

Green Technology and Trucking: An Investigation of Factors Impacting Fuel Consumption Using GPS Data

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Green Technology and Trucking: An Investigation of Factors Impacting Fuel Consumption Using GPS Data

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Executive Summary

This study explores factors impacting fuel consumption for short-haul trucking – that is, the shipment of goods within 200 and 300 kilometers of a driver’s home terminal. The data used in this study were provided by Transcare Logistics Corporation, a member of the Carego Group of Companies. The data consisted of GPS records for all trips undertaken by two trucks operating for the corporation, freight information, and fuel information. The study period extended from June 19th to July 31st, 2009. An examination of the literature identified numerous factors that impact fuel consumption. These factors were classified as relating to truck aerodynamics, driver behavior, and routing.

This study focused on factors relating to driver behavior – notably, acceleration and speed. The GPS data were processed to extract relevant information concerning these factors. For instance, average acceleration was calculated for each GPS record and later classified according to type. Straight-line distance between GPS points was also calculated according to the haversine formula. The record-based information was aggregated to the trip level. A total of 202 trips were identified from the GPS data.

The analysis consisted of three parts. First, a descriptive analysis of the trips was presented. This was followed by an analysis of acceleration. Twenty-nine percent of all trips experienced at least one hard braking event while 51% of all trips experienced at least one hard acceleration event. As discussed in the literature, both types of events are associated with increased fuel consumption. The analysis of speed found that 28% of total travel time was spent at speeds greater than 96 km/h. Again, as noted in the literature, reducing speed can result in significant fuel savings. The primary shortcoming of this investigation concerned the aggregate nature of the fuel data set, which consisted of 15 refueling events. In other words, trips were not associated with fuel consumed. Thus, multivariate modeling relating trip-based factors pertaining to fuel consumption to actual fuel consumed was precluded in the analysis. It is recommended that future research remedy this shortcoming.

Introduction

This study explores factors impacting fuel consumption for short-haul trucking. A direct focus is placed on driver behavior at the trip level captured through Global Positioning System (GPS) data. At present, trucking is the dominant mode of shipping for domestic freight (Ang-Olson and Schroeer, 2002; Schweitzer et al., 2008). Short-haul trucking is defined as the shipment of goods within 200 and 300 kilometers of a driver's home terminal. Today, many industries are adopting green technologies to curb their impacts on the natural environment. The trucking industry is no exception. Many studies have been designed to explore the effectiveness of various techniques for reducing the fuel consumption of trucks. A review of the literature, documented in this report, identifies factors that affect fuel consumption. These factors are categorized into three main areas: driver behavior, truck aerodynamics, and route choice.

The remainder of this report is organized as follows. The following section summarizes research that has explored truck fuel consumption. GPS as a method used to study fuel consumption is discussed, along with its strengths and weaknesses. Research relating to driver behavior, truck aerodynamics, and route choice is then discussed. Section three describes the data set used in this study. Specifically, GPS data were obtained for all trips undertaken by two trucks operating for Transcare Logistics Corporation, a member of the Carego Group of Companies, to explore driver behavior as related to fuel consumption. Freight (cargo) weight and fuel logs were also obtained for the study period, which extended from June

19th to July 31st, 2009. Because the fuel logs represent refueling events, it was not possible to associate each trip with fuel consumed during the trip. Thus, multivariate modeling relating trip-based factors pertaining to fuel consumption to actual fuel consumed was precluded in the analysis. Instead, the analysis is descriptive focusing on truck acceleration and speed. The method for processing the GPS data to extract the variables summarized in Appendices A and B is described in Section 4. Freight weight and fuel log processing are also discussed in this section. The analysis of the data is presented in Section 5, which begins with an analysis of the trips themselves followed by analyses of acceleration and speed. Conclusions are presented in the final section.



Background

The literature reviewed in this study is drawn from a variety of sources, including government reports and studies published in academic journals. Various studies provided applicable and quantifiable values for factors affecting fuel consumption in the trucking industry.

Although a host of studies identify fuel savings through physical modifications made to a truck's chassis, very few studies were found addressing how driver behavior impacts fuel consumption. For this reason, this study explores this particular gap in the literature – namely, the impact of acceleration and speed on fuel consumption for short-haul trucking.

The remainder of this section reviews GPS as a method used to study fuel consumption, along with issues associated with using GPS. This is followed by an examination of factors that affect fuel consumption classified under driver behavior, vehicle aerodynamics, and vehicle routing.

2.1 GPS as a Method for Studying Fuel Consumption

Over the past 40 years, academic research has identified several methods for the analysis of vehicle movement through space and time. Although numerous, these methods have a common purpose – recording the spatial and temporal information pertaining to a vehicle as it travels from an origin to a destination. In the context of trucking, a common and accurate method of tracing movement has been

the Global Positioning System (GPS), a United States space-based global navigation system consisting of satellites and GPS receivers (Qiao et al., 2005; Alessandrini et al., 2006; Agar et al., 2007; Hellstrom et al., 2009). The use of GPS has grown tremendously over the past 10 years and has advantageous implications for spatial analysis in research. Over the years, GPS has been incorporated into fleet management due to its high level of accuracy in tracking and tracing a vehicle's position based on set time intervals. The result is a route taken by the driver based on the recorded position history (Baumgartner et al., 2008). In addition to the analysis of previously collected data, GPS can deliver position information in real time, which has proven useful for real-time computation and analysis. Such is the case in a 2009 study to minimize fuel consumption where a GPS was used in combination with an onboard computer to measure and predict changes when approaching road slopes. GPS data were successfully transmitted to the modified cruise control system and fuel management was adjusted accordingly. The results of the study show that a heavy-duty diesel truck reduced its fuel consumption by approximately 3.5% for a 120 km stretch of road (Hellstrom et al., 2009).

Although GPS has gained much success and is identified as both the most robust and easily implemented method for vehicle tracking, there exist pitfalls due to its time interval functionality (Agar et al., 2007). The main issue that arises is the over-collection of data coupled with the cost associated with storing such large amounts of data. In addition, when processing an abundance of short time interval GPS data, undesirable fluctuations in GPS recordings often due to signal error may interfere with the accuracy of the sampled data (D'Este et al., 1999; Rakha et al., 2001). Another consideration to be made aware of is the accuracy associated with varying methods of processing GPS data. This is particularly important when monitoring acceleration. Such methods include calculating changes in velocity (speed) over time intervals as shown in the equation below where a backward-difference approach is used.

$$(1) \quad a = \frac{\Delta v}{\Delta t} = \frac{v_t - v_{t-1}}{\Delta t}$$

where a is average acceleration measured in m/s^2 for the interval between times t and $t-1$, v is velocity measured in m/s at times t and $t-1$, and Δt is time measured in seconds for the interval between times t and $t-1$.

Alternatively, a central-difference formulation can be used, which is noted to have half the error associated with the backward-difference approach (Rakha et al., 2001). The central-difference formulation is more effective in that the two times used are $t-1$ and $t+1$, essentially being on either side of the record for which acceleration is being calculated. The central-difference formulation is found to be at least one order of magnitude better than other methods for calculating average acceleration (Rakha et al., 2001).

There are numerous techniques for filtering GPS data. Much success is appointed to the Robust Simple Exponential Smoothing approach as it is able to remove all suspicious and erroneous data, usually associated with the over-collection of GPS data (Rakha et al., 2001). This method is capable of removing errors from the original data without altering the underlying trends. The robust smoothing techniques

are recognized by other research for producing a more simplified fuel consumption estimate for all trips studied when adjusting speed profiles (Rakha et al., 2001; Ko et al., 2008). Smoothing of the speed profile is important in order to eliminate inaccurate fluctuations in the GPS data. This results in more realistic driving behavior (Ko et al., 2008). However, upon performing this technique, the resulting data will also lose details of true fluctuations in fuel management, such as in the case of traffic congestion. It is, therefore, noted for best use in simulation analysis, or if need be, a reduced smoothing effect should be applied to collected GPS data in order to retain practicality. Alternatively, more modern GPS recording devices have an adaptive recording interval. The issue of data smoothing is removed entirely as the data are recorded on an “intelligent” time interval. It should be noted that an adaptive time interval was used when collecting the GPS data for this study.

2.2 Factors Affecting Fuel Consumption

Many factors are identified in the literature as influencing fuel consumption in the trucking industry. These factors are classified under driver behavior, vehicle aerodynamics, and vehicle routing. With respect to driver behavior, a host of studies have acknowledged particularly effective methods in reducing truck fuel consumption. One such method is adaptive driver training, which is essentially adjusting the behavioral habits of truck drivers to more energy-efficient operating styles (Vangi and Virga, 2003). Contributing factors underlying driver behavior are hard braking, gear changing behavior, pedal movements, and constancy of speed (Baumgartner et al., 2008). Such factors are mentioned as contributing to the increased consumption of fuel. In addition to modified driving styles, many technologies exist to assist in improving fuel economy such as advanced electronic controls and diagnostics, driver management systems, and satellite communications installed into the cabins of trucks. Such technologies are used for two reasons: to improve operational efficiency, and to maximize engine performance through reduced vehicle emissions and overall fuel consumption. Finally, through optimized routing, both driving time and distance can be minimized, ultimately reducing the amount of fuel that is required to travel from an origin to a destination.

