ASSESSMENT OF TRADEOFFS AMONG MULTIPLE VEHICLE CLASSES FOR URBAN DELIVERIES

by

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ABSTRACT

Effective intermodal corridor management, as its name suggests, must be aimed at ensuring an optimal use of the existing network. However, in order to achieve a quasi or optimal use, transportation agencies must be able to quantify the economic costs and benefits associated with the traffic of different vehicle classes.

In the case of commercial freight traffic, there is a severe lack of knowledge about the comparative advantages of fostering the use of small vs. large trucks. As it is widely known, a large truck generates more pollution and congestion than a small truck which is an obvious consequence of its larger size. However, what it is not frequently taken into account is that if the amount of cargo to be transported by each truck type is the same, large trucks are more efficient than small trucks. This is because, while the average payload for a semitrailer is 20 tons, the one for a single unit truck is 7 tons (Vehicle Inventory and Use Survey, 2002). As a consequence of this, transporting a given amount of cargo using single unit trucks would necessitate almost three times more traffic than if semitrailers are used. This leads to a situation in which, although the contribution to congestion and pollution of an individual small truck is smaller than that of a semi-trailer, their total impact may be greater because of the larger truck traffic.

This research is intended to be one of the first to shed light into the overall economic benefits and costs associated with different combinations of truck traffic. This was done by conducting micro-simulation, statistical modeling, valuation and optimization of a hypothetical network. The simulations are performed for different levels of demands with different combinations of traffic for passenger cars, small and large trucks in order to estimates the externalities as a function of a multimodal vector of traffic flow. Cost functions were generated to provide insight into the relative contributions to congestion pavement damage and pollution associated with the traffic. The costs obtained with these functions were used to find optimal combinations of truck traffic that minimize the total cost of externalities. The results demonstrate that heavy trucks are more optimal for minimum costs only if the payload of a small truck with respect to the payload of a heavy truck is 62.5% or less.

1. Introduction

Transportation systems are a crucial component of a nation's economy. An example of this is the highway system in the United States which revolutionized the nation's economy, safety and lifestyle (McNichol, 2005). Even though transportation systems contribute to economic development, they also create negative externalities such as congestion, pollution and pavement deterioration. This has become of great concern since approximately 28% of all green house emissions are produced by transportation (USDOT, 2006). As an example, the city of New York has proposed to reduce emissions up to 30% by the year 2030 (PLANYC, 2007). Also, government agencies like Environmental Protection Agency (EPA), United States Department of Transportation (USDOT), Department of Energy (DOE) and Metropolitan Planning Organizations (MPO) are continuously trying to reduce levels of pollution on these cities. This is based on the Congestion Mitigation and Air Quality Improvement Program. This program provided $8.6 million among DOT's and MPO's to invest in projects that reduced the amount of pollution and congestion during the period of 2005-2009 (FHWA, 2009). These projects incorporate major investments on repair of the existing infrastructure, construction of new infrastructure and policy generation.

Transportation agencies started noticing the problem of pollution during the 1950's. In 1963, the United States federal government passed the Clean Air Act which requires EPA to develop and enforce regulations that could help protect the environment and avoid adverse health effects on the population (EPA, 2008). This law had some major changes on 1970 and 1990 based on the improvements that some emerging technologies of the time provided. Thanks to this law EPA needs to constantly regulate and monitor pollution levels. Even though all of the efforts mentioned have helped reducing emissions, transportation is still one of the main contributors to this problem, being responsible for 95% of the CO_2 emissions produced every year (EPA, 2008). This is mainly because of the increasing number of vehicles on roads and the poor conditions of the existing infrastructure. According to the Bureau of Transportation Statistics (2002) commercial truck traffic alone increased by 75% and the forecast models for the next 10 years show that the trend is constant. It is obvious that pollution and traffic conditions are linked; the more congested traffic conditions are and the more pollution will be created. This is mainly because vehicles produce more emissions while idling or at speeds lower than 30 mph (Bart and Boriboonsomsin, 2007). This aggravates the pollution problem since congestion has increase more than a 10% in urban areas during the last decade according to a study conducted by Texas Transportation Institute in 2007 and it not only affects the environment but also the economy. It is estimated that congestion takes $78 billion away from the economy every year. In terms of labor, 4.2 billion hours are lost every year while employees are trying to get to work and an average of 36 hours per year per driver are lost. Around 2.9 billion gallons of fuel are wasted every year, in average 26 gallons per person per year of fuel are wasted on traffic. This accounts for an average loss per person of $710 per year (Shrank and Lomax, 2007).

Even though transportation agencies have become involved on the issue, there are still some areas on which research needs to be done to see if plausible outcomes are to be reached. Much research has been conducted regarding policies that help reduce congestion such as off peak deliveries, HOV lanes, truck lanes, advanced traveler information systems and advanced management systems. However as indicated by literature review, no one has performed research to determine the optimal combinations off traffic flows for different vehicle classes in order to minimize congestion, pollution or any other externalities.

There is a widespread misconception about the relative economic and environmental impact of small trucks vs. large trucks. As it is widely known, a large truck generates more pollution and congestion than a small truck which is an obvious consequence of its larger size. However, what it is not frequently taken into account is that if the amount of cargo to be transported by each truck type is the same, large trucks are more efficient than small trucks. This is because, while the average payload for a semitrailer is 20 tons, the one for a single unit truck is 7 tons (Vehicle Inventory and Use Survey, 2002). As a consequence of this, transporting a given amount of cargo using single unit trucks would necessitate almost three times more traffic than if semitrailers are used. This leads to a situation in which, although the contribution to congestion and pollution of an individual small truck is smaller than the one for a semi-trailer, their total impact may be greater because of the larger truck traffic.

The objective of this research is to study and analyze the tradeoffs between different types of vehicles on a network. This provides the basis to compute optimal traffic flows by minimizing cost of externalities (e.g. pollution, congestion and pavement deterioration). This research intended to shed light into the relationship between externalities and the vehicles traveling on roads. This is done by simulating the impacts of different levels of traffic of passenger cars, small and large trucks in a corridor network. The study utilizes these combinations and estimates the externalities as a function of a multimodal vector of traffic flows. This is accomplished with a micro-simulation of a fairly congested network in an urban area. In this case the simulation is conducted for Oakland, CA. Data and specific characteristics for this area were used, though it is important to point out that the results should not be considered representative of that city. The Oakland network was used because it fits the objective of this study i.e. to study a congested urban area with a traffic mix of cars and different truck classifications. This network is one of the most congested networks in the US with an average annual daily traffic of 268,000 vehicles (FHWA, 2002). It also has a lot of freight traffic since it is located near major urban areas such as San Francisco, CA. It also has other sources of traffic like the Oakland International Airport and the Port of Oakland. All of these characteristics make it a good match for these study objectives since it has a diverse mixture of vehicles on its traffic flow as well as the necessary congestion conditions to see significant numbers as the output for externalities.

The analysis will complement the simulations with the development of cost functions using values of travel time and economic valuations of different externalities. These models were estimated using Taylor series expansions of the results obtained from the micro simulation model. These cost functions provide insights into the relative contributions to congestion and pollution associated as a function of the traffic of each vehicle class. Total cost of externalities was minimized and optimal truck traffic combinations were found. Sensitivity analysis was used to see how valuation parameters, cargo demand and average payload by vehicle affected total cost and optimal truck traffic combination. This research contributes to understanding the interactions of externalities and multimodal traffic, which has significant implications for Intermodal Corridor Management and congestion pricing.

As indicated by literature review, this study will be the first to study such interactions by providing results in terms of costs. The development of such cost functions will help define policies to find optimal combination of traffic flow in which the amount of externalities produced will be minimized. Therefore, it is intended to foment the use of policies that could optimize the existing resources.

This document is divided as several chapters. The second chapter provides a complete literature review of the topic. Chapter 3 discusses the overall methodology used for this research. Chapter 4 discusses in detail the methodology for the micro-simulations runs. Chapter 5 discusses the statistical modeling used to generate the externality models, and presents the models obtained for different geographical areas. Chapter 6 provides the cost model for the externalities. Finally, Chapter 7 discusses the mathematical formulation for the optimization problem and presents the results for the sensitivity analysis experiments. Chapter 8 summarizes all the finding of this research.

2. Literature Review

This section is intended to discuss the key findings of an extensive literature review on the topics being investigated on this research. The literature review covers a wide variety of topics: estimation of externalities, valuation, congestion pricing, micro-simulation, and transportation planning. Estimation of externalities involves studying the different approaches and techniques to find the amount of pollution generated by different types of vehicles. Valuating those externalities is related on assigning economic value to different pollutants and travel time. Congestion pricing analyzes different policies that can help lower levels of congestion in urban areas, infrastructure and the environment. Corridor micro-simulation deals with the techniques used for modeling corridors and networks while incorporating as much information as possible about traffic conditions, geometric features, and trip choice. Transportation planning works by identifying problems, defining goals and objectives to resolve these problems, generating and evaluating alternatives, and developing solutions. This area usually adopts multi-disciplinary approaches, especially due to the rising importance of environmentalism.

Assessing the overall trade-off among multiple vehicle classes has not received a great deal of attention. This subject of externalities and their effects on society has been widely studied by transportation and economists (Pigou, 1920; Walters, 1961; Nelson 1962; Vickrey, 1963; Johnson, 1964; Beckman, 1965; Vickery, 1969), but not much research has been conducted regarding tradeoffs between different vehicles classes and externalities. Some research has been conducted to see the impact that a specific vehicle class has on pollution, congestion and safety. There are several studies which study the contribution of trucks on safety, pavement deterioration and truck regulations (FHWA, 2000; Kostyniuk et al., 2002; NHTSA, 1998; Stuster, 1999). Others use simulation to evaluate policies on trucks that can affect traffic flow, density and even the spatial distribution of pollution (Garber and Gadiraju, 1991; Lee et al., 2009) and even study the effects of trucks on congestion during peak hours (Grenzeback et al., 1991). These studies do not incorporate any car-truck or small-large truck interactions. Not much research has been conducted regarding tradeoffs between different vehicles in terms of their impacts on pollution and congestion. Few studies have targeted car-truck interactions as for example Yoo and Green (1999) which by using a driving simulator studied headways between car-truck and truck-truck interactions. Others focused on the behavioral aspect of the interactions between the different types of vehicles and used their results to implement mitigation strategies (Peeta et al., 2000; Peeta et al., 2005). However, none study the interactions between all different vehicle types by using quantifiable measures.

Understanding the impacts of different vehicle classes on pollution, congestion and pavement deterioration is important in the context of global warming, climate change and infrastructure funding crisis (NCHRP 289) even more as the rate of congestion, pollution, and infrastructure deterioration keeps increasing in exponential ways (EPA, 2008; Bureau of Transportation Statistics, 2002).

Congestion and the association with pollution are considered as some of the most critical externalities in urban areas. Billions of work hours are lost every year because of this problem (Shrank and Lomax, 2007). A.A. Walters (1961) was one of the firsts to explore more in detail the issue with congestion and social and economic effects created by vehicles in congested traffic. After identifying the marginal effects that drivers had on the roads they are traveling, research focused on computing the optimal values for tolls to support the economic theories established by Walters and Pigou (Arnot, 2007; DOT Australia, 2007; Walters, 1961; Vickrey, 1969). Several research study more in detail the effects that different vehicles and vehicles mix have on congestion and safety under these circumstances (Noland and Quddus, 2005; Parry et al., 2006; Sarvi, 2008). A number of publications study the economic effects that traffic have over real state and how this negative price effect should be reduced by charging vehicles (Hughes and Sirmans, 1992). Another important issue is the estimation of the economic cost or valuation of congestion and other externalities. This provides decision makers and policy makers with a better understanding when it comes making policies. Valuation of travel time is used in order to obtain estimates of the cost of travelling through a network. Travel valuation is not straightforward as it is depends on a wide range of factors like travel length, effort, comfort, safety, reliability, etc (Wardman et al., 2008; Steimetz and Brownstone, 2005; Hensher, 2008; Ackcelik, 2001; Brownstone and Small, 2005; Ozbay et al., 2006). Several studies have been conducted and estimate the value of travel time for passenger cars. One study reviews previous studies for valuation of travel time

(Small and Verhoef, 2007). Based on the author's findings, they concluded that this value might vary between 20 to 90 percent of the gross wage rate of drivers (Small and Verhoef, 2007). The U.S. Bureau of Labor Statistics shows that in 2008 the mean hourly wage was $20.32. Based on this it can be concluded that an actual valuation for travel time is between $4.06 and $18.29 per hour. Small and Verhoef (2007) suggested that the valuation could be average around 50 percent of the gross wage rate of drivers. Using this average measure, the value for travel time is around $10.16 per hour. Research also focused on analyzing data from pricing projects like interstate I-15 in San Diego, CA, using the choices that users make in real market situation, specifically comparing free-flow alternatives to congested alternatives (Steimetz and Brownstone, 2005). The authors found that the value of travel time is $30 per hour but can range from $7 to $65 per hour, depending on motorist characteristics. Another study took the opportunity to study data of two pricing demonstrations conducted in California. The authors found that value of travel time for morning commuters ranges from $20 to $40 per hour (Brownstone and Small, 2005). Additionally research publications focused on analyzing the implications of presence of passengers had in non-commuter driver's value of travel time (Heshner, 2008). The author found the values range from $13.22 to $19.99 per person per hour, and it declines as the vehicle occupancy increased (Heshner, 2008).

