IMPLEMENTATION OF A SELF-LEARNING, ON-BOARD GEO-CLUSTERING PLATFORM FOR REDUCING EMISSIONS IN DRAYAGE OPERATIONS

Parthav Desai
Volvo Group North America
7900 National Service Road, Greensboro, NC 27409
Tel: +1-336-291-9511; Email: parthav.desai@volvo.com

Eddie Garmon
Volvo Group North America
7900 National Service Road, Greensboro, NC 27409
Tel: +1-336-543-9092; Email: eddie.garmon@volvo.com

Hoda Yarmohamadi
Zenuity
Lindholmspiren 2, 41756 Göteborg, Sweden
Tel: +46-731258116; Email: hoda.yarmohamadi@zenuity.com

Jason Strait
Volvo Group North America
13403 Volvo Way, Hagerstown, MD 21742
Tel: +1-301-790-5857; Email: jason.strait@volvo.com

Pascal Amar
Volvo Group North America
575 Anton Boulevard, Suite 860, Costa Mesa, CA 92626
Tel: +1-240-308-9010; Email: pascal.amar@volvo.com

Aravind Kailas, Corresponding Author
Volvo Group North America
575 Anton Boulevard, Suite 860, Costa Mesa, CA 92626
Tel: +1-714-277-8172; Email: aravind.kailas@volvo.com

Word count: 213 (abstract) + 3035 (text) + 139 (references) = 3,387
Number of tables and figures: (2 tables + 5 figures) x 250 = 1,750
Total word count = 5,137

Submission Date: August 1, 2018

ABSTRACT

The paper presents an approach for dynamically managing mode of operation on Class-8 plug-in hybrid electric trucks (PHETs) to increase zero emission (ZE) operation per duty cycle without increasing battery size requirements. The prototype platform records many vehicle-specific (e.g., speed) and location-centric (e.g., GPS coordinates) data during each operational run to manage the on-board energy usage and driving maneuvers. As an example, it is desirable to go into the "ZE mode" when operating at lower speeds and propulsion energy demands. Using lower first- and second-order statistics of the truck speed and power requirement, it is possible to identify and group such geographical locations (to create "geo-clusters") along a route. The next time the truck is in a "geo-cluster," it can automatically transition to electric operation. While it has been established that incorporating operational characteristics will enhance the performance of hybrid-electric vehicles, implementation is most feasible when operations are repetitive or on fixed routes, like transit buses (herein referred to as "static geofences"). On the other hand, the proposed platform enables predictive controls on a vehicle-to-vehicle basis without imposing any operational constraints or knowledge. Deployment of the concept in customer operations at the ports of Los Angeles and Long Beach has demonstrated the potential to almost double the ZE mode mileage compared to the "static geofence" implementations on PHETs.

Keywords: Air Quality along Truck Corridors, Truck Technology and Emissions, Intelligent Transportation Systems, Geofences, Plug-in Hybrid Electric Vehicles, Commercial Vehicles, Zero Emission

INTRODUCTION

The paper describes a first deployment of an on-board "geo-clustering" platform that enables automatic switching between diesel propulsion with electric assist (hereinafter referred to as the "hybrid mode") and fully electric (hereinafter referred to as the "zero emission (ZE) mode") in Class-8 plug-in hybrid electric trucks (PHETs) in order to reduce pollution and diesel consumption. "Geo-clustering" is a machine learning-based approach to identify and group geographical locations (or "points" on a map) that correspond to similar truck operational characteristics. The groups of geographical locations are referred to as "geo-clusters (GCs)."

This paper summarizes findings from the deployment of two Mack trucks (Figure 1) in customer operations with the same fleet and driver, as a part of a pilot program that began in 2012. While both trucks had the same14 kWh battery and plug-in hybrid electric architecture, the dynamic, self-learned "geo-clustering" platform on PHET #2 is an evolution of the ZE mode control using static geofences as implemented in PHET #1. With PHET#2, we were able to show that ~16% of the miles driven during each duty cycle were in ZE mode, compared to ~9% with PHET#1.

