©2015

Rooholamin Shabihkhani

ALL RIGHTS RESERVED

ESTIMATION OF URBAN SCALE NETWORK-WIDE EMISSIONS BASED ON FUNDAMENTAL PROPERTIES OF THE NETWORK

By

ROOHOLAMIN SHABIHKHANI

A Dissertation submitted to the

Graduate School-New Brunswick

Rutgers, The State University of New Jersey

in Partial Fulfillment of the Requirements

for the Degree of

Doctor of Philosophy

Graduate Program in Civil and Environmental Engineering

Written under the direction of

Dr. Eric Gonzales

and approved by:

____

____

____

____

New Brunswick, New Jersey

May 2015

ABSTRACT OF DISSERTATION

Estimation of Urban Scale Network-Wide Emissions

Based on Fundamental Properties of the Network

By ROOHOLAMIN SHABIHKHANI

Dissertation Director

Dr. Eric Gonzales

One of the main criteria for evaluating traffic control systems, especially in large urban networks, is vehicular emissions, since it is the major contributor of urban air pollution. Decision makers in the cities want to minimize fuel consumption and emission of pollutants from traffic in addition to managing average speed and delay in the network. In order to optimize these parameters, a consistent estimation of the network-wide parameters is essential. Since existing macroscopic emission models based on average speed cannot provide accurate estimates for large-scale networks, there is a need for reliable emissions estimation based on the traffic features of a network.

In the first part of this study, in order to have a more reliable, network-wide emissions estimation, the Integrated Traffic Emissions Model (ITEM) has been introduced to integrate macroscopic traffic parameters that have a major influence on emissions with microscopically calculated emission factors. This mesoscopic emission model takes three aggregated traffic parameters, which include: number of vehicle stops, duration of time spent cruising, and the time spend idling, all expressed per Vehicle Mile Traveled (VMT), and multiply them with corresponding emission factors to estimate overall emissions of the network.

In the next step of this study, the macroscopic connection between three aggregated traffic parameters needed for ITEM and the average density on an idealized ring shape model has been investigated. The Macroscopic Fundamental Diagram (MFD) is used to understand the existence of a robust relationship between the average flow with the average number of vehicles circulating on the network. An analytical approach has been proposed to estimate the macroscopic traffic parameters based only on fundamental properties of the network.

In the final step, the proposed model and analytical approach have been tested on a more realistic grid network with heterogeneous traffic states across links of the network caused by turning movements. The results show that there is not only a robust and reproducible relationship between the aggregated traffic parameters and resulting total emissions with the average density on the network, but also the comparison of the analytical estimates with detailed calculations shows that the errors are in an acceptable range, especially for not completely jammed traffic conditions.

ACKNOWLEDGEMENTS

This dissertation as an abstract of 5 years of my work at Rutgers University could have not been written without the support, encouragement, and guidance of many people from the first day that I have started learning to the last day that this document approved by my committee.

First of all, I would like to express my sincere gratitude to my committee chair, my advisor, and my true friend, Prof. Eric Gonzales, who started his genuine support on the second year of my PhD program, when my former advisor had left the university. He was always available to me with his excellent guidance and support. I would also like to thank my committee members, Prof. Hao Wang, Prof. Peter Jin, and Prof. Eleni Christofa. I benefitted greatly from their valuable comments, especially those that I have received from Dr. Christofa.

Additionally, I would like to express my appreciation to all the faculty and staff of civil and environmental engineering department for their help and support. Especially, I have to acknowledge the financial support by the department chair, Dr. Gucunski. Also, I would like to thank my fellow graduate students and friends at Rutgers who made good memories for me.

Finally, I would like to extend my deepest gratitude to my family, especially my mother, who scarifies her life for me and my siblings to reach to the place that we are now. Also, my best thanks go to my beautiful wife for her understanding and support. My mother, my wife, my sister and my brother were the source of motivation, encouragement and inspiration, and I would like to dedicate this dissertation to them.

TABLE OF CONTENTS

Abstract of Dissertation ii

Acknowledgements iv

Table of Contents v

List of Figures ix

List of Tables xii

Chapter 1 : Introduction to the Study 1

1.1 Problem Statement 2

1.2 Research Objective 3

1.3 Novelty and Contribution of the Study 4

1.4 Organization of This Dissertation 5

Chapter 2 : Literature Review 7

2.1 Main Tailpipe Vehicular Emissions 7

2.2 Regulations and Standards for Air Quality and Emissions 10

2.3 Vehicular Emissions Modeling Methods 14

2.3.1 Microscopic emission models 15

2.3.2 Macroscopic emissions models 25

2.3.3 Mesoscopic emission models 32

2.4 Traffic Modeling and Real World Traffic Data 37

2.4.1 Transportation planning models 37

2.4.2 Traffic flow propagation models 38

2.4.3 Macroscopic Fundamental Diagram (MFD) 40

2.4.4 Real world traffic data 42

2.5 Summary 43

Chapter 3 : The Integrated Traffic Emissions Model (ITEM) 46

3.1 The Need for Better Emission Models at the Aggregated Level 47

3.1.1 The main shortcomings of macroscopic emission models 47

3.1.2 Effect of number of stop and average speed-based models 49

3.2 Proposed Integrated Modeling Approach 52

3.2.1 The integrated modeling tools 53

3.2.2 The model's traffic components and emission factors 54

3.2.3 Extracting characteristics of driving modes 56

3.2.4 Calculation of emission factors 60

Chapter 4 : Application of ITEM in a Signalized Intersection 66

4.1 Analytical Traffic Model 66

4.2 Validating the Analytical Traffic Model 72

4.3 Emission Estimates by ITEM 75

4.4 Validating the Integrated Emissions Model (ITEM) 78

4.5 Summary 81

Chapter 5 : Estimating Network-Wide Traffic Emissions by ITEM in an Idealized Ring Network 84

5.1 Framework for ITEM with Analytical Macroscopic Traffic Data 85

5.2 Microsimulation of an Idealized Network 90

5.2.1 Construction of the microscopic simulation 90

5.2.2 Macroscopic traffic and emission values measured from microsimulation 92

5.3 Analytical Estimation of Emissions from Measured MFD.............................95

5.3.1 Comparison of driving cycle components 95

5.3.2 Comparison of total emission 98

5.4 Analytical Estimation of MFD...99

5.4.1 Theoretical approximation of MFD 99

5.4.2 Calculation of MFD from the network features............................. 100

5.5 Effect of Changing Network Characteristics 103

5.5.1 Effect of changing the green ratio (G/C) 103

5.5.2 Effect of changing signal cycle length.. 105

5.5.3 Effect of different block length... 107

5.6 The model error evaluation 109

Chapter 6 : Validation of ITEM in a Grid Network...113

6.1 Grid Network Modeling...114

6.1.1 Validation of analytically estimated traffic parameters. 116

6.1.2 Validation of analytically estimated total emissions (ITEM)........ 120

6.2 Model Errors 123

6.2.1 Errors in estimation of total emission 123

6.2.2 Errors in estimation of the ITEM's components............................ 124

6.2.3 Sensitivity Analysis 127

6.3 Summary....129

Chapter 7 : Conclusion....132

7.1 Applicability and Usefulness of the Model....133

7.2 Real-World Data Collection and Use of ITS....134

7.2.1 Microscopic data collection.... 135

7.2.2 Macroscopic data collection.... 135

7.3 Future Work and Fields Tests....136

Bibliography....139

LIST OF FIGURES

Figure 1. The structure of modal emissions model of CMEM (Barth, et al., 2000)......... 20

Figure 2. The structure of the MOVES model (Beardsley, 2004)................................... 22

Figure 3. Macroscopic Fundamental Diagram, a) schematic concave MFD, b) simplified triangular MFD 41

Figure 4. Macroscopic Fundamental Diagram of the city of Yokohama recorded at different locations (Geroliminis & Daganzo, 2008) 43

Figure 5. Time-space diagram of similar trajectories with different number of stops 49

Figure 6. Variation of CO_2emissions for trajectories with various numbers of stops 50

Figure 7.Time-Space Diagram and Speed Profile of a Sample Trajectory Divided into Driving Modes. 60

Figure 8. Comparison of emissions calculated physically with the emissions directly computed by MOVES. 63

Figure 9.Comparison of emissions estimation based on regression with the emissions directly computed by MOVES... 64

Figure 10. Comparison of the Emission results Estimated by the Integrated Model (ITEM) with the Emissions Computed Directly by MOVES and CMEM. 65

Figure 11.Schematic of time-space diagram for (a) Under-saturated conditions, (b) over-saturated conditions 68

Figure 12.Schematic trajectory with constant acceleration rates (solid) and a simplified piecewise linear trajectory (dashed)... 69

Figure 13. Variation of number of stops for various degrees of saturation 73

Figure 14. Variation of number of stops for various degrees of saturation 74

Figure 15.Contribution of each driving state in total emissions (based on VHT) at different traffic states using the base case scenario (C = 60 sec, and G/C = 0.5). 76

Figure 16.Total network-wide emissions per Vehicle Miles Traveled (VMT) at various saturation conditions 77

Figure 17. Variation of total emissions for various degrees of saturation 79

Figure 18. Time space diagram of two consecutive signals and the condition that the platoon moving forward meets the back of queue at point A. 89

Figure 19. Idealized homogeneous network, a) infinite arterial with identical links and intersections, b) ring shaped arterial 92

Figure 20. Relationship between average flow and average density, MFD, recorded in the micro-simulated idealized network. 93

Figure 21. Network-wide relationship between number of vehicle stops with average density of vehicles on the network. 94

Figure 22. Comparison of analytically estimated number of stops and measured values from microsimulation 96

Figure 23.Comparison of analytically estimated total time spent in a) cruising mode, and b) idling mode with the measured values from the microsimulation as a function of the network density 97

Figure 24. Comparison of analytically estimated network-wide total emissions and microscopically computed total emissions using the second-by-second trajectories as a function of the network density 98

Figure 25. Comparison of the analytically Approximated MFD with the MFD measured from microsimulation 101

Figure 26. Approximated MFD of the idealized network with different given network features 102

Figure 27. Macroscopic traffic parameters and network-wide total emissions for scenarios with various green ratios 105

Figure 28. Macroscopic traffic parameters and network-wide total emissions for scenarios with various signal cycle length 106

Figure 29. Macroscopic traffic parameters and network-wide total emissions for scenarios with various block length 108

Figure 30. Simplified grid network used for simulation 114

Figure 31. Network flow-density relation (MFD) measured from the simulation for different turning movement ratios 115

Figure 32. Variation of total number of stops vs. average densities corresponding to each pair of flow-density 117

Figure 33. Variation of total number of stops vs. average densities for the analytical estimates and simulated results after a run of 10 minutes 118

Figure 34.Comparison of total time spent in a) cruising and b) idling vs. average densities estimated analytically with the simulated results after a run of 10 minutes 119

Figure 35. Variation of analytically estimated total network-wide emissions versus average network densities for different percent turning scenarios 120

Figure 36. Comparison of the analytically estimated emissions (solid lines) and the aggregated simulation outputs (points) after a) 2 minutes of simulation run and b) after 10 minutes of simulation run. 122

Figure 37. Comparison of the analytically estimated total emissions by ITEM with microscopically computed emissions by MOVES. 124

LIST OF TABLES

Table 1. Primary and Secondary standard concentration of pollutant 12

Table 2. Tier 1 emission standards (grams/mile) for light-duty vehicles 13

Table 3.Comparison of different approaches in traffic and emissions modeling 45

Table 4.Variation of pollutants caused by different trajectories with a same average speed 51

Table 5. Percent error of emission estimates from the analytical emission model relative to the microscopic simulation model 80

Table 6. Percent error of emission estimates from the aggregated analytical emission model relative to the microscopic simulation model (Base case: G/C=0.5; C=60sec; ℓ=0.30km) 110

Table 7. Variation of duration (ts) and emission factor (es) associated with each stop vs. average densities 126

Table 8. Sensitivity of estimated total emission to variation of densities....................... 128

Table 9. Sensitivity of estimated total emissions to variation of network's features 128

Chapter 1 :

Introduction to the Study

Road transportation plays a vital role in socioeconomic development. However, it causes several significant issues, including: congestion, incidents, noise, and air pollution. Transportation also is one of the main sources of energy consumption and greenhouse gas emissions (WBCSD, 2001). According to the US Treasury Department, traffic congestion wastes 1.9 billion gallons of gasoline per year, and it costs over $100 billion per year due to fuel consumption and delays (U.S. Department of the Treasury, 2012).In large urban networks, traffic emissions have drawn significant attention in addition to energy and time wasted in congestion, especially between the urban policy makers. Population growth and increases in car ownership have resulted in higher dependency on private vehicles and longer average hours traveled, which directly deteriorate the city's air quality.

The United States Environmental Protection Agency (US EPA) estimated that the road transportation sector accounts for 29 percent of hydrocarbon (HC) pollution, 31 percent of nitrogen oxides (NO_x) emissions and 60 percent of carbon monoxide (CO) emissions in the United States (US EPA, 2000). These emissions also contribute to urban smog through a photochemical reaction of nitrogen oxides (NO_x) and hydrocarbons (HC), which produces ground level ozone (US EPA, 2008). Overall, vehicles on the road are the source of over half of all dangerous air pollutants, and around 30 percent of total carbon dioxide (CO_2) emissions in the United States. This makes traffic one of the main contributors of greenhouse gases (GHGs), which are associated with the world-wide phenomena called “Global Warming” (US EPA, 2013).

These emissions have major health and environmental impacts on humans and other species. Air pollution becomes a more problematic issue at some times and locations, such as peak commuting hours in large and dense urban areas. Therefore, minimization of air pollution is an important objective for policy making and network planning in large metropolitans. However, in order to take the air pollution into the account for the evaluation of any transportation development, it is necessary to quantify traffic emissions in large-scale networks. This requires methods to estimate network-wide emissions easily and reliably.

1.1 Problem Statement

There are two major approaches to quantify traffic emissions. The microscopic approach, which requires second-by-second trajectories of each individual vehicle traveling in the network, is too data intensive and costly to be applied for large-scale network-wide emission evaluation. On the other hand, existing macroscopic emission models that are being used to evaluate total emissions in large networks only consider the average speed of vehicles traveling on the network using pre-defined driving cycles and several other assumptions. This is problematic, because two very different traffic states may have the same average speed on the network.

In order to evaluate aggregated traffic emissions at the urban-level, we need to take the traffic conditions and driving cycles into account. This means that different acceleration/deceleration patterns can have a significant effect on the generation of emissions. Additionally, the level of congestion on the network can result in different numbers of vehicle stops and duration of idling per unit distance traveled, which can have a direct impact on total emission production. This issue will be explained in detail in the following chapters.

1.2 Research Objective

The main objective of this study is to evaluate urban-level network-wide traffic emissions based on fundamental properties of the network and driving cycles. To achieve this objective, two major steps have been taken. In the first step, the robust relationship that exists between average vehicle density and average vehicle flow, known as a Macroscopic Fundamental Diagram, MFD (Daganzo, 2005.a), is used to estimate the important elements of the driving cycle that have the major influence on total emissions. The consistent relationship between the number of vehicles circulating within the network and the traffic conditions in a network is shown to be related to other useful measures of traffic performance. These include the elements of a typical driving cycle, which are closely related to pollutant emissions from vehicles: the time spent cruising at free-flow speed, the time spent idling, and the number of times that vehicles stop per distance traveled.

In the second step, the Integrated Traffic Emission Model (ITEM) is proposed to link the analytically estimated traffic parameters with corresponding emission factors. The emission factors are computed with a microscopic emission model (in this study, MOVES) by using a sample of detailed trajectories of vehicles driving through the network. The required sample size of the vehicle trajectories depends on various considerations such as the scope of the network and the level of desired accuracy. The result is an estimate of the aggregated network-wide emissions from traffic, which is sensitive to the traffic conditions across the network.

1.3 Novelty and Contribution of the Study

In recent years, several efforts have been made to evaluate network-wide emissions considering traffic conditions in a network. None of these studies has used the analytical approach and macroscopic properties of the network to estimate aggregated traffic parameters. In this study, the fundamental property of the network and the relationship between vehicle density in the network and other traffic parameters provides a simple and easily available insight to traffic conditions without the need for extensive microsimulation modeling. In this approach, as long as driving behavior is not changed and the basic properties of the network remain constant, the same emission factors (calibrated with microscopic emission model) can be utilized. Therefore, the variation of traffic flow or signal timings does not require a repeated data collection or microsimulation modeling.

Finally, whereas it has been proven that there is a robust and reproducible relationship between the number of circulating vehicles (or density) and the neighborhood's average speed of vehicles (or flow) known as the MFD, a new relationship between the number of vehicles in the network and approximate number of stops and time spent in idling and cruising can be constructed. Although, this might depend on several factors, it can be very useful for emission evaluation of any alternative scenario affecting the flow and density of vehicles in the network.

1.4 Organization of This Dissertation

The remainder of this dissertation is organized as follows. Chapter 2 presents the literature review for traffic emissions and its standards and regulations. Different approaches to estimate traffic emissions and example models for each group are introduced in this chapter. Chapter 3 explains the proposed Integrated Traffic Emissions Model (ITEM) and the components that are needed to estimate total emissions. In chapter 4, the implementation of the proposed ITEM approach on an isolated signalized intersection has been evaluated. Chapter 5 provides detailed explanation of the analytical approach to estimate aggregated traffic components. Then, using ITEM total emissions in an idealized ring-shaped model has been evaluated. Additionally, by implementing the mathematical methods to approximate MFD in the idealized network, network-wide total emissions are evaluated based on completely analytical calculations. In the last part of chapter 5, the effect of changing network characteristics on total emissions is evaluated. In chapter 6, by simulation of a simple grid network with some limited level of heterogeneity, the proposed analytical approach has been validated by comparing the analytical estimates with microscopically computed total emissions. Finally, the model error analysis is provided at the end of this chapter. In Chapter 7, in addition to a brief conclusion, the application and usefulness of the model are provided. The explanation of current technologies to collect real-time data and future work of this study are the other parts of this chapter.

Chapter 2 :

Literature Review

In this section, the background of the study is presented, including the main vehicular emissions and current regulations and standards. In addition, the existing approaches to model traffic flow in a network and evaluate vehicular emissions with a few examples of current traffic and emission models in each category are explained.

2.1 Main Tailpipe Vehicular Emissions

Vehicular emissions are generated by combustion in the engine of vehicles, evaporation of fuel at different stages, and brake and tire wear. Although a few models are able to estimate the emissions associated with all of these sources, tailpipe emissions draw the most attention in emissions evaluation studies, because the exhaust emissions cause the main portion of traffic emissions.

One of the main factors that affects emissions during the combustion process is the “air-to-fuel” mass ratio. It is estimated that a stoichiometric ratio of approximately 14.5 mass units of air is needed to completely burn a unit mass of fuel. However, this ratio changes according to the required power. During acceleration, hill climbing, or any other high load condition, a rich fuel mixture with low air-to-fuel ratio, known as enrichment, is used, while a lean mixture is utilized during deceleration, when no power is needed. This condition is known as enleanment (Cappiello, 2002).

Depending on the vehicle type, engine technology, and fuel type, a variety of pollutants may be generated during the combustion process. Four major pollutants are commonly emitted by all vehicle types: hydrocarbons (HC), carbon monoxide (CO), nitrogen oxides (NO_x), and particulate matters (PM). Ground level ozone (O_3) caused by post reaction of vehicular emissions, sulfur dioxide (SO_2), and lead (Pb) from some fuel additives are secondary air pollutants from vehicles. Finally, carbon dioxide (CO_2) is the main product of complete combustion, and it is one of the main greenhouse gases contributing to global warming. These emissions have different causes and can be generated at various processes (e.g. incomplete combustion, fuel evaporation and leaking). Following is the brief explanation of the causes and process of generation of each of these pollutants.

Unburned HCs are emitted to the atmosphere by incomplete combustion of fuel in the engine and evaporation of fuel in various conditions. The main causes of incomplete combustion are the low temperature of the engine during long idling or deceleration, and insufficient oxygen during enrichment and high power conditions (An, et al., 1998). The evaporation of fuel occurs during the hot-soak period (after the end of the trip when the engine is off but it is still hot), when temperature and pressure are high in a running engine, or during refueling or leaking from a defective fuel system (Cappiello, 2002). It is estimated that 29% of total HC emissions in the US are generated by on-road mobile sources (Rao, et al., 2013).

Another byproduct of incomplete combustion is CO, which is generated due to insufficient oxygen. Especially during the high power conditions and low air-to-fuel ratio, partial oxidation of the fuel is more likely, and the production of carbon monoxide is much greater than the production of carbon dioxide (Cappiello, 2002). According to US EPA evaluation, vehicular emissions are responsible for 60% of total CO in the United States (Rao, et al., 2013).

Nitrogen oxides are generated during the combustion of the fuel under high temperature and pressure circumstances in the engine. In this case, the nitrogen as well as the oxygen of the atmosphere react and may produce different forms of NO_x. Although, most NO_x are colorless, the reddish-brown plume over many urban regions is caused by NO_2 (Kirchstetter, et al., 1999). US EPA estimates that 31% of total NO_x in the United States is generated by the mobile sources on the roads (Rao, et al., 2013).

Particulate matter, which are evaluated based on the diameter of particles in micrometers are known as PM_{10} and $PM_{2.5}$. These are very fine suspended particles which can be smog, road dust, and droplets. These tiny particles, especially those that are smaller than 2.5 microns are known to cause respiratory problems, including lung cancer, in addition to the harms to the environment, structures, and visibility (Kirchstetter, et al., 1999). It is estimated that vehicular emissions cause 4% of total $PM_{2.5}$, a considerable portion of which originates from diesel vehicles (Rao, et al., 2013).

In addition to these four major vehicular emissions, ground level ozone is a secondary pollutant that can be generated in the atmosphere through photochemical reactions. NO_x and HC, in the presence of sunlight, react with the oxygen in the atmosphere and generate O_3. Although upper level ozone can protect the earth from ultraviolet radiation, ground level ozone damages human health and the environmental (Cappiello, 2002).

Carbon dioxide is the main product of fuel combustion in an engine. Therefore, we cannot prevent the production of CO_2, but it can be reduced by minimizing the fuel consumption through increasing the efficiency of the vehicles' engines or the efficiency of vehicles' movements in the network (e.g., reducing the number of stops and time spent idling). Although CO_2 is not considered as a pollutant, it is the main greenhouse gas (80% of total GHGs), and increasing of CO_2 has been shown to cause global warming. According to the US EPA, on-road mobile sources are responsible for over 30% of the total CO_2 emissions in the U.S. (US EPA, 2013). Therefore, because carbon dioxide is the most important world-wide air quality impact of transportation, and correlated to the volume and efficiency of the mobility in the network, in this project, only CO_2 is evaluated in different scenarios. However, based on the capability of the microscopic emissions model used to estimate the emission factors, the same method can be implemented to evaluate other pollutants.

2.2 Regulations and Standards for Air Quality and Emissions

The Clean Air Act of 1963 was the first step of a national program to regulate air pollution. However, the first enforcement procedures for vehicular emissions caused by interstate transportation were not authorized until 1967. Finally, the Clean Air Act of 1970 established the national emissions standards to control motor vehicle emissions. In following twenty years, despite numerous advancements in technologies and improvements in vehicular emissions, deterioration of air quality in large cities continued due to the growing number of cars. Stricter air quality control was needed, and Clean Air Act Amendments of 1990 were passed.

The Clean Air Act Amendments of 1990 established maximum allowable concentrations for six criteria air pollutants, including: ozone (O_3), sulfur dioxide (SO_2), carbon monoxide (CO), nitrogen dioxide (NO_2), lead (Pb), and particulate matter with an aerodynamic diameter less than 10 microns (PM_{10}) mandated in all the regions in the United States (National Research Council, 1995). These thresholds are expressed as the concentration of the pollutants in various temporal aggregations. The concentrations of ground level ozone and carbon monoxide, which may have a short-term health impacts, are defined as the accumulation of the pollutants in 24 hours or less. However, the other four air pollutants have the thresholds in the form of the annual average of the concentration.

In addition, the Clean Air Act categorizes the National Ambient Air Quality Standards (NAAQS) into two general groups based on the purpose of the standard and the objective groups. The primary standards are defined for the protection of public health, considering the most sensitive groups in society, including: children, the elderly, and asthmatics. The secondary standards, on the other hand, are defined to improve the public welfare, including preventing from reduced visibility and harms to animals, crops, vegetation, and buildings (US EPA, 2014.a). Table 1 shows selected primary and secondary standards for the main six air pollutants in various aggregation periods. Except lead and sulfur dioxide, which are mainly emitted by stationary industrial processes (in the past, gasoline and diesel were the considerable sources of Pb and SO_2 respectively), transportation is a significant contributor of four other pollutants.

Table 1. Primary and Secondary standard concentration of pollutant

Pollutant		Primary/ Secondary	Averaging Time	Level	Form
Carbon Monoxide		Pr.	8-hour	9 ppm	Not to be exceeded more than once per year
			1-hour	35 ppm	
Lead		Pr. & Sec.	3 month	0.15 μg/m3	Not to be exceeded (Rolling 3 month avg.)
Nitrogen Dioxide		Pr.	1-hour	100 ppb	98th percentile, averaged over 3 years
		Pr. & Sec.	Annual	53 ppb	Annual Mean
Ozone		Pr. & Sec.	8-hour	0.075 ppm	Annual fourth-highest daily maximum 8-hr concentration, averaged over 3 years
Particle Matter	$PM_{2.5}$	Pr.	Annual	12 $\mu g/m^3$	annual mean, averaged over 3 years
		Sec.	Annual	15 $\mu g/m^3$	annual mean, averaged over 3 years
		Pr. & Sec.	24-hour	35 $\mu g/m^3$	98th percentile, averaged over 3 years
	PM_{10}	Pr. & Sec.	24-hour	150 $\mu g/m^3$	Not to be exceeded more than once per year on average over 3 years
Sulfur Dioxide		primary	1-hour	75 ppb	99th percentile of 1-hour daily maximum
		secondary	3-hour	0.5 ppm	Not to be exceeded more than once per year

Note: From US EPA (2014) *National Ambient Air Quality Standards (NAAQS)*. Retrieved from US Environmental Protection Agency Website: http://www.epa.gov/air/criteria.html

The growing role of transportation in the deterioration of air quality in cities is a result of increasing car ownership and more vehicles miles traveled, so, the standards and regulations are getting more stringent. The Clean Fuel Vehicle Exhaust Emissions Standards and Tier 1-3 have emerged to limit vehicular emissions (US EPA, 2012.a). In this set of regulations, the tailpipe emissions are measured by considering the type of vehicle and total miles traveled. The pollutants considered in this standard include total hydrocarbons (THC), volatile hydrocarbons (VHC), non-methane hydrocarbons (NMHC), carbon monoxide (CO), nitrogen oxides (NO_x), and particulate matter (PM). These pollutants are expressed as the maximum permitted tailpipe emissions measured by chassis dynamometer testing and expressed in the form of grams per mile, according to specific driving cycles called the Federal Test Procedure-FTP (Cappiello, 2002). Table 2 shows the emissions standards of Tier 1 for light-duty vehicles.

Table 2. Tier 1 emission standards (grams/mile) for light-duty vehicles

	50,000 miles / 5 years					
Vehicle category	THC	NMHC	CO	NOx diesel	NOx gasoline	PM
Passenger cars	0.41	0.25	3.4	1.0	0.4	0.08
LLDT, LVW <3,750 lbs	-	0.25	3.4	1.0	0.4	0.08
LLDT, LVW >3,750 lbs	-	0.32	4.4	-	0.7	0.08
HLDT, LVW <5,750 lbs	0.32	-	4.4	-	0.7	-
HLDT, ALVW >5,750 lbs	0.39	-	5.0	-	1.1	-

	100,000 miles / 10 years					
Vehicle category	THC	NMHC	CO	NOx diesel	NOx gasoline	PM
Passenger cars	-	0.31	4.2	1.25	0.6	0.10
LLDT, LVW <3,750 lbs	0.80	0.31	4.2	1.25	0.6	0.10
LLDT, LVW >3,750 lbs	0.80	0.40	5.5	0.97	0.97	0.10
HLDT, LVW <5,750 lbs	0.80	0.46	6.4	0.98	0.98	0.10
HLDT, ALVW >5,750 lbs	0.80	0.56	7.3	1.53	1.53	0.12

Notes: THC denotes total hydrocarbons; NMHC denotes non-methane hydrocarbons; NO_x diesel denotes NO_x for diesel vehicles; NO_x gasoline denotes NO_x for gasoline vehicles. LLDT denotes light light-duty trucks; HLDT denotes heavy light-duty trucks; LVW denotes loaded vehicle weight (unloaded weight + 300 lbs.); ALVW denotes adjusted LVW, equal to (gross vehicle weight + loaded weight)/2. From US EPA Website (2012).*Light-Duty Truck -- Tier 0, Tier 1, and Clean Fuel Vehicle Exhaust Emissions Standards*. Retrieved from U.S. Environmental Protection Agency, Office of Transportation and Air Quality (OTAQ): http://www.epa.gov/otaq/standards/light-duty/tiers0-1-mdvstds.htm

It should be noted that although these standards are enforced across the United States, the State of California has more stringent regulations. Due to severe air pollution of Los Angeles before federal standards were established, the State of California has issued its own automobile emissions standards. Moreover, in the last decade 14 more states have decided to adopt the California standards which are defined by the California Air Resources Board (CARB). Finally the US EPA and the National Highway Traffic Safety Administration (NHTSA) have started to upgrade the regulations in order to reduce GHG emissions and improve fuel consumption by on-road vehicles with the cooperation of a broad range of stakeholders, including the State of California and major automobile and truck manufacturers. They decided to extend the standards to light-duty vehicles for model years 2017-2025 (US EPA, 2012.b).

2.3 Vehicular Emissions Modeling Methods

In order to have accurate estimates of emissions from on-road vehicles, it is important to consider the parameters that influence emissions. These parameters can be categorized as follows (Hassounah & Miller, 1994):

- ***Vehicle characteristics,*** which include vehicle design and manufacturing technology, such as vehicle weight and its aerodynamic features, engine type and technology, control systems, exhaust treatment systems, current vehicle status and mechanical condition based on the vehicle age, mileage, and maintenance (Faiz, et al., 1996). Any malfunctioning of the vehicle should be considered in this category.
- ***Vehicle operating conditions,*** which are significantly affected by driving behaviors. These parameters include vehicle kinematic variables, such as vehicle average speed and the rates *of* acceleration and deceleration (also known as speed fluctuation) and the engine conditions, such as the temperature of the engine and air-to-fuel mass ratio based on required power (Joumard, et al., 2000) and (Hansen, et al., 1995). Other parameters in this part may include the transmission gear and use of air conditioning.
- ***External parameters,*** which include road type and conditions, such as the road grade, curvature, and pavement quality, and meteorological conditions,

such as temperature, pressure, and humidity. Additionally, other factors may affect the dispersions of emissions in the atmosphere (Flagan & Seinfeld, 2012).

A wide range of parameters influence the vehicle emissions and may cause various inaccuracies in the results. Therefore, in order to have a more reliable estimate of traffic emissions the second-by-second movement of all individual vehicles should be considered based on instantaneous operating condition of the vehicle. However, this approach may not be applicable for the large networks. In general, the operating conditions of vehicles, which can be represented by the vehicle speed and acceleration or the engine load, are the primary input of the emission models, while the external parameters such as road and weather conditions are the secondary input of the model.

During the last decade, several approaches have been proposed in order to estimate vehicle emissions; however, based on the resolution of the simulation, all of these approaches can be classified into three major groups, namely, the microscopic, mesoscopic, and macroscopic emission models. In this section, in addition to explaining the main approaches in each group and provide a few examples, the strengths and weakness of each approach are discussed.

2.3.1 Microscopic emission models

Microscopic emission models provide instantaneous emissions estimation based on concurrent operating conditions of a vehicle. These models are typically calibrated based on the dynamometer tests, which continuously measures the tailpipe emissions of various vehicle types during standard driving cycles. Using this continuous measurement of emissions enables us to relate the influential parameters, such as second-by-second speed and acceleration or required engine power as independent variables, to the resultant emissions as the dependent variable. A more comprehensive model may consider the concurrent quantities of all contributing factors expressed in the previous section.

A variety of efforts have been made to estimate instantaneous vehicle emissions. Velocity-acceleration lookup tables (also known as emissions maps), regression-based models, and power-demand-based models are the most common approaches to estimate vehicle emissions microscopically. Following are a few examples of microscopic emission models.

2.3.1.1 MODEM

MODEM is an early-generation microscopic emission model, which was developed as a part of the DRIVE II research program by the European Commission (Jost, et al., 1994). The speed-acceleration lookup tables have been produced based on the emissions measurements of 150 vehicles sampled from the vehicle population of different European Union countries. The vehicle emissions of HC, CO, CO_2, and NO_x are measured during various operation conditions represented by 14 driving cycles.

