Texas A&M Transportation Institute

Explore Studies and Datasets to Assess the Applicability of Developing Heavy-Duty Vehicle Idling Activity Used in Onroad Emissions Inventories for Conformity and State Implementation Plans

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LIST OF ACRONYMS

- **AACOG**: Alamo Area Council of Governments
- **AADTT**: Annual Average Daily Truck Traffic
- **APU**: Auxiliary Power Unit
- **ATA**: American Trucking Associations
- **ATRI**: American Transportation Research Institute
- **BPA**: Beaumont–Port Arthur
- **CAPCOG**: Capital Area Council of Governments
- **CMV**: Commercial Motor Vehicle
- **DVIR**: Driver-Vehicle Inspection Report
- **ECU**: Engine Control Unit
- **ELD**: Electronic Logging Device
- **EMFAC**: Emission Factor Model
- **ERG**: Eastern Research Group
- **FAF4**: Freight Analysis Framework
- **FHWA**: Federal Highway Administration
- **FMCSA**: Federal Motor Carrier Safety Administration
- **GIS**: Geographic Information System
- **GVWR**: Gross Vehicle Weight Rating
- **HDDT**: Heavy-Duty Diesel Truck
- **HDV**: Heavy-Duty Vehicle
- **HOS**: Hours of Service
- **INRIX**: A provider of real-time traffic information and analytics
- **LSTM**: Long and Short Term Memory
- **MOVES**: Motor Vehicle Emissions Simulator
- **MPO**: Metropolitan Planning Organization
- **MSA**: San Antonio-New Braunfels Metropolitan Statistical Area
- **NCHRP**: National Cooperative Highway Research Program
- **NHS**: National Highway System
- **NOx**: Nitrogen Oxides
- **NPMRDS**: National Performance Management Research Dataset
- **OD**: Origin-Destination
- **PM**: Particulate Matter
- **SIP**: State Implementation Plan
- **SOC**: State of Charge
- **STAC**: State Transportation Advisory Committee

- **SXSW**: South by Southwest Conference and Festivals in Austin and Hurricane Imelda
- **TCEQ**: Texas Commission on Environmental Quality
- **TMC**: Traffic Management Centers
- **TPVR**: TxDOT Truck Parking Visualization Resource
- **TTI**: Texas A&M Transportation Institute
- **TxDOT**: Texas Department of Transportation
- **VDOT**: Virginia Department of Transportation
- **VOC**: Volatile Organic Compound

EXECUTIVE SUMMARY

Accurate determination of Heavy-Duty extended idling is crucial for emissions inventories, which are essential for conformity and State Implementation Plans (SIPs). The EPA's Motor Vehicle Emission Simulator (MOVES) currently estimates extended idling emissions using default values, activity data, and emission rates, but its accuracy relies on the quality of input data. MOVES uses national averages and assumptions that may not reflect local conditions and specific idling behaviors. Enhancing the precision of these estimates requires detailed data collection and analysis of real-world idling patterns, including idling duration, frequency, location-specific factors, and the use of auxiliary power units (APUs). Integrating high-resolution data from sources such as GPS tracking, electronic logging devices (ELDs), can develop more accurate and location-specific idling profiles.

The objectives of the study include reviewing previous studies and data sources to analyze past research and identify gaps, evaluating current data sources for relevance, accuracy, and completeness, proposing enhancements for more accurate estimation of truck idling activities and emissions, integrating probe data to improve granularity and accuracy of idling activity estimates, and developing a study plan for future data collection, analysis, validation, and model refinement.

The key findings from previous studies indicate that idling emissions, contribute substantially to overall on-road emissions, posing challenges to air quality and public health. Previous studies have evolved in their methodologies, from initial estimates to advanced data analytics. Despite advancements, gaps remain in capturing real-time idling behavior. EROAD data, collected from electronic logging devices (ELDs) due to Hours of Service (HOS) compliance, offers comprehensive insights into idling patterns, making it a valuable source for accurate idling activity estimation. The integration of advanced techniques like Bayesian optimization and machine learning can significantly enhance the accuracy and reliability of idling activity estimates.

The proposed study plan involves acquiring EROAD data and other data collection from various sources including GIS databases, and vehicle movement data. Advanced models such as Bayesian and machine learning models will be implemented to simulate idling behavior accurately. Facility typology will be defined to categorize types of parking facilities and quantify parking spaces by county and facility type. The study plan will also examine the availability and usage of Auxiliary Power Units (APUs) from EROAD data.

1 INTRODUCTION

1.1 BACKGROUND

Heavy-duty vehicle idling is a significant contributor to on-road emissions [1]. Accurate determination of heavy-duty extended idling is crucial for on-road emissions inventories, which are essential for conformity and State Implementation Plans (SIPs) [1]. The Environmental Protection Agency's (EPA) Motor Vehicle Emission Simulator (MOVES) is the current tool used to estimate extended idling emissions [2]. MOVES utilizes a combination of default values, activity data, and emission rates to model idling emissions from heavy-duty vehicles [3]. However, the accuracy of these estimates heavily depends on the quality and representativeness of the input data. MOVES estimates extended idling emissions based on parameters such as the frequency and duration of idling events, vehicle types, and environmental conditions. The tool relies on national averages and assumptions, which may not accurately reflect local conditions and specific idling behaviors [3].

Improving the accuracy of activity data used in MOVES is essential for enhancing the precision of on-road emissions inventories. Accurate determination of extended idling activities involves detailed data collection and analysis of real-world idling patterns, including the duration and frequency of idling events, location-specific factors, and the use of auxiliary power units (APUs) [4]. By integrating high-resolution data from sources such as GPS tracking, electronic logging devices (ELDs), and field surveys, it is possible to develop more accurate and location-specific idling profiles [5].

Previous studies have underscored the importance of understanding and mitigating idling emissions. For instance, the Texas Transportation Institute (TTI) has conducted multiple studies over the years, highlighting the evolution of methodologies and the persistent gaps in accurately estimating and addressing idling activities [1], [4], [5]. These studies have ranged from developing initial methodologies to employing advanced data analytics and integrating real-time data sources. Despite these efforts, the dynamic nature of freight movement and the variability in idling behavior necessitate ongoing research and refinement of estimation techniques.

1.2 OBJECTIVES

The primary objective of this study is to explore and evaluate the applicability of developing heavy-duty vehicle idling activity data for use in on-road emissions inventories. This involves a comprehensive review of existing data sources, methodologies, and studies related to truck idling in Texas. Specific objectives include:

- Reviewing Previous Studies and Data Sources: Analyzing past research and data to understand the methodologies used and identify gaps and limitations.
- Evaluating Current Data Sources: Assessing the available data sources for their relevance, accuracy, and completeness in estimating idling activities.
- Methodology Enhancement: Proposing enhancements to current methodologies for more accurate estimation of truck idling activities and emissions.
- Integration of Probe Data: Exploring the integration of probe data to improve the granularity and accuracy of idling activity estimates.
- Developing a Study Plan: Outlining a plan for future studies to collect and analyze data, validate findings, and refine estimation models.

This report aims to provide a robust framework for estimating heavy-duty vehicle idling activities and emissions, leveraging advanced data sources and analytical techniques.

2 LITERATURE REVIEW

Over the years, Texas has proactively addressed the environmental impact of heavy-duty diesel truck (HDDT) idling, with multiple studies aimed at understanding and mitigating these impacts. This section delves deeper into these studies, emphasizing the evolution of research methodologies, findings, and the remaining gaps, particularly highlighting the extensive study done by TTI in 2019.

2.1 2003 TTI STUDY

This study focused on developing a robust methodology for estimating extended idling emissions from heavy-duty diesel vehicles (HDDVs) in Texas. The study specifically catered to Classes 7 and 8 trucks, which are typically long-haul vehicles weighing more than 26,001 lbs [1].

