## Title

# A Tool to Predict Fleet-Wide Heavy-Duty Vehicle Fuel-Saving Benefits from Low Rolling Resistance Tires



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October 2018

A Research Report from the National Center for Sustainable Transportation

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## U.S. Department of Transportation (USDOT) Disclaimer



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## EXECUTIVE SUMMARY

The cost of fuel represents a major portion of the costs of operating on-road heavy-duty vehicles (HDV). According to the American Transportation Research Institute, fuel costs alone amounted to about 25 percent of truck operating costs in 2015. Within the U.S. on-road transportation sector HDVs consume a disproportionately high amount of the total refined petroleum-based fuel and carbon dioxide emissions from consumption of this fuel were estimated to be equivalent to over 400 million metric tons. HDVs also contributed a disproportionately high 2.5 million short tons of Oxides of Nitrogen (NOx) emissions, emitted as a by-product of fuel combustion in on-road vehicle engines. NOx is a precursor of ozone, which is an air pollutant harmful to humans, plants, and animals. Over the next couple of decades, the total energy demand from the HDV sector will likely increase due to forecasted growth in freight demand in many global markets, including the United States, and much of this energy will continue to be provided by fossil fuels. Therefore, carbon dioxide emissions from the HDV sector are also expected to increase in the absence of effective mitigating measures to reduce the sectors reliance on fossil fuels.

Along with other fuel-saving technologies, the United States Environmental Protection Agency identified the use of Low Rolling Resistance (LRR) tires as an effective method of reducing fuel consumption. It is estimated that LRR tires can improve fuel economy in HDV by about 10 percent. However, adoption of LRR faces many barriers and the most fundamental of these barriers relate to potential performance uncertainties under real-world operating conditions. Previous published decision support tools developed to help fleet operators and other stakeholders estimate the fuel-savings from LRR tires have been found to have limited accuracy due to inherent transient speed profiles in real-world operating cycles.

In this study, we develop a tool to predict the fleet-wide fuel-saving benefits from low rolling resistance tires. Unlike previous studies, the developed tool is applicable to both stabilized speed operations and transient speed operations. The tool is based on empirical models that estimate the fuel consumption contribution from tires as a function of vehicle payload, aerodynamic drag, road grade, duration of acceleration, duration of deceleration and, and road facility type (freeway, major arterial, and minor arterial/local road). We limited the scope of the developed tool to tractor-trailers in the U.S. heavy-duty vehicle market, because the United States has the second largest HDV market in the world and tractor-trailers account for the largest share of the market. The tool was developed with data generated by simulating real-world heavy-duty vehicle operating cycles with Autonomie®, the state-of-the-art model for automotive control-system design, and simulating vehicle energy consumption and performance. Autonomie® is a preferred vehicle simulation tool of the United States Department of Energy.

The primary purpose of the Tool to Predict Fleet-Wide Heavy-Duty Vehicle Fuel-Saving from Low Rolling Resistance Tires is to assist fleet operators, regulatory agencies, and policy analysts in assessing the fuel consumption savings from low rolling resistance tires. To facilitate ease-of-use by stakeholders, the statistical empirical models are embedded in a Microsoft Excel® spreadsheet. Fleet managers can customize the tool to their specific fleet and the tool is designed to inform fleet operators about the benefits and costs of making low rolling resistance tire investments. In addition to fuel consumption estimates, the spreadsheet tool further estimates related emission reductions. In the future, this tool can be extended to other vehicle segments. The spreadsheet algorithms can also be developed into a web-based computer program in the future to facilitate online use of the tool.

The HDV Low Rolling Resistance Tire Fuel and Emission Reduction Calculator is available to download as a spreadsheet tool here: http://transportation.ce.gatech.edu/node/95

## 1. Introduction

**In 2015 the U.S. transportation sector consumed over 70 percent of the total domestic demand for refined petroleum-based fuels, and among on-road vehicles this fuel was mainly used to meet the energy demands of light-duty vehicles (LDV) and heavy-duty vehicles (HDV) (*1*). Despite accounting for only about 4.2 percent of total on-road vehicle population and 9 percent of total vehicle-miles traveled, combination trucks and six-wheeler single-unit trucks, consume a disproportionate 16.8 percent of the total fuel (Figure 1). The cost of fuel represents a major portion of the costs of operating HDVs (**

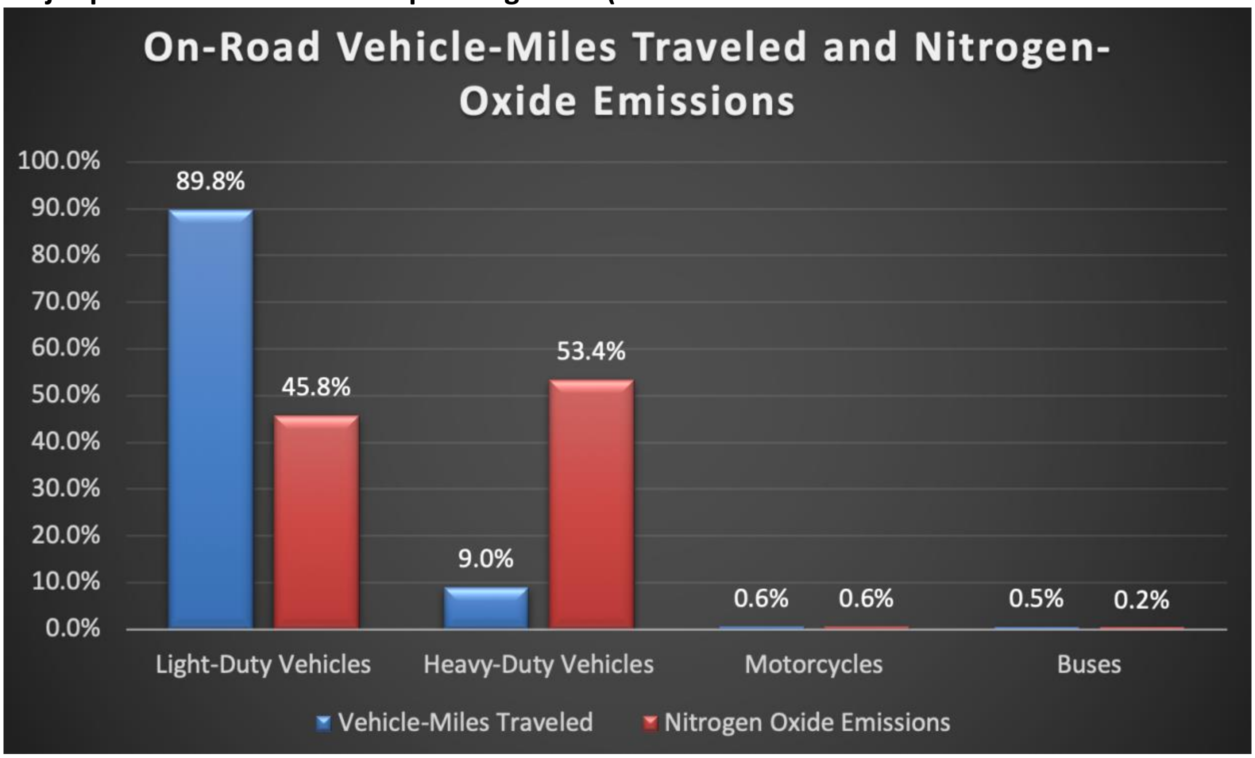


**Figure 2. On-Road Vehicle-Miles Traveled and Oxides of Nitrogen Emissions** (U.S. DOE (*1*))

Table 1) and HDVs emit 53.4 percent of total oxides of nitrogen (Figure 2), an important by-product of fuel combustion in on-road vehicle engines which react with volatile organic compounds in the atmosphere to produce ozone. Ozone is an air pollutant harmful to humans, animals, and plants. Carbon dioxide ($CO_2$) emissions from consumption of this fuel are also a major contributor to overall greenhouse gas emissions. In the United States, fuel consumption in the transportation sector contributes about 27 percent of total human-related emissions (*2*). Within the transportation sector HDVs, are the second largest contributor (Figure 3) to these emissions and were estimated to be equivalent to 402 million metric tons of carbon dioxide in 2015 (*1*).

