Utilization of Vehicle-Specific Power as a Powertrain Independent Platoon Controller Performance Metric

by

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Abstract

Heavy-Duty hauling faces challenges regarding the efficiency of transportation, which opens the door to new pathways to saving money while refueling via platooning. Platooning vehicles travel together intending to reduce aerodynamic resistance during operation. The increasing interest in autonomous solutions directs research toward applying these solutions to heavy-duty transportation. However, autonomous solutions are a relatively new concept and require significant research before implementation on public roads. This dilemma brings forth a new application of an emissions quantification metric called vehicle-specific power (VSP). VSP bridges the gap between passenger vehicle emissions rates and fuel consumption. VSP considers the total driving environment of a vehicle, which estimates powertrain effort to maintain current conditions. The present work utilizes the powertrain effort estimation aspect of VSP rather than its emissions investigative benefits to evaluate the efficacy of Cooperative Adaptive Cruise Control (CACC). Different controller strategies and platoon configurations are examined to determine the applicability of VSP to controller evaluation. Experimentation was completed at the National Center for Asphalt Technology (NCAT) circuitous track, the American Center for Mobility's (ACM) freeway loop, and a straightaway section of NCAT's track dubbed "ideal" for platooning efficiency. The influence of convoy position, following distance, road grade, speed, and acceleration are investigated via VSP. VSP aims to create a more complete cost function for assessing a controller's strategy while implementing a forward-looking evaluation technique to current controller strategies. This cost function provides incredible insight into increasing the efficiency of an autonomously driven platoon.

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This project could not have been completed without the direct and indirect assistance of several people I would be negligent not to mention here. As an integral part of my accomplishment not just here at Auburn University but also in life, they are the reason this project amounts to any success. These people have helped me grow as an engineer and pushed me to pursue more extraordinary things without settling. I am proud to call these people friends and family, and they deserve to be recognized before introducing the work done for this study.

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Mom and Dad, you are the reason I have this opportunity, and I am incredibly grateful. You have encouraged me to continue my education into graduate school and always inspired me

to take advantage of the opportunity education gives you. Without you guys, none of this would be possible… or maybe it would be but with more student loans. Either way, I wouldn't be here without you both, so thank you.

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"So long as your desire to explore is greater than your desire to not screw up,

you're on the right track" – Ed Helms

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2T	Two-truck
4T	Four-truck
A1	Lead vehicle in all platoons
A2	Follower vehicle in all platoons
ACM	American Center for Mobility
CACC	Coordinated Adaptive Cruise Control
CAN	Controlled Area Network
EPA	Environmental Protection Agency
EV	Electric Vehicle
GAVLAB	GPS and Vehicle Dynamics Lab
GPS	Global Positioning System
HD	Heavy-Duty
HWFET	Highway Fuel Economy Test
LOWESS	Locally Weighted Scatter Smoothing
MAD	Median Absolute Deviation
MATLAB	MathWorks' matrix laboratory
MOVES	Motor Vehicle Emissions Simulator
MSAD	Mean Sum of Absolute Differences
NCAT	National Center for Asphalt Technology
NMPC	Nonlinear Model Predictive Control
PID	Proportional Integral Derivative
SAD	Sum of Absolute Differences
STP	Scaled Tractive Power
T13	Armored Freightliner truck
T14	Unarmored Freightliner truck
US	United States
US06	Aggressive emissions cycle representative of Los Angeles driving
VSP	Vehicle-Specific Power

Chapter 1

Introduction and Motivation

Implementing new evaluation metrics for platooning behavior poses a significant overhaul of the way researchers view energy savings. Platooning aims to capitalize on the aerodynamic benefits of drafting behind preceding vehicles where substantial savings are realized while refueling. The energy savings method coined "platooning" has been implemented in multiple research areas to increase the efficiency of vehicles traveling in groups together. The term "platooning" refers to a collection of vehicles whose strategy is executed when multiple vehicles follow each other to reduce air drag and energy consumption. Due to the massive financial implications, reducing energy consumption is especially important to Class 8 Heavy-Duty (HD) trucking. Last year, 2021, diesel fuel consumption was about 46.82 billion gallons or 1.11 billion barrels [40] solely for the US transportation sector. This equates to over $249 billion spent on diesel fuel in the transportation sector (based on US average cost for diesel fuel of $5.319) [40]. Even if the fuel efficiency of these vehicles improved by 1%, the savings on fuel alone would equate to $2.49 billion. Therefore, any research pertaining to the efficiency of vehicle operation is highly valuable to the transportation sector. Previous experimentation with platooning HD trucks supports energy savings via increased fuel economy in groupings of two, three, and four [36, 37]. Without disturbances such as traffic congestion, cut-ins, road grade effects, etc., platooning results in more efficient operation for all participating members. However, when these disturbances are introduced, the platoon begins to experience accordion-like behavior where following distances become more fluid, expanding and shrinking the overall length of the platoon. This behavior is accompanied by aggressive power demands to maintain preset following speeds or distances, which is only worsened by increasing platoon size and following distance [34].

The test fleet includes four turbocharged diesel Class 8 heavy-duty trucks representative of common on-highway vehicles. Two Peterbilt 579s designated A1 and A2, have identical cabs but different engines. A1 uses a Paccar MX-13, while A2 uses a Cummins ISX15 415 ST2. The Freightliner trucks, T13 and T14 operate on Detroit Diesel DDEC IV S60 engines. The difference between the Freightliner trucks is that T13 has an armored cab while T14 does not. This supports the efforts made toward heterogeneity in the platoons. All tractors pull empty 53-foot trailers and are equipped with angled side skirts. A summary of test fleet specifications is contained in Table 1.

Table 1.1: Test Vehicle Overview

Truck ID	**A1**	**T14**	**T13**	**A2**
Manufacturer	Peterbilt	Freightliner	Freightliner	Peterbilt
Model	579	M915A5	M915A5	579
Model Year	2015	2009	2009	2015
Engine	Paccar MX-13	Detroit Diesel IV S60	Detroit Diesel IV S60	Cummins ISX15-415ST2
Peak Torque @ RPM	1,750 ft-lbs @ 1000	1,650 ft-lbs @ 1200	1,650 ft-lbs @ 1200	1,650 ft-lbs @ 1000
Rated Horsepower (bhp)	430 hp	500 hp	500 hp	415 hp
Truck & Trailer Gross Weight	35,660 lbs	37,996 lbs	46,947 lbs	38,020 lbs
2T Position	First	Second	First	Second
4T Position	First	Second	Third	Fourth

The groupings established for testing campaigns focus on investigating the disparate aerodynamic benefits experienced by respective platoon members. Much of the transiency analysis focuses on A2. A2 is the last truck in every configuration apart from baseline, where it does not engage in platooning behavior and is spaced far apart from other traffic to ensure it does not receive residual aerodynamic influences. Therefore, the highest amount of transiency will be demonstrated through A2's performance. 2T platoons consist of two trucks where the participating vehicles depend on which 2T platoon is in question. 4T platoons contain all test vehicles in the order explained in Table1. The platoon groupings can also be seen graphically in Figure 1.

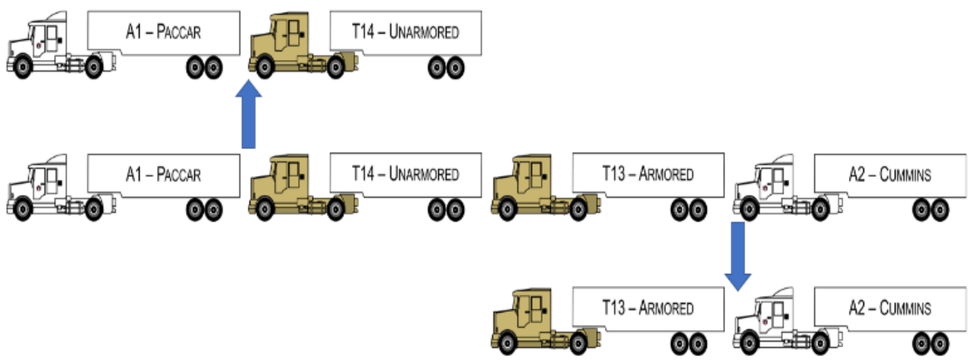


Figure 1.1: Test Fleet Platooning Configurations

The intentions of these groupings are three-fold:

1) Having platoons led by a Peterbilt (A1) and another by the armored military truck (T13) allows for different leading cruise controllers in two truck platoons and different lead truck aerodynamic profiles.
2) Positioning T13 as the lead truck in a two-truck platoon theoretically should maximize transient platooning behavior during cut-in events. This is due to its power to weight ratio being the lowest among the platoon members.
3) The cruise control of A2 is the most resistant to speed variance due to enhancements offered by Auburn University's GPS and Vehicle Dynamics Laboratory (GAVLAB). By contrast, A1 operates on the stock cruise controller. Therefore, A2 is the most resistant against passing velocity variations to following vehicles. For this reason, A2

did not lead any platoon configuration.

The 2T and 4T arrangements each completed laps at two following distances: 50 feet and 100 feet (15.24 m and 30.48 m with time gaps of 0.758 seconds, and 1.515 seconds at 45 mph, respectively). The testing configurations are denoted by the number of trucks and the following distance. For example, “2T 50” is a two-truck configuration operating with a 50-foot following distance. Each following distance presents benefits and drawbacks to freight efficiency and is evaluated in both the two- and four-truck platooning configurations. Each follower is subject to velocity dithers and inherits the transient behavior established in the preceding trucks regardless of platoon order. Depending on the controller, these dithers can either be magnified or dampened. Typically, the maximum dither magnification occurs at the rear of a platoon as the last truck inherits the compounded transient behavior from every other truck in the platoon. Increasing the compounding behavior significantly impacts the overall freight efficiency of a platoon. The controller response to these dithers makes convoying challenging and even disadvantageous in some instances.

The work discussed in this thesis addresses the effects of road grade, varying headway distances, and platoon size over tracks with disparate road grade profiles. Platooning is accomplished via two controller strategies: a PID-based Cooperative Adaptive Cruise Control (CACC) and a Nonlinear Model Predictive Control (NMPC) [42], [43]. These controllers were employed on truck platoons at the National Center for Asphalt Technology (NCAT) and the American Center for Mobility (ACM) test tracks. NCAT geography is displayed in Figure 1.2.

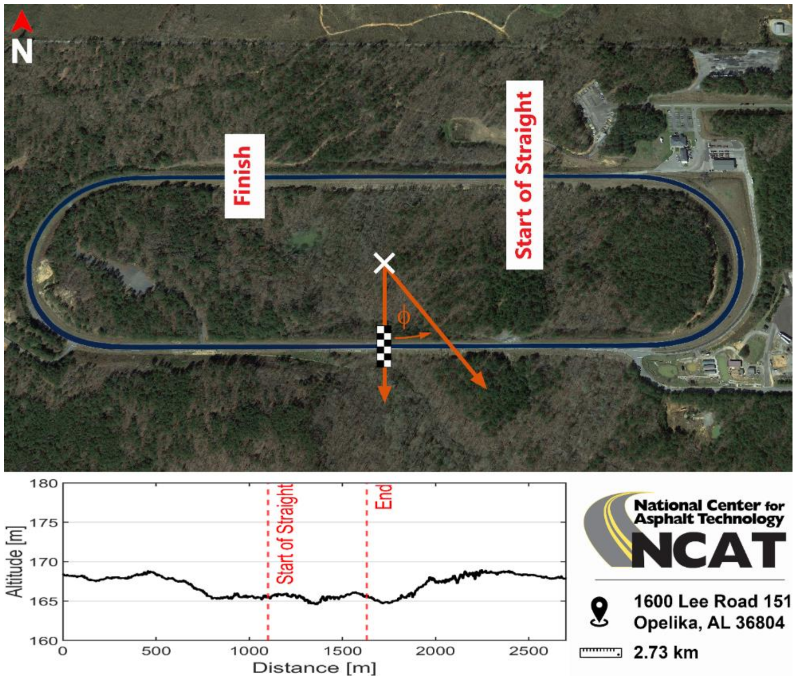


Figure 1.2: NCAT Geography

From NCAT's track, an "ideal" platooning case was extracted from the Northern straightaway. Data was collected at a 10 Hz frequency via the vehicles' Controlled Area Network (CAN). The trucks operated for hour-long tests at both tracks, running multiple daily tests at a constant speed of 45 mph (20.12 m/s). For NCAT's 1.7-mile oval track, this equates to ~26 laps. At ACM's 2.7-mile freeway loop track, the tests ran for ~18 laps. ACM's geography is found in Figure 1.3.

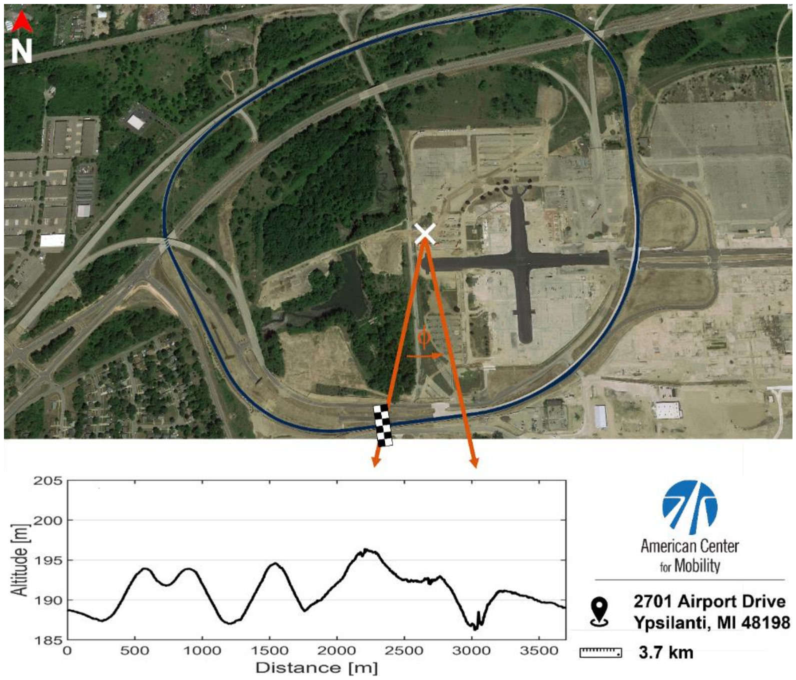


Figure 1.3: ACM Geography

After four testing campaigns (NCAT in 2019, 2020 and ACM in 2019, 2021) were completed, many data quality issues presented themselves in the raw data. These outliers had many causes, including, but not limited to:

- Drivers dropping out of the controller mid-test
- Equipment malfunctions
- Laps where the controller was being adjusted

In previous years, the outlier removal process was qualitative, which led to inconsistencies in data sets being analyzed between researchers. Thus, a new outlier removal process was developed herein to standardize the "clean" data set. This process applies to both tracks for all years of testing and should continue to effectively remove outliers from data sets in future testing. Efficiency, via computation time, and effectiveness, via self-similarity in remaining speed traces, were considered the most critical factors in deciding which outlier removal method would best accomplish desired goals.

After testing, it was apparent that a vehicle agnostic method for evaluating the controllers was necessary to determine not only the effectiveness of the controller design, but also a more descriptive demanded power estimate. Because each truck is equipped with various configurations of engines, aerodynamic components, and effective masses, developing a consistent method for application across all trucks is essential. This work investigates the metric “vehicle-specific power” (VSP) for its capability to capture a truck’s driving environment and estimate the required trucks effort output to maintain the current driving environment. The equation for VSP encapsulates the total driving environment; so VSP could potentially become an integral part of the controller cost function.

Another benefit VSP brings to the table is applicability across powertrain types. The current NMPC control strategies make decisions partially based on the fuel signal according to the specifications of each truck. In a world where the push for electric vehicles (EV) and hybrid alternatives is increasing, evaluation metrics must be able to adapt to various powertrains. In their current state, the NMPC control strategy used in Auburn University’s GAVLAB is reliant on a fuel signal. To prevent a complete overhaul of control design as platooning is implemented across a variety of powertrain choices, the control design must focus on parameters that are independent of powertrain architecture. VSP is blind to powertrain type, suggesting that its use in a control design would make said controller instantly applicable across a variety of vehicle architectures. Thus, VSP is potentially a future-proof solution to the problem of ever-changing powertrains, which are typically difficult to make fair comparisons between. In this thesis, VSP’s ability to precisely track the transient behavior is challenged by testing along the ideal platooning scenario, NCAT laps, and ACM where increasingly arduous road grade changes pose significant problems with the string stability of platoons. For this reason, the limitations of VSP are explored and will be evaluated over the body of this work.

Chapter 2

Data Processing: The Need for Quantitative Approaches to Outlier Removal

2.1 Data Acquisition

GAVLAB was responsible for outfitting the test fleet with their own data acquisition equipment and gathering data via the trucks' CAN systems. Data was recorded at 10 Hz each testing year and track. This data was organized onto hard drives and stored in files readable by MathWorks' matrix laboratory (MATLAB). MATLAB was then utilized to perform analysis on variables of interest. Raw data from all years, tracks, and trucks presented many outliers embedded within the driven lap populations. These "outliers" represent faults in the testing in some capacity. Faults include, but are not limited to, GPS drops, equipment malfunction, and drivers kicking vehicles out of controlled modes mid-run. Substantial effort was made to identify and remove outliers from the data set before performing analysis. Variables within the original data set were used to identify these outliers accurately. With hundreds of gigabytes of data streams, selecting indicative variables was challenging. Options such as engine and vehicle speed, fluid pressures and temperatures, and headway (the distance between the front of the truck to the rear of the preceding truck's trailer) distances or change rates were considered for outlier identification. Ideally, to find an outlier in such a multivariate problem, all variables would be considered to rule out laps due to testing inconsistencies. However, the vast amount of information collected from the trucks necessitated that the search be narrowed down to a few, preferably one, variables that could easily indicate which laps contained outliers.

2.2 Previous Qualitative Outlier Removal Methods

During previous testing campaigns, the outlier removal process was either highly qualitative in nature or nonexistent. Because the trucks are set to follow specific headway distances and vehicle speeds, it was determined that either headway distance or vehicle speed was the best variable to find outliers in the raw data set. Furthermore, the NMPC controller focuses on enhancing fuel utilization by allowing the truck to fall back and creep up to the preceding truck depending on the upcoming terrain. Consequently, the headway distance becomes more fluid and fluctuates around a specific value rather than strictly adhering to it. A difference in controller strategy like this suggests that headway distances and rates should not be used as the indicative outlier variable. Instead, the vehicle speed ought to be used to establish self-similar traces because the general mission across both controller strategies is to follow the preceding truck at the preset vehicle speed. After determining whether vehicle speed was the most suitable variable to select outliers, the removal method was chosen.

Prior methods were observationally driven, and laps were selected for removal based on how well they conformed to a self-similar trace. Each scientist on the team selected laps qualitatively based on what they perceived as outliers. This qualitative method could produce findings not arrived at by statistical procedures or other means of quantification [31]. Thousands of laps were driven, making it exceptionally challenging for two scientists to remove the same laps, let alone the same number. Additionally, if a third-party researcher attempted to remove outliers from the same raw data set, the odds of them selecting the same laps would be nearly 0 percent.

2.3 Limitations of Utilizing Qualitative Approaches

This brings up the first drawback of qualitative methods in this application: subjectivity. Personal perspective always leaves subjective quality up for interpretation, leading to research inconsistencies [22]. Furthermore, you can place three researchers in the same room to observe an event and receive three differing perspectives, which consist of highly detailed but also incredibly inaccurate information [22]. While this may be an exaggeration, the point stands: inaccuracies are introduced because of personal bias and perspective. Consequently, this opens the door to creativity and interpretation. While effective for some research methods, this research requires explicit facts instead of opinions and observations instead of creativity [11, 29]. Allowing things like preferences or gut feelings into data collection or outlier removal processes clouds the authenticity of creating a generalized method applicable to all tracks and years in which testing occurred. Human instinct invites the subconscious mind to obscure systematic results by allowing mysteries and surprises that we may not scientifically understand into the process [11]. When this happens, the researcher must identify unspoken data points left over in the data set once the outlier removal process is complete [22]. Drawing conclusions from data based on researcher bias is flawed science and splits an audience between two choices before presenting the results regardless of the value of the findings: support the qualitative nature in which the data was derived or reject the hypothesis strictly because the outlier removal process was biased. The rigidity of the analysis is highly dependent on the research method. Qualitatively removing outliers allows researchers to decide whether their data set is self-similar or not. This causes a potentially never-ending cycle of questioning whether the data set is "good enough" to perform analysis. Theoretically, each lap removed has the potential to create a self-similar trace upon its removal. When does the researcher cease lap removal? What is the minimum number of laps needed to draw conclusions from them? Every question raised is an opportunity to deprive research of reproducible results where opportunities for duplication would be beneficial – despite how rare they may be [22]. Qualitative research is a long hard road, with elusive data on one side and stringent requirements for analysis on the other, which creates an unnecessary tightrope for researchers and scientific results to walk over [31]. Luckily, quantitative methodologies alleviate the issues mentioned above with outlier removal.

2.4 Advantages of Applying Quantitative Methodologies

Quantitative analysis has proven incredibly useful, particularly for drawing conclusions based on mathematical results. Quantitative analysis, or the scientific method, has one basic underlying premise:

> "A simple and abiding faith in the rationality of nature leads to the belief that phenomena have a cause. If phenomena have a cause, the scientist contends that the mechanism or system underlying the observed facts can be discovered by hard work. Once the mechanism is known, nature's secrets are known and can be used to the investigator's own best advantage" [16].

The techniques utilized with quantitative analysis are a compelling medium through which we solve decision-making uncertainty and enhance projectability and efficiency [41]. The focus of quantitative analysis lies in objective measurement and analyzing numbers to make conclusions in problem-solving and decision-making [41]. The function of quantitative techniques are as follows [41]:

1) To facilitate the decision-making process
2) To provide tools for scientific research
3) To select an appropriate strategy
4) To help in the reduction of cost
5) To have a proper deployment of resources
6) To help minimize the time required to complete the task

Each of these points contributes to the success of data analysis via the efficiency of time and resources spent. Point 1 addresses facilitating the decision-making process, which can be simple or complex. Regardless, quantitative analysis allows researchers to apply repeatable techniques to simplify the process. The complexity of decision-making processes is resolved by using quantitative methods. These techniques help in decision-making to identify the factors that influence the decisions and quantify them [41]. This provides clarity for the audience and explains why certain decisions were made. Quantitative methods are valuable for making more accurate decisions than could be obtained through purely qualitative reasoning. This is because more clearly defined and functionally related facts are the primary bases of decision-making in the quantitative approach [16]. Point 2 focuses on the need for tools to fulfill the technical part of scientific research. Quantitative techniques enforce disciplined thinking about organizational problems and precisely describe the cause-and-effect relationship and risk elimination [41]. In other words, these techniques replace subjective and intuitive approaches with analytical and objective ones [41]. The tactic of selecting an appropriate strategy (Point 3) lies in making informed assessments on which method to use in the outlier removal process. For this research, the chosen outlier removal process was selected based on a combination of observing the strategies of others and applying common sense [41]. In business, this regularly looks like minimizing cost or maximizing profit [41]. However, selecting an appropriate strategy for this application reduces the time and resources spent removing outliers and maximizing the self-similarity of resulting speed traces. Concerning this research, reducing the number of passes in the outlier removal process and minimizing run-time are essential. While much of the time spent running outlier removal MATLAB scripts is inconsequential, more substantial data sets would require more significant optimization of the removal process. Time is valuable, and the reduction of cost (resources and time) is critical, emphasizing the importance of Point 4. The proper allocation of resources plays a vital role in the efficiency of decision-making. A good decision taken at the right time results in an automatically good outcome per [41], indicating proper resource allocation leads to beneficial choices at the right time. Much time should be given to the most optimal method of removing outliers, while far less attention should be given to other forms. Point 5 and Point 6 are easily accomplished by improving on Point 4. There are seven attributes of quantitative analysis that further promote the application of scientific methods to the outlier removal process [24]:

1) Researcher knows clearly in advance what they are looking for
2) Recommended during latter phases of research projects
3) All aspects of the study are carefully designed before data is collected
4) Researchers use tools, such as questionnaires or equipment to collect numerical data
5) Data is in the form of numbers and statistics
6) Quantitative data is more efficient and able to test hypotheses but may miss contextual detail
7) Researcher tends to remain objectively separated from the subject matter

Each of these attributes describes different aspects of this study's research and further validates the implementation of mathematical approaches to the outlier removal process.

2.5 Conclusion to Utilizing Quantitative Methodologies for Outlier Removal

Determining the most effective, efficient method of outlier removal is based heavily on the accuracy with which the technique can remove outliers. Table 2.1 displays the differences between quantitative and qualitative research methodologies.

Table 2.1: Differences Between Quantitative and Qualitative Research Methodologies

Dimension	Quantitative Research	Qualitative Research
Focus on understanding the context of the problem	Smaller	Larger
Dimension of group studies	Smaller	Larger
The proximity of the researcher to the problem being studied	Smaller	Larger
Scope of the study time	Immediate	Longer Range
Researcher’s point of view	External	Internal
Theoretical framework and hypotheses	Well Structured	Less Structured
Flexibility and exploratory analysis	Smaller	Larger

A minimal number of qualitative observations will be made to conclude the best outlier removal method. Because the data set is large and the goal is to reduce the original data set down to self-similar traces, the qualitative assumption made for this analysis is to identify whether the outlier removal method has eliminated enough outliers. Outside of this assumption, quantitative techniques dominate the outlier removal process. Many differences between alternative outlier removal methodologies are subtle, reinforcing the need to implement quantitative approaches throughout this investigation [16]. Statistical comparisons will be made to inform decisions between methods.

To determine the most optimal outlier removal method, quantitative analysis will be utilized because of its inherent advantage of producing more accurate solutions than those customarily obtained by purely qualitative means [16]. For field experiments like those in this study, quantitative techniques in the outlier removal method allow the researcher to observe more natural behavior, which gives better representativeness of the data population [30]. Additionally, in multivariate applications, the adopted statistical process should be adjusted to suit the environmental characteristics under analysis [30]. Therefore, a specialized statistical approach will remove outliers from the original data population. This method will be applied to all data sets without alteration, establishing generalizability to all testing completed as of the publishing of this work with aspirations of application in future work. While no method is perfect, the goal of establishing a well-researched outlier removal method is to be satisfied with an "optimal" solution under current circumstances that will guide future research [25]. The two overarching factors for evaluating each method will be their efficiency and effectiveness, as seen by statistical comparisons [25]. Investing massive amounts of time and effort into this outlier removal method is crucial to prevent future headaches and waste of resources.

Chapter 3

Data Analysis Methodology and Automation

3.1 Statistical Approach to Outlier Removal

The problem of outlier removal is dynamic and is not similar from application to application. Outlier analysis refers to the "task of identifying those patterns from the data whose behaviors do not conform to the expected one" or an "anomaly, discordant object, exception, aberration, surprise, [or] peculiarity" [15, 46]. Additionally, engineers have labeled outliers as an observation deviating so much from other observations that it arouses suspicion that a different mechanism generated it [18]. Outlier detection and removal can be complicated due to [13]:

1) Inaccurate boundaries between the outlier and normal behavior
2) A high possibility that the expected behavior to continue to evolve, and perhaps it might not be a correct representation in the future
3) Different applications and conflicting notions make it hard to apply techniques developed in one field to another
4) Noise in the data mimics real outliers and therefore makes it challenging to distinguish and remove them

The following sections attempt to uncover these complications and address solutions to them. Currently, many versions of how to accomplish outlier removal and a unified approach seem far from actualization. Every version provides benefits and drawbacks to the process. Selecting a suitable methodology for a "wide range of fields, including medical health, credit card fraud, intrusion detection," and many others is nearly impossible, particularly for high-dimensional data [46]. Traditionally, there are six categories of outlier detection techniques: "statistical-, distance-, density-, deviation-, clustering-, and subspace-based methods" [46]. These methods each have benefits for a specific application. However, because the goal is to narrow down the original population to a self-similar trace, only statistical-based methodologies make sense.

Further, statistical-based methods are easily quantifiable by their productivity. Productivity goes hand in hand with efficiency and is defined as the “ratio of outputs produced to inputs consumed” [17]. For this study, the number of outputs equals the number of laps being analyzed since each lap will be within or outside the bound criteria for outlier removal. The inputs consumed are limited to two parameters: the upper and lower bound criteria. The productivity ratio for an efficient process is greater than 1, as seen in Equation (3.1):

$$Productivity\ Ratio\ [-] = R_P = \frac{Outputs\ Produced}{Inputs\ Consumed} \geq 1 \tag{3.1}$$

A higher productivity ratio equates to more efficient processes. Regarding this study, the R_P varies anywhere from 16 to 140 depending on the evaluated data set.

As previously discussed, the outlier removal approach utilized for this study is statistically based and satisfies repeatability issues. Several methods were considered in this study, and their importance and impact on the final decision should be noted. Upon the initial technique’s inception, adjustments were made to test the effectiveness and efficiency of the investigated outlier removal method. These adjustments include applying upper and lower bounds based on the number of standard deviations, increasing and decreasing the number of time steps allowed outside those bounds before a lap is removed, and introducing median absolute deviation. These adjustments are described in more detail in the remaining sections of the chapter. They have been evaluated on their ability to efficiently remove enough outliers based on computation time, the number of laps removed, and variance. Computation time is calculated by MATLAB’s “tic” and “toc” functions to measure the elapsed time that passed while MATLAB was running the code in between “tic” and “toc”. “Tic” was placed at the beginning of each methodology’s script to begin the timer, and “toc” was placed at the end of the script to output the elapsed time. The number of laps removed was calculated at each iteration of the outlier removal method. The variance of remaining speed traces at each time step was also calculated after each technique was attempted to determine the self-similarity of the speed traces. To determine which remaining traces were the most self-similar, the variance will be utilized in two ways: the sum of variance and the average variance for each configuration. The variance will be calculated at each time step to produce a trace the same length as the speed trace.