FIGURE 1 Two Mack trucks (labeled PHET #1 and PHET #2) were deployed in customer operations at the San Pedro Bay ports. PHET #1 (truck on the left) operated for over 6 months and drove a total of 13,317 miles out of which 1,229 miles (~9%) were fully electric. On the other hand, PHET #2 (truck on the right) has been in operation for over 5 months and drove a total of 11,213 miles out of which 1,810 miles (~16%) were emissions free. This is a direct consequence of the evolved ZE mode control implemented in PHET #2.

Background

The sprawling Southern California port complex is the nation's largest in terms of annual freight tonnage handled (*1*). In late 2016, the governing boards of POLA and POLB voted to approve the landmark San Pedro Bay Ports Clean Air Action Plan (*2*), the most comprehensive strategy to cut air pollution by 45% within five years, thereby mitigating the health risks ever produced for a global seaport complex. To advance this agenda, the "Clean Truck" program was instituted to replace "dirty" diesel trucks with a new generation of clean or retrofitted vehicles (*2*).

This paper summarizes the outcomes of three consecutive programs co-funded by the US Department of Energy (DOE), South Coast Air Quality Management District (SCAQMD), the California Energy Commission (CEC), California Air Resources Board (CARB) and the Volvo

Group (Volvo) between 2012 and 2017; all programs aimed to accelerate the deployment of PHETs in port drayage operations at POLA and POLB. The implementation and field trials of the first prototype in customer operations inspired the design of the presented "geo-clustering" approach to extend the benefits of the plug-in hybrid electric technology.

Related Efforts

Among the other test programs in operation at POLA and POLB, a Cummins Westport Inc. venture is testing low NOx natural gas engines (*3*), Toyota is testing a fuel cell electric drayage truck (*4*), and a number of all-electric BYD drayage trucks are shuttling freight from the ports to area warehouses (*3*).

Additionally, Kenworth is developing both a fuel cell electric drayage truck (5) and a port truck using a natural gas generator (*5*) to extend the range of its battery-electric powertrain. Tesla, Inc. is developing a battery-electric Class 8 truck with drayage capabilities (*6*), and Ricardo recently began development work on a liquid nitrogen enhanced diesel engine that promises very low production of smog-producing nitrogen oxides, or NOx (7).

Why this research matters?

Despite the potential for cleaner air, market adoption of Class 8 PHETs has been impeded by the cost of the technology and the payload capacity limitations; this is mainly driven by cost and weight of the batteries. So, the significance of this work has been to successfully demonstrate increased ZE miles in real-world port drayage operations without re-sizing batteries. This was achieved by "smart" location-based approaches to adjust the mode of operation of the vehicle's drivetrain "on-the-fly." Our previous work investigated characterizing typical drayage routes in the San Pedro Bay ports that eventually helped identify regions that were favorable for the ZE mode (*8*). However, a limitation of that implementation was that these regions were fixed, and the truck could not "automatically" switch to the ZE mode when things changed along its route (e.g.., increased traffic congestion that limited the driving speed, new customer warehouse locations, etc.) To the best of our knowledge, there are no known self-learning "geo-clustering" solutions for ZE mode management in PHETs. Deployment in customer operations at POLA and POLB over a one-year period helped validate and refine our novel "geo-clustering" platform. Moreover, it demonstrated that plug-in hybrid electric technology combined with dynamic, location-triggered actions can mitigate fuel consumption and emissions in Class 8 trucks with relatively small battery packs without relying on opportunity charging (from the electric grid).

METHODOLOGY

The proposed "geo-clustering" platform executes in the following manner (Figure 2). First, the truck and location centric data is recorded as the truck moves. Then, this "new" data is consolidated with the "historical" data to define, create, and store ZE GCs as a map. Finally, the map is used by the truck to transition between the "hybrid" and ZE modes on-the-fly.

When the truck is in operation, the on-board system records a variety of truck- and location-centric data such as speed, torque, engine speed, gear, weight, GPS latitude, longitude, heading, altitude, etc.

Next, the recorded data set is processed to create GCs. "Offline" data processing can be scheduled when the truck is stationary, keyed OFF, charging its batteries using the wall charger, etc. The "new" data set is compared with the "historical" data set to determine the locations that are suitable for ZE operations. The latitude, longitude, and heading from the "new" data set (that define a point) are compared with points on the map (local to the host truck) generated using "historical"

data; if the point is not already on the map, a new point is created and the map is updated. Keeping in mind the legacy inaccuracies (and resolution) associated with GPS receivers, and the possibility of the truck being on different lanes or slightly different paths during each run, we use a combination of interpolation and extrapolation techniques to consolidate the data.