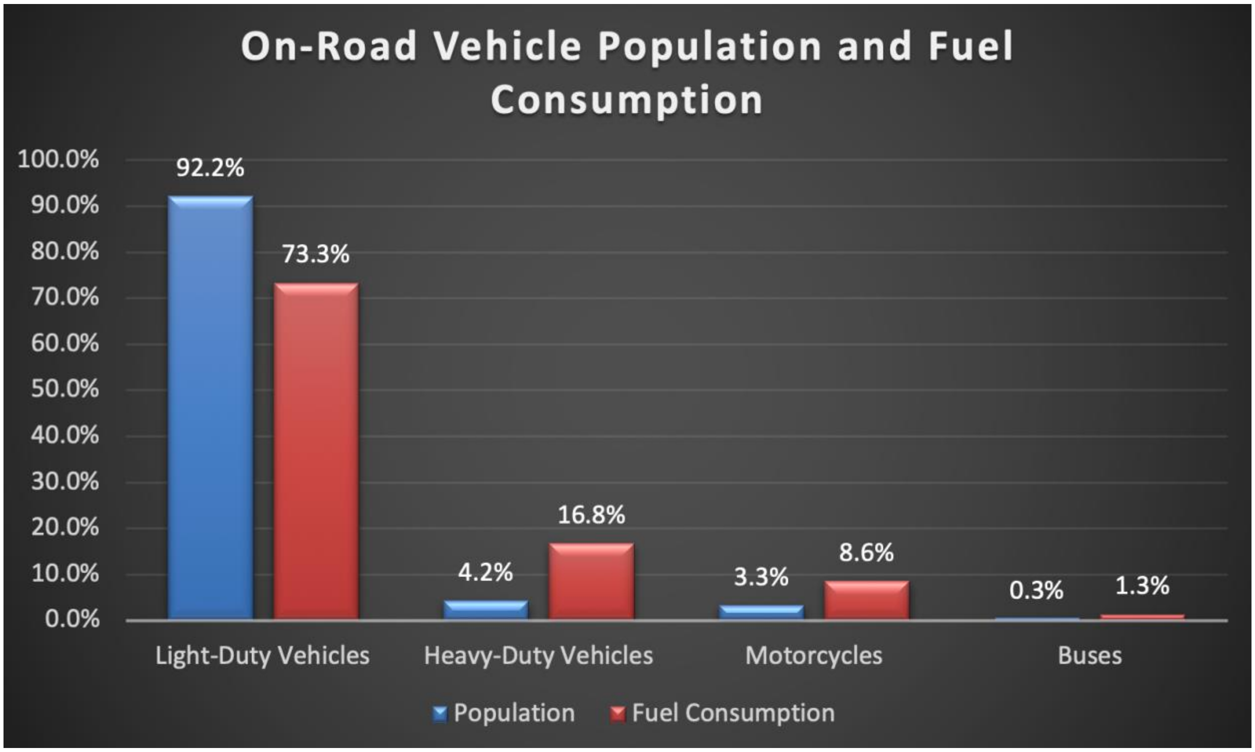


**Figure 1. On-Road Vehicle Population and Fuel Consumption** (U.S. DOE (*1*))

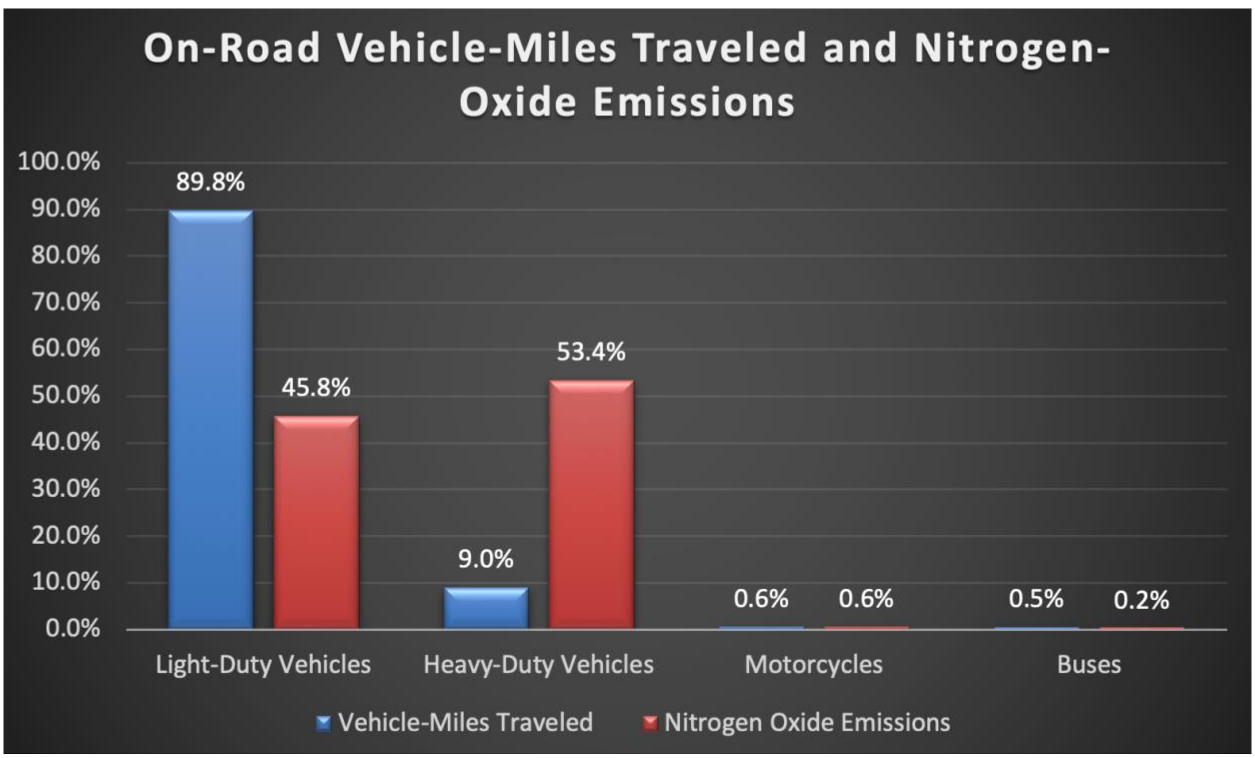


**Figure 2. On-Road Vehicle-Miles Traveled and Oxides of Nitrogen Emissions** (U.S. DOE (*1*))

**Table 1. Share of Total Average Marginal Motor Carrier Costs (ATRI (*3*))**

| Type of Cost | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
|---|---|---|---|---|---|---|---|---|
| Fuel Costs | 38% | 28% | 31% | 35% | 39% | 38% | 34% | 25% |
| Truck Trailer Lease or Purchase Payments | 13% | 18% | 12% | 11% | 11% | 10% | 13% | 14% |
| Repair & Maintenance | 6% | 8% | 8% | 9% | 8% | 9% | 9% | 10% |
| Truck Insurance Premiums | 3% | 4% | 4% | 4% | 4% | 4% | 4% | 6% |
| Permits and Licenses | 1% | 2% | 3% | 2% | 1% | 2% | 1% | 1% |
| Tires | 2% | 2% | 2% | 2% | 3% | 2% | 3% | 3% |
| Tolls | 1% | 2% | 1% | 1% | 1% | 1% | 1% | 1% |
| Driver Wages | 26% | 28% | 29% | 27% | 26% | 26% | 27% | 31% |
| Driver Benefits | 9% | 9% | 10% | 9% | 7% | 8% | 8% | 8% |

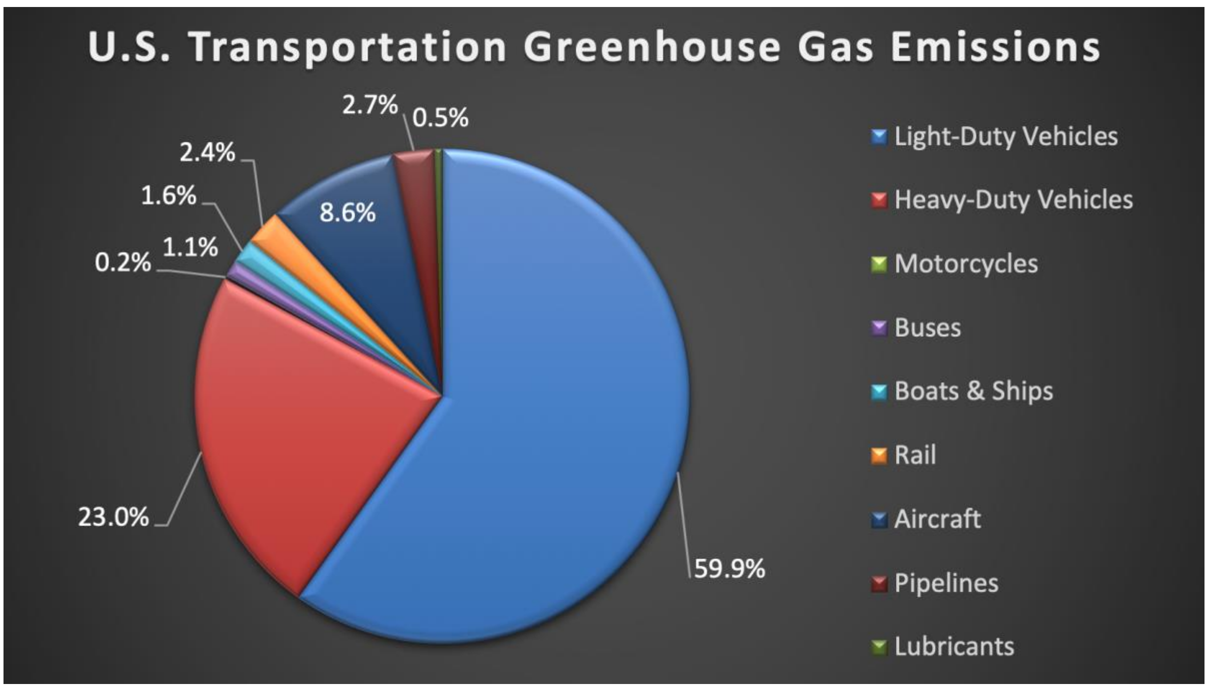


**Figure 3. U.S. Transportation Greenhouse Gas Emission by Vehicle Type (USEPA (*4*))**

Energy consumption by the HDV sector is expected to increase beyond the next decade due to projected growth in freight demand in many global markets, including the United States, and much of this energy will continue to be provided by fossil fuels. To mitigate these impacts, the U.S. Environmental Protection Agency (USEPA) proposed Phase 1 fuel efficiency standards in 2011 to encourage manufacturers to adopt fuel-saving technologies in designing engines, chassis, tires, and other components (*5*). Phase 2 fuel efficiency standards were proposed in

2015 to further encourage vehicle manufacturers to incorporate advanced fuel-saving technologies (*6*).

Along with other technologies, the USEPA identified the use of low rolling resistance tires (*7*) as an effective method of reducing fuel consumption. Rolling resistance is energy lost by vehicles due to the tires rolling on the road pavement. Light-duty vehicles and heavy-duty vehicles use approximately 3–11 percent and 15–30 percent of their fuel consumption to overcome rolling resistance (*8*). Installing low rolling resistance tires can improve fuel economy by about 3 percent and 10 percent for light-duty vehicles and heavy-duty vehicles respectively. However, adoption of the low rolling resistance (LRR) tire is faced with many barriers with the most fundamental being potential performance uncertainties under real-world operating conditions (*9*).

In this study, researchers developed a tool to predict the fleet-wide fuel-saving benefits from low rolling resistance tires. The tool is developed using data from real-world heavy-duty vehicle operating cycles. The tool offers fleet operators the flexibility to customize it to their specific fleet. The tool is designed to inform fleet operators about the benefits and costs of making low rolling resistance tire investments. The researchers limited the scope of the developed tool to tractor-trailers in the U.S. heavy-duty vehicle market, because the United States has the second largest HDV market in the world and tractor-trailers account for the largest market share (*6*). In the future, this tool can be extended to other vehicle classes.

The following section (Section 2) provides a literature review of the impact of low rolling resistance tires on vehicle fuel efficiency as well as the simulation tool used in this study. The main data inputs and the methodology for quantifying fuel-savings at different technology levels are presented in Section 3 and Section 4 respectively. The results of the simulation, developed empirical statistical models, and accompanying Microsoft Excel® spreadsheet based predicting tool are discussed in Section 5. The report then addresses model verification in Section 6 and concludes with a summary of results and recommendations in Section 7.

## 2. Literature Review

### 2.1. Tire Rolling Resistance

A tire's rolling resistance can be defined as "the energy consumed per unit distance of travel as a tire rolls under load" (*10*). Willet (*11*) explains that the energy loss occurs mostly through four mechanisms: 1) hysteretic loss within the tire, 2) inertial distortion of the tire, 3) aerodynamic drag, and 4) friction developed between the tire and the road surface. The most important contributors are hysteretic losses and inertial distortion. Hysteretic losses are due to the viscoelasticity character of the tire components and is relatively independent of speed. Inertial distortions arise from additional distortions at high speeds and can be considered negligible at speeds less than 56 miles per hour (mph). The contribution of aerodynamic drag is largely dependent on the size of the tires and becomes more important as speed increases. The friction developed between the tire and the road is insignificant compared to total rolling resistance under non-abrasive conditions. Therefore, Willet (*11*) states that the total rolling resistance of a tire can be represented by Equation 1:

$$\omega = \beta + \gamma \ldots\ldots (1)$$

Where: β is the rolling resistance due to hysteretic losses and γ is the rolling resistance due to inertial distortion of the tire. Many previous studies have shown that rolling resistance is linearly related to the vertical load on a tire (*10*). Hence, a tire's rolling resistance is commonly represented by a *Coefficient of Rolling Resistance* (CRR), representing the ratio of rolling resistance force over vertical load (kg/metric ton) in the ISO 28580 test (*12*). The USEPA uses the CRR to represent the low rolling resistance technology for simulation purposes.

### 2.2. Tire Rolling Resistance vs. Fuel Efficiency

Rolling resistance of tires greatly impacts fuel efficiency performance of HDVs due to the usually high loads on their tires. Up to 15-30 percent of overall vehicle energy consumption for a Class 8 tractor-trailer may be dedicated to overcoming tire rolling resistance (*8*). The fuel-saving benefits of low rolling resistance tires will differ significantly between fully-loaded and partially-loaded trucks, given the linear relationship between rolling resistance and overall vehicle weight. Furthermore, for the same type of tires, fleet operators may experience a wide range of fuel efficiency improvement levels due to differences in vehicle specifications and duty cycles.

The effectiveness of low rolling resistance tires depends on several variables, such as vehicle specifications, payloads, routes (e.g. flat or hilly terrain), and operating duty cycles (*9*). A sound and easily applicable methodology that captures the influences of these fleet-specific operating variables is needed to minimize market barriers and significantly increase the adoption of low rolling resistance tires by fleet operators. However, few studies (if any at all) have reported such capabilities. Instead most previous studies report a general value, e.g. 3% fuel-savings for combination long-haul trucks if using low rolling resistance tires as compared with conventional tires *(13)*.

Hall and Moreland propose the use of a return factor, i.e., a percentage change in fuel consumption corresponding to the percentage change in rolling resistance (*10*). However, a return factor that ignores the specificity of fleets would not be appropriate due to diversity of vehicle characteristics and fleet operations (*11*). For example, studies show that both driving cycles and difference in vehicle specifications can cause an 8–18 percent variation in the contribution of rolling resistance to overall fuel consumption (*10*). Such a wide variation may arise because low rolling resistance tires increase the total braking force required to fulfil the driving cycle. Therefore, the fuel-saving effectiveness can also be reduced during the braking portions of the trip.

