Framework for Accommodating Emerging Autonomous Vehicles

Final Report

by

Burak Eksioglu, University of Arkansas
Matthias Josef Al Schmid, Clemson University
Nathan Huynh, University of South Carolina
Gurcan Comert, Benedict College
Dahui Liu, Clemson University

Contact information
Burak Eksioglu, Ph.D.
Department of Industrial Engineering, University
of Arkansas, Fayetteville, AR 72701 email: burak@uark.edu

July 2022

Center for Connected Multimodal Mobility (C^2M^2)

200 Lowry Hall, Clemson University
Clemson, SC 29634

DISCLAIMER

ACKNOWLEDGMENT

The project is funded by the Center for Connected Multimodal Mobility (C^2M^2) (Tier 1 University Transportation Center) Grant from the U.S. Department of Transportation's University Transportation Centers Program.

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle Framework for Accommodating Emerging Autonomous Vehicles		5. Report Date 07/17/2022 6. Performing Organization Code
7. Author(s) Burak Eksioglu; ORCID: https://orcid.org/0000-0002-2999-6783 Matthias Josef Al Schmid; ORCID: https://orcid.org/0000-0002-5686-7418 Nathan Huynh; ORCID: https://orcid.org/0000-0002-4605-5651 Gurcan Comert; ORCID: https://orcid.org/0000-0002-2373-5013 Dahui Liu; ORCID: https://orcid.org/0000-0002-5062-3148		8. Performing Organization Report No.
9. Performing Organization Name and Address Department of Industrial Engineering, Clemson University Clemson, SC 29634 Department of Industrial Engineering, University of Arkansas Fayetteville, AR 72701		10. Work Unit No. 11. Contract or Grant No. 69A3551747117
12. Sponsoring Agency Name and Address Center for Connected Multimodal Mobility (C2M2) Clemson University 200 Lowry Hall, Clemson Clemson, SC 29634		13. Type of Report and Period Covered Final Report (August 2018 - July 2022) 14. Sponsoring Agency Code
15. Supplementary Notes		

16. Abstract

In the era of Connected and Autonomous Vehicles, platooning has the potential to increase roadway capacity and reduce energy consumption. However, vehicles may expend extra energy as they try to form platoons. Also, depending on its position within a platoon, the energy savings of each vehicle can be different. Thus, optimizing and quantifying the savings that may be gained from platooning is challenging. In this project, we develop a simulation-optimization framework to tackle the challenge of quantifying energy savings from platooning. Our optimization model determines vehicle-to-platoon assignments given the current location, speed, and destination of all the vehicles and platoons on the freeway. The simulation model takes these platooning decisions from the optimization model and implements them. Vissim is used to simulate the actions taken by all the vehicles and platoons and capture the energy expended by each vehicle over its entire trip duration. The system is simulated with and without platooning to quantify the energy savings. The optimization model is turned off when assessing the system's performance without platooning. In addition to the simulation-optimization framework, an accurate energy consumption model is developed in this project, inspired by Tadakuma and colleagues' work. The energy consumption model utilizes a hybrid prediction formula for aerodynamic drag reduction in multivehicle formations unifying both physical mechanisms and existing empirical study data. Our results show that a system-wide savings of about 3% can be realized over 160 kilometers when platoons are formed strategically.

17. Keywords	18. Distribution Statement
Platoon formation; autonomous trucks; energy consumption model; simulation; optimization.	This report or any part of this report is restricted to publication until prior permission from the authors.

19. Security Classification (of this report)	20. Security Classification (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	32	NA

TABLE OF CONTENTS

DISCLAIMER ii

ACKNOWLEDGMENT iii

TABLE OF CONTENTS v

LIST OF TABLES vi

LIST OF FIGURES vii

EXECUTIVE SUMMARY 1

CHAPTER 1 2
- Introduction 2

CHAPTER 2 3
- Literature Review 3
  - 2.1 Simulation-Optimization Platooning 3
  - 2.2 Prediction Model for Energy Consumption 4

CHAPTER 3 5
- Methodology 5
  - 3.1 Simulation 5
  - 3.2 Optimization Model 7
  - 3.3 Experimental Results 8
  - 3.4 Energy Consumption Prediction Model 10
  - 3.4.1 Aerodynamic Drag 10
  - 3.5 Results 14

CHAPTER 4 16
- Conclusions 16

REFERENCES 17

LIST OF TABLES

Table 1 Energy consumption experiment results 9
Table 2 Summary of Fitting Variables and Parameters 15

LIST OF FIGURES

Figure 1 Flow chart of the simulation-optimization framework 5
Figure 2 Prepared Safety Signs to Collect Field Data 6
Figure 3 Number of platoons in the system in experiments 1 (on the left) and 4 (on the right) 8
Figure 4 DRR Prediction / Experimental Results 14

EXECUTIVE SUMMARY

In the new era of Connected and Autonomous Vehicles, platooning is gaining popularity as a traffic management tool. Platooning can reduce energy consumption for vehicles due to draft. However, as vehicles form a platoon, they may also expend extra energy. Also, the energy savings of each vehicle can be different depending on its position within a platoon. These factors indicate that quantifying energy savings from platooning is indeed a challenging task. Hence, we develop a simulation-optimization framework to tackle this challenging problem. Our optimization model in this project assigns single vehicles to proper platoons, given the current location, speed, and destination of all the vehicles on the freeway. The simulation model takes these platooning decisions from the optimization model and implements them. VISSIM (a microscopic multi-modal traffic flow simulation software package) is used to simulate the actions taken by all vehicles and platoons. It captures the energy expended by each vehicle over a long time period. We simulate the system with and without platooning to measure energy savings. In other words, the optimization model is turned off when platooning is not allowed. Our results show that a system-wide savings of about 3% can be realized over 100 miles when platoons are formed strategically.

The project provides a hybrid prediction formula for aerodynamic drag reduction in multivehicle formations, unifying physical mechanisms and existing empirical study data. Inspired by the work of Tadakuma and colleagues, we modify the physical model by removing its previous limitations for short inter-vehicle distances and extend it to heavy-duty vehicles (tractor-trailer configurations) by adapting to full-scale on-road data as provided by McAuliffe and colleagues, for instance. The new model consistency for a short distance is of paramount importance for cooperative adaptive cruise control (CACC) applications. As a result, the provided self-contained model supplies an off-the-shelf solution for energy savings prediction in heavy-duty vehicle operations that can be directly embedded by other researchers in their platooning research (Liu (2020), Liu et al., (2020), Schmid et al., (2020), Liu et al., (2021)).

Our numerical experiment results indicate that savings are maximized if the focus lies on forming as many platoons as possible and forming longer platoons. In this study, we limited the platoon size to a maximum of five vehicles, but as part of our future work, we plan to study the impact of platoon size on energy savings as well as the impact of platoon speed and associated surrounding traffic conditions. In future work, we will allow single vehicles to join any platoon within the platooning zone instead of only considering those platoons currently behind the vehicles. This study considered a network consisting of only freeway segments. In future work, we plan to extend the analysis to include a network consisting of interstates and non-interstate national highway system routes to better quantify the potential energy savings with platooning at the regional/state level (Liu et al., (2021)).

