average speed less than 40 mph was assumed to be the beginning of a new trip, the true hourly average speed in the beginning hour of each trip was unknown. As shown in Figure 1, approximately 22% of total miles were driven at an unknown speed. More than half of total miles were driven at speed between 55 and 70 mph.

The platooning opportunities were identified by assuming that the miles driven when the hourly average speed was larger than a threshold value are considered platoonable. Figure 2 presents the share of platoonable miles with respect to the total traveled miles by setting different threshold speeds ranging from 50 to 70 mph with 5 mph increments. Results in Figure 2 indicate that the share of platoonable miles decreases from 63% to less than 16% with the increasing of the average speed threshold from 50 to 65 mph (namely, only 16% of miles would be platoonable if the minimum platoonable speed threshold was 65 miles driven in an hour).

In order to better assess the return on investment of installing platooning technology on a specific truck, the share of platoonable miles for each individual truck was computed. Figures 3 and 4 present the distribution of individual trucks' platoonable miles when 50 and 60 mph are used as threshold values to enable platooning. Figure 3 shows that 32% of trucks would account for 54% of the total platoonable miles if only trucks with platooning percentage larger than 70% were

FIGURE 1 Distribution of hourly average speed.

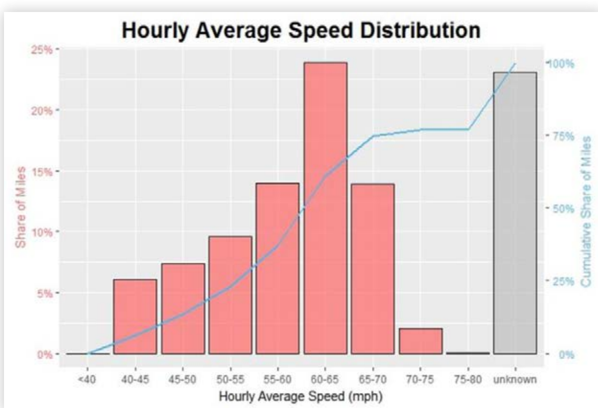


FIGURE 2 Platooning opportunities.

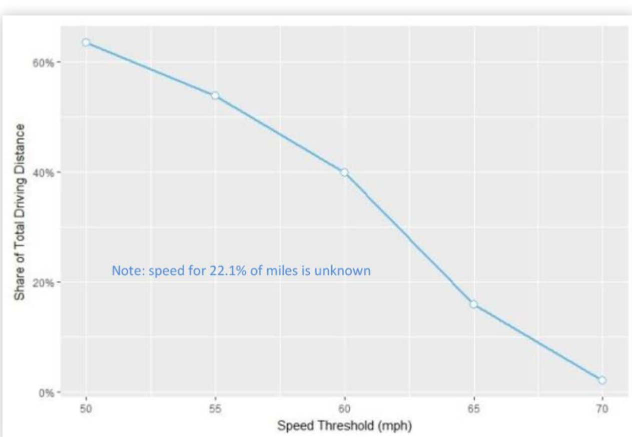
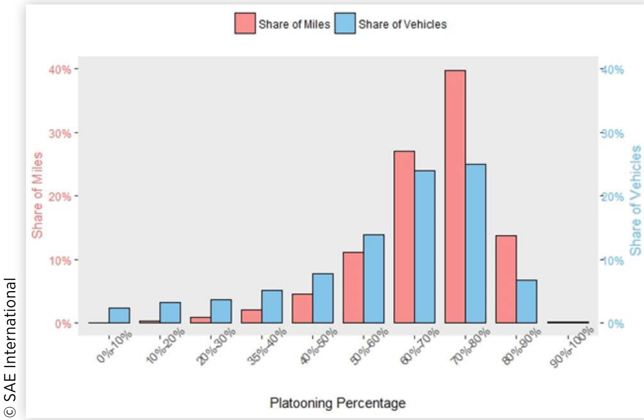


FIGURE 3 Distribution of platooning percentage of an individual truck with threshold greater than 50 mph.



equipped with platooning technology when 50 mph is the platooning threshold. Figure 4 shows that 25% of trucks would account for 52% of the total platoonable miles if only trucks with platooning percentage larger than 50% were equipped with platooning technology when 60 mph is the platooning threshold.

