Predicting road transport GHG emissions with application for Canada

Mohd Jawad Ur Rehman Khan

A Thesis

in the

Concordia Institute for Information Systems Engineering (CIISE)

Presented in Partial Fulfillment of the Requirements

For the Degree of Master of Applied Science (Quality Systems Engineering) at

Concordia University

Montreal, Quebec, Canada

September 2017

CONCORDIA UNIVERSITY
School of Graduate Studies

This is to certify that the thesis prepared

By: Mohd Jawad Ur Rehman Khan

Entitled: **Predicting road transport GHG emissions with application for Canada**

And submitted in partial fulfillment of the requirements for the degree of

Master of Applied Science (Quality Systems Engineering)

Complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

Signed by the final examining committee:

Dr. Jia Yuan Yu	Chair (CIISE)
Dr. Walter Lucia	Internal Examiner (CIISE)
Dr. Shannon Llyod	External Examiner (JMSB)
Dr. Anjali Awasthi	Supervisor (CIISE)

Approved by ______________________________

Chair of Department or Graduate Program Director

Date   Dean of Faculty

Abstract

Predicting road transport GHG emissions with application for Canada

Prediction of greenhouse gas (GHG) emissions is vital to minimize their negative impact on climate change and global warming. In this thesis, we propose new models based on data mining and supervised machine learning algorithms (Regression and classification) for predicting GHG emissions arising from passenger and freight road transport in Canada. Four categories of models are investigated namely artificial neural network multilayer perceptron, multiple linear regression, multinomial logistic regression and decision tree models. From the application results, it was found that artificial neural network multilayer perceptron model showed better predictive performance over other models. Ensemble technique (Bagging & Boosting) was applied on the developed Multilayer Perceptron model which significantly improved the model's predictive performance.

The independent variable importance analysis conducted on multilayer perceptron model disclosed that among the input attributes Light truck emissions, Car emissions, GDP transportation, Heavy truck emission, Light duty truck fuel efficiency, Interest rate (overnight), Medium Trucks Emission, Passenger car fuel efficiency and Gasoline Price have higher sensitivity on the output of the predictive model of GHG emissions by Canadian road transport.

Scenario analysis is conducted using widely available socioeconomic, emission and fuel efficiency attributes as inputs in multilayer perceptron (with bagging) model. The results show that in all Canadian road transport GHG emission projection scenarios, all the way through 2030,

emissions from Light trucks will hold a major share of GHG emissions. Thereby, rigorous efforts should be made in mitigating GHG emissions from these trucks (freight transport) to meet the ambitious GHG emission target for Canadian road transport.

Acknowledgements

First and foremost, I would like to thank God who bestowed upon me this wonderful opportunity to pursue my graduate studies at Concordia University under the supervision of Dr. Anjali Awasthi and for gifting me the power to be in the place where I am today personally and professionally.

I would like to acknowledge and extend wholeheartedly my sincere gratitude to my thesis supervisor Dr. Anjali Awasthi for providing me with immense continuous support, patience, motivation, and guidance throughout my thesis work. Her wisdom and words of encouragement encouraged me to perform best in my research work. Further, I would also like to extend my gratitude wholeheartedly to her for being so compassionate and understanding.

Additionally, I want to thank all the professors of Concordia Institute for Information Systems Engineering (CIISE) and Concordia University for providing the best knowledge and education in all the courses, which helped me to advance my knowledge in systems engineering. Also, I want to thank CIISE's administrative staffs who never failed to bring a smile on my face, thank you!

Most importantly, I would like to thank my creators (my parents) and my friends for providing me with their unconditional love and support in every possible way. Their faith and belief in me have given me enormous strength and courage to accomplish my goals.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Background

1.1.1 Green House Gases

Commonly referred as GHG are the natural and anthropogenic gaseous constituents of the atmosphere. They absorb and emit radiations emitted by Earth's surface, Atmosphere and clouds at specific wavelengths between spectrums of thermal infrared radiation (Metz et al., 2007). The intensity of Greenhouse Gases has increased quickly due to the increased anthropogenic activities along with population progress increasing earth's temperature. GHG's absorb the energy radiated by the sun causing the atmospheric lower part to trap the heat and raise its temperature this phenomenon is called natural greenhouse gas effect. This natural phenomenon got amplified since the advent of industrialization and urbanization. The continuous emission of GHG's post industrialization has increased its atmospheric concentration subsequently resulting in global warming and climate change (Wang et al., 1976).

The major greenhouse gases are Carbon dioxide (CO2), methane (CH4), nitrous oxide (N2O), hydrofluorocarbons (HFCs), sulfur hexafluoride (SF6) and perfluorocarbons (PFCs). Out of these major gases, the most dominant is CO2 which accounts 77% of global CO2 equivalent causing global warming (Metz et al., 2007).

1.1.2 Green House Gases Emissions

United Nations Organization established Inter-Governmental Panel on Climate Change (IPCC) in 1988 and formed United Nations Framework Convention on climate change (UNFCCC) these proceedings motivated to quantify the atmospheric concentration of GHG to avoid hazardous anthropogenic interference with earth's climate structure. In the year 1997, developed countries adopted Kyoto Protocol to collectively reduce the emissions of six important GHG gases by 5.2% compared to the level in 1990 during the 2008-2012 period (Breidenich et al., 1998). These framework and protocol obliged accounting of GHG emissions at regional levels. Carbon dioxide, nitrous oxide, and methane are major greenhouse gases (GHG).

Carbon dioxide (CO2) emissions: Since the advent and during industrialization era the CO2 emission level has exponentially increased from 280 ±20 (estimated level between last 10,000 years and 1750) (Delmas et al., 1980) (Indermühle et al., 1999) to 367 ppm in 1999 (Griggs et al., 2002) and 379ppm in 2005 (Houghton et al., 2001). In 2016 the CO2 emissions have crossed 400 ppm.

Methane (CH4) emissions: It is estimated that human related activities such as biomass burning, fossil fuel production, manure management, rice cultivation, fermentation in livestock and waste management release more than 50% of CH4 global emission (Anderson et al., 2010). The constant increase in CH4 emissions during the 20th century resulted in 1745 ppb emission value in 1998 (Houghton et al., 2001) and 1774 ppb in 2005 (IPCCEggleston et al., 2006).

Nitrous oxide (N2O) emissions: Concentration of N2O has a slow increase during the industrial revolution from 314 ppb in 1998 to 319 ppb in 2005 (Houghton et al., 2001). The sources of N2O are both natural and anthropogenic activities like Sewage treatment, animal manure management, agriculture soil management, combustion of nitric acid & fossil fuels and biological sources (microbial action) in soil and water (Anderson et al., 2010).

1.1.3 Green House Gases effects

Growing concentration of GHG gases in the atmosphere is raising earth's temperature. This steady rise in temperature will lead to forthcoming catastrophic conditions like a change in climate cycle and melting of ice glaciers leading to rising in sea levels (Wang et al., 1976). There are environmental, health and economic impacts of greenhouse gas emissions like Coastal flooding, increase in precipitation levels, flooding, forest fires as a result of increase heat wave, Increase in diseases and invasive species within wild life, heat strokes, health problems because of air pollution, economic impact on agriculture, forestry, tourism and recreation because of changing weather pattern and infrastructure damage and (Government of Canada, Environment, 2016).

1.2 Context of Study

Climate change and global warming are likely to lead to more extreme weather events as well as harvest failures and rising sea levels, all of which cause enormous damage and economic loss. Since industrialization began in the 19th century, annual GHG emissions have been increasing steadily, and a turning point is not in sight (Marland et al., 2003).

Greenhouse gases trap heat in the Earth's atmosphere. Human activities increases the amount of GHGs in the atmosphere, contributing to a warming of the Earth's surface. In Canada the national indicator tracks seven GHGs, carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), sulphur hexafluoride (SF_6), perfluorocarbons (PFCs), hydrofluorocarbons (HFCs) and nitrogen trifluoride (NF3) (Government of Canada, Environment and Climate Change Canada 2017) released by human activity (reported in Mt CO2 eq) (United Nations Framework Convention on Climate Change 2017)

The Kyoto Protocol and (UNFCC) United Nation Framework Convention on Climate Change initiated the first global effort in GHG emission reduction. To achieve significant sustainable emission reduction, all the involved countries need suitable methods and models to calculate their respective emission data and thereby trends.