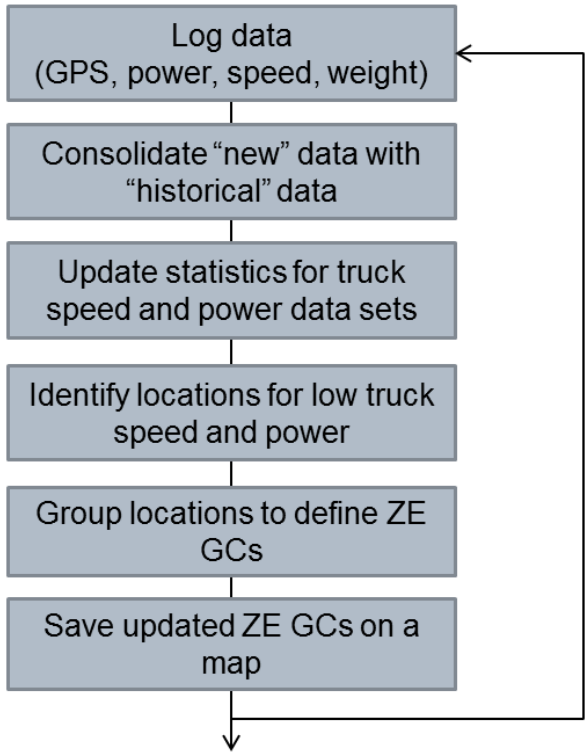


FIGURE 2 Flowchart illustrating the creation and updating of ZE GCs on a map using statistical learning.

For every run and location, trucks parameters such as speed, torque, and power are used to update their respective means and standard deviations; statistical variations in these parameters are used to identify points (that are used to construct GCs) for operating in ZE and "hybrid" mode. As an example, points that correspond to lower propulsion energy demands (and hence, suitable for ZE) are identified by lower first- and second-order statistics of speed and power requirement. Once these points are identified, a "neighborhood search" is carried out for the points not suitable for ZE. If there are only a "few" points separating two points that are unsuitable for ZE, they are also classified as points that unsuitable for ZE. Subsequently, a secondary "neighborhood search" is conducted on the points that are suitable for ZE. If the search results in a cluster of points that are suitable for ZE, the map is updated with these points. When there are only a "few" points that are unsuitable for ZE between two large GCs that have been identified as being favoirable for ZE, then they are also classified as being suitable for ZE provided they satisfy the following two criteria.

$$P_{\text{Mean}} < \min\left(1 + \frac{2.5}{N_{\text{Unsuitable for ZE}}}, 1.2\right) \cdot P_{\text{Threshold}}\text{, and}$$

$$v_{\text{Mean}} < \min\left(1 + \frac{2.5}{N_{\text{Unsuitable for ZE}}}, 1.2\right) \cdot v_{\text{Threshold}},$$

where P_{Mean}, v_{Mean}, $P_{\text{Threshold}}$, $v_{\text{Threshold}}$, $N_{\text{Unsuitable for ZE}}$ denote the mean power, mean truck speed, power threshold, truck speed threshold, and the number of points that were identified as being unsuitable for ZE mode along the truck route, respectively.

- To summarize, the following rules are considered when defining and updating GCs. Minimum length of the GCs is 1 km to ensure that the engine is not turned ON and OFF too frequently.
- There is no limit to the maximum size of the GCs.
- Adjacent GCs are connected whenever possible as long as they are not separated by points with speed or power requirements that greatly exceed the limits of the PHET while in ZE mode.
- There are no pre-defined GCs; they are set up after the first truck run.
- GCs are updated everytime the truck is keyed OFF.

During initial testing, it was observed that the power requirement of the truck was correlated to its weight. This prompted the design of GCs that factored in the weight of the truck. Specifically, GCs were designed for three different truck weight categories - 0 to 30,000 lbs, 30,000 to 60,000 lbs, and > 60,000 lbs. The resulting GCs are then stored in the form of three maps.