2.3.1.2 VT-Micro

The Virginia Tech microscopic energy and emissions model (VT-Micro model) is a regression-based microscopic emissions model (Ahn, et al., 1999; Rakha, et al., 2000; Ahn, et al., 2002).This model estimates instantaneous emissions based on a combination of linear, quadratic, and cubic terms of speed and acceleration as independent variables. The chassis dynamometer test was utilized for this model at Oak Ridge National

Laboratory. To construct the model six light duty vehicles (LDV) and three light duty trucks (LDT) have been tested, and 1300 to 1600 individual emissions measurements have been collected from each vehicle. These continuous measurements covered various driving conditions, which in some other models are based on a few driving cycles. In the regression model of VT-Micro, the various arrangements of speed and acceleration have been used as the explanatory variables in order to obtain the best fit. The general format of the regression model to estimate the instantaneous emissions is given as equation (1):

$$MOE_e = \begin{cases} \sum_{i=0}^{3}\sum_{j=0}^{3} \exp\left(k_{i,j}^{e}.v^{i}.a^{j}\right) & for\ \ a \geq 0 \\ \sum_{i=0}^{3}\sum_{j=0}^{3} \exp\left(l_{i,j}^{e}.v^{i}.a^{j}\right) & for\ \ a < 0 \end{cases} \tag{1}$$

Where:

$MOE_e$is the instantaneous fuel consumption or emissions rate in L/s or mg/s,

$a$is the instantaneous acceleration of vehicle in km/h/s,

v is the instantaneous speed of vehicle in km/h,

$k_{i,j}^{e}$ is the vehicle-specific acceleration regression coefficients for MOE_e, and

$l_{i,j}^{e}$ is the vehicle-specific deceleration regression coefficients for MOEe.

In the model, different coefficients for acceleration and deceleration have been considered and the natural logarithms have been used in order to avoid the negative fuel consumption or emissions rate. The model shows a good fit for a wide range of speeds and accelerations, and the estimated fuel consumption by the model are within 2.5 percent of the actual value of the consumption measured in the field (US EPA, 2012.c).

2.3.1.3 POLY

POLY is another regression-based microscopic emissions model, which was developed by the researchers at the Polytechnic University of New York and the Texas Southern University (Teng, et al., 2002). In this model, the road grade and past acceleration are also considered in addition to concurrent speed and acceleration. The general format of the regression model, which is estimated by ordinary least squares is shown in equation (2):

$$e(c,t) = \sum_{i=0}^{3} \beta_i . v^i(t) + \beta_{T'} . T'(t) + \beta_{T''} . T''(t) + \sum_{j=0}^{9} \beta_{A_t-j} . A(t-j) + \beta_W . W(t) \quad (2)$$

where:

$e(c,t)$ is the emissions rate of the vehicle category c at time t,

βs are the parameters calibrated for each vehicle category c,

$v(t)$ is the speed of the vehicle at time t,

$T^{'}(t)$ is the duration of acceleration since its inception up to the current time t,

$T^{''}(t)$ is the duration of deceleration since its inception up to the current time t,

$A(t-\bar{t})$ is the combined acceleration or deceleration at time $t-\bar{t}$ (t = 0,…,9) calculated from the acceleration $a(t)$ and the grade $g(t)$ (in %) as follows in equation (3):

$$A(t-\bar{t}) = a(t-\bar{t}) + 9.81.\left(\frac{g(t-\bar{t})}{\sqrt{1+g(t-\bar{t})}}\right) \quad (3)$$

and finally, $W(t)$ is the product of $v(t)$ and $A(t)$.

In this model the vehicle emissions database of the National Cooperative Highway Research Program (NCHRP) developed at UC Riverside has been used. This model has been calibrated and validated by the emissions data from the standard driving cycles including FTP data. In addition, the emission results of the model for a few specific vehicles have been compared with the emissions estimations from VT-Micro and CMEM.

Statistical microscopic emission models are developed based on various combinations of explanatory variables, including speed and acceleration, and may provide a good fit regression model with reasonable results. However, they may over-fit the data due to a large number of explanatory variables. Therefore, situations that are not covered in the calibration process may lead to estimated emissions with some undesirable results. Additionally, the regression-based models do not provide a clear understanding of the influence of physical processes on emissions generation, while power-demand models consider the physical and chemical phenomena that cause emissions to be generated.

2.3.1.4 CMEM

The Comprehensive Modal Emissions Model (CMEM) is a power-demand-based model, also known as load-based model. This model is developed at the University of California at Riverside and the University of Michigan (Barth, et al., 2000; Scora & Barth, 2006). This model estimates emissions based on physical processes which are decomposed into six modules, including (1) power demand, (2) engine speed, (3) air/fuel ratio, (4) fuel rate, (5) engine-out emissions, and (6) catalyst pass fraction. All modules are depicted in square boxes in Figure 1. As shown in the figure, the operating conditions directly affect the fuel-to-air ratio, engine-out emissions, and catalyst pass fractions.

CMEM has been developed based on extensive data collection of both engine-out and tailpipe emissions from the chassis dynamometer test of over 300 vehicles, including more than 30 high emitters. The data collection consists of second-by-second speed profile and emission rates of CO_2, CO, HC, and NO_x before and after the catalytic converter system. In order to develop the database, three driving cycles have been used, including: the FTP cycle, the US06 cycle, and an engineered cycle, called Modal Emissions Cycle (MEC01).

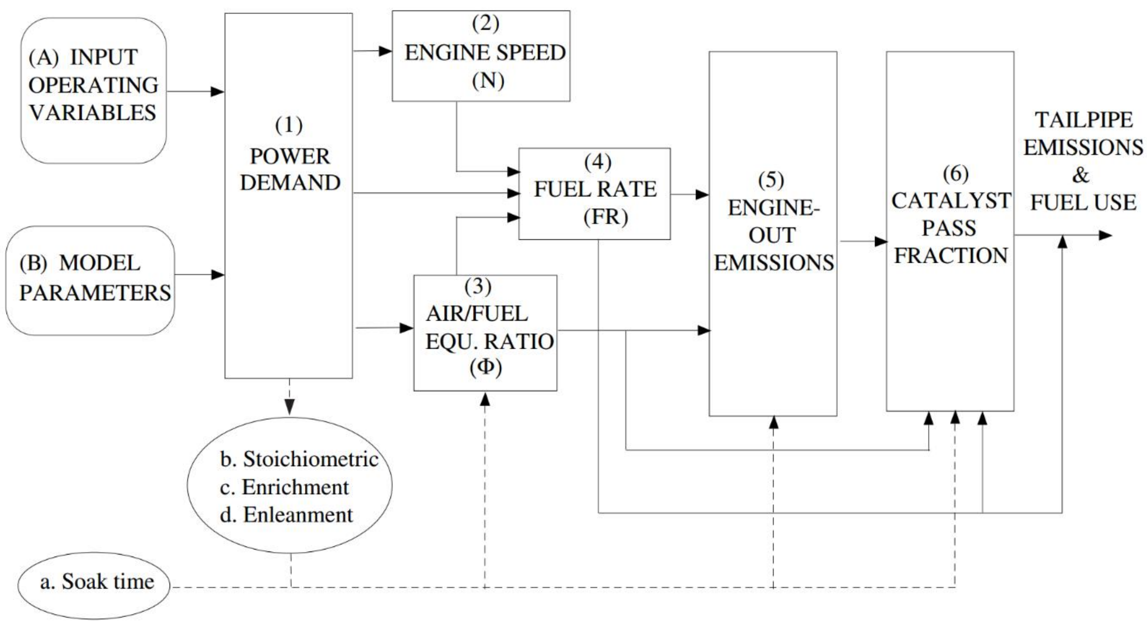


Figure 1. The structure of modal emissions model of CMEM (Barth, et al., 2000)

As the input data, both the vehicle operation variables (e.g., speed, acceleration, and road grade) and the model calibrated parameters (e.g., cold start coefficients, engine friction factor, and the enrichment/enleanment conditions) have been considered in the model. In order to utilize the model, based on a number of parameters, 28 categories have been constructed to estimate emissions for different vehicle in various conditions. These parameters include: vehicle type and the technology of engine, fuel system, and emissions control system, accumulated mileage, power-to-weight ratio, emissions certification level (tier0 and tier1), and emitter level category (high and normal emitter).

As a comprehensive model, CMEM considers the most influential factors on estimation of emissions under different conditions that make physically sense. However, this kind of microscopic model can be very data intensive and complicated to use.

2.3.1.5 MOVES (Project Level)

MOtor Vehicle Emissions Simulator, MOVES, is a software package developed by the US EPA, which is the next generation of the MOBILE series of emissions models (US EPA, 2012.c; US EPA, 2001). The MOBILE model and county/national level modules of MOVES are average-based emission models, which are discussed in the macroscopic emission models section. The Project Level of MOVES is a load-based emissions model. Similar to other microscopic emission models, this module of MOVES can be used to estimate instantaneous emissions associated with second-by-second movements of each individual vehicle. MOVES has been developed based on several emissions databases collected by US EPA, CARB, automobile manufacturers, and the inspection and maintenance (I/M) tests from several states. The additional driving cycle (supplemental FTP cycle) that has been used in the dynamometer test to enable the model to cover a wide range of speeds and accelerations, including aggressive driving with air conditioning operating (Bai, et al., 2009; Koupal, et al., 2010).

The MOVES model consists of four major functions, which include the activity generator, the operating mode distribution generator, the source bin distribution generator, and the emissions calculator (Bai, et al., 2009; Beardsley, 2004). As shown in

Figure 2, the emissions functions take the input data consisting of vehicle activities, fleet composition, meteorological conditions, and fuel formulation to estimate the emissions. The resulting emissions are delivered as the emission factors or emissions inventories generated over a desired geographic span (national, county, and project level) as well as temporal resolution (year, day, and hour)

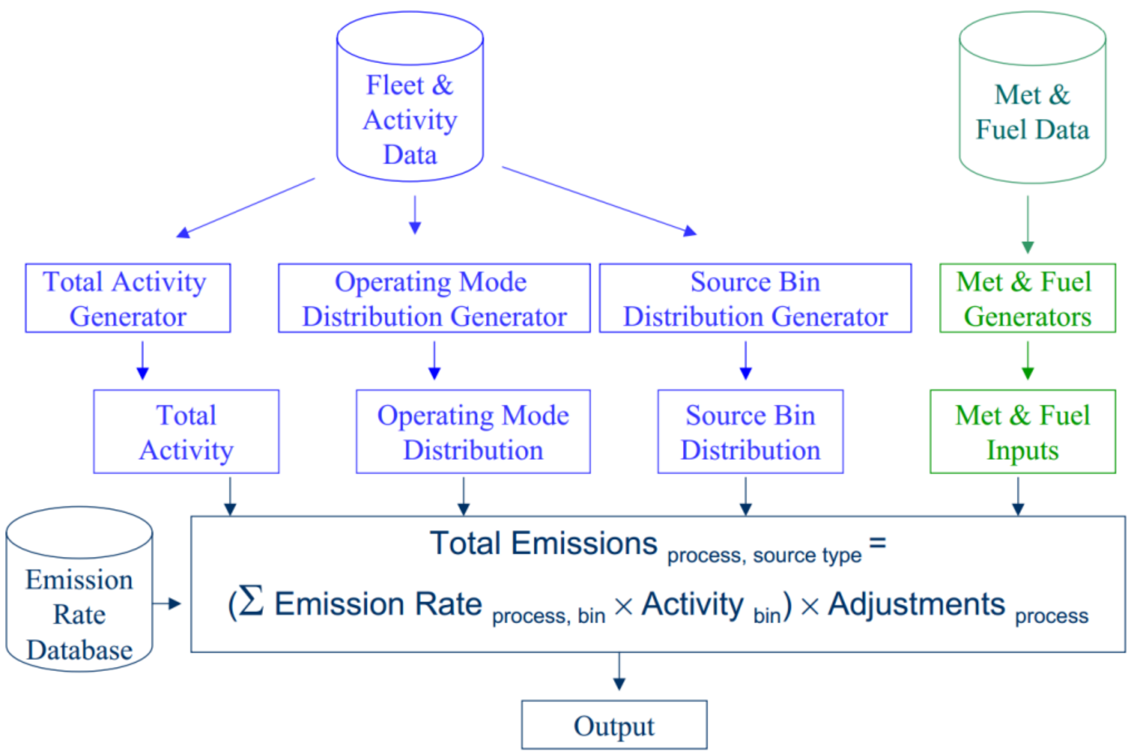


Figure 2. The structure of the MOVES model (Beardsley, 2004)

The model implements a set of correction factors to the initial emission rates, to take other influencing parameters into account. These parameters include the air temperature and humidity, the vehicle age and deterioration, and Inspection/Maintenance (I/M) programs. MOVES also can consider the impact of ramp, which is the off network extended idling, to estimate several air pollutants for a list predefined vehicle types, fuel types, and engine technologies. There is a feature to define a different fuel formulation and an Alternate Vehicle Fuels & Technologies (AVFT).

MOVES is a modal emissions model, which uses the variation of vehicle performance in different driving modes to estimate on-road vehicle emissions. There are two methods to provide the vehicle performance as the input into the model. By using the Operation Mode Distribution module, the distribution of the vehicle(s) activity on a link is entered into the model as the fraction of time spent in each mode of vehicle operation. Operating modes have been broken down into different bins representing various activities and emission processes, including running exhaust, start exhaust, hot soak, evaporation loss, brake ware, and tire wear. For instance, the running exhaust bins are defined by the speed and Vehicle Specific Power (VSP), which is the instantaneous power demand of the vehicle divided by its mass. The main advantage of using VSP is that several physical parameters contributing to emissions generation and fuel consumption can be combined into a single factor showing the overall required power (normalized by the vehicle weight) to overcome different forces and resistances. These influencing parameters include: vehicle speed, acceleration, road grade, and road load factors such as aerodynamic drag and rolling resistance.

On the other hand, the Project-Level of MOVES can simply take the vehicle trajectories to estimate the emissions. The Link Drive Schedule uses the second-by-second speed and grade profile of the vehicle to calculate instantaneous required power. MOVES utilizes an internal algorithm to calculate an Operating Mode Distribution and subsequent emission factors from the Link Drive Schedule (US EPA, 2012.c).

The US EPA mandated that the MOVES emissions model be implemented as the only approved emissions model for project-level analyses and conformity determinations in all states. The only exception is the State of California, which must use the approved emissions model of EMFAC (US EPA, 2014.b).

2.3.1.6 EMIT

Emissions from Traffic, EMIT, is also a statistical emissions model, which is developed at the Massachusetts Institute of Technology (Cappiello, 2002; Cappiello, et al., 2002). Although this model is a regression-based model, it is also based on simplified physical processes in the engine that contribute in the generation of emissions; therefore, this model can be considered a combination of regression-based and load-based approaches. In this model, the explanatory variables have been derived from the load-based approach in order to the instantaneous vehicle emissions and fuel consumption of light-duty vehicles. Similar to many other microscopic emission models, second-by-second speed and acceleration are the main input of the model.

2.3.1.7 Summary of microscopic emission models

Microscopic emission models may have a sophisticated and complex structure, which makes the model capable of detailed emissions estimation under a wide range of circumstances. However, this complex model requires intensive data collection. This also may cause an extensive computation, which is time consuming and costly. On the other hand, the simplified and regression-based models may provide instantaneous emission estimates based on a second-by-second speed profile; however, these models can be over-fitted due to a large number of explanatory variables, or cannot be calibrated for some conditions.

In addition to these weaknesses, in general, the microscopic emission models cannot be utilized for large urban networks, since second-by-second movements of vehicles cannot be tracked. Not only is it not an easy task to collect detailed trajectories of numerous vehicles with corresponding vehicle information, storing and processing this massive information is impossible even with existing super computers. Finally, even if a microscopic simulation of a large urban region were conducted, the detailed information resulting by the microscopic model may not be very helpful for urban planners and policy makers. In large-scale urban decision making aggregated data and overall evaluation are often more useful. Therefore, for large-scale evaluation of traffic emissions as well as traffic management, macroscopic traffic modeling can be more beneficial. In the next section, the main approaches of macroscopic emission models, with a few examples are discussed.

2.3.2 Macroscopic emissions models

While microscopic simulations consider instantaneous movements of all individual vehicles and evaluate second-by-second emissions of small-scale networks (project level), macroscopic emission models utilize the aggregated traffic parameters to evaluate network-wide emissions usually on a large-scale network (urban level). In most cases, the average speed of vehicles is used as the higher level traffic parameter representing the traffic conditions. In general, the total emissions of a species in a given area during a given period of time can be predicted by estimation of average speed along the given time and space span. Equation 4 is one of the general formats of average-speed-based model:

$$E_i = \sum_c \sum_l VKT_l . f_c . BER_i(\overline{s_l}, c) \tag{4}$$

Where:

E_i is the total emission of the species i,

c is the vehicle category of interest,

l is the sub-region of interest where the average speed of vehicles is $\overline{s_l}$,

VKT is the vehicle-kilometers-traveled in a given network and period of time,

f_c is the fraction of vehicles of category c to total number of vehicles,

$BER_i(\overline{s_l}, c)$ is the Base Emissions Rate per distance (kilometer or mile) for the emissions species i, associated with vehicle category c and average speed of $\overline{s_l}$ in the sub-region l.

The network-wide average speeds and the dependent emission factors are usually computed based on the standard driving cycles for different vehicle categories. A correction factor can also be applied to the model to take the other relevant factors into account. Since this type of model takes the network-wide average speed of vehicles as the main input of the emissions model, it can estimate the emissions more accurately when the conditions are near steady state. The best application of these models is the analysis of large networks with uniform flow and average speed, such as the uninterrupted flow in highways. The following are a few examples of macroscopic emission models.

2.3.2.1 Elemental Model

The Elemental Model is a one of the earliest macroscopic emission models (Evans & Herman, 1978; Chang & Herman, 1981). This model simply relates the fuel consumption and emissions linearly to the average travel time per unit distance, which is the reciprocal of average speed on the network. The general format of the Elemental Model is shown in equation 5:

$$\emptyset = K_1 + K_2 T \qquad when : V < 55_{km/h} \tag{5}$$

where:

$\emptyset$ is the fuel consumption per unit distance,

T is the average travel time per unit distance,

V $(= \frac{1}{T})$ is the average speed of vehicles on the network,

K_1, K_2 are the calibration parameters in the model. K_1(in mL fuel/km) represents the fuel consumption associated with the mass of the vehicle mass. K_2 (also in mL/sec) is the fuel consumption factor associated with the average speed of the vehicle.

In order to avoid the impact of aerodynamic drag resistance at high speeds, most of the average-speed-based models are a function of travel time, travel distance at a low average speed. Therefore, these models can only be implemented for the average speeds of less than 50 km/h (Evans, et al., 1976; Akcelik, 1985).

2.3.2.2 Watson Model

This also another average-speed-based model, developed to estimate overall fuel consumption (Watson, et al., 1979). In this model, as shown in equation (6), the variation of the kinetic energy during acceleration has been considered in addition to the average speed.

$$F = K_1 + \frac{K_2}{V_s} + K_3 V_s + K_4 PKE \tag{6}$$

where:

F is the fuel consumption in L/km,

V_s is the space mean speed in km/hr,

$K_1, K_2, K_3,$ and K_4 are the calibration parameters in the model, and

PKE is the sum of the positive kinetic energy changes during acceleration in m/s^2, and is calculated as follows in equation (7):

$$PKE = \sum (V_f^2 - V_i^2)/(12.96X_s) \tag{7}$$

where:

V_f is the final speed at the end of acceleration in km/hr,

V_i is the initial speed before the acceleration in km/hr, and

X_s is the total length of the segment in km.

In this model, the average speed should be less than 55 km/hr to prevent the impact of drag force by the aerodynamic effects (Evans, et al., 1976; Akcelik, 1985). The early generation average-speed-based emission models considered the average speed of the trips to evaluate general emissions generated by the individual vehicles. However, the same method could be implemented to estimate overall emissions in the network.

In the last decade, a few macroscopic emission models have been developed and utilized, which are specifically proposed to evaluate the vehicular air pollution in the large networks. MOVES, EMFAC, and COPERT are the most well-known and widely-used tools in this category, which will be discussed in the following sections.

2.3.2.3 EMFAC

The EMFAC (Emission factors) model is an average-speed-based model, developed by the California Air Resources Board (CARB, 2011). The EMFAC model is one of the two officially approved models for the regulatory purposes, and it is widely used in the United States (beside the MOVES model). EMFAC is commonly being used in the State of California to evaluate network-wide traffic emissions and fuel consumption (US EPA, 2014.b).

The model estimates aggregated emissions based on the emission rates database collected by the chassis dynamometer tests on different vehicle classes with various driving cycles. These emission rates are generated based on the fixed Vehicle Specific Power (VSP) distribution embedded in the underlying driving cycles. The model uses a set of correction factors to take a variety of influential parameters into account (Bai, et al., 2009).

The EMFAC model takes the vehicle miles traveled (VMT), and breaks it down into bins with a speed interval of 5 MPH as the activity data, and uses the local-specific emission rates and combines them internally to generate hourly or daily total emissions for various geographic areas in California. EMFAC can estimate a set of vehicle air pollutants, including: hydrocarbons (TOG, ROG, THC and CH_4), carbon monoxide (CO), oxides of nitrogen (NOx), carbon dioxide (CO_2), particulate matter (PM_{30}, PM_{10}, and $PM_{2.5}$), oxides of sulfur (SO_x), lead (Pb), and fuel consumption in different emission processes such as: running exhaust, start exhaust, idle exhaust, diurnal, hot soak, resting and running loss, and tire and brake wear.

2.3.2.4 MOBILE/MOVES

In addition to the microscopic simulator provided at the project level of MOVES, the model is capable of estimating the emissions based on the average speed of vehicles in different domains of national, county, and project levels (US EPA, 2012.c). The initial macroscopic emissions model that was developed in the United States for regulatory purposes was MOBILE, which has been replaced by the MOVES model in 2010 by the

US EPA. Since then, the model has started to officially be adopted for evaluation of on-road emission estimates for the state implementation plans (SIPs) and regional or project-level transportation conformity analyses in all states other than California (in the State of California, the EMFAC model must be used for this type of project) (US EPA, 2014.b).

In the national and county domains, the network-wide average speed of vehicles distributed into speed bins from 2.5 to over 75 mph with 5 mph interval, according to source type, road type, and hour-day. One the differences between MOVES and EMFAC is that the EMFAC model uses the average speed distribution defined as miles traveled (fraction of distance), and the MOVES model is based on the vehicle operating time (SHO – Source Hours Operating) defined to provide the vehicle performance data to the model (Bai, et al., 2009). Similarly, for the project level, a link-wide average speed of different vehicle types can be used to simulate a network at project level macroscopically.

In addition to the activity data (speed/VSP), the model requires some more inputs, including temporal and spatial span, fleet composition and its age distribution, network configuration and proportion of the vehicles activities on the network, fuel formulation, meteorological data, inspection and maintenance (I/M). However, for the nationwide emissions modeling, national default vehicle fleet and VMT distributions, national default driving schedules, meteorological data, and some other default data are provided. Also, for the county level modeling, built-in allocation factors can be used to estimate county level default data.

A wide range of pollutants can be evaluated by the MOVES model, including total hydrocarbons (THC), methane (CH_4), oxides of nitrogen (NO_x), nitrous oxide (N_2O), carbon monoxide (CO), atmospheric carbon dioxide (CO_2), CO_2 equivalent, sulfur dioxide (SO_2), ammonia (NH_3), particulate matter (PM_{10} and $PM_{2.5}$), toxic air pollutants, and energy consumption. These pollutants can be estimated from different emission process, such as running exhaust, start exhaust, extended idling, off-gassing (well-to-pump), evaporative fuel permeation, evaporative fuel vapor venting, evaporative fuel leaking, brake wear, and tire wear. Estimated emissions can be generated in the form of a rate of grams pollutant per distance, per profile, or per vehicle, or it can be estimated as a total weight of the emissions or as inventory (Vallamsundar & Lin, 2011).

2.3.2.5 COPERT

COPERT 4 (COmputer Program to calculate Emissions from Road Transport) is a well-known tool for mobile source emissions inventories in Europe. It is an application to calculate air pollutant and greenhouse gas emissions from the road-transport sector developed with the support of the European Environment Agency (EEA) and European Commission (Gkatzoflias, et al., 2007; Ntziachristos & Samaras, 2013). COPERT is an average-speed-based model, which is designed to macroscopically estimate the vehicle fleet emissions at the country level. In addition to European countries, this model is used officially world-wide in other countries and some of the United Nations' projects, including the submission of national road transport inventories to satisfy the requirements of the Convention on Long Range Trans-boundary Air Pollution (CLRTAP) and the UN Framework Convention on Climate Change (UNFCCC) (EEA, 2011).

In order to develop the database, the Euro series emissions standards have been considered and emission factors for 241 individual vehicle types from all European countries have been measured. However, since detailed information for all the vehicle types were not available in all countries, in several cases a number of parameters are required to be assessed. The model estimates the regional fuel consumption and wide range of pollutants, including CO, CO_2, NO_x, NM-VOC, CH_4, N_2O, NH_3, $PM_{2.5}$, PM_{10}, SO_2, Pb, Cd, Cr, Cu, Ni, Se, Zn in different processes, namely the thermal stabilized engine operation (hot emissions), the warming-up phase (cold start emissions), and non-exhaust emissions (fuel evaporation, tire and brake wear emissions) (Smit & Ntziachristos, 2013).

2.3.2.6 Summary of macroscopic emission models

Although, macroscopic emission models are currently in use for evaluation of emissions and fuel consumption in the county, state, and national levels, microscopic emission models are only suitable to be used to evaluate overall vehicular emissions in smaller scale networks. Additionally, macroscopic emission models are usually based on the network-wide average speed of different vehicle classes on various road types, and they do not have the capability to accurately estimate emissions in various traffic conditions. Therefore, in recent years, some efforts have been made to estimate network-wide emissions, considering different parameters by developing mesoscopic emission models which will be explained in the next section.

2.3.3 Mesoscopic emission models

Mesoscopic emission models require more disaggregate inputs than macroscopic models, therefore, they can predict emissions more accurately than the macroscopic models. Moreover, the mesoscopic models do not need detailed input like the instantaneous movements of all individual vehicles as it is required in the microscopic model; therefore,they are not as complex and data intensive as the microscopic models.

2.3.3.1 Akcelik Model

The model which was developed by Akcelik et al. estimates fuel consumption based on the averaged parameters on different driving modes (Richardson & Akcelik, 1981). The model is composed of three components of cruising, idling, and deceleration-acceleration. In the two first terms, the fuel consumption rate is defined as the rate per distance traveled with the cruising speed time and rate per time spent in stop position, and for the deceleration-acceleration mode, the rate is defined per stop. The general format of the model is presented in equation (8)

$$F = f_1 X_s + f_2 d_s + f_3 h \tag{8}$$

where:

F is the average fuel consumption in mL,

X_s is the length of the section in km,

d_s is the average duration of idling per vehicle in sec,

h is the average number of stops per vehicle,

f_1 is the fuel consumption rate in cruising mode in mL/km,

f_2 is the fuel consumption rate in idling mode in mL/sec,

f_3 is the fuel consumption rate per vehicle stop in mL.

2.3.3.2 MEASURE Model

The Mobile Emissions Assessment System for Urban and Regional Evaluation (MEASURE) is a GIS-based modal emissions model originally developed by researchers at the Georgia Institute of Technology in cooperation with the U.S. Environmental Protection Agency (Bachman, et al., 1996; Bachman, et al., 2000). The model was initially introduced for the metropolitan region of Atlanta, Georgia to evaluate trip-based traffic activity and its corresponding fuel consumption and emissions.

The model uses a hierarchical tree-based regression technique to select explanatory variables among modal variables (such as average speed and percentage of cycle exceeding a specific level of acceleration, power, etc.) and a few dummy variables representing the vehicle characteristics (such as fuel injection system, emissions control system, mileage, high or normal emitter, etc.). The model estimates HC, CO, and NO_x in different processes using two major modules, including a start emissions module and an on-road emissions module. For the start emissions module, start characteristics of the fleet are obtained using available vehicle registration data. For the on-road emissions module, the operating mode distribution is estimated based on traffic conditions (traffic flow and network saturation ratio), average travel speed, and the road conditions. These vehicle activity data can be obtained from real-world data or traffic simulations.

The MEASURE model is calibrated based on a large database constructed by tailpipe emissions tests on more than 13,000 vehicles from various classes and age distributions, and especially adjusted to represent the fleet composition of Atlanta. In fact, this is the main weakness of the model, which is that it is a place-specific model and calibrated for Atlanta. In order to adapt the model to another urban network, several variables have to be calculated based on the distribution of vehicle type, age, and technology of the region of interest.

2.3.3.3 VT-Meso

The VT-Meso is a recently developed mesoscopic emission model developed at the Virginia Polytechnic Institute and State University (Yue, 2008). This is a kind of modal emissions model, which has been built on the VT-Micro model (discussed in the microscopic emission models section) (Rakha, et al., 2011; Ahn, et al., 2002). In other words, the VT-Meso model is sensitive to the different vehicle operation modes, however, the second-by-second trajectories of vehicles are not required for the modeling.

The proposed model utilizes the link-by-link average speeds, number of vehicle stops, and stopped delay as the aggregated traffic parameters. Using this traffic information, the model synthesizes a typical driving cycle and estimates the average link fuel consumption and emission rates by utilizing the microscopic emissions model. Total link-based fuel consumption and emissions are then computed by multiplying the estimated average fuel consumption and emission rates by its corresponding vehicle kilometers traveled. Finally, the network-wide emissions and fuel consumption are computed by aggregating all values of emissions from all links of the network.

Similar to VT-Micro, this model estimates HC, CO, CO_2, and NO_x in addition to fuel consumption, in various modes of operation. However, since the model is built on VT-Micro, the model estimates the emissions only under normal operation of LDVs and LDTs (hot-stabilized conditions), and it cannot estimate emissions associated with the cold starts and air conditioning usage.

2.3.3.4 Gori's Model

In 2012, Gori et al. proposed another mesoscopic emission model, which uses a dynamic traffic assignment model to estimate the aggregated traffic parameters (Gori, et al., 2012). These traffic parameters include: distance traveled at free-flow speed, the average speed of vehicles in queues, and the length of the queues, and are used to consider the within-day variations of traffic conditions in a wide urban network. The model is developed to consider different states of vehicles and driving behavior under congested and uncongested conditions.

2.3.3.5 Zegeye's Model

In another approach, Zegeye et al. proposed a general framework to integrate macroscopic traffic flow models with microscopic emission and fuel consumption models, in order to estimate total emissions, and fuel consumption for traffic control purposes (Zegeye, et al., 2013). To illustrate the approach, they integrated the macroscopic traffic flow model METANET used to generate macroscopic traffic parameters with the microscopic emission and fuel consumption model VT-micro to estimate total emissions

2.3.3.6 Summary of mesoscopic emission models

Although in the mesoscopic emission model the aggregated modal-based traffic parameters are usually used to evaluate overall emissions, the relationship of these kind of parameters and fundamental properties of the network, especially the Macroscopic Fundamental Diagram (MFD) has not been investigated explicitly. These relationships can be a valuable tool to introduce a reproducible diagram of emissions under certain assumption, which can be very helpful to predict network-wide emissions corresponding to real-time traffic conditions (flow and density) in the network. In the next chapters these relationships between the network features and traffic parameters and emissions will be investigated at different levels.

2.4 Traffic Modeling and Real World Traffic Data

In order to evaluate traffic emissions, a good understanding of traffic flow in the network, and reliable estimation of traffic parameters is necessary. Traffic parameters can either be obtained based on field data collection using various methods of traffic data measurements, or they can be estimated by different types of traffic modeling and simulation. In this section a brief introduction to different traffic models is provided. In addition, the required input data for various types of traffic models and their interface to the emission models are discussed.

2.4.1 Transportation planning models

These models, also known as Strategic Planning Models (SPMs), are used to estimate the current and future travel demand and evaluate the performance and efficiency of a metropolitan road network. These models are usually useful to evaluate the impact of new policies or planning within the network, such as any development and expansion infrastructure. They are proposed to estimate aggregated traffic parameters in small to very large networks over a short or long period of time. Transportation planning models can be in the form of land-use models, trip-based transportation models, and activity-based transportation models, which may refer to travel demand models, urban transport models, and strategic network models. CUBE, UTPS, EMME2, TRANSTEP, MINUTP, and TRIPS are a few examples of transportation planning models (Brindle, et al., 2000).

The network in planning models is divided into zones which cover different parts of the urban area with a centroid representing the average features of the zone and the origin and destination of trips associated to the zone. The network is constituted by the links and nodes which represent the road specifications such as the road type, number of lanes, road capacity, free flow speed or the speed limit of each link. Utilizing the traffic assignment function, these models can generate the aggregated outputs, including traffic volume, mean travel time and speed. The results of this type of models may be used in macroscopic emission models; however, the emissions estimation based on the average speed is based on several assumptions which may affect the accuracy of estimation (Helali & Hutchinson, 1994; Grant, et al., 2000).

