UNIVERSIDADE FEDERAL DE MINAS GERAIS
PROGRAMA DE PÓS-GRADUAÇÃO EM SANEAMENTO, MEIO AMBIENTE E RECURSOS HÍDRICOS

URBAN TRAFFIC EMISSIONS ESTIMATES USING COUPLED MODELS

Janaina Antonino Pinto

Belo Horizonte
2020

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Ph.D. thesis presented to the Programa de Pós-Graduação em Saneamento, Meio Ambiente e Recursos Hídricos of the Universidade Federal de Minas Gerais as a requirement to obtain the title of Ph.D. in Sanitation, Environment and Water Resources.

Focus Area: Environment

Research Line: Characterization, prevention, and control of pollution

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Belo Horizonte
Engineering School of UFMG
2020

P659u

Pinto, Janaina Antonino.
Urban traffic emissions estimates using coupled models [recurso eletrônico] / Janaina Antonino Pinto.- 2020.
1 recurso online (110 f. : il., color.) : pdf.

Orientadora: Taciana Toledo de Almeida Albuquerque.
Coorientador: Marcelo Félix Alonso.

Tese (doutorado) - Universidade Federal de Minas Gerais, Escola de Engenharia.

Bibliografia: f. 90-110.
Exigências do sistema: Adobe Acrobat Reader.

1. Engenharia sanitária - Teses. 2. Meio ambiente - Teses. 3. Ar - Controle de qualidade - Teses. 4. Ar - Poluição - Belo Horizonte (MG) - Teses. 5. Mobilidade urbana - Belo Horizonte (MG) - Teses. 6. Trânsito - Fluxo - Belo Horizonte (MG) - Teses. 7. Trânsito - Fluxo - Modelos matemáticos - Teses. I. Albuquerque, Taciana Toledo de Almeida. II. Alonso, Marcelo Félix. III. Universidade Federal de Minas Gerais. Escola de Engenharia. IV. Título.

CDU: 628(043)

Ficha catalográfica: Biblioteca Profº Mário Werneck, Escola de Engenharia da UFMG

UFMG

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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

ACKNOWLEDGEMENTS

Thanks to my advisor, Professor Taciana Toledo de Almeida Albuquerque for confidence, for support in all phases in the doctoral process and always encouraging my professional and personal growth;

Thanks to my co-advisor, Professor Marcelo Félix Alonso for accepting the co-advising of this work and for sharing his vast knowledge in the air quality area;

Thanks to all friends in GPAMA (Grupo de Pesquisa em Poluição do Ar e Meteorologia Aplicada) for always be willing to help and share the knowledge acquired over the years. Special thanks to Willian, Rizzieri, Fábio, Felipe e Amanda;

Thanks to Professor Prashant Kumar for welcoming me to the University of Surrey, for presenting the extensive field of research in air quality and for allowing me to be part of Global Centre for Clean Air Research (GCARE);

Thanks to Universidade Federal de Itajubá (UNIFEI) for encouraging the training of professors and collaborating for the achievement of a doctorate;

Thanks to Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES) for funding the doctoral scholarship in the United Kingdom for six months;

Thanks to Empresa de Transportes e Trânsito de Belo Horizonte (BHTrans) for providing radar and traffic data for Belo Horizonte city. Special thanks to Luciano, Dayane, and Vinícius from Gerência de Planejamento da Mobilidade (GEMOB) and Gustavo Morais from Gerência de Análise e Processamento de Infrações (GEAPI);

Thanks to Programa de Pós-Graduação em Saneamento, Meio Ambiente e Recursos Hídricos (SMARH) for all dedication and knowledge adressed. Special thanks to Júlio and postgraduate staff for all support;

Thanks to my friend and research Sérgio Alejandro Ibarra Espinosa for teaching me how to use the Vehicular Emission Inventory Model (VEIN), for his time dedicated in discussions and to solve many questions about my vehicular emissions;

Thanks to my friends who always supported, encouraged and believed me to perform this hard work: Sara, Jackie, Kívia, Mara, Sabrina, Érica, Pat (Xuca), Helen, Pati, Isadora, Didi, Thaís, Marci, Vânia, Cláudia, Sandrine, Amilton, Vitor (Vô), Laís, Ciça, Léo (Dog), Vivi, Dri, Isa, Flávio, Iara, Mari, Carol, and Rosi;

Thanks to my new friends from the University of Surrey: Jeet, Sachit, Naresh, Joan, Gopinath, Marvin, Precious, and Adela. Thank you for making all-time in the United Kingdom unforgettable;

Thanks to my friend Veronika for her friendship, for helping me to understand some questions about my thesis and for sharing good times in the United Kingdom and São Paulo city;

Thanks to my partner Thiago for his patient, for his support in all moments and for always encouraging and showing that the result of all effort would be worth it;

Thanks to my siblings Iubatan and Camila for their friendship and unconditional support;

Thanks to my parents, Valdemir and Maria de Lourdes, who always did everything for my personal growth and professional training of their children. They believe and teach that love and knowledge are the foundation of a happy and prosperous life. Thank you so much!

