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CHARACTERIZATION OF ARMY GROUND VEHICLE DRIVE CYCLES

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ABSTRACT

The US Army Ground Vehicle Programs use various drive cycles for testing and validation of new vehicle systems and models. These cycles have traditionally been characterized by run speed, number of stops, and terrain profile. For the sake of powertrain analysis, there have been a number of additional metrics proposed for characterization of such drive cycles in the context of fuel economy evaluation. This paper examines several metrics related to fuel economy, comparing standard Army test circuits, simulated drive cycles, and commercially standardized drive cycles. By comparing these cycles and identifying key metrics, we can develop better testing plans and bench cycles for technology evaluation. Field data from a mountainous region shows substantial variability that is not fully captured by current test cycles. Kinetic intensity is able to differentiate between the human in the loop scenarios, with values higher in simulated cycles than in field data. However, number of stops remains an important criteria for characterizing drive cycles

MOTIVATION

Multiple drive cycles and test circuits are used in development and testing of new Army ground vehicle technologies. The use of these courses has been shown to influence the performance of a power system from an energy perspective [1]. In fact, a significant challenge of the Hybrid-Electric Vehicle Experimentation and Assessment (HEVEA) program, which was initiated in 2005, was to develop realistic drive cycles and the testing methodology for non-traditional powered military vehicles [2]. In the commercial or passenger vehicle sector, there has been a large focus on the determination of generic test schedules to represent real driving conditions [3] [4] [5] [6]. However, a survey conducted by Bata et al. [7] and testing by Rykowski et al. [8] show these approaches to be problematic. From a military perspective, efforts have been made to characterize a military drive cycle, however rigor and applicability are still a challenge [9] [10]. A more complete set of classification metrics have been developed by O'Keefe *et al.*, and adapted by NREL to create the Drive-cycle Rapid Investigation Visualization and Evaluation (DRIVE) Tool [11] [12]. This tool strives to define a standard drive cycle so that the correct metrics are captured. By looking at these metrics for multiple data sets, we seek to evaluate 1) the usefulness of particular metrics and 2) the effectiveness of current proving ground cycles according to those metrics.

INTRODUCTION

The Army currently has a number of proving ground cycles used for the testing and validation of ground vehicles [13]. These cycles are typically defined by the grade profile, number and duration of stops, and a target running speed. Each proving ground has multiple test cycles intended to represent different terrain and mission conditions.

These drive cycles are needed to capture a wide variety of information about vehicles related to key requirements, such as fuel economy, total range, and mobility, amongst others. It is therefore important that cycles used for vehicle proving grounds are consistent with those developed for models and that both are reflective of real-world situations.

Data Set Generation

This paper evaluates datasets generated from modeling and simulation, compared to commercial cycles, field data and proving ground cycles. Due to the variety of data sources involved in this analysis, there are restrictions imposed according to availability of specific types of information. In some cases, it will be necessary to post-process the available data set to make direct comparisons possible.

The NREL DRIVE tool currently only accepts speed and time data: hence, we are focusing on metrics that do not have an explicit grade dependency. However, terrain grade is included in the speed determinations for current proving ground courses. Fuel data is beyond the scope of the current analysis. Future updates to the data uploading capabilities of this tool are expected to enable these additional analyses.

A summary of the data sets in this work is presented in Table 1.

Table 1. List of Data Sets

Course Type	# of Data Sets
Army Test	22
Commercial	5
Simulated Convoy	16
Simulated Urban	29
Simulated Mountain	14
Field Batch 1	245
Field Batch 2	101
Field Batch 3	193
Field Batch 4	161

Data for the Duty Cycle Experiments (DCE) Convoy, Urban, and Mountain cycles were all obtained via human in the loop (HIL) simulations [9]. The experiments were developed to evaluate the use of motion simulators to measure the fuel economy of hybrid electric vehicles, with cycles selected to relevant proving ground courses (Perryman Paved, Harford Loop and Munson Standard Fuel Course). Due to user-related issues, there is one run that must be eliminated as an outlier due to excessive time spent stopped. Another 8 runs are eliminated due to data acquisition errors, resulting in time-sequence discontinuities. These errors result in instantaneous accelerations well beyond the range of physical reasonability. In other cases, sections of 1-2 seconds were removed from the beginning of the data due to false starts that were not part of the duty cycle.

