Proceedings of the 14th International Green Energy Conference
IGEC 2022
July 4-8, 2022

MODELING FREIGHT TRAFFIC DEMAND AND HIGHWAY NETWORKS FOR HYDROGEN FUELING STATION PLANNING: A CASE STUDY OF U.S. INTERSTATE 75 CORRIDOR[1]

Majbah Uddin, Yuandong Liu, Fei Xie, Vivek Sujan, Adam Siekmann
National Transportation Research Center, Oak Ridge National Laboratory
2360 Cherahala Blvd, Knoxville, TN 37932, USA
{uddinm, liuy, xief, sujanva, siekmanna}@ornl.gov

ABSTRACT
The use of hydrogen as an alternative transportation fuel has gained much interest in recent years. Hydrogen can be utilized in electric vehicles equipped with hydrogen powertrains (including hydrogen internal combustion engines or fuel cells). Given that most of the freight in the U.S. is transported via diesel trucks, transition to hydrogen fuel would help achieve significant environmental benefits as well as accelerate the decarbonization of the freight transportation sector. This paper presents the methodology and results of a case study on modeling freight traffic demand and highway networks based on publicly available data for the Interstate 75 freight corridor. The purpose of this study is to prepare input traffic and network data that can support the planning of a hydrogen fueling station infrastructure. In particular, the data can be used for siting and characterizing an optimized framework of hydrogen fueling stations from candidate diesel stations along the Interstate 75 corridor. The methodologies developed and presented in this paper may be readily expanded and applied to any transport corridor given the data availability. This paper is the first in a series that will build out a comprehensive model to optimize a consolidated national hydrogen refueling infrastructure eco-system targeted at commercial vehicles.

Keywords: Hydrogen fueling station, freight traffic, highway network, freight corridor, infrastructure planning

INTRODUCTION
Greenhouse gas (GHG) emissions from the transportation sector is one of the largest in the U.S. According to Environmental Protection Agency, transportation sector accounted for about 29 percent of the total U.S. GHG emissions in 2019. Most of these emissions from transportation are resulting from the combustion of petroleum-based fuels (EPA, 2022). The introduction of a decarbonized energy economy will, in part, necessitate the development of a decarbonized commercial freight truck transportation system and supporting eco-system. Characterizing and optimizing a national refueling infrastructure to support this decarbonized freight system is critical, where identifying both “spatial” (location) and “temporal” (time-based evolution) requirements will be necessary to successfully launch and advance a sustainable solution. This process will need to factor in the specific characteristics of the fuel type and correlate that to the anticipated demand (due to freight volume and adoption scale up in time) to determine the optimized refueling sites on public access roadways. One of the ways to reduce emissions associated with freight truck transportation is to switch to alternative fuels that emit fewer emissions than fuels currently being used. Hydrogen is one of those alternative fuel sources. The use of hydrogen has gained much interest in recent years. Hydrogen consumption in a vehicle may be achieved either thermodynamically through an internal combustion engine or electrochemically through a fuel cell. It is a critical element in the decarbonization of the transportation sector.

According to Freight Analysis Framework, U.S. transportation system moved 19.2 billion tons of freight in 2020; of which, 12.5 billion tons (about 65%) of freight were moved by truck (FAF, 2022). Multimodal freight volume data across the U.S. freight corridors are shown in Figure 1. This substantial volume indicates the need for transitioning to zero-emission fuels (e.g., hydrogen) to achieve a significant reduction in GHG emissions from the freight transportation sector. With the roll-out of hydrogen trucks, there will also be a need for adequate refueling infrastructure. To this end, this study conducts a case study on modeling freight traffic demand and highway networks for the Interstate 75 corridor. The traffic and network data will be used to determine the optimal location of hydrogen fuel stations from candidate diesel fuel stations.

Previous studies have largely focused on the emerging needs of the electric charging infrastructure (for battery electric vehicles) with the primary focus on passenger vehicles and a secondary focus on commercial vehicle needs (California Governor’s Interagency Working Group on Zero-emission Vehicles, 2013; Fetene et al., 2016; Ge et al., 2011; Gusrialdi

---

[1] This manuscript has been authored by UT-Battelle, LLC, under contract DE-AC05-00OR22725 with the US Department of Energy (DOE). The US government retains and the publisher, by accepting the article for publication, acknowledges that the US government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this manuscript, or allow others to do so, for US government purposes. DOE will provide public access to these results of federally sponsored research in accordance with the DOE Public Access Plan (http://energy.gov/downloads/doe-public-access-plan).

et al., 2014; He et al., 2015; Jochem et al., 2016; Li et al., 2020; Peterson, 2011; Xie et al., 2018; Xie and Lin, 2021). In the absence of a significant technology disrupter, it is quite probable that the future zero-emission commercial vehicle fuel will likely remain multi-faceted, including a mix of battery electric vehicles, fuel cell electric vehicles, and other powertrains. This will necessitate a more comprehensive assessment of the vehicle and infrastructure systems such that a complete application and temporal roadmap of the powertrain and the supporting eco-system may be developed. The efforts in the paper create a critical step in this endeavor.