2.2.1 Driver Behavior

With respect to driver behavior, it is known from studies on emissions that sharp accelerations consume significantly more fuel than gradual accelerations from a stationary velocity (Varhelyi, 2002). The increase in speed at which fuel is consumed results in an increase of undesirable emissions due to the significantly less efficient combustion process (Air Pollution Prevention Directorate, 2001). Consequently, the literature reports that lighter trucks are more sensitive to changes in speed than larger and more weighted trucks simply due to the mass and energy required to modify their current velocity (Ang-Olson and Schroeer, 2002). An Environment Canada case study found that for a 13,600 kg truck to increase speed from 90 km/h to 105 km/h, fuel consumption is increased by about 28% (Air Pollution Prevention Directorate, 2001). As reviewed in more detail later in this study, both mass and velocity affect the rate of fuel consumption as more energy is required for the mass to overcome its resistance forces. Therefore, the key factor pertaining to driver behavior to reduce fuel consumption would be to allow the truck to operate at steady speeds and avoid frequent “stop-and-go traffic,” which

is often the case during the morning and evening rush hours in urban areas (Air Pollution Prevention Directorate, 2001; Varhelyi, 2002; Pandian et al., 2009).

Anticipating traffic and performing “technical driving” would optimize driving behavior and improve fuel economy, as described by Pandian et al. (2009). The underlying theory behind this is that when a vehicle accelerates to the posted speed limit, a substantial amount of energy is transferred into the momentum of the vehicle. As a result, deceleration indicates the loss of both momentum and energy that the vehicle will need to replace once traffic undergoes constant flow once again (Pandian et al., 2009). The well-accepted theory can be extended for real-world traffic situations. For instance, while the vehicle is both stationary and idling, the engine continues to consume fuel with no productivity with regards to movement (Varhelyi, 2002). Preferably, avoiding complete momentum loss will conserve motion and stored energy and as a result, less fuel is required to overcome resistance forces once traffic continues its flow (Air Pollution Prevention Directorate, 2001; Yu et al., 2006; Pandian et al., 2009). Similar to the stop-and-go traffic of urban areas, traffic congestion on highways exhibit fluctuations in acceleration and deceleration. A well-known solution is the use of cruise control wherever possible as it minimizes these small fluctuations (Air Pollution Prevention Directorate, 2001).

Modern diesel engines have electronic computer modules (ECMs) that govern engine operation and allow manufacturers to optimize specific engine controls to improve fuel efficiency as desired (Mitschke, 1981; Fujita, 2008; Hellstrom et al., 2009). Vehicle ECMs maintain a log of various operating parameters such as the vehicle’s speed and engine revolutions per minute (RPM), which can then be later used for diagnostic monitoring or maintenance testing. Variable output from ECMs such as total operation time, distance traveled, number of hard braking events, and the amount of fuel consumed provide for the effective calculation of fuel economy (Huai et al., 2006). In a study performed by Huai et al. (2006) with three private industry truck companies, brake actuations per 1000 miles was noted as a key variable in impacting fuel economy. This further highlights the importance of maintaining steady velocity while traveling between an origin and a destination to maximize efficiency. Similar variables appear in a host of publications concerning overall trucking efficiency, fuel economy, and schedule optimization for freight trucking (Tolouei and Titheridge, 2009; Forkenbrock, 1999; Hellstrom et al., 2009; Larsson and Ericsson, 2009).

2.2.2 Aerodynamics

Identified by Ang-Olson and Schroeer (2002), certain methods of improving trucking efficiency have had more success through market penetration. Specifically, aerodynamics was identified as a key determinant of fuel consumption. Ang-Olson and Schroeer (2002) quantify the effects of physical modifications made to trucks on fuel consumption (see Table 2.1). Traveling at 80 km/h, aerodynamic drag and rolling resistance consumes up to 40% of available horsepower (Taylor and Nix, 1999; Air Pollution Prevention Directorate, 2001; Ang-Olson and Schroeer, 2002). Furthermore, the aerodynamic drag force increases exponentially with an increase in velocity. As a result, when vehicle speeds approach 110 km/h, aerodynamic drag accounts for 65% of total energy loss and fuel consumption (Taylor and Nix, 1999; Ang-Olson and Schroeer, 2002). As Canadian posted highway speeds are upwards from 80 km/h, improving vehicle aerodynamics greatly reduces the amount of wasted power and

improves fuel economy especially for highway and expressway travel (Air Pollution Prevention Directorate, 2001).

A drag coefficient is a value given to an object or shape provided its ability to pass through air. Fluid dynamics is essential when considering the aerodynamics of a vehicle. Different shapes such as spheres, rectangles, or angled cubes, among many others, each have varying drag coefficients and are incorporated into vehicle design. With advancing technology in aerodynamic modifications to tractor trailers over the years, the coefficient of drag has dropped from 0.8 in the 1970s to 0.6 in the year 2000, and is expected to be close to 0.45 at present using commercially available modifications (Taylor and Nix, 1999; Ang-Olson and Schroeer, 2002). Modifications of trailers can include installing more aerodynamically shaped roofs to reduce the classic square box shaped trailers. Specific aerodynamic vehicle modifications are listed in Table 2.1, which displays a summary of their effects on fuel consumption for trucks. Interestingly, as summarized in the table below, speed reductions from 112 km/h to 104 km/h and from 104 km/h to 96 km/h can save 6% and 7% of overall fuel used per truck, respectively.

Table 2.1 Summary of Modification Impacts

Vehicle Modification	Fuel Savings Per Truck (%)
Roof deflector	6.0
Integrated cab-roof fairings & closed sides	15.0
Closing side curtains	4.5
Securing loose tarpaulins	2.5
Trailer side skirts	5.0% - 18.0
Improved trailer aerodynamics	3.8
Wide-base tires	2.6
Automatic tire inflation system	0.6
Tare weight reduction	1.8
Low-friction engine lubricants	1.5
Low-friction drive train lubricants	1.5
Idling reduction: direct fire heater	4.3
Idling reduction: auxiliary power unit (APU)	8.1
Idling reduction: automatic engine idle	5.6
Speed reduction: 112km/h to 104km/h	6.0
Speed reduction: 104km/h to 96km/h	7.6
Driver training and monitoring	3.8

Source: Ang-Olson and Schroeer, 2002

Truck maintenance is also necessary to reduce fuel consumption. The proper tire with optimal inflation, in addition to minimizing truck weight and its carrying load, all affect fuel consumption. In the case of physical modifications to the vehicle structure, each change equates to a small increase in fuel economy. Existing theories on rolling resistance has lead to several studies identifying that the use of wide-base tires in place of dual tires is more efficient due to less rolling resistance (Bond, 1985; G.W. Taylor Consulting et al., 2002; Taylor and Patten, 2006; Al-Qadi and Elseifi, 2007). Wide-base tires are

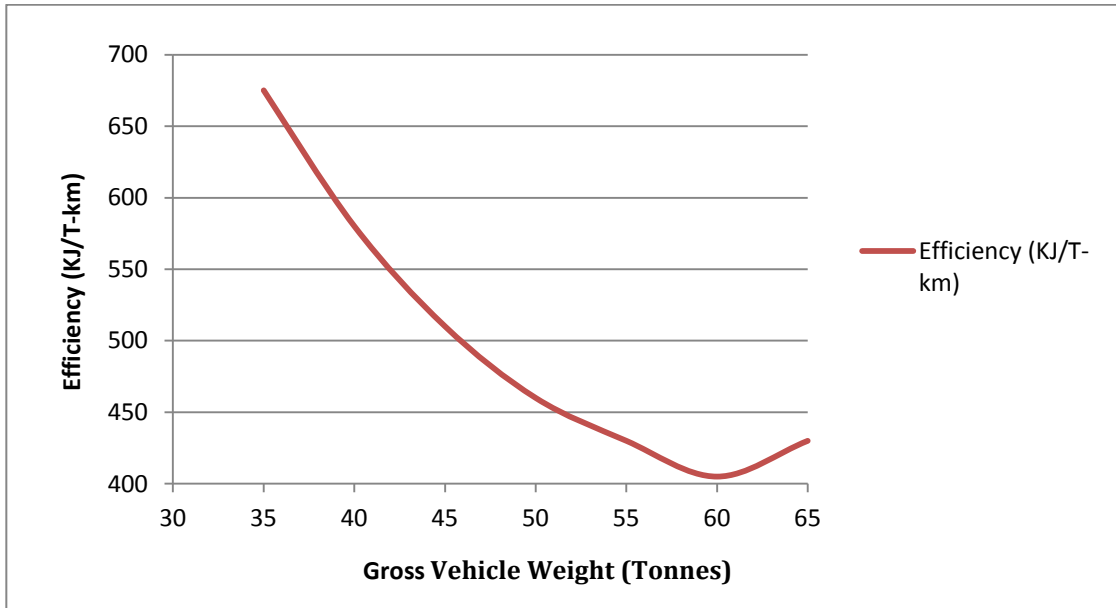
measured to improve fuel economy by 3.7% to 4.9% (Ang-Olson and Schroeer, 2002). A general trend is identified such that a 10-PSI drop in tire pressure will increase rolling resistance by 2% and fuel consumption by 1% (Ang-Olson and Schroeer, 2002). Therefore, an effective method for insuring proper tire inflation is the use of an automatic tire inflation (ATI) system that senses when tire pressure drops below optimal levels and acts by supplying pressurized air to the tires on a continuous basis (Air Pollution Prevention Directorate, 2001; Ang-Olson and Schroeer, 2002).

With regards to vehicle mass, weight reduction is beneficial for fuel efficiency. As engine horsepower and fuel are greatly consumed to overcome the forces resisting motion, reduction in tractor trailer tare weight (or base weight) is preferred. According to publications about trucking efficiency, a 1,360 kg reduction in vehicle weight improves fuel economy by approximately 26 L/100 km when traveling at a velocity of 105 km/h (Ang-Olson and Schroeer, 2002). As summarized in Figure 2.1, fuel efficiency, measured in kilojoules per tonne-km (KJ/T-km), tends to decrease as mass increases. Furthermore, Figure 2.2 presents data documenting the relationship between power requirements and truck speed (Air Pollution Prevention Directorate, 2001). The horsepower required to achieve the desired speed is much greater at higher speeds due to wind resistance, rolling resistance, and aerodynamics.