Special thanks to co-authors of each paper written:

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 (CO_2, CH_4 e N_2O), 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 CH_4 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.

The Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES)- Finance Code 001, Brazil partially funded this research. 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 PEDALS (Particles and Black Carbon Exposure to London and Sao Paulo Bike-Lane Users) and NOTS (Novel high-resolution spatial mapping of health and climate emissions from urban transport in Sao Paulo megacity) projects, and through the CArE-Cities (Clean Air Engineering for Cities) project and the support received from the FAPESB/CIMATEC/SENAI were also essential to this research.

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.

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 partially funded this research. 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 São Paulo megacity) projects.

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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 1: 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 1: 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 2: 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).

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

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. 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 3: 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 4: 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.

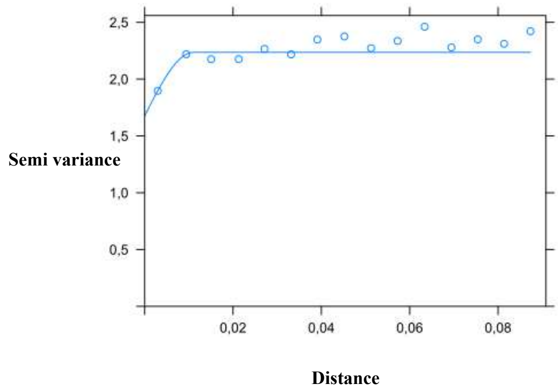

Figure 2: Result of vehicle flow in the peak hour (semivariogram).

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:

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

Equation 2

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 5: 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 6: 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 7: 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 8: 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.

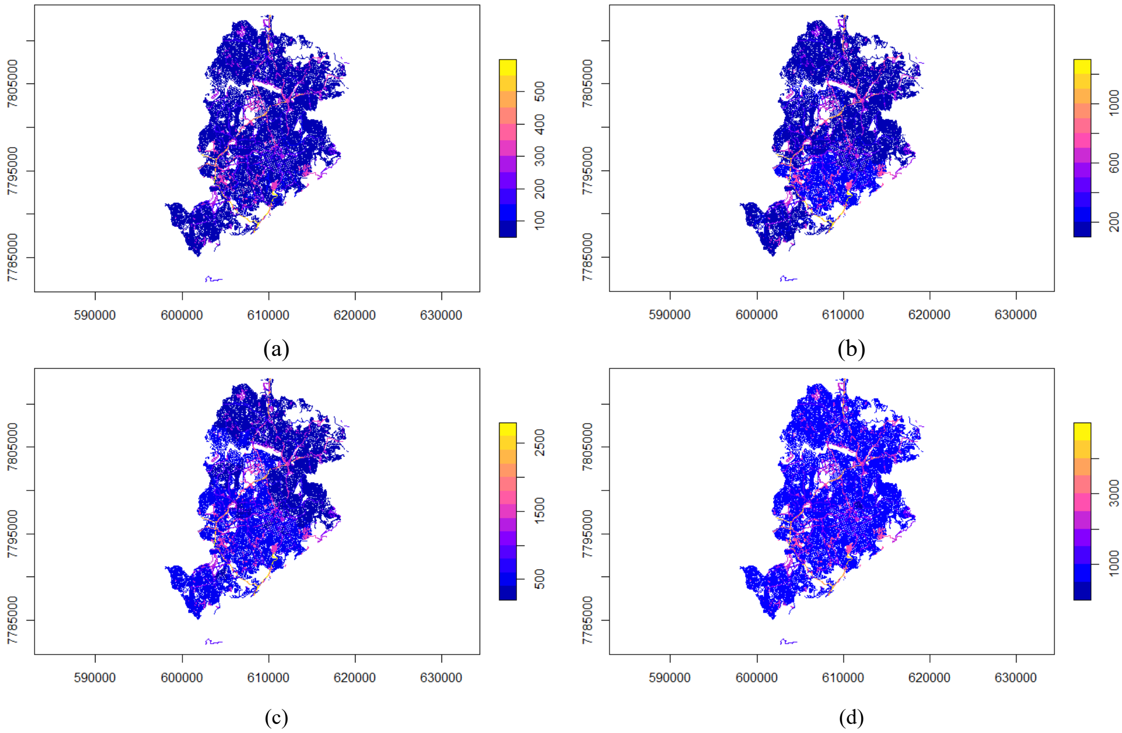

Figure 3: Spatialization of vehicle flow: (a) Without radar type and (b) Radar Type CJG, (c) Radar Type DAS and (d) Radar Type RF.

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 9: 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 10: 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 11: 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 12: 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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