Emission inventories, which are collections of huge number and variants of input parameters, are the main sources of GHG emissions. Depending on the emission model used, these parameters are distinctly harnessed to aid the calculations.

In Canada, transportation is the second largest contributor to the GHG emissions and road transport has the greatest GHG footprint of the transport sector and recently reducing it is the main priority of sustainable transport policies.

1.4 Contribution of the Study

In this thesis, we present an alternative method for modeling and predicting GHG Emissions specifically from Road transportation (passenger and freight).

The models are developed using machine learning approach because:

- The models learn the relationship between inputs and outputs by adapting and capturing historical data and the underlying functional relationship.
- With the help of learning on historical data, future predictions are performed on unseen data set.

Machine learning models compared to traditional inventory based models are less complex, need a small number of inputs, minimal in depth field knowledge and most notably inputs are not predetermined as compared to traditional (COPERT, MOVES, and GAINS) models. The existing road traffic emissions prediction models require a set of predefined input variables (generally, emission factor (EF) and activity rate (A)) which are sometimes difficult to discover.

The best performing model (Multilayer Perceptron with Bagging) proposed in the thesis is flexible, and regional and provincial governments can utilize its variant as well as developing and developed countries, by employing the relevant inputs available at their discretion for GHG Emission predictions. Further, simulations can be performed on the developed model to analyze changes in future projections by introducing relevant changes in inputs resonating with the policy implications.

In this thesis, we implemented model performance improvement techniques (ensemble learning) on the best performing machine learning model to further improve its performance. This is a novel approach which has not been utilized in the context of GHG emissions projections by road transportation before.

The traditional models like COPERT, MOVES, and GAINS used for GHG emissions evaluation give emission values of a specific pollutant as output. The model proposed in this thesis is designed to predict overall values of Canadian GHG emissions specifically by Road transport using Socio-economic, demographic & emission input data.

1.3 Thesis Objectives/Thesis Statement

The objective of this research is to undertake the study of data mining/machine learning models to predict the GHG emission caused by road transportation in Canada. The focus is on projecting

GHG emission values by considering the impact of historical data trend, current & potential future technology and policy measures adopted by provincial and Federal Government on socioeconomic, demographic & emission input data. Ensemble learning techniques are implemented to boost performance improvement of algorithm followed by variable importance analysis to identify the sensitive input parameter to the model respectively

Furthermore, different scenarios projection given by best performing supervised machine learning model are assessed and additional policy measures echoing with current and future policy proposed by the federal and provincial government, to mitigate GHG emissions caused by road transportation in Canada are investigated. The following tasks are undertaken to achieve the objectives of our thesis:

1. In depth analysis of GHG emissions in Canada and its provinces with a special focus on GHG emission by Road Transport (passenger & freight).
2. Identifying the most influencing parameter (Feature selection) among the available socioeconomic, demographic & emission indicators for efficient and accurate GHG prediction.
3. Implementing Regression and Classification supervised machine-learning algorithms and analyzing their performances.
4. Improving the performance of best performing supervised machine-learning model using ensemble technique.
5. Conducting Independent variable importance analysis/sensitivity analysis to test the robustness of the model and to understand the relationship between input factors and GHG emissions by road transport.

6. Conducting Scenario Analysis and projecting GHG Emissions by road transportation for each scenario till the year 2030 by considering historical trend, technological improvement, current federal & provincial policy measures and potential policies to be introduced in future. Concerning the findings, new policy suggestions to mitigate GHG Emissions by constituents of road transport are echoed.

1.5 Thesis Organization

The rest of the report is organized as follows:

Chapter 2 presents literature review. Traditional methods to evaluate GHG emissions & their limitations are outlined. Further, research gap is discussed.

Chapter 3 presents the methodology of data mining and machine learning algorithms and performance improvement algorithms (ensemble techniques).

Chapter 4 presents the application of research methodology and GHG emission future projections and scenario analysis for Canadian road transport through 2030.

Chapter 5 presents conclusions and future scope of this research.

Chapter 2

Literature Review

2.1 Methods to Evaluate GHG emissions

The main source of GHG emission data is GHG inventories (National Inventory Submissions 2017). These inventories contain a large number of input parameters, which are used to calculate total emissions. Each model uniquely utilizes this parameter to determine the final emission total. Most emission sectors like Oil and Gas, Electricity, Transportation, Heavy Industry, Buildings, etc. are the product of a statistical parameter of the respective source, i.e., Activity data (A) and an Emission factor (EF) (Winiwarter et al., 2001).

$$GHG\ Emissions = Activity\ data\ \times Emission\ factor$$

Where:

Activity data refer to the estimated quantitative amount of human activity resulting in emissions during a given time period E.g. The total amount of fossil fuel burned is the activity data for fossil fuel combustion sources (Government of Canada, Environment and Climate Change Canada 2017).

The emission factor is the average emission rate of a given GHG for a given source, relative to units of activity. It relates the quantity of a pollutant released to the atmosphere with an associated activity. Emission factors are generally expressed as the weight of pollutant divided by a unit weight, volume, distance, or duration of the activity emitting the pollutant (United

States Environmental Protection Agency 2016), e.g., Kilograms of particulate emitted per mega gram of coal burned.

2.1.1 Road Transport Emission Inventory Models

In this section, we will discuss the most commonly used inventory models namely COPERT and MOVES, which provide estimates of road transport emissions.

COPERT

COPERT (Computer Programme to Calculate Emissions from Road Transport) is European Road Transport Emission Inventory Model. It is a software tool used worldwide to calculate air pollutant and greenhouse gas. The development of COPERT is coordinated by the European Environment Agency (EEA) (Dimitrios et al., 2012).

COPERT estimates emissions from road transport. The program estimates quantities of GHG emissions; carbon dioxide (CO_2), methane (CH_4), nitrous oxides (N_2O) and local emissions; carbon monoxide (CO), nitrogen oxides (NO_x), non-methane volatile organic compounds (NMVOC), PM, and fuel-related emissions such as lead (Pb) and sulphur dioxide (SO_2), which are emitted from road transport vehicles (passenger cars, light duty vehicles, heavy duty vehicles, mopeds and motorcycles) (Ren et al., 2016).

COPERT model is an average speed model (XIE et al., 2006). COPERT is based on the driving cycle named NEDC (New European Driving Cycle) and the calculation of emission factors depends on fixed driving cycle (Dimitrios et al., 2012). COPERT calculates the emissions separately for urban, rural, and highway driving modes. The cold-start emissions are identified to the urban driving mode, and hot emissions are recognized to rural and highway driving modes. In cases, where the distance driven during the cold-start period is over the urban trip distance, portions of the cold-start emissions are recognized to rural driving. Also, the program considers evaporative emissions for gasoline-fueled vehicles. The calculation is given by below Equation as follows (Soylu, 2007). (Sun et al., 2016):

$$E_{Total} = E_{Urban} + E_{rural} + E_{Highway}$$

Where:

E_{Urban},E_{rural}, and $E_{Highway}$ are the emissions of pollutants for the appropriate driving mode.

The products of the driving mode activity data and the relevant emission factors give the quantity of the driving mode emissions.

Figure 1 shows the following data required as input for the calculations:

Figure 1. Required input data for COPERT model (Source: Dimitrios et al., 2012).

(1 & 2) Meteorological data

(3) Fuel consumption for the road transport.

(6) The maximum and minimum ambient temperatures (monthly average).

(4 & 5) Fleet data (number of vehicles in each category).

Also, also, it requires (Song et al., 2016).

- The official date of introduction of the emission regulations

- Mileage distribution (urban, rural, highway) and average vehicle speeds.

The understanding of any study using COPERT has been highly sensitive to the possibility of obtaining reliable estimations of the input data (Burón et al., 2004).

Once the input data are ready, the program can be run for nationwide estimation of the emissions on a yearly basis.

Mobile 6.2 model and Motor Vehicle emission simulator (Moves)

The US EPA used the MOBILE model in the past to estimate the vehicle emission factors for regulatory purposes. The MOBILE6.2 model (the latest version in the MOBILE series) is a fuel based emission factor model that broadly classifies vehicles into gasoline motorcycles, diesel, and gasoline powered cars, trucks and buses (Kota et al., 2014). Recently, the US EPA replaced the MOBILE6.2 model with the MOVES (Motor Vehicle Emission Simulator) model (U.S. Environmental Protection Agency, 2012) as the official model for estimating on-road vehicle emissions.