It is important to recognize that the relationships seen in Figure 2.2 exist only for steady-state conditions, and do not take into account acceleration and deceleration fluctuations, which exist in realistic traffic conditions. When these fluctuations are added to the experiment, the influence of mass typically has a much higher impact on actual power demand from the vehicle's engine due to the constant adjustments to speed during traffic conditions (Air Pollution Prevention Directorate, 2001). This is directly related to the before-mentioned driver behavior impacts on fuel consumption.

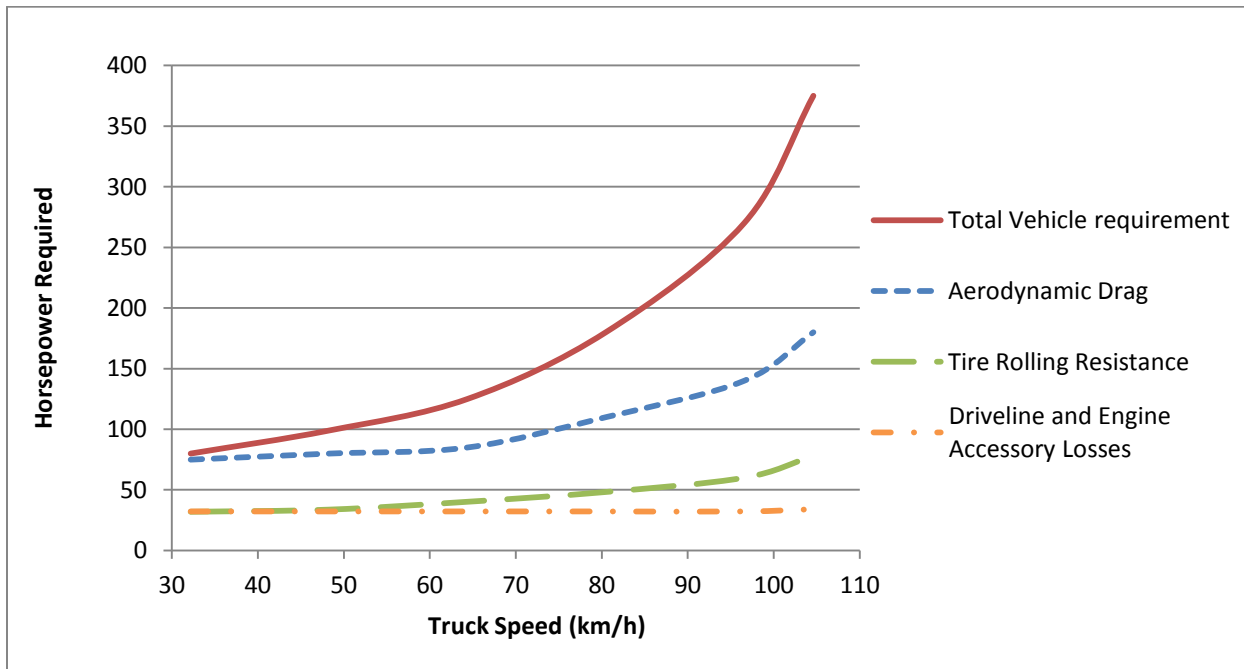
As mentioned above, reduced speeds improve fuel economy for several reasons. Coupled with the aerodynamic impact, truck fuel economy drops significantly as speeds increase above 90 km/h (Taylor and Nix, 1999). Simulation of trucks of various weights shows that fuel economy drops at a measurable rate (i.e., fuel consumption increases) at various speeds as summarized in Figure 2.3. This characteristic coupled with a Canadian study's estimates that 50% of the mileage of all combination trucks occurs at speeds higher than 88 km/h suggests that there is opportunity to reduce the amount of fuel consumed by adjusting speed (Taylor and Nix, 1999; Ang-Olson and Schroeer, 2002).

Figure 2.1 Relationship Between Fuel Efficiency and Vehicle Weight



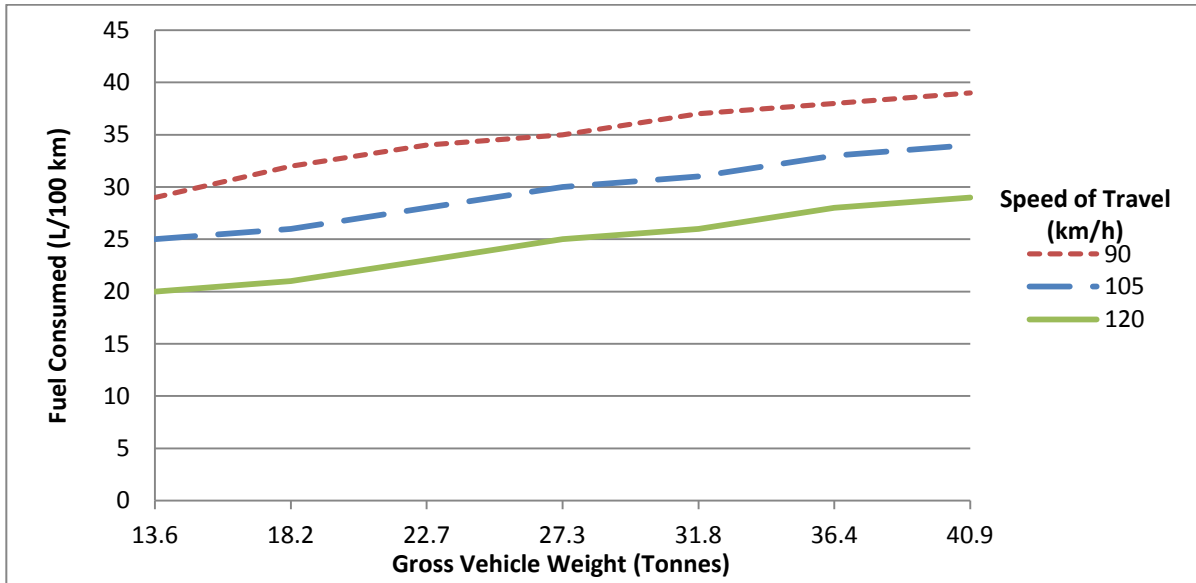
(Air Pollution Prevention Directorate, 2001)

Figure 2.2 Power Required to Overcome Aerodynamic Drag, Tire Rolling Resistance, and Driveline and Engine Accessory Losses at Various Speeds



Driveline losses refer to energy lost due to powertrain inefficiencies. Engine accessory losses refer to energy lost due to fan, alternator, air-conditioning, power steering, and any other engine-driven accessories. Horsepower is calculated for a tractor-trailer (4.1m high van trailer) combination weighing 35,600kg with -11R22.5 radial tires.

(Goodyear, Factors Affecting Truck Fuel Economy, Report 492700-3/93)

Figure 2.3 Effect of Speed on Truck Fuel Consumption for Various Truck Weights

(Air Pollution Prevention Directorate, 2001)

2.2.3 Routing

Previous research has shown that computerized routing, scheduling, and vehicle telematics can all effectively contribute to a beneficial increase in fuel economy for trucking companies (Baumgartner et al., 2008). At the forefront of real-time navigation research are on-board navigation systems that integrate current traffic information into a shortest path analysis for optimal route planning (Baumgartner et al., 2008; Hellstrom et al., 2009).

At present, shortest path algorithms are used in comprehensive data analysis to measure the minimization of time or distance travelled between two points in space. The purpose of a shortest path approach is to connect two points, namely, an origin and a destination, in the shortest distance or time possible. This effectively determines an optimal path which minimizes a defined cost. Shortest path analysis has been implemented for minimizing fuel consumption, maximizing efficiency, and tracking vehicle productivity (Baumgartner et al., 2008). A GPS position history compared to a shortest path between the same origin and destination can identify the efficiency and effectiveness of the chosen path (Baumgartner et al., 2008).

As previous research has identified, the choice of paths can greatly influence the quantity of fuel consumed (Varhelyi, 2002). However, it is important to recognize that minimizing distance is not always entirely proficient at maximizing fuel economy. Realistic road networks experience a host of factors that must be accounted for such as traffic congestion, reduced traffic speeds, and intervening opportunities of road choice (Yu et al., 2006). For example, in the event of traffic-laden road segments, the shortest path by time may result in a longer path with regards to distance, but an overall reduced fuel consumption (Yu et al., 2006). As a result, shortest path analysis is another technique that can be used to minimize fuel consumption.

Data

The data used in this study were provided by Transcare Logistics Corporation, a member of the Carego Group of Companies. The data were collected between June 19th and July 31st, 2009. The data had three components. The first component consisted of GPS data for all trips undertaken by two trucks operating for Transcare during the study period. The GPS data recorded chronologically space (i.e., latitude and longitude) and time coordinates for the various deliveries made by the two trucks in the Greater Golden Horseshoe region of Ontario. The second component consisted of the freight (cargo) weight associated with each trip. The third component was the fuel log, which identified the volume of fuel in liters purchased at various times throughout the study period between certain trips for each truck. Combining both trucks, a total of 15 refueling stops were made dispersed among the 202 individual freight trips.

As mentioned, the spatio-temporal truck position data were collected using GPS units installed on two transport trucks making scheduled shipments during the months of June and July, 2009. The GPS data were output in the comma-separated values (.csv) standard file format. These raw GPS data were the basis for the analysis as they systematically logged trip progress in space and time. Also included in these data were scheduled stopping locations such as a depot for loading or unloading cargo. The GPS data were recorded using time intervals predefined by the GPS unit on each truck, which in turn determined the overall GPS data resolution. The time intervals were adaptive according to the travelling

speed of the vehicle. When a truck travelled below 80 km/h, the recording interval was set at 30 seconds or less. This effectively captured stop-and-go traffic and driving behaviors, such as sharp acceleration and hard braking events. When traveling above 80 km/h, the units recorded position every 60 seconds.