Field data was taken from several vehicles in a mountainous region, starting in 2010, continuing until 2013, with most data taken in 2010 and 2011. One data set, 3-36AS includes data over all years. Data was then split by day, which occasionally involved long periods of idle time. Days for which files were 2KB or fewer were eliminated for insufficient cycle length. Not all days had data logged, but all months were represented at some point in the data. Speed was determined from GPS speed over ground data.

Army test courses included multiple courses from the Aberdeen and Yuma Proving grounds, representing a variety of terrain and road conditions. The constant speed courses for Munson, Churchville B, Harford and multiple courses from Yuma were converted from constant input speed to time-based speed, accounting for slope and stops. The Munson and Churchville B courses were analyzed for several speeds in addition to the standard course speed. Values for commercial courses were determined similarly, using the same vehicle profile throughout to accommodate direct comparisons.

Variability analysis is restricted to the simulated and field data. Average values for the field data are taken for each vehicle, as determined by the identification number given in the original data files.

Cycle Characterization

While there are many metrics to characterize duty cycles, we are considering those which can be defined only from speed and time data, occasionally considering grade as well. Included in this work are:

-average speed
-stops per mile
-characteristic acceleration
-aerodynamic speed
-kinetic intensity

Cycles taken from field data include substantial idle time over the course of the day. However, the DRIVE tool is able to automatically neglect these extended zero speed periods.

Characteristic acceleration, as defined below and by O'Keefe [11], quantifies the positive work per mass acting on the vehicle. On a horizontal surface, it is equivalent to the positive acceleration. On a surface with some gradient, it includes the work used to raise the mass of the vehicle. For the proving ground cycles, this grade will be incorporated. Due to current limitations of the DRIVE tool, the height is treated as a constant for the DCE and field cycles. The characteristic acceleration is defined in Eq. 1.

$$\tilde{a} = \frac{\frac{1}{2}d(v^2) + g\,dh}{dx} \tag{1}$$

Where v is velocity, g is the force due to gravity, h is height and x is position. This function is collapsed to a single value by taking the integral of the positive value, normalized by mass and distance.

Aerodynamic speed is the speed as it relates to drag. This value can vary significantly from actual velocity, and is defined such that the square is the ratio of the time average of velocity cubed to the time average of velocity, as seen in Eq. 2 [11]:

$$v_{aero}{}^2 = \frac{\int_0^T v^3\,dt}{\int_0^T v\,dt} \tag{2}$$

If the speed is constant over the cycle, this collapses to the average speed squared, but otherwise is uniquely defined for a particular drive cycle.

We also considered kinetic intensity, which is derived from the previous two, and intended to characterize the aggressiveness of a duty cycle. Kinetic intensity (KI) is defined in Eq. 3, as characteristic acceleration divided by the square of aerodynamic speed:

$$kinetic\ intensity = \frac{\tilde{a}}{(v_{aero})^2} \tag{3}$$

As it combines characteristic acceleration and aerodynamic speed, KI is a single metric for comparing duty cycles to one another. It also has been shown to relate well to fuel usage by O'Keefe *et. al.* [11]. For the same average speed, kinetic intensity is a way to differentiate between cycles with frequent or intense acceleration events and cycles with more gradual changes, which typically corresponds to engine loading.

These metrics also avoid many vehicle-specific assumptions. For the sake of converting constant speed elevation profiles to time based profiles, it will be assumed that the same vehicle is being considered in all cases. The parameters for this vehicle are given in Table 2.

Table 2. Notional Vehicle Parameters

Parameter	Value
Coefficient of Drag	0.7
Frontal Area	3.16451 m^2
Rolling Resistance	0.15
Mass	14741.74 kg
Non-propulsion Power	2000W

Vehicle frontal area and mass are accounted for when deriving time-incremented speed for proving ground tracks and commercial cycles. These parameters are chosen to reflect the vehicles used in field.