Transportation agencies have also conducted studies to find valuation for travel time of different vehicles. The Oregon Department of Transportation (2006) recently conducted a study that estimated values of travel time for vehicles on this region. They found values for passenger cars, light trucks and heavy trucks. The values per hour are $16.31, $20.35 and $29.50 correspondingly. Government agencies like Federal Highway Administration consider these values to be $25.24 for large trucks and $15.71 for passenger cars (Forkenbrock and March, 2005). Washington DOT estimates travel time valuation for passenger cars, small trucks and heavy trucks of $12-$16, $20-$24 and $25-$29 correspondingly (Washington State DOT, 2005).

Valuation of travel time for other vehicles classes such as small and heavy trucks has also being estimated. A research conducted by De Palma et al. (2006) in which they conduct economical analysis to find out the feasibility of implementing truck lanes and truck tolls, found that travel time valuations for small and heavy trucks are $12 and $50 correspondingly. It has also being found that travel time value for trucks can be as high as $193.80 with a mean of $51.80 (Forkenbrock and March, 2005). Holguin-Veras and Broom conducted a study to provide cost models by using econometric modeling and cost accounting. The authors suggest travel time value for small and heavy trucks of $34 and $50 per hour.

Air pollution is directly linked with congestion since the biggest levels of pollutions are generated when vehicles are idling or traveling at speeds lower than 30 mph (Bart and Boriboonsomsin, 2007). Scientists estimate that 30% of air pollution comes from vehicle traffic (USDOT, 2006). This has created pressure among the government sector in order to minimize the levels of pollutions generated in metropolitan areas (Concas and Winters, 2007; Kanaroglou and Buliung, 2008). Some studies aimed to find the different levels of pollution produced by a specific vehicle class (Lee et. al, 2009). Research has been conducted in order to find the cost inquired by vehicles to polluting and deteriorating the infrastructure and environment in which they travel. Researchers have found that the cost of polluting roads on large metropolitan areas was around $0.03 per mile and the total cost can be between $34 to $527 (Delucchi, 2000), based on health effects as secondary reactions (Small and Kazimi, 1995). Several studies have been conducted in urban areas to obtain pollution levels and cost of different air pollutants. For example, Small and Kazimi (1995) found the cost of air pollution in the urban area of Los Angeles, CA. to be $0.03 per mile. Another study conducts literature review related to the health effects of different pollutants on the population and latter quantifies these effects as a cost (McCubbin and Delucchi, 1999). This research uses these values to calculate the costs of the pollutants discussed on this document. The monetary values had to be adjusted using the consumer price index, since the values provided from McCubbin and Delucchi (1999) were for 1991 dollar values. The values are shown on Table 1.

Table 1: Cost of Air Pollutants (cents/kg) (2009 US dollars)

Pollutant	Low Value ($)	Medium Value ($)	High Value ($)
VOC	0.16	0.99	1.81
CO2	0.02	0.08	0.14
NOX	1.84	14.50	27.15
PM	15.31	112.69	210.06

A series of publications have also revealed the conditions and parameters under which pollution and fuel consumption are most critical and have suggested several options that could help reduce emission by up to 20%, such as policies, Intelligent Transportation Systems, and management policies (Bart and Boriboonsomsin, 2006; Bart & Boriboonsomsin, 2007; Bart et al., 2006; Bart & Boriboonsomsin, 2008). Research has also tried using simulation to evaluate policies on trucks that can affect traffic flow, density and even the spatial distribution of pollution (Garber and Gadiraju, 1991). Lee et al. (2009) is probably the one that has a closest match to the topic discussed on this paper. They estimated vehicle emission impacts for heavy trucks, on the areas surrounding San Pedro Bay ports in California. They did this by using microscopic traffic simulation and analyzed scenarios which considered changing cargo transport to other modes like rail and reducing heavy trucks with new units that can produce up to zero emissions. Their conclusions suggest that replacing truck fleets with zero emission trucks is the most feasible option. In summary, the majority of research conducted on this topic concentrates on studying large urban areas in which congestion and pollution are more severe. Most of the studies concentrated on finding the effects that vehicles have on these areas and corridors, but have not consider the effects that a mix flow of vehicles have on these systems and finding optimal combination of traffic flows to minimize the adverse effects of externalities.

In terms of pavement deterioration, more research has been conducted as a number of publications have assessed the damage produced by vehicle type; time of day vehicle is traveling, season, and a series of other factors (Meyburg et al., 1998). Another study showed that the current tolling policies can undercharge vehicles by up to 179% (Hussain and Parker, 2009). Other research studies the contribution of trucks on safety and pavement deterioration through the use of quantifiable measures. This research provides insight into the issues surrounding truck regulations and reduction in shipping costs associated with modifying weight and size limits to avoid increasing pavement deterioration (FHWA, 2000). One particular study reveals the effects of trucks on congestion during peak hours and suggests strategies to improved traffic management, incident management, mandatory night shipping and receiving policies, and mandatory peak-period truck bans policies, and later analyzes the economic effects of these strategies (Grenzeback et al., 1991). Similar publications found that pavement damaged is mainly due to heavy vehicles, with the damage increasing at congested conditions and proving this by analyzing different types of roads with different levels of congestion (Roberts et al., 1999, Saber et al., 2009). These studies use Equivalent Single Axle Load (ESAL) as the measure of the load that each axle puts on the road surface. Some other research provides economic valuations of the impact of trucks on pavements. Saber et al. (2009) conducted a study to see if the fees imposed on heavy trucks in the state of Louisiana are proportional to the amount of damage that these vehicles impose on roads. The authors found that the pavement damage created by a heavy truck can reach up to $5,500/year. Roberts and Djakfar (2000) also conducted a similar analysis in Louisiana by forecasting what would happened if the vehicle weight limits were increased. The authors found that the cost could be $0.6/ESAL-mile for local roads, $0.2/ESAL-mile for U.S. highways and $0.4 ESAL-mile for Interstate highways. Meyburg et al. (1998) did the same study using data from the state of New York. The authors found that the cost for state highways is $0.12 ESAL-mile and $0.74 ESAL-mile for local highways. Federal Highway Administration calculates pavement damage cost to be $0.2 ESAL-mile on rural Interstates and $1.5 ESAL-mile for urban Interstates (United States Department of Transportation, 1995). The costs estimated on these studies were adjusted using the consumer price index and are used for the analysis presented on this document.

A series of studies analyzed more in detail of the effects of other factors such as weather and how these factors therefore marginal cost does not rely totally on users deteriorating the infrastructure (Newberry, 1998; Robert et al., 1999). One particular study analyzed pavement deterioration as a function of intensity of use (Hussain and Parker, 2009). This way the damage incurred on the road surface can be categorized by vehicle type, time of day and season sensitive. Incorporating such characteristics provides a better infrastructure of pricing based on vehicle type (Hussain and Parker, 2006; Martin, 2008).

Simulation is very helpful in evaluating the impact of policy changes at the micro or macro level as well as for obtaining data to assess the environmental and economic impacts of traffic. For example, researchers have used micro-simulation to analyze policy impacts on urban areas. This way the social impacts of these policies such as job transformations can be quantified (Ballas et al., 2006; Vance and Iovanna, 2008). Also, research have improved micro simulation techniques utilizing single loop detectors instead of double loop detectors for data collection for corridor micro-simulation (Ban et al., 2007). Incorporating more agents like pedestrian flow rather than only using vehicular flow are some of the other improvements used lately in micro-simulation (Blue and Adler, 2001). Modeling of large corridors in dense urban areas while incorporating multi-modal data has been more widely studied in order to obtain more accurate results from simulations (Singh et al., 2008; Madanat and Benouar, 2006; Lee et al., 2009).

Transportation planning works by identifying problems, defining goals and objectives to resolve these problems, generating and evaluating alternatives, and developing solutions. One of the alternatives used by transportation planners is road pricing. Take for example the implementation that PANYNJ made in January 25, 2001 concerning a new toll structure varying through different times of the day and vehicle type in order to reduce congestion. These policies intend to charge users in terms of how congested a road is, type of network (i.e. multimodal), type of vehicle or user class and number of axels (Beckham et al., 1955; Gentile et al., 2005; Johnson, 1964; Nelson, 1962; Ozbay et al., 2007; Sheffi, 1984; Verhoef, 2005). Glazer and Nishkanene, (2000) propose a toll on a slow mode rather than a faster mode, so instead of inducing people to stop traveling, users can consider switching to other modes. A particular finding from research is that vehicles, especially trucks, were charged disproportionally higher based on the externalities they produced (Holguin-Veras et al., 2006). Also studies have analyzed the behavioral aspects of trucking companies towards pricing methodologies. Researchers found that users were interested on policies that could save them money as well as time they spend on congestion (Holguin-Veras et al., 2005; Holguin-Veras et al. 2006).

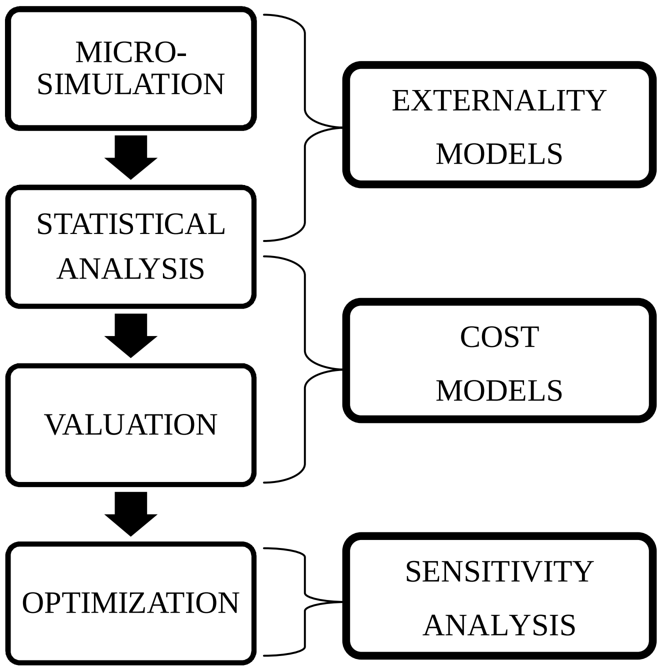
Many of the policies regarding congestion pricing and pricing of other externalities are applied to intermodal corridors mainly because of the effects that freight have on these networks (FHWA, 1995). Much of the research conducted on this area is based on the effects that trucks weight, size and other trucks characteristics have on networks (Beagan and Grenzeback, 2002). During the past decade, planning research has focused on evaluating the magnitude and distribution of commercial vehicles in urban transportation planning models (Chatterjee and Cohen, 2003; Thornton et al., 1998). A series of studies analyzed the economical, structural and environmental impacts that freight generate on roads and communities (Weisbrod & Fitzroy, 2008; Batelle, 1995; Newberry, 1988; Hugghes & Sirmans, 1992). Also transportation agencies such as Federal Highway Administration have conducted studies in order to account for commercial vehicles in urban transportation models (Chatterjee & Cohen, 2003; Batelle, 1995). More recent research have studied the generation of new policies concerning the reduction of congestion by implementing time of day pricing as well as the behavior of commercial carriers concerning these policies (Ozbay et al., 2006; Holguin-Veras et al., 2006, Holguin-Veras et al. 2005). These studies recognize the reliability that business should have for carriers as well as the connectivity and multimodal interactions in order to minimize transportation costs as well as the economical benefits and dis-benefits from the externalities created by these systems.

There are still some topics that have not been widely discussed in the transportation. In a recent publication, Holguin-Veras et al. (2008) conducted an analysis of toll policy in U.S. and concluded that commercial vehicle tolls seem to be disproportionally higher with respect to the externalities they produce (Holguin-Veras, Cetin et al., 2006). This is mainly because of the lack of sufficient research regarding the tradeoff between different vehicle classes.

3. Overall Methodology

This chapter provides a detail description of the methodology followed in order to complete this research. Figure 1, shows a flow chart of the overall methodology for this research.

Figure 1: Research Methodology



The research methodology was executed on the following order. First micro-simulations for an urban area were done. In order to do this, an experimental setup was used to generate different combinations of passenger cars, small and heavy truck traffic which were used to adjust the demand levels of the simulations. This way the simulation results captured the tradeoffs between different vehicle types. The simulation runs provided results for total travel time, vehicle miles traveled and pollution levels which were further used for statistical analysis. Simulations were done for three different areas: 1) entire network; 2) interstate 880 and 3) downtown Oakland. The purpose of this is to see how tradeoffs between different vehicle classes vary by area or sector.

The second part of the methodology consisted on using the results obtained from the simulation runs and conduct statistical analysis in order to generate models that quantify the externalities created by different traffic combinations of passenger cars, small and heavy trucks. Ordinary least squares were used as the statistical tool to estimate the parameters of the externality models. The models functional form consisted of a second order Taylor series expansions of the externality models. The dependent variables on these models are the different measurement of pollution, congestion and pavement deterioration. The independent variables are the traffic flows for three different vehicle types: passenger cars, small trucks and heavy trucks. Therefore, quantification for externalities can be obtained in terms of traffic levels of different vehicle types. Tradeoffs between the vehicles were obtained from the models.

The third step was to use these models to find the cost of the externalities generated by different vehicles. This was done by using valuation factors for travel time, pollutants and pavement damage. The valuation values and cost functions for externalities were obtained through an extensive literature review. The traffic flows from the demand matrices used to code and calibrate the original network were used to obtain cost. These costs were identified as the results of the base case.