CHAPTER 1

Introduction

Platooning, a method to form and maintain a group of vehicles traveling together, is becoming more prevalent on U.S. highways thanks to advanced technologies like Connected and Autonomous Vehicles (CAVs) and Cooperative Adaptive Cruise Control (CACC). A platoon formed of CAVs is expected to maintain shorter inter-vehicle distances and maintain a constant speed than platoons with human-driven vehicles. Short inter-vehicle distances lead to air drag reduction, decreasing the energy needed to move these vehicles. Increased driving comfort, reduced traffic congestion, and improved roadway capacity are other potential benefits of platooning. On the other hand, vehicles may consume extra energy when accelerating or decelerating to join or leave platoons. We investigate the effect of platooning on energy consumption for a fleet of connected and autonomous trucks traveling over a long freeway stretch with on- and off-ramps. Energy consumption and fuel consumption are closely related, but the latter depends on the engine's specifications of each vehicle. We focus on energy consumption which eliminates the need to specify engine types for various vehicles. Once energy consumption is calculated, it can be used to calculate the corresponding fuel consumption. Then, given the destination for each truck in the fleet, the goal is to identify opportunities such that these CAVs can dynamically join and leave platoons. A simulation-optimization framework is developed to optimize and quantify the potential savings. In this framework, the optimization model, a centralized formulation, is used to form appropriate platoons for energy savings, while the simulation model captures realistic vehicle movements, traffic conditions, and energy consumption.

Energy consumption and fuel consumption are closely related, but the latter depends on the engine specifications of each vehicle. In this study, we focus on energy consumption which eliminates the need to specify engine types for various vehicles. Once energy consumption is calculated, it can be used to calculate the corresponding fuel consumption. Existing research either focuses on assessing aerodynamic forces through simulation, scaled testing in wind tunnels, or limited full-scale track testing by involving actual vehicles, pressure sensors to measure drag, and scales to measure the change in fuel. To date, models to predict the energy consumption of vehicles in a platoon traveling at the same speed with very short inter-vehicle distances are limited. These models are paramount for cooperative adaptive cruise control (CACC) applications. This study fulfills this gap in the literature by proposing a model that combines empirical data and physics-based modeling.

CHAPTER 2

Literature Review

2.1 Simulation-Optimization Platooning

As Intelligent Transportation Systems (ITS) and Connected and Autonomous Vehicles (CAVs) are becoming more advanced, vehicle platooning is becoming an important tool to reduce energy consumption. A platoon is a group of vehicles that travel at the same speed and have equal spacing between them. The short inter-vehicle distances reduce the air drag on the vehicles, reducing the energy required to move these vehicles. On the other hand, however, vehicles may consume more energy as they accelerate or decelerate to join and maintain platoons. In this project, we investigate the effect of platooning on energy consumption for a fleet of connected and autonomous trucks traveling over a long freeway stretch with on- and off-ramps. A simulation-optimization approach where the optimization model forms platoons and the simulation model captures the realistic vehicle movements, traffic conditions, and the energy consumption is used to quantify the potential savings.

Researchers have been investigating platooning since the early 1950s. However, due to the technology of the time, these research efforts were mostly theoretical without any real-life applications. From 2005 to 2009, the German project KONVOI conducted a study on a platoon of four trucks (Kunze et al., 2009). The platoon drove on German highways (a human driver drove lead vehicle) with a gap of 10 meters (*m*) between vehicles. They reported an increase of up to 9% in road capacity and a decrease of up to 10% in fuel consumption. The Japanese project, "Energy ITS," starting in 2008, built a platoon of 3 heavy trucks and 1 light truck with a gap of 4.7*m* and an average speed of 80 kilometers per hour (*km/h*) (Tsugawa, 2014). The project reported a 15% savings in fuel consumption based on their field experiments. Rakha et al., (2004) reported fuel savings of 8-11% for a platoon with two trucks. Bonnet and Fritz (2000) studied a platoon of two trucks traveling at 60*km/h* and 80*km/h* on a highway with additional traffic. They showed that the decrease in fuel consumption ranged from 15% to 21% at 80*km/h* and 10% to 17% at 60*km/h* for the tail truck, and 3% to 10% at 80*km/h* and 3% to 7% at 60*km/h* for the lead truck. Tsugawa (2013) showed an average of 14% decrease in fuel consumption in a study with three trucks driving at 80*km/h* with 10*m* inter-vehicle gaps.

In addition to the field studies provided above, there have also been studies that used optimization and simulation to quantify fuel or energy savings. Tsugawa et al. (2011) developed a Computational Fluid Dynamics (CFD) simulation model with a platoon of three vehicles traveling at 80*km/h* with an inter-vehicle gap of 4*m*. Their results showed that all three trucks consumed less fuel compared to when they were traveling separately, but the middle truck had the highest fuel savings. Larson et al. (2013) developed a distributed method for optimizing platoon routing with a local controller where vehicles may deviate from their shortest paths to form platoons for maximal energy savings. However, their work ignored the energy consumed when vehicles are joining or leaving the platoon, a and the extra energy consumed to maintain a platoon's speed. They also did not consider the position of the vehicles in a platoon. Dao et al. (2008, 2013) studied a platooning problem similar to ours. They provided an optimization-simulation model in which the objective function is to maximize the total distance that platoons stay intact with the aim of improving lane throughput. In our study, we mainly focus on optimizing energy savings via the strategic formation of platoons, simulating the traffic stream that consists of platoons and individual vehicles, and determining actual energy consumption from the microscopic simulation model. The remainder of the report is organized as follows. Chapter 3 provides details of our simulation-optimization approach. Chapter 4 includes an analysis of our results and provides some managerial insights. Chapter 5 concludes with directions for future work.

2.2 Prediction Model for Energy Consumption

With the current aggressive expansion of efforts in transportation systems, an accurate prediction model for energy consumption in vehicle platoons is of key necessity for research in both planning/routing and simulation. Existing research either focuses on assessing aerodynamic forces through simulation, scaled testing in wind tunnels, or limited full-scale track testing by involving the use of actual vehicles, pressure sensors to measure drag, and scales to measure the change in fuel (McAuliffe et al. (2018), Bonnet and Fritz (2000), Lammert et al (2014), Al Alam et al. 2010, Muratori et al. (2017)). Except for the work in Tadakuma et al. (2016) none of the existing studies attempts to establish a simplified analytical prediction model consistent with experimental results. As the use of actual vehicles and human drivers limits how closely the vehicles can safely follow each other in tests, a numerical prediction model that incorporates actual experimental data can be of utmost importance for the research community. In literature, there are two types of models that have been used to quantify vehicle energy consumption: statistical and physical. The statistical model tries to establish a statistical relationship between vehicle system inputs and fuel consumption. The fuel consumption is usually estimated at each second, which requires input data at the same time resolution. Barth et al. (1996) were the first to build a linear regression model to estimate energy consumption and emissions of vehicles based on engine output power. Later, Rakha et al. (2004) developed the VT-Micro model, which statistically estimates fuel consumption based on a vehicle's second-by-second travel speed and acceleration. Although the statistical model is widely used to estimate the fuel consumption of vehicles, one known drawback of such a model is that the statistical relationship is only valid within the experimental parameters and is difficult to extrapolate to other vehicle driving conditions. The physical model simulates the physical powertrain working processes to quantify vehicle energy consumption.

Examples of a physical model include FASTSim, used in a study by Brooker *et al.* (2015), and Autonomie, used in a study by Halbach *et al.* (2010). Since these models are based on physical simulation, the drag coefficient is included as an influencing factor that determines vehicle energy consumption. Existing studies have utilized physical models to assess energy consumption of many driving cycles (*e.g.*, Rousseau et al. (2014), Lane et al. (2017)). A physics-enabled model provides the flexibility to comprehensively examine the effect of inter-vehicle distance, speed, vehicle type, etc., on fuel savings. A major factor that significantly affects a vehicle's fuel savings is its drag coefficient. Hence, the potential aerodynamic drag reduction when platooning at short or intermediate distances is the predominant motivator for large-scale research, testing, and development efforts to realize platooning operations.