RESULTS

The average speed for our 3 simulated cycles, 22 proving ground cycles, 5 heavy vehicle commercial cycles and field cycles are plotted versus kinetic intensity (KI) in Figure 1.

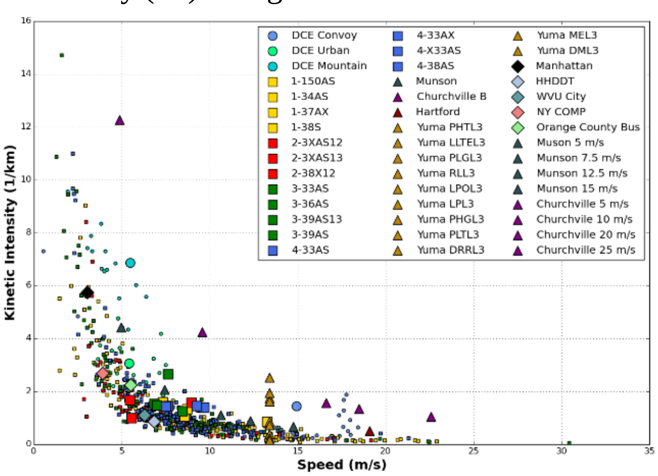

Figure 1. Average speed over the cycle versus the kinetic intensity for simulated cycles (circle), field cycles (squares), test cycles (triangles) and commercial cycles (diamonds)

Kinetic intensity is significantly higher for lower average speeds, following a power law decay trend. The included commercial cycles for heavy duty vehicles fall well within the band of field data. However, some of the constant speed test cycles have higher KI compared to field cycles at similar speeds. The Churchville B test course (maroon triangles) in particular has a higher KI. This cycle has a 5 second stop at a fixed distance interval. The Yuma test courses (dark yellow triangles) are all run at the same average speed, but have a range of kinetic intensity from 0.22 to 2.5 1/km. The simulated cycles, shown as circles, also tend to the higher side of the envelope of values. This may be reflective of the lack of haptic feedback in HIL simulations leading to somewhat more aggressive driving behavior.

To better understand the distribution of values, the simulated and field cycle median and quartile values are presented in Figure 2. The HIL simulations are the left 3 columns (periwinkle, light green, aqua) , while all others are field data (yellow, red, green, blue).

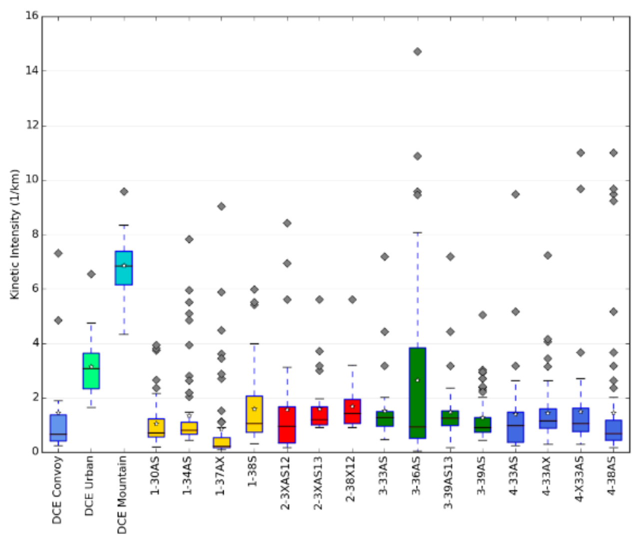

Figure 2. Variability in kinetic intensity for simulated cycles (left 3) and field data

The kinetic intensity is able to effectively differentiate between the three simulated scenarios.

The average KI of field cycles is lower than might be expected, given essentially mountainous conditions. The field cycles with the greatest variability in KI are also those with the greatest range of average speeds. However, the range of KI is not reflective of the number of cycles in a particular data set. The cycle with the largest spread, 3-36A6, has the same number of cycles (57) as 3-39AS, which has much less spread in data.

Two sample cycles taken from the field data with similar average speed and maximum speed are shown in Figure 3, for a low KI cycle in solid blue, and a higher value in dashed red.