MOVES model is designed to work with databases. In this model, new data may become available and can be more easily incorporated into the model (U.S. Environmental Protection Agency, 2012). The free access database structure provides convenience for modifying emission data in MOVES (Liu et al., 2013).

MOVES applies the relationship between vehicle specific power (VSP) and emissions and then establishes the emission rates database based on VSP. It uses the distribution of VSP to describe vehicle-operating modes, which is more flexible than COPERT and MOBILE who are based on fixed driving cycles. Furthermore, in MOVES, operating modes are binned according to second-by-second speed and VSP (Vallamsundar et al., 2011).

MOVES uses an activity based approach and classifies vehicles based on their utilities (passenger cars, passenger trucks, light commercial trucks, refuse trucks, single unit short-haul trucks, single unit long-haul trucks, combination short-haul trucks, combination long-haul trucks, motorcycles, motor homes, and buses) (U.S. Environmental Protection Agency, 2012). In this model, each vehicle type can be combined with one of several fuel types (diesel, gasoline, natural gas, electric, etc.) to estimate their emission factors (Kota et al., 2014). MOVES include both regional emission component to support the development of national and regional emission inventories and project-level emission component to support local-scale emission and air quality modeling (Kota et al., 2014).

2.2 Other Emission Inventory Models

In this section the model GAINS is discussed which calculates generalized emission inventories by bringing together information on future economic, energy and agricultural development, emission mitigation potentials and costs, atmospheric dispersion and environmental sensitivities towards air pollution (GAINS EUROPE, 2013).

GAINS (Gas and Air pollution Interactions and synergies)

GAINS (GAINS EUROPE, 2013) estimates current and future emissions based on activity data, uncontrolled emission factors, the removal efficiency of emission control measures and the extent to which such measures are applied.

The model reports threats to human health by fine particles and ground-level ozone, and potential risks posed by acidification, nitrogen deposition (eutrophication) and exposure to elevated levels of ozone. These impacts are considered in a multipollutant context, quantifying the contributions of all major air pollutants as well as the six greenhouse gases considered in the Kyoto protocol (Amann et al., 2011) (GAINS EUROPE, 2013).

The current and future emissions are estimated according to below equation by varying the activity levels along with external factors projections of anthropogenic driving forces and by adjusting the implementation rates of emission control measures (Amann et al., 2011).

$$E_{i,p} = \sum_{k} \sum_{m} A_{i,k}\ ef_{i,k,m,p}\ x_{i,k,m,p}$$

Where:

i, k, m, p - Represents Country, activity type, abatement measure, pollutant, respectively.

$E_{i,p}$ - Emissions of pollutant p (for SO_2, NO_x, VOC, NH_3, PM2.5, CO_2, CH_4, N_2O, F-gases) in country *i.*

$A_{i,k}$ - Activity level of type *k* (e.g., coal consumption in power plants) in country *i.*

$ef_{i,k,m,p}$ - Emission factor of pollutant p for activity k in country *i* after application of control measure *m*.

$x_{i,k,m,p}$ - Share of total activity of type *k* in country *i* to which a control measure *m* for pollutant *p* is applied.

2.3 Limitations of the models used to evaluate road transport GHG emissions

To implement effective policies to mitigate road transport emissions, determination of pollutant emissions from transport sector is the first step. Upon providing sufficiently reliable input, data emission inventory models such as COPERT and MOVES can provide reliable estimates of road transport emissions. For policy makers to make a better decision for future a set of well-defined input parameters is a must and preparation of detailed statistical data for different vehicle categories, and their unique operating conditions are challenging to be overcome (Burón et al., 2004) (Saija et al., 2002).

2.4 Research papers

Table 1 presents few research papers relevant to the field of GHG emissions modeling and estimations.

Table 1 Methods in the Field of GHG Emission Modeling and Estimation

Sr. no	**Paper Title**	**Model Used / Description**	**Authors**
1	Vehicular emission trends in the Pan-Yangtze River Delta in China between 1999 and 2013	COPERT Used to determine emission inventories of CO, NMVOCs, NOx, BC, OC, PM2.5, and PM10.	Song et al. (2016)
2	Estimation of Turkish road transport emissions	COPERT Inventory of Turkish road transport emissions was calculated	Soylu, S. (2007)
3	Evaluation of on-road vehicle CO and NOx National Emission Inventories using an urban-scale source-oriented air quality model	MOBILE6.2 and MOVES On-road vehicle CO and NOx inventories were estimated	Kota et al. (2014)
4.	Modeling GHG emissions and carbon sequestration in Swiss agriculture: An integrated economic approach	Swiss INTegrated Agricultural Allocation model (S_INTAGRAL)	Hediger (2006)
5	Estimating GHG emission mitigation supply curves of large-scale biomass use on a country level	This study evaluates the possible influences of a large-scale introduction of biomass material and energy systems and their market volumes on land, material, and energy market prices and their feedback to greenhouse gas (GHG) emission mitigation costs	Dornburg et al. (2007)
6	Forecasting of Greenhouse Gas Emissions in Serbia Using Artificial Neural Networks	The main goal of this study was to investigate and evaluate the possibility of using the artificial neural network technique for predicting the environmental indicators	Radojević et al. (2013)
7	Forecasting based on sectoral energy consumption of GHGs in Turkey and mitigation policies	ANN has been successively applied for predicting GHG emission based on sectoral energy consumption in turkey	Sözen et al. (2007)

2.5 Research Gap

The Literature review and cited research papers provide insightful information about road transportation emissions inventory models and neural network models for GHG emissions prediction. Also, to the best of our knowledge, it was found that no in-depth studies have been conducted in regards to distribution of GHG emission future projections by road transportation in Canada, and no ensemble techniques have been utilized for improving machine learning models performances for road transport GHG emissions modeling.

In Table 1 the mentioned research studies using road transport emission models are extensively focused on estimating vehicle emissions inventory by considering only freight relevant and meteorological data for, eg. Vehicle types, fuel type, driving speed, etc. Many research papers focused on only calculating emission factors using several emission monitoring and inventorying tools such as (COPERT and MOVES) to calculate the emission with respect to region, vehicle type, etc. while others just focused on forecasting overall GHG emissions (at country level) using simple neural networks.

In general, most of the emission sectors are estimated by multiplying the emission factor (EF) with the activity rate (A), a statistical parameter for the respective source. In practice, none of the input parameters (EF or A) is exactly known. In an emission inventory, the values of the parameters are determined as best "estimates" (Winiwarter et al., 2001). The review of the above papers points out that a limited number of studies have been done on the topic of Road transport GHG emissions by using data mining & machine learning models and independent & widely available indicators for, eg. Socioeconomic parameters, emission data, fuel efficiency, etc., compared to pre-determined input variables.

Compared to inventory based models, machine-learning models are less complex, requires fewer input parameters and does not require pre-determined parameters and hence these models can be implemented and assessed for GHG emission predictive modeling using available parameters. In addition to our study the data sources in Canada are widely available and grant access to relevant activity/emission input parameters needed for the machine learning models, we can use such a model for predicting Road transport GHG emissions.

Chapter 3

Methodologies

3.1 Feature Selection

It is also known as attribute or variable selection in machine learning and statistics. It is used to detect relevance among the features and help in distinguishing irrelevant, redundant, or noisy variable data.

Feature selection method helps in achieving the following aims (Shardlow, 2016):

- To reduce the size of the problem - reducing compute time and space required to run machine learning algorithms.
- To improve the predictive accuracy of classifiers. Firstly by removing noisy or irrelevant features. Secondly by reducing the likelihood of over fitting to noisy data
- To identify which features may be relevant to a specific problem.

Unrelated features provide no useful information, and redundant features provide no more information than the presently selected features (Manikandan et al., 2015). Feature selection is one of the most frequent and important techniques in data preprocessing and has become a necessary component of the machine learning process (Kalousis et al., 2007).

In our research, we implemented filter method for feature selection using WEKA's attribute evaluator and search method to determine set of relevant input indicators among the field of socio-economic, demographic and emission data.