CHAPTER 3

Methodology

We developed a microscopic simulation model that realistically simulates the movements of a fleet of vehicles on the freeway. The optimization model partitions the traffic network into platooning zones around each on- and off-ramp. For each zone created, the model finds the best possible assignment of every single vehicle to a platoon by considering the location, speed, and destination of all the vehicles. As can be seen in Figure 1, we simulate the system for T periods (T=4 hours in our experiments). The optimization model is run every τ period (τ=20 seconds in our experiments). Each time the optimization model is run, single vehicles are assigned to nearby platoons in the best possible way to minimize energy consumption. The simulation model takes these platooning decisions and simulates the system under realistic traffic conditions until the next optimization period when new vehicles enter the highway, and some vehicles reach their destinations. This dynamic process is repeated until the end of the planning horizon, at which point system performance measures are collected.

Figure 1 shows our simulation-optimization approach.

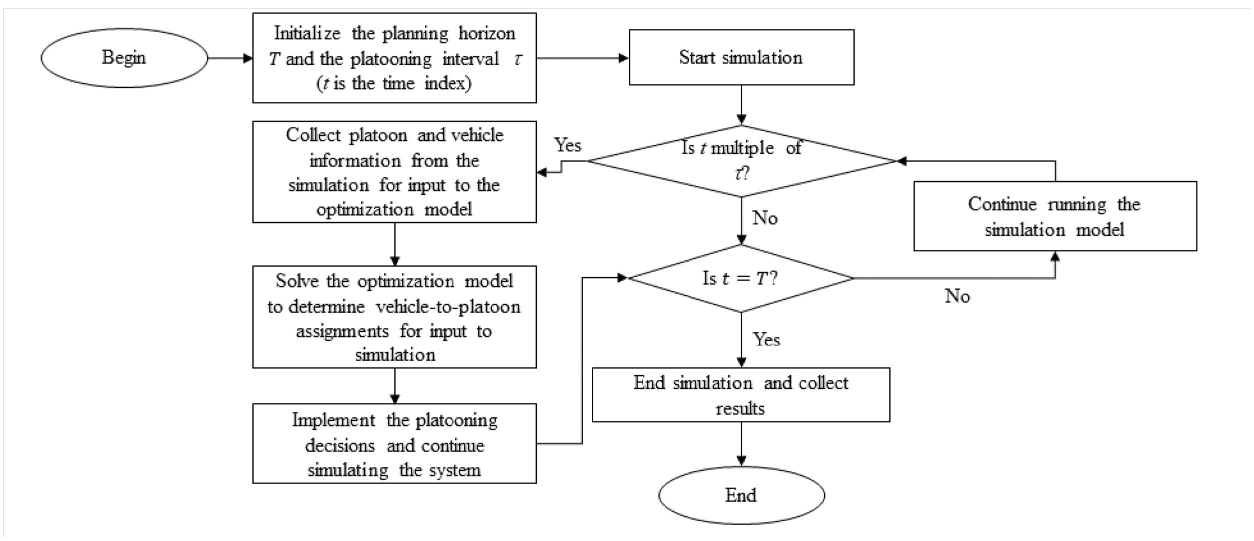


Figure 1 Flow chart of the simulation-optimization framework

3.1 Simulation

VISSIM is utilized to generate the traffic network and simulate the movement of single vehicles and platoons on this network. While we use most of the default settings in VISSIM, we also use its COM interface via Python scripts to manage the platoons. A 100-mile highway stretch, which mimics a level terrain with no curves, is set up with a width of 12 feet (*ft*) per lane in VISSIM. This highway stretch has three lanes with all vehicles traveling in the same direction. There are 36 on- and 36 off-ramps distributed almost evenly over this highway stretch. All vehicles in our simulation are Heavy Goods Vehicles (HGVs), where single vehicles follow the desired speed distribution of 62.5 miles per hour (*mph*) which corresponds to 100*km/h*. On our highway, we refer to the right-most lane as Lane 1, the middle lane as Lane 2, and the left-most lane as Lane 3. Platoons are allowed only in Lanes 2 and 3. The average speed of the platoons in Lane 3 is set to 65*mph,* and those in Lane 2 to 60*mph*. Platoons are not allowed in Lane 1 because our preliminary simulations lead to heavy congestion and traffic jams. Moreover, the inter-vehicle distance in the platoons is set to 0.5 seconds (s) headway for both control and energy savings proposed. We use the HGVs' default values in VISSIM for acceleration, size, weight, and power distributions. Unlike the single vehicles in the system, platoons are not allowed to change lanes. This is done to avoid additional energy consumption due to acceleration and deceleration. Also, we assume that the HGVs in our fleet have cooperative adaptive cruise control (CACC), which allows us to have them travel at closer inter-vehicle distances. Clearly, HGVs in a platoon need to accelerate or decelerate to maintain the inter-vehicle distances. In particular, when a vehicle approaches its destination, it begins to move to Lane 1. The other vehicles (if any) in the platoon that were behind beginning to accelerate to close the gap.

Platoons enter the highway at mile zero every 60s. The first platoon in Lane 3 is generated as soon as the simulation begins, whereas in Lane 2, the first platoon enters the highway after the 30s. Each platoon has anywhere between 2 and 5 vehicles determined randomly using a uniform distribution. Once a vehicle (single or in a platoon) enters the network, its destination is picked randomly as follows: Let N_D be the number of off-ramps in the network after the ramp from which a vehicle enters the highway. One of these $N_{.D.}$ ramps is randomly assigned as a destination for the vehicle. In our initial set of experiments, we picked one of these $N_{.D.}$ ramps uniformly which led to extreme congestion in the network. To eliminate this problem, we adopted a probability mass function that resembles a geometric distribution with some modification. Let p_l (l=1, 2, ..., N_{D-1}) be the probability that off-ramp l (after the one on which the vehicle enters the highway) is assigned as the destination for this vehicle. The only exception to this is that p_1 and p_3 are swapped, i.e., p_1 is the probability that the 3rd ramp after the entry is the destination for this vehicle and p_3 is the probability that the 1st one is the destination. This modification ensures that vehicles do not leave the highway too soon (i.e., they get an opportunity to join a platoon), and they do not stay in the highway too long to cause congestion. The probabilities are calculated as follows:

$$p_l = \frac{\rho}{(1+\rho)^{N_D-1}}(1+\rho)^{l-1},\ l = 1,2,\dots,N_D - 1 \tag{1}$$

where $0 < \rho < 1$ is the shape parameter. After fine-tuning $\rho = 0.2$ was chosen since it resulted in stable traffic flow with opportunities for platooning. Figure 2 shows the cumulative distribution and probability mass functions for p_l.

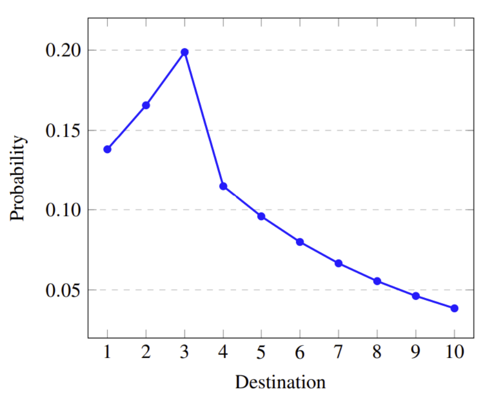


Figure 2 Prepared Safety Signs to Collect Field Data

We allow single vehicles to only join platoons that are behind them to minimize energy consumption due to acceleration. Once the optimization model determines which platoon a particular vehicle needs to join, that vehicle moves to Lane 1 and slows down. Its desired speed is set to 40*mph*. When the platoon is within a specified distance, then the vehicle starts to speed up and move to Lane 2 or 3, depending on where the platoon is.