The fourth step was to generate an optimization problem in which the total cost of externalities was minimized with respect to the amount of cargo tonnage requested by the population. This way the optimal truck traffic combination that minimizes cost can be found. A sensitivity analysis was done using different ranges of valuation, average payload by vehicle type and cargo demand to see how the total cost and optimal traffic truck traffic conditions could change.

The following chapters are organized as follows. Chapter 4 discusses in detail the methodology for the micro-simulations runs and how the network of study was generated according to these research objectives. Chapter 5 discusses the statistical modeling used to generate the externality models, and presents the models obtained for different geographical areas. Chapter 6 provides the cost model for the externalities. Finally, Chapter 7 discusses the mathematical formulation for the optimization problem and presents the results for the sensitivity analysis experiments.

4. Micro-Simulation Methodology

A micro-simulation was conducted utilizing state of the practice software. The purpose of this was to obtain results for levels of pollution, total travel time and vehicle miles travel for a typical urban area. The network used for this research was previously coded and calibrated as part of a project funded by the California Department of Transportation in coordination with the University of Berkeley. Section 4.1 discusses the methodology that the authors at UC Berkeley followed to generate the network code and some of the changes that were done to the code in order to adjust it to the objectives of this study. Section 4.2 discusses the experimental setup used to obtain the parameter values needed for the analysis part of this research.

4.1 Base Network

This network was developed as part of the Corridor Management Plan Demonstration conducted by the California Department of Transportation in coordination with the University of Berkeley at California, University of California at Irvine and Systems Metric Group (Madanat and Benuar, 2006; Ban et al., 2007; Ban et al., 2006). The network used for the analysis incorporated Interstate 880 in Oakland, California an area with a population of 400,000 habitants and a total area of 78 square miles. This is an inter-regional and multi-modal corridor located at the east of San Francisco. It includes a 34 mile urban highway with parallel arterials and cross roads including 143 metered lanes, 157 actuated traffic signals and 25 fixed time signals. This network incorporates transit and inter-modal facilities such as the sea port and airport in Oakland. It is also a major freight route and highly congested freeway. It has been proven that this corridor suffers from high levels of congestion during its AM and PM peak hours which is a key component of this study as it is easier to obtain information about externalities in such critical conditions (FHWA, 2002). Other important criteria for this network and project objectives are: sufficient inter-regional travel, multi-modal in nature, high levels of congestion and this network serves as a main freight corridor due to its proximity to sea ports and airports.

The system selected is able to consider a micro-simulation which is advantageous in terms of dynamic characteristics of traffic, capability of incorporating any existing

Intelligent Transportation Systems on the network such as traffic signal control and coordination and ramp metering control. The micro-simulation also includes key geometric information for the corridor such as HOV lanes, major structures such as bridges, key intersections with other highways and detail arterial geometric information.

Researchers obtained origins - destination data through local planning agencies, in this case the Metropolitan Transportation Commission who developed a region model that includes a calibration year as well as several forecasts. Information about origin destination matrices is dynamic since micro-simulation produces accurate results only if dynamic travel information is used. In order to do this 42 time periods of 5 minutes each were used for the simulation. This trip information was combined with overview of current land-use to see the effect that this had on travel choices. In terms of inter-modal facilities such as the Oakland Airport and the Port of Oakland, information about container versus cargo, annual tonnage, typical commodities carried, trading destinations, access modes and routes, passenger and freight services was incorporated in the analysis of trip origins and destinations. This is very advantageous as it provides a vehicle mix that fits very well the purpose of this study.

For the purpose of assessing the tradeoffs, the simulation considers multiple vehicle types for the purpose of simulating traffic conditions as close to reality as possible. The FHWA vehicle classification system was used and different percentages of each vehicle type were assigned based on data collected at Weight-In-Motion stations at I-880. Three matrices were created, each matrix is for one of the vehicle groups being studies; cars, small trucks and large trucks. Matrix 1 includes FHWA vehicle classification 1-4, matrix 2 includes vehicles 5-7 and matrix 3 includes vehicles 8-13. This differs from the original format that UC Berkeley research group selected for their study. They used two matrices, one for trips on the interstate and the other for city trips. For this study, the author though it was more appropriate to have a matrix for each of the vehicle groups being studied, since this facilitated the analysis to a great extent. The calibration was not altered when making the alterations.

The microscopic simulation network was developed utilizing the information described before. First the skeleton of the network was coded in Paramics, including traffic control devices such as actuated signals. The zones and demand were also incorporated into the code. As part of the basic inputs for coding the network three parameters are considered: link definition, vehicle definition and demand structure. For the purpose of this study, link definitions were kept as the original ones but necessary modifications were done to vehicle and demand codes.

Paramics can incorporate information for vehicles varying from attribute data like vehicles physical size, color, etc. to behavior data like perturbation and familiarity. This can be done by coding the information on a text file under the name of “vehicles”. This file can incorporate as much vehicle types as one prefers but in order to decide how many vehicle types should be incorporated into the simulation, factors such as demand matrices and level of detail should be considered. For this study seven vehicle groups were used: 1) type 1-6 are cars and SUV’s; 2) type 7-12 are HOV cars and SUV’s; 3) type 13 are buses; 4) type 14 are trucks with FHWA classifications 5-8 that are traveling with no cargo; 5) type 15 are trucks with the same classification but traveling with cargo; 6) type 16 are trucks with FHWA classification 9-14 and are empty; 7) type 17 are the same classification but travel loaded. Each matrix represents a vehicle group. This is shown in Table 2.

Table 2: Vehicle Groups on Demand Matrices

	FHWA Classification				
	Class 1-2 (Cars)	**Class 3 (SUV)**	**Class 4 (Buses)**	**Class 5-8 (Small Trucks)**	**Class 9-14 (Heavy Trucks)**
MATRIX 1	74.998%	24.898%	0.100%	N/A	N/A
HOV (20%)	15.000%	4.980%	0.020%	N/A	N/A
Regular (80%)	59.998%	19.918%	0.080%	N/A	N/A
MATRIX 2	N/A	N/A	N/A	100.000%	N/A
Empty (30%)	N/A	N/A	N/A	30.000%	N/A
Loaded (70%)	N/A	N/A	N/A	70.000%	N/A
MATRIX 3	N/A	N/A	N/A	N/A	100.000%
Empty (30%)	N/A	N/A	N/A	N/A	30.000%
Loaded (70%)	N/A	N/A	N/A	N/A	70.000%

Table 2 shows that there are three matrices; matrix 1 included vehicle classifications 1-4, matrix 2 includes vehicle classification 5-8 and matrix 3 includes vehicle classification 9-14. For this study three matrices are used for the purpose of facilitating the measurement of the vector of flows for three vehicle groups: cars, small trucks and large trucks which are identified on matrix 1, 2 and 3 correspondingly. These matrices are basically the demand structure of the network.

The HOV percentages were estimated using lane by lane volume data and HOV reports from the area. The empty and loaded ratios for trucks on matrices 2 and 3 were obtained from previous research conducted on this topic (Holguín-Veras and Thorson, 2003) . More in detail information for the peak hour periods is shown in Table 3.

Table 3: HOV Percentage Estimation

	lane by lane data		**HOV reports**	
	AM	PM	AM	PM
NB	19%	20%	25%	20%
SB	21%	20%	21%	21%

It is important to mention that even though for this study none of the features for the skeleton code were modified, originally a great level of detail was incorporated on coding this network. The following is a list of the criteria and parameters used for coding the skeleton of the network: background images such as aerial pictures for the purpose of having geometric measurements as close to reality as possible, road and geometry data, node naming conversion to keep track of actual street names on the network, links, curbs and stop lines, junction and next lanes, zones in which the vehicle enter and leave the network, intersection control, ramp metering (Madanat and Benuar, 2006; Ban et al., 2007; Ban et al., 2006). Some of these measurements incorporated the use of third part plugins such as actuated signals, ramp meters and loop detectors. All the information incorporated shows the great level of detail that this simulation uses, providing results that might be very similar to the ones one could see in real traffic conditions. Further details for the above mentioned parameters and model calibration are not going to be explained since none of them were altered for this study. For further details about this please refer to *Corridor Management Plan Demonstration Final Report*, 2006 or Ban et al. (2006 and 2007) publications.

4.2 Experimental Setup for Micro-Simulations

The objective of this study is to assess the tradeoffs among multiple vehicle classes, in terms of total travel time different pollution parameters and pavement deterioration. In order to do this, data for the above parameters was measured and collected with micro-simulation in order to generate models that could provide more information about the tradeoffs. The data was later used to generate ordinary least square models that could estimate externalities as a function of a multivariate vector of traffic flows. These models were estimated using Taylor series expansions of the results obtained from the micro simulations of a hypothetical case. Each point on the model represents one scenario for a specific demand level and a specific percentage of vehicles on the traffic flow for the three vehicle types being analyzed. It was understood that at least 100 points would be needed for each of the models since 10 variables are available for each of the models; therefore 104 combinations or scenarios were created. Each scenario was simulated three times and the averages of the results were used as the final values for the models. This was done in order to obtain results at the desired level of confidence. To determine the number of simulation runs required for micro-simulation software, the following equation is considered (FHWA, 2004):

$$N = \left(\tau_{\alpha/2} \times \frac{\delta}{\mu \times \varepsilon}\right)^2 \quad (1)$$

On equation (1) μ and δ are the mean and standard deviation of the parameters being measured on the simulation runs; ε is the allowable error; $\tau_{\alpha/2}$ is the value of the t-distribution at confidence interval 1- α. Based on this and assuming a confidence interval of 90% and an error of 5%, it was found that 3 runs was sufficient to obtain the desires level of confidence for the results of the parameters being studied.

Table 4 shows the eight different levels of demand and traffic that were simulated: 20%, 40%, 60%, 80%, 100%, 120%, 140%, and 160%. Each of these demand levels had four different levels of truck traffic, 0%, 20%, 30% and 40%. Additionally, these four truck levels where subdivided into large trucks and small trucks. For each of the levels small trucks accounted for 0%, 33%, 67% and 100%. The remaining percentages accounted for heavy trucks. These different combinations were run for a period of 2 hours during the peak hours of the morning. Each model contains 10 independent variables and 1 dependent variable. Table 5 shows the variables used on each of the models. Q_C, Q_{ST}, Q_{LT} represent the vector of traffic flows for cars, small trucks and large trucks correspondingly. The flow was measured in vehicles per hour. The simulation creates a file in which link flows are provided for all the links in the network. The problem relies in the fact that utilizing all the flows for all the links is an incorrect estimation of the values needed for the models. Since vehicles are created or appear in the network trough zones, the values used for the flows were for those links located directly after each zone. The values obtain for the flows are a combination of the different vehicle types in the network. Therefore in order to obtain the desire percentage of traffic flow values, the results obtained for traffic flows were multiplied by the corresponding percentages of each scenario. Using as an example a scenario for demand level of 20 and a percentage of traffic flow for cars, small and heavy trucks of 80%, 13% and 7% correspondingly and adding all the flows for the links directly after each zone, the total traffic flow was 23,818 vehicles for a 2 hour period of simulation. Therefore, the flows for cars, small and heavy trucks will be 19,054 vph, 3,096 vph and 1,667 vph correspondingly. This could only be done if the demand matrices for each scenario were defined with the corresponding percentages for each vehicle. This was done for all 42 demand matrices for the 104 scenarios studied. Since there is no purpose on running a simulation if these vector were already defined on the demand matrices, three simulations with different seed were run and the average of these were used as the final value for the regression model.

Table 4: Combinations for Scenarios

Level of Demand	% Cars	% Small Trucks	% Large Trucks
20	100%	0%	0%
40	80%	20%	0%
60	80%	13%	7%
80	80%	7%	13%
100	80%	0%	20%
120	70%	30%	0%
140	70%	20%	10%
160	70%	10%	20%
	70%	0%	30%
	60%	40%	0%
	60%	27%	13%
	60%	13%	27%
	60%	0%	40%

The other independent variables are interaction terms between the vectors of traffic flow of the different vehicles. The dependent variables are the different parameters for the externalities being studied. Total travel time (TTT) is the time it takes a vehicle to traverse through the entire network from the moment the vehicle is generated until it leaves the network. This value is measured in seconds. The simulation generated a file which provided this value for every minute the simulation ran. This value was cumulative so the last value generated by the simulation was used as the total travel time. The first thirty minutes of the simulation were subtracted from this value for the purpose since this period of time is the warm up period of the simulation. Therefore the data used was from 6:30 AM to 8:30 AM. Vehicle Miles Traveled (VMT) was used as the measurement of for pavement deterioration when multiplied by valuation of ESAL-mile.