The steps in Figure 2 iterate to update the GCs periodically and the resulting maps are saved on-board the truck. During each run, the truck "knows" its location using a GPS sensor. The on-board "geo-clustering" platform projects its location onto the stored map to identify whether the truck is in or approaching a GC. If the current operating conditions of the truck meet the performance criteria for ZE mode, the truck will automatically switch to ZE mode when entering a GC on the map associated with the truck's current weight. If there are no known GCs, then the truck continues operating in the same mode as it was at the last known location.

Additional information such as truck parameters may be used to supplement GCs from the stored maps when deciding the appropriate driveline mode. As an example, the truck will remain in ZE mode if the speed and power requirements of the truck remain low upon exiting a ZE GC. Extending ZE operation in this manner is desirable in confined areas such as warehouses, container terminals, parking lots, etc., where the stored maps ("historical" data) may not cover the entire geographical area. On the other hand, if the speed or power requirements become high when the truck is in a ZE GC, the on-board "geo-clustering" platform may decide to keep the engine ON or even start the engine if it is already turned OFF. This function prevents ZE operation in situations where it would result in a highly underpowered truck.

When the truck is outside ZE GCs, the batteries are charged using internal combustion engine (ICE) power and regenerative brake recovery. Using ICE to recharge the batteries enables the PHETs to operate in ZE mode for a considerable portion of their duty cycle without requiring a large battery capacity. It also eliminates the need for opportunity grid charging and allows the truck to operate without the need for significant charging infrastructure. The charging rate is determined by the plugin hybrid electric driveline controls a function of the the state of charge of the battery and driveability.

A unique feature of this implementation is the ability to adapt to extend ZE operation under varying operating conditions. In order to find out which points in the historic data are

suitable for ZE GCs the mechanism looks at the average and variation of torque, speed, power etc. When these quantities cross certain threshold, the truck classifies the points as suitable for ZE mode and processes them further. The size of ZE GC will depend on the threshold for these quantities. For example if the maximum speed limit for the truck to be in a ZE GC is higher, the size of the ZE GC will be larger. This might lead to a situation where the hybrid system battery drains fast and completely depletes itself even before it crossed and exited a ZE GC.