3.2 Optimization Model

As mentioned above, our optimization model attempts to find the best vehicle to platoon assignments. The highway network is divided into platooning zones that are about 1 mile in radius. We obtain the location, speed, and destination of each vehicle and platoon for each zone from the simulation model. Then, we use them as parameters in the optimization model presented below. We start with introducing the parameters, sets, and variables used in the modeling.

Parameters		Sets	
d_i :	current location of vehicle i (including those in a platoon)		
n_j :	number of vehicles in platoon j	P :	set of all platoons in a given zone
C :	maximum number of vehicles allowed in a platoon	V_s :	set of all single vehicles in a given zone
w_q :	weight assigned to each component of the objective function	P_i :	set of all platoons that vehicle i can join
S_r :	total energy saved (in percentage) by a platoon with r vehicles	V_j :	set of all vehicles in platoon j
D_i :	destination of vehicle i		
D_k^j :	destination of the k^{th} vehicle (sorted by destination) in platoon j	Decision variables	
$D_k^{i,j}$:	destination of the k^{th} vehicle (sorted by destination) in platoon j if single vehicle i is also part of the platoon	x_{ij} :	1 if vehicle i joins platoon j, 0 otherwise

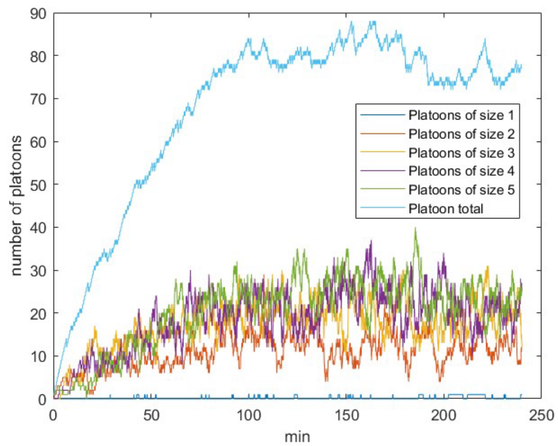
Given this notation, our optimization model can now be written as

$$\text{minimize} \sum_{i\in V_s}\{w^1 \sum_{j\in P_i} \frac{x_{ij}}{n_j}\sum_{k\in V_j}|D_i - D_k| + w^2 \sum_{j\in P_i} x_{ij}\{\left[(D_1^j - d_i)s_{n_j} + \sum_{k=1}^{n_j-2}(D_{k+1}^j - D_k^j)s_{n_j-k}\right] - [(D_1^{i,j} - d_i)s_{n_j+1} + \sum_{k=1}^{n_j-1}(D_{k+1}^j - D_k^{i,j})s_{n_j-k+1}]\}\}$$

$$\text{subject to } n_j + \sum_{i\in V_s} x_{ij} \le C, \quad \forall j \in P$$

$$\sum_{j\in P} x_{ij} \le 1, \quad \forall i \in V_s$$

As seen from the mathematical formulation above, the objective function in our optimization model has two terms. The first term is assigned a weight of w^1, and the second term is a weight of w^2 ($w^1 + w^2 = 1$). Because minimizing energy consumption directly would lead to a nonlinear mathematical model, which would be difficult to solve, we decided to minimize the energy consumption indirectly. The first term in the objective function is simply trying to create platoons in which the vehicles have destinations that are close to each other. The intent here is to minimize the number of times vehicles have to join or leave a platoon so that energy is not expended unnecessarily. The second term in the objective function is trying to estimate the savings if vehicle i joins platoon j. The first half of this term estimates the energy savings for platoon j when vehicle i is not part of the platoon, and the second half estimates the savings with vehicle i as part of platoon j. Note that since we modeled this as a minimization problem, we are considering the negative of the savings. The constraints are relatively straightforward. The first constraint simply says that the current number of vehicles in a platoon plus all the new vehicles that are assigned to join this platoon should not exceed the capacity which is set to 5 ($C = 5$). The second constraint ensures that every single vehicle is assigned to at most one platoon. The S_r values used in the objective function come from the experimental results mentioned above. The details of how these were obtained are omitted due to space constraints, but the final values were S_2=13%, S_3=28%, S_4=43%, and S_5=59%.



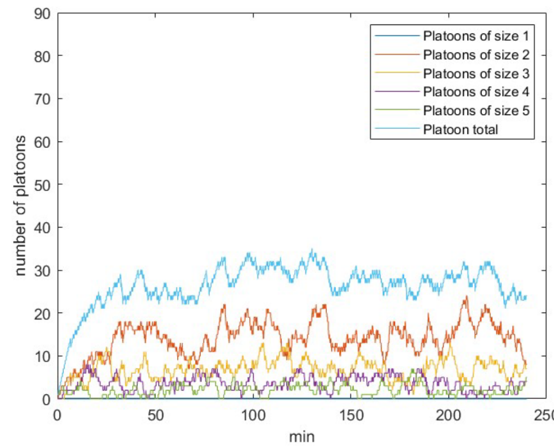


Figure 3 Number of platoons in the system in experiments 1 (on the left) and 4 (on the right)

3.3 Experimental Results

We conducted a large number of experiments and a host of sensitivity analysis in order to evaluate our simulation-optimization framework. However, we only present four of the experiments due to space limitation. In each experiment, the simulation model begins with an empty system and runs for 4 hours ($T = 4hr$). Platoons enter the highway from mile zero every 60*s*, but single vehicles enter the highway from each of the on-ramps at a rate of 100 vehicles per hour. Our initial experiments considered higher throughput rates which resulted in congestion which led to using more energy as captured by our simulations. Each experiment is initialized with the same random seed to ensure a fair comparison, and a total of exactly 16,034 vehicles go through the system in each simulation run. In experiments 1-3, single vehicles are allowed to join the platoons on the highway, the optimization model is run every 20 seconds ($\tau = 20s$), and the simulation model records the state of the system every 0.5 seconds. Platooning is not allowed in experiment 4(*i.e.*, the optimization model is turned off). Note, however, that there are still platoons in experiment 4 but these are the platoons that enter from mile zero and not new platoons. In experiments 1, 2, and 3, w^1 is set to 0, 0.25 and 0.125, respectively. Recall that $w^1 + w^2 = 1$ and w^1 is the weight assigned to the first term in our objective function, which assigns vehicles to platoons based on their destinations. The second term maximizes the energy savings but note that this is an overestimation of the savings.

The statistics collected during the simulation are then analyzed offline once the experiment ends. To ease the analysis of the large amount of data collected, we developed a MATLAB code that generated figures and tables, some of which are presented below. Figure 3 shows the number of vehicles in the system for experiment 1 (on the left) and experiment 4 (on the right). The total number of platoons seemed to stabilize after the 90*th* minute of the simulation. Thus, to eliminate the effect of the warm-up period we focus our attention to the last 2 hours of our 4-hour simulation. As can be seen from the figure, in experiment 1 there are about 80 platoons in the system in a steady state. Of this total, the majority are platoons with 5 vehicles. Note that there are occasionally platoons with only 1 vehicle. This occurs because when an HGV leaves a platoon with 2 vehicles, the system momentarily records the remaining vehicle as a platoon. In experiment 4, the number of platoons in a steady state is only about 30, of which the majority are platoons with 2 vehicles. This makes sense because in experiment 4 the optimization is turned off, meaning new platoons are not formed, and vehicles eventually leave the existing platoons which entered the highway at mile zero. The figures for experiments 2 and 3 are similar to that of experiment 1 and are not provided for the sake of brevity.