In addition to travel time data and vehicle miles traveled, different estimates for pollution were collected: volatile organic compounds (VOC), carbon monoxide (CO2), nitrogen oxide (NOX) and particulate matter (PM). These represent the total amount of emissions produces in milligrams per second. These variables were selected since they are known to be the most commonly emitted pollutants by vehicles and are also considered to be some of the most hazardous pollutants to health and environment (EPA, 2002). Particulate Matter are inhalable coarse particles that can be made up of hundreds of different chemicals. These particles can be emitted from fires, unpaved roads, fields etc, but it is known that most of the fine particle pollution in the United States comes from the reactions of chemicals such as sulfur dioxide and nitrogen oxide which are emitted by automobiles and trucks (EPA, 2009). Volatile Organic Compounds are vapors emitted by various solids or liquids, generating mild to high adverse health effects. The most common VOCs can be found on untreated exhaust emissions of vehicles (EPA, 2002). Nitrogen Oxides are created when fuel burns at high temperatures. This is more usual in motor vehicle engines and these are the source of more than half of the NOX emissions produced in the United States (EPA, 2002). Diesel vehicles such as trucks, account for 42% of these emissions. NOX is one of the most hazardous emissions since gases and particles can travel long distances being able to create health and environmental problems on locations far away from the point where the emissions were generated. Carbon Monoxide is considered the major air pollutant in many cities in US. This poisonous gas forms when carbon in fuel is not burn completely. Vehicle emissions account for 95% of the CO2 emissions in the US (EPA, 2009).

Table 5: Variables on Models

Dependent Variables	Independent Variables
TTT (s)	Q_C (vph)
VMT (mi)	Q_{ST} (vph)
CO2 (mg/s)	Q_{LT} (vph)
NOX (mg/s)	Q_C^2 (vph)
VOC (mg/s)	Q_{ST}^2 (vph)
PM (mg/s)	Q_{LT}^2 (vph)
	$Q_C Q_{ST}$ (vph)
	$Q_C Q_{LT}$ (vph)
	$Q_{ST} Q_{LT}$ (vph)

The micro-simulation software requires the definition and coding of these pollutants. This is done by incorporating a plug-in or module that helps the simulation software to track and record traffic emission levels through the different links on the network. This is done by adding the emissions of all vehicles on the network. In order for the software to create results as accurate as possible, certain data must be input on the network such as vehicle types, pollution factors of these vehicles based on parameters like speed, acceleration, gradient, etc and the different pollutants which want to be analyzed. For the purpose of this study, Mobile6 software values for pollutants were used. These values are based on vehicle speed. Table 6 summarizes these values (U.S. Environmental Protection Agency, 2008).

Table 6: Emission Factors Incorporated in Micro-Simulation

Speed (mph)	Volatile Organic Compounds			Carbon Monoxide			Nitrogen Oxide			Particulate Matter		
	C	ST	LT	C	ST	LT	C	ST	LT	C	ST	LT
2.5	4.01	0.92	1.41	15.91	4.41	12.53	0.87	8.95	18.04	0.02	0.20	0.34
10	3.17	2.61	4.00	25.39	10.33	29.32	2.12	27.64	57.92	0.07	0.78	1.34
20	4.28	3.52	5.40	42.00	11.58	32.88	3.24	43.53	95.27	0.14	1.56	2.68
30	5.65	3.82	5.87	62.08	11.39	32.33	4.88	57.94	130.06	0.21	2.33	4.02
40	6.99	4.00	6.14	90.00	11.93	33.89	6.56	78.77	176.06	0.28	3.11	5.37
50	8.26	4.32	6.64	126.67	14.42	40.92	8.58	118.61	255.28	0.35	3.89	6.71
60	9.53	4.97	7.63	169.67	21.03	59.70	10.80	207.90	420.95	0.43	4.67	8.05

Note: C= passenger car, ST= small truck (2-axle), LT = heavy or large truck (5-axle)

For all 104 scenarios numerical values for traffic flow for different types of vehicles and pollution factors were obtained from a micro-simulation. The purpose is to see how changes on these different combinations of independent variables impact the dependent variables i.e. travel time, particle matter, carbon monoxide. This way the interaction between the different types of vehicles in the network can be obtained.

The simulation outputs were collected for different geographical areas: (1) entire network; (2) interstate system; (3) downtown Oakland, CA. The zone for the entire network consisted of an interstate system going through the cities of Oakland, San Leandro, Hayward, Fremont and San Jose. It also incorporates the downtown zone of

Oakland. The entire network geographical area is shown in Figure 2. The interstate system zone only incorporates the links on interstate I-880, none of the areas surrounding the interstate were considered. This was done for the purpose of finding the numerical values for externalities produced only at the interstate system in the network. In Figure 2, the links that go through the interstate that were used for this research starts at I-880 on Alameda county and end on the intersection of I-880 with road 237 in Milpitas county.

Figure 2: Entire Network

The zone for downtown Oakland focus on getting numerical values for externalities produced only at the city area of the network. This scenario only includes the links that go through this area in order to obtain the traffic flows and the different numerical values for the externalities produced. The downtown Oakland geographical area is shown in Figure 3. The purpose of studying these zones is to see how the cost of externalities varies depending on zones and road classes were the vehicles are travelling. Figure 4 shows a screen shot of the links on the network.

Figure 3: Downtown Oakland

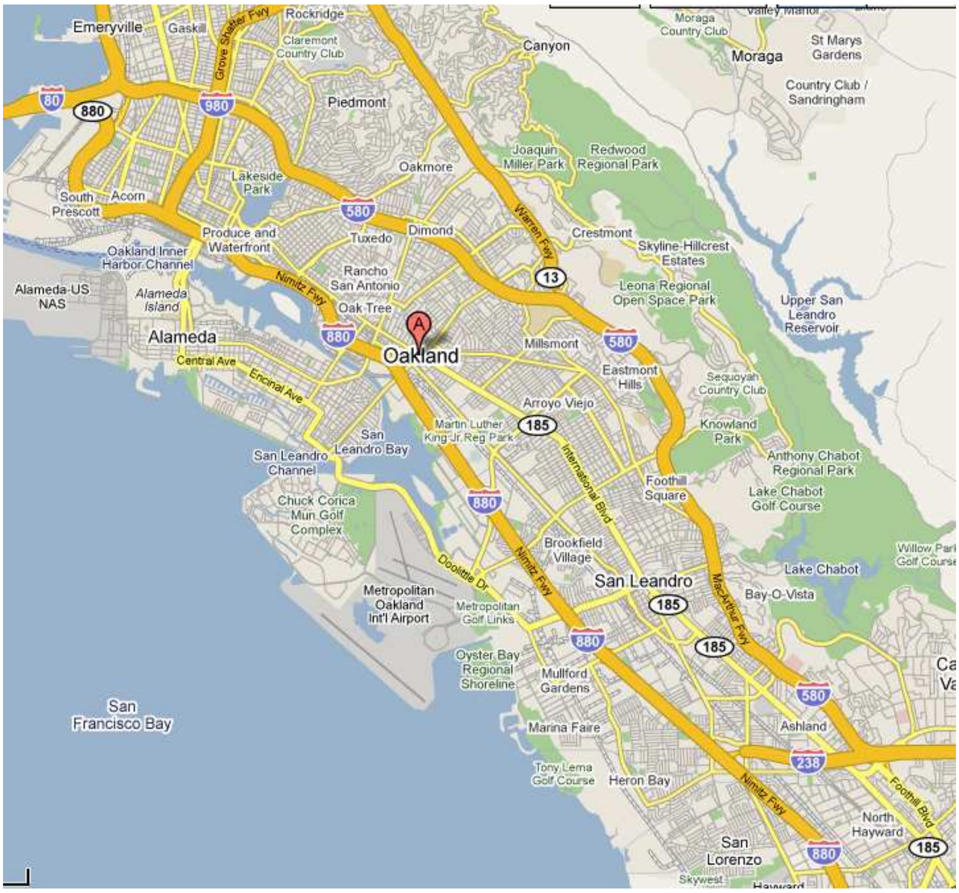
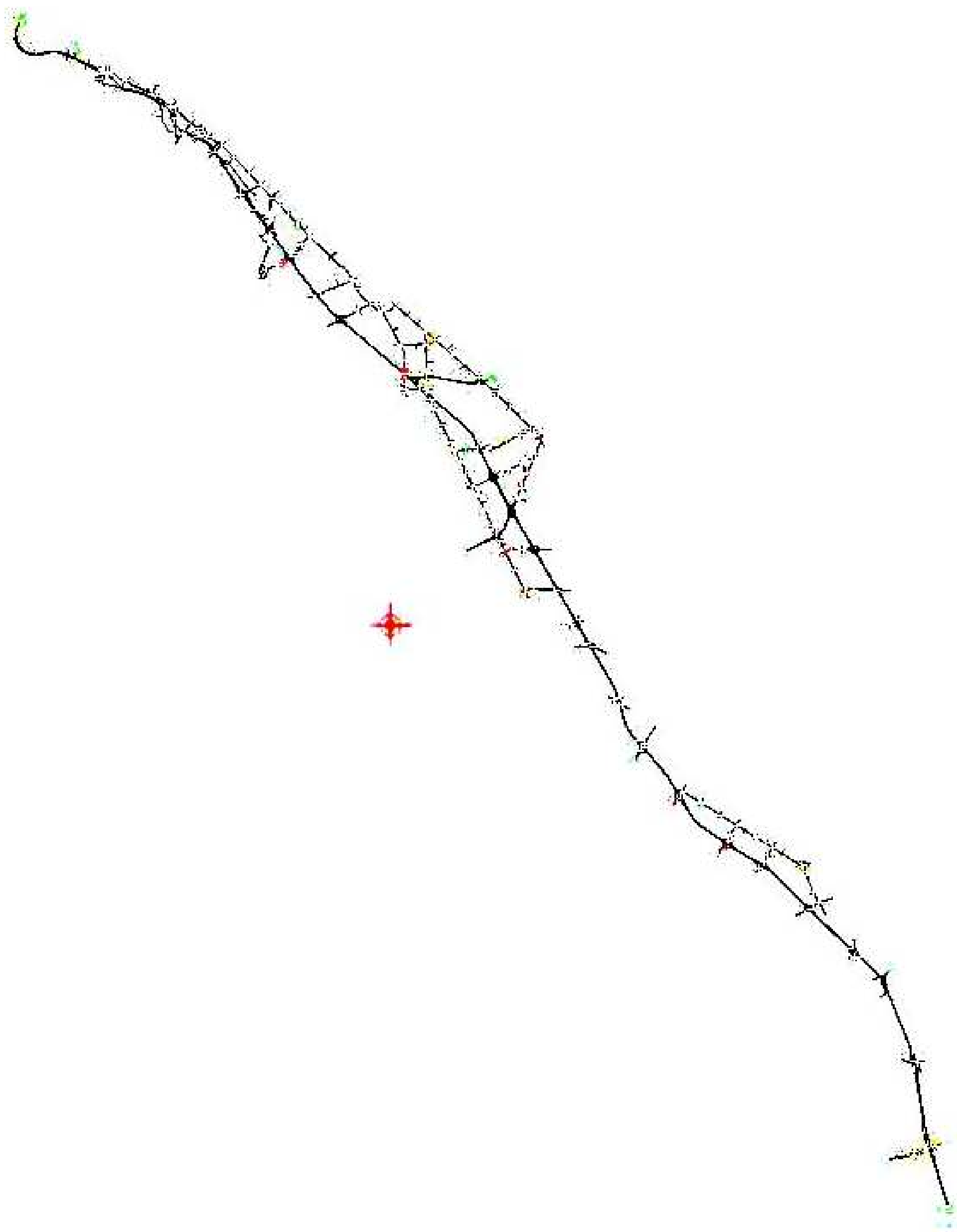


Figure 4: Paramics I-880 Network



5. Statistical Modeling and Analysis

Using the data obtained from the micro-simulation, externality models were generated to assess the tradeoffs between different vehicle classes and the different scenarios studied. The models discussed on the following sections were generated based on the variables discussed in chapter 4. Total travel time, VMT and different parameters for pollution levels were used as the dependent variables on these models. The independent variables are the vector of traffic flow for the different vehicle classes mentioned in chapter 4, as well as interaction terms between these variables.

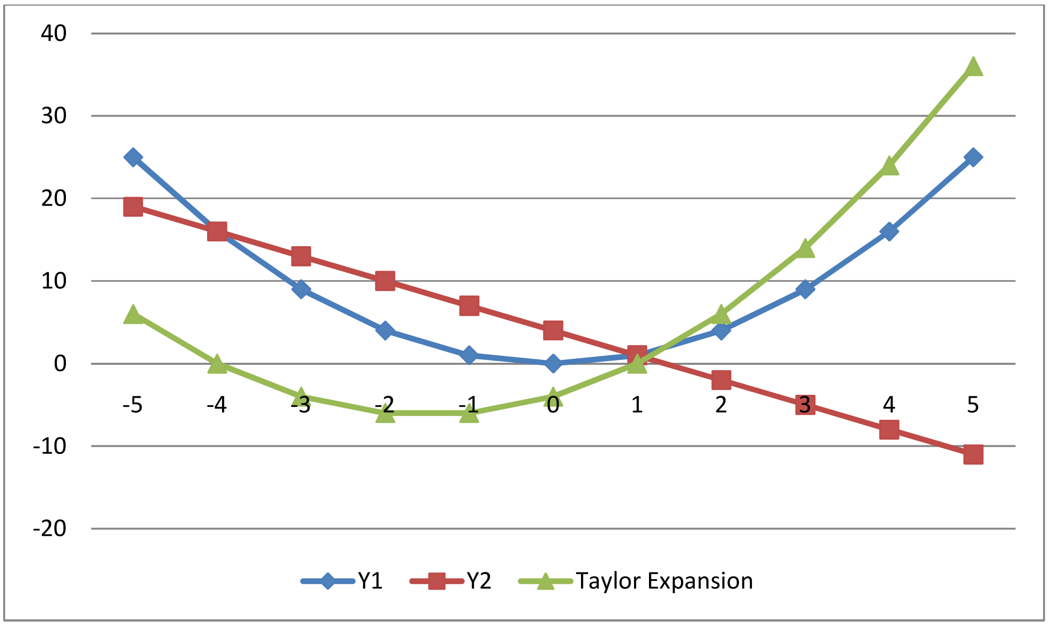
5.1 General Approach

The tradeoffs models were generated using Ordinary Least Squares models in order to estimate the parameters. The models were analyzed to ensure statistical significance and conceptual validity. The coefficients of the model were also checked to verify that the signs followed the logic of the definition of each variable (i.e., coefficients for traffic flows cannot be negative). Since these models incorporate linear and polynomial terms, the models use Taylor series expansions to approximate the nonlinear regression models with linear terms. Taylor series expansion state that if the derivatives for a Taylor polynomials such as Equation (1) exist for f in an interval about (x^0), then a solution can be found as n approaches infinity (Greene, 2003, Kutner et al., 2004).

$$Tp_n = f(x^0) + \frac{f'(x^0)}{1!}(x - x^0) + \frac{f''(x^0)}{2!}(x - x^0)^2 + \frac{f^n(x^0)}{n!}(x - x^0)^n \qquad (1)$$

A graphical example of Taylor series expansions is shown in Figure 5. As shown in the figure, there can be cases in which any of the terms has a negative coefficient and therefore the expansion might also have a negative coefficient. For situations like this, the model is forced to start at the origin in the cases were the definitions of the variables only follow positive values.

