layer-

2： Calculate the dilation of T by M_t:$T_1 = T \oplus M_t = \{z \in E \mid (M_t{}^s)_z \cap T \neq \emptyset\}$, where E is a Euclidean space or an integer grid, $M_t{}^s = \{x \in E \mid -x \in M_t\}$, and $(M_t{}^s)_z$ is the translation of $M_t{}^s$ by the vector z, i.e.,$(M_t{}^s)_z = \{b + z \mid b \in M_t\}, \forall z \in E$;

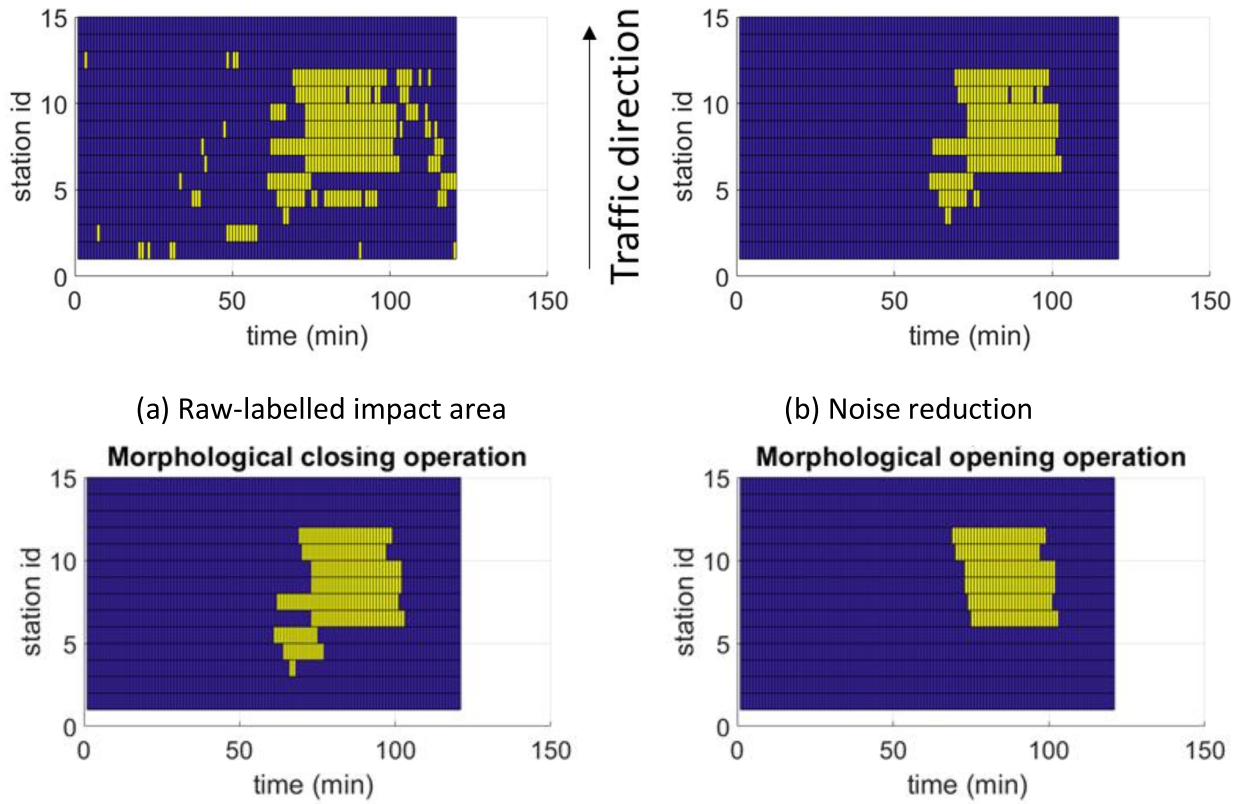
3： Calculate the erosion of T_1 by M_t:$T_2 = T_1 \ominus M_t = \{z \in E \mid M_{t_z} \subseteq T_1\}$, where M_{t_z} is the translation of M_t by the vector z;

-Morphological opening layer-

4: Calculate the erosion of T_2 by M_s: $T_3 = T_2 \ominus M_s$;

5: Calculate the dilation of T_3 by M_s: $T_{ult} = T_3 \oplus M_s$;

Figure 5. Impact Area during the Process of Impact Boundary Determination



(a) Raw-labelled impact area

(b) Noise reduction

(c) Morphological closing operation

(d) Morphological opening operation

Incident-Free Traffic Condition Prediction

Once we identify the spatiotemporal region affected by an accident, we can reconstruct (predict) traffic conditions of the “what-if” scenario, i.e., assuming if the accident did not occur. In this study, we adopt the *Long Short-Term Memory* (LSTM) model [*38*] to predict “accident-free” traffic condition, due to its capability to capture both historical traffic patterns for long-term reference and short-term information right before accident occurrence. The data structure for LSTM is illustrated in Figure 6, where the normal traffic dataset (without accident) at each station over a long period (e.g., one month) is differentiated by the day of week (considering different traffic patterns for weekdays and weekends). The model is then trained for each day of week across all the stations within the spatiotemporal impact region identified in previous section. As presented in Figure 7, the network consists of two LSTM layers, each followed by one dropout layer, and four fully connected layers. This network takes traffic measurements of certain time window, right before the accident (based on the region described above) to predict traffic states for the next time window. The selection of prediction window may depend on the identified temporal span due to the accident.

