Heavy-Duty Vehicle Port Drayage Drive Cycle Characterization and Development

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Abstract

In an effort to better understand the operational requirements of port drayage vehicles and their potential for adoption of advanced technologies, National Renewable Energy Laboratory (NREL) researchers collected over 36,000 miles of in-use duty cycle data from 30 Class 8 drayage trucks operating at the Port of Long Beach and Port of Los Angeles in Southern California. These data include 1-Hz global positioning system location and SAE J1939 high-speed controller area network information. Researchers processed the data through NREL's Drive-Cycle Rapid Investigation, Visualization, and Evaluation tool to examine vehicle kinematic and dynamic patterns across the spectrum of operations. Using the k-medoids clustering method, a repeatable and quantitative process for multi-mode drive cycle segmentation, the analysis led to the creation of multiple drive cycles representing four distinct modes of operation that can be used independently or in combination. These drive cycles are statistically representative of real-world operation of port drayage vehicles. When combined with modeling and simulation tools, these representative test cycles allow advanced vehicle or systems developers to efficiently and accurately evaluate vehicle technology performance requirements to reduce cost and development time while ultimately leading to the commercialization of advanced technologies that meet the performance requirements of the port drayage vocation. The drive cycles, which are suitable for chassis dynamometer testing, were compared to several existing test cycles. This paper presents the clustering methodology, accompanying results of the port drayage duty cycle analysis and custom drive cycle creation.

Introduction and Background

The U.S. Department of Energy's (DOE) National Renewable Energy Laboratory (NREL) is the only research laboratory solely dedicated to the research and development of energy efficiency and renewable energy technologies. As part of its mission, NREL's Fleet Test & Evaluation (FT&E) group, funded by the DOE's Vehicle Technologies Office within the Vehicle & Systems Simulation and Testing Activities, works in partnership with commercial and government fleets and industry partners to evaluate the performance of alternative fuels and advanced technologies in medium- and heavy-duty fleet vehicles.

One way to evaluate and compare advanced vehicle technologies is through the use of standard chassis dynamometer test cycles. Another is through the use of modeling and simulation tools running analyses on standard test cycles. Previous testing and analysis conducted by NREL has illustrated the influence of drive cycles on both energy consumption and greenhouse gas emissions [1-4].

Researchers from NREL's Fleet Test & Evaluation group identified port drayage heavy-duty truck operations as a candidate for further research on the potential fuel savings impact of advanced technologies. Port drayage operation is a unique and specialized type of goods movement. Drayage refers to the movement of cargo containers, often called intermodal containers, between a port terminal and an inland distribution center or rail yard terminal.

Due to the varied operational modes inherent in drayage, standard heavy-duty chassis dynamometer tests [5] do not accurately or fully characterize the real-world port drayage duty cycle seen at the San Pedro Port of Los Angeles (POLA) and Port of Long Beach (POLB). The POLA and POLB are located in Southern California in the South Coast Air Quality Management District, which is a nonattainment area for criteria air pollutants as determined by the U.S Environmental Protection Agency's national ambient air quality standards. Collectively the two ports form the largest and busiest container port in the United States and the fifth busiest in the world [6] with over 15 million twenty-foot equivalent units processed in 2015 [7, 8]. With over 15,000 acres of land and sea under port authority, there are 15 primary container terminals that process the majority of drayage container freight in and out of the ports (Figure 1) with nine in the POLA and six in the POLB.

Figure 1. Map of Port of Long Beach and Port of Los Angeles showing 15 container terminals. Eleven have on-dock rail lines. [9, 10]

Field Data Collection

Starting in October 2014, NREL researchers began to collect in-use duty cycle data using data loggers installed on drayage trucks operating at the POLA and POLB. The researchers worked with three different trucking companies to collect a more representative sample of drayage operations. Over 75 channels of data were collected at a 1-Hz sampling rate from the vehicles' SAE J1939 controller area network bus, along with global positioning system (GPS) data using Isaac Instruments DRU900/908 data logging devices (Figure 2). These standalone data loggers connect to the vehicle's diagnostic port and do not interfere with vehicle operation.

Figure 2. Isaac DRU908 data logger (Image Courtesy: Isaac Instruments).