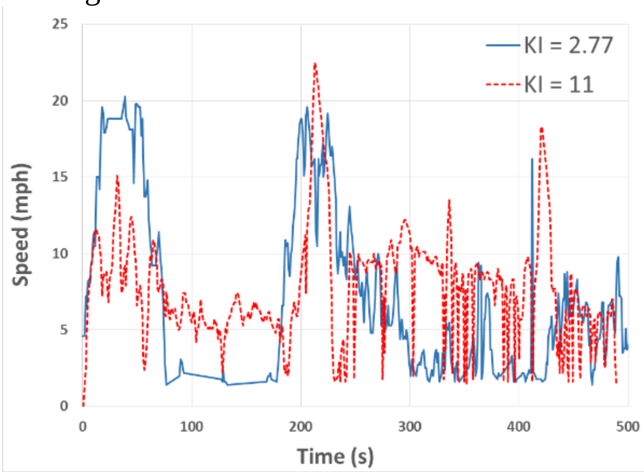

Figure 3. Example drive cycles for a KI value of 2.77 (solid blue) and a KI value of 11 (red dashed)

The higher kinetic intensity cycle (red dashed) has more frequent large acceleration events, particularly near complete stops. The lower KI cycle (solid blue) shows longer speed plateaus and more gradual deceleration events. However, some rapid acceleration events are still present of a similar magnitude to those seen in the high KI cycle.

The kinetic intensity depends on both the characteristic acceleration and the aerodynamic speed. The distribution of characteristic acceleration values in presented in Figure 4. The HIL simulations are again the left 3 columns (periwinkle, light green, aqua) , while all others are field data (yellow, red, green, blue).

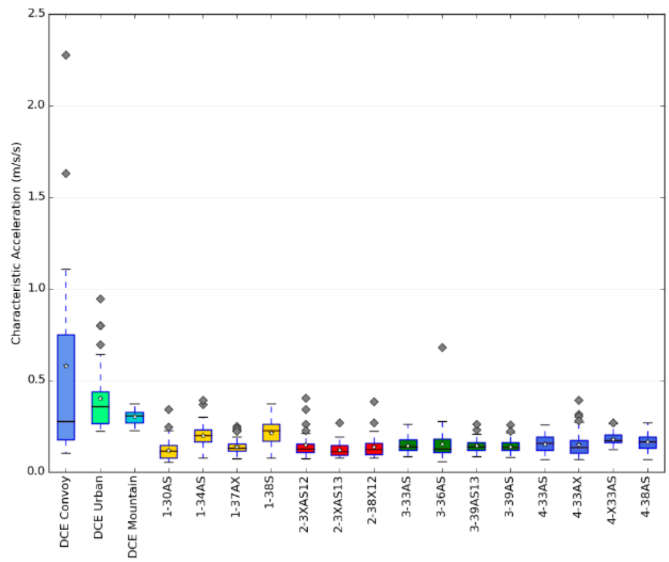

Figure 4. Variability of characteristic acceleration for simulated cycles (left 3) and field data

Variability in characteristic acceleration is significantly larger for HIL simulations than field data. The spread is largest in the convoy scenario, which has the highest values presented. The lack of haptic feedback for these human-in-the-loop simulations may contribute to the large value as drivers accelerate more aggressively. However, the higher speeds also require additional acceleration to initially achieve.

To understand if a particular behavior is dominating the KI, we examined the characteristic acceleration (numerator) versus the aerodynamic speed (denominator) in Figure 5.