The study used the EPA's MOBILE6 model, which categorizes heavy-duty vehicles based on gross vehicle weight rating (GVWR), focusing on vehicles over 26,001 lbs (Classes 7 and 8). The study used the EPA's MOBILE6 model, which categorizes heavy-duty vehicles based GVWR, focusing on vehicles over 26,001 lbs (Classes 7 and 8).

The Beaumont–Port Arthur (BPA) area was selected as a study area due to its nonattainment status and significant truck traffic. The area's high ozone levels are exacerbated by local industry emissions and traffic from major truck routes like the I-10 corridor. The data collection was conducted on Thursday, July 10, and Friday, July 11, 2003.

Observations and interviews were conducted at truck stops, rest areas, industries, and ports. The study noted the extensive amenities at major truck stops like Petro Stopping, Flying J, and Pilot, which influenced idling behavior.

Emissions factors varied significantly based on engine load, idle speed, and engine type. The study adopted NOx emissions rates of 135 g/h and $PM_{2.5}$ rates of 3.68 g/h for its analysis. The methodology involved calculating emissions based on the truck-hours of idling, integrating truck stop capacities, average occupancy, and idling rates. A significant finding was that, on average, 70% of trucks at any given truck stop were idling. The methodology developed from the BPA case study was expanded to estimate emissions across Texas. Additional data points included railway yards and statewide truck stops identified through various databases. The methodology developed from the BPA case study was expanded to estimate emissions across Texas. Additional data points included railway yards and statewide truck stops identified through various databases. The study highlighted that extended truck idling contributed 2.0% and 3.7% to the total on-road NOx and $PM_{2.5}$ emissions, respectively, in nonattainment areas. These emissions, while seemingly small, play a crucial role in achieving conformity with air quality standards.

The study suggested several improvements to enhance the accuracy of emissions estimates, including better spatial and temporal coverage and a more detailed analysis of vehicle types and idling patterns. The findings underscore the importance of targeting truck idling emissions as part of broader strategies to reduce transportation-related air pollution in Texas[1].

2.2 Eastern Research Group (ERG) and Collaborative Efforts:

ERG's August 2004 study developed a comprehensive on-road heavy-duty vehicle (HDV) extended idling activity database for Texas [6]. By surveying various idling locations including truck stops and intermodal facilities, ERG provided an emission estimate of 29.61 tons/day for the 2004 base year. The study was conducted from June 28, 2004, and ending August 27, 2004 at different time frames as below

- Daytime – All MPOs
- 24 hr – Houston and Dallas
- Nighttime – Intermodal Hubs and Border crossings

Collaborative efforts with Cambridge Systematics Inc. and Alliance Transportation Group, Inc. supported ERG's initiative, enhancing the scope and accuracy of the emissions database and modeling processes [6].

2.3 AACOG STUDY

The AACOG study provides an extensive examination of heavy-duty truck idling in the San Antonio area, focusing on the environmental impact of emissions from long-haul diesel trucks during mandatory rest periods. This analysis highlights the importance of assessing idling emissions due to the high volume of truck traffic, particularly along major highways such as IH-35 and IH-10, which intersect in San Antonio [7].

Key data sources for this study include truck stop surveys, direct observations, and various databases provided by governmental and private entities such as TxDOT and facility managers. The study utilized a combination of visual surveys and data analysis to identify and categorize truck idling patterns across different locations, including truck stops, rest areas, and picnic areas within the San Antonio-New Braunfels Metropolitan Statistical Area (MSA).

The methodology employed in the study is comprehensive, involving multiple data collection phases to ensure robust emissions inventories. Surveys were conducted at different times of day and week to capture temporal variations in idling behavior. Each surveyed location was visited multiple times to validate data consistency and reliability. The study was conducted in different phases as listed below

- November 2010 - 9 surveys
- March 2011 - 48 surveys
- April 2011 - 38 surveys
- May 2011 - 61 surveys June 2011 - 59 surveys

The emissions were calculated using the MOVES model 2010, which factors in the idling hours and specific idling locations to provide a detailed view of potential environmental impacts.

The study found significant idling at truck stops and rest areas, with the primary data indicating that idling contributes substantially to local NOx and VOC emissions. This is critical for air quality management, especially considering San Antonio's proximity to non-attainment status under national air quality standards due to elevated ozone levels. The findings underscore the need for targeted interventions to reduce idling times and promote cleaner technologies, such as truck stop electrification and the use of auxiliary power units.

Moreover, the study discusses the implications of idling for regional air quality planning and compliance with environmental regulations. It suggests integrating the findings into photochemical modeling to better predict ozone formation and evaluate emission control strategies effectively.

In summary, the Alamo study offers valuable insights into the scale of emissions from truck idling in a key logistical hub and outlines the necessity for ongoing research and policy measures to mitigate the environmental impact of freight operations in urban areas [7].

2.4 CAPCOG Study

In December 2013, TTI collaborated with the Capital Area Council of Governments (CAPCOG) to develop a regional inventory of extended idling locations and emissions in counties such as Bastrop, Caldwell, Fayette, Hays, Travis, and Williamson. This study involved extensive field surveys and interviews, providing a detailed analysis of idling patterns and their environmental impacts. As part of this study, TTI conducted: a) initial site visits to 16 potential trucks idling locations in Bastrop, Caldwell, Fayette, Hays, Travis, and Williamson counties; b) 176 observations at seven truck stops in Caldwell, Hays, Travis, and Williamson counties; c) 10 observations along interstate frontage roads in Hays, Travis, and Williamson counties; d) 14 observations at Walmart stores in Hays, Travis, and Williamson counties; and e) 118 interviews with truck drivers. The study was conducted during July 2011 through October 2011 [8].

2.5 NCHRP Guidebook to Truck Activity Data for Emission Modeling

The guide created under National Cooperative Highway Research Program (NCHRP) Project 08-101 is designed to aid transportation practitioners in capturing crucial truck activity data, vehicle characteristics, and operational details to estimate and forecast emissions from the movement of goods and services [9]. It focuses on providing input preparation methods for the EPA's Motor Vehicle Emissions Simulator (MOVES) model, which is widely used across the United States for emissions modeling, though it also offers insights useful for users of California's Emission Factor (EMFAC) model and other emissions estimation methods. This guide does not mandate specific practices but presents various data-gathering and processing options to enhance the accuracy of emissions models.

The guidebook detailed methodologies for estimating truck hotelling activities to improve emission modeling, specifically through the MOVES model. Hotelling refers to the periods when truck drivers rest in their vehicles, typically during mandatory rest times in long-haul deliveries. This activity is particularly noted in tractor-trailer combinations and involves significant idling times which are influential in emission calculations.

In MOVES2014, hotelling is defined with specific operational modes like extended idling of the engine, use of auxiliary power units (APUs), power from external sources, or having all systems off. Notably, before the 2010 model year, it was assumed that trucks used extended idling by default. Post-2010 models see a mixture of extended idling and APU use. However, the guide also points out that emissions from other types of trucks and non-highway idling scenarios (like loading or queuing) are not fully captured by the current MOVES model but are expected to be addressed in future updates.

The guide discusses project and county scale analysis for estimating hotelling hours. At the project scale, the focus is on specifying hotelling activity through the MOVES input tables like OffNetworkLink, with activities defined as fractions of the vehicle population engaged in extended idling. For county-scale analysis, total hotelling hours are input based on available data which might come from direct measurements or from proxies like parking space usage or telematics data, which can provide more granular insights into hotelling behavior.