The second data component was the weight of cargo transported for each trip logged. This was crucial for matching trip characteristics to the amount of cargo carried. These data were provided as hardcopy records containing weight and the type of goods shipped, in addition to the time of unloading and loading cargo at each depot. These data corresponded to stops recorded by the GPS unit on each truck.

The third and final component of the data provided by Transcare was the fuel log. This contained the amount of fuel purchased at 15 specific times throughout the study period. When refueling occurred, it was done between freight trips, and not systematically after every trip, which prohibited the determination of fuel consumed per trip. These data were collected separately in the form of a refueling invoice for each truck. These logs included useful information such as the volume of fuel purchased, its cost, and the location of the refueling stop.

4

Methods

4.1 Derivation of Variables from the GPS Data

The GPS data retrieved from each truck consisted of spatial coordinates (i.e., latitude and longitude), time stamps, velocity, and scheduled stops. These data were manipulated to derive a host of additional variables, which are documented in Appendices A and B. The variables presented in Appendix A are derived for each GPS record in the GPS data stream, while the variables shown in Appendix B pertain to each trip. These variables in Appendix B were then used to assess trip characteristics and specific driver behaviors hypothesized to impact fuel consumption. Some variables were derived using existing formulas such as average acceleration (see Equation 1) and straight-line distance (SLD) between GPS coordinates. SLD was calculated using the haversine formula (Robusto, 1957):

$$(2) \quad SLD = \arcsin [\sin(\Phi_1) \times \sin(\Phi_2) + \cos(\Phi_1) \times \cos(\Phi_2) \times \cos(\Delta\lambda)] \times R$$

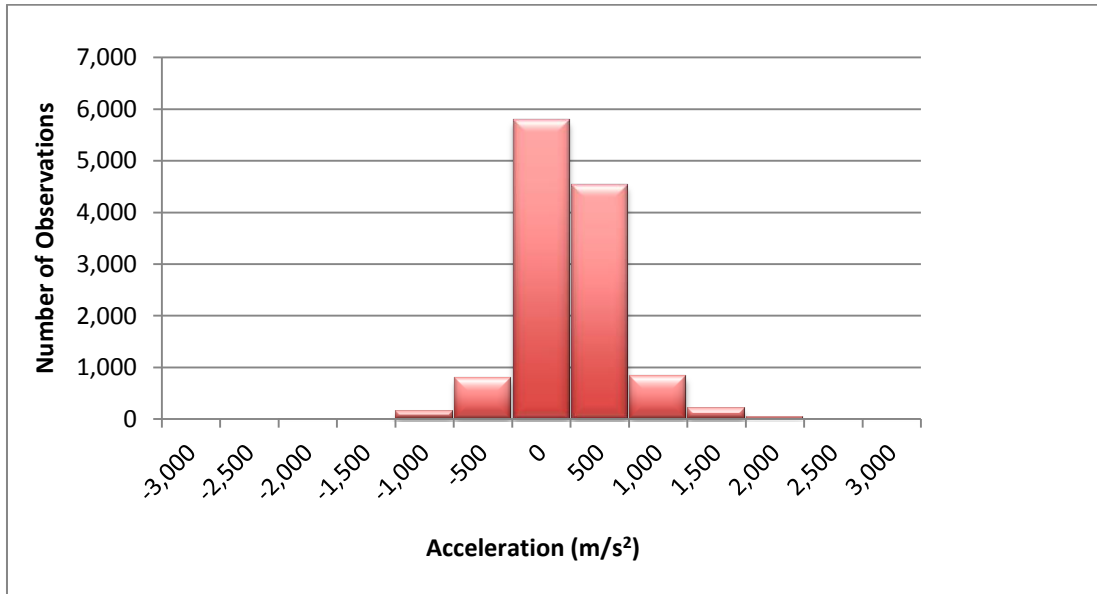
where Φ_1 is the latitude of point 1, Φ_2 is the latitude of point 2, $\Delta\lambda$ is the longitude separation, and R is the radius of the sphere representing the Earth. The advantage behind using the haversine formula for distance calculations, especially when using GPS position data, is the increase in accuracy compared to straight distance calculations given the spherical nature of the Earth's surface. Alternatively, a Geographic Information System (GIS) containing a digital road network for Ontario could have been

used to derive trip distance. In a preliminary analysis, a comparison examining the quantitative difference between distances derived using the haversine formula and road network distances was performed for a sample of trips. From the results, it was determined that the difference was insignificant. Therefore, to reduce computational time, a GIS was not used for distance calculations. Nevertheless, a GIS containing a digital road network for Ontario was used to visualize the GPS records for each trip in order to verify data accuracy.

In order to capture trip detail through space and time, the GPS units self-adjusted the recording time interval according to the speed of travel (i.e., at travel speeds over 80 km/h, position was recorded once every minute; at speeds under 80 km/h, the recording interval was 30 seconds or less to capture stop-and-go traffic and hard braking events). This proved to be quite effective since even recording at the minimum data resolution (i.e., recording once every minute) provided a sufficiently detailed trace of the journey to account accurately for turns and bends in the road. On average, 1,700 km were travelled between refueling events for a total of approximately 23,000 km travelled during the study period. The limited storage capacity of the GPS units and the need for capturing small time intervals is a balance between data resolution and storage capacity. As a result, the provided time intervals perform suitably for the purposes of this study. In addition, although the literature placed a significant focus on the smoothing of GPS data before processing, due to the adaptive recording interval used in this study, it was determined that the potential for detrimental data fluctuations were already removed during the collection process.

The GPS data were used to examine acceleration and speed – both aspects of driver behavior. Truck speed was output from the GPS units in miles per hour (mi/h) and converted to kilometers per hour (km/h). Once velocities were obtained, average acceleration was computed according to Equation 1. It should be noted that in this study, a negative value of acceleration is referred to as deceleration and a value of zero is referred to as coasting. Positive values are referred to as acceleration. Figure 4.1 presents the distribution of acceleration values obtained from the GPS data, which consisted of 12,333 records. In the data set (see Appendix A), acceleration is measured in km/s^2 . For Figure 4.1, these values have been converted to m/s^2 .

Since threshold values for hard acceleration and hard braking were not defined in the literature, they were therefore defined in this study as values greater than three standard deviations from a value of zero acceleration. Specifically, acceleration greater than $1,125 \text{ m/s}^2$ was considered to be hard acceleration, acceleration greater than 750 m/s^2 but less than or equal to $1,125 \text{ m/s}^2$ was considered moderate acceleration, and acceleration greater than 0 m/s^2 but less than or equal to 750 m/s^2 was considered light acceleration. Negative values of acceleration – that is, deceleration – were classified in the same way except that the intervals were defined by negative numbers. Values of 0 m/s^2 were classified as coasting. This approach to classifying acceleration resulted in 1.5% and 0.6% of acceleration records being classified as hard acceleration and hard braking events, respectively. The overwhelming majority of records were, however, classified as either light acceleration or light deceleration events – 40.8% and 37.4%, respectively.

Figure 4.1 Distribution of Acceleration for the GPS Records

In addition to classifying each GPS record according to its acceleration, the duration and distance travelled for each event was also computed. These metrics were summed for each trip to arrive at the trip-based variables presented in Appendix B. Given the adaptive nature of the GPS units, it should be noted that certain driver behaviors summarized as event counts may be over-represented in the data. As mentioned, when traveling at slower speeds (i.e., under 80 km/h), the GPS unit records position every 30 seconds, which ultimately equates to more detailed recording of acceleration and deceleration events at that time. However, at higher speeds (i.e., greater than 80 km/h), while speed adjustments do occur, they are not captured at the same temporal resolution. Instead, since the recording interval is set for once every minute, acceleration or deceleration events may not be as well-documented unless significant enough to reduce speeds to under 80 km/h.

4.2 Freight Data

For each trip made by the two trucks during the study period, a freight data set was developed from hardcopy records provided by Transcare. The data set contained the weight of cargo in kilograms, the origin and destination depots, the arrival and departing times, as well as the cargo type (e.g., steel coils). The data from the hardcopy records were entered into the data set by matching date and time information provided to the GPS data. However, since these two sources of data were recorded using two distinct methods and for different purposes, there were some discrepancies. These mismatches included stops recorded in the cargo data that were not flagged explicitly as stops in the GPS data. Corrections were made utilizing the GPS data to search for significant stops (see Appendix A) – a variable derived to identify points in time where the truck stopped moving while recording time continues, and to differentiate these from mere GPS recording errors.

4.3 Fuel Data

A fuel data set was developed pertaining to refueling events during the study period. For each event, several variables were recorded – namely, time of fuel purchase, location, fuel cost, and fuel volume in liters. The total volume of fuel pertaining to these events during the study period was 6,695 liters. These events were joined to the GPS and freight data sets by using date and time as well as a derived variable, stop number, to ensure that all three data sets linked accurately. Due to the aggregate nature of the fuel data set, which had 15 recorded refueling events, a many-to-one join was created between the fuel data and the GPS data combined with weight. An aggregation was performed summing variables pertaining to the 202 trips by the 15 refueling events. While it was hoped that a multivariate analysis relating fuel consumption to various explanatory variables could be performed using this data set, the modeling effort failed given the aggregate nature of the fuel data. In light of this outcome, it is recommended that such an analysis be trip-based, which means that fuel consumption must be measured per trip, not over a range of trips.