2.4.2 Traffic flow propagation models

In contrast to the previous type of models, which describes high level traffic parameters for planning purposes, traffic flow models, also known as traffic performance models, explicitly describe the physical propagation of traffic flows and clearly illustrate the traffic streams in the network. However, the models can be classified based on whether they operate in continuous or discrete time, whether they are purely deterministic or stochastic, or depending on the level of detail. Therefore, based on the level of aggregation, the models are categorized as macroscopic, mesoscopic, and microscopic traffic models (Maerivoet & De Moor, 2008)

2.4.2.1 Macroscopic traffic flow models

The macroscopic models are the highest level of traffic flow modeling, which are introduced based on kinematic wave model (KWM) which is also known as the Lighthill–Whitham–Richards (LWR) Model. In this approach, using the concept of the continuity in fluid dynamic, traffic can be considered as an inviscid but compressible fluid. Therefore, the continuous variables of traffic densities, mean speeds, and flows can be defined at each point in time and space. Based on this concept, the Macroscopic Fundamental Diagram (MFD) has been introduced which relates these three variables together at the aggregate network-wide level. This method provides the analytical and numerical solutions for the network-wide traffic parameters based on the LWR model. In Chapter 5, the macroscopic traffic flow modeling will be used to derive the analytical model to estimate aggregated traffic parameters macroscopically. Due to the importance of the macroscopic traffic model, and use of the concept of the MFD in the rest of this study, the Macroscopic Fundamental Diagram (MFD) will be explained further in the following section.

A finer resolution model is the Cell Transmission Model (Daganzo, 1994; Wai Yuen, 2008), which is a discretized implementation of the kinematic wave model. The model represents macroscopic traffic dynamics in smaller cells in a way that is consistent with the MFD of the road section. In this approach, the highway segment is partitioned into smaller units known as cells, and the number of vehicles in each cells is estimated during short time intervals. In order to keep track of the cell contents, the numbers of vehicles that cross the boundary separating each pair of adjoining cells are evaluated during the corresponding clock interval. Although this model represents dynamics of queuing and delay that are consistent with finer kinematic wave models, the approach treats traffic in each cell as an aggregate quantity, so individual trajectories are not directly constructed.

2.4.2.2 Mesoscopic traffic flow models

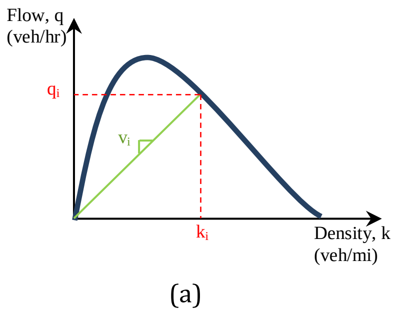
Similar to macroscopic traffic flow models, the mesoscopic models also describe traffic streams at an aggregated level; however, these models incorporate microscopic characteristics of traffic flow such as driving behavior. The three most popular approaches in this part are: the cluster models, the headway distribution models, and gas-kinetic models.

2.4.2.3 Microscopic traffic flow models

Microscopic traffic flow models, that consider the detail interactions between individual vehicles are based on car following and lane changing models. These models consider a wide range of parameters, such as vehicle lengths, speeds, accelerations, and time and space headways, vehicle and engine capability, as well as some rudimentary human characteristics that describe the driving behavior. In this type of model second-by-second movements of all individual vehicles are estimated. Additionally, in order to reflect the stochastic nature of traffic flow and human behavior, random variables with different distributions can be utilized in different parts of modeling. Since microscopic traffic flow modeling requires complex and intensive computation, this type of modeling is usually carried out by powerful computers. Therefore, several software packages have been developed to simulate traffic networks microscopically. AIMSUN, PARAMICS, VISSIM, CORSIM, and ARTEMIS are a few examples of microscopic traffic simulators.

2.4.3 Macroscopic Fundamental Diagram (MFD)

A macroscopic relationship between the vehicle density in a network (number of vehicles per distance) and the average flow (number of vehicles per time) has been shown to exist in many networks. This relationship which is known as the Macroscopic Fundamental Diagram or MFD, and it is a property of a network. Well-defined MFDs are expected to exist in multi-block, signal-controlled street network with homogeneous distribution of vehicles across the links (Daganzo, 2005.a; Daganzo, 2005.b). Figure 3(a) shows a schematic concave MFD which can be simplified to the triangular format shown in Figure 3(b)



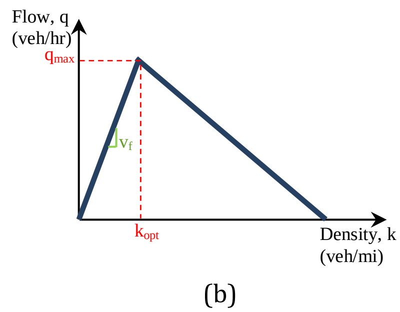


Figure 3. Macroscopic Fundamental Diagram, a) schematic concave MFD, b) simplified triangular MFD

This graph, in addition to pairs of flow and density, can express the average speed in the network ($v = q/k$), which is the slope of connecting line from the origin to the point representing the traffic state of interest. The left branch of the curve refers to the under-saturated conditions where the number of vehicles is less than the capacity of the network, and driving cycles consist of cruising with free flow speed (maximum allowed speed) and minimum possible number of stops and duration of idling due to traffic signals. Therefore, the total emissions corresponding to the number of vehicles is expected to be the minimum possible volume. The right branch of the curve reflects the over-saturated conditions, where the number of vehicles' stops and duration of idling are more than the values caused by the signals. They are increased due to congestion and stop-and-go movements caused by over-saturated intersections. In this situation, more traffic emissions are generated by the accelerations, decelerations, and idling modes, and the emission increases exponentially without any additional traveled distance due to congestion.

The main assumption of this relationship is that the network should be homogeneous, well-connected, and unaffected by turning movements, where the vehicles are distributed uniformly over the network (Daganzo, 2007; Geroliminis & Daganzo, 2008). However, the networks that violate this assumption also appear to have a consistent relationship up to a point below the upper bound of MFD (Daganzo & Geroliminis, 2008). Heterogeneous networks also can be divided into sub-networks with homogeneous features.

2.4.4 Real world traffic data

Although, instantaneous field traffic data at the microscopic level may not be readily available and it can be quite expensive to acquire, real-world traffic data can provide more accurate traffic parameters as required inputs for emission models. Based on current technology several aggregated traffic parameters can be collected which can be useful for estimation of total emissions; however, collecting second-by-second movements of all individual vehicles is costly and inapplicable for many projects. The link-based average flow and density can be collected using the loop detectors, and the aggregation of this data can provide the network's MFD. Figure 4 shows the real-world example of MFD recoded from the road network in Yokohama, Japan (Geroliminis &

Daganzo, 2008). As depicted in the graph, in real-world MFD, we may not observe a complete MFD. This is because, in the urban networks, it is not desired to experience the completely congested conditions.

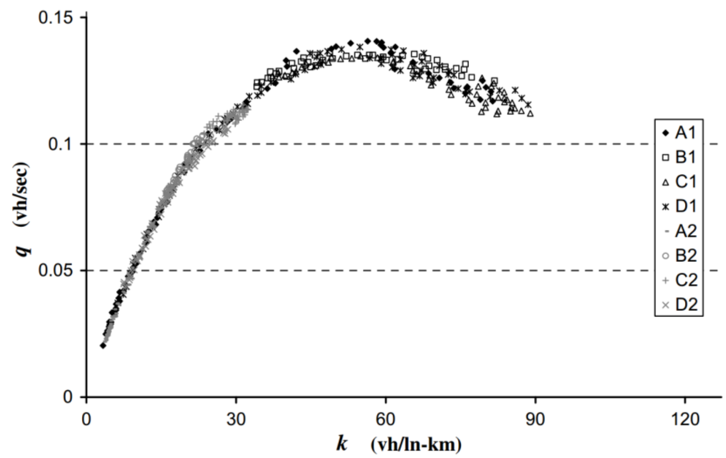


Figure 4. Macroscopic Fundamental Diagram of the city of Yokohama recorded at different locations (Geroliminis & Daganzo, 2008)

Global Positioning System (GPS), smartphone applications for data collection, and image processing of recorded traffic video (e.g. Next Generation Simulation-NGSIM) are examples of technologies that can be used to collect detailed traffic data. Furthermore, other traffic parameters like traffic counts, delay, space mean speed, mean travel time, etc. can provide the aggregated traffic parameters as the input for macroscopic emission models.

2.5 Summary

In this chapter, in addition to explanation of major tailpipe emissions and corresponding emission standards and regulations, different types of traffic and emission models have been discussed. While current average speed-based macroscopic emission models cannot provide an accurate estimation of network-wide emissions, implementation of the microscopic emission models for evaluation of overall emissions of a large urban network is costly and time consuming. Although microscopic emission models consider the detailed movements of all vehicles, and as a result, they are able to estimate total emissions more accurately, this method is data intensive and impractical for use on a large network. Therefore, mesoscopic emission models have been introduced to cover the shortages of macroscopic emission models and still estimate the overall emissions in aggregated level by considering traffic conditions, and operational modes of vehicles, in any large urban network.

Traffic data can be provided from different sources with various resolutions. Fine resolution field recorded traffic data is one source; however, this type of data is not usually available for the microscopic emissions modeling for many networks. The results of transportation planning models also provide the aggregated traffic data. Finally, traffic flow models can be classified as microscopic, mesoscopic, and macroscopic levels based on level of aggregation and detail analysis. In this study, in addition to the utilization of the microscopic traffic simulator of AIMSUN to generate detailed traffic data, the macroscopic traffic flow modeling approach is used to derive analytical models for different cases. Table 3 shows the comparison of microscopic and macroscopic traffic and emission models.

Table 3. Comparison of different approaches in traffic and emissions modeling

Modeling Tools	**Traffic**	**Emissions**
Microscopic	Detailed analysis of all individual vehicles at each moment provides an accurate traffic, but it can time consuming and costly for a large network, e.g. Aimsun, Paramics, CORSIM, INTEGRATION	Detailed emission estimates based on the second-by-second speed profiles of all individual vehicles for a limited network, but it is computationally intensive for a large network, e.g. CMEM, VT-Micro, MOVES (project level)
Mesoscopic	Describes traffic streams at an aggregated level, however, considers the microscopic characteristics of traffic flow, such as driving behavior e.g. Cube/Avenue, DYNASMART, TRANSIMS	Utilizes aggregated traffic inputs, however, traffic conditions and congestions as well as typical driving behavior can be considered using driving modes, e.g. VT-Meso,Gori's model, Zegeye models, and ITEM (this study)
Macroscopic	Aggregated models reduce data required to estimate traffic features at a facility. They can be in a form of planning models (Cube/Voyager, EMME/2, TRANPLAN) or analytical model based on KWT	Uses aggregated traffic data to estimate network-wide emissions, typically average speed, especially for large networks, but over-simplifies the effect of speed fluctuations, e.g. EMFAC, MOVES (county level), COPERT

In general, in the last decade, a few efforts have been made to introduce integrated traffic emission models as a mesoscopic approach to estimate aggregated emissions in large-scale traffic networks. These methods use various traffic parameters to consider traffic conditions on the network; however, none of them has made use of macroscopic traffic models to estimate physically realistic drive cycles as a function of network characteristics and network-wide density of vehicles on the network. The MFD provides a way to define traffic states in networks in terms of the fewest number of variables. Therefore, in this study, we use the macroscopic approach and the MFD to construct driving cycles that recognize the effect of traffic conditions on stopping and idling. The proposed approach provides reliable and reproducible emission curves for different levels of congestion, and the result of the model can be used to estimate overall emissions without a need for extensive data collection or repeating the simulation.

Chapter 3 :

The Integrated Traffic Emissions Model (ITEM)

In the last few decades, several approaches to evaluate traffic emissions have been proposed. Microscopic traffic emission models provide the most detailed emission estimation for small and limited networks, while for the large-scale urban networks, macroscopic vehicle fuel consumption and emission models are more feasible for estimating overall emissions. For macroscopic models, the aggregated traffic parameters such as average speed, number of vehicles, and vehicle miles traveled should be provided to the model. These aggregated traffic parameters may be based on a summary of recorded real data, estimates from a traffic simulation, or the results of a macroscopic transportation planning model (Rakha, et al., 2003).

It is common that microscopic fuel consumption and emission models are utilized based on the results of a microscopic traffic simulation, where the detailed traffic characteristics of the network and instantaneous movements of vehicles are produced by the traffic model and are directly used as inputs by the emissions model. For regional planning purposes, aggregated traffic parameters are often estimated by macroscopic traffic models in order to be fed into the macroscopic fuel consumption and emission models. However, existing macroscopic emission model use oversimplified representations of traffic at the aggregated state, which do not recognize the effect of traffic conditions on the driving cycles of vehicles in the network.

3.1 The Need for Better Emission Models at the Aggregated Level

The current state-of-practice is that several emission models are currently in use to evaluate the network-wide emissions generation. However, there are several weaknesses in these models. Although the microscopic fuel consumption and emission models enable us to precisely assess the air pollution generated by vehicles in different scenarios, this type of model requires massive detailed information, which usually is not accessible in a large urban network. Moreover, the computation time for the modeling of a large network can be prohibitive for analyzing and comparing the effectiveness of many potential traffic management strategies. Finally, the output of a microscopic traffic model, which is the input for a microscopic emission model, consists of second-by-second trajectories for every single vehicle. This generates huge datasets that make the microscopic emissions modeling impractical for a large metropolitan network.

3.1.1 The main shortcomings of macroscopic emission models

Macroscopic emission modelling is the main approach to evaluate overall emissions in large urban networks. The current implementation of these models does not provide accurate and dependable estimates, because there is no consideration for the driving behavior of the vehicles. In addition, many assumptions are made for macroscopic traffic modeling, for example that all vehicles travel with a predefined driving cycle without considering the variation of acceleration and deceleration pattern under different conditions. Furthermore, the emission rates applied in the model have been generated under specific circumstances in a laboratory which may be different than estimating them from sample of trajectories traveling on the real network. Finally, another set of assumptions should be made in macroscopic traffic-emission models, which is the negligible effect of variation of external conditions on the emission rates. The external conditions include temperature and humidity, (weather conditions), vehicle load and the variety of engine technologies (vehicle features) and geometry of the links (road conditions).However, in the mesoscopic approach it is possible to consider any of these conditions proportionally by selecting the trajectories or running the probe vehicle under those conditions of interest.

The most critical assumption, which directly reflects the impact of traffic conditions and congestions on emissions, is the usage of an average speed instead of the speed profiles of vehicles in typical macroscopic emissions models. Although the assumption of constant speed may have a negligible impact on the emission results for highway traffic, the stop and go traffic due to signals and the long idling caused by congestion constitute the main part of traffic flowing cities. Therefore, using the average speed of vehicles oversimplifies the fluctuation of speeds and underestimates the emissions. The number of times that vehicles stop and the proportion of time spent in acceleration, deceleration, and idling should be taken into account in some way by considering the vehicle trajectories.

3.1.2 Effect of number of stop and average speed-based models

In order to investigate the impact of the number of vehicle stops as one of the influential factors on overall emissions, the following example has been constructed. Artificial trajectories for 7 cases have been generated with the same average speed of 40 mph and cruising speed of 60 mph, on a segment of a road that us 5.15 miles long. A unique acceleration and deceleration has been used for each trajectory. As shown in Figure 5, the only differences between these trajectories are the number of stops and duration of idling. The other factors of trajectories are kept the same. Using the microscopic emissions model of MOVES (US EPA, 2012.c), the equivalent CO_2 emissions corresponding to each trajectory have been computed. These values are compared with the equivalent CO_2 emissions estimated using the average-speed-based module of MOVES.

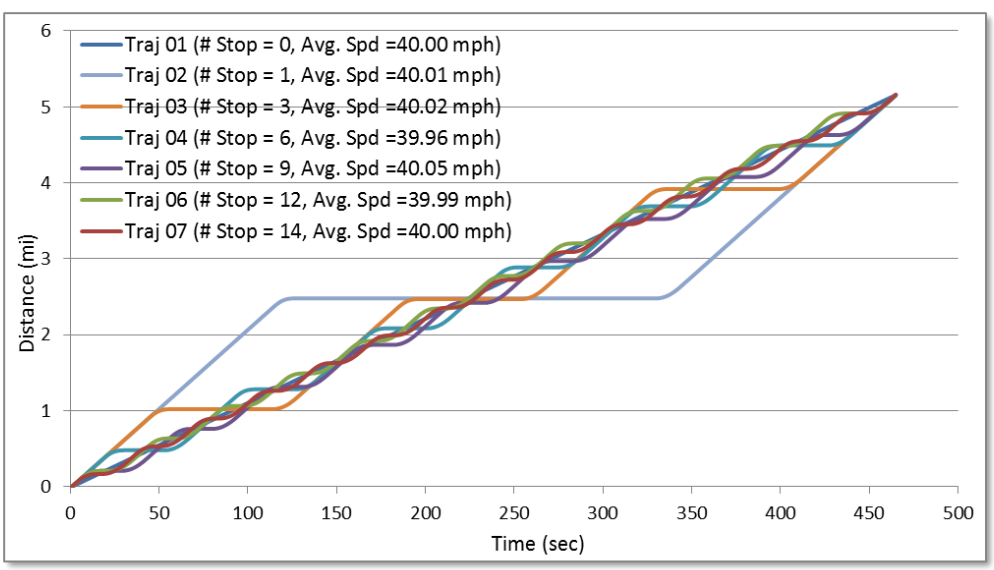


Figure 5. Time-space diagram of similar trajectories with different number of stops

As shown in Figure 6, the increase in the number of vehicle stops increases the total emissions dramatically. Additionally, the comparison of the average-speed-based emissions (the first column in the graph), which is estimated by the macroscopic module of the model, with the emissions of the other scenarios shows that using the macroscopic emissions model may cause significant error in the results.

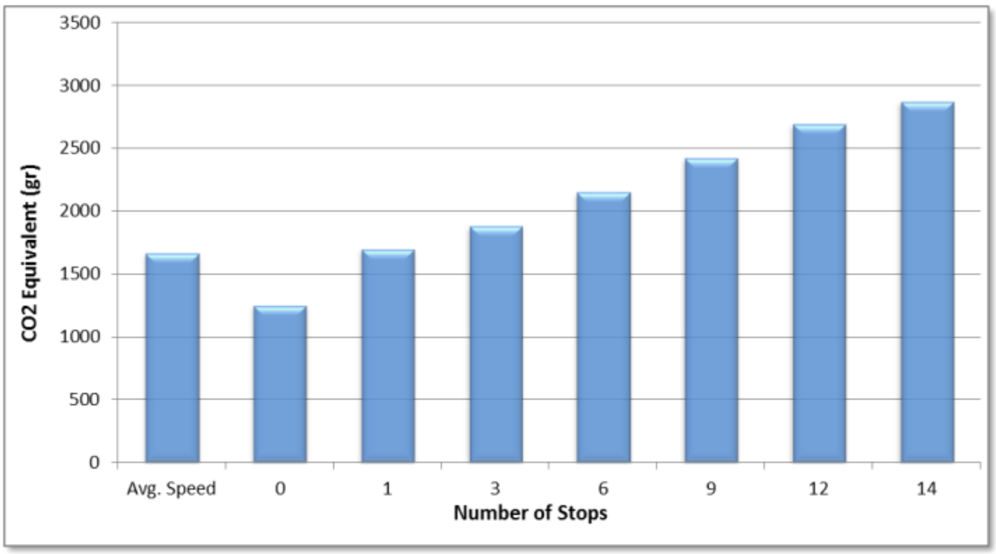


Figure 6. Variation of CO_2emissions for trajectories with various numbers of stops

Table 4 shows the variation of different pollutants caused by each trajectory. These pollutants include: total gaseous hydrocarbons (HC), carbon monoxide (CO), oxides of nitrogen (NO_x), particulate matter (PM_{10}), and total energy consumption for each scenario. In this investigation, only the effect of the number of vehicle stops has been evaluated, however, other traffic factors such as the magnitude and duration of acceleration and deceleration may also have a significant impact on total emissions.

Table 4. Variation of pollutants caused by different trajectories with a same average speed

No. of Stops	HC (gr)	CO (gr)	NO_x (gr)	Equ. CO_2 (gr)	PM_{10} (gr)	Total Energy Consumption (J)
Using Avg. Speed	0.31	10.10	1.65	1664	0.03	2.32E+07
0	0.23	7.60	0.92	1253	0.01	1.74E+07
1	0.29	9.89	2.03	1699	0.03	2.36E+07
3	0.37	16.79	2.35	1880	0.06	2.62E+07
6	0.50	27.14	2.80	2148	0.10	3E+07
9	0.63	37.52	3.23	2422	0.14	3.37E+07
12	0.75	47.88	3.63	2691	0.17	3.74E+07
14	0.84	54.80	3.89	2872	0.20	4.00E+07

As a brief conclusion for this simple analysis, it can be expressed that in order to evaluate total emissions in any large-scale traffic network, it is very important that the traffic conditions are taken into account. On the other hand, due to the size of large networks, a method with reasonable computational requirements should be taken that considers the effect of congestion but does not require an extensive microscopic modeling.

In recent years, mesoscopic emission models have been introduced based on the movement of vehicles in different traffic conditions. In this approach, aggregated traffic parameters such as average cruising speed, the number of vehicle stops, and average stop duration (idling), and average characteristics of acceleration and deceleration are estimated in order to capture the effect of traffic conditions and the impact of congestion (Rakha, et al., 2011; Zegeye, et al., 2013). The major difference between mesoscopic modeling and macroscopic modeling is that mesoscopic emission models utilize the driving cycle components (or similar macroscopic traffic inputs) to take the traffic conditions into account, whereas macroscopic emission models are based on the average speed and total miles travel. Therefore, having the duration of idling and cruising and number and intensity of the acceleration/deceleration, the total emissions can be computed in a way that considers the traffic conditions.

Although this approach has more advantages than macroscopic traffic emission models, there are several disadvantages, especially for estimating the driving-mode-based average traffic parameters. This issue becomes more important in large urban networks, where the number of vehicle stops, and duration of cruising and idling need to be measured or predicted by a microscopic traffic model.

3.2 Proposed Integrated Modeling Approach

To address the issues with recent mesoscopic emission models, in this study two objectives have been followed in parallel. As the first objective, in order to estimate the aggregated driving cycle components, the relationship between the fundamental properties of a network and modal-based aggregated traffic parameters has been investigated. Three main traffic parameters that represent driving cycles and provide the insight to the network-wide traffic conditions include: number of vehicle stops and duration of time spent in cruising and idling modes. In the first step of this phase, an analytical model is used to determine traffic conditions at a single isolated signalized intersection. Therefore, using the kinematic wave theory, the macroscopic connection of the three parameters with the physical characteristics of the intersection is explored. In the second step, microscopic traffic simulation of a simplified arterial represented by a ring network is used to evaluate the similar relationship between the three traffic parameters (number of stops, duration of idling, and duration of cruising) and the fundamental properties of the network. These parameters provide an insight to traffic conditions, and using them for modeling emissions takes into account the impact of stop-and-go traffic in cities.

The second and the main objective of this dissertation is developing the Integrated Traffic Emissions Model (ITEM) in order to provide a tool for regional evaluation of emissions based on mesoscopic connection of modal-based aggregated traffic parameters to the microscopically computed emission rates. This model can assess vehicular emissions in any large-scale urban network by considering concurrent traffic situations without the need for extensive data collection and complex microscopic simulation. In order to show this relationship at this level, an idealized homogeneous, infinite length arterial is considered, which is modeled by a ring network with a single intersection. In the third and last phase of the study, a more realistic grid network is studied, and a similar relationship (between the number of vehicles circulating in the network and the corresponding total emissions) has been evaluated.

3.2.1 The integrated modeling tools

In order to implement the proposed modeling framework, a microscopic traffic simulator and a microscopic emissions model are required. For the traffic simulation, the microscopic traffic model of AIMSUN (Barceló, 2013) has been used; however, this model can be replaced by any other microscopic simulator or even fine resolution real-world data. Three microscopic emission models have been considered as the possible emission models, including: the Comprehensive Modal Emissions Model (CMEM) (Scora & Barth, 2006), MOtor Vehicle Emissions Simulator (MOVES) (US EPA, 2012.c), and Virginia Tech Microscopic energy and emissions mode (VT-Micro) (Ahn, et al., 2002). Since there is no major difference in the methodology and results of these models and MOVES is widely used and mandated to be used for wide range of projects in all states other than California, MOVES will be utilized for microscopic computation of emissions in the rest of this study.

Depending on the selected emissions model and its ability to estimate different air pollutants, various emissions can be evaluated with the same method. Due to the importance of the contribution of road transportation to the generation of CO_2 emissions and the impact of CO_2 on climate change and global warming, the amount of CO_2 equivalent has been selected for the evaluation of emissions. Equivalent CO_2 is a good representative of different pollutants which are considered greenhouse gases by using the index of global warming potential (GWP). However, by using the same method, any other pollutant of interest can be evaluated by the proposed Integrated Traffic Emissions Model (ITEM).

3.2.2 The model’s traffic components and emission factors

In the first step of developing the traffic emissions model, the most influential parameters that contribute to the generation of vehicle emissions are investigated. Then, according to them, the general format of the model is derived. Although, a number of factors affect the vehicle emissions, in this study only traffic parameters, known as operating parameters (e.g. speed and acceleration), are considered in the proposed model. It is assumed that the other factors, including average vehicle characteristics and external conditions remain the same across the scenarios that are evaluated. This would be a reasonable assumption for assessing the effect of traffic control policies on emissions.

Idling in a queue as a result of congestion and acceleration and deceleration, mainly caused by stop-and-go traffic, are the major influencing parameters on total emissions. Driving behavior, which is generally known as the pattern of driver acceleration or deceleration, the magnitude and duration of acceleration and the frequency of speed fluctuations are other important factors that affect total emissions. In this section, using simulated trajectories generated by the Aimsun traffic micro-simulation software, the components of driving cycles have been extracted. A complete driving cycle may include cruising and idling and a complete cycle of deceleration and acceleration associated with a complete stop. A complete acceleration and deceleration is defined when a speed profile changes between zero and free flow speed using predefined thresholds for speed and acceleration (will be explained in the next section). In order to analyze drive cycles, an algorithm has been used (written in a Matlab code) which will be explained in the next section. Then, by using MOVES, the emissions for each cycle of acceleration and deceleration have been calculated, and the resulting greenhouse gas emission estimates show the distribution and average emissions per vehicle stop. In the same way, emission factors per unit time spent in idling and cruising have been estimated.

The main objective of this study is to investigate the impact of traffic control on network-wide emissions. So, simplified analytical models have been derived in the next two chapters to estimate the number of stops and proportion of time spent in cruising and idling modes. However, simulated trajectories have been used only to obtain the average values for driving behavior as well as to validate the proposed method.

3.2.3 Extracting characteristics of driving modes

In order to extract the characteristic of driving modes, including the typical pattern of acceleration and deceleration, and the average free flow speed, a vehicle's trajectory must be divided into four driving modes of acceleration, deceleration, cruising and idling. Depending on the origin of data (real-world or simulated data) a screening and selection of trajectories may be needed. For example, if real trajectories acquired by video processing or similar methods are used, some screening and preprocessing of trajectories may be needed due to noise and errors involved with data recording and processing. Furthermore, if the analysis is used in a larger metropolitan network with numerous vehicles, instead of the whole population of trajectories a sample of them should be selected that represents typical characteristics of the driving modes. In screening the trajectories, improper vehicle trajectories (like noisy data, very short trajectories, and vehicles that leave the section before the intersection) should be eliminated. In some cases, the noise and errors caused during image-processing can be removed, by a procedure called smoothing of the trajectories.

3.2.3.1 Selection of Trajectories

In this project, Aimsun has been used to generate simulated data within a single isolated signalized intersection, a ring network, and a simple grid network. In each of these models, hundreds of trajectories have been generated in various traffic conditions.

All model parameters are considered to be random variables with specified distributions. Various traffic conditions, including free flow and saturated conditions have been tested and vehicles' trajectories have been recorded with one second resolution.

Since in this simple isolated intersection, it is assumed to have no turns at the intersection(s), all vehicle trajectories can be used for extracting driving mode characteristics. However, for the case of over-saturated condition with numerous vehicles, a number of trajectories are randomly selected. Next, we present how to divide the trajectories to driving modes.

3.2.3.2 Selection of Acceleration/Deceleration Event

In order to relate the emissions of greenhouse gases to the number of vehicle stops in traffic, we need to look at the complete driving cycle of a stop, which is composed of one deceleration from free flow speed to stop and one acceleration from stop to free flow speed. For some trajectories there may be more than one pair of acceleration and deceleration events and for other trajectories there may be only a partial stop or no stop at all depending on the relative signal timings. An algorithm has been developed to extract only complete acceleration and deceleration cycles and filter those which do not begin or end at the stop or free flow speed.

The algorithm, which has been developed in Matlab, uses threshold values to filter the vehicle trajectory and only select those cycles that have a continuous trend of speed change with minimal interruptions. These thresholds are:

- *Speed Threshold (ST=1 mph):* the vehicle moving slower than this speed is assumed to be stopped.

- *Acceleration Threshold (AT=0.2 mph/s):* when the absolute value of acceleration is less than this threshold, the speed is assumed to be constant.
- *Speed Fluctuation (SF=5 mph):* the vehicle is assumed to be accelerating (or decelerating) as long as no deceleration (or acceleration) is observed for more than this range of speed variation.
- *Maximum Duration of Reverse Acceleration (MDRA=1 sec):* the vehicle is assumed to be accelerating (or decelerating) as long as no deceleration (or acceleration) is observed for longer than this period.
- *Maximum Duration of Low Acceleration (MDLA=3 sec):* a single acceleration event is assumed to end if acceleration below AT is observed for more than this duration.
- *Minimum Duration of Acceleration (MDA=2 sec):*a single acceleration event is neglected if it is shorter than this duration.

The screening algorithm that selects the relevant acceleration and deceleration events takes the following steps:

1. *Reading Trajectory:* For each trajectory, the code parses the lines of the dataset to extract complete acceleration and deceleration events. When the end of a trajectory is reached, the next trajectory in the data set is parsed.
2. *Finding the start of acceleration / deceleration:* An acceleration or deceleration event is recorded starting at the first time when $|a(t)| > AT$. We denote this start time as t_s.
3. *Recording the main event:* The event is recorded until an interruption happens that indicates a possible end of the acceleration/deceleration

event. The time of the potential end of the event is designated t_e, so the conditions at time $t = t_s + dt$ are:

- the acceleration has changed direction, $a(t) \times a(t_e) < 0$;
- the acceleration drops below the threshold, $|a(t)| < AT$; or
- the speed drops below the threshold, $v(t) < ST$.

When the end of the trajectory is reached, the algorithm proceeds directly to step 5.

4. *Temporary recording:* When a potential end of an acceleration or deceleration event is identified, the algorithm begins temporarily recording until either:

   a) the sequence of data meets at least one of the criteria to end the event:

   - $v(t) < ST$;
   - $v(t) - v(t_e) > SF$ and $a(t).a(t_e) < 0$;
   - $t - t_e > MDRA$ and $a(t).a(t_e) < 0$; or
   - $t - t_e > MDLA$ and $|a(t)| < AT$.

   or b) none of the criteria are violated, so the temporary recording is added to the main event and the recording of the main acceleration/deceleration event continues (return to step 3).

5. *Decision making for the event:* If recording of the main event is interrupted for any reason, it should be decided whether or not this recorded data is good to keep as an acceleration cycle or if it should be discarded. If the end of the trajectory is not reached, the algorithm proceeds to step 2 to identify the next event, otherwise the algorithm

proceeds to step 1 to process the next vehicle trajectory. The conditions to keep the event are:

- $t_e - t_s > MIDA$;
- $v(t_s) < ST$ and $v(t_e) > v_f - ST$; or
- $v(t_s) > v_f - ST$ and $v(t_e) < ST$.

Using this algorithm to select complete acceleration and deceleration cycles, the trajectories are divided into four driving modes of acceleration, deceleration, cruising, and idling. Figure 7(a) shows a sample trajectory of vehicle in a time-space diagram and Figure 7(b) shows the speed profile of the vehicle that is divided into four driving cycle components.

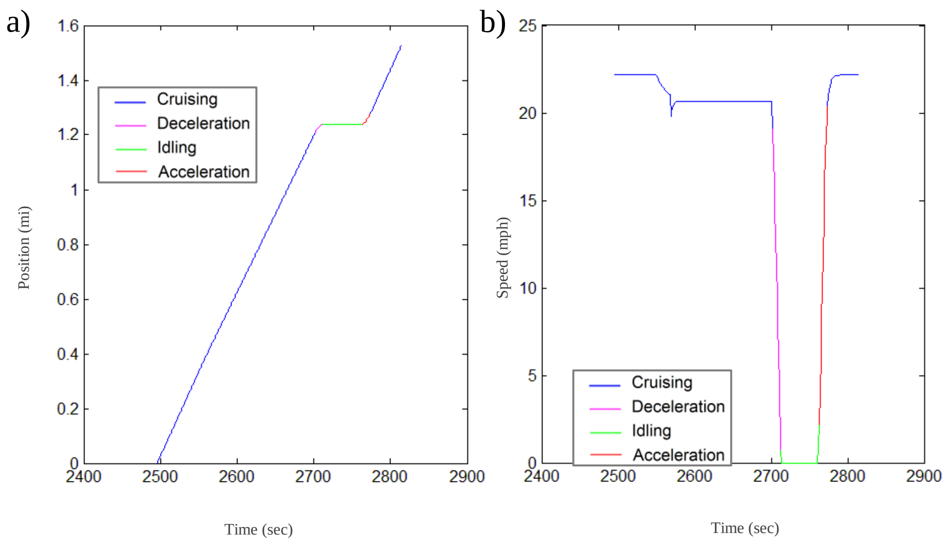


Figure 7. Time-Space Diagram and Speed Profile of a Sample Trajectory Divided into Driving Modes

3.2.4 Calculation of emission factors

After preprocessing the data and extracting the driving modes, we have numerous speed profiles representing accelerations and decelerations, which can be associated with emission values by using the microscopic emissions model. In order to run the Project Level of EPA-MOVES as the emissions model, in addition to the vehicle speeds, the model requires some non-traffic information (e.g., time and spatial span, meteorological data, road and vehicle type, etc.), which have an effect on the total magnitude of emissions. Since we are interested in comparing the effect of different traffic conditions on emissions, all other non-traffic inputs of MOVES are held fixed for the analysis. Therefore, the model isolates the effect of traffic volumes and signal timings on emissions. The Link Drive Schedule method is used in MOVES to calculate emissions by converting second-by-second trajectory data into operating mode distributions that MOVES uses to calculate detailed emission estimates. Thus, an emission rate for each acceleration and deceleration event is calculated from the second-by-second list of speeds extracted using the algorithm described in the preceding section.