Barrand and Bokar developed the *Empirical Law* to predict fuel-saving benefits. Their analysis considered tire rolling resistance, vehicle weight, and engine fuel type (*14*). The authors performed vehicle fuel economy simulations using the version 3.1 of AVL Cruise® software. They simulated 14 different vehicles ranging from passenger cars to heavy-duty trucks on both standardized cycles and real-world cycles collected with a global positioning system (GPS) device. The vehicles had different combinations of fuel type, rated power, and transmission. The authors estimated the average rolling resistance of each vehicle by weighting each tire's CRR by the vertical load on the tire. They measured the fuel savings in liters per 100 kilometers (L/100km). The *Empirical Law* developed by Barrand and Bokar is shown below in Equation 2 (*14*).

$$\Delta B_e = \alpha * m * \Delta f \dots \dots \dots (2)$$

Where: Δf is the difference in rolling resistance, m is the mass of the vehicle and α is a correlation coefficient which depends primarily on the fuel type (gasoline/diesel) and only slightly on the cycle. The authors verified their model with actual fuel-saving measurements by: 1) using two passenger cars and three tire types in coast down tests from 120 km/h to 20km/h on a track, and 2) using one heavy-duty truck and two tire types with the truck rolling at 80 km/h. Both verification tests did not involve transient speed conditions and hard accelerations. Unsurprisingly, the estimates from the *Empirical Law* were found by Guillou and Bradley (*15*) to have limited accuracy outside of stabilized speed operations.

In another study (*16*)*,* the authors developed a tool using Matlab/Simulink® software to predict fuel consumption for different driving cycles, powertrain configurations, and rolling resistance percentage reductions. Fuel consumption and rolling resistance were measured on a chassis dynamometer as well as a real-world track under constant speed conditions and the European Transient Cycle (*17*). The European Transient Cycle is a transient cycle including urban, rural, and motorway driving conditions. The fuel consumption was measured with the help of flow meters installed on the vehicle. Among other research tasks, the authors checked the *Empirical Law* proposed by Barrand and Bokar (*14*). Their results showed that under constant high speed heavy-duty tractor driving conditions, there is a much better agreement between the correlation coefficient (α) and their simulation model and real-world track test. Higher variation existed in the coefficient at constant low speed conditions and in the European Transient Cycle. This observation is due to lower engine efficiency at lower speeds and in transient cycles.

Therefore, they advise that the real vehicle behavior must be modeled to accurately predict effective fuel consumption. Note that the Matlab/Simulink® tool developed by Mammetti et al. (*16*) outperforms the basic *Empirical Law* (*14*). However, it is data intensive and requires inputs which may not be readily available to fleet operators.

The best method to accurately measure fuel-saving benefits due to the use of low rolling resistance tires would require vehicle instrumentation technologies where measurement of fuel consumption is done *in-situ* by flow meters as the vehicle is in operation. However, such an approach is very time-consuming and cost-intensive. Generating enough data to develop a robust tool that can be applied to multiple vehicle specifications, driving cycles, and roadway conditions would be very costly. The best alternative is to generate the data using a simulation tool that models vehicle energy consumption. The ideal simulation tool must be able to take various data inputs to realistically model vehicle technologies (including engine efficiency, powertrain, and control technologies, etc.) and operating conditions (driving cycle, route characteristics, payloads, etc.). This approach can result in a more robust empirical model-based tool that gives a reasonable approximation of real-world fuel consumption without the need for intensive and sophisticated data requirements that may not be readily available to fleet operators.

## 2.3. Simulation Tool

Autonomie® is the state-of-the-art model for automotive control-system design, and simulating vehicle energy consumption and performance. Previously known as PSAT, Autonomie® was developed by Argonne National Laboratory (ANL) in collaboration with General Motors. Autonomie® is the primary vehicle simulation tool selected by the United States Department of Energy to support its U.S. DRIVE Program and Vehicle Technologies Office (VTO). Autonomie® runs in a Matlab® software environment and can be easily integrated into several third-party tools including economic and environmental models like component cost, LCOD, and GREET (*18*).

Autonomie® can incorporate a variety of vehicle classes (light-duty vehicles and heavy-duty vehicles), and powertrain configurations (conventional, start-stop, battery electric vehicles, parallel hybrid electric vehicles, series hybrid electric vehicles, fuel cell hybrid electric vehicles, etc.). Autonomie® also covers a variety of fuel types, such as gasoline, diesel, E-85, CNG, hydrogen, and electricity. Autonomie® is user-friendly and offers many customizable settings including environment, driver, vehicle propulsion architecture, vehicle propulsion controller for advanced powertrain vehicles, etc. Additionally, data can be readily visualized and/or post-processed in Matlab®. Autonomie® can output a high-resolution energy consumption data for each second of a trip for the entire vehicle and/or the component parts, such as engines and tires. Many recent published studies assessing heavy-duty fuel consumption have relied on Autonomie® for simulation purposes; Daw et al. (*19*) simulated fuel economy and emissions performance of heavy-duty hybrid trucks during city and interstate driving; Delgado and Lutsey (*20*) examined potential efficiency of advanced tractor-trailers in the 2020–2030 timeframe; Delgado et al. (*21*) used Autonomie® to estimate the fuel efficiency technology potential of heavy-duty trucks in major markets around the world; and Delgado and Li (*22*) analyzed the fuel efficiency technology potential of heavy-duty vehicles in the Chinese market. Based on its established versatility and capabilities, the researchers in this study used Autonomie® to generate data on the impact of rolling resistance changes on HDV fuel consumption. This data was then used to develop a robust empirical model-based tool to predict fuel-savings from using low rolling resistance tires on U.S. tractor-trailers.

## 3. Data

The researchers used second-by-second speed and location data to model actual vehicle operations. This data were originally collected and stored in the Georgia Tech Freight Data Collector system in 2009 (*23*). The data were collected using GPS devices installed on commercial tractor-trailers serving a chain of grocery stores in the Atlanta metropolitan area. The data cover three days of distribution trips by the trucks. Further information about the data collection system as well as the deployment plan can be found in Wood (2010) (*24*).

The researchers analyzed the data and segmented it by: 1) vehicle ID, 2) vehicle deployment ID, 3) extended periods of missing GPS data, 4) periods of on-road movement, and 5) periods of truck loading and unloading. Trip portions with extended periods of missing GPS data were omitted from the analysis. The data analyses identified a total of 85 trips and their characteristics by distance, duration, and average speed are summarized in Table 2 and **Error! Reference source not found.**. Figure 5 shows the spatial distribution of the trips on the metro Atlanta road network.

**Table 2. Characteristics of Trips used in Study**

| | Distance (mile) | Duration (hour) | Average Speed (mph) |
|---|---|---|---|
| Minimum | 16 | 0.5 | 17 |
| Maximum | 121 | 4 | 57 |
| All Trips | 3,411 | 107 | 32 |

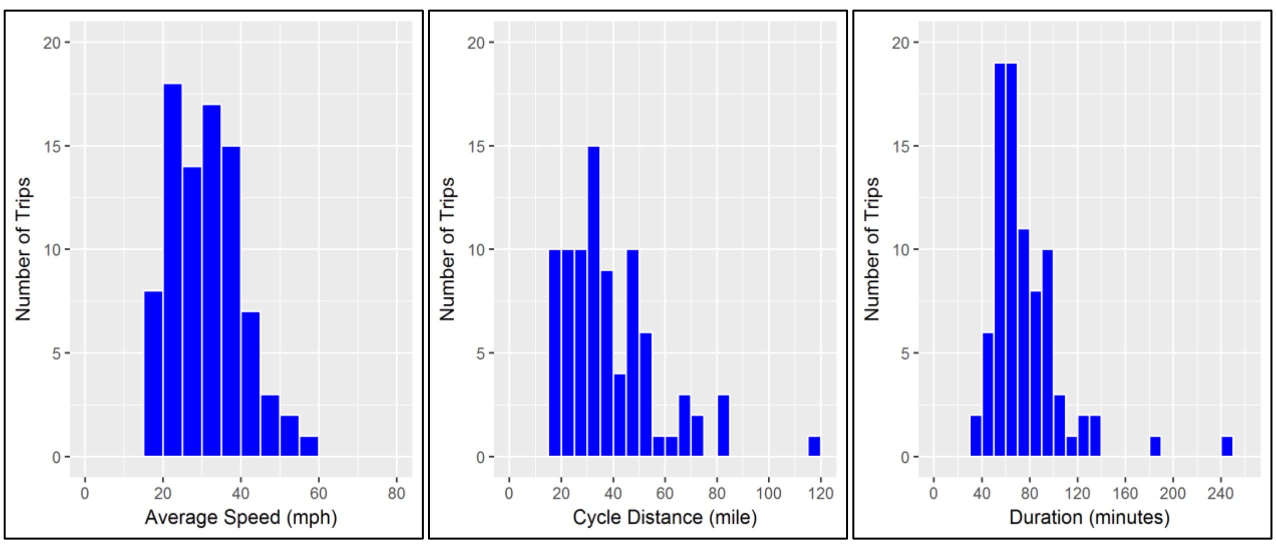


**Figure 4. Number of Trips by Average Speed, Distance, and Duration**

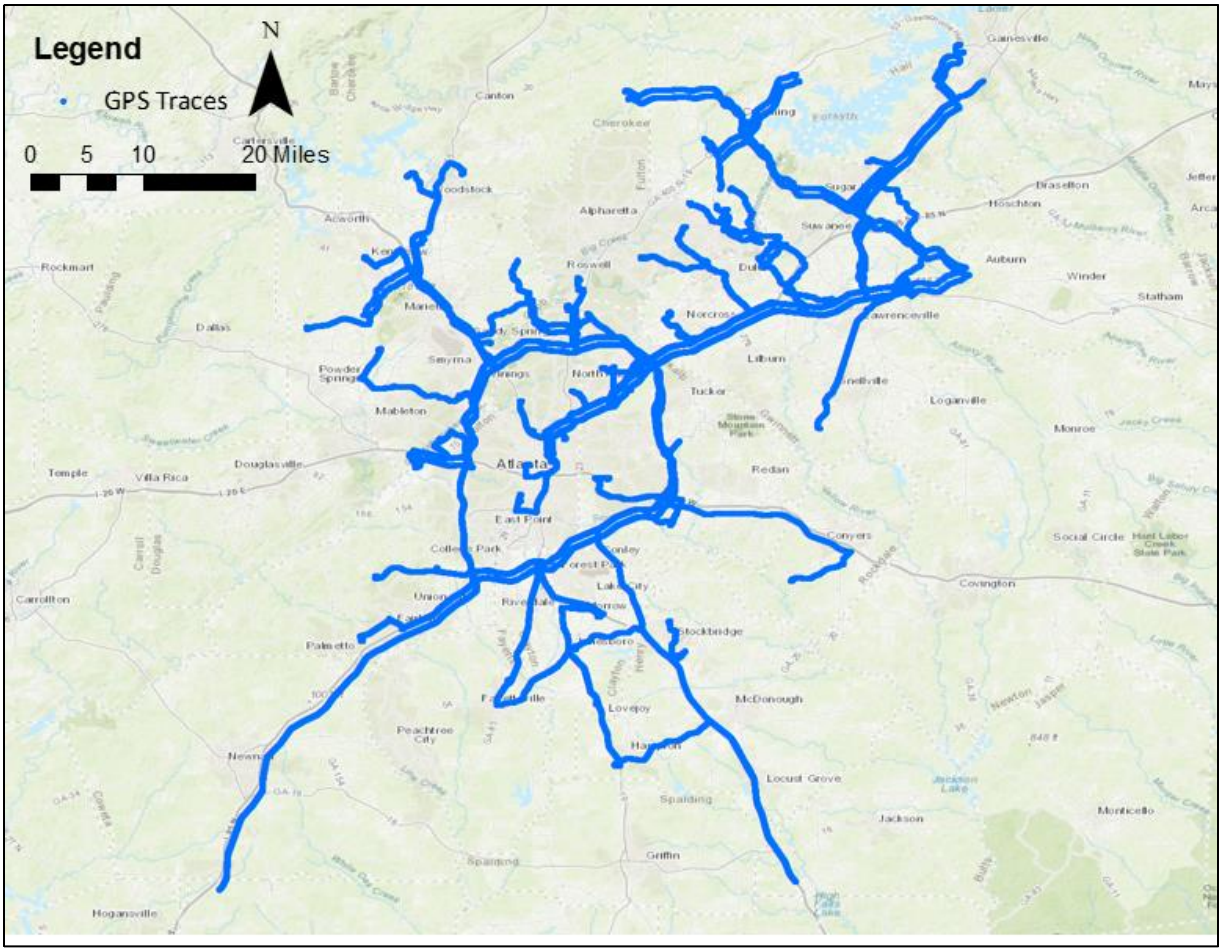


**Figure 5. Spatial Coverage of Collected Trailer Tractor Operations Data in Metro Atlanta**

## 4. Methodology

This study developed a tool to predict fleet-wide fuel-saving benefits from low rolling resistance tires based on simulation and empirical models. Figure 6 illustrates the methodology used to develop the fuel-saving prediction tool. The methodology includes four main steps (data input and pre-processing, simulation, model development, and tool development) as explained below.