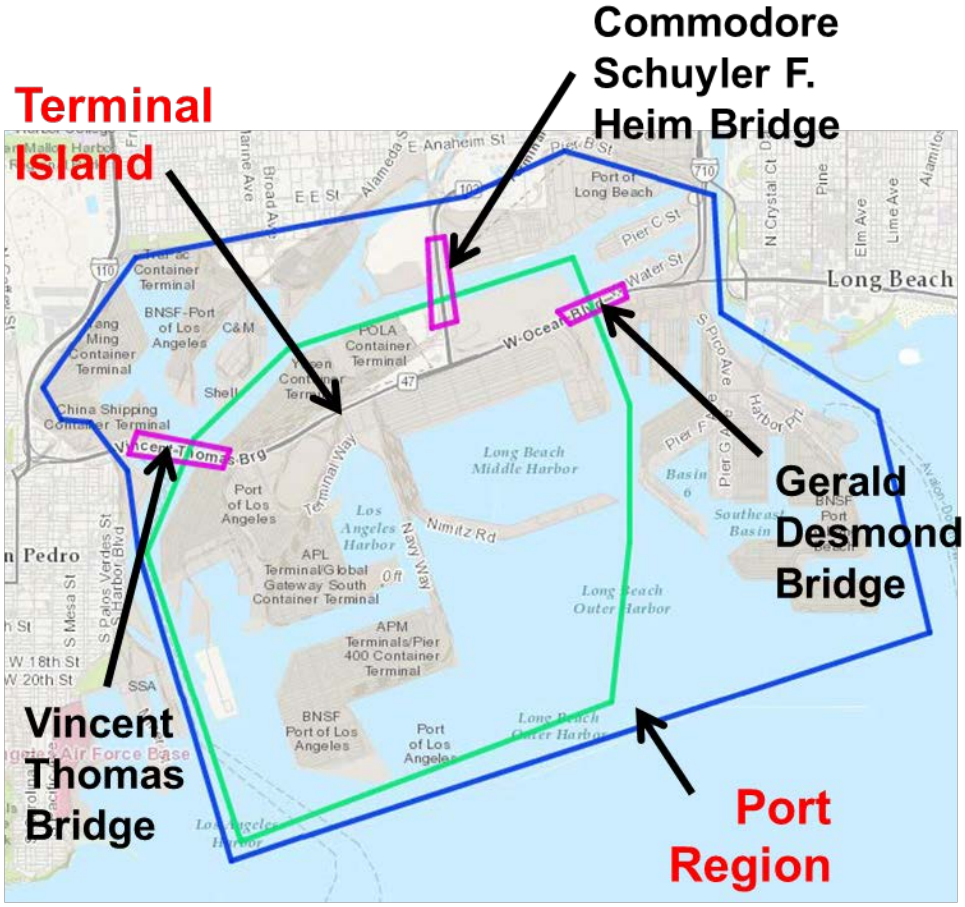
FINDINGS

The "geo-clustering" platform was verified using simulations and real-world deployment. Initially, complete vehicle models for hybrid driveline configurations were used to validate performance using MATLAB. The models were calibrated using data from actual conventional truck runs at POLA.

TABLE 1 Select parameter values used in the creation of "geo-clusters"

Parameter	Value	Unit
Power threshold	120	kW
Truck speed threshold	60	km/h
Distance between points	20	m
Minimum length of a GC	1	km

PHET#2 was shipped to California and provided to a Port Drayage operator. The vehicle has been in a revenue generating service for over 5 months. Combining data collected from PHET#2 runs with the parameters listed in Table 1 resulted in the creation of GCs (Figure 3). In Figure 3, the Cyan lines show locations appropriate ZE mode, while the Black lines denote locations for the "hybrid" mode. When compared to the "static geofence" from PHET#1, it was seen that proposed "geo-clustering" platform resulted in ZE regions that not only had a higher resolution, but also extended beyond the port terminals. Because the data did not include the weight of the trucks, only one map was created initially.


Commodore
Schuyler F.
Heim Bridge
Terminal
Island
Gerald
Desmond
Bridge
Vincent
Thomas
Bridge
Port
Region
Long Beach
Port of Los Angeles
Long Beach Middle Harbor
Los Angeles Harbor
Long Beach Outer Harbor
APM Terminals/Pier 400 Container Terminal
APL Terminal/Global Gateway South Container Terminal
POLA Container Terminal
BNSF-Port of Los Angeles
China Shipping Container Terminal
Pedro

(a)


Long Bea
Aquarium of the Pacific
The Queen Mary
PEDRO

(b)

(c)

Figure 3 Consistent low power and operating speed form the basis creating GCs. The Blue and Green lines in (a) denote fine "static geofences" that were created from PHET#1 runs near the ports. In contrast, the ZE GCs shown in (b) and (c) are more intricate, and incorporate the effects of every high and low speed road as well as road slopes. It can also be noted that the ZE GCs are more widespread compared to geofences in (a).

Creation of Zero Emission "Geo-Clusters" for Different Truck Weights

The GC maps for the three truck weight categories are shown in Figure 4.The Green lines indicate where the truck is forced into the ZE mode, and the Red points represent locations ZE mode is not recommended.