In total, 557 days of vehicle operation were recorded from 30 vehicles from various manufacturers, operating at three different companies, totaling 36,444 miles. The vehicles were all configured as Class 8 day cab tractors with a mixture of automatic, automated, and manual transmissions. An example of one of these vehicles is shown in Figure 3. Additional details of the data collection can be seen in Table 1.

Figure 3. Class 8 diesel tractor operating at the San Pedro ports from which field data were collected.

Table 1. Field Data Collection Summary

Total Mileage	36,444 Miles
Total Hours of Operation	2,809 Hours
Driving days	557 Days
Operating companies	3 Companies
Unique vehicles	30 Vehicles
Vehicle Manufacturers	Navistar, Volvo, Mack, Freightliner, Peterbilt & Sterling

The controller area network bus data form the basis for the technical analysis of this paper and are supported by the GPS data, which were used for the identification of each trip's origin and destination as well as for an additional means to confirm data integrity. An example of the GPS traces collected within the POLA can be seen in Figure 4.

Figure 4. GPS route (shown in red) of drayage truck data collection at the Port of Los Angeles.

After the data loggers were retrieved from the field, the data were downloaded, reviewed, and then securely stored in NREL's Fleet DNA database which acts as the clearing house for all field deployment data from NREL's Fleet Test & Evaluation activities [11].

Field Data Geographic Analysis

After the field data were uploaded to the Fleet DNA database, the results were processed using NREL's semi-automated Drive-Cycle Rapid Investigation, Visualization, and Evaluation (DRIVE) processing tool [12]. DRIVE quickly filters large sets of raw data, identifying erroneous data points and missing data sections that may require additional processing routines while outputting summary statistics on over 175 unique drive cycle metrics such as average driving speed, number of stops per mile, maximum speed, etc. These metrics can be used to quantitatively describe daily vehicle operation as well as compare and contrast in-field duty cycles with chassis dynamometer drive cycles.

To better understand the components of port drayage operation, field data were analyzed at the trip level. A trip is defined as the time between "key cycles" or when a vehicle ignition is turned on and when it is turned off. Using the trip data as opposed to daily aggregate statistics better revealed the unique operation of the drayage trucks and offered a clearer picture of how the vehicles operated throughout the day.

Initial analysis was focused on characterizing the different operating modes of drayage operation based on the geography of where trips originated and ended. Researchers hypothesized that the vehicle trip kinematics were highly correlated to the geographic attributes of trip. Four distinct regions and an "other region" (Figure 5) were created to represent the primary locations of drayage trips. All of the trips were then categorized based on the geographic location of their start and stop location into one of the 25 possible groups and a geospatial analysis was run on all of the trip data.

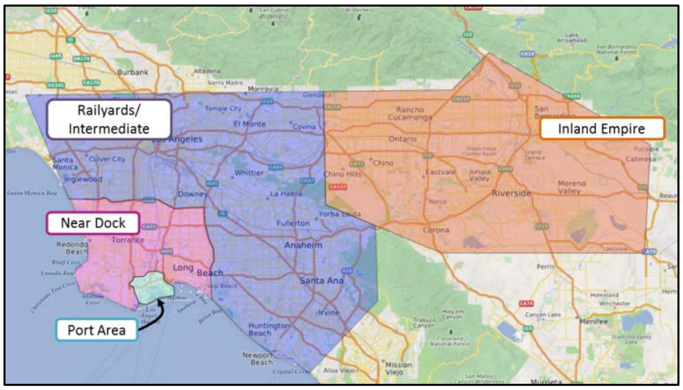

Figure 5. Geographic regions for trip-level origin and destination analysis.

This trip-level geospatial origin and destination analysis indicated that of the possible 25 combinations of start and end locations, 74% of the mileage, 75% of the fuel and 83% of operating time could be accounted for in just six of the combinations (see Table 2) as follows:

- From: Port Area | To: Port Area
- From: Near Dock | To: Near Dock
- From: Port Area | To: Near Dock
- From: Near Dock | To: Port Area
- From: Near Dock | To: Inland Empire
- From: Inland Empire | To: Near Dock