4.4 Database Formation

After processing and formatting the data sets as separate components, it was necessary to combine all three into a single database for analysis. The synthesis of data was completed initially through the use of Microsoft Access 2007 – a database management software package. Primary keys and foreign keys were identified in order to link the individual data sets together to form a cohesive single database. Several attempts were undertaken to join the data sets using date and time as a key identifier; however, the approach proved to be too cumbersome and error prone due to small data mismatches. Issues arose concerning inconsistencies among the data sets with regards to how time was recorded in each data set. Specifically, the GPS data were assumed to have the most accurate time recording. However, when comparing these data to the cargo weight invoices, which were documented by workers at each depot, it was evident that the hand-written records by workers were rounded in time to the nearest 10-minute interval and in some cases by as much as 20 minutes from the actual time. This made an automated matching very difficult. Thus, during pre-processing of the GPS data, a stop number variable was added to indicate, similar to a sequential ID, which number the stop was in reference to the origin. This stop number was added to the freight data by manually matching times entered by depot workers on paper invoice forms. As a result, the three data sets were successfully linked into a single database containing all required variables for analysis.



Results and Discussion

5.1 Analysis of Trips

This section presents and discusses the descriptive statistics associated with attributes of the trips recorded. In total, 202 trips were made between the two trucks included in this study. Among these trips, 25 are considered tours, making several stops before returning. Due to the data provided, tours are recorded as a single trip. Tables 5.1 and 5.2 provide summary information for these trips and tours, respectively.

The statistics presented are based on two trucks, which have varying shipping schedules. For instance, one truck would have a tendency to make tours over longer distances (e.g., from Hamilton to Ottawa, Ontario), while the other tended to make shipments to adjacent cities in the Greater Golden Horseshoe region of Ontario. For the purposes of this study, data collected for both trucks were combined to yield a larger data set for analysis. The issue of separating each tour into its multiple trips had the potential for introducing errors and was therefore not performed. Essentially, this process would involve cross referencing weight information with GPS records and identifying when a tour was being performed. Measures were taken to identify that tours existed in the GPS data by implementing a variable that recognized when the truck had remained stationary for a substantial amount of time without an official stop being recorded. As a result, 25 “trips” had several of these pseudo stops suggesting that they were

in fact tours. This was verified with the cargo information. However, due to the resolution of the GPS data compared to the cargo information, error would be associated with separating tours into their multiple trips. For the purposes of this study, working with tours and trips together did not prove to impact driver behavior factors measured – notably, acceleration and speed. Weight data were classified into bins of 5,000 kg to summarize weights shipped (see Figure 5.1).

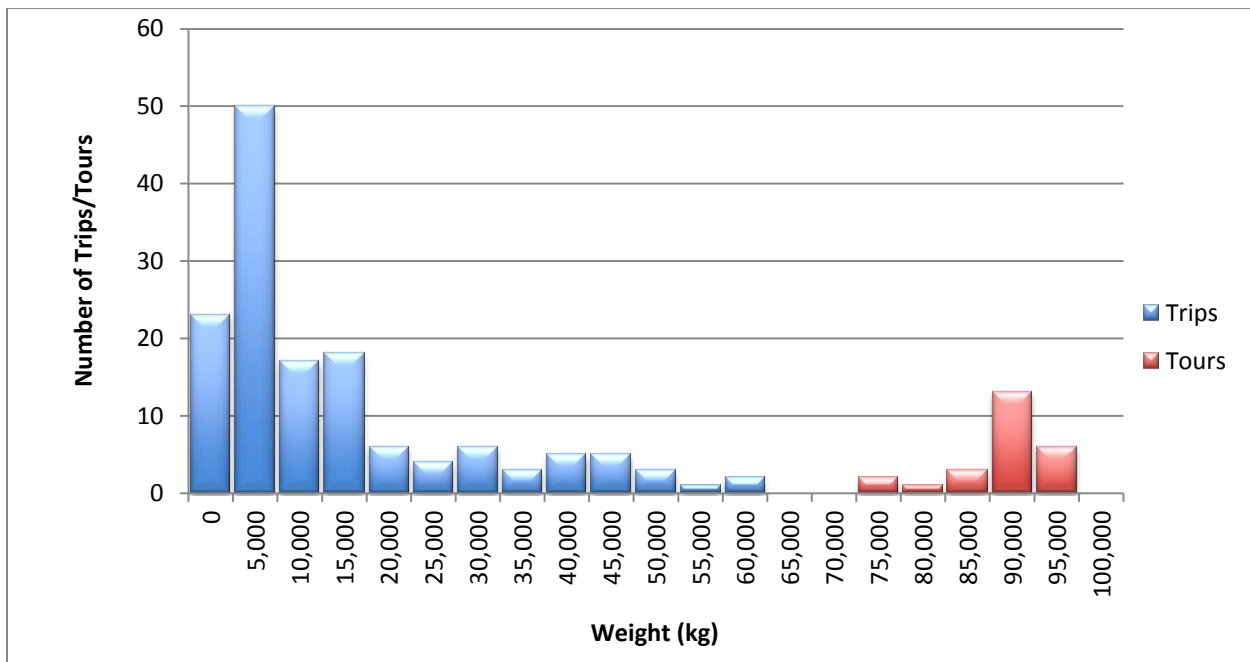
Table 5.1 Summary Statistics for Trips

Category	Min.	Max.	Mean
Distance (km)	0.5	357.5	63.3
Time (hours)	0.0	14.4	2.7
Average speed (km/h)	0.6	101.0	58.2
Weight transported (kg)	0.0	56,734.0	12,459.4
T-km	0.0	11,183.7	887.2
Number of GPS records	5	214	59

Table 5.2 Summary Statistics for Tours

Category	Min.	Max.	Mean
Distance (km)	13.1	232.3	93.3
Time (hours)	0.4	15.0	5.0
Average speed (km/h)	41.0	79.0	59.2
Weight transported (kg)	73,712.0	93,682.0	87,185.8
T-km	1,122.8	21,538.4	8,072.9
Number of GPS records	14	233	93.96

Figure 5.1 Distributions of Trips and Tours with Respect to Weight of Goods Shipped



5.2 Acceleration Analysis

Acceleration, both positive and negative (i.e., deceleration), is one of the major influences drivers can have on fuel consumption. Coasting is an additional component, where speed remains constant over time. Due to the scope of this study and available data resolution, there is no evidence of idling, which suggests that it was not captured. However, idling has been mentioned in previous studies as an additional factor that negatively impacts fuel economy.

For the purposes of more detailed analysis, acceleration and deceleration have been subdivided into classes based on severity – namely, hard, moderate, and light – as outlined in Section 4.1. The percentage of each of these classes was examined by distance travelled, travel time, and frequency. Figure 5.2 shows the results by distance, while Figure 5.3 details the results by travel time. It is clear from the figures that different metrics result in different percentages. For instance, light acceleration accounts for 45% of total trip distance for the sample of trips compared to 75% of total travel time. This finding illustrates the importance of varying the method used to measure observed events.

