ASSESSING PASSENGER CAR/VEHICLE EQUIVALENT
TRAVEL TIME OF A TRUCK

by

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ABSTRACT

RAVINA N. JAIN. Assessing passenger car/vehicle equivalent travel time of a truck. (Under the guidance of DR. SRINIVAS S. PULUGURTHA)

Freight transportation is an indicator of the regional economy. In the United States, transportation by trucks accounted for 63.8% of total freight during the year 2015. The demand for freight transportation is increasing from time to time. It is anticipated that freight transportation will increase by 43% over the next 20 years. The increase in population, employment, and e-shopping (online shopping) along with the introduction of free shipping, 2-day fast shipping, etc. are some of the related factors that are expected to contribute to the increase in freight transportation over time.

The movement of freight can be directly linked to the percentage of trucks on roads. These trucks differ in their physical and operational characteristics compared to passenger vehicles (in general, cars). The Highway Capacity Manual (HCM) recommends adopting the Passenger Car Equivalent (PCE) concept to account for the effect of trucks on road capacity and operational performance. The PCE varies from one location to another location and depends on geometric and traffic conditions.

Many researchers have worked on computing and calibrating the PCE. However, it is not clear if the effect would be similar in terms of travel time (truck travel time compared to passenger car travel time). The area type, time-of-the-day, day-of-the-week, reference speed (free-flow speed), and the number of vehicles observed in a given time period (an indicator of data density) influence the travel time of a truck when compared to the travel time of a passenger car or other vehicle types. Therefore, the goal of this research is to

examine the relationship between the travel time of trucks and the travel time of passenger cars or all vehicles to assess PCE of a truck from a travel time perspective. The objectives of this research are:

1. to examine the relationship between the travel time of trucks and the travel time of passenger cars or all vehicles at the link-level,
2. to examine to what extent the area type (the urban and rural) influences the relationship,
3. to examine the relationship between the travel time of trucks and the travel time passenger cars or all vehicles by data density, day-of-the-week (DOW), time-of-the-day (TOD), and reference speed, and,
4. to identify significant factors influencing the ratio of the travel time of trucks to the travel time of passenger cars or all vehicles.

Travel time data for an urban area (Mecklenburg County) and a rural area (Iredell County), North Carolina was gathered from the National Performance Management Research Dataset (NPMRDS) under the Regional Integrated Transportation System (RITIS) website for the year 2017. In the urban area and the rural area, three travel time datasets were considered; the first dataset includes travel time data for trucks only, the second dataset includes travel time data for passenger cars only, and the third dataset includes travel time for all vehicles. In the urban area, travel time data for 894 links were considered for trucks only, 798 links were considered for passenger cars only, and 894 links were considered for all vehicles. Likewise, in the rural area, travel time data for 137 links were considered for trucks only, 133 links were considered for passenger cars only, and 137 links were considered for all vehicles.

The data was processed to compute the average travel time of trucks, the average travel time of passenger cars, and the average travel time of all vehicles at link-level by area type, TOD, DOW, reference speed, and data density. Ordinary Least Square (OLS) regression models and Generalized Estimating Equations (GEE) models were developed to examine the relationships. The average travel time of trucks was considered as the dependent variable while the average travel time of passenger cars or all vehicles were considered as the independent variable when developing OLS regression models.

The Pearson correlation coefficients were then computed to examine the relationship between travel time measures, area type, data density, DOW, TOD, and reference speed. A sample of 7654 records was used for this analysis and developing GEE models. The ratio of the average travel time of trucks to the average travel time of passenger cars or all vehicles was considered as the dependent variable while the area type, TOD, DOW, reference speed, and data density were considered as the independent variables when developing GEE models.

Overall, one-hundred and seven models were developed using data for the urban and rural areas in this research. Of these, thirty-eight OLS regression models were developed after categorizing data by TOD (morning peak period, off-peak period, evening peak period, and night-time period). Forty-three OLS regression models were developed after categorizing data by the reference speed (<= 30mph, >30mph to <=40mph, >40mph to <=50mph, and >50mph). Twenty-two OLS regression models were developed by categorizing data by DOW. Four GEE models were developed considering area type, TOD, DOW, reference speed, and data density altogether. The GEE models were validated using the Root Mean Square Error (RMSE), and the Mean Absolute Percentage Error (MAPE).

The average travel time of trucks was observed to be greater than the average travel time of passenger cars and all vehicles irrespective of the area type. Likewise, the average travel time of trucks was observed to be greater than the average travel time of passenger cars on links with a reference speed of less than 30 mph irrespective of the area type. In the rural area, the average travel time of trucks was more than the average travel time of passenger cars and all vehicles during the weekday when compared to the weekend. In the urban area, no trends in the relationship between the average travel time of trucks and the average travel time of passenger cars were observed by DOW. In the rural area, the average travel time of trucks was observed to be greater than the average travel time of passenger cars during the evening peak period when compared to other times of the day. However, the average travel time of trucks was observed to be greater than the average travel time of passenger cars during the off-peak period and the evening peak period for data density A, night-time period for data density B, and the morning peak period for data density C.

Gamma log-link distribution-based models were observed to be a best-fitted model in this research. The results obtained indicate that the area type, data density, DOW, TOD, and reference speed have a significant influence on the ratio of the average travel time of trucks to the average travel time of passenger cars. The reference speed and DOW were observed to be negatively associated with the ratio of the average travel time of trucks to the average travel time of passenger cars. All the other variables were observed to be positively associated with the ratio of the average travel time of trucks to the average travel time of passenger cars. The DOW did not have a significant influence on the ratio of average travel time of truck and the average travel time of all vehicles.

The findings from this research help practitioners and professionals to better plan, design, and operate the transportation infrastructure. They can also be used to assess the effect of the trucks on the travel time of other vehicles and the transportation system performance.

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LIST OF ABBREVIATIONS

DOW	day of the week
FHWA	Federal Highway Administration
HCM	Highway Capacity Manual
MSSQL	Microsoft Structures Query Language
PCE	Passenger car equivalent
RITIS	Regional Integrated Transportation Information System
SPSS	Statistical Package for Social Sciences
TOD	time of the day
TMC	traffic message channel

CHAPTER 1: INTRODUCTION

Freight transportation by trucks influences the operational performance of surrounding vehicles sharing the same driving environment. An increase in the number of trucks influences the traffic flow, and hence, the transportation system performance. Therefore, this thesis focuses on researching the influence of trucks on the transportation system performance from a travel time perspective. The motivation for this research, problem statement, the objectives of this research, and the organization of this thesis are presented in detail in this chapter.

1.1 Motivation and Background

American life relies on the transportation system to move goods and services effectively and efficiently. Transportation services are needed to deliver raw and intermediate materials to the manufacturer and the final product to the suppliers or final customer. Freight transportation has grown dramatically over time with the increase in population and economic activity within the United States. The interdependence of economies across the globe is an uplifting factor of freight transportation (BTS, 2015).

Heavy vehicles, hereafter referred to as trucks in this research, is the dominant mode of freight transportation in the United States. The freight transportation by trucks accounted for 63.8% of the total freight transported in the United States in the year 2015 (BTS, 2017).

Millions of people in the United States currently purchase more than half of the goods online (The Wall Street, 2019). The demand for online shopping and, hence, freight transportation is increasing from time to time. The introduction of free shipping, 2-day fast shipping, etc. is expected to make online shopping even more lucrative in the coming years. It is anticipated that freight transportation will increase by 43% over the next 20 years (BTS, 2017).

The success of firms that sell products online relies on the road network and logistics supply chain. The increase in online shopping is putting pressure on the logistics companies and the transportation system managers to better incorporate the effect of trucks when planning, designing, and managing transportation facilities.

Congestion is the primary factor restricting the efficient and timely delivery of goods (Crowley et al., 1975). On the contrary, the growth in truck transportation is a significant contributor to congestion, traffic delay, and road crashes (Crowley et al., 1975). This could be attributed to the physical and operational characteristics of trucks. They create psychological and physical intimidation to motorists.

The Highway Capacity Manual (HCM) recommends the use of an adjustment factor to account for the adverse effect of trucks on the transportation system performance. The effect is addressed by converting the mixed traffic volume to an equivalent passenger car volume. HCM 2000 defines the Passenger Car Equivalent (PCE) as “the number of passenger cars that are displaced by single heavy vehicle under the specified roadway, traffic, and control conditions”. Microscopic and macroscopic parameters such as headway

(Kockelman et al., 2000; Anwaar et al., 2011), delay (HCM, 1965; HCM, 2000), speed (HCM, 1965, HCM, 2000), density (HCM, 1965; HCM, 2000), capacity (Elefteriadou et al., 1995; Geistefeldt et al., 2009), and traffic flow (Demarchi et al., 2003) have been taken into consideration to estimate the PCE of trucks in the past.

The average density of the traffic stream is used as the equivalent criteria to develop the PCE in HCM (1965; 2000). Generally, the trucks are larger than passenger cars, and the average gap between the front and back of trucks are more than for the passenger cars. Under this condition, headway plays an important role in estimating the PCE. A speed difference between passenger cars and trucks may occur due to vehicle characteristics, road geometry, driving behavior, and their presence in the adjacent lane. The speed of a truck declines as they travel on upgrades. This is usually less than the average speed of the passenger car. The HCM (2000) publishes PCE values only under steady-state traffic condition. This can be considered as a limitation of the HCM method.

The success of logistics companies relies on on-time delivery or supply. Travel time can be considered as a better indicator to examine the effect of trucks on the transportation system performance. It is easy to comprehend by transportation engineers/planners/managers and general transportation system users. Additionally, the influence of trucks on the transportation system performance in terms of travel time could be different than when expressed in terms of PCE.

1.2 Problem Statement

Trucks and passenger cars typically share the same driving environment, but their physical and operational characteristics are different. Many researchers examined the influence of the difference in operational and physical characteristics between trucks and passenger cars in terms of PCE (Anwaar et al., 2011). These efforts include developing regression and simulation models to estimate PCE based on headway, speed difference, density, and delay. Also, several studies incorporated the road geometry, vehicle geometry and driver behavior for estimating the PCE of trucks (Al-Kaisy et al., 2005; HCM, 1965; HCM, 2000).

The availability of continuous and extensive raw travel time data opened opportunities for systematic evaluation of transportation facilities from a travel time perspective. The data can also be used to assess the reliability of the road network (FHWA, 2005). In recent years, many researchers focused on assessing transportation system performance from a travel time perspective (Pulugurtha et al., 2016, and Duddu et al., 2018)).

The travel time along a link varies by area type, time-of-the-day (TOD), day-of-the-week (DOW), posted speed limit or reference speed, and traffic composition. However, there are not many studies on the difference in travel time of trucks and passenger cars or on factors that influence truck travel time.

1.3 Research Objectives

The goal of this research is to better understand the influence of trucks on the transportation system performance from a travel time perspective. The objectives are:

1. to examine the relationship between the travel time of trucks and the travel time of passenger cars or all vehicles at the link-level,
2. to examine to what extent the area type (the urban and rural) influences the relationship,

3. to examine the relationship between the travel time of trucks and the travel time passenger cars or all vehicles by data density, day-of-the-week (DOW), time-of-the-day (TOD), and reference speed, and,
4. to identify significant factors influencing the ratio of the travel time of trucks to the travel time of passenger cars or all vehicles.

The findings from this research help practitioners and professionals to better plan, design, and operate the transportation infrastructure. They can also be used to assess the effect of the trucks on the travel time of other vehicles and the transportation system performance.

1.4 Organization of the Thesis

The rest of the thesis is structured as follows. Chapter 2 presents a review of literature based on previous studies related to physical and operational characteristics of trucks, e-shopping, freight models and PCE calculation methods. Chapter 3 presents a description of the study area, data collection, and data processing. Chapter 4 presents the methodology adopted to assess travel time relationships. Chapter 5 discusses the results obtained from the model development and analysis. Chapter 6 presents conclusions and scope for future work.

CHAPTER 2: LITERATURE REVIEW

This chapter presents a review of the previous studies on freight transportation, freight transportation facts and statistics, and e-shopping facts and statistics. A review of the factors influencing crashes involving trucks is also presented in this chapter. Furthermore, a review of the physical and operational characteristics of trucks and previous studies on estimating PCE is also discussed in this chapter.