Figure 6. Data Structure for LSTM

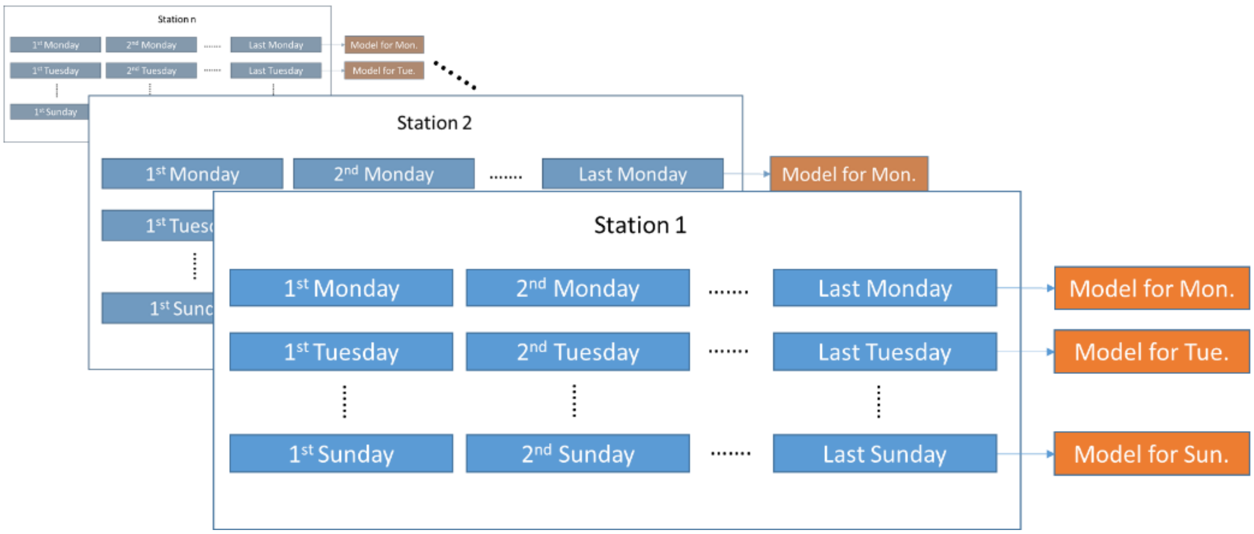


Figure 7. LSTM Network Structure

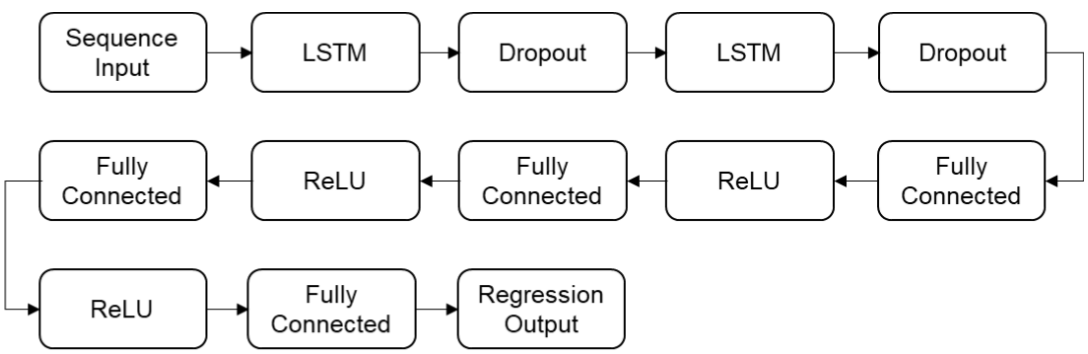
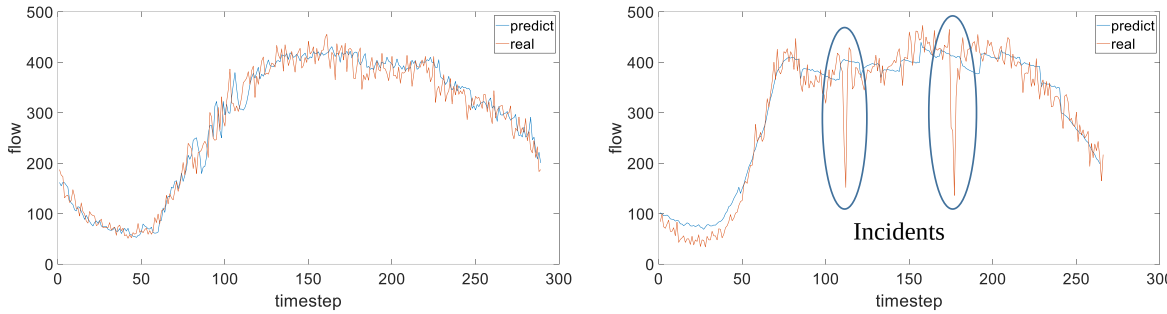


Figure 8 presents two examples of flow (the number of vehicles passing a reference point per unit time, e.g., 5 minutes) prediction from the model, one for a normal day and the other for an accident day, where predicted flow (in blue) can fit actual flow (in red) very well. In particular, for the day with two incidents (Figure 8(b)), our model is effective in predicting the hypothetical flow if those two accidents did not occur. The root mean square errors (RMSE) of our LSTM model (after training) are 2.7 mph for speed prediction, 1.9 vehicles per hour for flow prediction in a validation dataset.