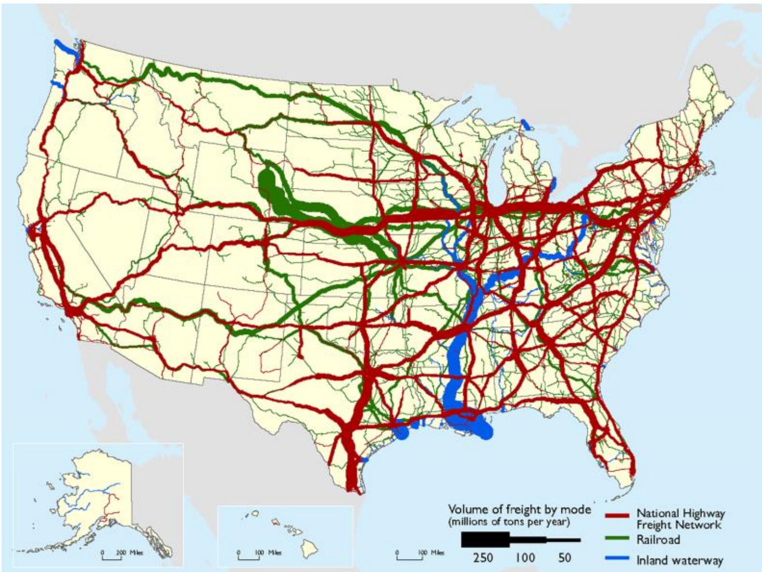


Fig.1. Major freight corridors and volume (roads, rail, and inland waterways) (FHWA, 2022).

Publicly available freight demand data and highway network information are used. The data sources used in modeling freight traffic demand include Freight Analysis Framework (FAF, 2022), Travel Monitoring Analysis System Weigh-in-motion data (TMAS, 2022), and Commodity Flow Survey data (CFS, 2022). The objective of this modeling is to estimate the number of heavy-duty trucks, Federal Highway Administration (FHWA) Classes 9 to 13, going from origins to destinations via the Interstate 75 corridor based on Freight Analysis Framework (FAF) flow tonnage and truck weights as measured by Travel Monitoring Analysis System Weigh-in-motion devices. FAF highway network represents the nation's highways comprised of Rural Arterials, Urban Principal Arterials, and all National Highway System routes. The objective of this modeling is to generalize the network components (nodes and links) so that it provides a graphical representation of highway routes on the entire segment of Interstate 75 corridor (~1,786 miles with the North end located near the U.S.-Canada border in Michigan and South end located in West Miami, Florida).

RELATED STUDIES

Average payloads are major inputs for converting freight tonnage into the number of trucks. Table 1 summarizes the related studies where truck payloads were analyzed or modeled based on truck weights. As evident, most of the studies employed Gaussian Mixture Model (GMM) with a varying number of components on truck weight data collected from weight-in-motion (WIM) stations located in the study region. None of the studies provide a methodology to estimate the number of trucks with explicit consideration of season as well as at origin-destination (OD) levels. This current study builds models to overcome the shortcoming by considering both of those parameters in the outputs.

Table 1. Summary of previous literature on truck payload estimation.

Study	Study Area	Data Source	Modeling Approach	Seasonality Consideration	OD Truck Volume Estimation
Nichols and Cetin (2007)	Indiana	Weigh-in-motion (WIM) [one station and FHWA Class 9 vehicle]	Mixture Model [three components]	No	No
Hyun et al. (2015)	California	WIM [three stations]	Gaussian Mixture Model (GMM) [three components]; Customized Decision Tree Model	No	No

Federal Highway Administration (2016)	U.S.	Vehicle Inventory and Use Survey (VIUS); Freight Analysis Framework (FAF)	Average Payload; Truck Equivalency Factor	No	Yes (not distinguished by weights)
Hernandez (2017)	California	WIM [four stations]	GMM [three components]	No	No
Hwang et al. (2019)	U.S.	Travel Monitoring Analysis System (TMAS); VIUS	GMM [three components]	No	No
Kaisar et al. (2019)	Florida	WIM [37 stations]	GMM [two or three components]	No	No
Regehr et al. (2020)	Manitoba, Canada	Static scale measurement [3 stations]; WIM [one station]	GMM [two or three components]	No	No

Table 2 provides a summary of related studies that use large-scale highway networks and national-level freight data. Given the scope of the studies, emphasis was provided to obtain traffic flow on the network based on user-equilibrium traffic assignment. This assignment is not always suitable for a route-specific traffic flow, especially for freight trucks.

Table 2. Summary of previous literature on freight assignment and network preparation.

Study	Study Area	Network Data Source	Freight data	Traffic Assignment Approach
Hwang (2007)	U.S.	Simplified U.S. interstate highway network (178 nodes & 588 links)	FAF version 3	User equilibrium traffic assignment
Uddin et al. (2021)	U.S.	Simplified U.S. road-rail intermodal network	FAF version 3	User equilibrium traffic assignment

DATA SOURCES

Four major data sources were used in this study: (a) Travel Monitoring Analysis System (TMAS) Weigh-in-motion (WIM), (b) Freight Analysis Framework (FAF) version 5, (c) Commodity Flow Survey (CFS) Public Use File (PUF), and (d) FAF Highway Network.