Table 2. Trip level origin and destination statistics

Percent of Total Mileage					
From \ To	Port Area	Near Dock	Rail Yard/Inter.	Inland Empire	Other
Port Area	14.9%	13.7%	1.8%	2.1%	0.0%
Near Dock	12.3%	10.4%	4.6%	12.2%	1.9%
Rail Yard/Inter.	3.3%	3.1%	1.2%	0.7%	0.0%
Inland Empire	3.7%	10.2%	0.7%	1.6%	0.0%
Other	0.5%	0.9%	0.1%	0.1%	0.1%

Percent of Total Fuel Consumed					
From \ To	Port Area	Near Dock	Rail Yard/Inter.	Inland Empire	Other
Port Area	18.1%	14.1%	2.1%	1.9%	0.0%
Near Dock	11.3%	10.5%	4.8%	12.8%	2.0%
Rail Yard/Inter.	2.6%	2.8%	1.6%	0.7%	0.0%
Inland Empire	2.8%	8.3%	0.6%	1.7%	0.0%
Other	0.4%	0.7%	0.0%	0.1%	0.2%

Percent of Total Operating Time					
From \ To	Port Area	Near Dock	Rail Yard/Inter.	Inland Empire	Other
Port Area	28.2%	15.0%	0.9%	0.7%	0.0%
Near Dock	10.6%	20.4%	2.8%	4.5%	0.7%
Rail Yard/Inter.	1.6%	2.0%	3.2%	0.3%	0.0%
Inland Empire	1.3%	4.1%	0.4%	2.4%	0.0%
Other	0.3%	0.3%	0.0%	0.1%	0.2%

Further trip-level drive cycle analysis of the origin and destination method indicated that while the vehicles may start and stop their trips in the same region, the trip activity could vary widely with trip maximum speed and average driving speed as shown in Figure 6.

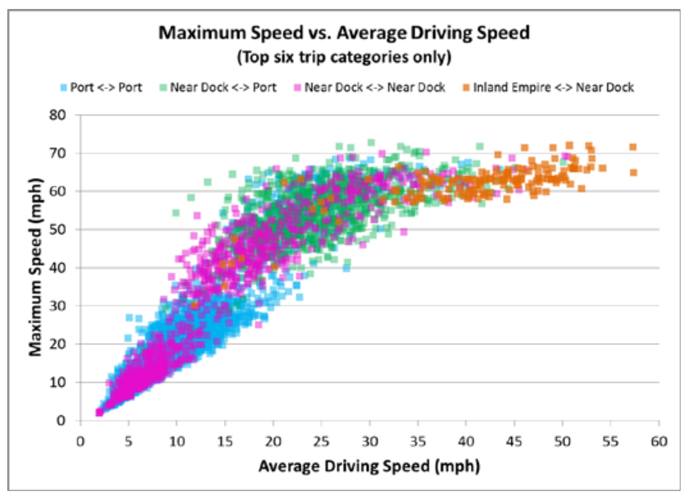

Figure 6. Trip results from the top six categories identified in Table 2.

As more metrics were analyzed, researchers began to see multiple overlapping modes in each of the six selected categories, which showed that although aggregate mileage, fuel use, and operational time could be discretely categorized by trip origin and destination, driving behavior could not.

Field Data Clustering Methodology

Using the same trip-level data, a clustering analysis was performed to organize the data into functional groupings that would better describe the different drive cycle components. Clustering is the process of placing statistically similar data in the same cluster and dissimilar data in different clusters. The first step in the clustering analysis was to identify the optimal number of clusters in the data set to describe the data, using the mean shift method of cluster selection. It was determined that there are four clusters in the data set. The mean shift method uses a non-parametric iterative algorithm to identify the optimal number of clusters by creating a temporary window around data points, calculating the mean value of those surrounded data points, and then shifting the window location to the new mean and iterating until it converges on the mean of the cluster [13].

As there are several well-accepted methods for determining the number of clusters present in a data set, the results of the mean shift method were confirmed by using the elbow method. The results from the elbow method analysis are shown in Figure 7. The elbow method seeks to reduce the unexplained variance expressed as the sum of squared error within the clusters using the fewest number of clusters; the first cluster explains a large portion of the variance in the data and each successive cluster explains less and less of the overall variance. The point at which only marginal reduction of the variance occurs is the optimal number of clusters and through visual inspection is also where the explained variance curve flattens out.