As mentioned before, this method can be applied to evaluate various vehicular emissions depending on the capability of the microscopic emission model used at this stage, however, due to the importance of CO_2, the focus of this study is on estimating the CO_2 equivalent (CO2e) as a representation of GHGs generated by the vehicles.

By aggregating the results, we can have the average characteristics of accelerations and decelerations. According to the simulation results, the average acceleration takes 13.2 seconds, which causes approximately 34.54 g CO2e (grams of CO_2 equivalent) and the average deceleration takes 8.8 seconds with corresponding emissions of 14.33 g CO2e. A combination of one complete deceleration and one complete acceleration results in average emissions associated with a single complete stop of 48.88 g CO2e. On the other hand, using the same method and the microscopic emissions model the emissions rate for cruising and idling can be computed. Based on the simulated trajectories, the average free flow speed of vehicles is 23.7 mph and the corresponding emissions rate is 2.187 g CO_2e/sec while cruising. Similarly, the emissions rate of idling is 0.881 g CO_2e/sec.

There is an alternative way to calculate the emission factors based on the recorded traffic data. In this method instead of physically dividing the trajectories into driving modes, we can use the linear regression analysis to relate total emissions of each trajectory, calculated directly by the microscopic emissions model as the dependent variable, to its corresponding traffic parameters including number of vehicle stops and duration of time spent in cruising and idling as independent variables. The fitted model provides the emission factors per stop and time spent cruising and idling, which are 51.498 g CO2e per stop, 2.037g CO2e per second of cruising with an average speed of 23.7 mph, and 0.685g CO2e per second of idling.

Having the estimated emission factors for each driving mode, the overall network-wide emissions can be calculated by the Integrated Traffic-Emissions Model (ITEM). As shown in equation (9), the total emissions are the sum of aggregated traffic parameters multiplied by the emission factors obtained from the typical characteristics of each driving mode:

$$E_{total} = N_s E_s + T_{id} E_{id} + T_{cr} E_{cr} \tag{9}$$

where:

N_s is the total number of vehicles' stops;

E_s is the corresponding emissions factor per stop (gram/stop);

T_{id} is the total time spent in idling mode (sec)

E_{id} is the idling emissions factor (gram/sec of idling)

T_{cr} is the total time spent in cruising mode (sec)

E_{cr} is the cruising emissions factor (gram/sec of cruising)

Comparing estimated total emissions using emission factors obtained from different methods, the emission factors for different driving modes can be evaluated. In order to compare the two sets of results, total emissions of each trajectory estimated by using each set of emission factors are plotted versus total emissions of the trajectory directly calculated by the microscopic emissions model. Figure 8 and Figure 9 show the comparison of both estimates using the physically calculated and mathematically regressed emission factors with the emission factors directly computed by the microscopic emissions model (MOVES).

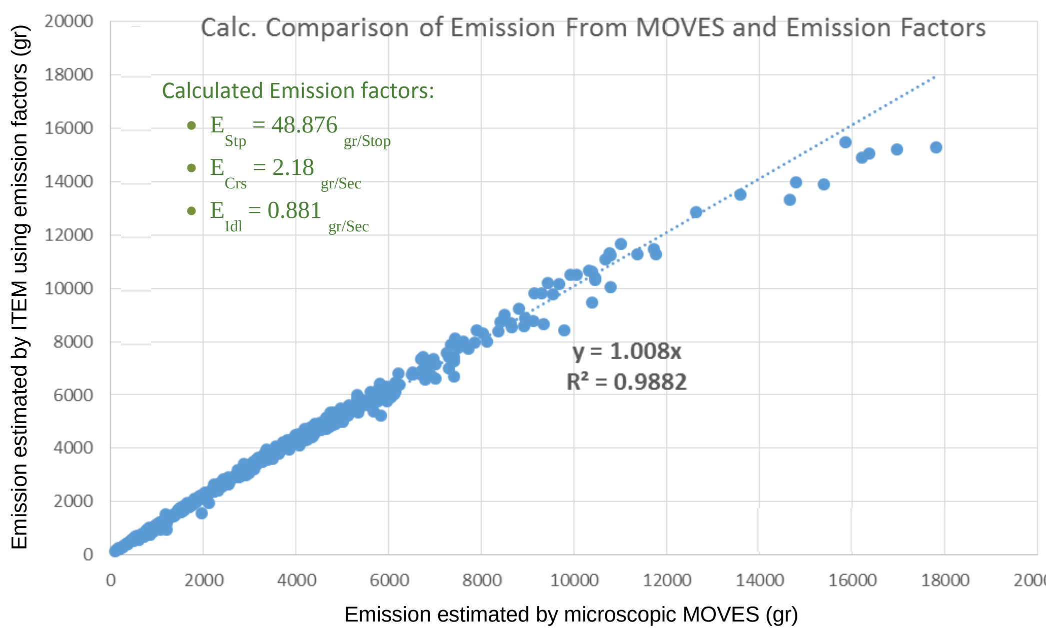


Figure 8. Comparison of emissions calculated physically with the emissions directly computed by MOVES

As shown in the figures, both sets of emission factors provide reliable estimates, however, comparison results show that the slope of the line of the calculated emission factors is negligibly higher than 1 (y = 1.008x) which means slight overestimation while the regressed emission factors has a slope of less than 1 (y = 0.963x) which causes underestimation. In addition, the calculated emission factors provide an acceptable R squared value (R^2) of 0.988. Therefore, in the rest of this study, we used the emission factors derived from the extracted characteristics of the driving modes.

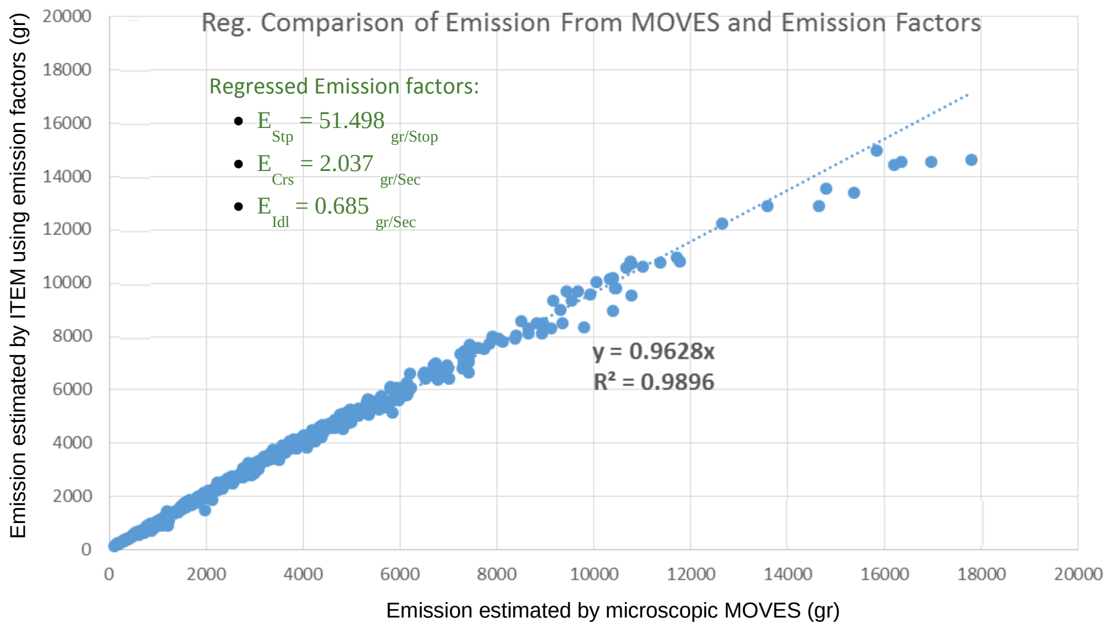


Figure 9. Comparison of emissions estimation based on regression with the emissions directly computed by MOVES

A similar method can be implemented with other microscopic emission models to calculate emission factors. For example, we have used the CMEM microscopic emissions model with the same speed profiles of the accelerations and decelerations, and we have calculated the emission factors for each driving mode. According to the results, the new emission factors are 36.02 grams CO_2 per stop, 1.78 grams CO_2 per second cruising with an average speed of 23.7 mph, and 1.02 grams CO_2 per second idling. The results show a consistency between the estimates and exact emission values computed by the emissions model. Figure 10 shows the comparison of the results from CMEM and MOVES. Although there is a general difference between the estimates from these two models, the estimated emissions by ITEM and those using the emission factors computed by a microscopic emissions model (e.g., MOVES or CMEM) are consistent with the emission results computed directly from the same model. Furthermore, the errors caused by using ITEM (i.e., using the emission factors and average traffic parameters) are less than the difference between the magnitudes of estimates by the models.

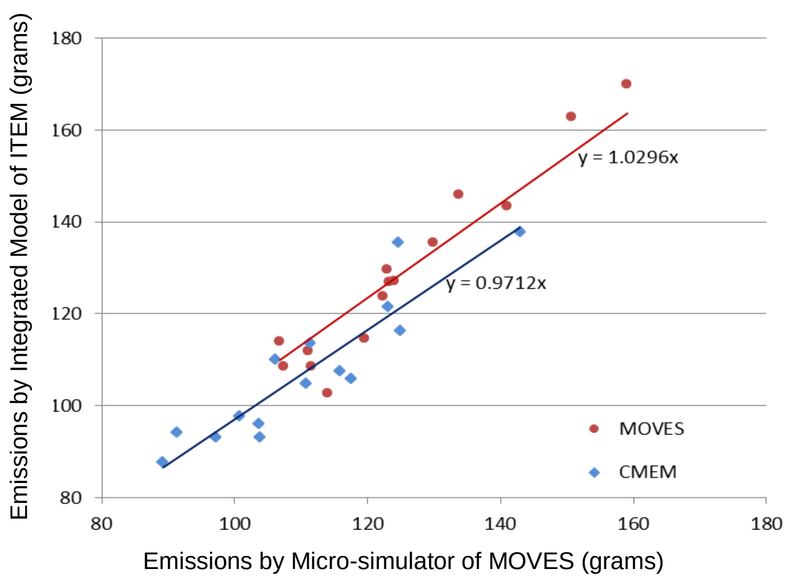


Figure 10. Comparison of the Emission results Estimated by the Integrated Model (ITEM) with the Emissions Computed Directly by MOVES and CMEM.

Chapter 4 :

Application of ITEM in a Signalized Intersection

The proposed Integrated Traffic-Emissions Model (ITEM) can be used with aggregated traffic data originated from field data collection, simulation, or analytical modeling. In the first part of this chapter, an analytical traffic model is derived for a single isolated signalized intersection. Then, the aggregated characteristics of driving modes are fed to the ITEM to estimate total emissions under various conditions. Several scenarios are defined to evaluate the effect of traffic volume and signal timing on vehicular emissions. In order to calculate CO_2emissions, the emission factors estimated by MOVES associated with each driving mode are utilized to estimate total emissions.

4.1 Analytical Traffic Model

In this section, the traffic states at an intersection approach are modeled analytically based on kinematic wave theory (Lighthill & Whitham, 1955; Richards, 1956). In the past decades, numerous efforts have been made to estimate queue length, number of stops, and delay at an isolated signalized intersection for either under-saturated or over-saturated conditions (Webster & Cobbe, 1966; Cronje, 1983). Some other studies have been conducted to estimate these macroscopic traffic parameters based on kinematic wave theory (Zheng & van Zuylen, 2010; Cheng, et al., 2011). Finally, in other research the number of stops has been estimated based on speed profiles (Rakha, et al., 2001), and then the impact of vehicle stops on fuel consumption and emissions is investigated (Rakha & Ding, 2003).

In this study, the kinematic wave theory is used to estimate three traffic parameters that represent driving cycle components, and have a major influence on vehicular emissions. These parameters include total number of stops, total time spent in cruising and total time spent in idling. In the isolated intersection, it is assumed that the approach is a homogeneous road section exhibiting a triangular fundamental diagram characterized by free flow speed (v), saturation flow (s), and jam density (k_j). It is assumed that vehicles arrive at a flow $q < s$. In this section, in order to keep the calculations simple, it is assumed that the arrivals are uniform; however, in the next section, for the ring-shape network, this assumption is not necessary since the arrivals are controlled by the upstream intersection, which in the ring model is represented by the platoon arriving from the previous signal cycle. In the case of networks (either ring shape or grid), the stochasticity in driving behavior and vehicles' speed and acceleration, causes non-uniform arrivals to the downstream intersections. Non-uniform arrivals do not change the proposed equations significantly; however, it adds a random variable to the model that accounts for the probability of the arrival flow. In this case, the intersection may experience over-saturated conditions in some signal cycles and under-saturated conditions in other cycles.

The traffic approaches a signal that is timed with cycle length C, which is composed of effective red time, R, and effective green time, G, such that $C = R + G$. Additionally, in order to consider possible over-saturated conditions, there may be a residual queue of n_r vehicles that were not served in the previous cycle. A time-space diagram of the traffic states in the road segment upstream and immediately downstream of the intersection are shown in Figure 11. If the vehicles accelerate and decelerate infinitely fast, then the vehicles will instantaneously change speed on the interface between the vehicles idling in the queue and the vehicles traveling at the cruising speed as shown in Figure 11(a) and (b).

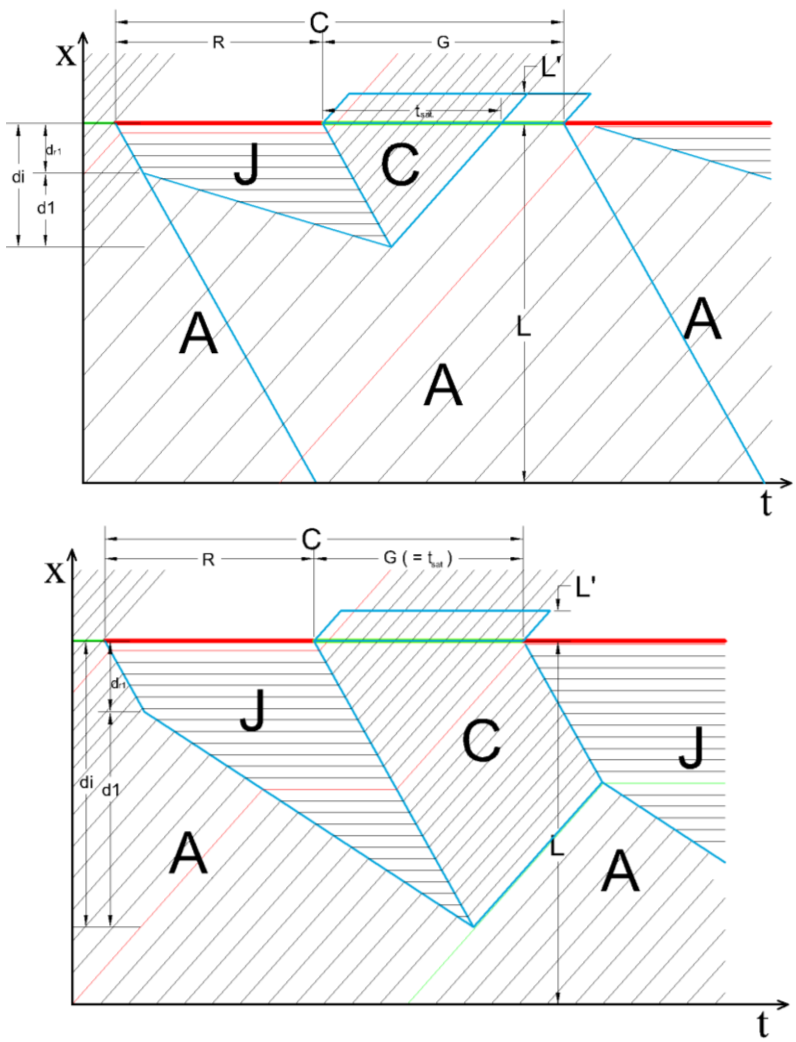


Figure 11. Schematic of time-space diagram for (a) Under-saturated conditions, (b) over-saturated conditions

If the vehicles accelerate and decelerate infinitely fast, then the interface between the vehicles idling in the queue and the vehicles traveling at the cruising speed is straight (dashed) line as shown in the Figure 12. However, in reality, the vehicles at an intersection require some time to decelerate from cruising speed to a stop and to accelerate from a stop up cruising speed. If the vehicle speed changes at a constant rate for the duration of acceleration, then the curvature of the more realistic trajectory is parabolic as shown by solid line in Figure 12. Half of the vehicle hours traveled while accelerating is displaced from the idling state and the other half is displaced from the cruising state. So, the calculation of the idling and cruising times is straightforward it can be calculated by using the simple shockwave model. These calculations depend on the average duration of acceleration, t_{acc}, and the average duration of deceleration, t_{dec}.

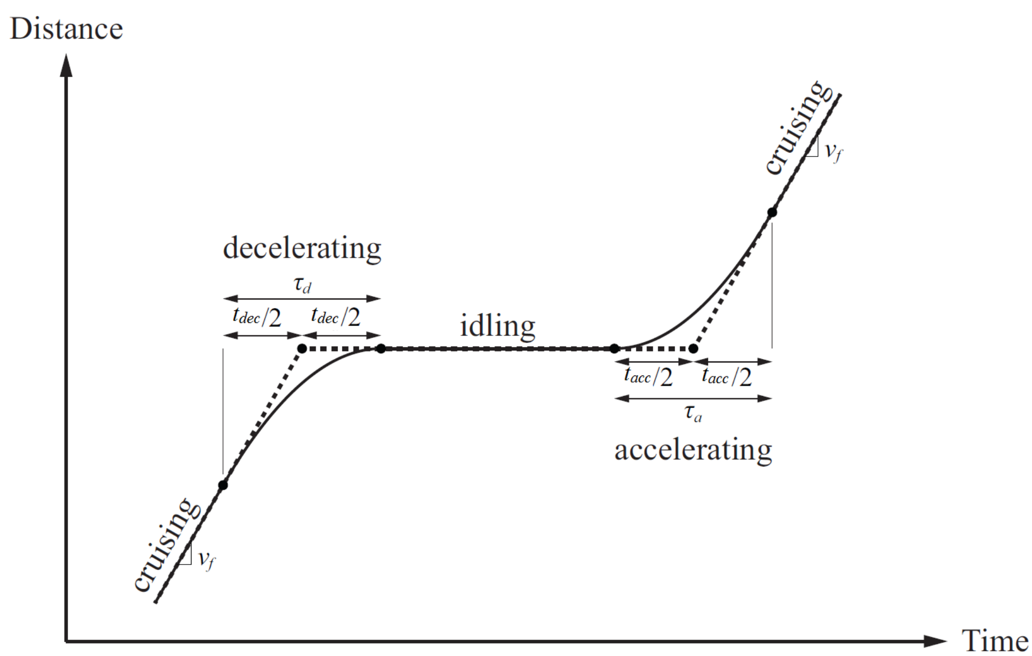


Figure 12. Schematic trajectory with constant acceleration rates (solid) and a simplified piecewise linear trajectory (dashed)

Based on the length of the queue, including the vehicles in the residual queue, it is straightforward to estimate the number of vehicles that stop during the cycle, N_s. This follows from the geometry of the triangular queued state in Figure 11:

$$N_s = N_r + \frac{Rsq}{s-q} \tag{10}$$

This expression can also be obtained from queuing theory. In order to make fair comparisons between the emissions that result from different traffic conditions, we want to ensure that we analyze a long enough road segment L to contain the entire queue of vehicles that may develop during a signal cycle of interest. Therefore, the analysis section should extend $L \geq N_s/k_j$ upstream of the intersection and also $L' = t_{acc}v_f/2$ downstream in order to account for the cruising distance that is lost due to acceleration.

The total vehicle time spent idling, T_{id}, is calculated by adding the time that vehicles in the residual queue spend idling to the time that vehicles arriving at the back of the queue spend idling. Without accounting for the effects of acceleration and deceleration, these times would be based on R. Accounting for acceleration and deceleration time, the longest time spent completely idling is $R - (t_{acc} + t_{dec})/2$. Thus, the total time spent idling per signal cycle is:

$$T_{id} = N_r\left(R - \frac{t_{acc} + t_{dec}}{2}\right) + \frac{sq}{2(s-q)}\left(R - \frac{t_{acc} + t_{dec}}{2}\right)^2 \tag{11}$$

Finally, in order to capture all of the driving states that are associated with vehicular emissions, we must account for the total vehicle time spent traveling at the free flow speed, T_{cr}. We considered the elements of the expression for cruising time associated with under-saturated traffic conditions and then we used an adjustment factor to account for over-saturated conditions. Making use of the fact that in the simple shockwave model with infinite acceleration vehicles are either stopped or traveling at the free flow speed, the cruising time is simply the total vehicle distance traveled divided by the free flow speed. In under-saturated conditions, each vehicle that arrives at the intersection is served within one cycle, and travels the full distance of the analysis segment $L + t_{acc}v_f/2$. Each vehicle from the residual queue travels on average half of the length of the residual queue and the downstream segment $N_r/2k_j + t_{acc}v_f/2$. From this total time, half of the acceleration and deceleration time attributed to the number of vehicle stops must be subtracted. Thus, the total vehicle time spent traveling at the free flow speed is:

$$T_{cr} = \left(\frac{{N_r}^2}{2k_j v_f} + \frac{N_r t_{acc}}{2}\right) + qC\left(\frac{L}{v_f} + \frac{t_{acc}}{2}\right) - \frac{Rsq}{s-q}\frac{t_{acc} + t_{dec}}{2} - \psi \qquad (12)$$

where, ψ is the cruising time lost when the signal is over-saturated, and the number of vehicles must stop before they are served is $N_{r,next} = N_s - sG$. Since the first three terms of (12) are derived assuming that all vehicles are served, the distance (and vehicle time) not traveled by the $N_{r,next}$ vehicles must be accounted for. Therefore,

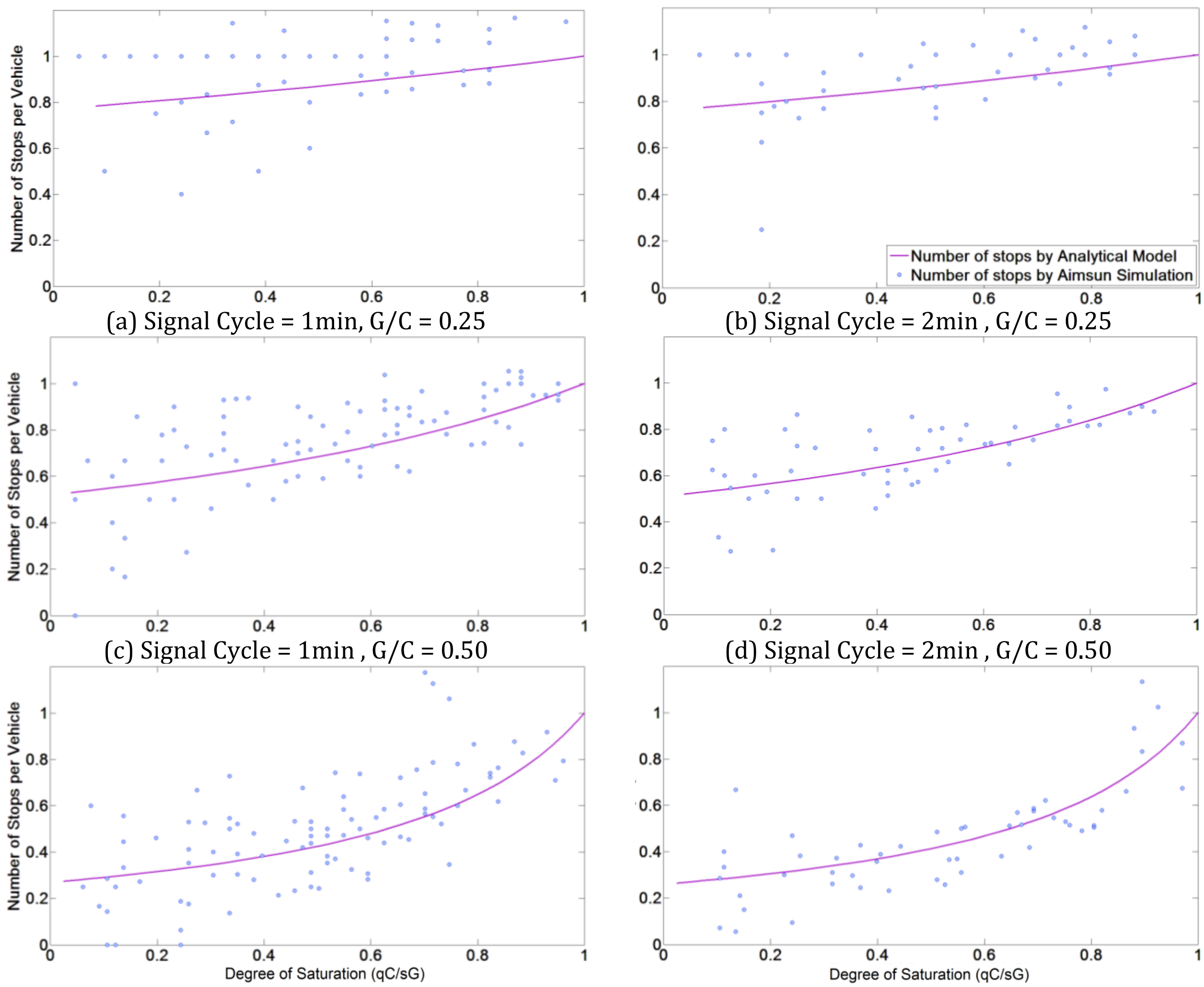
$$\psi = \begin{cases} \dfrac{{N_{r,next}}^2}{2k_j v_f} + \dfrac{N_{r,next} t_{acc}}{2} & \text{if} N_r + qC > sG \\ 0 & \text{if} N_r + qC \le sG \end{cases} \qquad (13)$$

where, the condition determining whether the signal is over-saturated or under-saturated based on the residual queue, arriving demand, and effective green time.

4.2 Validating the Analytical Traffic Model

The number of stops, the time spent idling, and the time spent cruising at free flow speed are the components of the driving cycle for vehicles approaching an intersection. The analytical expressions presented in the previous section enable us to estimate each of these values based on traffic volume and signal characteristics such as the cycle length, effective green and red times, and the saturation flow when a queue is served. In order to validate the results estimated by the analytical traffic model, the estimated results are compared with results computed by Aimsun for various traffic conditions and signal timings. We used 6 different scenarios with two signal cycles (C) of 1 and 2 minutes, and three green ratios, i.e. green to signal cycle length, (G/C) of 0.25, 0.50, and 0.75.

Figure 13 shows the variation of the number of vehicle stops calculated by the analytical model and the simulation for various arrival flows relative to the intersection capacity (degrees of saturation). The number of stops estimated by the analytical model is presented by the magenta line which provides a continuous and smooth estimation for various traffic conditions, while each blue dot represents a simulation run with specific arrival rate. Comparison of different conditions shows that for a very low capacity of the intersection there is only a limited time for a few cars to pass and the intersection is very vulnerable to becoming saturated with any fluctuation in arrival flow. Therefore, the analytical model's estimation is not matched very well with the simulated scenarios; however, it shows the increasing trend of the number of stops as the demand approaches the capacity of the intersection. When the capacity of the intersection is increased by increasing the signal cycle length or G/C ratio, the analytical model easily predicts the number of stops that may occur in reality. It should be noted that except for the scenarios with very low capacity, the mean of simulated results agrees with the one from the analytical model; therefore, there is no systematic bias. However, the variance of the results depends on the time interval for aggregation, and large variation may be seen due to a short aggregation period.



(a) Signal Cycle = 1min, G/C = 0.25
(b) Signal Cycle = 2min , G/C = 0.25
(c) Signal Cycle = 1min , G/C = 0.50
(d) Signal Cycle = 2min , G/C = 0.50
(e) Signal Cycle = 1min , G/C = 0.75
(f) Signal Cycle = 2min , G/C = 0.75

Figure 13. Variation of number of stops for various degrees of saturation

Similarly, the time spent cruising and idling can be predicted by the analytical model at different traffic conditions. Figure 14 shows the variation of the time spent in cruising and idling states estimated by the analytical model versus degree of saturation (the ratio of demand to capacity of the intersection), and they are validated by the simulated results under different scenarios.

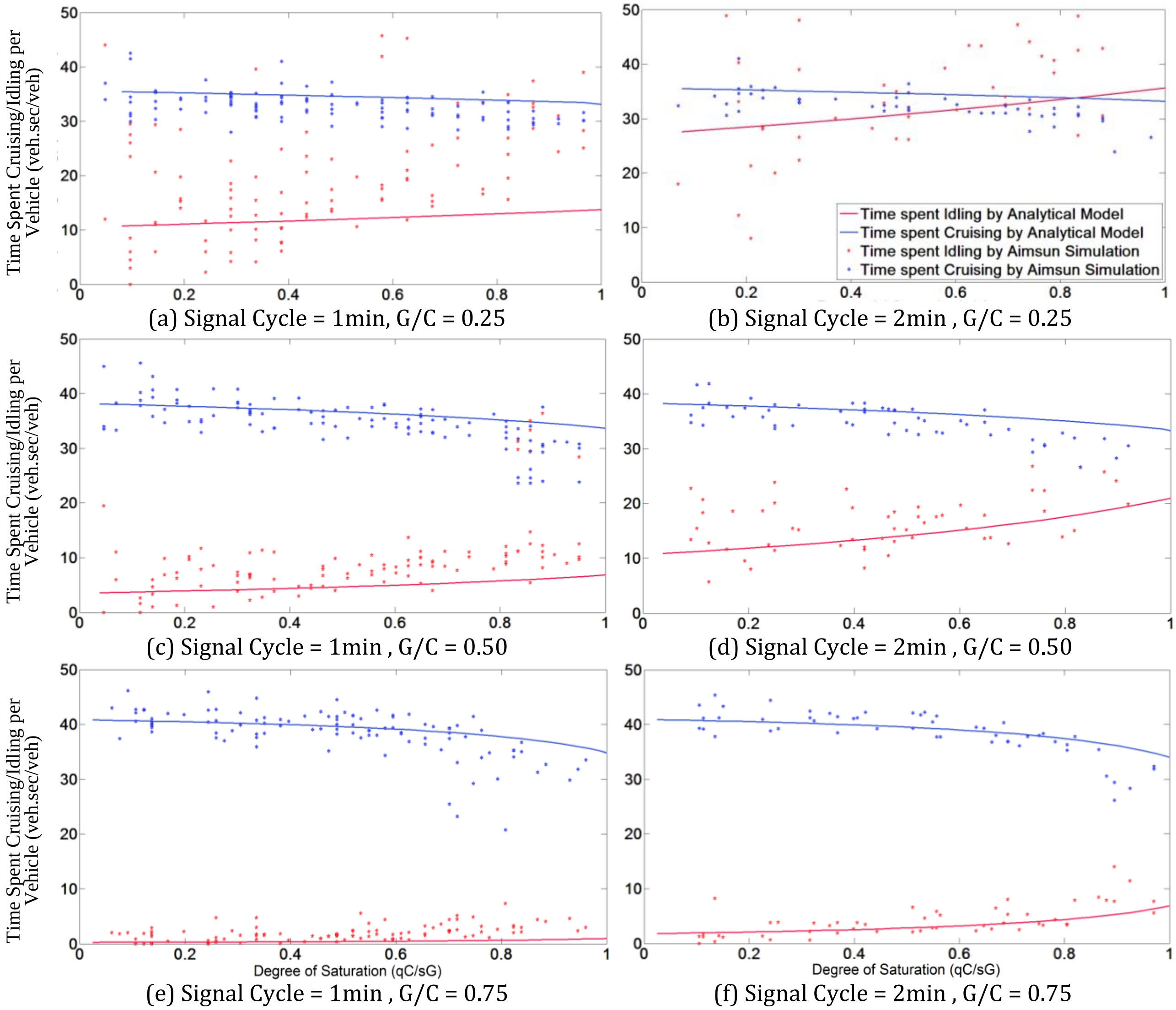


Figure 14. Variation of number of stops for various degrees of saturation

Similar to the number of stops, by reducing the capacity of the intersection though signal timings, the chance of over-saturated intersection increases and it may cause more outliers in the simulation results. In other words, because of the stochasticity in the simulation and the inclusion of some over-saturated phases in the averages over a specific period of time, the results of the simulation do not present a perfectly smooth trend. At the same time, because of the deterministic nature of the analytical model, the results will always be under-saturated. This results to underestimation of the time spent in idling as well as the number of stops and overestimation of the time spent in cruising. It is basically because an over-saturated cycle will result in more stops in the simulation than predicted. It can be seen that the longer signal cycles and higher green ratio, the trend of variation becomes more similar in both the analytical and microsimulation results.