One of the key discussions in the guide is the sensitivity of emissions estimates to the amount of hotelling activity. Recent data suggests that actual idling rates may be significantly lower than those assumed in MOVES2014, indicating potential overestimations in current emission forecasts.

For data collection, the guide recommends field surveys and purchasing GPS/ECU (Engine Control Unit) data, though it notes the challenges and high resource requirements of these methods. It also emphasizes the importance of local data generation, suggesting that field data can provide valuable real-world insights into idling patterns, which are crucial for refining emission models.

Overall, the guide stresses the evolving nature of data collection and modeling techniques and the need for continuous updating and validation of emission models to reflect the most accurate and current data available [9].

2.6 2019 TTI Study

In the 2019 Texas A&M Transportation Institute (TTI) report, researchers undertook a detailed analysis to identify and characterize potential hoteling idling sites for heavy-duty trucks across Texas [4]. These locations are vital for understanding the distribution and frequency of truck idling behaviors and include truck stops, rest areas, travel centers, and picnic areas. Data collected for each site encompassed attributes such as amenities, number of parking spaces, and the availability of overnight parking. This critical data collection facilitated the creation of a comprehensive database of hoteling locations, essential for projecting idling activities statewide.

The scope of potential hoteling locations in the study was broad, extending beyond typical rest areas and travel centers to include picnic areas and Walmart stores adjacent to freeways. The accuracy of the data was enhanced through collaborations with Texas Department of Transportation (TxDOT) facilities staff and thorough internet searches to compile and verify information from multiple sources. This rigorous data collection was crucial for the accuracy of the master idling location database, which featured an extensive list of sites with overnight parking capabilities.

The integration of Geographic Information System (GIS) datasets was a key component of the study, used primarily for quality assurance. Through the use of GIS, the TTI team was able to conduct spatial analyses to refine the data quality, particularly for truck stops, which constitute a significant portion of hoteling idling sources. Techniques included the use of satellite imagery to confirm the accuracy of location data and the number of parking spaces, along with visual inspections using Google Earth and Street View to verify the presence and condition of the facilities.

The report also explored the use of advanced data sources such as the Freight Analysis Framework (FAF4), which provides comprehensive data on freight movement and truck volumes. This framework was instrumental in refining the master idling location database by identifying potential utilization based on adjacent roadway truck volumes. It was noted, however, that FAF4 data might not always accurately reflect current active freight corridors, highlighting the limitations of using this data for detailed regional analysis.

A significant advancement in the study was the application of vehicle probe data to assess hoteling idling behavior. The team utilized large-scale datasets from the American Transportation Research Institute (ATRI) and INRIX, which provided detailed temporal and spatial data on vehicle movements. This information enabled a nuanced analysis of idling patterns at truck stops, rest areas, and other designated locations, thereby providing insights into idling durations and the distribution of idling incidents across different times and places.

In summary, the 2019 TTI report represents a comprehensive approach to estimating hoteling activity of heavy-duty trucks using advanced data sources and analytical techniques. The creation of a detailed idling location database, combined with the strategic application of GIS and vehicle probe data, offers valuable insights that could help inform policies and strategies aimed at reducing the environmental impact of truck idling [4].

2.7 2020 Cambridge Systematics Study on Truck Parking Inventory and Utilization

The 2020 study conducted by Cambridge Systematics for TxDOT evaluated the existing supply and demand for truck parking in Texas, identifying gaps and recommending solutions to address these needs [10]. This comprehensive study highlighted the importance of truck parking for the safe and efficient movement of freight, especially in light of Federal Motor Carrier Safety Administration (FMCSA) HOS regulations, which mandate rest periods for drivers.

The study documented the truck parking inventory across Texas, categorizing it by public and private ownership. The inventory included authorized truck parking locations such as publicly owned rest areas, privately owned truck stops, and other designated parking facilities. Attributes tracked for each location included the number of parking spaces, amenities, ownership type, and geographic coordinates. Texas has approximately 2,324 truck parking spaces at publicly owned locations, primarily in rural areas, to complement private facilities in urban regions. In contrast, there are around 25,000 truck parking spaces at 482 privately owned truck stops, which are preferred by truck drivers due to essential amenities such as fuel, food, restrooms, and repair services.

To analyze truck parking demand, the study used the Federal Highway Administration (FHWA) model and GPS data analysis. The FHWA model estimates demand based on key inputs such as Annual Average Daily Truck Traffic (AADTT), corridor length, and average speed, categorizing demand into short-term and long-term parking needs. GPS data from the American Transportation Research Institute (ATRI) provided detailed insights into truck parking utilization patterns, identifying peak parking times, stop durations, and regional disparities in parking demand.

Utilization of truck parking spaces was assessed through GPS data analysis, focusing on publicly owned locations. Metrics included the number of trucks parked, duration of parking, and utilization rates by time of day and day of the week. This analysis revealed significant variability in parking utilization, with some locations experiencing high demand while others were underutilized.

The study identified several challenges in managing truck parking, such as data inconsistencies from various sources, the dynamic nature of truck parking needs, and the impact of unauthorized parking on safety and infrastructure. Recommendations included enhancing data collection using advanced techniques like GPS tracking and crowdsourcing, increasing parking capacity by developing new facilities and expanding existing ones, implementing policy interventions to manage truck parking more effectively, and leveraging technology to provide real-time information on parking availability.

It is important to note that while the study provided a detailed and comprehensive analysis of truck parking inventory and utilization, it did not compute emissions associated with truck idling or parking activities. This omission highlights the need for further research to integrate emissions data into truck parking studies, enabling a more holistic understanding of the environmental impacts of truck parking and idling.

In conclusion, the 2020 Cambridge Systematics study offered valuable insights and practical recommendations to address truck parking needs in Texas. By integrating advanced data sources and analytical techniques, the study contributed significantly to enhancing the efficiency and safety of freight movement across the state[10].

2.8 2022 TxDOT Study on Truck Parking Using Advanced Analytics of Truck Probe Data

The 2022 study conducted by the Texas Department of Transportation (TxDOT) focused on enhancing the understanding of truck parking needs through advanced analytics of truck probe data [5]. This study aimed to address the growing truck parking challenge, driven by the need for truck drivers to comply with FMCSA HOS regulations, which mandate rest periods for drivers.

The study leveraged truck probe data to develop a comprehensive visualization resource, the TxDOT Truck Parking Visualization Resource (TPVR), and explored new uses of this data to analyze truck parking demand, facility usage, and the impact of different freight generators, disruptive events, and border crossings. Key findings from this study include:

1. **Truck Probe Data Utilization**:
    - TxDOT utilized truck probe data from INRIX for travel time, origin-destination, and other analyses to show truck parking demand and facility usage.
    - The data provided insights into statewide demand, showing consistent clusters of parking activity, particularly along major freight corridors such as IH-35 and in metropolitan areas.
2. **Visualization and Analytical Tools**:
    - The TPVR was developed to visualize truck parking stops statewide, offering detailed views of parking clusters and usage statistics.
    - The resource allows users to filter parking data by duration and weight class, providing a granular look at parking patterns and demand.
3. **Assessment of Freight Generators**:
    - The study analyzed truck parking related to major freight generators such as the Alliance in Dallas/Fort Worth, the Port of Houston, and the HEB distribution center in San Antonio.
    - The analysis showed how different types of freight generators impact parking demand, highlighting the need for both short-term and long-term parking solutions.
4. **Impact of Disruptive Events**:
    - The study examined the effects of disruptive events like the South by Southwest (SXSW) Conference and Festivals in Austin and Hurricane Imelda on truck parking patterns.

- The findings indicated that such events could significantly affect truck parking demand and travel patterns, necessitating targeted emergency parking strategies.