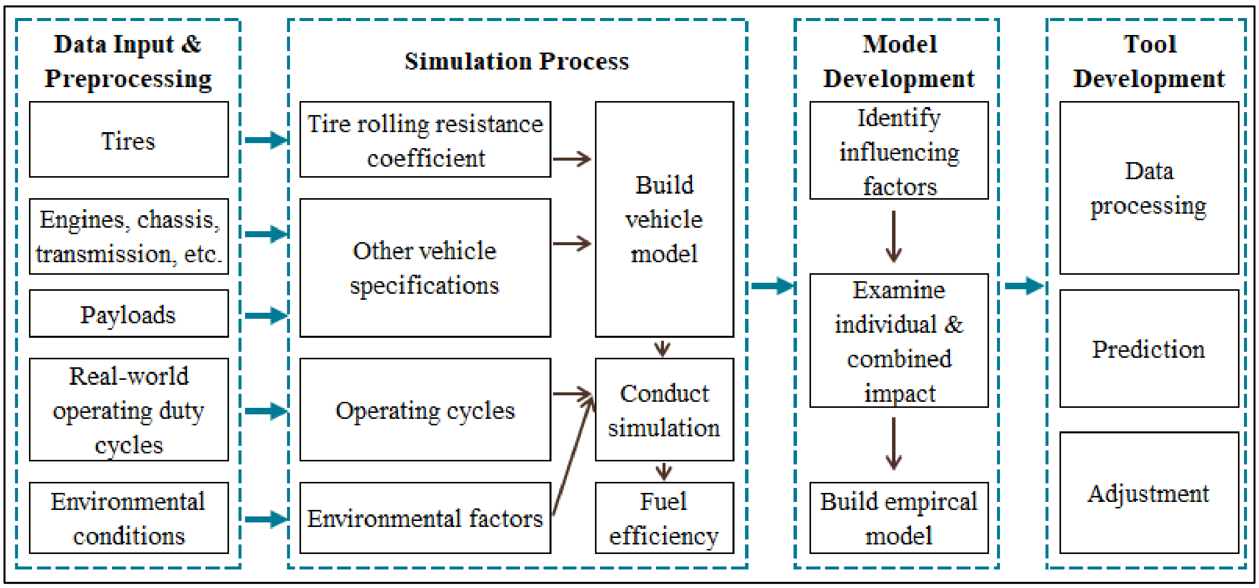


**Figure 6. Methodology Flowchart**

a) **Step 1 - Data Input & Preprocessing:** This step processes the fleet-wide vehicle characteristics and operations data into the required input format for Autonomie®. Some of the required data sets include vehicle specifications, operations (payload and duty cycles), and environmental conditions (roadway terrain).

b) **Step 2 - Simulation**: This step conducts the simulations with Autonomie®. It takes as input the data processed from step 1. This methodology uses the CRR to represent the different levels of low rolling resistance tires, because CRR is a factor in the decision-making for consumers and it can be used as an input in simulations (*25*). This step outputs the fuel efficiency performance, in L/100km and L/t-100km, corresponding to different CRR levels. The researchers conducted extensive simulations to obtain the fuel efficiency performance for different combinations of vehicle specifications, fleet operations, and environmental conditions.

c) **Step 3 - Model Development:** This step uses the data generated from Step 2 to build empirical models to predict fuel-saving benefits based on vehicle specifications, operations, and environmental conditions. First, the researchers employed statistical analysis to identify the key individual and combined factors that influence the fuel-saving benefits. The empirical models were then constructed using the factors identified.

d) **Step 4 - Tool Development:** This step develops a Microsoft Excel® spreadsheet-based tool incorporating the empirical models developed in Step 3. The spreadsheet facilitates ease-of-use by fleet operators and other stakeholders. The tool consists of three main modules:

    1) Data processing: Includes data quality assurance and quality control (QA/QC), and formatting of fleet-wide vehicle characteristics and real-world operations data into a form required by the empirical model.
    2) Prediction: This employs the empirical models developed in the previous step to predict the fleet-wide fuel-saving benefits.
    3) Adjustment: Provides a post-processing subcomponent that may be useful, depending on the eventual performance of the empirical model.

## 4.1. Operating Cycle Generation

Operating cycles are created based on the collected second-by-second GPS data from the HDVs described earlier. GPS data collected from vehicle monitoring requires a series of pre-processing steps before they can be input into the simulation model. The details of these steps are described below.

### *4.1.1. Correcting Erroneous Speed Data*

The GPS data were subjected to a rigorous quality assurance/quality control (QA/QC) procedure before inputting the GPS data into the simulation software. The QA/QC process uses a cubic spline smoothing algorithm to identify instances along moving sections of the trip where there was a loss of GPS signal. Such instances typically appear in monitored data as zero-speed data points. Figure 7 (a) shows sample raw speed trajectory with GPS drop-outs. The points of GPS drop-outs are shown in red. Figure 7 (b) shows the corrected speed trajectory data set with points of GPS drop-outs adjusted into the shape of the observed speed trajectory.

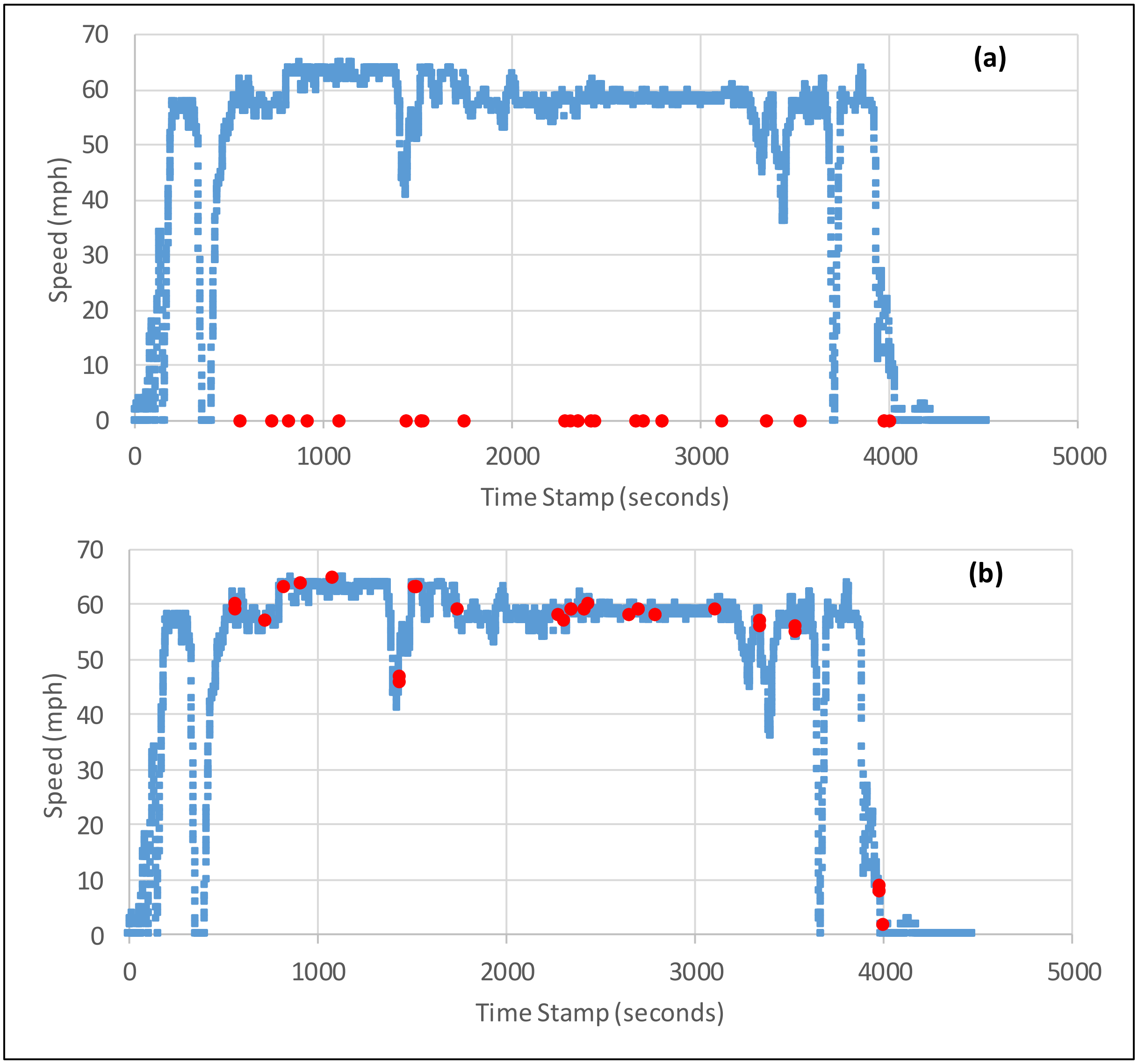


**Figure 7. (a) Sample Raw HDV Speed Trajectory; (b) Sample Corrected HDV Speed Trajectory**

### *4.1.2. Road Grade Assignment*

Road grade is an an important contributor to vehicle fuel consumption, especially for heavy-duty vehicles. However, only a few published studies have been able to consider the impact of road grade, due to the lack of available realworld road grade data. A team of researchers from the Georgia Institute of Technology have developed a streamlined method to extract and process roadway elevation profile from the United States Geological Survey's Digital Elevation Model (DEM) database (*26*). Their method generates road grade at high-resolution, with root mean-square error (RMSE) of 0.20%-0.23% for highways and 0.5-0.6% for local roads. The researchers in this study applied this method to the collected GPS second-by-second vehicle operations data and extracted the corresponding road grade information. Figure 8 shows an example of an extracted road grade profile.

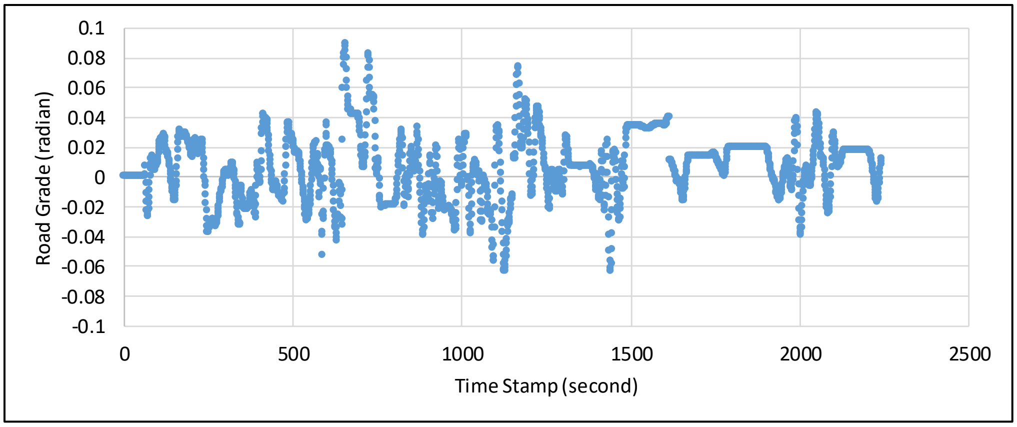


**Figure 8. Example of an Extracted Road Grade Profile**

Figure 9 shows the distribution of grade information for the cycles in terms of average value of grade and average absolute grade. Average grade is calculated as the average of road grade value per second across the cycle, while average absolute grade is calculated as the average of road grade absolute value. We can see that most of the segments fall within an overall grade of 0.01 radians. However, some have more undulating grade profile with average absolute grade over 0.02 radians, whereas some are mostly flat with average absolute grade close to zero.