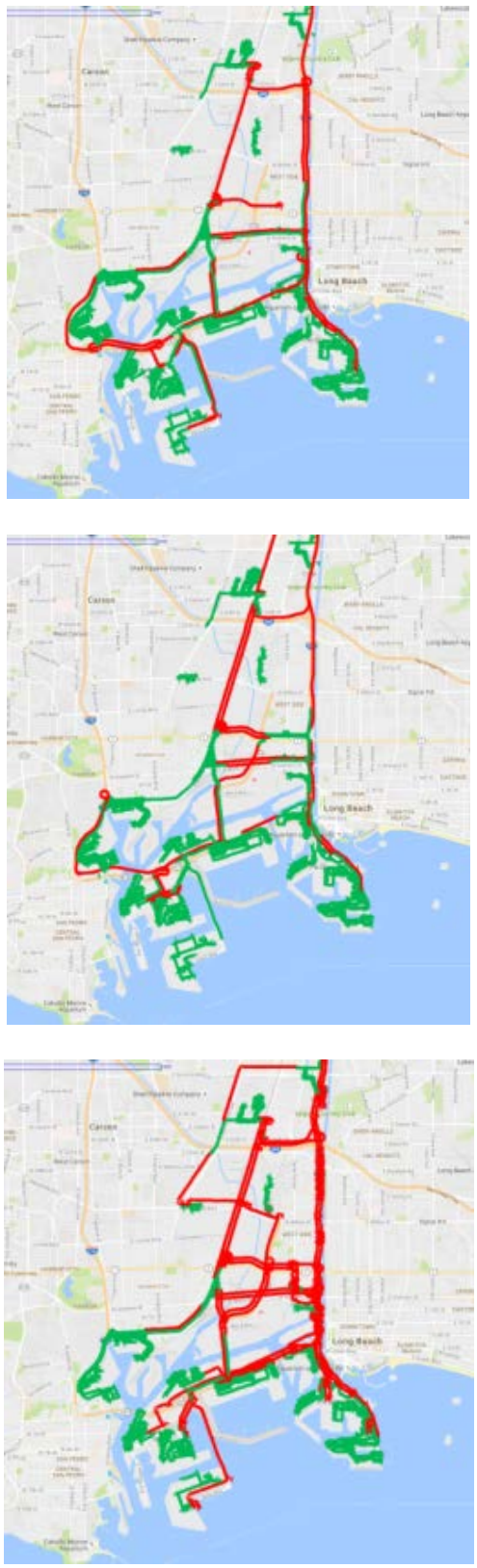


FIGURE 4 Visual representation of maps created using statistical learning during PHET#2 operation at the San Pedro Bay ports. In all three maps, the ZE GCs are denoted by Green lines, while the locations unsuitable for ZE in Red. Each map corresponds to a different

truck weight. The top map corresponds to trucks weighing up to 30, 000 lbs, the one in the middle between 30,000 and 60,000 lbs, and the bottom map for trucks weighing over 60,000 lbs.

Fuel Saving Benefits

Accurately quantifying fuel savings through data collection of a PHET and a reference drayage truck in a revenue generating operation is almost impossible due to the very high variability of routes and loads. Therefore, a simulations-based approach was preferred to study and quantify fuel saving benefits, and forverifying vehicle performance used in customer operations in diverse settings. Using Volvo proprietary complete vehicle simulation platform, we were able to replicate the behavior of the vehicle at the ports for specific driving cycles (Figure 5).