Both temporal and spatial variations of hourly average speed were investigated. Based on the assumption of the study that a truck stopped during a time interval if the corresponding truck hourly average speed is lower than 40 mph, trucks were considered to be inactive if hourly average speed was lower than 40 mph. Figure 5 shows the geospatial representation of hourly average speed of all active trucks in the dataset at different times of a weekday. Overall, there are more trucks traveling on the roadway networks during day-hours than night-hours and early morning. The traveling speed during night operations is generally higher compared to day-operations due to lower traffic volumes at night. Figure 5 also implies that the east coast, west coast, and urban areas have higher temporal dependency than the central part of the US.

The potential truck platooning opportunities for different hours of the day is also examined. By adopting the 50-mph threshold speed to enable platooning opportunities, the percentage of active trucks that can be classified as platoonable was calculated for every hour of a day and is displayed in

FIGURE 4 Distribution of platooning percentage of an individual truck with threshold greater than 60 mph.

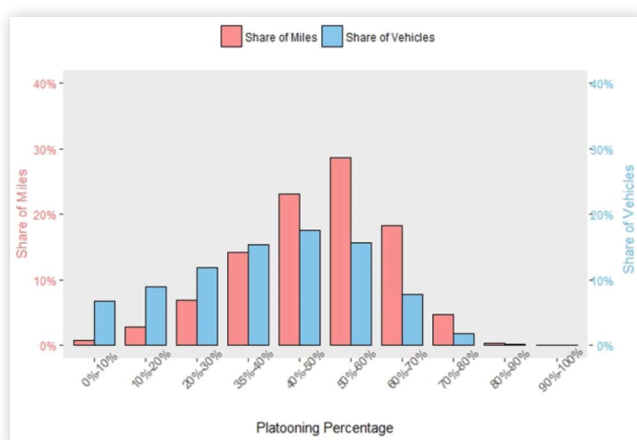


FIGURE 5 Geographic representation of hourly average speed in different time of day. Map created with *ggmap* R package [10].

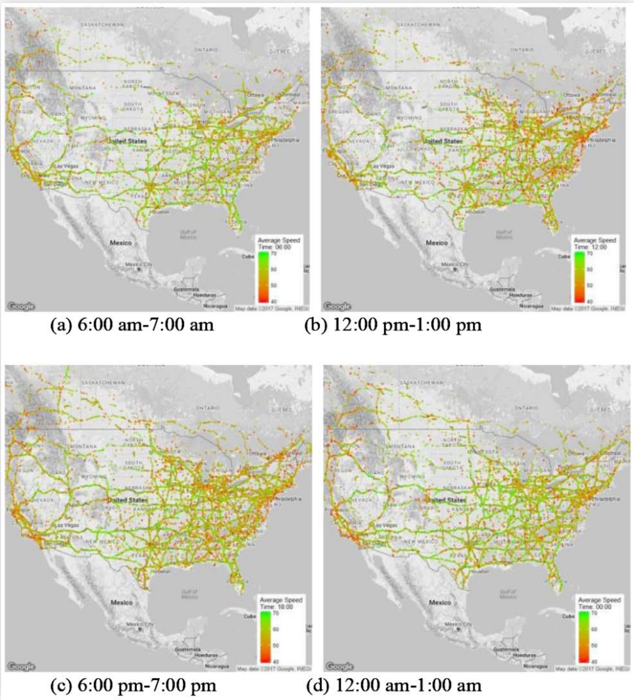


FIGURE 6 Percentage of platoonable vehicles at different time of the day.

