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URBAN TRAFFIC EMISSIONS ESTIMATES USING COUPLED MODELS

Janaina Antonino Pinto

Belo Horizonte

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Urban Traffic Emissions Estimates Using Coupled Models

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"O saber a gente aprende com os mestres e os livros.
A sabedoria se aprende é com a vida e com os humildes"
Cora Coralina

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Traffic data in air quality modeling: A review of key variables, improvements in results, open problems, and challenges in current research: Prashant Kumar, Marcelo Félix Alonso, Willian Lemker Andreão, Rizzieri Pedruzzi, Fábio Soares dos Santos, Davidson Martins Moreira, and Taciana Toledo de Almeida Albuquerque.

Kriging method application and traffic behavior profiles from local radar network database: A proposal to support traffic solutions and air pollution control strategies: Prashant Kumar, Marcelo Félix Alonso, Willian Lemker Andreão, Rizzieri Pedruzzi, Sérgio Ibarra Espinosa and Taciana Toledo de Almeida Albuquerque.

Coupled model using radar network database to assess vehicular emissions: mobility and traffic solutions for future scenarios in an urban area: Prashant Kumar, Marcelo Félix Alonso, Willian Lemker Andreão, Rizzieri Pedruzzi, Sérgio Ibarra Espinosa, Felipe Marinho Maciel, and Taciana Toledo de Almeida Albuquerque.

RESUMO

As principais fontes de poluentes atmosféricos nas áreas urbanas são as fontes móveis (veículos). Além da diversidade da frota, os veículos brasileiros usam diferentes tipos de combustíveis e várias tecnologias para controlar as emissões. Entre as ferramentas desenvolvidas para auxiliar na implementação de soluções que minimizem os impactos negativos da emissão de poluentes veiculares, existem os modelos de tráfego, de emissão e de qualidade do ar. Portanto, estimar os efeitos das emissões veiculares usando modelagem computacional é uma oportunidade de pesquisa para áreas urbanas densamente povoadas e com frotas representativas. Considerando o contexto, o objetivo principal deste trabalho foi estimar as emissões veiculares acoplando modelos estatísticos à modelo de emissões a partir de dados de radares e contagem de veículos e, com isso, aprimorar as técnicas de modelagem numérica por meio do desenvolvimento de uma metodologia para realizar transferências de informação de tráfego para modelos de qualidade do ar já existentes. O estudo foi realizado em Belo Horizonte (Minas Gerais), uma cidade localizada em uma área de 331 km^2 e com uma população de aproximadamente 2,5 milhões de habitantes. Estimou-se o comportamento periódico do tráfego nas vias urbanas e as curvas características desse comportamento por categoria de veículos com base em dados de contagem de fluxo (radares e contagens manuais). A partir dessa etapa, foi feita a espacialização dos dados de fluxos de veículos usando diferentes modelos estatísticos, sendo o modelo de efeito misto normal–bairro vizinho o mais indicado para a espacialização do fluxo nas vias urbanas. O resultado da espacialização dos dados de fluxo nas vias da cidade foi o dado de entrada para a quantificação das emissões por categoria de veículos e por tipo de combustível, usando o modelo brasileiro de emissões veiculares (*Vehicular Emissions Inventories* -VEIN). Foram modelados cenários atuais e futuros (2025, 2030 e 2050) com estratégias de redução de frota para o cálculo do impacto na redução das emissões veiculares. Na avaliação dos cenários, verificou-se que as ações como a implantação do rodízio de veículos na cidade, a implementação de um programa de inspeção veicular, a remoção da frota com mais de 30 anos das vias urbanas, a substituição da frota de ônibus por veículos elétricos geram reduções de até 44% nas emissões de CO, 42% de NOx e 38% de MP2.5. A implementação das estratégias sugeridas em conjunto a campanhas que incentivem a não utilização do veículo particular, bem como a construção de infraestrutura de transporte público de qualidade, como linhas de metrô e ciclovias conectando as regiões da cidade, podem contribuir satisfatoriamente para a melhoria da qualidade do ar em Belo Horizonte.

Palavras-chave: Dados de Radar; Comportamento de Tráfego; Método de Krigagem; Modelos de Efeitos Mistos; Inventário de Emissão Veicular; Soluções em Mobilidade Urbana.

ABSTRACT

The primary sources of air pollutants in urban areas are mobile (vehicles). In addition to fleet diversity, Brazilian vehicles use different types of fuels and various technologies to control emissions. Among the tools developed to assist the implementation of solutions that minimize the negative impacts of vehicular pollutant emissions, there are traffic, emission, and air quality models. Therefore, estimating the effects of vehicular emissions using computer modeling is a research opportunity for densely populated urban areas with representative fleets. Considering the context, the main objective of this work was to estimate the vehicle emissions by coupling statistical models to the emissions model using radar and count vehicle database. Thus, to improve numerical modeling techniques, it was developed a methodology for performing traffic information transfers to air quality models. Belo Horizonte (Minas Gerais), a city located in an area of 331 km2 and with a population of approximately 2.5 million inhabitants, was selected to develop this study. The periodic behavior of traffic on urban roads and the characteristic curves of this behavior by vehicle category were estimated based on flow count data (radars and manual counts). Different statistical models were used to calculate the spatialization of vehicle flow. The result showed that the mixed model normal-neighbor was suitable for the flow spatialization in urban roads. The result of flow data spatialization on the city was the input data for the quantification of emissions by vehicle category and fuel type, using the Brazilian Vehicle Emissions Inventories – VEIN. Current and future scenarios were modeled with fleet reduction strategies to calculate the impact on vehicle emission reduction. The evaluation scenarios showed that actions such as the implementation of road space rationing and vehicle inspection program, the removal of the over 30-year-old fleet from urban roads, the replacement of the bus fleet by electric vehicles lead to reductions of up to 44% in CO emissions, 42% of NOx and 38% of MP2.5. The implementation of the strategies suggested adding the non-use of the private vehicle, as well as the construction of quality public transport infrastructures (subway lines and bike paths connecting the city regions), can contribute satisfactorily to improve the air quality in Belo Horizonte.

Keywords: Radar Traffic Data; Traffic Behavior; Kriging Method; Mixed-Effects Model, Vehicular Emission Inventory, Urban Mobility Solutions.

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LIST OF ABREVIATIONS, SIGNS AND SYMBOLS

AADT - Average Annual Daily Traffic
AIMSUM2 - Advanced Interactive Microscopic Simulator for Urban and Non-Urban Networks
AQMs - Air quality models
ARTEMIS - Assessment and Reliability of Transport Emission Models and Inventory Systems ,
BHTRANS - Empresa de Transportes e Trânsito de Belo Horizonte
BRICS - Brazil, Russia, India, China and South Africa
CAMQ – Community Multiscale Air Quality Modeling System
CAPES - Coordenação de Aperfeiçoamento de Pessoal de Nível Superior
CArE-Cities - Clean Air Engineering for Cities
CETESB - Companhia Ambiental do Estado de São Paulo
CEV - Electronic Speed Control
CF/LWR - Cell Transmission Model/Kinematic Waver Model
CH_4 - Methane
CIMATEC/SENAI - Centro Tecnológico de Manufatura e Tecnologia
CJG - Combined Equipment (DIF + CEV)
CNPq - Conselho Nacional de Desenvolvimento Científico e Tecnológico
CMEM - Comprehensive Modal Emissions Model
CNT – Confederação Nacional dos Transportes
CO - Carbon Monoxide
CO_2 - Carbon Dioxide
CONAMA – Conselho Nacional de Meio Ambiente
COPERT - Computer Program to Calculate Emissions from Road Transport
CORSIM - Corridor Simulation
CTB – Código de Trânsito Brasileiro
DAS - Move Semaphore Advance Detector
DENATRAN - Departamento Nacional de Trânsito
DETRAN – Departamento de Trânsito
DETRAN MG - Departamento de Trânsito de Minas Gerais
DIF - Exclusive Intrusion Detector and Truck Circulation Detector
DNIT - Departamento Nacional de Infraestrutura de Transportes
DRACULA - Dynamic Route Assignment Combining User Learning and microsimulAtion
DTA - Dynamic Traffic Assignment
EEA – European Environmental Agency
EF - Emission Factors
EMFAC - EMission FACtor Model
EMME/2 - Equilibre Multimodal/ Multimodal Equilibrium
EP - Evening Peak
EUA – Estados Unidos da América
FAPESB - Fundação de Amparo à Pesquisa do Estado da Bahia
FAPESP - Fundação de Amparo à Pesquisa do Estado de São Paulo
EF – Emission Factor

FEAM – Fundação Estadual de Meio Ambiente de Minas Gerais
GCARE - Global Centre for Clean Air Research
GIS - Geographic Information System
GPS - Global Positioning System
HC - Hydrocarbons
IAG - USP - Instituto de Astronomia, Geofísica e Ciências Atmosféricas da Universidade de São Paulo
IBAMA – Instituto Brasileiro do Meio Ambiente e dos Recursos Naturais
IBGE – Instituto Brasileiro de Geografia e Estatística
IPEA – Instituto de Pesquisa Econômica Aplicada
ITS - Intelligent Traffic Systems
IVE - International Vehicle Emissions
MAD - Mean Absolute Deviation
MAPE - Mean Absolute Percentage Error
MABH – Metropolitan Area of Belo Horizonte
MARJ – Metropolitan Area of Rio de Janeiro
MASP – Metropolitan Area of São Paulo
MMA – Ministério do Meio Ambiente
MOVES - Motor Vehicle Emissions Models
MP - Morning Peak
MULTISIM - Simulation Model for Multi–lane Traffic Flows
N_2O - Nitrous Oxide
NETSIM - Network Simulation
NETSIM/ICG - Network Simulation/Interactive Computer Graphics
NMHC - Non-methane hydrocarbons
NO_2 – Nitrogen Dioxide
NOTS - Novel high-resolution spatial mapping of health and climate emissions from urban transport in Sao Paulo megacity
NOx - Nitrogen Oxides
O_3 - Ozone
PBH – Prefeitura de Belo Horizonte
PEDALS - Particles and Black Carbon Exposure to London and Sao Paulo Bike-Lane Users
PLANMOB – Plano Diretor de Mobilidade Urbana de Belo Horizonte
PM - Particulate Matter
PROCONVE – Programa de Controle da Poluição do Ar por Veículos Automotores
PROMOT – Programa de Controle da Poluição Atmosférica por Motociclos e Veículos Similares
PRONAR – Programa Nacional de Controle da Qualidade do Ar
RCHO – Aldehyde
RF - Fixed Speed Control Radar
RMSE - Root Mean Square Error
SIGOP II - SIGnal Optimization
SIMRO - Simulation Model of Roundabout Operations
SINDIPEÇAS – Sindicato Nacional da Indústria de Componentes para Veículos Automotores
SLR - Systematic Literature Review

SO_2 – Sulfur Dioxide
SUMO - Simulation of Urban Mobility
TMS - Traffic Management Strategies
TRAFLO - Traffic Simulation Model
US EPA – United States Environmental Protection Agency
UTCS-1 - Urban Traffic Control System
VEI - Vehicular Emission Inventory
VEIN - Vehicular Emissions Inventories Model
VOC´s – Volatile Organic Compounds
VT-Micro - Virginia Tech-Micro
WHO - World Health Organization

LIST OF EQUATIONS

CHAPTER 1:

INTRODUCTION

1.1. BACKGROUND AND JUSTIFICATION

Pollution is the environmental quality degradation resulting from activities that, directly or indirectly, harm the health, safety, and well-being of the population. Besides, it can create adverse conditions to social and economic activities, adversely affect the biota and aesthetic or sanitary conditions of the environment, also launching materials or energy in disagreement with the established environmental standards (Brazil, 1981). CONAMA resolution nº 491/2018 (MMA, 2018) defines a critical air pollution episode as being a situation characterized by the presence of high pollutants concentrations in the atmosphere in a short period, resulting from the occurrence of unfavorable meteorological conditions to their dispersion.

Air pollution is a serious environmental problem and a health risk that affects the whole world. According to the World Health Organization (WHO), outdoor air pollution is responsible for approximately 4.2 million deaths around the world, both in urban and rural areas. The causes of premature deaths varied, but there are cases in which air pollution is one of the leading causes of them, such as ischemic heart disease and strokes (58%), chronic obstructive pulmonary disease and acute lower respiratory infections (18%), in addition to lung cancer (6%) (Andreão *et al*., 2018; WHO, 2018).

The growth in the presence of contaminants or air pollutants happens mainly due to the expansion of industrial facilities close to large cities, and the rise in the number of vehicles circulating in urban centers. Air pollutants, such as particulate matter (PM), ozone (O3), nitrogen dioxide (NO2), and sulfur dioxide (SO2) have guidelines recommended by WHO. Places where the concentrations of these pollutants exceeded established standards, it is possible to damage the population health (WHO, 2006).

The research directed to air pollution study from different sources and its consequences for the environment and society has essential and has to carried out for year (Faiz et al., 1995; Faiz et al.,1996; Onursal and Gautam, 1997; Molina and Molina, 2004; Ketzel et al., 2007; Bukowiecki et al., 2010; Kanakidou et al., 2011; Oliveira et al., 2011; Wang and Hao, 2012; Pérez – Martinéz et al., 2015; Andrade et al., 2017; Kumar et al., 2018). It remains essential in the search for solutions to the problems faced by the population exposed to air pollution.

In urban areas, the main source of air pollution are vehicles, mainly the burning of fuels such as ethanol, gasohol (a mixture of gasoline and ethanol) and diesel (Sbayti et al*.*, 2001; Alonso et al., 2010; Nagpure et al., 2010; Albuquerque et al., 2012; Andrade et al., 2012; Mahmod et al*.*, 2013, Uddin, 2013; Kumar and Goel, 2016; Vouitsis et al., 2017). The harmful effects on the environment and health depend on the concentration of pollutants emitted to which human beings are exposed.

Due to the diversity of the fleet, and the use of different types of fuels and technologies to control emissions, Brazil has become an essential place for studies about air pollution caused by vehicular emissions. By the end of 2019, the country had approximately 104.4 million vehicles, including passenger cars, motorcycles, trucks, buses, among others. One of the central regions of the country, the southeast region, stands out for having 48.5% of the total national vehicle fleet. The state of Minas Gerais accounts for 23.1% of the fleet in the Southeast Region, followed by the state of Rio de Janeiro, (13,7%) and Espírito Santo (4,0%), second only to the state of São Paulo (59,3%) (DENATRAN, 2019).

The negative impacts on the air quality of the cities due to the growth of the fleet led the national government to develop different actions that contributed to minimizing the negative impacts. National programs such as Programa de Controle da Poluição do Ar por Veículos Automotores (PROCONVE) created by CONAMA resolution no18 /1986 (MMA, 1986), which defined the first emission limits for light vehicles; the Programa Nacional de Controle da Qualidade do Ar (PRONAR) established by resolution no 05/1989 of the Conselho Nacional de Meio Ambiente (CONAMA) (MMA, 1989); the Programa de Controle da Poluição do Ar por Motociclos e Veículos Similares (PROMOT) created by resolution CONAMA no 297/2002 (MMA, 2002) are examples of actions taken to reduce vehicle emissions and to improve air quality, especially in cities.

The vehicles emit various pollutants in variable amounts, such as carbon monoxide (CO), carbon dioxide (CO2), methane (CH4), aldehyde (RCHO), nitrogen oxides (NOx), sulfur dioxide (SO2) and particulate matter (PM). Ozone (O_3), a secondary pollutant, is the result of complex chemical reactions that take place between nitrogen dioxide (NO_2) and volatile organic compounds (VOC's) in the presence of solar radiation. In Brazil, Pacheco *et al*. (2017) showed that the metropolitan area of São Paulo (MASP), Rio de Janeiro (MARJ) and Belo Horizonte (MABH) reduced the concentrations of fine particulate matter (PM2.5) when compared to other cities in the world, such as Delhi (India) and Beijing (China). They also pointed out that the implementation of programs like PROCONVE and the increased use of biofuels was efficient in reducing the concentration of some pollutants such as CO, NOx, and

PM in urban areas. Andrade *et al*. (2012) showed the significant contribution of vehicles to environmental concentrations of PM2.5 in six Brazilian capitals (São Paulo (40,0%), Rio de Janeiro (50,0%), Belo Horizonte (17,0%) and Recife (37,0%)) and the importance of developing a public transport system based on clean energy sources.

Other studies also present relevant results for the air quality theme and are references for the continuity of the research, mainly, in the case of fine particles (Kukkonen et al., 2005; Lapuerta et al., 2008; Martins et al., 2008; Kumar et al., 2010; Schmitt et al., 2011; Randazzo and Sodré, 2011; Carvalho et al., 2015; Nogueira et al., 2015; Nagpure et al., 2016; Kong et al., 2016; Kumar et al., 2018; Jeong et al., 2019).

Pollutants regulated by PROCONVE (CO, NOx, non-methane hydrocarbons-NMHC, RCHO, PM, greenhouse gases (CO2, CH4 e N2O), in addition to particulate matter emissions due to tire wear, brakes, and track) have maximum emission limits based on international experiences (USEPA - EUA, 1997; EMEP – EEA, 2016). The criteria were adapted to the Brazilian reality and are established through guidelines, deadlines, legal, and emissions standards permissible for different categories of national and imported vehicles (IBAMA, 2011).

The contribution of each vehicle category combined with the fuel type is different, considering air emissions. Around 47.0% of CO emissions, for instance, correspond to emissions for passenger cars, and 33.0% are from motorcycles, similar to what happens with NMHC (47.0% of NMHC emissions are attributed to passenger cars and 23.0% to motorcycles). In the case of PM, the ones responsible for the highest pollutant emissions are passenger cars (14.0%), buses (urban, minibusses, road) (12.0%), heavy trucks (19.0%), semi-heavy trucks (23.0%) and medium trucks (11.0%). In the case of NOx, trucks are responsible for most emissions, with 23.0% attributed to heavy trucks, 24.0% for semi-heavy trucks, 10.0% to medium trucks, and 9.0% to light trucks. Most CH4 emissions are associated with passenger cars (48.0%) and motorcycles (23.0%). RCHO come from passenger cars (89.0%) and light commercial vehicles (11.0%) (CNT, 2019).

The fleet growth associated with fuel consumption increases vehicle emissions and, consequently, deteriorates the air quality of cities. Besides, existing combustion engine technologies, incomplete fuel burning, and driving cycles carried out by drivers also help to increase vehicle emissions.

Different studies report the importance of the real contribution of traffic with its different types of vehicles and fuels, to atmospheric emissions and, consequently, to air quality, contributing to the elaboration of action plans that minimize the negative impacts of vehicular emissions (Hellström et al., 2009; Herner et al., 2009; Piecyk and Mckinnon, 2009; Carslaw et al., 2011; Figliozzi, 2011; Weiss et al., 2011; Coelho et al., 2012).

The problems caused by poor air quality are diverse and require work and research that seeks answers to assist managers in making decisions. Among the tools developed to assist in the search for solutions that minimize the negative impacts of the emission of pollutants from mobile sources, the vehicle emission models stand out. Vehicle emissions are one of the input data for air quality models. The calculation of these emissions requires accurate information on vehicle emission factors, the vehicle fleet composition, including fuel consumption, age, and type of vehicles, as well as the distribution of vehicle flows on urban roads in the evaluated area.

Air quality models, in general, do not use detailed information on traffic behavior and, consequently, have limitations to truthfully represent emissions resulting from traffic and urban mobility in an area. Also, with the computational advance and the consequent increase in the resolution of the simulations, it becomes increasingly necessary to improve the input information of the models (emission models), mainly about the temporal and spatial distribution of vehicles.

In this context, Belo Horizonte was selected for the development of this research. Belo Horizonte, the principal city of Minas Gerais state, has a fleet equivalent to 19.3% of state's fleet, with 69.2% of passenger cars, light commercial vehicles corresponding to 15.7%, trucks to 3.0%, buses to 0.7% and motorcycles represent 11.5% of Belo Horizonte's fleet (DENATRAN, 2019). This city shows the representativeness of the city's fleet compared to the vehicle fleet that circulates in the state. In addition to vehicles, the number of fixed sources, such as the metallurgical industry, boilers in hospitals, pizzerias, and laundries, also contribute to the degradation of air quality in cities. According to Santos *et al*. (2019), the number of companies and fixed sources licensed in Belo Horizonte increased by approximately 57.4% and 22.7%, respectively, between 2003 and 2015. Fuel oil, firewood, natural gas, among other fueled these sources, which also contributes to increased emissions of air pollutants.

Currently, Belo Horizonte develops actions and projects for urban infrastructure, transport, and mobility through the implementation of the Belo Horizonte Urban Mobility Plan (PlanMob-BH). The PlanMob aims to recommend physical interventions, operational and public policy coherently and completely (PLANMOB-BH, 2010). Among the plan's proposals, there is an offer of more attractive public transport and discouraging the use of passenger cars, which is mainly responsible for vehicular emissions in urban centers.

The better representation of vehicular emissions, including actions that improve the urban mobility of the city, will bring greater accuracy in the representativeness of air quality. Therefore, from the detailed view of vehicle emissions, including studies of the periodic behavior of urban traffic on the roads and the result of characteristic curves of traffic behavior by vehicle category, it is possible to propose a contribution to a more adequate and detailed view of the vehicle's actions on air quality. This study proposes the use of statistical models to calculate the traffic flow, showing that this is an alternative to minimize costs with source-destination surveys and with the use of commercial software designed for traffic modeling. Estimating the main effects of vehicle emissions through the use of modeling for the most densely urban regions, with a representative vehicle fleet, presents itself as an essential and relevant topic for research.

1.2. OBJECTIVES

1.2.1. General objective

To estimate vehicle emissions by coupling statistical models to vehicle emission model from radar and vehicle count data.

1.2.2. Specific objectives

1.2.2.1. To identify the traffic behavior on urban roads and to derive the characteristic curves of this behavior by vehicle category;

1.2.2.2. To spatialize vehicle flow data using a statistical model;

1.2.2.3. To estimate emissions by vehicle category and by type of fuel considering the traffic behavior inserted in the Vehicle Emission Inventory Model (VEIN);

1.2.2.4. To assess the impact of detailed traffic data on vehicle emissions estimates.

1.3. DOCUMENT STRUCTURE

This thesis is divided into six chapters. Chapter 1, already presented, shows the introduction, justification, and general and specific objectives of the thesis. Chapter 2 presents a systematic review of the literature (SRL) in which the main traffic variables used in modeling emissions and air quality are presented and the discussion of the relationships, connections, and relevance between these variables. Besides, the step by step to generate traffic data using different traffic models were presented and, finally, a list of main traffic variables to be used as input data in the modeling of vehicle emissions was proposed. This work also presented the main pollutants inventoried in the selected works (NOx, PM, SO2, CO, and VOC), the differences between air quality modeling in developed and developing countries, and the importance of accurate modeling results to understand and evaluate the main issues inherent to air quality.

Chapter 3 presents the methodology used to structure and integrate traffic data inputs for modeling vehicle emissions. This chapter also shows that the demand to identify the real contribution of pollutants emitted by road vehicles to investigate air quality and its impacts on human health is increasing. However, it is necessary to consider the limitations of vehicle emission models. The specific objectives 1.2.2.1;1. 2.2.2 and 1.2.2.3 of the thesis are presented in chapter 3 since a statistical analysis of the monthly traffic behavior was performed, and the specific average traffic flow was determined using local radar data. The hourly behavior of the vehicle type was also analyzed, emphasizing the importance of the daytime cycle by vehicle type in the accuracy of the emissions inventory. Finally, a vehicle emissions inventory was calculated using VEIN, the Brazilian model of vehicle emissions inventory. The inventory considered data from different traffic behavior profiles (constant daytime cycle and by vehicle type) established from local radar data. The Kriging interpolation method to determine the spatial/temporal distribution of vehicle flows in urban roads in the Belo Horizonte city is a low-cost method used in this work.

Chapter 4 improves specific objectives 1.2.2.2 and 1.2.2.3 and fulfills specific objective 1.2.2.4, which corresponds to the assessment of the impact of detailing traffic data on vehicle emissions estimates. In this chapter, the spatial statistical analysis of radar data is presented, calculating the traffic flow using local radar data in different statistical models and analyzing future scenarios (2025, 2030, and 2050) from the vehicle emissions inventory projected for 2020. Results may serve as a reference for the policy definitions focused on traffic and environment in Belo Horizonte, as well as improving understanding of the dynamics of mobility in the city.

Finally, chapter 5 presents the final considerations and suggestions for future work, and chapter 6 presents all the bibliographic references used in the thesis.

CHAPTER 2:

TRAFFIC DATA IN AIR QUALITY MODELING: A REVIEW OF KEY VARIABLES, IMPROVEMENTS IN RESULTS, OPEN PROBLEMS AND CHALLENGES IN CURRENT RESEARCH

The paper “Traffic data in air quality modeling: a review of key variables, improvements in results, open problems and challenges in current research” (https://doi.org/10.1016/j.apr.2019.11.018) was developed by the author of this thesis in collaboration with researches Professor Prashant Kumar, Professor Marcelo Félix Alonso (co-advisor), Willian Lemker Andreao, Rizzieri Pedruzzi, Fábio Soares dos Santos e Professor Taciana Toledo de Almeida Albuquerque (advisor). The paper provided a review of the main concepts about traffic, emissions, and air quality modeling, as well as how the main traffic variables are treated in vehicle emissions and air quality models.