Weigh-in-motion (WIM) systems record gross vehicle weight, dynamic axle loads and spacing, the number of axles, speed of vehicle, lane, and direction of travel, vehicle classification by Federal Highway Administration (FHWA), axle weights, date, and time stamp, etc. The entirety of the traffic count collection map including the WIMs is shown in Figure 2. The WIM stations that are located on I-75 corridor were filtered and used as input in the modeling performed.

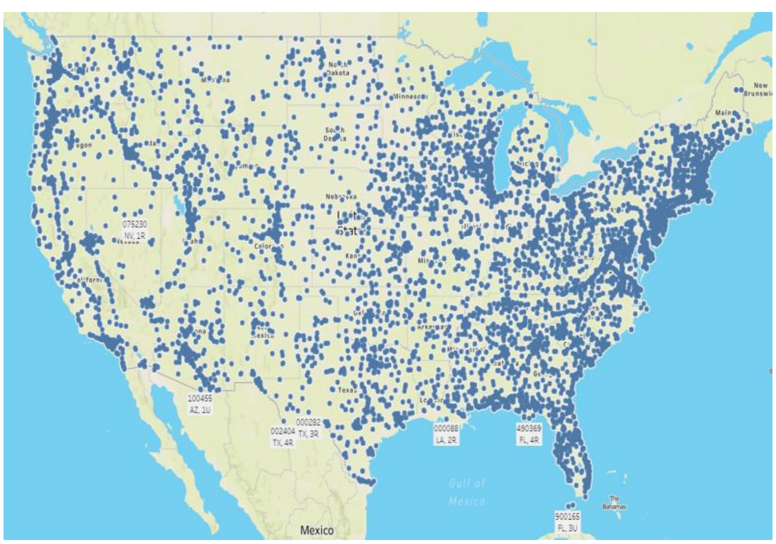


Fig.2. There are approximately 7,000 data collection sites nationally with 600 of them having WIM capabilities (FHWA, 2020)

Freight Analysis Framework (FAF) version 5 integrates data from various sources to create a comprehensive picture of freight movement among states and major metropolitan areas by all modes of transportation. The areas are defined as

FAF zone in the database. FAF adopted these areas from Commodity Flow Survey (CFS) geographical areas. There are a total of 132 areas in 2017 CFS. The areas can be classified as one of the three types: metropolitan area, the remainder of state, and whole state. All FAF zones crossed by or located near the I-75 corridor were included in the initial dataset on freight tonnage moving from origin FAF zone to destination FAF zone. Figure 3 shows the I-75 corridor and selected FAF zone and associated zone centroid.

Fig.3. FAF zone and Interstate 75 corridor.

CFS is the primary source of national and state-level data on domestic freight shipments by establishments in mining, manufacturing, wholesale, auxiliaries, and selected retail and services trade industries located in the 50 states and the District of Columbia. The Public Use File (PUF) provides characteristics for all usable shipment records collected by CFS. One important characteristic is the quarter of the survey year in which the shipment was made. This assisted in estimating quarterly tonnage for a specific FAF origin-destination (OD) pair.

FAF Highway Network is one of the most comprehensive public truck network datasets that contain roads at different road functional class levels. Functional classification is the process by which roadways are grouped into classes, or systems according to the character of traffic service that they are intended to provide. The functional classification of a road is the class or group of roads to which the road belongs. There are three main functional classes as defined by the FHWA: arterials, collector, and local. While Arterials, Collectors and Locals span the full range of roadway functions, the Federal functional classification scheme uses additional classification categories to describe these functions more accurately. Distinctions between access-controlled and full-access roadways, the urban and rural development pattern, and subtleties between “major” and “minor” sub-classifications, are key considerations when determining the Federal functional classification category to which a particular roadway belongs. The process of determining the correct functional classification of a particular roadway is largely left to the individual states based on the federal guidelines. The FAF network consists of 670,427 road links. Attributes of each link that were used in truck routing include speed limit, road length, FAF ID, etc. This network was simplified to generate a graphical representation and the subset of the network that represents the I-75 corridor was considered.

MODELING OF FREIGHT TRAFFIC

The procedure to estimate OD truck count by FHWA class and quarter comprises eight steps. Note that only heavy-duty trucks (FHWA Classes 9 to 13) were considered. The steps are (1) obtain FAF OD payload tonnage, (2) obtain truck allocation factor by FHWA class and distance range, (3) estimate payload tonnage by FHWA class, (4) obtain quarterly tonnage share from CFS PUF, (5) estimate payload tonnage by FHWA class and quarter, (6) obtain TMAS WIM data, (7) apply Gaussian Mixture Model by FHWA class, quarter, and travel direction, and (8) estimate average daily truck counts by FHWA class and quarter. Figure 4 illustrates the estimation workflow. Brief discussions on each step are provided below.

Step 1: Obtain FAF OD payload tonnage

For each of the selected FAF OD pairs, obtain payload tonnage for year 2017 from the FAF database. Data for 2017 were extracted since it is the base year for FAF version 5.

Step 2: Obtain truck allocation factor by FHWA class and distance range
FAF documentation on freight traffic assignment provides truck allocation factors by FHWA class and distance range. Based on the distance from origin FAF zone and destination FAF zone, truck allocation factors by FHWA classes were obtained.