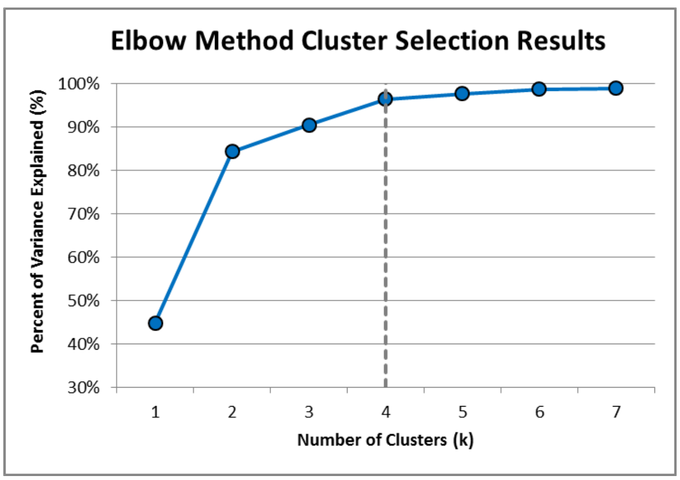

Figure 7. Elbow method clustering results.

After it was determined that the data could be explained in four clusters, a k-medoids clustering analysis was performed using the partitioning-around-medoids method. The k-medoids algorithm is a non-hierarchical clustering algorithm related to the k-means algorithm. Both the k-means and k-medoids algorithms are partitional and attempt to minimize the distance between points in a cluster and a point designated as the center of that cluster. K-medoids was selected over the more commonly used k-means, as it is based on the most centrally located data point in each cluster, the medoid, rather than the most centrally located average value of all the points in the cluster; because of this, k-medoids is also less sensitive to outliers [14, 15]. The k-medoid algorithm function is shown in Equation 1 where F(x) is the primary function to minimize, d(i,j) is the dissimilarity measurement between the entities i and j, and z_{ij} is the variable or metric to be analyzed.

$$F(x) = minimize \sum_{i=1}^{n}\sum_{j=1}^{n} d(i,j) z_{ij} \quad (1)$$

The clustering process starts with the selection and scaling of the metrics of interest. In this analysis, the following nine variables or drive cycle metrics were used to determine the make-up of the clusters:

- Aerodynamic speed
- Average driving speed
- Characteristic acceleration
- Kinetic intensity
- Maximum speed
- Stops/mile
- Total average speed
- Total distance
- Total stops

These drive cycle metrics were selected for this analysis as they each help to characterize different attributes of a drive cycle. While some of these variables have been shown to be highly correlated [16], they do not necessarily describe the same driving attributes and, unlike studies that focused on the correlation between these drive cycle metrics and fuel consumption, these selected metrics are sufficient to accurately cluster the data for kinematic drive cycle analysis.

To account for the differences in scales and units of the different variables they were transformed to a common scale using the z-score scaling method where the resulting variables will have a mean equal to 0 and a standard deviation equal to 1.

After the variables were scaled appropriately, they were entered into the k-medoid clustering algorithm. The clustering process is an iterative process with the first step being the calculation of the Euclidean distance of each data point to randomly chosen medoids [17]. The data are then clustered according to the medoid they are most similar to, and the medoid set is optimized via an iterative process until a final optimal solution is realized.

Clustered Trip Results and Statistics

Using the k-medoid clustering results one can see that each of the four clusters have minimal overlap with neighboring clusters and all data within a cluster are similar. When compared to the region and destination method shown in Figure 6, the k-medoid clustering approach offers a much better method for partitioning the kinematic data for drive cycle analysis, as shown in Figure 8, with average driving speed plotted vs. aerodynamic speed.

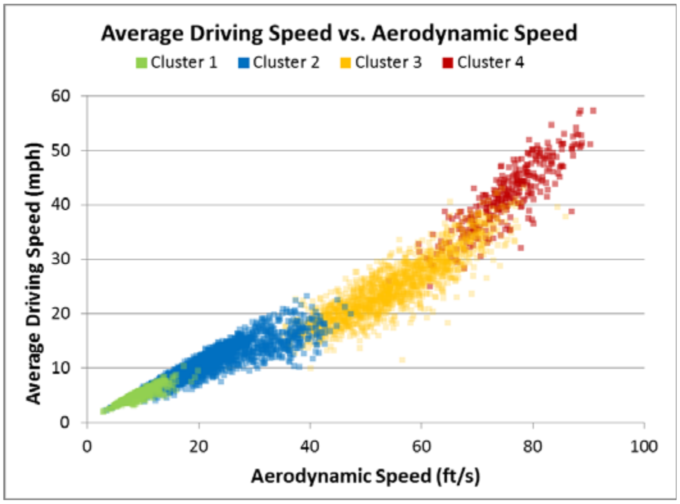

Figure 8. Average driving speed vs. aerodynamic speed using the k-medoid, four cluster grouping results.