The importance of this work within the thesis is to show the state of the art of detailing traffic variables in emission and air quality modeling. There are still many differences in terms of advances in studies when comparing developing and developed countries. In developing countries, the air quality monitoring network is precarious and incipient. It was challenging to collect data and make use of the models being the main alternative to analyze the conditions of air quality in the cities. The establishment of research networks is crucial for search solutions applicable in the places where pollution comes from vehicles significantly impact the health of the population.

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2.1. INTRODUCTION

Significant vehicle fleet growth in large urban areas is one of the main causes of air pollution, which may affect air quality and, consequently, the health and well-being of exposed populations (Pant and Harrison, 2013; Andrade et al., 2017; Kumar et al., 2018). The effects on the environment and human health depend on the concentrations of the pollutants, topography, and weather conditions (Heal et al., 2012).

According to the World Health Organization (WHO), outdoor air pollution is responsible for approximately 4.2 million deaths around the world in both urban and rural areas. Ischemic heart disease and strokes (58%), chronic obstructive pulmonary disease and acute lower respiratory infections (18%), and lung cancer (6%) are the key causes of premature death (WHO, 2018).

In urban areas, vehicles are the main sources of air pollution mainly due to the burning of fuels such as gasoline, ethanol, gasohol (a mixture of gasoline and ethanol), diesel, biodiesel (a mixture of vegetables oils or animal fats and diesel), and natural gas (Sbayti, et al., 2001; Alonso et al., 2010; Gurjar et al., 2010; Albuquerque et al., 2012; Andrade et al., 2012; Mahmod et al., 2013; Uddin, 2013; Kumar et al., 2016; Andrade et al., 2017). The growth of the vehicular fleet and the related fuel consumption can lead to an increase in the emission of air pollutants. Therefore, the development of a robust vehicle emissions inventory (VEI) is required for a given study area, which may support policymakers and researchers to develop strategies in urban centers to reduce pollutant emissions and their concentration in the environment (Kumar et al., 2011a; Jain et al., 2016; Nagpure et.al., 2016). It should consist of as much of the vehicular fleet as possible, varying according to the type of vehicle (passenger cars, buses, trucks, motorcycles), age (older vehicles emit more pollutants), fuel used, and average distance traveled (ADT). All these data are needed for each road link in a study area (Coelho et al., 2014; Ho et al., 2014; Fu et al., 2017; Dias et al., 2018; Gómez et al., 2018).

The traffic-emission-air quality modeling has evolved over the years, but some gaps remain due to the quality of input data, especially in developing countries, and the complexity inherent in this type of modeling. Air quality models (AQMs) are among the tools developed to assist authorities responsible for researching, designing, and applying effective strategies to reduce the emission of harmful pollutants into the atmosphere. These models allow an understanding of the relationship between the sources of pollutant emissions and their impacts on ambient air quality. There are substantial differences between air quality models in terms of the formulation of models to estimate atmospheric parameters and the concentration of pollutants. However, one of the major differences between them is the capacity to simulate many chemical reactions and formation of secondary pollutants, such as secondary aerosols and ozone, while maintaining the representativeness of the physical phenomena in the atmosphere (US EPA, 2015). Photochemical models are more suitable to perform this task. Despite the advantages of photochemical models, one of the most critical aspects is the need for a high-quality emissions inventory (EI), with a complete emissions dataset that includes the main sources of emissions in a region, different pollutants, chemical speciation for VOC and PM, temporal variations in emissions and a representative tridimensional meteorological field (Arya, 1999; Pulles and Heslinga, 2010).

Some recent reviews have treated microsimulations tools, spatial projection and traffic flow to evaluate vehicular emissions (e.g., Fontes et al., 2015); systematically reviewed and analyzed available source apportionment studies on particulate matter (Karagulian et al., 2015); discussed coupling different air pollution modelling (Zhong et al., 2016); presented roadmaps and technical options to emission control (Wu et al., 2017); and highlighted co-operation to enforcement environmental policies (Isley and Taylor, 2018). This paper intends to fill the gaps in the area of the need of traffic emissions for air quality modelling. The aims of this work are (1) to carry out a systematic literature review (SLR) to present the main traffic variables used in emissions and air quality modeling and discuss their relationships, connections, and relevance; (2) to show a consistent sequence by which to generate traffic data using different traffic models; and (3) to propose a list of key traffic variables to use as input data in vehicle emissions modeling. This work also presents the main pollutants inventoried (NOx, PM, SO_2, CO, and VOCs), the differences between air quality modeling in developing and developed countries, and the importance of accurate modeling results to understand issues of air quality. Section 2 provides a systematic literature review using the VOSViewer tool. Section 3 highlights the review of traffic models and presents a sequence in which to generate traffic data. Section 4 presents an enhanced review of the relevant emissions and air quality models, presenting air quality modeling from different countries. Section 5 proposes a list of traffic variables and provides an analysis of uncertainty in air quality modeling. Finally, Section 6 summarizes the key findings, open problems, challenges in current research and conclusions.

2.2. APPROACH USING A SYSTEMATIC LITERATURE REVIEW

The first step in the systematic literature review was to select papers that described the importance of having detailed traffic data to improve results generated by an air quality model. The selection was made by analyzing bibliographic data such as authors, titles, abstracts, and keywords. A total of 826 scientific articles was found, and 125 were selected for detailed analysis. The databases consulted included Scopus, Compendex, ProQuest, and Periódicos Capes portal (a Brazilian virtual library which has a collection of 134 databases including Web of Science). Table 1 shows the combination of the keywords, database searched, and time period using different strings associated with different combinations of search terms.

Table 1: Systematic Literature Review (SLR): Database and papers found during the study period.

Database	SLR number	Keywords	Papers found	Period researched
Capes Portal	SLR1	“traffic models” and “emission models”	209	1999 to 2019
Capes Portal	SLR2	“vehicle emission model” and “air quality model”	411	Last 10 years
Capes Portal	SLR3	“review air quality model” and “review traffic emission model”	27	Last 10 years
Capes Portal	SLR4	“emission” and “traffic model” and “review”	56	Last 10 years
Scopus	SLR1	“traffic model” and “emission model” and “air quality model”	1	Last 10 years
Scopus	SLR2	“traffic model” and “emission model”	48	Last 10 years
Scopus	SLR3	“traffic model” and “air quality model”	2	Last 10 years
Compendex	SLR1	Traffic congestion; Highway traffic control and Air pollution control (OR particulate emissions OR Nitrogen oxides (NOx)OR Air quality standards and Emission control	21	1969 to 2019
Compendex	SLR2	traffic model and emission model	28	1969 to 2019
Compendex	SLR3	traffic model and air quality model	1	1969 to 2019
ProQuest	SLR1	“traffic model” and “emission model” and “air quality model”	2	Last 10 years
ProQuest	SLR2	“traffic model” and “emission model”	16	Last 10 years
ProQuest	SLR3	“traffic model” and “air quality model”	4	Last 10 years
		Total: 826		

VOSviewer software (Eck and Waltman, 2010) was used to investigate the strength of links between keywords. This strength is a similarity measure or the proximity index. The similarity between two items is calculated from the relationship between the number of items that co-occurrences and the total number of occurrences or co-occurrences. The strongest connections in the papers are between 'air quality', 'ozone', 'vehicle emission', 'road traffic', 'congestion', 'emission inventory', 'emissions' and 'fuel consumption' respectively (Table 2).

Table 2: Selected keywords and the relationships between them.

Keyword	Occurrences	Strength Connection
Air quality	16	22
Ozone	6	12
Vehicle Emissions	11	11
Road Traffic	5	10
Congestion	5	9
Emission Inventory	8	9
Emissions	6	8
Air quality modeling	4	7
Fuel Consumption	4	7

Figure 1 illustrates the density of the keywords (the most used) in selected papers and shows a strong link between vehicle emissions and air quality, traffic, and mobile source. Red areas indicate a high density of keywords (i.e., repetition of most used keywords) as opposed to the blue colour representing a low density of keywords (Eck and Waltman, 2016). This density view is particularly useful to obtain a quick overview of the important areas on a map. There are three main density areas that include keywords related to (1) emissions and traffic; (2) air quality and vehicle emissions; and (3) pollutants and air quality.

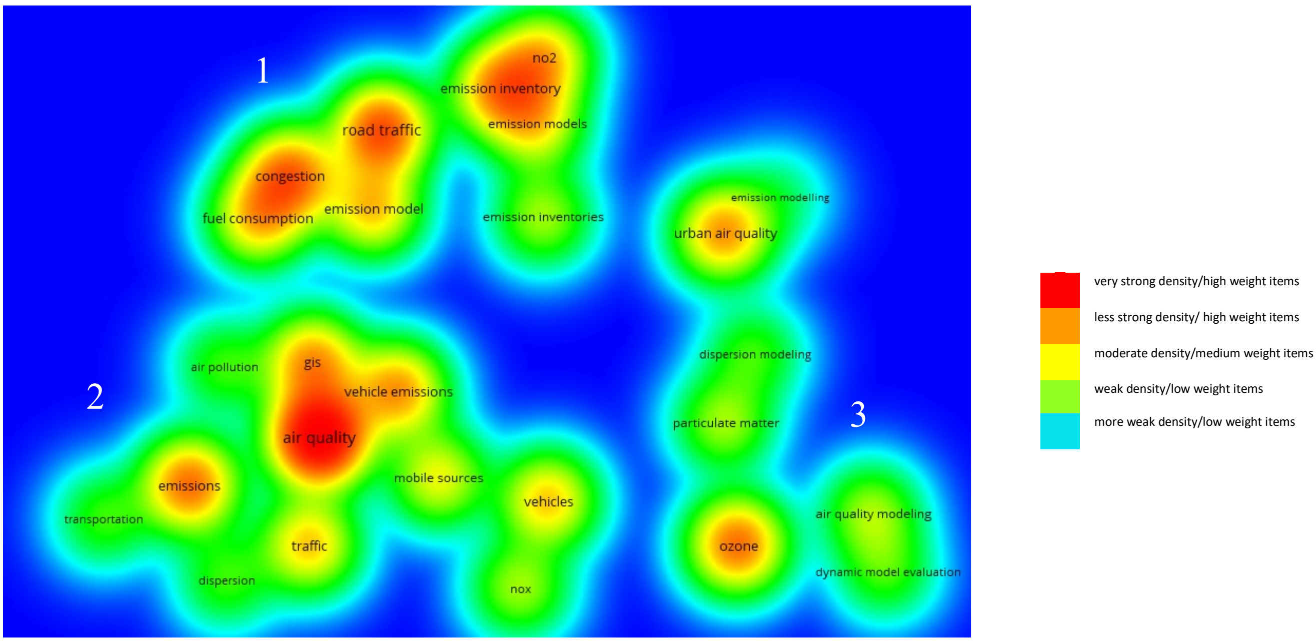

Figure 1:Density view diagram of keywords.

The systematic review literature also shows where the studies are most concentrated to introduce how traffic variables are connected, and which connections have strong and weak relationships between traffic variables and air quality. The network of connections between the variables showed that ozone, NOx, and particulate matter (PM) was the most studied pollutants. NOx and PM are characteristic of vehicular emissions in urban centers (Miranda et al, 2012; Fu et al., 2013; Lang et al., 2014) and have a direct effect on human health (Cesaroni et al., 2013; Crouse et al., 2015; Thurston et al., 2015; Pope et al., 2019).

Further analysis was carried out using correlation maps generated from the textual data. This included an analysis of the titles and abstracts that considered a combination of at least six occurrences of the variables. Occurrences indicate the number of times the selected variables appeared in the selected articles and relevance is a score (weight) of each variable. The variables traffic flow, fuel consumption, speed, average speed and acceleration occurred in a range between 11 and 6 times and relevance varied from 3.04 to 0.71. These traffic variables are the ones that need to be considered when drawing up a vehicular emission inventory. Other variables such as accuracy, ozone, roadway, air quality model, vehicular emission, congestion, and CO_2 were also relevant. When the years of publication are analyzed, the term ‘accuracy’ stands out in publications from the last four years. The term ‘accuracy’ (the most proximity of a value obtained with respect to a reference value) has large correlation with the term ‘air quality model’ (it is highly related to the topic of the review), while its correlation to other variables is weak.

Finally, the arrangement of connections between variables related to traffic-emissions- air quality models are shown in three clusters (Figure 2): cluster 1: traffic variables and connections between emission models and accuracy; cluster 2: traffic variables that are commonly used in traffic and emission modeling; and cluster 3: pollutants and variables related to air quality models and connections to traffic and emissions variables.

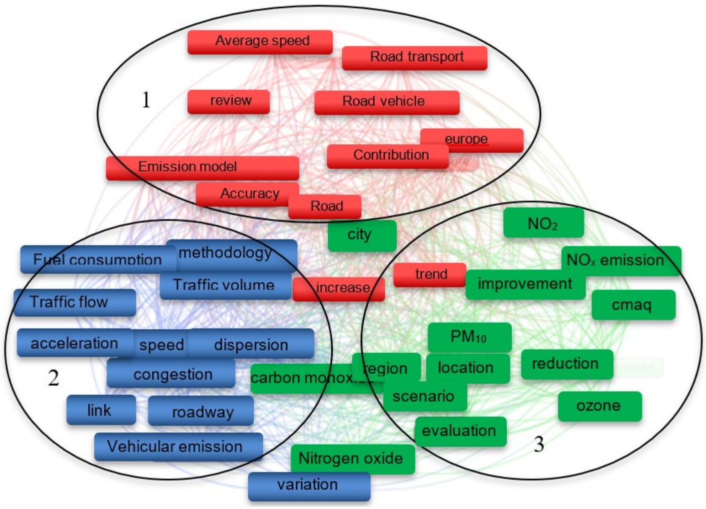

Figure 2: Network of connections between the variables used in different but related research articles.

The cluster analysis is showed a set of items included in a map and the item may belong to only one cluster. This analysis shows how the variables to traffic-emission-air quality modeling are linked in the literature review. All the above variables are part of the network, and all connections from clusters are important in the analyses of vehicle emissions and their impacts on urban air quality.

2.3. VEHICLE EMISSIONS AND THE USE OF TRAFFIC MODELS

In developing a vehicular emission inventory, the main pollutants characterized for fuel combustion were nitrogen oxides (NOx), carbon monoxide (CO), hydrocarbons (HC), non-methane hydrocarbons (NMHC), PM, greenhouse gases such as carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O). PM emissions due to tire/brake/road wear and dust resuspension are also accounted for and evaporative emissions still are considered because they may increase HC concentrations.

Vehicular emissions are classified either as direct or indirect. Direct emissions are those resulting from the combustion of fuel in a vehicle engine (hot exhaust emissions) which increases with the characteristics of driving cycles. Indirect vehicular emissions are caused by the resuspension of PM deposited on the track surface and by the wear of brake pads, tires and road surface (Pant and Harrison, 2013; Andrade et al., 2017; Kumar and Goel, 2016; Kumar et al., 2017). Vehicle emission rates can be calculated using emissions inventories and mathematical models. In this work, the emission rate is the representative value that relates the mass of a given element to the atmosphere considering "time" (mass/time) and must be expressed in tons per year (t/year) (Cetesb, 2009).

The vehicular emission inventory can be developed using both top-down and bottom-up methodological approaches (Aparicio et al., 2016; Wang et al., 2016; Ibarra-Espinosa and Ynoue, 2017). The top-down approach is based on statistics on vehicle composition, representative speeds, and country balances. It calculates the total emissions of some regions using generic indicators, such as sales data or fuel consumption. Emissions are then disaggregated according to specific emission factors. This approach reduces the accuracy of the spatial distribution of emissions, although it is fast, cheap, and does not require much technical skill (Costa and Baldasano, 1996; Bieser et al., 2010; Kumar et al., 2011a; Santos et al., 2019).

The bottom-up approach is based on traffic counts, vehicle compositions, road lengths, speed recordings, and a good knowledge of a given study area. This approach is based on estimations of emissions that use detailed data on each source of emissions. A study region is divided into sectors using traffic typologies, vehicle categories, and type of fuel used. The sources are the location of the emitter, the activities are standard temporal emissions, and emissions factors determine the quantity of pollutants emitted (Bieser et al., 2010; Santos et al., 2019).

Both methodologies require emissions factors (EFs) that describe the relationship between the activity data (traffic) and the emissions related to these data (Pulles and Heslinga, 2010; EEA 2016; Ibarra-Espinosa and Ynoue, 2017). The choice of methodology depends on the goal of the study, the information available, and the requirements of the inventory. In both cases, traffic information (activity data) is a key variable.

The dynamics and behavior of urban traffic (activity traffic data) can be represented on temporal and spatial scales using traffic modeling. Traffic models have been in development since the 1960s and have been refined over the years. These models can use macroscopic, mesoscopic, and microscopic approaches that are differentiated by the level of detail in input information such as speed, acceleration, traffic flow, and the aggregation of variables (Portugal, 2005; Darbha et al., 2008; Kumar et al., 2014) (Table 3).

Table 3: Types of traffic models.

Model	**Representation of traffic**	**Traffic flow variables**
Macroscopic	Traffic flow	Aggregated
Mesoscopic	Vehicle unit	Aggregated
Microscopic	Vehicle unit	Disaggregated

The decision regarding the most appropriate traffic model to select is made by the analyst. Figure 3 presents a sequence of processes followed to generate input data for vehicle emissions models with data from traffic models. For the study area, the study scale (country, state, city, neighborhood, or smaller areas), types of routes (regional, arterial, collector, or local) and time periods (annual, monthly, daily, hourly or by data fraction) must be defined.

The traffic data can be collected using an origin-destination survey, Global Positioning System (GPS) data, schedules of routes (for buses), radar databases, traffic counts, and traffic simulations (Ibarra-Espinosa and Ynoue, 2017; IEMA, 2017; Dias et al., 2018). However, some of this information does not consider all roads in the study area, and/or all hours of the day. In these cases, it is necessary to interpolate available traffic data to areas and hours for which such information is unavailable. Traffic models provide activity data with flow for every road in the area of interest.

Macroscopic models show the spatial and temporal evolution of traffic. The flow of traffic is considered fluid, such as in the study of hydrodynamics. Vehicles neglected at the individual level and for variables such as counts, and the vehicle flows are aggregated to a level equal to that of traffic performance measurement systems. These models are not very flexible, have low levels of detail and computational advantage in terms of their running speed (Hoogendoorn and Bovy, 2001; Esteves-Booth et al., 2002; Portugal, 2005; Barceló, 2010; Mohan and Ramadurai, 2013; van Wageningen-Kessels et. al., 2015).

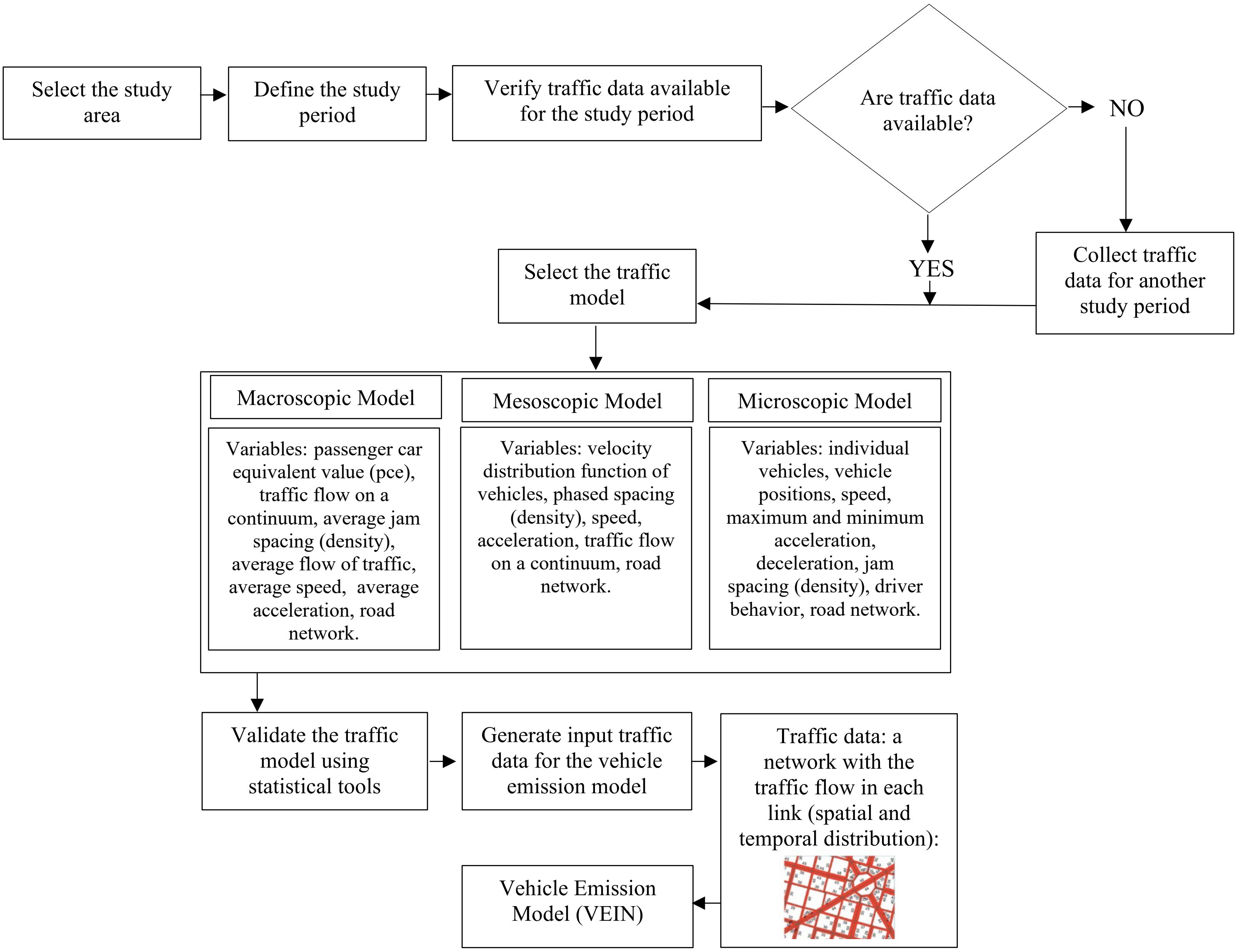

Figure 3: Steps to use traffic modeling to generate input data for vehicle emissions models.

Mesoscopic models use slightly more detailed variables than macroscopic models. Vehicles can be grouped (into platoons) or represented individually. Their behavior rules are specified in the form of probability distribution functions of the flow/capacity relationship. Vehicles are categorized based on their size, location, speed, and acceleration, which are important variables when traffic simulation is combined with air quality modeling (Hoogendoorn and Bovy, 2001;

Burghout et al., 2005; Portugal, 2005). The mesoscopic analysis deals with the constituents of traffic streams and seeks to explain the spatial and temporal behavior of vehicles based on the theory of traffic flow dispersion (Portugal, 2005; Barceló, 2010).

In microscopic models, vehicles are treated individually, and each retains all characteristics of interest to be modeled by the system. Table 4 presents a brief summary of traffic models and their classification. These models represent traffic processes and the interactions between vehicles and road infrastructure in detail. Defining the application context (spatial and temporal) is also fundamental to choosing these models, as they require a high computational capacity high due to the complexities of road networks (arcs and nodes).

Table 4: Summary of Traffic Models.

Decade	Model	Type
1970	Urban Traffic Control System (UTCS-1)	Microscopic
	Network Simulation (NETSIM)	Microscopic
	Simulation Model for Multi–lane Traffic Flows (MULTISIM)	Microscopic
	SIGnal Optimization (SIGOP II)	Macroscopic
	Microassignment	Macroscopic
1980	Network Simulation/Interactive Computer Graphics (NETSIM/ICG)	Microscopic
	Simulation Model of Roundabout Operations (SIMRO)	Microscopic
	Traffic Simulation Model (TRAFLO)	Macroscopic
1990	Advanced Interactive Microscopic Simulator for Urban and Non-Urban Networks (AIMSUM2)	Microscopic
	Corridor Simulation (CORSIM)	Microscopic
	Dynamic Route Assignment Combining User Learning and microsimulAtion (DRACULA)	Microscopic
	INTEGRATION	Microscopic
	PARAMICS	Microscopic
	SATURN	Microscopic
	TPS VISION	Microscopic
	TRAF–NETSIM	Microscopic
	VISSIM	Microscopic
	CONTRAN	Mesoscopic
	EMME	Macroscopic
2000-Presently	Simulation of Urban Mobility (SUMO)	Microscopic
	Cell Transmission Model/Kinematic Waver Model (CF/LWR)	Macroscopic/Microscopic
	Cluster	Mesoscopic
	Generic GK	Mesoscopic
	Fastlane	Macroscopic
	Kinematic Waver Model MC/LWR with pce	Macroscopic

Source: Adapted from Portugal (2005), Barceló (2010), Li and Sun (2012); Mohan and Ramadurai (2013) and Kessels et al. (2015)).