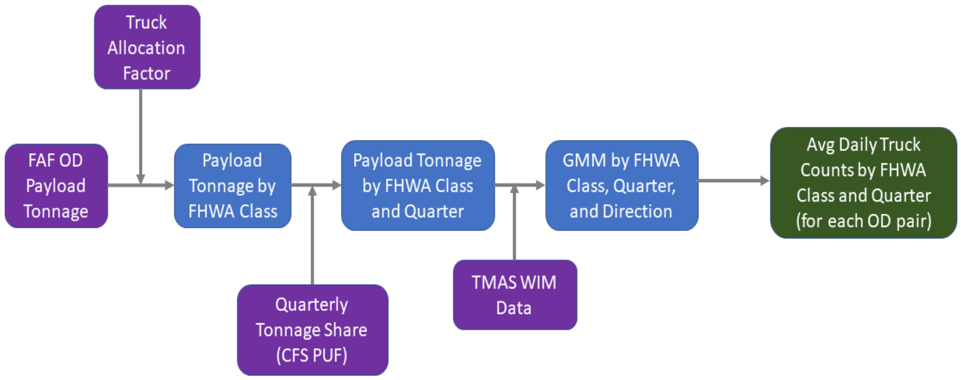


Fig.4. Procedure for estimation of OD truck count by FHWA class and quarter.

Step 3: Estimate payload tonnage by FHWA class
Use outputs from Steps 1 and 2, and then estimate payload tonnage by FHWA class.

Step 4: Obtain quarterly tonnage share from CFS PUF
CFS PUF contains shipment records along with information about the quarter in which the shipment was made. For a certain OD pair, shipments were aggregated by quarter and tonnage shares were estimated.

Step 5: Estimate payload tonnage by FHWA class and quarter
Use outputs from Steps 3 and 4, and then estimate payload tonnage by FHWA class and quarter.

Step 6: Obtain TMAS WIM data
Filter WIM truck weight data to only include stations that are located on the I-75 corridor from TMAS database. Data were extracted for FHWA Classes 9 to 13 and for year 2017.

Station-level truck weights by FHWA Classes 9 to 13 were investigated to determine if there are monthly or quarterly variations. Figure 5 shows FHWA Class 12 truck weight distributions by month of the year for one WIM station in Florida on the Interstate 75 corridor; Figure 6 shows the weight distributions on a single plot. Note that, for this particular WIM station, weight data for the months October to December were missing. Possible reasons might be WIM being offline due to instrument issues or simply not reporting data to FHWA. As we can see, truck weights are a bit different month over month. The peaks for different months are at a different weight level. This highlighted the need for analysis with explicit consideration of seasonal (i.e., quarterly or monthly) variation. Similar figures may be generated for the other weigh stations. It is important to not aggregate these to maintain the distinct traffic characteristics along different segments of the freight corridor.

Step 7: Apply Gaussian Mixture Model by FHWA class, quarter, and travel direction
A Gaussian Mixture Model (GMM) procedure was used to define the empty, partially loaded, and loaded to weight limit for each FHWA vehicle class, quarter, and travel direction from the TMAS WIM data. The GMM is a linear composition of Gaussian distributions combined using a mixing proportion parameter.

$$f(x) = \sum_{m=1}^{M} \lambda_m \, \mathcal{N}(x; \mu_m, \Sigma_m) \tag{1}$$

where,
m = number of mixture components,
M = total number of mixture components, $m = 1, \ldots, M$
λ_m= mixing proportion, and
$\mathcal{N}(x; \mu_m, \Sigma_m)$ = Gaussian distribution with mean μ and covariance matrix Σ.