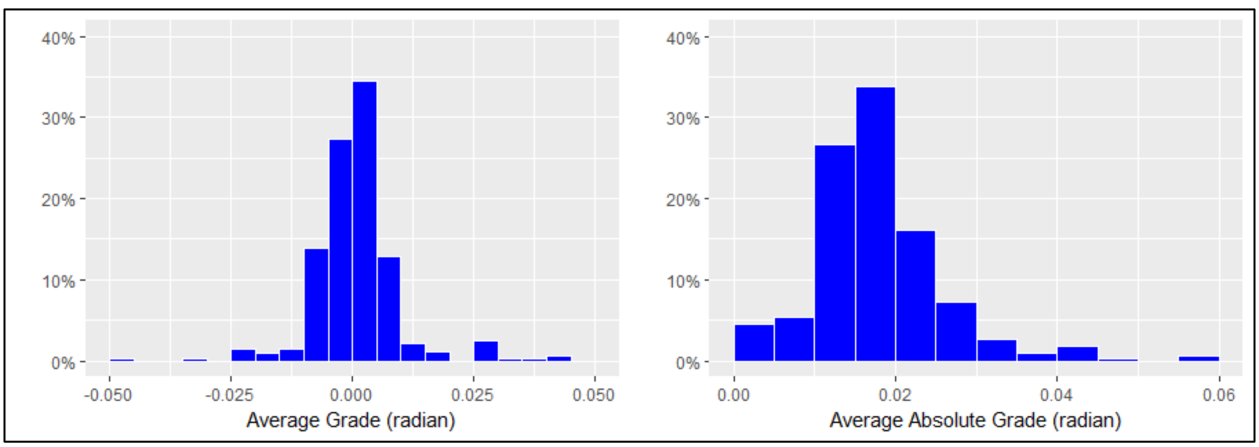


**Figure 9. Segment Average Grade and Average Absolute Grade**

### *4.1.3. Facility Type Identification*

**Speed profiles of vehicles can differ greatly depending on the type of road facility. For example, more transient speed profiles are likely to be observed on local roads than on freeways, due to the presence of traffic signals and congestion. On the other hand, higher speeds are likely to be seen on freeways than on local roads. Different speed profiles have different impacts on fuel efficiency. Therefore, the researchers explored the importance of facility type as an explanatory variable in the empirical models. Different facility types were identified and assigned by conducting a spatial join analysis between the GPS data points in the obtained operations data**

**and a GIS shapefile of roads in the Atlanta area. This study classifies road facilities into: 1) freeways, 2) major arterials, 3) minor arterials/local roads, and 4) off-network (including travel on other local roads not shown on the Atlanta GIS road map, and idling during loading and unloading, or stops at gas stations to refuel). Table 3 shows the duration of travel and average speeds on these facilities.**

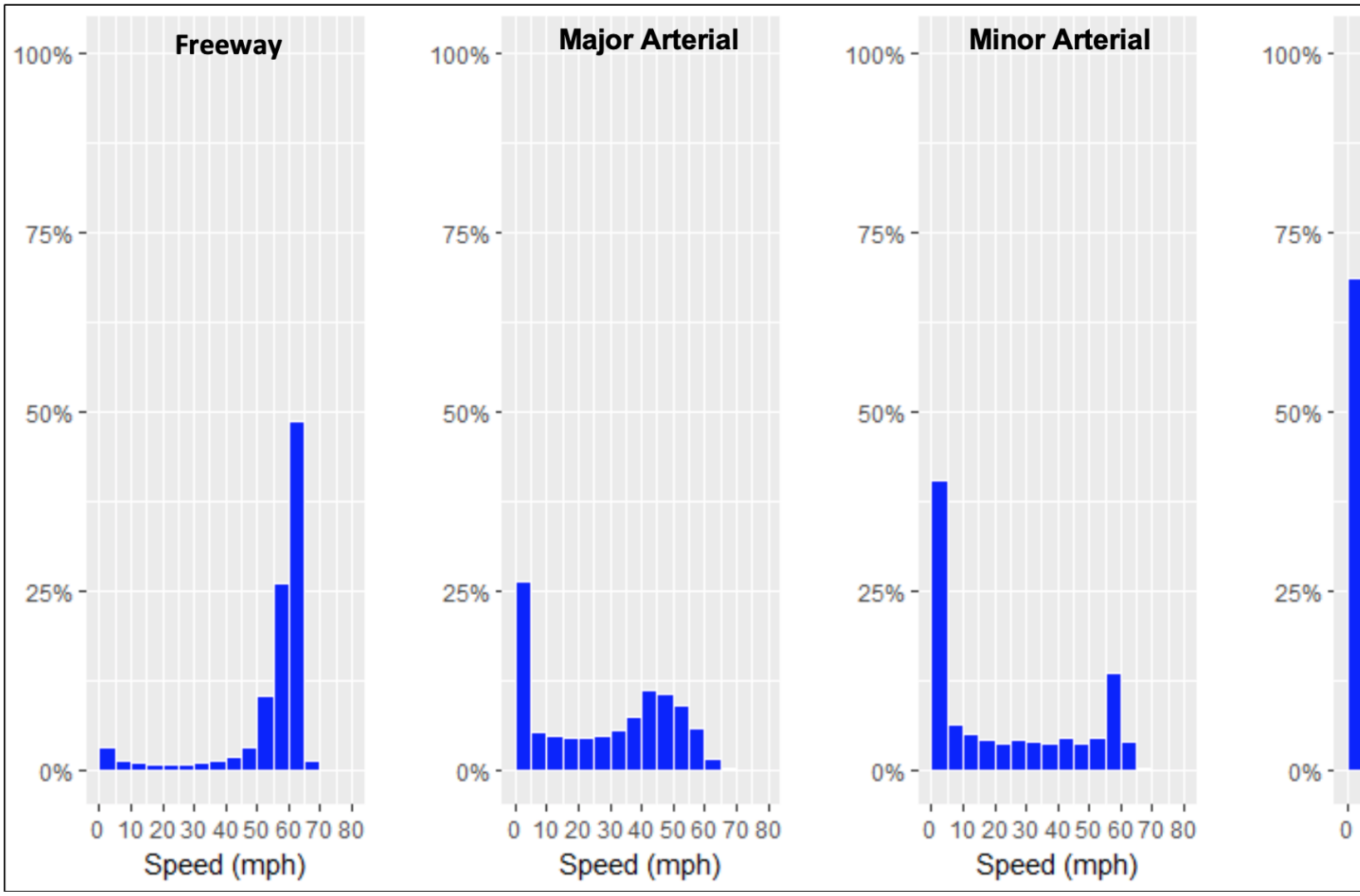


Figure 10 presents the distribution of vehicle speeds on each facility type. Freeway speed profiles concentrate at higher speeds (50-70 mph) while arterial speed profiles are spread over the whole spectrum of observed speeds. Off-network operations concentrate at lower speeds (0-30 mph) with majority of the operations occurring in idling mode. Off-network operations were excluded from the analysis given the predominance of low speed off-network operations (the fuel consumption contribution from tires is zero when vehicles are static). Based on the freeway and arterial facility types, the researchers split the initial 85 cycles into 334 segments, composed of 87 freeway, 211 major arterial, 20 minor arterial, and 16 off-network segments.

**Table 3. Vehicle Operating Characteristics by Facility Type**

| | Freeway | Major Arterial | Minor Arterial /Local | Off-network | Total |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| Duration (Hour) | 37 | 38 | 4 | 28 | 107 |
| Average Speed (mph) | 56 | 27 | 23 | 8 | 32 |

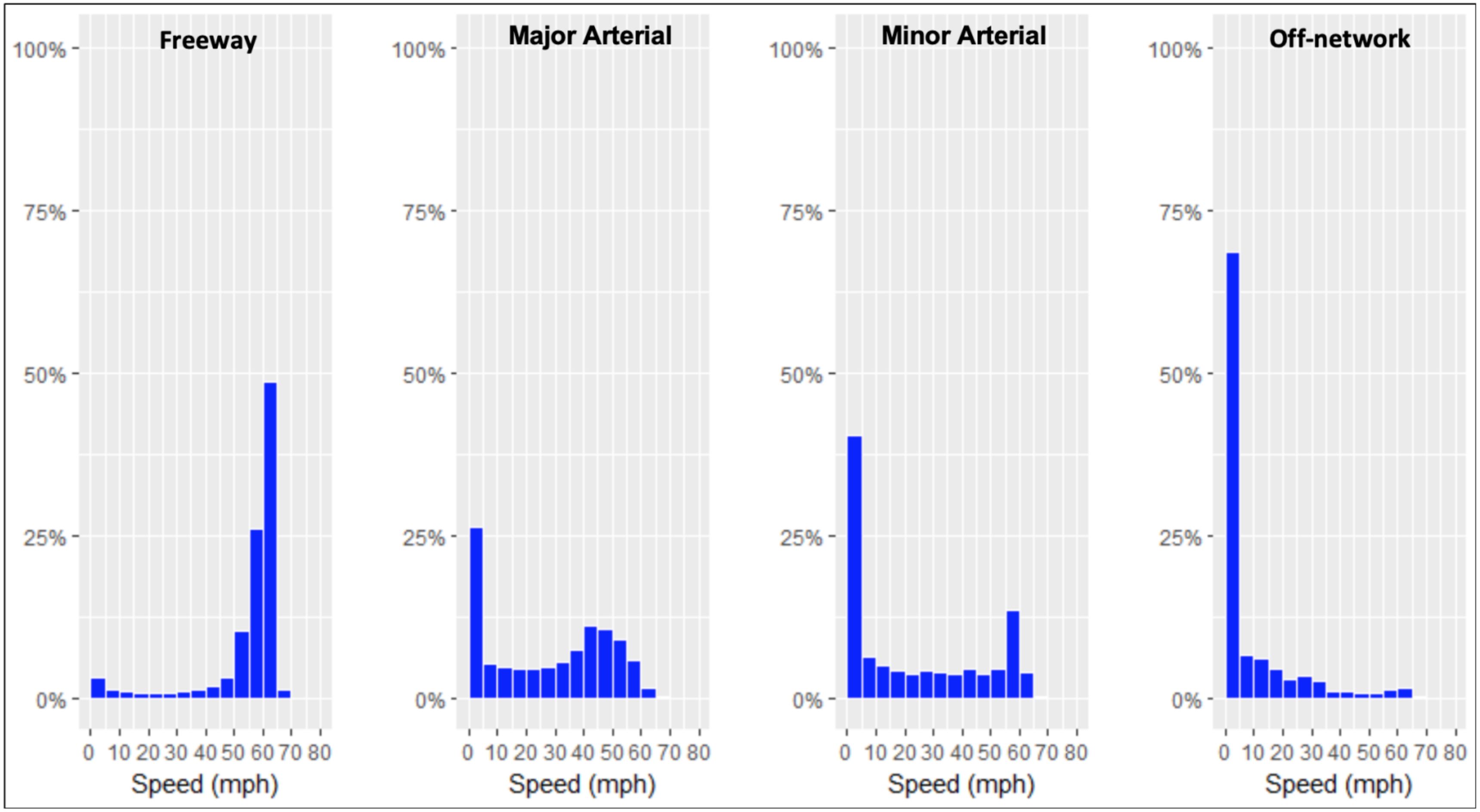


**Figure 10. Vehicle Speed Distribution by Facility Type**

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## 4.2. Baseline Vehicle Development

The simulation process ultimately involved the development of a model for a baseline vehicle model where its fuel consumption characteristics could be compared against various modified vehicles. The modified vehicles reflect various combinations of payloads, tire rolling resistances, and aerodynamic drag. The modeled baseline vehicle is a Class 8 day-cab tractor-trailer and its specifications are based on the proposed US Phase 2 fuel efficiency standards (*6*). Key parameter values are listed in Table 4.

**Table 4. Key Specifications of Baseline Vehicle Model**

| Parameter | Values |
|---|---|
| Roof type | High Roof |
| Tractor tare weight (lbs) | 17,500 |
| Trailer tare weight (lbs) | 13,500 |
| Payload (lbs) | 38,000 |
| Aerodynamic drag (CdA in $m^2$) | 6.38 |
| Axle configuration | 6x4 |
| Gear ratios | 12.8, 9.25, 6.76, 4.90, 3.58, 2.61, 1.89, 1.38, 1.00, 0.73 |
| Rear axle ratio | 3.7 |
| Engine horsepower (hp) | 455 |
| Transmission type | Automatic Transmission |
| Coefficient of tire rolling resistance (CRR in kg/metric ton) | Steer Tires: 6.87; Drive Tires: 7.26; Trailer Tires: 6 |

To verify the fuel efficiency performance of the baseline vehicle, the researchers simulated the vehicle configuration on the US Phase 2 test cycle (duty-cycle exhaust testing) (*27*). This test cycle consists of three segments, a transient segment that was developed by California Air Resources Board to represent urban stop-and-go driving patterns, and two steady-state cruise segments (55-mph and 65-mph) with road grade information. The fuel consumption performance of the baseline vehicle was calculated as a weighted average from the three segments; 5% from the transient segment, 9% from 55-mph steady-state cruise segment, and 86% from the 65-mph steady-state cruise. This resulted in an estimated fuel consumption rate of 40.6 L/100km, which is consistent with the previous studies (*21*).