5. **Border Crossings Analysis**:

    - The study included a detailed analysis of truck parking in the El Paso metropolitan region, focusing on the relationship between parking demand and land use near border crossings.
    - The data showed a strong correlation between truck parking and commercial and industrial land uses, supporting the need for dedicated parking infrastructure near border areas.

The study identified several challenges in using probe data, such as data inconsistencies and the need for more comprehensive data coverage. Despite these limitations, the data proved valuable in providing insights into truck parking behaviors and needs.

The findings from this study offer opportunities for TxDOT to work with stakeholders, including local governments, metropolitan planning organizations (MPOs), and industry partners, to identify and implement solutions for truck parking challenges. Additionally, the study highlights the potential for integrating truck parking data with other transportation data sources to provide a more complete picture of freight movement and parking needs.

Overall, the 2022 TxDOT study advanced the understanding of truck parking in Texas through the use of advanced analytics and visualization tools, offering practical recommendations to address the ongoing and future challenges of truck parking. Notably, this study did not compute emissions associated with truck idling or parking activities, underscoring the need for further research to integrate emissions data into truck parking analyses for a more holistic understanding of the environmental impacts[5].

2.9 Ongoing Study

TTI is currently conducting one study, sponsored by FMCSA, for characterize CMV driver parking behavior to inform truck parking investments. This study focuses on the enforcement of safe CMV operations and compliance with safety regulations. This study aims to answer the following questions:

- When and where do truck drivers stop because of HOS?
- Where are unauthorized truck parking clusters relative to the nearest truck parking facilities?
- What are the sizes of unauthorized truck parking clusters along the corridors?
- What is the capacity of truck parking facilities relative to the unauthorized truck parking clusters?
- Where are the nearby truck parking facilities when the closest truck parking facility to the unauthorized parking cluster is full?

TTI acquired one year of ELD data covering the Contiguous United States to address the questions described above. Once the study is complete, it will provide a great asset for extended idling for emissions inventory, since previous studies focused on authorized parking facilities.

3 EVALUATION OF CURRENT DATA SOURCES

Data acquisition in transportation has been increasing, allowing for more comprehensive studies of traffic flow. This section discusses the main data sources available and used in recent studies, as well as the key characteristics of each data source.

3.1 INRIX DATA

INRIX[1] data provides a real-time anonymous mobile phone, connected cars, trucks, delivery vans, and other fleet vehicles equipped with GPS locator devices, and also from road sensors. Data is provided as raw data, processed data, and/or as shape files. Roadway locations are referenced as traffic management centers (TMC). Data is processed to provide travel time, time-cost delays, trends maps and charts, bottleneck and incident data, and can provide the underlying anonymized historical data for download. The data collected is processed in real-time 24-hours a day, creating traffic speed information for major freeways, highways, and arterials across North America.

INRIX provides various attributes related to trips and trajectories, where the trip dataset covers every trip by focusing on the locations of origins and destinations, and the trajectories datasets keep records of all routes for each trip. The data can be extracted

[1] https://inrix.com/

from all devices that entered a requested area at a specified time, regardless of whether the device started or ended the trip in the selected area[2]. The INRIX data covers all 50 states of the USA with a temporal coverage starting in 2002 until the present, with time resolution varying defined as 1, 5, 15, 30, and 60 minutes. The variables present in the data include volume, speed, and trip destinations.

3.2 American Transportation Research Institute (ATRI)

ATRI[3], part of the American Trucking Associations (ATA) Federation, is a 501(c) (3) not-for-profit research organization headquartered in Arlington, Virginia. ATRI collects GPS-based spatial and temporal information for a large sample of Trucks with onboard, wireless communication systems in the U.S. The dataset provided by ATRI contains the following variables: geospatial (coordinates) and temporal (time/date stamp) information for the corresponding trucks. Currently, more than 100 million GPS data points are collected per day by ATRI. The temporal coverage started in 2002 and the data has been collected until the present. In terms of spatial coverage, this data is available for all 50 states of the USA. The ATRI represents over 35,000 motor carriers through the affiliated trucking associations in 50 states.

3.3 EROAD Data

EROAD is a regulatory telematics company that focuses on fleet management and safety products, with activities starting back in 2000. EROAD started implementing the network-wide GPS/cellular-based road user charging system and in 2017 it became compliant with Electronic Logging Devices (ELD) and Driver-Vehicle Inspection Report (DVIR)[4]. The ELD has been required in commercial motor vehicles in December 2017 to track HOS[5].

Thus, the trucking companies use ELD to ensure HOS compliance, and fleet management systems help track trucks, keep up with maintenance, and loss prevention, as well as enhance safety. Because ELD and fleet management system vendors also have access to customer data (e.g., vehicle type, organization size, industry classification, etc.),

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[2] Exploration of cross-border trip characteristics using crowdsourced data (2021).

[3] https://truckingresearch.org/

[4] https://www.eroad.com/about

[5] https://www.fmcsa.dot.gov/regulations/hours-of-service

ELD and fleet management system data (referred to as telematics data) provide a potentially detailed data source to inform freight planning, freight policy, and freight operations. EROAD has 226,000 vehicles worldwide, with approximately 90,000 in the USA.

Specifically, EROAD collects data on:

- GPS Data (time, speed, bearing, distance from road, status type such as moving, stopped, ignition on/off, braking, and idling)
- HOS Compliance
- Acceleration
- Harsh Events (hard breaks, hard accelerations, hard corners)
- Customer Data (vehicle type, organization size, industry, vehicle make and model, vehicle classification, fuel usage reporting)
- Trip Data (origin and destination, timestamps of breaks)

However, due to the sensitivity of the data, EROAD typically operates with Robinsight to certify the data acquired does not violate the customers' privacy. For example, in 2022, TTI worked with EROAD and Robinsight on extracting, analyzing, and visualizing Origin-Destination (OD) data for trucks that have an origin or destination in Texas. Later, two studies were conducted by TTI and sponsored by TxDOT with the goals of analyzing the harsh braking events distribution and whether trucks reduce the speed when driving through a work zone. Before acquiring the data, TTI elaborated on general transportation issues and questions to be addressed, and the data was customized for that purpose.

3.4 StreetLight and WEJO Data

StreetLight[6] provides information related to mobility and contextual data. The mobility dataset contains GPS for commercial, aggregated GPS data, connected vehicle, LBS, GPS personal, and telco. The contextual data includes road network data, census data, vehicle counters, bike, and pedestrian counters, as well as places and land markers, land use, parcel, POI, weather, vehicle registration along with other information. Streetlight data applications span from origin and destination, trip routes, vehicle miles traveled, vehicle hours of delay, demographics data (income, race, and education), trip, speed, travel time, and distance. In terms of transportation modes, Streetlight datasets include personal vehicles, bicycles and pedestrians, bus and rail, and commercial trucks.

[6] https://www.streetlightdata.com/

StreetLight data has a temporal coverage, starting from 2012 until the present, and the special coverage extends to the USA.

Similarly to StreetLight, Wejo data provides trip characteristics for connected and electric vehicles. The Wejo dataset contains nearly every second with the location (latitude and longitude) with 3-meter precision, heading, and speed. It also includes vehicle characteristics, and the trips (journeys) are defined from the ignition-on until the ignition-off. The data also contains the H3 index, which is a hierarchical geospatial indexing system. This facilitates visualizing the trip's trajectory. Wejo has been operating since 2014.