The importance of using traffic models to generate input data for emissions models is directly related to the detail level of variables used in the former. Highly detailed (microscopic) models are complex but are supposed to describe reality more accurately, whereas simple and traceable (macroscopic) models are used in real-time applications such as proactive traffic management.

Therefore, descriptive and predictive accuracy must be weighed against the need for fast simulations. Traffic models that can enable rapid simulations and, preferably, that has simplified mathematical formula (van Wageningen-Kessels et. al., 2015, Forehead and Huynh, 2018) are recommended. Table 5 presents a selection of papers that used traffic models and their related variables to generate precise data to insert into vehicle emissions models. These studies showed the importance and impact of traffic models used to improve input data for vehicle emissions models and, consequently, for air quality models.

Table 5: Review of traffic models.

Reference	Pollutants	Models	Traffic Variables	Country	Remarks
Wei et al. (2019)	CO, CO_2, NOx, VOC	PARAMICS	Road network; traffic signs; intersections; traffic zone; routes; bus stations; vehicles type	China	A genetic algorithm was used to calibrate the traffic simulation model, so the vehicle activity data simulation could be closed to real world. The focus to control vehicular emissions must be different: buses (CO, VOC); trucks (NOx, CO_2) and cars (CO).
Stern et al. (2019)	CO, CO_2, HC, NOx	Traffic - waves	Behavior; autonomous capability (adaptive cruise control, lane following, etc.)	USA	Significant emission reductions from vehicle may be possible with more technologically advanced vehicles, even with a limited number of vehicles on the road recovered.
Hofer et al. (2018)	CO_2	Agent-based	Traffic flow travel distance; road network; type, size, and age of car used	Austria	Electric cars were used to reduce CO_2 emissions. A significant result in CO_2 emissions would be observed only if many old cars were banned.
Xu et al. (2018)	NOx, PM10, PM2.5	VISSIM	Vehicle drive cycles; hourly traffic data; traffic volume and composition; radar speeds	Canada	The emissions estimated using vehicle speeds from radar were at least three times lower than those derived from simulated vehicle trajectories. Careful attention must be paid when raw radar data is used for emissions modeling.
Jiang et al. (2018)	CO_2, NOx, PM	Dynamic Traffic Assignment (DTA)	Density of urban traffic; travel speed; traffic acceleration	China	The model estimates various traffic-related exhaust emissions in urban areas and may serve to quantify the environmental impacts of various traffic management and control strategies.
Jamshidnejad et al. (2017)	CO, HC, NOx	SUMO	Traffic behavior; network; group of vehicles; time-speed curves	Netherlands, Greece	The model considered an aggregated behavior of group of vehicles and afforded a great accuracy and a low computational time when compared the behavior of individual vehicle.
Tang et al. (2017)	CO, HC, NOx	LWR* Model	Driver behavior; fuel consumption; traffic - waves	China	The driver´s bounded rationality has decisive effects on the fuel consumption
Borrego et al. (2016)	NOx, PM10	VISSIM	Driver behavior; car – following parameters; GPS data	Portugal	The detailed traffic data when combined with instantaneous exhaust emissions data can provide an accurate
Han et al. (2016)	HC	Lighthill–Whitham–Richards (LWR)	Vehicle occupancy; flow; network; link flow capacity	United Kingdom, USA	Reduced models allow emissions to be easily calculated in a network traffic model structure, as against to conventional techniques that require the trajectory of individual drivers in the network.
Hosseinlou et al. (2015)	CO, CO_2, HC, NOx,	AIMSUM	Travel speed and time; fuel consumption	Iran	From a societal perspective, 73 km/h would be an optimal speed; from a road user's perspective, this speed would be 82 km/h. The speed may influence pollutant emissions and the societal cost of travel.
Rowangould (2015)	PM	Travel Demand Model	Trip per link; vehicle classes; time periods	USA	A new methodology using a dispersion model to create regional PM2.5 maps using vehicular exhaust data. The detailed concentration maps could be used, for example, to improve the siting of air quality monitors.

Table 5: Review of traffic models (continuation).

Reference	Pollutants	Models	Traffic Variables	Country	Remarks
Vieira da Rocha et al. (2015)	CO_2, NOx, PM	Newell and Gipps	Traffic at peak hours; speed; acceleration; car-following; fuel consumption; fleet composition	USA	At an individual vehicle level, it takes more than a precise calibration of the car-following rules to obtain accurate estimates of fuel consumption, NOx, and PM emissions. Marginally counterparts on the traffic model accuracy could improve the accuracy of vehicle emissions.
Sun et al. (2015)	CO, CO_2, HC, NOx	GPS	Fuel consumption; mobile sensing data; state-dependent acceleration; vehicle trajectory	China	For vehicle-based estimates, if the number of vehicles is estimated properly, the corresponding fuel/emissions results are usually close to real ground values.
Alam and Hatzopoulou (2014)	Greenhouse gases	VISSIM	Network congestion; roadway grade; passenger load; fuel type	Canada	Compressed natural gas emissions are related to traffic congestion, transit signal priorities, and improved technology.
Hernádez-Moreno and Mugica-Álvarez (2014)	Black Carbon (BC), CO, CO_2, HC, NOx, SO_x, PM10, PM2.5.	TRANSIMS	Instantaneous fuel consumption; average speed	Mexico	The method for integrating polynomial regression models is an alternative for developing regional emissions models.
Ma et al. (2014)	CO, HC, NOx	VISSIM, SUMO	Light signal; vehicle actuated control; traffic flow rate; speed; fuel; stops; delays	China	There is a visible improvement in urban mobility, but the reduction of fuel consumption and vehicle emissions is not as evident.
Misra et al. (2013)	CO, NOx	PARAMICS	Route choice; driver behavior; vehicle category	Canada	Microscale urban traffic emissions were estimated using integrated model. CO and NOx concentrations observed by sensors were used to validate the model.
Zegeye et al. (2013)	CO, HCs, NOx	VT-micro, VT – macro, METANET	Average density; flow and average space mean speed; fuel consumption	Netherlands	The integration of macroscopic traffic flow models with microscopic emissions and fuel consumption models provided good estimates of the emissions and fuel consumption over a short simulation time.
Zhu and Ferreira (2013)	CO_2	AIMSUM, Monte Carlo Simulation	Vehicle speed; acceleration; free flow stage; congested stage	Australia	Under free-flowing traffic conditions, the CO_2 model produced low overall uncertainty. However, under congested conditions, there were significant errors associated with emissions estimates.
Tchepel et al. (2012)	PM2.5	TREM-HAP, Monte-Carlo technique	Hourly traffic counts; number of vehicles; vehicle categories; average speed; road segments	Portugal	Cold start emissions can contribute to up to 45% of total daily emissions. Uncertainties in the transport activity data affected the uncertainty of the model application.
Xie et al. (2012)	CO, NOx, SO_2	PARAMICS	Traffic volume; vehicle type; link volume; speed data; rate per Vehicle Miles Traveled (VMT)	USA	A change from diesel to compressed natural gas in transit buses reduced SO_2 emissions rates; however, it increased CO emissions rates. Electric cars reduced energy consumption and SO_2 and CO_2 emissions.
Kumar et al. (2011a)	PM	Activity based approach	Type of vehicle; Vehicle Kilometers Traveled (VKT)	India	This is the first study that calculated the total mortality due to exposure of ambient PM concentrations in an Indian megacity (Delhi).
Gurjar et al. (2010)	CO_2, CO, NOx, SPM, VOC´s	Activity based approach	Number of vehicles of each type; distance traveled in a year by each vehicle type	India	Pollutants were emitted mainly from a high number of commercial goods vehicles and buses, cars, and taxis. The increasing demand for personal vehicles contributes to emissions of CO, VOCs, and other pollutants.

The systematic literature review showed that approximately 61% of the articles used microscopic model to design traffic network; 22% adopted macroscopic models and 17% determined traffic flow using agent-based and activity-based approach. The predominance of microscopic models can be explained by the purpose of the research, the size of the study area, and the existence of detailed traffic data.

Although the microscopic model performed with more detailed traffic data, there are some inherent problems with traffic data, and it can be impacted on the final accuracy of traffic-emission-air quality modeling. Fallahshorshani et al. (2012) reported some of traffic data problems: traffic varies temporally and a disturbance in one location can be reflected in the traffic over a large area; traffic is ubiquitous and includes heavy traffic flow on major roadways with traffic distributed over surface streets and a vehicle fleet composition defined as stochastic is far from reality. On the other hand, the detail is necessary, and some solutions are being studied and applied at traffic modeling such as the use of real-time traffic data, data from intelligent traffic systems (ITS), dynamic traffic assignment (DTA) models agent-based models and neural networks (Forehead and Huynh, 2018; Qi et al., 2018; Wang et al., 2018).

2.4. EMISSION AND AIR QUALITY MODELS

To estimate emissions for a specific region, emissions models must use emission factors (EF) as an input. Therefore, to develop accurate emission factors for road vehicle emissions models, intensive testing is required to properly cover all the relevant vehicle types and driving conditions (Franco et al., 2013; Fontaras et al., 2014; Mishra and Goydal, 2014; Ramírez et al., 2019). A consistent approach to using an EF, treating transformation processes in air quality models appropriately, and evaluating the performance of models against measured data is required to produce accurate modelled results (Kumar et al., 2011b; EEA, 2016). Vehicle emissions models are divided into static and dynamic (or modal) models, based on the types of variables used, such as speed and acceleration, and how they are combined (Barth et al., 1996; Barth et al., 2000; Davis et al., 2005).

Static models are based on the average vehicle speed and consider vehicle dynamics using this concept. These models are used in cities to calculate emissions and work based on specific emission factors for each type of vehicle or engine, disaggregation factors, and average traffic situations (Davis et al., 2005; Esteves-Booth et al., 2002). They are suitable for large-scale strategic analysis and in cases where the average speed characterizes the traffic flow in an appropriate manner for the purpose of the study. Some examples of static models used in the literature are EMission FACtor (EMFAC) and the Computer Program to calculate Emissions from Road Transport (COPERT) (Samaras and Zierock, 1990; Barth et al., 1996; Ekström et al., 2004; Gkatzoflias et al., 2007; Ntziachristos et al., 2009).

Dynamic models are more detailed and they consider the variations in vehicle operating modes over time and represent continuous emissions, usually measured on a second-by-second basis. These types of models use variables such as engine speed, throttle position, air conditioner use, gear shifts, variations in constant operating modes, and accelerations or decelerations (Barth et al., 1996; Barth et al., 2000; Hoogendoorn and Bovy, 2001). To calibrate dynamic models, emissions are measured continuously using a chassis dynamometer test or through equipment installed in vehicles and stored by time intervals (Barth et al., 2000). The most popular dynamic models are the Virginia Tech-Micro (VT-Micro), International Vehicle Emissions (IVE), Assessment and Reliability of Transport Emission Models and Inventory Systems (ARTEMIS), Comprehensive Modal Emissions Model (CMEM), and the Motor Vehicle Emissions Models (MOVES) (Koupal et al., 2002; Koupal et al., 2003; Davis ET AL., 2005; Scora and Barth, 2006; Boulter and McCrae, 2007; Rakha et al., 2003; Hui et al., 2007). As with traffic models, the selection of vehicle emissions models goes through different stages, and the result generated shows emissions by type of vehicle in certain spatial and temporal conditions. This is the information that could be used as input data in an air quality model.

Among the variables that should be considered in the models, the resolution of the temporal variable is crucial, as the way emissions are redistributed from annual to hourly fluxes determines the accuracy of the pollutant modelled concentrations (Menut et al., 2012). Another important variable is traffic dynamics, which it is difficult to measure because, for example, there are spatial and temporal variations in traffic states (i.e., heterogeneity), which could result in emissions being underestimated since accelerations and decelerations are neglected (Lin and Ge, 2006). The configuration of the AQM (e.g., the horizontal and vertical grid resolution), parameterization of dispersion processes (e.g., the vertical and lateral turbulent diffusion coefficients), spatial and temporal allocation of emissions , and vehicle fleet information (e.g., regional variations in fleet composition and fuel used) also influence the results of modeling (Kota et al., 2014).

During the systematic literature review, 24 articles related to emissions models that were coupled with air quality models are highlighted. Table 6 shows the selected works, traffic variables, emissions models, AQMs used, and some remarks.

Table 6: Reviews of relevant emissions and air quality models.

Reference	Pollutants	Emission Model	Air Quality Model	Traffic Variables	Country	Remarks
Khan et al. (2019)	NOx, NO_2, PM10, PM2.5	THOR	AirGis	Road network; vehicle category; travel speed; Annual Average Daily Traffic (AADT)	Denmark	The new AirGis overestimated the observed concentrations for some datasets. The model can be used for short- and long-term air pollution exposure assessments.
Sampaio et al. (2019)	CO_2, NOx, NMVOC, PM2.5	VSP, COPERT	EMEP, URBAIR	Speed (second by second, average); traffic flow	Portugal	The approach showed the development of a dynamic link based eco-indicator allowing for potential exposed people to traffic-related consequences.
Dias et al. (2018)	CO, NOx, PM10, VOC	TREM	URBAIR	Vehicle speed; spatial variation	Portugal	A GPS-based approach improves the understanding of the temporal variability of vehicle speeds within urban areas and quantifies and reduces the uncertainty in road transport inventories.
González et al. (2018)	O_3, PM10	IVE	WRF – Chem	Vehicle categories, traffic flow levels, road network distribution	Colombia	Local emission inventory allowed a more realistic analysis of emission representation. It led to a better understanding of both dispersion and transformation of air pollutants
Jezek et al. (2018)	BC, NOx	EMEP/EEA	Gaussian Dispersion	Fleet composition; street lengths; speed limits; AADT	Slovenia	The reduction around 10% in composition fleet reduced BC and NOx emission in 39% and 33% respectively.
Jensen et al. (2017)	NO_2, PM2.5, PM10	COPERT IV	AirGis	AADT; Vehicle distribution; travel speed in each road; diurnal vehicle profiles	Denmark	The predict street concentrations present a reasonably accurate report of the annual mean air quality levels at Danish address, its geographic distribution and relative difference between areas.
Sun et al. (2017)	CO, CO_2, HC	MOVES	-	Vehicle amount per age; vehicle kilometer traveled; speed	China	The engine speed has the highest correlation with carbon emission in microscopic level study.
Borrego et al. (2016)	NOx, PM10	VSP and EMEP/EEA	URBAIR	Driving cycles; traffic flow; speed; travel time,	Portugal	Instantaneous vehicle emissions combined with filtered urban backgrounds determine the accuracy of the urban Gaussian model.
Oduro et al. (2016)	NOx, CO, CO_2 Total Volatile Hydrocarbon (THC)	CART–BMARS	-	Speed; acceleration; load; power; ambient temperature	Australia	A comparison of the CART–BMARS hybrid model with BMARS and artificial neural network algorithms versus on-board measurements and chassis dynamometer tests demonstrated the effectiveness and efficiency of the combined model in estimating vehicular emissions.
Csikós et al. (2015)	CO, HCs, NOx	COPERT IV	Gaussian Dispersion	Traffic flow; traffic density; space mean speed of traffic	Hungary	A new simple dynamic dispersion model was proposed for motorway traffic emissions, and verifications and numerical and sensitivity analyses were provided.
Rowangould (2015)	PM	EMFAC2011	AERMOD	Trip in each link; vehicle classes; time periods	USA	High-resolution air dispersion modeling was successfully applied to large transportation networks when a novel rastering approach and a few simplifying assumptions were applied.
Borge et al. (2014)	NO_2	SMOKE	CMAQ	Intensity; activity data; fleet composition; average speed	Spain	A very detailed bottom-up emissions inventory was prepared for Madrid based on the SMOKE system. Local traffic represents the major source of NO_2 concentration levels.
Kota et al. (2014)	CO, NOx	MOVES, MOBILE6.2	CMAQ	Traffic hours; county-specific vehicle fleet information; vehicle miles traveled (VMT)	USA	Emissions models overestimated both CO and NOx on-road vehicle emissions. The meteorology field in the air quality model also influences the performance of the latter.

Table 6: Reviews of relevant emissions and air quality models (continuation).

Reference	Pollutants	Emission Model	Air Quality Model	Traffic Variables	Country	Remarks
Pallavidino et al. (2014)	CO, CO_2, NH_3, NMVOCs, NOx, PM10, SO_2	COPERT IV	-	Circulating fleet; vehicle category; traffic flows; fuel consumption	Italy	If data is available, a bottom-up methodology should be used because it allows a better estimation of road transport emissions and apportionment among vehicle types.
Amirjamshidi et al. (2013)	CO, CO_2, HCs, NOx	CMEM	Gaussian Plume Model	Fuel consumption; speed/acceleration profiles; traffic composition	Canada	Despite the fact that pollutant concentrations were higher along freeways, the central business area presented higher exposure to pollutants.
Zhang and Batterman, (2013)	NO_2	CMEM and MOBILE6.2	CALINE4	AADT; fuel consumption; road type; fleet mix and speed; vehicle age	USA	Travel time, the duration of the rush hour, congestion-specific emissions estimates, and uncertainties are variables that must be considered in evaluations of the risk associated with congestion.
Beevers et al. (2012)	NOx, NO_2, O_3	SMOKE	CMAQ/ADMS (CMAQ-urban)	Traffic counts	United Kingdom	The CMAQ–urban model captured the spatial heterogeneity of NO_2 and O_3 concentrations in London. The WRF meteorological model influenced NOx concentrations.
Vijayaraghavan et al. (2012)	O_3, PM2.5	MOVES	CAMx	Vehicle age; fuel; other factors	USA	The modeled results showed a large improvement in O_3 and PM2.5 concentration, based on an improvement in air quality standards.
Gokhale (2011)	CO, NO_2, PM	COPERT IV	CALINE4, CAL3QHC and HV-GFLSM	Traffic flow rate; modal fleet composition; traffic speed; traffic density	India	Different traffic flow conditions influenced the dispersion of pollutants, thereby affecting the spatial distribution of the concentrations.
Kumar et al. (2011b)	Nanoparticles	CFD, OSPM	-	Traffic flow; average vehicle speed	United Kingdom	Appropriate treatment of particle transformation processes in dispersion models is a key point in extending the applicability of gaseous dispersion models to nanoparticles. Measured data is essential to evaluate model performance.
Madireddy et al. (2011)	CO_2, NOx	VERSIT+	-	Road speed limits; traffic light synchronization; green wave traffic lights	Belgium	Lowering speed limits reduced CO_2 and NOx emissions in a residential area, as did the implementation of a green wave along an arterial road.
Alonso et al. (2010)	CO, NOx, O_3	Emission Preprocessor (PREP-CHEM – SRP)	CCATT–BRAMS	Vehicle density	Brazil	The proposed inventory improved the performance of atmospheric chemistry simulations on the local scale and significantly affected the regional spatial distribution of O_3 and its precursors.
Hatzopoulou and Miller (2010)	CO, CO_2, NOx, VOCs	CALMET	CALLPUF	Link-based attributes (speed and volume); fuel; vehicle fleet attributes; engine on/off profile	Canada	The use of an activity-based travel demand model to generate vehicle activity inputs resulted in more comprehensive emission results that accounted for the time of day. An improved spatial representation of NOx was achieved by treating the individual link emissions as individual line sources within the dispersion model.
Zhang and Batterman (2010)	CO, PM2.5	MOBILE6.2	CALINE4	Traffic counts	USA	The model performed reasonably well for CO concentrations but significantly underestimated those for PM2.5 concentrations due to the underestimations of PM2.5 emissions factors. Comparisons of statistical and simulation models are necessary.

The systematic literature review showed that 22% of the articles used COPERT, a static model and 26% used MOVES/MOBILE 6.2, a dynamic model. The percentage of researches that used the combination between the emission model and air quality model was found to be approximately 74%. Furthermore, dispersion models were more prevalent than photochemical models, which may be linked with the size of area and pollutant investigated.

Smit et al. (2010) conducted a meta-analysis of 50 studies that validated several types of vehicle emissions models, including data on average speed, traffic flow, other traffic variables, cycle variables, and modes of transportation. In addition to their data analysis, the authors showed that it is still necessary to know the methods used to validate the vehicle emissions models, and the relationship between the increase in the complexity of the models and the accuracy of forecasts, to determine the accuracy of the vehicle emission models. Two comparisons of different methods of calculating mobile emissions have shown variability of approximately 35% and 47% (Parrish, 2006; Dallmann and Harley, 2010).

Improvements in air quality model results can be obtained using detailed traffic data. For example, Borrego et al. (2016) developed a modeling approach using detailed traffic flows derived from microscopic traffic models calibrated with GPS data and road traffic emissions of exhaust estimated using a combined VSP/EMEP methodology, among other considerations, thereby improving the analysis of model performance metrics. Another important fact is the relevance of topography and meteorological data for the dispersion of vehicle emissions. Data such as wind velocity and direction, temperature, relative humidity, atmospheric pressure, solar radiation, and precipitation require rigorous validation before being used in AQMs (Jacobson, 2002; Abdul-Wahab and Fadlallah, 2014). The meteorology is one of the most influential factors in air quality modeling, but it is important to say that this topic is beyond the scope of this study and hence will be explored in a future study.

Lin and Ge (2006) argued that roadside dispersion models require hourly or daily traffic volumes, fleet compositions, and average vehicle speeds on a road segment. However, average link-based traffic parameters persist as a limitation to these models. Nevertheless, These models shows are more prevalent than photochemical models, mainly due to the study area (roads and their surroundings).

The modeling of traffic emissions and air quality is a complex process and simplifications are necessary for modeling approaches. Some of the simplifications, for example, include on limitations of instantaneous emission models to predict pollutants of exhaust emission; aerodynamic effect of street geometry; traffic turbulence impact in dispersion around urban areas and spatial/temporal scale distribution. Therefore, the essential elements should be represented in functional mathematical models to transform traffic data in a vehicular emission inventory and into air quality concentrations and thus the modelling chain should be able to manage those diverse aspects in a realistic manner (Fallahshorshani et al., 2012).

2.5. FINDINGS AND PROPOSAL

2.5.1. Systematic Literature Review results

The systematic literature review method is considered innovative in the application and presentation of traffic-emissions-air quality modeling analysis. The variables highlighted in this study show that the relationships and interactions between traffic variables, pollutants and modeling objectives are fundamental to simulate the environmental impacts of traffic at the local urban scale. This systematic review shows that many questions related to input data, spatial/temporal scales, accuracy, compatibility among models and interfaces between model remain open (Fallahshorshani et al., 2012).

The systematic literature review found that approximately 23% of the articles reviewed modeled NOx emissions; 18% of them modeled CO; 13% examined PM, including PM10 and PM2.5; and 13% studied CO_2. Other pollutants such as HCs, VOCs, and NO_2, were modeled and their emission rates were used in air quality models.

The modeling of NOx, CO, PM (PM10 and PM2.5) and CO_2 emissions are directly related to negative impacts in air quality, climate change, fuel consumption and driver´s behavior. Models can overestimate (60%) or underestimate (40%) emissions and modeling results should be used with other analyzes to define new strategies to reduce vehicular emissions. The development new engine technologies, urban mobility strategies definition, efforts to understand driver´s behaviors and creation of synergies to low vehicle emissions are the key to reduce emissions and improve air quality in urban areas.

Although VOC´s were not modeled in these paper’s selection, some recent studies show that industrial, transport, and natural emissions can be calculated/estimated, but projecting highly diffuse VOC´s sources from consumer products is extremely challenging and usually depends on predictions of air exchange between outdoor and indoor environments. VOC´s is not a single pollutant, they have diverse chemistry and lifetime range from only a few minutes to several months; they can perform in heterogeneous process that modifies or compose aerosol properties and understanding these degradation processes is decisive for both air quality and climate applications (Galvão et al., 2016; Lewis, 2018).

2.5.2. Air Quality Researches: the difference between developed and developing countries

In this systematic literature review, most of the studies with traffic models were conducted in developed countries (63%) and the USA is the leader in research related in traffic and air quality modeling (22%), followed by Canada (13%), and Europe (Netherlands, Portugal United Kingdom, Austria(13%)). The BRICS (Brazil, Russia, India, China and South Africa) are responsible for 30% of surveys and China accounting for 22% considering all studies. The analysis of emission and air quality models showed a similar situation. The USA stands for 21%, followed by Europe (Denmark, Portugal, Spain, Italy, United Kingdom and Belgium, 42%) and BRICS (13%). Canada (8%), Australia (4%) and Colombia (4%) also developed researches in emission and air quality modeling.

There is a major concern between air quality modeling in developed and developing countries, however, there were significant gaps in the consistency of emissions factors, allocation of emissions on grid cells, inventories and spatial and temporal distributions of sources, and the performance of the meteorological models, in all searches.