Looking at the distribution of the clustered data as a function of characteristic acceleration and aerodynamic speed (Figure 9), the principal components of kinetic intensity [18], one can see that the clusters still exhibit distinct separation from one another and that Cluster 1 has on average the highest level of kinetic intensity and Cluster 4 has the lowest. A high kinetic intensity ratio represents driving with more energy used for accelerations (higher characteristic acceleration) while a low kinetic intensity value is indicative of driving at more constant speeds (higher aerodynamic speeds).

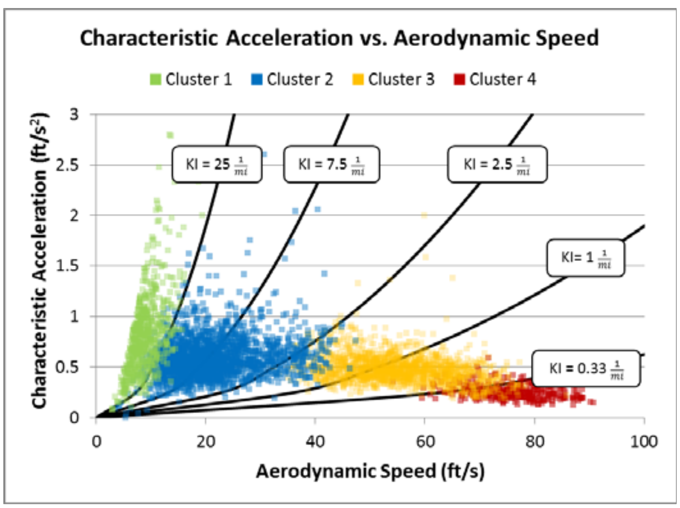

Figure 9. Characteristic acceleration vs. aerodynamic speed using the k-medoid, four cluster grouping results with constant kinetic intensity curves.

To better understand the drive cycle kinematics present in each individual cluster, one can examine the average trip level, drive cycle metrics and their associated standard deviations for all trips in a cluster, the tabulated results are shown in Table 3. Cluster 1 is composed of very short, low speed trips with high kinetic intensity, while at the other end of the spectrum, Cluster 4 includes on average much longer, higher speed, low kinetic intensity trips.

Table 3. Trip statistics by cluster using the k-medoid, four cluster grouping method.

	Cluster 1	σ	Cluster 2	σ	Cluster 3	σ	Cluster 4	σ
Number of Trips in Cluster	625	N/A	1874	N/A	1551	N/A	314	N/A
Average Trip Length (mi)	0.12	0.13	1.06	0.92	11.05	6.43	54.93	25.39
Average Driving Speed (mph)	4.90	1.20	10.76	3.38	24.81	5.74	41.76	6.08
Average Total Speed (mph)	0.94	0.70	4.33	2.87	14.74	6.61	32.53	8.34
Average Total Stops	2.83	3.17	4.54	4.15	13.73	9.53	14.97	11.38
Average Stops per Mile	20.15	15.57	5.53	3.97	1.41	0.92	0.28	0.18
Average Maximum Speed (mph)	8.81	3.03	22.72	8.64	54.89	7.21	63.44	3.40
Average Kinetic Intensity (1/mi)	55.10	22.17	8.84	6.45	0.94	0.50	0.24	0.09
Average Aerodynamic Speed (ft/s)	9.10	2.52	21.82	7.60	54.91	9.24	75.63	6.53
Average Characteristic Acceleration (ft/s^2)	0.82	0.43	0.60	0.27	0.48	0.14	0.25	0.07
Percent of Zero Speed Time (%)	81%	13%	61%	21%	42%	18%	22%	14%