2.1 Freight Transportation

Freight is transported using different modes of transportation (rail, truck, water, and air). Traditionally, freight mode choice is modeled using a classic economic model, inventory-theoretic model, trade-off model, and constrained optimization model. The economic model is based on the fixed and variable cost of transportation modes (Meyer et al., 1959). Morton (1972**)** studied the competitive interface between truck and rail by the length of haul, shipment size, and the commodity type. He found that transportation of freight by rail and trucks was more competitive if the shipment weighs between 10,000 and 90,000 pounds. Ronald (1977) concluded that trucks are the primary mode choice for a light-weight shipment while rail is the primary mode choice of transportation for heavy weight shipment. Either rail or trucks can be used for medium weight shipment.

Inventories such as transportation cost, trade-offs among freight rates, a carrying cost, ordering cost, etc. are considered in the inventory model. Baumol et al. (1970) and

In general, mode choice is determined using a discrete choice model. For a pair of origin-destination, there are discrete transportation alternatives characterized by service, price and function. Discrete choice models can be classified as aggregate models and disaggregate models. The models where the basic unit of observations is an aggregate share of particular freight mode at the regional or national level is an aggregate model (Winston, 1981). Perle (1964), Mortan (1969), and Levin (1981) developed aggregate freight mode split models in the past.

The market share is a function of the price difference between modes and other differences such as transit time. Unfortunately, the model fails to create cross-elasticity between the demands for alternate modes with respect to the attribute of any given mode. To overcome this drawback, Oum (1979) and Friedlaender and Sapdy (1980) developed a neo-classic economic aggregate model, also termed as cost-minimizer, where a choice of freight mode is a function of underlying cost and production cost.

Disaggregate models take behavioral aspects into account and capture the characteristics of a decision maker, attributes of a mode, and the type of commodity to be shipped. Winston (1981) have researched on mode choice behavior at the individual level by considering large shipments, length of haul, and origin-destination. It was observed that each mode attracts traffic either by price or by service.

Samimi et al. (2011) carried their study into two parts: determine the influence of shipment-specific variable (distance, weight, and value), and mode-specific variable (haul time and cost), and choice based on fuel price. They concluded that shipping cost influences shipment by rail while the hauling time influences shipment by trucks, irrespective of the fuel rate. Accounting for the interrelationship between underlying factors, Norojono and

Young (2003) developed a multinomial logit model using stated preference (SP) data. They have compared nine decision variables such as time reliability, safety, travel route, truck condition, the frequency of service and access to the rail terminal. It was observed that safety, reliability, and responsiveness are the significant factors which influence mode choice.

2.2 Freight Transportation Facts and Statistics

Freight transportation has grown dramatically over time with the expansion and dispersion of population and economic activity within the United States. The United States Department of Transportation (USDOT), Federal Highway Administration (FHWA), and the Bureau of Transportation Statistics (BTS) provide insights into freight history, facts, and statistics.

The United States population grew by 27% between 1980 and 2002, with an estimate of 288.3 million in 2002 (BTS, 2013). Further, the population grew by 13% between 2000 and 2014, escalating to an estimate of 319 million in the year 2014 (BTS, 2015). The United States economy as measured by Gross Domestic Product (GDP) doubled between 1980 and 2002 (BTS, 2013), while it increased by 24.9% between 2000 and 2014 (BTS, 2015).

Long-term economic growth leads to an increase in demand for freight transportation. The freight transportation demand changes with the geographic distribution of population and economic activity. The economic activity and population have grown faster in Southern and Western parts of the United States compared to the Northeast and Midwest regions. However, the Northeast region has a higher economic activity per capita and is increasing at a faster rate (BTS, 2015).

Trucking employment is correlated with industrial production such as declining in recession and increasing in recoveries (BTS, 2014). The employment in truck transportation, rail transportation, water transportation, and pipeline transportation increase with the increase in freight transportation and population. Trucking in the United States accounted for 30.54% of the total transportation in 2014. Truck drivers accounted for a total of 2.83 million jobs in the year 2014 (BTS, 2015).

The highway infrastructure primarily drives the freight transportation. With the anticipated increase in the number of freight vehicles, population, and other conveyances, both public and private sectors are over-dependent on the current infrastructure as more segments of the network reached capacity affecting the overall performance.

Industries draw natural resources and manufactured products from many locations to serve the market at home and abroad. Freight is moving farther distances as a part of supply chains to the distant traders. Freight transportation moved a daily average of 55 million tons valued at more than $49.3 billion in 2013 (BTS, 2013). Trucks carried the largest share of value, tons, and ton-miles of shipments. They are the dominant mode of freight transportation in the United States today. Freight transportation by trucks accounted for 63.8% of total freight shipments and 11.5 billion of tonnage shipped in the United States in 2015 (BTS). This is expected to increase to 16.5 billion by 2045, about 43% increase as forecasted by the freight analysis framework (BTS, 2017).

2.3 E-Shopping Facts and Statistics

Conventionally, people travel to stores looking for particular items. The choice of a store depends on previous experience, distance, and relation with the shopkeeper.

Shoppers browse goods and interact with store employees to gain information before making a purchase.

The introduction of the Internet is an alternative to conventional shopping system. Shoppers go to the website to browse for goods, pay electronically, and receive goods to their home, leading to the growth of non-store shopping (electronic commerce) (Bigne et al., 2005; Shih, 2004). The Statistics Portal (2014) indicates that 42% of the United States consumers had searched and purchased products online, while 14% of consumers prefer to purchase goods in-store. They also provided estimated retail e-commerce statistics from 2014 to 2021. In 2014, retail e-commerce sales worldwide accounted for 1.3 trillion, which is expected to rise to 4.8 trillion by the year 2021 (The Statistics Portal, 2014).

Around 79% of the United States citizens shop online, which was 22% back in 2000 (Pew Research Center, 2016). E-commerce is an entirely new infrastructure to manage online businesses (Joong-Kin Cho et al., 2008). It works on disintermediation and reintermediation chain of a mechanism (Anderson et al., 2003). The success of firms in e-commerce depends on distribution networks and supply chain logistics.

Inventory management such as organizing incoming supplies, work-in-process inventory, and final product are the key pieces of any business. Another role of inventory management is that delivery should be made by faster freight transportation (Matthews and Hendrickson, 2002).

The establishment of warehouses is a paradigm adopted for inventory management, fast delivery, and customer satisfaction. Warehouses are widely spread geographically to dispatch goods at faster and lower costs. Air and highway transportation accessibility strongly influenced the location of warehouse establishment (Bowen, 2008).

The adoption of just-in-time delivery, free delivery, and same day delivery services resulted in a partnership among package delivery companies such as Federal Express (FedEx), United Parcel Service (UPS) and other big firms (Korper and Ellis, 2000). It also increased competition between transportation industries and resulted in growth in the trucking industries (Engel, 1998).

2.4 Crashes Involving Trucks

As the nation's economy increases, the number of trucks is expected to increase. The increase in the number of trucks poses many challenges for transportation engineers and planners to operate and maintain the transportation system performance. Lord et al. (2005) stated that, by the year 2025, automobile traffic will increase by 62% while truck traffic is projected to grow by 118%, clearly outpacing the automobile traffic. The National Highway Cooperative Research Program (NCHRP, 2003) examined the dangers associated when trucks and passenger cars coexist in the highways.

Statistics showed that large trucks have been part of more fatalities in the United States than passenger vehicles based on registered vehicles and vehicle-miles traveled (VMT) (FHWA, 2010; NHTSA, 2008). In the United States, trucks represent 4% of the total registered vehicles and 8% of the total miles driven. In 2013, trucks were engaged in 11% of all passenger vehicle occupant deaths, 70% of those were riding passenger car while 14% were bicycling or walking (Dong et al., 2015).

Information on actual crash performance is required to identify trends and examine the relationship. Lemp et al. (2011) developed standard and heteroskedastic probit models to identify significant variables contributing to truck crashes. They considered a number of trucks, number of passenger cars, weather, light condition, number of lanes, gradient, crest/sag, length, weight, etc. for analysis. The outcomes suggested that least severe injury crashes increased when the crash occurred at a sag curve, involved an overweighed truck, or if the driver is under the influence of drugs. The fatality type increased with the light condition and if the crash involved truck trailers.

Dong et al. (2015) identified the contributing factors to the severity of crashes involving trucks. They inferred that the percentage of trucks, weather condition, and non-standard geometric design are responsible for high severity. Castillo-Manzano et al. (2015) examined the relationship between the increasing number of trucks and passenger cars with road safety. They observed that the motorization of trucks leads to fatalities. Schneider et al. (2009) also concluded that truck crashes increases with the increase in horizontal curvature and volume of passenger cars.

Long term exhaustion can also lead to loss of vigilance and alertness, a decrease in performance, and failure to anticipate and avoid a crash. Some of the symptoms are reflected in physical and mental health, tiredness, sweating, and headaches (Mayolino, 2000). Truck drivers driving time, resting time, and the presence of break during the trips are some of the explanatory variables associated with fatigue and vehicular crashes. A total of 5.1% of fatal road crashes are primarily driven by fatigue (Baas et al., 2000). Hakkanen and Summala (2001) found that 2% of drivers fell asleep, 4% were drowsy and 51% were not able to anticipate risk and avoid a crash before the occurrence of a crash.

Dingus et al. (2011) showed that truck drivers sleep an average of 6.28 hours while the crash investigation reports showed that sleep taken was less than 6.28 hours. Similarly, Torregroza-Vargas et al. (2014), surveyed truck drivers and performed single variable and multivariate regression analysis in their research study. Their results suggested that risk increased with less break time (10-20 min) while it decreased with a minimum of 8 hours rest (sleep).

Crashes involving vehicles imposes a variety of costs on the vehicle as well as on the drivers. Miller et al. (1991) researched truck crash cost based on the Maximum Abbreviated Injury Score (MAIS). The score ranges from 0 representing (minimum loss) to 6 representing (fatal situation). The purpose was to identify crashes by severity. Later Miller et al. (1998) and Zaloshnja et al. (2000) identified the unpublished estimates of the cost of highway crashes. They estimated the costs of highway crashes involving large trucks for the year 2000 in their study. The total cost incorporated medical cost, emergency service cost, property damage cost, lost productivity and monetized value of pain, suffering and lost the quality of life. The results from their study indicate that the combination of trucks accounts for the highest cost per crash (USD 130,619). Also, the crash cost per 1000 truck miles was US $232 for only trucks, US $194 for single combination trucks (single trailer) and US $93 for multiple combinations (multiple trailers). The aforementioned crash costs are estimated today’s dollars for the year 2019.

2.5 Congestion

Traffic congestion is a consequence of the nature of supply and demand. The highway capacity remains constant for a long time, however, demand changes with time (Lindsey and Verhoef, 2000). Freight serving shipment operations are a well-established contributing factor of congestion (Crowley et al., 1975). The heavy vehicle has a direct effect on road traffic capacity, degrading the traffic condition.

Congestion is categorized into three types; recurrent congestion, non-recurrent congestion, and pre-congestion (Kockelman and Shabih, 2000). Recurrent congestion occurs at regular time and is anticipated by the transportation system users. Non-recurrent congestion is mainly due to incidents involving trucks and other vehicles. Congestion in the freight industry reduces productivity and increases the overall cost (transportation cost) (Kockelman and Shabih, 2000).

Campbell (1995) conducted speed sensitivity analysis with the shift of trucks from regular time to off-peak hours. The results obtained suggest that travel distance and pollutants increase with the shift from the regular time to off-peak hours. However, it will allow operating at higher speed and hence lower emission rates. Fadare and Ayantoyinbo (2010) defined congestion as a result of unreliable trip time and missed deliveries of goods. Grenzeback et al. (1989) suggested management strategies such as truck restrictions, road pricing, lane restrictions, high-occupancy vehicle lane, off-peak operations, incident management, and traffic information.

2.6 Physical and Operational Characteristics of Trucks

Trucks have different physical and operational characteristics than passenger cars. The vehicle characteristics are categorized into dynamic characteristics, axle group characteristics, dimensions, articulate geometry, and gross vehicle mass. These characteristics govern geometric design elements, safety, signal timings, pavement designs, maintenance cost, and bridge designing (FHWA, 2005).