In these graphs, the duration of the cruising state depends on the length of the links. If these links are too long, the effect of cruising will dominate and may affect the other states. In this case, a 0.4-mile link is used upstream of the intersection, and a 0.1-mile link is used downstream of the intersection. Having estimates for the number of stops and cruising and idling durations, and implementing the emission factors, total emissions for each traffic state can be estimated.

4.3 Emission Estimates by ITEM

Similar to the evaluation of the number of stops and time spent in each driving mode for different levels of arrival flow and degrees of saturation, the variation of emissions caused by these factors can be quantified. As explained before, typical emission factors corresponding to each driving state have been calculated using MOVES. For example, to estimate emissions corresponding to the number of stops, the average emissions value for a complete cycle of acceleration and deceleration is used as the emissions factor per stop; $E_s = 4.88$ g CO_2eq per stop. In addition, as described in the previous section, to calculate the emission factors for the idling and cruising states, the MOVES model is used and two simple vehicle trajectories are considered: zero speed and free flow speed (24 mph). The emission rates estimated from MOVES for these constant speed trajectories are $E_{id} = 0.881$ g CO_2eq per second of idling and $E_{cr} = 2.187$ g CO_2eq per second of cruising with the speed of 24 mph.

As explained in the previous chapter, total emissions can be calculated by the integrated model presented in equation (9). Even simple inspection of the equation is useful for understanding the relative impact of idling time (delay) and the number of vehicle stops on total emissions. Figure 15 shows the contribution of each of these components to the total emissions at different degrees of saturation. It is clear from the figure that as arriving traffic demand growths, total emissions increase, even though the emissions from cruising vehicles decline due to spending more time in acceleration, deceleration, and idling.

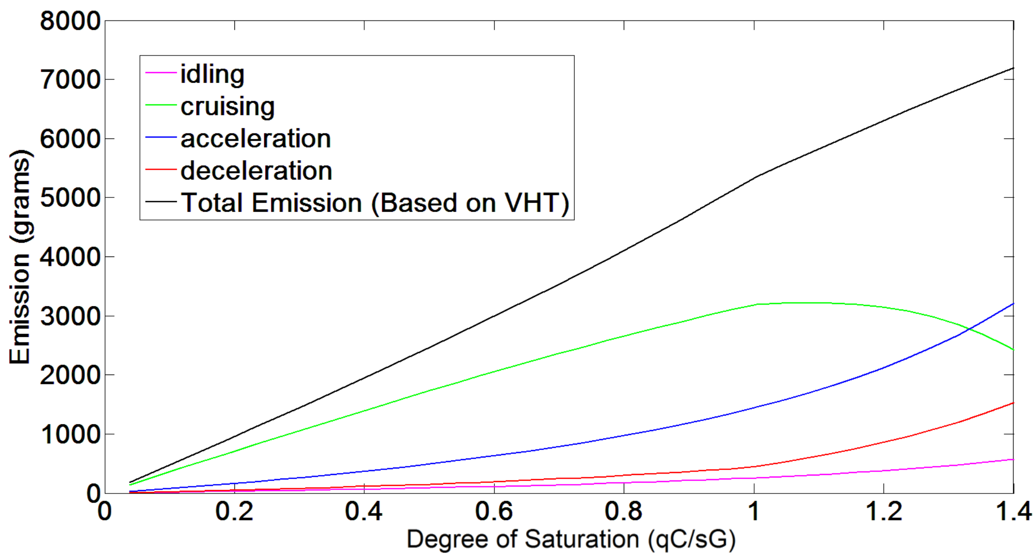


Figure 15. Contribution of each driving state in total emissions (based on VHT) at different traffic states using the base case scenario (C = 60 sec, and G/C = 0.5)

It is also clear from the figure that the emissions associated with the vehicle stops (summation of acceleration and deceleration) are significantly more than the emissions caused by the vehicle delay which is associated with the idling mode. Furthermore, the comparison of each driving mode's emission contribution shows that the higher the capacity of the intersection, the less the percentage of emissions caused by stopping and idling and the higher the contribution from cruising. Finally, and importantly, as shown in Figure 16, the average emissions per vehicle miles traveled increases dramatically once the intersection becomes over-saturated.

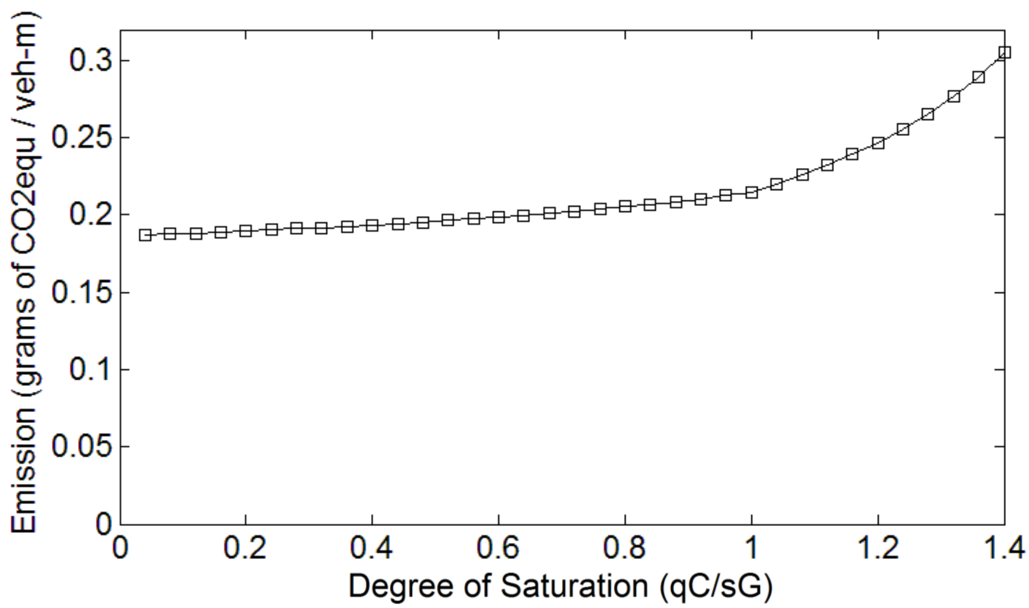
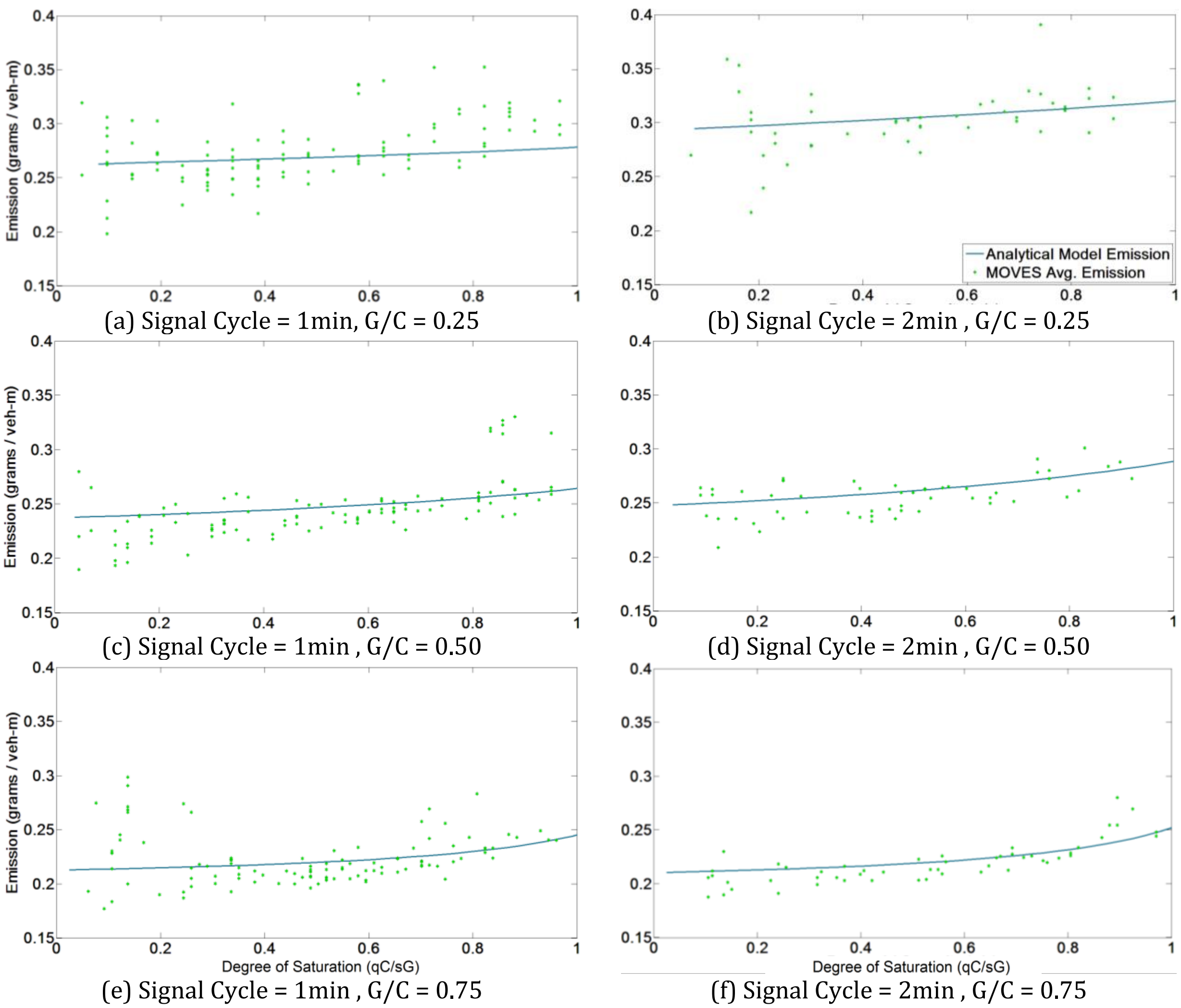


Figure 16. Total network-wide emissions per Vehicle Miles Traveled (VMT) at various saturation conditions

It should be noted that in Figure 15, in order to show the contribution of idling in total emissions, the graphs are plotted based on emissions per time traveled (VHT) which is not very useful as emissions per distance (VMT) for the evaluation emissions generation of trips, since the main purpose of a trip is traveling for a specific distance. In general, it is best to compare total emissions per vehicle-mile traveled, because the increased congestion changes the amount of time that vehicles spend on the road, but at least in the short run it does not change the distance of their trips. Although estimating total vehicular emissions is commonly the goal of modeling traffic and performing emissions analyses, the total value does not tell the whole story. Increasing the degree of saturation increases the mobility of the system only until the intersection becomes over-saturated. Then, additional traffic just adds to stopping and delays and vehicle hours of travel without adding vehicle miles traveled. In other words, in congested conditions, emissions volume increases while the distance traveled is reduced, implying that the system becomes rapidly less efficient. Figure 16 illustrates the emissions per VMT as the degree of saturation varies, and the results show the dramatic increase in pollutants associated with traveling in traffic congestion.

4.4 Validating the Integrated Emissions Model (ITEM)

In this section, having the emission factors of each driving mode and total number of vehicle stops and time spent in cruising and idling, and using the ITEM presented in equation (9), the total emissions for each scenario can be estimated. Figure 17 compares the estimated total emissions using the integrated emissions model with the total emissions directly computed by the microscopic emissions model. Since the emissions calculated by the integrated traffic emission model use the macroscopic estimates of traffic parameters, a smooth and continuous function for emissions estimation will be available that can be used in various scenarios and different levels of saturation without the need for modeling repetition, despite the fact that the total emissions computed by the microscopic emissions model (presented by green dots in the graphs) need a run for each scenario. This is not only data intensive and time consuming, but also because of the stochasticity in the results generated by the simulation, possible error caused by the analytical model and probable over-saturated conditions in the simulation when the arrival flow is approaching capacity, the estimated total emissions using the simulation may not show a smooth and predictable trend.



(a) Signal Cycle = 1min, G/C = 0.25
(b) Signal Cycle = 2min , G/C = 0.25
(c) Signal Cycle = 1min , G/C = 0.50
(d) Signal Cycle = 2min , G/C = 0.50
(e) Signal Cycle = 1min , G/C = 0.75
(f) Signal Cycle = 2min , G/C = 0.75

Figure 17. Variation of total emissions for various degrees of saturation

As it can be seen in the graphs in Figure 17 as the capacity of the intersection increases, the sparseness of the simulation results decreases and the trend of them becomes more similar to the trend of the continuous emission estimates by the integrated model. As expected approaching to the capacity of the intersection the emissions per vehicle-mile-traveled increases dramatically.

Although the existence of any error in the estimated number of stops, and duration of idling and cruising can directly affect the resulted emission estimations, the comparison of the estimated line and calculated dots (true values of emissions averaged over a specific time period of simulation) verifies the results of ITEM for the simulated single isolated signalized intersection. As shown in Table 5, a level of biased results is observed for a single isolated intersection due to a specific combination of the intersection specifications, arrival flow and signal timing; however, as shown in the next chapters, the application of ITEM in networks (ring and grid networks) do not show this kind of biased error due to averaging out the random error that causes biased results. Additionally, approaching the saturated density increases the number of over-saturated cases that are averaged with others and increases the level of over-estimation.

Table 5. Percent error of emission estimates from the analytical emission model relative to the microscopic simulation model

Signal Timing		Degree of saturation				
G/C	C (sec)	0.2	0.4	0.6	0.8	1.0
0.25	60	3.6%	4.2%	7.7%	10.3%	11.9%
0.50	60	-2.1%	-3.4%	-2.8%	0.9%	3.8%
0.75	60	3.4%	-1.8%	-0.9%	3.2%	6.1%
0.50	120	-7.3%	-3.1%	-0.5%	4.4%	9.2%
0.50	120	-6.9%	-5.2%	2.7%	-0.6%	9.3%
0.50	120	-10.9%	-8.1%	-5.7%	-0.9%	7.1%

This integrated traffic-emissions model is useful not just for estimating the total emission values, but also for connecting the characteristics of the traffic and signal timings with the emission estimates in a way that allows for systematic comparisons and making comparative decisions between different traffic control strategies or intersection improvements. This provides a valuable tool for designers, for example, in order to optimize the signal timings. Although it is common for the objective of a signal timing plan to minimize the delays or number of vehicle stops, equation (9) can be used to determine the best balance of those objectives to minimize vehicular emissions. Furthermore, this analytical model can serve as a building block for more systematic analysis of more complicated systems such as networks as an alternative to more costly and time-consuming simulation studies. In fact, the great value of this method is that it is based on aggregated traffic characteristics to provide aggregated emission estimates. We don't typically care about the emissions from each individual vehicle. It is more important that we design streets and intersections to perform well as a system. Therefore, this model is a step towards improving our ability to assess total emissions associated with traffic in street networks.

4.5 Summary

The main objective of this chapter is to implement and validate the Integrated Traffic-Emissions Model (ITEM) by using it to estimate vehicular emissions given traffic signal timings and traffic volumes at an isolated signalized intersection. An analytical model has been developed based on fundamental traffic flow theory in order to compute the number of stops, and time spent in cruising and idling states. On the other hand, in order to account for realistic characteristics of vehicle acceleration and deceleration in a signalized intersection, simulated vehicle trajectories generated by the microscopic traffic model of AIMSUN have been used to obtain the characteristics of the speed profile for a complete stop. The first is the average duration of acceleration and deceleration between free flow speed and the stop, which is used to calculate time spent in each driving mode. The second is a second-by-second speed profile of the vehicles during their accelerations and decelerations, which are used in MOVES to provide an average emissions factor per stop. Similarly, MOVES is used to estimate emission factors per unit time of cruising and idling modes. Finally, an integrated model has been used to calculate total emissions and emissions per VMT.

In the second part of this chapter, the traffic estimates from the analytical model and emission results from the ITEM are validated by comparing the results with the values directly calculated from the microscopic traffic and emission models. Aggregation of microscopic traffic data shows a similar pattern as the estimations of traffic parameters by the analytical model. Also, evaluation of the results of the emissions model shows that by increasing the arriving flow of vehicles, total emissions increase and this is caused primarily by the contribution of emissions associated with vehicle stops. This shows the importance of minimizing the number of vehicle stops in comparison with reducing delays, in order to minimize emissions. Interestingly, when a residual queue exists, the total emissions per VMT may decrease with lower arrival flows because the growth of the VMT exceeds the increase in emissions. However, when the signal approaches saturated conditions, the emissions per VMT increase dramatically regardless of the size of the residual queue. The main value of this model is that it is possible to relate changes in emissions to various contributing factors such as arriving vehicle flow and residual queue length with direct analytical relationships, as illustrated in this chapter. Insights about how changes in an intersection are likely to affect emissions can be quickly and easily quantified with this modeling approach.

In the next chapter, using a sample network and the macroscopic fundamental diagram information, the number of stops and duration of idling and cruising will be estimated within a network for different flows and densities. By establishing this relationship, a reliable and reproducible macroscopic emission curve can be derived based on fundamental properties of a network.

Chapter 5 :

Estimating Network-Wide Traffic Emissions by ITEM in an Idealized Ring Network

This chapter is the second step to estimate the network-wide traffic emissions based on the fundamental properties of the network and to find the relationship between total vehicular emissions and the average density of vehicles in the network. In this chapter, the main goal is to analytically investigate the macroscopic relationship between traffic parameters and emissions using the concept of the macroscopic fundamental diagram (MFD) in a simple infinite arterial simulated by a ring model with a single intersection that represents infinite similar intersections. In addition to the macroscopic relationship of average flow-density, we look at some network-wide connections between other traffic parameters such as the number of vehicle stops, total time spent in cruising, and total time spent in idling. In order to validate the analytical model, we show that a relationship exists between these parameters and fundamental diagram properties by using different scenarios in the microscopic traffic simulation using Aimsun. Then, by using the integrated traffic-emissions model (ITEM) presented in Chapter 3, the macroscopic relationship of the network-wide vehicular emissions with average density (or flow) in the networks is evaluated. Finally, as part of the application of the proposed model, the effect of a few network properties (e.g. signal timing and block length) on total emissions generated within the network has been evaluated.

5.1 Framework for ITEM with Analytical Macroscopic Traffic Data

Based on the required information for ITEM, it is necessary to provide the aggregated traffic parameters to the model, in addition to the emission factors. These parameters, which include total number of vehicle stops and total time spent in cruising and idling modes, can be estimated using different methods. In this section, using the macroscopic relationship between the average density and flow within the network, known as Macroscopic Fundamental Diagram (MFD) and the kinematic wave theory, these aggregated traffic parameters have been estimated.

Existing macroscopic models for network-wide traffic conditions relate the average network flow, q, to the average network density, k. These two variables imply the average speed of vehicles in the network, v, by the well-known relation:

$$v = \frac{q}{k} \tag{14}$$

These variables alone provide a lot of useful traffic information about the capacity of a network and the delays that drivers in the network experience. Ongoing research is being conducted to better understand the behavior of the macroscopic flow-density relation for different types of realistic networks. For the proposed model, we suppose that the MFD for a network is known or has been measured, and we use it to provide an analytical approximation for the idling time, cruising time, and number of stops for vehicles in the network. The goal is to develop a model with sufficient detail to estimate aggregated emissions in the network without the need to track the details of each vehicle's movements.

As presented in previous chapter, the complexities of a second-by-second vehicle trajectory can be simplified into three key parts of the driving cycle that are related to emissions: time spent moving at cruising speed per vehicle-distance, T_{cr}; time spent idling per vehicle-distance, T_{id}; and the number of times that vehicles stop per vehicle-distance traveled, n. We will first consider how T_{cr} and T_{id} can be estimated if n is known. Then we will consider how the number of stops per distance can be estimated as well.

Suppose that traffic on a homogeneous network has a triangular fundamental diagram with free-flow speed of v_f. If we ignore for the moment the range of speeds that are associated with acceleration and deceleration, vehicles will have piecewise linear trajectories with speed v_f while moving (i.e., cruising) or stopped while idling. All travel time for vehicles can be classified as effectively cruising or effectively idling. The kinematic waves associated with these idealized trajectories are the same as the aggregated dynamics of traffic with more realistic acceleration and deceleration patterns (Lighthill & Whitham, 1955; Richards, 1956).

Every vehicle that stops must decelerate from v_f to 0 and then accelerate from 0 back to v_f. The duration of the deceleration is t_{dec} and the duration of the acceleration is t_{acc}, and these values depend on the behavior of drivers in a particular network. If the deceleration and acceleration are at constant rates, then half of t_{acc} and t_{dec} is effectively cruising time and the other half is effectively idling time. Figure 12 in Chapter 4 shows how a more realistic trajectory with constant rates of deceleration and acceleration is simplified to a piecewise linear trajectory. For simplicity, we will consider a single time associated with the cycle of deceleration and acceleration for each vehicle stop $t_s = t_{acc} + t_{dec}$. Therefore, each stop reduces the actual time spent cruising by $t_s/2$ and the actual time spent idling by $t_s/2$. It is important to account for t_s when modeling traffic emissions, because the emission rates for cruising and idling should be multiplied by the actual cruising and idling times rather than the effective times.

The effective cruising time per unit distance is simply the inverse of the free-flow cruising speed, because no distance is traversed while idling. The actual cruising time per unit distance is then calculated by reducing the effective cruising time by half of deceleration and acceleration time for each stop:

$$T_{cr} = \frac{1}{v_f} - \frac{t_s}{2} n \tag{15}$$

where *n* is the number of times a vehicle stops per unit distance traveled.

The effective idling time is the difference between the total travel time per unit distance, which is the inverse of the average traffic speed, and the effective cruising time. The actual idling time per unit distance is again calculated by reducing the effective idling time by the other half of the deceleration and acceleration time per stop:

$$T_{id} = \frac{1}{v} - \frac{1}{v_f} - \frac{t_s}{2} n \tag{16}$$

In many cases, it may be possible to measure n from the same data source used to obtain the estimated macroscopic traffic state k and q (i.e., traffic data from probe vehicles could provide an indication of this value). In the absence of direct measurements, it is useful to be able to express the number of stops analytically. Although an individual vehicle makes a discrete number of stops per distance traveled, this could vary across vehicles or road segments. Therefore, it is useful to be able to have an analytical approximation for the average n.

The simplest approximation is simply to suppose that on average vehicles are stopped once per cycle. The average distance traveled during a signal cycle of length C is vC, so,the number of stops per distance is given by:

$$n = \frac{1}{vC} \tag{17}$$

This approximation is appropriate when the signal offset is 0 and when the duration of the red signal exceeds the time required to travel the length of a block at free-flow speed: $C - G \geq \ell/v_f$, where G is the effective length of the green phase and ℓ is the length of the block. In this case, the red phase is sufficiently long that a vehicle will always have to stop once per cycle when caught at a red signal. It should be noted that when block lengths are long enough or red phases are short enough that $C - G < \ell/v_f$, it is possible for some vehicles to traverse the network without stopping during every cycle. This may become a source of error, although the condition does not occur for any of the examples in this research.

A complication occurs in urban networks because the platoon of vehicles being served by an upstream signal may reach the back of a queue at a downstream signal before it has completely dissipated causing every vehicle to stop a second time. This condition can be identified by tracking whether the front of the platoon moving at free flow speed v_f reaches the interface at the front of the dissipating queue moving backward at speed w illustrated by point A in Figure 18. If the queue exceeds length d, the platoon gets blocked and each vehicle stops a second time.

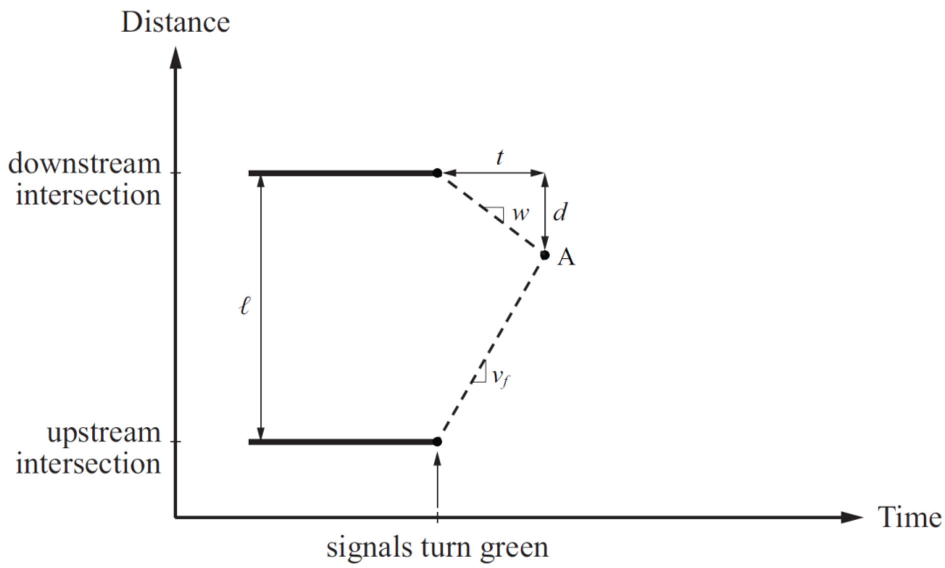


Figure 18. Time space diagram of two consecutive signals and the condition that the platoon moving forward meets the back of queue at point A

Mathematically, the condition that the platoon gets blocked occurs if the number of vehicles queued on the link exceeds the number that would be in a queue of length d. The number of vehicles in a queue of length d is $k_j d$ and the number of vehicles on the link may be defined as $k\ell$, so,the blockage of the platoon is implied by the following condition:

$$k\ell > k_j d \tag{18}$$

From the geometry of Figure 18, it follows that $d = wt$ and $\ell = wt + v_f t$. By substituting these expressions into (18), cancelling t from all terms, and using this as the condition to determine if the average vehicle stops once or twice per cycle, (17) can be re-written as:

$$n = \begin{cases} 1/_{vC} & if \quad k(w + v_f) \leq k_j w \\ 2/_{vC} & otherwise \end{cases} \tag{19}$$

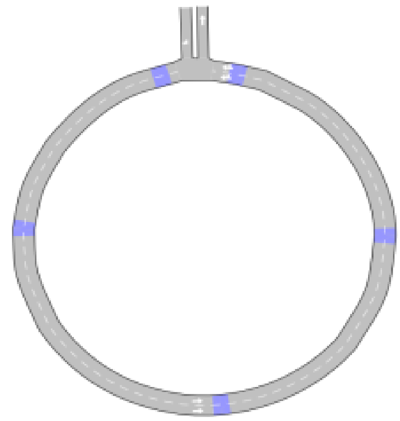
5.2 Microsimulation of an Idealized Network

In this section, a microscopic simulation of an idealized ring-shaped model has been used to illustrate the macroscopic relationship of aggregated traffic parameters of the number of stops, cruising time, and idling time with the total number of vehicles in the network (average density). Since one of the initial assumptions of the analytical model based on the MFD is that the traffic on the network is homogeneous, this specific ring-shaped network has been used for simulation, which is explained in the next section.

5.2.1 Construction of the microscopic simulation

In order to construct the idealized homogeneous network, a street with fixed number of lanes, constant spatial speed limit, constant capacity, and any number of intersections should be considered. To have an evenly distributed flow in the network, the upstream flow into the section should be matched to the flow at the downstream end of the section. In this situation, the number of vehicles in the network is fixed which creates a constant density over the period of simulation (Daganzo & Geroliminis, 2008). Although it is assumed that the vehicles are evenly distributed in the network, the number of vehicles (density) on the link(s) is constant. As stated in previous section, there is no need for the arrival flow to the intersections to be uniform at the network level. The arrival flow at each intersection is controlled by the platoons coming from the upstream intersection. The random variation of the speed of vehicles and platoon dispersion causes a non-uniform arrival at the intersection. Since, in this section the analytical model is constructed based on the aggregated traffic counts and macroscopic fundamental diagram, the non-uniform arrivals do not affect the proposed model.

In order to simulate this network, we can put an infinite number of identical street segments end-to-end of each other, similar to Figure 19(a), in which the outflow of each segment is the inflow of the next one. However, running this plan in a traffic simulation and keeping the number of vehicles in the network fixed may not be possible. Another way to model this homogeneous network with constant density is with a ring-shaped road, as shown in Figure 19(b), in which the beginning and end of the section meet at a signalized intersection. During the feeding period of the simulation, a controlled number of cars enters the link, and then during the simulation period, no cars are added to the network. This feeding process is repeated from zero density to jam density to cover all levels of saturation. Therefore, the single ring network with a signalized intersection can work as an idealized homogeneous network with no turning movements, where vehicle density is homogeneous during the simulation period and flows are perfectly correlated across all links.

(a) (b)

Figure 19. Idealized homogeneous network, a) infinite arterial with identical links and intersections, b) ring shaped arterial

5.2.2 Macroscopic traffic and emission values measured from microsimulation

In this model, different scenarios are defined, and in each of them the number of vehicles is increased during the feeding period and the model rerun for the new density. This adding procedure continues until the link becomes fully congested (gridlock) and there is no movement in the network. This is the jam density of the section. During each level of density, traffic parameters, including average flow of the link and flow at different locations, average density, the number of circulating vehicles, the number of vehicles' stops, total duration of cruising, total duration of idling, and the second-by-second trajectories of the vehicles are recorded. Figure 20 shows the relationship between average flow and average density (i.e., the MFD) recorded in simulation of the base case scenario. It should be noted here that the analytical models and microsimulation of an idealized and homogeneous network can be used to record the complete MFD covering all densities from 0 to jam density. In reality however, it is not only undesirable, but it is also not possible to observe the completely congested conditions on the network, as shown in the MFD of Yokohama in Figure 4. Therefore, in the graphs provided for the modeling in the networks (both ring-shape and grid network) the traffic states after saturated conditions are demonstrated by a lighter color, indicating an unrealistic traffic state.

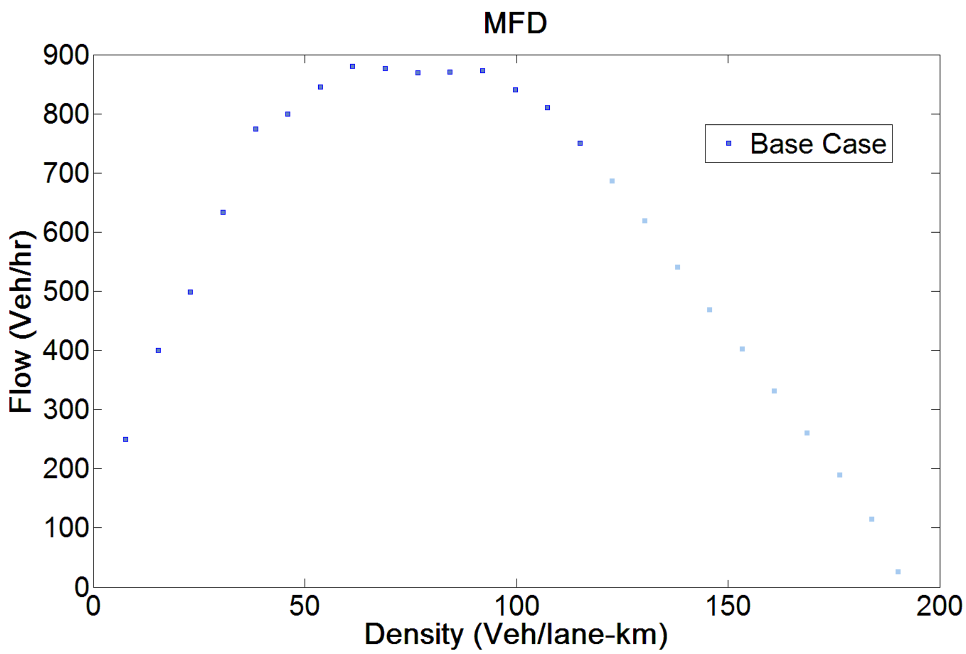


Figure 20. Relationship between average flow and average density, MFD, recorded in the micro-simulated idealized network

In addition to data recorded by the model, all parameters are computed from the recorded trajectories by using an algorithmic Matlab code explained in Chapter 3. Using this code and some predefined and calibrated thresholds, all trajectories are divided into four driving modes of acceleration, deceleration, cruising, and idling. In addition to counting the number of vehicle stops, the aggregation of a typical (average) acceleration and deceleration and the corresponding features (e.g., duration and magnitude) of a vehicle stop can be defined. Also, by averaging over cruising states, the average speed of cruising is computed. In an ideal situation, it is assumed that the average cruising speed is the same as the free flow speed; however, due to reduction of speed in saturated traffic conditions, the cruising speed might not reach free flow speed in the real-word and in simulation, which can cause some errors due to incomplete accelerations and decelerations cycles. Figure 21 shows the macroscopic relationship between a) the total number of vehicle stops, b) time spent in idling, and c) time spent in cruising and the average density of vehicles on the network. In the rest of this study the macroscopic parameters are evaluated per vehicle kilometer traveled (VKT).