## 5. Simulation and Results

The results presented in this section are based on 5,355 simulations conducted by the research team to explore the impact of various operating conditions and vehicle characteristics on fuel consumption. Operating conditions are represented by second-by-second speed and location data obtained from GPS devices, and the vehicle characteristics are represented by different tire rolling resistance levels and payload. This study does not consider all factors that influence a vehicle's fuel consumption, it only considers those factors that relate directly to the fuel consumption contribution from the tires. Table 5 shows the different values of the simulation variables. The 85 monitored duty cycles included 87 highway segments and 231 arterial segments with road grade information. For each cycle, the research team conducted multiple simulation runs to capture the effect of each possible combination of payload, CRR, and aerodynamic drag combination.

**Table 5. Simulation Input Values**

| Input Variable | Values |
|---|---|
| Trip Cycle | 85 operating cycles |
| Payload | Typical full load, half payload, and empty payload |
| CRR | 0.003, 0.004, 0.005, 0.006, 0.007, 0.008 |
| Aerodynamic Drag | 10% reduction, 20% reduction |

The *Empirical Law* proposed by Barrand and Bokar (*14*) to predict the fuel consumption contribution from tires was based only on the vehicle weight and the CRR difference, as shown in Equation 3. As pointed out prior in the literature review section, their *Empirical Law* has been tested in previous works and found to have acceptable accuracy under only steady-state conditions. Therefore, it should not be applied to real-world truck data. In this study, the researchers first checked this empirical law against the real-world truck operations data to shed more light on why it is not suitable for real-world application and to understand how best to incorporate it in the new empirical model to be proposed.

$$\Delta FC = \alpha M \Delta CRR \ldots \ldots \ldots (3)$$

Where:

$\Delta FC$: difference of fuel consumption (L/100km)

$\alpha$: coefficient of the Empirical Law

$M$: vehicle weight (kg)

$\Delta CRR$: difference of coefficient of rolling resistance

## 5.1. Variability of the Coefficient of the Empirical Law

Barrand and Bokar (*14*) estimated the coefficient of the Empirical Law, i.e. $\alpha$, based on only numeric average of results from several standard cycles. In this study, we applied their empirical model to our context as shown below.

$$\begin{cases} \Delta FC_{i,j,k} = \alpha_{i,j,k} M_j \Delta CRR_k \\ \Delta FC_{i,j,k} = FC_{i,j,CRR_k} - FC_{i,j,CRR_{Base}} \\ \Delta CRR_k = CRR_k - CRR_{Base} \end{cases} \quad \dots\dots\dots (4)$$

Figure 11 shows the distribution of α. The estimated average of $\alpha_{i,j,l}$ is 0.0460 and the estimated standard error is 0.0079. Therefore, the 90 percent confidence interval within which α can be found is 0.0329–0.0590. Based upon the confidence interval, it appears that it is unsuitable to apply a universal average alpha (this also underscores the importance of incorporating factors that have an impact on $\alpha_{i,j,k}$ in any model designed to predict the fuel efficiency performance of different rolling resistance levels).

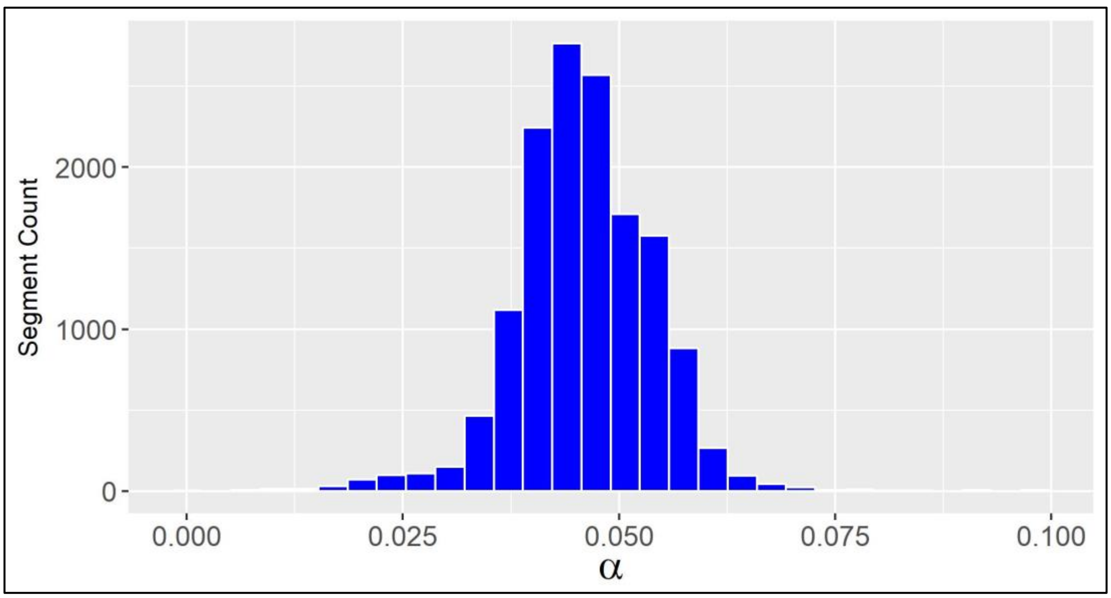


**Figure 11. Distribution of Coefficient of the Empirical Law**

Figure 12 plots $\Delta FC_{i,j,k}$ against $M_j \Delta CRR_k$. It can be inferred that uncertainty in the predicted $\Delta FC_{i,j,k}$ increases with the absolute value of $M_j \Delta RRC_k$. This further implies that single average $\alpha$ cannot capture all important sources of influence.

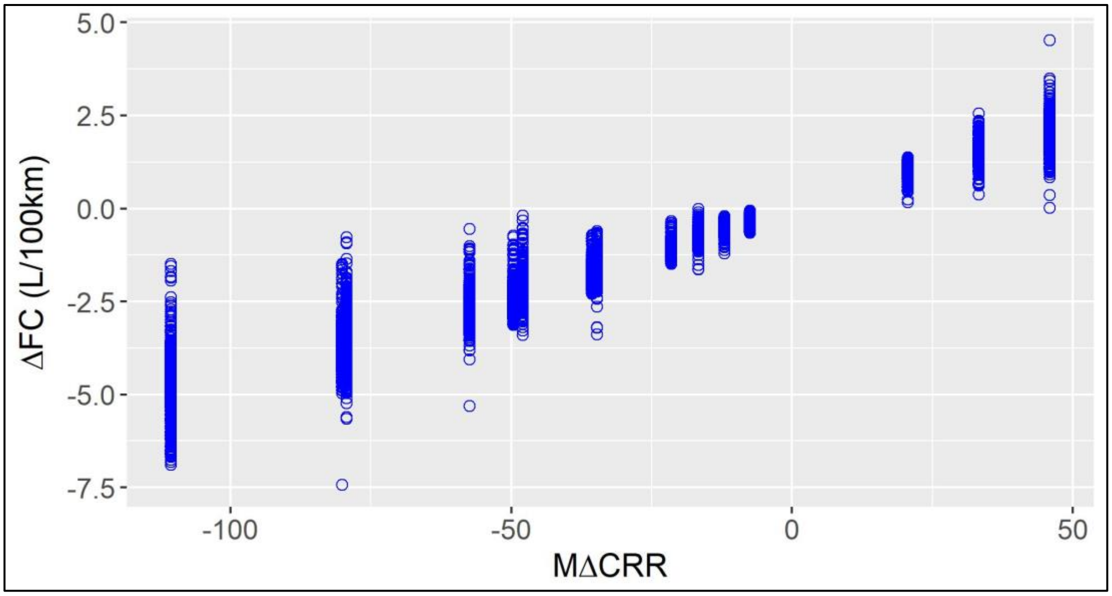


**Figure 12. Uncertainties in Predicted Fuel Consumption with the Empirical Law Equation**

## 5.2. Coefficient of the Empirical Law vs. Payload

Table 6 shows the estimated average $\alpha$ for each payload category. The data shows a clear increasing trend of the coefficient of the Empirical Law,$\alpha$, as payload decreases.

**Table 6. Payload vs. Coefficient in the Empirical Law (α)**

| Payload | Mass ($M_j$) | $\alpha$ |
|---|---|---|
| Full | 31,298 | 0.0425 |
| Half | 22,680 | 0.0461 |
| Empty | 14,061 | 0.0492 |

Furthermore, Figure 13 shows that a single $\alpha$ is still not sufficient to model the impact of tire rolling resistance on fuel efficiency performance each of the payload categories. The corresponding $\Delta FC_k$ for the data shown in Figure 13 ranged from 0.26 L/100km to 5.41 L/100km.

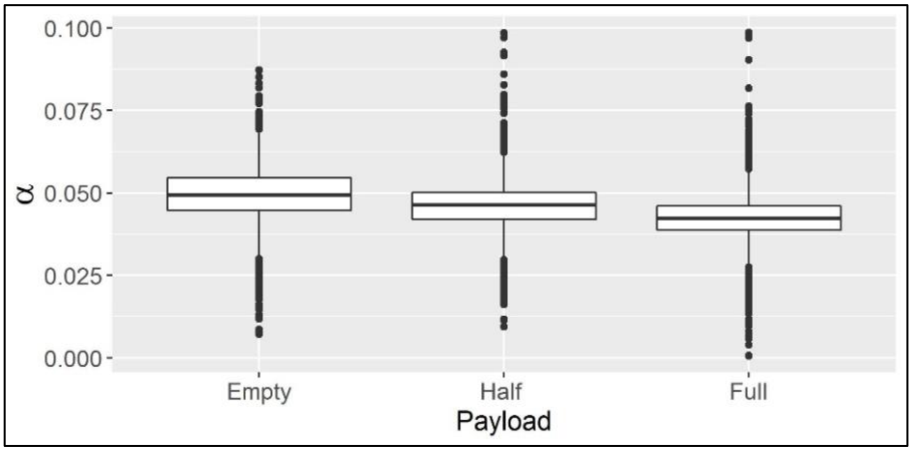


**Figure 13. Distribution in Coefficient of the Empirical Law by Payload**

## 5.3. Coefficient of the Empirical Law vs. Average Speed

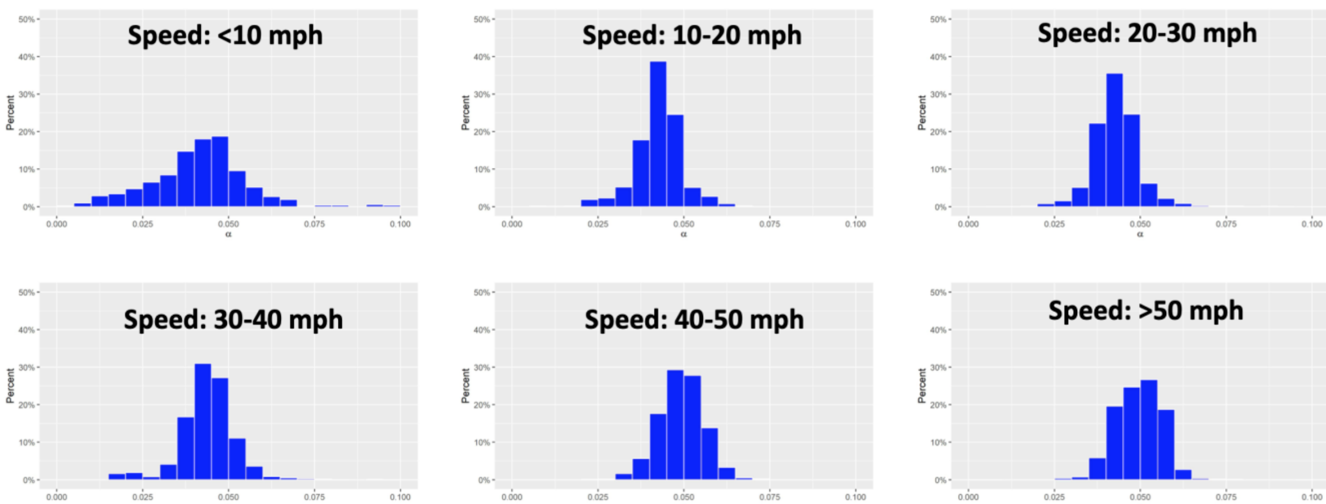


Figure 14 shows the distribution of α for different operating speeds. The plot indicates a different $\alpha$ distribution for different speed categories. This observation is due to the transient nature of real-world vehicle operations, i.e. stop-and-go due to traffic signals and/or congestion. This distribution is an indication that average speed could be a potential explanatory variable in an empirical model to predict fuel consumption contribution from tires with different rolling resistance.