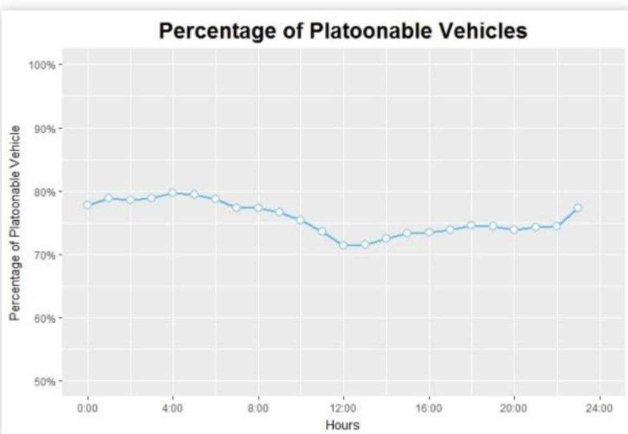
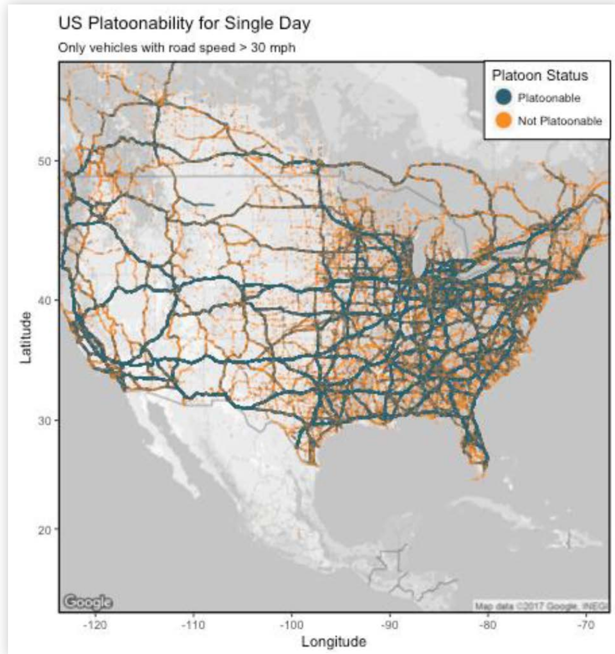


Figure 6. It demonstrates that the platooning ratio reaches to the peak of 80% at 4:00 am and drops down to the lowest of 71% at 12:00 pm.

Geospatial / Partner Method Results

Our exploratory geospatial analysis focused on all observations observed on a single day (Wednesday, July 13, 2016) across the United States. This results in a data set of 919258 unique observations over 54247 unique vehicles. Since this partner analysis

FIGURE 7 Snapshot of US platoonability based on partner analysis for a single day. Observations with speed less than 30 mph are omitted for clarity. Map created with *ggmap* R package [10].



requires pairwise comparison with algorithmic complexity bounded above by $O(N^2)$ computations, a single day was chosen for our analysis to limit computational burden.

Following the assumptions laid out in the "Geospatial partner method description" section; based on road speed and partner availability approximately 33% of all observations were deemed platoonable. Approximately 83% of all vehicles observed had at least one platoonable observation. Within this 83% of vehicles the average proportion of platoonable observations was 37%.

Figure 7 highlights the spatial distribution of platoonable observations with partner considerations for our single day snapshot. The patterns evident in Figure 5 are also present here. The highest regions of platoonability occur across major shipping corridors and interstate highways. Urban areas, particularly those in dense regions on the East Coast, West Coast, and Great Lakes, appear to have fewer opportunities than West and Midwest regions. There is also significant opportunity on Canadian shipping corridors.

Investigating Platoonable Mileage As with the results from the vehicle speed method discussed above, a more apt metric of investigation for the impact of platooning focuses on the miles driven by a vehicle while in a platoonable state. This is a relatively simple classification for the individual vehicle speed method. However when we add the constraint of partner availability, calculating platoonable miles becomes more cumbersome. Our method for classifying distance traveled is as follows:

- The cumulative distance traveled by a vehicle between two consecutive platoonable observations is classified as **platoonable**.

- The cumulative distance traveled by a vehicle between two consecutive non-platoonable observations is classified as **non-platoonable.**
- Any distance traveled between observations that switch states (platoonable to non-platoonable or vice versa) is classified as **unknown**.

The rationale behind the addition of the unknown classification is that we lack the ability to accurately describe the when the partner vehicle behavior changes to cause a state change in our vehicle of interest (e.g. when do we "lose" our platooning partner?). More advanced investigations that incorporate interpolation models, auxiliary data, etc. could potentially reduce or adequately remove the need for unknown classifications.