Figure 5.2 Percentage of Total Distance Driven by Acceleration Classes

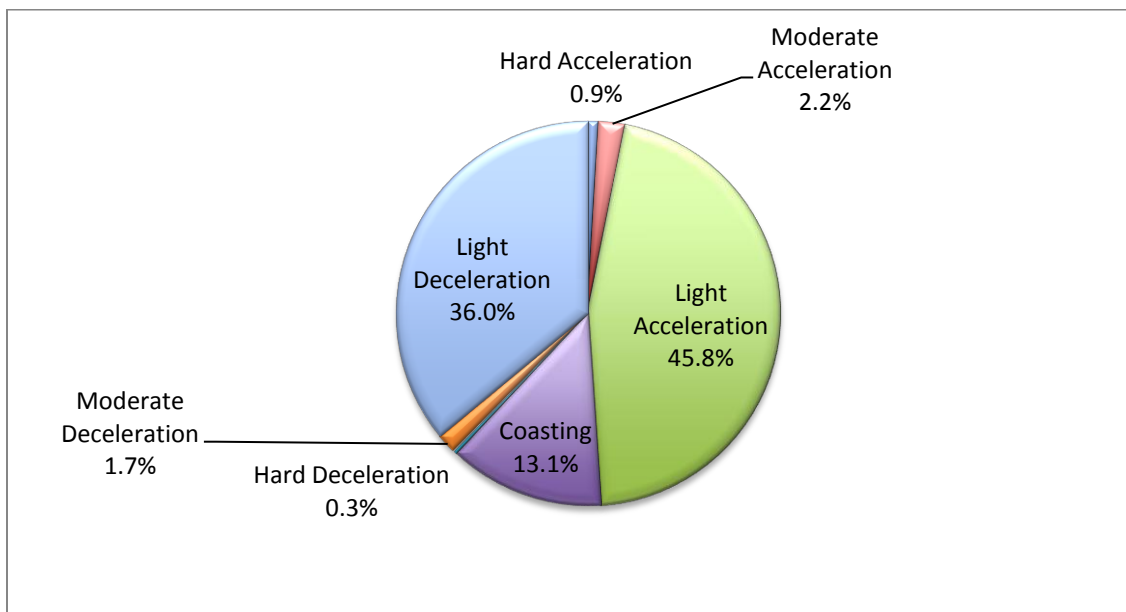
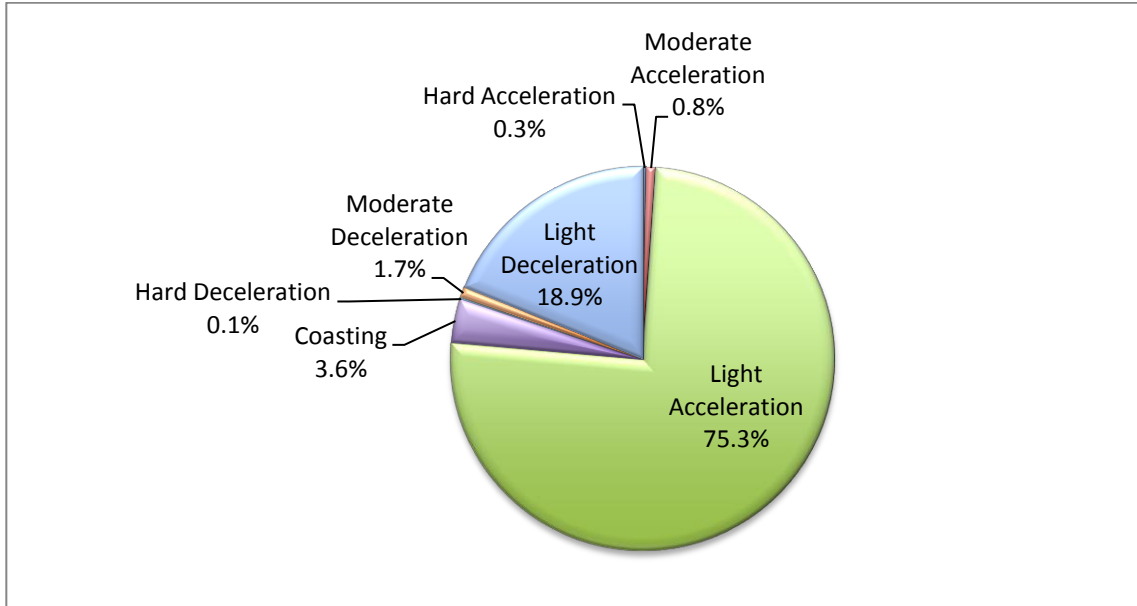
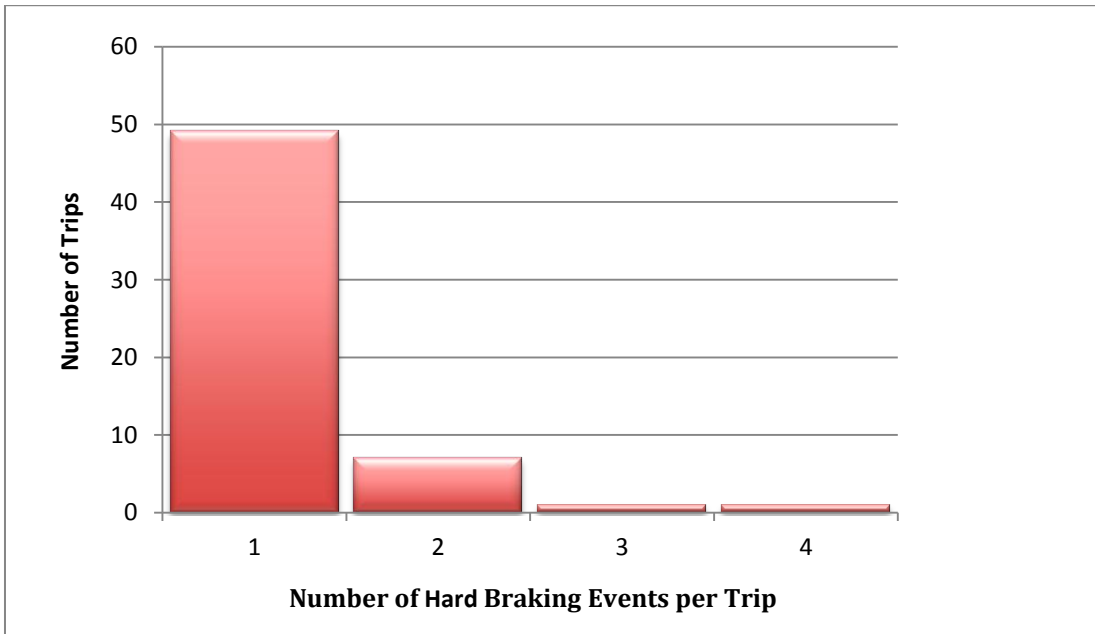


Figure 5.3 Percentage of Total Travel Time by Acceleration Classes



As past studies have made a general connection between the conservation of energy during a trip and the positive effects on fuel economy, the number of hard braking events is an important aspect to investigate. Therefore, the approach chosen to measure these events was frequency of occurrence during a trip. The data indicate that 29% of all trips made experienced at least one hard braking event. For these trips, the distribution of hard braking events per trip is shown in Figure 5.4.

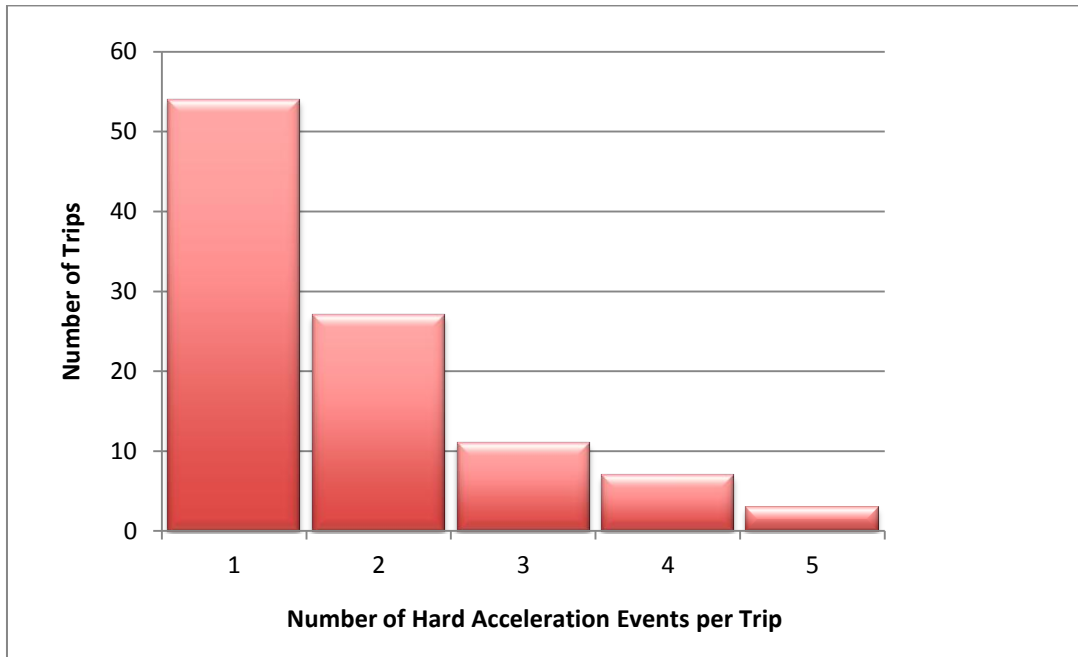
Figure 5.4 Distribution of the Number of Hard Braking Events Per Trip for Trips Experiencing Such Events



For trips that experienced hard braking, it is evident that there is a much higher percentage of a single occurrence as opposed to multiple occurrences during the same trip. Specifically, the above distribution (Figure 5.4) shows the following: 84% of trips experienced one hard braking event, 12% experienced two, 2% experienced three, and 2% experienced four. When addressing the conservation of energy throughout a trip, these hard braking events are a critically important factor impacting fuel consumption. The elimination of such events would improve the fuel economy of the trip.

Similarly, as discussed in the literature, a single sharp acceleration event produces more emissions and consumes unnecessarily larger quantities of fuel. Figure 5.5 presents the distribution of hard acceleration events per trip for trips experiencing such events. The data indicate that 51% of all trips in the Transcare sample experienced one or more hard acceleration events (recall that hard acceleration is defined as 1,125 m/s² or greater). Intuitively, acceleration is a necessity for travel as it converts energy into the initial movement of the vehicle. For this reason, it is therefore expected to occur more frequently compared to hard braking.

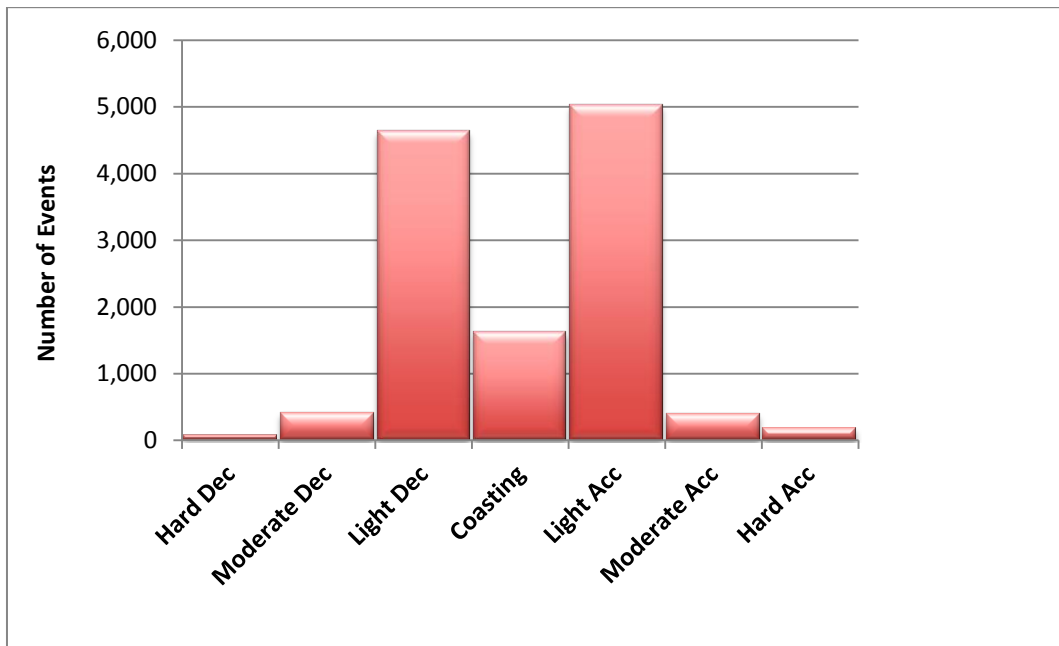
Figure 5.5 Distribution of the Number of Hard Acceleration Events per Trip for Trips Experiencing Such Events



For trips that experienced hard acceleration, it is clear from Figure 5.5 that the majority experience only one occurrence per trip. However, unlike hard braking, the pattern shows much more acceleration activity overall – that is, higher percentage of trips experience two such events, three such events, and so on. The distributions for hard braking (Figure 5.4) and hard acceleration (Figure 5.5) provide evidence that fuel consumption may be impacted by driver behavior or more specifically factors that influence driver behavior. Figure 5.6 presents the number of acceleration events found in the GPS data set classified by type of acceleration.