Input data is the main gap in air quality/emissions modeling because a large number of reliable datasets are required. In developed countries, traffic data is extracted from GPS data logger vehicles using Geographic Information System (GIS) software, remotely sense tailpipe exhaust, and chassis dynamometer tests and other sources (ITS, DTA and agent-based models and neural networks). It is possible to measure real traffic flow in peak and non-peak periods on typical weekdays over four seasons (winter, spring, summer, and fall) because the required logistical facilities are available when experimental campaigns are set up. There are also numerous networks by which to monitor emissions and air quality, mobile laboratories are available to measure real-time data, and satellite information and detailed topographical and meteorological data are available. In developed countries like the USA and the United Kingdom, there are consolidated methodologies for elaborate national emissions inventories, including emission factors that represent reality; this is not so in developing countries.

In developing countries, gathering all the information required to build a vehicular emission inventory or conduct air quality modelling is a challenging task. It is necessary to combine diverse information sources (peer-reviewed literature reports and contacts in local and non-local agencies (both private and governmental) to obtain data for modeling (Sharma and Chung, 2015). Additionally, it is necessary to use socio-economic indexes (such as the Human Development Index, population, and vehicle density) to estimate and develop local inventories, using extrapolated data instead of measured data, in addition to emission factors that do not represent local vehicle fleet and fuel used. This approach is even more necessary in regions that are typically poorly represented in global inventories due to the scarcity of national inventories and measurement campaigns, which is the case for the majority of countries in South America (Alonso et al., 2010). It is important to recognize the efforts to change this situation, reinforced the results that improve air pollution management system and contribute to integrating environmental and transportation local public policies decisions (Rodríguez et al., 2016; González et.al., 2017; Mangones et al., 2019).

2.5.3. Uncertainty Analysis

All the models (traffic, emissions, and air quality) have uncertainties that are reflected in the accuracy and results. One of the critical issues in air pollution is the determination of emission factors; consequently, there are limitations and uncertainties in existing emissions inventories and when emissions inventory modeling is performed (Collet et al., 2012). The uncertainties in emissions inventories are, however, propagated in emissions models and air quality modeling.

The spatial and temporal concentration of pollutants around buildings, in hotspots, and on roads can vary by orders of magnitude. Thus, the real environment must be represented carefully in numerical simulations. Kumar et al. (2011b) showed that aerosol dispersions used in dispersion models are affected more, compared to gaseous dispersions, by uncertainties (both structural and parametric) caused by the inappropriate treatment of particulate transformation process. The solutions needed for more accurate modeling are not simple, and include tools for the pre-treatment of input data, detecting outliers, correcting missing values, and estimating uncertainties. Most of the uncertainties reported in the studies reviewed seem very optimistic and may not have noted all feasible sources of error, such as variability in the source profiles (Belis et al., 2013).

There are a range of solutions, but obtaining consistent emission factors and reducing differences between models and measurements is one of the first alternatives (Kumar et al., 2011b). For vehicle emissions, in particular, it is important to improve current average speed models or at least acquire data on congestion levels to obtain more accurate emissions predictions and achieve correct applications (Smit et al., 2008).

Finally, the use of advanced factor analysis techniques able to manage complex and heterogeneous data and improve uncertainty estimations should be promoted (Belis et al., 2013). Smit et al. (2010) showed that the design of future models or improvements to existing ones should account for the errors allowable for different applications or at least provide an estimate of the prediction errors in models.

2.5.4. Proposed a list of key traffic variables

There are currently guides accompanying every model, focusing only on the model manuals and technical operation (Givoni et.al, 2012). The following list is a suggestion to guide the modeling process and it shows the proposed list of key traffic variables based on this systematic literature review and the research conducted in this study (Table 7). The objective is to show that emissions modeling must include these variables, at least, and that their details must be evaluated for each application type and study region. The list presents the variables without considering the type of model (traffic, vehicular emissions, or air quality) that should be chosen by the researchers; this can be determined according to their purpose. ‘Vehicle’ included types, age, categories and size; ‘behavior’ considered traffic or driver behavior; ‘time’ means travel times and time periods and density means density of urban traffic.

Table 7: List of key traffic variable to traffic-emission-air quality modeling.

Key traffic variables	%	Key traffic variables	%
1. Traffic flow	20	6. Behavior	5
2. Vehicle	20	7. Acceleration	4
3. Speed	12	8. Time	3
4. Network	12	9. Density	3
5. Fuel	9	10. Other	11%

For each model, it is necessary to evaluate the set of variables that will be used in detail and consider how they will be combined. There are several combinations of models possible and it would not be feasible to present all of them here.

2.6. SUMMARY AND CONCLUSIONS

A systematic literature review was performed that integrates traffic, emissions, and air quality models. The result showed that there are several combinations of different traffic and emissions models and emissions and air quality models. The combinations are used to improve and develop the analysis of air quality data, but limitations of different models and interfaces need to be evaluated depending on the purpose of the study they are used for. The findings showed that there is no best and perfect combination of traffic-emission-air quality modelling. This combination is defined to aggregate the purpose of the model, the scientific treatment, the methods used to calculate the emissions, available data, and how and for what the decision-makers will use the modeling results; there is no single model qualified to describe all relevant spatial scales of the air pollution phenomena (local, regional and global) and emissions are reported the most uncertain input in air quality modelling and differences between state of art and current practices shows that is necessary increased compatibility in this modelling practices. Furthermore, transparency, simplicity, satisfaction of different users with different models and friendly user interface is mandatory to combine who mainly work in transport policy, transport and air quality modelling to think how a state-of-the-art model might be used (Fallahshorshani et al., 2012; Kaewunruen et al., 2016; Tominaga and Stathopoulos, 2016; Sun et al., 2016; Williams, 2017; Sallis et al., 2016).

Existing models will, therefore, need to be improved and adapted to address all issues in air quality modeling. All model types need to be calibrated, with input data requiring many adjustments in the parameters and the variables that they are composed of. It was identified that there are still gaps in the consistency of emissions factors, spatial and temporal distributions, allocations of emissions in grid cells, and performances of meteorological models. Furthermore, the average link-based traffic parameters are a persistent limitation. However, even when adjustments are made, the input data may not represent the reality of the study object, causing errors in representation. The classification of the models was conducted to facilitate the selection of the most appropriate models to be coupled in order to construct an integrated and efficient modeling system. Some strengths and limitations of different models in terms of precision (statistical variability) in some physical representation of processes were found. The precision of models can be evaluated by statistical analysis including assessing prediction errors. In the case of traffic, although the flows of vehicles on individual roads were known, even broken down by vehicle type, there is seldom information to break the flows down further by fuel type or engine size and age of vehicle.

There is a strong dependence on data on traffic patterns, vehicle speeds, and traffic intensity to determine the accuracy of the information generated by the traffic models and, consequently, the emissions generated by vehicle emissions models. Due to the nature of modeling, the propagation of inherent errors has a relevant impact on the process. Therefore, a comprehensive analysis of the uncertainties in model input variables is necessary to improve their results (Napelenok et al., 2011).

The studies reviewed showed that models are important tools for evaluating the implementation of policies using practical guidelines for traffic and that they can improve the performance of air quality models. Accurate traffic data generates reliable results in vehicle emissions models and air quality models. However, Smit et al. (2010) showed that truly accurate road traffic emissions models are hard to obtain as real emissions values are unknown and cannot be easily determined by measurements. Therefore, it is only feasible to construct partially validated models; to be more accurate, complex models require detailed input data (Smit et al., 2006). Even a small positive change in the accuracy of traffic models can improve the accuracy of vehicle emissions models (Vieira da Rocha et al., 2015) and that increasing the complexity of models can introduce more parameters with uncertain values, decline transparency and depreciate the accuracy of the responses given by the models.

Traffic emissions continue to be a fundamental variable for globally accurate simulations, especially in urban centers, apart from their use in the development of air quality models (Borrego et al., 2016). Although detailed inputs increase the accuracy of emissions estimates, collecting reliable input data is a complex task that demands time and resources (Alam and Hatzopoulou, 2014).

Traffic data is essential for air quality modeling in urban centers, but it is necessary to first analyze uncertainties in traffic data. Real traffic data, such as that from radar, can reduce the uncertainties in models, thereby improving their accuracy. The term "accuracy" was found in approximately 22% of the studies examined in the systematic review, which shows that more research is necessary to improve the discussion of this term. Efforts to develop better traffic flow representations need to integrate traffic engineering data into emissions models and improve the results of air quality models as a result. Finally, it would be important to propose a guideline for an acceptably accurate reference for distinct applications in different regions.

This systematic literature review indicates several open problems and challenges in current research. The key areas to be addressed by research and innovation, the framework to select the traffic model, and the key traffic variables list can help researches to find a way to start their works. The definition of right proportion of traffic emissions attributed to different vehicles categories and fuel consumption is mandatory to find acceptable answers for the vehicle emissions issues. More attention is needed to develop integrated modelling systems that can simulate the impact of traffic on air environments in urban areas in development countries. GPS data in real-time can be used to derive typical driving cycles for each road link; the surveys can be target to propose transport systems, especially to reduce emissions and to improve the mobility.

Moreover, this study highlights some challenges in current researches for both developing and developed countries. In developed countries, the researches can expand their investigations in: to review and evaluate the efficiency and efficacy of traffic management strategies (TMS) used to improve the air quality and reduce human exposure; to assist users to reduce air pollution exposure in their mobility and daily activities using real traffic data; to use Internet of Things (IoT) platform to obtaining, managing, and analyzing sensing data and other (road structure such as intersections, traffic, weather and other conditions) to advise drivers to adjust their behaviors (departure time, route selection, window and air condition system configuration and vehicle maintenance); to use real traffic data to discover more traffic pollution insights and support sustainable traffic management and green mobility; to develop fine-grained air quality prediction models associated with traffic, road, and weather conditions; to evaluate, to review and to compilation existing traffic emission methodologies and define the best practices and input data information apply to traffic emission (Fallahshorshani et al., 2012; Kaewunruen et al., 2016; Tominaga and Stathopoulos, 2016; Sun et al., 2016; Williams, 2017; Bigazzi and Rouleau, 2017; Sallis et al., 2016).

The situation in developing countries is considerably different. Applications that have already taken place in developed countries, for instance, considering emission factors, road traffic characteristics and inventory tools for road transport emissions (Joumard, 1999) can be applied in developing countries. Considering the topic “emission factor”: to develop co-operative work to analyses the large difference about emissions levels measurement by car manufactures and research organizations laboratories; to create a local emission factor dataset including all kind of vehicles; to consolidate traffic emission methodology and to generate emissions maps and the effects of fuel quality, different fuels, and alternative technologies on the emissions from passenger cars, duty vehicles, bus and motorcycles. Considering the topic “Road Traffic Characteristics”: to develop accurate modelling of the future composition of the vehicle type and usages combining socio-economic approaches, land use and human demographic parameters; to analysis of driving behavior according to the road infrastructure and to model using microscopic driving behavior by traffic models. Considering the topic “Inventory tools for road transport emissions”: to developed measurement campaigns to check the accuracy of the models. Most of these actions have already been established in developed countries (Joumard, 1999).

Finally, it is necessary to develop and improve research networks between countries to allow addressing questions about scientific, operational and diagnostic evaluation in air quality area.

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CHAPTER 3:

KRIGING METHOD APPLICATION AND TRAFFIC BEHAVIOR PROFILES FROM LOCAL RADAR NETWORK DATABASE: A PROPOSAL TO SUPPORT TRAFFIC SOLUTIONS AND AIR POLLUTION CONTROL STRATEGIES

The paper “Kriging method application and traffic behavior profiles from local radar network database: a proposal to support traffic solutions and air pollution control strategies” (https://doi.org/10.1016/j.scs.2020.102062) was developed by the author of this thesis in collaboration with researches Professor Prashant Kumar, Professor Marcelo Félix Alonso (co-advisor), Willian Lemker Andreao, Rizzieri Pedruzzi, Sérgio Ibarra Espinosa and Taciana Toledo de Almeida Albuquerque (advisor). The paper presented the methodology of this work and suggested the Kriging method to define the traffic flow in each link in a Brazilian capital called Belo Horizonte. The study area is the largest city in the metropolitan area composed of 34 municipalities and has a local radar network located on the main avenues of the city. The radar network counts vehicles per type (passenger cars, motorcycles, trucks/buses) for 24 hours. The count data were used to trace the profile behavior per vehicle type in the city, information that directly impacts vehicle emissions during a weekday and weekend.

The results showed that Kriging is a low-cost method when compared to traffic modeling and can be used to spatialized vehicle flow information on urban roads. It also showed that caution is needed in the use of the method as the counting data must meet specific requirements, such as the existence of a spatial correlation between data used in the interpolation by the Kriging method. The result of spatialization was used as input data in the VEIN to calculate the vehicle emission inventory for Belo Horizonte, Brazil.

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3.1. INTRODUCTION

The urban air pollution is a significant health and environment hazard. The World Health Organization estimated that air pollution is responsible for 7 million deaths worldwide every year as a result to household exposure (indoor) and ambient (outdoor) pollution. Vehicles are commonly the outdoor main source of air pollution in urban areas. The consumption of different fuels (i.e, gasoline, ethanol, gasohol - a mixture of gasoline and ethanol, diesel) and traffic behavior (average annual daily traffic-AADT, morning peak-MP and evening peak-EP) lead to a huge increase in the emission of air pollutants, and consequently, in the deterioration of air quality and degradation of health (Kumar et al., 2016; Andrade et al., 2017; Kumar et al., 2017; Pacheco et al., 2017; Albuquerque et al., 2018; Wang et al., 2018; Santos et al., 2019).

Air quality monitoring network needs to provide dataset and information to government, scientists and companies to development solutions to solve air quality impacts in urban areas. It is essential to reduce air pollution and raise awareness people to change their own daily routine to reduce personal exposure to air pollution (Andreão et al., 2018; Silva et al., 2018; Mahajan et al., 2020). In development countries, for instance in Brazil, it is essential for government and society to create a collaborative network to build sustainable plans and actions for the cities. Programs to review and evaluate the efficiency and efficacy of traffic management strategies (TMS) and action plans, as example, to assist users to reduce air pollution exposure using real traffic data and to utilize Internet of Things (IoT) platform can support sustainable traffic management and green mobility in smart cities (Wang et al., 2017; Silva et al., 2018; Pinto et al., 2019; Abhijith and Kumar, 2019). In Brazil, there is specific law introduce the guidelines of the National Urban Mobility Policy. In Belo Horizonte (BH), a densely populated urban city in southeast Brazil where this study was conducted, has a document called PlanMob. The plan proposes demand management as the main strategy for improving the urban mobility system, combining a set of infrastructure projects for public and non-motorized transport with measures to regulate the use of individual transport (BHTRANS, 2010).

The collaborative network can be used not only to develop new technologies but also to create new partnerships to planning the integration between transportation and air quality in smart cities. There are several ways to develop solutions using available dataset to provide better service for traffic management and air quality. Sensors to detect vehicles types are used to track and monitor traffic flow and it can be used to update traffic details providing solution through predictive analysis (Jamil et al., 2015; Rizwan et al., 2016; Fernández-Ares et al., 2017; Menouar et al., 2017).

In this context, this paper highlights the importance to exchange information between municipalities agencies (i.e. local environmental protection and traffic agencies) changing dataset as radar technology to improve vehicular emissions estimative, and, consequently, to raise air quality awareness in urban areas. The results also provide useful information to local Climate Change Committee to establish law proposals, effective implementations actions to reduce emissions and to improve air quality in the city. It shows the importance and impacts of the current methods on air pollution control.

The demand to identify the real contribution of pollutants emitted by on-road vehicles to investigate the air quality must have to consider the limitations of emission models when distinct traffic behavior profiles from radar data and fine spatial/temporal distribution are used. The prediction of traffic data has proven to be a useful for reducing high costs from origin destination survey and traffic modeling using commercial software. Radar databases and traffic counts using statistical modelling is an alternative and a low-cost approach to produce traffic activities data in each urban street to use as input to predict vehicular emissions (Fu et al., 2017).

The spatial and temporal vehicle flow distributions can be performed using kriging interpolation (Shen and Hadi, 2013; Lowry, 2014; Shamo et al., 2015; Yang et al., 2018), spatial Pearson correlation coefficients (Chen et.al., 2016); GIS techniques and modelling (Adedeji et. al., 2016; Requia et al., 2017), neural network (Fu et al., 2017); thiessen polygons (Gómez et.al., 2018); spatial autoregressive moving average (SARMA) regression model (Sun et.al., 2018), land use regression (LUR) and geographically weighted regression (GWR) models (Kanaroglou et al., 2013; Song et. al., 2019), hybrid-kriging/land-use regression model (Wu et al., 2018) among others. Additionally, models may provide the required activity data and therefore, they can provide a well representative flow for every urban street in the study area.

To improve this knowledge and fill some gaps, the aims of this work are: (1) to carry out a statistical analysis of monthly traffic behavior and to determine a specific average traffic flow using local radar data; (2) to analyze the vehicle type hourly behavior and show the importance of the diurnal cycle per vehicle type in the emission inventory accuracy ; (3) to develop an emission inventory using a National Vehicle Emission Inventory model (VEIN), emission factor from São Paulo State Environmental Protection Agency (CETESB), methodology from National Environment Ministry, input data from different traffic behavior profile (constant and different diurnal cycle) established from local radar data, and kriging interpolation method to find the appropriate spatial/temporal distributing.

3.2. MATERIALS AND METHODS

3.2.1. Site description and vehicle data

The study area is Belo Horizonte, a capital of Minas Gerais state and a densely populated urban city with a representative vehicle fleet in Brazil. The Minas Gerais state has the third largest metropolitan region of the country. Its metropolitan area is divided into 34 municipalities that occupy a territory around 9,500 km^2 and the capital is in a territorial area of 331.4 km^2, with a population of approximately 2.5 million inhabitants (IBGE, 2018) and approximately 2.0 million vehicles in 2018 (DENATRAN, 2018). The vehicles fleet in Belo Horizonte is mostly composed by cars (75.7%), followed by light commercial vehicles (11.4%), motorcycles (10.7%), trucks (1.6%) and buses (0.5%). Regarding fuel consumption, flex fuel vehicles are the majority (65.2%), and the other fuels are distributed as follows: gasoline (25.8%), diesel (6.2%) and ethanol (2.8%). The fleet age is also a relevant data and it is characterized by vehicles aged 0 to 10 years (73.3%), 11 to 20 years (19.7%), 21 to 30 years (6.0%), and over 30 years (0.9%) (DETRAN MG, 2019; Pinto et al., 2017; Santos et al., 2019).

3.2.2. Traffic Behavior and Vehicle Flow

3.2.2.1. Local radar and count point data

The data collection sites were all over the city in the main avenues. The radars have been installed by the Transportation and Transit Company of Belo Horizonte (BHTRANS) to control the speed limit of the vehicles in the city, reducing the number and severity of accidents, creating a safety transit. Along the years, the car crash situation reduced because of radars (BHTRANS, 2018). In this work, it was used data from 304 radars and 87 count points. Figure 4 shows the radar distribution sites (blue). In red, there are counts points also used to determine the proportion between buses and trucks.

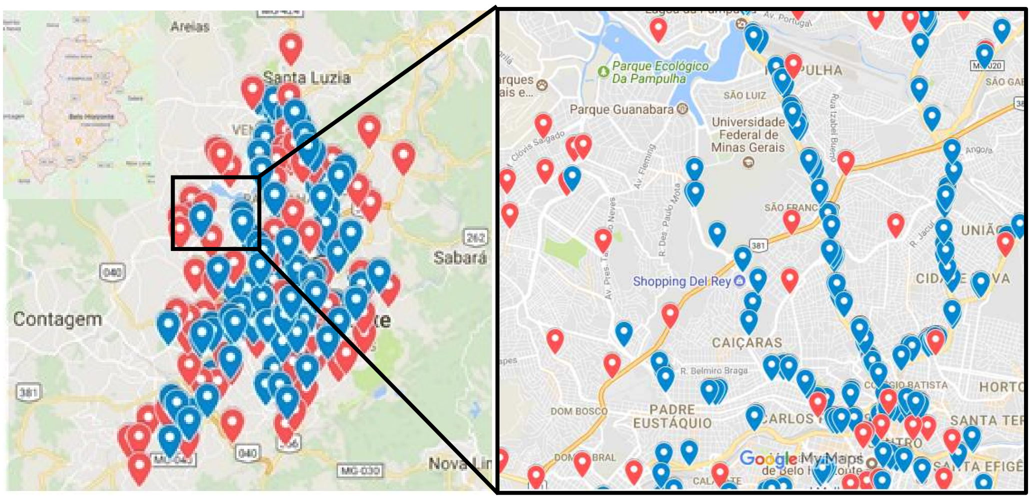


Figure 4: Radar (blue) and count points (red) in Belo Horizonte (Brazil).
Source: Adapted from Google Maps.

Radars or electronic controllers are divided into Metrological and Non-Metrological. Metrological measure the speed of the vehicles, which is the case of speed controllers of the fixed and static radar type. On the other hand, the non-metrological ones verify the invasion of the exclusive bus lanes. (BHTRANS, 2018). Each radar counts three types of vehicle (passenger cars, motorcycle and trucks/buses) every 15 minutes, 24 hours in a day, week, month and year. Trucks and buses have the same proportion and similar weight and the radar counts them as the same category. The calibration and operation of local radar is made by Electronic Surveillance Management Department in BHTRANS.

3.2.2.2. Monthly traffic behavior for trucks and buses

This analysis was performed to identify buses and trucks. Radar use magnetics layers or optical sensors to counts vehicle types. They identify vehicle type through magnetic field or sensor during vehicle reading.

The survey of the vehicle count followed the methodology proposed by National Department of Transport Infrastructure (DNIT) in Brazil. The volumetric counts aim to determine the quantity, direction and composition of vehicles flows passing through the selected sites of the road system in a unit of time. The manual counts were performed with the purpose of classifying vehicles based on similar operating characteristics (passenger cars, motorcycles, buses and trucks) (DNIT, 2006), according to the following steps:

- *Counting sites selection:* the points were selected according to the type of track and intensity of vehicle flow and covered all regions in the city. The main reference was the Emission Inventory of the Metropolitan Region of Belo Horizonte published by the environmental agency (FEAM, 2018). The points were in different type of street (8% in primary, 50% in secondary and 42% in tertiary road);

• *Counting period selection:* Wednesdays and Thursdays. These days are selected because peak hours in urban street are concentrated on weekdays. Generally, traffic flows on Tuesday, Wednesday and Thursday are roughly similar, while on Monday may be lower than average and Friday slightly higher.

• *Counting method selection:* the counting was performed manually during the four, five and six-minutes period.

3.2.2.3. Traffic behavior profile

In this step, a Python code was developed to read the radar data from the dataset. The script is constituted for six steps and it considers the hourly data of vehicle flows, separated by type (passenger cars, motorcycles, trucks, buses) on weekdays and weekends in 2016. As a result, tables are generated with vehicles flows for 24-hour period for 12 months. The normalized data were used to define the diurnal cycle per vehicle type in the main roads of Belo Horizonte city. The Python program was write using these steps:

- Step 1: To read spreadsheets with local radar time data;
- Step 2: To create lists and variables;
- Step 3: To create a loop for reading all local radar data in available spreadsheets;
- Step 4: To sum in each vehicle count range on each track that has radar;
- Step 5: To split flow data in weekday and weekends;
- Step 6: To create the result spreadsheet with normalized flows by time and period of week.

This program generated a database with 864 data, but it was necessary to select a week in August 2016 (08/08/2016 to 08/14/2016) in the local morning peak hour (07:00-08:00h; local time because a VEIN restriction.

3.2.2.4. Urban streets characterization

The urban streets in Belo Horizonte are classified in six types of streets according to the Open Street Map (OSM), as showed in Table 8: residential (routes in residential area); primary (paved routes that is the main circulation network); secondary (paved routes that links neighborhoods); tertiary (routes used to link with secondary streets); trunk (main high-speed highways that cross the city and connect several neighborhoods) and motorway (freeway).

Table 8: Urban street type in Belo Horizonte

Classification OSM	Classification CTB*	Quantity	%
Residential	Local	14,414	76.9
Primary	Arterial	448	2.4
Secondary	Arterial	1,205	6.4
Tertiary	Collector	2,077	11.1
Trunk	Regional link	466	2.5
Motorway	Regional link	131	0.7
TOTAL	**-**	**18,741**	**100.00**

*Brazilian Traffic Code

Further, the speed can be used to differ each street and the range varies between 20 and 120 km/h. The urban street precision used in this study is suitable with transportation planning and traffic modeling.