Drive Cycle Development

Having partitioned the data into four distinct clusters based on a multivariate drive cycle clustering analysis, NREL researchers used the drive cycle generation portion of DRIVE to generate representative drive cycles. DRIVE uses a deterministic multivariate hierarchical clustering method to generate representative drive cycles from the source data of each cluster. The custom cycle developed for Cluster 1 (Figure 10) is the shortest, lowest speed cycle and has the highest kinetic intensity. This cycle is most similar to the Heavy-Heavy Duty Diesel Truck (HHDDT) Creep standard cycle [19] and represents trips where vehicles would be waiting in line with short durations of driving followed by extended stationary idle time. Cluster 2's representative drive cycle (Figure 11) includes segments of extended idle as well as medium speed driving components. This cycle is representative of trips that primarily start and end either in the Port Area or in the Near Dock area. The custom cycle for Cluster 3 (Figure 12) is representative of local higher speed, shorter trips that start and/or end in the Port area and the Near Dock area. The representative drive cycle for Cluster 4 (Figure 13) is the longest cycle of the four and has the highest average speed and lowest average kinetic intensity. This cycle is representative of vehicles making longer, higher speed trips on the metropolitan area highways, originating near the Ports and ending in the Inland Empire.

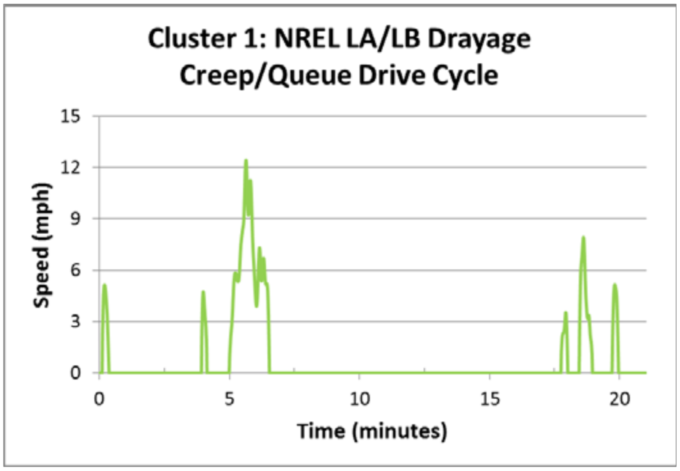

Figure 10. Cluster 1 custom drive cycle generated from in-field data using DRIVE.

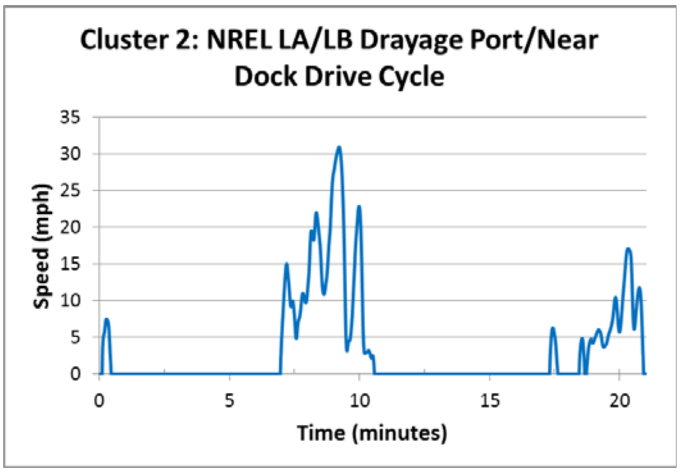

Figure 11. Cluster 2 custom drive cycle generated from in-field data using DRIVE.

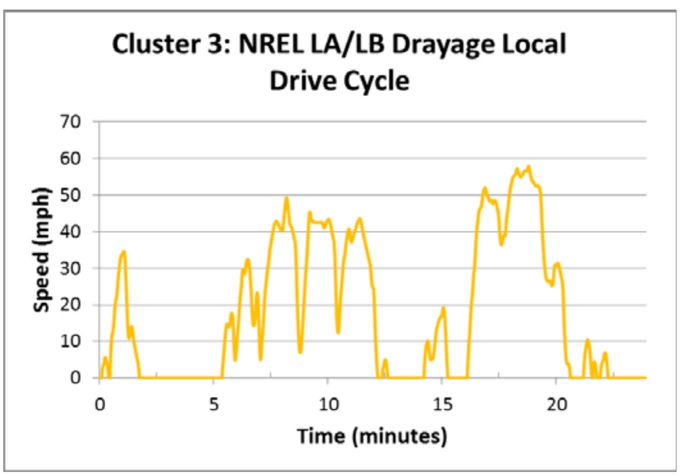

Figure 12. Cluster 3 custom drive cycle generated from in-field data using DRIVE.