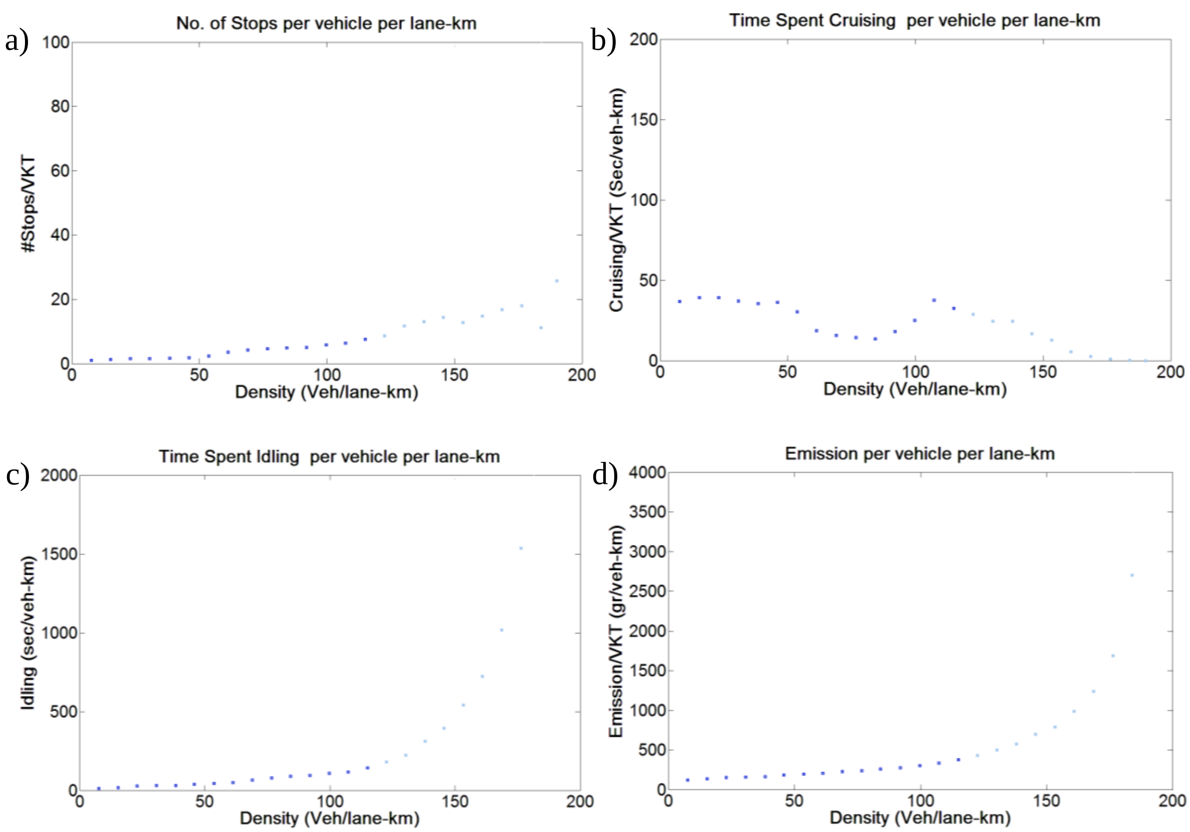


Figure 21. Network-wide relationship between number of vehicle stops with average density of vehicles on the network.

Based on calculated macroscopic traffic parameters, which are the aggregated driving cycle components, and using ITEM, the total emissions from the network can be calculated. The model multiplies the macroscopic traffic parameters and microscopically computed emission factors. Figure 21.d shows the network-wide aggregated traffic emissions calculated based on measured macroscopic traffic parameters from microsimulation.

5.3 Analytical Estimation of Emissions from Measured MFD

In Section 5.2, the macroscopic traffic parameters and total emissions are calculated based on recorded trajectories in microsimulation. However, as explained in Section 5.1, macroscopic traffic parameters can be estimated using the analytical approach, based on the measured MFD. In this section, analytical estimates of traffic parameters and resulting emissions are compared with simulation measurements.

5.3.1 Comparison of driving cycle components

Based on the measured MFD shown in Figure 20 and equation (19), the total number of stops in the network for different densities can be analytically estimated. Figure 22 shows the comparison of the analytically estimated number of stops and measured values from microsimulation. As shown in the graph there is a close match between the estimated results and measured values, especially for lower densities. However, the analytical estimates rise significantly, since the analytical approach counts all low speed stop-and-go movements. In reality and simulation, the speed variations in congested conditions do not pass the threshold to be considered as a stop.

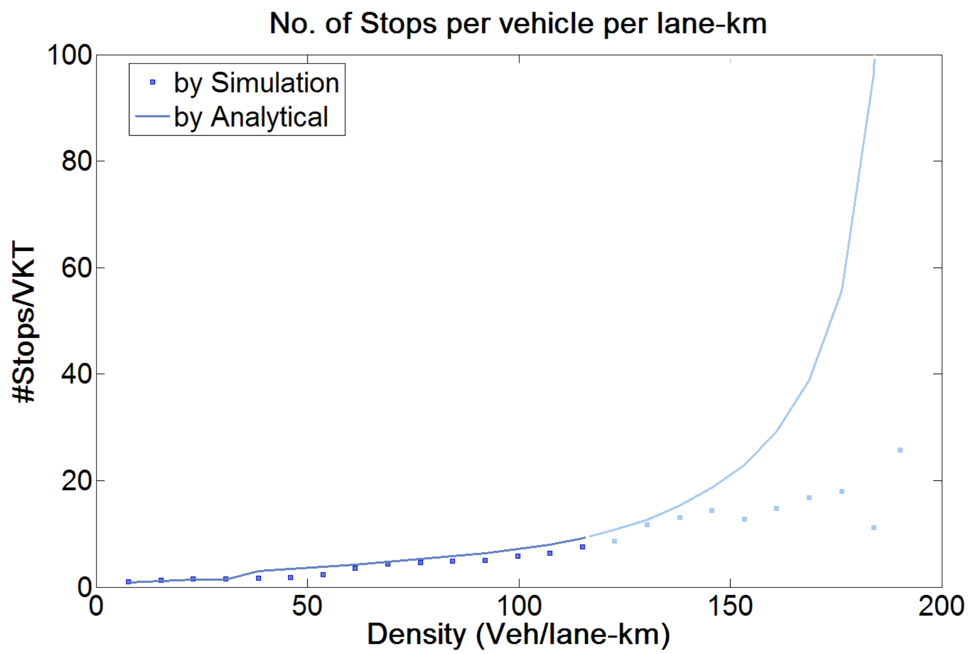


Figure 22. Comparison of analytically estimated number of stops and measured values from microsimulation

Similarly, network-wide total time spent in cruising and idling modes are analytically estimated for the base case scenario using equations (15) and (16). Figure 23 shows the analytically estimated a) total cruising time and b) total idling time, and the comparison of them with measured values from microsimulation.

As shown in Figure 23(b), there is a close match between analytical estimates and measured values of idling time, but some inconsistency in estimation of cruising time can be observed in Figure 23(a). However, since cruising time has a low contribution in total emissions and the underestimation error caused by cruising time is being canceled out with overestimation of the idling time and the number of stops, the observed errors in cruising time not only do not have a negative impact on the estimation of total emissions, but they also reduce the amount of total emissions overestimated by the analytical model.

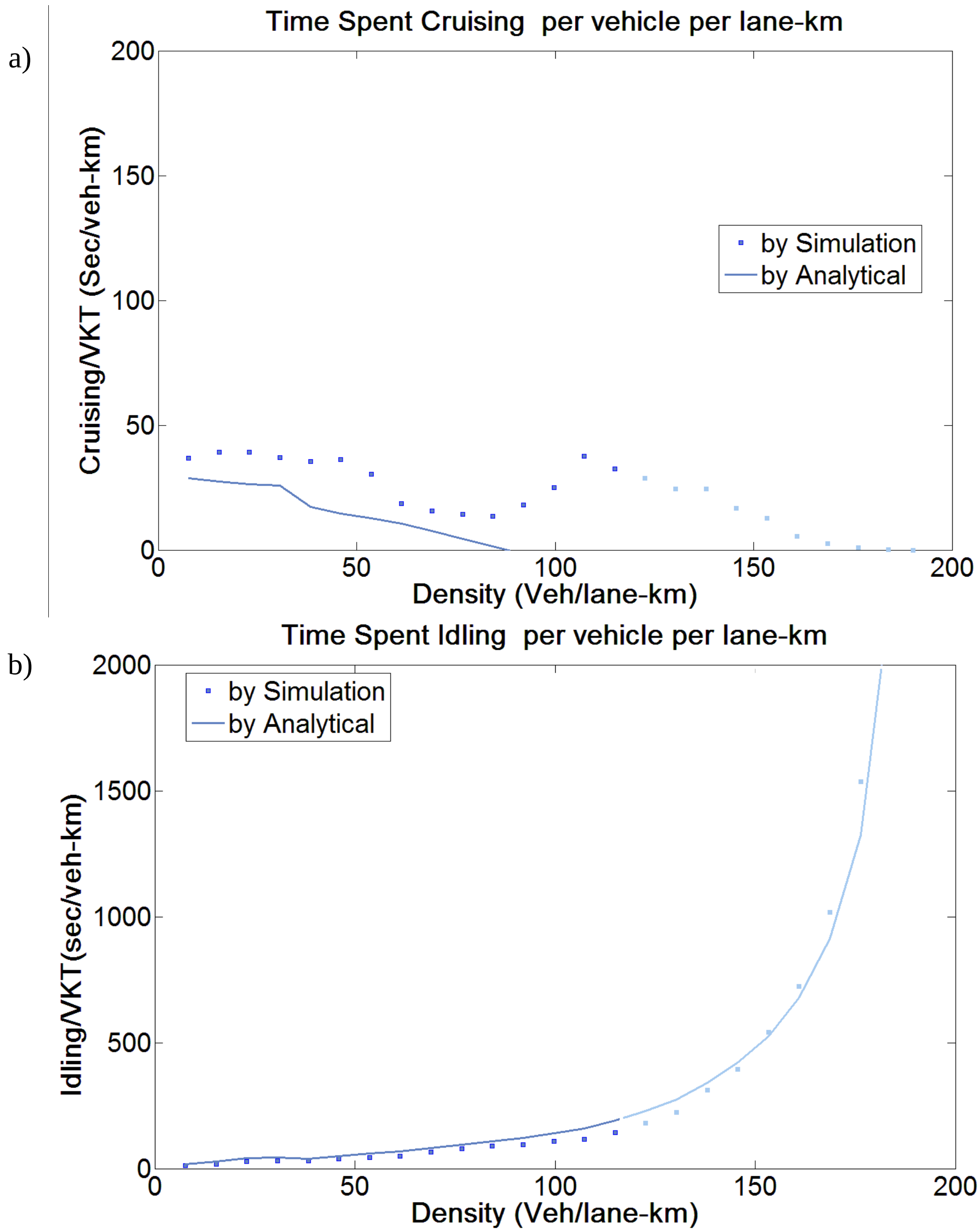


Figure 23. Comparison of analytically estimated total time spent in a) cruising mode, and b) idling mode with the measured values from the microsimulation as a function of the network density

5.3.2 Comparison of total emission

Using the analytically estimated macroscopic traffic parameters shown in the previous section and microscopically computed emission factors explained in Chapter 3, the network-wide total emissions can be calculated using ITEM. In order to evaluate the consistency of the analytically estimated total emissions, the estimated values of total emissions are compared with the microscopically computed total emission using the second-by-second trajectories of all individual vehicles on the network, as shown in Figure 24.

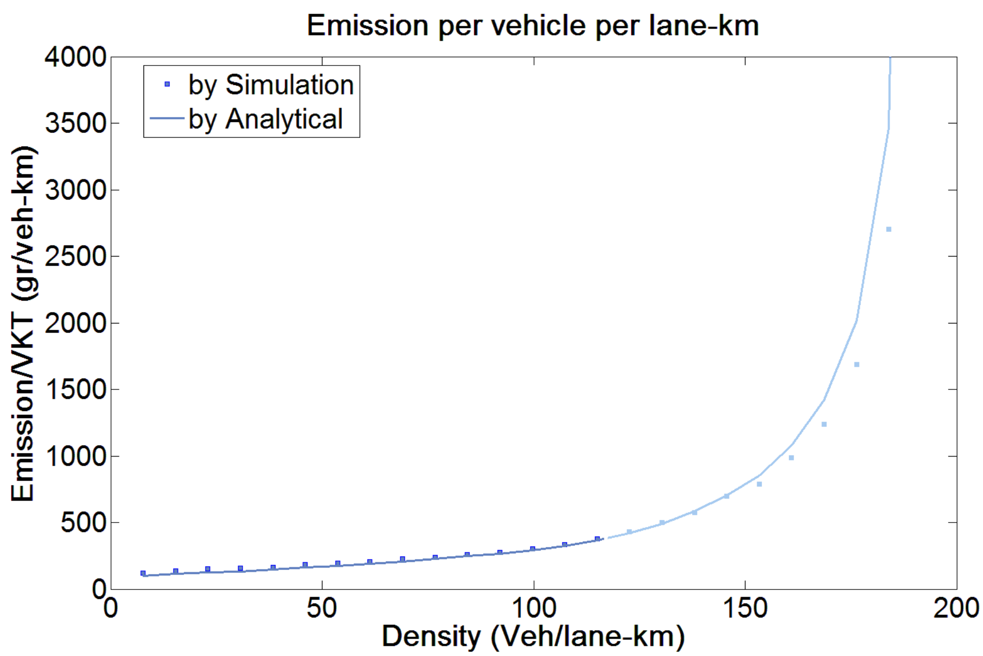


Figure 24. Comparison of analytically estimated network-wide total emissions and microscopically computed total emissions using the second-by-second trajectories as a function of the network density

5.4 Analytical Estimation of MFD

In previous sections the macroscopic traffic parameters and also total emissions were estimated analytically, and in order to implement this analytical approach, the fundamental properties of the network including the network's MFD need to be given from measurements. In the simulation or real-world network, the MFD can be measured by intelligent transportation system (ITS) technologies. However, if the network is homogeneous, similar to the ring model, the MFD of the network can also be estimated analytically. This approach can be useful in some cases where the network can be divided into multiple homogeneous sub-regions.

5.4.1 Theoretical approximation of MFD

A complete explanation of the analytical approximation of MFD is beyond the scope of this study, it has been the topic of several research projects in the last few years such as (Daganzo, 2005.b; Daganzo & Geroliminis, 2008). However, in this section, a simple conceptual description of the method is provided. In order to offer a recipe to approximate the MFD, it is first proven that an exact, unique, concave MFD exists for any homogeneous network that can be described as a multi-block, signal-controlled street network without significant turning movements. In this approach, a moving observer method has been used to identify the capacity of the street.

Using variational theory, the maximum rate that a moving observer can be passed by vehicles in the network can be formulated as a shortest path problem. The solution gives several linear cuts that define the upper bound of feasible flow-density points that can be observed in the network. The lower envelope of these cuts defines a concave

MFD, which is the theoretical upper bound for the flows that the network can serve at each vehicle density in the network. This upper bound will be tight if the network is homogeneous and well-connected, as in the ring model or a grid network with uniform traffic density (Daganzo & Geroliminis, 2008).

In the next step, it is shown that this upper bound is the maximum total flow on an idealized network for any given number of circulating vehicles. However, heterogeneity in the network, which is introduced in the form of non-uniform distribution of vehicles across the network, reduces the average flow on the network for a given density. This means a point below the MFD curve, and the magnitude of flow can be changed. In the next section the idealized ring model has been used to estimate the MFD of the network, because homogeneity of traffic conditions is always maintained in this network.

5.4.2 Calculation of MFD from the network features

In this section, the analytical approximation approach has been used to estimate the MFD of the base case scenario. Similar to the ring model used in microsimulation, the network used for the analytical approximation of MFDs consists of a 2-lane road with the base case features as follows: the block length l = 300 m, capacity of s = 1900 veh/hr, jam density of k_j = 400 veh/km, signal cycle of C = 60 sec, and green ratio of G/C = 0.5. Figure 25 shows the comparison between the MFD estimated by the analytical approach with the MFD measured from the microsimulation.

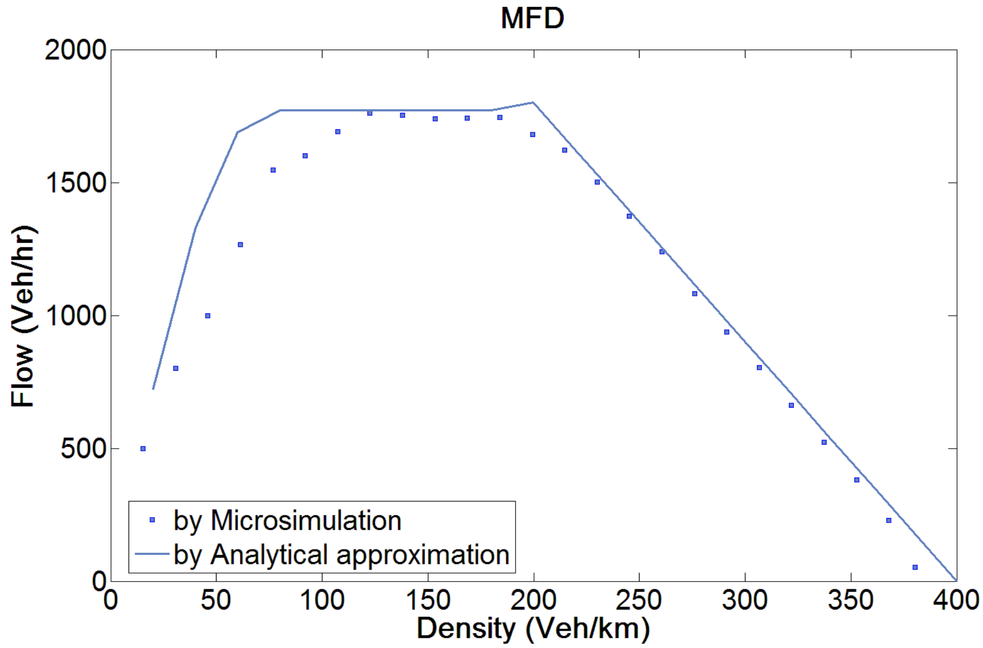


Figure 25. Comparison of the analytically Approximated MFD with the MFD measured from microsimulation

Additionally, several scenarios have been defined to show the analytical approximation of MFD for different characteristics of the network. Figure 26 shows the estimated MFD of a ring-shaped network under different scenarios. Three network variables of green ratio (G/C), cycle length (C), and block length (l) are used to show how network features are reflected on the approximation of the MFDs.

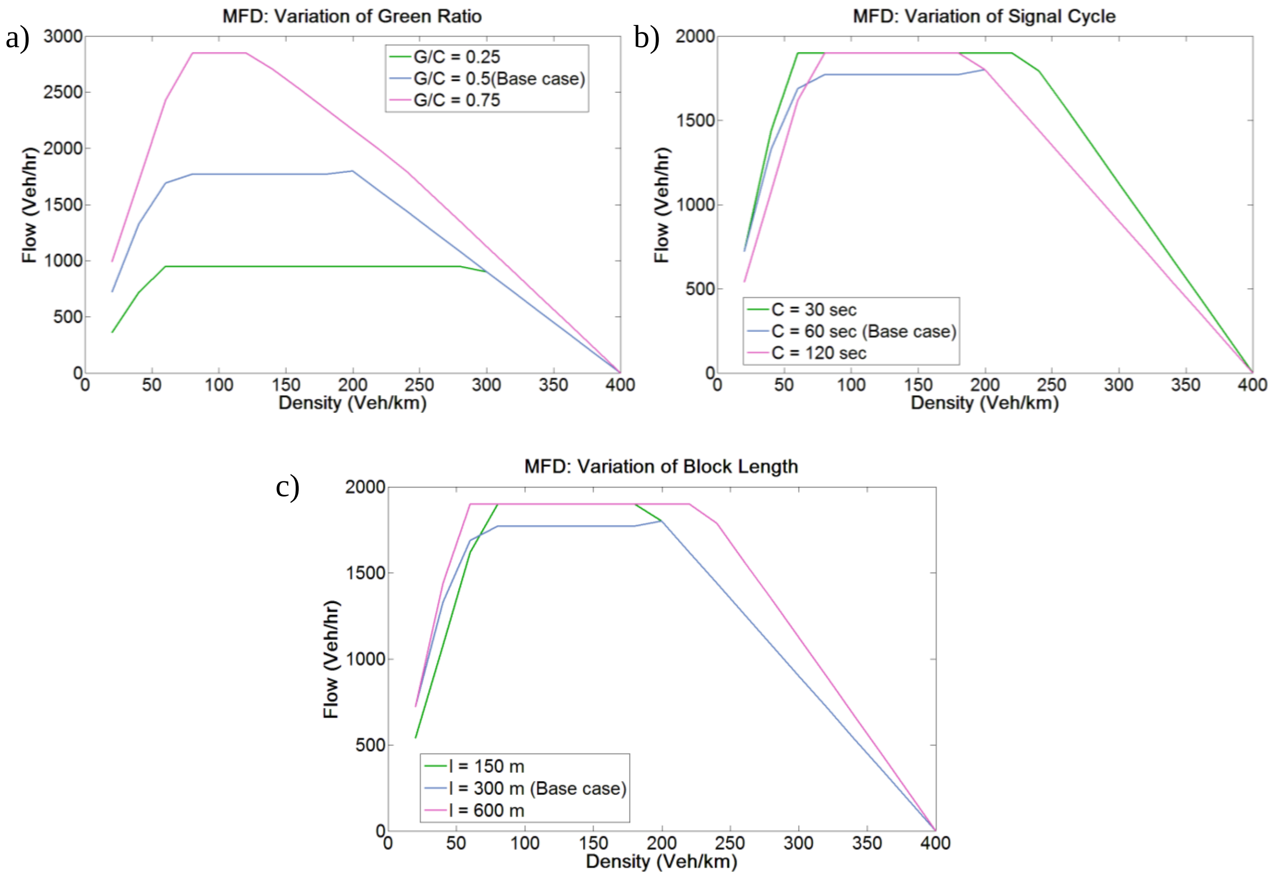


Figure 26. Approximated MFD of the idealized network with different given network features

Utilizing the estimated MFDs, the macroscopic traffic parameters required for ITEM can be estimated. Therefore, using the ITEM method and analytical approximation method of MFD, the network-wide total emissions on an idealized network can be estimated using only analytical methods; no simulation is needed at all. This approach can be more helpful for providing a rough estimate of total emissions in a relatively homogeneous network. In the next section, the effect of changing network characteristics on the driving cycle components and the resulting total emissions are evaluated.

5.5 Effect of Changing Network Characteristics

The value of an analytical model for emissions from the vehicles in urban networks is that the effect of changing the network and demand characteristics can be quantified quickly. Whereas the conventional simulation and microscopic emission modeling approach require that the network be reconstructed and recalculated for each scenario considered, the analytical approach allows for systematic comparisons of network performance based on evaluation of mathematical functions. This makes the analytical model especially useful for large-scale analysis of the effects that transportation policies are likely to have on the performance of the traffic network, including the emissions from vehicles. Unlike existing macroscopic emission models, this analytical approach explicitly accounts for the physical interactions of vehicles in the network; therefore, the effect that changes in signal timings and vehicle densities have on the driving cycles and resulting emissions from vehicles is captured.

5.5.1 Effect of changing the green ratio (G/C)

One characteristic of a network that can be changed relatively easily is the ratio of the cycle time that is effectively green for each approach, G/C. Using all of the same network parameters as in the base case presented in the previous section, an evaluation of the effect of changing the green ratio is conducted. Figure 26(a) shows the analytical MFD for each of the green ratios $G/C \in \{0.25; 0.5; 0.75\}$. The green ratio of 0.5 is the same as the base case presented in the previous section. The green ratio for through traffic in a network may be reduced if signals are timed to include dedicated turning phases, and one effect of reduced green time is the obvious reduction in the maximum flow that can progress through the network. Reduced green times also reduce the speed that vehicles can traverse the network at lower densities as indicated by the lower slopes on the left side of the MFDs for lower values of G/C in Figure 26(a).

The analytical approach to estimate driving cycle components is used, and the macroscopic traffic parameters needed for ITEM are calculated. Figure 27 shows a) the analytical estimated total number of stops, b) total time spent in idling, c) total time spent in cruising, and d) the estimated total emissions. As shown in the graph, the smaller the green ratio causes the higher the number of stops and idling time. Similar to the traffic parameters, the results indicate that the more restricted green ratios are associated with greater emissions per vehicle distance traveled. Although this qualitative effect may be expected, the analytical model allows us to quantify the effect over the full range of vehicle densities. The effect on emissions per distance traveled increases dramatically as the green ratio is restricted. A reduction of G/C from 0.75 to 0.5 results in a modest increase in the emissions per vehicle distance traveled compared to a further reduction to 0.25. Emissions do not differ much at the lowest densities, when traffic is freely flowing, and at the highest densities, when conditions are nearly gridlocked.

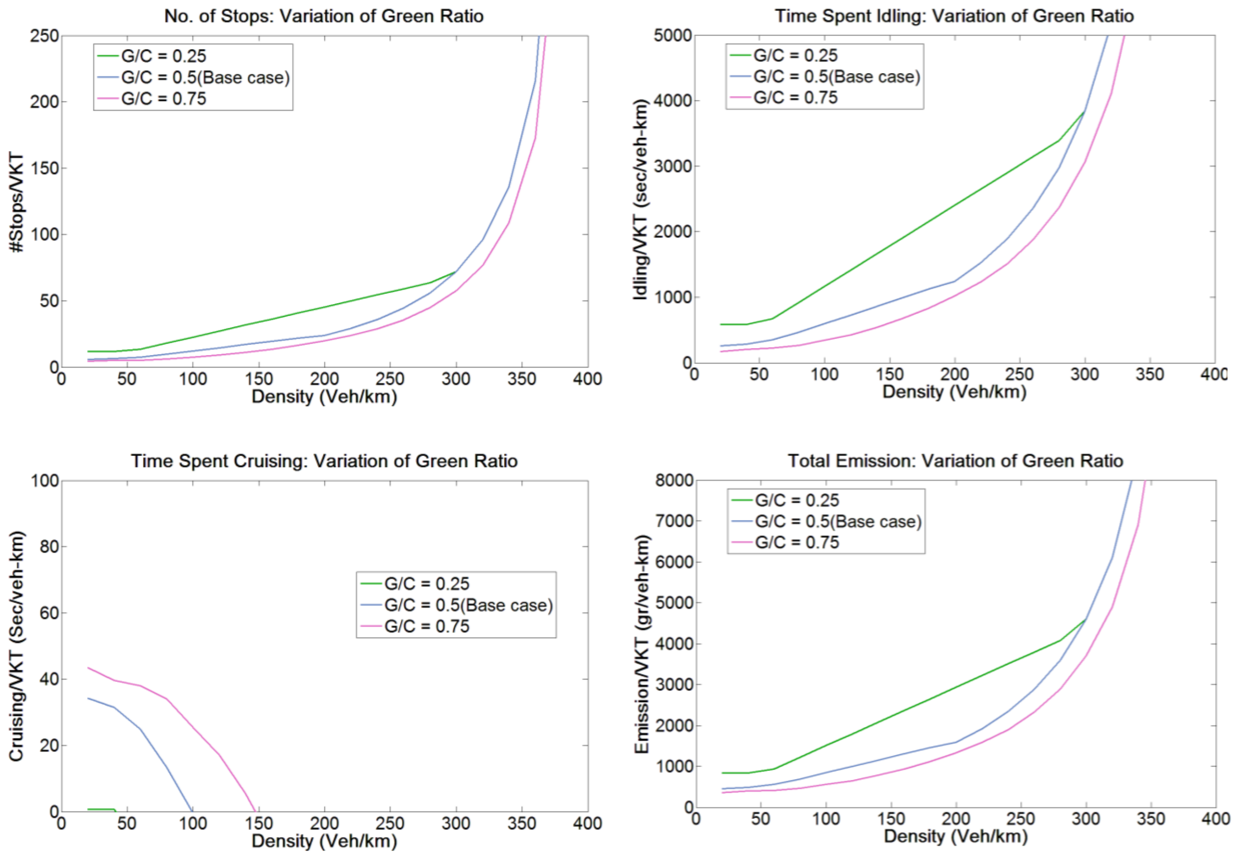


Figure 27. Macroscopic traffic parameters and network-wide total emissions for scenarios with various green ratios

5.5.2 Effect of changing signal cycle length

Another characteristic of the network that can be changed as part of a traffic control plan is the length of the signal cycle, C. Figure 26(b) shows the analytical MFD for cycle lengths $C \in \{30, 60, 120\}$ seconds with the green ratio held constant at G/C = 0.5. It should be noted that in practice, a longer cycle usually allows a higher green ratio to be achieved, because the lost time due to switching signals makes up a smaller portion of the whole cycle. We ignore this effect here to focus our attention on the effect of changing only one parameter on the resulting emissions.

Changing the cycle length has little effect on the MFD, especially in free flowing conditions. In fact the MFD for *C* = 30 seconds is almost identical to the MFD for *C* = 60 seconds. Although the MFD is similar, the driving cycle components and total emissions results vary as shown in Figure 28. Total number of stops, total time spent in cruising and idling are respectively presented in Figure 28(a), (b), and (c).

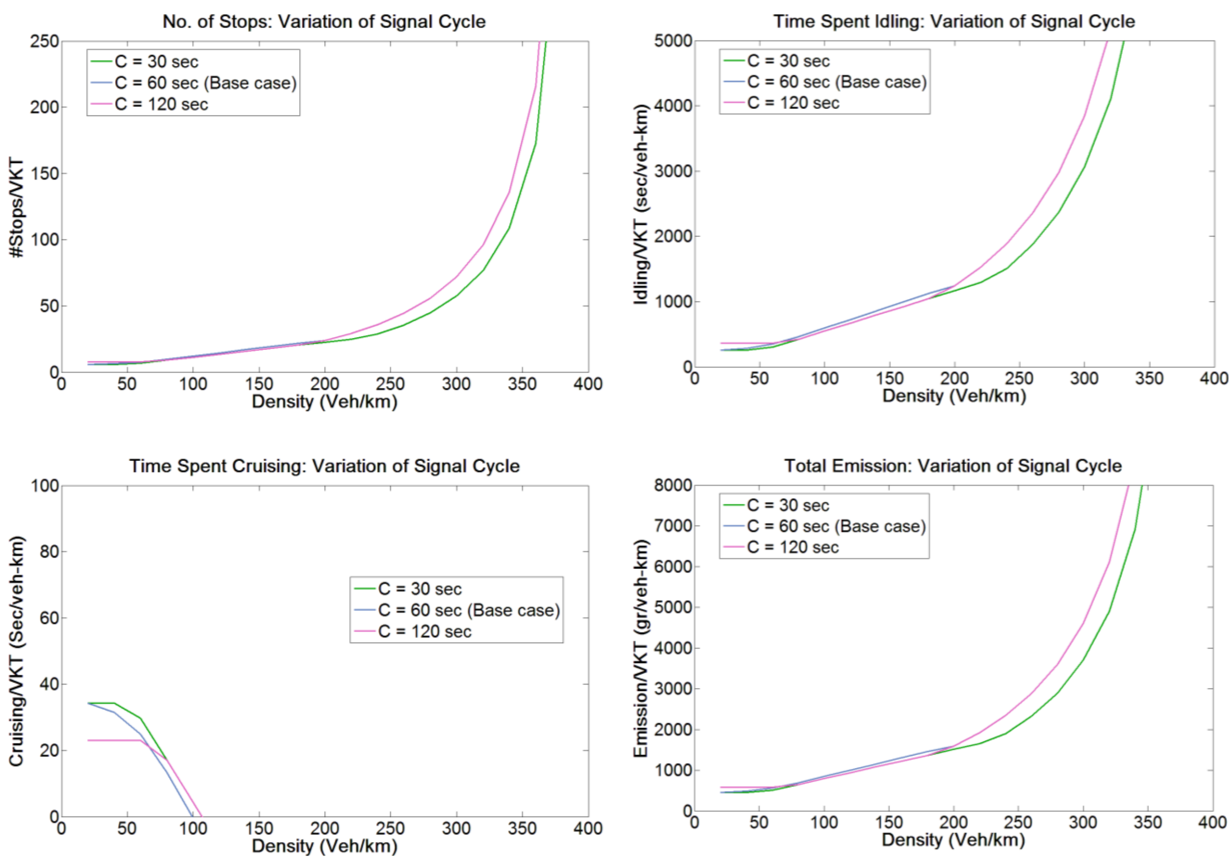


Figure 28. Macroscopic traffic parameters and network-wide total emissions for scenarios with various signal cycle length

Figure 28 shows the total emissions estimated by ITEM using the aggregated traffic cycle components and emission factors. As shown in the graph, the higher cycle length causes more emissions due to a larger number of vehicle stops in the driving cycle and the average speed of traffic as given by (19). For the same flow and density, a longer cycle length results in fewer stops per distance traveled, and this translates to reduced emissions. However, the cycle length of C = 120 seconds is associated with a longer red phase, which causes additional queueing that constrains flows on the congested branch of the MFD. The reduced speeds in congested conditions result in greater emission per distance traveled. Evidently, the detailed effects of the cycle length on the driving cycle matter for the resulting emissions, and the analytical model accounts for these effects.