Figure 8. Examples of Traffic State Prediction with the Proposed LSTM Model



(a) Normal day (b) Accident day

Energy/Emissions Impact Estimation

Based on: 1) the actual traffic state (e.g., average speed) with incident occurrence; and 2) predicted traffic state with the assumption of no accident, we can synthesize snippets of representative second-by-second driving cycles for each cell in the identified spatiotemporal region under two scenarios (actual vs. hypothetical), and estimate the environmental performance for comparison. To construct the typical trajectories, we employ the default driving cycles in USEPA's MOVES database differentiated with source type, roadway type and average speed. Table 2 lists the index of default driving cycles in MOVES for light-duty vehicles. These driving cycles have approximate average speeds ranging from 2.5 mph to 76 mph. Note that some driving cycles may apply to freeways (in either rural or urban areas), while others are for non-freeways. In this study, we only use those driving cycles collected from urban freeway scenarios.

Table 2. MOVES Driving Cycle Index for Light-duty Vehicles (Adapted from [*39*])

ID	Cycle Name	Average Speed	Non-Freeway		Freeway	
			Rural	Urban	Rural	Urban
101	LD Low Speed 1	2.5	X	X	X	X
1033	Final FC14LOSF	8.7			X	X
1043	Final FC19LOSAC	15.7			X	X
1041	Final FC17LOSD	18.6	X	X		
1021	Final FC11LOSF	20.6			X	X
1030	Final FC14LOSC	25.4	X	X		
153	LD LOS E Freeway	30.5			X	X
1029	Final FC14LOSB	31.0	X	X		
1026	Final FC12LOSD	20.6		X		
1020	Final FC11LOSE	46.1			X	X
1011	Final FC02LOSDF	49.1	X			
1025	Final FC12LOSE	46.1		X		
1019	Final FC11LOSD	58.8			X	X
1024	Final FC12LOSC	63.7	X	X		
1018	Final FC11LOSC	64.4			X	X
1017	Final FC11LOSB	66.4			X	X
1009	Final FC01LOSAF	73.8	X	X	X	X
158	LD High Speed Freeway 3	76.0	X	X	X	X

With MOVES default driving cycle, the second-by-second representative speed trajectory for each cell can be synthesized by following these steps:

1. Select two MOVES driving cycles whose average speeds bracket the observed traffic speed at a detection station. For example, if the observed traffic speed in $cell(i,j)$ is 55 mph, then Driving Cycle 1019 (with the average speed of 58.8 mph) and Driving Cycle 1020 (with the average speed of 46.1 mph) were selected for trajectory synthesis;
2. Create speed-acceleration frequency distributions for the two selected driving cycles. In this study, bin sizes for speed and acceleration values are 2 mph and 2 mph/s, respectively;
3. Set the initial speed $v(0)$ as the observed traffic speed at detection station (e.g., 55 mph);
4. Randomly pick one of the two selected driving cycles as a lottery pool for determining acceleration value of next step. The probability of choosing the target driving cycle is calculated by how close the current speed is to the average speed of the target driving cycle. The closer these two values are, the more likelihood the target driving cycle would be selected. Using the same example, since $v(0)$=55 mph, the probability of choosing Driving Cycle 1019 is

$$p_1 = 1 - \frac{(58.8 - 55)}{(58.8 - 46.1)} = 0.701$$

while the probability of choose Driving Cycle 1020 is $1 - p_1 = 0.299$;