As seen from Figure 3, turning off the optimization results in a significant decrease in the number of platoons (specifically platoons with 5 vehicles). However, we are interested in how this change in the number of platoons translates to a change in energy consumption. The results are summarized in Table 1. As we explain the results presented in the table note that they are for the last 2 hours of the simulation, i.e., the warm-up period is not considered in these results. The first column in Table 1 simply indicates the experiment for which the results are being reported. The second column shows the total energy consumed by all vehicles under the assumption that the drag coefficient is low (i.e., the worst case from a savings perspective). The third and fourth columns show the total energy consumed if the drag coefficient is average and high. The last column shows the energy consumed due to acceleration. Recall that vehicles expend extra energy when HGVs are joining or leaving a platoon. Vehicles also consume energy to maintain the platoon traveling at a constant speed. Thus, the last column in the table reports this additional energy consumed by the HGVs.

As expected, the total energy consumed is lower in experiments 1-3 compared to experiment 4. Among experiments 1, 2, and 3 the best results are obtained in experiment 1. This means we should set w1 = 0, which implies that when we decide which platoon a particular single vehicle should join, we need not consider the destinations of all the vehicles in that platoon. In other words, the first term in our objective function can be dropped from the formulation. Also, if the drag coefficient is high, the savings from platooning are higher than expected. For example, the total energy consumed drops from 298,464kWh to 289,177kWh (a savings of more than 3%) if the drag coefficient is high. This is lower than most of the savings reported in the literature, but a closer look reveals that those studies ignored the energy consumed due to acceleration. Comparing the numbers in the last column for experiments 1 and 4 show that the additional energy consumed to maintain the platoons increased from 23,588kWh to 30,835kWh (an increase of over 30%). In light of this, the 3% savings reported earlier is quite significant. Also, note that this is a system-wide average saving. We also analyzed the percentage of time each vehicle spent in a platoon in all of our experiments. For example, we observed that each vehicle in experiment 1 spent 35% of their time in a platoon. The same number for vehicles in experiment 4 was only 9%. Thus, vehicles spend significantly more time in platoons, saving energy. While the savings seem small, it is significant considering that forming and maintaining platoons requires additional energy.

Table 1 Energy consumption experiment results

Experiment	Total			Acceleration
	Low	Average	High	
1	223,171	249,573	289,177	30,835
2	226,379	254,307	296,199	26,665
3	224,437	251,311	291,623	29,757
4	226,817	255,476	298,464	23,588

3.4 Energy Consumption Prediction Model

To supply an assessment model for potential fuel savings in traffic networks when platooning, this study modifies the prediction formulas developed by Tadakuma et al. (2016) and adapts them to experimental data for heavy-duty vehicles. In order to maintain consistency of the prediction model for long, medium, and short distances, several phenomena must be included: reduction of the main flow velocity in a vehicle's wake, stagnation pressure created in front of a follower vehicle as well as behind a leading vehicle, nonuniformity of flow at short distances, and unmodeled effects for long platoons. We partially utilize functional forms from Tadakuma et al. (2016) while expanding the relationship for stagnation pressure and introducing a concatenation correction. The introduced shift parameter effectively removes the previously unrealistically high reduction in aerodynamic drag for short distances, while the concatenation term allows for omitting the nonuniform flow correction. A least squares regression is employed for parameter estimation and fitting of the physical model to data from heavy-duty truck testing.

The total energy consumed in truck platooning is usually reported in fuel consumption. Yet, the operating fuel consumption of a vehicle depends on a multitude of factors, i.e., the efficiency of the engine to convert chemicals into mechanical energy, transmission characteristics, weight of the vehicle, aerodynamic resistance, rolling resistance of the tires, driving cycle, and driver behavior (Wong (2008)). While engine and transmission losses are significant, they can be represented in the simplified form of a constant scaling factor (for driving with or without platooning). Hence, this study focuses only on the energy necessary to physically move a vehicle along (which can be converted to fuel consumption). The forces which need to be overcome to maintain a constant speed, i.e., the road load, yield

$$R(t) = [mg\cos(\alpha) - F_L] \cdot (f_0 + k_R\, v(t)^2\, F_D) + mg\sin(\alpha) \tag{2}$$

with m and g being the mass and the gravitational constant, α representing the grade of the road, $F_{.L.}$ denoting the aerodynamic lift force, f_0 and k_R being constant and velocity-dependent rolling resistance coefficients, and $F_{.D.}$ designating the aerodynamic drag. For heavy-duty vehicles, the effect of aerodynamic lift on the rolling resistance can be neglected. As this study aims to provide a drag reduction ratio (DRR) prediction (and subsequently an energy reduction rate) for platooning operations, the development of this ratio will be independent of the road grade. It is, therefore, acceptable, without loss of generality, to limit the analysis to a level road. Hence, the vehicle-specific power (Zhang et al. (2017)) reduces to

$$VSP = [R(t) + m\,a(t)]\,v(t) = [(f_0 + k\,v(t)^2) + m\,a(t) + F_D]\,v(t) \tag{3}$$

Here, $v(t)$ is the instantaneous speed at time t, and $a(t)$ is the instantaneous acceleration. As the promised fuel savings in platoon operations arise from reduced aerodynamic drag, the following sections will detail the methodology to arrive at a hybrid prediction formula for the DRR.

3.4.1 Aerodynamic Drag

In general, the force resulting from aerodynamic drag in the context of single vehicle driving is expressed via the following relationship:

$$F_D = \frac{1}{2}\rho C_D A_f\, v(t)^2 \tag{4}$$

Here, ρ denotes the density of air, C_D the drag coefficient, A_f the total projected frontal area, and $v(t)$ the vehicle's velocity. The use of the drag coefficient reflecting the aerodynamic behavior resulting from the vehicle's shape allows for this simplified representation. Additionally, the drag coefficient for a given vehicle can be easily obtained experimentally (*e.g.*, in a wind tunnel) by measuring the perceived drag force for a given air velocity. As Eq. (3) only holds for single vehicle driving, the travel velocity coincides with the air velocity received by the vehicle's frontal area. This will, in general, not be true for vehicles driving in a platoon. In addition, Eq. (3) is subject to additional assumptions: (*i*) uniform flow, (*ii*) no atmospheric wind, and (*iii*) no skin friction. All employed coefficients of drag within this study should be interpreted as coefficients of pressure drag.

With the goal of a hybrid expression for fuel savings in mind, the role of aerodynamics under platooning can be expressed by comparing pressure drag between solo driving, $F_{.D.s}$, and platooning, F_{Dp}, to arrive at the DRR, *i.e.*,

$$DRR = \frac{F_{Ds} - F_{Dp}}{F_{Ds}} = \frac{C_{Ds}\, A_f\, q_s - C_{Dp}\, A_f\, q_p}{C_{Ds}\, A_f\, q_s} = 1 - \frac{q_p}{q_s}\frac{C_{Dp}}{C_{Ds}} \tag{5}$$

Here, the dynamic pressures (velocity pressures) received at the frontal area of the vehicle under solo driving and under platoon driving, q_s and q_p, are utilized instead of the vehicle velocity v as $q = \frac{1}{2}\rho u^2$ for compressible fluids at low Mach numbers (with u being the flow speed). Note that this ratio will be 1 for the first vehicle. The dynamic pressure ratio q_p/q_s as well as the uniform flow equivalent drag coefficient under platooning C_{Dp} need to be determined by including correction terms for four distinct effects apparent for each vehicle in the interior of the platoon:

1. The wake of a leading vehicle reduces the main flow velocity and, thereby, the dynamic pressure received by a follower. This phenomenon can be expressed via the ratio of the center line air velocities for a vehicle in the wake and solo driving, u_w/u_s. This effect appears over a wide range of distances (long, medium, and short).

2. For short inter-vehicle distances, stagnation pressure is created in the front of the ego vehicle (if the ego vehicle is not the lead vehicle of the platoon). The increase of pressure over the frontal area raises the main flow velocity again, thereby adversely affecting the ratio of the center line velocities u_w/u_s. Thus, a correction factor for the previous wake velocity deficiency needs to be introduced.