3.5 National Performance Management Research Dataset (NPMRDS)

The NPMRDS contains field-observed travel time and speed data collected anonymously from a fleet of probe vehicles (cars and trucks) equipped with mobile devices. Using time and location information from probe vehicles, the NPMRDS generates speed and travel time data aggregated in 5-minute, 15-minute, or 1-hour increments. The data is available across the National Highway System (NHS), with a spatial resolution defined by Traffic Message Channel (TMC) location codes[7]. The data is represented by a directional segment about a half mile in urban areas and up to a five-mile radius in rural areas. This dataset contains the following variables: travel time for all vehicles (seconds), travel time for passenger vehicles (seconds), and travel time for freight vehicles (seconds). The temporal coverage of a 5-minute interval. This data is available from 2011 to present, with spatial coverage extending for the entire NHS.

3.6 TxDOT In-House Datasets

3.6.1 TxDOT Vehicle Detection Units

Vehicle detection units are installed on local highways and are used to measure traffic speeds and traffic volumes. Information from the vehicle detection units is transmitted to TxDOT districts, alerting staff to any changes in traffic operating speeds. Changes in traffic operating speeds allow staff to determine the locations of any potential incidents that may restrict traffic flow. These units are mounted alongside highways and are typically spaced one mile apart. Each detector records volume, speed, and occupancy by

[7] https://ops.fhwa.dot.gov/publications/fhwahop20028/index.htm

lane and at 20-second intervals. This dataset contains the volume and speed by lane with temporal coverage from 2015 to the current date and spatial coverage statewide.

3.7 Data sources advantages and limitations

The data sources presented before have one characteristic in common of being near or almost near-time data collection, which is a main advantage to understanding the current traffic conditions. Besides that, these data sources have around one decade of data collection that would allow researchers to also understand the historical partners along with the most updated traffic conditions on roads. Another important component of these data sources is the time resolution of data collection which can be at a minimum of one second. In terms of spatial coverage, all of them, except for data specifically collected in Texas, have national coverage and have been important in performing comparisons among the states. However, the number of vehicles collecting data varies among the data sources, as well as the type of vehicle represented. For example, while INRIX does not disclose the number of vehicles, EROAD and ATRI disclose around 35,000 and 90,000 trucks, respectively.

In terms of limitations, it is important to consider that it might be affected by the specificity of the application. For example, INRIX data aggregated to trips/tours on roadways, which can be a disadvantage for studies that focus on GPS waypoints. In addition, the vehicle identification (ID) is changed from one day to the next, which makes it difficult to track specific patterns (e.g., average hours parked in one location). EROAD data, on the other hand, provides tailored information case by case, which would require less amount of work developing algorithms to analyze the data, but the information acquired might be too specific for one particular study and not be useful to other studies.

However, despite the advantages and limitations of each data source, to analyze the hotelling activity, EROAD data is one of the most complete sources, once these data are transmitted because the drivers need to inform the worked and rested hours due to HOS compliance, it would be feasible to understanding the hotelling and extended idling with this data source.

4 METHODOLOGY FOR ESTIMATING IDLING ACTIVITIES

This section explores various methodologies for estimating truck parking demand and idling activities, focusing on enhancing the accuracy and effectiveness of these estimations. It begins with an overview of the FHWA methodology for truck parking demand, highlighting its key inputs and calculations. The integration of probe data into truck parking analysis is then discussed, emphasizing the benefits and methodologies for processing GPS data to improve understanding of truck parking patterns. Finally, a review of recent studies is provided, summarizing advancements in data collection, machine learning, and optimization techniques that can be applied to refine existing methods for estimating truck idling activities and emissions. These enhancements aim to develop more effective strategies for managing truck operations and reducing their environmental impact.

4.1 Overview of FHWA Methodology

FHWA methodology provides a foundational approach for estimating truck parking demand. It incorporates various parameters and calculations to determine the need for truck parking, both for short-term and long-term periods, along different corridors [11]. This methodology is particularly useful for understanding parking needs at a corridor level and has been adapted and updated by several subsequent studies, including those by the Pennsylvania State Transportation Advisory Committee (STAC)[12] and the Virginia Department of Transportation (VDOT) [13].

4.1.1 Key Inputs and Core Calculations

The FHWA methodology relies on five key user inputs to estimate truck parking demand:

1. **Truck AADT (AADTT)**: The annual average daily truck traffic.
2. **Corridor Length (L)**: The length of the corridor in miles.
3. **Corridor Speed Limit or Average Speed (S)**: The speed at which trucks travel on the corridor.
4. **Percent of Trucks Making Short-Haul Trips**: The proportion of trucks that complete their trips within a single day.
5. **Percent of Trucks Making Long-Haul Trips**: The proportion of trucks that require overnight parking.

The core equation for estimating truck parking demand (D) is:

$$D = THT \times Pavg$$

Where:

- D = Truck parking demand
- THT = Truck hours traveled
- $Pavg$ = Average truck parking duration

Truck hours traveled (THT) is calculated as:

$$THT = AADTT \times (L/S)$$

Where:

THT = Truck hours traveled

AADTT = Annual average daily truck traffic

L = Corridor length (in miles)

S = Average speed

This calculation takes into account the volume of truck traffic and the time it takes for trucks to traverse the corridor. The longer the time and the higher the truck volume, the greater the parking demand.

4.1.2 Short-Term Truck Parking Demand

To estimate short-term truck parking demand, the following steps are followed:

1. **Calculate AADTT**: Use the annual average truck counts from TxDOT's roadway inventory data, excluding urban areas to avoid skewing the average.
2. **Calculate Buffer AADTT**: Apply a 15% buffer to account for variances in daily truck traffic.
3. **Calculate Segment Length (L)**: Use GIS data to determine the length of the corridor.
4. **Calculate Speed (S)**: Use an average speed of 65 mph.
5. **Calculate Truck Hours Traveled (THT)**: Apply the formula $THT = AADTT \times (L/S)$
6. **Calculate Truck Hours Parked**: Multiply THT by a parking/operating ratio (0.083) derived from the FHWA study.

7. **Calculate Daily Short-Term Truck Stops**: Multiply truck hours parked by a median short-term parking duration (0.367 hours).

8. **Calculate Peak Truck Parking Demand (Short-Haul)**: Use a peak utilization rate (2.11%) to determine peak demand.

4.1.3 Long-Term Truck Parking Demand

For long-term truck parking demand, additional factors related to FMCSA HOS regulations are considered. The steps include:

1. **Calculate AADTT and Buffer AADTT**: Similar to the short-term demand but focus on long-haul trips.

2. **Calculate Truck Hours Traveled (THT)**: Using the same methodology.

3. **Calculate Truck Hours Parked**: Factor in the parking ratio for long-haul trucks, which accounts for HOS regulations.

4. **Calculate Daily Long-Term Truck Parking Stops**: Use a median long-term parking duration (7.25 hours).

5. **Calculate Peak Truck Parking Demand (Long-Haul)**: Apply a peak utilization rate (45.33%).

4.1.4 Integration of FHWA Methodology with Recent Data

The FHWA methodology serves as a baseline and is cross-checked with data from ATRI. This ensures that the estimates are aligned with actual parking behaviors and trends observed in the field. The methodology can be enhanced by integrating probe data, which provides real-time insights into truck movements and parking patterns. This integration helps in refining the estimates and addressing gaps identified in previous studies.

4.1.5 Advantages and Limitations

Advantages:

- Provides a systematic approach to estimate truck parking demand.
- Can be adapted and updated with recent data and regulatory changes.

Limitations:

- May not fully account for real-time variations in truck traffic and parking behaviors.
- Differentiation between public and private parking facilities is not practical with the level of specificity available.

By following this detailed methodology, transportation planners can develop accurate estimates of truck parking demand, which is crucial for ensuring adequate parking facilities and reducing the negative impacts of truck idling on emissions and road safety.

4.2 Integration of Probe Data into Truck Parking Analysis

4.2.1 Overview and Benefits of Probe Data

Probe data, particularly from GPS tracking, has become a vital component in transportation studies, offering real-time insights into vehicle movements and behavior. The integration of probe data into truck parking analysis allows for a more detailed and accurate understanding of parking patterns, which is crucial for developing effective parking strategies and policies.