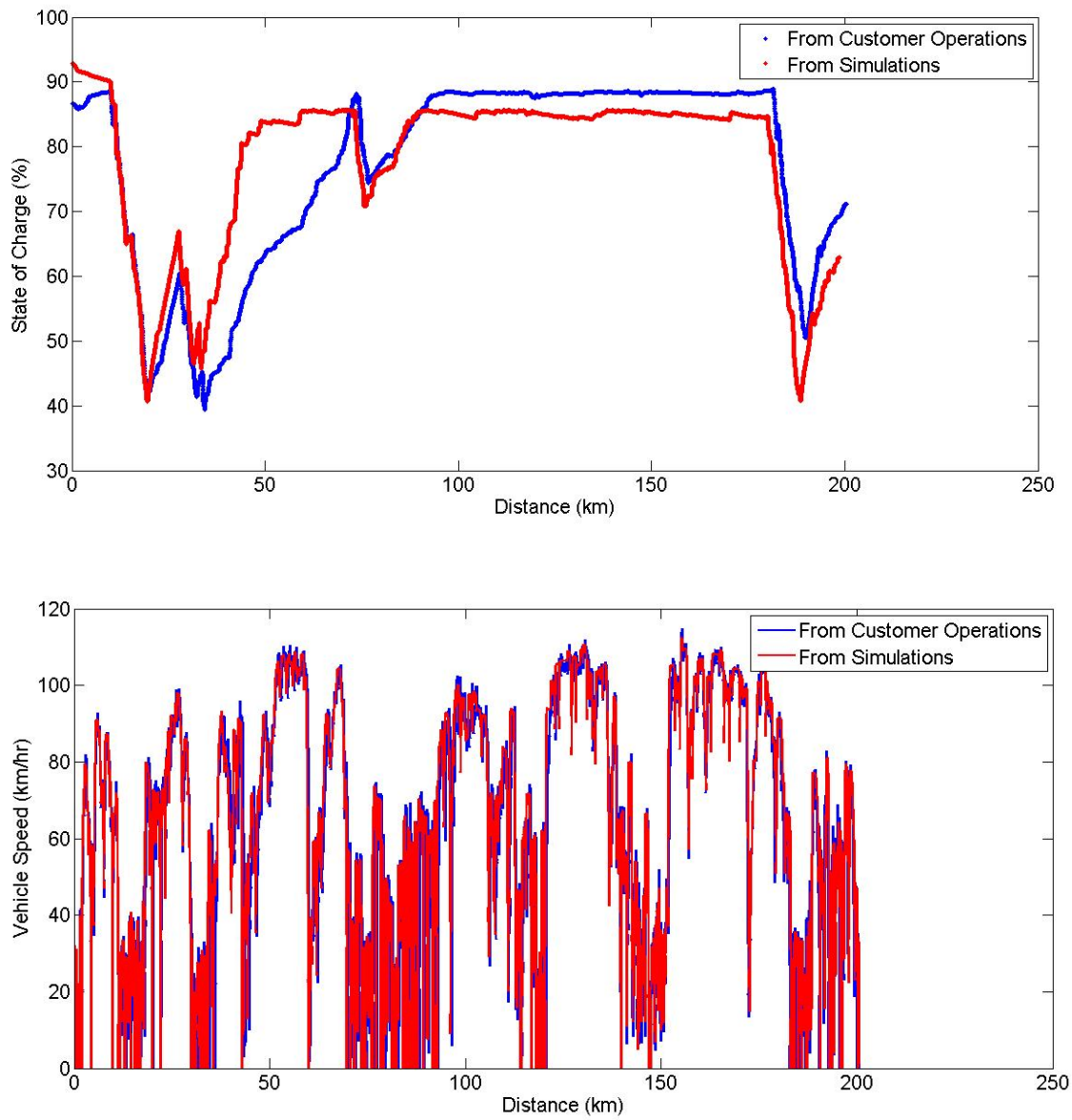


FIGURE 5 Battery state-of-charge and truck speed comparisons between data from customer operations and simulations. The high correlation in these plots is indicative of the

"goodness" of the simulation platform that was used to compute fuel consumption under different scenarios.

The fuel consumption numbers from simulations and customer operations were within 1.5%, and the variance can be attributed to extranous factors. Once this was established, simulations were used to evaluate the fuel consumption of the truck under numerous other conditions, some very different from the customer operations. Table 2 shows the "Fuel Index" for three truck configurations under a variety of operational scenarios. Fuel savings are quantified using "Fuel Index," defined as the normalized fuel consumption where the fuel consumption for the conventional Diesel truck is 100 units. So, a Fuel Index of 80 implies that PHET#2 consumes only 80% of the fuel compared to the conventional Diesel truck, implying a savings of 20%. With the "static geofence" implementation, the fuel saving would be about 12% relative to the conventional Diesel truck.

TABLE 2 Simulations-based fuel savings for convetional diesel truck and PHET "static geofences" (PHET #1) and GCs (PHET#2) for port drayage operations

Truck Configuration	Conventional Diesel	PHET#1	PHET #2
Fuel Index	100	88	80

Future Work

While the extensive verification of the proposed "geo-clustering" prototype proved very effective and robust in the port drayage operations at the San Pedro Bay ports, parameter calibrations may not be directly suited to applications with very drastically different operational characteristics. Therefore, an additional self-learning functionality was defined to dynamically adjust the size of the ZE GCs to any environment based on statistical learning; however, this has not been implemented yet. This functionality basically identifies the way in which the battery will be used in ZE GCs. If the battery drains beyond a threshold for more than a fixed percentage of locations, then the maximum speed and/or power limit is descreased to enable ZE mode at that location. On the other hand, if the battery state of charge when exiting a ZE GC is higher than the threshold for more than a fixed percentage of locations the maximum speed and/or power limit is increased to enable ZE mode at that location.