3. On the other hand, stagnation pressure is also created by a follower vehicle at the rear base of the ego vehicle for short distances in a platoon. This rear base pressure lowers the pressure drop over the body of the ego vehicle and, thus, the flow. Hence, another correction term reflecting this effect is needed for the drag coefficient C_{Dp}. In contrast to the stagnation pressure created in the frontal area of the ego vehicle, this phenomenon yields a pushing effect, *i.e.,* increases DRR.

4. The expression in Eq. (3) inherently assumes uniform flow to allow for the simplifying use of the drag coefficient C_D. However, if inter-vehicle distances in a platoon are short to medium, nonuniform flow effects arise. Therefore, Tadakuma *et al. (2016)* introduced a flow correction term in the modified drag coefficient C_{Dp} in Tadakuma *et al.* (2016). As will be specified later, our approach does not necessitate this correction term but requires a concatenation factor for long platoons, *i.e.*, those with 3 or more vehicles.

Stagnation Pressure: The stagnation pressure created at the base of the ego vehicles by the following vehicle leads to a pushing effect reflected in a decrease of the drag coefficient under platooning. This is the only platooning impact apparent for the lead. Tadakuma *et al.* (2016) introduce an analytical expression for the base pressure of the *i*th vehicle that is "based on a formula that expresses the changes in the coefficient of pressure caused by a potential flow" as

$$\frac{\Delta C_{Dp,i}}{C_{Ds,i}} = 1 - [1 - [\frac{\varepsilon}{d_{i(i+1)} + \varepsilon}]^3]^2 \quad (6)$$

Here, ε is an empirically established constant (determined as ε = 6.3 for sedan-type vehicles), whereas $d_{i(i+1)}$ is the distance between vehicles at positions *i* and (*i*+1) in the platoon. However, the reasoning for this expression cannot be confirmed as the referenced work in Tadakuma *et al.* (2016) is only available in Japanese. Additionally, the functional form of Eq. (5) requires adjustments when used to assess the fuel-saving benefits of platooning at small inter-vehicle distances:

$\Delta C_{Db}/C_{.D.s}$ approaches 1 for $d_{i(i+1)}$ going to 0, *i.e.*, the lead vehicle in the platoon will have no drag for very small distances. This does not correspond to physical reality. Especially for the small inter-vehicular distances to be exploited in platooning when utilizing CACC, the expression in Eq. (5) becomes highly erroneous and over-promises fuel savings. This is one of the reasons that the prediction formula in Tadakuma *et al.* (2016) fails to follow the trend of the empirical data obtained, for instance, by McAuliffe *et al.* (2018). Hence, we suggest a new functional form for the stagnation pressure correction that maintains a hyperbolic character but introduces a second parameter for the horizontal shift. This new expression does not exhibit a singularity at $d_{i(i+1)} = 0$ and yields

$$\frac{\Delta C_{Dp,i}}{C_{Ds,i}} = 1 - [1 - [\frac{X_1}{d_{i(i+1)} + X_1 X_2}]^3]^2 \quad (7)$$

The parameters X_1 and X_2 will be determined by a least-squares fit from empirical data in section 3.

Wake Effect and Centerline Deficit Velocity: The wake effect of a leading vehicle yields a reduced air velocity, and hence reduced dynamic pressure, received by a follower vehicle. This velocity deficit can be expressed for a 2-vehicle combination via the maximum deficit velocity rate occurring at the centerline of the wake, *i.e.*, u_w

$$\frac{u_w}{u_s} = 1 - \xi \quad (8)$$

The maximum deficit velocity rate in the wake of a vehicle, ξ, is the ratio between the velocity drop at the centerline of the wake and the air velocity received by the vehicle under solo driving. Tadakuma *et al.* (2016) provide an analytical expression in Tadakuma *et al.* (2016) for this maximum deficit velocity rate at distance d_{12} between two vehicles at positions 1 and 2 as

$$\xi_1 = \alpha\left(C_{Ds,1}\right)^{\beta}\left(1 - \frac{\Delta C_{Dp,1}}{C_{Ds,1}}\right)^{\beta}\left(\frac{d_{12}}{\sqrt{A_{f,1}}}\right)^{-\frac{2}{3}} \quad (9)$$

where, the additional index in the subscripts denotes the corresponding vehicle with 1 leading and 2 following. Then, $C_{.D.s,1}$ represents the solo driving drag coefficient of the lead vehicle, $\Delta C_{Db,1}/C_{Ds,1}$ is the stagnation pressure correction at the rear base of the lead vehicle, $A_{f,1}$ the projected frontal area, and d_{12} the distance of the follower vehicle. The coefficients α and β have been empirically determined in Tadakuma *et al.* (2016) as α = 1.05 and β = 0.2 for sedan-type passenger vehicles. Note that it is important not to double count effects: Although the stagnation pressure is a coupled effect between leader and follower, the drag increasing (negative) effect on the pushing vehicle is completely absorbed in the maximum velocity rate, while the (positive) impact from being pushed is entirely captivated in the drag coefficient correction. The purpose of this study is the creation of a hybrid prediction model for energy savings in a platoon based upon fitting of a simplified physical model to experimental data. Unfortunately, most studies do not publish drag coefficients or frontal areas of the utilized vehicles employed. One solution could be to estimate the corresponding vehicle parameters in Eq. (9) and to only fit α and β to the experimental outcomes. However, we suggest a different approach by decoupling the first two bracketed expressions in Eq. (8) and by collecting all vehicle parameters into one unknown variable, yielding

$$\xi_1 = X_3\left(1-\frac{\Delta C_{Dp,i}}{C_{Ds,i}}\right)^{X_4}\left(d_{i(i+1)}\right)^{-\frac{2}{3}} \tag{10}$$

In order to incorporate Eqs. (9) and (10) into Eq. (4), it should be noted that these velocity drops have been derived for a 2-vehicle combination in which the first vehicle is subject to the speed-corresponding uniform main flow. The ratio $q_{p,i}/q_{s,i}$ in Eq. (4), on the other hand, reflects the ratio of the received dynamic pressure by vehicle *i* in platooning and its dynamic pressure under solo driving. A concatenation of pressure drops would be possible if the ratio of uniform flow equivalent velocities U_{i+1}/U_i were available, including all accumulated effects caused by vehicles in front of the ego vehicle *i*. Yet, this uniform flow equivalent (corresponding to the actually experienced aerodynamic drag) can precisely be determined from the previously calculated DRRs up to vehicle $i-1$. Hence, the concatenation of the velocity drops yields

$$\frac{q_{p,i}}{q_{s,i}} = \left(\frac{U_2}{u_{s,i}}\frac{U_3}{U_2}\dots\frac{U_{i-1}}{U_{i-2}}\frac{u_{w,i}}{U_{i-1}}\right)^2 = (1-DRR_{i-1})(1-\xi_{i-1})^2 \tag{11}$$

Concatenation Correction Factor

As previous considerations have been performed under the assumption of uniform flow, a correction factor accounting for the span-wise parabolic pressure distribution around the centerline of a sedan-type vehicle has been suggested by Tadakuma *et al.* (2016). This correction factor corresponds to an increase of the coefficient of forebody pressure to counteract overestimated wake effects. Yet, the correction value as suggested in Tadakuma *et al.* (2016) is not bounded and exceeds 1 for small inter-vehicle distances. Not only is this a physically inconsistent modification, but it has also been evident that this suggested correction for passenger vehicles is not directly applicable for our approach. However, when concatenating vehicles in a long platoon, a significant dampening factor must be introduced to keep predictions consistent with real data. The heuristic term is more pronounced for short distances. This behavior is potentially due to the considerable differences in aerodynamics between passenger vehicles and heavy-duty trucks with significant unmodeled effects (turbulence) at short distances. As the velocity deficit will be maximum at the center line, the ratio q_p/q_s will overestimate the dynamic drag reduction rate. We achieve excellent results when comparing prediction to actual data from testing with the following concatenation damping for vehicles at position three and higher:

$$\Delta C_{Dc,i} = 1 + \min\left[0.23391,\ X_5 e^{X_6 d_{(i-1)i}}\right] \tag{12}$$