Figure 5: Example of Taylor Series Expansion



5.2 Externality Models for the Entire Network

The following tables summarize the results obtained from the regression models generated by using the micro-simulation results for all the links and routes of the entire network.

Table 7: Model for Total Travel Time (seconds) for the Entire Network

	Dependent	**Independent**								
Variable	t(**Q**)	Q_C	Q_{ST}	Q_{LT}	Q_C^2	Q_{ST}^2	Q_{LT}^2	Q_CQ_{ST}	Q_CQ_{LT}	$Q_{ST}Q_{LT}$
Coefficient					6.161E-03			9.666E-03	1.0716E-02	
t-stat					13.35			4.90	5.41	
R^2	0.784									

Table 8: Model for Vehicle Miles Traveled (miles) for the Entire Network

	Dependent	**Independent**								
Variable	V(**Q**)	Q_C	Q_{ST}	Q_{LT}	Q_C^2	Q_{ST}^2	Q_{LT}^2	Q_CQ_{ST}	Q_CQ_{LT}	$Q_{ST}Q_{LT}$
Coefficient		10.0178	9.7410	6.2969	-1.996E-05			-3.494E-05		
t-stat										
R^2	0.99	18.22	5.93	10.23	-5.52			-2.29		

Table 9: Model for Particulate Matter (mg) for the Entire Network

	Dependent	Independent								
Variable	$g_{PM}(\mathbf{Q})$	Q_C	Q_{ST}	Q_{LT}	Q_C^2	Q_{ST}^2	Q_{LT}^2	Q_CQ_{ST}	Q_CQ_{LT}	$Q_{ST}Q_{LT}$
Coefficient	150994	20.401	31.881	39.647	4.481E-05					
t-stat	2.99	11.430	25.750	31.680	4.580					
R^2	0.991									

Table 10: Model for Volatile Organic Compounds (mg) for the Entire Network

	Dependent	Independent								
Variable	$g_{VOC}(\mathbf{Q})$	Q_C	Q_{ST}	Q_{LT}	Q_C^2	Q_{ST}^2	Q_{LT}^2	Q_CQ_{ST}	Q_CQ_{LT}	$Q_{ST}Q_{LT}$
Coefficient					1.3784E-02			2.2609E-02	2.4892E-02	
t-stat					17.95			6.89	7.55	
R^2	0.862									

Table 11: Model for Nitrogen Oxide (mg) for the Entire Network

	Dependent	Independent								
Variable	$g_{NOX}(\mathbf{Q})$	Q_C	Q_{ST}	Q_{LT}	Q_C^2	Q_{ST}^2	Q_{LT}^2	Q_CQ_{ST}	Q_CQ_{LT}	$Q_{ST}Q_{LT}$
Coefficient	8386400	214	1099.4	1490.65	4.0175E-03					
t-stat	2.87	2.07	15.37	20.61	7.1					
R^2	0.973									

Table 12: Model for Carbon Monoxide (mg) for the Entire Network

	Dependent	Independent								
Variable	$g_{CO2}(\mathbf{Q})$	Q_C	Q_{ST}	Q_{LT}	Q_C^2	Q_{ST}^2	Q_{LT}^2	Q_CQ_{ST}	Q_CQ_{LT}	$Q_{ST}Q_{LT}$
Coefficient	123913027		14626	15332	7.8012E-02					
t-stat	3.62		12.4	13.0	32.3					
R^2	0.938									

Table 7 to Table 12 shows the externality models for the externalities measured with the micro-simulations for the entire urban network presented in chapter 4. Partial derivatives for the externalities were taken with respect of Q_{ST} and Q_{LT}, since there are interaction terms with these variables. The ratios of the partial derivatives of small trucks to heavy trucks were calculated to obtain the tradeoffs between these vehicle types. Equation 2 shows the mathematical formulation to obtain this ratio.

$$\frac{\partial Q_{ST}}{\partial Q_{LT}} = \frac{\partial f(\boldsymbol{Q}) / \partial Q_{LT}}{\partial f(\boldsymbol{Q}) / \partial Q_{ST}} \tag{2}$$

Table 13 summarizes the tradeoffs between small and heavy trucks. It was found that if the traffic flow for cars is kept steady and trucks flows vary, it will be more likely for a vehicle to spend more travel time if there are more heavy trucks rather than small trucks. The ratio on Table 13 shows that heavy trucks create 10% more delay than small trucks, which means that heavy trucks tend to create more congestion in urban areas but not by a wide margin.

Table 13 : Tradeoff Ratios for Trucks in Urban Areas

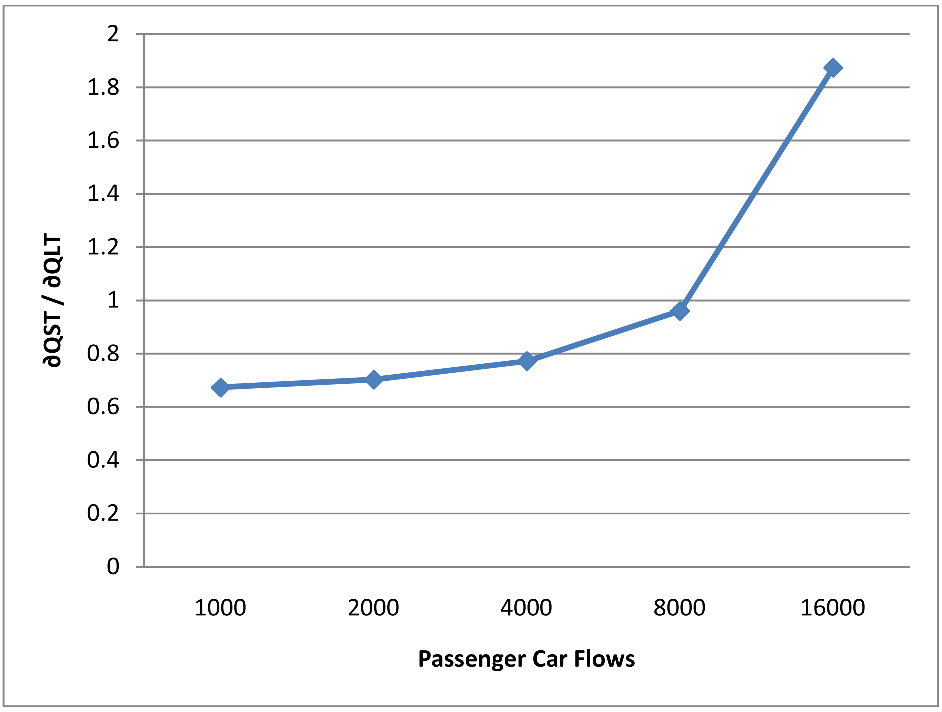
Externality Model	$\partial Q_{ST} / \partial Q_{LT}$
Total Travel Time	1.11
Vehicle Miles Traveled	$1/(1.550 - 6.35E\text{-}5Q_C)$
Particulate Matter	1.24
Volatile Organic Compounds	1.01
Nitrogen Oxide	1.36
Carbon Monoxide	1.05

Tables 7 to 12 show the models for the different externalities. As shown, heavy trucks produce on average anywhere in between 1.01 to 1.36 more externalities than small trucks. The ratio for particulate matter on Table 13 shows heavy trucks differ significantly from other types of vehicles when it comes to produce this pollutant. These vehicles can produce 1.24 times more particulate matter than small trucks in urban areas. This value will be the same for any combination of traffic, since the ratio does not have any interaction terms associated with it.

The ratio for volatile organic compounds shows that heavy trucks and small truck produce almost the same amount of this pollutant. The ratio for nitrogen oxide shows that there is a significant difference between the pollution emitted by a heavy truck versus a small truck. Heavy trucks can produce as much as 1.36 more nitrogen oxides than small truck in urban areas. Since no other terms show up on the derivatives, the amount of pollutant produced for any traffic mix will be the same. The ratio for carbon monoxide shows that a heavy truck produces 1.05 more carbon monoxide than a small truck in urban areas. This ratio will be constant no matter what traffic mix exists on the network.

For vehicle miles traveled the relationship is not constant since an association with an interaction term exists. In this case the amount of externality depends on the traffic flow of passenger cars. Figure 6 shows how the tradeoff of pavement damage between trucks changes as the passenger car traffic increases. The figure suggests that on average heavy trucks will produce more damage than small trucks as passenger car flows increases. The relationship is not constant as for low values of passenger car small trucks can be more hazardous than heavy trucks but not by a wide margin. For large values of passenger car traffic heavy trucks are significantly more hazardous than small trucks.

Figure 6: Pavement Damage Tradeoff between Trucks



In overall, the models show that heavy trucks can produce 1.01 to 1.36 times more pollution than small trucks and can create up to 1.11 times more delays than small trucks. The remaining models show that no matter what combination or conditions of traffic exists; the rate of change for the amount of pollutant emitted by large and small trucks will be the same for all scenarios. The only externality that is dependent on the traffic conditions is vehicle miles traveled (pavement damage). The relationship suggests that heavy trucks will produce more damage for as passenger car flow increases. Nitrogen oxide is the primary source of pollution of heavy trucks in urban areas. Sadly, this is one of the most dangerous pollutants since once its created it can travel a considerable amount of miles before dissipating. Not much has been done to reduce the level of NOX pollution if compared to carbon monoxide which has been reduce drastically by implementing catalytic converter on the exhaustion pipes for all types of vehicles (EPA, 2006). Also, this equipment has been found to promote the formation of nitrogen oxide (EPA, 2006.

5.3 Externality models for Interstate 880

The following tables summarize the results obtained from the regression models generated by using the micro-simulation results for all the links on Interstate 880. On this section models for total travel time and vehicle miles traveled could not be provided due to results limitations of the micro-simulation software.

Table 14: Model for Particulate Matter (mg) for Interstate I-880

	Dependent	**Independent**								
Variable	$g_{PM}(\mathbf{Q})$	Q_C	Q_{ST}	Q_{LT}	Q_C^2	Q_{ST}^2	Q_{LT}^2	Q_CQ_{ST}	Q_CQ_{LT}	$Q_{ST}Q_{LT}$
Coefficient	183252	17.842	27.888	35.104	3.145E-05					
t-stat	3.29	9.06	20.43	25.44	2.92					
R^2	0.985									

Table 15: Model for Volatile Organic Compounds (mg) for Interstate I-880

	Dependent	**Independent**								
Variable	$g_{VOC}(\mathbf{Q})$	Q_C	Q_{ST}	Q_{LT}	Q_C^2	Q_{ST}^2	Q_{LT}^2	Q_CQ_{ST}	Q_CQ_{LT}	$Q_{ST}Q_{LT}$
Coefficient					9.4208E-03			1.9214E-02	2.1090E-02	
t-stat					18.85			9	9.83	
R^2	0.89									

Table 16: Model for Nitrogen Oxide (mg) for Interstate I-880

	Dependent	Independent								
Variable	$g_{NOX}(\mathbf{Q})$	Q_C	Q_{ST}	Q_{LT}	Q_C^2	Q_{ST}^2	Q_{LT}^2	Q_CQ_{ST}	Q_CQ_{LT}	$Q_{ST}Q_{LT}$
Coefficient	7684883	221.76	926.2	1286	2.8414E-03					
t-stat	3.46	2.82	17.01	23.37	6.6					
$\mathbf{R^2}$	0.976									

Table 17: Model for Carbon Monoxide (mg) for Interstate I-880

	Dependent	Independent								
Variable	$g_{CO2}(\mathbf{Q})$	Q_C	Q_{ST}	Q_{LT}	Q_C^2	Q_{ST}^2	Q_{LT}^2	Q_CQ_{ST}	Q_CQ_{LT}	$Q_{ST}Q_{LT}$
Coefficient	190160751		6712	6464	5.3324E-02			5.738E-02	6.665E-02	
t-stat	6.31		2.54	2.47	23.3			2.23	2.6	
$\mathbf{R^2}$	0.956									

Table 14 to Table 17 show the models for the different pollutants by only measuring their levels on the interstate component of the network. Partial derivatives for the externalities were taken with respect of Q_{ST} and Q_{LT}, since there exist interaction terms with these variables. The ratios of the partial derivatives of small trucks to heavy trucks were calculates and this way tradeoffs between these vehicle types were obtained. The tradeoff ratios are shown in Table 18.