CONCLUSIONS

The overarching objective of our proposed "geo-clustering" platform was to increase the time duration of the ZE mode without increasing the size of the battery for PHETs. This platform was implemented on a Class 8 Mack truck and deployed in customer port drayage operations. Our findings suggest great potential for reduced emissions and fuel consumption in operations at the San Pedro Bay ports, where the trucks are operating at low speeds and/or idle for extended periods of time. It was also shown that our "geo-clustering" approach dramatically increased the ZE mode time duration compared to our previous "static geofence" implementation. Keeping in mind the inherently unpredictable nature of drayage routes, the proposed platform is a practical alternative for advanced predictive energy management in PHETs.

A key goal was to enable "on-the-fly" decision-making with regards to mode selection of the plug-in hybrid electric driveline. Traditionally, locations with low speeds and power requirement, and a large number of stops are better suited for ZE operation. Using the GCs created

using statistical learning, the truck was able to determine the locations that corresponded to low speeds and torque requirements, thereby automatically transitioning into the ZE mode.

Although not incorporated in our prototype platform, the "geo-clustering" approach provides the framework for advanced on-board energy management. Once the ZE GCs have been created, "historical" data could be used to identify points leading up to their boundaries. By utilizing the average speeds at these points, one could define the charging rates to ensure that the truck is charged when it enters the ZE GCs. These points would then make up a "charging" GC that would also be stored on truck, and would enhance the battery charge management when approaching ZE GCs. In a similar manner, it is also possible to use "historical" data to evaluate the energy required to cross any particular GC. This knowledge can be used to manage the battery charge before entering a ZE GC to ensure the battery has "just enough charge" to drive through it.

In general, the "geo-clustering" platform can be used for dynamically controlling drivetrain mode selection in hybrid vehicles, limiting acceleration, increasing vehicle power, etc. The proposed methodology will be applicable in hybrid vehicles, autonomous vehicles, and construction and off road vehicles, to name a few.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge the discussions and generous financial support from the US DOE, SC AQMD (Contract Number: 12862), the CEC (Contract Number: ARV-11-014) and CARB (Contract Number: 17225).

AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: Parthav Desai, Eddie Garmon, Hoda Yarmohamadi, Jason Strait, Pascal Amar; simulations and data collection: Parthav Desai; analysis and interpretation of results: Parthav Desai, Eddie Garmon, Hoda Yarmohamadi, Jason Strait, Pascal Amar, Aravind Kailas; draft manuscript preparation: Y. Aravind Kailas, Pascal Amar. All authors reviewed the results and approved the final version of the manuscript.

REFERENCES

1. *NAFTA Container Port Ranking 2017*. http://aapa.files.cms-plus.com/Statistics/NAFTA%20Container%20Port%20Ranking%202017.pdf. Accessed Aug. 1, 2018.
2. *2017 Clean Air Action Plan*. http://www.cleanairactionplan.org/2017-clean-air-action-plan-update/. Accessed Aug. 1, 2018.
3. *March 2017 Sustainable Freight Advisory Committee.* https://www.portoflosangeles.org/environment/progress/wp-content/uploads/2017/05/SFAC-March-2017-Meeting-Summary_051717.pdf. Accessed Aug. 1, 2018.
4. *Toyota Opens a Portal to the Future of Zero Emission Trucking.* Jana Hartline. http://corporatenews.pressroom.toyota.com/releases/toyota+zero+emission+heavyduty+trucking+concept.htm. Accessed Aug. 1, 2018.
5. *Kenworth Advances Low - Zero Emission Prototype Projects on T680 Day Cab Drayage Trucks for Southern California Ports.* https://www.kenworth.com/news/news-releases/2017/may/advanced-prototype-projects/. Accessed Aug. 1, 2018.
6. *Tesla Semi.* https://www.tesla.com/semi. Accessed Aug. 1, 2018.
7. *Ricardo Developing Liquid Nitrogen-Diesel Engine for Trucks.* John O'Dell. https://www.trucks.com/2018/02/22/ricardo-liquid-nitrogen-diesel-engine-trucks/. Accessed Aug. 1, 2018.
8. Desai, P., Amar, P., Kailas, A., and Gallo, J. -B. Development of a Duty Cycle for Design and Optimization of Advanced Heavy-Duty Port Drayage Truck. *Transportation Research Record: Journal of the Transportation Research Board*, 2017. 2609. https://doi.org/10.3141/2609-03.