Complete Drag Reduction Model: The unknown ratios q_p/q_s and C_{Dp}/C_{Ds} in Eq. (4) can now be expressed via the correction terms modeled above, yielding the following complete model for the drag reduction rate of the *i*th vehicle in the platoon:

$$DRR_1 = \frac{\Delta C_{Dp,1}}{C_{Ds,1}}$$
$$DRR_2 = 1 - (1 - \xi_{i-1})^2 [1 - \frac{\Delta C_{Dp,2}}{C_{Ds,2}}]$$
$$DRR_i = 1 - (1 - DRR_{(i-1)})\,(1 - \xi_{i-1})^2 (\Delta C_{Dc,i})[1 - \frac{\Delta C_{Dp,i}}{C_{Ds,i}}]$$
$$DRR_N = 1 - (1 - DRR_{(N-1)})\,(1 - \xi_{N-1})^2 (\Delta C_{Dc,N}) \quad (13)$$

3.5 Results

The prediction model in Eq. (13) has been fitted to the results from the SAE J1321 fuel consumption tests, which are summarized in (McAuliffe et al. (2018)). Here, particularly the data from the 2017 3-Truck and 2-Truck, as well as the 2016 3-Truck configurations, have been utilized. As existing on-road tests of heavy trucks only report a reduction in total fuel consumption, data cannot be directly employed for fitting the DRR model. In order to isolate the DRR from total fuel savings, the contribution of the rolling resistance as part of the road load has to be removed, *i.e.*,

$$DRR = FRR \cdot [1 + FR/FD] \quad (14)$$

Here, *FRR* is the published fuel reduction rate (fuel savings) in (McAuliffe et al. (2018)), $F_{.R.}$ corresponds to the load due to rolling resistance, and $F_{.D.}$ is the nominal drag force apparent under solo driving. For the nominal drag force, a frontal area of A_f = 10m^2 has been determined from the truck and trailer combination's specifications (McAuliffe et al. (2018)). No information for the nominal drag coefficient of the utilized truck and trailer combination has been published. Therefore, a low nominal value of C_d = 0.568 has been assumed according to Wong (2008) as the trailers were outfitted with side-skirts and a boat-tail. The international standard atmosphere at sea level and 15 degrees Celsius has been applied for the air density, yielding ρ = 1.225*kg/m*^{3}. For an assessment of the rolling resistance, velocity-dependent (dynamic) components have

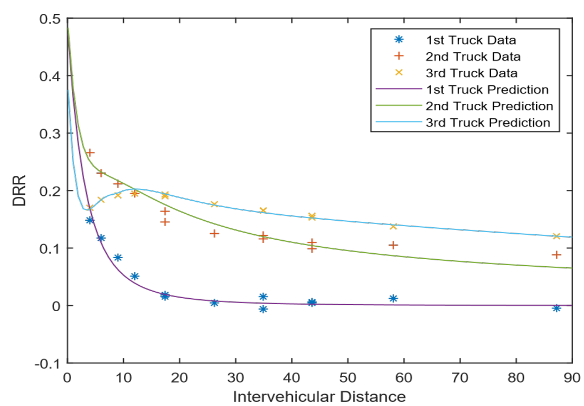


Figure 4 DRR Prediction / Experimental Results

been neglected as their contribution is only a very small fraction compared to the static resistance. A static rolling resistance coefficient of f_0 = 0.0055 has been assumed. Whereas the static rolling resistance coefficient is highly tire and surface dependent and varies widely in literature, this particular choice has been based upon the multi-surface average value in a recent study (Paterlini

(2015)) (mainline cells at 30*mph*). The published vehicle mass of 29,400kg in (McAuliffe et al. (2018)) has been implemented for the necessary normal forces.

In order to render parameter fitting more robust, the experimental data has been preprocessed by a nonlinear transformation to allow for the application of linear least squares. The stagnation pressure coefficients X1 and X2 in Eq. (6) have been determined based solely on lead truck data, as stagnation pressure is the only apparent effect. For the unknown parameters X3 and X4 in Eq. (9), the data for the trailing vehicle in 2-vehicle platoons and the data for the middle vehicle in 3-vehicle platoons have been utilized. The experimental drag reductions have again been preprocessed by a nonlinear transformation and by removing the stagnation pressure effects via the previously fitted Eq. (6). At this point, the residual error between the predicted DRR and the experimental data was examined for the 2nd vehicle. Tadakuma et al. (2016) suggested including a nonuniform flow correction for the drag coefficient in Eq. (4) for small distances as experimental analysis for sedan-type vehicles exhibited a parabolic shape of the actual velocity distribution. Yet, our fitting approach yielded such a small and unstructured residual error that no further inclusion of their unconstrained nonuniform flow correction has been deemed necessary.

Yet, a comparison of the predicted results for the last vehicle in 3-vehicle platoons with the experimental data exhibited discrepancies, as previously discussed in section 2.3. While this discrepancy was initially thought to be of hyperbolic character in accordance with the physical flow models, a semi-logarithmic plot revealed almost perfect exponential character. With the parameters in Eq. (11) fitted to the concatenation error for the 3rd vehicle, the performance of the introduced hybrid prediction model for energy savings in heavy-duty platoons is depicted in Figure 1. Here, the developed prediction model exhibits excellent consistency with the data for 3-vehicle platoons (McAuliffe et al. (2018)). Table 2 summarizes fitted variables and suggestions for all other parameters in Eqs. (2) and (12). To complete the vehicle-specific power model in Eq. (2), we suggest employing an average vehicle mass for simulation in Table 2 based upon the average observed mass of class 9 to class 13 vehicles weighted by their actual distribution on road group J as published in (Schmoyer et al. (1998)). The nominal drag coefficient in Table 2 corresponds to the average value for the different tractor-semitrailer configurations as shown in (Lane et al. 2017).

Table 2 Summary of Fitting Variables and Parameters

X_1	X_2	X_3	X_4	X_5	X_6	m[kg]	$f0$	k	ρ	C_D	A_f [m^2]
0.182	1.521	0.664	8.934	0.337	-0.041	25370	0.005	0.0005	1.22	0.68	10

CHAPTER 4

Conclusions

In this study, we developed and evaluated three models: a platoon formation optimization model, a traffic microsimulation model, and an energy prediction model. The optimization model divides the freeway link into platooning zones, then determines whether or not each vehicle should join a specific platoon within each zone. This determination is based on each vehicle's destination and the estimated energy savings at the macro level. The experimental results indicate that considering the destinations in the vehicle-to-platoon assignment decisions leads to lower total energy savings for the single freeway network. The microsimulation model takes the vehicle-to-platoon assignments as input and simulates the movement and behavior of each platoon and each vehicle using Vissim's car-following model to provide realistic traffic flow and conditions. Each vehicle's location, speed, and destination are recorded from the simulation model and utilized as input to the optimization model every 20 seconds. This iterative process continues for four hours. From observations, it takes two hours before the steady state is reached. Thus, our conclusions are drawn from observations over the last two simulation hours (*i.e.*, in steady-state).