WEKA (Waikato Environment for Knowledge Analysis)

It is free software used widely in the field of data mining, business, and machine learning. It inhibits algorithms for predictive modeling and data analysis, with a GUI for easy access to those functions. WEKA is competent to assess in data preprocessing, clustering, classification, visualization, and feature selection (Witten et al., 2016).

3.1.1 Relief Attribute Evaluator

The Relief algorithm was first described by Kira and Rendell (Kira et al., 1992), it is an effective method to attribute weighing.

Feature selection has been used widely to determine the quality of the attributes to be used for analysis with the help of machine learning algorithms for either classification or regression. In case of feature selection Relief algorithms (Relief, ReliefF, and RReliefF) are efficient and can correctly estimate the quality of attributes in a given experiment and considers strong dependencies among attributes (Robnik-Šikonja et al., 2003). Relief algorithms are commonly considered for feature selection method before applying any learning. According to (Dietterich, 1997), Relief algorithms are one of the most successful pre-processing algorithms. Relief algorithms have been used as an attribute weighting method (Wettschereck et al., 1997) and feature selection for price forecasting (Amjady et al., 2008).

The original Relief algorithm (Kira et al., 1992) was limited to classification problems with two classes. The extension of Relief, i.e., ReliefF that was able to perform more efficiently in the presence of noise and missing data was given by (Kononenko, 1994). It can also deal with the multi-class problem. Further, in the year 1997, (Robnik-Šikonja et al., 1997) improved the algorithm for its adoption to continuous (numeric) class values. In our research, for feature selection, we used the numeric value of our dependent variable GHG emission by road transport. In the below section we will have an overview of the RReliefF algorithm.

Basic Relief Algorithm

The output of the Relief algorithm is a weight between −1 and 1 for each attribute, with more positive weights indicating more predictive attributes (Rosario et al., 2015).

According to (Kira et al., 1992), the basic idea of Relief algorithm is to estimate the quality of attributes. Relief's estimate of the quality of weight W [*A*] is an approximation of following differences of probabilities (Kononenko, 1994).

W [*A*] = P (diff. value of A | nearest inst. From diff. class) - P (diff. value of A | nearest inst. from same class) – (Equation 1)

The attribute weight estimated by Relief has a probabilistic interpretation. It is proportional to the difference between two conditional probabilities, namely, the probability of the attribute's value being differently conditioned on the given nearest miss and nearest hit respectively (Robnik-Šikonja et al., 1997)

Pseudo code: Relief Algorithm (Robnik-Šikonja et al., 1997):

Input: for each training instance a vector of attribute values and the class value

Output: the vector W of estimations of the qualities of attributes

1. Set all weights W [A] = 0.0;

2. **for** i := 1 **to** m **do begin**

3. randomly select an instance R_i;

4. find nearest hit *H* and nearest miss *M*;

5. **for** A = 1 **to** *a* **do**

6. W[A] = W[A] – diff (A, R_i, *H*)/m + diff(A, R_i, *M*)/m;

7. end;

In Relief algorithm, The positive updates of weight (+ diff(A, R_i, *M*)/m;) are establishing the probability estimate that the attribute discriminates between instances with different class values and the negative updates of weight (– diff (A, R_i, *H*)/m) are establishing the probability estimate that the attribute discriminates and separate instances with same class value.

RReliefF Algorithm

RReliefF algorithm deals with continuous/numerical predicted value. In such problems with numeric predictive value nearest hits and misses and hence the knowledge of whether two instances belong to the same class or different class is useless. To resolve this, the probability that the predicted values of two instances are different is introduced. With the help of relative distance between predicted (class) values of two instances, this probability can be modeled.

As W[A] is estimated by the contribution of Positive and negative weight terms, in the continuous predicted class value problem these terms are missing (where hits end and misses start). Hence to overcome it the equation 1 can be modified as (Robnik-Šikonja et al., 1997):

$$W[A] = \frac{P_{diffC|diffA} P_{diifA}}{PdiffC} - \frac{(1-P_{diffC|diffA})\, P_{diffA}}{1-P_{diffC}}$$

Where:

$P_{diifA} = P$ (different value of A | nearest instances)

$P_{diffC} = P$ (different prediction | nearest instances)

And $P_{diffC|diffA} = P$ (diff. prediction | diff. value of A and nearest instances)

Pseudo code: RReliefF Algorithm (Robnik-Šikonja et al., 1997):

Input: for each training instance a vector of attribute values x and predicted value τ(x)

Output: vector W of estimations of the qualities of attributes

1. set all $\mathrm{N_{dC}}$, $\mathrm{N_{dA}[A]}$, $\mathrm{N_{dC\&dA}[A]}$, $\mathrm{W_A}$ to 0;

2. for I = 1 to m do begin

3. randomly select instance R_i;

4. select k instances I_j nearest to R_i;

5. for j = 1 to k do begin

6. $N_{dC} = N_{dC}$ + diff $(\tau(.), R_i, I_j)$.*d(i,j);*

7. for A = 1 to a do begin

8. $N_{dA}[A] = N_{dA}[A]$ + diff (A, R_i, I_j). *d(i,j);*

9. $N_{dC\&dA}[A] = N_{dC\&dA}[A]$ + diff $(\tau(.), R_i, I_j)$.

10. diff (A, R_i, I_j). *d(i,j);*

11. end;

12. end;

13. end;

14. for A= 1 to a do

15. $W_A = N_{dC\&dA}[A] / N_{dC}$ - $(N_{dA}[A]$ - $N_{dC\&dA}[A]/(\mathrm{m}- N_{dC})$

Alike Relief, the algorithm select random instance R_i (line 3) and its K nearest instance I_j (line 4). The weight for different prediction value $\tau(.)$ is collected in N_{dC} (line 6)

The weight for different attribute is collected in $N_{dA}[A]$ (line 8). The weight for different prediction and different attribute is collected in $N_{dC\&dA}[A]$ (line 9). The final estimation of each attribute is given by $W_A = N_{dC\&dA}[A] / N_{dC}$ - ($N_{dA}[A]$ - $N_{dC\&dA}[A]$/(m- N_{dC}) (line 15).

The term $d(i,j) = e^{-\left(\frac{rank\left(R_i, I_j\right)}{\sigma}\right)^2}$

The term d(i,j) is exponentiated and decreased (-) to avoid the influence of I_j with the distance from given instance R_i as the motivation behind this measure is that closer instances will have greater influence.

Where:

$rank\left(R_i, I_j\right)$ is the rank of instance I_j in a sequence of instances ordered by the distances from R_i and σ is a user defined parameter to control the influence of the distance.

To get a probabilistic reading of results, the contribution of each k nearest instance is normalized, by dividing it by the sum of all K contributions. The ranks are used to make sure that the nearest instances always have the same impact on weights (Robnik-Šikonja et al., 1997).

3.2 Data Mining

Data mining is about explaining the past and predicting the future using data analysis and modeling. It is a multi-disciplinary domain which combines statistics, machine learning and database technology (Sayad 2011). The most significant application of data mining is machine learning. Human beings frequently make a mistake when trying to create a relationship between a set of multiple attributes or potentially during analysis of those attributes. Potential hindrances are created while finding a solution to a problem involving those variables. In such situation, machine learning can often be successfully applied to these problems thereby improving designs and efficiency of the system (Ayodele, T 2010).

3.2.1 Supervised Learning

Supervised learning is based on training a data sample from a data source with correct classification already assigned or in other words; then the learning is called supervised. In supervised learning instances within a dataset can be represented as independent and target attributes. The kind of modeling depends on the target attribute if the target is discrete the modeling is classification, but if the target is continuous, the modeling is a regression (Sathya et al., 2013) (Ayodele, T 2010).