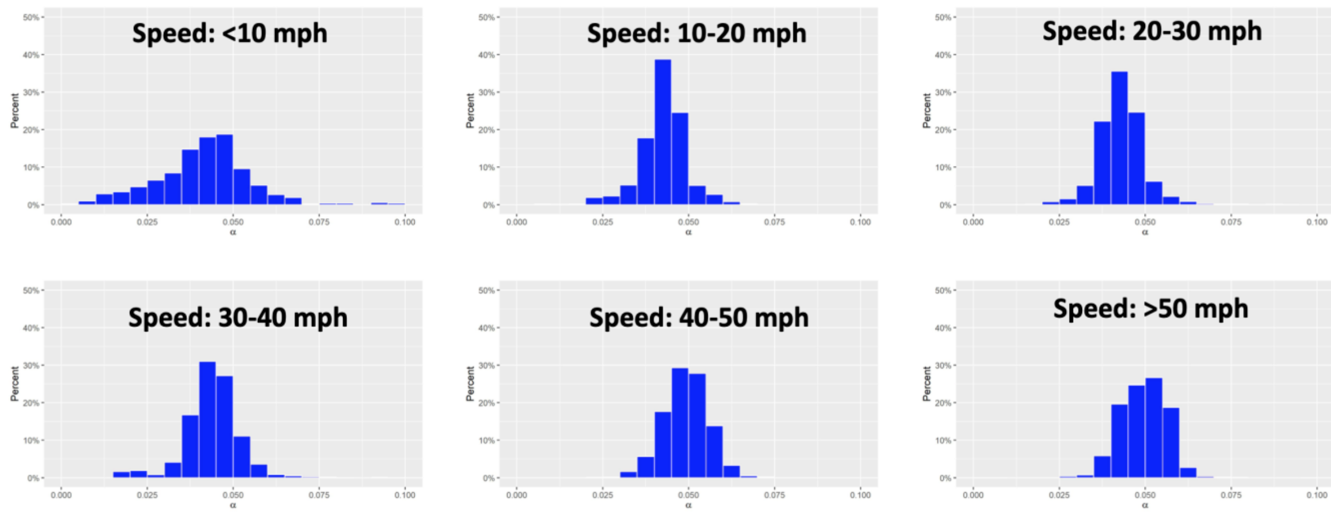


**Figure 14. Coefficient of the Empirical Law vs. Average Speed**

## 5.4. The Developed Empirical Models

As shown prior in Figure 11, α is approximately normally distributed. Therefore, the researchers opted for an empirical linear regression model. Several formulations of the empirical model were tested by the research team. The general formulation of these models is as shown in Equation 5.

$$\Delta FC = f(M, \bar{v}, C_d, \Delta CRR, G_{abs}, G, P_{acc}, P_{dec}, Ft) \dots \dots \dots (5)$$

Where:

$\Delta FC$: Difference of fuel consumption;

$\Delta CRR$: Difference of rolling resistance coefficient;

$M$: Mass of vehicle;

$\bar{v}$: Average speed of vehicle;

$C_d$: Aerodynamic drag coefficient;

$G_{abs}$: Segment-averaged absolute grade (radian);

$P_{acc}$: Percentage of trip time spent accelerating;

$P_{dec}$: Percentage of trip time spend decelerating;

$Ft$: Facility type, i.e. 1: highway, 2: major arterial, 3: local roads.

This section of the report presents the two best models. Both models incorporate the explanatory variables as stand-alone independent terms or as interaction terms with other explanatory variables. Table 7 presents the results of the parameter estimates for the first model. Overall, the model has an adjusted R-square of 0.9669 and standard error of 0.3407 L/100km, which is not surprising given that the empirical model is derived from the output of a simulation model that incorporates similar relationships. Most signs or directions of the estimated parameters are as expected; however, the direction of the variable $C_d\bar{v}^3$ seems counter intuitive because the fuel consumption contribution from the tires is expected to increase with both aerodynamic drag and speed. All the explanatory variables are significant at the 0.05 level except for $P_{dec}$ which is significant at the 0.06 level. The overall model is significant with p-value less than 2.2 x $10^{-16}$.

**Table 7. Parameter Estimates for Empirical Model 1**

| | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| Intercept | -2.77E-01 | 4.54E-02 | -6.100 | 1.09E-09 |
| $\bar{v}$ | 2.43E-03 | 6.10E-04 | 3.99 | 6.69E-05 |
| $M$ | 1.01E-05 | 4.22E-07 | 23.84 | < 2e-16 |
| $M\Delta CRR$ | 3.88E-02 | 1.70E-04 | 228.25 | < 2e-16 |
| $C_d\bar{v}^3$ | -1.40E-06 | 2.07E-07 | -6.75 | 1.51E-11 |
| $Ft$=2 | -8.30E-02 | 1.07E-02 | -7.78 | 7.87E-15 |
| $Ft$=3 | -1.36E-01 | 1.64E-02 | -8.26 | < 2e-16 |
| $P_{acc}$ | 1.22E-01 | 5.11E-02 | 2.39 | 0.0167 |
| $P_{dec}$ | -1.09E-01 | 5.68E-02 | -1.93 | 0.0543 |
| $G_{abs}$ | 3.92E+00 | 4.16E-01 | 9.43 | < 2e-16 |
| $M\bar{v}\Delta CRR$ | 1.40E-04 | 4.06E-06 | 34.43 | < 2e-16 |

Figure 15 shows the comparison between predicted $\Delta FC$ by Model 1 and actual $\Delta FC$ obtained from Autonomie®. The points shown in the plot concentrate around the 45-degree line, indicating that the model makes a good fit of predicted and actual $\Delta FC$. Figure 16 also shows the plot of residuals from Model 1.

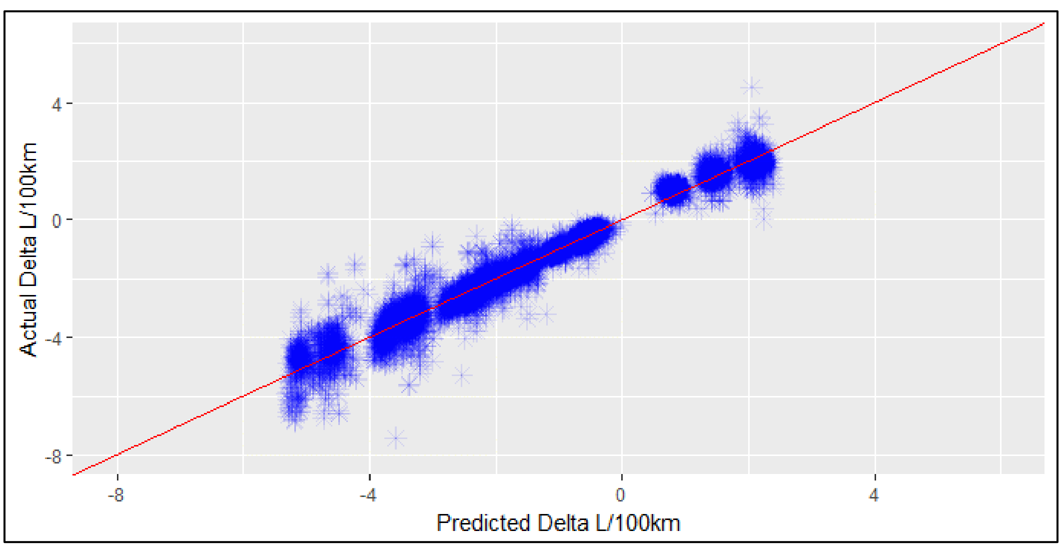


**Figure 15. Predicted vs. Actual Fuel Consumption Difference in Model 1**

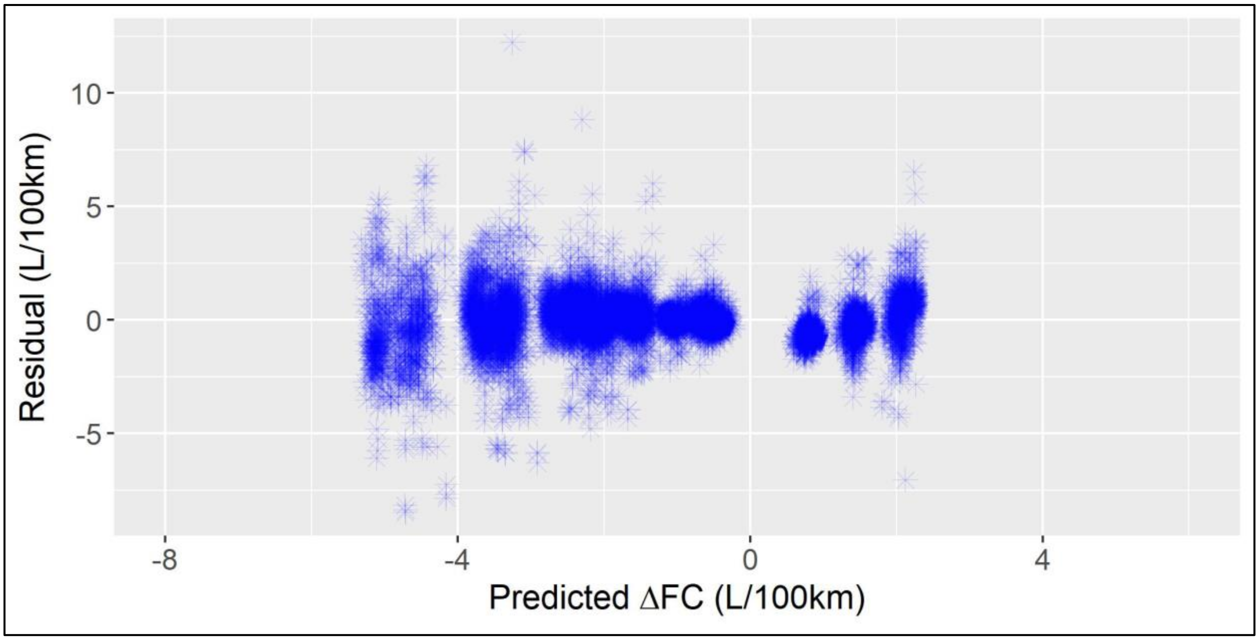


**Figure 16. Plot of Residuals from Model 1**

Due to the direction of the parameter estimate for $C_d\bar{v}^3$, a second model formulation that excludes aerodynamics ($C_d$) was developed to evaluate if goodness of fit would be adversely affected. The explanatory variables and their parameter estimates are as shown in Table 8. The signs or directions of the parameter estimates are as expected. The goodness of fit of the second model is also comparable with the first model; adjusted R-square of 0.9664 and the standard error of 0.3433 L/100km. All the explanatory variables are significant at the 0.05 level, except for $P_{acc}$ that is significant at the 0.10 level. The overall model is significant with a p-value less than 2.2 x $10^{-16}$.

**Table 8. Parameter Estimates for Empirical Model 2**

| | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| Intercept | -8.29E-02 | 4.52E-02 | -1.83 | 0.06671 |
| $M\Delta CRR$ | 3.85E-02 | 1.62E-04 | 237.98 | < 2e-16 |
| $M\bar{v}\Delta CRR$ | 1.42E-04 | 3.83E-06 | 37.11 | < 2e-16 |
| $Ft$=2 | -3.77E-02 | 7.09E-03 | -5.32 | 1.08E-07 |
| $Ft$=3 | -1.00E-01 | 1.37E-02 | -7.30 | 3.10E-13 |
| $P_{acc}$ | 8.09E-02 | 4.90E-02 | 1.65 | 0.09859 |
| $P_{dec}$ | -1.46E-01 | 4.84E-02 | -3.02 | 0.00256 |
| $MG_{abs}$ | 3.14E-04 | 1.38E-05 | 22.79 | < 2e-16 |

Figure 17 shows the plot comparing fitted $\Delta FC$ and actual $\Delta FC$ obtained from Autonomie®. It can be seen that there is generally a good correlation between predicted fuel consumption difference and the actual fuel consumption difference. Figure 18 also shows the plot of standardized residuals and predicted from Model 2.