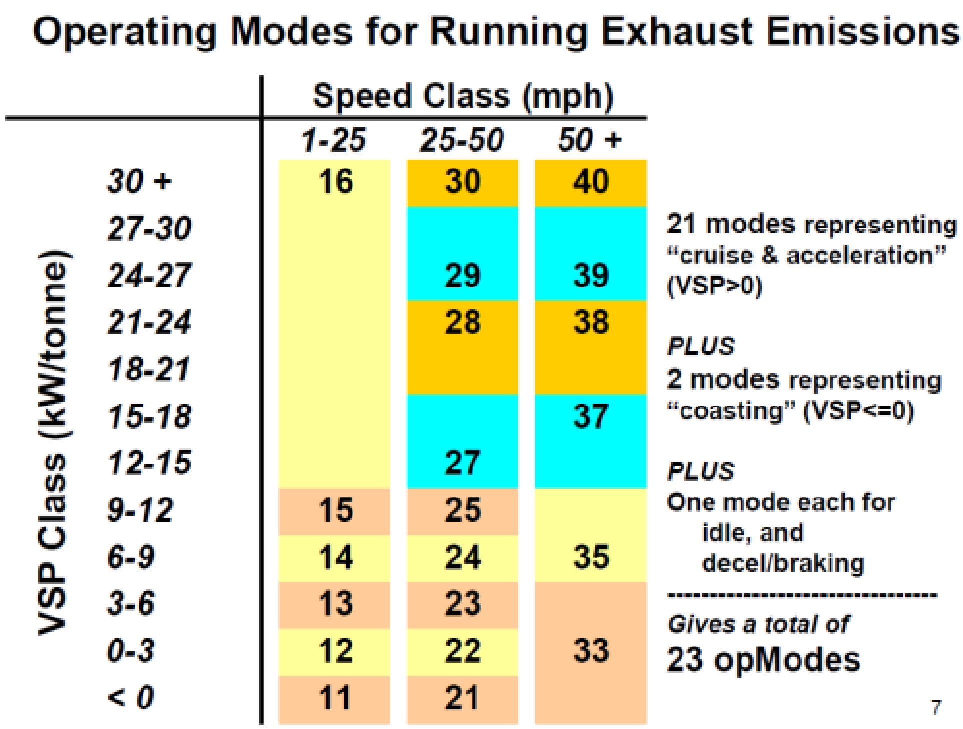
5. Randomly draw an acceleration value from the selected driving cycle in *Step 4* and use it to calculate the speed of the next time step;
6. Repeat *Step 4* and *Step 5* until cumulative travel distance of the synthesized trajectory is not less than the spatial coverage of $cell(i, j)$.

After synthesizing the second-by-second trajectory as a representative driving cycle for each cell, we can estimate the corresponding second-by-second Vehicle Specific Power (VSP) values (in kWatt/metric ton) for a light-duty vehicle (e.g., passenger car) using the equation below:

$$VSP = \frac{A \cdot v + B \cdot v^2 + C \cdot v^3 + m \cdot v \cdot (a + g \cdot \sin\theta)}{f_{scale}}$$

where A, B and C are road-load related coefficients for rolling resistance ($\mathrm{kW} \cdot \mathrm{sec/m}$), rotating resistance ($\mathrm{kW} \cdot \mathrm{sec}^2/\mathrm{m}^2$), and aerodynamic drag ($\mathrm{kW} \cdot \mathrm{sec}^3/\mathrm{m}^3$), respectively; m is mass of passenger car (metric ton); and f_{scale} is fixed mass factor for the source type (kg). Default values of these parameters are provided in [*39*]. In addition, v is vehicle speed (m/sec); a is vehicle acceleration (meter/sec^2); g is the gravitational acceleration (m/sec^2); and θ is the angle of road segment inclination (rad).

Figure 9. Vehicle Operating Mode Bin Definition in MOVES



Once second-by-second VSP values are calculated, they are used in conjunction with speed and acceleration data to determine the corresponding operating modes according to the definition in Figure 9 defined by MOVES. Based on second-by-second operating modes of the representative driving cycle for each cell, energy consumption and pollutant (e.g., CO, HC, NO_X, PM and CO_2) emissions at the cell level can be estimated from the lookup tables available in MOVES database. Therefore, the overall environmental impacts due to an accident can be calculated by summing the energy consumption and pollutant emissions of all the cells within the spatiotemporal region.

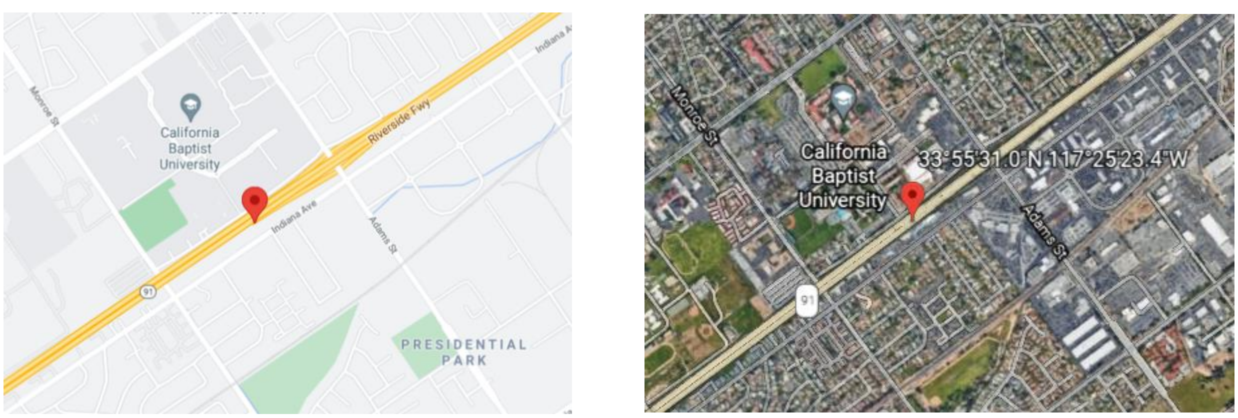
Case Study

In this section, we use real world data to prove the efficacy of our methodology for estimating accident-related environmental impacts, by assuming that AEB system was adopted in these accident-involved vehicles and took effects to avoid these collisions.