Based on the acceleration analysis, it is evident that vehicle speed experienced dynamic adjustment or acceleration 87% of the time that the trucks were in motion. Coasting (i.e., maintaining constant speed) accounted for the remaining 13% of the time. Therefore, the vast majority of a typical trip appears to be impacted by factors that increase fuel consumption, thereby reducing fuel economy. Such external factors include physical attributes of the road such as turns, bends, and changes in terrain or the presence of hills. In addition to these, traffic congestion, traffic accidents, or obstructions causing the driver to dynamically adjust speed throughout the course of the trip will also impact fuel consumption. As the literature has documented, driving styles or specific driver habits can significantly impact fuel consumption. According to Ang-Olson and Schroerer (2002), as much as 3.8% of total fuel used in a trip can be conserved through the implementation of driver training programs.

Figure 5.6 Distribution of Acceleration by Type of Acceleration



5.3 Analysis of Speed

As documented in the literature (see Section 2), speed also impacts fuel consumption. For this reason, speed was also analyzed in this study. Table 5.3 summarizes the speed characteristics of all trips made by the two trucks for which data were collected by Transcare.

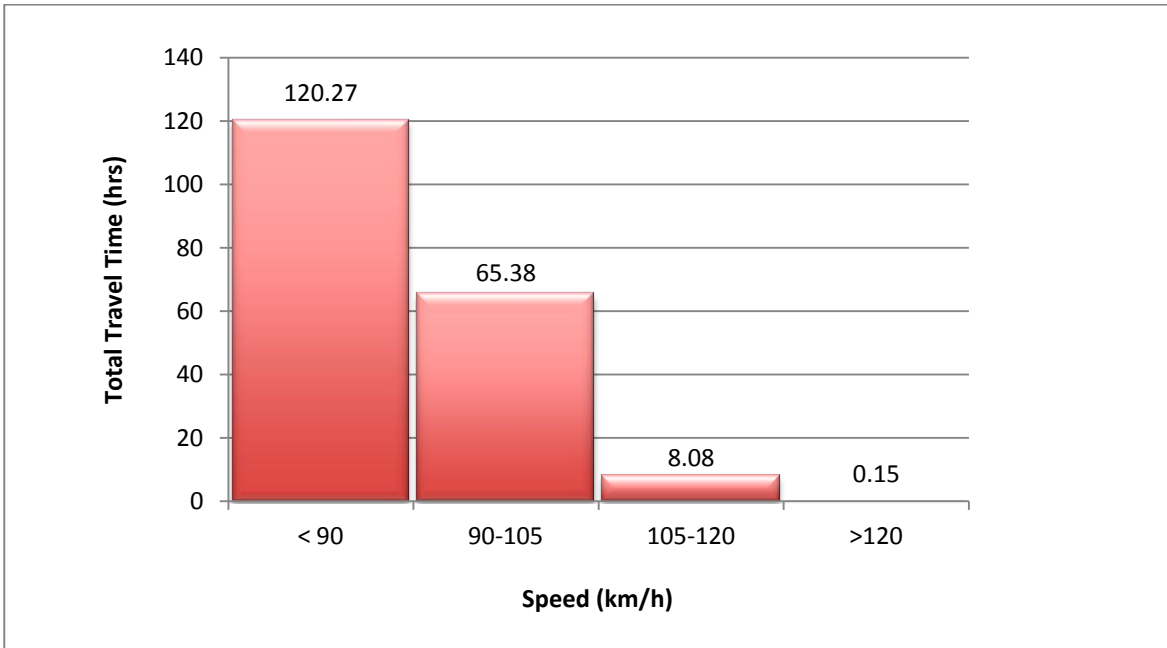
For a more detailed inspection, further analysis was performed at the trip level. As outlined in past studies, when analyzing the impact of speed on fuel economy, a specific interest has been placed on four speed intervals: less than 90 km/h, between 90 and 105 km/h, between 105 and 120 km/h, and speeds exceeding 120 km/h. Each of these intervals impacts fuel consumption with varying severity due to such variables as aerodynamics, friction, and engine efficiency (recall Figure 2.2). Total travel time and total distance driven were summarized by speed category and presented in Figures 5.7 and 5.8, respectively. The categories forming the speed profiles are those mentioned above. From Figure 5.7, it is

apparent that the greatest amount of time was spent traveling at speeds less than or equal to 90 km/h. However, as seen in the distance distribution (Figure 5.8), a greater distance was travelled while maintaining speeds between 90 and 105 km/h.

Table 5.3 Summary Statistics for Trip Speed

Category	Value
Minimum Speed (km/h)	0
Maximum Speed (km/h)	137
Average Speed (km/h)	59
Standard Deviation	28.84
Variance	954.33

Figure 5.7 Total Travel Time (in Hours) Driven in Each Speed Category)



The information presented can be compared to previous study results. Specifically, recall the results of Ang-Olson and Schroerer (2002) as presented in Table 2.1 (i.e., a summary of modifications and their impacts on fuel consumption). A speed reduction from 112 km/h to 104 km/h was noted as reducing fuel consumption by 6.0%. Furthermore, a decrease from 104 km/h to 96 km/h reduces fuel consumption by an additional 7.6%. Figure 5.9 shows the percentage of time the two trucks were traveling at these defined speed intervals. As seen, 27% of all travel time was spent in these two intervals. An additional 1% of total travel time was spent at speeds greater than 112 km/h, which is also identified with potential for further savings.

Figure 5.8 Total Distance (in Kilometres) driven in Each Speed Category

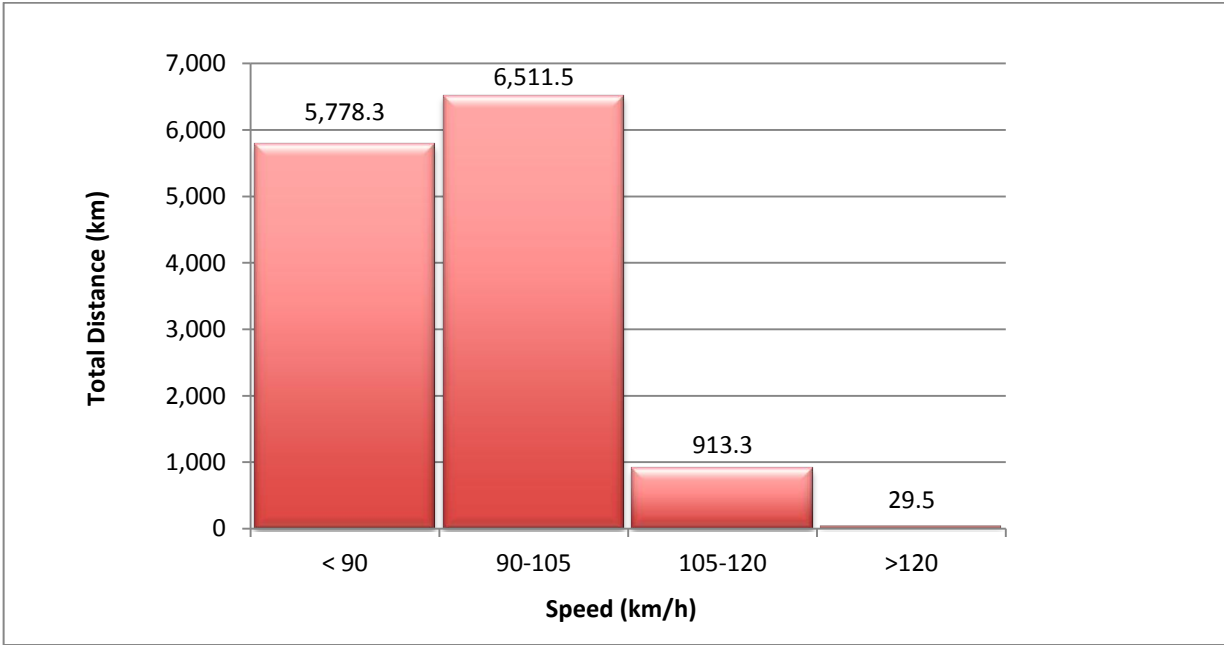
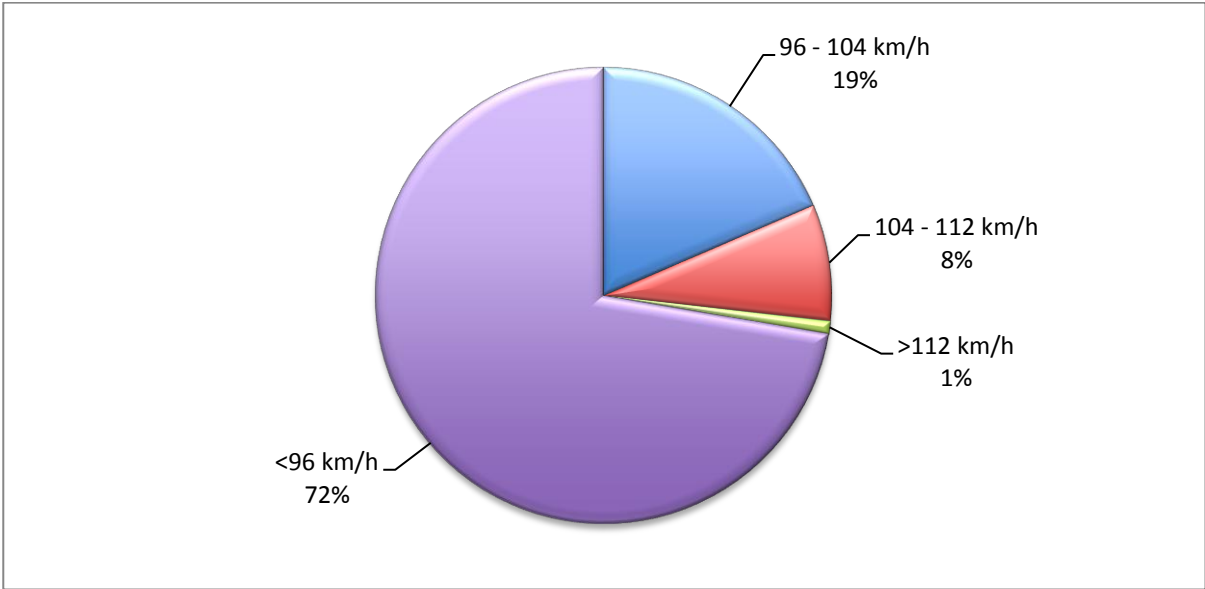