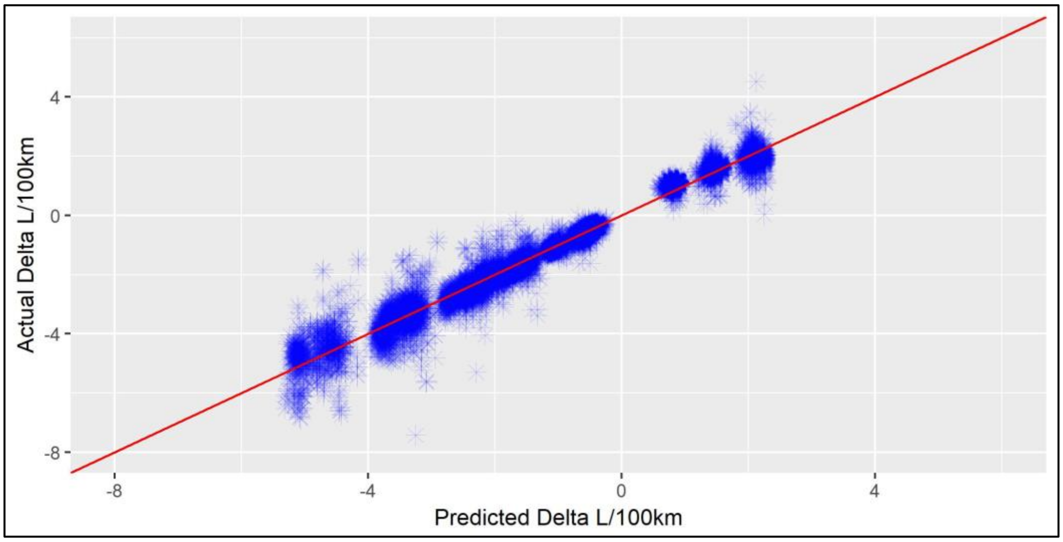


**Figure 17. Predicted vs. Actual Fuel Consumption Difference in Model 2**

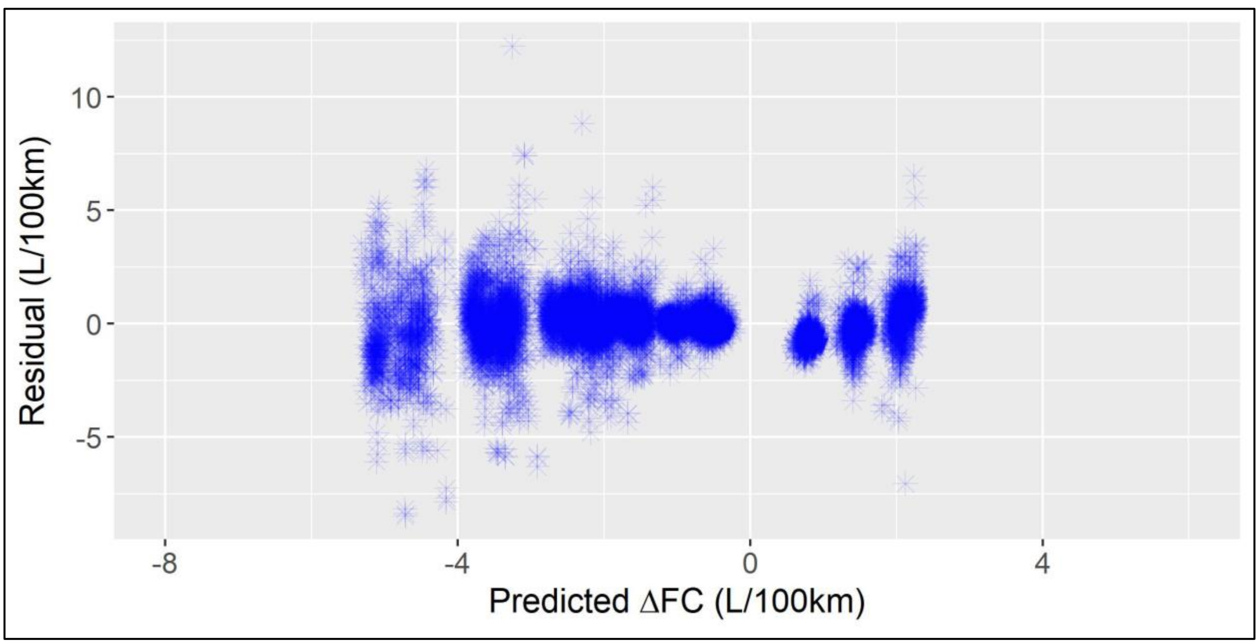


**Figure 18. Plot or Residuals from Model 2**

## 5.5. Tool Development

Both models discussed above have very strong goodness of fit statistics. This is not surprising considering the simulation source of the data, but is comforting in that the goal of this work is to develop a simplified approach that can be applied to fleet evaluation. The main difference between Model 1 and Model 2 is that Model 2 does not include the aerodynamics parameter. This is fundamentally similar to Willet's (*11*) proposed formula for evaluating tire rolling resistance (shown in Equation 1), which ignores aerodynamic drag. However, the researchers believe that aerodynamic drag is an important policy variable that should be included, especially since Model 1 is overall a very good model. Therefore, the researchers developed the Microsoft Excel® spreadsheet tool to predict fuel consumption contribution from tires as an average of the estimates from the two models. In addition to fuel consumption estimates, the spreadsheet tool further estimates the related emission reductions.

## 6. Model Verification

The researchers used four sets of HDV operating data to verify the proposed prediction tool. Two of the datasets consist of operating cycles from the minor arterials facility type and the other two consist of operating cycles from the freeway facility type as described previously. Table 9 presents the characteristics of the four verification datasets and the calculated average percentage error in the estimated fuel consumption. The average percentage error was calculated as shown in Equation 6.

$$\text{Average \% Error } = \text{abs}\left[\frac{\Delta \text{FC}_{\text{Fitted}} - \Delta \text{FC}_{\text{Actual}}}{\Delta \text{FC}_{\text{Actual}}}\right] * 100\% \dots \dots \dots (6)$$

Where:

$\Delta FC_{fitted}$ = predicted fuel-savings from developed tool

$\Delta FC_{actual}$ = estimated fuel-savings from Autonomie®

**Table 9. Verification Datasets and Average Percentage Error in Estimated Fuel Consumption**

| Verification Set | Facility Type | Average Speed | Duration (Min.) | Average % Error |
|---|---|---|---|---|
| 1 | Minor Arterial/Local | 35.1 | 7.6 | 3.73% |
| 2 | Minor Arterial/Local | 31.1 | 14.6 | 4.71% |
| 3 | Freeway | 55.5 | 6.7 | 6.23% |
| 4 | Freeway | 53.9 | 7.0 | 6.34% |

The verification results indicate that the developed generally has the prediction error of less than 6.5 percent. However, the prediction error seems less for arterials than for freeways. Figure 19 presents the verification results as plots of predicted fuel savings against actual fuel savings.

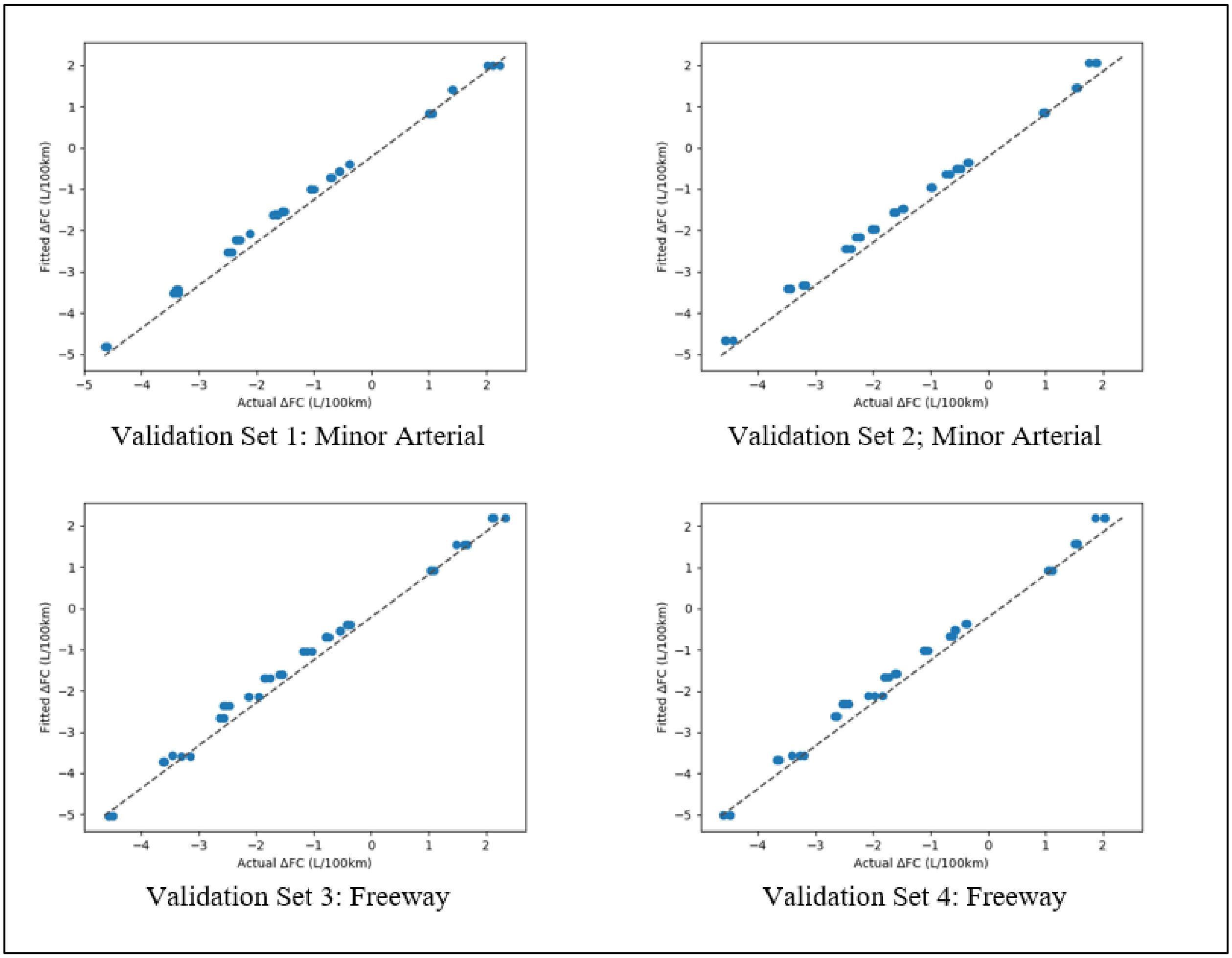


**Figure 19. Verification Results**

## 7. Conclusions

Low rolling resistance tires are of particular importance to the HDV sector as they can help significantly reduce vehicle fuel consumption. Fleet operators need a robust and straightforward tool to analyze their vehicle operations and make informed tire investment decisions. The research presented in this report found that previously-published empirical model to predict fuel consumption contribution from tires is not well-suited to real-world vehicle operations data with transient speed operations. This research used real-world vehicle operations data and a simulation tool to generate vehicle fuel consumption and performance data and develop robust empirical models that are sensitive to vehicle operations (i.e., payload, speed and acceleration), vehicle specifications (i.e., mass and aerodynamics drag), and route characteristics (i.e., road grade). The developed models show very high goodness of fit statistics; adjusted R-square values are greater than 0.96 and standard error values less than 0.35 L/100km. The researchers also developed spreadsheet-based tool to help fleet operators evaluate the effectiveness of adopting low rolling resistance tires. The developed tool was verified with four sets of real-world operating data and the results show that average prediction error from the tool is less than 6.5 percent.

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