Trucks and cars have distinctive braking capabilities, particularly at higher speeds. The federal law regulated a minimum of 14 ft/s^2 deceleration rate must be sustained by a truck braking system and a minimum of 21 ft/s^2 deceleration rate must be sustained by a passenger car braking system (FHWA, 2005). Therefore, the stopping sight distance of a truck is approximately twice the stopping sight distance of a passenger car. This variation is because of the braking system, and the loading capacities. These variations particularly result in red light violations, rollovers and rear-end collisions at intersections (Zimmerman and Bonneson, 2004).

The braking system of trucks influences the stopping distance and downgrade holding capability resulting in collisions with passenger cars (Kati, 2013). Yu et al. (2008) developed a rollover vehicle detection system to improve the stability of trucks. The mechanism increases the safety at J-turn and fishhook maneuver.

Peng et al. (2000) studied the heavy vehicle rollover models and analyzed different ways to control it. They used TruckSim and Matlab/Simulink software to study the performance of vehicle dynamics control. The results obtained showed maneuvers utilizing models and prescribed steering inputs. Takano et al. (2003) developed a simulation model incorporating different roll angles and lateral acceleration to predict rollover. They considered the center of gravity, height, and roll steer in simulation to examine the relationship between planar and roll motions.

The size and shape of the truck are dictated by materials to be hauled and the distance to be traveled. The American Association of State Highway and Transportation Officials (AASHTO) distinguishes trucks by length, width, and height. The classification ranges from a single-unit truck (SU-30, for local delivery, cement trucks and large rental trucks) to a turnpike double-semitrailer/trailer (WB-109D, large semi-trailer truck for freight transportation). The height, width, and length of trucks range from 11 ft to 13.5 ft, 8 ft to 8.5 ft, and 30 ft to 114 ft, respectively. They are more than the dimensions of a passenger car. The height, width, and length of a passenger car as specified in AASHTO is 4.3 ft, 7 ft, and 19 ft, respectively.

To account for the effect of the difference in length, Balint et al. (2013) investigated severe crash rates as a function of vehicle length. Further, trucks are defined as those vehicles having gross vehicle weight of 9000-lb (4000-kg) or more and have dual tires on at least one of the rear axle. Sadeghi et al. (2014) compared the performance-based characteristics of long heavy vehicle combinations with a simulation model to analyze the negative road safety impacts. Both, longitudinal and lateral factors were considered and a few new ones such as yaw damping and downgrade holding capability were defined. They concluded that vehicle performance depends on the design parameters.

Trucks influence the microscopic and macroscopic traffic flow characteristics because of the involvement they have with the surrounding traffic. The front and rear space gaps for trucks are larger when compared to passenger cars. In addition, trucks drivers keep a constant speed and do not change their speed frequently (Moridpur et al., 2010). This difference in physical and operational characteristics of vehicles influence the driving behavior.

Truck and passenger car drivers have inherently different driving behaviors (Moridpur et al., 2010). Peeta et al. (2005) captured interactions between cars and trucks on a freeway. The interactions were examined to assess discomfort level of non-truck drivers with the presence of trucks. Fuzzy logic models were developed considering socioeconomic characteristics, situational factors, and behavioral tendencies. They concluded that the number of interactions increases with the increase in the percentage of trucks to a certain point and then decreases thereafter.

Sarvi (2013) and Aghabayk et al. (2014) developed models and investigated the vehicle following and lane changing the behavior of truck drivers. Al-kaisy et al. (2005) found that passenger car drivers either avoid being in the vicinity of trucks or provide large space gaps or changed the lanes.

Moridpur et al. (2010) developed a simulation model using the trajectory data of Berkeley Highway, California. Data were separated into two classes based on the length; less than 49.2ft and equal to or greater than 49.2ft. Their results indicate that the number of crashes and average travel time increases with the increase in the percentage of trucks in each lane. Aghabayk et al. (2012) studied different car-following behavior in congested heterogeneous conditions. Combinations such as truck following a passenger car, passenger car following a truck, passenger car following a passenger car, and truck following a truck were considered. They found that the headway between two trucks was the longest while the headway between two passenger cars was the shortest.

2.7 Passenger Car Equivalent (PCE)

The PCE of a truck is the number of passenger cars which, if replaced by that truck in the traffic flow, would have the same effect as the truck on the drivers. The PCE for two-lane highways was defined by relative speed reduction. However, the PCE for multilane highways accounts for the effect of grade curves.

In addition to the definition of PCE as stated previously, HCM 2000 also defined trucks as any vehicle with more than four tires in contact with the surface (HCM, 2000). The base saturation flow rate with mixed vehicles types is converted to an equivalent flow rate of passenger cars using heavy vehicle adjustment factor, measured in passenger cars per hour. The heavy vehicle adjustment factor is calculated separately for trucks and recreational vehicles.

The HCM 2000 presents PCEs for freeways and multilane highways based on the impedance of trucks and buses operating at free-flow or under-saturated conditions. It is used for under-saturated and over-saturated flows neglecting the effect of trucks on congestion and queuing.

Al-Kaisy et al. (2005) derived queue discharge flow model for PCE estimation on freeways and multilane highways under over-saturated flow. The approach reflects the bottleneck condition. Level terrain, specific grades, and length of the gradient were considered in their research. The results from their calibrated model indicate a PCE value of 3.243 for a particular site and dataset. The factors influencing the PCE are observed as the grade, percent of trucks, and grade length.

The capacity is defined as the maximum hourly rate at which vehicles are expected to transverse a point or uniform section of highway during a given time period under prevailing roadway, traffic and control conditions (FHWA, 2007). It is expressed in terms of passenger cars per hour per lane (pc/hr/ln). HCM assumes constant highway capacity for traffic analysis. However, the maximum traffic capacity on freeway varies constantly (Elefteriadou et al., 1995). Geistefeldt (2009) proposed PCE values based on stochastic capacity. The PCE is minimum for sections with more number of lanes while it is maximum at steep hills.

The impedance of all types of trucks should be considered for the conversion of mixed flow to PCE flow. Demarchi and Setti (2003) proposed a new PCE value based on the classification of vehicles in the flow. The procedure adopted is based on the flow rate of the base stream (passenger cars only) and mixed stream flow rate with varying percentages of trucks, as proposed by Huber (1982). Traffic flow with the number of vehicle classes was accounted for based on the same impedance level. The speed of base and mixed stream, the density of both streams, and passenger car speeds in both the streams were considered. The results obtained showed that error is negligible when density is more than 6.21 veh/mile/lane.

The headways are influenced by traffic flow and composition. Kockelman and Shabih (2000) developed the PCE regression model based on estimated headways. Factors such as vehicle length, vehicle performance, and driver behavior influencing headways were considered in developing the model. The results obtained showed that, on average, light-duty trucks replaced 1.2 passenger cars in the traffic stream. In addition to vehicle length, the effect of vans on headways was statistically significant. Their research also showed that with the presence of light-duty trucks as the first vehicle at the intersection, more time is needed to clear the stop bar when compared to the passenger car.

Anwaar et al. (2011) estimated PCE based on lagging headways as detected from video-recording. Three-stage-least-squares regression was adopted to estimate PCE for three class of vehicles: passenger car, single unit trucks, and combination trucks. Nine models were developed based on the vehicle following characteristics. They showed that the model predicting PCE for single unit trucks and combination trucks were reliable than others.

2.8 Limitations of Previous Research

The past literature documents the comparison of trucks and passenger cars based on operational and physical characteristics. Moreover, parameters such as density, speed, headway, and delay were investigated to examine the relationship between truck and passenger car in terms of PCE.

Travel time is an important parameter that is easy to comprehend by transportation engineers/planners/managers and the transportation system users. It is influenced by factors such as traffic characteristics, vehicle characteristics, incidents, recreational activities, and most importantly geometric characteristics of the road.

When the area type changes, the traffic stream or flow differs and thus the travel time. In the rural area, the traffic flows at either under-saturated or saturated condition (Hallenbeck et al., 1997). However, traffic flows at saturated or over-saturated conditions during peak hours in urban areas (Hallenbeck et al., 1997). The reason for such a discrepancy is the composition of vehicles in the traffic stream (Hallenbeck et al., 1997). Moreover, the difference in the traffic flow of the urban area and the rural area occurs due to the percentage of trucks as trucks are the one filling the capacity of the road network.

As discussed previously, e-shopping and online shopping has an increasing effect on the percentage of trucks on the road. However, not many researchers focused on truck travel time or examined the relationship between the travel time of trucks and the travel time of passenger cars. Furthermore, a number of vehicles on the link (example, data density), DOW, TOD, and reference speed could influence the travel time of trucks and the relationships. Examining the relationships could help assess the PCE of trucks from a travel time perspective. This research contributes by exploring these aspects and contribute to the body of knowledge

CHAPTER 3: STUDY AREA, DATA COLLECTION, AND DATA PROCESSING

Nowadays, travel time is a key parameter for planning, operating, and managing the transportation system. Travel time information assists transportation engineers/planners/managers and the transportation system users, and most importantly logistics operators. The operational performance of any link or corridor can be assessed using reliable travel time information. This chapter outlines the study area, data collection and data processing adopted in this research.

3.1 Probe Data

Transportation systems require reliable information for monitoring and managing operations. Providing access to this traffic information is a major challenge for both private companies and public institutions. The emergence of new technologies and reliable information have influenced the transportation system user's decisions.

Technological advances have favored an improvement of existing means of traffic data collection. One of the actual trends is probe data. Probes are either a program or a device carried by the transportation system users or vehicles.

In the case of probe vehicle data technique, vehicles on the road shift from a passive attitude to an active one and act as a moving sensor, continuously feeding information to the traffic central. A sensor is installed on trucks, transit, taxis, and other vehicles. The automatic vehicle identification technology incorporates vehicle tags, automatic license plate matchings, and the global positioning systems (GPS) as vehicle detection devices. The mobile applications include Google map, Lyft, Uber, Waze and HERE maps which collect origin-destination, time, speed, and location data utilizing the GPS.

Besides, with the growth in wireless communications and the spread of cellular phones, the cellular tracking system has also acted as traffic probes. This technology collects travel time, speed and traffic volume data. Technologies such as automatic vehicle location (AVL), toll-tags based on ground-based Radio Navigation, and E-ZPass based on radio frequency identification (RFID) are some other sources of probe data owned by road authorities.

3.2 Regional Integrated Transportation System (RITIS) and National Performance Management Research Dataset (NPMRDS)

RITIS is a leading platform for data aggregation and dissemination for solving complex transportation problems (RITIS, 2018). RITIS is an awareness, data archiving, and analytics platform used nationwide by thousands of decision-makers in planning, operations, research, military, and homeland security for developing smart, cost-effective mobility, safety, and security solution (RITIS, 2018). The data available is shared from/by many agencies, systems, public institutes, and even private sectors thus obsoleting the barrier between different agencies for sharing, collaborating and coordinating traffic data. It involves data fusion in a secured private cloud from where it is disseminated to the transportation system users through website, applications, and application programming interfaces (APIs) (www.ritis.org).

RITIS is constantly evolving to include the latest transportation data from various sectors. It incorporates traffic data such as traffic volume, speed, and occupancy (HERE, INRIX, TomTom, and NPMRDS), events, work zone, and incident information (DMS, HAR), Crowdsource Waze data, weather data, device operational, managed lane and signal status, AVLs, parking data, travel time, routing data, and freight movements (www.ritis.org).

In this research, NPMRDS travel time data is used to estimate PCE of trucks from a travel time perspective. In 2013, FHWA offered state DOTs and Metropolitan planning organizations (MPOs) access to a dataset of travel times for all the National Highway system (NHS) roads. CATT lab, University of Maryland developed tools to explore NPMRDS data. It has been procured by FHWA and provided by INRIX and HERE from February 2017.

NPMRDS) is a vehicle probe-based and cellphone-based travel time dataset acquired by FHWA to support Freight Performance Measures (FPM) and Urban Congestion Report (UCR) programs. This data is available to state and MPOs to meet their Moving Ahead for Progress in the 21st Century Act (MAP-21).