In the following sections, different parameters of outlier removal are adjusted to investigate the impact of those parameters on how efficiently the method removes outliers. The median has proven to be the most robust to outliers, as opposed to the mean, when evaluating the average for a data set. Situations where the median is more helpful include “heavy-tailed distributions” or “large local deviations” [108]. The data collected in this study contains heavy tails in nearly every truck configuration, indicating median measurements are more insightful than mean. The heavy-tail distribution at a particular time step can be seen in Figure 3.1.

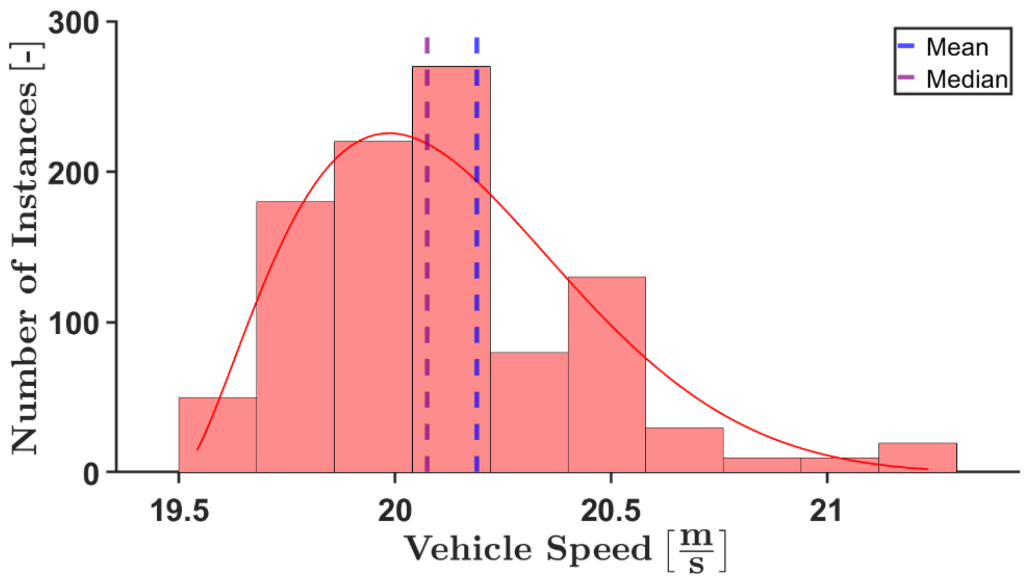


Figure 3.1: Heavy-Tailed Distribution of One Lap Data – NCAT 2019 A2 2T 100

The nomenclature utilized for testing involves two parts: number of platooning vehicles and headway spacing. For example, "2T 100" refers to a configuration with two trucks with a following distance of 100 feet. The mean of the distribution in Figure 3.1 is significantly influenced by the tail of data to the right of the peak, around 20 m/s. Concerning the lap completed, this tail indicates that A2 had several instances where it traveled much faster than the desired speed of 20.1 m/s (45 mph). In the larger scope, several trucks displayed this behavior, which suggests a demand for a more robust metric to evaluate the average of the population of laps. Median allows a more efficient route to identify outliers and remove correctly labeled laps to correct the data population of experimental errors [44]. Laps containing enough of these errors (GPS drops, drivers kicking out of cruise control, etc.) should be removed to correct the original data population [44]. There are three main concerns regarding the identification of outliers: outlier labeling, accommodation, and identification [18]. Outlier accommodation is essential when adjusting the outlier removal process parameters from that list. This refers to modifying the statistical analysis to more appropriately account for observations labeled as outliers [18]. This is accomplished by applying robust statistical techniques that will not unduly affect outliers. The goal of implementing a robust method to identify and remove outliers is to enhance the quality of the data being analyzed and to clean the data population of poor equipment performance or other external factors.

3.2 Tuning Cumulative Lap Percentage

The first tuning knob in the outlier removal process is the percentage of the lap considered large enough that it should be removed from the data set. In other words, if 10% of the lap contains a speed trace outside the standard deviation bounds, is it plausible that the lap has enough data to warrant removal? This section investigates three tolerances: 0, 10, and 25%. If a certain percentage of the speed trace time steps per lap falls outside of the bounds, then the lap will be removed:

- Cumulative 0%: If any time steps fall outside the bounds, remove the lap
- Cumulative 10%: If 10% of the time steps in the lap fall outside the bounds, remove the lap
- Cumulative 25%: If 25% of the time steps in the lap fall outside the bounds, remove the lap

The data set utilized to evaluate the lap percentage changes is A2's 4T 100 lap data extracted from the 2019 ACM campaign. The reasoning behind this lap data set is four-fold:

1) A2 is the follower vehicle in every platooning configuration and therefore experiences the most transient effects from preceding trucks.
2) 4T 100 platoons are the most transient platoon type due to the increased number of platooning vehicles and following distance.

3) ACM's grade profile is the most challenging of the tracks experimented on and causes platoon length to experience an accordion-like behavior (increased transiency).

4) Year 1 of testing utilized the PID-based controller, which proved to induce aggressive maneuvers by all follower trucks, which was addressed in the optimal controller implemented in year 2 (2021).

Therefore, evaluating the effects of the adjustments made to the outlier removal process will be the most noticeable when paired with A2's 4T 100 data from 2019 at ACM.

The first attempt at removing outliers in the data set included a single pass where three standard deviations were calculated from the median at each time step. Each time step has its own distribution (seen in Figure 3.1) associated with it, where three standard deviations outline the upper and lower bounds of an outlier identification criteria. The result of this calculation at each time step and how it applies to the data set can be seen in Figure 3.2.

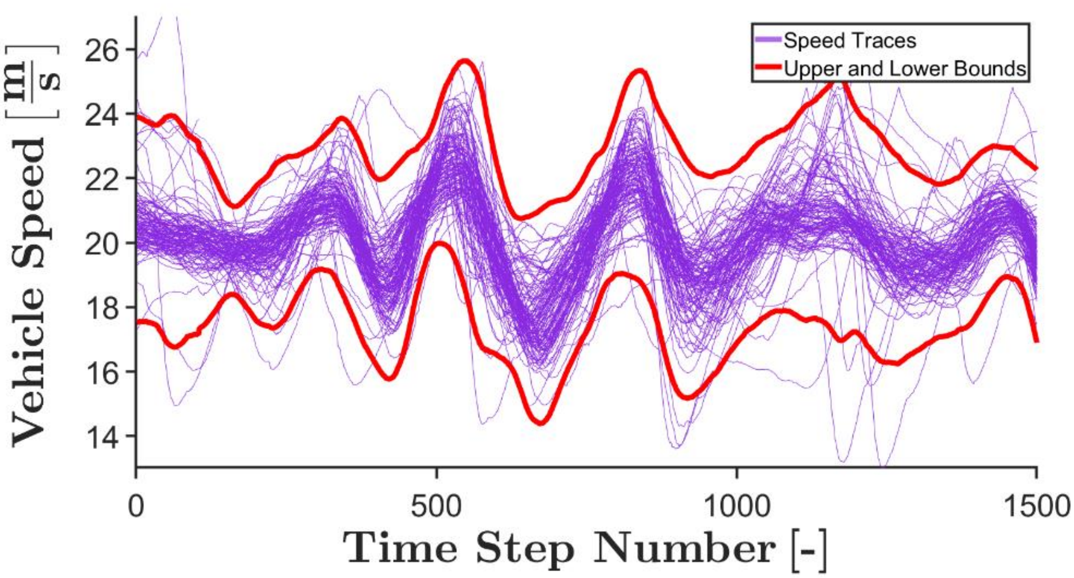


Figure 3.2: Raw ACM 2019 A2 4T 100 Speed Traces with 3σ Bounds

Any laps containing a single data point (cumulative 0%) outside these bounds were identified as outliers and consequently removed from the data set. The result of this can be seen in Figure 3.3.

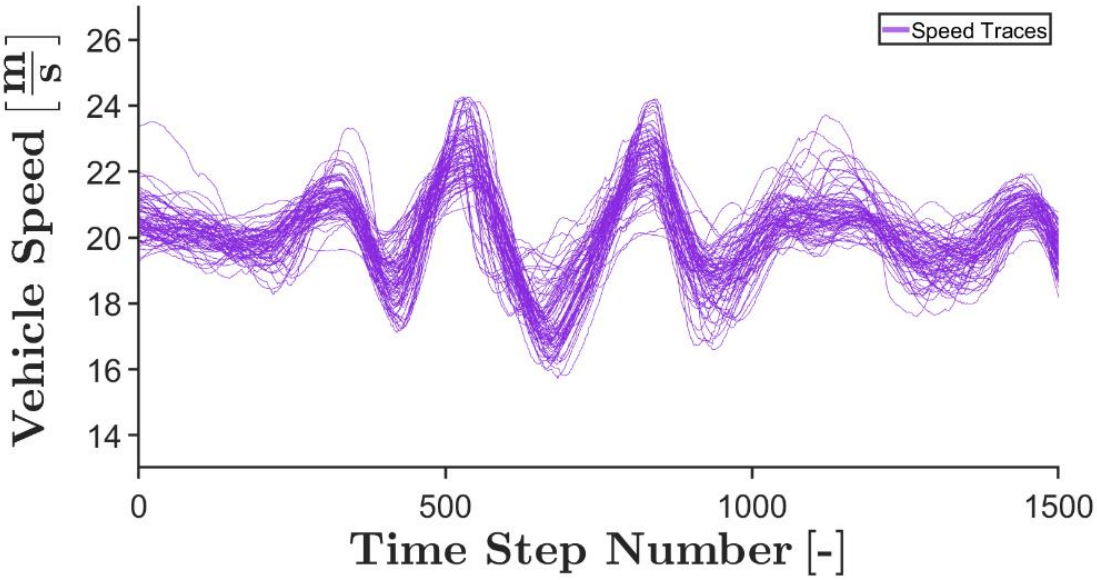


Figure 3.3: Single 3σ Process for AMC 2019 A2 4T 100 – 0% Cumulative Sum

While this method seems to have done a marvelous job at first glance, there are drawbacks to continuing to pursue this method. The main problem with utilizing this method appears when a truck's speed traces are nearly self-similar before the outlier removal process. For example, a standalone baseline operation does not deviate much from a self-similar trace. Consequently, the outlier bounds criteria are incredibly narrow. Several baseline configuration laps are removed unnecessarily by not allowing points outside the standard deviation bounds. In some data sets, there aren't enough laps to afford to remove good laps. Without any lenience on how much of the lap exceeds the bounds, usable data is at risk of removal. While the raw data had an average standard deviation of 1.09 m/s, the data leftover from this method has an average standard deviation of 0.65 m/s after 4.97 seconds of computation time, which shows drastic improvement in the self-similarity of the speed traces. The subsequent adjustment to the outlier removal process increased the allowable cumulative lap percentage outside the 3σ bounds from 0% to 10%. This adjustment allows part of the lap to trend outside the bounds to preserve more transient behavior in the vehicle's speed trace. More representative traces are retained by permitting more transient behavior in the kept laps, as seen in Figure 3.4.

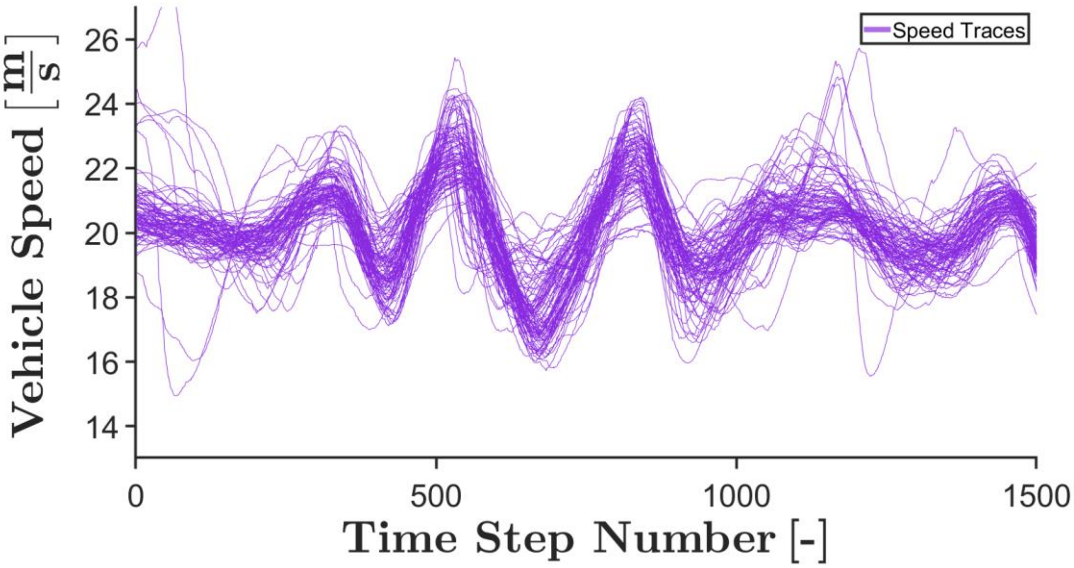


Figure 3.4: Single 3σ Process for ACM 2019 A2 4T 100 – 10% Cumulative Sum

Allowing more outlier-like behavior into the laps kept after outlier removal, problems stemming from experimental factors begin to show. The 10% tolerance appears worse than no tolerance but is practically more sensical. Unfortunately, widening the outlier criteria results in an average standard deviation value of 0.81 m/s with a computation time of 5.53 seconds, which is worse in both cases compared to a tolerance of 0%. The third option of the outlier lap tolerance was 25%, and the resulting speed traces can be found in Figure 3.5.

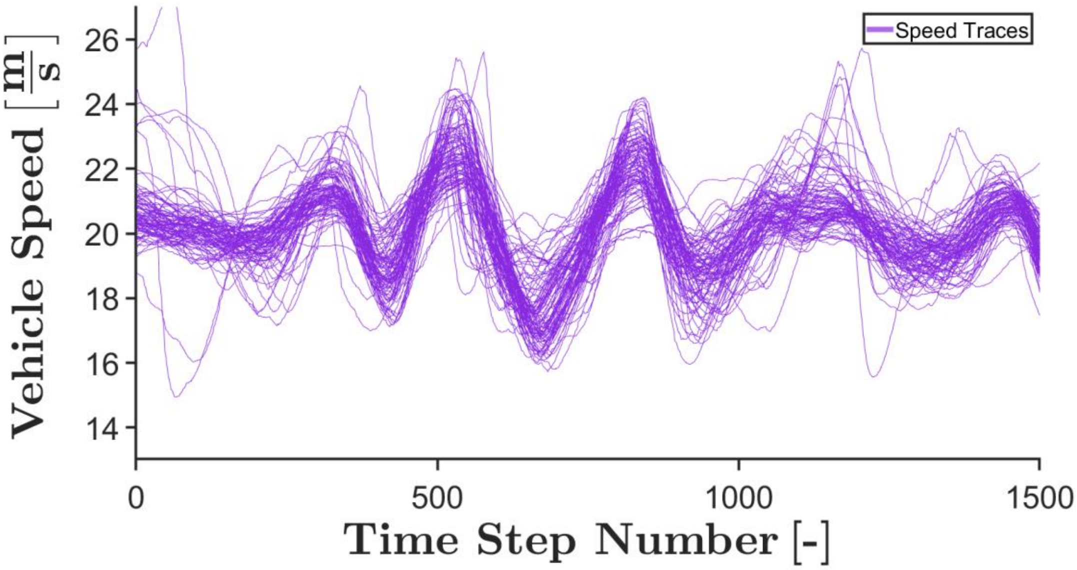


Figure 3.5: Single 3σ Process for ACM 2019 A2 4T 100 – 25% Cumulative Sum

Broadening the tolerance to 25% allows only a few extra laps into the data set kept for analysis. In quantitative comparison, the average standard deviation for 25% tolerance increases to 0.83 m/s with an increased computation time of 6.05 seconds – worse than a 10% tolerance. While the difference between 10% and 25% tolerance limits is marginal, the practicality has unique implications. 10% allows for some experimental deviations away from a self-similar trace but moving to 25% tolerance allows for a significant portion of the lap to fall outside the standard deviation bounds. Because this work was done on closed tracks and the controllers utilized throughout the study are parts of other research, 25% eccentricity away from expected behavior is unacceptable. On the other hand, 0% eccentricity is arguably too ambitious. For this reason, a 10% tolerance is utilized for the outlier removal process. To further reduce the data set, another knob can be adjusted: the size of standard deviation bounds.

3.3 Adjusting Standard Deviation Bounds

The second adjustment made to the outlier removal process is to narrow the size of the upper and lower bounds used as criteria for labeling outliers. Rather than calculating three standard deviations away from the median, this section will investigate the effects of narrowing the bounds to two standard deviations. As previously discussed, the standard deviation of values was calculated at each time step. Two and three standard deviation bounds are plotted over the raw data found in Figure 3.6.

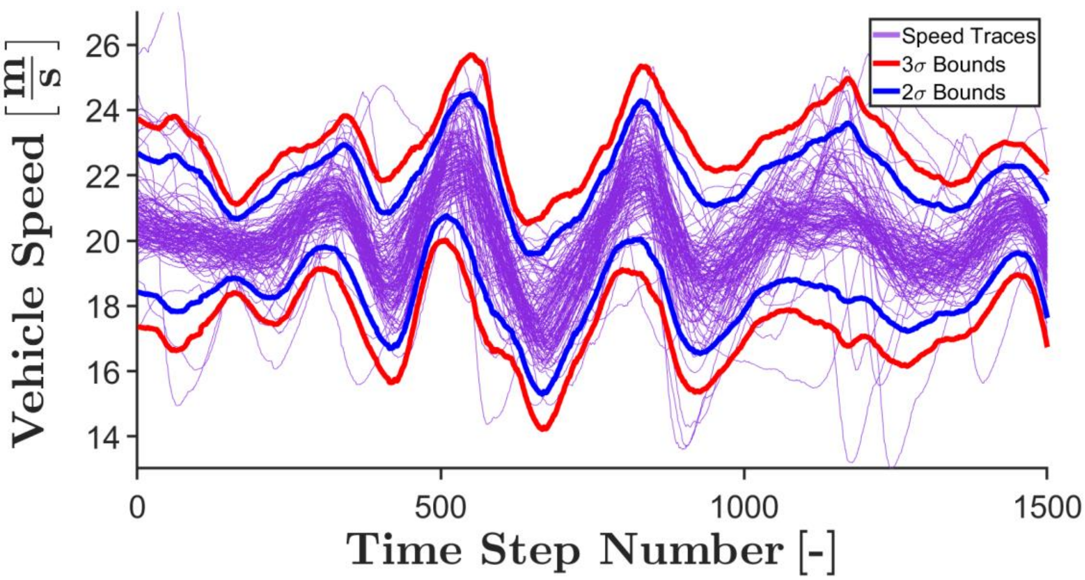


Figure 3.6: Raw ACM 2019 A2 4T 100 Speed Traces with 2σ and 3σ Bounds

The tighter window will label more data points as outliers and remove more laps from the original data set. Outside of narrowing the outlier criteria bounds, the same process was run and produced the results seen in Figure 3.7.

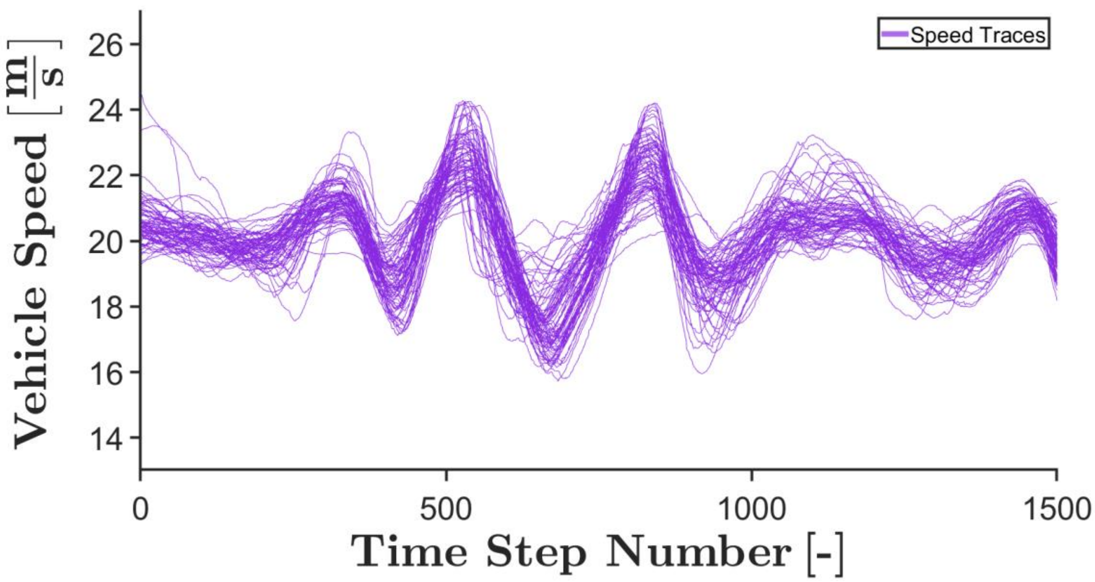


Figure 3.7: Single 2σ Process for ACM 2019 A2 4T 100

Narrowing bounds to two standard deviations with 10% tolerance produces nearly the same results as three standard deviations with 0% tolerance. In other words, the results from the most efficient outlier removal methodology can be closely replicated while correcting the problems with 0% tolerance and large bounds. Quantitatively, the average standard deviation of this method resulted in 0.68 m/s and a computation time of 4.84 seconds (0.65 m/s and 4.97 seconds, respectively, for 3σ and 0% tolerance). However, some laps are not caught by the outlier removal process with just one pass. The following section discusses the effects of running the outlier process a second time to remove any lingering laps that appear to contain outliers.

3.4 Effects of Making a Second Pass at Outlier Removal

Figure 3.7 displays the benefits of narrowing the outlier criteria bounds but also shows weakness in the overall removal of outliers. There are a few laps in the first ~200-time steps with apparent outlier behavior. Additionally, a small cluster around the 750- and 1,100-time step mark exhibit peaking behavior with the potential for outlier labeling. While one pass of the outlier removal process performs well, the remaining laps suggest that making a second pass would alleviate the problems previously mentioned. On the second pass, the standard deviation will be recalculated at each time step to establish a new upper and lower bound for the outlier removal criteria. With a shrinking band across the lap, increased lap removal is predicted and can be seen in Figure 3.8.

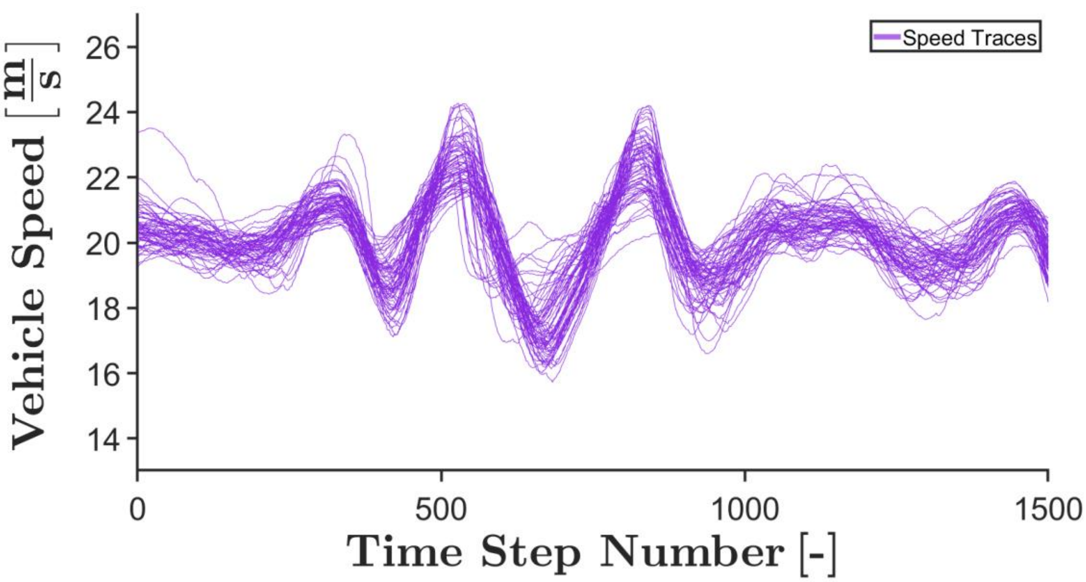


Figure 3.8: Two-Pass 2σ Process for ACM 2019 A2 4T 100

Based on the results in Figure 3.8, making multiple passes on the same data set is extremely valuable for removing straggler traces that deviate from the self-similar trace. This methodology performs slightly better in the self-similarity comparison – decreasing the average standard deviation to 0.62 m/s – but performed significantly worse from a resource allocation perspective – increase to 12.58 seconds. One concern remaining upon making a second pass is leftover outliers. In some instances, data sets contain several traces above and below the self-similar trace, which spread out the outlier identification criteria. Consequently, several outliers are skipped as they are not identified as outliers. It is predicted that every outlier will be removed by allowing the outlier removal process to iterate until 0 laps are removed. To explore this phenomenon, the subsequent adjustment to the outlier removal process evolves into an iterative process.

3.5 Iterative Pass Process

An iterative outlier removal process allows researchers to generalize the exclusion methodology further. The idea behind developing an iterative process is three-fold:

1) Variability between configuration data sets
2) Prevention of outlier identification
3) Partiality removed from exclusion process

While Chapter 3 has focused exclusively on ACM 2019 A2 4T 100 runs, other data sets have exhibited resistance to removing laps with apparent outliers. For instance, data sets with several laps above and below self-similar traces are much slower to identify and remove outliers due to their expanding effect on standard deviation bounds. Applying 2σ bounds once or twice in this scenario only removes two or three laps. However, in data sets such as ACM 2019 A2 4T 100, significant deviations are easily identified and removed from the data set. The variability between data sets prevents the current method – two-pass 2σ bound – to efficiently exclude outliers across all data sets (year, truck, configuration). Additionally, as mentioned in section 3.4, it is predicted that all outliers will be removed if allowed to iterate until 0 laps are removed. To further the generality of the methodology, an iterative method will be introduced to each data set to exclude partiality to particular data sets. Figure 3.9 displays the results of applying an iterative technique to the outlier removal process.

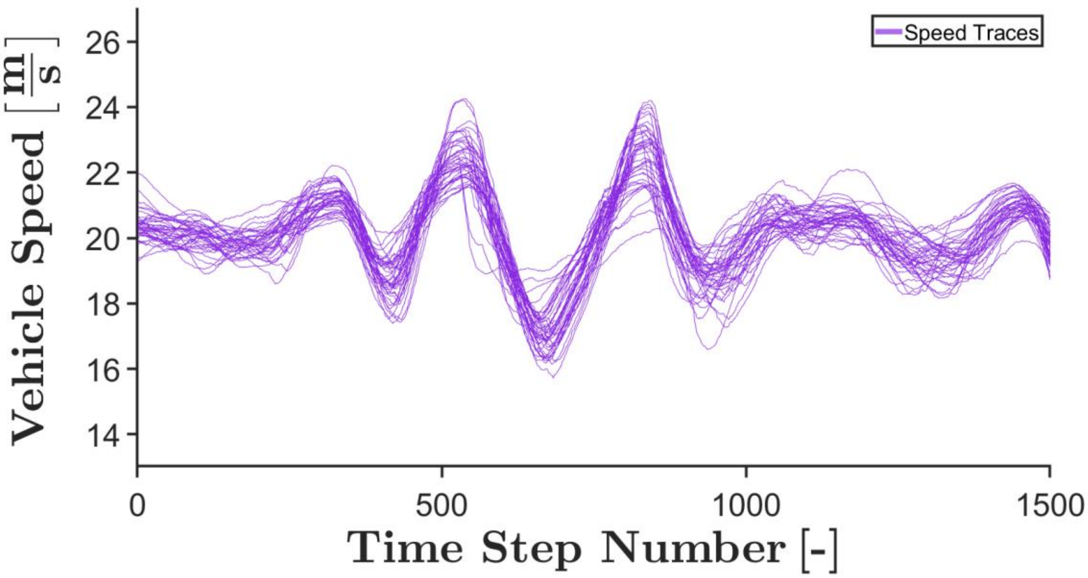


Figure 3.9: Iterative 2σ Process for ACM 2019 A2 4T 100

Iterating the outlier removal process until 0 laps are removed allows the code to remove as many outliers as possible (average standard deviation value of 0.55 m/s), leaving the data set in Figure 3.9 behind for analysis. Another concern regarding an iterative process is answered by the results seen in Figure 3.9: removal of too many laps to perform analysis on. However, plenty of laps remain to draw conclusions. The iterative process is costly in computation time (a resource starving 33.39 seconds). While an iterative process effectively removes outliers, it leaves much to be desired from an efficiency standpoint. Another more robust approach is discussed in the next section that addresses this dilemma.