3.2.2.5. Emission factors and fuel consumption data collection

To estimate emissions for a specific region, emissions models must use accurate emissions factors (EF´s) as input. Therefore, to develop accurate EFs for road vehicle emissions models, intensive testing is required to properly cover all the relevant vehicle types and driving conditions (Franco et al., 2013). In this study, the emission factors used are from the emission inventory developed by Environmental Company of São Paulo State (CETESB) whereas they have the most current publication about vehicular emissions in Brazil. The emission factor used was estimated considering exhaust (fuel consumption) and non-exhaust (evaporative, wear of brake, pads and tires) (CETESB, 2017). The EF´s are used to predict the emissions from vehicles and the emission pollutants estimated in this work were: carbon monoxide (CO), non-methane hydrocarbons (NMHC), nitrogen oxide (NOx), particulate matter (PM) and sulfur dioxide (SO_2). Additionally, it was considered the carbon dioxide (CO_2) and methane (CH_4). The combination between EFs, fuel consumed (Table 9), fleet composition (Table 10) and transport activity (vehicle flow) associated with a vehicle emission model result in a Vehicular Emission Inventory (VEI).

Table 9: Fuel sale in Belo Horizonte

Fuel Type*	Fuel density	Fuel Consumption (m^3)	Fuel weight (t)
Gasohol (25% of ethanol) (E25)	0.754	783,614,431	591,041
Ethanol (E100)	0.809	268,884,302	217,527
Diesel (5% de biodiesel) (B5)	0.840	287,872,518	205,541 (85%) **

*E25: Gasohol; E100: Ethanol and B5: Diesel. **Fuel used by vehicles. Source: ANP, 2018.

Table 10: Vehicle type and fuel combination to use in VEIN in 2018.

Code	Description	Fleet (%)
PC_E25	Passenger car using gasohol	17.50
PC_FE25	Flex passenger car using gasohol	40.60
PC_FE100	Flex passenger car using ethanol	15.00
PC_E100	Passenger car using ethanol	2.60
LCV_E25	Light commercial vehicle using gasohol	1.20
LCV_FE25	Flex light commercial vehicle using gasohol	4.30
LCV_FE100	Flex light commercial vehicle using ethanol	1.60
LCV_E100	Light commercial vehicle using ethanol	0.20
LCV_B5	Light commercial vehicle using diesel	4.10
SLT_B5	Semi light truck using diesel	0.10
LT_B5	Light truck using diesel	0.40
MT_B5	Medium truck using diesel	0.20
SHT_B5	Semi heavy truck using diesel	0.40
HT_B5	Heavy truck using diesel	0.50
UB_B5	Urban bus using diesel	0.30
SUB_B5	Small urban bus using diesel	0.10
MB_B5	Motorway bus using diesel	0.10
M_E25_150	150cc motorcycle using gasohol	6.20
M_E25_150_500	150cc to 500cc motorcycle using gasohol	0.70
M_E25_500	500cc using gasohol	0.20
M_FE25_150	150cc flex using gasohol	2.30
M_FE25_150_500	150cc to 500cc flex using gasohol	0.30
M_FE25_500	500cc flex using gasohol	0.10
M_FE100_150	150cc flex using ethanol	0.90
M_FE100_150_500	150cc to 500cc flex using ethanol	0.10
M_FE100_500	500cc flex using ethanol	0.02

* Details of fleet composition are in Supplementary Information: vehicle fleet per age, type and fuel; vehicle fleet distribution and vehicle fleet distribution according PROCONVE and PROMOT Phases. PROCONVE and PROMOT are Brazilian government programs to reduce vehicle emissions.

3.2.3. Kriging Interpolation Method

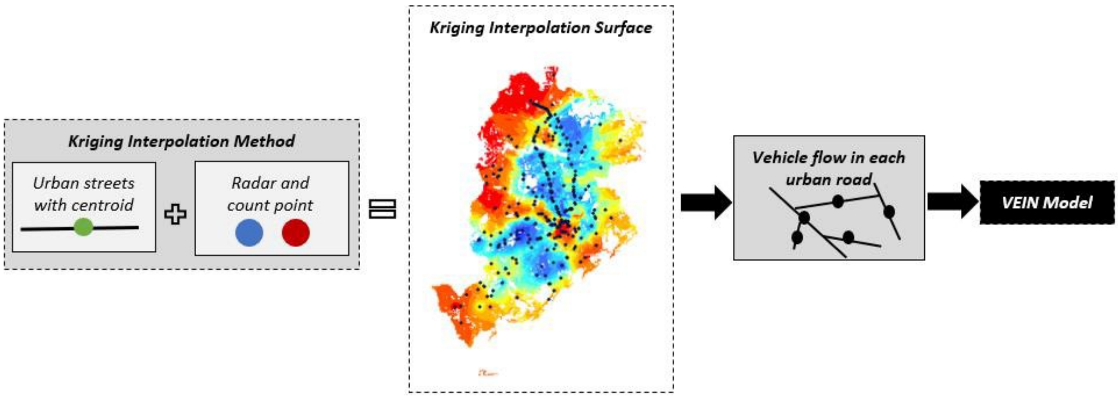
The kriging method was select because it is an interpolation technique that can improve predictions of traffic volume at unmeasured locations based on limited data. This method is most useful in uncounted and unsampled locations. Traffic count data are collected less frequently than in order areas because of high cost and complexity of measurement. The radar database can be used as an input data in kriging interpolation method (Wang and Kockelman, 2009; Kim et al., 2016; Prasetiyowati et al., 2016; Klatko et al., 2017; Rocha et al., 2017; Song et al., 2018; Shukla et al., 2019).

The comparison of Kriging between other methods, for instance, regression models, shows that kriging carry out more accurate predictions than regression models. The reason is that regression assumes that the prediction errors are white noise whereas Kriging permits errors that are correlated; i.e., the closer the inputs are the more positive are the output correlations. Further, regression models use a single estimated parameter set for all input values, whereas Kriging adapts its parameters (Kriging weights) as the input to be predicted changes (Van Beers and Kleijnen, 2004).

Neural network can be used to predict AADT and vehicle flow but may disregard underlying issues such as parameter stability and error distribution (Fu et al., 2017). Thiessen polygons can be applied to distribute the traffic counts to road segments without information, but the segments in the area covered by the polygon were assumed to have the same traffic counts of the point that generate the polygon (Gómez et al., 2018). The LUR is used to calculate vehicle flow but there are some disadvantages, such as, the lack of cause-effect relationship, large input requirements and measurements cost (Khan et al., 2018). All the methods cannot replace traffic counting entirely, but they can reduce the need for such counts.

The kriging interpolation was performed with software ArcGis v.10.6, adopting some repeatability during interactions. The spatial modeling for linear kriging was performed based on Shamo et al. (2012) with some settings. The four basic steps were: (1) data exploration; (2) structural analysis; (3) crossvalidation; and (4) ranking of results. The step 1 involved data examination and statistical analysis and provides understanding of spatial correlation and distribution. Step 2 included the selection of kriging method and combination with semivariogram (spherical, exponential and gaussian). In the step 3, it was validated the model results (kriging method and semivariogram) and finally, step 4 consisted in a rank considering the best set of variogram and kriging method produces the best results.

The application of kriging method was used to characterize the spatial/temporal distributing of an event dispersion (traffic activity), evaluating the uncertainty parameters when spatial variability to obtain a continuous surface estimate. The centroid in a polyline shapefile was calculated (green point), and it was used to interpolate radar data (red and blue points) that had an average vehicle flow in a local morning peak hour (07h to 08h) during one week in August 2016 (Part 1). The kriging interpolation surface was transformed in a network with vehicle flow in each link (Part 2). These are the input data of traffic activity to VEIN model (Part 3) (Figure 5). The parameters used in kriging method are described in results.



(Part 1) (Part 2) (Part 3)

Figure 5: Steps to interpolate radar data (vehicle flow) to urban streets.

This is a critical step in an emission modeling because there is an intense dependence on traffic patterns data and traffic intensity to determine the accuracy of emissions generated by the emission models. Spatial and temporal distributions is a gap in vehicular emission modeling and the average link-based traffic parameters are a persistent limitation.

3.2.4. Vehicle Emission Model

Many studies have used different emission models, which take traffic information (fleet composition, vehicle speed or link – based speed, etc.) as inputs to estimate traffic related emissions that cause air pollution (Pan et al., 2016). The Brazilian Vehicular Emissions Inventories (VEIN) is a vehicle emission model, free and open source, developed in the Institute of Astronomy, Geophysics and Atmospheric Sciences of the University of São Paulo (IAG - USP) (Ibarra-Espinosa et al., 2018; Ibarra-Espinosa et al., 2019). VEIN model followed four phases to calculate the vehicular emission inventory, which has scripts to represent each phase (Figure 6).

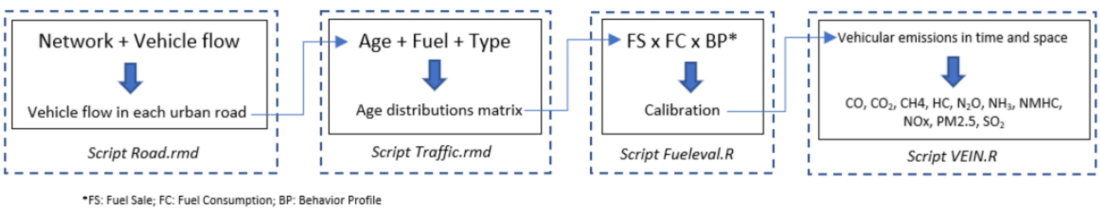


Figure 6: Flow chart of Brazilian Vehicle Inventory Model

The model was developed using free software R (R Core Team, 2017) and generates pollutants emission from motor vehicles of different categories and fuels, and it was also elaborated considering transport activity and EFs (Equation 1) (Pulles and Heslinga, 2010; Ibarra-Espinosa et al., 2018; Ibarra-Espinosa et al., 2019).

$$Emission_{polutant} = \sum_{activity} \left(AR_{activity} * EF_{polutant,activity} \right) \quad \textbf{Equation 1}$$

The equation shows that the emission of any pollutant depends on the activity rate (AR) and the EF. The transport activity corresponds to the number of vehicles multiplied by the distance traveled (km). VEIN reads the traffic flow on each route. Regarding emission factors, VEIN considers emission factors for exhaustion, evaporative emissions, and emissions due to deterioration and wear emissions (tire). The model reads the traffic data and then organizes the data by the fleet composition according to Equation 2.

$$F^{*}_{i,j,k} = Q_i * VC_{i,j} * Age_{j,k} \quad \textbf{Equation 2}$$

The term $F^{*}_{i,j,k}$ corresponds to the vehicular flow in path i for vehicle type j by age of use k. The term j corresponds to the vehicle composition according to the type of use, fuel type, engine size and gross weight (Corvalán et al., 2002; Ibarra-Espinosa et al., 2018; Ibarra-Espinosa et al., 2019). Q_i is the flow of traffic on route i, $VC_{i,j}$ is the fraction of vehicles which varies according to the type of vehicle j of the fleet in route i and age j; k is the age distribution of vehicles according to the composition of the fleet j and age of use k.

After reading the data, the model extrapolates the vehicular flow to the i routes of the network considering the vehicle type j and the age of use k. The result of this step is the vehicular flow for the week time. It is important to emphasize that the vehicle traffic behavior profile must be mapped and inserted in the emission model. Equation 3 shows how the calculation is performed by the model.

$$F_{i,j,k,l} = F^{*}_{i,j,k} * TF_{j,l} \quad \textbf{Equation 3}$$

In Equation 3, the term $TF_{j,l}$ corresponds to time factors that vary according to each hour l and vehicle type j. This term represents a matrix with 24 lines that correspond to 24 hours a day and 7 columns, the period corresponding to one week (Sunday to Monday).

3.2.5. Scenarios Description

3.2.5.1. Scenarios 1 and 2

Scenario 1 and 2 was characterized as the base case. The base case was prepared considering the vehicle fleet and fuel consumption for Belo Horizonte in 2018; the day cycle of different vehicle types (24-hour traffic profile) based on local radar data and counting points and the EF´s published by CETESB for 2018 (CETESB, 2019). The main difference between scenarios 1 and 2 is the diurnal cycle, i.e., constant diurnal cycle for all vehicle type (figure 7) and different diurnal cycle per day for vehicle type (figure 8) respectively.

3.2.5.2. Scenario 3

Scenario 3 considered 10% reduction in the fleet circulation (passenger cars and light commercial vehicles) for all types of fuel. The percentage used in this study followed the initial reference of São Paulo city, where road space rationing in the city led to a reduction in the average levels of all primary pollutants since its implementation. Road space rationing is a solution that defines the demand for vehicle use, usually within a given coverage area, and takes into consideration vehicle license plates and days of the week. It is one of the strategies used by the traffic authorities to reduce traffic congestion and, consequently, vehicle emissions.

3.2.5.3. Scenario 4

Scenario 4 considered 20% reduction in the current truck fleet (semi-light, light, medium-heavy and heavy) indicating the possibility of implementing vehicle inspection in Belo Horizonte and withdrawing the circulation of old heavy vehicles (over 20 years). Furthermore, this scenario considered simultaneously 20% reduction in the current fleet of diesel buses indicating the renewal of the bus fleet by electric vehicles. Changes in the public bus transportation system is one of the alternatives used by managers to minimize vehicle emissions.

3.3. RESULTS

3.3.1. Average traffic flow using local radar and count point data

The vehicle flow was determined using radar data and it was used to formulate the VEI. The vehicle flow counted was used to interpolate the vehicle flow in the urban street network. Table 11 shows a descriptive statistic per each radar type and count point.

Table 11: Average vehicle flow per type.

Radar	Description	Quantity	Average Vehicle Flow*	S.D**	1º Q	2º Q	3º Q
CEV and CEV Move	Electronic Speed Control	39	2,444	1,162	1,571	2,493	3,117
DAS, DAS Busway and Move	Semaphore Advance Detector	143	959	1,016	181	493	1,484
CJG and CJG - Busway	Combined Equipment (DIF + CEV)	20	483	811	91	120	207
DIF	Exclusive Intrusion Detector and Truck Circulation Detector	36	73	36	47	62	105
RF	Fixed Speed Control Radar	66	2,259	893	1,794	2,293	2,829
Count Points	Manual count	87	144	101	72	102	203
	TOTAL	391					

*Vehicle flow per day in the morning peak hour. **Standard Deviation

The most of radar CEV and RF type are in trunk (48%) and primary (40%) streets and average vehicle flow are higher than DIF and count points. RF is a fixed speed control radar that are in main avenues around the city, while DIF is a specific type of radar that counts intrusion vehicle in specific lanes and are in secondary streets (60%). The street type is a one of the variables that define average vehicle flow.

The real vehicle flow is a relevant data to represent traffic activity. It was found that there are differences in average vehicle flows according to the radar type and this information was combined with vehicle type to be used in kriging interpolation method.

3.3.2. Buses and trucks proportion using manual count point

It is important discriminate vehicle type when it is analyzing the traffic behavior. In this work, it was used manual count points to define buses and trucks proportion on streets. The results show the average per interval during the weekday, and the same proportion was adopted to the weekend. The same fraction was assumed for intervals 1 and 4 (Table 12).

Table 12: Percentage between trucks and buses in 2016 from count point.

Period	Interval	% Bus	% Truck
1	12 am to 5 am	43.4%	56.6%
2	6 am to 11 am	60.0%	40.0%
3	12 pm to 5 pm	63.8%	36.2%
4	6 pm to 11 pm	43.4%	56.6%

By changing diurnal profile of traffic behavior, one can expect to better represent the diurnal cycle of pollutant emissions. The percentage is changed throughout the day and this improvement can impact the emissions rate for 24 hours. The result of vehicles counting is being considered as a complement to the vehicle flow data counted by the radars. These indexes were used in the step to analyze the hourly behavior from radar data and to determine the diurnal cycle per vehicle type. It was noticed that, approximately, 60% of vehicles are buses at 5 pm, which is consistent with municipal law that prohibits truck traffic in some areas in the city. The results reflect the municipal traffic control policy already implement in the city.

3.3.3. Statistical analysis of traffic behavior profiles

The regression analyses (polynomial level 5) using an average traffic flow per month during 2016 (Table 13) was calculated. The variable x represents the hour of the day. There is a good adherence for all months, i.e. r^2 values are equal or higher than 0.86.

Table 13: Regression Analyses for average traffic flow in each month.

Month	Equation	r^2
January	$y = -4E\text{-}07x^5 + 2E\text{-}05x^4 - 0.0006x^3 + 0.0060x^2 - 0.0201x + 0.0234$	$r^2 = 0.86$
February	$y = -4E\text{-}07x^5 + 3E\text{-}05x^4 - 0.0006x^3 + 0.0062x^2 - 0.0208x + 0.0236$	$r^2 = 0.88$
March	$y = -4E\text{-}07x^5 + 3E\text{-}05x^4 - 0.0007x^3 + 0.0067x^2 - 0.0220x + 0.0236$	$r^2 = 0.87$
April	$y = -4E\text{-}07x^5 + 3E\text{-}05x^4 - 0.0007x^3 + 0.0066x^2 - 0.0218x + 0.0236$	$r^2 = 0.88$
May	$y = -4E\text{-}07x^5 + 3E\text{-}05x^4 - 0.0006x^3 + 0.0065x^2 - 0.0213x + 0.0231$	$r^2 = 0.87$
June	$y = -4E\text{-}07x^5 + 3E\text{-}05x^4 - 0.0007x^3 + 0.0066x^2 - 0.0214x + 0.0226$	$r^2 = 0.87$
July	$y = -4E\text{-}07x^5 + 3E\text{-}05x^4 - 0.0006x^3 + 0.0064x^2 - 0.0208x + 0.0223$	$r^2 = 0.87$
August	$y = -4E\text{-}07x^5 + 3E\text{-}05x^4 - 0.0006x^3 + 0.0065x^2 - 0.0212x + 0.0227$	$r^2 = 0.87$
September	$y = -4E\text{-}07x^5 + 3E\text{-}05x^4 - 0.0007x^3 + 0.0067x^2 - 0.0219x + 0.0235$	$r^2 = 0.87$
October	$y = -4E\text{-}07x^5 + 3E\text{-}05x^4 - 0.0007x^3 + 0.0068x^2 - 0.0223x + 0.0244$	$r^2 = 0.88$
November	$y = -4E\text{-}07x^5 + 3E\text{-}05x^4 - 0.0006x^3 + 0.0066x^2 - 0.0221x + 0.0250$	$r^2 = 0.88$
December	$y = -4E\text{-}07x^5 + 3E\text{-}05x^4 - 0.0006x^3 + 0.0066x^2 - 0.0223x + 0.0258$	$r^2 = 0.88$

3.3.4. Diurnal cycle per vehicle type

The diurnal cycle and vehicle type were used to develop an emission inventory using VEIN v.0.7.12. The first analysis considered the same diurnal cycle for all vehicle types, which showed a good adherence ($r^2 = 0.90$) and a 5º degree polynomial to represent the average behavior (Figure 7). This plot showed an average for 12 months and 24 hours. It is a good estimation of reality considering that the city does not have real traffic data to calculate vehicular emission inventory.

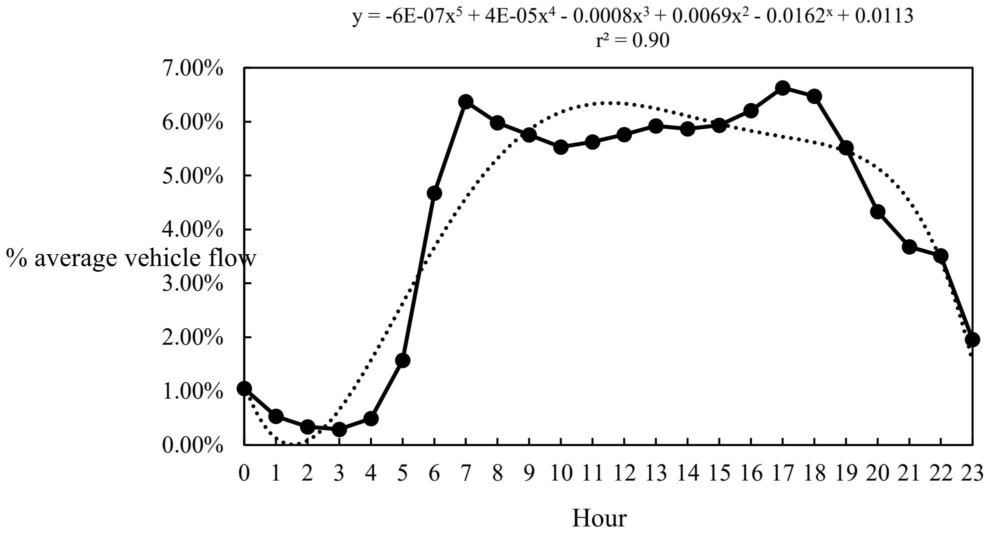


Figure 7: Average traffic behavior in local time.

The dataset permited an analysis per vehicle type and the behavior between vehicles are similar in the peak hour. The percentage represents a vehicle flow normalizaded. It was considered a percentage to represent the traffic behavior in the city during 24 hours. For instance, the peak hours for passenger cars are on 07:00h am local time (6.25%) and 05:00h pm local time (6.64%). The peak hour for motorcycles are on 07:00h am (7.18%) and 06:00h pm (7.18%). For buses and trucks, the peak hour in the morning is 07:00h am and in the evening is 05:00h pm and 06:00 h pm respectivily (Figure 8). All the behaviors (average and vehicle type) are used to calcuted the veichular emission inventory.

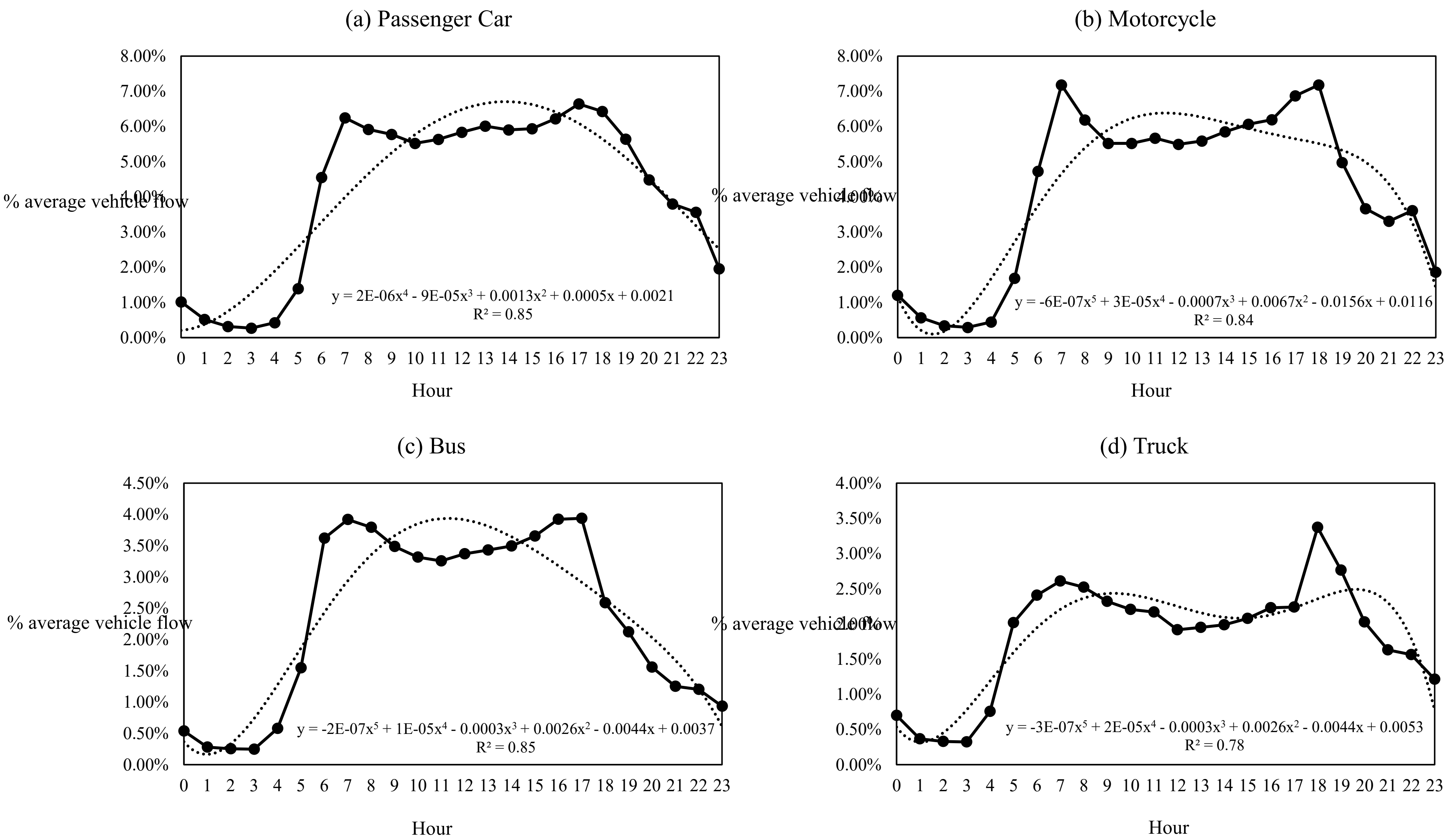


Figure 8: Average traffic behavior per vehicle type in local time

3.3.5. Kriging interpolation using vehicular flow counts by radars

The kriging interpolation method requires the verification if there is spatial autocorrelation between data. There are some techniques to calculate spatial autocorrelation and the Moran Index, one of the most classic method to confirm this condition, was used in this work. The result is interpreted as a correlation coefficient, i.e., the values close to 1 indicate a strong spatial pattern (high value tend to be located close to each other and low values tend to be located close to each other), values close to -1 indicate a strong negative spatial pattern (low values tend to be close to high values) and values close to 0 indicate absence of spatial pattern (Rogerson, 2012). Some tests were performed with local radar data combination to identify if the data followed normal distribution. The normal distribution was found when the specific radar type was select, i.e., RF and CEV type. In this case, the Moran Index was approximately 0.30 and p-value was 0.013 (p-value <0.05: statistically significant, i.e., there is spatial autocorrelation) (Table 14). There is a spatial autocorrelation in clustered pattern (Figure 9). It was presented the same calculation with 391 radar points, but there is no spatial correlation in this event.