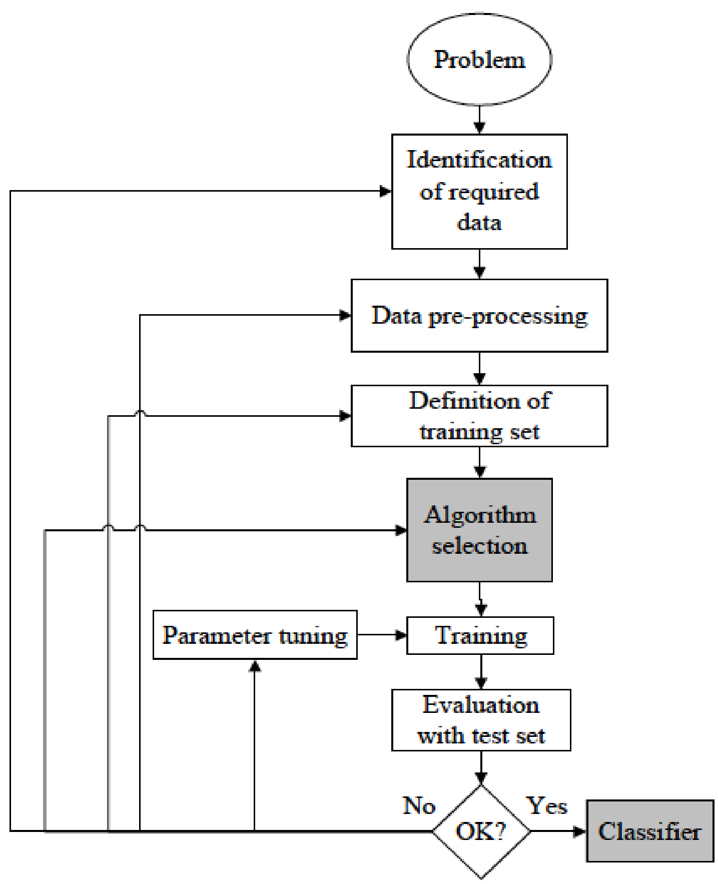


Figure 2 Process of applying supervised machine learning Source: (Kotsiantis et al., 2007).

Figure 3 describes the process of applying supervised machine learning to a real world problem. The first step is data collection followed by data preparation and preprocessing. The next critical step is Algorithm selection. Once initial testing is found to be satisfactory, the classifier is available for routine use. The classifier's evaluation is most often based on prediction accuracy (the percentage of correct prediction divided by the total number of predictions) and by the magnitude of errors, i.e., RMSE, MSE, etc. (Kotsiantis et al., 2007).

The three most popular techniques used to calculate classifiers prediction accuracy are:

- Splitting data into training and test set.
- Cross validation
- Leave-one out validation (a special case of cross validation)

During the process should the evaluation of performance parameter of classifier is not satisfactory, we should return to previous stages of supervised machine learning process, i.e., more focus should be given on relevant feature selection, on fine tuning the training parameters or the dimensionality of the input data set (training set) (Kotsiantis et al., 2007) (Ayodele, T 2010).

Supervised classification is one of the tasks most frequently carried out by Intellectual Systems. Thus, a big number of techniques have been designed based on Artificial Intelligence (Kotsiantis et al., 2007).

In this thesis, we developed models using Logical, Perceptron and Statistics techniques algorithms, i.e., Decision Tree (C4.5), Multilayer Perceptron and Multiple Linear Regression & Multinomial Logistic Regression respectively. In the following section, we will discuss more in depth about these mentioned supervised machine learning techniques.

Multiple Linear Regression

When the outcome of a problem is numeric and all input attributes are continuous linear regression is deployed frequently (Zou et al., 2003). The purpose of linear regression analysis is to evaluate the relative impact of a predictor variable on a particular outcome. Regression with the single attribute is called as simple linear regression and regression with multiple attributes is called as multiple linear regression. The Linear regression serves as building blocks of complex learning methods (Witten et al., 2016).

Linear Regression helps in the easy fitting of models, which depends linearly on their attributes. Linear Regressions are extensively used statistical tool in various practical applications majority of them being forecasting and predictive modeling (Yan et al., 2009)

Considering a given data set $\{ y_i, x_{i1}, x_{i2}, \dots, x_{ik}\}$ where i = 1 to *n.* The linear Regression model is given by (Lang, H. 2013):

$$y_i = \beta_0 + x_{i1}\beta_1 + x_{ik}\beta_k + e_i$$

Where $i = 1,2,3..n$

y_i – Dependent variable

x_{ik} – Independent variable for the Dependent variable y_i

β_k – Unknown parameters (to be estimated from data)

e_i – Error term

The regression equation can also be denoted in the matrix form for convenience:

$$Y = X\beta + e$$

$Y\ is\ a\ n\ \times 1$ vector:

$$Y = \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix}$$

$X\ is\ a\ n \times (k+1)$ matrix:

$$X = \begin{matrix} 1 & x_{i1} & \cdots & x_{ik} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & \cdots & x_{nk} \end{matrix}$$

$\beta\ is\ (k+1) \times 1$ vector:

$$\beta = \begin{pmatrix} \beta_0 \\ \vdots \\ \beta_k \end{pmatrix}$$

$e\ is\ n \times 1$ vector:

$$e = \begin{pmatrix} e_1 \\ \vdots \\ e_n \end{pmatrix}$$

The values for unknown parameters will be calculated using training data. Let's say the first instance will have a dependent variable value y_1 and independent variable values as $x_{11}, x_{12}, \dots, x_{1k}$, where the subscript value 1 denotes it's a first example.

The predicted value for a first instance dependent variable can be written as (Witten et al., 2016):

$$x_{10}\beta_0 + x_{11}\beta_1 + x_{12}\beta_2 + x_{1k}\beta_k = \sum_{j=0}^{k} x_{1k}\beta_k$$

The difference between the predicted and the actual value is vital in linear regression. The core of Linear Regression methodology is to select the values of unknown parameters β_k and β_o(constant/offset) to minimize the sum of square errors over all training instances.

Then the sum of squared difference over all training instance is:

$$\sum_{i=1}^{n} \hat{e_i}^2 = \sum_{i=1}^{n} (y_i - \sum_{j=0}^{k} x_{ik}\beta_k)^2$$

$$\sum_{i=1}^{n} \widehat{e_i}^2 = \sum_{i=1}^{n} (y_i - \hat{y})^2$$

Where the expression $(y_i - \hat{y})$ is the difference between the *ith* example's actual class and its predicted class.

Ordinary Least Square Estimation (OLS)

The OLS estimator is considered the optimal estimator of unknown parameters β (Kennedy, P. 2008). The estimated $\hat{\beta}$ gained by the application of this method minimizes the sum of square errors. This is achieved by taking the derivative of sum of square errors with respect to $\hat{\beta}$ and equating it to zero (Lang 2013).

$$\sum_{i=1}^{n} \widehat{e_i}^2 = \sum_{i=1}^{n} (y_i - \hat{y})^2$$

$$= (y - X\widehat{\beta})^T (y - X\widehat{\beta})$$

$$= y^T y - X\hat{\beta} - \widehat{\beta^T} X^T y + \widehat{\beta^T} X^T X\hat{\beta}$$

The derivative with respect to β:

$$\frac{\partial (y^T y - X\hat{\beta} - \widehat{\beta^T} X^T y + \widehat{\beta^T} X^T X\hat{\beta})}{\partial \hat{\beta}} = 0$$

$$-2X^T y + 2X^T X\hat{\beta} = 0$$

$$X^T y = X^T X\hat{\beta} y$$

Therefore:

$$\hat{\beta} = (X^T X)^{-1} X^T y$$

The OLS method under multiple linear regression is unbiased and thus $E(\hat{\beta}) = \beta$.

Multinomial Logistic Regression

Logistic regression also called logit model, is a statistical modeling technique. It evaluates the relationship between multiple independent variables and categorical dependent variable and estimates the probability of occurrence of an event by fitting data to a logistic curve. Depending on the type and value of dependent variable logistic regression can be classified as binary and multinomial logistic regression models (Hosmer & Lemeshow 2000). Multinomial Logistic regression is a generalization of logistic regression (Hosmer et al., 2013). Binary logistic regression is used when the dependent variable is dichotomous, and the independent variables are either continuous or categorical. When the dependent variable is not dichotomous and is comprised of more than two categories, a multinomial logistic regression can be employed (Hosmer et al., 2013) (Park 2013).

The aim of Multinomial logistic regression based supervised learning algorithm is to design a classifier based on L labeled training samples, that is capable of distinguishing K classes when feature vector (S) is given as an input for classification (Hosmer et al., 2013).