3.6 Introducing Median Absolute Deviation

Median absolute deviation (MAD) is known for its robustness as a scale estimator and the best possible breakdown point of 50% [32, 33]. This means the median becomes meaningless when more than 50% of the observations are infinite [19]. Previous studies [12, 32] have indicated that the sturdiness of MAD is ideal for screening data and outlier identification, where MAD uses the median absolute difference between all data points to the sample's median. The MAD is a statistic measuring the variability of a set of quantitative elements with robust characteristics against heavy-tailed distributions and standard deviation fluctuations [3, 28]. Similar to the previous outlier removal processes, MAD was calculated according to Equation (3.2) at each time step.

$$Median\ Absolute\ Deviation\ (MAD) = b * Median(|X_i - \overline{X_i}|) \tag{3.2}$$

Where:

b = Multiplicative factor, based on the distribution

X_i = Datum at each time step

$\bar{X}_i$ = Time step median

It is recommended by Fritriyah et al. and Leys et al. [12, 19] that a multiplicative factor of 2.5 (moderately conservative) be utilized for generic data sets without investigating the distribution. Because the goal of the outlier removal process is to generalize a method to all years, trucks, and configurations, this advice will be applied in the calculation of MAD for this work. Evidence of its robustness can be seen in Figure 3.10, where outliers are introduced into a sample data set, and the MAD and standard deviation are calculated.

Figure 3.10: Effects of Outliers on MAD vs. Standard Deviation Approaches [3]

Additionally, the robustness compared to standard deviation approaches can be seen in Figure 3.11, where the MAD and 2σ bounds are plotted together on the raw data.

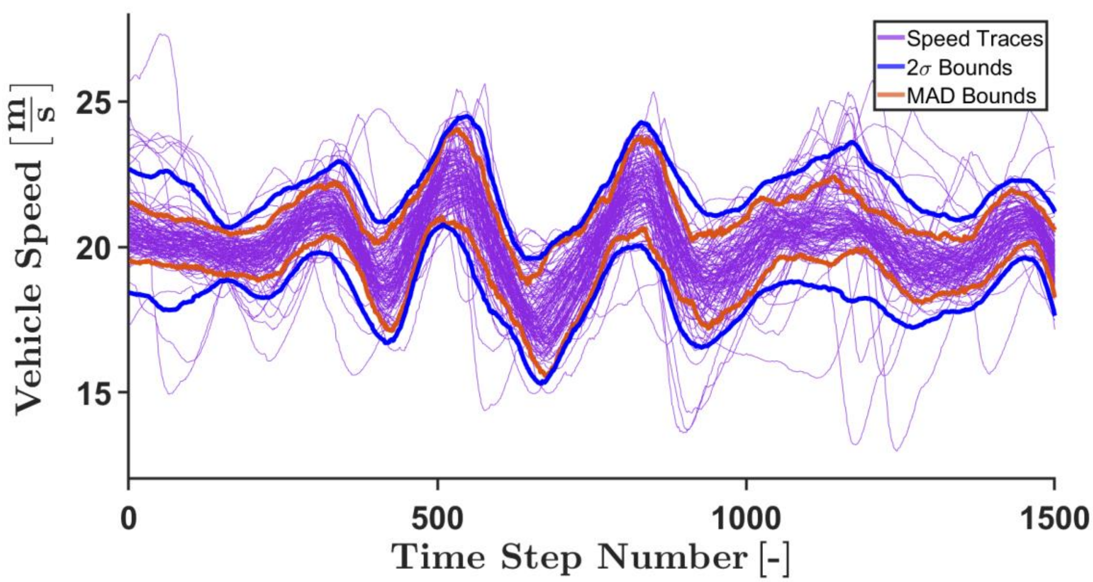


Figure 3.11: MAD and 2σ Bound Comparison on Raw Data

The demonstrated robustness of MAD indicates a more expedient route to removing outliers efficiently. With less influence from outliers, the MAD will allow the swift identification of outliers. In other words, one pass of MAD equivalates to several of the previously described standard deviation passes. One pass of MAD with another pass of 2σ bound was made on the original data set; the results can be seen in Figure 3.12.

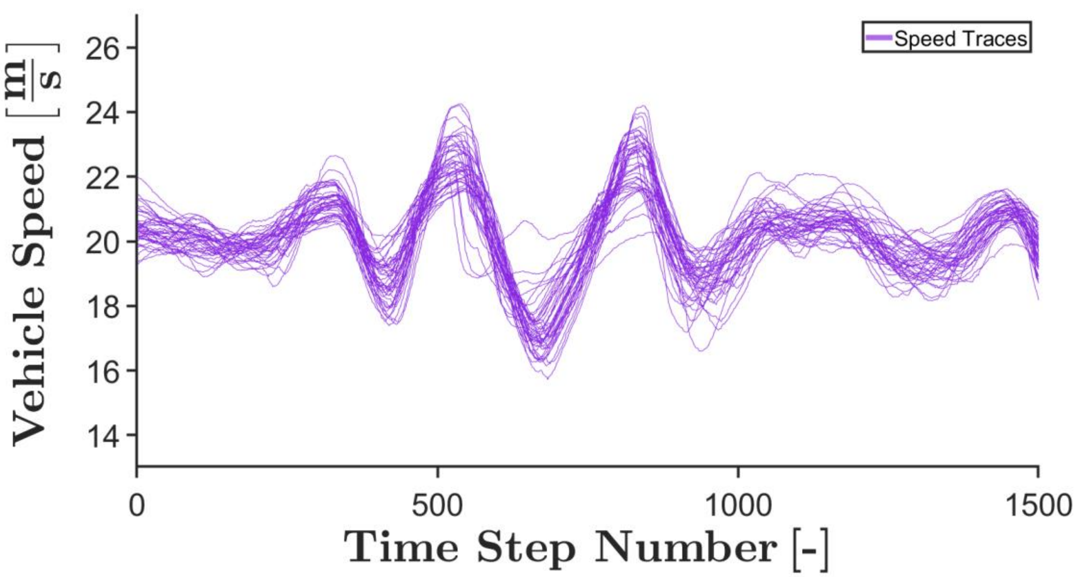


Figure 3.12: MAD and 2σ Process for ACM 2019 A2 4T 100

Based on the results in Figure 3.12, only a few more laps were removed (average standard deviation value of 0.56 m/s), but not at the expense of having enough data to perform analysis. All potential outliers that remained after the previous processes have been removed in significantly less time. With a significantly improved computation time of 7.16 seconds and comparable self-similarity results, MAD successfully displays efficient and effective identification and exclusion of deviant behavior.

3.7 Methodology Comparisons and Conclusions

After running several types of outlier removal processes to determine the most optimal version to proceed with, a combination of MAD and a 2σ bound emerged as the most efficient and effective option. The results of this study are included in Table 3.1, where the technique, computation time, and average standard deviation are tabulated.

Table 3.1: Outlier Removal Methodology Summary

Methodology	**Computation Time [s]**	**Average Standard Deviation ($\overline{\sigma}$) [m/s]**
Raw Data	-	1.09
Single Pass 3σ 0% Tolerance	4.97	0.65
Single Pass 3σ 10% Tolerance	5.53	0.81
Single Pass 3σ 25% Tolerance	6.05	0.83
Single Pass 2σ 10% Tolerance	4.84	0.68
Two-Pass 2σ 10% Tolerance	12.58	0.62
Iterative 2σ 10% Tolerance	33.39	0.55
MAD + Single Pass 2σ 10% Tolerance	7.16	0.56

The raw data set had the worst self-similarity, which makes sense since removing more outliers leaves more self-similar traces. While a single 3σ pass with 0% tolerance works exceptionally well, it is not the most practical method since it does not allow for much deviation. This becomes a problem when the sample set contains very few outliers to begin with, and the standard deviation bounds are tight. Usable data is wrongfully removed at this point, which defeats the purpose of developing an outlier removal process. As the tolerance increases past 10% to 25%, the self-similarity begins to struggle but is more sensical than eliminating a lap for containing any deviation outside the bounds. The difference in computation time is negligible when comparing 10% and 25% tolerances (~0.5 seconds of run time), forcing the focus onto the average standard deviation, which favors 10% tolerance. Tightening the bounds to 2σ as opposed to 3σ and at 10% tolerance restores the benefits – both in computation time and average standard deviation – seen in the larger-bounded 0% tolerance method without losing the practicality of the tolerance. However, outliers remained in the data set after only making one pass. This gave reason to make a second pass to explore its effects on remaining outliers. For a significant drop in average standard deviation (down 0.05 m/s), the computation time suffered (almost three times as much). Depending on the application, this may become a problem if time is more valuable than getting a near self-similarity. Assuming time was not as valuable, the iterative process provided the most effective results of any methodology as expected, which gives the nod to the phrase "with enough time, anything is possible." An all-time low average standard deviation value of 0.55 m/s is best in class at the expense of an egregious amount of computation time – nearly 33.4 seconds. MAD was applied to the raw data set backed by a 2σ pass to achieve analogous self-similarity results without the astonishing computation time. Incredibly, this methodology resulted in nearly identical effectiveness (average standard deviation value of 0.56 m/s) with drastically improved efficiency (computation time of 7.16 seconds). Because MAD enables the outlier removal process to occur in ¼ the amount of time (2 hours of computation versus 8, for example, which saves significant amounts of time), more analysis can be performed once the outlier removal process is completed. For this reason, MAD backed with a 2σ bound pass is used to identify and remove outliers from all data sets analyzed in this study. This methodology can potentially be applied in other contexts, especially for future testing parallel to what is performed for this work.

Chapter 4

Extracting an "Ideal" Platooning Scenario

4.1 Establishing what "Ideal" Means in a Platooning Scenario

Platooning benefits have previously been compared to standalone baseline operation along the same route [8, 22]. However, doing so only extracts the advantages of platooning efforts assuming baseline single truck operation represents the highest level of energy savings. This false notion is exposed due to its limited insight into an ideal platooning scenario's full potential energy savings. Similarly, the assessment of thermodynamic devices is compared to isentropic ones, i.e., how well a platoon performs relative to the ideal. Chapter 4 establishes "ideal" platooning performance by extracting data representative of the most efficient and realistic parameters for energy savings: aligned platooning on level ground.

4.2 Importance of Guidelines Regarding Level Ground

Standard practice for experiments and racing involving elevation changes – not limited to the automotive sector – oftentimes requires net altitude differences to be net 0 or net positive (uphill). For time or speed-based results in both automotive and foot race sectors, the route traveled is nearly flat to provide the most optimal conditions for records to be achieved. Similarly, the production car speed record, officiated by the Guinness Book of World Records, states that a vehicle must make two passes in opposite directions on the same path. The highest speed reached for both passes is then averaged, resulting in the submitted speed for record consideration [9]]. Regardless of the path's surface, this rule must be followed to ensure the net elevation change is 0 to not give any advantage to vehicles due to the chosen route.

The same principles are enforced in foot races. World Athletics, the governing body of running events, dictates that world records for road race distances longer than 10 km (6.25 miles) must be set on courses with an overall decrease in elevation between the start and finish not exceeding 1:1,000. In other words, the elevation drop must not be more than 1 m per 1 km of distance – or 0.1% [3]. Distances shorter than 10 km are typically run on a track where the net elevation change is 0 because of the circuitous shape of the course. For this reason, the rule is enforced for road races only where the start and finish are in different locations. Any rankings or records must come from courses that pass this rule. Any top lists, entry standards, or world records are nullified without validating this rule's passing [46]. When applied to this study, both tracks are circuitous and therefore meet the criteria similar to a foot race on a track. However, these criteria should be enforced when extracting data representative of an "ideal" scenario.

These standards are borrowed from sectors unlike the platooning experimental world but have their benefits if utilized correctly. It is rare and unreasonable to expect a substantially downhill path on a typical drive cycle. Therefore, the standards set by Guinness and World Athletics are applied to the experimental research and ought to be considered for standardization in future comparisons of platooning benefits. With this in mind, a section of experimentation consisting of aligned platooning along a net 0 or slightly positive elevation change will be termed "ideal" as it represents an optimal and realistic driving condition to compare energy savings.

4.3 Straightaway Extraction from NCAT data

NCAT's track contains two straightaways that are potential candidates for extraction as part of the ideal platooning scenario comparisons. These straightaways each have slight grade changes – uphill in the north and downhill towards the south. The northern straightaway contains a section of track that meets the requirements described in the previous section and is displayed in

Figure 4.1 and Figure 4.2.

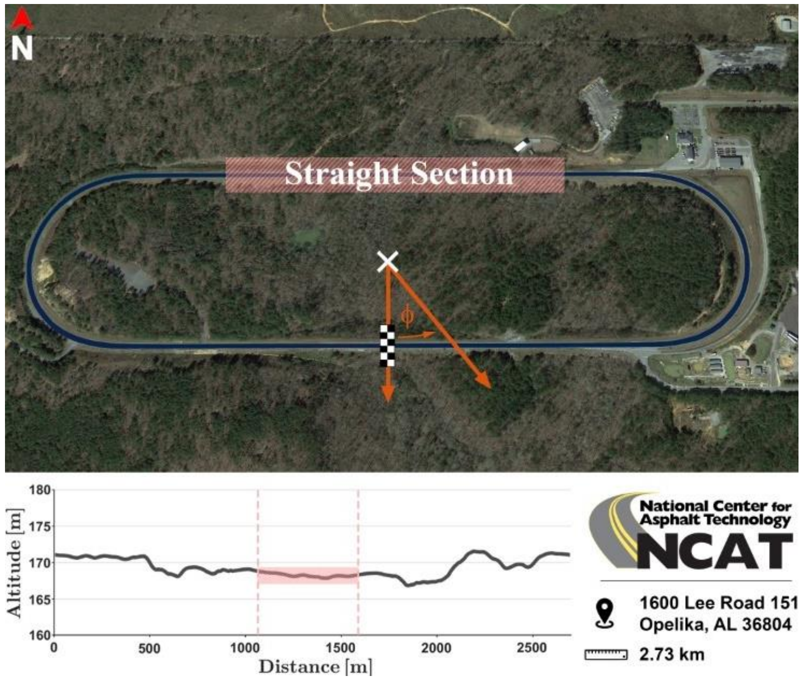


Figure 4.1: NCAT Track Overview with Straightaway Identifiers [36]

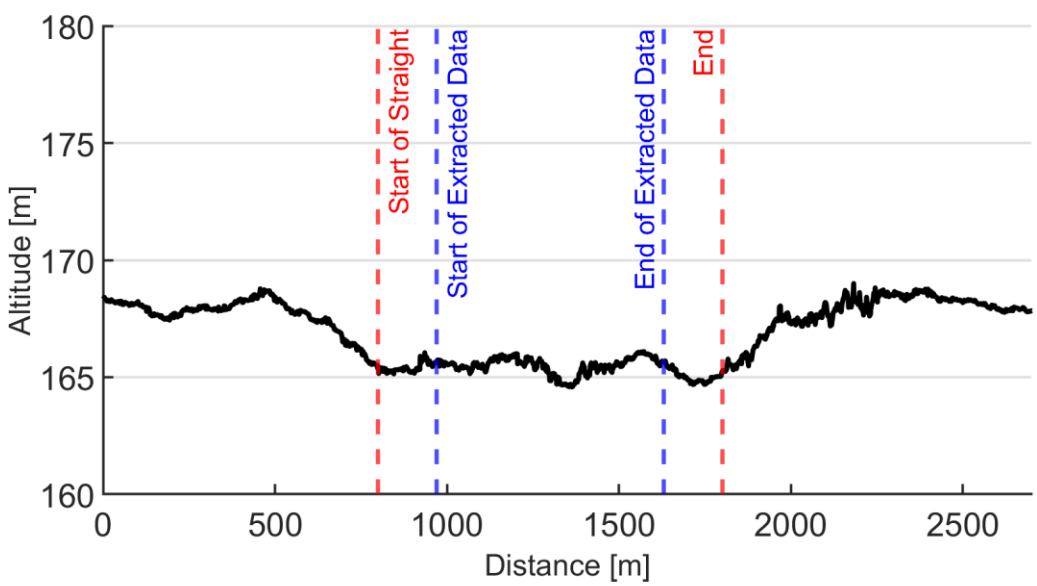


Figure 4.2: Identification of NCAT Ideal Platooning Scenario

From the 800 m mark until the 1,800 m mark, NCAT's track provides just over half a mile's worth of ideal platooning where the start and end of the straightaway are estimated within 1m and are contained between the red dashed lines. The length of a 4T platoon is ~176 m, which was removed from both ends of the original straightaway to account for grade change effects induced by the curves at NCAT (uphill in the west curve and downhill in the east). This section is contained between the dashed blue lines. Additionally, this allows the entire platoon to align itself. After identifying the beginning and end of the straightaway (marked between the dashed blue lines), this section of track was found to have a slightly positive overall grade change (+0.0376°), which passes the criteria set by World Athletics and Guinness. Figure 4.3 shows the average fuel traces calculated for A2, the follower truck in any platooning configuration, which would reveal the influence of the curves due to changes in fuel demand to maintain desired speed and headway. A2 is of particular interest because it is the last truck in the largest platoon and, as a primary check, should aid in identifying whether the removal of curvature influence was successful.

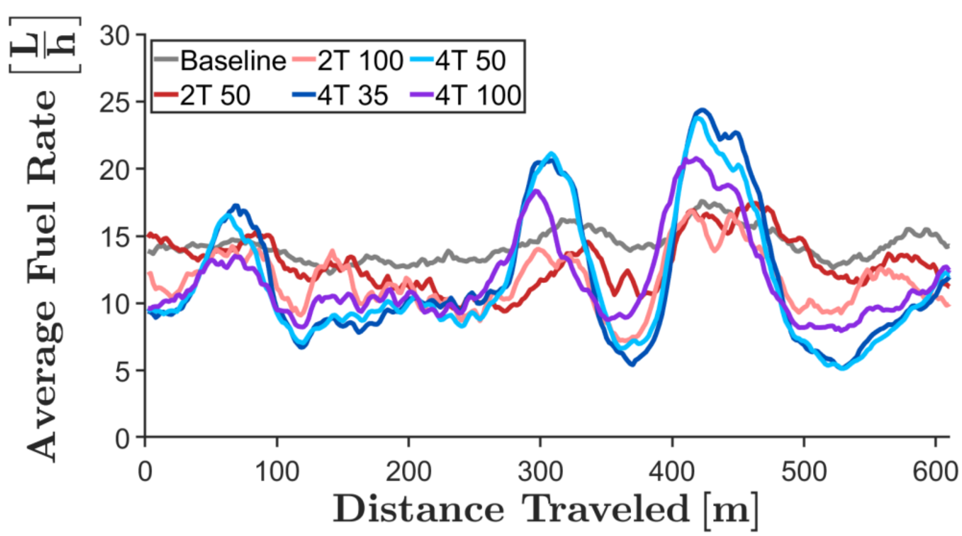


Figure 4.3: Average Fuel Traces, A2 NCAT Northern Straightaway 2019 [36]

Based on the average fuel traces, the influence of grade changes in the curves of NCAT can be safely assumed to be removed from the ends of the straightaway. The relative calm trace towards the beginning indicates no fuel demand changes. The second half of the trace shows a little transiency but is explained by the slight drop in elevation. Concern lies in the transient behavior experienced by A2 in 4T configurations where the fuel rate dramatically shifts up and down across the baseline trace. As a second check, average speed traces for all trucks and configurations at NCAT 2019 in the northern straightaway were calculated and plotted in Figure 4.4.

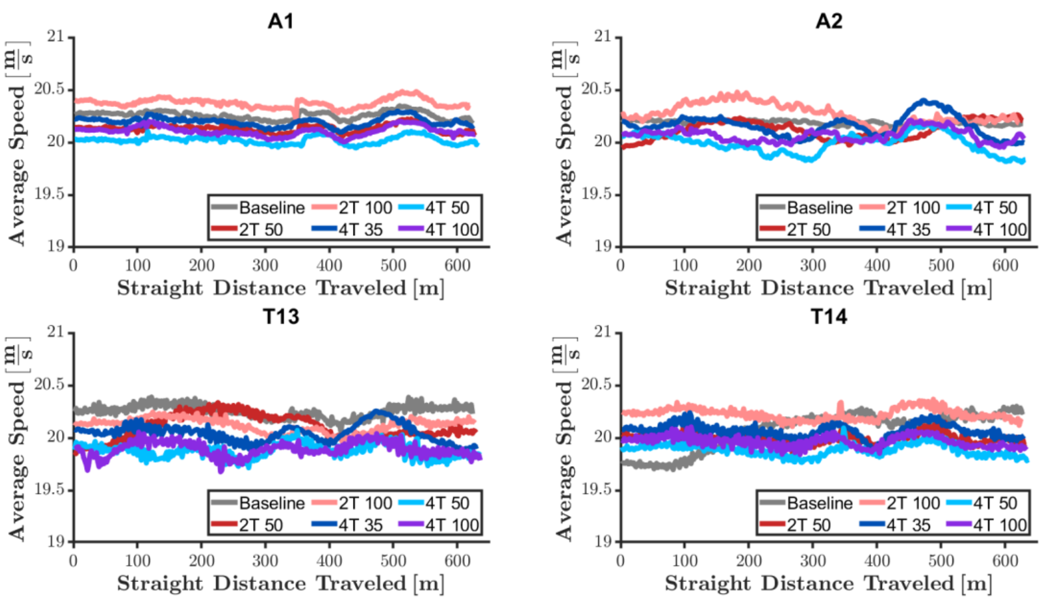


Figure 4.4: Average Speed Traces, A2 NCAT Northern Straightaway 2019 [36]

With the absence of spiking behavior in the average speed traces for each truck and configuration, the concern brought up by the transient behavior found in A2's average fuel trace is alleviated. Similarly, the average speed traces suggest that the influence of grade change has been eliminated from the extracted data. Assessing the results shown in Figure 4.3 and Figure 4.4, it is safe to conclude that the transient behavior seen in A2's 4T average fuel traces is attributed to

A2 falling behind in headway distance. This causes a torque demand from the controller, which can be visualized by the sudden increase in fuel rate while A2 returns to the specified following distance. A jump in fuel rate does not necessarily correlate to a similar jump in speed, which is explained by a slight decrease in elevation followed by an increase. This behavior induces a spiking reduction in fuel demand followed by a similar but opposite spike in the positive direction due to preceding trucks encountering a downhill slope before A2. In conclusion, the effects of grade changes in the curves of NCAT's track have been removed from the data extracted and labeled as an "ideal" platooning performance scenario.

4.4 Track Road Grade Review

This study analyzes three driving conditions: a straightaway extracted from NCAT, NCAT on a lap basis, and ACM. The road grade changes for each scenario provide ample opportunity to compare transiency in speed profiles for heavy-duty platooning trucks. The differences in routes offer analysis potential for ideal platooning scenarios to drive cycles with more grade variance than the national average [22]. To demonstrate these differences, Figure 4.5 and Table 4.1 show the distribution of road grade for all three driving scenarios via a histogram with Gaussian curve fits as well as a tabulated summary.

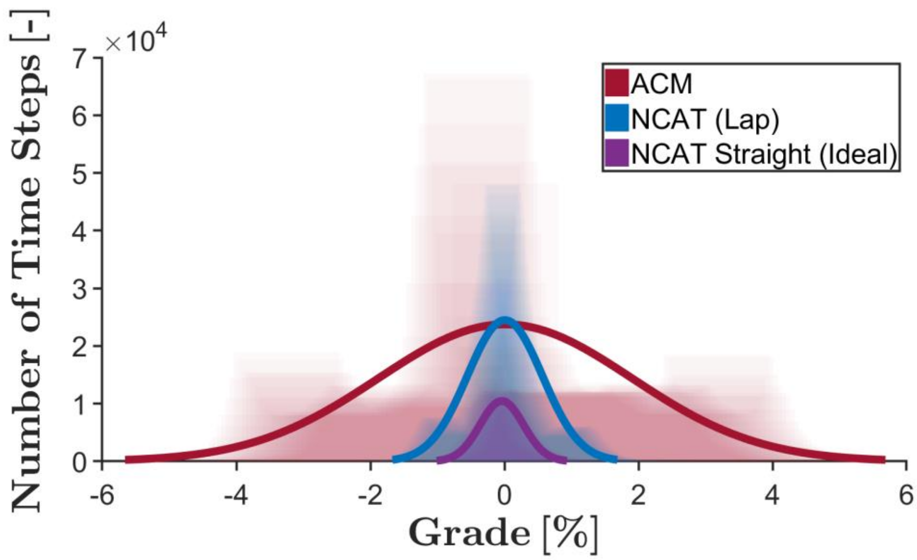


Figure 4.5: Road Grade Distribution Plot for all Drive Cycles [36]

Table 4.1: Track Road Grade Review Evaluated by Median and Standard Deviation [36]

Track	Median [%]	Standard Deviation (σ) [%]
NCAT Straightaway (Ideal)	-0.0407	0.33
NCAT Lap	0.0066	0.56
ACM	0.0156	1.89

The peak of the distributions is insignificant. Rather, the width (standard deviation, σ) or shape is of intrinsic value for this study. For ideal platooning performance, the distribution is tightly centered around 0 ($\sigma = 0.33\%$) while whole-lap NCAT data represents a more widespread distribution ($\sigma = 0.56\%$), indicating more transiency is expected. ACM's track contains several hills making stable platoons challenging to achieve with the highest variance of road grade ($\sigma = 1.89\%$). ACM's relatively flat distribution suggests the highest transiency and absolute road grade excursions. One concern from Table 4.1 is a negative median road grade. However, trucks spend more time going downhill than uphill on a time-step basis, which forces the median to trend in the negative direction. As discussed in section 4.3, the overall elevation change is positive. Therefore, NCAT's northern straightaway passes the ideal platoon scenario identification criteria. In comparison, the southern straightaway not only averaged downhill but also netted slightly downhill, which does not meet those criteria.

Chapter 5

Vehicle-Specific Power and Scaled Tractive Power

5.1 Introduction of Vehicle-Specific Power

Vehicle-specific power (VSP) is a metric developed by Jimenez-Palacio [26] to correlate emissions rates to fuel consumption with units of instantaneous power per unit mass of a vehicle. More specifically, VSP is a direct measure of the road load on a vehicle by characterizing vehicles and their driving profiles using real-world on-road measured data [26]. VSP considers power demand, vehicle mass, speed, acceleration, and road grade. Equations 5.1 – 5.3 can be utilized for the VSP calculation of light-duty vehicles [26].

$$VSP \left[\frac{kW}{kg}\right] = \frac{\frac{d}{dt}\left(E_{Kinetic} + E_{Potential}\right) + F_{Rolling} * v + F_{Aerodynamic} * v}{m} \tag{5.1}$$

$$= \frac{\frac{d}{dt}\left(\frac{1}{2}m * (1+\gamma) * v^2 + mgh\right) + C_{RR}mg * v + \frac{1}{2}\rho_a C_D A (v + v_w)^2 * v}{m} \tag{5.2}$$

$$= v * (a * (1+\gamma) + g * grade + g * C_{RR}) + \frac{1}{2}\rho_a \frac{C_D * A}{m}(v + v_w)^2 * v \tag{5.3}$$

Where:

m = vehicle mass

v = vehicle speed

a = vehicle acceleration

γ = “Mass Factor”, which is the equivalent translational mass of the rotating components in the powertrain and is gear dependent

h = altitude of the vehicle

$grade$ = vertical rise/slope length

g = acceleration due to gravity (9.8 m/s^2)

C_{RR} = coefficient of rolling resistance

C_D = drag coefficient

A = frontal area of the vehicle

ρ_a = ambient air density

v_w = headwind into the vehicle

Knowledge of the driving environment is critical for calculating VSP, and complete characterization of each vehicle is required for VSP to help correlate emissions to fuel rate. Engine power is used to overcome the rolling resistance and aerodynamic drag to increase the kinetic and potential energies of the vehicle [26]. Increased engine power correlates to increased fueling and emissions. VSP bridges the gap between light-duty vehicles to compare small vehicles to light-duty trucks. The Environmental Protection Agency (EPA) adopted VSP as part of their initiative to reduce emissions and normalize comparisons between light-duty vehicles. The Motor Vehicle Emission Simulator (MOVES, the EPA is now on MOVES3) is an emission modeling system that estimates emissions for mobile sources at the national, county, and project levels for criteria air pollutants, greenhouse gases, and air toxins [49]. MOVES heavily relies on VSP and its capabilities of implementing a driving environment to calculate vehicle emissions. Three main components or terms exist in VSP calculation: speed and acceleration, rolling resistance, and aerodynamic drag. The speed and acceleration terms can be resolved via signals intercepted on the vehicle's CAN. The rolling resistance term can be simplified by solving for the rolling resistance coefficient and multiplying it by the vehicle's speed, which will vary during testing. Finally, the aerodynamic drag term is similarly simplified and multiplied by the cubed vehicle speed.

5.2 Applicability of VSP to Emissions Drive Cycles

To demonstrate the impact of those terms on VSP, a sample speed trace was derived from the US06 emissions drive cycle. The US06 emissions cycle is a high acceleration, aggressive driving schedule used for emissions performance under high load. With some assumptions being made, the VSP at each time step was calculated and is shown in Figure 5.1.