Table 18: Tradeoff Ratios for Trucks on Interstate Roads

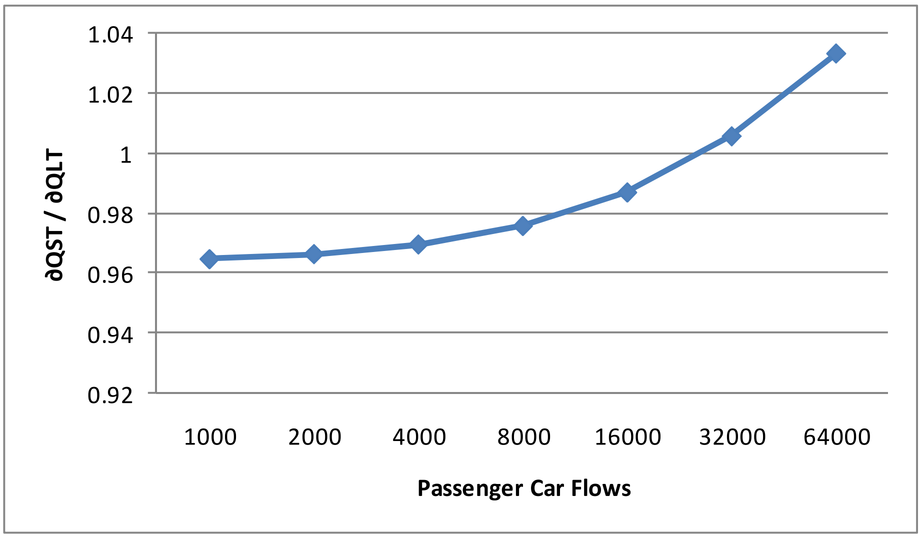
Externality Model	$\partial Q_{ST} / \partial Q_{LT}$
Particulate Matter	1.27
Volatile Organic Compounds	1.10
Nitrogen Oxide	1.39
Carbon Monoxide	$1/ (1.0281 + 0.0092Q_C - 0.0025Q_C^2)$

As shown, heavy trucks produce on average anywhere in between 1.10 to 1.39 more externalities than small trucks. The ratio for particulate matter shows that heavy trucks differ significantly from small trucks, producing 1.27 times more particulate matter than small trucks on interstates. Since no other terms show up on the derivatives, the amount of pollutant produced for any traffic mix will be the same; therefore this externality is non-dependant of traffic flows. This ratio is slightly larger than for the ones obtain for the entire network since interstate roads are more commonly transit by heavy trucks. Therefore this numbers make sense with the logic that is expected.

The ratio for volatile organic compounds shows that heavy trucks can produce 1.10 times more pollution than small trucks on interstate systems. This ratio changes from being almost the same for urban areas, to now giving more weight to heavy trucks.

The ratio for nitrogen oxide again shows the largest level of difference between the amounts of pollutant that each vehicle produces. Heavy truck can produce up to 1.39 times more pollution than small trucks on interstates. The relationship between the two truck types is constant, therefore does not vary as traffic conditions change. The ratio for carbon monoxide is now dependent on traffic conditions. Figure 7 shows this relationship. The figure suggests that on average as passenger car flow increases, heavy trucks will produce more carbon monoxide than small trucks on interstates. The relationship is not constant as for low values of passenger car small trucks can be more hazardous than heavy trucks but not by a wide margin. For large values of passenger car traffic heavy trucks are more hazardous than small trucks.

Figure 7: Carbon Monoxide Tradeoff between Trucks



In overall, the models show that heavy trucks on interstate systems can pollute between 1.10 to 1.39 times more than small trucks. The most significant difference between the vehicles is for levels of pollution of nitrogen oxide which can be up to 1.39 for heavy trucks. The pollutant that was found to be dependent upon traffic conditions is carbon monoxide. The relationship shows that on average, heavy trucks will produce more pollution than small trucks as passenger car flows increases.

5.4 Externality Models for Downtown Oakland

The following tables summarize the results obtained from the regression models generated by using the micro-simulation results for all the links in downtown Oakland which is the city center. On this section models for total travel time and vehicle miles traveled could not be provided due to results limitations of the micro-simulation software.

Table 19: Model for Particulate Matter (mg) in Downtown Oakland

	Dependent	**Independent**								
Variable	$g_{PM}(\mathbf{Q})$	Q_C	Q_{ST}	Q_{LT}	Q_C^2	Q_{ST}^2	Q_{LT}^2	Q_CQ_{ST}	Q_CQ_{LT}	$Q_{ST}Q_{LT}$
Coefficient	18509				4.62E-06			9.24E-06	8.18E-06	
t-stat	7.38				19.4			9.09	7.98	
R^2	0.991									

Table 20: Model for Volatile Organic Compounds (mg) in Downtown Oakland

	Dependent	**Independent**								
Variable	$g_{VOC}(\mathbf{Q})$	Q_C	Q_{ST}	Q_{LT}	Q_C^2	Q_{ST}^2	Q_{LT}^2	Q_CQ_{ST}	Q_CQ_{LT}	$Q_{ST}Q_{LT}$
Coefficient					6.6216E-04			6.1640E-04	6.8250E-04	
t-stat					14.96			3.26	3.59	
R^2	0.89									

Table 21: Model for Nitrogen Oxide (mg) in Downtown Oakland

	Dependent	**Independent**								
Variable	$g_{NOX}(\mathbf{Q})$	Q_C	Q_{ST}	Q_{LT}	Q_C^2	Q_{ST}^2	Q_{LT}^2	Q_CQ_{ST}	Q_CQ_{LT}	$Q_{ST}Q_{LT}$
Coefficient	530058				1.7746E-04			3.0563E-04	2.6757E-04	
t-stat	4.88				17.18			6.93	6.02	
R^2	0.86									

Table 22: Model for Carbon Monoxide (mg) in Downtown Oakland

	Dependent	**Independent**								
Variable	$g_{CO2}(\mathbf{Q})$	Q_C	Q_{ST}	Q_{LT}	Q_C^2	Q_{ST}^2	Q_{LT}^2	Q_CQ_{ST}	Q_CQ_{LT}	$Q_{ST}Q_{LT}$
Coefficient					3.082E-03			4.183E-03	4.469E-03	
t-stat					17.24			5.48	5.82	
R^2	0.822									

Tables 19 to 22 show the models for the different pollutants only measuring their levels on the downtown sector of Oakland. Partial derivatives for the externalities were taken with respect of Q_{ST} and Q_{LT}, since there exist interaction terms with these variables. The ratios of the partial derivatives of small trucks to heavy trucks were calculates and this way tradeoffs between these vehicle types were obtained. The tradeoff ratios are shown in Table 23.

Table 23: Tradeoff Ratios for Trucks in Downtown Areas

Externality Model	$\partial Q_{ST} / \partial Q_{LT}$
Particulate Matter	0.88
Volatile Organic Compounds	1.11
Nitrogen Oxide	0.88
Carbon Monoxide	1.06

The ratios on the following tables summarize the results obtained from the regression models generated by using the micro-simulation results for all the links in downtown Oakland. On this section models for total travel time and vehicle miles traveled could not be provided due to results limitations of the micro-simulation software. The following tables summarize the results obtained from the regression models generated by using the micro-simulation results for all the links in downtown Oakland which is the city center. On this section models for total travel time and vehicle miles traveled could not be provided due to results limitations of the micro-simulation software.

Table 19 shows for particle matter and nitrogen oxide tradeoffs between trucks, heavy trucks can produce 0.88 times less pollution than small trucks on downtown areas. These relationships do not depend on traffic conditions. This number was found to be odd since heavy trucks produce more pollution than any small truck. One possible explanation is that the parameters used for the simulation do not correspond for city center, therefore creating problems on the estimations made by the simulations

The ratio for volatile organic compounds shows that heavy trucks can produce up to 1.11 times more pollution than small trucks and the ratio for carbon monoxide says that heavy trucks can produce up to 1.06 times more pollution than small trucks on city centers.

In overall, the models show that the interactions between different truck classes in terms of congestion, pavement damage and pollution is usually constant, not depending on traffic conditions. Only pavement damage in urban areas and carbon monoxide levels for interstates vary depending on passenger car traffic conditions. The analysis also showed that the tradeoffs corresponding to levels of pollution can vary on different sectors of a network. This could be because of the following reasons. The time of congestion is usually higher in urban areas, such as the one used for this study, therefore high values of pollution should be expected for such areas, since pollution levels are higher under congested condition (Bart and Boriboonsomsin, 2007). If the models for the three different scenarios are compared, it shows that the models for I-880 network in comparison with the models for I-880 interstate and downtown Oakland yield much higher values for the levels of pollution emitted by heavy trucks. If the models for I-880 interstate and downtown Oakland are compared, the interstate portion of the network yields much higher values for pollution than for the downtown area. This is because not only there are more vehicles transiting on interstate but also because the faster a vehicle travels the more pollution it produces. In the case of downtown area, there is a great concentration of businesses that are in constant need of cargo deliveries. These deliveries are often made by small trucks mainly because of restrictions imposed to trucks based on truck size and road design and other factors such as noise and air pollution. Also there are more small businesses than big chains therefore when making deliveries it is often more cost efficient to deliver by using small trucks. Many times trucks do not have parking space available for when delivering cargo pushing drivers to park on the street and often even on traffic lanes. This obviously worsens traffic conditions by impeding vehicle traffic to flow under normal condition and therefore creating more congestion and externalities. One would expect small truck traffic to be much higher in downtown areas and therefore this could create tradeoffs between the vehicles in which small trucks could be more hazardous than heavy trucks. The models on section 5.3 showed these atypical tradeoffs. The models for nitrogen oxide and particulate matter are the only ones that show tradeoffs for heavy trucks higher than for small trucks but not by a wide range. This is also in part because the difference between small and heavy trucks with respect to the amount of pollutant generated is bigger for nitrogen oxide and carbon monoxide as shown in Table 24. These differences were calculated using the emission rates by vehicle type shown in Table 6. Also nitrogen oxide emissions can travel long distances, and create hazardous effects far away from the point where the emissions were generated. Interstate 880 is only a mile away from downtown Oakland.

Table 24: Difference between Small and Heavy Truck Pollution Rates (mg/s)

Speed (mph)	Volatile Organic Compounds	Carbon Monoxide	Nitrogen Oxide	Particulate Matter
2.5	0.492	8.114	9.093	0.14
10	1.397	18.989	30.273	0.563
20	1.883	21.3	51.744	1.127
30	2.05	20.941	72.116	1.69
40	2.144	21.956	97.289	2.254
50	2.32	26.5	136.667	2.817
60	2.666	38.667	213.05	3.38

6. Externality Cost Models

On sections 5.1 to 5.3, the regressions models obtained for the different externalities were generated and analyzed. These models can help to better understand the interactions between the different vehicle classes. In this chapter valuation of the externalities is used to complement the externality models to produce cost models that quantify cost of externalities. Later on, these cost models are used to find the optimal traffic mix that minimizes the cost of the externalities produced by these vehicles.

In order to generate policies aimed at minimizing the cost of externalities such as congestion, pavement deterioration, and pollution, economic valuation of these externalities must be done to estimate their monetary values. These externalities are considered to be site independent, which means that specific characteristics of the environment in which the road is located will affect their value. For example, noise pollution and accidents mostly depend on objects that obstruct the path of sound and specific geometric characteristics of the road. Therefore, these types of externalities are not a good example since they vary greatly from road to road. These externalities were not included in this study for these reasons.

A literature review was conducted in order to obtain published estimates of valuation of externalities and develop cost functions. Based on the values found on literature review and taking the average of those values, the author selected values for travel time valuation for passenger cars, small trucks and heavy trucks of \$20, \$35 and \$55. For pavement deterioration valuation of the cost of ESAL-mile and Vehicle Miles Traveled were used to obtain a cost function. Based on the finding from literature review the values used for ESAL-mile cost will be \$0.05, \$0.30 and \$1.00 for low, medium and high values. Table 26 and Table 27 show more in detail the different margins of values for these externalities.

Table 25: Range of Valuation for Air Pollutants

Pollutant	Low Values ($)	Medium Values ($)	High Values ($)
VOC	0.16	0.99	1.81
CO2	0.02	0.08	0.14
NOX	1.84	14.50	27.15
PM	15.31	112.69	210.06

Table 26: Range of Valuation for ESAL-Mile Costs

Scenario	ESAL-mile ($)
Low	0.05
Medium	0.53
High	1.00

Table 27: Range of Valuation for Travel Time

Vehicle	Low Values ($)	Medium Values ($)	High Values ($)
Car	7	20	50
Small Truck	20	35	65
Large Truck	29	55	120

The values used for the volatile organic compounds, carbon monoxide, nitrogen oxide and particle matter were also obtained through literature review. The values used for the cost functions are summarized in Table 25. The mathematical formulations for costs based on a previous study (Holguin-Veras, Cetin, 2008) are discussed next.