Today, the logistic regression models are one of the most widely used models in the analysis of categorical data. There are a lot of research papers available where the function of Logistic was applied to model population growth, health care situations and Market penetration of new products and technologies.

The important concept in logistic / multinomial logistic regression is the concept of Odds; Odds of an event are the ratio of the probability that an event will occur to the probability that it will not occur. If the probability of an event occurring is p, the probability of the event not occurring is (1-p). Then the corresponding value of odds is a value given by odds of an event (Park, H. 2013).

Odds of an Event= $\frac{P}{1-P}$

The impact of independent variables is usually explained in terms of odds, as multinomial logistic regression estimates the probability of an event occurring over the probability of an event not occurring. The multinomial logistic function is used when the dependent variable has *k* possible outcomes. MNL uses a linear predictor function *f(k, i)* to predict the probability that observation *i* has outcome *k.*

The function can be described as:

$$f(k,i) = \beta_{0,k} + \beta_{1,k}x_{1,i} + \beta_{2,k}x_{2,i} + \dots\dots\dots + \beta_{M,k}x_{M,i}$$

$$f(k,i) = \beta_{0,k} + \beta_k . X_i$$

Where:

X_i, is the set of independent variable

β_k, is set of regression coefficients associated with outcome k

Unfortunately, the probability given by this function is not a good model because extreme values of *x* will give values of $\beta_{0,k} + \beta_k . X_i$, and these values does not fall between 0 and 1. The logistic regression solution to this problem is to transform the odds using the natural logarithm (Peng et al., 2002).

When there are *K* possible categories of the response variable, the model consists of *k-1* simultaneously logit equation. With multinomial logistic regression we model the natural log odds as a linear function of the explanatory variable:

$$\text{Logit (Y)} = \ln \frac{P_r(y_i=k-1)}{P_r(y_i=k)} = \beta_{0,k} + \beta_k . X_i$$

To implement MNL with K possible dependent variable outcomes, one outcome is considered as baseline category. In the above log odd equation category, *K* is considered as baseline category.

In the model, the same independent variable appears in each of *K* categories and separate intercept $\beta_{0,k}$ and slope parameter β_k is estimated for each category. The slope parameter β_k represents the additive effect of a unit increase in the independent variable x, on the log odds of being in category k-1, rather than the reference category (Wang 2005).

Further to calculate and interpret the effect of an independent variable it is good to take exponential of both sides of the equation to get predicted probabilities (Wattimena 2014).

$$P_r(Y_i = k-1) = \frac{e^{\beta_{k-1}.X_i}}{1 + \sum_{k=1}^{k-1} e^{\beta_k.X_i}}$$

The probability of the reference category, *"K"* can be calculated as (Wang 2005):

$$\left(P_r(Y_i = k)\right) = 1 - \left(\frac{e^{\beta_{k-1}.X_i}}{1 + \sum_{k=1}^{k-1} e^{\beta_k.X_i}}\right)$$

Multilayer Perceptron

The most significant invention in the field of soft computing is Neural Networks (NN), inspired by biological neurons in the human brain. The concepts of Neural Networks were first mathematically modeled by McCulloch and Pitts (McCulloch et al., 1943). Over the last decade, the high performance of the mathematical model has made it remarkably popular. The Feed Forward Neural Network (FNN) is the simplest and most widely used among different types of NNs (Fine 2006).

Single-Layer Perceptron (SLP) and Multi-Layer Perceptron (MLP) are two types of FNN. The difference between the two types is the number of Perceptron. SLP has a single perceptron, and MLP has more than one perceptron. SLP is suitable for solving linear problems (Rosenblatt

1957) whereas, due to having more than one perceptron, MLPs are proficient of solving nonlinear problems (Werbos 1974) (McCulloch et al., 1990).

The greatest advantage of Multilayer perceptron (MLPs) is that a priori knowledge of the specific functional form is not required. MLPs are not only a 'black box' tool. In fact, they have the potential to significantly enhance scientific understanding of empirical phenomena subject to neural network modeling (Mirjalili et al., 2014). The applications of MLPs are categorized as pattern classification (Melin et al., 2012), data prediction (Guo et al., 2012), and function approximation (Gardner et al., 1998), Pattern classification implies classifying data into predefined discrete classes (Barakat et al., 2013), whereas prediction refers to the forecasting of future trends according to current and previous data (Guo et al., 2012) and function approximation involves the process of modeling relationships between input variables.

The MLP model is a flexible and general-purpose type of ANN composed of one input layer, one or more hidden layers, and one output layer (Dawson et al., 1998).

The MLP is a network formed by simple neurons called perceptron. The perceptron calculates a single output from multiple real-valued inputs by forming combinations of linear relationships according to input weights and even nonlinear transfer functions. (Mirjalili et al., 2014).

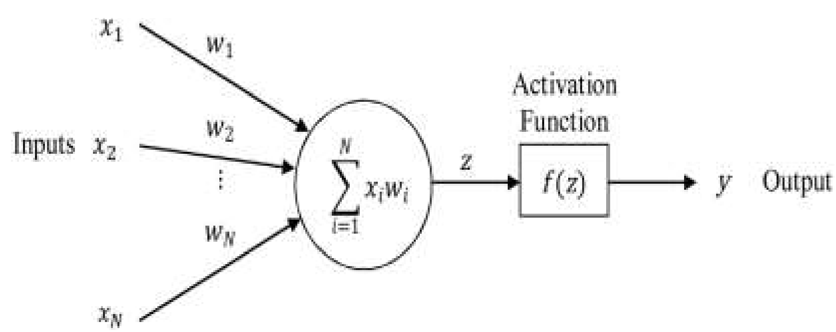


Figure 3 Artificial model of a Neuron. Source: (de Pina et al., 2016).

MLPs are fully connected feed-forward nets with one or more layers of nodes between the input and the output nodes. Similar, to a biological neural network, MLPs are composed of simple interconnected units (the neurons). Each layer is composed of one or more neuron in parallel. Figure 4 represents an artificial model of a neuron, the McCulloch-Pitts neuron (McCulloch et al., 1943) Upon receiving a given number of inputs $x_i, i = 1,2,..N$, each neuron calculates a linear combination of the inputs using synaptic weights w_i to generate the weighted input z; then, it provides an output y via an activation function $f(z)$ (de Pina et al., 2016).

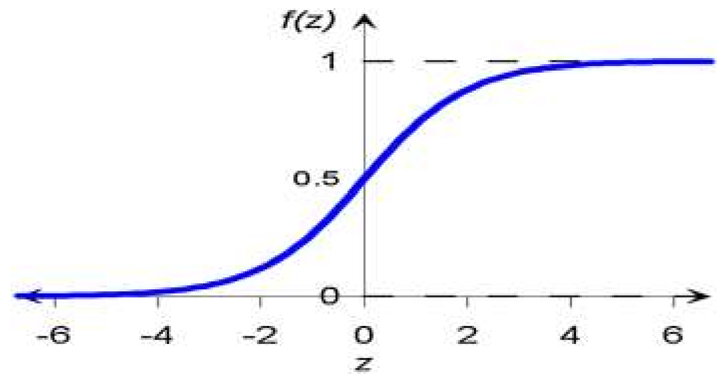


Figure 4 Output Sigmoid Activation Function. Source: (de Pina et al., 2016)

The sigmoid activation function as shown in figure 5 is given by:

$$y = f(z) = \frac{1}{1 + e^{-z}}$$

The activation function should present an increasing monotonic behavior over a determined range of values for z, with inferior and superior limits. Ideally, it should also be continuous, smooth and differentiable on all points (de Pina et al., 2016). In this research, we implemented a sigmoid function, which is the most common type of activation function.

Figure 6 below shows an MLP with three layers, where the number of input nodes is *n*, the number of hidden nodes is *h*, and the number of output nodes is *m*. It can be seen that there are one-way connections between the nodes since the MLP belongs to the FNN family.