Table 14: Moran Parameters.

Parameters	Global Moran´s Summary	
	391 radar points (a)	105 radar points (b)
Moran´s Index	-0.319695	0.295447
Variance	0.045805	0.015148
z-score	-1.481780	2.478643
p-value	0.138399*	0.013188*

*p-value>0.05: there is no spatial correlation; p-value<0.05: there is spatial correlation

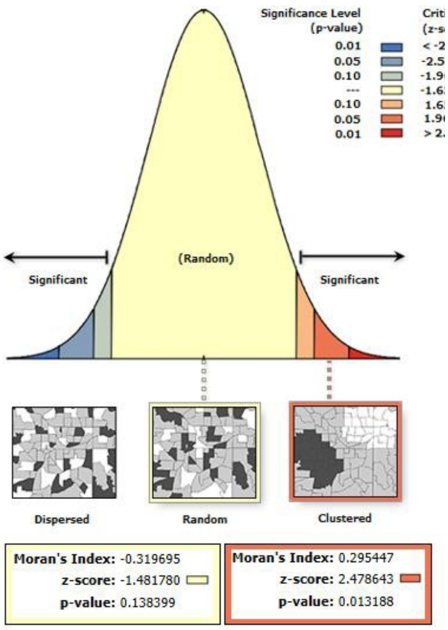


Figure 9: Moran Index.

Kriging assumes that the distance or direction between sample points reflects a spatial correlation that can be used to explain variation in the surface. The kriging interpolation method resulted in a surface presented in Table 15 and Figure 10. The surface represents the predict values in a grid and each cell contains an attribute value that represent a change in Z value. Tests were made with different semivariogram models (spherical, exponential and gaussian) and the gaussian model generated the best result for the spatial distribution of vehicle flow from radar data.

Table 15: Kriging Parameters.

Type	Ordinary
Semivariogram model	Gaussian
Number of points	12
Number of streets	18,741
Number of centroids	18.741

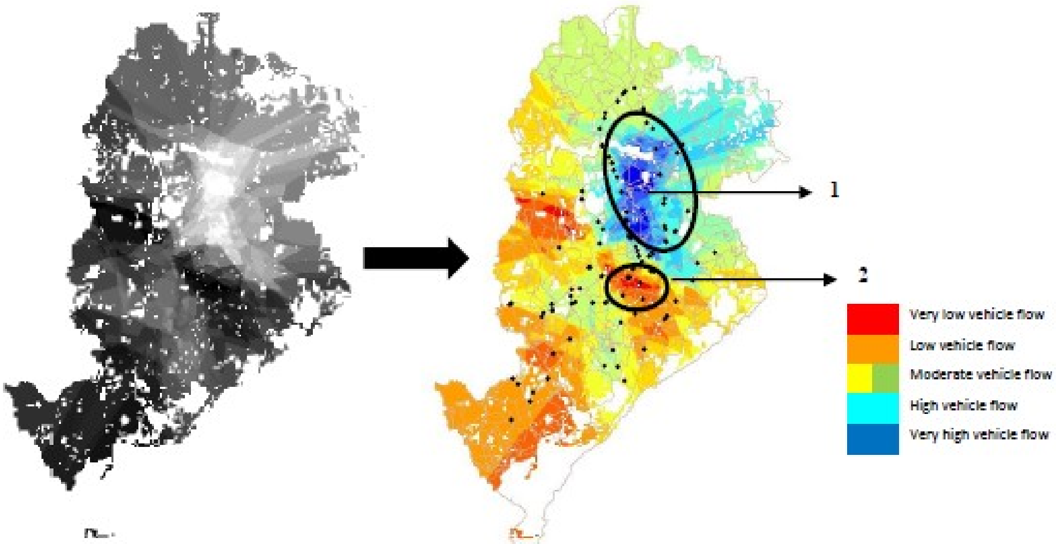


Figure 10: Kriging Surface.

The surface shows the higher flows were concentrated in radar points where there is a larger number of vehicles (1). Locations with many radars with smaller vehicle flows resulted in lower interpolation flows (2). This result reinforces the vehicle concentration is in the main streets and consequently it is where occur higher pollutant emissions. The dataset structure is determinant to define the best kriging technique using in the statistic modeling. The Mean Absolute Percentage Error (MAPE) was approximately 50%.

3.3.6. VEI for Four Different Scenarios

3.3.6.1. Integration of street maps and vehicle flow

The first script of VEIN (road.rmd) reads the network with vehicle flows, i.e., vehicle flow in each link calculated using spatial interpolation resulted from kriging method. (Figure 11).

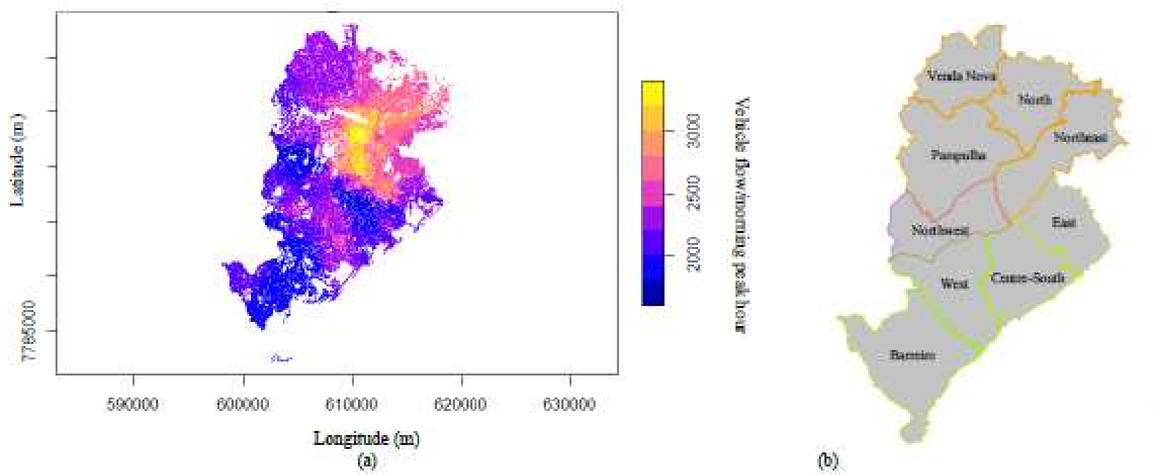
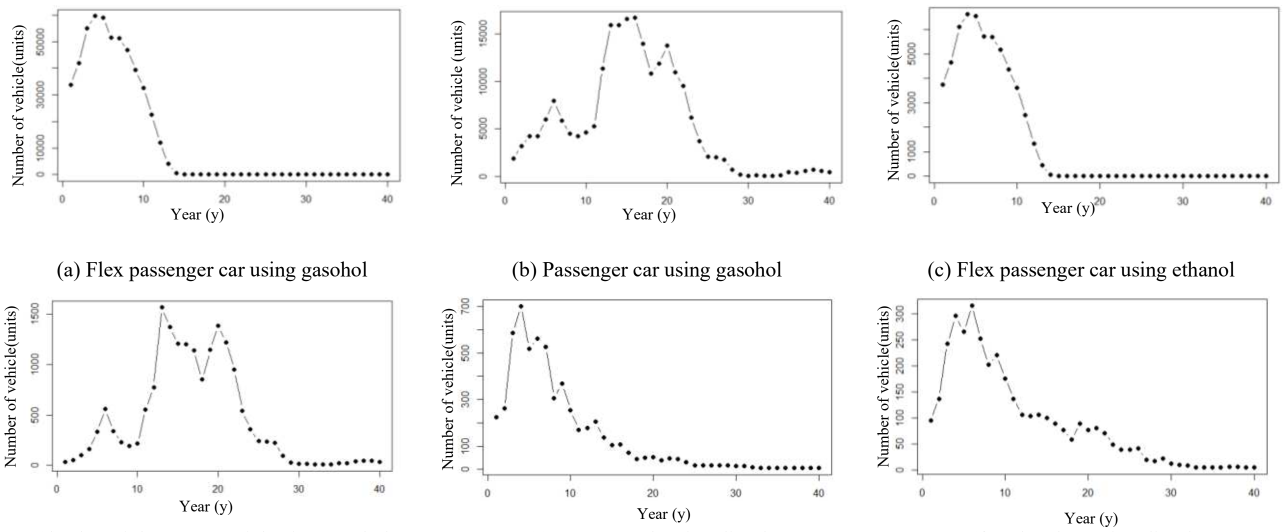


Figure 11: (a) Vehicle Flow in each urban street and (b) Regions of Belo Horizonte
Source (b): Adapted from www.pbh.gov.br

The vehicle flow was concentrated in North, Northeast, Pampulha and East regions in Belo Horizonte. This result represents the real situation in morning peak hour, and they are climate changes vulnerability assessment of Belo Horizonte in which interventions must be focused, giving support to decision-making (SMMA, 2016).

3.3.6.2. Integration of fleet composition and fuel consumption

The second script (traffic.rmd) include all information about fleet composition and fuel consumption. The fleet composition (ANFAVEA, 2017; ABRACICLO, 2017) is used to divide the vehicle flow already allocate in each street (step 1). The fleet composition is per vehicle type and age. The results consist in a matrix with vehicle flow and type of vehicle and indicate vehicles in circulation per year of use (Figure 12), which is settled using the scrip 3 (fuel_eval) simultaneously.



(a) Flex passenger car using gasohol (b) Passenger car using gasohol (c) Flex passenger car using ethanol

(d) Flex Light Commercial using gasohol (e) Heavy truck using diesel (f) Urban bus using diesel

Figure 12: Examples of vehicle in circulation per year of use.

The Programa de Controle da Poluição do Ar por Veículos Automotores (PROCONVE) and the Programa de Controle da Poluição do Ar por Motociclos e Similares (PROMOT) establish pollutants emission standard in different phases (interval of years) for diverse categories of vehicles. These programs enable the effective vehicle emissions reductions and the companies can adopt a mix of vehicle models with less emissions, such as flex-fuel and electric vehicles. The flex-fuel vehicle (a,c) is an example of vehicle whose design allows use gasohol, ethanol or any mixture between two fuels that allowed a reduction in the number of vehicles that use exclusive gasohol (b). It is important to consider vehicle per year of use because older vehicles (d,e,f), which already have a higher emission than current vehicles, have increased emission due to deterioration. Vehicle whose design allows the use of gasoline C, hydrous ethanol or any mixture between the two fuels.

3.3.6.3. Comparison between scenarios

The next step was the calculation of VEI using the fourth phase use the script "vein.R" to calculate all the emissions. Furthermore, four scenarios using kriging interpolation method was defined and modeled (Table 16).

Table 16: Scenarios description.

Scenario	Description
Scenario 1 (S1)	Vehicle flow: constant diurnal cycle for all vehicle type
Scenario 2 (S2)	Vehicle flow: different diurnal cycle per day for vehicle type
Scenario 3 (S3)	Scenario 2 + 10% reduction in passenger car and light commercial vehicle fleet
Scenario 4 (S4)	Scenario 2 + 20% reduction in trucks and buses fleet

The VEI was calculated using vehicle flow, urban network, fleet and fuel consumption and the results for each scenario are presented in Table 17. The reduction in passenger car and light commercial vehicle fleet consumption led to a reduction in CO (8.5%) and CO_2 (8.8%) emissions (S2 and S3) and the reduction in diesel consumption showed a reduction in NOx (8.4%) and $PM_{2.5}$ (8.6%) emissions (S2 and S4). The reduction in NMHC emissions are most evident when reducing the fleet of vehicles that consume gasohol and ethanol, i.e, 8.0% (S2 and S3) against 0.7% in S4 (Table 18). Dominutti *et al*. (2016) showed that gasoline is one of the most important sources of hydrocarbons in urban area.

Table 17: Results of scenarios considering vehicle flow from kriging interpolation ($t.year^{-1}$).

Scenarios	CO	CO_2	NMHC	NOx	$PM_{2.5}$	SO_2
Scenario 1 (S1)	17,132	2,846,763	1,820	4,032	125	207
Scenario 2 (S2)	17,198	2,893,226	1,827	4,038	128	208
Scenario 3 (S3)	15,730	2,639,526	1,681	3,817	121	194
Scenario 4 (S4)	17,137	2,838,606	1,815	3,700	117	196

Table 18: Reduction of emissions pollutants between scenarios (%).

Pollutant	S2 vs. S3	S2 vs. S4
CO	8.5	0.4
CO_2	8.8	1.9
NMHC	8.0	0.7
NOx	5.5	8.4
$PM_{2.5}$	5.5	8.6
SO_2	6.7	5.8

The fleet reduction adopted in S3 and S4 is accompanied by reduction in fuel consumption in different proportions. In S3, 10% in fleet reduction of passenger car and light commercial vehicles leads to a decrease of 6% in diesel and 10% of gasohol and ethanol consumption. In S4, 20% in fleet reduction of trucks and buses lead a decrease of 8% in diesel reduction. These findings explain the difference in CO, CO_2, NOx and PM emissions reductions in each scenario.

3.3.7. NOx Emissions

The reduction of 20% on fleet of trucks and buses causes a reduction in total emissions of NOx. In the morning peak time (08:00 h, local time) the reduction is visible when the fleet composition is implemented (Figure 13).

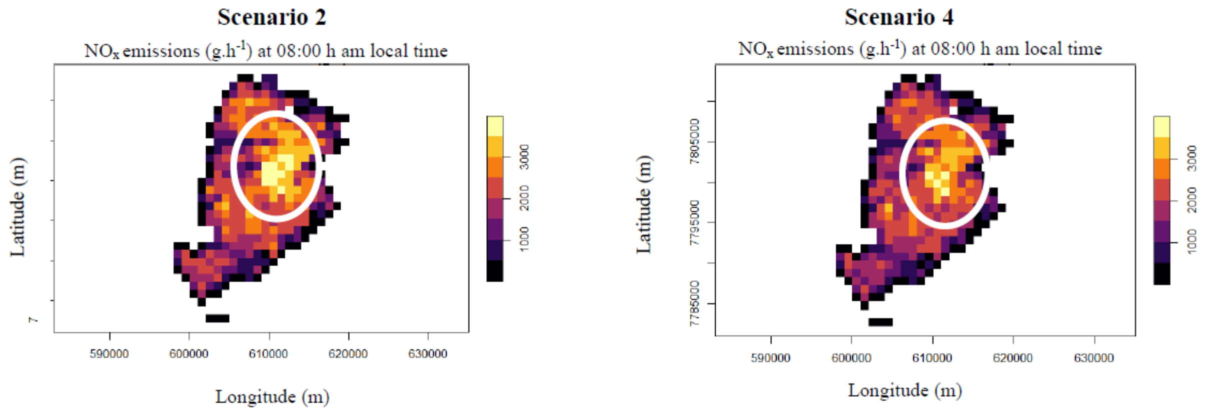


Figure 13: Difference on NOx emissions in the morning peak hour using kriging interpolation method.

The reduction in NOx emissions reaches part of 6 regions (North, Northeast, Northwest, Pampulha, Centre-South and East) in the Belo Horizonte city. Therefore, it is necessary carry out measures to gain benefits in air quality to decrease pollutant emissions.

In other analysis, NOx emissions per year of use can be check in the VEIN (Figure 14). The combination between number of vehicles, year of use and fuel consumption results that the main NOx emission occurred for vehicle with between 5 and 10 years old in both scenarios (S2 and S4).

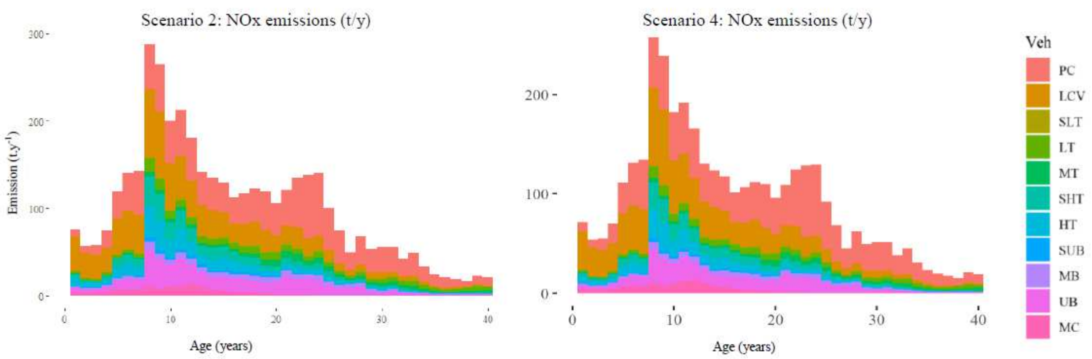


Figure 14: NOx emissions per year of use and vehicle type.

The Brazilian Vehicle Air Pollution Control Program (PROCONVE) has set emission standards for diesel vehicles based on European standards (EURO) (Carvalho, 2015; Andrade et al., 2017; CETESB, 2018; Santos, 2018). The phases (P1 to P7) show the maximum allowable NOx values in g/(kw·h) (P1: 18.02; P2: 14.4; P3: 9.0; P4: 7.0; P5: 5.0; P6: 3.5 and P7: 2.00). In addition, the program defined sulfur reduction that began with 3,000 to 10,000 ppm (P2 to P4), 500 to 2,000 (P5), 50 (P6) and 10 ppm (P7). The phases were between 1977 to 2001 (P1 to P4), 2002 to 2003 (P4), 2004 to 2007 (P4/P5), 2008 to 2011 (P5) and 2012 to 2018 (P7) and engine technologies and fuel were improving to meet the legislation requirements. The phase P6 was not possible due to the unavailability of low sulfur diesel. The age between 5 and 10 years old corresponds to phases P5 and P7 (2008 to 2013). The highest NOx emission corresponds to the phases with the lowest emissions rates, therefore the number of vehicles (42.9% of the total fleet) is the main cause of the largest emissions of vehicles with 5 and 10 years old.

The model calculated the emissions during the week in g/h. For NOx, the emission distribution during the week shows light commercial vehicle, all types of trucks and buses decrease had a decrease in NOx emissions in all days (Figure 15).

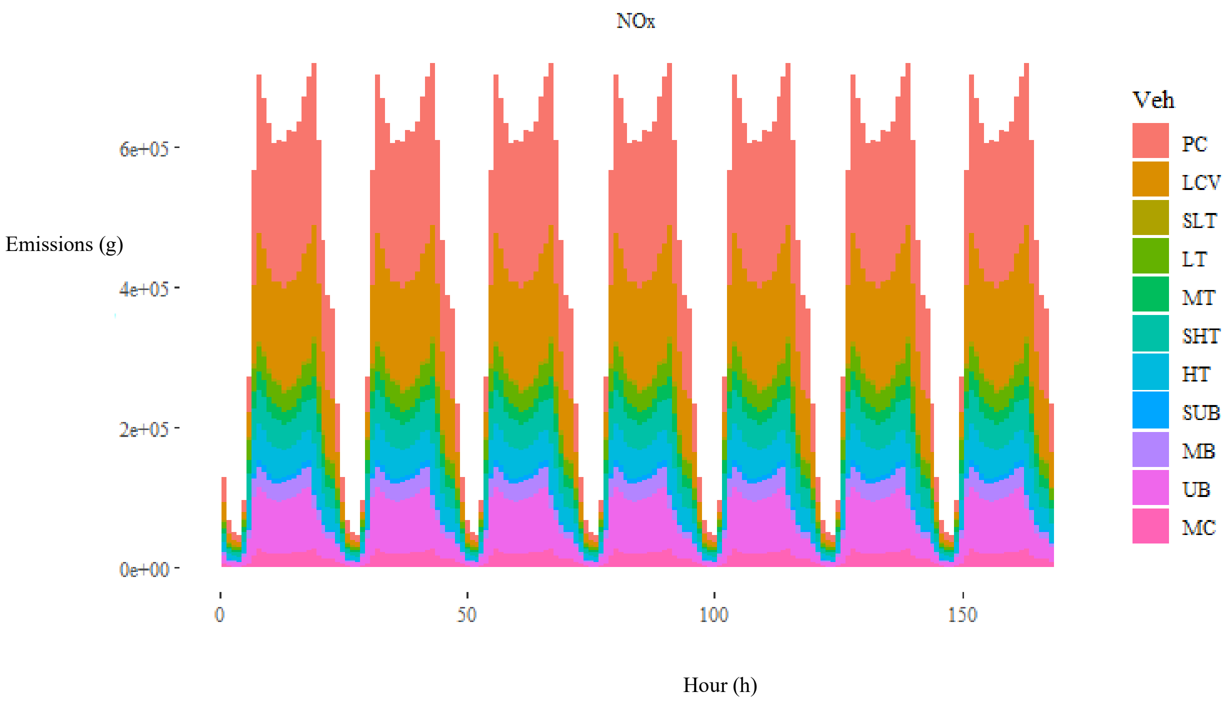


Figure 15: NO_x emissions for 168 hours (one week) per vehicle type in scenario 2.

The morning peak hour (07:00-08:00h am; local time) and evening peak hour (06:00-07:00h pm; local time) shows similar emissions during weekday. In the weekends, the emissions are lower than weekdays. In the morning peak hour in weekdays, the differences between scenarios : 4.9% (S2 and S3) and 9.6% (S2 and S4). In the evening peak hour in weekdays, the differences between scenarios are: 5.8% (S2 and S3) and 7.8% (S2 and S4).

3.3.8. Comparison with local vehicular emission inventories

The effect of radar data resolution and spatial distribution on the vehicle emission modeling in an urban area contributed to discuss the accuracy of vehicle emissions and the impacts on air quality modeling. The premises definition is an important step to analyze the VEI results. Even considering different assumptions, there are two studies that calculate the vehicle emissions in Belo Horizonte, and it is possible to compare the results carefully. Santos (2018) showed a vehicular emission inventory to Belo Horizonte in 2015 and the State Environmental Agency in Minas Gerais also published a bottom-up vehicle emissions inventory (FEAM, 2018) (Table 19).

Table 19: Different Vehicular Emission Inventory to Belo Horizonte.

References (t/year)	Base year	CO	NOx	$PM_{2.5}$	SO_2
Santos (2018)*	2015	16.574	13.992	1.220**	581
FEAM (2018)	2015	3,081	1,599	132	89
Present study (S2)	2018	17.198	4,038	128	208

*PM = PM_{10} and $PM_{2.5}$; **Considering fleet segregation

The results obtained with VEIN showed that CO is the main pollutant from mobile sources followed by NOx, $PM_{2.5}$ and SO_2.When the comparison between the present study and bottom-up vehicle emission inventory (FEAM, 2018), the main differences between emissions may be justified by at least two relevant variables: emission factors and the network configuration, i.e., the number of inventoried streets. The emission factors used in the bottom-up approach did not vary with fleet age and the network represented just 0.37% of the network used in present study. The comparison between Santos (2018) and the present study shows similar value for CO emissions but there is a huge difference for NOx and $PM_{2.5}$ emissions. The main reason is the premises adopted in each study. The performance of present study could be considered reasonable although there are differences between results.

3.4. DISCUSSION

The kriging method is a good and reasonable solution to solve a persistent problem in vehicular emission inventory, i.e., traffic activity in each link of the urban street network. The local radar data is an existing database that can be used to calculate input data of traffic. In this work, the discussion of scenarios may guide traffic agencies and environmental protection agencies to decide about transportation public policies and infrastructure that integrate mobility solutions and air pollution control.

The S1 and S2 did not present differences in terms of total emissions. The profiles “constant diurnal cycle for all vehicle type” and “different diurnal cycle per day for vehicle type” set up differences in the spatial distribution of emissions over 24 hours. This information is relevant to investigate which types of vehicles are primarily responsible for raising or declining vehicle emissions on city network. The comparison between S3 and S4 showed the impacts on reduction in different types of fleet. This comparison showed that road space rationing reduced in CO (8.9%) and CO_2 (7.5%) emissions. The scenario 4 was proposed considering the reduction only in trucks and buses using diesel. The results showed a reduction in NOx (3.2%) and PM (4.4%). For trucks, the vehicle inspection can contribute significantly to reduction of some pollutants, such as NOx. In general, the control inspection must be carried out on all motor vehicles and motorcycles regardless of the type of fuel they use. Vehicles are currently not inspected in the Brazilian states.