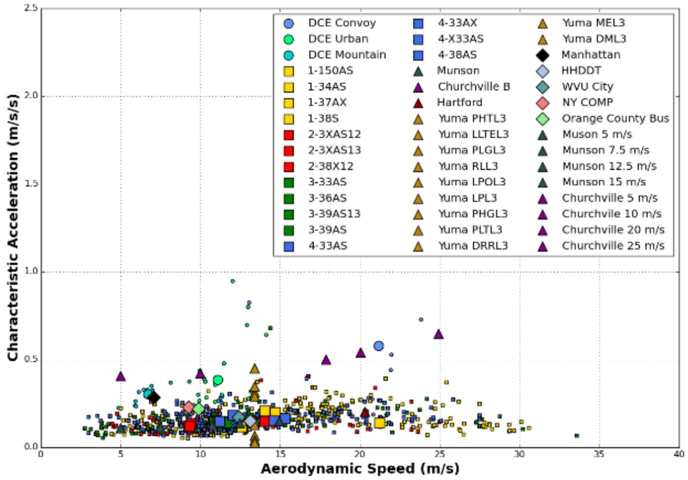

Figure 5. Characteristic acceleration versus aerodynamic speed for simulated cycles (circle), field cycles (squares), test cycles (triangles) and commercial cycles (diamonds)

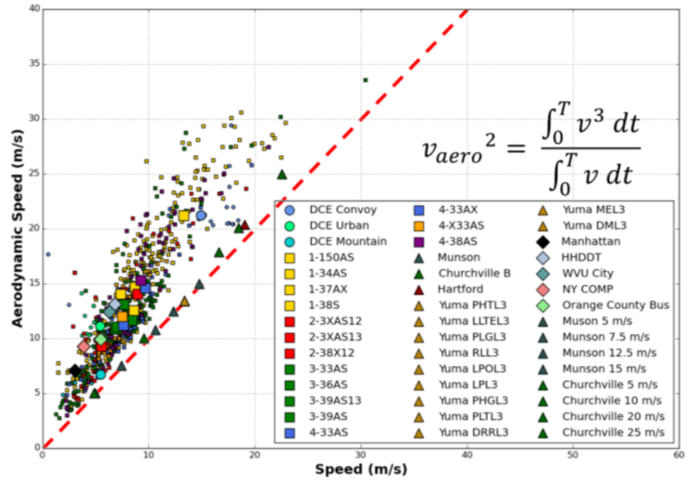

Figure 6. Aerodynamic speed versus cycle average speed for simulated cycles (circle), field cycles (squares), test cycles (triangles) and commercial cycles (diamonds). The 1:1 ratio is given by the red dashed line.

The characteristic acceleration is not generally correlated with aerodynamic speed in the field data. For the constant speed Churchville B test course, where the same course is evaluated at different speeds, there is a monotonic increase with CA as speed is increased. Given the fixed stops in this course, this behavior is expected and verifies the difference in behavior is rooted in course differences, not just speed. This can also been seen by comparing the Yuma courses (dark yellow triangles), which have different stop behaviors, but the same constant speed. While all Yuma courses have the same aerodynamic speed, the CA varies from 0.02 to 0.45 m/s/s. There is also proportionately more variability in the aerodynamic speed than the CA.

Assuming a constant speed over the trip, the aerodynamic speed will be equal to the average speed, and is indicated on Figure 6 as a dashed line.

Many test cycles fall along this line, including courses with and without stops. The field test, commercial courses and HIL simulations largely fall above the line within a fairly consistent cluster. The further a point deviates from the line, the more aggressive the acceleration/deceleration behavior. The widest spread away from the line is in the field test data, which may be reflective of the varying terrain seen in theater.

The number of stops per mile is plotted in Figure 7. The HIL simulations are again the left 3 columns (periwinkle, light green, aqua) , while all others are field data (yellow, red, green, blue). Outliers are shown as gray diamonds. Not all test cycles include stops, and full stop frequency data was unavailable for commercial cycles. Values are from the filtered representative cycles, excluding any long stops during the day.