5.5.3 Effect of different block length

A third characteristic of the network that can be compared is the effect of the block length on emission rates. As a policy, it is difficult to change the length of city blocks once the street network has been built, but when new neighborhoods are developed there is an opportunity to choose the size of city blocks and to consider the effect that this will have on traffic flows and emissions. Figure 26(c) shows the comparison of analytical MFDs for $\ell \in \{150, 300, 600\}$ meters.

In free flowing conditions, the block length does not make much difference, but in congested conditions, the length of blocks determines the storage space for queues of vehicles and the likelihood of a queue spillback. The effect of block length on the total number of stops, time spent in cruising, and time spent in idling are shown respectively in Figure 29(a), (b) and (c). As shown in the graphs, the results of block length of 150 m are almost identical with the base case scenario with l = 300 m and higher than the ones for the block length of 600 m.

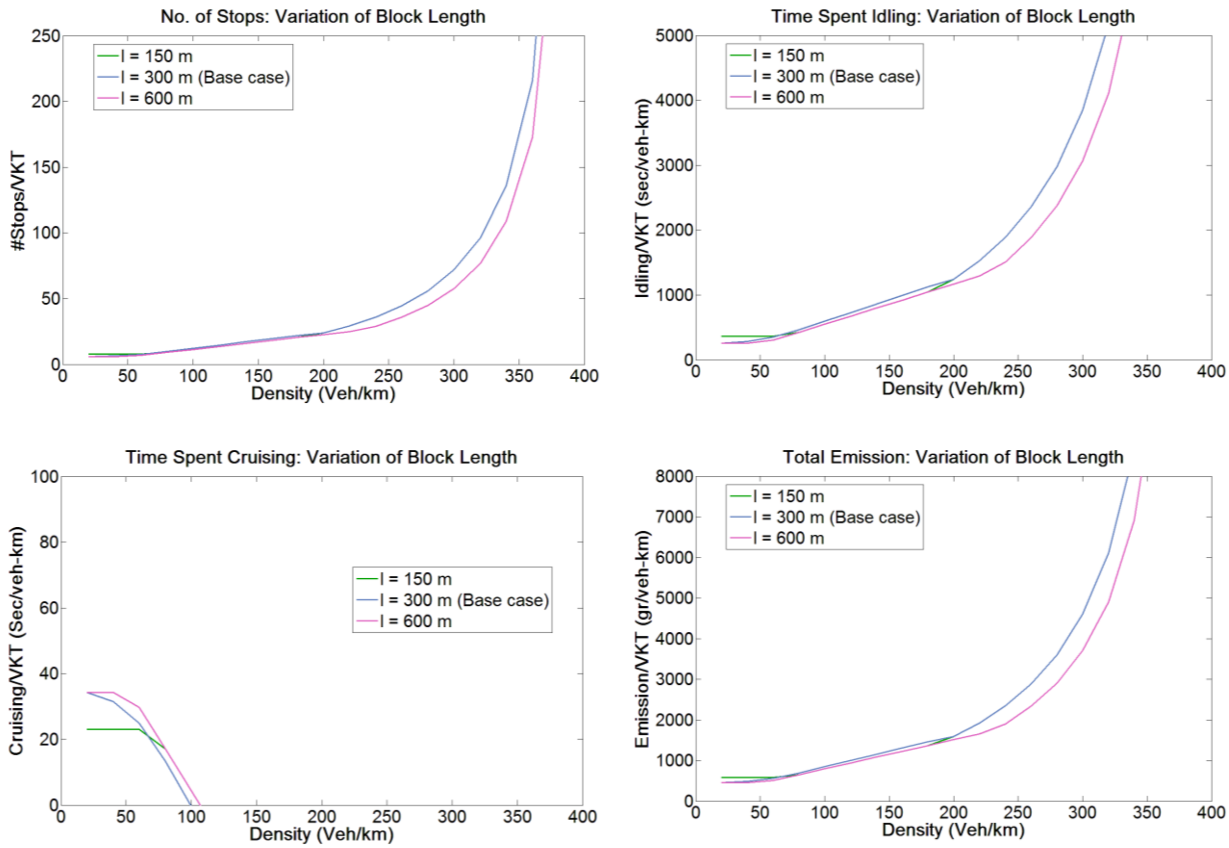


Figure 29. Macroscopic traffic parameters and network-wide total emissions for scenarios with various block length

The effect of this network characteristic on emissions is shown in Figure 29(d). For the lowest densities (i.e., free-flowing conditions), the traffic states and emissions do not vary. From a flow and emissions perspective, there is a benefit to increasing block lengths, but in practice this is only necessary up to a point. From ℓ = 300 m to 600 m, the emissions are only improved in the most congested conditions, which an efficient traffic management program should seek to avoid anyway.

The analytical model for emissions based on the MFD is flexible for many analyses, but it does have limitations. All of the cases presented are associated with the same free-flow speed, v_f, so, the set of the emission factors (e_c, e_i, and e_s) and the duration of each acceleration and deceleration cycle (t_s) remains the same as for the base case. If the free-flow speed in the network were to change, these factors would have to be re-estimated because the acceleration and deceleration associated with each stop would span a different variation of speeds. In practice this may not be a big problem, because free-flow speeds on city streets tend to be stable, and the effect of traffic policies for urban networks tend to be more geared toward signal control and demand management strategies, which the MFD is appropriate for addressing.

5.6 The model error evaluation

In this section in order to assess the consistency of the total emissions analytically estimated by ITEM, the analytical estimates are compared with microscopically computed total emissions using the second-by-second trajectories. As explained in section 5.3, the analytical emission values are calculated based on analytically estimated macroscopic traffic parameters based on the measured MFD and microscopically computed emission factors.

To quantify and evaluate the errors, the percent error of each analytically calculated emission value relative to the microscopically simulated one is calculated. Starting from the base case presented in the previous section with G/C = 0.50, C = 60 sec, and ℓ = 0.30 km, a systematic error analysis is conducted in the ring model for each of the following variations in isolation: the green ratio, $G/C \in \{0.25, 0.50, 0.75\}$; the signal cycle length, $C \in\{30, 60, 120\}$ sec; and the block length, $\ell \in\{0.15, 0.30, 0.60\}$ km. For each case a separate ring simulation was constructed to generate the MFD for the analytical approximation and to generate the detailed vehicle trajectories for the conventional microscopic analysis. The percent error of the proposed analytical approach relative to the conventional microscopic simulation approach is summarized in Table 6.

Table 6. Percent error of emission estimates from the aggregated analytical emission model relative to the microscopic simulation model (Base case: G/C=0.5; C=60sec; ℓ=0.30km)

Network Properties			**Network Density, k (veh/lane-km)**				
G/C	C *(sec)*	ℓ *(km)*	**25**	**50**	**100**	**150**	**200**
Variation of the Green Ratio							
0.25	60	0.30	2.1%	4.9%	0.9%	1.7%	15.9%
0.50	60	0.30	-7.7%	1.3%	10.5%	-7.6%	19.5%
0.75	60	0.30	-8.4%	-5.1%	-7.2%	-17.4	22.4%
Variation of the Signal Cycle Length							
0.50	30	0.30	9.3%	10.1%	5.5%	0.4%	49.7%
0.50	60	0.30	-7.7%	1.3%	10.5%	-7.6%	19.5%
0.50	120	0.30	-11.0%	-10.0%	0.2%	-1.8%	1.1%
Variation of the Block Length							
0.50	60	0.15	-5.0%	8.5%	6.7%	-1.2%	22.6%
0.50	60	0.30	-7.7%	1.3%	10.5%	-7.6%	19.5%
0.50	60	0.60	-10.3	-7.5%	1.4%	0.2%	22.4%

The network scenarios are clustered into three groups, each group showing the results of varying one of the network variables. The center row of each cluster is the base case so that the effect on the percent error from increasing and decreasing each variable can be compared one at a time. In almost all cases when the network is not completely jammed (k< 200 veh/lane-km), the model is within 11% of the simulated value. These errors do not appear to have a systematic bias and the magnitudes are small relative to the variation in emission rates for different values of k as shown in Figure 24. Therefore, the proposed analytical model provides a good approximation for the detailed microscopic estimates.

Only at jam density (k = 200 veh/lane-km), the errors are very large and consistently positive. These large errors occur when the network is near a state of complete gridlock, because the model predicts a large number of stops but the traffic moves so little with each cycle that the vehicle trajectories in the simulation never move faster than a slow crawl.

5.7 Summary

In order to find a macroscopic connection between network-wide traffic emissions and fundamental properties of a network, including the MFD of the network, this chapter first investigated the relationship of three aggregated traffic parameters that reliably represent traffic conditions in the network and can be used to estimate overall emissions in the network. These three parameters include the number of vehicle stops, the total time spent in idling (in queue), and the total time spent in cruising (at free-flow speed) per vehicle distance traveled.

The Aimsun traffic microscopic simulation has been utilized to generate and record second-by-second trajectories of all individual vehicles on the network to compare the estimated traffic parameters with microsimulation results. Using the driving cycle components and emission factors, total emissions are also analytically estimated and compared with microscopically computed emission values using the detailed trajectories.

In order to evaluate the effect of the network characteristics on macroscopic traffic parameters and total emissions, three comparative scenarios are generated. The effect of duration of the signal cycle, green ratio (G/C), and the link length, on the network's fundamental diagram and other macroscopic traffic parameters in the network are assessed.

The results of aggregation of the number of stops and cruising and idling time show the existence of a robust relationship between these parameters and the network's properties and MFD. Additionally, aggregated emissions for different scenarios from the microscopic emissions model MOVES show a strong connection between network-wide traffic emissions per Vehicle Kilometer Traveled (VKT) and the average density in the network.

Chapter 6 :

Validation of ITEM in a Grid Network

In order to validate the analytical approach to estimate aggregated traffic parameters and the proposed Integrated Traffic Emission Model (ITEM), this chapter presents results from the microsimulation of a grid network with heterogeneity of vehicle densities caused by turning movements at the intersections. Two comparisons are made. First, the second-by-second trajectories of all individual vehicles obtained from simulation have been utilized to calculate the aggregated traffic parameters, which include total number of vehicles, total time spent in cruising at free-flow speed, and total time spent in idling mode. These aggregated traffic parameters are compared with analytically computed traffic estimates. Second, the trajectories have been directly used in the microscopic module of the emission model MOVES to estimate the total emissions generated in the network. The resulting emissions from the microsimulation are compared with the total network-wide emissions estimated with ITEM to validate the proposed model.

An error analysis has been performed to compare the estimated traffic parameters and emissions from the analytical model with the results of a detailed simulation and microscopic emission model. This analysis includes assessment of the consistency and robustness of the results generated by the analytical approach and proposed ITEM model by comparing them with much more detailed microscopically calculated results derived from the second-by-second vehicle trajectories. The different sources of errors and their impacts on the results are investigated.

6.1 Grid Network Modeling

In order to perform a microsimulation in a grid network a simple grid model was constructed with several one-way links of length ℓ = 150 m, as shown Figure 30. For the base case scenario, an identical number of vehicles are loaded onto each line and there are no turning movements at the intersections; therefore, the numbers of vehicles on each link remain constant over time. Therefore, the traffic conditions on the network in the base case remain homogeneous, and the simulation also represents an idealized network.

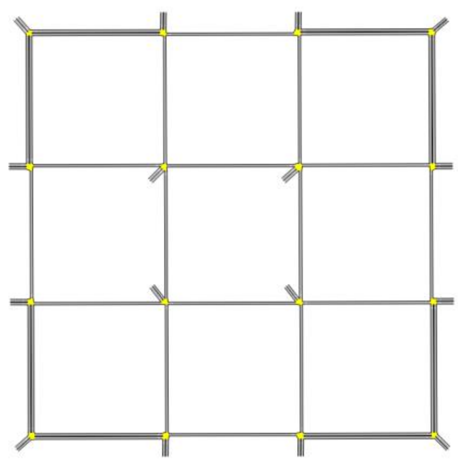


Figure 30. Simplified grid network used for simulation

During each time interval of the simulation, the model runs with a certain number of vehicles to recreate traffic operations at a specific vehicle density. Then, more vehicles are fed onto each link of the network, and simulation resumes to represent traffic at an increased density. The procedure of feeding and running continue to cover all densities from free flow to jam density (k_j= 200 veh/km). Other properties of the grid network that are used to illustrate the performance of the proposed analytical model for the base case scenario include: free-flow speed, v_f= 53 km/hr; saturation flow, s = 1900 veh/lane-hr; green ratio (length of green phase divided by signal cycle length), G/C = 0.50; signal cycle length, C = 60 sec; block length, ℓ = 150 m; and no signal offset. Running the simulation for a range of densities between 0 and k_j, the average network flow q is plotted for each density k in Figure 31.

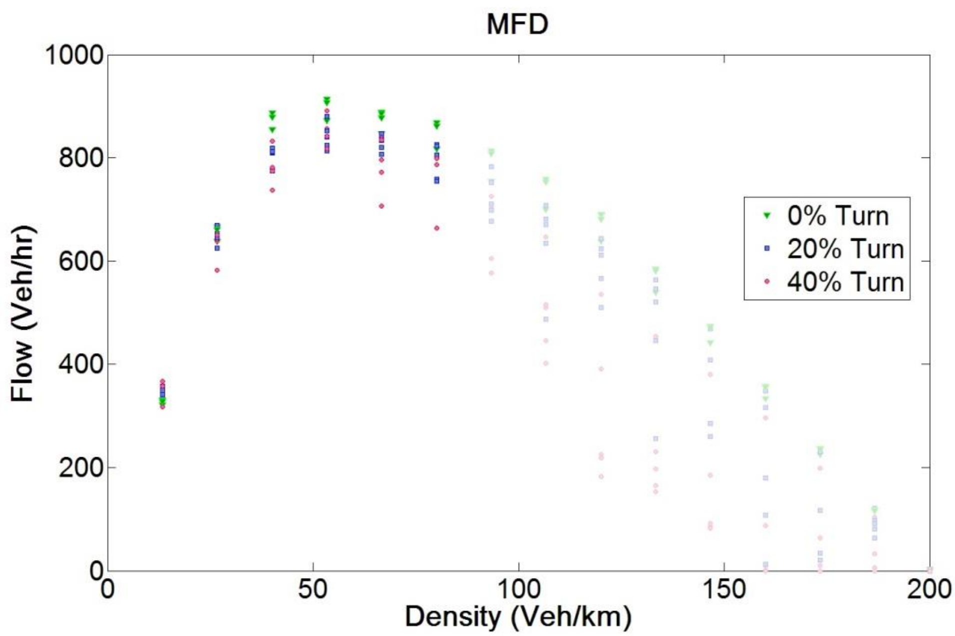


Figure 31. Network flow-density relation (MFD) measured from the simulation for different turning movement ratios

In order to relax the assumption that vehicle density is homogeneous across links, two scenarios with 20% and 40% random turning movements at each intersections have been evaluated. As shown in Figure 31, the average network flow drops at higher average densities in networks with turning. This is due to the blockage of some links while some other parts the network are not fully utilized. The turning movement has less impact on the free-flow branch of the MFDs, because variability in vehicle density does not affect the network's average flow if there are no queue spillbacks. The reduction in vehicle flow at higher densities is associated with dynamically changing traffic conditions. In Figure 31, scenarios that exhibit multiple dots at a certain density show that even while the total number of vehicles on the network is constant, the longer the model runs, the more uneven the distribution of vehicles becomes, which causes decreases in the average flow in the network.

6.1.1 Validation of analytically estimated traffic parameters.

Using the definition of the MFD and the relationship between the average flow, average density and average speed on the network presented in equation (14) the average network speed at each density is: $v(k) = Q(k)/k$. Having the average speed as a function of density and other required input for the equation (19) the number of vehicles stops can be estimated as a function of density. As explained in Chapter 5, based on the average network density (number of vehicles in queue), vehicles may stop either one or two times per signal cycle. By aggregating the total number of stops over each density, a consistent relationship between the average density and total number of stops appears. The analytical approach provides a corresponding number of stops for each pair of flow and density on the MFD. The longer the run continues with the presence of turning movements, the more heterogeneous the network becomes, and the average flow decreases. As shown in Figure 32, the reduced flow cases are reflected on the higher number of stops.

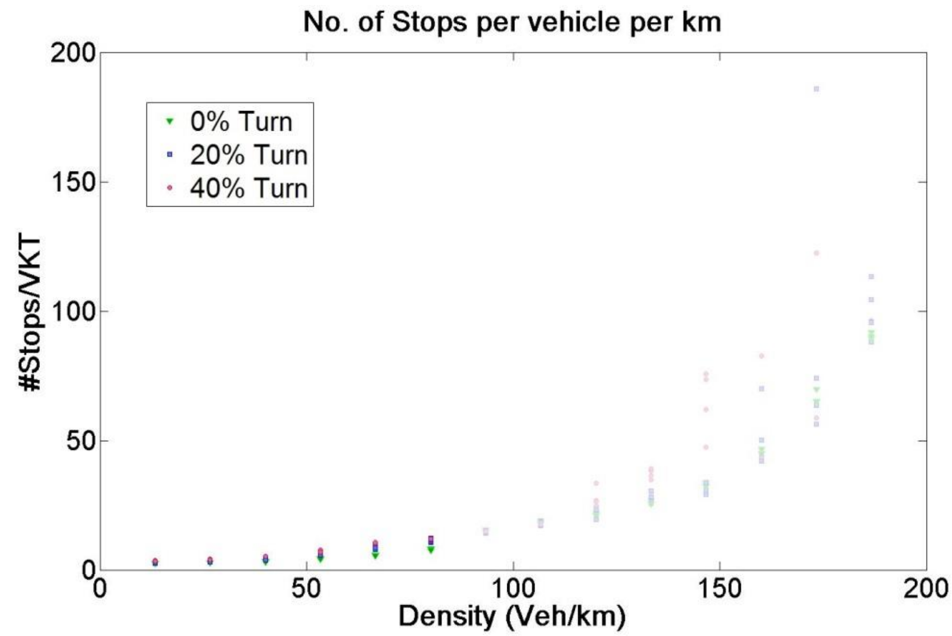


Figure 32. Variation of total number of stops vs. average densities corresponding to each pair of flow-density

To validate the analytically estimated number of stops, the estimated values are compared with the simulated results. The longest run in the network with turning movements shows the highest level of heterogeneity on the network. Figure 33 shows the comparison of the analytically estimated number of vehicle stops (solid lines) with the total number of stops measured from the simulated vehicle trajectories (points).

As shown in Figure 33, the analytically estimated number of stops follows a similar trend as the simulated values. At the highest densities (k> 150 veh/lane-km), where traffic is nearly completely jammed, the estimated number of stops per distance soars while the observed number of stops actually declines. This is due to the fact that in extremely congested conditions, vehicles move so little during each cycle that the trajectories do not trigger the necessary thresholds for the stops to get counted.

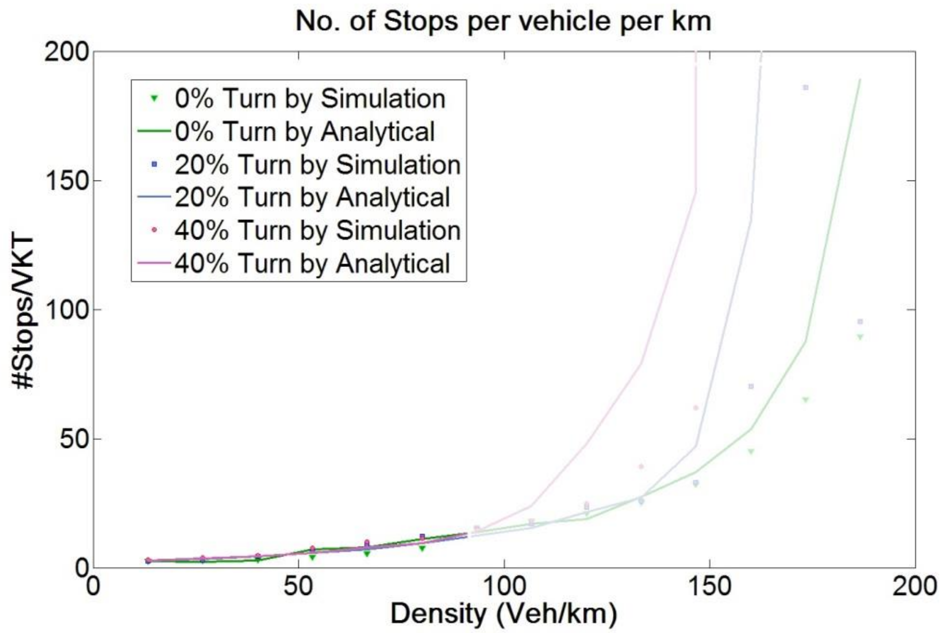
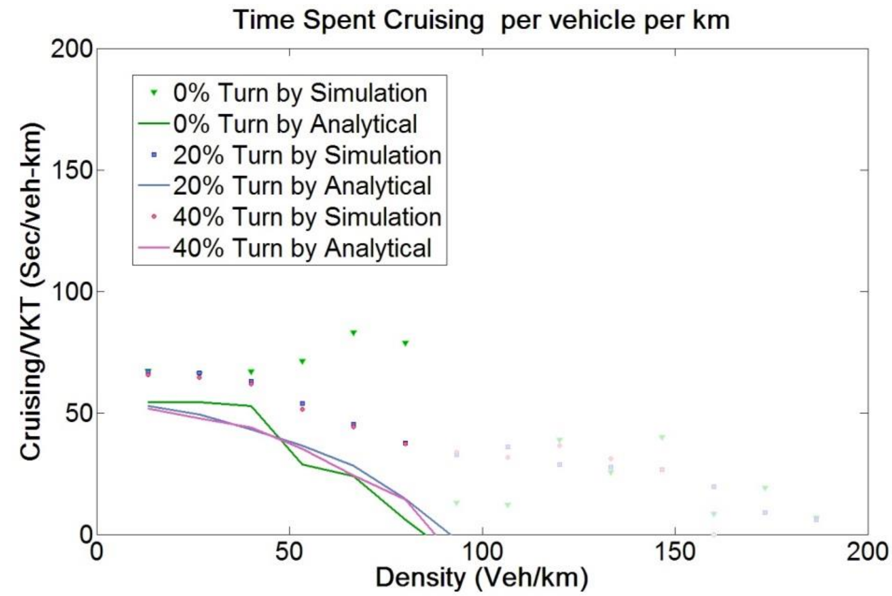


Figure 33. Variation of total number of stops vs. average densities for the analytical estimates and simulated results after a run of 10 minutes

The analytically computed values for the number of stops are then used along with the measured values of $v(k)$ to estimate the time per distance spent cruising using equation (15) and the time per distance spent idling using equation (16). Figure 34 shows the analytically estimated cruising and idling times (solid lines) and the cruising and idling times measured from the simulated vehicle trajectories (points).

As shown in Figure 34(b), the analytical approximation of idling time closely matches the simulated values. However, analytical estimates of cruising time shown in Figure 34(a) include some level of error. This underestimation can be caused by the variation of free-flow speed and the approximation of the acceleration/deceleration speed profile, but the error is not significant enough to affect total emissions estimation, because cruising time is a small portion of the total travel time, especially at higher densities. Additionally, the underestimation of cruising time and the resulting emissions are counterbalanced by the overestimation of time spent idling and number of stops. In the error analysis section, this issue has been addressed more clearly.

a)



b)

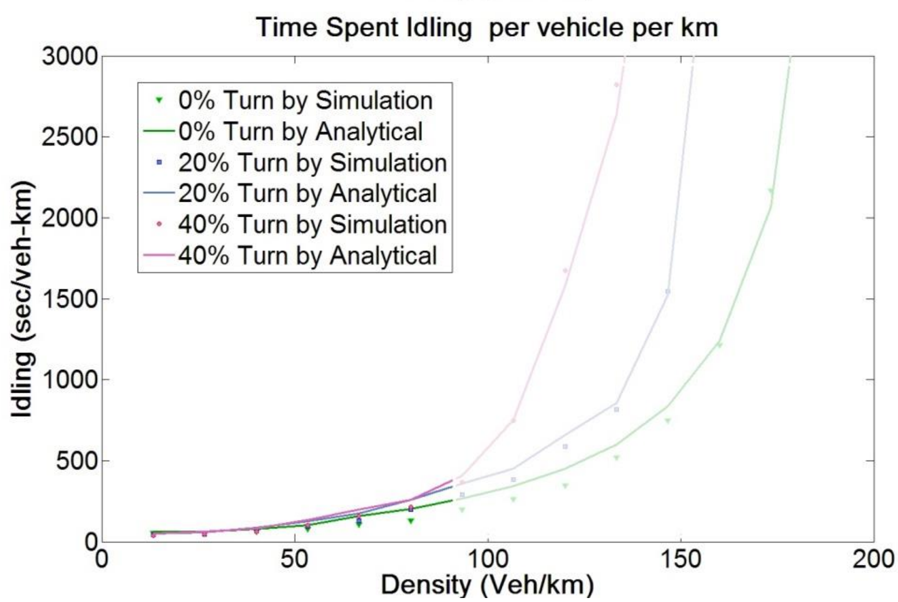


Figure 34. Comparison of total time spent in a) cruising and b) idling vs. average densities estimated analytically with the simulated results after a run of 10 minutes

6.1.2 Validation of analytically estimated total emissions (ITEM)

The total greenhouse gas emissions per vehicle distance traveled are calculated by multiplying each of the estimated driving cycle components by the associated emission factors as shown in equation (9). As explained earlier, by using the analytical approach for each pair of flow and density in MFD (shown in Figure 31), a corresponding total emissions can be estimated. Figure 35 shows the variation of network-wide total emissions under various traffic conditions. Reduced average flows in the network due to longer runs under heterogeneous conditions are reflected in the higher total emissions.

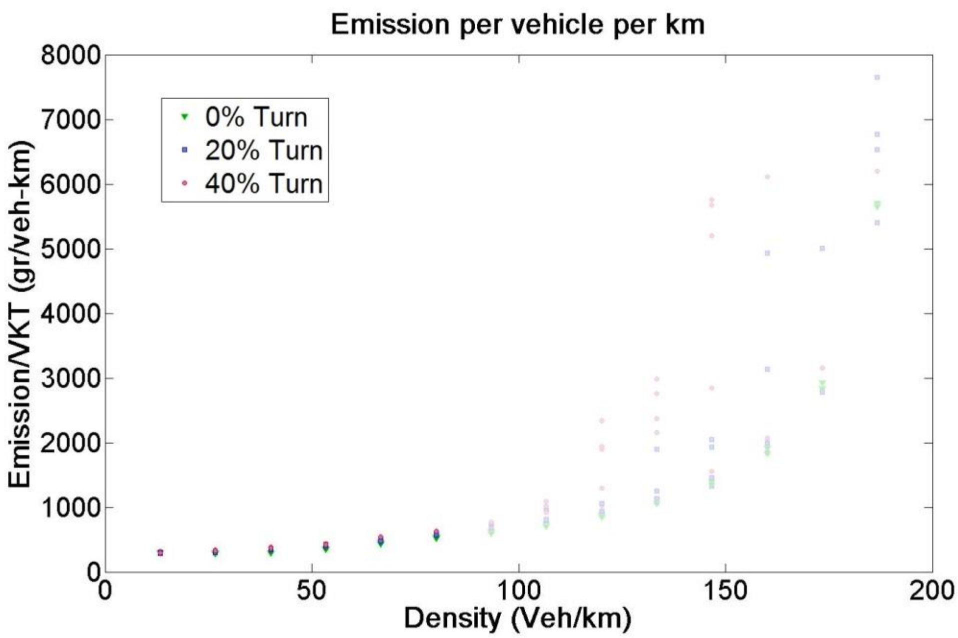
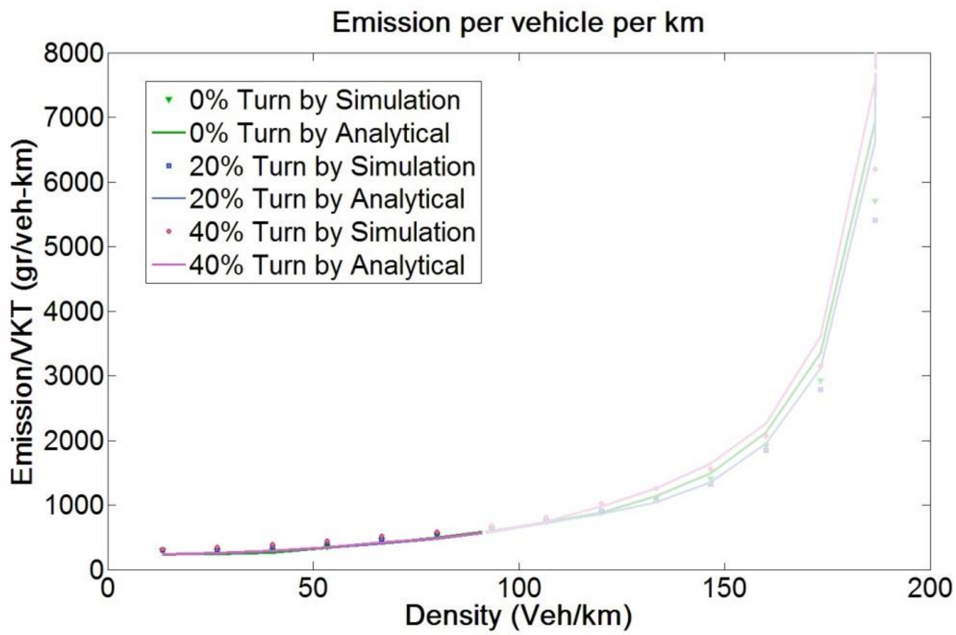


Figure 35. Variation of analytically estimated total network-wide emissions versus average network densities for different percent turning scenarios

These analytically estimated emissions can be validated by comparing them with the outcome of a conventional microscopic emissions analysis using the detailed second-by-second simulated vehicle trajectories. In order to make the comparison graphs more clear and understandable, the comparison results of only two cases are depicted in Figure 36. The analytically estimated emissions presented by solid lines and the aggregated simulation outputs are shown by points. Figure 36(a) shows the comparison of the scenarios after 2 minutes of microsimulation, when traffic conditions are still relatively homogeneous. Figure 36(b) shows the results after 10 minutes of microsimulation. The longer run causes more heterogeneous conditions on the network.

The analytical estimation of total emissions based on the measured MFD and associated estimates of the driving cycle components has a robust trend, and it is very close to the measured emissions from simulation. Except for very high densities, which are almost completely jam conditions, in most cases the analytically estimated emissions are within 10% of the measured values. Model errors, such as error in estimating the number of stops and error in averaging the emission factors, will be discussed in detail in the error analysis section. The close agreement between the analytical macroscopic model and the detailed simulation model occurs because aggregating the emissions from all vehicle trajectories together has the effect of averaging out variations from vehicle to vehicle.

a)



b)

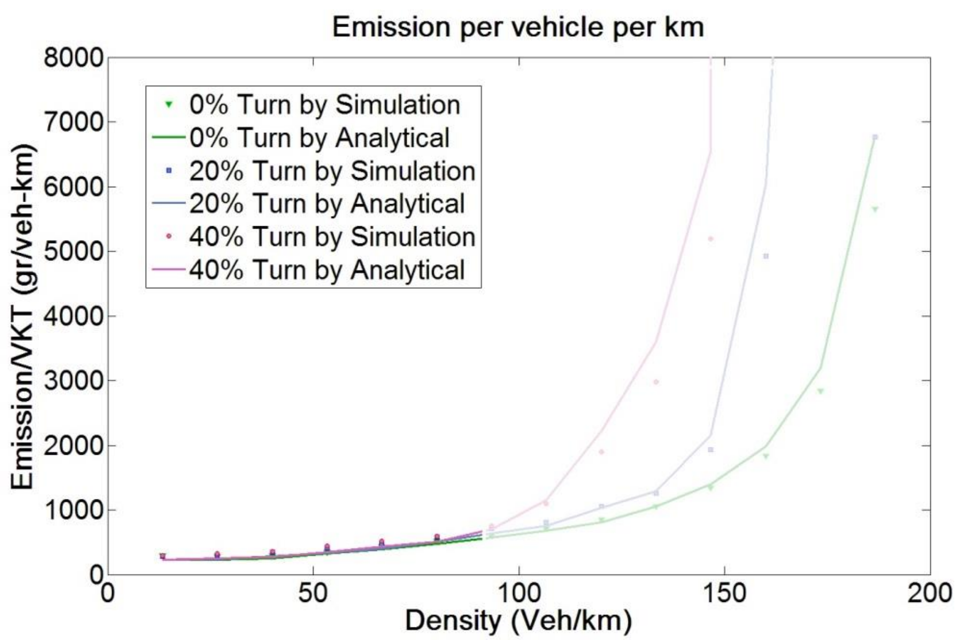


Figure 36. Comparison of the analytically estimated emissions (solid lines) and the aggregated simulation outputs (points) after a) 2 minutes of simulation run and b) after 10 minutes of simulation run

6.2 Model Errors

In order to assess the consistency and robustness of the proposed analytical model, an error analysis has been performed to compare the estimated emissions from the analytical model with the results of a detailed simulation and microscopic emission analysis. Similarly, analytical estimates of traffic parameters can be compared with measured values from the simulation. In the following sections, the consistency of analytical estimates is evaluated by comparing with the values computed by microsimulation.