In addition to reducing the truck fleet, it was proposed to replace the bus diesel fleet. A possible solution it to substitute the current fleet for electric buses. Electric buses are advantageous options because they have, for example, higher efficiency and less noise than internal combustion engines, also increase energy efficiency and do not emit atmospheric pollutants (Falco et al., 2017; Slowik et al., 2018). The implementation of hybrid (diesel - electric) and electric buses can lead to significant reductions in CO_2 and other pollutant emissions and contribute to the decarbonization of the Brazilian transportation sector (Slowik et al., 2018).

3.5. CONCLUSIONS

Vehicles associated with consumption and burned of different fuels, topography and weather conditions are generally the main source of air pollution in urban areas. The continuous monitoring of vehicular flow in real time using radars results in an improvement of the spatial and temporal distribution of traffic activity, a remain gap of a vehicular emission inventory. In this way, this study analyzed the effect of radar data resolution to simulate vehicular emission and it was estimated an emission inventory using VEIN (a National Vehicle Emission Inventory Model) considering four different scenarios. The study used input data from different traffic behavior profile (constant and different diurnal cycle) established from local radar data and kriging interpolation method to find the appropriate spatial/temporal distributing. Furthermore, it was carried out a statistical analysis of monthly traffic behavior; determined a specific average traffic flow using local radar data; analyzed the vehicle type hourly behavior and showed the importance of the diurnal cycle per vehicle type in the emission inventory accuracy.

Differences between emission inventory using diverse vehicle profiles showed that the process to selecting the best vehicle profile depends on the main goal of the study and the vehicle flow dataset to set the input data in a vehicular emission modelling. Vehicular emissions vary with the method adopted to structure the data inputs and these findings are important to develop a relevant reference in a city that have data traffic limitations and do not have hourly traffic behavior profiles.

The scenarios showed some solutions to decrease vehicular emissions. In scenario 3, it was discussed the vehicle rotation implementation. In Belo Horizonte, the Urban Mobility Plan (PlanMob) foresees the vehicle rotation for 2020. The restriction was effectively linked to the improvement of public transport and the encouragement of the use of clean means of transport, as it was done in other major cities of the world. Other actions such as increasing the BRT (Bus Rapid Transit) network, subway and the cycling structure are also planned. The plan does not define the percentage of vehicle fleet reduction on the roads to represent discouragement of car use through vehicle rotation.

Considering that urban mobility public policies should stimulate public transport in its diverse modalities, in order to attract individual transport users and faced with the need to find solutions that minimize vehicle emissions, scenario 4 was also defined taking into account mobility public transport by bus. In Belo Horizonte, tests with a 100% electric minibus were performed in 2016, but they still formatting economic analyses. In addition, this scenario is aligned with the "Sustainable City" axis described in PlanMob - BH 2030 which presented the status of the investments in the Electric Bus Pilot Project, which is in the economic viability study phase.

This study is pioneer in Brazil and reinforced the importance of detailing traffic activities using real data to estimate vehicular emissions in an urban area. Recently, São Paulo city hall has promoted a challenge for the development of solution for smarter and safer urban mobility in the city using radar database. The approach adopted in this research can be followed for conducting research on other urban transport systems and can support traffic agencies and environmental protection agencies in the entire country to decide about public transport polices to reduce vehicular emission around the city, improving air quality. Further investigations to improve kriging method and spatial distributing in VEIN model is necessary as well as validation of the emission inventory estimated and also the effects of input data in air quality modeling simulations. The vehicle flow is a dynamic attribute and the kriging method based on an estimator (semivariogram) change when any change in the dataset results occur. In addition, development of more extensive profiles to represent weekday and weekends would allow to analyze specific actions to reduce vehicular emissions in urban areas, investigate air pollution exposure in specific roads in the city, develop project-level emissions and hot-spot analysis.

CHAPTER 4:

COUPLED MODEL USING RADAR NETWORK DATABASE TO ASSESS VEHICULAR EMISSIONS: MOBILITY AND TRAFFIC SOLUTIONS FOR FUTURE SCENARIOS IN AN URBAN AREA

The paper "Coupled model using radar network database to assess vehicular emissions: mobility and traffic solutions for future scenarios in an urban area" was developed by the author of this thesis in collaboration with researches Professor Prashant Kumar, Professor Marcelo Félix Alonso (co-advisor), Willian Lemker Andreão, Rizzieri Pedruzzi, Sérgio Ibarra Espinosa, Felipe Marinho Maciel and Taciana Toledo de Almeida Albuquerque (advisor). It is under review in the Journal of Environmental Science. The paper provided an improvement in the methodology of this thesis and analyzed future scenarios (2025, 2030, and 2050) to assess vehicular emissions.

The statistic mixed effect model called the "Normal-Neighborhood Model" (i.e., the mixed effect model with random effect in the neighborhood, radar type, and the regional area) was developed and used to spatialized the radar data in each urban road in Belo Horizonte. Then, the result was coupled in VEIN to calculated vehicular emission inventory for future scenarios in Belo Horizonte, considering the strategies defined in PlanMob (Plano de Diretor de Mobilidade Urbana de Belo Horizonte). The results can support decision-makers to define transport and environment public policies to minimize the negative impacts of vehicle emissions in the city.

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES) – Finance Code 001, Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPQ), Empresa de Transporte e Trânsito de Belo Horizonte (BHTRANS) and Prefeitura de Belo Horizonte (PBH), Brazil. The support of the Global Centre for Clean Air Research (GCARE), Department of Civil and Environmental Engineering, Faculty of Engineering and Physical Sciences, University of Surrey, United Kingdom; the support received from the FAPESP and the University of Surrey through the CarE-Cities (Clean Air Engineering for Cities) funded by Research England under the University of Surrey's Global Challenge Research Funds (GCRF) and NOTS (Novel high-resolution spatial mapping of health and climate emissions from urban transport in Sao Paulo megacity) projects were also outstanding.

4.1. INTRODUCTION

The health effects of short and long-term exposure due to ambient air pollution are a world problem. More than 90% of the world´s population lives in places exceeding WHO air quality guidelines (Andrade et al., 2017; Kumar et al., 2017; Pacheco et al., 2017; Andreão et al., 2018; WHO, 2018), this fact increases the population risks. Vehicles are one of the most significant emissions sources of air pollutants in an urban area (Wu et al., 2017; Wong et al., 2019; Singh et al., 2020) and the real contribution of vehicular emissions to predict air quality remain a challenge. Traffic activities combined with fuel consumption rise air pollutant emissions, and consequently, raise deterioration of air quality and degradation of health (Hatzopoulou and Miller, 2010; Andrade et al., 2012; Zhang and Batterman, 2013; Kumar et al., 2016).

The vehicular emission inventory (VEI) is a tool used to identify the emission contributions from mobile sources. Every link level of each urban street in the network requires traffic activities. Speed, flow (counts of vehicles) and road density are variables used in traffic network modeling (Morris and Trivedi, 2013; Xu et al., 2018) and the accuracy of each data contribute for more reliable results (Nagpure et al., 2016; Fu et al., 2017; Dias et al., 2018; Pinto et al., 2019). Furthermore, the better traffic flow representations with fine spatial and temporal distributions result in a satisfactory allocation of emissions on grid cells.

In developed countries, Global Position System (GPS), Intelligent Transport System (ITS), Dynamic Traffic Assignment (DTA), agent-based models, statistical models, traffic models (macroscopic, mesoscopic, microscopic), neural networks, chassis dynamometer tests are sources of traffic data (Rowangould, 2015; Borrego et al., 2016; Jamshidnejad et al., 2017; Hofer et al., 2018; Jiang et al., 2018; Wei et al. 2019). In developing countries, in most cases, traffic data are collected from combinations between internet searches, reports, and contacts with private and governmental agencies. Moreover, the majority of countries in South America are typically poorly represented in global inventories due to the scarcity of measurement campaigns and national inventories. The use of socio-economic indexes to develop local inventories using extrapolated data instead of measured data is frequent (Saide et al., 2009; Alonso et al., 2010; Sharma and Chung, 2015).

Gaps remain on spatial and temporal distributions, on consistent emissions factors, allocations of emissions on grid cells, and available data to validate the estimations (Pinto et al., 2019). The average link-based traffic parameters are a persistent limitation.

The most uncertain input in air quality modeling are emissions and differences between state of the art, and current practices show that is necessary increased compatibility in this modeling practices (Fallahshorshani et al., 2012; Kaewunruen et al., 2016; Tominaga and Stathopoulos, 2016; Sallis et al., 2017).

The prediction of traffic data has shown to be suitable for minimizing costs from an origin-destination survey and the use of commercial software with traffic models. Radar databases and traffic counts using statistical modeling is an alternative and a low-cost approach to producing traffic activities data in each urban street to use as input to predict vehicular emissions (Fu et al., 2017). Real traffic data is a way to determine traffic activities, and it is possible to integrate with exploratory variables, such as type of road (urban or rural), functional classification, area type, speed limit and others (Eom et al., 2006; Yu et al., 2010; Morris and Trivedi, 2013; Lowry, 2014; Nantes et al., 2016; Pan et al., 2016; Chang and Cheon, 2018; Xu et al., 2018).

The spatial and temporal vehicle flow distributions can be performed using kriging interpolation (Shamo et al., 2015, Pinto et al., 2020), spatial Pearson correlation coefficients (Chen et al., 2016); GIS techniques and modeling (Adedeji et. Al., 2016; Requia et al., 2017), neural network (Fu et al., 2017); Thiessen polygons (Gómez et al., 2018); spatial autoregressive moving average (SARMA) regression model (Sun et al., 2018), land-use regression (LUR) and geographically weighted regression (GWR) models (Kanaroglou et al., 2013; Song et al., 2019), among others. Additionally, models may provide the required activity data, and therefore, a well representative flow for every urban street in the study area.

Traffic data is critical data to improve the input data in emission modeling and, consequently, air quality modeling. The potential of using radar data to produce traffic data is a way to integrated environmental and transportation planning areas. Simple, low-cost, and accurate methods for assessing the spatial distribution of traffic data and vehicular emissions are essential for environmental management and transportation public policy definition. Besides, it is essential for analyzing future scenarios and projections.

The approach to structuring traffic data inputs for emission modeling can change the spatial vehicular emissions and to improve this knowledge, the aims of this work are: (1) perform a spatial statistical analysis of local radar data; (2) to calculate traffic flow using local radar data using different statistical models; (3) to analyze scenarios about a Brazilian vehicle emission inventory to define public policies in an urban area. This study was conducted in Belo Horizonte (BH), the capital of the third-largest metropolitan area in Brazil, investigating current (2020) and future scenarios (2025, 2030, and 2050).

4.2. MATERIALS AND METHODS

4.2.1. Study area

Belo Horizonte (BH), the capital of Minas Gerais state, is a densely populated urban city (over 2.5 million inhabitants), with nine sub-regions (Figure 16), and a representative vehicle fleet (over 2 million vehicles). The Minas Gerais state has the third-largest metropolitan region of the country, and BH was selected because of the availability and accuracy of vehicle data, which is used by the city traffic agency and in the local and national government officials reports**.**

Figure 16: Belo Horizonte and sub-regions.

The city network has 31,905 urban streets, where residential roads represent 65.80%, followed by service road (10.80%). In the west region are located 13.24% of the streets, 12.74% are in the northeast region, and 12.73% in the *Pampulha* region, a tourist place in the city. Table 20 presents the street and urban street type of radar and manual count points, while Table 21 shows the sub-region where the street is located. The radars have been installed by the Transportation and Transit Company of Belo Horizonte (BHTRANS) to control the speed limit of the vehicles in the city, reducing the number and severity of accidents, creating a safe transit. In this work, it was used data from 304 radars and 87 count points. The radar types are CEV and CEV MOVE (Electronic Speed Control); DAS, DAS Busway, and MOVE (Semaphore Advance Detector); CJG and CJG Busway (Combined Equipment (DIF + CEV)); DIF (Exclusive Intrusion Detector and Truck Circulation Detector) and RF (Fixed Speed Control Radar.

Table 20: Percentage of urban street type in Belo Horizonte.

Description	Urban Street Type		Urban Street Type of Radar and count points	
	Sample (S)	%	Sample (S)	%
Residential	20,986	65.78	5	1.28
Service	3,379	10.59	21	5.37
Tertiary	3,333	10.45	35	8.95
Secondary	2,071	6.49	106	27.11
Trunk	924	2.90	129	32.99
Primary	813	2.55	81	20.72
Motorway	399	1.25	14	3.58
Total	31,905	100.00	391	100.00

Table 21: Percentage of urban street per sub-region in Belo Horizonte.

City region	Urban Street	%	Radar Type	%
Barreiro	3,404	10.67	16	4.09
Centre-South	1,845	5.78	70	17.90
East	2,226	6.98	30	7.67
Northeast	4,065	12.74	30	7.67
Northwest	3,815	11.96	68	17.39
North	2,755	8.64	27	6.91
West	4,223	13.24	38	9.72
Pampulha	4,061	12.73	70	17.90
South	2,492	7.81	16	4.09
Venda Nova	3,019	9.46	26	6.65
Total	31,905	100.00	391	100.00

The major urban streets are in West, *Pampulha*, and Northeast, whereas there are the lowest urban streets in Downtown, South, and East regions. The most of radar is in secondary and trunk street, and most are downtown (17.90%), Northwest (17.39%), and *Pampulha* (17.90%).

4.2.2. Descriptive Statistical Analysis

The qualitative variables were the type of the radar, type of street, and regional, while quantitative variables are vehicle flow, street length, population, traffic zone, and per capita income. Absolute and relative frequencies measures in the descriptive analysis of the qualitative variables were used, whereas quantitative variables were describing using measures of position, dispersion, and central tendency. The Mann-Whitney and Kruskal-Wallis tests are statistical tests used to the comparison between vehicle flow and qualitative variables. The Spearman correlation was used to correlate vehicle flow and quantitative variables (Hollander and Wolfe, 1999) and is a limited measure between -1 (negative correlation) and 1 (positive correlation).

Moran Index and semivariogram were applied to describe spatial correlation. Moran index is one of the most classic methods to measure spatial autocorrelation. A correlation coefficient is the result interpretation, e.g., values close to 1 indicate a dense spatial pattern (high values tend to be located close to high values, and low values tend to be located close to low values). The values close to -1 indicate a dense negative spatial pattern (low values tend to be close to high values), and values close to 0 indicate an absence of spatial pattern (Rogerson, 2012). The semivariogram is also used to describe spatial correlations of point observations and consists of evaluating if the variables follow a specific pattern in space. The semivariogram is a measure of the variability of the variable concerning distance (as the distance between the observation increases the semi-variance also increases since the observations that are close to each other tend to have more features in common than the observations that are distant).

4.2.3. Traffic Modelling using Statistic Model

The vehicular flow was estimated with kriging and mixed-effects models. The Backward Method (Efroymson, 1960) was the method used for the selection of explanatory variables in the mixed-effects model. This method is a procedure of removing, at a time, the variable with the highest p-value. The interaction repeated until only significant variables remain in the model. In this study, the Backward Method adopted a significance level of 5%. The models chosen were Linear Regression, Poisson Regression, and Negative Binomial Regression, and the Linear Regression was modeled with the logarithm of daily vehicle flow in the morning peak hour.

4.2.3.1. Kriging Model

The kriging model is the most regression method used in geostatistics (Oliver and Webster, 2015). The technique assumes that the closer points tend to have more similar values, while the points that farther tend to have more different values, i.e., the values presented a spatial correlation. According to Landim (2003), kriging is a method of estimation by moving averages of measurements distributed in space from the values of its surroundings. In this method, a semivariogram is a function that relates spatial dependence (Landim and Sturaro, 2002). Therefore, the kriging method consists in minimizing the estimated variance from the model that considers spatial dependence (Landim, 2003).

4.2.3.2. Mixed – Effect Model

In regression models, measurements in the same place or point, or both generate a clustering structure that must be appropriately addressed, once it violates the underlying assumption of independence of observations. In the presence of pooled data, there is a correlation between observations of the same place or point and that there is no correlation between observations of different places or points. The correlation between repeated measurements of the same locations or points is approached using mixed-effect models, also known as subject-specific models since interpretation is performed at the subject level (Pinheiros and Bates, 2000; Fitzmaurice et al., 2011). Therefore, to estimate vehicle flow, a mixed-effect model with random on the intercept was adjusted. The subject was radar type, regional and neighboring neighborhood or address.

The generalized linear models present the possibility of using counting models and include the logarithm binding (Mccullagh and Nelder, 1989). The Poisson distribution is widely used to model count data, but Poisson models consider the variance equal to mean, but this usually does not occur in practice, causing sub or super dispersion (Hair et al., 2009). Thus, it is common to use Poisson models with robust variance or to use Negative Binomial distribution. The estimation of vehicle flow was realized using the kriging model and two types of mixed effect models. The mixed-effect models were adjusted for each distribution adopted (Linear, Poisson, and Negative Binomial). The first one considered the random effect on the address, radar type, and regional area, and the second model was fitted considering the random effect on the neighborhood, radar type, and regional area. To choose the best model, i.e., the model with the smallest errors, cross-validation was used.

Prediction analysis was also performed to complete the statistic model selection. The database used for the prediction did not contain the variable "radar type." Therefore it was decided to perform the prediction considering the following types of radar: without radar (the prediction adjustment did not use the radar type); Semaphore Advance Detector (DAS), Fixed Speed Control Radar (RF), Electronic Speed Control (CEV) and Combined Equipment (CJG). The variable "radar type" is significant for the model, since it reduces the model error by approximately three times.

4.2.3.3. Cross-Validation

The cross-validation principle was used to select the best model to verify if the model had an appropriate fit and a good predictive ability. The following adjust quality measurements were calculated: Mean Absolute Deviation (MAD), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE). The cross-validation assesses model performance in a new database, and it is necessary processing to verify how accurate the model is in practice. Cross-validation avoids the overfitting problem. This problem can occur when the model fits too much in the training set and performs far less than a validation database (Hair et al., 2009). The cross-validation process consists of a split database into two mutually exclusive subsets and then using one for model estimation (training database) and the other for model validation (test database). Thereby, k-fold cross-validation was used, which consists of a data into k partitions, where the validation set is the first partition, and the model is estimated using the rest of other partitions. The error is verified in the test partition. Therefore, the average of the k partition average errors resulted in the prediction error estimation. Vehicular emissions vary with the method adopted to structure the data inputs, and the findings presented in this work are essential to developing a relevant reference in a city that has data traffic limitations. The developed approach can serve as a means of reliably estimating of vehicular emissions, as well as offering a robust means of spatially analyzing road transport activity.

This study is new in Brazil and reinforced the importance of detailing traffic activities using real data to estimate vehicular emissions in an urban area. Radar data can provide many potential benefits for research and analysis in an environmental and planning transportation. For many developing countries, data from traffic counters can improve understanding of the city's mobility dynamics, as well as harnessing this data in online services or via traffic monitoring applications.

In this study, the focus was to provide a suitable statistical model based on local radar data to predict traffic flow for a Brazilian city and use a national vehicular emission model to analyze different scenarios and the impacts on vehicular emission in the city. These findings can be incorporated in future investigations to implement public policies to reduce vehicular emission in the urban area and in advance environmental health effects research and human health risk assessment. Some suggestions like development a tool to allow users to query information such as flow, average speed, infractions, and vehicular emissions as well as to provide quality and quantity traffic data to traffic simulation systems allowing better studies on possible traffic interventions in the city road plan and air quality estimates can implement using this research

4.2.4. Vehicular Emission Model – VEIN

The Brazilian Vehicular Emissions Inventories (VEIN) (Ibarra-Espinosa et al., 2018; Ibarra-Espinosa et al., 2019) is a vehicle emission model, free and open source. The model was developed using free software R (R Core Team, 2017) and generates pollutants emission from motor vehicles of different categories and fuels, and it was also elaborated considering transport activity and emission factors (EFs) (Equation 4) (Pulles and Heslinga, 2010; Ibarra-Espinosa et al., 2018; Ibarra-Espinosa et al., 2019).

$$Emission_{pollutant} = \sum_{activity} (AR_{activity} * EF_{pollutant,activity})$$ **Equation 4**

The equation shows that the emission of any pollutant depends on the activity rate (AR) and the EF. The transport activity corresponds to the number of vehicles multiplied by the distance traveled (km). VEIN reads the traffic flow on each route. The model reads the traffic data and then organizes the data by the fleet composition. After reading the data, vehicular flow is extrapolated to the routes of the network, considering the vehicle type and the age of use. The expected result is a one-week vehicular flow. VEIN reads the traffic flow on each route and organizes the data by the fleet composition. Then, the vehicular flow is temporally extrapolated using hourly traffic counts (Ibarra-Espinosa et al., 2018; Ibarra-Espinosa et al., 2019). The hourly traffic flow generated covered 168 hours of a typical week. The emission factors are averaged emissions measurements by type of vehicle and age of use, published by the Environmental Agency for São Paulo (CETESB, 2018).

The vehicular emission inventory was developed for four scenarios (S1, S2, S3, and S4). The S1 is a projection of vehicular emission inventory from 2018 to 2020. The S2 represents a reduction of the fleet over 30 years, indicating the possibility of implementing vehicle inspection in Belo Horizonte and withdrawing the circulation of old vehicles. The S3 and S4 illustrate a projection to 2025 and 2030, respectively. The Belo Horizonte Urban Mobility Plan (BHTRANS, 2010) and the Energy National Plan 2030 (EPE, 2007) were references used in the definition of the scenarios in this work. Furthermore, optimistic scenarios were modeled for 2025, 2030, and 2050.

4.3. RESULTS

4.3.1. Data Exploratory Analysis

Data exploratory analysis is shown in Table 22, where p-value represents Mann-Whitney[a], and Kruskal-Wallis[b] tests from the comparison between variables and vehicle flow (in the morning peak hour).

Table 22: Comparison between variables and vehicle flow (in the morning peak hour).

Variables		Sample (S)	Average vehicle flow	S.D	1º Q.	2º Q.	3º Q.	p-value
Count point	Manual	87	144.03	10.83	72.50	102.00	201.50	<0.001[a]
	Radar	304	1,295.56	70.52	138.50	986.00	2,256.50	
Type of radar and manual count point	CEV	38	2,506.03	180.24	1786.00	2,495.00	3,117.00	<0.001[b]
	CEV move	1	99.00	-	99.00	99.00	99.00	
	DIF + CEV	7	1,131.43	434.69	85.00	1,259.00	1,720.00	
	DIF + CEV Busway	13	134.31	13.61	95.00	117.00	189.00	
	DAS	95	1,372.17	104.81	493.50	1,117.00	2,025.50	
	DAS Busway	26	153.27	8.94	115.00	175.50	190.00	
	DAS move	22	128.36	18.35	82.00	124.50	140.00	
	DIF	36	72.86	5.94	47.50	62.00	104.00	
	Manual	87	144.03	10.83	72.50	102.00	201.50	
	RF	66	2,258.61	109.87	1,802.00	2,293.00	2,787.00	
Urban street type where radar type is located.	Motorway	14	316.64	20.69	247.00	305.50	368.00	<0.001[b]
	Primary	81	1,308.83	110.07	351.00	1,325.00	1,975.00	
	Residential	5	406.20	139.16	222.00	330.00	708.00	
	Secondary	106	619.65	83.12	71.00	147.50	1,029.00	
	Service	21	131.81	18.63	83.00	124.00	140.00	
	Tertiary	35	276.77	64.79	55.50	97.00	293.50	
	Trunk	129	1,672.59	126.54	181.00	1,906.00	2,881.00	
Regional where radar type is located	*Barreiro*	16	767.06	234.61	98.50	222.50	1,514.00	<0.001[b]
	Downtown	70	705.27	100.62	83.00	291.50	1,111.00	
	East	30	1,005.67	214.26	212.00	490.00	1,316.00	
	Northeast	30	1,193,00	274.38	91.00	162.00	2,505.00	
	Northwest	68	1,118.53	158.87	137.00	316.00	1,830.50	
	North	27	1,543.74	274.22	82.50	1,814.00	2,977.50	
	West	38	1,663.53	187.86	380.00	1,837.50	2,461.00	
	Pampulha	70	1,034.91	139.33	129.00	198.50	2,314.00	
	South	16	931.69	278.12	118.50	533.50	1,363.50	
	Venda Nova	26	402.81	116.49	47.00	88.50	330.00	

Radar data obtained significantly higher daily vehicle flow (p-value <0.001) than the manual count point, which was expected since radars automatically count vehicles over 24 hours during weekdays and weekends. Manual counts follow the methodology developed by the National Department of Transportation Infrastructure (DNIT) (DNIT, 2006) and can be extrapolated to 24 hours per day. The counting was performed manually during the four, five, six, until fifteen minutes period during the morning peak hour. Automatic counts tend to be more robust than manual counts. There was a significant difference (p-value <0.001) between the type of road, the radar points localization, and the daily vehicle flow. The multiple comparison test showed primary, and trunk road types presenting much flow than secondary, service, and tertiary urban street. For regional where radar type is located, significant differences were also found (p-value <0.001).