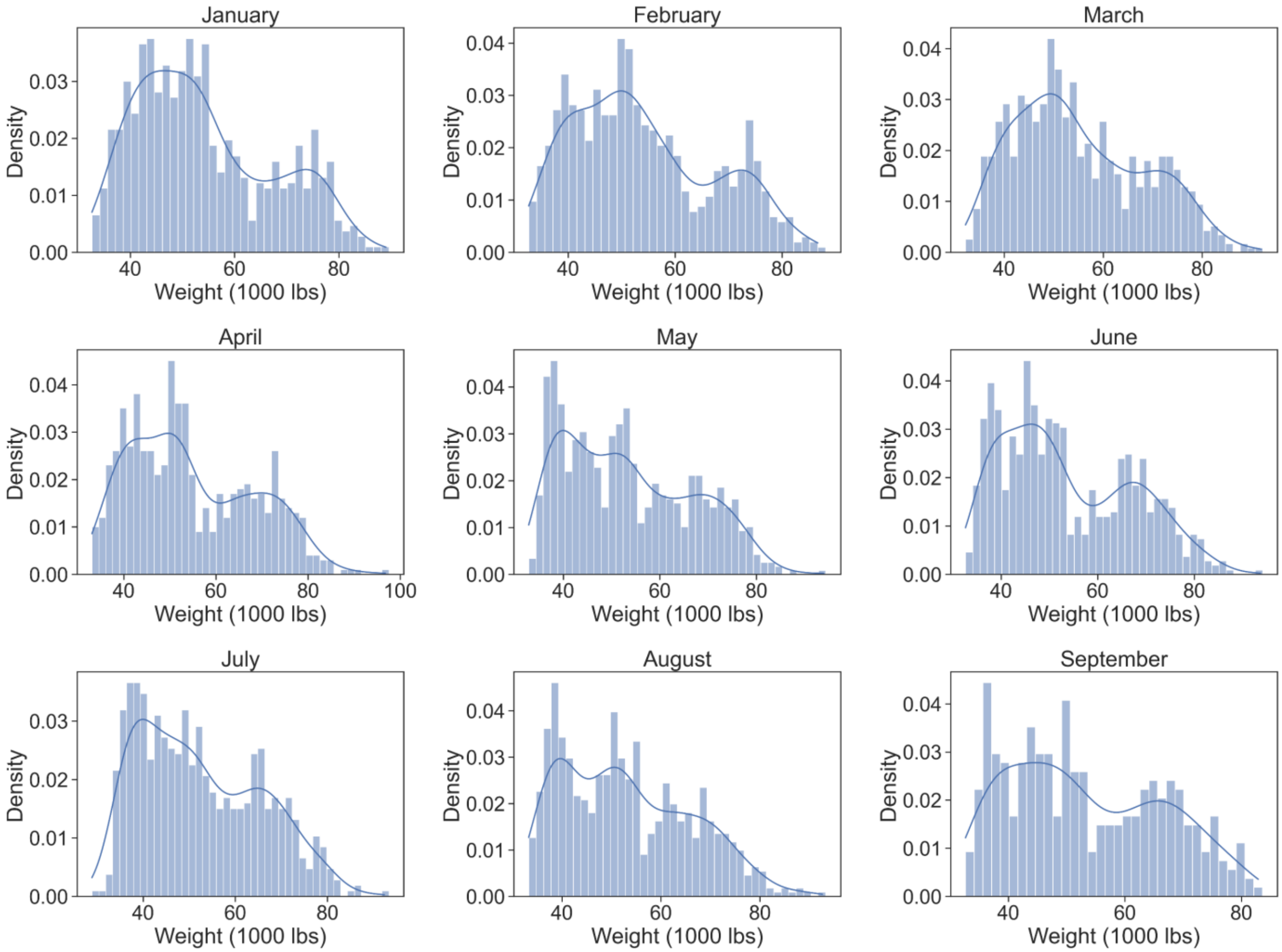


Fig.5. Distribution of FHWA Class 12 truck weights in one WIM station in Florida.

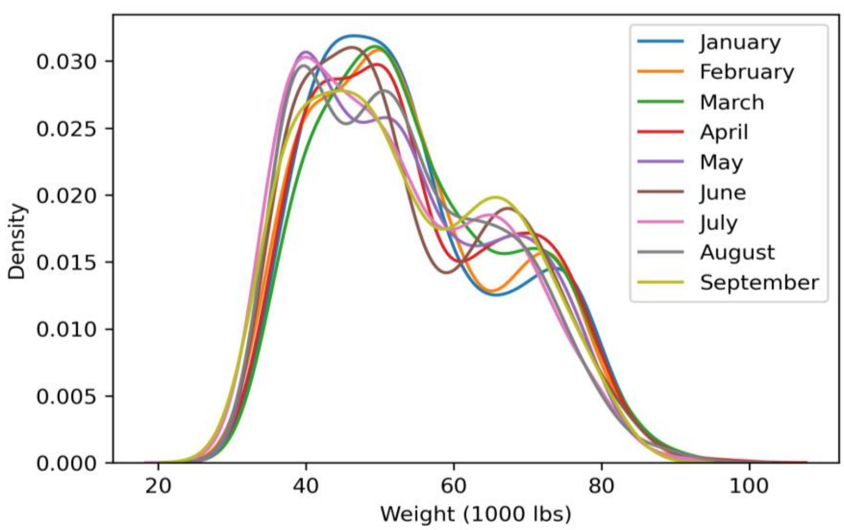


Fig.6. Monthly Distribution of FHWA Class 12 truck weights.

Step 8: Estimate average daily truck counts by FHWA class and quarter

Once a best-fit GMM was established, the means for 3 components were considered as μ_e, μ_p, and μ_f; and the corresponding mixing proportions were λ_e, λ_p, and λ_f. Then, the number of trucks empty, number of trucks partially loaded, and number of trucks loaded to weight limit were calculated as follows.

Number of trucks partially loaded, $N_p = \frac{T_i\left(\frac{\lambda_p}{\lambda_p+\lambda_f}\right)}{\mu_p-\mu_e}$ (2)

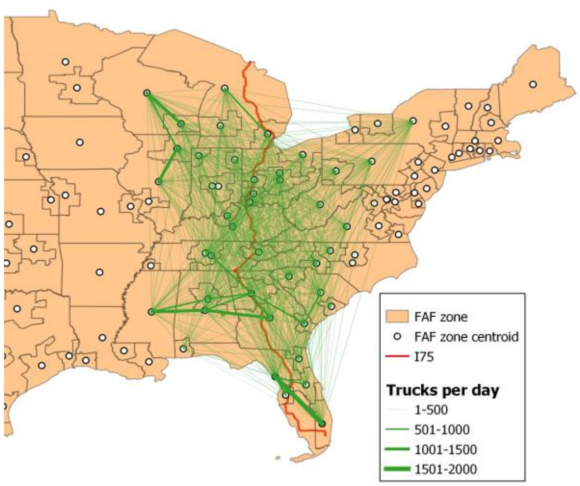
Number of trucks loaded to weight limit, $N_f = \frac{T_i\left(\frac{\lambda_f}{\lambda_p+\lambda_f}\right)}{\mu_f-\mu_e}$ (3)