6.2.1 Errors in estimation of total emission

In order to evaluate the usefulness the proposed model of ITEM, the final estimates of network-wide emissions estimated by the analytical traffic calculation are compared with the emissions obtained by directly feeding the second-by-second trajectories of vehicles into the microscopic emission model, MOVES. Figure 37 shows the comparison of analytically estimated total emission by ITEM, and microscopically computed total emissions by MOVES. There is a close relationship between analytical estimates and microscopic emission values. For the most part, ITEM overestimates total emissions by less than 10% in comparison with the microscopic results. However, at higher emission values, while the traffic conditions tend to be completely congested, the errors may exceed 10%. The main reason for larger overestimation at higher densities is that the analytical model tends to overestimate the number of stops in congested traffic conditions. In reality and simulation, the vehicle speeds in congested conditions may not pass the threshold to register as a measured stop in the trajectory processing algorithm, but the analytical approach accounts for every stop-and-go movement even at very low speeds as one stop.

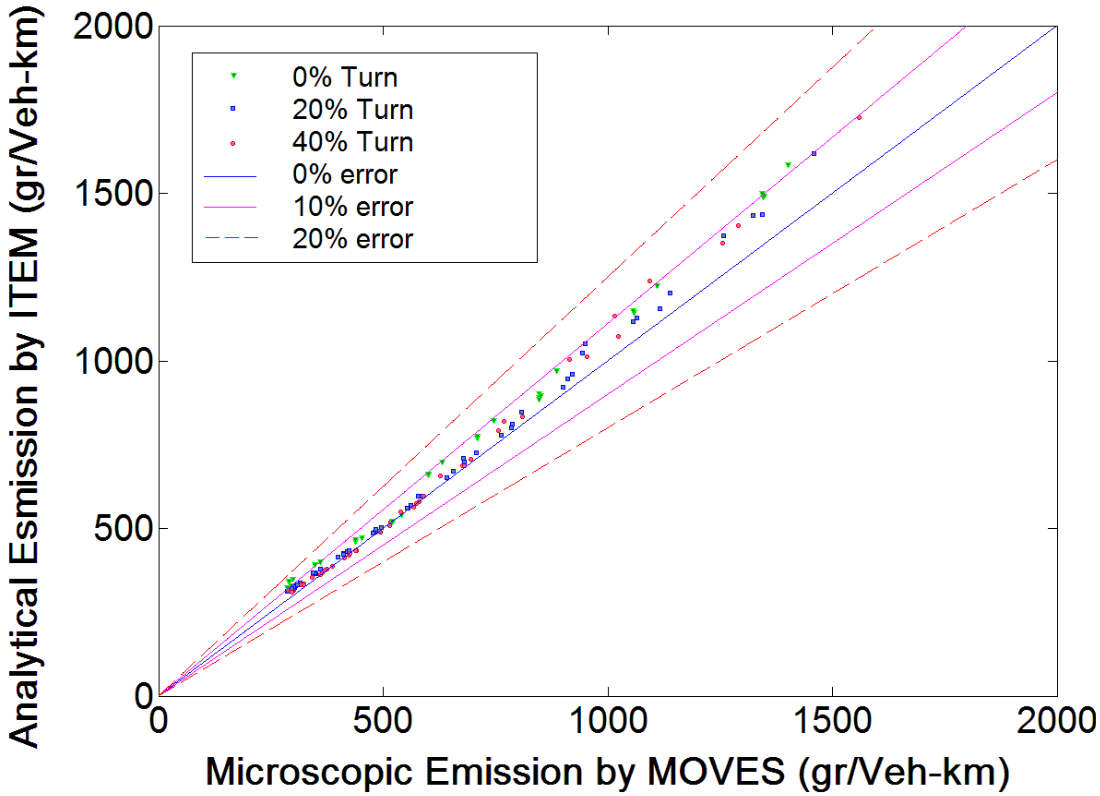


Figure 37. Comparison of the analytically estimated total emissions by ITEM with microscopically computed emissions by MOVES

6.2.2 Errors in estimation of the ITEM's components

The main sources of errors that contribute to all three traffic parameters (number of stops and time spent cruising and idling) are those that are affecting the analytical calculation of the total number of stops. Not only does the total number of stops have the highest contribution to total emission, but it is also used to compute the two other driving components, which are the total time spent in cruising and idling. Errors in the number of stops can be caused by two major sources. The first source of error is the threshold density at which the upstream vehicles hit the back of the queue and cause the second stop on each link. It becomes more complicated when vehicles are unevenly distributed and on some links the second stop is observed, while other links are in free flow conditions and only one stop per signal cycle is counted. This threshold is defined in equation (19). However, due to level of heterogeneity in the network, it can be a source of error in estimating the number of stops. The impact of spatial variation of density on the threshold can be estimated using the cumulative distribution function of the density on each link based on the mean and spatial variance of the densities. Investigation of the effect of spatial variance of densities on the MFD and the resulting number of stops is beyond the scope of this study, and in this study, it is assumed that these values are given or measured by ITS devices.

Another source of errors in the estimation of total emissions by ITEM is the emission factor (e_s) and duration (t_s) associated with each stop. This type of error is caused by variation of speed profiles (acceleration/deceleration patterns), which can be observed due to various traffic conditions or driving behaviors. As explained before, the emission factor for a single stop is calculated by adding the emissions that result from a complete deceleration from free flow speed to stop and a complete acceleration from stop to free flow speed. However, when density increases and the network approaches the saturated conditions, vehicles accelerate more slowly, and one complete stop $(t_{acc} + t_{dec})$ takes longer time. Longer stops (t_s) not only affect the analytical estimates of the traffic parameters, but they also cause higher emission rates associated with each stop.

This is because more cruising and idling time is replaced by the deceleration and acceleration modes. The variation of duration (t_s) and emission factor (e_s) associated with each stop versus average densities is shown in Table 7. In order to resolve this issue, different emission factors (e_s) and stop times (t_s) can be used for different traffic conditions (e.g. one for free flow conditions, one for capacity conditions, and one for jam density).

Table 7. Variation of duration (t_s) and emission factor (e_s) associated with each stop versus average densities

Avg. Density (veh/km)	Stop Duration t_s (sec)	Emissions per stop e_s (gr/veh-stop)
13.33	7.58	22.23
26.67	8.97	24.58
40	10.68	26.68
53.33	12.13	28.67
66.67	12.05	29.36
80	12.97	30.14
93.33	13.90	28.67
106.67	13.66	27.61
120	11.63	23.07
133.33	11.86	23.29
146.67	11.31	21.39
160	9.79	18.37

Finally, averaging across various driving behaviors and different vehicles emission generation can be another source of error in estimating emission factors using the real-world data. By increasing the number of samples (e.g. probe vehicles), this kind of error can be minimized. A greater number of sampled trajectories can reduce the errors caused by the heterogeneity. The sample size depends on the scope of the network, the level of desired accuracy, the level of variations in the network (e.g. special variation of densities caused by various capacities in different parts of the network, variation of driving behavior, distribution of vehicle types, technology and age, etc.) and available resources. One easy method to make a decision about the sample size that allows us to achieve a desired confidence interval is that an initial sample of vehicles can be selected, and based on the standard deviation of the resulting emission factors the size of the selected vehicles can be increased.

To deal with the heterogeneity, the network can be divided into multiple homogeneous sub-regions, or multiple emission factors can be used for different influencing conditions (e.g. various degrees of congestion, various vehicle type, age, and technology, etc.). For example, in a network with a fleet with considerable buses which might have different driving cycles, numbers of stops, and emission generation rates, equation (9) can be divided into the fleet-specific components as follows:

$$E_{total} = (N_s E_s + T_{id} E_{id} + T_{cr} E_{cr})_{veh} + (N_s E_s + T_{id} E_{id} + T_{cr} E_{cr})_{bus} \tag{20}$$

6.2.3 Sensitivity Analysis

In order to evaluate the sensitivity of the estimated network-wide total emissions to different network characteristics and comparison of the involving errors, the estimated total emissions under various scenarios are computed and the results of the model are compared with simulated values. Table 8 shows the variation of errors for changing the density for under-saturated and over saturated conditions.

Table 8. Sensitivity of estimated total emission to variation of densities

Density, k (veh/km)	Total Emissions (gr/veh-km)		
	Simulated	Modeled	Error
25	299.74	276.81	-8%
50	319.34	323.37	1%
change	7%	17%	
75	369.49	409.70	10.9%
100	469.37	518.73	10.5%
change	27%	27%	

The results show that the error in analytically estimated total emissions is much less than the variation of total emissions due to changes in density. This variation even more increase at higher densities. Similarly, the variation of error in the estimated total emissions due to change of other network's features are shown in Table 9.

Table 9. Sensitivity of estimated total emissions to variation of network's features

Variable		k = 25 veh/lane-km			k = 100 veh/lane-km		
		Simulated	Modeled	Error	Simulated	Modeled	Error
G/C	0.25	327.70	334.44	2%	901.57	910.07	1%
	0.50	299.74	276.81	-8%	469.37	518.73	11%
	change	-9%	-17%		-48%	-43%	
C	30	218.81	239.09	9%	582.16	613.96	5%
	60	299.74	276.81	-8%	469.37	518.73	11%
	change	37%	16%		-19%	-16%	
L	150	335.27	300.68	-10%	694.98	704.85	1%
	300	299.74	276.81	-8%	469.37	518.73	11%
	change	-11%	-8%		-32%	-26%	

The errors are evaluated for both under- (k = 25 veh/lane-km) and over-saturated (k = 100 veh/lane-km) conditions. As shown in Table 9, the error in estimated total emissions by the proposed ITEM model is less than the variation of total emissions due to the change in network characteristics. Also, the trend of variation of the estimated results is always similar to the trend of variation of the simulated values. Finally, while the model results are more sensitive at higher densities, the error observed in the estimated results is not increased significantly.

6.3 Summary

In this chapter, a grid network has been simulated to record microscopic vehicles' trajectories and macroscopic traffic parameters. In addition to the base case scenario, which is an idealized network with homogeneous traffic conditions across all links, two additional scenarios have been introduced to evaluate the effect of heterogeneity on the network. By allowing 20% and 40% random turning movements at all intersections, traffic that is uniformly loaded onto the network eventually gets clustered in more congested parts of the network, leaving other links with fewer vehicles.

The initial results show a robust relationship between average flow and average density, known as MFD, for all scenarios; however, by increasing the percentage of turning movements, the capacity of the network decreases and the observed flow deteriorates the longer the simulation runs. The reason for the flow reduction in these scenarios is that the random turns cause uneven distribution of vehicles in the network, which may result is congestion and spillbacks in some parts of the network, while other parts are underutilized.

A comparison of the analytically estimated driving cycle components (i.e., idling time, and number of stops, but not cruising time) with measured values from the simulated vehicle trajectories shows a close match. A level of inconsistency was observed in the analytical estimations of cruising time. The low contribution of cruising emissions in the grid network, and the neutralization of the error in cruising time by the errors of time spent idling and number of stops cause the observed cruising time error not to have a negative impact on the total emissions estimation. The close match between analytical estimates and measured values is an indication of robust relationship between fundamental properties of the network and these macroscopic traffic parameters and resulting total emissions. The estimated traffic components and their corresponding emission factors have been used by ITEM to estimate network-wide total emissions. Comparison of this analytically calculated result with microscopically computed emissions shows that the proposed analytical model provides an approximation of total emissions within 11% of the estimates from conventional microscopic analysis for all but the most congested traffic states.

Further error analysis for various scenarios shows that in almost all cases while the network traffic conditions are not completely jammed, there is no systematic error in the estimated results, and the maximum observed errors are always lower than 11%; however, at jam densities, while the network is completely congested, the model results show a dramatic overestimation of total emissions. The main reason for this large error is the difference between the number of stops estimated analytically and the simulated values. While the analytical approach records extremely high number of stops due to stop-and-go traffic, the simulation does not record considerable number of stops when they occur at very low vehicle speeds. Fortunately, widespread jammed conditions are rare in real cities, and the model performs well for a wide range of uncongested traffic conditions and a wide range of network characteristics.

Chapter 7 :

Conclusion

This research has been conducted to investigate existing network-wide emission models and propose a new method to estimate vehicular emissions at the network level. The proposed approach utilizes the macroscopic relationship between average flow and density known as the MFD. As shown in this study, a robust relationship exists between the components of the driving cycle that are associated with vehicular emissions and the fundamental properties of the network, just as a robust flow-density relation exists for many urban street networks. The components of the driving cycle per vehicle distance traveled (i.e., cruising time, idling time, and number of stops) are estimated based on the aggregated flow-density relation (MFD), the free-flow speed in the network, the duration of a typical acceleration and deceleration associated with a vehicle stop, and the signal cycle length. These components are then multiplied by emission factors that are developed using a detailed microscopic emission model, such as the project level of MOVES.

Although the average vehicle speeds in the network and the length of a signal cycle play a large role in determining the average emission rates from vehicles in a network, it is important to account for the effects of network characteristics such as the block length and signal timings on the driving cycles for each vehicle. Whereas existing macroscopic models tend to use a set of pre-defined driving cycles to derive emission rates based on average speeds, we know that real vehicle trajectories are more complex. Changes in network characteristics may change the frequency of acceleration and deceleration cycles associated with stops without affecting the overall flow or average speed in the network. There remains a role for microscopic emissions modeling in finding ways to optimize individual driving behavior or to quantify localized impacts for pollutants that must be monitored at individual facilities. The proposed model provides new value, because it provides a less data-intensive way for estimating aggregated network emissions, which is especially important for tracking pollutants like greenhouse gases that have a global impact.

7.1 Applicability and Usefulness of the Model

The conventional approaches to estimate traffic emissions have serious shortcomings, especially for evaluating total emissions in large-scale networks. The proposed Integrated Traffic Emission Model (ITEM) provides reliable emission estimation at the aggregated level. Unlike the microscopic emission models, ITEM does not require vehicles in street networks to be tracked in exact detail in order to make reliable estimates of the network-wide emissions. Therefore, the model is less data intensive and costly than microscopic emission models, which are only applicable for limited project level simulations.

On the other hand, the benefits of the MFD are useful for traffic analysis, because knowledge of a small number of network parameters and the average density of vehicles in the network provides sufficient information to predict the average flows, speeds, and delays in the network. The use of network-level traffic information in estimation of network-wide traffic emission makes the proposed model more reliable than existing macroscopic emission models, which mainly base their emissions estimation on the network-wide average speed of vehicles. In other words, ITEM estimates network-wide total emissions while considering driving cycles and traffic conditions based on the same aggregated quantities that are used to characterize the MFD for a network.

The proposed model can be applied for a wide range of emission evaluation purposes. In fact, this simple analytical tool lowers the barrier for quantifying emissions and including consideration of environmental impacts in analysis of area-wide policies related to traffic control and demand management, such as adaptive signal control or congestion pricing strategies. The model can also be used to compare different alternatives of transportation development projects based on their resulting traffic conditions.

7.2 Real-World Data Collection and Use of ITS

Although the proposed model does not require intensive data collection of second-by-second trajectories of all vehicles in the network, this approach needs data for two different purposes. The model needs a sample of microscopic trajectories for estimation of driving behavior and establishing the appropriate emission factors. Also, real-time macroscopic network-wide traffic information is required in order to consider the real-time traffic state and associated driving cycle components for estimating total emissions in real-time.

7.2.1 Microscopic data collection

As expressed earlier, the microscopic trajectories of selected vehicles are used to extract the speed profiles of typical acceleration and deceleration, as well as, average free flow speed of vehicles. These values are used to compute corresponding emission factors in addition to calculating other parameters, such as duration of a typical stop (i.e., summation of one acceleration and one deceleration). The required number of sampled trajectories depends on the scope of the network, the level of desired accuracy, the level of variations in the network (e.g., driving behavior, spatial distribution of vehicles, vehicle types, age, etc.) and available resources.

Due to recent advancements, there are several methods to record fine resolution vehicles trajectories. In addition to microscopic simulation, which is used in this study, image processing of video-taped moving vehicles, GPS data, smartphone data, and using a sample of probe vehicles are other available technologies that can be implemented to collect microscopic trajectory data. Additionally, equipped vehicles with real-time emission measurement instruments can be used to directly measure emission factors associated with driving cycle components. However, the distribution of vehicles' ages and technologies should be carefully considered as part of the sample size decision making process, in order to accurately represent the network fleet.

7.2.2 Macroscopic data collection

The main contribution of this model is that it can estimate real-time network-wide emissions based on instantaneous traffic conditions. Therefore, macroscopic traffic data associated with networks play an important role in this model. These data include the network MFD, real-time average flow, and average density to make rough estimations of real-time emissions. Network features such as block length, signal timing, spatial variation of vehicle distribution are especially important during congested conditions.

Various ITS technologies can be utilized to record this type of required data. In particular, loop detectors and similar vehicle detectors can be used not only to estimate the flow within the network, but also the level of heterogeneity of vehicle accumulations across links in the network. For example, vehicle detectors can be used to detect the back of the queue to determine if it has passed the threshold that causes a second stop per cycle on each individual link.

7.3 Future Work and Fields Tests

This study is an initial investigation of this new proposed analytical approach that considers macroscopic traffic conditions and the network's MFD in estimating network-wide emissions. In this study, a simplified grid network with some level of heterogeneity caused by turning movements has been evaluated. However, additional work is needed to consider the effect of some other important network characteristics on aggregated emissions. For example, the signal offset between adjacent traffic signals plays a very important role in how smoothly traffic progresses along an arterial corridor. There are methods to analytically approximate the MFD for a network with signal offsets (Geroliminis & Daganzo, 2008), and accounting for this effect on the number of stops requires making some adjustments to equation (19).

Another important difference between the simulations of idealized networks presented in this study and traffic in real cities is that the vehicles are often not uniformly distributed across the network. This can be caused by heterogeneous link capacities in different parts of the network, or an uneven distribution of demand in the network. This means that in real networks it is more likely that some links will incur queue spillbacks while other streets are underutilized. This reduces the average flows sustained on the network. Although preliminary findings suggest that if the realized flow on a network can be obtained by measurement or estimation, the model continues to provide a close approximation of the emissions calculated through extensive analysis of second-by-second vehicle trajectories. However, the application of this model in real-world networks and in particular, the use of real-world trajectories will provide better feedback calibrating and improving the model. Furthermore, several other issues that can affect the MFD and other macroscopic traffic parameters (such as network spatial characteristics, various type of heterogeneities in the network and traffic dynamics) are currently topics of research in the field of traffic flow theory. All of these issues can similarly impact the macroscopic relationship between the average density and total emissions.

Potential future work includes calibrating the model of total emissions aggregated over a network with fixed emission detectors, considering dispersion and other similar affecting parameters. However, this kind of study might become more complicated, because in addition to wind and other dispersion parameters, other local and regional air pollution sources need to be considered.

Despite the additional complexities of real-world traffic that need to be evaluated in future studies, the value of the proposed model has been demonstrated in this study is the capability of evaluation of network-wide total emissions by considering traffic conditions and driving cycles in the network. This is the first proposed analytical approach that connects the fundamental properties of the network, including the network's MFD with total traffic emissions. The model provides an easy tool to estimate real-time aggregated emissions given the current density on the network, by using the robust and reproducible relationship between the average density of vehicles on the network and the total emissions generated by vehicles.

BIBLIOGRAPHY

Ahn, K., Rakha, H., Trani, A. & Van Aerde, M., 2002. Estimating Vehicle Fuel Consumption and Emissions Based on Instantaneous Speed and Acceleration Levels. *Journal of Transportation Engineering*, 128(2), p. 182–190.

Ahn, K., Trani, A., Rakha, H. & Van Aerde, M., 1999. *Microscopic fuel consumption and emission.* Washington DC, s.n.

Akcelik, R., 1985. An Interpretation of the parameters in the simple average travel speed model of fuel consumption. *Australian Road Research*, March, 15(1), pp. 46-49.

An, F., Barth, M., Scora, G. & Ross, M., 1998. Modeling enleanment emissions for lightduty vehicles. *Transportation Research Record*, Volumen 1641, pp. 48-57.

Bachman, W., Sarasua, W. & Guensler, R., 1996. Geographic Information System Framework for Modeling Mobile-Source Emissions. *Transportation Research Record*, Volumen 1551 , pp. 123-132.

Bachman, W., Sarasua, W., Hallmark, S. & Guensler, R., 2000. Modeling regional mobile source emissions in a geographic information system framework. *Transportation Research Part C: Emerging Technologies*, 8(1-6), p. 205–229.

Bai, S., Eisinger, D. & Niemeier, D., 2009. *MOVES vs. EMFAC: A Comparison of Greenhouse Gas Emissions Using Los Angeles County.* Washington, DC., s.n.

Barceló, J., 2013. *Microscopic Traffic Simulation of Aimsun, Version 8.0, User's Manual,* s.l.: TSS-Transport Simulation Systems.

Barth, M. y otros, 2000. *Final Report: The Development of a Comprehensive Modal Emissions Model.* [En línea]
Available at: http://www.cert.ucr.edu/cmem/docs/NCHRP_Final_Report.pdf

Beardsley, M., 2004. *MOVES Fleet & Activity Inputs 1999 Base Year.* s.l.:s.n.

Brindle, R. y otros, 2000. *Improving urban transport demand models and their use,* Sydney, Australia: Austroads.

Cappiello, A., 2002. *Modeling Traffic Flow Emissions (Master Thesis),* s.l.: Massachusetts Institute of Technology.

Cappiello, A. y otros, 2002. A Statistical Model of Vehicle Emissions and Fuel Consumption. *The Proceedings of 5th IEEE International Conference on Intelligent Transportation Systems,*, September.

CARB, 2011. *EMFAC2011 User's Guide (updated in 2013).* [En línea] Available at: http://www.arb.ca.gov/msei/emfac2011-ldv-users-guide-final.pdf

Chang, M.-F. & Herman, R., 1981. Trip Time Versus Stop Time and Fuel Consumption Characteristics in Cities. *Transportation science*, August, pp. 183 - 209.

Cheng, Y. y otros, 2011. Cycle-by-Cycle Queue Length Estimation for Signalized Intersections Using Sampled Trajectory Data. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 2257, pp. 87-94.

Cronje, W. B., 1983. Derivation of Equations for Queue Length, Stops, and Delay for Fixed-Time Traffic Signals. *Transportation Research Record,* Issue 905, pp. 93-95.

Daganzo, C., 1994. The cell transmission model: A dynamic representation of highway traffic consistent with the hydrodynamic theory. *Transportation Research Part B: Methodological*, 28(4), p. 269–287.

Daganzo, C. F., 2005.a. A variational formulation of kinematic waves: basic theory and complex boundary conditions. *Transportation Research Part B: Methodological*, February, 39(2), p. 187–196.

Daganzo, C. F., 2005.b. A variational formulation of kinematic waves: Solution methods. *ransportation Research Part B: Methodological*, December, 39(10), p. 934–950.

Daganzo, C. F., 2007. Urban gridlock: macroscopic modeling and mitigation approaches. *Transportation Research Part B: Methodological*, January, 41(1), p. 49–62.

Daganzo, C. F. & Geroliminis, N., 2008. An analytical approximation for the macroscopic fundamental diagram of urban traffic. *Transportation Research Part B: Methodological*, November, 42(9), p. 771–781.

EEA, 2011. *COPERT 4 — Estimating emissions from road transport.* [En línea] Available at: http://www.eea.europa.eu/publications/copert-4-2014-estimating-emissions

Evans, L. & Herman, R., 1978. Automobile Fuel Economy on Fixed Urban Driving Schedules. *Transportation Science,* May, pp. 137 - 152.

Evans, L., Herman, R. & Lam, T., 1976. Multivariate Analysis of Traffic Factors Related to Fuel Consumption in Urban Driving. *Transportation Science,* May, pp. 205-215.

Evans, L., Herman, R. & Lam, T., 1976. Multivariate Analysis of Traffic Factors Related to Fuel Consumption in Urban Driving. *Transportation Science*, May, pp. 205 - 215.

Faiz, A., Weaver, C. & Walsh, M., 1996. *Air Pollution from Motor Vehicles: Standards and Technologies for Controlling Emissions.* Washington, D.C.: The World Bank.

Flagan, R. & Seinfeld, J., 2012. *Fundamentals of Air Pollution Engineering.* s.l.:Dover Publications.

Geroliminis, N. & Daganzo, C. F., 2008. Existence of urban-scale macroscopic fundamental diagrams: Some experimental findings. *Transportation Research Part B: Methodological*, November, 42(9), p. 759–770.

Gkatzoflias, D., Kouridis, C., Ntziachristos, L. & Samaras, Z., 2007. *Computer Programme to calculate Emissions from Road Transport, COPERT 4, Version 5, User manual.* [En línea]
Available at: http://www.emisia.com/docs/tech01.pdf

Gori, S., La Spada, S., Mannini, L. & Nigro, M., 2012. *Within-Day Dynamic Estimation of Pollutant Emissions: A Procedure for Wide Urban Network.* Paris, s.n., p. 312–322.

Grant, C., Gillis, B. & Guensler, R., 2000. Collection of vehicle activity data by video detection for use in transportation planning. *Journal of Intelligent Transportation Systems*, 5(4), pp. 343-361.

Hansen, J. Q., Winther, M. & Sorenson, S. C., 1995. The influence of driving patterns on petrol passenger car emissions. *Science of The Total Environment*, July, 169(1-3), p. 129–139.

Hassounah, M. & Miller, E., 1994. Modelling air pollution from road traffic: a review. *Traffic Engineering and Control*, 35(9), pp. 510-514.

Helali, K. & Hutchinson, B., 1994. Improving road link speed estimates for air quality models. *Transportation research record*, Volumen 1444, pp. 71-78.

Jost, P., Hassel, D., Joumard, R. & Hickman, A. J., 1994. *Emission and fuel consumption modeling based on continuous measurements.* Beijing, China, s.n., pp. 158-166.

Joumard, R. y otros, 2000. Influence of driving cycles on unit emissions from passenger cars. *Atmospheric Environment*, January, 34(27), p. 4621–4628.

Kirchstetter, T. y otros, 1999. On-road measurement of fine particle and nitrogen oxide emissions from light- and heavy-duty motor vehicles. *Atmospheric Environment*, August, 33(18), p. 2955–2968.

Koupal, J. y otros, 2010. *Design and Implementation of MOVES: EPAís New Generation Mobile Source Emission Model.* [En línea]
Available at: http://www.epa.gov/ttnchie1/conference/ei12/mobile/koupal.pdf

Lighthill, M. J. & Whitham, G. B., 1955. *On Kinematic Waves. II. A Theory of Traffic Flow on Long Crowded Roads.* s.l., s.n., pp. 317-345.

Maerivoet, S. & De Moor, B., 2008. Transportation Planning and Traffic Flow Models. *Physics and Society*.

National Research Council, 1995. *Expanding Metropolitan Highways: Implications for Air Quality and Energy Use*, Washington, D.C.: National Academy Press, .

Ntziachristos, L. & Samaras, Z., 2013. *EMEP/EEA air pollutant emission inventory guidebook.* [En línea]
Available at: http://www.eea.europa.eu/publications/emep-eea-guidebook-2013

Rakha, H. & Ding, Y., 2003. Impact of Stops on Vehicle Fuel Consumption and Emissions. *Journal of Transportation Engineering*, 129(1), p. 23–32.

Rakha, H., Kang, Y.-S. & Dion, F., 2001. Estimating Vehicle Stops at Under-Saturated and Over-Saturated Fixed-Time. *Transportation Research Record*, Issue 1776, pp. 128-137.

Rakha, H., Kyoungho, A. & Antonio, T., 2003. Comparison of MOBILE5a, MOBILE6, VT-MICRO, and CMEM models for estimating hot-stabilized light-duty gasoline vehicle emissions. *Canadian Journal of Civil Engineering*, December, 30(6), pp. 1010-1021.

Rakha, H., Van Aerde, M., Ahn, K. & Trani, A., 2000. Requirements for Evaluating Traffic Signal Control Impacts on Energy and Emissions Based on Instantaneous Speed and Acceleration Measurements. *Transportation Research Record*, Volumen 1738, pp. 56-67.

Rakha, H., Yue, H. & Dion, F., 2011. VT-Meso model framework for estimating hot-stabilized light-duty vehicle fuel consumption and emission rates. *Canaian Jornal of Civil Engieering*, November, 38(11), pp. 1274-1286.

Rao, V., Tooly, L. & Drukenbrod, J., 2013. *2008 National Emissions Inventory: Review, Analysis and Highlights.* [En línea]
Available at: http://www.epa.gov/ttn/chief/net/2008report.pdf

Richardson, A. & Akcelik, R., 1981. *Fuel consumption Models and Data Needs for the design and Evaluation of Urban Traffic System Australian Road Research Board.* Brisbane, Australia, Barton, ACT: Institution of Engineers, pp. 21-28.

Richards, P. I., 1956. Shock Waves on the Highway. *Operations Research*, February, 4(1), pp. 42-51.

Scora, G. & Barth, M., 2006. *Comprehensive Modal Emission Model (CMEM), version 3.01 User's Guide.* [En línea]
Available at: http://cmscert.engr.ucr.edu/cmem/docs/CMEM_User_Guide_v3.01d.pdf

Smit, R. & Ntziachristos, L., 2013. *COPERT Australia: a new software to estimate vehicle emissions in Australia.* Brisbane, Australia, s.n.

Teng, H., Yu, L. & Qi, Y., 2002. *Statistical microscale emission models incorporating acceleration and deceleration.* Washington, DC., s.n.

U.S. Department of the Treasury , 2012. *A new economic analysis of infrastructure investment.* [En línea]
Available at: http://www.treasury.gov/resource-center/economic-policy/Documents/20120323InfrastructureReport.pdf

U.S. Department of the Treasury, 2012. *A new economic analysis of infrastructure investment.* [En línea]
Available at: http://www.treasury.gov/resource-center/economic-policy/Documents/20120323InfrastructureReport.pdf

US EPA, 2000. *National Air Pollutant Emission Trends, 1900 – 1998.* [En línea]
Available at: http://www.epa.gov/ttn/chief/trends/trends98/trends98.pdf

US EPA, 2001. *EPA's New Generation Mobile Source Emissions Model: Initial Proposal and Issues.* [En línea]
Available at: http://www.epa.gov/OMS/models/ngm/r01007.pdf

US EPA, 2008. *Latest Findings on National Air Quality - Status and Trends Through 2006.* [En línea]
Available at: http://www.epa.gov/airtrends/2007/report/trends_report_full.pdf

US EPA, 2012.a. *Light-Duty Truck -- Tier 0, Tier 1, and Clean Fuel Vehicle Exhaust Emission Standards.* [En línea]
Available at: http://www.epa.gov/otaq/standards/light-duty/tiers0-1-mdvstds.htm

US EPA, 2012.b. *EPA and NHTSA Set Standards to Reduce Greenhouse Gases and Improve Fuel Economy for Model Years 2017-2025 Cars and Light Trucks.* [En línea]
Available at: http://www.epa.gov/otaq/climate/documents/420f12051.pdf

US EPA, 2012.c. *Motor Vehicle Emission Simulator (MOVES): User Guide for MOVES2010b.* [En línea]
Available at: http://www.epa.gov/otaq/models/moves/documents/420b12001b.pdf

US EPA, 2013. *Light-Duty Automotive Technology, Carbon Dioxide Emissions, and Fuel Economy Trends: 1975 Through 2013.* [En línea]
Available at: http://epa.gov/fueleconomy/fetrends/1975-2013/420r13011.pdf

US EPA, 2014.a. *National Ambient Air Quality Standards (NAAQS).* [En línea]
Available at: http://www.epa.gov/air/criteria.html

US EPA, 2014.b. *Policy and Technical Guidance.* [En línea]
Available at: http://www.epa.gov/oms/stateresources/transconf/policy.htm#require

Vallamsundar, S. & Lin, J., 2011. MOVES Versus MOBILE: Comparison of Greenhouse Gas and Criterion Pollutant Emissions. *Transportation Research Record*, Volumen 2233, pp. 27-35.

Wai Yuen, S., 2008. Enhanced Lagged Cell-Transmission Model for Dynamic Traffic Assignment. *Transportation Research Record: Journal of the Transportation Research Board*, Volumen 2085, pp. 76-85.

Watson, H., Milkins, E. & Marshall, G., 1979. *A simplified method for quantifying fuel consumption of vehicles in urban traffic.* Melbourne, Australia, s.n.

WBCSD, 2001. *Mobility 2001 - World mobility at the end of the twentieth century and its sustainability*. [En línea]
Available at: http://www.greenbiz.com/sites/default/files/document/O16F21480.pdf

Webster, F. V., 1958. Traffic Signal Settings. *Road Research Technical Paper*, Issue 39.

Webster, F. V. & Cobbe, B. M., 1966. Traffic Signals. *Road Research Technical Paper*, Issue 56.

Yue, H., 2008. *Mesoscopic Fuel Consumption and Emission Modeling (Doctorate dissertation)*, Blacksburg, Virginia: Virginia Polytechnic Institute and State University.

Zegeye, S. K. y otros, 2013. Integrated macroscopic traffic flow, emission, and fuel consumption model for control purposes. *Transportation Research Part C: Emerging Technologies*, June, Volumen 31, pp. 158-171.

Zheng, F. & van Zuylen, H., 2010. *Reconstruction of delay distribution at signalized intersections based on traffic measurements.* Funchal, Portugal, s.n., p. 1819–1824.