Table 23 brings the correlation between vehicle flow and quantitative variables, showing that there was no significant association (p-value >0.05). The variation on vehicle flow did not depend on the quantitative variable length of an urban street, the population in traffic zones, and the per capita income of traffic zones in this case.

Table 23: Spearman correlation between vehicle flow and quantitative variables

Variables	Vehicle flow	
	r	p-value
Length of an urban street (meters)	-0.08	0.105
Population in traffic zones (inhabitant)	-0.02	0.741
Per capita income of traffic zones	-0.02	0.675

4.3.2. Spatial Exploratory Analysis

The non-spatial correlation may be attributed to Moran Index, which was equal to 0.00 (p-value = 0.905). Figure 17 illustrates the result of the spatial correlation model of the peak hour vehicle flow in a semivariogram graphic. The semivariogram model is used to describe the continuity of the spatial correlation in the data, and the points in the graph indicate the spatial data structure. There was no spatial correlation since the value of semivariance did not increase with the distance, i.e., the flow of vehicles did not present a spatial pattern.

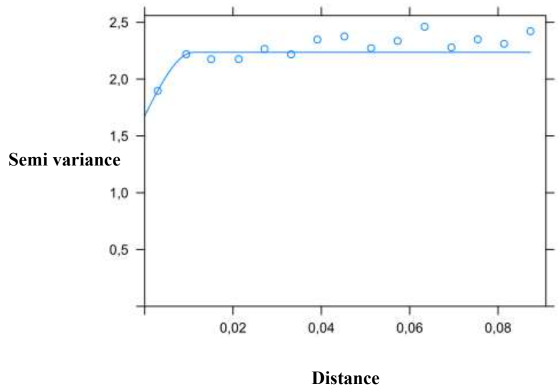


Figure 17: Result of vehicle flow in the peak hour (semivariogram).

The lack of spatial correlation can also be explained by the different types of urban streets (variable "type of road") in Belo Horizonte. The urban streets have different widths and lengths and, therefore, different vehicle flow at modeled peak hour.

4.3.3. Mixed – Effects Model and Cross Validation

The selected model "Normal-Neighborhood Model" (i.e., the mixed effect model with random effect in the neighborhood, radar type, and the regional area) is given by the following equation 5:

$$E(\boldsymbol{Vehicle\ Flow_{ijk}}) = \exp\{\boldsymbol{\beta_0} + \boldsymbol{\alpha_i} + \mu_j + \gamma_k + \boldsymbol{\beta_1}\,(\boldsymbol{Primary}) + \boldsymbol{\beta_2}\,(\boldsymbol{Residential}) + \boldsymbol{\beta_3}\,(\boldsymbol{Secondary}) + \boldsymbol{\beta_4}\,(\boldsymbol{Service}) + \boldsymbol{\beta_5}\,(\boldsymbol{Tertiary}) + \boldsymbol{\beta_6}\,(\boldsymbol{Trunk})\}$$

Equation 5

where $\alpha_i \sim N(0,\ \sigma_\alpha{}^2)$, $\mu_j \sim N(0,\ \sigma_\mu{}^2)$ e $\gamma_k \sim N(0,\ \sigma_\gamma{}^2)$, for i = 1, 2, ..., 8 (radar type), for j = 1, 2, ..., 10 (regional area) and for k = 1, 2, ..., 110 (neighborhood). The term $exp(\alpha_i)$ gives the expected average vehicle flow value for the i-th radar type; the term $exp(\mu_j)$ gives the expected average value for vehicle flow to the j-th regional area, and the term $exp(\gamma_k)$ provides the average value for the vehicle flow to the k-th neighborhood. This model is the model with mixed effects because it has a fixed effect $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5\ e\ \beta_6$ and random effect (α_i, $\mu_j e\ \gamma_k$).

4.3.3.1. Cross-Validation

The cross-validation results according to the vehicle flow modeling used are in Table 24. The analysis showed that the Normal-Neighborhood Model presented the lowest error values (in bold in Table 24) for all three statistic indices (MAD, MAPE, and RMSE). Therefore, this model was selected for predictive analysis. Even without presenting the spatial correlation necessary for the kriging model application, it was calculated and presented the most significant error (MAPE=0.88) among all models, as expected. The mixed model with random effect in address, radar type, and the regional area had similar results than a mixed model with random effect in the neighborhood, radar type, and the regional area. This similarity is justified because the address and neighborhood are variables that impact equivalently on the flow of vehicles.

Table 24: Vehicle flow cross-validation for different models used.

Model	MAD	MAPE	RMSE
Kriging	925.04	0.88	1321.24
Normal-Address	395.89	0.38	652.01
Poisson-Address	415.92	0.40	705.16
Negative Binomial-Address	384.62	0.37	625.62
Normal-Neighborhood	**376.37**	**0.36**	**619.95**
Poisson-Neighborhood	465.75	0.44	840.83
Negative Binomial-Neighborhood	393.62	0.37	637.66

The analysis of the statistical distribution used has an impact on the results of the models, and the normal distribution was the most appropriate in both models. Besides, the backward method was applied to select the explanatory variables for the model. The variable “type of road” was the variable that remained in the select statistic model (Table 25).

Table 25: Influence of explanatory variables on vehicle flow.

Variable	Exp (β)	95% C.I.	p-value
Motorway	1.00	-	-
Residential	0.18	[0.091; 0.357]	<0.001
Service	0.63	[0.359; 1.105]	0.110
Tertiary	0.19	[0.119; 0.289]	<0.001
Secondary	0.35	[0.234; 0.537]	<0.001
Trunk	0.65	[0.407; 1.044]	0.080
Primary	0.48	[0.303; 0.751]	0.002

There was a significant influence on the type of road in the peak hour vehicle flow. For instance, when different types of roads are compared with the "motorway" type, the primary road showed a 52% reduction in vehicle flow, the secondary road had a 65% decrease, and tertiary road type had an 81% reduction in vehicle flow. Table 26 presents a description of random effects by the radar type. When the radar is RF, the vehicle flow increased 7.81 times. When the radar is DIF type (Exclusive Intrusion Detector and Trucks Circulation Detector), vehicle flow decreased by 67%. The radar CJG and DAS have the smallest random effect in the vehicle flow.

Table 26: Description of random effects by the radar type.

Radar Type	Exp(β_i)	95% C.I.
RF	7.81	[6.73; 9.06]
DAS[1]	4.64	[3.97; 5.43]
CJG[2]	2.16	[1.38; 3.38]
CEV-MOVE[3]	0.43	[0.15; 1.24]
DIF	0.33	[0.26; 0.42]

*[1]DAS and DAS-MOVE: Semaphore Advance Detector; [2]CJG and CJG-Busway: Combined Equipment (DIF and CEV); [3]CEV and CEV-MOVE: Electronic Speed Control.

For the prediction analysis, it was selected three radar types (RF, DAS, and CJG) and "without radar." This selection explains the importance of radar type variable for the model.

4.3.3.2. Prediction Analysis

The descriptive prediction analysis of vehicle flow in the peak hour considered the model adjustment without radar and with three different radar: RF, DAS, and CJG. The prediction of vehicle flow in the peak hour is underestimated as no specific radar type is considered (Table 27).

Table 27: Descriptive Analysis of vehicle flow (vehicle per peak hour) estimation.

Radar	Average	S.D.	Min.	1º Q.	2º Q.	3º Q.	Max.
Without radar	131.22	91.67	64.02	81.53	88.08	103.52	580.77
DAS	609.32	425.70	297.30	378.60	409.00	480.73	2,696.91
RF	1,024.63	715.86	499.93	636.64	687.78	808.40	4,535.11
CJG	283.55	198.10	138.35	176.18	190.33	223.71	1,254.99

4.3.3.3. Vehicle Flow Spatialization

The inventory was calculated using spatial interpolation resulted from a mixed-effects model with random effect in the neighborhood, radar type, and regional because the model showed the lower MAD, MAPE, and RMSE. The traffic flow without radar was underestimated when comparing with selected counting points and concerning the use of radar data, as showed by the traffic flow spatialization in Figure 18 considering (a) no radar data and (b) CJG radar data, which presented the best spatialization, (c) DAS radar data and (d) RF radar data.

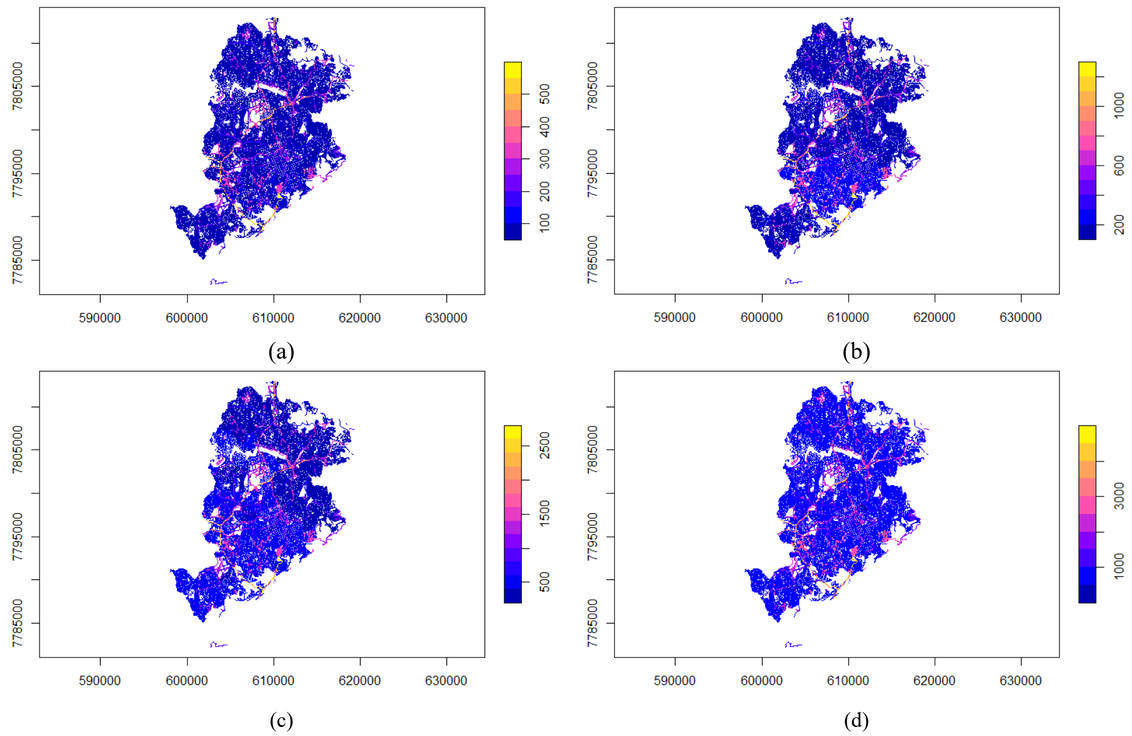


Figure 18: Spatialization of vehicle flow: (a) Without radar type and (b) Radar Type CJG, (c) Radar Type DAS and (d) Radar Type RF.

In this work, the inventory was calculated using vehicle flow, urban network, fleet (age and categories of vehicles) and fuel consumption. The State Environmental Agency in Minas Gerais developed an inventory using 118 main streets in BH in 2015 (FEAM, 2018) and a comparison was performed with this work. The comparison with the base scenario (the year 2018) must consider the assumptions and parameters, such as emissions factors values and vehicle flow spatialization. The emissions of CO, NMHC and NOx had increased by 29%, 22%, and 19% respectively when compared with FEAM (2018). The emissions of PM2.5 and SO_2 had decreased by 23% and 41% when compared with the same work.

4.3.3.4. Results of different scenarios

Four scenarios were evaluated (Table 28) and their results present the emissions for carbon monoxide (CO), hydrocarbon (HC), dinitrogen monoxide (N_2O), non-methane hydrocarbons (NMHC), nitrogen oxides (NOx), fine particulate matter (PM2.5) and sulfur dioxide (SO_2). Additionally, it was considered the carbon dioxide (CO_2) and methane (CH_4) (Table 29).

Table 28: Scenarios description.

Scenario	Description
Scenario 1 (S1)	VEI projection to 2020
Scenario 2 (S2)	Scenario 1 + Reduction in all fleet over 30 years
Scenario 3 (S3)	Scenario 1 designed to 2025
Scenario 4 (S4)	Scenario 1 designed to 2030

The analysis of different scenarios allowed the suggestions of solutions proposals focused on mobility and transport issues in Belo Horizonte.

Table 29: Vehicular Emissions Inventory ($t.y^{-1}$).

Scenario	Pollutants								
	CH_4	CO	CO_2	HC	N_2O	NMHC	NOx	PM2.5	SO_2
S1	415	15,000	3,034,190	2,069	270	1,664	4,809	146	233
S2	410	14,817	2,996,369	2,044	266	1,644	4,748	145	230
S3	435	14,339	3,546,694	2,032	323	1,616	4,647	136	267
S4	459	13,825	4,138,287	2,015	384	1,581	4,596	130	310

It is highlighted the differences between S1 (2020) and S3, where the fleet over 30 years old was considered out of the urban street. The fleet reduction causes a 1.2% average decrease in pollutant emissions. The comparison between future scenarios (S3, S4) and S1 shows a decrease in CO, HC, NMHC, NOx, and PM2.5. The main reason is the decrease in emission factors values that are caused by the improvement in vehicular technologies and fuel quality. On the other hand, the emissions of CH4, CO2, N2O, and SO2 were increased (Table 30).

Table 30: Difference emissions between each scenarios (%).

	Pollutants								
	CH_4	CO	CO_2	HC	N_2O	NMHC	NOx	PM2.5	SO_2
Difference between S2 and S1	-1.2	-1.2	-1.2	-1.2	-1.5	-1.2	-1.3	-0.7	-1.3
Difference between S3 and S1	+4.8	-4.4	+16.9	-1.8	+19.6	-2.9	-3.4	-6.8	+14.6
Difference between S4 and S1	+10.6	-7.8	+36.4	-2.6	+42.2	-5.0	-4.4	-11.0	+33.0
Difference between S4 and S3	+5.5	-3.6	+16.7	-0.8	+18.9	-2.2	-1.1	-4.4	+16.1

This work also presented a simulation of three future scenarios considering an optimistic and a pessimistic projection considering the year 2025, 2030, and 2050. In the pessimistic projection, 2025 and 2030 scenarios were maintained as S3 and S4 despite the reduction in vehicular emissions in both scenarios. The main reason for considering them as a pessimistic projection was the fact that both scenarios had an increase in the fleet composition, i.e., an increase of 25% for 2025 and 57% in the 2030 scenario. The fleet composition was estimated using the mobile average from the last ten years. The projection of emissions factors and fuel consumption was calculated by following the same procedure.

In the optimistic view, the simultaneous reduction in the fleet composition of passenger cars, light commercial vehicle, motorcycles, trucks, and buses for all fuel (gasohol, ethanol, and diesel) was applied, and the results to CO, HC, NMHC, NOx, and PM2.5 are in Table 31.

Table 31: Vehicular Emissions Inventory (t.y-1) in an optimistic and pessimistic projection.

Year	Pessimistic projection					Fleet Reduction		Optimistic Projection				
	CO	HC	NMHC	NOx	PM2.5	Type of vehicle	%	CO	HC	NMHC	NOx	PM2.5
2025	14,339	2,032	1,616	4,647	136	Passenger car Motorcycles Light Commercial Vehicles Trucks Buses	10 5 10 15 20	12,954 (-10%)	1,837 (-10%)	1,460 (-10%)	4,018 (-14%)	117 (-14%)
2030	13,825	2,015	1,581	4,596	130	Passenger car Motorcycles Light Commercial Vehicles Trucks Buses	25 15 25 20 30	10,553 (-24%)	1,544 (-23%)	1,212 (-23%)	3,507 (-24%)	99 (-24%)
2050	5,983	904	669	1,867	42	Passenger car Motorcycles Light Commercial Vehicles Trucks Buses	50 25 35 25 100	3.323 (-44%)	515 (-43%)	381 (-43%)	1,075 (-42%)	26 (-38%)

In 2025, the reduction in emission is more significant for NOx and PM2.5 (14%). In 2030, the decrease is similar for all pollutants (24%) even reduction in fleet composition do not being the same for all vehicle type. In 2050, it was supposed 100% of reduction in diesel buses and 50% in passenger cars using fossil fuel, and the impact in vehicular emissions is substantial, around 42% smaller. In this hypothetical scenario, the fleet would be composed of electric vehicles, for instance.

4.4. DISCUSSION

The results of this work can be used to define practical actions to reduce vehicular emissions not only in Belo Horizonte, Brazil, but also in any city that has this kind of dataset. Actions such as the implementation of the vehicle inspection program for the removal of vehicles older than 30 years on urban streets may generate a decrease in pollutant emissions.

These solutions implemented in conjunction with actions that encourage do not to use the private vehicle as they reduce the passenger car fleet rate applied for reducing CO, NOx, and PM2.5 emissions. The implementation of suggested actions with the construction of quality public transport infrastructures, such as subway lines and bike lanes connecting regions of the city, can contribute satisfactorily to the improvement of air quality in Belo Horizonte.

The proposed statistical model can be used in different cities that have radar database. It is essential to provide statistical assumptions, such as the existence or not of spatial correlation between the flow data. This methodology is an alternative solution to predict vehicle flow to use as input data in vehicular emission models. Recently, São Paulo city hall has promoted a challenge for the development of a solution for smarter and safer urban mobility in the city using radar database. The approach adopted in this research can be followed for research on other urban transport systems. It can support traffic agencies and environmental protection agencies in the entire country to decide about public transport polices to reduce vehicular emission around the city, improving air quality.

Furthermore, it is necessary to investigate the impacts on air quality. The vehicular emission inventory is an essential data to improve the mobile source input data in air quality modeling and allow understanding the relationship between pollutant emission sources and their real impacts on ambient air quality.

The reductions observed in PM2.5, CO, HC, NMHC, and NOx for the scenarios designed to 2025 and 2030 are mainly associated with improvement in vehicular technologies and fuel quality. Otherwise, the increase in CH4, CO2, and N2O emissions, associated with the fleet increase, shows that greenhouse gases from vehicles can push for a cleaner fuel policy for the city, which has become a trend mainly in European countries. The increase in SO2 emissions also indicates a policy to reduce the sulfur content in fuels. The scenarios considering fleet reduction demonstrate the benefits of adopting cleaner technologies.

4.5. CONCLUSIONS

Vehicular emissions vary with the method adopted to structure the data inputs, and the findings presented in this work are essential to developing a relevant reference in a city that has data traffic limitations. The developed approach can serve as a means of reliably estimating of vehicular emissions, as well as offering a robust means of spatially analyzing road transport activity.

This study is new in Brazil and reinforced the importance of detailing traffic activities using real data to estimate vehicular emissions in an urban area. Radar data can provide many potential benefits for research and analysis in an environmental and planning transportation. For many developing countries, data from traffic counters can improve understanding of the city's mobility dynamics, as well as harnessing this data in online services or via traffic monitoring applications.

In this study, the focus was to provide a suitable statistical model based on local radar data to predict traffic flow for a Brazilian city and use a national vehicular emission model to analyze different scenarios and the impacts on vehicular emission in the city. These findings can be incorporated in future investigations to implement public policies to reduce vehicular emission in the urban area and in advance environmental health effects research and human health risk assessment. Some suggestions like development a tool to allow users to query information such as flow, average speed, infractions, and vehicular emissions as well as to provide quality and quantity traffic data to traffic simulation systems allowing better studies on possible traffic interventions in the city road plan and air quality estimates can implement using this research.

CHAPTER 5:

FINAL CONSIDERATIONS

This work had as main objective to estimate vehicle emissions by coupling statistical models to a vehicle emissions model from radar and vehicle count data. Scenarios were evaluated based on the execution of different strategies to reduce vehicle emissions in Belo Horizonte, Minas Gerais state in Brazil, as well as future scenarios considering the years 2025, 2030, and 2050. This study is unique and strengthened the importance of detailing traffic activities, using local radar data to estimate vehicle emissions in an urban area. Other cities whose urban transport systems have vehicle count data in different locations in the urban space can adopt the approach of this research. In this sense, it may support local traffic agencies and environmental agencies in the joint decision of public policies that seek to reduce vehicle emissions in cities. For many developing countries, such as Brazil, data from traffic counters can be used more comprehensively, such as, for example, to improve understanding of the mobility dynamics. Also, it can serve as a reference in predicting vehicle flows on urban roads and enable the use of this data in services online, through applications that monitor traffic in real-time.

It was initially held a systematic literature review, which mapped studies that united traffic, emissions, and air quality modeling. The results showed that there is no ideal combination among models and that it must be defined by the user and differs according to the objectives of the study. The availability of data, the methods used to calculate emissions, and how results in modeling can assist decision-makers in their actions to improve air quality in cities also contribute to the decision of the best combination between the available models. Besides, the gaps in some studies remain in the consistency of emission factors, in spatial and temporal distributions, in the allocation of emissions in grid cells and the performance of meteorological models. It is also worth mentioning that the average traffic flows on urban roads remain a limitation.

This work verified that vehicles associated with the consumption of different fuels and the fleet age are two of the most important sources of air pollution in urban areas to be considered. The continuous monitoring of vehicle flow in real-time through the use of radars results in the improvement of the calculation of the spatial and temporal distribution of traffic activity. It promotes the improvement of the method of transferring vehicle flow information to the vehicle emissions model. The calculation of the emission inventory by coupling the statistical model of mixed effect normal-neighboring neighborhood to the Brazilian model of vehicle emissions inventory (VEIN) proved to be adequate for Belo Horizonte. The kriging method also proved to be satisfactory and can be used, as long as there is a spatial correlation between the data. The hourly traffic behavior by vehicle type and the calculation of the average traffic flow using local radar information showed the importance of the daytime cycle by vehicle type to obtain more precision in the emissions inventory. The definition of the correct proportion of traffic emissions, attributed to different categories of vehicles and fuel consumption is mandatory when calculating emissions from mobile sources.

The conclusions when evaluating the scenarios are that actions such as the execution of road space rationing in the city, a reality already in force in São Paulo, are a viable alternative, as it generates, on average, emission reductions of the order of 7.2% considering all pollutants inventoried. The implementation of a vehicle inspection program for the 20 years old fleet removal combined with the replacement of the bus fleet by electric vehicles generated reductions in NOx emissions (8.4%), PM2.5 (8.6%), and SO2 (5.8%). These results show that the suggested measures have great potential for reducing pollutant emissions by vehicles. The implementation of the strategies adding the non-use of the private vehicle, as well as the construction of quality public transport infrastructures (Bus Rapid Transit, subway lines, exclusive lanes, and cycle paths), can contribute satisfactorily to improve the air quality in Belo Horizonte.

In the analysis of future scenarios, different combinations for reducing the fleet of passenger cars, light commercial vehicles, motorcycles, trucks, and buses were suggested, and the results showed that emission reductions varied, on average, 11.6% in 2025, 23.6% in 2030 and 42.0% in 2050. The reduction of the fleet combined with the success of government programs for the reduction of vehicle emissions, coupled with the technological advancement of vehicles and the improvement of fuel quality, contributes to a reduction in vehicle emissions.

The results presented in this work are essential, as they become references for the design and improvement of public policies in the environmental area and transportation planning in Belo Horizonte, given the context of limitations in the production, analysis, and dissemination of traffic data. The proposals presented can be incorporated into future investigations for the application of new public policies that aim to reduce vehicle emissions in the urban area, and that guide research on the effects of air quality on human health.

From the results obtained and the limitations of this study, some future works are suggesting:

- development of a tool using the Internet of Things (IoT) platform that gathers, analyzes, and manages traffic data and allows users of public transport and drivers to check information such as vehicle flow, average speed and vehicle emissions in the city, contributing to their mobility and daily activities (setting the departure time, selecting the route, configuring the air conditioning system, maintaining the vehicle, among others);
- development of a tool that, acting as a source of useful traffic data to traffic simulation systems, allowing more detailed studies of interventions in urban traffic and estimates of air quality;
- evaluation of the efficiency and effectiveness of traffic management strategies (Transport Management Strategies-TMS) used to improve air quality, reducing human exposure to pollutants;
- evaluation and compilation of existing methodologies for calculating vehicle emissions, defining best practices, and input data information appropriate to Brazilian cities;
- development of cooperative work between companies and research laboratories to analyze differences in the measurement of emission levels by vehicles manufacturers;
- creation of a database with local emission factors, including all types of vehicles and consolidation of the vehicle emissions methodology to generate emission maps and their effects, based on the insertion of new vehicle technologies (passenger cars, light commercial vehicles, motorcycles, trucks, and buses) and the quality of fuels;
- development of measurement campaigns to verify the accuracy of the traffic, emissions, and air quality modeling;
- modeling the air quality in the proposed scenarios of this work to verify the impact on the environmental concentrations of pollutants.

CHAPTER 6:

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