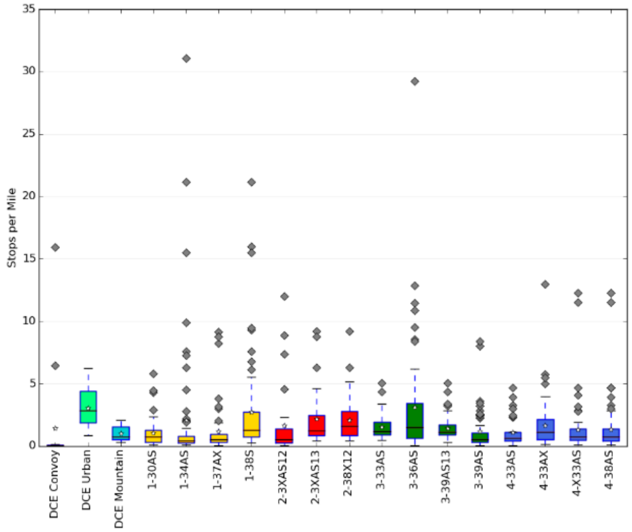

Figure 7. Variability of stop per mile for simulated (left 3) and field data cycles

As expected, there are substantially more stops for the DCE Urban cycles than other HIL simulations. There are two outliers in the convoy that are driving the mean up substantially, with the typical convoy having no stops. The field data has substantial variability, with frequent stops. The mean values are typically 3 or fewer stops per mile. Outliers had as many as 30 steps per mile, or an average of 175 feet between stops. The DCE Mountain simulated cycles are in good agreements with the majority of the field data, with an average of one stop per mile.

DISCUSSION

Drive cycles from proving grounds, HIL simulations, commercial cycles and field data were characterized by several metrics. Kinetic intensity was effectively able to differentiate between the different HIL simulation scenarios. While the field data has a wide distribution, the average KI is consistently lower than the most similar HIL results. When looking at KI as a function of speed, there are several interesting outliers. Notably, the Churchville B test course consistently has higher KI than other courses run at comparable speeds. This test has a 5 second stop at fixed distance intervals, and significant grade changes. Several of the Yuma cycles also show higher KI values than might be expected for the speed, again associated with large and rapid changes in grade. Commercial test cycles, which typically have less aggressive grade changes, fall within the spread of data observed in the field data.

The kinetic intensity in the field is largely controlled by the differences in aerodynamic speed, rather than characteristic acceleration. The low variance in characteristic acceleration indicates it may be dominated by the vehicle performance rather than driver behavior. However, as can be seen from the varied speed proving grounds cycles, grade variations in the terrain profiles can also substantially contribute. It may be possible in the future to link field data to terrain maps, but that information is currently not available in this data set. Nevertheless, kinetic intensity seems to effectively capture common sources of variation.

The stop frequency in field varies significantly, but is generally at least one stop per mile. However, not all test courses include stops, which may make them more accurate for understanding convoy operations than the mountainous type operations represented in the current data set. Accordingly, when developing a test plan, it is necessary to consider the expected uses.

Looking at the above plots, it is interesting to note that the NYC COMP cycle is near several individual DCE Urban cycles, while the HHDDT Cruise segment is similar to the DCE Convoy Cycle. The DCE Mountain cycle, while sharing similar KI and average speed with NYBUS cycle, has a dramatically different number of stops per cycle. However, this HIL simulation agrees well with the field data for typical number of stops per miles, even though it overestimates the kinetic intensity.

Overall, the proving ground cycles focus on running at a constant speed over varied terrain for practical reasons. For convoy-type operations, this is a reasonable assumption. However, the use of stops is clearly important for comparing to patrol-like operations. As shown by comparing the

Churchville B profile at different speeds, stops may be able to tune the characteristic acceleration of proving ground tests over existing tracks.

CONCLUSION

Kinetic intensity was able to differentiate between different HIL scenarios, though these scenarios typically had a higher KI than similar speeds of field data. The various test cycles are able to reflect the spectrum of behavior seen in the field data.

Another key metric is stop frequency: many test cycles fail to include stops, while the field data from patrols represented in this set typically has at least one stop per mile. Number of stops remains a key metric for test cycles. As shown by comparing the Churchville B track at different speeds, stops may be an effective way to adjust the KI of test cycles to capture a wider range of field behavior.

FUTURE INVESTIGATION

Due to the size of this data set, there is certainly additional insight to be gleaned from further analysis. In particular, future efforts will explicitly look at fuel usage data and generating representative drive cycles. Furthermore, the addition of electrical system duty cycle could be particularly interesting given the ever increasing electrical power demands on military vehicles.

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