Number of trucks empty, $N_e = \left(\frac{\lambda_e}{\lambda_p+\lambda_f}\right)\left(N_p + N_f\right)$ (4)

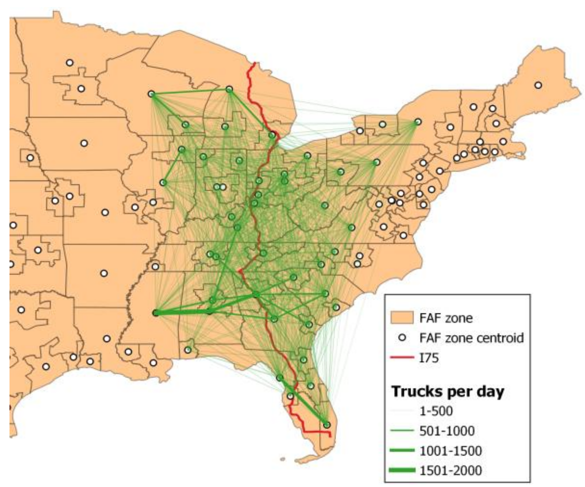
Total number of trucks for an OD pair,

$$N = \sum_{i=\{9,10,11,12,13\}}\left[\frac{T_i\left(\frac{\lambda_p}{\lambda_p+\lambda_f}\right)}{\mu_p-\mu_e}+\frac{T_i\left(\frac{\lambda_f}{\lambda_p+\lambda_f}\right)}{\mu_f-\mu_e}+\left(\frac{\lambda_e}{\lambda_p+\lambda_f}\right)\left(\frac{T_i\left(\frac{\lambda_p}{\lambda_p+\lambda_f}\right)}{\mu_p-\mu_e}+\frac{T_i\left(\frac{\lambda_f}{\lambda_p+\lambda_f}\right)}{\mu_f-\mu_e}\right)\right] \quad (5)$$

Lastly, average daily truck counts for the above 3-components by truck type (i.e., FHWA Classes 9 to 13) and quarter were estimated. This freight traffic data will be used as the input for demand in the planning of hydrogen fueling station. Figure 7(a) presents OD flow map for FHWA Class 9 partially loaded trucks during first quarter of the study year whereas Figure 7(b) presents the same during second quarter of the study year.



(a)



(b)

Fig.7. FHWA Class 9 partially loaded truck flow map: (a) quarter 1 and (b) quarter 2.

MODELING OF HIGHWAY NETWORKS

To simulate truck movements from origin to destination and obtain fuel consumption along the route, truck routing information, including which road a truck takes and the road length is needed. This section illustrates the process to obtain truck routes from all FAF origins to FAF destinations that traverse the I-75 corridor. The modeling comprises two steps: (1) network preparation and (2) truck routing.

Step 1: Network preparation

FAF highway network was utilized for truck routing purposes. To speed up truck routing, a network simplification process was first introduced to consolidate the network and to reduce the number of total highway links without losing information. In the process, for any two adjacent links $L_{a,b}$, $L_{b,c}$, if (i) no additional truck links are connected to the junction of the two links, denoted by node j, and (ii) the two links have the same speed limit, then the two adjacent links can be consolidated into one link connecting node a and c: $L_{a,c}$. A simple network example is shown in Figure 8(a). Green dots are the vertices of each road link before simplification while red circles represent the vertices after simplification. The speed limit of each link is marked in the figure. In the example, $L_{a,c}$ and $L_{c,e}$ cannot be consolidated because there is another link $L_{c,d}$ that connect to node c. $L_{c,d}$ and $L_{d,e}$ cannot be consolidated because the two links have different speed limits. $L_{a,b}$ and $L_{b,c}$, on the other hand, can be merged into one link $L_{a,c}$ given both conditions are satisfied. Figure 8(b) shows a portion of the simplified FAF4 network. Similarly, green dots are the vertices of each road link in the FAF4 network. Red circles represent the vertices after simplification.