6.1 Congestion Cost

The congestion costs are equal to the total travel time in the network is represented by $t(\mathbf{Q})$. This value will be associated with the vector of traffic flow $\mathbf{Q}$ .The monetary value for travel time for any vehicle class will be v_{avg}. The total travel cost is the total travel times the average travel time values. The formulation looks as follows:

$$C^C(\boldsymbol{Q}) = v_{avg}t(\boldsymbol{Q}) \tag{3}$$

6.2 Environmental Pollution Cost

In order to measure air pollution levels, four different pollutants were selected this research, taking in account that these are the most hazardous pollutants generated by vehicles (EPA, 2002). Holguin-Veras and Cetin (2008) suggest that the mathematical formulation for pollution cost is:

$$C^E(\boldsymbol{Q}) = \sum_{\ell} \gamma_{\ell} g_{\ell}(\boldsymbol{Q}) \tag{4}$$

Where:

$$C^E(\boldsymbol{Q}) = \gamma_{PM}g_{PM}(\boldsymbol{Q}) + \gamma_{CO2}g_{CO2}(\boldsymbol{Q}) + \gamma_{VOC}g_{VOC}(\boldsymbol{Q}) + \gamma_{NOX}g_{NOX}(\boldsymbol{Q}) \tag{5}$$

The term γ_{ℓ} is the economic valuation of pollutant ℓ and $g_{\ell}(\boldsymbol{Q})$ is the total amount of pollutant ℓ produced by traffic$\boldsymbol{Q}$. Equation (4) represents the total cost of pollution for period *i*. Equation (5) is the final equation that will be used in this study according to the pollutants recovered with the micro-simulation.

6.3 Pavement Damage Cost

Pavement deterioration is affected by a large spectrum of factors such as vehicle axle weight, axle weight distribution, speed at which vehicle travels, how good is the design of the road pavement, etc (Hussain and Parker, 2009). Recent studies found that as a vehicle travels at lower speeds, the pavement damage increases since the load is applied to a specific point for a longer period of time (Hussain and Parker, 2006). Holguin-Veras and Cetin (2008) indicates that is fairly difficult to obtain a typical cost for pavement damage as it depends on a large number of parameters such as the design number of ESAL (Equivalent Single Axis Load) repetitions for the specific facility, and the LEF (Load Equivalency Factor) depending on vehicle class. Most micro-simulation software does not have the level of detail required for such an analysis. For that reason, the author suggests using some of the general parameters used for pavement design and maintenance. These are: Vehicle Miles Traveled (VMT) and the cost of ESAL per mile. These parameters combined provide the cost of pavement deterioration by vehicle type

(Equation 6). Therefore the mathematical formulation for pavement cost is used for this research is:

$$C^{PV}(\boldsymbol{Q}) = \lambda_{\text{avg}} \text{V}(\mathbf{Q}) \quad (6)$$

Where $\lambda_{\text{avg}}$is the ESAL per mile valuation for road; $\boldsymbol{Q}$ is the vector of traffic flow and V are the Vehicle Miles Traveled in the network.

6.4 Total Cost

Holguin-Veras and Cetin (2008) put together the previous cost functions for the different externalities. They found that the tradeoffs between different vehicles can be asses by obtaining a total cost function. This will be:

$$C^* = C^C(\boldsymbol{Q}) + \ C^E(\boldsymbol{Q}) + C^{PV}(\boldsymbol{Q}) \quad (7)$$

$$C^* = v_{avg} t(\boldsymbol{Q}) + \sum_{\ell} \gamma_{\ell} \text{g}_{\ell}(\boldsymbol{Q}) + \lambda_{\text{avg}} \text{V}(\mathbf{Q}) \quad (8)$$

7. Optimization

The objective of this research is to find the tradeoffs among different vehicles classes in order to minimize the costs incurred by these vehicles. In order to do this an optimization problem needs to be developed. The objective here is to find the combination of traffic flows that minimize the cost of externalities estimated with the cost functions from sections 6.1 to 6.4.

7.1 Mathematical Formulation

The mathematical model is shown in equations 9 to 11. As shown, two constrains have been included. The first one is to ensure that the total amount of cargo is transported, while the second one restricts the solutions to non representative values. The problem looks as follows:

$$\min C^* = C^C(\boldsymbol{Q}) + C^{PM}(\boldsymbol{Q}) + C^{VOC}(\boldsymbol{Q}) + C^{CO2}(\boldsymbol{Q}) + C^{NOX}(\boldsymbol{Q}) + C^{PV}(\boldsymbol{Q}) \quad (9)$$

s.t.

$$\sum_2^3 \rho_i Q_i \geq K \quad (10)$$

$$Q_i \geq 0 \qquad \forall_i = 1,2,\ldots \quad (11)$$

Where i = 1 is for cars, i = 2 equals small trucks, i = 3 equals heavy trucks, $C^C(\boldsymbol{Q})$ is the cost of congestion, $C^{PM}(\boldsymbol{Q})$is the cost of particle matter, $C^{VOC}(\boldsymbol{Q})$ is the cost of volatile organic compounds, $C^{CO2}(\boldsymbol{Q})$ is the cost of carbon monoxide, $C^{NOX}(\boldsymbol{Q})$ is the cost of nitrogen oxide and $C^{PV}(\boldsymbol{Q})$ is the cost of pavement damage. Equations 10 states that the summation of the optimal combination for truck traffic flows (Q_i), multiplied by the vehicle's corresponding average payload, (ρ_i), has to be equal or greater than the amount of cargo K required by the population. The solution of the problem will be feasible as long as the truck traffic flow (Q_i) is equal or larger than zero.

Several experiments were done with the purpose of seeing how optimal solutions change with different input values. This was done by computing the optimal traffic flows of small and heavy trucks, i.e. the ones that minimize the total cost of externalities. Three different experiments were done based on changing the following factors: (1) levels of cargo to be delivered to the city, (2) valuation factors for the different pollutants pavement damage and travel time value, and (3) average payload factors. For these experiments three different ranges for valuation of externalities were used: low, medium and high values. The values for air pollutants are shown on Table 25 and the ones for ESAL-mile cost are shown on Table 26. Values for travel time are shown in Table 27. These tables can be found in chapter 6.

The base case scenario was set as the point of comparison with the experiments. This base case represents the traffic conditions of the network used to calibrate the simulation.

7.2 Base Case Results

In this section the total cost of externalities was calculated by using data for the base case traffic conditions on the network. In the base case, the flows are the following: 217,649 passenger cars; 9,069 small trucks and 7,637 heavy trucks. According to VIUS (2002), the average payload for small and heavy trucks for the United States is 7 and 20 tons correspondingly. Therefore the amount of cargo by truck type for this scenario can be estimated as 63,481 tons for small trucks and 152,740 for heavy trucks. Also, to calculate the cost of each of the externalities, the average values for valuation of these externalities were used. The cost for each of the externalities and the total cost are shown in Table 28.

Table 28: Total Cost for the Base Case ($/day)

Externality	Amount of Externalities	Social Cost	% of Total Cost
Total Travel Time (h)	91314	$1,983,428	72.06%
Pavement Damage (mi)	1302301	$690,219	25.08%
Particulate Matter (kg)	662	$74,594	2.71%
Nitrogen Oxide (kg)	267	$3,866	0.14%
Carbon Monoxide (kg)	4069	$326	0.01%
Volatile Organic Compounds (kg)	48	$48	0.00%

Table 28 shows that congestion is the primary source of cost generating losses of $1.9 million/day followed by pavement damage with $690,219/day. Congestion is responsible for 72% of the total cost of externalities while pavement damage account for 25% of the total cost. Together they account for 97% of the total costs, suggesting that more emphasis has to be given to congestion pricing and infrastructure damage in urban areas. The total quantity of pollution generated by adding up all the pollutants on Table

28 is 5,046 kg/day. In terms of quantity, carbon monoxide is the primary source of pollution accounting for 80% of the total amount of pollution generated. Everyday 4069 kg of this pollutant are generated. However translating this into losses, only $326/day are lost in carbon monoxide pollution. It is reasonable that quantities are high since passenger car vehicles are the main source of carbon monoxide pollution and this are the main source of traffic on roads. However, in terms of costs, it seems as if the valuation does not account for the disproportional quantities produce with respect to other pollutants. The second most common source of pollution is particulate matter (13%), which accounts for 662 kg/day and losses of $74,594 per day. This is followed by nitrogen oxide (5%) which accounts for 267 kg/day and losses of $3,866. These two pollutants are the most common pollutant emitted by trucks. Therefore, around 18% of pollution levels on urban areas are created by truck traffic. However, their levels are much smaller than carbon monoxide but their costs are significantly higher than this pollutant.

Applying the optimization problem explained in this chapter to this scenario, the optimal truck traffic flows were found and as expected lead to lower externality costs. The results are shown in Table 29. For comparison purposes Table 30 shows the difference between the results for optimal and the base case.

Table 29: Optimal Solution for Base Case ($/day)

Externality	Amount of Externalities	Social Cost	% of Total Cost
Total Travel Time (h)	88071	$1,907,277	71.26%
Pavement Damage (mi)	1302301	$690,544	25.80%
Particulate Matter (kg)	662	$74,575	2.79%
Nitrogen Oxide (kg)	261	$3,791	0.14%
Carbon Monoxide (kg)	3985	$319	0.01%
Volatile Organic Compounds (kg)	44	$44	0.00%
Total Cost		$2,676,550	100.00%

Table 30: Difference between Optimal and Non-Optimal Base Case

Externality	% difference	Cost Difference
Total Travel Time (h)	-3.84%	-$76,151
Pavement Damage (mi)	0.05%	$325
Particulate Matter (kg)	-0.02%	-$18
Volatile Organic Compounds (kg)	-8.68%	-$4
Carbon Monoxide (kg)	-2.06%	-$7
Nitrogen Oxide (kg)	-1.96%	-$76
Total Quantification	-2.76%	-$75,931

Table 29 found the optimal traffic mix to be 10,811 heavy trucks and zero small trucks, suggesting that heavy trucks are the best option to minimize the cost of externalities. The primary source of cost for both cases is congestion followed by pavement damage. Table 30 shows that when an optimal traffic mix is reached, total cost saving can be reduced by 2.76% or $75,931/day. The average time of congestion is now reduced by 3.84% or $76,151/day. This is the largest saving from all the externalities. Pavement damage increases but not significantly since now the traffic combination will be 217,649 cars, zero small trucks and 10,811 heavy trucks. Now pavement damage will increase by $325/ day. In terms of pollution, the different pollutants now show saving in costs ranging from 0.02% to 8.68%. However the net impact for cost shown in Table 30 suggests that nitrogen oxide is the pollutant that shows the highest cost saving, followed by particle matter. These pollutants are the most common pollutants generated by trucks. Therefore the results suggest that using optimal truck traffic provides significant costs saving to these vehicles and pollution costs.

7.3 Sensitivity Analysis using Different Ranges of Valuation

This section discusses sensitivity analysis done by changing the different valuations shown on Tables 25 to 27. The models used for calculating the costs of externalities are the ones for the entire network in section 5.2. The first section of this chapter shows the total cost for existing traffic conditions on the network of study and then the optimal traffic conditions were calculated to obtain the amount of saving of externality costs. The optimal results obtained from the base case were the ones used for comparison purposes with the experiments described on the following sections.

The results for this analysis are shown on Table 31. The externality costs were calculated using the regression models for the entire network. The total cost of externalities was minimize according to constrains and parameters shown in section 7.1. The values used for the base case analysis were the same ones used for this analysis. The only values that change are the ones for valuation of the different externalities. The analysis assumes that if valuation for an externality reduces the other will also reduce.

Table 31: Results for Sensitivity Analysis for Entire Network using Valuation

	Low Value	Base Case	High Value
Number of Small Trucks	0	0	0
Number of Heavy Trucks	10811	10811	10811
Total Cost	$783,661	$2,676,550	$6,144,921

Table 32: Cost of Externalities for Low Valuation

Externality	Amount of Externalities	Cost	% of Total Cost
Total Travel Time (h)	88,071	$708,181	90.33%
Pavement Damage (mi)	1,302,301	$65,146	8.31%
Particulate Matter (kg)	662	$10,132	1.29%
Volatile Organic Compounds (kg)	44	$7	0.00%
Carbon Monoxide (kg)	3,985	$80	0.01%
Nitrogen Oxide (kg)	261	$481	0.06%
Total Cost		$784,027	100.00%

Table 33: Cost of Externalities for High Valuation

Externality	Amount of Externalities	Cost	% of Total Cost
Total Travel Time (h)	88,071	$4,695,260	76.41%
Pavement Damage (mi)	1,302,301	$1,302,913	21.20%
Particulate Matter (kg)	662	$139,012	2.26%
Volatile Organic Compounds (kg)	44	$80	0.00%
Carbon Monoxide (kg)	3,985	$558	0.01%
Nitrogen Oxide (kg)	261	$7,097	0.12%
Total Cost		$6,144,921	100.00%

These results show that in terms of cost imposed on vehicles for the externalities they produce, it is often more optimal to use as much heavy trucks as possible to deliver cargo. This can be done by using the most amount of cargo space as possible on heavy trucks by coordinating deliveries with receivers. One way of promoting this is by providing incentives to truck companies that maximize the use of cargo space on their trucks.

Table 32 and Table 33 show that as valuation of externalities reduces, congestion becomes a major component of the total cost. Meaning that the values found on literature review for high low and average suggest that valuation for pollutants and pavement damage could be under-estimated or that the rate of change at which these valuation values change is disproportional.