Case I: CA-91 in Riverside, CA

The first case is a rear-end one (involved with two vehicles), which occurred at 07:48:00 (PST time) on 05/16/2017 (Wednesday) along CA-91 highway in Riverside, California, whose location is illustrated in Figure 10. The update rate of this dataset (PeMS) is 5-minute. Following the aforementioned methodology, we obtain the speed contours for both typical day and accident day, and identify the continuous spatiotemporal affected region (in yellow) as shown in Figure 11. In total, there are 39 affected cells, covering the region of 6 stations (in space) and 55 minutes (in time), and 6 LSTM models are trained for traffic state prediction. As shown in Figure 12, there are two speed drops on that day. The LSTM model identifies the first speed drop from 69 to 79 (time step) is due to the accident, and the second one is a normal traffic jam predicts a normal speed, and thus generates a hypothetical speed for this accident.

Figure 10. Location of the Accident



(a) Google map (b) Satellite image

Figure 11. Incident Affected Area Analysis

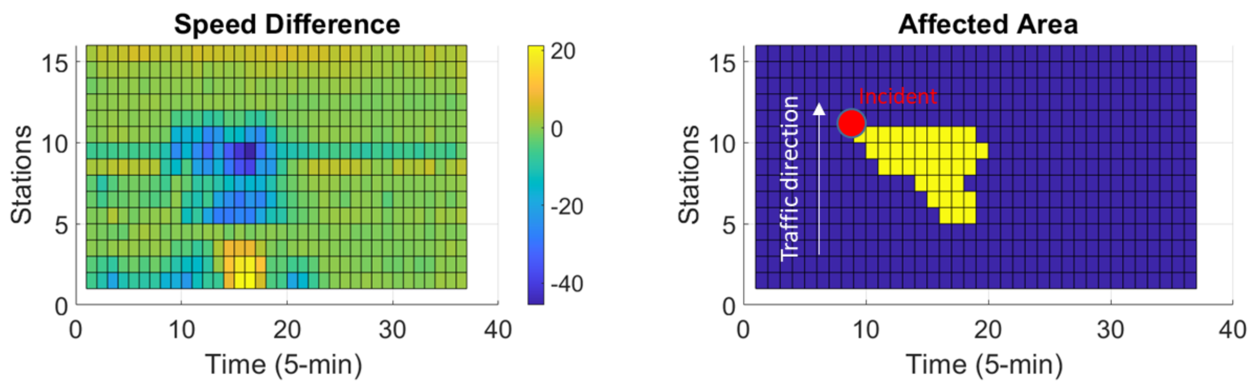
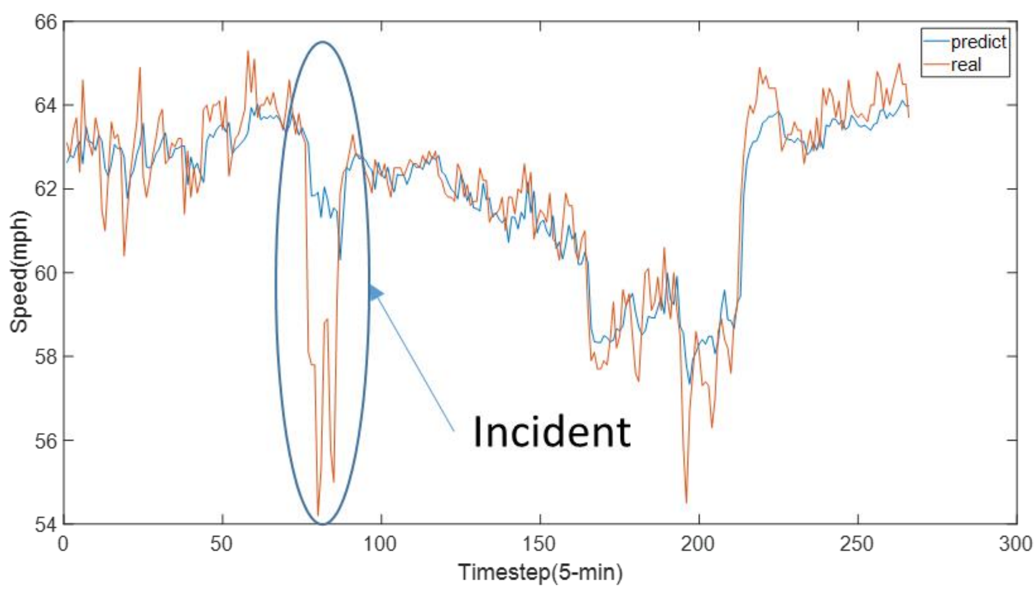


Figure 12. Speed profile (5-minute) Prediction Result for An Affected Station



We calculate the emission and fuel consumption as shown in the Table 3. It can be observed that if this studied accident could be avoided or significantly mitigated, then energy consumption within the spatiotemporal impact region would be reduced by up to 14.99% and the resultant pollutant emissions (such as CO, HC, NOx, PM and CO2) would decrease by as much as 17.59%.