Probe data provides several advantages:

- **High Resolution and Granularity**: Continuous tracking of truck movements offers a granular view of stops and travel patterns, which traditional data sources may not capture.
- **Real-Time Updates**: The ability to receive real-time data ensures that the analysis is based on the most current information, reflecting actual conditions.
- **Comprehensive Coverage**: Probe data covers a wide range of vehicles and geographic areas, providing a broad dataset for analysis.

4.2.2 Methodology for Processing Probe Data

The process of integrating probe data into truck parking analysis involves several steps to transform raw GPS data into usable information. This section summarizes the procedures and steps employed in the study to achieve this goal, based on the methods outlined in the recent truck parking report from TxDOT [10].

4.2.3 Data Collection and Pre-Processing

1. **Raw Data Acquisition**: GPS data should be collected for trucks operating in Texas during four different representative months for each season (Winter, Spring, Summer, and Fall) to capture seasonal variations and weekday differences. Each period included GPS traces for every truck that operated in Texas, with intervals between data points ranging from 60 seconds to 15 minutes.

2. **Initial Data Handling**: The raw data, amounting to billions of points, should be imported with some platform that can handle large datasets efficiently. This step involves:

    - **Filtering Out-of-State Points**: Removing data points recorded outside Texas.
    - **Assigning Truck IDs**: Unique identifiers were assigned to each truck.
    - **Sorting and Formatting**: Data was organized into smaller, manageable files for further analysis.

4.2.4 Identifying Truck Stops

The critical step in utilizing probe data is accurately identifying truck stops, which involves distinguishing between actual stops and pauses due to traffic or other temporary conditions. The following heuristics and rules were applied:

1. **Defining a Stop**: A stop was defined as a truck remaining in one location for at least 15 minutes. This duration filters out pauses due to congestion or brief stops.

2. **Handling Movements Within Facilities**: Trucks may move short distances within a parking facility, so a stop only ends when a truck travels a certain distance based on the moving average of GPS points.

3. **Filtering Waypoints**: Points representing trucks moving on highways were identified and excluded from stop analysis, based on speed and reporting frequency.

4. **Merging Consecutive Stops**: Stops that were close in time and location were merged to avoid overcounting.

4.2.5 Categorizing Stops

The identified stops were categorized into different types based on their duration and the context of the trips:

1. **Overnight Stops**: Stops starting before 3 am and ending after 3 am, with a duration of at least 4 hours.
2. **Long-Haul Stops**: Stops between trips of at least 3 hours each.
3. **Staging Stops**: Stops lasting between 1 and 4 hours, following a trip of at least 1 hour and followed by a trip of less than 2 hours.
4. **Local Stops**: Stops of less than 2 hours between trips of up to 1 hour each.

4.2.6 Challenges and Solutions

Processing such a vast amount of data presents several challenges, including the need for computational efficiency and accuracy. These challenges can be addressed through:

- **Efficient Algorithms**: Using Spark and Python to handle large datasets efficiently.
- **Heuristic Filtering**: Developing sophisticated heuristics to distinguish true stops from temporary pauses.
- **Accuracy and Precision**: Ensuring the GPS data's accuracy and precision to distinguish between closely located facilities.

The processed data will provide a detailed picture of truck parking patterns, including the frequency and duration of stops. In conclusion, integrating probe data into truck parking analysis enhances the ability to understand and manage truck parking demand. By leveraging high-resolution GPS data, transportation planners can develop more accurate and effective strategies to address parking needs and reduce the negative impacts of truck idling and parking shortages.

4.3 Review and Enhancement of Methodologies for Estimating Truck Idling Activities and Emissions

In recent years, extensive research has been conducted to understand and mitigate the emissions from long-haul truck idling activities. The integration of advanced data collection techniques, machine learning, and optimization algorithms has significantly enhanced the accuracy and reliability of these estimations. This review synthesizes findings from several key studies and proposes modifications to existing methodologies to further improve the estimation of idling activities and emissions.

One of the earlier studies by Frey et al. (2008) utilized real-world data collected from electronic control units (ECUs) and satellite uplinks to monitor idling times, auxiliary power unit (APU) usage, and shorepower capability in 20 trucks over a year [14]. This study highlighted significant variability in idling patterns among drivers, emphasizing the need for large sample sizes to reliably characterize activity patterns. Detailed and continuous data collection was shown to be crucial for accurate estimation of idling activities, suggesting that future models should incorporate driver behavior variability to enhance accuracy [14].

Bayesian Optimization has emerged as a powerful tool for optimizing complex transportation models. Liu et al. (2020) demonstrated its application in optimizing area-based road pricing schemes, showing its efficiency in finding optimal solutions even in high-dimensional scenarios. While the study focused on road pricing, the Bayesian Optimization framework can be adapted to optimize parameters influencing truck hoteling behavior, providing a structured approach to handle high-dimensional optimization problems, which is beneficial for modeling truck idling patterns [15].

The integration of machine learning techniques, particularly Long and Short Term Memory (LSTM) networks, has also shown promise in predicting idling behavior and energy consumption patterns. Khuntia et al. (2022) used LSTM to predict the electrical loads experienced by a battery pack during the hoteling period of long-haul trucks. By training the model on synthetic load profiles derived from baseline electrical power load profiles, the study highlighted the importance of predicting auxiliary power loads to manage battery State of Charge (SOC) and reduce unnecessary idling. This approach can be adapted to model idling behavior more accurately, leveraging real-time data to refine predictions [16].

Moreover, Yao et al. (2023) introduced a method to calculate on-road truck emissions considering different trip purposes and dynamic load changes. The study analyzed massive trajectory data to decompose the relationship between trip purposes and emissions, revealing significant variations in NOX and PM2.5 emissions based on trip purposes. This method provides a more accurate estimation of truck emissions by accounting for different trip purposes and load status changes, demonstrating the necessity of incorporating these factors into emission models [17].

Building on these insights, several modifications and enhancements can be proposed to improve the existing methods for estimating truck idling activities and emissions:

1. **Enhanced Data Collection**: Implementing continuous and detailed data collection using advanced sensors and satellite uplinks can capture real-time idling patterns and variability among drivers more effectively. This approach ensures that models are based on comprehensive and accurate data, reflecting actual conditions.
2. **Incorporation of Driver Behavior**: Accounting for inter-driver variability in idling patterns by using large sample sizes and diverse datasets can improve the accuracy of activity characterizations. This consideration is critical for developing robust models that accurately reflect real-world behaviors.
3. **Advanced Optimization Techniques**: Applying optimization frameworks, such as Bayesian Optimization, can efficiently handle high-dimensional parameters and improve the precision of idling activity models. This approach allows for more accurate calibration of models, enhancing their predictive capabilities.
4. **Integration of Recent Technological Advancements**: Utilizing recent advancements in data analysis and machine learning, such as LSTM networks, can enhance the robustness and reliability of models for estimating truck idling and hoteling activities. These technologies enable more sophisticated and dynamic modeling processes, capable of adapting to real-world complexities and uncertainties.
5. **Adaptive Modeling Approaches**: Developing adaptive models that can update and refine estimations based on new data ensures that the models remain accurate and relevant over time. Continuous model improvement is essential for maintaining the effectiveness of emission reduction strategies and optimizing truck operations.

By incorporating these modifications and enhancements, the methodologies for estimating truck idling activities and emissions can be significantly improved. This leads to more effective strategies for reducing emissions and optimizing truck operations, ultimately contributing to better environmental and operational outcomes in the transportation sector.