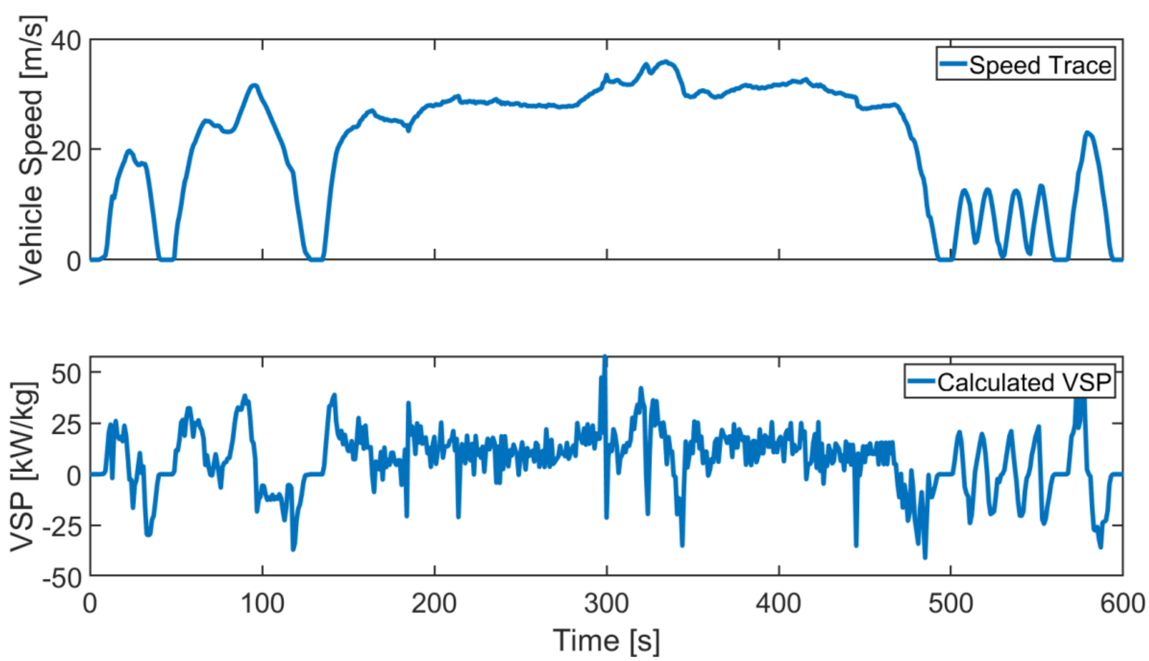


Figure 5.1: Sample VSP Calculation Derived from US06 Emissions Drive Cycle

Assumptions made are as follows [26]:

1) The term $\frac{C_D * A}{m}$ is approximated to 0.0005

2) 0.0135 used for C_R

3) Grade is not represented in the cycle and therefore not used as part of the calculation

The first two assumptions apply to average light-duty passenger vehicles. The third assumption is characteristic of the US06 drive cycle where the grade is not factored into the aggressive speed trace. Based on the VSP trace found in Figure 5.1, drastic changes in speed and acceleration impact the overall calculation of VSP while maintaining relatively constant VSP during highway driving. Small changes in speed and acceleration appear to be accurately calculated into the VSP equation. This is of particular interest for this study because testing was done at a constant 45 mph (or nearly that speed). Speed dithers during testing are relatively small but need to be accurately tracked and calculated by VSP. A similar process was done to investigate this phenomenon further based on the Highway Fuel Economy Test (HWFET), which represents highway driving conditions under 60 mph and a 15-second idle time. Figure 5.2 displays the vehicle speed trace and the calculated VSP trace underneath.

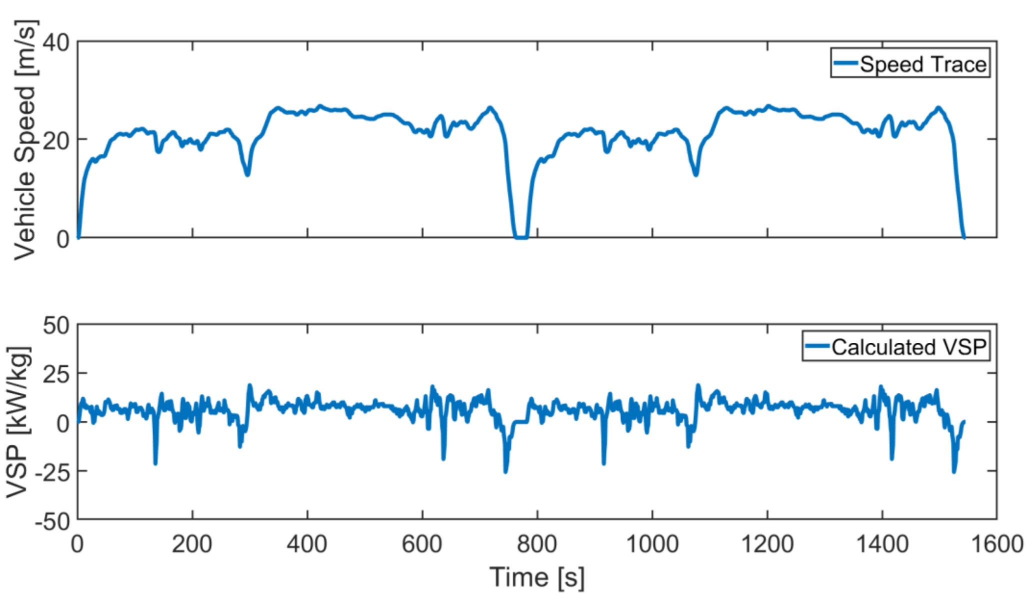


Figure 5.2: Sample VSP Calculation Derived from HWFET Emissions Drive Cycle

Once the vehicle is up to speed, the corresponding VSP is calm and nearly constant at around 10 kW/kg. Compared to the more aggressive US06 cycle, VSP is significantly smaller during the constant speed section. The slow deceleration and idle section also show a slight drop in VSP. However, the drop is not nearly as substantial, in rate or magnitude, as the drops seen in US06. Also, HWFET contains two repeated smooth speed traces: one at 20 m/s and another around 25 m/s. VSP follows each segment with a change in VSP of ~3 kW/kg on average, verifying VSP's capability to track and decipher minute changes in driving conditions. Applying VSP to light-duty vehicles is trivial. If VSP is to be applied to heavy-duty vehicles, such as the ones utilized in this study, modifications are required.

5.3 Benefits and Drawbacks of Scaled Tractive Power

Because VSP was meant for light-duty vehicles instead of heavy-duty ones, problems arise when calculating VSP for the trucks used in this study. Shortly after VSP was introduced, a heavy-duty equivalent entered the scene and allowed researchers to make similar calculations for Class 3 and above vehicles. This equivalent came in the form of scaled tractive power (STP). STP accounts for the significant mass and emissions rate/content differences between light and heavy-duty vehicles via a scale factor and road load coefficients. The formula for STP calculation is described by Equation 5.4 [1].

$$STP\ [\frac{kW}{kg}] = \frac{Av + Bv^2 + Cv^3 + Mva}{f_{scale}} \tag{5.4}$$

Where:

A = rolling road load coefficient

B = rotating road load coefficient

C = aerodynamic road load coefficient

f_{scale} = fixed mass factor

STP proposes an alternative to VSP for heavy-duty calculations but waters down the equation and applies generalized coefficients [1, 48]. A lookup table provided by Yao et al. [48], where each road load coefficient and scaling factor is reproduced in Table 5.1.

Table 5.1: STP Road Load Coefficient and Scaled Factor Breakdown [48]

Regulatory Class	Class Name	Avg. Running Weight [metric tons]	A	B	C	f_{scale}
LHD	Light-Heavy Duty	5.0	0.000226	0	1.470000024	2.06
MHD	Medium-Heavy Duty	11.4	0.000452	0	1.930000027	17.10
HHD	Heavy-Heavy Duty	27.7	0.000831	0	2.890000019	17.10
Bus	Urban Bus	16.6	0.000484	0	3.220000023	17.10

The trucks used in the experiment are between 17 – 23 tons and fit in the middle of MHD and HHD, which are separated by an average running weight of 16 tons. The road load coefficients are also introduced, but no explanation of how these coefficients were calculated is supplied. Thus, reversion to the original equation to hand calculate these values and enhance the accuracy of STP for this study is impossible. Another drawback of STP is the omission of grade influences on the engine load. While many highways are relatively flat, the testing done in this study includes hills well above the national average (±2.5%) steepness to test the limits of the platooning controllers [45]. ACM's freeway loop contains several hills in the ±3.5% range. Road grade is vital in determining a convoy's string stability, particularly for larger platoons. Therefore, the grade cannot be overlooked when evaluating controller strategies via VSP or STP. In summary, STP proposes three main roadblocks which restrict its application herein:

1) Lack of resolution between regulatory classes due to empty trailer operation
2) Black box nature of road load coefficients and scale factor
3) Formulaic exclusion of road grade

These STP shortcomings force a return to VSP for the controller evaluation proposed herein. Despite the current applications of VSP, this study benefits significantly from an evaluation tool like VSP for controller strategy and string stability in heterogeneous platoons. Thus, an investigation into VSP calculation for standalone baseline operation and platoon configurations is required.

Chapter 6

Application of VSP to Empty Trailer Class 8 Heavy-Duty Vehicles

6.1 Vehicle Mass, Grade Estimation, and Rolling Resistance Coefficient

The first variable discussed for VSP calculation is vehicle mass. Each truck has an empty trailer as it convoys with the other platoonmates. Consequently, an assumption of a full load is inaccurate. This introduces a need for a mass estimator or physical measurement. GAVLAB previously developed mass estimators for the truck-trailer combinations and are used for vehicle mass in the VSP equation. The estimated mass of each truck-trailer combination can be found in Table 6.1.

Table 6.1: Truck-Trailer Mass Breakdown

Truck	Estimated Mass [lbs]	Estimated Mass [kg]
A1	35,660	16,175.10
A2	38,020	17,245.58
T13	46,947	21,294.80
T14	37,996	17,234.70

Similarly, GAVLAB designed grade estimators that are equipped on each truck, which are used to calculate the road grade of the path traveled by the truck. This information was recorded with the other data during testing.

Prior experimentation [35] has shown that the coefficient of rolling resistance (C_{RR}) for all trucks is approximately 0.0045, which will continue to be implemented for this study.

6.2 Rotating Mass Factor (γ)

Different transmissions and gear ratios cause the rotating mass factor changes between the Peterbilt and Freightliner trucks. To maintain the individuality of VSP calculations for each truck-trailer combination, the mass factor (γ) was explicitly calculated for each vehicle according to Equation 6.1 [38].

$$Rotating\ Mass\ Factor\ (\gamma)\ [-] = 1 + (0.04 + 0.0025 * \zeta^2) \qquad (6.1)$$

Where:

ζ = reduction ratio or speed ratio

This equation works for passenger and heavy-duty vehicles due to the proportionality of drive component size to vehicle capacity [38]. A collection of reduction ratios and rotating mass factors for each truck-trailer combination are detailed in Table 6.2.

Table 6.2: Reduction Ratio and Rotating Mass Factors

Truck	Reduction Ratio [-]	Rotating Mass Factor [-]
A1	1.0 (9^{th})	1.0425
A2	1.0 (9^{th})	1.0425
T13	0.764 (5^{th})	1.0415
T14	0.764 (5^{th})	1.0415

6.3 Frontal Area and Drag Coefficient

The frontal area of each truck was calculated by multiplying the width by the height of the truck-trailer combination. Generally, the width and height are the same for each vehicle.

Therefore, the calculation of one truck-trailer combination is satisfactory for the frontal area. Based on measurements, the calculated frontal area is 10.66 m^2.

The drag coefficient (C_D) of the Peterbilt trucks is different from the Freightliner military trucks because of an altered profile from added fairings. Per Chowdhury et al. [5], drag coefficients for heavy-duty trucks consistent with the styles operated in this study were experimentally derived from 1/10th scale models in a wind tunnel. No fairings were attached to the baseline model, which is representative of the Freightliner trucks. From the baseline, more air fairings were introduced to determine their effect on drag reduction. The additions to the model are seen in Figure 6.1, and the study results are displayed in Figure 6.2.

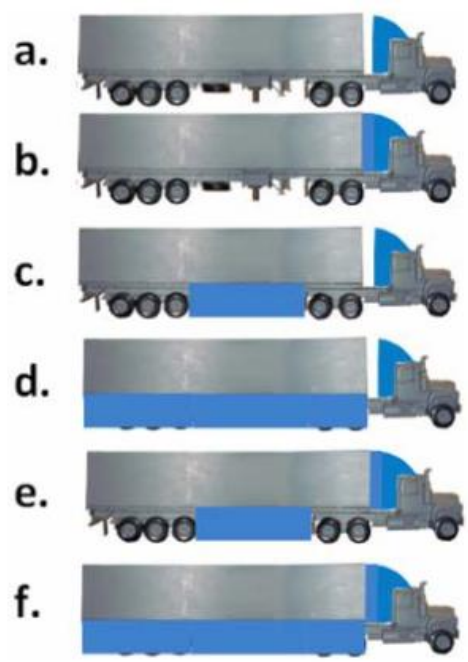


Figure 6.1: Air Fairing Additions [5]

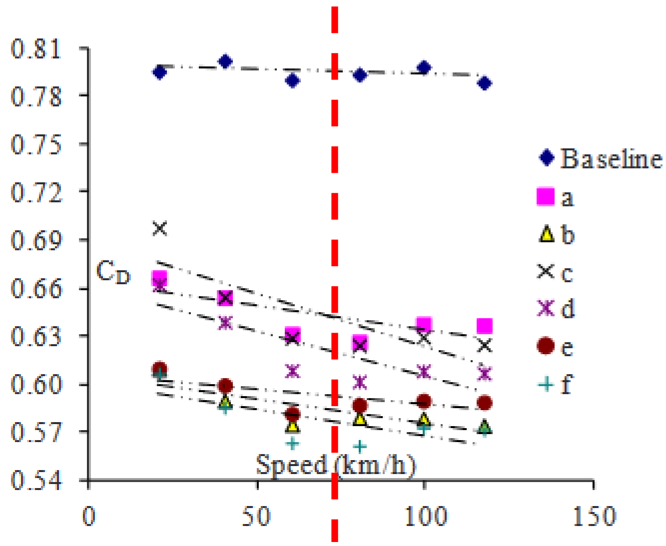


Figure 6.2: Drag Coefficient Results [5]

The baseline model did not vary much when the airspeed was increased and, at 45 mph (72.4 km/h – marked by the dashed red line), the C_D is approximately 0.79. At that same speed using the "C" model, which is representative of the Peterbilt trucks, the C_D is roughly 0.63. These values are located in Table 6.3, where the truck type and respective C_D are tabulated.

Table 6.3: Drag Coefficient for Experiment Trucks

Truck Type	C_D **[-]**
Peterbilt	0.63
Freightliner	0.79

6.4 Ambient Air Density and Headwind into the Vehicle

Due to the lack of a weather station during portions of testing and testing environments in different parts of the country, ambient air density is found based on an average testing temperature of 70°F. An air density value (ρ_a) of 1.2 kg/m^3 is retained for the remainder of this study. Future experimentation should include weather station results to improve the accuracy of VSP calculation.

Unfortunately, anemometers were not placed on trucks to measure wind speed and pressure. This oversight will be adjusted in future testing to account for headwind effects. Moving forward, the headwind (v_w) will be assumed to be negligible since the tracks are circuitous in nature, and headwind calculations would cancel each other out. For the ideal platooning scenario outlined in Chapter 4, logically, the ideal convoy would not battle any headwind, and it is also assumed to be negligible for this section of track. Future testing should include measurements from an anemometer to calculate VSP more accurately.

6.5 Vehicle Speed, Acceleration, and Altitude Signals

Each truck is outfitted with data acquisition equipment capable of intercepting signals from the CAN system. Included in that package are vehicle speed, acceleration, and altitude values ready to be utilized in calculating VSP. Data were recorded and stored on hard drives where variables of interest could be extracted and examined via MATLAB. All variables not extracted from the trucks' CAN and related to VSP calculation can be found in a summarization table (see Appendix A).

Chapter 7

Results and Discussion

7.1 Sample VSP Calculations Using the Ideal Platooning Scenario

The northern straightaway at NCAT provides an ideal case for platooning, as described in Chapter 4. Experimental convoys are perfectly aligned to maximize the benefits of aerodynamic drag reduction with negligible interference caused by road grade variance. The first step in applying VSP to the operating conditions employed in this study concerns the suitability of VSP to relatively calm standalone baseline operation and convoy configurations.

The US06 emissions drive cycle is designed to test vehicles in an aggressive scenario, which results in VSP values ranging between -40 and +50 kW/kg. The sharp acceleration and deceleration events heavily influence the overall calculation of VSP since, in relative magnitude, minor changes of 1 or 2 m/s (~10% increase or decrease in vehicle speed from 20 m/s) are much less impactful than changes of 1 or 2 m/s^2 (~100% increase or decrease in acceleration from 1 m/s^2). Based on this information, it is predicted that VSP values for the NCAT straightaway will be less variant due to the relative lack of intermittent acceleration and deceleration events.

The HWFET cycle fluctuates between 20 and 30 kW/kg, with most of its duration spent above 25 kW/kg. The NCAT straightaway closely resembles the HWFET emissions cycle outside idle time due to its calm speed trace with little influence of grade. Experimentation was done near 20 m/s at NCAT, which suggests that the average VSP calculation will result in values lower than 20 kW/kg with significantly reduced spiking behavior due to the calm terrain of the straightaway.

The following list summarizes the predicted behavior of VSP based on the information previously described:

1) The range of values will be more tightly bound than $-40 \leq VSP \leq +50$ kW/kg
2) Lack of acceleration and deceleration events will produce significantly smoother VSP traces than the US06 or HWFET emissions drive cycles
3) Operating speed is lower than what is found in the HWFET cycle, which suggests calculated VSP values will be lower than 20 kW/kg

After calculating VSP traces for each lap, an average VSP trace was plotted for each truck and platoon configuration within the estimated range on the y-axis utilizing a locally weighted scatterplot smoothing (LOWESS) technique to follow the transient behavior expected to occur in calculation. An example of the calculated average VSP trace based on a LOWESS technique is demonstrated by Figure 7.1.

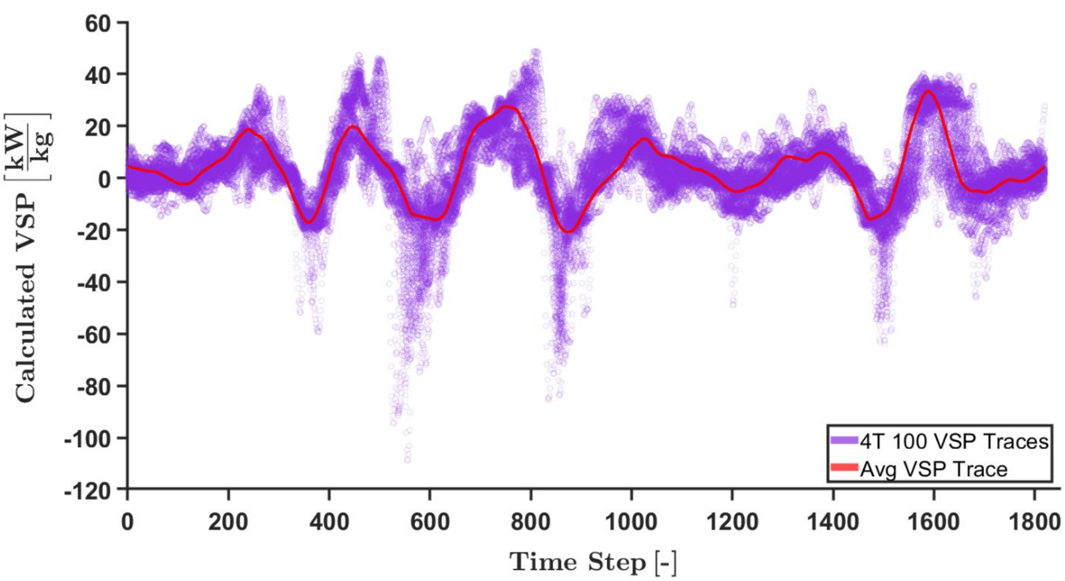


Figure 7.1: LOWESS-Derived Average VSP Trace, ACM 2019 A2 4T 100

The goal of following the major self-similar trace as closely as possible is to capture any variance in the trace while preventing massive spikes in calculation to distort the average trace unnecessarily. Figure 7.1 represents the average VSP trace that was calculated for the most transient data set gathered during testing. ACM 2019 A2 4T 100 platoons are by far the most variant traces and therefore provide the most important case for demonstrating the validity of applying a LOWESS-based average VSP trace. It is clear the scatterplots of each lap for the most transient configuration are well-described by the red average VSP trace.

The resulting traces for A1 (lead truck) can be seen in Figure 7.2.

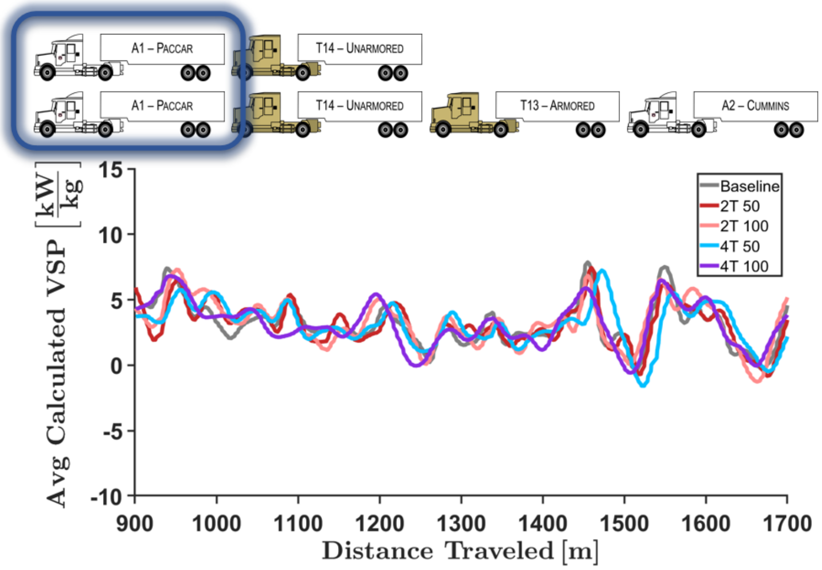


Figure 7.2: A1 Average VSP Trace in Ideal Platooning Scenario, All Configurations

A1 leads all platoons during testing and operates on the stock cruise control. This is evident from the similarity between baseline and platooning configurations' VSP traces. Since A1 leads in all platooning configurations, it is unaffected by platoon dynamics. The range of VSP values is calm between -3 and +8 kW/kg, which is a tighter bound than the US06 drive cycle and appears to be a steadier state than even the HWFET cycle, as predicted. For two brief moments, the truck encounters a scenario where its VSP drops below 0, indicating the truck either requires no input from the powertrain to maintain current driving conditions or that the truck must brake to maintain current speed. Compared to the emissions cycles, spiking behavior is nearly nonexistent. The average value for each configuration is around 3 kW/kg. This is an excellent indicator of the ease at which heavy-duty trucks can potentially lead a platoon, given ideal conditions. The traces found in Figure 7.2 bolster confidence in the modifications made in adapting VSP to heavy-duty trucks in an ideal driving environment.

Following A1 in every convoy is T14, the unarmored Freightliner, which experiences increased transiency due to the accordion-like deviations in speed when attempting to maintain a constant headway. VSP calculations for T14 are seen in Figure 7.3.

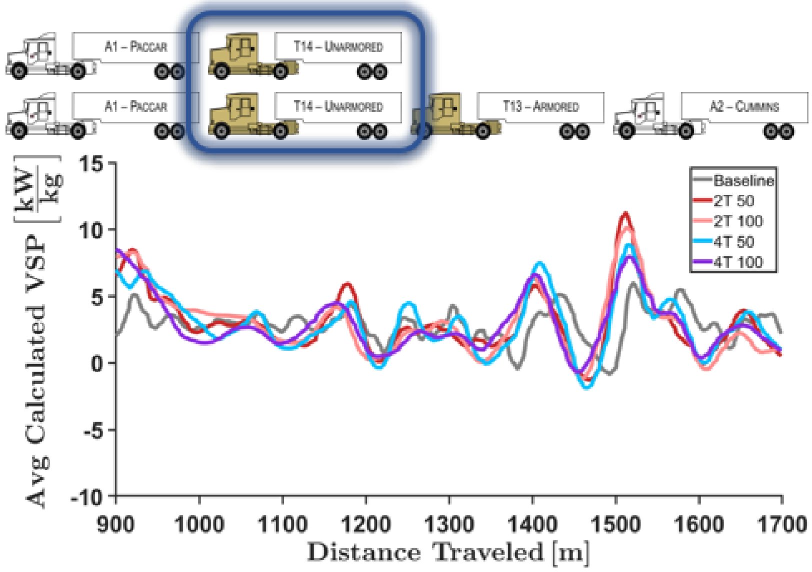


Figure 7.3: T14 Average VSP Trace in Ideal Platooning Scenario, All Configurations

T14 follows A1 in every configuration besides standalone baseline operation. The differences between 2T and 4T platoon traces are negligible, which is expected since there is no change in controller strategy or platoon order. Baseline operation shows similar behavior as A1. T14 experiences similar spikes as A1 as it reacts to information sent to it by A1. It is expected that any spiking behavior would mimic A1's but with a slightly larger amplitude. T14's range of VSP values, $-3 \leq \text{VSP} \leq +11$ kW/kg, is slightly wider than A1 as expected. The average VSP at which the traces seem to oscillate around mirrors that of A1, with the slight differences being trivial when compared to the magnitude of the values calculated for the US06 and HWFET emissions drive cycles. Additionally, VSP tracks the set headway separation between A1 and T14. For 50-foot platoons, T14's offset is smaller than that displayed by 100-foot platoon traces. The same drop in VSP around the 1,500 m mark is experienced at different distances along the straightaway. 50-foot platoons have between 10-20 m offset and this offset is doubled when comparing baseline to 100-foot platoons.

Third in 4T platoons is T13, the armored Freightliner. Because T13 leads a 2T platoon (followed by A2) and follows in a 4T platoon, the differences in dynamics from platoon order placement are demonstrated by the average VSP traces found in Figure 7.4.

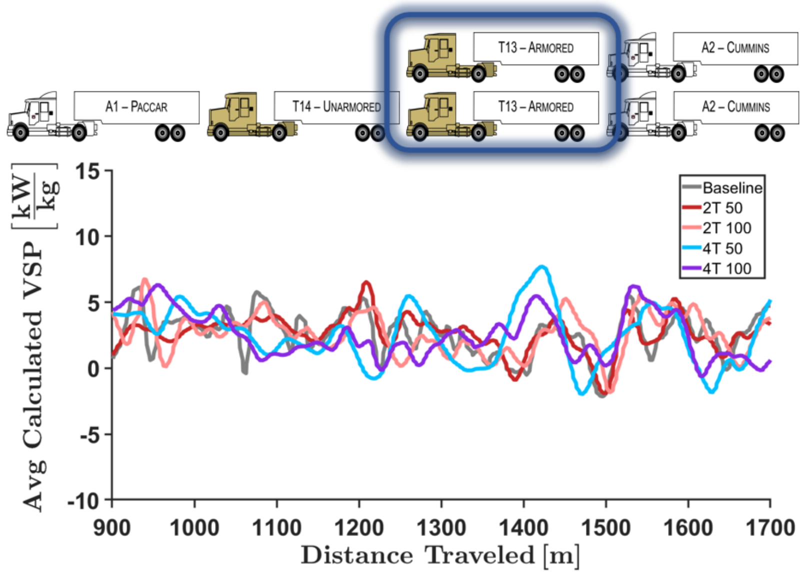


Figure 7.4: T13 Average VSP Trace in Ideal Platooning Scenario, All Configurations

T13 exhibits similar behavior to T14 in a 4T platoon, but the overall transiency is higher throughout the straightaway. This is consistent with dynamics being passed down the platoon order as previously predicted. Because T13 has the most mass out of the experimental trucks, it is proposed that significant positive accelerations are relatively tricky for T13 to manage. However, it is clear that T13 responds to T14's dynamics with increased transiency. Rather than damping the reaction to small accelerations, T13 displays increasingly erratic behavior with more prominent spikes in both the positive and negative directions. The accordion-like nature of platooning transiency is exemplified in comparing the VSP traces of T14 and T13. 2T platoons are nearly identical to baseline operation as expected. For much of the straightaway, 2T traces are located right on top of the baseline traces. These relatively tranquil traces sensibly indicate little to no change in the cruise controller adapted to T13 for its baseline and 2T operation, which is true in this study.

The final truck in all platoons is A2 and is interesting from the perspective of platoon size and its effect on VSP calculation. Because A2 follows regardless of which convoy it participates in, it is expected that VSP traces from platooning data will be the most transient out of all trucks, which can be seen in Figure 7.5.

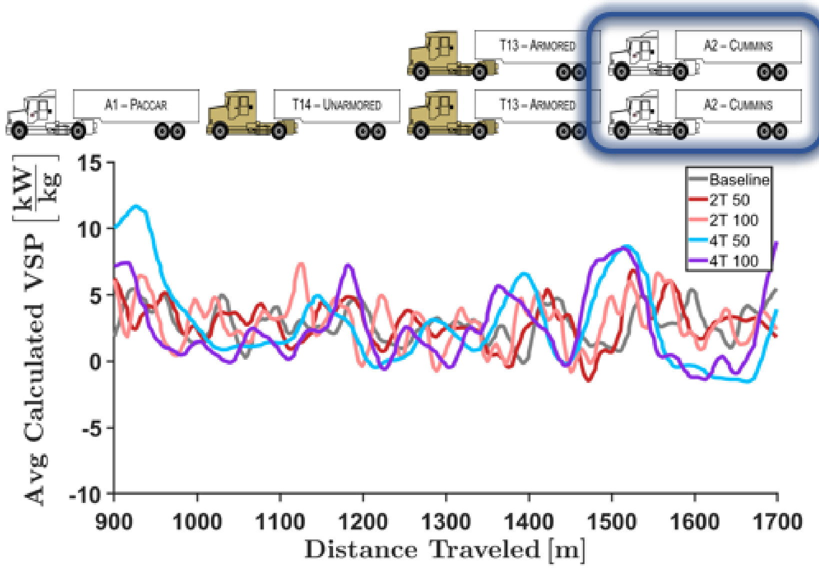


Figure 7.5: A2 Average VSP Trace in Ideal Platooning Scenario, All Configurations

A2 shows the most variance as the last truck regardless of which platoon it is in. However, the difference in variance when comparing 2T and 4T platoons is minute at most. Neither 2T nor

4T configurations provide clear evidence of one being more transient over the other. This is explained by the similar transiency passed down from T13 to A2 in both 2T and 4T configurations. Looking at T13 2T and 4T traces, the differences between the two are insignificant. Because of the minute differences, it is expected that A2 would exhibit similar behavior in 2T and 4T platoons. VSP spikes are more emphasized as A2's VSP range expands to $-3 \leq VSP \leq +12$ kW/kg – the largest span of any truck.