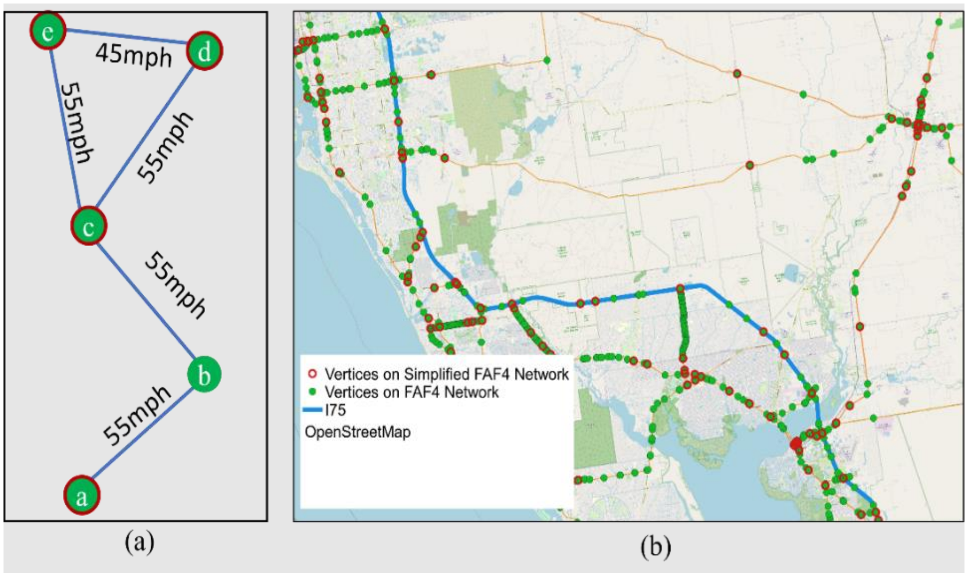


Fig.8. (a) Network simplification example; (b) FAF4 network vertices vs simplified FAF4 network vertices.

Step 2: Truck routing

It was assumed that all trucks will choose the shortest path between Origin (O) and Destination (D). There is a total of 132 origin FAF zones and 132 destination FAF zones in the FAF4 network. All truck movements were assumed to start from the centroid of the origin region and end at the centroid of the destination region. The same assumptions were adopted in previous studies (Hwang, 2007). The shortest path from 132 origin zones to 132 destination zones was obtained. All paths that traverse the I-75 corridor were then identified. Figure 9 shows an example of the resulting shortest path from the Detroit-Warren-Ann Arbor area to the Birmingham-Hoover-Talladega area. The shortest path (green lines) uses the I-75 corridor (black lines) from node E1 to node E2.

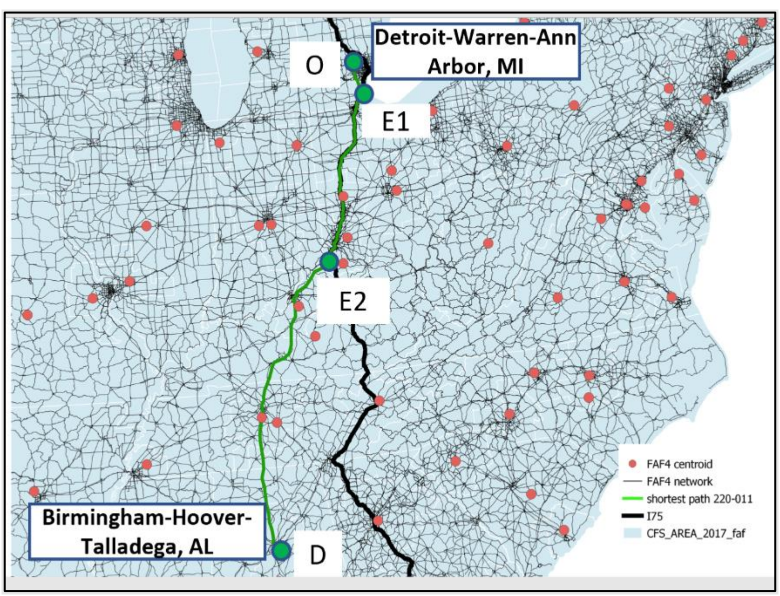


Fig.9. The shortest path from Detroit-Warren-Ann Arbor area to Birmingham-Hoover-Talladega area.

Based on the routing results, each route from O to D is divided into three segments: (i) the segment from a FAF origin to the I-75 corridor entrance (e.g., O to E1 in Figure 9); (ii) The segment from the I-75 corridor entrance to the I-75 corridor exit (e.g., E1 to E2 in Figure 9); and (iii) the segment from the I-75 corridor exit to a destination (e.g., E2 to D in Figure 9). Note that a truck may leave the I-75 corridor for a bypass and reenter the same corridor again before reaching the destination. In these cases, there are more than three segments. The resulting O, D, and routed distance for each segment are the primary input data for truck hydrogen fuel consumption simulation.

CONCLUSIONS

The introduction of a decarbonized energy economy will, in part, necessitate the development of a decarbonized commercial freight truck transportation system and supporting ecosystem. Characterizing and optimizing a national refueling infrastructure to support this decarbonized freight system is critical, where identifying both "spatial" and "temporal" requirements will be necessary to successfully launch and advance a sustainable solution. This process will need to factor in the specific characteristics of the fuel type and correlate that to the anticipated demand (due to freight volume and adoption scale up in time) to determine the optimized refueling sites on public access roadways. This paper is the first in a series that will build out a comprehensive model to optimize a consolidated national hydrogen refueling infrastructure eco-system targeted at commercial vehicles. The study provided a framework for modeling freight traffic demand and highway networks for planning hydrogen fueling stations. The framework was applied using publicly available freight data from Freight Analysis Framework (FAF), Travel Monitoring Analysis System Weigh-in-motion, Commodity Flow Survey, and FAF highway network. Outputs from the study will serve as primary inputs in the fueling station planning. These include average daily truck counts by FHWA class and quarter for different types of trucks by weight distributions and routes via the I-75 corridor from origins to destinations. The data can be used for siting and characterizing an optimized framework of hydrogen fueling stations from candidate diesel stations along the Interstate 75 corridor. The methodologies developed and presented in this paper may be readily expanded and applied to any transport corridor given the data availability.