5 STUDY PLAN DEVELOPMENT

The study plan for estimating emissions from heavy-duty vehicle idling activities involves several key steps, mirroring the comprehensive approach seen in previous studies like the 2019 TTI Heavy-Duty Vehicle Idle Activity Study. This plan will focus on developing a detailed methodology for data collection, processing, and analysis to accurately estimate idling activities and emissions. The steps are designed to ensure the collection of high-quality data, robust analysis, and reliable results.

The outputs of the study will include estimates of the duration of hotelling activities (extended idling and APU usage) for all Texas counties. These estimates will be broken down by weekdays and weekends, as well as summer and winter seasons. The data will be collected using a combination of existing data sources and new data collection efforts where necessary. The modeling approach will provide confidence intervals and errors for the estimates to ensure the validity of the models and assumptions. The overall approach is split into three parts.

A. Number of HDV parking spaces by facility type.

B. Idling factor, defined as the expected/average hours of extended idling taking place per HDV parking space over a desired time period.

C. A statewide distribution of hotelling extended idling operating mode (either using the truck main engine, or electric or diesel APUs).

5.1 DETERMINE THE NUMBER OF PARKING SPACES

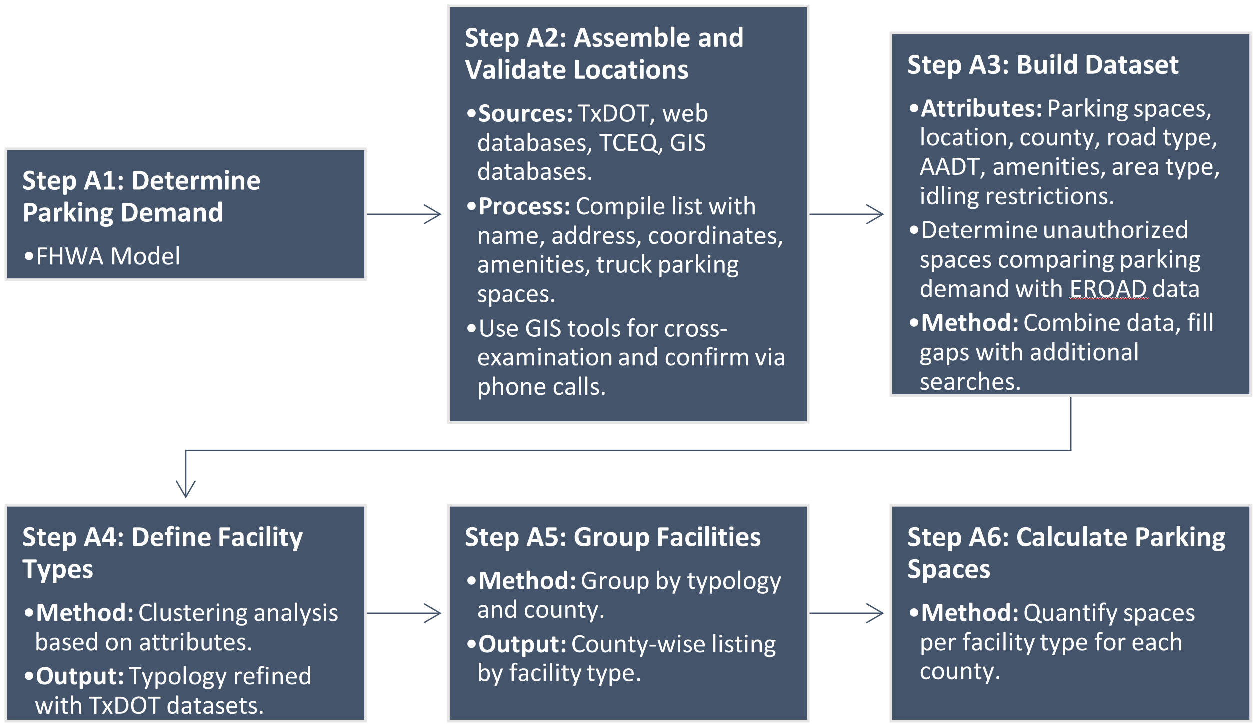

Figure 1 Data Collection Plan and Methodology for Number of Parking Spaces.

Figure 1 summarizes the proposed methodology and data collection plan to estimate the number of parking spaces. The first step in the study plan is to determine the parking demand using the FHWA Model. This model helps estimate the parking demand for heavy-duty vehicles across different corridors, considering factors like truck traffic volume and travel speeds.

Next, the study will involve assembling and validating locations of truck parking facilities. Data will be sourced from TxDOT-maintained rest areas, web-based databases such as TruckMaster Fuel Finder and TruckStopInfoPlus.com, TCEQ Petroleum Storage Tanks Registrations, and GIS databases from Texas MPOs. This process entails compiling a comprehensive list of facilities, including their names, addresses, coordinates, amenities, and the number of truck parking spaces available. To ensure the accuracy of the compiled list, GIS tools will be employed for cross-examination, and phone calls will be made to confirm the current operational status of the facilities.

Following this, the collected information will be used to build a robust dataset of truck parking facilities. The dataset will include attributes such as the number of parking spaces, location, county, road type, AADT, amenities, area type, nonattainment status, and existing idling restrictions. This step involves determining unauthorized spaces by comparing parking demand with Eroad data, combining the data, and filling any gaps with additional searches.

The next step is to define the types of facilities. This will involve conducting a clustering analysis based on various attributes such as location, type of facility, characteristics of adjacent roadways, and the number of parking spaces. The resulting typology of facilities will be refined through discussions with TCEQ to ensure it is comprehensive and accurate.

Once the facility types are defined, the facilities will be grouped by typology and county. This step will result in a county-wise listing of facilities with hotelling and extended idling categorized by facility type. Finally, the number of parking spaces per facility type for each county will be quantified, providing a detailed overview of available parking infrastructure.

5.2 Determine Idling Factor

Figure 2 summarizes the proposed methodology and data collection plan to determine the idling factor. The determination of the idling factor begins with assembling information from previous studies. Sources include studies conducted by TTI (2003, 2019, 2022), ERG (2004), TTI/CAPCOG (2013), and Cambridge Systematics (2020). The data collected from these studies will include facility names, locations, amenities, parking spaces, occupancy rates, and idling fractions.

The next step involves extracting parking and idling activity parameters from the assembled studies. This involves organizing the data in a consistent tabular format to facilitate analysis. Parameters such as the hourly distribution of occupancy rates and idling fractions will be extracted and meticulously organized.

Following this, vehicle movement data from EROAD will be used to gain further insights into parking and idling activities. This involves overlaying truck and facility locations, filtering for stops longer than 15 minutes, and extracting the hourly distribution of these stops. Additionally, necessary data will be purchased to analyze hourly idling events, which will be scaled based on previous studies.