Table 1 details the classification breakdown for all observed distance traveled. Omitting all unknown classifications results in 55.7% of all classifiable miles driven being platoonable. This is in line with the results from Figure 2 where 60% of all miles driven occurred above the 50 mph threshold. Such good agreement suggests that speed based analysis is sufficient for outer envelope calculations.

Figure 8 shows the distribution elapsed distance between consecutive observations of individual vehicles based on platoonability classification. The main result here is that the platoonable observations tend to encompass longer distances travelled versus non-platoonable segments. This is obviously expected given the higher rate of speed required to be classified as platoonable. It should be noted here that observation times, while tending to occur hourly, are not always equally spaced. This is either due to missing data or other data cleaning requirements.

TABLE 1 Breakdown of mileage platoonability based on geospatial partner method.

	Platoonable	Non Platoonable	Unknown
All Data	34.0%	27.4%	38.6%
Known Data Only	55.7%	44.3%	NA

FIGURE 8 Distribution of segment length by platoonability classification. Each observation represents the cumulative mileage traveled by a vehicle between two consecutive observations.

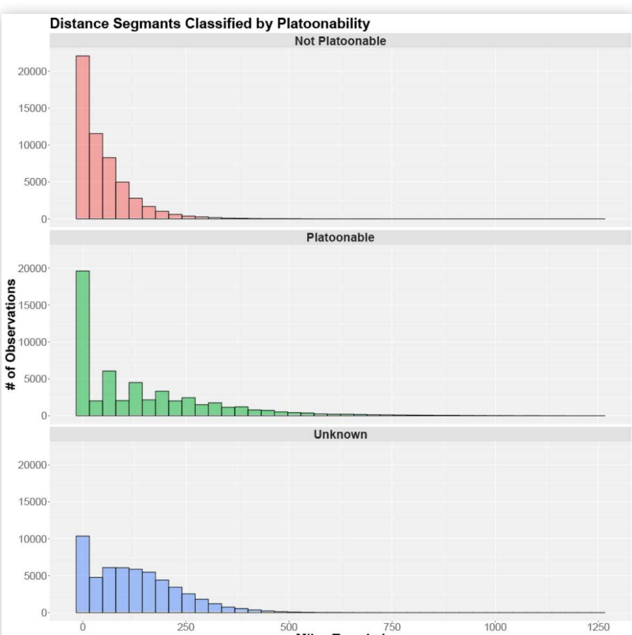


FIGURE 9 Number of available platooning partners distribution.

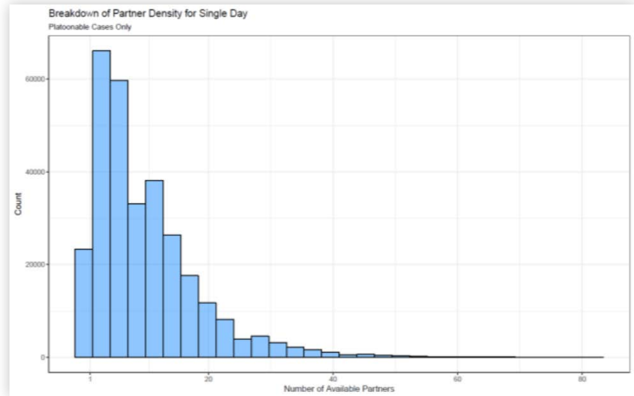


Figure 9 shows distribution of the number of available platooning partners for the platoonable cases. Of significant note is that when one partner is available there are usually many more available partners with a peak occurrence around 2-3 partners and a mean of 10. This means the opportunity for 3 and 4 truck platoons needs to be investigated, not just 2 truck platoons. This also likely means that even some level of fleet non cooperation and technology incompatibility could have minimal impact on partner availability.