The observed average travel time measurements are collected 24 hours a day at one-minute intervals. The source reports separate travel time data for trucks and passenger, as well as combined travel time. The data is available in GIS format for spatial analysis.

3.3 Study Area

Data for an urban area (Mecklenburg County) and a rural area (Iredell County) in the state of North Carolina was considered for research. The selection of the study areas is based on many factors. Notably, the truck percentage in traffic stream is much higher in the urban areas than in rural areas. This discrepancy may be partly explained by population difference, environment, employment, road geometry, and traffic characteristics. Other explanations related to the generation of freight movement are land use development (physical form of the city), vicinity of warehouses, and goods consumption demand. Traffic characteristics such as link travel time, speed, control, and operations are other driving factors.

The primary focus of this research is to estimate the impedance of trucks on surrounding vehicles (passenger cars and other vehicles) from a travel time perspective. Therefore, defining the area type to an extent is essential to quantify the results. Hence, the road links were considered in both the urban and rural areas. Figure 1 illustrates the study area considered in this research.

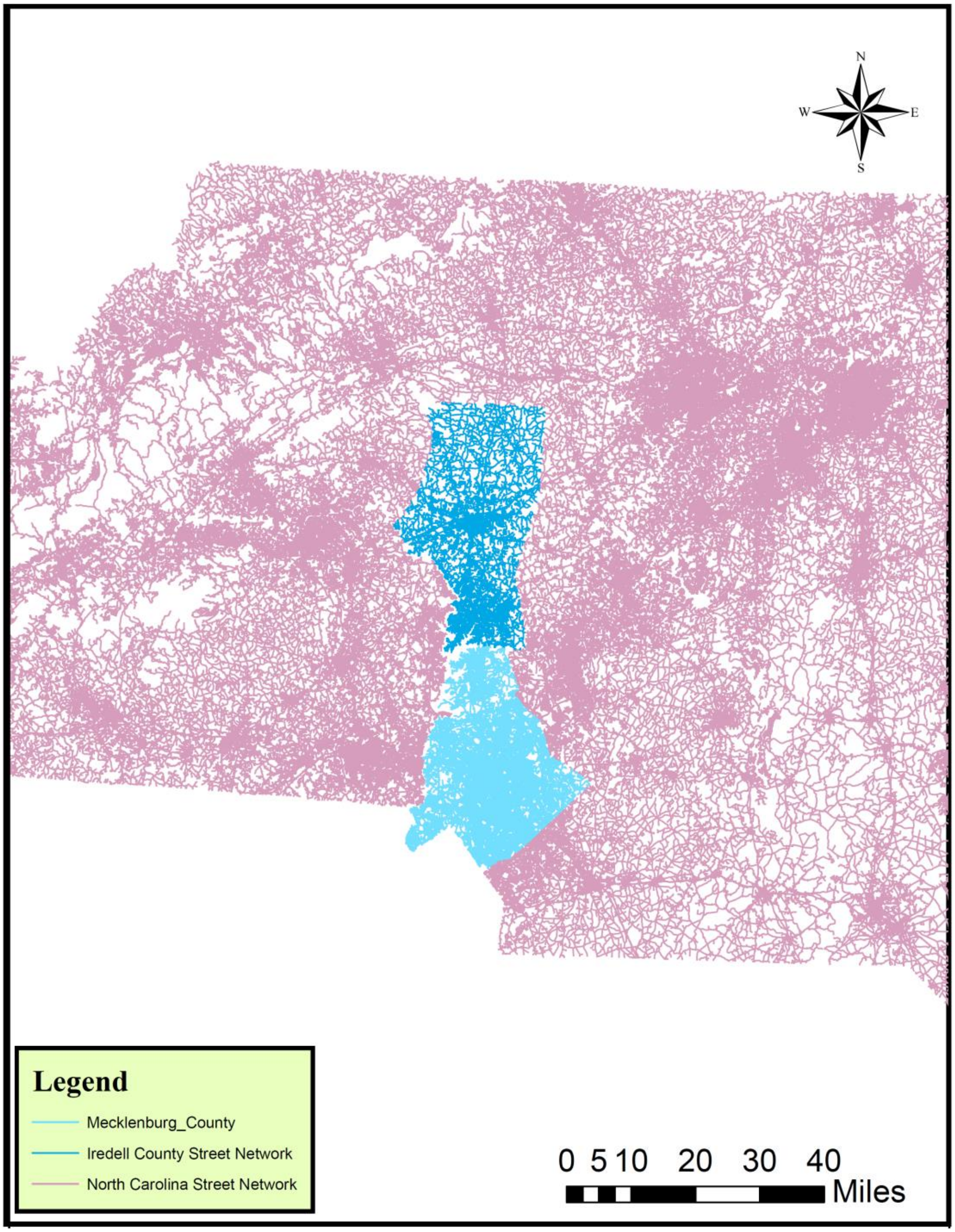

FIGURE 1 Selected Links in Mecklenburg County and Iredell County.

3.4 Selection of Road Links

NPMRDS provides comprehensive real-time travel information for the study areas. Massive data downloader could be utilized to download raw-vehicle probe data for any time ranges. Downloading the data incorporates numerous steps. Firstly, the area of interest is pinned down through the search tool. The road links, termed as Traffic Message Channel (TMC), are specified by road classification and directions. The data is filtered by date and time ranges. Lastly, the source of data is customized within its fields. The data is downloaded once all the required fields are indicated.

Figure 2 shows the study area and the selected road links (TMCs) in Mecklenburg County. Similarly, Figure 3 shows the selected links in Iredell County. For Mecklenburg County, a total of 894 links (1,78,722 samples), 798 links (1,19,191 samples), and 894 links (1,97,229 samples) were obtained for passenger cars only, trucks only and all vehicles, respectively. Similarly, for the Iredell County, a total of 137 links (25,427 samples), 133 links (30,200 samples), and 137 links (37,150 samples) were obtained for passenger cars only, trucks only and all vehicles, respectively.

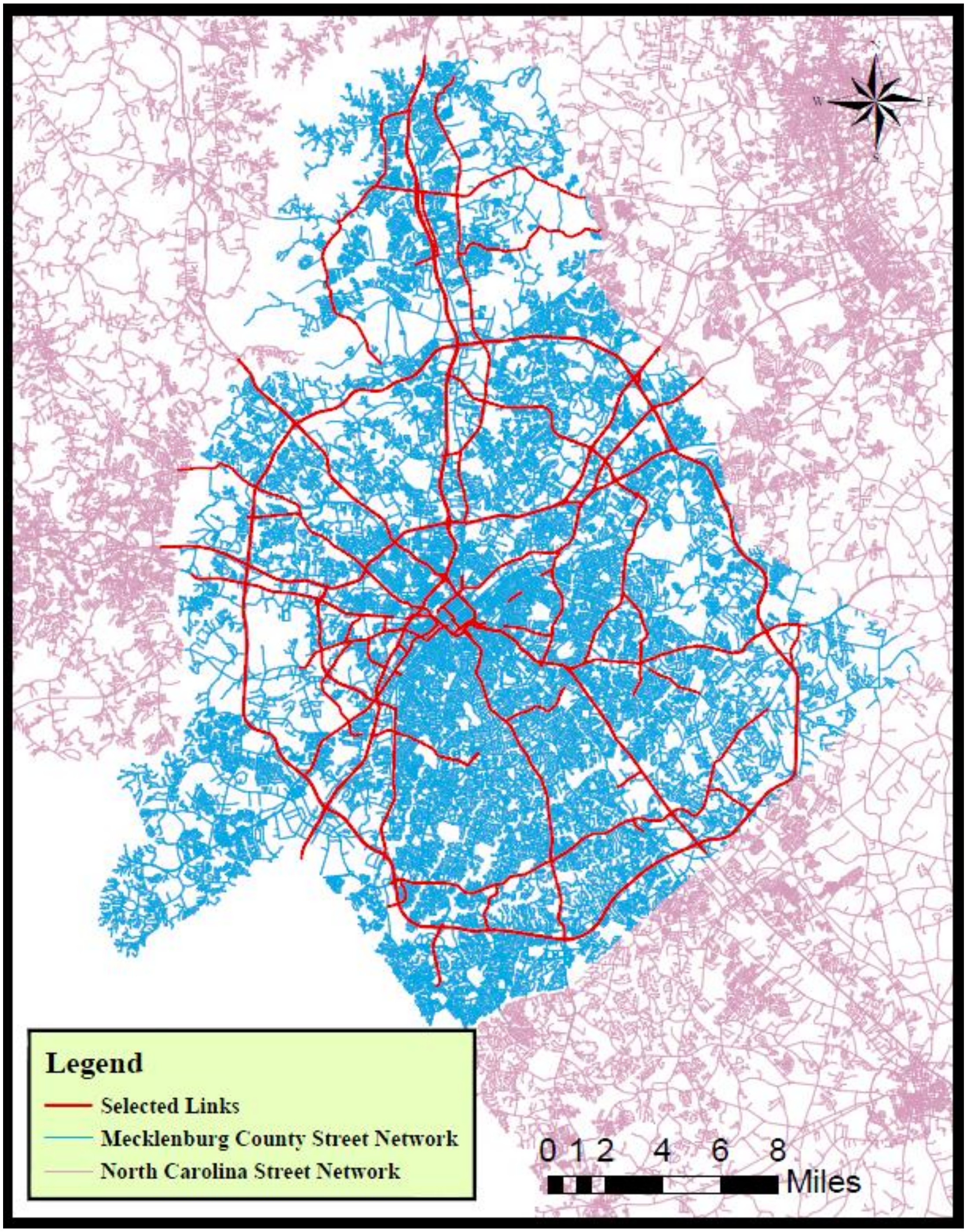

FIGURE 2 Selected Links in Mecklenburg County.

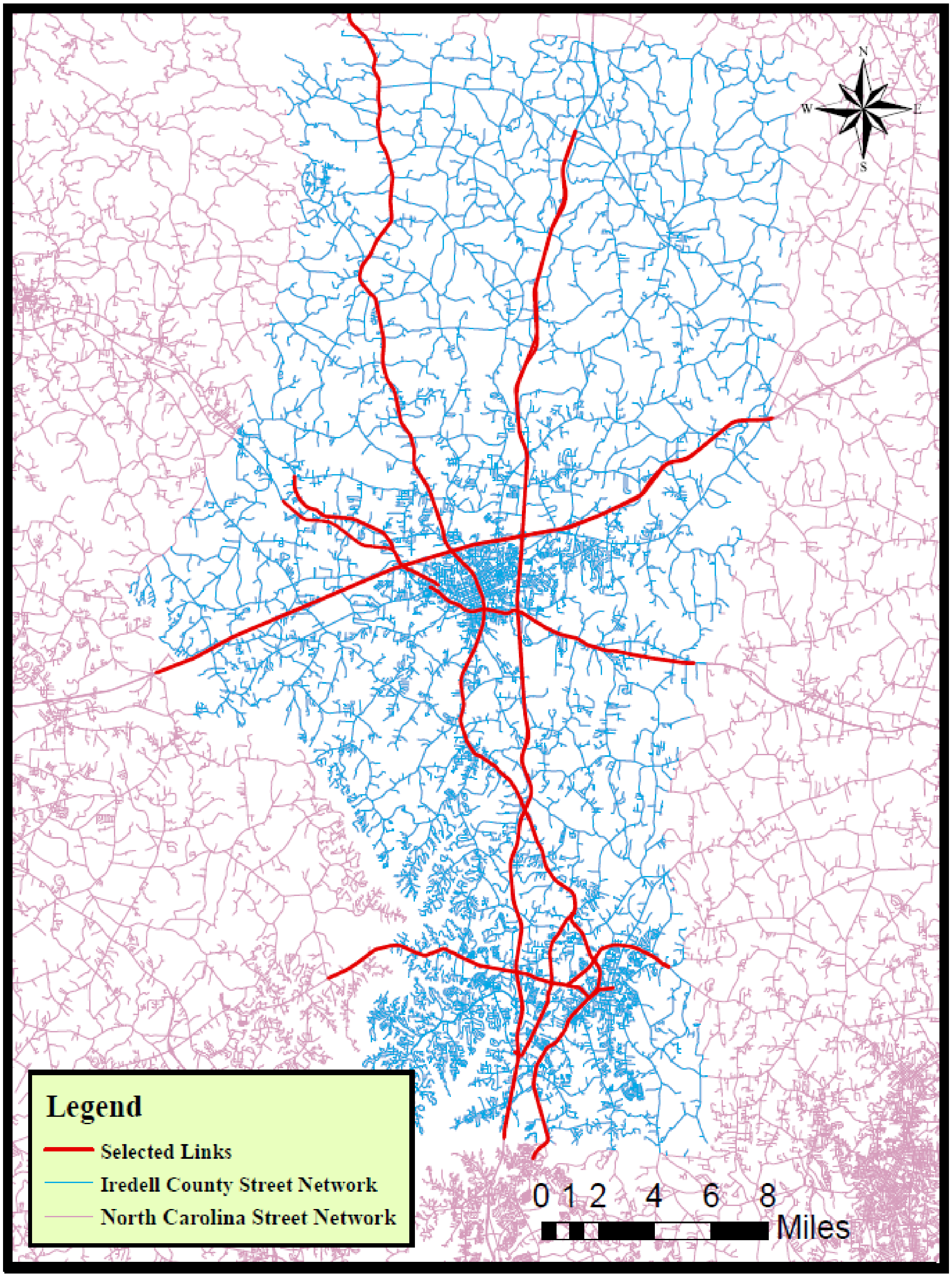

FIGURE 3 Selected Links in Iredell County.