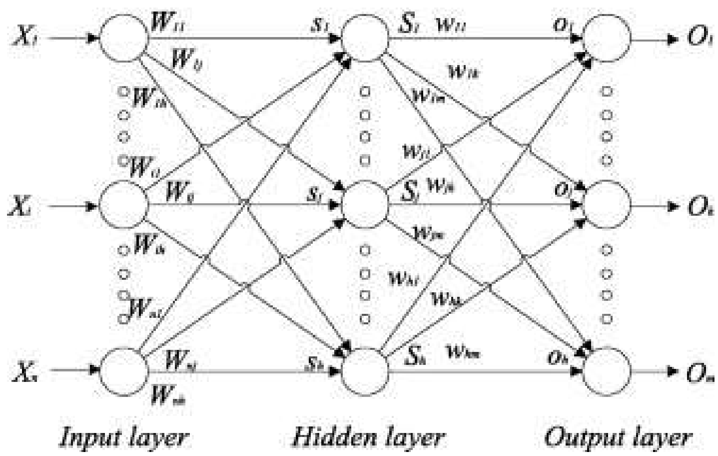


Figure 5 Multilayer Perceptron with Three Layers. Source: (Mirjalili et al., 2014).

The output of the MLP is calculated as follows (Mirjalili et al., 2014):

Step 1: Equation below first calculates the weighted sums of inputs:

$$s_j = \sum_{i=1}^{n} (W_{ij} X_i) - \theta_j, \qquad j = 1,2, \dots \dots h$$

Where *n* is the number of the input nodes, W_{ij} shows the connection weight from the *i*th node in the input layer to the *j*th node in the hidden layer, θ_j is the bias (threshold) of the *j*th hidden node, and X_i indicates the *i*th input.

Step 2: The output of each hidden node is calculated as follows:

$$S_j = sigmoid\ (s_j) = \frac{1}{(1 + e^{(-s_j)})}\ , \ \ j = 1,2, .. h$$

Step 3: After calculating the outputs of hidden nodes, the final outputs are defined as below:

$$o_k = \sum_{j=1}^{h} (W_{jk} S_j) - \theta'_k, \qquad k = 1,2, \dots \dots m$$

$$O_k = sigmoid\ (o_k) = \frac{1}{(1 + e^{(-o_k)})},\ \ k = 1,2,..m$$

Where, W_{jk} is the connection weight from the *j*th hidden node to the *k*th output node, and θ'_k is the bias (threshold) of the *k*th output node.

The most important parts of MLPs are the connection weights and biases. As may be seen in the above equations, the weights and biases define the final values of output. Training an MLP involves finding optimum values for weights and biases to achieve desirable outputs from certain given inputs (Mirjalili et al., 2014).

Back-propagation Algorithm

In our thesis, we used back propagation algorithm to train the Multilayer perceptron model.

The MLP learning algorithm involves a forward-propagating step followed by a backward-propagating step. The pseudo code for back propagation learning algorithm in the MLP is given below:

Pseudo code for Back propagation learning algorithm in the MLP (Lek and Park, 2008):

1. Randomize the weights *w* to small random values.
2. Select an instance *t*, a pair of input and output patterns, from the training set.
3. Apply the network input vector to the network.
4. Calculate the network output vector *z*.
5. Calculate the errors for each of the outputs *k*, the difference (δ) between the desired output and the network output.
6. Calculate the necessary updates for weights $\Delta \boldsymbol{w}$ in a way that minimizes this error.
7. Add up the calculated weights' updates $\Delta \boldsymbol{w}$ to the accumulated total updates $\Delta \boldsymbol{w}$.

8. Repeat steps 2–7 for several instances comprising an epoch.
9. Adjust the weights w of the network by the updates $\Delta \boldsymbol{w}$.
10. Repeat steps 2–9 until all instances in the training set are processed. This constitutes one-iteration.
11. Repeat the iteration of steps 2–10 until the error for the entire system (error δ defined above or the error on cross-validation set) is acceptably low, or the predefined number of iterations is reached.

Forward propagating step

In forward-propagation, the input is fed to the input layer(s), and input propagates and undergoes the calculations of activation levels and further propagates forward through hidden layer till the output layer(s). In every successive layer, each neuron sums its inputs and then applies a transfer function to compute its output. The final answer is the estimate of target value produced by the output layer of the network (Lek and Park 2008).

Backward-propagating step

In this step, the comparison of the network's output to the target value is initiated, and the difference (or error δ) is calculated. The error parameter is used during the weight-correction procedure. Consider the output layer is designed by *k*, then error value is given by:

$$\delta_k = (t_k - x_k) f'(a_k)$$

Where, t_k is the target value of unit *k*, x_k is the output value for unit *k*, f' is the derivative of the sigmoid function, a_k is the weighted sum of input to *k,* and the quantity $(t_k - x_k)$ reflects the amount of error. When the sum a_k is near the rapid rise in the sigmoid curve, the derivative of the sigmoid function forces a stronger correction.

The error value for the hidden layer (*j*), is computed as:

$$\delta_j = \left[\sum_k \delta_k w_{kj}\right] f'(a_j)$$

The connection weight alteration for processing unit is done by using the δ values of the unit. Every single weight is adjusted by considering the δ value of the unit that receives input from that interconnection. The connection weight adjustment is executed as mentioned below (Lek and Park 2008):

$$\Delta w_{kj} = \eta \delta_k x_j$$

The weight $\boldsymbol{w_{kj}}$ alteration, which pass to unit k from unit j, depends on three factors: $\boldsymbol{\delta_k}$ (error value of the target unit) $\boldsymbol{x_j}$ (output value for the originating unit) and $\boldsymbol{\eta}$ learning rate which is chosen by user commonly between 0 and 1. $\boldsymbol{\eta}$ represents the learning rate of the network.

Training the network (Lek and Park, 2008)

In back propagation, the error surface of the gradient vector is calculated. This vector points along the line of steepest descent from the current point, so it is known that if moved along it a "short" distance, we will decrease the error (Ayodele, 2010). The backpropagation algorithm executes gradient descent on the error surface by adjusting each weight. The adjustment in weight is made in proportion to the gradient of the surface at its location. As can be seen in figure 7 preferably, a global minimum (lowest error value possible) is most desirable but sometimes gradient descent leads to achieve local minima as a result of the network getting stuck in a depression in the error surface. These local minima correspond to a partial solution for the network in response to the training data. A network can be pulled out of local minimum by changing the learning parameter, the number of hidden units and momentum term (α) in the algorithm. The momentum term improves movement in a fixed direction, the algorithm "picks up speed" if several steps are taken in the same direction which sometimes provides it the ability to escape local minimum, and also to move rapidly over flat spots and plateaus. The momentum term is chosen generally between 0 and 1. Taking into account the momentum term (α), the formula of modifications of weights at epoch t+1 are given by (Lek and Park, 2008):

$$\Delta w_{kj}\ (t+1) = \ \eta \delta_k x_k + \ \alpha \Delta w_{kj}\ (t)$$

The learning rate η and the momentum term α play a vital role in the learning process of Back propagation network. Efficient selection of the values of these parameters is important to avoid the network getting into oscillation and getting stuck in local minimum.

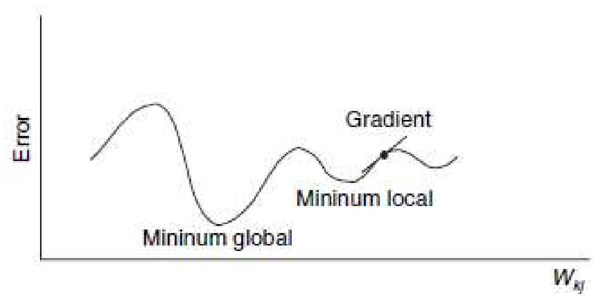


Figure 6 Error Surface as Function of a Weight Showing Gradient and Local and Global Minima. Source: (Lek and Park 2008)

Decision trees (ID3 & C4.5)

Decision trees are one of the prominent methods in supervised learning. The trees partition a data set into groups as similar as possible in terms of the variable to be predicted. It takes a set of classified data as input and outputs a tree that resembles an alignment diagram where each end node (leaf) is a decision (a class), and each non-final node (internal) represents a test. Each leaf represents the decision of belonging to a class of data verifying all tests path from the root to the leaf (Hssina et al., 2014). Instances are classified starting at the root node and sorted based on their feature values. (Kotsiantis et al., 2007).

J. Ross Quinlan originally developed ID3 (Iterative DiChaudomiser 3) (Quinlan, 1986) at the University of Sydney. The ID3 algorithm builds a tree based on the information (information gain) obtained from the training instances and then uses the same to classify the test data. ID3 algorithm uses nominal attributes for classification with no missing values (Quinlan, 1986).