ACKNOWLEDGMENT

This research was supported by the Oak Ridge National Laboratory's Sustainable Transportation Program office.

REFERENCES

California Governor's Interagency Working Group on Zero-emission Vehicles, 2013, ZEV Action Plan: A Roadmap Toward 1.5 million Zero-Emission Vehicles on California Roadways by 2025.
Available from https://opr.ca.gov/docs/Governors_Office_ZEV_Action_Plan_(02-13).pdf.

Commodity Flow Survey (CFS), 2022, Public Use File.
Available from https://www.census.gov/data/datasets/2017/econ/cfs/historical-datasets.html.

Environmental Protection Agency (EPA), 2022, Sources of Greenhouse Gas Emissions.
Available from https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions#transportation.

Federal Highway Administration, 2016, FAF4 Network Database and Flow Assignment: 2012 and 2045.
Available from https://ops.fhwa.dot.gov/freight/freight_analysis/faf/faf4/netwkdbflow/index.htm.

Federal Highway Administration, 2020, Traffic Continuous Count Station Map, Office of Highway Policy Information.
Available from https://explore.dot.gov/#/views/2020CCSSiteMap/Sheet1?:iid=1.

Federal Highway Administration, 2022, Major Freight Corridors Map.
Available from https://ops.fhwa.dot.gov/freight/freight_analysis/nat_freight_stats/tonhwyrrww2012.htm.

Fetene, G. M., G. Hirte, S. Kaplan, C. G. Prato, and S. Tscharaktschiew, 2016, The economics of workplace charging. *Transportation Research Part B: Methodological* 88:93-118.

Freight Analysis Framework (FAF), 2022, Data Tabulation Tool. Available from https://faf.ornl.gov/faf5/dtt_total.aspx.

Ge, S., L. Feng, and H. Liu, 2011, The planning of electric vehicle charging station based on Grid partition method, International Conference on Electrical and Control Engineering, September 16-18, 2011. Yichang, China.

Gusrialdi, A., Z. Qu, and M. A. Simaan, 2014, Scheduling and cooperative control of electric vehicles' charging at highway service stations, 53rd IEEE Conference on Decision and Control, December 15-17, 2014. Los Angeles, CA, USA.

He, F., Y. Yin, and J. Zhou, 2015, Deploying public charging stations for electric vehicles on urban road networks. *Transportation Research Part C: Emerging Technologies* 60:227-240.

Hernandez, S., 2017, Estimation of average payloads from weigh-in-motion data. *Transportation Research Record* 2644:39-47.

Hwang, H. L., H. Lim, S. M. Chin, R. Wang, and B. Wilson, 2019, Exploring the use of FHWA truck traffic volume and weight data to support national truck freight mobility study. Available from https://info.ornl.gov/sites/publications/Files/Pub134008.pdf.

Hwang, T., 2021, Assignment of freight truck shipment on the US highway network. *Sustainability* 13(11):6369.
Hyun, K., S. Hernandez, A. Tok, and S. G. Ritchie, 2015, Truck body configuration volume and weight distribution: Estimation by using weigh-in-motion data. *Transportation Research Record* 2478:103-112.

Jochem, P., C. Brendel, M. Reuter-Oppermann, W. Fichtner, and S. Nickel, 2016, Optimizing the allocation of fast charging infrastructure along the German autobahn. *Journal of Business Economics* 86:513-535.

Kaisar, E. I., D. Liu, and T. Ardalan, 2019, Evaluation of truck tonnage estimation methodologies.
Available from https://rosap.ntl.bts.gov/view/dot/49954.

Li, S., F. Xie, Y. Huang, Z. Lin, and C. Liu, 2020, Optimizing workplace charging facility deployment and smart charging strategies. *Transportation Research Part D: Transport and Environment* 87:102481.

Nichols, A. P., and M. Cetin, 2007, Numerical characterization of gross vehicle weight distributions from weigh-in-motion data. *Transportation Research Record* 1993:148-154.

Peterson, D., 2011, Addressing challenges to electric vehicle charging in multifamily residential buildings. Available from https://luskin.ucla.edu/sites/default/files/EV_Multifamily_Report_10_2011.pdf.

Regehr, J. D., K. Maranchuk, J. Vanderwees, and S. Hernandez, 2020, Gaussian mixture model to characterize payload distributions for predominant truck configurations and body types. *Journal of Transportation Engineering, Part B: Pavements* 146:04020017.

Travel Monitoring Analysis System (TMAS), 2022, Travel Monitoring and Traffic Volume.
Available from https://www.fhwa.dot.gov/policyinformation/travelmonitoring.cfm.

Uddin, M., N. Huynh, and F. Ahmed, 2021, Assignment of freight traffic in a large-scale intermodal network under uncertainty. arXiv preprint arXiv:2101.04189.

Xie, F., C. Liu, S. Li, Z. Lin, and Y. Huang, 2018, Long-term strategic planning of inter-city fast charging infrastructure for battery electric vehicles. *Transportation Research Part E: Logistics and Transportation Review* 109:261-276.

Xie, F., and Z. Lin, 2021, Integrated U.S. nationwide corridor charging infrastructure planning for mass electrification of inter-city trips. *Applied Energy* 298:117142.