3.5 Data Collection

The travel time data for Mecklenburg County and Iredell County were downloaded from RITIS in a raw unprocessed format from January 1, 2017 to December 31, 2017 (one year). The data were obtained at one-minute intervals. For every link, NPMRDS (INRIX) provides unique identification code (called as traffic message channel, TMC), measurement time stamp (date and time the travel time data sample was collected), speed (harmonic average speed), reference speed (free flow mean speed, 85th percentile speed), travel time (time to traverse that link), and data density.

The reference speed is frequently used for estimating the operating free-flow speed. Also, it is an indicator of the effect of road geometry such as grade, length of the grade, sight distance, number of lanes and radius of curvature. Leong (1968), Duncan (1974), and Galin (1981) found that vehicle speeds are strongly affected by upgrade and downgrade, the number of lanes, and the volume of traffic stream.

Data density indicates the number of vehicles traversing through the link during the time interval (say, one-minute). It is categorized into three types; A, B, and C. Data density is A if the number of vehicles reporting is less than four. Data density is B if the number of vehicles reporting is greater than five but less than nine while data density is C if the number of vehicles reporting is greater than 10. Data density is used as an indicator of traffic volume in this research.

The travel time data for trucks only, passenger cars only and all vehicles, for both the counties, were obtained from NPMRDS (INRIX).

3.6 Data Processing

The raw travel time data for the year 2017 was processed using Microsoft SQL Server, MS Excel, and ArcGIS software. The one-minute interval data for both the counties were uploaded in Microsoft SQL to compute the average travel time for each link, for various analytical scenarios. The links with null values or missing values were eliminated from the database.

Microsoft SQL queries were performed to compute average travel times for each link by data density, DOW, and TOD. Queries were written to compute the average travel time of trucks, the average travel time of passenger cars, and the average travel time of all vehicles for each link.

The developed datasets were joined with the TMC identification file, which has details such as link length and road classification for each link. Initially, the processed dataset was segregated based on the data density; one dataset each for data density A, data density B, and data density C. The dataset generated based on data density for each link was further categorized by DOW, TOD, and reference speed.

DOW was classified as Wednesday representing a weekday and Saturday representing a weekend day. TOD was classified as the morning peak period (8 AM – 9 AM), afternoon peak period (12 PM – 1 PM), evening peak period (5 PM – 6 PM), and night-time period (8 PM – 9 PM). The reference speed was categorized into four groups: <=30mph, >30mph & <=40mph, >40mph & <=50mph, and >50mph.

The average travel time was converted into the average travel time per mile by dividing with the link length in order to eliminate any inconsistency due to different link lengths. Since a segment is divided into numbers of links with different link lengths, biases may occur due to small link length. Therefore, the links with link length less than 1/16th of the mile (330 ft) were eliminated from the dataset. The link length for the links considered in this research ranges from a minimum of 0.06 mile and a maximum of 6.1 miles.

The sample size is one of the important factor driving the analysis. The sample size is defined as part of the population which helps to draw inferences about the population. If the sample size is small, it will not yield valid results. Researchers in the past suggested a minimum sample size of 30 for three independent variables (Statistics Solutions, 2019). Therefore, the links with sample less than 30 were removed from the final dataset to maintain the accuracy of research work.

A total of one-hundred and three datasets with more than 30 samples were generated based on area type, data density, DOW, TOD, and reference speed.

A different dataset was generated for developing the GEE models. For each link, the average travel times by area type, data density, DOW, TOD, and reference speed was considered as a separate record. The record for a link is considered only if the average travel time of trucks, the average travel times of passenger cars, and the average travel time of all vehicles are available. Overall, this dataset has a sample of 7654 records

CHAPTER 4: METHODOLOGY

This chapter presents the basic premise of the research that the travel time of trucks is directly related to the area type, data density, DOW, TOD, and reference speed. The methodology adopted for the research is discussed in the following sections. Figure 1 shows the systematic flowchart of the methodology adopted for the research.

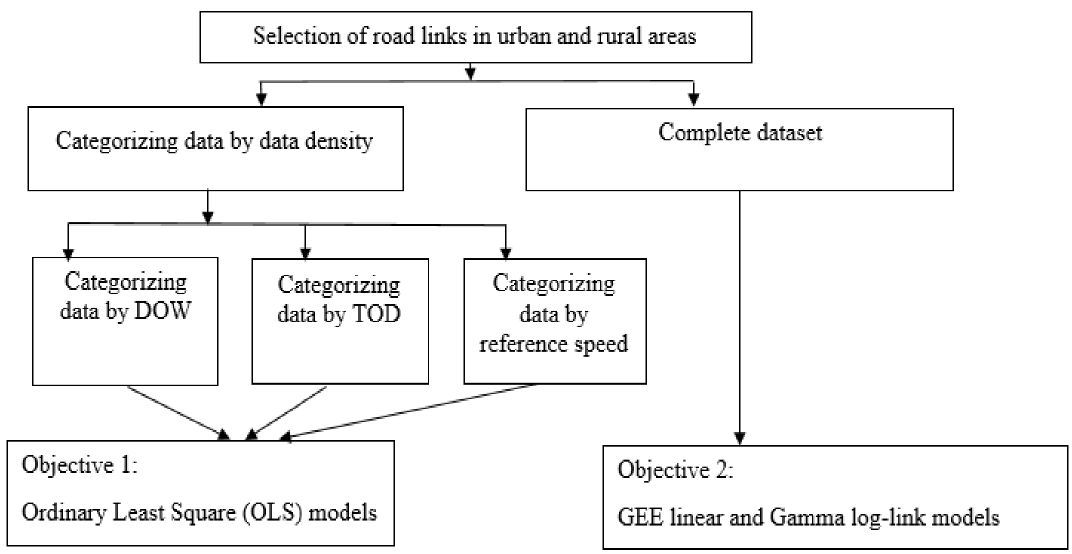

FIGURE 4 Flowchart - Methodology.

4.1. Sample Size for Analysis and Modeling

The sample size of the datasets used to examine the relationships between the average travel time of truck and the average travel time of passenger car or all vehicle by area type, data density, DOW, TOD, and reference speed is summarized in Table 1 and Table 2.

TABLE 1 Sample Sizes for Urban & Rural Areas - Trucks and Passenger Cars Comparison

Parameters	Urban Area			Rural Area		
	Density A	Density B	Density C	Density A	Density B	Density C
Wednesday	13712	3463	965	2719	932	–
Saturday	10691	1864	–	2515	167	–
8 AM - 9 AM	3827	1072	60	819	327	–
11 AM - 12 PM	4364	1476	425	848	380	–
5 PM - 6 PM	3830	1168	126	836	337	–
8 PM - 9 PM	3629	604	–	766	28	–
<= 30 mph	18179	728	148	2562	39	–
> 30 & <= 40 mph	12159	706	129	1980	43	–
> 40 mph & <= 50 mph	10350	1463	353	581	175	–
> 50 mph	46424	16487	3385	13447	4513	33
Sum	**127162**	**29031**	**5591**	**27073**	**6941**	**33**

Note: ‘-’ indicates the sample size is less than 30 and hence regression models were not developed.

TABLE 2 Sample Sizes for Urban & Rural Areas - Trucks and All Vehicles Comparison

Parameters	Urban Area			Rural Area		
	Density A	Density B	Density C	Density A	Density B	Density C
Wednesday	11661	4319	1198	2599	1601	440
Saturday	10739	2446	42	2596	833	31
8 AM - 9 AM	3392	1087	65	812	486	–
11 AM - 12 PM	3670	1510	566	748	515	205
5 PM - 6 PM	3514	1202	141	820	497	61
8 PM - 9 PM	3623	872	–	773	334	–
<= 30 mph	18311	970	189	2901	86	–
> 30 & <= 40 mph	12227	881	177	2197	71	–
> 40 mph & <= 50 mph	9861	1687	469	573	236	78
> 50 mph	40671	20938	4119	12789	8734	1581
Sum	**117669**	**35912**	**6966**	**26808**	**13393**	**2396**

Note: '-' indicates the sample size is less than 30 and hence regression models were not developed.

4.2. Model Development

The datasets were used for developing the models to examine the relationship between the average travel time of trucks and the average travel time of passenger cars or all vehicles. Ordinary Least Squares (OLS) regression models were developed to explore the association between the average travel time of trucks and the average travel time of passenger cars or all vehicles. Generalized Estimating Equation (GEE) models were developed to examine and identify the significant factors influencing the ratio of the average travel time of trucks to the average travel time of passenger cars, and the ratio of the average travel time of trucks to the average travel time of all vehicles.

The DOW and TOD are the subject variables. In addition, DOW and area type was considered as a dichotomous variable; weekday as '1' and weekend as '0'and the urban as '1' and the rural as '0'. Additionally, TOD (morning peak period, afternoon peak period, evening peak period, and night-time period) and data density (Density A, Density B, and Density C) were considered as the binary variable.

4.2.1 OLS Regression Models

OLS regression analysis minimizes the sum of differences between the observed and the predicted values (XLSTAT, 2017). It is an approach to examine the relationship between scalar responses with one or more explanatory variables. The R-squared statistical measure is used to determine how closely the data are to the fitted regression line. R-squared value of '0%' indicates that the variables are not related to each other. However, the R-squared value of 100% indicates that the model explains the variability of response data. The model best fits the data if the R-squared value is high.

The average travel time of trucks is the dependent variable for OLS models by area type, data density, DOW, TOD, and reference speed. The average travel time of passenger cars or all vehicles was considered as the independent variable.

4.2.2 GEE Models

The GEE based models were developed to identify critical variables for estimating the ratio of the travel time of trucks to the travel time of passenger cars or all vehicles. GEE's were first introduced by Liang and Zeger (1986). It is an extension of the Generalized Linear Model (GLM) to analyze longitudinal data. In this framework, a semi-parametric approach is used, which can be opted when the dependent variable is non-normally distributed. There are a few important points to keep in mind when developing GEE models. The subject variables uniquely define the subjects within the dataset.

Different types of models can be developed in GEE based on the distribution and the link function. A linear model specifying the normal distribution and gamma with log-link distribution were developed in this research.

As GEE uses the quasi-likelihood method, the Quasi-likelihood under independence criterion, QIC and the corrected version of the quasi-likelihood criterion, QICC were considered as the statistical parameters to test the model goodness-of-fit. The value of QIC and QICC should be as low as possible for the best-fitted model. Also, the difference between the QIC and QICC should be as low as possible.

The ratio of the average travel time of truck to the average travel time of passenger car is the dependent variable for two models. The first model assumed that data is linearly related while the second model assumes that gamma log-link distribution best fits the data.