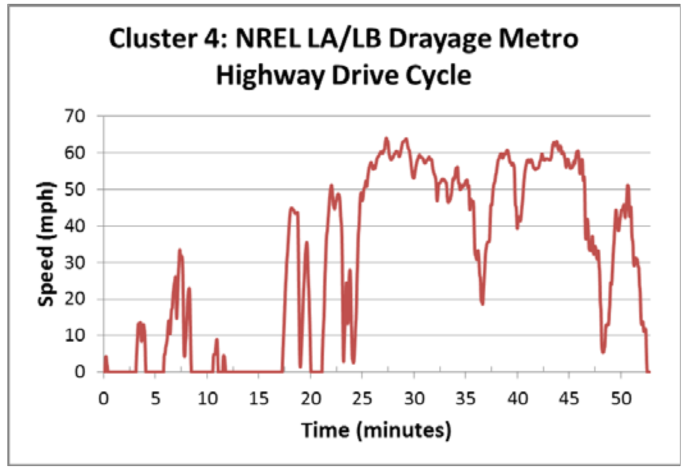

Figure 13. Cluster 4 custom drive cycle generated from in-field data using DRIVE.

The resulting kinematic drive cycle metrics from each of these four representative drive cycles are shown in Table 4.

Table 4. Drive cycle metrics from custom representative cycles.

Cluster	Cluster 1	Cluster 2	Cluster 3	Cluster 4
NREL Custom Cycle	Creep/ Queue	Port/ Near Dock	Local	Metro Highway
Drive Cycle Length (mi)	0.26	1.17	7.12	26.66
Drive Cycle Duration (minutes)	22.17	21.02	23.93	52.82
Average Driving Speed (mph)	5.20	10.61	28.53	41.23
Average Total Speed (mph)	0.70	3.34	17.86	30.29
Total Stops	6	5	9	7
Stops per Mile	23.33	4.27	1.26	0.26
Maximum Speed (mph)	12.46	30.98	57.90	64.17
Average Kinetic Intensity (1/mi)	15.89	3.79	0.69	0.24
Average Aerodynamic Speed (ft/s)	10.40	25.88	59.30	75.07
Average Characteristic Acceleration (ft/s^2)	0.33	0.48	0.46	0.25

After the custom representative drive cycles were created and analyzed, the results were compared to more common, standard chassis dynamometer test cycles (Figure 14). For example, the HHDDT Cruise cycle is a close representation of Cluster 4 in terms of maximum speed and average driving speed, the Urban Dynamometer Driving Schedule-Heavy Duty (UDDS-HD) cycle is a close representation of Cluster 3, and at low average speeds, the HHDDT Creep cycle is a good representation of Cluster 1. However, due to the unique driving patterns of port drayage operation, there are not many widely accepted drive cycles that matched the kinematic characteristics of Cluster 2 for drayage operation.

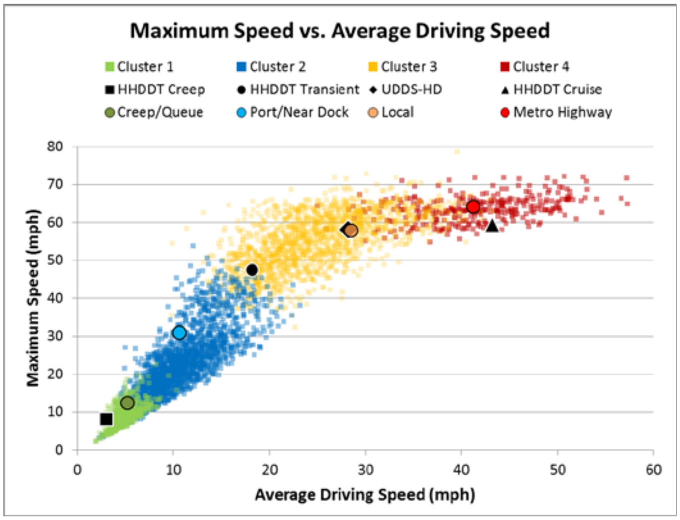

Figure 14. Maximum speed vs. average driving speed using the k-medoid, four cluster grouping; results shown with custom drive cycle results and standard test cycles.