Figure 13. Incident Affected Area Analysis

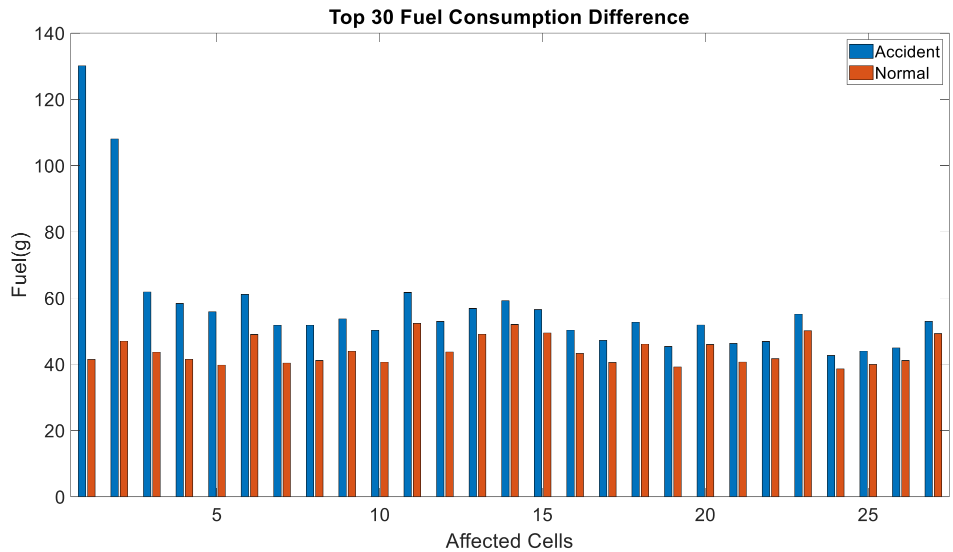


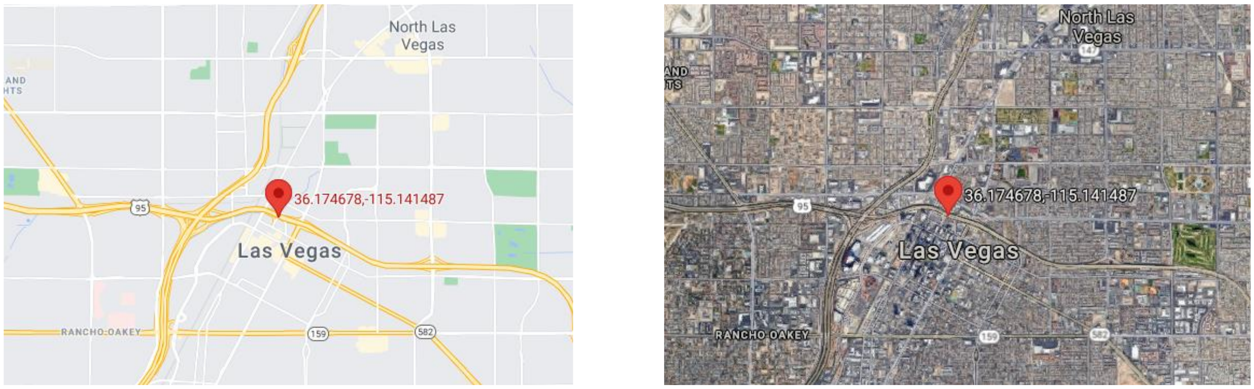
Table 3. Estimated Environmental Impact of Entire Spatiotemporal Region due to the Accident

	CO(g)	HC(g)	NOx(g)	PM2.5_Ele(g)	PM2.5_Org(g)	Energy(KJ)	CO2(g)	Fuel(g)
Actual (with accident)	12.14	0.117	0.55	0.008	0.04	107295.99	7633.90	2390.80
Predicted (if incident-free)	10.00	0.115	0.71	0.007	0.03	91212.48	6489.59	2032.42
Reduction (%)	17.59	1.71	-28.31	12.5	16.67	14.99	14.99	14.99

Case II: US-95 in Las Vegas, NV

The second rear-end case occurred at 21:27:00 (UTC time) on 01/02/2020 (Thursday) along US-95 highway in Las Vegas, Nevada, whose location is illustrated in Figure 14. The traffic data were collected from inductive loop detectors with 1-minute update (different from the 5-minute resolution dataset in Case 1). Based on the location of the accident, we first identify the set of nearest detection stations (upstream) according to the road section and detector configuration information. The set of stations is large enough to spatially cover potential impacted area by this incident. Following the aforementioned methodology, we obtain the speed contours for both typical day and accident day, and identify the continuous spatiotemporal affected region (in yellow) as shown in Figure 15. In total, there are 174 affected cells, covering the region of 6 stations (in space) and 34 minutes (in time). Therefore, we train 6 LSTM models for traffic state prediction, and Figure 16 presents the predicted speed profile (in blue) of the fourth (upstream) affected station during the accident period.