Even in an "ideal" driving scenario, VSP can accurately represent and track the slightest dithering behavior. While VSP has been shown sufficient in short distances with little to no acceleration events, VSP remains to be proven for longer, more challenging sections of track. This will be investigated further by applying the same calculations to an entire NCAT lap where grade changes introduce new challenges to the string stability of the convoy.

7.2 Expansion of VSP Calculation in the Presence of Road Grade Disturbances

Expanding VSP for NCAT on a whole lap basis is the next logical step in vetting VSP as a potential cost function candidate. Similar to NCAT's straightaway, each truck's average VSP traces will be evaluated for accuracy and representation of acceleration and deceleration events. NCAT's circuitous track contains an uphill and downhill slope in opposing corners providing a case for both scenarios. Grade changes have previously caused significant interference for a convoy of trucks [36]. The intent behind expanding VSP into NCAT is to introduce increasingly challenging road grade profiles. Increasing the magnitude of road grade during platooning tests the string stability of the convoy by inducing transient behavior in torque demand to maintain the following speed and headway distances. Accurately capturing these transient events is the goal of implementing VSP as a metric. Each truck's average VSP was calculated at each time step with the same nomenclature and coloring scheming as in previous figures. The results for A1 can be seen in Figure 7.6, where, for demonstration purposes, only year 2 (NCAT 2020) traces are shown. Year 1 average traces were also calculated for A1 at NCAT (see Appendix B).

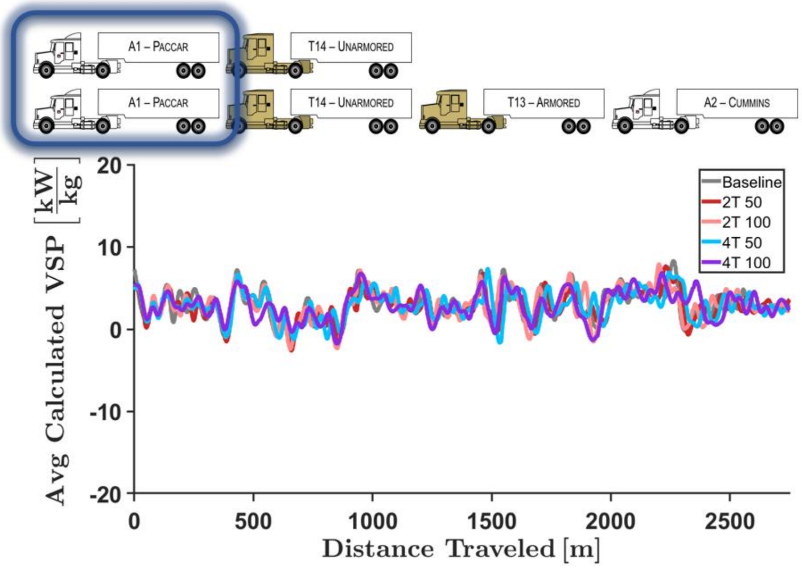


Figure 7.6: A1 Average VSP Trace NCAT 2020, All Configurations

A1 leads all platoons while operating on its stock cruise controller. On a wider ranged y-axis, it may appear as though A1 is smoother over the course of the entire lap as opposed to the extracted straightaway. This is not the case. The bounds of the y-axis were expanded to better capture the spikes in trucks later in the platoon order. Viewing the entire lap exposes relatively calm spikes throughout the entire lap. As A1 drives into the downhill corner (~500 – 900 m mark), there is a minor drop in VSP of about 3 kW/kg in magnitude where it settles into a VSP value of 2 kW/kg offset slightly lower than the value from the straightaway. With the help of negative grade, A1's powertrain does not need to overcome as much to maintain the current driving conditions. A similar shift in the opposite direction occurs as it enters the uphill slope in the opposite corner (~2,000 – 2,250 m mark). As A1 overcomes more resistance due to increased road grade, VSP increases to slightly above 6 kW/kg. Overall, transient behavior is smooth, and changes are minute when comparing different configurations.

T14 is expected to demonstrate the consequences of passing down transient dynamics in both 2T and 4T platoons. T14 is unaffected by the follower trucks behind it, suggesting dithering in 2T platoons should mimic those seen in 4T platoons. Results from average VSP calculation for NCAT 2020 whole laps are displayed in Figure 7.7.

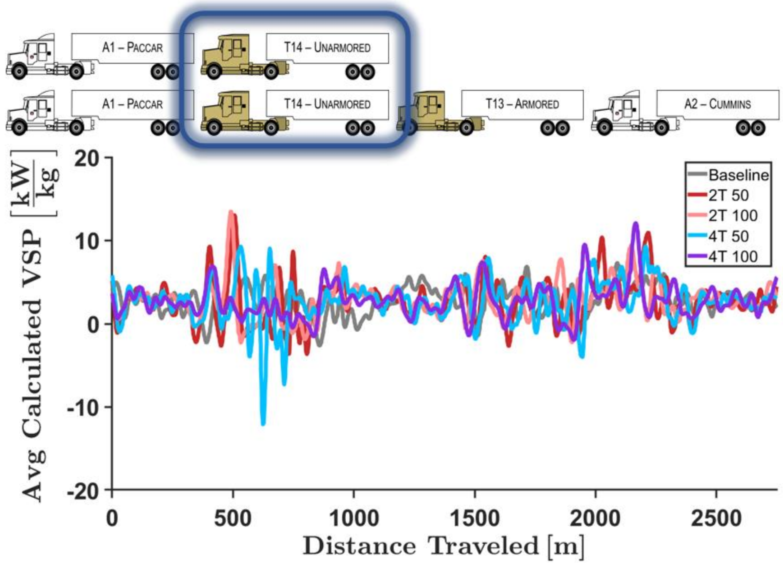


Figure 7.7: T14 Average VSP Trace NCAT 2020, All Configurations

Based on the average VSP traces, T14 experiences the effects of follower vehicle dynamics induced by A1. T14 baseline operation follows closely with A1's average VSP trace. In both the uphill and downhill sections of NCAT's track, T14 experiences significant spiking behavior as the truck attempts to maintain the preset headway distance and vehicle speed. Positive and negative acceleration events to correct positioning and speed cause the corresponding VSP spike. As A1 enters the downhill (~500 m mark) and speeds up before correcting, T14 follows suit and accelerates to maintain the preset headway distance as shown by the initial positive spike. Then, as A1 corrects its speed, T14 adjusts to A1 by decelerating as indicated by the steep negative spikes where the VSP values drop well below 0 kW/kg. This process is repeated until A1 and T14 settle in the upcoming straightaway. These overcorrections cause the accordion-like dynamics experienced by platoons. A similar behavior is displayed in the uphill corner of NCAT where T14 adjusts its speed and positioning by making several minor accelerations, which are easily tracked by VSP and represented by the positive spiking between 2,000 – 2,250 m. Generally, the average VSP trace is noisier for T14 than A1 due to A1 passing down transient behavior to all follower trucks.

T13 also experiences transient behavior inherited from the preceding trucks. However, there is a clear difference between T14 and T13's average VSP trace as seen in Figure 7.8.

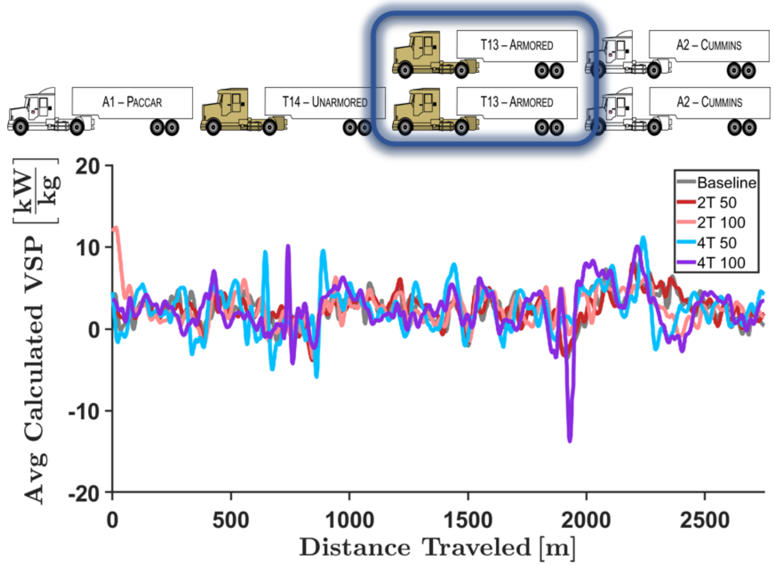


Figure 7.8: T13 Average VSP Trace NCAT 2020, All Configurations

T13's average VSP traces, apart from brief moments in 4T 100 configurations, appear to be dampened when compared to T14. Due to the increased mass of T13, significant acceleration events are more difficult to perform. This will inherently dampen any spiking behavior that would otherwise be more prominent in T13's average VSP traces. The up and downhill sections of NCAT show similar behavior to A1 where slight increases and drops demonstrate the effects of road grade changes in VSP calculation. 2T platoons exhibit similar results to baseline, as expected. The major spiking behavior in T13's traces comes from 4T platoons where the transient behavior of the two trucks preceding it cause T13 to force significant adjustments to conform to the platoon requirements. The magnitude of the spikes in 4T platoons surpasses those seen in either A1 or T14 with a range of $-15 \leq \text{VSP} \leq +12$ kW/kg. Even with added mass, T13 still struggles coping with the inherited transiency from A1 and T14. As the number of trucks in front increases, so does the frequency and magnitude of spiking behavior in both the positive and negative directions.

Considering the efforts T13 made to conform to platoon requirements, it is expected A2's average VSP traces will validate concerns of increased spiking behavior as platoon truck counts rise. Average VSP calculation results for A2 at NCAT in year 2 are found in Figure 7.9.

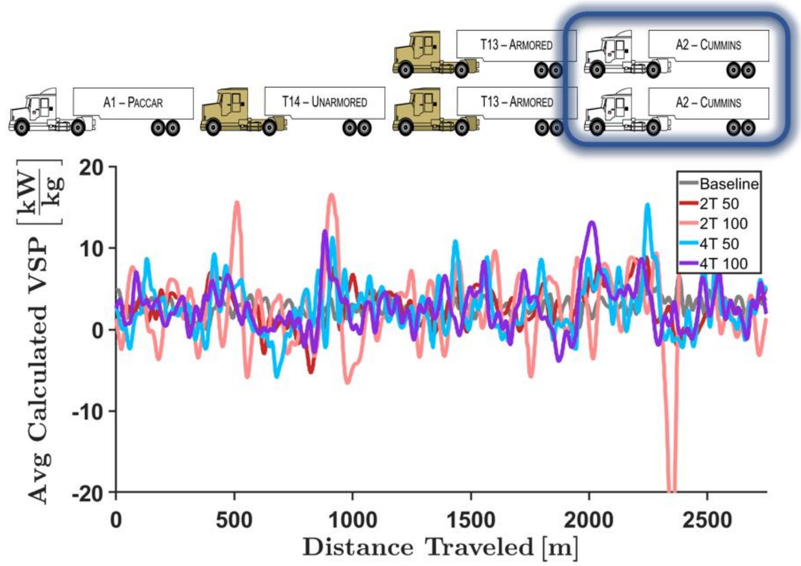


Figure 7.9: A2 Average VSP Trace NCAT 2020, All Configurations

It is difficult to distinguish between the up and downhill slopes by respective increases and decreases in VSP for A2. As the number of follower vehicles increases, the average VSP trace becomes noisier. The increased dithering from the dynamics passed down from preceding trucks nearly masks the effect of road grade on the platoon. Minute decreases occur for the downhill section of the track and vice versa for the uphill section of the track. While these changes are relatively small in comparison to A1's traces, they still exist. Regardless of which configuration A2 is in, it exhibits poor platooning performance as shown by significant swings in VSP, indicating noticeable acceleration and deceleration events populate much of the truck's operation. The amount of dithering in portions of the track without road grade changes encapsulates the accordion-like behavior of follower vehicles. Overall, the average VSP trace variance is not outstanding by any means. However, NCAT does not pose much of a threat to the string stability of a platoon because of its comparatively pedestrian road grade. Due to the lack of road grade, there also lacks definition from a VSP standpoint that follows the road grade well. The frequency and magnitude of the spiking behavior is much greater in A2 than for T13. VSP impressively tracks these dithers well, which gives confidence going into analysis of ACM's challenging track.

7.3 Further Development of VSP Calculation for Challenging Road Grade Profiles

ACM's track contains road grade steeper than the national average. The increased road grade provides a greater challenge for the control strategy. The string stability of a platoon will be tested by ACM as VSP attempts to track more substantial changes in velocity, acceleration, and road grade. For demonstration purposes, the figures analyzed in this section are derived from data recorded in 2019 ACM testing (year 1). Testing results from year 2 were also calculated (see Appendix C). A more string stable controller strategy was used in year 2. While this provides better platooning performance, it fails to challenge VSP as much as evaluating the year 1 controller for the same track with road grade deviations like ACM's. In year 1, testing was completed utilizing a PID-based controller similar to NCAT testing. For this reason, year 1 results are shown in the body of this work and year 2 results are shown in the Appendix.

Beginning with A1, the lead truck is expected to have similar traces regardless of configuration. ACM's challenging track should induce more transient behavior due to increased road grade variance. A1's average VSP traces at ACM are shown in Figure 7.10.

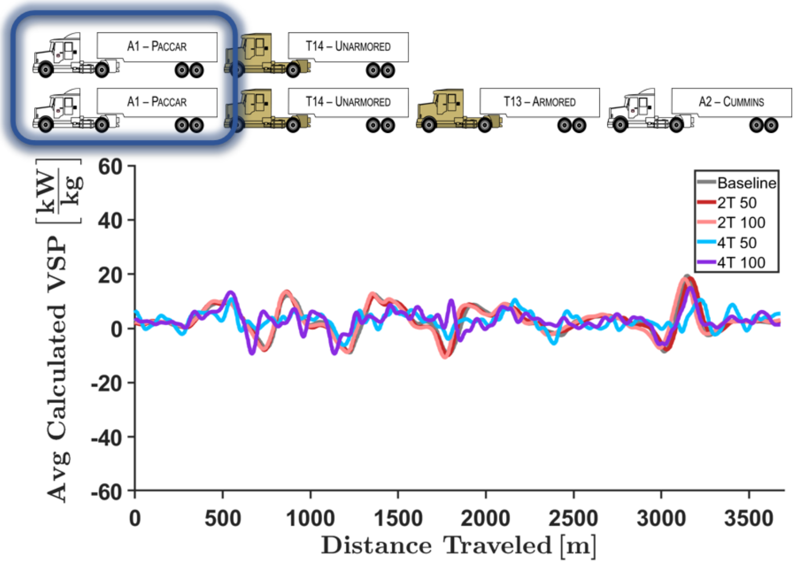


Figure 7.10: A1 Average VSP Trace ACM 2019, All Configurations

A1 shows expected performance as the road grade changes cause speed and acceleration spikes – enough to result in a VSP range between ±20 kW/kg. This is double the range found at NCAT, suggesting ACM's road grade profile forces the trucks to make more aggressive acceleration maneuvers to maintain platoon conformity. Even in relatively flat sections of ACM's track, A1 exhibits some dithering as it comes out of portions of the track with significant road grade. An example of this is between the 2,000 m and 2,500 m marks where A1's stock cruise controller battles with maintaining the set speed of 45 mph (20.12 m/s). A1's dithers track well with road grade and the magnitude of any spiking behavior reflects the intensity of road grade changes.

While the testing campaigns changed, the order in which the trucks operate did not. T14 still follows A1 in 2T and 4T platoons and is predicted to show increased dithering and spiking behavior as it attempts to adjust to conform to preset headway requirements for each platoon type.

Average VSP traces for each configuration are displayed in Figure 7.11.

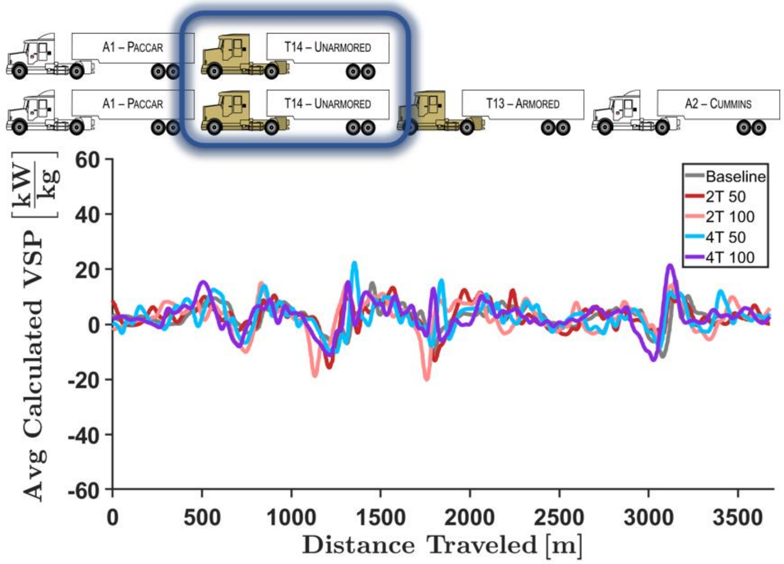


Figure 7.11: T14 Average VSP Trace ACM 2019, All Configurations

The 2T and 4T traces confirm increased dithering when compared to baseline operation. Dithering for T14 is higher than A1, but generally follows its baseline trace. The range of VSP values is ±25 kW/kg, which is larger than A1. Interestingly, more negative spiking occurs for T14 along the challenging track, indicating sudden decelerations to keep certain headways when A1 enters an uphill slope. As A1 slows at the beginning of a hill, T14 also slows down to correct the following distance between the trucks. However, this spike is larger for T14 than it was for A1. It is predicted that the negative spikes at the 1,200 m, and 1,750 m marks will continue to grow for each truck after this one in the platooning order. The adjustments made by T14 to conform to the platoon are tracked by VSP calculation where small accelerations are exposed as spiking behavior in both positive and negative directions.

Further investigating platoon behavior, T13's average VSP traces for year 1 ACM results can be found in Figure 7.12.

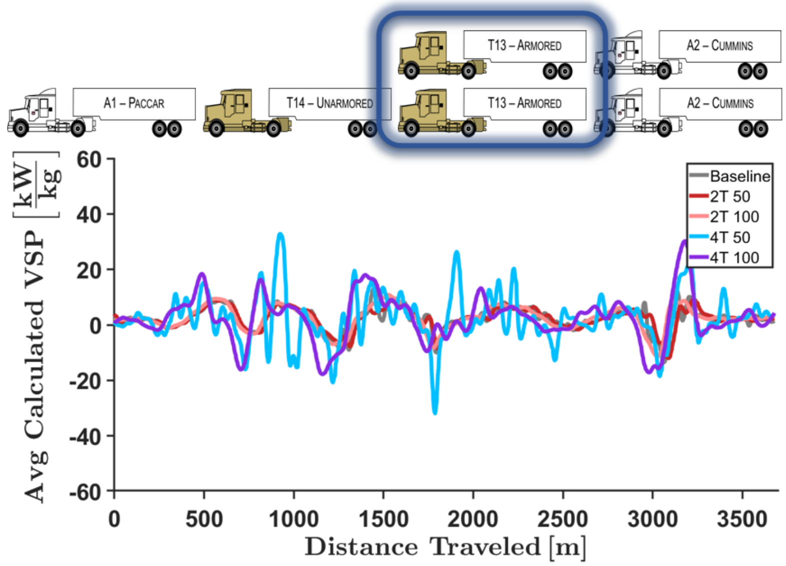


Figure 7.12: T13 Average VSP Trace ACM 2019, All Configurations

A prime example of increased dithering with increased number of preceding trucks is shown in the difference between 2T and 4T platoons for T13. 2T platoons logically follow very closely with baseline as the same cruise control is dictating dynamics in these configurations. Seeing how strictly the traces match is reassuring as VSP tracks similarly between configurations that should match. However, when T13 is placed third in platoon order, spiking behavior is abundant in both positive and negative directions. Not only is the spiking behavior more frequent throughout the lap, but the two significant drops pointed out in T14's traces are noticeably worse in magnitude. With a VSP range of ±35 kW/kg, T13 must overcome its own mass to speed up and slow down aggressively to uphold the continuity of the platoon at specified following distances.

With the cascading effects of the platoon in mind, it is expected A2's traces to be even more erratic, particularly in 4T configurations. Average VSP trace results for A2 are found in Figure 7.13.

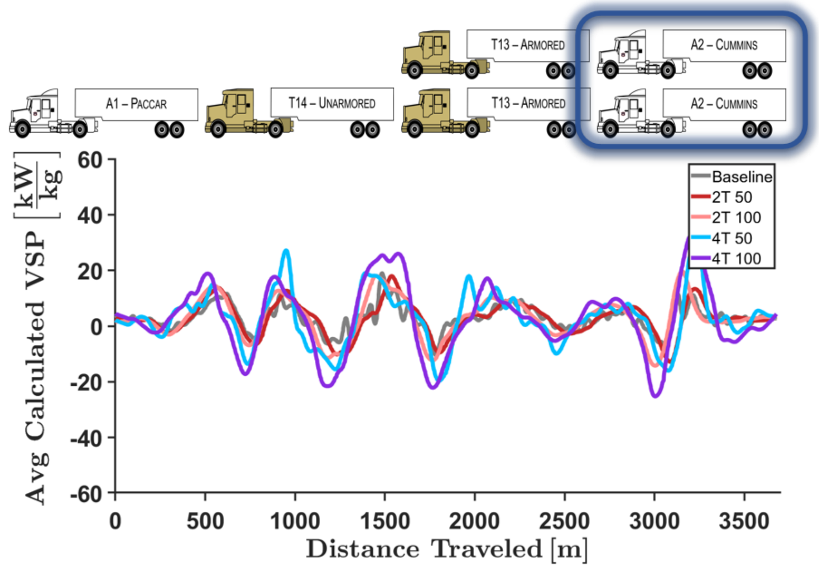


Figure 7.13: A2 Average VSP Trace ACM 2019, All Configurations

As predicted, A2 displays terribly aggressive maneuvers regardless of platooning configuration. Compared to baseline, 2T platoon dithering is only marginally more variant, which can be attributed to T13's relatively steady leading performance. The increase is comparable to the first 2T platoon, A1 and T14. A2 experienced similar deviations from T13 as T14 from A1. 4T platoons are incredibly transient as indicated by a VSP range of ±38 kW/kg, by far the largest range of VSP for any truck or configuration. A2's 4T platoons are littered with significant acceleration and deceleration events. Based on the magnitude of the spikes, it is expected that braking events are substantial enough to eradicate the aerodynamic benefits of platooning.

Overall, ACM exposes the weaknesses of controller strategy for larger platoon sizes. As VSP fluctuations get passed from leader to follower vehicles, the cascading effect could entirely counteract the aerodynamic benefits. Additionally, increasing the magnitude and frequency of road grade changes challenges the string stability of a platoon as demonstrated by A2's struggles to produce nonaggressive platoon performance. However, VSP tracks the acceleration behavior well even when considering large and frequent acceleration events. VSP exposes the weaknesses in a controller strategy when it comes to tracking significant changes in acceleration. Damping these changes are the foundation of developing string stable platoons capable of taking advantage of aerodynamic benefits regardless of platoon size.

7.4 VSP vs Track Road Grade

With average VSP traces calculated for each truck and configuration at each track, the next step is to investigate VSP's sensitivity to variables related to platoon stability. Vehicle speed and acceleration, fuel rate, and road grade are all explored to determine their impact on VSP calculation. Vehicle speed is a variable of interest because the platoon moves together at 20 m/s and any dithering above or below that causes aggressive acceleration or braking events, which are passed down to follower vehicles. Each subsequent vehicle adjusts its speed and spacing based on the truck in front of it, which causes even more transient behavior. Ideally, each truck in a platoon always travels at the set speed. Vehicle acceleration comes in the form of a vehicle increasing its speed to catch up to the platoon or braking to maintain the correct headway distance. Either of these occurrences induce transient behavior, which affects the string stability of a platoon. This also erases the aerodynamic benefits experienced by convoying. Acceleration events are induced by increasing fuel demand. For this reason, the fuel rate of A2 is important to understand the fuel demand and correlate those values to the acceleration of the vehicle. Road grade plays a relatively small role in VSP calculation, but still provides insight into how VSP is affected by it. Because ACM 2019 is the most transient driving conditions in this experiment, data from A2's 4T 100 runs will be used in the following sections and figures. Each scatter represents data from one time step in a lap.

Road grade, as seen in previous sections, induces significant acceleration events in the positive and negative direction. Each truck passes this instability to the truck behind it, which adjusts itself according to the previous truck's behavior. It is expected that A2's VSP values would be wide in range while vehicle acceleration is drastically negative. This is due to two driving scenarios:

1) When cresting a hill, A2 must catch up to T13 to maintain correct spacing. Even when traveling downhill, A2 must accelerate to correct the spacing.
2) Once A2 has caught up to T13 on a downhill slope, it is likely A2 will slow down (potentially to the point of braking) to maintain preset headway. This results in massive negative spikes in VSP.

During sections of uphill slope, A2 is predicted not to brake. Rather, A2 would need to accelerate to keep up pace with the rest of the platoon. In this scenario, VSP will increase with road grade. A scatter plot of corresponding VSP values and road grade are plotted in Figure 7.14.

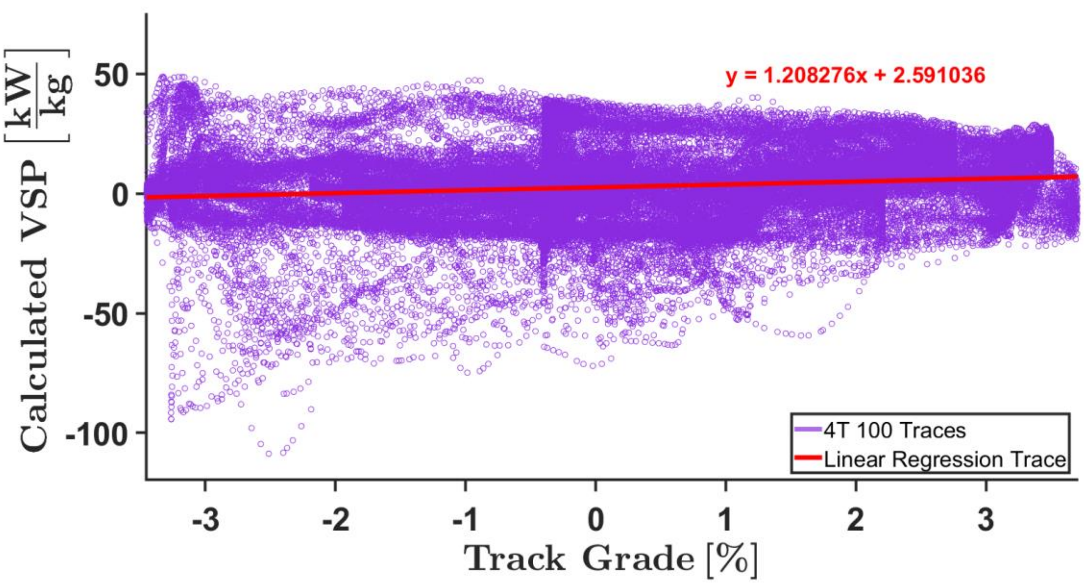


Figure 7.14: VSP vs Track Road Grade, ACM 2019 A2 4T 100

It is clear A2's dithering is increased when operating on a downhill slope where it could be speeding up or slowing down, depending on the section of track. This is represented by the wide range of cloud-like scatter exhibited by VSP values corresponding to negative road grade. Most of the transient behavior occurred when A2 was moving down a slope as predicted. However, outside of forecasted braking events, the correlation between road grade and VSP is slightly positive, indicating increasing slope increases VSP. The logic behind this is simple: increasing the road grade forces a vehicle to work harder to maintain current operating conditions. This is due to the need to overcome increasing potential energy. As the road grade decreases into being negative, the truck encounters conditions requiring both positive and negative acceleration events to adjust according to preset parameters. Overall, the trend between VSP and track road grade is positive, but the distribution of points around the trend line is large. This is explained by the overall magnitude of VSP, and the small influence road grade has on it. Vehicle speed provides more insight to the predicted "catch-up" dilemma A2 experiences while platooning, particularly at ACM. The assumptions made in this section are backed by the VSP and altitude traces found in Figure 7.15.