Method Comparison

As mentioned in the previous section, both the proportion of platoonable miles traveled for known data (Table 1) and the overall spatial patterns of platoonable observations (Figure 7) track with the general conclusions of the vehicle speed method. This suggests that the computationally simpler vehicle speed method may be sufficient for "outer envelope" platooning analysis. The increased behavioral information gathered from the proximity analysis provides additional context for the analysis and will be critical for more advanced analysis of adoption scenarios where different platooning systems are incompatible, or fleets do not have platooning cooperation agreements in place. The proximity analysis also provides decision makers with information on the value of platooning technologies capable of connecting more than 2 trucks by identifying how often larger platoons could be formed. Additional partner characteristics such as vehicle type, load, heading, etc. could be included in future analyses but were omitted here.

Discussion

The high opportunities for class 8 trucks to platoon identified by these results, combined with track test analysis on platooning fuel savings in test scenarios, suggest that truck platooning could be an effective fuel saving strategy nationally. Combination trucks drove 174 billion miles in 2016 consuming 29.6 billion gallons of fuel [7]. If the nation's truck fleet were to save 6.4% [3] of fuel with a conservatively spaced 2 truck platoon teams on 56% of miles traveled the overall reduction in fuel consumption would be on the order of 1.1 billion gallons of fuel per year and approximately 10.7 million metric tons of CO_2 emissions [9]. Platoons of 3 close following trucks saving a combined 13% [6] on fuel consumption would save closer to 2.1 billion gallons of fuel per year.

The authors note some unique limitations of low time-resolution data sets such as this one. Depending on the method used, 22-39% of miles driven end up being unclassified as they relate to assigning platoonability. If all those observations resulted from a vehicle being parked for 30 minutes and then driving at highway speeds with partner available for the other 30 minutes of the hour, half of the unknown miles would in fact be platoonable. As such, any higher time resolution would have significant impact on the share of unknown miles and would improve the accuracy of this kind of analysis.

Summary/Conclusions

NREL previously conducted research estimating the share of platoonable miles driven by class 8 combination trucks using over 3 million miles of high resolution data from 194 tractors in the FleetDNA database [8]. The purpose of this previous work was to assess if trucks are significantly driven at platoonable speeds, without any trip coordination, and the impact of large-scale platooning in terms of fuel savings and reduction of carbon emissions, concluding that about 65% of the total miles driven by combination trucks could be driven in platoon formation, leading to a 4% reduction in total truck fuel consumption [8].

This study used a much larger database of unique vehicles, but at a lower time resolution, confirming previous findings and providing a framework for a more rigorous analysis that accounts for trucks proximity as well as speed. In particular, previous estimates of platoonability were based on the proportion of miles that trucks traveled at least at 50 mph for at least 15 consecutive minutes. The results presented here are inherently different as platooning is defined by incorporating spatial proximity, speed, and time variables differently.

Overall, the results presented here compliment those found in previous studies. Using a minimum 50 mph speed threshold 55% to 63% of classifiable segments were deemed platoonable depending on whether partner proximity is considered. Key findings include:

- 32% of trucks would account for 54% of the total platoonable miles if only trucks with platooning percentage larger than 70% were equipped with platooning technology, indicating targeted early adoption may see high impact.
- 71-80% of active trucks are travelling at platoonable speeds
- The share of platoonable vehicles for different hours of the day are relative flat, reaching a peak of 80% at 4:00 am and a minimum of 71% at 12:00 pm.
- 55.7% of all classifiable miles driven were platoonable when taking partner availability into account.
- When one platooning partner is available there are usually many more available partners with a mean of 10 partners and as such systems capable of more than 2 trucks in a platoon should be considered.

Future studies should focus on studying datasets with higher time resolutions to better estimate the true potential impact of platooning by decreasing the need for unknown classifications. Given the differences in computational feasibility, the vehicle speed method is acceptable for large datasets where spatial proximity comparisons prove cumbersome and the added value regarding number of available partners and technology penetration rate for savings rate are not required. These methods could potentially be augmented to included drive cycle information, regional data, vehicle type, and other additional characteristics that could potentially impact platoonability. Finally, studying fleets that incorporate behavioral changes to improve platoonability effectiveness will be an interesting area of study. Self-selecting fleets with duty cycles and route scheduling more ideal than the general population studied here likely will increase platooning opportunities. Additionally, fleets choosing to optimize operations to prioritize truck platooning opportunities could realize additional savings beyond the scope of this analysis.

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