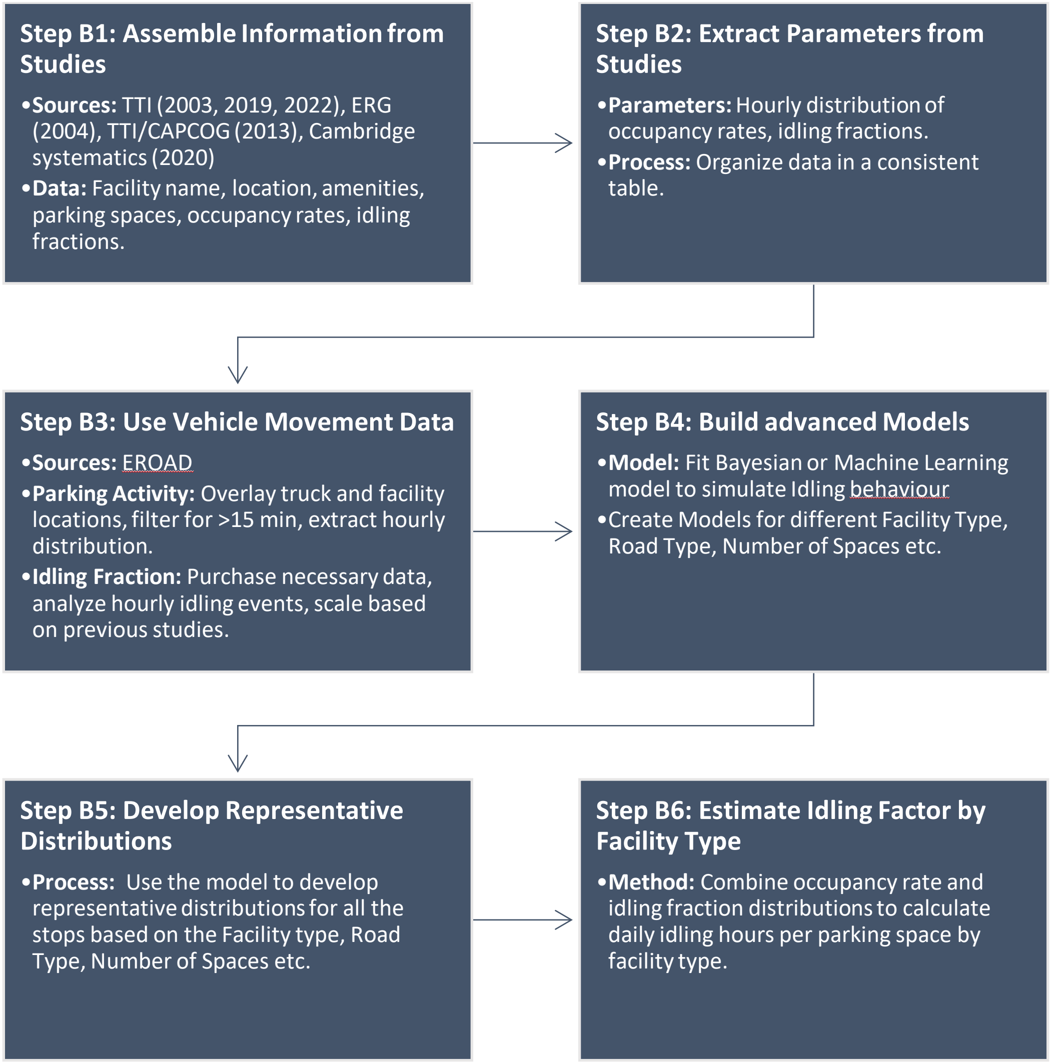

Figure 2. Data Collection Plan and Methodology for Idling Factor

Building advanced models is the next critical step. Bayesian or machine learning models will be fitted to simulate idling behavior. These models will be tailored for different facility types, road types, and the number of parking spaces, providing a detailed simulation of idling activities.

Once the models are developed, they will be used to create representative distributions for all the stops. These distributions will be based on the facility type, road type, and the number of parking spaces, ensuring they accurately reflect real-world conditions. The final step in this phase is to estimate the idling factor by facility type. This involves combining the occupancy rate and idling fraction distributions to calculate daily idling hours per parking space for each facility type.

5.3 APU Availability and Use

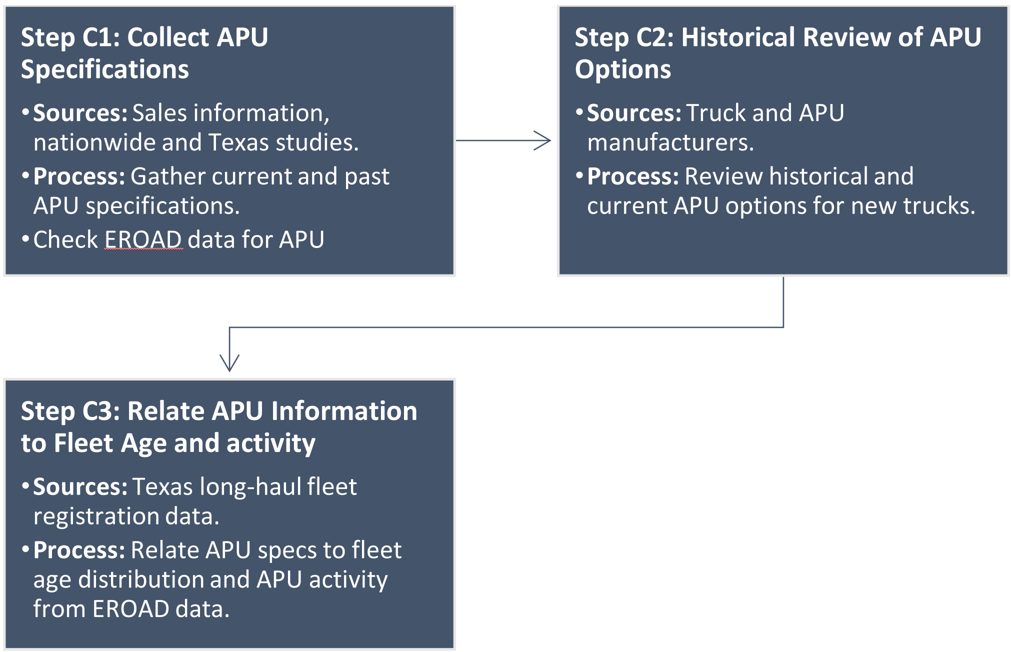

Figure 3. Data Collection Plan and Methodology for APU Usage

The study will also examine the availability and use of Auxiliary Power Units (APUs) among heavy-duty vehicles. This begins with collecting APU specifications from sales information and studies conducted both nationwide and in Texas. The process involves gathering current and past APU specifications and cross-referencing them with EROAD data for additional insights.

A historical review of APU options will be conducted next. Information from truck and APU manufacturers will be reviewed to understand the historical and current options available for new trucks. This review will help relate APU specifications to the age distribution of the Texas long-haul fleet registration data and the APU activity data from EROAD. This final step will result in determining APU availability and use with good accuracy

6 CONCLUSIONS AND RECOMMENDATIONS

The review of previous studies and data sources highlighted the evolution of methodologies over the years, with advancements in data collection techniques and analytical models. However, it also identified persistent gaps and limitations, particularly in capturing real-time idling behavior and integrating high-resolution data.

One of the key findings is the potential of EROAD data as one of the most complete sources for understanding hotelling and extended idling activities. EROAD data, which is transmitted by drivers who must inform their worked and rested hours due to HOS compliance, provides a comprehensive and detailed view of idling patterns. This data source allows for a feasible and accurate estimation of idling activities, given its richness and granularity.

The development of a detailed study plan is based on a robust approach to estimating idling activities and emissions. The plan emphasizes the importance of accurate data collection, validation, and advanced modeling techniques to enhance the reliability of estimates. By leveraging data from diverse sources, including GIS databases and vehicle movement data, the study aims to provide a comprehensive understanding of idling patterns across different facility types and regions.

The integration of advanced models, such as Bayesian optimization and machine learning, offers significant potential to simulate idling behavior more accurately. These models can adapt to the dynamic nature of freight movement and provide nuanced insights into the factors influencing idling activities.

In summary, two recommendations are proposed to improve the estimation and management of heavy-duty vehicle idling activities and emissions in Texas. It is recommended to purchase and utilize EROAD data to ensure that models are based on the most current and accurate information, reflecting actual idling conditions and behaviors. Additionally, the use of advanced modeling techniques, such as Bayesian optimization, machine learning, and other analytical methods, should be expanded to enhance the accuracy and reliability of idling activity estimates.

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