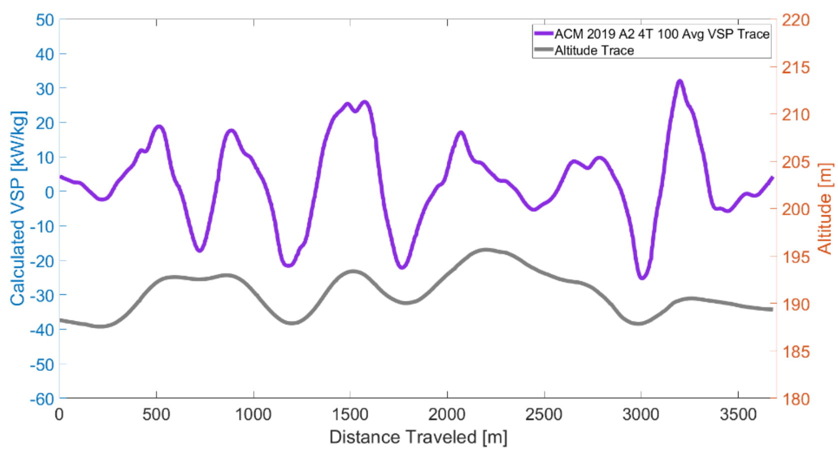


Figure 7.15: VSP Tracking with Altitude Changes

It can be seen that VSP increases when A2 encounters an uphill slope requiring more powertrain effort to maintain current operating conditions. Alternatively, each section of downhill terrain is accompanied by declines in calculated VSP. The slightest changes in road grade appear to have significant impact on the behavior of a platooning vehicle. A2 exhibits this behavior in the slight downhill section around 750 m where the drop in VSP is significant. Additionally, at 2,600 m, changes in road grade from downhill to flattening out induce an increase in calculated VSP. Therefore, the assumptions made about road grade heavily impacting the demanded powertrain output are validated and will be referenced in the upcoming sections of this study.

7.5 VSP vs Vehicle Speed

Investigating the effect of road grade on calculated VSP led to a few questions regarding the exact behavior during downhill slopes. During downhill sections of ACM, it was seen that the range of VSP values stretched from $-110 \leq \text{VSP} \leq +50$ kW/kg. This suggests acceleration events in the positive and negative direction and can be further explained by investigating the vehicle speed. Vehicle speed provides more insight into that behavior and is plotted in Figure 7.16.

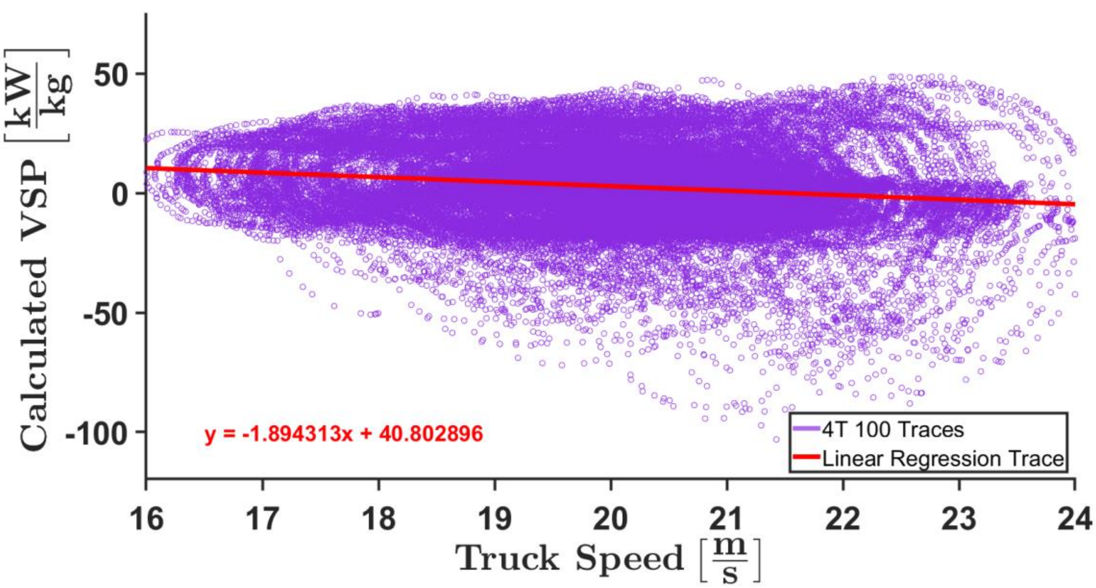


Figure 7.16: VSP vs Vehicle Speed, ACM 2019 A2 4T 100

Generally, the trend between VSP and vehicle speed is slightly negative with a large cloud of data points around the trend line. This is odd since increasing speed increases calculated VSP. Clearly there is more at play than just increasing speed to increase VSP. At first, this might appear to be a problem. The argument here is VSP calculates values that encompass the entire driving environment of the vehicle, which allows VSP to more accurately describe the effort exerted by the truck to maintain current operating conditions. For example, just because vehicle speed is high does not mean the truck is working hard to hold that speed. On the contrary, VSP sees that a truck moving downhill is likely braking, which causes a negative spike in VSP as seen in high vehicle speed and low VSP ranges. Additionally, A2 exerts significant effort to catch up to the platoon as indicated by the bulbous behavior above the regression line in high-speed ranges. A2 experiences braking and aggressive acceleration events at speeds above 20 m/s: the desired testing speed as seen in Figure 7.16. When A2 is above the desired speed, the vehicle is in one of two scenarios: catching up to a platoon or traveling downhill before braking. To shed light on this phenomenon, acceleration was also examined.

7.6 VSP vs Vehicle Acceleration

Based on A2's road grade and vehicle speed figures, assumptions have been made regarding the occurrence of acceleration events. It has been hypothesized throughout this study that VSP is heavily impacted by the acceleration of the vehicle. Even in sample calculation, significant swings in VSP occurred during times of drastic changes in vehicle acceleration. Acceleration dithering is potentially the most detrimental behavior to a platoon's benefits. For this reason, vehicle acceleration is a variable of interest. VSP's ability to track acceleration is plotted in Figure 7.17.

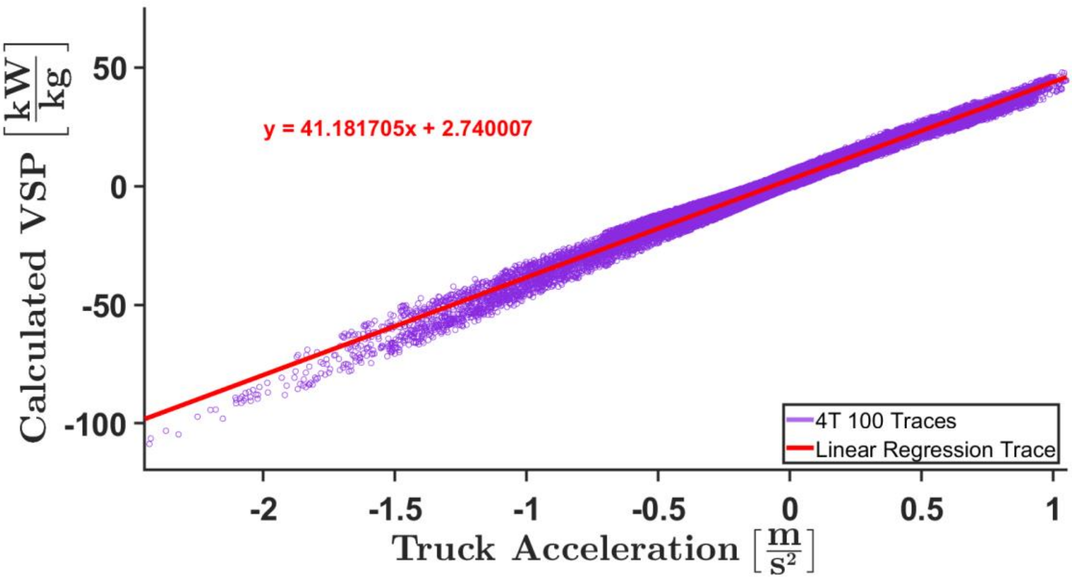


Figure 7.17: VSP vs Vehicle Acceleration, ACM 2019 A2 4T 100

Based on these results, there is a strong positive trend between acceleration and VSP where the variance around the trend line is minimal. Figure 7.17 is confirmation of VSP's ability to monitor a vehicle's acceleration. The narrow shape of the cluster is indication of VSP's sensitivity to acceleration. For positive acceleration events, corresponding VSP values are nearly all greater than 0. From a controller strategy evaluation tool perspective, following acceleration changes is the most important aspect. Because significant magnitudes of acceleration (positive or negative) are harmful to the string stability of a platoon, it is essential the evaluation tool tracks minute changes in acceleration. Reflecting on the traces seen in Figure 7.17, VSP strictly follows the changes in acceleration while also considering other variables of interest. This makes sense since VSP originally was used to correlate emissions to fuel rates where hard accelerations would lead to drastically higher emissions rates. This similarity is the prime purpose behind utilizing VSP in another automotive sector. Having said that, it is still important to investigate the correlation between VSP and the fuel rate of the test vehicle.

7.7 VSP vs Fuel Rate

In order to cause changes in acceleration in heavy-duty diesel applications, it is mandatory to increase fuel delivery with all other things being equal. It is predicted, then, that based on the results found in Figure 7.17, fuel rate should follow the same trends as acceleration. The fuel rate scatter is explored in Figure 7.18.

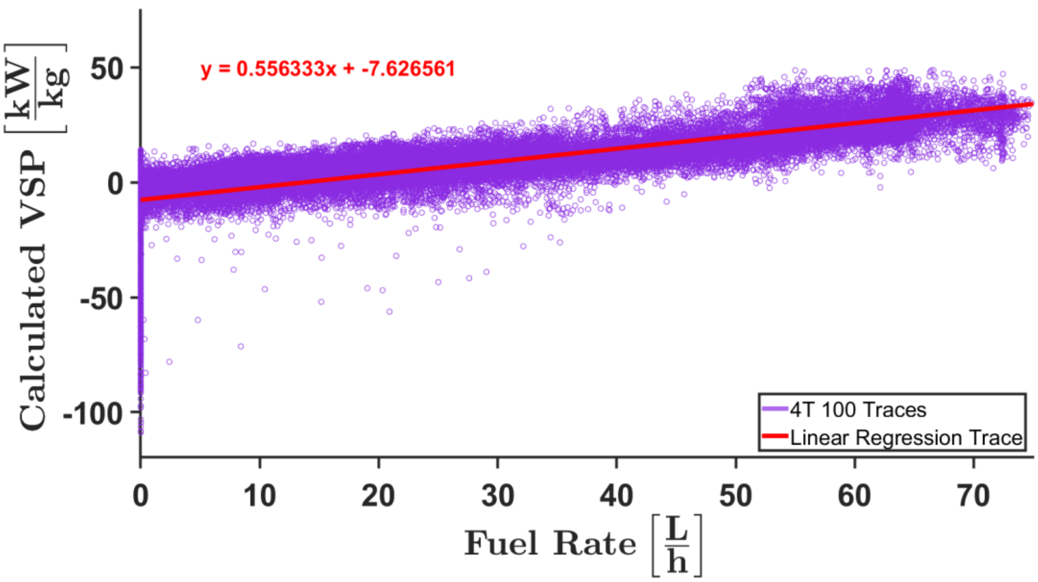


Figure 7.18: VSP vs Fuel Rate, ACM 2019 A2 4T 100

The cluster of fuel rate scatter is wider than the scatter seen with acceleration but is still relatively tight compared to the speed and road grade traces. There is a strong positive trend between VSP and fuel rate, as expected. Apart from coasting fuel rates around 0 L/h, fuel demand is directly related to acceleration for heavy-duty applications. However, the vast majority of scatter that is on the y-axis corresponds to a VSP value above 0 kW/kg. This cluster indicates braking or coasting behavior (as seen in Figure 7.17), which parallels with fuel rates approaching or equal to 0 L/h.

To investigate VSP's sensitivity to both acceleration and fuel rate, a 3D scatter plot was created to show the impact both parameters have on VSP calculation. This scatter plot is shown in Figure 7.19.

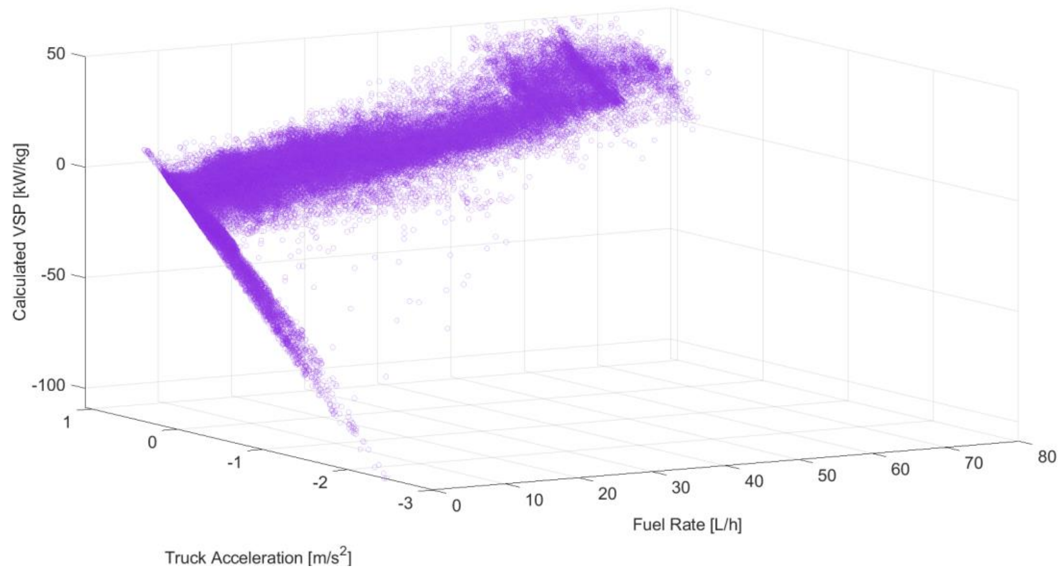


Figure 7.19: 3D Scatter of Acceleration and Fuel Rate Effects on VSP, ACM 2019 A2 4T 100

There is a definite relationship between the two variables and VSP as previously described, but the scatter confirms suspicions about A2 requiring positive acceleration to increase calculated VSP above 0 kW/kg. To initiate an acceleration, torque demand increases correspond to increased fuel demand. However, VSP values below 0 kW/kg suggest the truck's powertrain does not have to output any effort to overcome current driving conditions. Coasting requires 0, if not nearly 0, fuel demand as demonstrated by the dark cluster along the 0 L/h fuel rate axis. This dark cluster expands from $-3 \leq$ Acceleration ≤ 0 m/s^2. Most of the scatter falling in those parameters are below 0 kW/kg on the VSP axis. This is confirmation of fuel rates dropping to nearly 0 L/h during deceleration events explained by A2 not being required to output torque to maintain current operating conditions.

Now that VSP has been examined for its sensitivity to operating parameters and how they interact to result in certain VSP values, confidence is instilled in utilizing VSP as a method of controller strategy evaluation. VSP captures the essential characteristics of driving conditions and strictly tracks the influence of the most critical parameter: acceleration. Moving forward, it is important to employ the knowledge gained from this chapter so far and apply that foundation to different platoon performances. To compare controller strategies from year to year and track to track, a "target" VSP value must be established.

7.8 Establishing "Target" VSP Behavior

The target VSP value is crucial to establishing a goal for a platoon to accomplish during operation. This technique is completed by addressing the unforced values of the VSP equation and adjusting them to hold to certain values instead. Three assumptions must be made:

1) The platoon travels at a constant speed of 45 mph (20.12 m/s).
2) Because there is constant speed, no acceleration events occur and therefore the acceleration term is always set to 0 m/s^2.
3) The best possible performance (yet realistic) of a platoon exists on level ground (even more so than the NCAT straightaway) and consequently the grade term is also set to 0.

This platooning goal or target is nearly achieved along the NCAT straightaway data extracted in Chapter 4, but the previous assumptions made pursue a higher optimization. Once applied, these assumptions simplify the VSP equation down to Equation 7.1.

$$VSP_{Target}\left[\frac{kW}{kg}\right] = 20.12 * (9.8 * C_{RR}) + 0.6 * \frac{C_D * 10.66}{m}(20.12^3) \tag{7.1}$$

Target VSP values are different for each truck since their characteristics are dissimilar. The assumptions made to achieve the target VSP are extremely optimal and are only possible with a perfect controller strategy on level ground. However, an extremely optimal baseline is immensely useful for comparing any controller strategy at any track. Therefore, the target VSP value is essential for keeping VSP traces in perspective. The target VSP value for each truck is unique and represents the minimum effort exerted by the powertrain to maintain current driving conditions. The values calculated using Equation 7.1 for each truck are tabulated in Table 7.1.

Table 7.1: Target VSP Calculations

Truck	$VSP_{Target}\left[\frac{kW}{kg}\right]$
A1	2.92
T14	2.79
T13	2.43
A2	2.79

Moving forward, controller strategies from different years of testing and different tracks are compared with the intention of aiming to achieve enhanced string stability by following these target VSP values. One future adjustment that would further specify each trucks' target VSP values is performing experiments revolved around determining drag coefficients for each truck configuration, which can be done along the NCAT straightaway with careful attention to alignment and coasting data. It is recommended that future work include these tests to improve the accuracy of VSP calculation, particularly the target VSP value for each configuration. With the baseline of comparison made, the comparison technique must be chosen.

7.9 Applying Normalized Sum of Absolute Differences

Deciding which comparison technique to utilize that is fair across all years and tracks directs attention towards statistics. In this section, the sum of absolute differences (SAD) between the average VSP trace and the target VSP value are calculated for each configuration at every track and year according to Equation 7.2.

$$SAD\ \left[\frac{kW}{kg}\right] = \sum_{i=1}^{N} \left| VSP_{i,AVG} - VSP_{Target} \right| \tag{7.2}$$

Where:

N = Total number of time steps

i = Time step number

$VSP_{i,AVG}$ = Value of average VSP trace at a time step

VSP_{Target} = Target VSP value

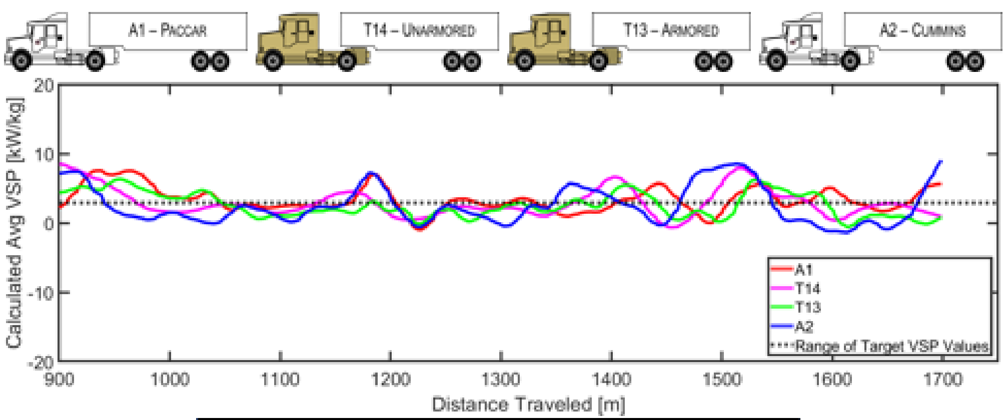
Given each track length is dissimilar from one another, these values were then normalized by the number of time steps considered, resulting in Equation 7.3.

$$MSAD\left[\frac{kW}{kg}\right] = \frac{\sum_{i=1}^{N} \left| VSP_{i,AVG} - VSP_{Target} \right|}{N} \tag{7.3}$$

Where MSAD represents the normalized SAD or mean SAD (MSAD). The MSAD will be accompanied by other truck characteristics in analysis such as fuel rates, vehicle speed and acceleration, and road grade. One benefit of SAD is it measures the amount of deviation away from the target VSP value. Further, the units of SAD remain kW/kg, which provides more meaningful data than something like sum of squares which results in units of kW^2/kg^2. From an energy perspective, this unit has far less value to researchers than what SAD provides. Another benefit is SAD sums the absolute difference, which works best when applied in a setting where measurements can be both positive and negative. Therefore, an analysis of each controller will be completed employing MSAD and evaluating the variance around the target VSP value for each truck.

7.10 Ideal Platooning Compared to Target VSP

The ideal platooning scenario represents a condition where perfect alignment and no road grade interruptions exist. To determine the efficacy of VSP and MSAD to accurately represent and evaluate the platoon performance of a vehicle, VSP and MSAD are calculated along the NCAT straightaway for year 1 testing in 2019. Each following vehicle's average VSP trace is expected to vary around the target VSP value as the controller corrects the truck to maintain platooning requirements. All 4T 100 platoons are investigated to evaluate the ability of VSP and MSAD to track the differences in each truck's transiency during 4T platooning. The results of the average VSP calculations can be found in Figure 7.20.



Truck	Target VSP [kW/kg]	MSAD [kW/kg]
A1	2.92	1.47
T14	2.79	1.73
T13	2.43	2.43
A2	2.79	2.44

Figure 7.20: Ideal Platooning 4T 100 Configuration, NCAT 2019

Also found in Figure 7.20 are the Target VSP and MSAD values for each truck in the order of the platoon. Target VSP values for each truck are close together and are therefore all represented by the grey dashed line to prevent clutter on the plot. MSAD is calculated based on each truck's respective target VSP value. The NCAT straightaway is the least transient course from all testing campaigns. During NCAT straightaway operation, much of the road grade influence has been removed and the trucks have been aligned to maximize aerodynamic drag reduction.

From Figure 7.20, marginal amounts of dithering occur along the straightaway. This amount of dither is expected due to small corrections made by the trucks to maintain 100-foot spacing. Meanwhile, the target VSP values represent the perfect platooning performance. Furthermore, each truck exhibits oscillating behavior around their target VSP, indicating a sweet spot for the trucks to maintain the best platooning performance.

Based on the calculated MSAD results, there is an obvious trend between the variance of VSP from the target value and platoon order. Trucks towards the front of the platoon (A1 and T14) demonstrate less transient behavior as expected. However, MSAD values of the rear most trucks are higher. This is due to the inherited transient behavior from truck to truck. As the truck number in a platoon increases, so does the MSAD value. This trend inspires confidence in VSP and MSAD's ability to differentiate transient behavior from truck to truck even in a relatively calm, idealized, operational environment. However, it is important to expand analysis to more challenging platooning missions such as whole NCAT laps and ACM testing.

7.11 Controller Performance Comparison for PID-Based Strategies

For both testing campaigns, NCAT's controllers were PID-based. In year 1, the controller's primary mission was to maintain the preset headway as closely as possible. Year 2 brought changes to the controller strategy that were intended to aid the trucks in smoother operation during platooning via dampening of velocity and headway spacing excursions. However, this did not happen in some cases. This body of work is not concerned with discussing exact changes in controller strategy or suggesting improvements for the controllers. Instead, this work suggests a new metric with which to compare controller strategies at different tracks alongside platoon string stability and performance.

A2 is the most transient vehicle in the testing fleet and therefore will exhibit the most erratic behavior during platooning. Even in 2T convoys, A2 displays speed variance behavior that leads to poor platooning performance. A2 2T 50 ensemble average of VSP calculation results are found in Figure 7.21.

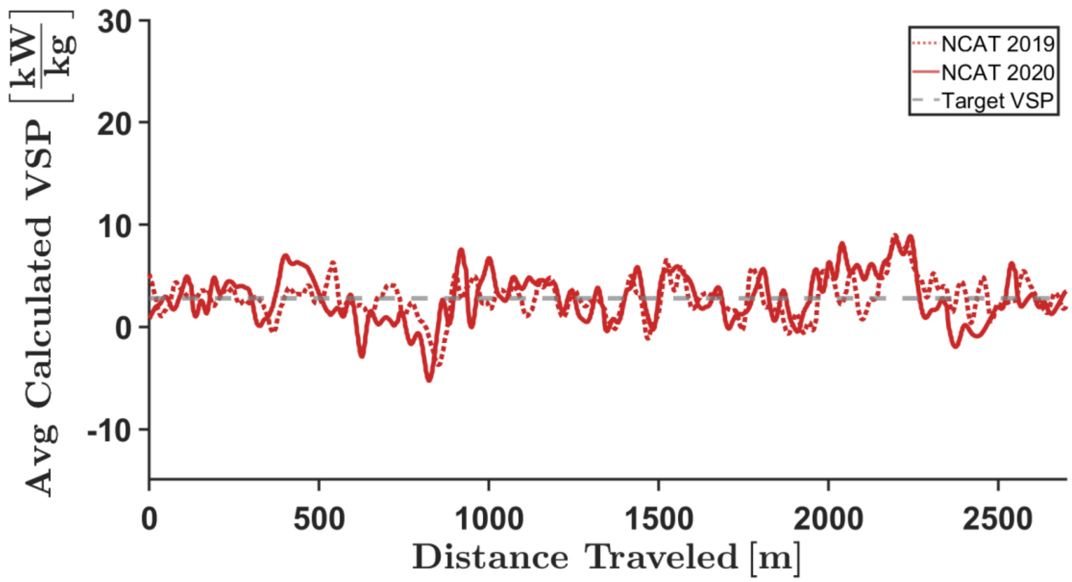


Figure 7.21: NCAT Controller Comparison, A2 2T 50 Platoons

Being forced to react and adjust to the behavior of a lead truck, T13, proposes problems from a dithering aspect. Starting at 500 m, there is a clear decline in VSP for around 800 m. This is due to the downhill slope in NCAT's track. Dithering still exists in this section – worse than in NCAT's two straightaway sections (one straightaway is from 1,000 m to 1,800 m and the other connects the two ends of the traces). This phenomenon is caused by the PID controller commanding corrections to maintain current headway spacing. In sections of NCAT's track containing road grade changes, these occurrences are more prominent in magnitude and frequency.

Once A2 returns to a relatively flat section of track between 1,000 m and 1,800 m, transient behavior diminishes. Moving into the uphill section of NCAT's track around the 2,000 m mark, A2's average VSP trace appears to increase 3 kW/kg in offset with similar dithering to the straightaway section. On another note, the calculated average VSP traces for both year 1 and year 2 testing oscillate around the target VSP value, indicating there is a sweet spot for A2 to operate in. The MSAD value for year 1 testing was 1.48 kW/kg, which is certainly higher than anything found while operating on the NCAT straightaway. However, this is predicted to be relatively low compared to any 4T configuration. In year 2, the controller did not appear to make much difference in platoon operation. If anything, the VSP trace appears to be more transient in year 2 than in year 1 due to small spiking behavior that year 1 did not have. Consequently, the MSAD for year 2 was 2.11 kW/kg. This results in a decrease in improvement of 42.57%. While the percentage appears to be high at first glance, the magnitude of MSAD for a comparatively calm track is not concerning. Overall, both controllers performed well and that is seen by the smooth average VSP trace.

Increasing truck spacing to 100 feet introduces new challenges from a control strategy standpoint. Increasing the headway spacing leaves more room for error because there is more space for a truck to adjust relative to the platoon. However, at the same time, this poses a threat to the string stability of a platoon. The results of A2's 2T 100 configurations are plotted in Figure 7.22.

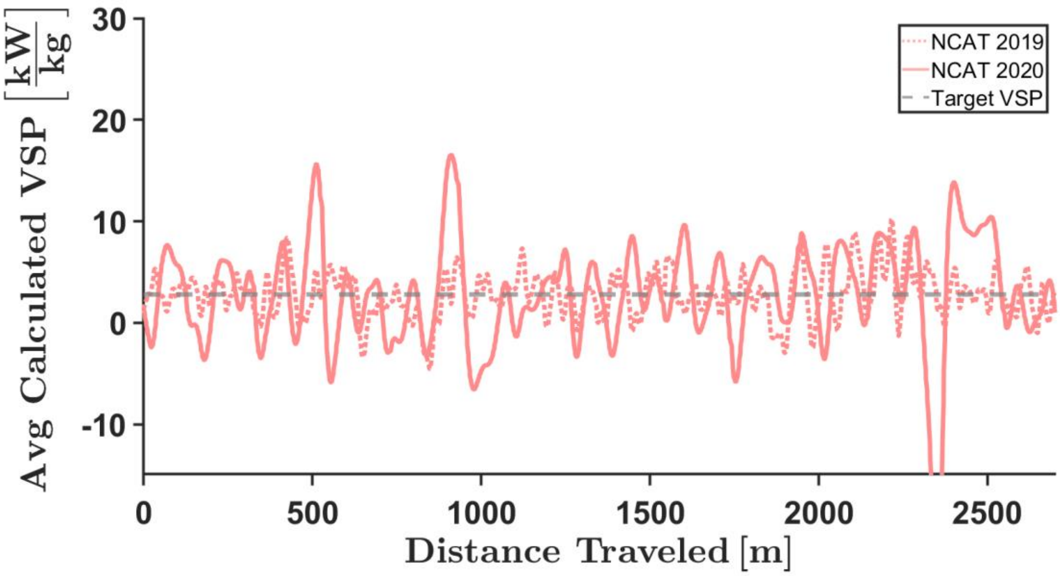


Figure 7.22: NCAT Controller Comparison, A2 2T 100 Platoons

Based on the average VSP traces found in Figure 7.22, A2 shows clear signs of struggle with increasing headway spacing, even in a small 2T platoon. The oscillating behavior previously seen in Figure 7.21 is worsened in magnitude and frequency for the 100-foot headway spacing. This is seen by the positive spiking behavior between 500 m and 1,000 m as well as the negative spiking around 2,250 m. This is mainly an issue relating strictly to year 2 testing but can be seen in year 1. Both positive spikes are rapidly followed by massive drops of around -20 kW/kg. Similar but opposite to that, incredible amounts of braking exist shortly after exiting the uphill slope at NCAT. This is because A2 attempts to catch up to T13 to maintain following distance. Thus, A2 comes out of the track corner with high amounts of speed. Once the controller realizes it needs to slow down, the truck brakes hard causing enormous deceleration resulting in a massive negative VSP spike around 2,300 m. This is reflected in MSAD values where year 1 resulted in 1.91 kW/kg and year 2 resulted in 4.31 kW/kg. The large MSAD increase, 125.65%, accurately reflects the harsh acceleration events seen in year 2's testing. While this is not beneficial from a controller standpoint, this is helpful in validating VSP as an evaluation tool. VSP is capable of tracking hard braking events and, accompanied by MSAD, paints a clear picture of how transient a vehicle operates along a route. Even at NCAT's calm track, VSP meticulously finds weak points in platoon performance.