Likewise, the ratio of the average travel time of truck to the average travel time of all vehicles is the dependent variable for two models, one each based on linear and gamma log-link distribution. The area type, data density, DOW, TOD, and reference speed were considered as the independent variables.

4.3 Model Validation

The validation approach gives the extent to which each developed model is reliable and feasible for estimation of the ratio of the travel time of trucks to the travel time of passenger cars or all vehicles. About 20% of the final dataset (1,529 samples) was considered to validate the developed models. This data was not used for model development.

The validation was measured using the Mean Absolute Percentage Error (MAPE) and Root-Mean-Square-Error (RMSE). They are expressed as Equation 1 and Equation 2. In general, the model's predictability is high if the MAPE and RMSE values are lower.

$$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n} \left| \frac{\mathrm{Actual\_ATT} - \mathrm{Predicted\_ATT}}{\mathrm{Actual\_ATT}} \right| \quad (1)$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{t=1}^{n}(\mathrm{Actual}_{\mathrm{ATT}} - \mathrm{Predicted}_{\mathrm{ATT}})^2}{n}} \quad (2)$$

where

n = number of observations,

Actual_ATT= observed average travel time, and,

Predicted_ATT= predicted average travel time.

CHAPTER 5: RESULTS

This chapter presents the results obtained developing OLS regression and GEE models.

5.1 OLS Regression Models

The minimum, maximum, mean and standard deviation (SD) of the average travel time of trucks, the average travel time of passenger cars, and the average travel time of all vehicles were computed before developing OLS regression models. Table 2 summarizes the descriptive statistics for both urban and rural areas.

TABLE 3 Descriptive Statistics

Data set	Parameters	Average Travel Time	
		Urban Area	Rural Area
Trucks only	Minimum	0.87	0.91
	Maximum	9.83	8.04
	Mean	1.46	1.26
	SD	0.84	0.68
Passenger Car only	Minimum	0.81	0.83
	Maximum	10.17	6.59
	Mean	1.69	1.32
	SD	0.97	0.74
All vehicles	Minimum	0.84	0.88
	Maximum	10.17	10.11
	Mean	1.66	1.27
	SD	0.96	0.69

The OLS regression models were developed to examine the relationship between the average travel time of trucks and the average travel time of passenger cars or all vehicles. These models were developed with no intercept since the average travel time cannot be either negative or zero except when the vehicle is not moving or there is no traffic. The best-fitted model was determined using the R-squared value. Primarily, OLS models were developed based on data density in terms of DOW, TOD, and reference speed.

A total of 57 models were developed for the urban area while 46 OLS models were developed for the rural area. Tables 4, 5, and 6 summarize the OLS models developed for the urban area for data density A, B, and C while tables 7, 8, and 9 summarize the OLS models for the rural area for data density A, B, and C. The models were developed at a 95% significant level. The coefficient, standard error (Std. Error), p-value (or significance value), and R-squared values are summarized for each model in the tables.

5.1.1 OLS Regression Models for the Urban Area

It can be inferred from Table 4, for data density A, that the average travel time of passenger cars or all vehicles are positively associated with the average travel time of trucks. The average travel time of trucks is 1.12 times the average travel time of passenger cars on a Wednesday while the average travel time of trucks is 1.07 times the average travel time of passenger cars on a Saturday. However, the average travel time of trucks is 1.07 times the average travel time of all vehicles on a Wednesday or Saturday.

The average travel time of trucks is higher during the afternoon and evening peak periods when compared to the average travel time of passenger cars. A similar trend was observed when the average travel time of all vehicles was considered as the independent variable. The average travel time of trucks was less during the morning peak period and night-time period when the average travel time of passenger cars or all vehicles was considered as the independent variable.

TABLE 4 OLS Models Developed for Passenger Car and All Vehicles for Density A

Parameters	Compared to Passenger Cars				Compared to All Vehicles			
	Coeff.	Std. Error	P-value	R^2	Coeff.	Std. Error	P-value	R^2
Wednesday	1.12	<0.01	<0.01	0.98	1.07	<0.01	<0.01	0.99
Saturday	1.09	<0.01	<0.01	0.98	1.07	<0.01	<0.01	0.99
7 AM - 8 AM	1.11	<0.01	<0.01	0.97	1.11	<0.01	<0.01	0.97
12 PM - 1 PM	1.14	<0.01	<0.01	0.98	1.13	<0.01	<0.01	0.98
5 PM - 6 PM	1.14	<0.01	<0.01	0.98	1.13	<0.01	<0.01	0.98
8 PM - 9 PM	1.09	<0.01	<0.01	0.98	1.07	<0.01	<0.01	0.99
<= 30 mph	1.16	<0.01	<0.01	0.97	1.14	<0.01	<0.01	0.98
> 30 & <= 40 mph	1.11	<0.01	<0.01	0.98	1.10	<0.01	<0.01	0.98
> 40 mph & <= 50 mph	1.11	<0.01	<0.01	0.98	1.07	<0.01	<0.01	0.99
> 50 mph	1.06	<0.01	<0.01	0.99	1.04	<0.01	<0.01	0.99

Likewise, the average travel time of trucks is greater than the average travel time of passenger cars on the links with reference speed less than or equal to 30 mph. The increase in the average travel time of trucks on the links with reference speed greater than 30 mph is less when compared to the increase on the links with reference speed less than or equal to 30 mph. It was observed that the increase in the average travel time of trucks when compared to the average travel time of passenger cars is minimal on the links with reference speed greater than 50 mph. Identical results were obtained when the average travel time of trucks was compared with the average travel time of all vehicles.

Table 5 summarizes the OLS models developed to examine the relationship between the average travel time of trucks and the average travel time of passenger cars or all vehicles for data density B. The average travel time of trucks on a Wednesday or Saturday is 1.03 times the average travel time of passenger cars. However, the average travel time of trucks was observed to be greater than the average travel time of all vehicles on a Saturday when compared to on a Wednesday. The average travel time of trucks is 1.12 times the average travel time of passenger cars during the evening peak period. The average travel time of trucks is 1.04 times the average travel time of passenger cars during morning peak (7 AM – 8 AM), afternoon peak (12 PM – 1 PM), and night time peak (8 PM – 9 PM). It was observed that the average travel time of trucks is 1.02 times the average travel time of all vehicles during the morning peak (7 AM – 8 AM), evening peak (5 PM – 6 PM) and night-time periods (8 PM – 9 PM). The average travel time of trucks is less than the average travel time of all vehicles during the afternoon peak period.

The average travel time of trucks is 1.04 times the average travel time of passenger cars on the links with reference speed less than or equal to 30 mph and greater than 50 mph. It is 1.03 times the average travel time of passenger cars on the links with reference speed greater than 30 mph but less than or equal to 40 mph and greater than 40 mph but less than or equal to 50 mph. However, the average travel time of trucks is less than the average travel time of all vehicles for links with reference speed greater than 30 mph but less than or equal to 40 mph and greater than 40 mph but less than or equal to 50 mph.

TABLE 5 OLS Models Developed for Passenger Car and All Vehicles for Density B

Parameters	Compared to Passenger Cars				Compared to All Vehicles			
	Coeff.	Std. Error	P-value	R^2	Coeff.	Std. Error	P-value	R^2
Wednesday	1.03	<0.01	<0.01	0.99	0.99	<0.01	<0.01	0.99
Saturday	1.03	<0.01	<0.01	0.99	1.03	<0.01	<0.01	1.00
7 AM - 8 AM	1.04	<0.01	<0.01	0.99	0.99	<0.01	<0.01	0.99
12 PM - 1 PM	1.03	<0.01	<0.01	1.00	1.01	<0.01	<0.01	1.00
5 PM - 6 PM	1.05	<0.01	<0.01	0.99	0.99	<0.01	<0.01	0.99
8 PM - 9 PM	1.12	<0.01	<0.01	0.98	1.02	<0.01	<0.01	1.00
<= 30 mph	1.04	<0.01	<0.01	0.99	1.03	<0.01	<0.01	0.99
> 30 & <= 40 mph	1.03	<0.01	<0.01	0.99	0.99	<0.01	<0.01	0.99
> 40 mph & <= 50 mph	1.03	<0.01	<0.01	1.00	0.98	<0.01	<0.01	0.99
> 50 mph	1.04	<0.01	<0.01	0.99	1.01	<0.01	<0.01	0.99

Table 6 represents the OLS models developed for data density C. Models were not developed for Saturday and NTP as the sample size is less than 30. On a Wednesday, the average travel time of trucks is 1.02 times the average travel time of passenger cars. Likewise, the average travel time of trucks is 1.01 times the average travel time of all vehicles on a Wednesday and 1.02 times the average travel time of all vehicle on a Saturday. It was observed that the average travel time of trucks, when compared to the average travel time of all vehicles, remain elevated on Saturday when compared to Wednesday.

The models developed for different times of the day showed no specific trend. Higher average travel time of trucks is observed during the morning and evening peak periods than the average travel time of passenger cars. The results showed that the average travel time of trucks is 1.11 times the average travel time of passenger cars during the morning peak period. The average travel time of trucks is observed to be 1.01 times the average travel time of passenger cars during the afternoon the peak period. Further, the average travel time of trucks is observed to be 1.07 times the average travel time of passenger cars during the evening peak period.

TABLE 6 OLS Models Developed for Passenger Car and All Vehicles for Density C

Parameters	Compared to Passenger Cars				Compared to All Vehicles			
	Coeff.	Std. Error	P-value	R^2	Coeff.	Std. Error	P-value	R^2
Wednesday	1.02	<0.01	<0.01	1.00	1.01	<0.01	<0.01	1.00
Saturday	––	––	––	––	1.02	0.01	<0.01	1.00
7 AM - 8 AM	1.11	0.02	<0.01	0.99	0.98	0.01	<0.01	0.99
12 PM - 1 PM	1.01	<0.01	<0.01	1.00	1.01	<0.01	<0.01	1.00
5 PM - 6 PM	1.07	0.01	<0.01	1.00	1.00	0.01	<0.01	1.00
8 PM - 9 PM	––	––	––	––	––	––	––	––
<= 30 mph	1.01	0.01	<0.01	0.99	1.02	0.01	<0.01	0.99
> 30 & <= 40 mph	1.01	0.01	<0.01	0.99	0.99	0.01	<0.01	1.00
> 40 mph & <= 50 mph	1.03	0.01	<0.01	0.99	1.00	<0.01	<0.01	1.00
> 50 mph	1.04	<0.01	<0.01	1.00	1.01	<0.01	<0.01	1.00

However, the average travel time of trucks is observed to be less than the average travel time of all vehicles during the morning peak period. The average travel time of trucks is observed to be 1.01 times during the afternoon peak period and evening peak period than the average travel time of all vehicles. The average travel time of trucks did not differ substantially than the average travel time of all vehicles for all times of the day except the night-time period.

The average travel time of trucks increases with the average travel time of passenger cars and the reference speed of a link. It was observed that the average travel time of trucks is 1.04 times the average travel time of passenger cars on the links with reference speed greater than 50 mph when compared to a value of 1.01 for the links with reference speed less than or equal to 30 mph. However, the average travel time of trucks is greater than the average travel time of all vehicles on the links with reference speed less than or equal to 30 mph.

5.1.2 OLS Regression Models for the Rural Area

The results related to an analysis by data density A and rural area are summarized in Table 7. The average travel time of trucks is higher than the average travel time of passenger cars on a Wednesday when compared to on a Saturday. The average travel time of trucks is 1.11 times the average travel time of passenger car on a Wednesday. A similar trend was observed for the average travel time of trucks when compared to the average travel time of all vehicles. The average travel time of trucks is greater than the average travel time of passenger car during the evening peak period when compared to other times of the day. The average travel time of truck is 1.09 times the average travel of passenger cars during the morning and afternoon peak periods. However, the average travel time of trucks is close to the average travel time of passenger cars during the night-time period. Similar trends were observed when the average travel time of trucks were compared with the average travel time of all vehicles.