Figure 14. Location of the Accident



(a) Google map

(b) Satellite image

Figure 15. Incident Affected Area Analysis

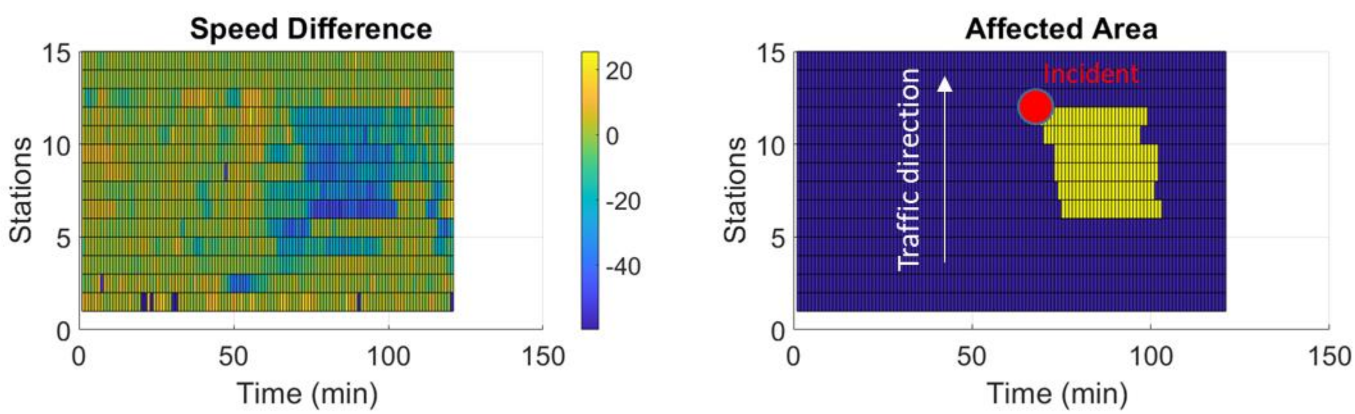
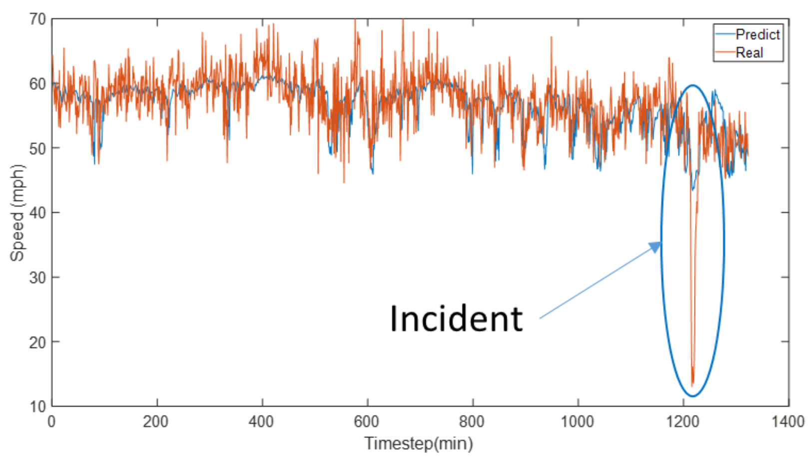
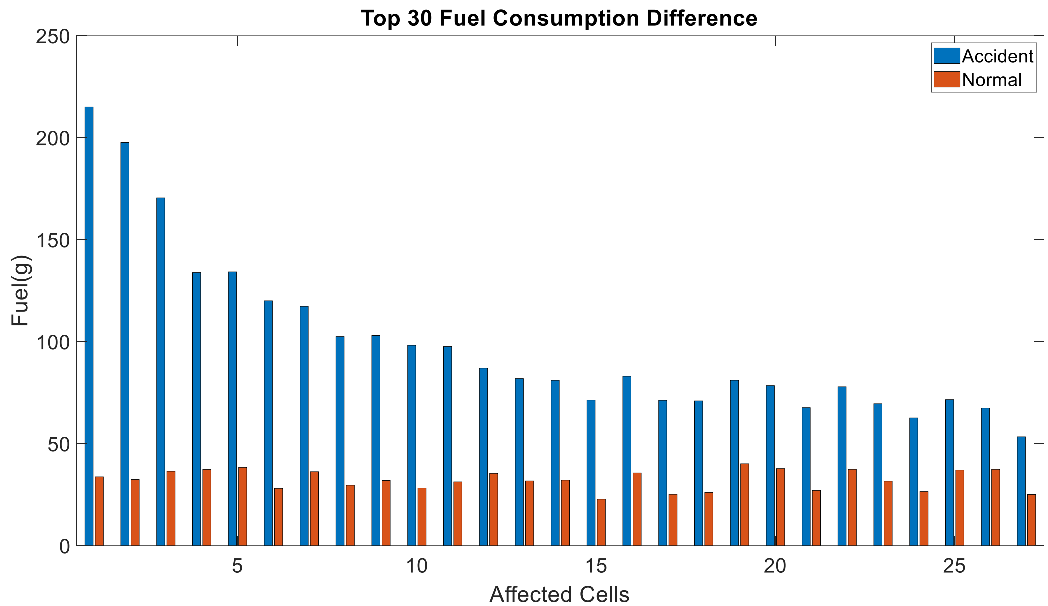


Figure 16. Speed Profile (1-minute) Prediction Result for An Affected Station



Pacific Southwest Region UTC
University Transportation Center

Figure 17. Top 30 Cells with Most Significant Fuel Consumption Difference between Normal States and Accident States



Next, we synthesize second-by-second speed trajectory for each cell within the spatiotemporal impact area and estimate the accident-induced energy/emissions effects with MOVES model. Figure 17 shows the results for the top 30 cells (out of 174 cells) whose estimated environmental impacts by the accident (i.e., the difference in fuel consumption between the actual and predicted conditions) are most significant. By summing up all affected cells, the overall accident-induced environmental impacts in terms of energy consumption and pollutant emissions are summarized in Table 4. As shown in the table, if this studied accident could be avoided or significantly mitigated, then energy consumption within the spatiotemporal impact region would be reduced by up to 34.6% and the resultant pollutant emissions (such as CO, HC, NOx, PM and CO_2) would decrease by as much as 22.5%.