Based on the 2T results, the 4T results are expected to exhibit even more transient behavior with significant oscillation around the target VSP value. Figure 7.23 displays A2 4T 50 average VSP traces from year 1 and year 2 NCAT testing.

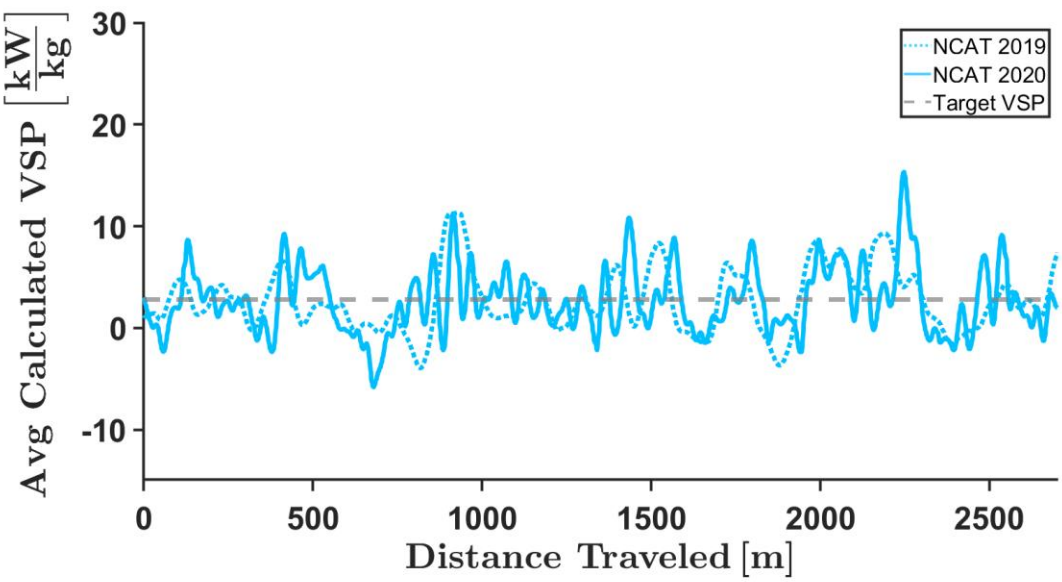


Figure 7.23: NCAT Controller Comparison, A2 4T 50 Platoons

The dithering experienced by A2 in 4T 50 platoons is comparable to 2T 100. Inheriting the transient behavior of three preceding trucks results in more transient operation than inheriting the behavior of one truck, which causes the increased frequency in VSP slope as seen in Figure 7.23. With smaller room for error due to shorter spacing, A2 makes more impactful braking events during the downhill portion of NCAT's track, which is traced easily by VSP beginning at the 500 m mark. In the opposite corner, the same positive offset in VSP is seen as A2 pushes up the hill to correct any differences in spacing. As predicted, the average VSP trace for 4T 50 platoons mimics that of 2T 50 but in larger magnitude. The amplitude of the oscillating behavior is higher as well as any significant spiking behavior in the corners of the track. In year 1, the MSAD value was 2.78 kW/kg and in year 2 was 2.77 kW/kg. With nearly identical MSAD values, the technique presented herein would consider the controller performance to be roughly equivalent for 4T 50 operation. Again, from a controller standpoint, this is not beneficial. However, it is impressive that VSP and MSAD can quantify that the overall difference between the two controllers is almost nonexistent. At first glance at average VSP traces, that assumption appears to be true, indicating VSP accurately reflects the platoon performance despite differences in transient behavior.

Based on 2T results, the transient behavior experienced by A2 in 4T 50 convoys is expected to be elevated when operating at a headway spacing of 100 feet in the 4T configuration. This transient behavior is investigated in Figure 7.24.

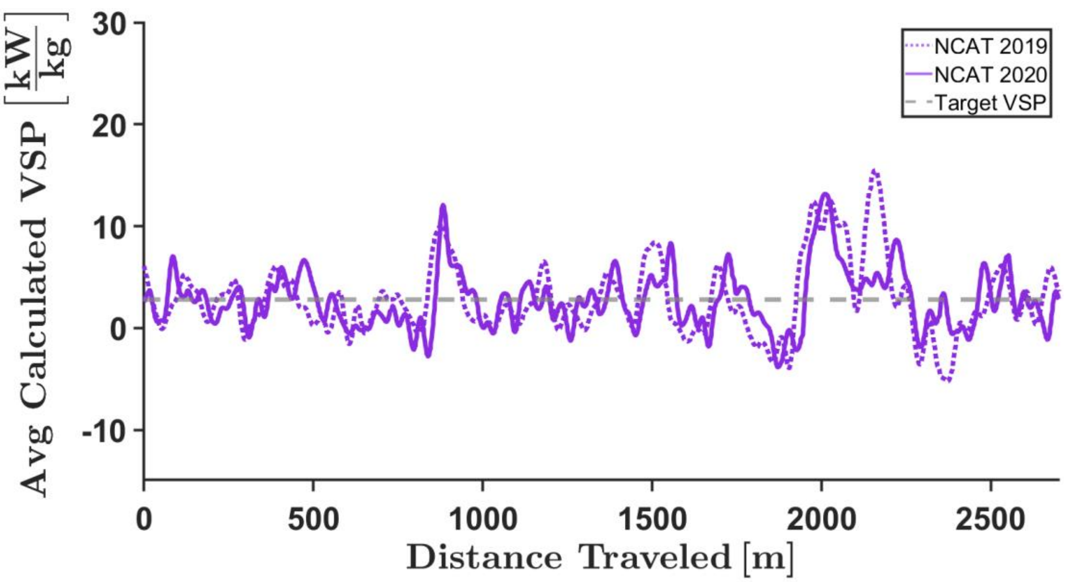
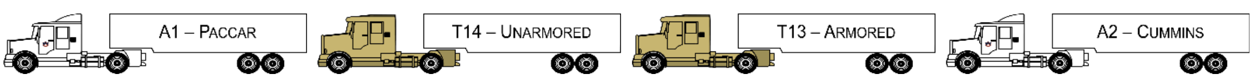


Figure 7.24: NCAT Controller Comparison, A2 4T 100 Platoons

Indeed, A2's 4T 100 dithering is noticeably worse than in 50-foot platoons. For the PID controllers, extending the headway distance to 100 feet worsened the platoon string stability. Year 1 and year 2 display significant transient behavior in both corners of NCAT's track where substantial road grade exists. The uphill slope was particularly difficult for A2 exhibited by the considerable positive spiking behavior seen just after the 2,000 m mark. Whether the acceleration events were small or large in magnitude, VSP tracks those changes and displays that when plotted next to the target VSP. A2's 4T 100 MSAD value from year 1 was 3.05 kW/kg, which is the worst of all NCAT year 1 testing configurations. Logically, this makes sense. If A2 struggles with increasing headway distance and platoon size, the worst MSAD value plausibly would occur in 4T 100 configurations. In year 2, the MSAD value decreased to 2.44 kW/kg, which is a 20% improvement from year 1. Much of the improvement is seen in the latter section of the uphill slope. At the end, A2 does not accelerate hard into the straightaway, which gives it the opportunity to make a softer deceleration maneuver. Between these two occurrences, the MSAD value is certain to improve in year 2 as seen in Table 7.2. For MSAD values for each configuration at NCAT in both years of testing, see Appendix D.

Table 7.2: A2 MSAD Comparison, NCAT



Truck	Configuration	MSAD NCAT 2019 (PID) $[kW/kg]$	MSAD NCAT 2020 (PID) $[kW/kg]$	Percent Improvement
A2	Baseline	1.34	0.91	32.09%
	2T 50	1.48	2.11	-42.57%
	2T 100	1.91	4.31	-125.65%
	4T 50	2.78	2.77	0.36%
	4T 100	3.05	2.44	20.00%

Greyed out cells indicate VSP is not applicable from a platooning perspective. This includes all A1's configurations, any standalone baseline traces, or T13 2T configurations due to it being the leader of the platoon. From Table 7.2 and Appendix D, it can be seen that as trucks are added to a 4T platoon, the MSAD value gets increasingly worse without fail for both years. This is encouraging from a controller evaluation perspective since each follower vehicle inherits the transiency from the ones in front of it. Therefore, each subsequent truck should have worse transiency than the preceding truck. This occurs in both years of testing, indicating VSP's ability to accurately calculate and track variance around a target VSP value as well as general transient behavior is validated. Even in 2T platoons, the follower in their respective platoon produced more transient behavior than the leader in both years. VSP was traced meticulously even during extremely transient periods as seen in A2's 2T 100 trace in year 2. Overall, the VSP/MSAD technique could successfully distinguish between control variations over NCAT on a whole lap basis. The ability of VSP/MSAD to sense relatively minor road grade platoon disturbances bodes well for other use cases with more grade variation and disturbances.

7.12 Controller Performance Comparison with Varying Strategies in Challenging Road Grade Profiles

While NCAT's year to year controller upgrades only attempted to improve upon an existing PID-based controller, ACM testing was conducted using two dissimilar controller strategies. In 2019, year 1, ACM testing was completed utilizing a PID controller, which was modified to accommodate road grade disturbances. The 2021 testing campaign, year 2, implemented a new control strategy dubbed "NMPC" or "optimal". In short, the main difference between the two strategies is a focus on maintaining the preset headway while platooning. The PID controller demands an accurate longitudinal headway spacing, even at the expense of accelerating in relatively calm sections of the track. However, the optimal controller anticipates road grade changes by extracting road grade information from a lookup table based on track location. For example, a long and steep hill exists in the northeast corner of ACM's track. Each follower vehicle will anticipate the platoon entering the uphill slope. This means if the gap between trucks is smaller than the preset headway, then the NMPC control allows the positive road grade to slow the vehicle down as opposed to braking. The opposite is true for downhill slopes. This makes for much smoother driving with fewer significant acceleration events.

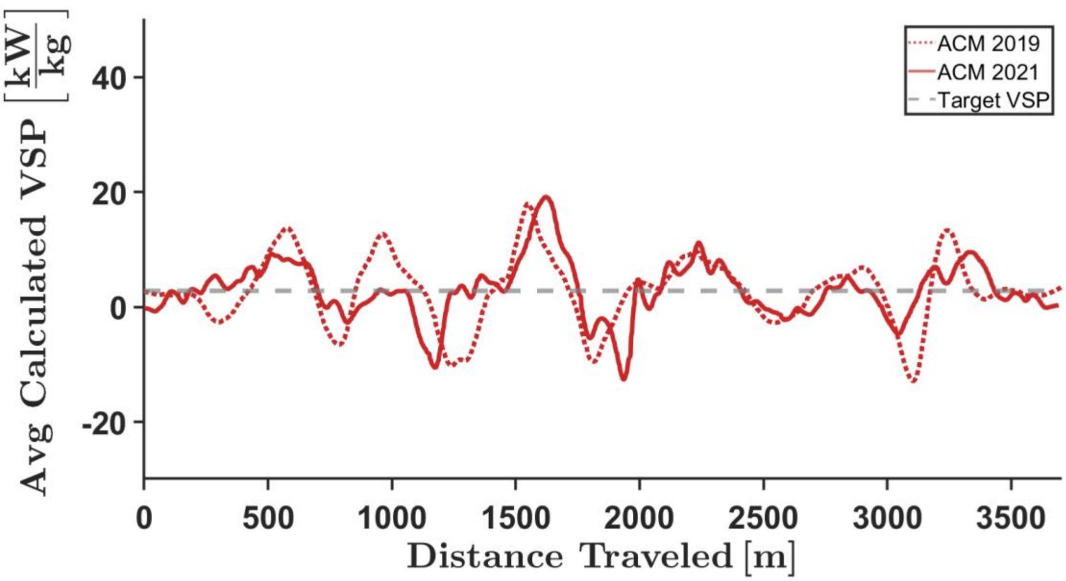


Figure 7.25: ACM Controller Comparison, A2 2T 50 Platoons

A2's 2T 50 platooning behavior for ACM testing campaigns is plotted in Figure 7.25. 2019 testing resulted in moderate dithering with significant peaks throughout the lap, indicating hard accelerations to reach the top of uphill slopes while still maintaining the desired headway distance. The peaks in VSP match the peaks observed in the altitude map for ACM found in Figure 1.3. In 2021, some of those peaks disappear and/or are truncated, resembling plateaus more than peaks. The MSAD for year 1 testing is 5.07 kW/kg, which is worse than anything seen at NCAT. This is beneficial from a research perspective for two reasons: logically, more transiency is expected at ACM than any configuration at NCAT due to the road grade variations and the VSP/MSAD results are reflecting that with higher MSAD values at ACM. The MSAD for year 2 decreases to 4.16

kW/kg, which is a drop of 17.95% from year 1. In other words, VSP/MSAD shows an improvement of nearly 18% between year 1 and 2 controller strategies. However, there is still significant VSP dithering for 50-foot platooning.

Expanding the headway distance to 100 feet should allow the NMPC controller more time/distance to further dampen VSP dithers by using road grade to correct the truck spacing as opposed to accelerating to accomplish the same goal. To investigate this phenomenon, A2 2T 100 controller comparisons are plotted in Figure 7.26.

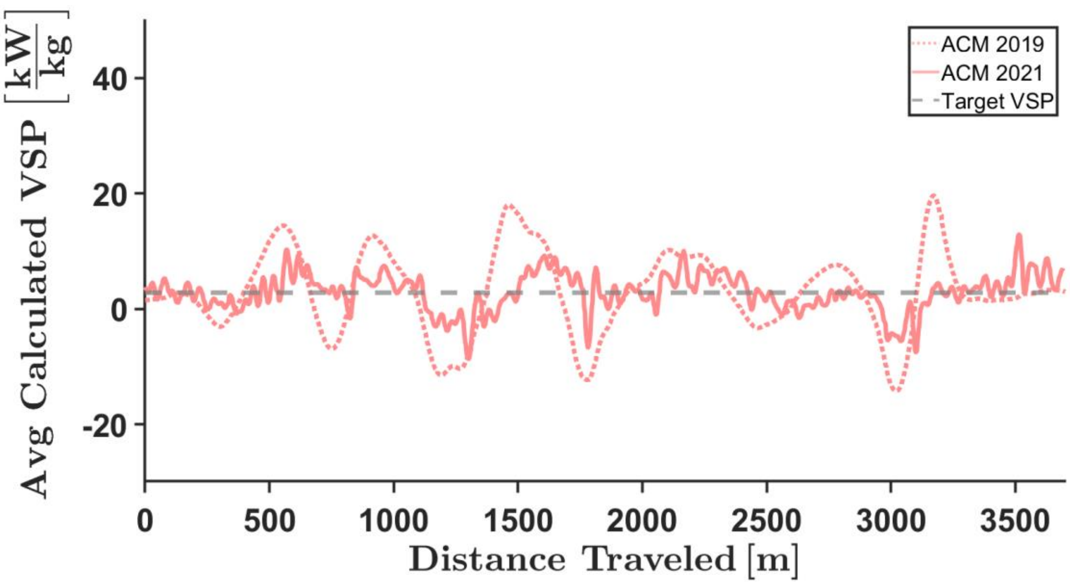


Figure 7.26: ACM Controller Comparison, A2 2T 100 Platoons

Year 1 2T 100 results show similar behavior to 2T 50 largely because there is no predictive aspect in the PID control strategy. Therefore, differences between headway distances are expected to be marginal. However, platoon length does affect the transiency experienced by the truck and will be explored later in this section. When comparing year 1 results to year 2, there is clear damping in the latter's average VSP trace. Because A2 is given more space, allowing the NMPC to make natural corrections by road grade, the average VSP peaks are significantly reduced from year 1. The oscillating behavior of year 2 is closer to the target VSP value, indicating less aggressive operation.

The VSP MSAD of year 1 is 6.06 kW/kg, which is higher than A2's 2T 50 configurations as well as anything A2 experienced at NCAT for either year of testing. This suggests 100-foot platoons are more transient than 50-foot platoons when employing a PID controller. For the 2021 NMPC testing campaign, the final MSAD value is 2.65 kW/kg, which is a 56.27% decrease. The >50% VSP MSAD improvement shows that VSP can accurately track platoon controller behavior via its transiency around a target VSP value. While ACM contains exaggerated road grade changes in comparison to the national average, a 56.27% improvement is too significant to ignore. A2 is passed down transient behavior solely from T13 in 2T convoys but inherits the transiency of the three trucks preceding it in 4T convoys. The differences between years of testing for 2T platoons is expected to be similar for 4T platoons. 4T 50 platooning performance is demonstrated in Figure 7.27.

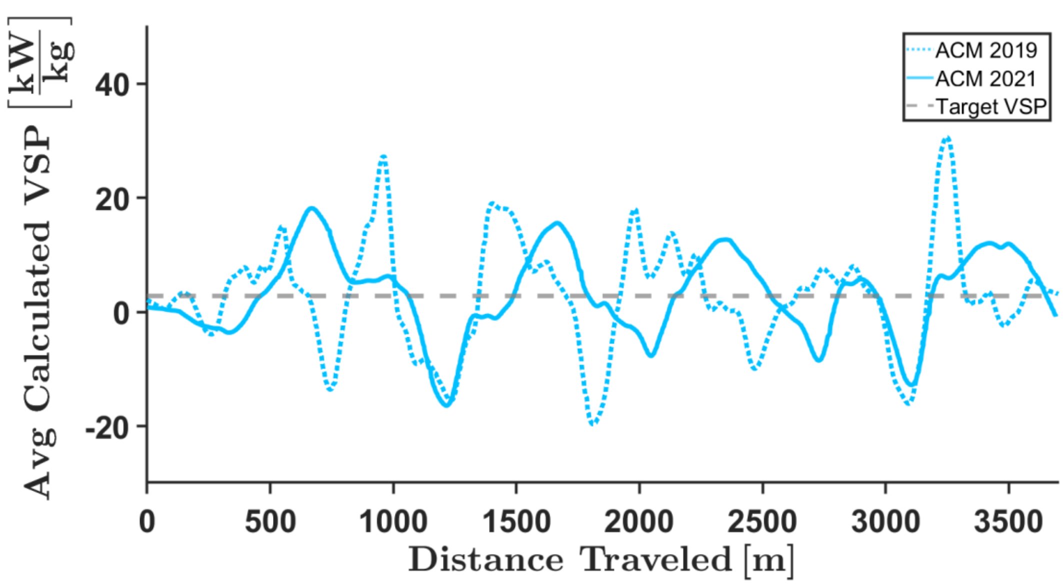


Figure 7.27: ACM Controller Comparison, A2 4T 50 Platoons

The optimal controller showed small improvements in platooning behavior in 4T 50 configurations indicated by lower magnitude of spiking VSP events. Additionally, some of the spiking behavior exhibited by the PID controller was dampened in year 2, suggesting that even in one of the most transient conditions tested, the optimal controller handled acceleration events better than the PID-based controller. These differences are tracked well by VSP. The MSAD for year 1 is 7.84 kW/kg, which is the highest up to this point. This is expected because 4T platoons are more transient for A2 than 2T platoons. Meanwhile, the MSAD value for year 2 is 6.46 kW/kg. With an improvement of 17.60%, the optimal controller once again proves its ability to handle challenging road grade amid A2 inheriting the transiency from three preceding trucks. Thanks to VSP, this improvement is not only experienced when riding in the truck, but also tangibly presented in the form of dampened traces and quantified via VSP MSAD. A 50-foot headway spacing does not offer A2 much room to allow natural positioning corrections to occur, which is why A2 remains erratic throughout the lap. However, similar to 2T NMPC operation, extending the headway to 100 feet can enhance the NMPC benefits, see Figure 7.28.

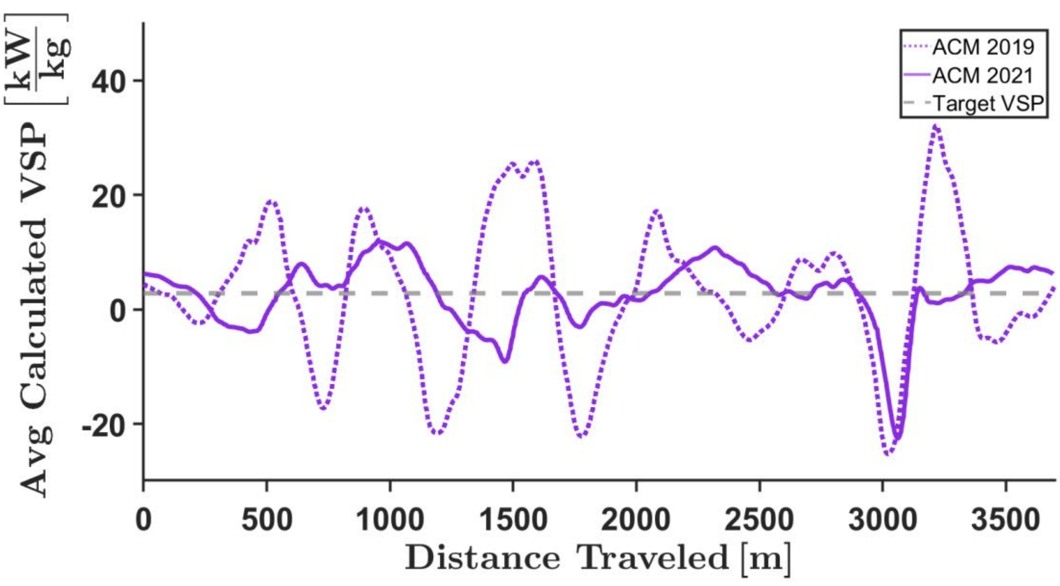
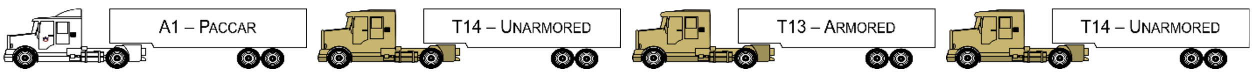


Figure 7.28: ACM Controller Comparison, A2 4T 100 Platoons

The dampened behavior of year 2 operation indicates 100-foot separation between trucks is better for platooning performance than shorter headway distances when employing an NMPC with forward-looking grade information. Compared to year 2, the year 1 trace is much more transient as the PID-based controller overly excites acceleration events to maintain platooning requirements. Massive swings in VSP are detrimental to the string stability of a platoon. VSP carefully follows these swings, suggesting it can accurately track the performance of a truck while platooning as well as the overall performance of a convoy of vehicles. These swings are reduced by implementing the optimal controller, which is also tracked meticulously by VSP calculation. For 4T 100, A2's average VSP oscillation around the target VSP value is much tighter in year 2 than year 1. Additionally, the MSAD for year 1 testing resulted in a campaign-high 10.50 kW/kg. This is by far the worst of any configuration, which is expected from the PID-based controller in the most transient configuration at the most challenging track. However, during year 2 testing, the optimal controller displayed significant improvement to the platooning performance of the vehicles' string stability. Year 2 platooning resulted in an A2 VSP MSAD value of 4.44 kW/kg – a 57.71% decrease in MSAD. Similar to 2T 100 findings, improvements of over 50% are too significant to ignore. The NMPC optimal controller, based on A2 platooning configurations, is a superior strategy to a PID-based one.

Overall, it is clear VSP can record the performance of a platoon member during operation as a means to evaluate competing controller strategies. In the most transient conditions, VSP diligently calculates and represents the overall effort exerted by the vehicle's powertrain. Few testing environments are more challenging for string stability from a highway operation perspective, and, for that reason, it is safe to conclude VSP is a viable parameter to track how a controller commands platoon performance under different conditions and how efficient that platoon completes its route. The MSAD values for each truck and configuration for year 1 and 2 testing campaigns are located in Table 7.3. For more information on all MSAD values in both testing campaigns at ACM, see Appendix E.

Table 7.3: A2 MSAD Comparison, ACM



Truck	Configuration	MSAD ACM 2019 (PID) $[kW/kg]$	MSAD ACM 2021 (Optimal NMPC) $[kW/kg]$	Percent Improvement
A2	Baseline	3.64	2.36	35.16%
	2T 50	5.07	4.16	17.95%
	2T 100	6.06	2.65	56.27%
	4T 50	7.84	6.46	17.60%
	4T 100	10.50	4.44	57.71%

From Table 7.3 and Appendix E it can be seen T14, the second truck in 4T configurations, exhibited the least transient behavior with MSAD values below the truck behind it. T13's MSAD values are higher than T14, indicating the inherited transient behavior from trucks preceding it played an important role in the dithering it experienced. This is true for both years. A2 is the caboose in every configuration, and its deviation is obvious when comparing the MSAD values to the trucks preceding it. A2's values are significantly higher than the rest of the platoon as expected. These trends are similar for 4T 50-foot and 100-foot platoons.

In every configuration where VSP is applicable, improvements to the platooning performance were exhibited by each truck using year 2's NMPC controller. With decreases in MSAD between 17% and 57% from year 1 to year 2, it is clear the optimal controller handled the challenging road grade better than the PID controller. Generally, the trucks' performance was more efficient in 100-foot platoons than 50-foot ones during year 2 testing. Apart from T14's 2T configurations, this improvement in performance can be attributed to the larger headway spacing between trucks. The larger headway spacing gives the NMPC trucks more opportunity for natural corrections such as road grade, rolling resistance, and aerodynamic drag, allowing the trucks to operate inside a relatively fluid headway spacing range more calmly. In year 1, the primary PID control objective was to maintain a preset following distance. In year 2, the NMPC cost function weighed alterations to the acceleration profile with variance to the prescribed headway, ultimately allowing the trucks to coast when advantageous. This broadened the headway spacing range the trucks were permitted to operate within and consequently decreased the frequency and magnitude of acceleration events.

7.13 MSAD Comparisons to Ideal Platooning Scenario

Comparisons between years of testing and controller strategy performance provide insight into the effects of alterations made between strategy versions. However, the optimal performance exists within the bounds of the ideal platooning performance scenario. Since the goal of convoying is to achieve the ideal platooning performance, comparisons made to that scenario provide more insightful results regarding the nearness to ideal. Therefore, in addition to controller-to-controller comparisons, referral back to ideal is also analyzed. The variance in VSP around the target VSP for A2 in each configuration and track are calculated using the MSAD value. Then, those values were used to find the percent difference between them and the ideal platooning scenario's MSAD values. The results of those findings are plotted in Figure 7.29 where a higher percent increase in variance represents higher transiency while platooning. Any values above 0 indicate a configuration performed worse than ideal scenario. Therefore, it is predicted that each VSP-MSAD value will be above the x-axis since each track poses more threats to the string stability of a platoon in the form of increased road grade excursions.

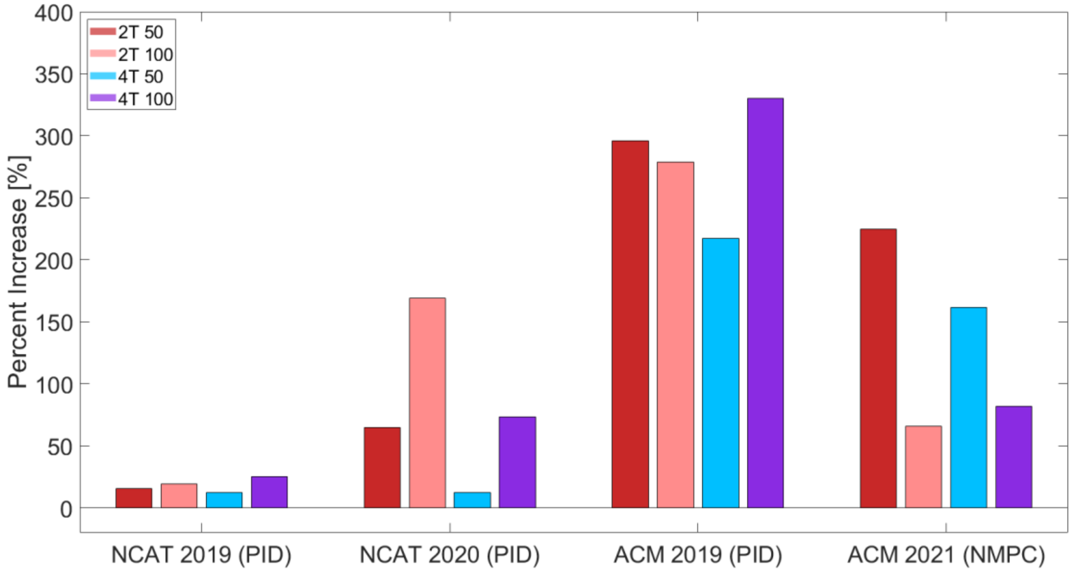


Figure 7.29: MSAD Comparison to Ideal Platooning Performance, All Years

The color scheme mimics that of previous analysis done in this study and the raw values are tabulated in Appendix F. Differences in baseline configurations have been omitted because no changes in controller strategy were made since the trucks do not follow each other in those configurations. Because each VSP MSAD value is higher than the ideal platooning performance scenario for each configuration, confidence is instilled regarding the idyllic nature of the NCAT straightaway.