When considering how the four individual drive cycles together represent the real-world data collected at the POLA and POLB, all four of the cycles can be run in a sequence as shown in Figure 15 as the *NREL LA/LB Drayage Composite* drive cycle. The results can then be analyzed directly or synthesized using a similar method to that in the U.S. Environmental Protection Agency's Title 40 Code of Federal Regulations§1037.510 [20], where the results of each emissions test are weighted by the distance travelled over that specific cycle.

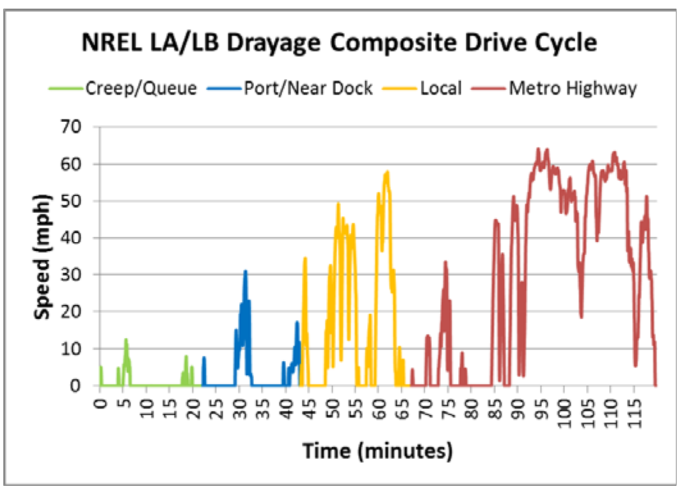

Figure 15. NREL LA/LB Composite Drive Cycle.

The U.S. Environmental Protection Agency uses distance and vehicle type as the primary weighting metrics for aggregating individual cycle results, but due to the uniqueness of port drayage operation, NREL researchers included four possible contribution factors for consideration (Table 5).

Table 5. Distribution of distance, trips, operating time, and fuel consumption by cluster.

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
	Creep/ Queue	Port/ Near Dock	Local	Metro Highway
Distance	0.22%	5.65%	48.82%	45.32%
Number of Trips	14.40%	43.17%	35.73%	6.70%
Operating Time	4.16%	23.02%	53.30%	19.52%
Fuel	0.99%	10.38%	49.47%	39.16%

The values presented in Table 5 are percentages based on all of the collected field data, separated by cluster. While this paper is focused on the application of data clustering methodology and drive cycle creation, the researchers felt it was valuable to include the distribution of diesel fuel consumed by trips in each cluster.

Summary/Conclusions

This paper outlines an application of an alternative methodology of processing in-field data to characterize drive cycles by means of clustering the data based on kinematic characteristics. Analyzing over 36,000 miles of driving data, from 30 vehicles, operating at three different companies, the k-medoid partitioning around medoids clustering method resulted in four distinct clusters representative of the port drayage operation at the POLA/POLB. The clustered data were used to generate four statistically representative drive cycles that characterize the unique operation of port drayage trucks. Each cluster was mathematically derived to represent the different components of port drayage operation; these discrete kinematic nuances found in the clustering analysis results may otherwise be missed in non-clustered aggregate drive cycle creation. This analysis demonstrates the importance of fully understanding both the general operation of vehicle usage as well as the trip level statistics of driving behavior before attempting to create or use representative test cycles.

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Definitions/Abbreviations

DOE	U.S. Department of Energy
Drayage	The trucking service from an ocean port to a rail ramp, warehouse, or other destination
DRIVE	Drive Cycle Rapid Investigation, Visualization, and Evaluation tool
GPS	global positioning system
HHDDT	Heavy Heavy-Duty Diesel Truck
J1939	SAE standard for internal vehicle communication and diagnostics
Kinetic Intensity	Derived from ratio of aerodynamic speed and characteristic acceleration it is a measure of drive cycle kinetics.
NREL	National Renewable Energy Lab
POLA	Port of Los Angeles
POLB	Port of Long Beach
UDDS	Urban Dynamometer Driving Schedule