Table 4. Estimated Environmental Impact of Entire Spatiotemporal Region due to the Accident

	CO(g)	HC(g)	NOx(g)	PM2.5_Ele(g)	PM2.5_Org(g)	Energy(KJ)	CO2(g)	Fuel(g)
Actual (with accident)	36.92	0.31	1.14	0.024	0.11	378107.4	26901.59	8425.09
Predicted (if incident-free)	28.62	0.3	1.51	0.02	0.09	247451.1	17605.65	5513.77
Reduction (%)	22.5	4.1	-32.1	16.7	17.4	34.6	34.6	34.6

Conclusions and Future Work

In this study, we developed a methodology to estimate potential environmental impacts due to the introduction of AEB system, owing its effectiveness of collision avoidance. The main idea of this approach was to first identify the target accident that can be potentially avoided by AEB system. Then, the spatiotemporal impact region by the target accident was estimated with the *Otsu*'s method and morphological operations. Once the region was determined, the *Long Short-Term Memory* (LSTM) technique was applied to historical data to predict hypothetical traffic conditions if the accident was successfully avoided due to the deployment of AEB system. Based on both the predicted ("what-if" scenarios without accident) and actual (scenarios with accident occurrence) traffic states, we applied the U.S. EPA's MOVES model to estimate energy/emissions effects within the affected region, and estimated the differences between two types of scenarios. It is noted that due to the complexity in real-world traffic (e.g., re-routing) and unavailability of traffic information on the local streets, we estimated the environmental impact based on speed variation (i.e., assuming a typical speed trajectory traversing the affected region under the "what-if" scenario and actual scenario). We used real-world data of an accident collected in Riverside, California to show the efficacy of our approach. The results showed that the energy consumption and pollutant (such as CO, HC, NOx and PM) emissions could be reduced by up to 15% and 18%, respectively, if AEB technology were adopted in the accident-involved vehicles and effectively prevented the studied accident from occurrence.

As one of the future steps, we will evaluate the proposed method in extensive datasets by further considering other factors such as road grade, vehicle mix, and meteorological conditions, which may affect the effectiveness of AEB system. In addition, comprehensive models will be developed for traffic state prediction, which should not only model the spatial and temporal correlation across all the affected stations but also address potential re-routing effect due to the accident occurrence.

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Data Management Plan

Products of Research

In this project, two types of data are used: the accident data from the Highway Safety Information System (HSIS) and the traffic data from the Caltrans Performance Measurement System or PeMS (http://pems.dot.ca.gov/). The HSIS data will be used for accident analysis. The traffic data will be used to calculate the "baseline" spatiotemporal speed table and to train the Long Short-Term Memory (LSTM) model.

Basically, HSIS is a multi-state database, where the California portion is derived from the California TASAS (Traffic Accident Surveillance and Analysis System). This system, maintained by the Traffic Operations Office (TO) of CALTRANS, is a mainframe-based system based on COBOL programming. The accident data from TO Office provides not only accident inventory but also detailed information about the geometrics and other characteristics of roadways, interchange ramps, and intersections, such as the number of lanes, roadway width, design speed, ramp's location, and horizontal and vertical alignment, as well as weather and lighting conditions.

PeMS receives real-time measurements (with different temporal resolutions) on traffic count and lane occupancy from each inductive loop detector (ILD) throughout the California freeway system. In this study, we focus on the segment affected by the accident in Southern California and extract 5-min aggregated data from the affected vehicle detection stations (VDS) in PeMS. The temporal span would be 24 hours.

Data Format and Content

The format of HSIS data is in .csv, and four types of data files are provided, including accident data, vehicle data, occupant data, and roadway inventory data.

The data archived in PeMS can take the format in .txt, containing only one type of data, which is the 5-min aggregated data from the affected vehicle detection stations (VDS).

Data Access and Sharing

In this project, for HSIS data, we requested it from the official website of HSIS: (https://www.hsisinfo.org/datarequest.cfm).

For PeMS data, we will download the zipped file (in .txt after unzipping) from the "Data Clearing House".

The data are available publicly via DataDRYAD: https://doi.org/10.6086/D1D11H

Reuse and Redistribution

The PIs and Regents of the University of California will hold the intellectual property right for the data created, e.g., tailored PeMS data and HSIS data. The data from Waycare Technologies, Inc. is considered to be confidential. The PIs do not see any other legal requirements that need to be addressed.