TABLE 7 OLS Models Developed for Passenger Car and All Vehicles for Density A

Parameters	Compared to Passenger Cars				Compared to All Vehicles			
	Coeff.	Std. Error	P-value	R^2	Coeff.	Std. Error	P-value	R^2
Wednesday	1.11	0.00	<0.01	0.98	1.08	0.00	<0.01	0.99
Saturday	1.10	0.00	<0.01	0.97	1.07	0.00	<0.01	0.99
7 AM - 8 AM	1.12	0.01	<0.01	0.98	1.09	0.00	<0.01	0.99
12 PM - 1 PM	1.12	0.01	<0.01	0.98	1.09	0.00	<0.01	0.99
5 PM - 6 PM	1.14	0.01	<0.01	0.98	1.10	0.00	<0.01	0.98
8 PM - 9 PM	1.09	0.01	<0.01	0.97	1.06	0.00	<0.01	0.99
<= 30 mph	1.18	0.00	<0.01	0.97	1.12	0.00	<0.01	0.99
> 30 & <= 40 mph	1.08	0.00	<0.01	0.98	1.06	0.00	<0.01	0.74
> 40 mph & <= 50 mph	1.04	0.01	<0.01	0.98	0.96	0.01	<0.01	0.97
> 50 mph	1.04	0.00	<0.01	1.00	1.01	0.00	<0.01	1.00

As the reference speed increases, the average travel time of trucks is close to the average travel time of passenger cars or all vehicles. It is observed that the average travel time of trucks is 1.18 times the average travel time of passenger car on links with reference speed less than or equal to 30 mph. The average travel time of trucks is observed to be 1.09 times the average travel time of passenger cars on links with reference speed greater than 30 mph but less than or equal to 40 mph. Further, a decrease in the average travel time of trucks when compared to the average travel time of passenger cars is observed for the links with reference speed greater than 40 mph. Likewise, a similar relationship between the average travel time of trucks and the average travel time of all vehicles was observed based on reference speed categories.

The OLS results obtained for data density B and rural area are summarized in Table 8. The average travel time of trucks is greater than the average travel time of passenger cars on a Wednesday when compared to a Saturday. However, the opposite trend was observed when the average travel time of trucks is compared with the average travel time of all vehicles.

No particular trend is observed when the analysis was conducted by TOD. The average travel time of trucks is observed to be 1.08 times the average travel of passenger cars during the evening peak period. Further, the average travel time of trucks is observed to be 1.04 times the average travel time of passenger cars during the morning peak period. The average travel time of trucks increases by the same amount when compared with the average travel time of passenger cars during the afternoon peak period and night-time period. However, the average travel time of trucks is observed to be greater than the average travel time of all vehicles during the morning and evening peak periods. The average travel time of trucks is observed to be 1.01 times the average travel time of all vehicles during the afternoon peak period and the night-time period.

The average travel time of trucks estimated for the links with different reference speed ranges followed the same trend as in the case of data density A. The increase in the reference speed of the links is inversely associated with the predicted average travel time of trucks. The average travel time of trucks for the links with a reference speed less than or equal to 30 mph is 1.10 times the average travel time of passenger cars. The average travel time of trucks is 1.09, 1.05, and 1.03 times the average travel time of passenger cars on the links with reference speed >30mph and <= 40 mph, > 40mph and <= 50mph, and >50 mph, respectively.

The average travel time of truck is 1.02 times the average travel time of all vehicles on the links with reference speed less than or equal to 30 mph. However, the average travel time truck is 1.01 times the average travel time of all vehicles on links with reference speed greater than 30 mph.

TABLE 8 OLS Models Developed for Passenger Car and All Vehicles for Density B

Parameters	Compared to Passenger Cars				Compared to All Vehicles			
	Coeff.	Std. Error	P-value	R^2	Coeff.	Std. Error	P-value	R^2
Wednesday	1.04	0.00	<0.01	0.99	1.01	0.00	<0.01	1.00
Saturday	0.96	0.01	<0.01	0.99	1.02	0.00	<0.01	1.00
7 AM - 8 AM	1.04	0.00	<0.01	0.99	1.03	0.00	<0.01	1.00
12 PM - 1 PM	1.02	0.00	<0.01	1.00	1.00	0.00	<0.01	1.00
5 PM - 6 PM	1.08	0.01	<0.01	0.99	1.02	0.00	<0.01	1.00
8 PM - 9 PM	1.02	0.00	<0.01	1.00	1.01	0.00	<0.01	1.00
<= 30 mph	1.10	0.02	<0.01	0.98	1.02	0.01	<0.01	0.99
> 30 & <= 40 mph	1.09	0.02	<0.01	0.99	1.01	0.01	<0.01	0.99
> 40 mph & <= 50 mph	1.05	0.01	<0.01	0.98	1.01	0.01	<0.01	0.99
> 50 mph	1.03	0.00	<0.01	1.00	1.01	0.00	<0.01	1.00

As shown in Table 9, only 6 models were developed for data density C and rural area. The remaining models were not developed because of the small sample size. The average travel time of trucks is less than the average travel time of passenger cars on the links with reference speed greater than 50 mph.

The average travel time of truck is 1.02 times the average travel time of all vehicles on a Wednesday. The average travel time of trucks is the same as the average travel time of all vehicles during the afternoon peak period. However, it is 1.01 times the average travel time of all vehicles during the evening peak period.

The average travel time of trucks is 1.01 times the average travel time of all vehicles on the links with reference speed greater than 40 mph and less than or equal to 50 mph. The same value is observed on the links with reference speed greater than 50 mph.

TABLE 9 OLS Models Developed for Passenger Car and All Vehicles for Density C

Parameters	Compared to Passenger Cars				Compared to All Vehicles			
	Coeff.	Std. Error	P-value	R^2	Coeff.	Std. Error	P-value	R^2
Wednesday	––	––	––	––	1.02	0.00	<0.01	0.99
Saturday	––	––	––	––	––	––	––	––
7 AM - 8 AM	––	––	––	––	––	––	––	––
12 PM - 1 PM	––	––	––	––	1.00	0.00	<0.01	1.00
5 PM - 6 PM	––	––	––	––	1.02	0.01	<0.01	0.99
8 PM - 9 PM	––	––	––	––	––	––	––	––
<= 30 mph	––	––	––	––	––	––	––	––
> 30 & <= 40 mph	––	––	––	––	––	––	––	––
> 40 mph & <= 50 mph	––	––	––	––	1.01	0.01	<0.01	0.99
> 50 mph	0.96	0.01	<0.01	0.99	1.01	0.00	<0.01	1.00

5.1.3 Summary of OLS Regression Model Results

All the models for the urban and rural areas were found to be better-fit models to examine the relationship between the average travel time of trucks and the average travel time of passenger cars or all vehicles. A coefficient value greater than 1.0 indicates that the average travel time of trucks is more than the average travel time of passenger cars or all vehicles. A coefficient value of less than 1.0 indicates that the average travel time of trucks is less than the average travel time of passenger cars or all vehicles.

The average travel time of trucks is greater than the average travel time of passenger cars on Wednesday in both urban and rural areas for all the three data density conditions. However, no specific trend is seen in the case of all vehicles by DOW. The average travel time of trucks is greater than the average travel time of passenger cars during the evening peak period (5 PM – 6 PM) in all the data density conditions for a link in the rural area. A similar trend is generally observed between the average travel time of trucks and the average travel time of all vehicles. However, no specific trend was observed in the urban area by TOD.

The average travel time of trucks is greater than the average travel time of passenger cars or all vehicles on the links with reference speed less than or equal to 30 mph in both urban and rural areas. The average travel of trucks decreases with an increase in the reference speed of a link. The average travel time of trucks is close to the average travel time of passenger cars or all vehicles on a link with reference speed greater than 50 mph.

The best-fitted model is selected based on the standard error and R-squared value. It was observed that for all the models developed, the standard error is less than 0.02. Therefore, the average distance of the data points from the fitted line is less than 0.02%. Further, the R-squared is greater than 90%, indicating that the model explains more than 90% of the variability of the response data around the mean.

5.2 GEE Models

Pearson correlation coefficients were first computed to examine the relationship between the average travel time of trucks, the average travel time of passenger cars, the average travel time of all vehicles, area type, density A, density B, density C, DOW, TOD and reference speed. The parameters are listed in Table 9. Table 10 summarizes the computed Pearson correlation coefficients. The correlation results are represented in three different colors, defining the type of correlation. The green color indicates low correlation while blue and pink colors indicate a moderate and high correlation. The selection of the type of correlation was based on the cut-off value of the Pearson correlation coefficient.

The Pearson correlation coefficient between -0.3 to +0.3 is considered as low correlation. The correlation coefficient greater than 0.3 or less than -0.3 is considered as a positive correlation

It can be observed from the results that the average travel time of trucks, the average travel time of passenger cars and the average travel time of all vehicles are highly correlated to each other. Likewise, the average travel time of trucks, passenger cars, and all vehicles are highly correlated with the area type and link with reference speed less than or equal to 30 mph. The ratio of average travel time of trucks to the average travel time of passenger cars and the ratio of average travel time of trucks to the average travel time of all vehicles are highly correlated with each other.

The average travel time of trucks, the average travel time of passenger cars, the average travel time of all vehicles, and density A are high (negatively) correlated with reference speed greater than 50 mph. All the other variables are insignificantly correlated with each other. Based on the Pearson correlation coefficients, independent variables were selected to minimize collinearity and develop GEE models. The independent variables with significance value greater than or equal to 0.05 (at a 95% confidence level) were considered as insignificant and eliminated (one by one) when developing the models.

TABLE 10 List of Variables

Parameter	Representation
ATT of Truck	1
ATT of All-vehicles	2
ATT of Passenger Car	3
Density_A	4
Density_B	5
Density_C	6
MPP	7
OPP	8
EPP	9
NTP	10
Ratio(Truck/Passenger Car)	11
Ratio(Trucks/All-vehicles)	12
Wednesday	13
Saturday	14
Area	15
<= 30 mph	16
> 30 & <= 40 mph	17
> 40 mph & <= 50 mph	18
> 50 mph	19

TABLE 11 Pearson Correlation Coefficient Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1																			
2	0.96																		
3	0.96	0.99																	
4	0.28	0.26	0.27																
5	-0.25	-0.23	-0.24	-0.92															
6	-0.08	-0.08	-0.08	-0.26	-0.11														
7	0.00	0.00	0.00	0.00	0.04	-0.05													
8	0.00	0.00	0.00	-0.12	0.06	0.17	-0.36												
9	0.17	0.17	0.17	0.00	0.03	-0.04	-0.34	-0.38											
10	-0.17	-0.17	-0.17	0.18	-0.14	-0.09	-0.28	-0.31	-0.29										
11	0.51	0.30	0.28	0.21	-0.18	-0.07	0.00	0.00	0.09	-0.07									
12	0.51	0.28	0.30	0.24	-0.22	-0.07	0.00	0.00	0.08	-0.09	0.89								
13	0.01	0.02	0.02	-0.03	0.02	0.03	0.00	0.00	0.00	0.02	-0.03	-0.03							
14	0.00	-0.02	0.00	0.03	-0.02	-0.02	0.00	0.00	0.00	0.00	0.04	0.03	-1.00						
15	0.33	0.32	0.32	0.09	-0.13	0.11	-0.06	0.04	0.00	0.04	0.18	0.22	0.00	0.00					
16	0.62	0.59	0.61	0.25	-0.23	-0.05	-0.13	0.12	0.00	0.02	0.27	0.30	0.00	0.00	0.26				
17	0.18	0.18	0.19	0.16	-0.15	-0.03	0.01	0.01	-0.02	0.00	0.12	0.14	0.00	0.00	0.20	-0.15			
18	0.02	0.03	0.03	0.08	-0.07	0.00	0.01	0.00	-0.03	0.01	0.01	0.01	0.02	0.00	0.12	-0.14	-0.11		
19	-0.60	-0.58	-0.60	-0.34	0.32	0.07	0.09	-0.10	0.04	-0.02	-0.28	-0.32	0.00	0.00	-0.40	-0.58	-0.45	-0.43	

Four GEE models were developed. In the first two models, the ratio of the average travel time of trucks to the average travel time of passenger cars was considered as the dependent variable. For the other two models, the ratio of the average travel time of trucks to the average travel time of all vehicles was considered as the dependent variable. The independent variables are area type, data density, DOW, TOD, and reference speed. The general form of the models is represented as Equation 4 and Equation 5.

$$\ln\{Ratio(ATT\ of\ Trucks)/(\ ATTof\ Passenger\ Car)\} = f(ToD, DoW, Density, and\ Speed\ Limit) \quad (4)$$

$$\ln\{Ratio(ATT\ of\ Trucks)/(\ ATTof\ Passenger\ Car)\} = f(ToD, DoW, Density, and\ Speed\ Limit) \quad (5)$$

5.2.1 Factors Influencing the Ratio of the Average Travel Time of Trucks to the Average Travel Time of Passenger Cars – Linear Model

The results obtained from the GEE linear model with the ratio of the average travel time of trucks to the average travel time of passenger cars as the dependent variable are summarized in Table 12. The area type, data density, DOW, TOD, and reference speed incorporated in the model were significant at a 95% confidence limit. The parameters of the linear model indicate that all the independent variables have a positive effect on the ratio of the average travel time of trucks to the average travel time of passenger cars, except DOW. The ratio of the average travel time of trucks to the average travel time of passenger cars on a Saturday in a rural area is 0.971 if the reference speed is greater than 50 mph and data density is C. The ratio of the average travel time of trucks to the average travel time of passenger cars is higher for a link in an urban area when all the other variables are kept constant.