Every 0.5 seconds, detailed vehicle and platooning states are collected from the simulation model, which is subsequently processed utilizing the developed prediction model to determine the energy consumed by each vehicle. Before employing the prediction model for energy consumption estimations, we validated its accuracy through a regression model. The results were encouraging as we demonstrated a significantly improved fit of our prediction model to empirical data compared to other models proposed in the literature. In particular, our analytical prediction model can accurately reproduce empirical results for short inter-vehicle distances where other existing models fail. Furthermore, we included the additional energy required to form and maintain platoons in our assessment which has not been performed in any previous studies. Therefore, a key contribution of this work is the developed energy prediction model that is more applicable to real traffic systems. Its reported energy savings are much more realistic compared to previous studies.

Our numerical experiment results indicate that savings are maximized if the focus lies on forming as many platoons as possible and forming longer platoons. In this study, we limited the platoon size to five vehicles. Still, as part of our future work, we plan to study the impact of platoon size on energy savings and the impact of platoon speed and associated surrounding traffic conditions. In future work, we will allow single vehicles to join any platoon within the platooning zone instead of only considering those platoons currently behind the vehicles. This study considered a network consisting of only the freeway segment. In future work, we plan to extend the analysis to include a network consisting of interstate and non-interstate national highway system routes to better quantify the potential energy savings with platooning at the regional/state level.

REFERENCES

B. McAuliffe, M. Lammert, X. Y. Lu, S. Shladover, M. D. Surcel, and A. Kailas, “Influences on Energy Savings of Heavy Trucks Using Cooperative Adaptive Cruise Control,” SAE Tech. Pap., vol. 2018-April, pp. 1–20, 2018.

C. Bonnet and H. Fritz, “Fuel consumption reduction in a platoon: Experimental results with two electronically coupled trucks at close spacing,” SAE Tech. Pap., no. 724, 2000.

M. P. Lammert, A. Duran, J. Diez, K. Burton, and A. Nicholson, “Effect of Platooning on Fuel Consumption of Class 8 Vehicles Over a Range of Speeds, Following Distances, and Mass,” SAE Int. J. Commer. Veh., vol. 7, no. 2, pp. 626–639, 2014.

A. Al Alam, A. Gattami, and K. H. Johansson, “An experimental study on the fuel reduction potential of heavy duty vehicle platooning,” IEEE Conf. Intell. Transp. Syst. Proceedings, ITSC, pp. 306–311, 2010.

M. Muratori, J. Holden, M. Lammert, A. Duran, S. Young, and J. Gonder, “Potentials for platooning in U.S. highway freight transport,” SAE Int. J. Commer. Veh., vol. 10, no. 1, pp. 45–49, 2017.

K. Tadakuma, T. Doi, M. Shida, and K. Maeda, “Prediction formula of Aerodynamic Drag Reduction in MultipleVehicle Platooning Based on Wake Analysis and On-Road Experiments,” SAE Int. J. Passeng. Cars - Mech. Syst., vol. 9, no. 2, 2016.

M. Barth, F. An, J. Norbeck, and M. Ross, “Modal emissions modeling: A physical approach,” Transp. Res. Rec., no. 1520, pp. 81–88, 1996.

H. Rakha, K. Ahn, and A. Trani, “Development of VT-Micro model for estimating hot stabilized light duty vehicle and truck emissions,” Transp. Res. Part D Transp. Environ., vol. 9, no. 1, pp. 49–74, 2004.

A. Brooker, J. Gonder, L. Wang, E. Wood, S. Lopp, and L. Ramroth, “FASTSim: A Model to Estimate Vehicle Efficiency, Cost and Performance,” SAE Tech. Pap., vol. 2015-April, no. April, pp. 21–23, 2015.

S. Halbach, P. Sharer, S. Pagerit, A. P. Rousseau, and C. Folkerts, “Model architecture, methods, and interfaces for efficient math-based design and simulation of automotive control systems,” SAE Tech. Pap., 2010.

A. Rousseau, S. Halbach, L. Michaels, N. Shidore, N. Kim, N. Kim, D. Karbowski, and M. Kropinski, Electric drive vehicle development and evaluation using system simulation. IFAC, 2014, vol. 19, no. 3. [Online]. Available: http://dx.doi.org/10.3182/20140824-6-ZA-1003.02832

B. Lane, B. Shaffer, and G. S. Samuelsen, “Plug-in fuel cell electric vehicles: A California case study,” Int. J. Hydrogen Energy, vol. 42, no. 20, pp. 14294–14300, 2017. [Online]. Available: http://dx.doi.org/10.1016/j.ijhydene.2017.03.035

J. Y. Wong, Theory of ground vehicles. Hoboken, N.J: Wiley, 2008.

S. Zhang, L. Yu, and G. Song, “Emissions characteristics for heavy-duty diesel trucks under different loads based on vehicle-specific power,” Transp. Res. Rec., vol. 2627, pp. 77–85, 2017.

G. Paterlini, “Rolling resistance validation,” Minnesota Department of Transportation, Tech. Rep., July 2015.

R. Schmoyer, P. S. Hu, and P. Swank, Analysis of vehicle classification and truck weight data of the New England states. Oak Ridge National Laboratory, 1998.

R. Kunze, R. Ramakers, K. Henning, & S. Jeschke. Organization and operation of electronically coupled truck platoons on German Motorways. In International Conference on Intelligent Robotics and Applications (pp. 135-146). Springer Berlin Heidelberg, 2009.

S. Tsugawa. Results and issues of an automated truck platoon within the energy ITS project. In Intelligent Vehicles Symposium Proceedings, 2014 IEEE (pp. 642-647). IEEE.

F. Browand, J. McArthur, J., & C. Radovich. Fuel saving achieved in the field test of two tandem trucks. California Partners for Advanced Transit and Highways (PATH), 2004.

C. Bonnet & H. Fritz. Fuel consumption reduction in a platoon: Experimental results with two electronically coupled trucks at close spacing (No. 2000-01-3056). SAE Technical Paper, 2000.

S. Tsugawa. An overview on an automated truck platoon within the energy ITS project. IFAC Proceedings Volumes, 46(21), 41-46, 2013.

S. Tsugawa, S. Kato, & K. Aoki. An automated truck platoon for energy saving. In Intelligent Robots and Systems (IROS), 2011 IEEE/RSJ International Conference on (pp. 4109-4114). IEEE, 2011.

J. Larson, C. Kammer, K. Y. Liang, & K. H. Johansson. Coordinated route optimization for heavy-duty vehicle platoons. In 16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013) (pp. 1196-1202). IEEE, 2013.

T. S. Dao, J. P. Huissoon, & C.M. Clark. A strategy for optimization of cooperative platoon formation. International Journal of Vehicle Information and Communication Systems, 3(1), 28-43, 2013.

T. S. Dao, C. M. Clark, & J. P. Huissoon. Distributed platoon assignment and lane selection for traffic flow optimization. In 2008 IEEE Intelligent Vehicles Symposium (pp. 739-744). IEEE, 2008.

D. Liu, B. Eksioglu, M. J. Schmid, N, Huynh, & G. Comert. Optimizing energy savings for a fleet of commercial autonomous trucks. IEEE Transactions on Intelligent Transportation Systems. 2021 Apr 16.

M. J. Schmid, D. Liu, B. Eksioglu, N. Huynh, & G. Comert. Prediction Model for Energy Consumption in Heavy-Duty Vehicle Formations. In IIE Annual Conference. Proceedings 2020 (pp. 1176-1181). Institute of Industrial and Systems Engineers (IISE).

D. Liu, B. Eksioglu, M. J. Schmid, N. Huynh, & G. Comert. Simulation-Optimization Platooning Model for of a Fleet of Commercial Autonomous Trucks. In IIE Annual Conference. Proceedings 2020 (pp. 1-6). Institute of Industrial and Systems Engineers (IISE).

D. Liu. Optimizing Energy Savings for a Fleet of Commercial Autonomous Vehicles via Centralized and Decentralized Platooning Decisions (Doctoral dissertation, Clemson University), 2020.