7.4 Sensitivity Analysis using Different Payload Combinations

The purpose of this analysis is to use different combinations of payloads for small and heavy trucks to see how total cost is affected and to find what ratio of small truck payload to heavy truck payload yields the same cost no matter what type truck is used to transport cargo. The cost of externalities are calculated using the regression models for the entire network and then minimize as discussed in chapter 7, section 7.1. The values shown on chapter 6 were kept constant for the purposes of this analysis.

Table 34: Results for Sensitivity Analysis for Low Values for Payload Combination

	Medium Values			
Payload Small truck	10			
Payload Heavy Truck	14	15		16
Number of Small Trucks	19,760	20,524	0	0
Number of Heavy Trucks	0	0	20,524	21,288
Total Cost ($)	$2,723,600	$2,738,067	$2,738,067	$2,752,548
ST Payload / HT Payload	71.43%	66.67%		62.50%

Table 35: Sensitivity Analysis for Medium Values for Payload Combination

	Medium Values			
Payload Small truck	10			
Payload Heavy Truck	14	15		16
Number of Small Trucks	19,760	20,524	0	0
Number of Heavy Trucks	0	0	20,524	21,288
Total Cost ($)	$2,723,600	$2,738,067	$2,738,067	$2,752,548
ST Payload / HT Payload	71.43%	66.67%		62.50%

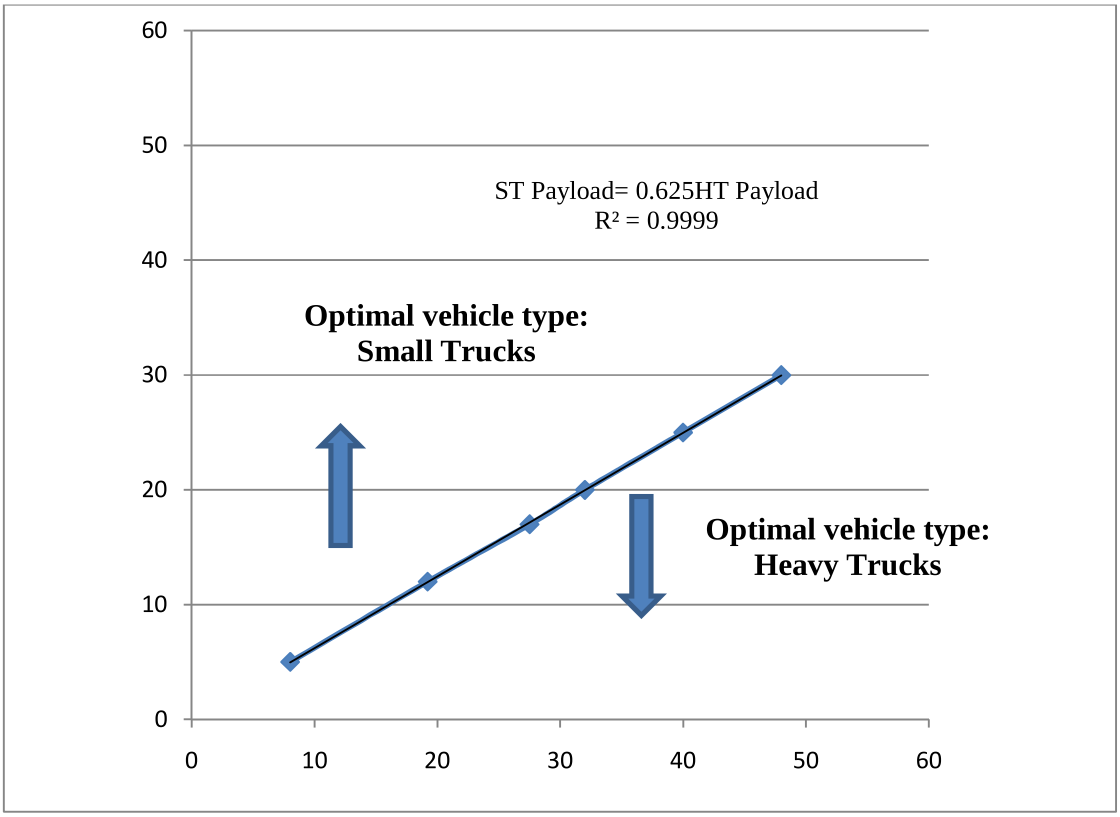
Table 36: Results for Sensitivity Analysis for High Values for Payload Combination

	High Values			
Payload Small truck	20			
Payload Heavy Truck	31	32		33
Number of Small Trucks	20,906	21,288	0	0
Number of Heavy Trucks	0	0	13,305	13,133
Total Cost ($)	$2,745,306	$2,752,225	$2,752,225	$2,746,998
ST Payload / HT Payload	64.52%	62.50%		60.61%

The experiments showed that for low value payloads, as the payload of a small truck fluctuates between 66.67% to 71.43 % of a heavy truck payload, then small trucks lead to lower costs in terms of the externalities associated with the amount of total cargo that needs to be delivered to the area. Therefore for ratios of small trucks to heavy trucks payloads fluctuation from 0.667 to 0.714 or more, heavy trucks become optimal. Also, as the gap between the payload factors increases, then large trucks will be more optimal as long as the use of cargo space is maximize. The experiments for medium values of payloads suggests the same finding as for the low values experiments. The experiments of high values of payloads suggest that as the payload of a small truck fluctuates between 62.50% to 64.52% of a heavy truck payload then small trucks will lead to lower costs. If a small truck can carry less than 62.50% of a heavy truck cargo then heavy trucks will become optimal.

Tables 34 to 36 also show that there is a ratio of small truck payload to heavy truck payload in which using any type of truck will be an optimal solution. This relationship is stated more in detail on Figure 8. Figure 8 shows the breakeven boundary where the payloads lead to the same total cost by either small or heavy truck traffic. The figure shows that for any points above the equilibrium boundary, small trucks are more optimal and for any point below the line, heavy trucks are more optimal. The points on the line represent the optimal payload combination for minimum cost. A linear regression models was estimated to find a mathematical function that states the payload relationship between these two vehicles.

Figure 8: Breakeven Boundary for Optimal Truck Traffic



The mathematical model shown in Figure 8 shows that on average if the payload of a small truck is 62.5% of the payload of a heavy truck, then any type of truck will be optimal to use. But if the payload of a small truck is larger than 62.5% of the payload of a heavy truck then small trucks are optimal.

7.5 Sensitivity Analysis using Different Levels of Cargo Demand

The purpose of this analysis is to use different demand levels for cargo to see how the optimal traffic and the costs vary. Costs of externality are calculated using the regression models for the entire network. The total cost of externalities was minimize according to constrains and parameters shown in chapter 9 and 10. The values used on section 11.1 were kept constant for the purpose of this analysis.

Table 37: Results for Sensitivity Analysis for Different Cargo Demand Levels

	Demand of Cargo			
	100,000	217,649	500,000	600,000
Number of Small Trucks	0	0	0	0
Number of Heavy trucks	5,000	10,882	25,000	30,000
Total Cost ($)	$2,502,094.581	$2,678,710.141	$3,113,019.889	$3,270,017.274
% of Congestion Cost	74.50%	73.75%	71.27%	70.04%
% of Pavement Damage Cost	23.08%	23.70%	25.79%	26.82%
% of Pollution Cost	2.42%	2.54%	2.94%	3.14%

These results show that no matter what demand level exists, it is better to use as many heavy trucks as possible to deliver cargo. Cost of congestion decreases as the cargo level increases but pavement damage increases since the number of heavy trucks increases. The cost of pollution also increases since as the cargo demand increases. Around 95% of this cost relies on particle matter which is the main source of pollution created by heavy trucks.

8. Conclusions

The objective of this research is to study and analyze the tradeoffs between small trucks and large trucks on urban areas. The analyses were conducted using a combination of micro-simulations, statistical analyses, econometric analyses, and optimization. Micro-simulations captured the tradeoffs of these combinations in terms of levels of pollution, total travel time and vehicle miles travel for a typical urban area. Using the data obtained from the micro-simulations, externality models were generated to assess the tradeoffs between different vehicle classes. Valuation of the externalities was used to complement the externality models to produce cost models that quantify cost of externalities. Finally, an optimization formulation was developed to find the tradeoffs among different vehicles classes in order to minimize the costs incurred by these vehicles. The analyses provide the basis to compute optimal traffic flows by minimizing cost of externalities (e.g. pollution, congestion and pavement deterioration).

The analyses of the externality models indicate that heavy trucks produce on average anywhere in between 1.01 to 1.36 more externalities than small trucks in urban areas. More specifically, large trucks can produce 1.24 times more particulate matter, 1.36 times more nitrogen oxides and 1.05 times more carbon monoxide than small trucks on urban areas. The levels of volatile organic compounds are about same for both types of vehicles. In terms of congestion, it was found that large trucks can create 1.11 times more congestion than small trucks. This also leads to higher pavement damage sine as truck loads have larger effects on road surfaces as these vehicles travel at lower speeds and produce more VMT on the network. The model for pavement damage shows this, as it suggests that for higher passenger car flows the larger the effect a heavy truck will have on the road surface. This relationship depends on the passenger car traffic volumes.

Externality models for pollutants were also estimated for interstate roads and downtown areas. These models suggest that in the system considered, interstate heavy trucks produce on average anywhere in between 1.10 to 1.39 more externalities than small trucks. The ratio for these pollutants is slightly larger than for the ones obtain for the entire network since interstate roads are more commonly transit by heavy trucks.

For the downtown area, the externality models suggest that small trucks can produce more particle matter and nitrogen oxide than large trucks. Large trucks can generate 0.88

times less particle matter and nitrogen oxides than small trucks. However for volatile organic compounds and carbon monoxide, heavy trucks generate 1.11 times more pollutants than small trucks. This is a surprising result that may indicate that the parameters used for the simulation do not correspond for downtown conditions, therefore creating problems on the estimations made by the simulations.

Externality costs were calculated using the externality models generated on this research and valuation factors found from the literature. It was found that for an urban area such as Oakland, CA, congestion is the primary source of cost generating losses of $1.9 million/day followed by pavement damage with $690,219/day. Congestion is responsible for 72% of the total cost of externalities while pavement damage account for 25% of the total cost. Together they account for 97% of the total costs, suggesting that more emphasis has to be given to congestion pricing and infrastructure damage in urban areas. The total quantity of pollution generated by all pollutants is 5,046 kg/day. In terms of quantity, carbon monoxide is the primary source of pollution accounting for 80% of the total amount of pollution generated. Everyday 4069 kg of this pollutant are generated which is an economic cost of $326/day of carbon monoxide pollution. It is reasonable that quantities are high since passenger car vehicles are the main source of carbon monoxide pollution and this are the main source of traffic on roads. The second most common source of pollution is particulate matter (13%), which accounts for 662 kg/day and losses of $74,594 per day. This is followed by nitrogen oxide (5%) which accounts for 267 kg/day and losses of $3,866/day. These two pollutants are the most common pollutant emitted by trucks. Therefore, around 18% of pollution levels on urban areas are created by truck traffic. However, their levels are much smaller than carbon monoxide but their costs are significantly higher than this pollutant.

An optimization formulation was developed to obtain the optimal traffic flows that minimize the costs produced by these vehicles. The application of this formulation to the base case scenario of Oakland, CA, found that the best option is to only use heavy trucks for deliveries. This leads to total cost savings of 2.76% and costs reductions of 3.84%. Results show that when an optimal traffic mix is reached, total cost can be reduced by 2.76%, or $75,931 per day. The average time of congestion is reduced by 3.84%, or $76,151/day. This is the largest saving from all the externalities. Pavement damage increases by $325/ day. In terms of pollution, the different pollutants show cost savings ranging from 0.02% to 8.68%. However the net impact for cost calculated suggests that nitrogen oxide is the pollutant that shows the highest cost saving ($76/day), followed by particle matter ($18/day).

Sensitivity analyses were done to see how total cost of externalities and truck traffic mix could change. These results show that in terms of cost imposed on vehicles for the externalities they produce, it is often more optimal to use as much heavy trucks as possible to deliver cargo. Results also suggest that as valuation of externalities reduces, congestion becomes a major component of the total cost.

Additional sensitivity analysis was done using different levels of cargo demand. The purpose of this analysis is to use different demand levels for cargo to see how the optimal traffic and the costs vary and payload combinations. The results for the level of demand show that no matter what level is, it is better to use as many heavy trucks as possible to deliver cargo. Costs decrease as the cargo level increases but pavement damage impacts increases since the number of heavy trucks increases.

Another analysis was conducted using different combinations of payloads for small and heavy trucks to see how total cost is affected and what ratio of small truck payload to heavy truck payload yields the same cost no matter what type truck is used to transport cargo. This value fluctuates between 61% and 71% depending on how large the payloads are. An Ordinary Least Square model was estimated to represent the relationship of truck traffic breakeven boundary between the payloads. The model indicates that as the payload of a small truck is 62.5% of the payload of a heavy truck, then any type of truck will be optimal to use. However if the payload of a small truck is larger than 62.5% of the payload of a heavy truck then small trucks are optimal, otherwise large trucks are the best option to obtain minimal costs. This research shows that using optimal truck traffic mix can reduce congestion levels, pollution levels and pavement damage on urban areas. This research addresses an important area not studied previously, since no previous research has attempted the methodology and analysis presented on this document.

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