Figure 5.9 Percentage of Travel Time at Each Speed Interval





Conclusion

This study explored factors impacting truck fuel consumption through the use of GPS data collected from two trucks operating for Transcare Logistics Corporation. Collectively, the two trucks made 202 trips during a two-month study period, which extended from June 19th to July 31st, 2009. Shipments were delivered mostly to destinations in the Greater Golden Horseshoe region of Ontario. However, some extended as far as Ottawa, Ontario. This study included three analyses – notably, a discussion of trip characteristics, an evaluation of acceleration, and an analysis of vehicle speed. The primary shortcoming of this study concerned the aggregate nature of the fuel data set, which consisted of 15 refueling events. In other words, trips were not associated with fuel consumed. Thus, multivariate modeling relating trip-based factors pertaining to fuel consumption to actual fuel consumed was precluded in the analysis.

The analysis of driver behavior focused primarily on identifying the potential impact of hard acceleration and hard deceleration (braking) events. For the purposes of this study, hard acceleration events were defined as acceleration in excess of $1,125 \text{ m/s}^2$, while hard braking events were defined as deceleration in excess of $-1,125 \text{ m/s}^2$. The results of the analysis indicated that a hard braking event occurred at least once in 29% of all trips made. Since braking works against maximizing fuel economy, this is a potential area for improvement. Furthermore, as noted in literature, hard acceleration events are also detrimental to fuel economy and produce harmful emissions. This study found that 51% of all trips made

experienced at least one of these hard acceleration events. Eliminating these extreme accelerations and decelerations would go a long way toward improving the fuel economy of trucks.

For the analysis of speed, specific intervals were identified in past research to be particularly unfavorable for fuel consumption. When comparing such intervals to vehicle speed in this study, it was determined that 19% of all travel time was spent in the 96 to 104 km/h speed interval. As documented in past research (recall Table 2.1), there are potential fuel savings of 7.6% as speeds are reduced to 96 km/h. Furthermore, 9% of travel time exists within the upper speed interval of 104 to 112 km/h. Fuel savings are estimated to be 6% if speed is reduced to 104 km/h. Based on the analysis, significant fuel savings can be garnered through speed reductions alone. A future direction for research should, however, include a cost-benefit analysis of fuel savings against the presumably increased travel time associated with slower driving.

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Appendix

Appendix A: Variables Derived from the GPS Data for Each GPS Record

Variable	Definition
VEH_NAM	GPS vehicle ID
SPEED_KPH	Vehicle speed as recorded by GPS unit (km/h)
DISTANCE_KM	Distance (km) calculated between GPS records using Haversine's formula (see Section 4.1)
DURATION_SEC	Duration (seconds) since last GPS point was recorded
SIG_STOP	Significant stops not marked in the GPS data stream as official stops. These identify stops on tours as opposed to trips
DURATION_SIG_STOP_SEC	Duration (seconds) of a significant stop
ACCELERATION	Average acceleration (referred to as acceleration in this study and measured as km/s^2) calculated by change in speed (km/hr) divided by change in time (seconds)
ACC_MARKER	Acceleration classified according to standard deviations (stdev.) from 0 (values are -3, -2, -1, 0, 1, 2, 3)
HARD_ACC_DIST	Distance (km) travelled under hard acceleration (acceleration > 3 stdev.)
MODERATE_ACC_DIST	Distance (km) travelled under moderate acceleration (2 stdev. < acceleration \leq 3 stdev.)
LIGHT_ACC_DIST	Distance (km) travelled under light acceleration (0 < acceleration \leq 2 stdev.)
COASTING_DIST	Distance (km) travelled for which acceleration was 0 km/s^2
HARD_DEC_DIST	Distance (km) travelled under hard deceleration (acceleration < -3 stdev.)
MODERATE_DEC_DIST	Distance (km) travelled under moderate deceleration (-3 stdev. \leq acceleration < 2 stdev.)
LIGHT_DEC_DIST	Distance (km) travelled under light deceleration (-2 stdev. \leq acceleration < 0)
HARD_ACC_TIME	Time (seconds) travelled under hard acceleration (acceleration > 3 stdev.)
MODERATE_ACC_TIME	Time (seconds) travelled under moderate acceleration (2 stdev. < acceleration \leq 3 stdev.)
LIGHT_ACC_TIME	Time (seconds) travelled under light acceleration (0 < acceleration \leq 2 stdev.)
COASTING_TIME	Time (seconds) travelled for which acceleration was 0 km/s^2
HARD_DEC_TIME	Time (seconds) travelled under hard deceleration (acceleration < -3 stdev.)
MODERATE_DEC_TIME	Time (seconds) travelled under moderate deceleration (-3 stdev. \leq acceleration < 2 stdev.)
LIGHT_DEC_TIME	Time (seconds) travelled under light deceleration (-2 stdev. \leq acceleration < 0)

Appendix B: Variables Derived from the GPS Data for Each Trip

Variable	Definition
VEH_NAM	GPS vehicle ID
HARD_ACC_TOT_DIST	Total distance (km) travelled under hard acceleration (acceleration > 3 stdev.)
MODERATE_ACC_TOT_DIST	Total distance (km) travelled under moderate acceleration (2 stdev. < acceleration ≤ 3 stdev.)
LIGHT_ACC_TOT_DIST	Total distance (km) travelled under light acceleration (0 < acceleration ≤ 2 stdev.)
COASTING_TOT_DIST	Total distance (km) travelled for which acceleration was 0 km/s ²
HARD_DEC_TOT_DIST	Total distance (km) travelled under hard deceleration (acceleration < -3 stdev.)
MODERATE_DEC_TOT_DIST	Total distance (km) travelled under moderate deceleration (-3 stdev. ≤ acceleration < 2 stdev.)
LIGHT_DEC_TOT_DIST	Total distance (km) travelled under light deceleration (-2 stdev. ≤ acceleration < 0)
TOTAL_TRIP_DIST_KM	Total distance (km) travelled for a trip from one depot stop to another
HARD_ACC_TOT_TIME	Total time (seconds) travelled under hard acceleration (acceleration > 3 stdev.)
MODERATE_ACC_TOT_TIME	Total time (seconds) travelled under moderate acceleration (2 stdev. < acceleration ≤ 3 stdev.)
LIGHT_ACC_TOT_TIME	Total time (seconds) travelled under light acceleration (0 < acceleration ≤ 2 stdev.)
COASTING_TOT_TIME	Total time (seconds) travelled for which acceleration was 0 km/s ²
HARD_DEC_TOT_TIME	Total time (seconds) travelled under hard deceleration (acceleration < -3 stdev.)
MODERATE_DEC_TOT_TIME	Total time (seconds) travelled under moderate deceleration (-3 stdev. ≤ acceleration < 2 stdev.)
LIGHT_DEC_TOT_TIME	Total time (seconds) travelled under light deceleration (-2 stdev. ≤ acceleration < 0)
TOTAL_TRIP_TIME_SEC	Total time (seconds) travelled for a trip from one depot stop to another
MIN_ACC	Minimum acceleration (km/s ²) for the trip
MAX_ACC	Maximum acceleration (km/s ²) for the trip
MEAN_ACC	Mean acceleration (km/s ²) for the trip
STDEV_ACC	Standard deviation (stdev.) of acceleration (km/s ²) for the trip
1_STDEV_ACC	1 st stdev. value of acceleration (km/s ²) derived from GPS data stream (i.e., 0.375159 km/s ²) – note: value is the same for all trips
2_STDEV_ACC	2 nd stdev. value of acceleration (km/s ²) derived from GPS

	data stream (i.e., 0.750318 km/s ²) – note: value is the same for all trips
3_STDEV_ACC	3 rd stdev. value of acceleration (km/s ²) derived from GPS data stream (i.e., 1.125477 km/s ²) – note: value is the same for all trips
HARD_ACC_NUM	Number of hard acceleration events
HARD_DEC_NUM	Number of hard deceleration events
MODERATE_ACC_NUM	Number of moderate acceleration events
MODERATE_DEC_NUM	Number of moderate deceleration events
LIGHT_ACC_NUM	Number of light acceleration events
LIGHT_DEC_NUM	Number of light deceleration events
COASTING_COUNT	Number of coasting events
TOTAL_RECORDS	Number of GPS records comprising the trip
AVG_SPEED_KM	Average recorded speed (km/h) for the trip
MAX_SPEED_KM	Maximum recorded speed (km/h) for the trip
UNSCHEDULED_STOPS	Number of significant stops not marked in the GPS data stream for the trip as official stops
UNSCHEDULED_STOP_TOTAL_TIME_SEC	Total time (seconds) spent at unscheduled stops during the trip