In NCAT 2019, introducing road grade to the platoon impacted the performance of the convoy where higher transiency was experienced. This makes sense since adding road grade to a drive cycle will surely induce transient behavior in vehicle speed, which is especially true for non-predictive control strategies. This phenomenon is generally applicable to all configurations apart from 2T 100 operation at NCAT where the VSP MSAD value is higher than at ACM in year 2 with the NMPC controller. This is due to the adjustments made in the controller strategy where the year 2 PID controller did not perform as well as in year 1. These adjustments induced more transiency in platoon behavior as seen by the increase in MSAD from the ideal scenario compared to year 1 in 2019. From an analysis perspective, this inspires confidence in VSP and MSAD's ability to capture the transient nature of a control strategy along the same route.

Year 1 (2019) ACM PID testing exhibited highly concerning struggles with string stability which is rightfully captured by the largest increases in MSAD in any testing campaign. However, in year 2 testing, the NMPC controller dampened significant portions of MSAD by allowing the truck to correct its longitudinal headway spacing via natural corrections such as road grade. The MSAD in NMPC testing was less than year 1 PID testing at ACM in every configuration with varying degrees of success. The smoother VSP traces indicate less transient behavior that are reflected by the results seen in Figure 7.29. Comparatively, the transient behavior exhibited by A2 4T 100 at NCAT and ACM in second year testing campaigns is nearly equal. This is a testament to the importance of controller strategy and how it affects the platooning performance of a participating vehicle. This also emphasizes the value of comparing the transiency of a vehicle to the ideal performance scenario. Normalizing the variance of VSP trace around the target VSP value back to the ideal scenario allows you to perform fair and balanced comparisons for various terrains, which is one of the many benefits brought forth by the VSP/MSAD combination for analysis.

Chapter 8

Conclusions

This research identified an effective outlier removal technique for data processing and a new metric for evaluating heavy-duty platooning efficiency and control strategies. The effectiveness of introducing MAD-based outlier identification outperforms the typical standard deviation outlier identification approach. Additionally, implementation of MAD cuts the data processing computation time down dramatically when compared to the iterative standard deviation approach. In the case of this data set, the difference in run/execution time between methodologies is significant and only becomes more apparent when applied to larger data sets. The repeatability of applying MAD and one pass of 2σ outlier elimination allows future researchers to rid a data set of outliers effectively, consistently, and efficiently. Specific to the testing completed in this study, reducing time spent finding a self-similar, representative data trace equates to more accurate decisions when adjusting controller settings and less down time between tests. Based on the MAD results, a generalized MATLAB script was prepared to remove outlier laps, preventing users from performing a lengthy, and potentially biased, qualitative lap removal process. Revising and challenging the way outliers are detected and removed from a data set was necessary to improve the scientific soundness of results stemming from labs involved with truck testing.

Additionally, the extraction of an "ideal" platooning scenario from the NCAT data standardizes an idyllic point of comparison for all platoon testing. "Ideal" platooning on the NCAT straightaway serves as a controller performance reference point for other platooning scenarios that experience road grade changes. Previously, control strategy alterations are simply compared with the preceding version, which works well if the goal is to be better than the previous controller. However, to develop an optimal control strategy, the "ideal" platooning reference point now sets an ambitious target for controller performance that can be employed at any track or testing condition with any controller strategy. In other words, a platoon should perform at or above (in the case of downhill driving) the ideal platooning performance if the controller strategy has been perfected. Reframing the reference point towards ideal operation opens the possibilities of controller improvements more than comparisons to the previous version.

VSP is a two-pronged aid for autonomous solutions: evaluating current controller strategies and replacing cost functions. Optimization of VSP presents opportunities other strategies cannot quantify, which makes it the perfect candidate for assessing the performance of autonomously platooning vehicles, not just HD trucking. Because VSP is vehicle-specific, it can be adapted to light-duty passenger vehicles and medium-duty vehicles such as transit buses. For the current work, only HD trucks were assessed.

Finally, the combination of VSP and MSAD proved to be an excellent evaluation tool for platooning performance. After investigating the sensitivity of VSP, it was found acceleration has the most direct impact on VSP calculation. This suggests VSP most accurately follows the trend of acceleration values. From a real-world application standpoint, a truck outputs significant effort or power to make speed changes via acceleration bursts. From a controller standpoint, increasing the magnitude of acceleration bursts harms the platoon string stability. This problem is exacerbated in driving conditions involving substantial transient behavior as demonstrated by ACM's road grade profile. Therefore, VSP's heightened sensitivity to acceleration changes bodes well for VSP from a controller strategy evaluation tool aspect. These trends were demonstrated in the calculated average VSP traces for each configuration for all years and tracks. In more transient conditions, VSP validated its ability to follow changes in acceleration as the trucks attempted to adjust their headway spacing in the first year of testing at both tracks. A PID-based controller was used at NCAT and ACM in year 1, which showed signs of struggle at ACM when significant road grade changes were introduced. This was reflected in the average VSP traces for year 1 ACM testing.

Merely calculating the average VSP trace was not enough to justify VSP as an evaluation tool, however. Extracting the ideal platooning performance scenario from NCAT's straightaway inspired a move towards establishing the ideal VSP value. This is called the "target" VSP value and represents the calculated VSP for a perfect controller. In other words, regardless of the driving environment, the controller will maintain the platoon at the correct speed and following distances at all times. This assumes constant speed (45 mph or 20.12 m/s in this study) and 0 acceleration with no dithers in road grade. This value changed for each truck due to varying drag and rolling resistance coefficients and vehicle masses. The goal of establishing a target VSP value is forward-looking. The cost functions associated with NMPC currently in use by the GAVLAB rely on a fuel signal for functionality. With the imminent rise of hybrid vehicles coming, the controller strategies employed now will require an overhaul before cooperating with hybrid, EV, hydrogen, or other uncommon powertrain types as the fuel signal will lose either some or all meaning for hybrids and EVs, respectively. VSP is fuel source blind, making it an exemplary alternative for future control strategies. Since an optimal VSP trace can be calculated for a forward-looking road grade profile, future control strategies can easily employ VSP in their cost functions.

When applied to real-time calculation of VSP, minute acceleration events were tracked whether they were positive or negative. Operation along the straightaways at NCAT was sensibly uneventful, while transient behavior in the corners was meticulously traced by VSP. This is supported by the consequent MSAD values in a 4T platoon where each subsequent truck displayed increasingly worse MSAD values. When comparing controller versions at NCAT, it is clear adjustments were made in nearly all configurations. However, when A2 exhibited more transient behavior in year 2 testing, VSP tracked that behavior precisely as seen by the increased dithering around the target VSP value (MSAD). The controller strategy difference between years of testing at ACM exemplifies the applicability of VSP to controller evaluation. Year 1 testing was riddled with transient behavior where the string stability of the platoon was nearly extinguished as indicated by massive swings in VSP and the worst MSAD values calculated in the study. Year 2 brought forth changes to the control strategy (the switch to NMPC) and consequently reduced the variance of VSP around the target value. The amplitude of the oscillation behavior displayed in the average VSP traces is dampened in year 2, which is a result of allowing the trucks to predict sections of the track where natural corrections to the headway spacing were possible. This led to the trucks drastically reducing the magnitude of acceleration events. Decreases in VSP MSAD were experienced in every applicable configuration, indicating VSP accurately tracked the differences in acceleration events and the operational improvements of the NMPC controller.

Because VSP is normalized by weight, this metric is applicable to heavy-duty trucks and light-duty passenger vehicles. Any vehicle can be evaluated by VSP whether in a platoon or not. Experimentation with other vehicles is possible, regardless of powertrain. This makes VSP a powerful tool. While there are still improvements to be made to the VSP calculation process for heavy-duty vehicles, the current work shows the strength behind implementing a new, powertrain-neutral metric capable of accurately tracking transient platooning behavior.

Chapter 9

Future Recommendations

The "ideal" section of track includes a completely level route devoid of road grade changes along with perfect alignment of the trucks that have settled in their platoon configuration. In an ideal scenario, this would be done in a wind tunnel where the wheels of the trucks are allowed to rotate to mimic on-road operation. Such a dedicated test setup was outside the purview of the funded project but should be implemented in future testing to find the true ideal platooning scenario results. Even so, the section of NCAT's track extracted for comparison provided ample opportunities for an ideal operating condition that inspired the derivation of a target VSP value.

To improve the accuracy of VSP calculation, an anemometer could be deployed to generate more accurate headwind measurements during operation. Also, experimentation on the aerodynamic drag coefficients for follower vehicles participating in platooning would be a worthwhile endeavor to maximize the precision of the drag coefficients for those vehicles. The aerodynamic drag coefficients of a vehicle change based on convoy position should be investigated. The implementation of a lookup table for temperature versus air density also proposes enhancements to the accuracy of VSP calculation rather than assuming an average testing temperature. More precise measurements of air data and quality provide more confidence in results regarding VSP comparisons.

While this study investigates the platoon dynamics for a singular vehicle in the platoon, A2, analysis performed on the remaining vehicles would provide more insight into the platoon dynamics experienced by the other platoon members. A1's results would detail the effects of platoon dynamics on the lead truck in various configurations. T14 provides insight into the first following vehicle where comparisons based on vehicle mass and profile differences can be investigated between T14 and A2 for 2T configurations. Because of their diverse profiles, platoon dynamics experienced by these two trucks would produce interesting results. Additionally, T13 results would show the impact of leading a small platoon versus following in a larger platoon. The changes in vehicle dynamics via VSP would show the impact of a heavier lead vehicle being placed at the front versus the middle of a large platoon.

One testing scenario that was performed at NCAT and ACM is implementing a cut-in passenger vehicle to determine the impact of vehicle interference with the platoon. Trucks behind the cut-in vehicle are demanded to fall further back to accommodate the disturbance. Analysis into how this procedure affects the calculated VSP traces of the follower vehicles would offer perspective into how efficiently the follower vehicles perform this maneuver. In real-world application, this analysis could prevent the likelihood of a highway traffic jam and increase the freight efficiency of heavy-duty vehicles. Another interesting testing scenario would introduce the inclusion of light-duty passenger vehicles to the heterogeneous platoon utilized in this study. Introducing passenger vehicles to the platoon represents more realistic on-highway operation where the platoon dynamics are more representative of actual platoon performance. Because VSP is powertrain independent, traces in VSP for these new vehicles can be calculated and compared among the other heavy-duty vehicles. An interesting result would be how those traces compare to each other, particularly in challenging sections of track where the string stability of the platoon is tested.

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Appendices

Appendix A

Tabulated Forced VSP Values

Table A – 1: Values Provided to VSP Equation for Calculation

Truck	Vehicle Mass [kg]	C_{RR} [-]	γ [-]	Frontal Area [m^2]	C_D [-]	ρ_a [kg/m^3]	v_w [m/s]
A1	16,175.10	0.0045	1.0425	10.66	0.63	1.2	0
A2	17,245.58						
T13	21,294.80		1.0415		0.79		
T14	17,234.70						

Appendix B

NCAT 2019 Lap Average VSP Calculations

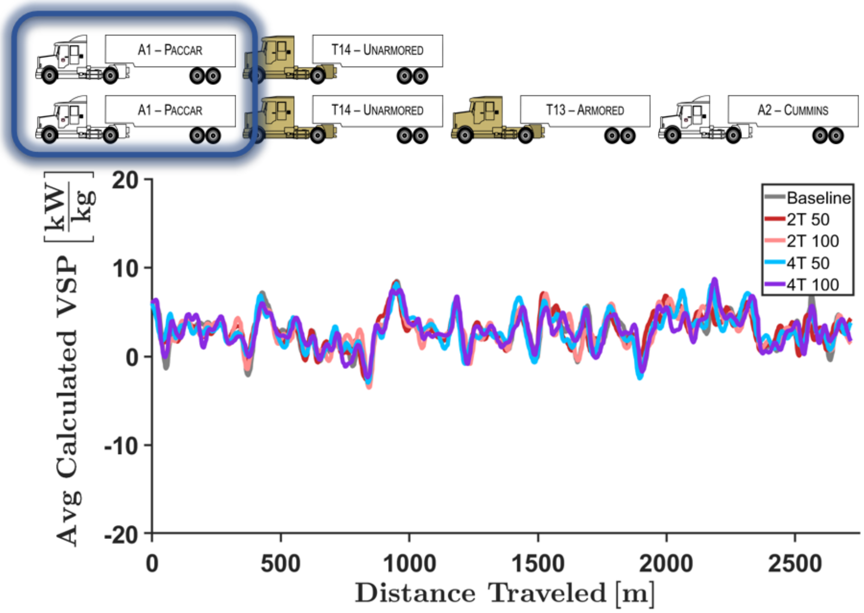


Figure B – 1: A1 Average VSP Traces, All Configurations

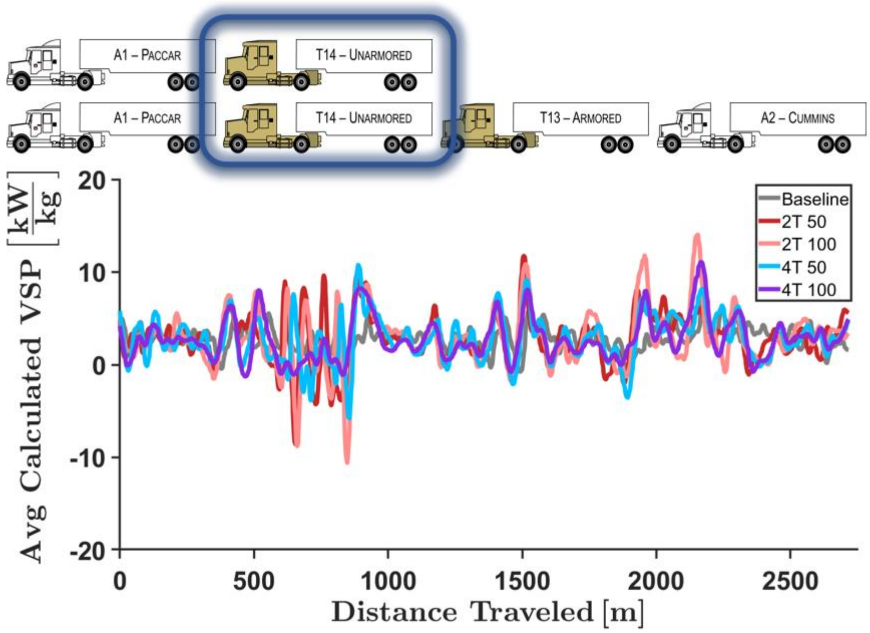


Figure B – 2: T14 Average VSP Traces, All Configurations

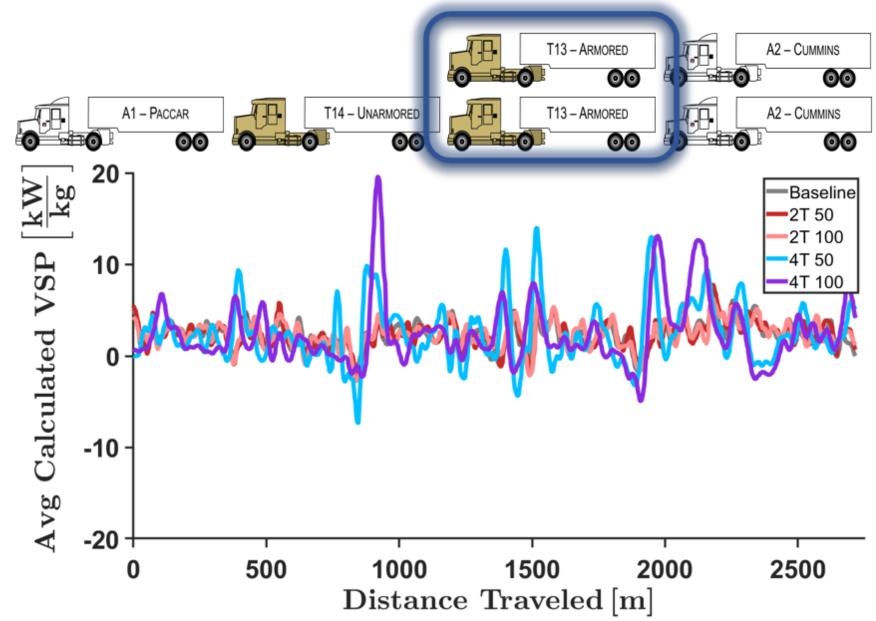


Figure B – 3: T13 Average VSP Traces, All Configurations

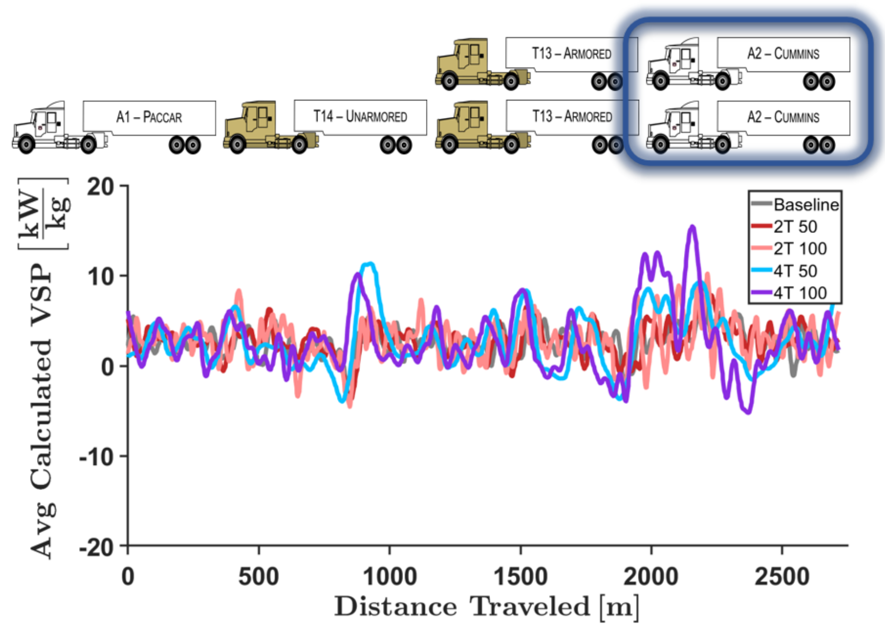


Figure B – 4: A2 Average VSP Traces, All Configurations

Appendix C

ACM 2021 Lap Average VSP Calculations

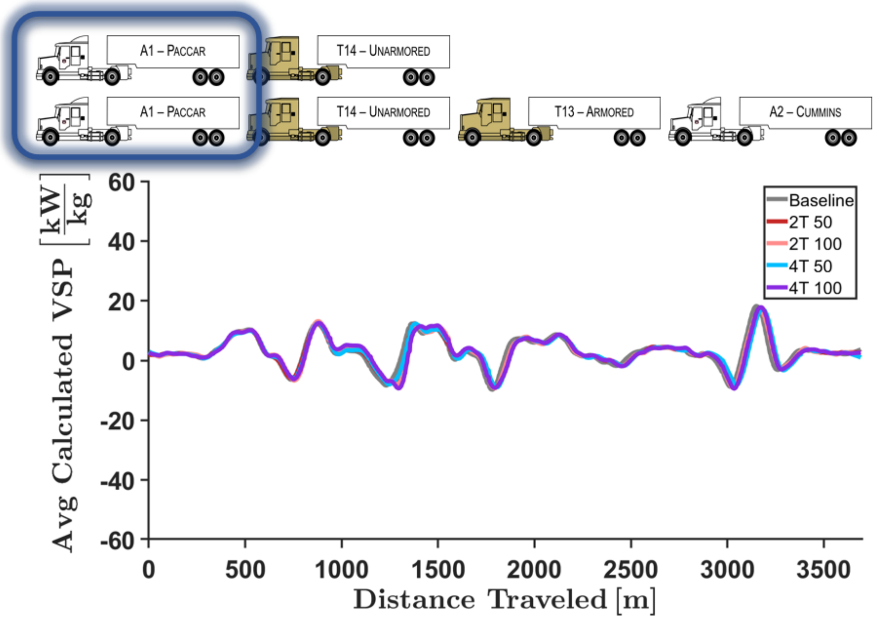


Figure C – 1: A1 Average VSP Traces, All Configurations

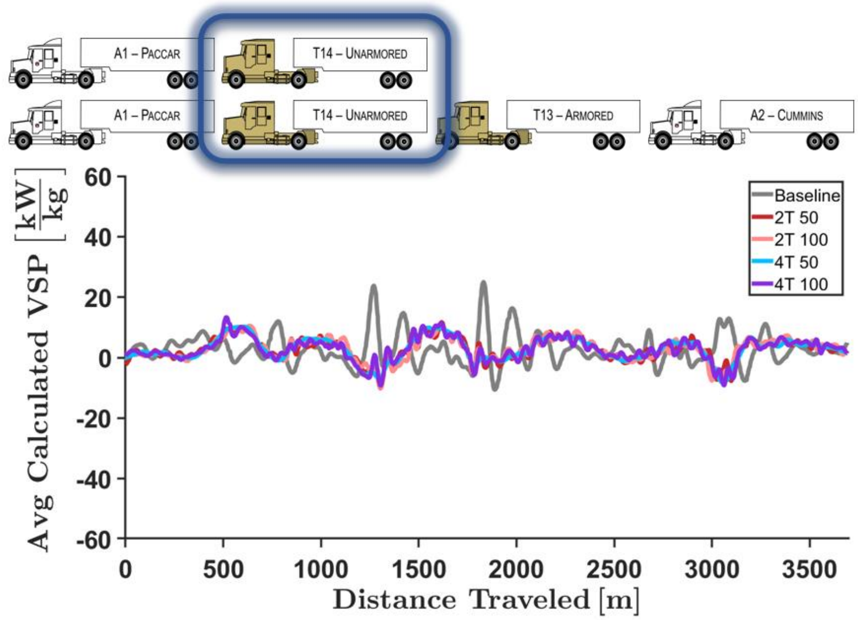


Figure C – 2: T14 Average VSP Traces, All Configurations

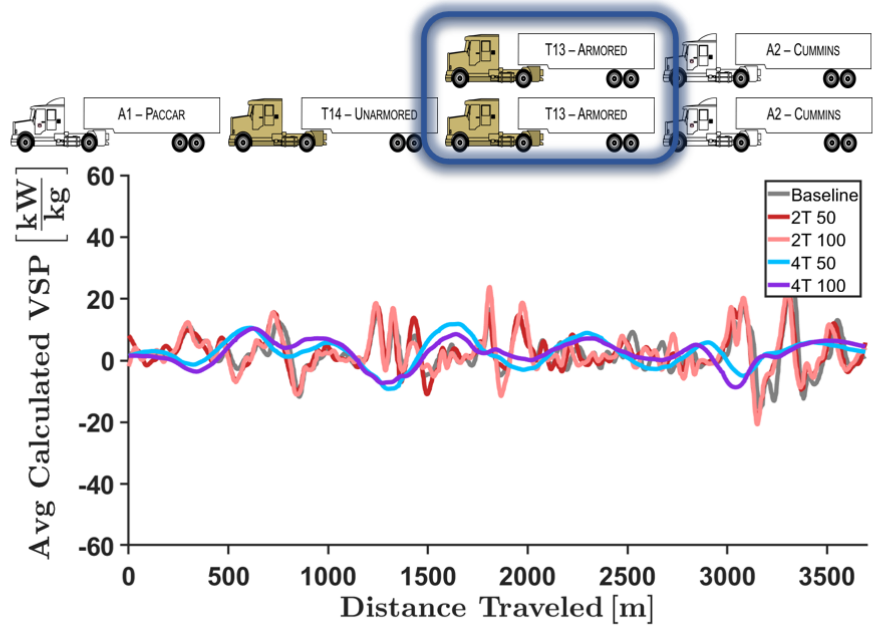


Figure C – 3: T13 Average VSP Traces, All Configurations

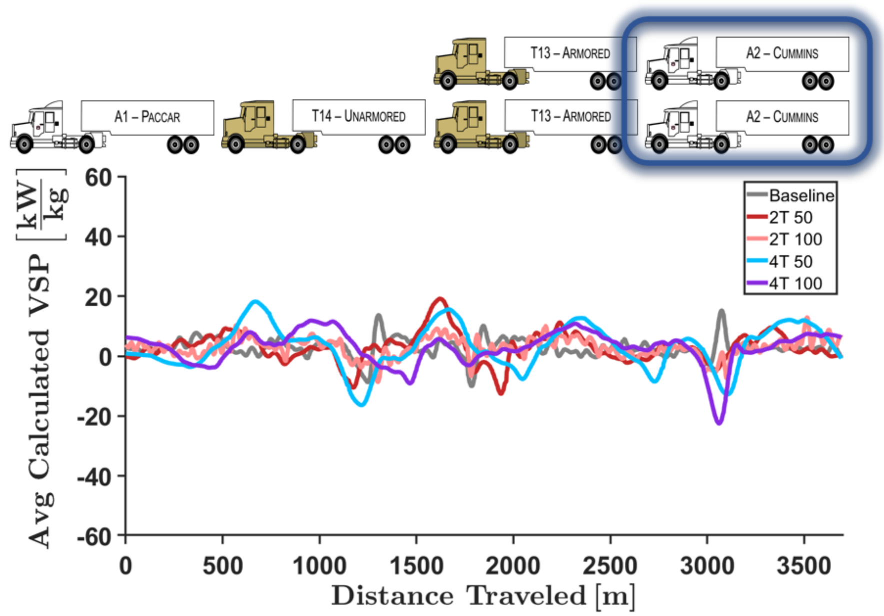
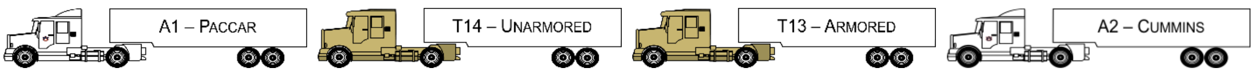


Figure C – 4: A2 Average VSP Traces, All Configurations

Appendix D

MSAD Comparison, NCAT Both Years

Table D – 1: Tabulated NCAT MSAD Values for Controller Comparison

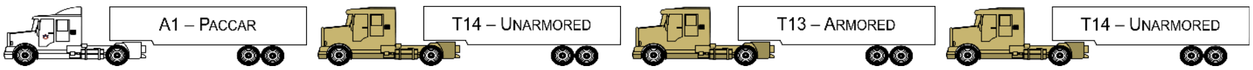


Truck	Configuration	MSAD NCAT 2019 (PID) $[kW/kg]$	MSAD NCAT 2020 (PID) $[kW/kg]$	Percent Improvement
A1	Baseline	1.71	1.53	10.53%
	2T 50	1.54	1.51	1.95%
	2T 100	1.62	1.58	2.47%
	4T 50	1.60	1.46	8.75%
	4T 100	1.63	1.54	5.52%
T14	Baseline	1.10	1.47	-33.64%
	2T 50	2.16	2.05	5.09%
	2T 100	2.35	1.75	25.53%
	4T 50	2.04	1.96	3.92%
	4T 100	1.91	1.64	14.14%
T13	Baseline	1.18	1.61	-36.44%
	2T 50	1.23	1.42	-15.45%
	2T 100	1.21	1.71	-41.32%
	4T 50	2.69	2.21	17.84%
	4T 100	2.73	2.18	20.15%
A2	Baseline	1.34	0.91	32.09%
	2T 50	1.48	2.11	-42.57%
	2T 100	1.91	4.31	-125.65%
	4T 50	2.78	2.77	0.36%
	4T 100	3.05	2.44	20.00%

Appendix E

MSAD Comparison, ACM Both Years

Table E – 1: Tabulated ACM MSAD Values for Controller Comparison



Truck	Configuration	MSAD ACM 2019 (PID) $[kW/kg]$	MSAD ACM 2021 (Optimal NMPC) $[kW/kg]$	Percent Improvement
A1	Baseline	4.18	4.02	3.83%
	2T 50	4.19	3.97	5.25%
	2T 100	4.26	4.09	3.99%
	4T 50	2.69	3.90	-44.98%
	4T 100	2.98	4.15	-39.26%
T14	Baseline	3.43	4.26	-24.20%
	2T 50	4.03	3.10	23.08%
	2T 100	4.88	3.35	31.35%
	4T 50	4.40	3.40	22.73%
	4T 100	4.32	3.15	27.08%
T13	Baseline	3.31	4.96	-49.85%
	2T 50	3.25	5.15	-58.46%
	2T 100	3.73	5.07	-35.92%
	4T 50	6.89	4.01	41.80%
	4T 100	6.70	3.75	44.03%
A2	Baseline	3.64	2.36	35.16%
	2T 50	5.07	4.16	17.95%
	2T 100	6.06	2.65	56.27%
	4T 50	7.84	6.46	17.60%
	4T 100	10.50	4.44	57.71%

Appendix F

MSAD Comparison to Ideal Platooning Scenario

Table F – 1: Tabulated MSAD and Percent Increases for All Testing Campaigns

	Ideal	NCAT 2019		NCAT 2020		ACM 2019		ACM 2021	
Configuration	MSAD [kW/kg]	MSAD [kW/kg]	% Increase	MSAD [kW/kg]	% Increase	MSAD [kW/kg]	% Increase	MSAD [kW/kg]	% Increase
2T 50	1.28	1.48	15.63%	2.11	64.84%	5.07	296.09%	4.16	225%
2T 100	1.6	1.91	19.38%	4.31	169.38%	6.06	278.75%	2.65	65.63%
4T 50	2.47	2.78	12.55%	2.77	12.15%	7.84	217.41%	6.46	161.54%
4T 100	2.44	3.05	25%	4.23	73.36%	10.5	330.33%	4.44	81.97%