The ratio of the average travel time of trucks to the average travel time of passenger cars is higher for density B and density C when all the other variables are kept constant. The models developed indicate that, compared to night-time period, the ratio of the average travel time of trucks to the average travel time of passenger cars is higher during the morning peak period, off-peak period, and evening peak period when all the other variables are kept constant.

The result obtained indicate that the ratio of the average travel time of trucks to the average travel time of passenger cars is lower on a Wednesday. Further, the ratio of the average travel time of trucks to the average travel time of passenger cars is higher on a link with reference speed less than or equal to 50 mph, when all the other variables are kept constant.

5.2.2. Factors Influencing the Ratio of the Average Travel Time of Trucks to the Average Travel Time of Passenger Cars – Gamma Log-Link Model

The results obtained from the GEE gamma log-link model with the ratio of the average travel time of trucks to the average travel time of passenger cars as the dependent variable are also summarized in Table 12. The ratio of the average travel time of trucks to the average travel time of passenger cars is {exp (-0.024)}= 0.977 on a link in a rural area with reference speed greater than 50 mph and data density is C on a Saturday during night-time. The ratio of the average travel time of trucks to the average travel time of passenger cars is higher in an urban area when all the other variables are kept constant. It is higher for density A and density B when all the other variables are kept constant. The results obtained also indicate that the ratio of the average travel time of trucks to the average travel time

time of passenger cars is higher during morning peak period, afternoon peak period, and evening peak period, when compared to the night-time period.

The DOW is negatively associated with the ratio of the average travel time of trucks to the average travel time of passenger cars on a Wednesday when all the other variables are kept constant. It is higher on the links with reference speed less than or equal to 50 mph when all the other variables were kept constant.

TABLE 12 GEE Models - Ratio of the Average Travel Time of Trucks to the Average Travel Time of Passenger Cars

Parameter	Linear Model			Log-Link Gamma Model		
	B	Std. Error	P-value	B	Std. Error	P-value
Intercept	0.971	0.0068	<0.05	-0.024	0.0063	<0.05
Area	0.026	0.003	<0.05	0.024	0.0028	<0.05
Density A	0.057	0.0054	<0.05	0.052	0.0051	<0.05
Density B	0.024	0.0049	<0.05	0.022	0.0046	<0.05
MPP	0.032	0.004	<0.05	0.029	0.0037	<0.05
OPP	0.026	0.0041	<0.05	0.023	0.0037	<0.05
EPP	0.048	0.0047	<0.05	0.043	0.0042	<0.05
Wednesday	-0.007	0.0031	<0.05	-0.007	0.0028	<0.05
<= 30 mph	0.083	0.0064	<0.05	0.074	0.0055	<0.05
> 30 & <= 40 mph	0.05	0.0066	<0.05	0.046	0.0059	<0.05
> 40 mph & <= 50 mph	0.018	0.0052	<0.05	0.016	0.0048	<0.05
QIC	100.205			82.191		
QICC	95.546			75.239		
RMSE	0.11			0.11		
MAPE	0.06			0.06		

5.2.3. Factors Influencing the Ratio of the Average Travel Time of Trucks to the Average Travel Time of All Vehicles – Linear Model

The results obtained from the GEE linear model with the ratio of the average travel time of trucks to the average travel time of all vehicles as the dependent variable are summarized in Table 13.

The DOW was not significant at a 95% confidence limit during the initial steps of model development. Therefore, DOW was not considered in subsequent steps of model development. The results obtained for the linear model indicate that the ratio of the average travel time of trucks to the average travel time of all vehicles is 0.937 on a link with reference speed greater than 50 mph and data density is C on a Saturday in a rural area.

The ratio of the average travel time of trucks to the average travel time of all vehicles is higher on a link in an urban area when all the other variables are kept constant. It is higher if data density is A and B when compared to data density C when all the other variables were kept constant. Further, it is higher during the morning peak period, afternoon peak period, and evening peak period when all the other variables are kept constant. It is also higher on a link with reference speed less than or equal to 50 mph when all the other variables are kept constant.

5.2.4. Factors Influencing the Ratio of the Average Travel Time of Trucks to the Average Travel Time of All Vehicles – Gamma Log-Link Model

The results obtained from the GEE gamma log-link model with the ratio of the average travel time of trucks to the average travel time of all vehicles as the dependent variable are also summarized in Table 13.

The ratio of the average travel time of trucks to the average travel time of all vehicles is {exp (-0.057)} = 0.945 on a link with reference speed less than 50 mph, during night-time period and data density is C in a rural area. It is higher for data density A and B when all the other variables are kept constant.

The results obtained also indicate that the ratio of the average travel time of trucks to the average travel time of all vehicles is higher during the morning peak period, afternoon peak period, and evening peak period when all the other variables are kept constant. Further, it is higher on a link with reference speed less than or equal to 50 mph.

TABLE 13 GEE models - Ratio of the Average Travel Time of Trucks to the Average Travel Time of All Vehicles

Parameter	Linear Model			Log-Link Gamma Model		
	B	Std. Error	P-value	B	Std. Error	P-value
Intercept	0.937	0.005	<0.05	-0.057	0.005	<0.05
Area	0.032	0.003	<0.05		0.003	<0.05
Density A	0.057	0.004	<0.05	0.054	0.004	<0.05
Density B	0.020	0.003	<0.05	0.019	0.003	<0.05
MPP	0.042	0.004	<0.05	0.039	0.003	<0.05
OPP	0.030	0.004	<0.05	0.027	0.003	<0.05
EPP	0.050	0.004	<0.05	0.046	0.004	<0.05
<= 30 mph	0.088	0.006	<0.05	0.08	0.005	<0.05
> 30 & <= 40 mph	0.059	0.006	<0.05	0.054	0.006	<0.05
> 40 mph & <= 50 mph	0.016	0.005	<0.05	0.015	0.005	<0.05
QIC	85.750			73.187		
QICC	83.627			69.702		
RMSE	0.11			0.11		
MAPE	6%			6%		

5.2.5. Summary of Results from GEE Models

The results from the GEE models indicate that the ratio of the average travel time of trucks to the average travel time of passenger cars is lower on a Wednesday. All the other variables are positively associated with the ratio of the average travel time of trucks to the average travel time of passenger cars.

For the links with reference speed less than 50 mph, the ratio of the average travel time of trucks to the average travel time of passenger cars and the ratio of the average travel time of trucks to the average travel time of all vehicles is higher when compared to the reference speed greater than 50 mph. Also, the ratios are higher during the morning peak period, afternoon peak period, and evening peak period when compared to the night-time period.

The best-fitted model is selected based on QIC, QICC, RMSE, and MAPE. It was observed that the gamma log-link model was the best-fitted model with the lower value of QIC and QICC. The RMSE and MAPE are same for all the developed model.

CHAPTER 6: CONCLUSIONS

The concept of PCE has been introduced to account for the effect of trucks on the transportation system performance. Density, speed, headway, and delay were used to assess PCE in the past. With increasingly available continuous travel time data, this research focuses on the effect of trucks on the transportation system from a travel time perspective.

The objective adopted in this research is to determine the relationship between the average travel time of trucks and the average travel time of passenger cars or all vehicles. The role of area type, data density, DOW, TOD, and reference speed in the relationships is also examined. The data density is considered as an indicator of traffic volume and its composition. The reference speed is an indicator of the free-flow speed of the road segment in miles per hour. It is used in this study as a factor influenced by road geometry and posted speed limit.

The correlation between the average travel time of trucks, the average travel time passenger cars, the average travel time of all vehicles, area type, data density, DOW, TOD, and reference speed was computed prior to developing statistical models.

One hundred and four OLS regression models were developed considering the average travel time of trucks as the dependent variable and the average travel time of passenger cars or all vehicles as the independent variable. These models were developed by categorizing data by area type, data density, DOW, TOD, and reference speed.

It was observed that the average travel time of trucks is higher on a Wednesday when compared to on a Saturday. The reason being, the logistics industry delivers most of the packages on weekdays except for certain priority mail and Amazon packages. When the number of vehicles reporting is less than 4 i.e., data density is A, the average travel time of trucks is higher during afternoon and evening peak periods. This could be attributed to the delivery of products during these periods.

The average travel time of trucks is higher during the night-time period if data density is B. It decreases with the increase in the number of vehicles reporting (traversing through the point of interest) in a minute. Therefore, the average travel time is higher for density A followed by density B, and then by density C. Further, the average travel time of trucks on a link with a reference speed limit less than 30 mph is higher when compared to other reference speed groups. Such links are either on lower functional class roads or because of the magnitude, length of road grade, or curvature.

The gamma log-link distribution-based model was observed to be the best-fitted model to estimate the ratio of the average travel time of trucks to the average travel time of passenger cars or all vehicles. The ratio of the average travel time of trucks to the average travel time of passenger cars and the ratio of the average travel time of trucks to the average travel time of all vehicle is higher on a link in an urban area when compared to a rural area. The rural area has fundamentally different characteristics with regard to traffic volume, road geometry, intersections, and speed. Studies have found that rural traffic mainly comprises of trucks.

The linear model showed that weekday (Wednesday) has a negative influence on the ratio of the average travel time of trucks to the average travel time of passenger cars.

However, DOW does not have any influence on the ratio of the average travel time of trucks to the average travel time all vehicles.

The proposed methodology successfully examined the relationship between the average travel time of trucks and the average travel time of passenger cars or all vehicles. It can be adopted to identify significant factors influencing the ratio of the average travel time of trucks to the average travel time of passenger cars or all vehicles.

6.1 Practical Application

Practitioners and road users value travel time. From the past, highway agencies determine the operational performance of the road based on the level of service (LOS). However, LOS does not capture the variability in travel time. Travel time varies by traffic volume (data density), day-of-the-week, time-of-the-day, area, and the reference speed. Therefore, there is a need to determine LOS from a travel time perspective.

Fundamentally, LOS has been determined by calculating heavy vehicle adjustment factor to convert base flow rate to equivalent passenger car flow rate, which is further used to determine density. The LOS of the transportation system (typically, freeways) is defined as a function of travel time. The computed travel times for trucks, passenger cars, and all vehicles help practitioners to cut down the above mentioned process and assess LOS based on the travel time measures.

The obtained travel time regression equation using average travel time of passenger car as the independent variable can be used to compute the travel time of trucks. The computed average travel time of trucks can be further used in the equation to determine the average travel time of all vehicles, which is generally used to determine the LOS of a facility. Alternatively, one could also explore the applicability of the computed ratios as an indicator of PCE from travel time perspective.

6.2 Limitations and Scope for Future Work

This research examined the relationships area type, data density, DOW, TOD, and the reference speed. However, due to data availability and sample size restriction, other variables or factors were not explored. These factors include driver behavior such as speeding, aggressive driving, distracted driving, and drowsy driving. Likewise, variables such as road geometry grade, length of grades, surface type, number of lanes, and curvature could influence but were not considered in this research. These variables should be captured and explored in future research.

The socio-economic characteristics and demographic characteristics surrounding the road network could also be captured and explored as future research.

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