The feature that best divides the training data would be the root node of the tree. There are numerous methods for finding the feature that best divides the training data such as information gain (Hunt et al., 1966) and Gini index (Breiman et al., 1984) (Kotsiantis et al., 2007).

Decision trees have been used as classifiers for numerous real-world domains, some of which are mentioned and used as examples by Quinlan; e.g., labor negotiations, hypothyroid diagnosis, soybean disease diagnosis, and credit approval (Quinlan, 1993).

Information Theory (Hssina et al., 2014):

Entropy is a vital component of Decision tree algorithm. Entropy first defines the amount of information provided by an event, the higher the probability of an event is low (it is rare), the more information it provides is great.

Entropy:

If we are given a probability distribution P = (p1, p2,…, pn) and a sample S then the Information carried by this distribution, also called the entropy of P is giving by:

$$E = -\sum_{i=1}^{n} p_i \times log_2 p_i$$

Information gain:

The functions that measure the degree of mixing of classes for all sample and therefore any position of the tree in construction. It remains to define a function to select the test that must label the current node. It defines the gain for a test T and a position p

$$Gain(p, T) = Entoropie(p) - \sum_{j=1}^{n}(p_j \times Entoropie\,(p_j))$$

Where values (p_j) is the set of all possible values for attribute T. We can use this measure to rank attributes and build the decision tree where at each node is located the attribute with the highest information gain among the attributes not yet considered in the path from the root.

C4.5 Decision Tree

There were few limitations of the ID3 algorithm and in 1993, Ross Quinlan proposed C4.5 to overcome those limitations. C4.5 algorithm acts similar to ID3 but improves a few of ID3 behaviors (Hssina et al., 2014):

- Possibility to use continuous data.
- Using unknown (missing) values
- Ability to use attributes with different weights.
- Pruning the tree after being created.

A tree is constructed by considering the top-down approach. The tree is initialized with construction at the root node first, where each attribute is assessed using a statistical test, to determine its classification efficiency of the training samples. The best attribute is chosen as the test at the root node of the tree. If the attribute is discrete in nature a descendant of the root node is created for each possible value of this attribute. If the attribute is continuous in nature a descendant of the root node is created for each possible discretized interval of this attribute.

In the next step, the training samples are sorted to the suitable descendant node. Further, the process is repeated using the training samples related with each descendant node to choose the best attribute specific at that point in the tree, for testing. This forms a greedy search (problem-solving heuristic of making the locally optimal choice at each stage with the hope of finding a global optimum) for a decision tree. During this process, the algorithm propagates in forward direction, i.e., the algorithm never backpedals to reconsider earlier node choices. A node can be introduced to the tree only when there are a sufficient number of samples left from sorting. After the complete tree is constructed, in C4.5 tree pruning (depth/size reduction of **decision trees** by eliminating parts that provide little information to classify instances) is usually carried out to avoid data over-fitting (Setsirichok et al., 2012). **J48** is an implementation of the C4.5 algorithm in the Weka data-mining tool.

Statistical test:

Alike ID3 the statistical test used in C4.5 also employs an entropy-based measure for allocating an attribute to each node in the tree. Like ID3 the data is sorted at every node of the tree to determine the best splitting attribute. The difference is C4.5 uses gain ratio impurity method to evaluate the splitting attribute (Quinlan, 1993). At every node, C4.5 selects data attribute which best splits data into subsets rich in one class or the other. The selection criterion is the normalized information-gain (difference in entropy) that results from choosing an attribute for splitting the data. The attribute with the highest normalized information gain is chosen to make the decision (Quinlan, 1993) (Hssina et al., 2014).

The information gain ratio is given by:

$$GainRatio(p,T) = \frac{Gain\ (p,T)}{SplitInfo(p,T)}$$

Where:

$$Gain(p,T) = Entoropie(p) - \sum_{j=1}^{n} (p_j \times Entoropie\ (p_j))$$

$$SplitInfo(p,test) = -\sum_{j=1}^{n} P'\left(\frac{j}{p}\right) \times \log(P'\left(\frac{j}{p}\right))$$

$P'\left(\frac{j}{p}\right)$ is the proportion of elements present at the position p, taking the value of j-th test.

Pseudocode C4.5 (Kotsiantis et al., 2007)**:**

1. If ({All the samples in the list belong to the same class}

   Then {create a leaf node to choose that class})

   If ({None of the features provide any information gain}

   Then {create a decision node higher up the tree using the expected value of the class})

   If ({Instance of previously unseen class encountered}

   Then {create a decision node higher up the tree using the expected value})

2. Check for above cases
3. For each attribute *a*, evaluate information gain ratio (normalized) from splitting on *a*.
4. Let *a_best* be the attribute with the highest normalized information gain.
5. Create a decision *node* that splits on *a_best*.
6. Recurse on the sublists obtained by splitting on *a_best*, and add those nodes as children of the *node*.

3.3 Method Improvement (Ensemble Learning)

Ensemble learning techniques train multiple classifiers instead of just one classifier to solve the same learning problem (Zhou, 2012). Many researchers have investigated the technique of combining the predictions of multiple classifiers to produce a single classifier. The resulting classifier is generally more accurate than any of the individual classifiers making up the ensemble (Opitz et al., 1999).

An ensemble contains a number of classifiers called base learners. Base learners are usually generated from training data by a base learning algorithm which can be decision tree, neural network or other kinds of learning algorithms. Ensemble methods construct a set of learners and combine them. Base learners are also called as weak learners because the generalization power of an ensemble is usually stronger than base learner and hence provide improved prediction accuracy. Ensemble methods using the same base learner for learning are called homogenous ensembles (Zhou 2012). Figure 8 represents generalized ensemble architecture.

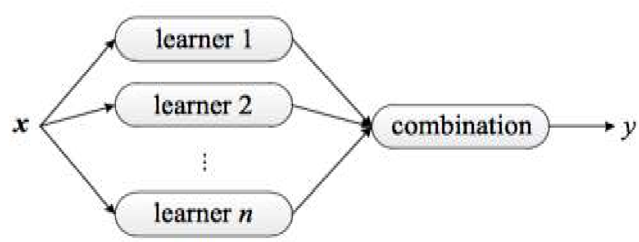


Figure 7. General Ensemble Architecture. Source: (Zhou 2012).

The individual decisions of base learners in an ensemble are combined in some way (usually either by averaging or weighted/unweighted voting) to classify new examples. As an ensemble can be trained and used for classification, these learning algorithms lie under the category of supervised learning (Dietterich, 2000). The empirical analysis presented by Hanson and Salmon in 1990, showed that prediction accuracy of an ensemble of classifiers is often more accurate than individual best single classifier. Figure 9 illustrates the simplified version of observation obtained by marking noise level vs. error (Hansen et al., 1990).

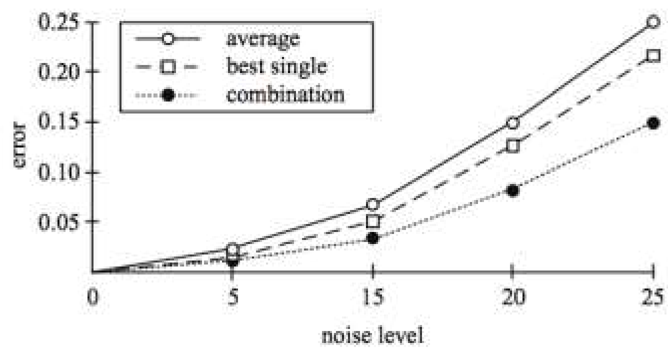


Figure 8. Classifier Performance Marked on Noise Level vs. Error. Source: (Zhou 2012).

According to (Hansen et al., 1990), in order for an ensemble to be more accurate than its base learners, the important condition is that the base learners/classifiers should be accurate (error rate on new input values should be better than guessing) and diverse (different error rate on new input values).

Ensembles learning for weak learners were extensively studied in the machine learning community. Extensive work by the researchers in this domain led to the birth of two popular methods for creating accurate ensembles, i.e., Bagging (Breiman, 1996) and Boosting (Freund et al., 1996). In this research, we used ensemble methods like bagging and boosting to improve the prediction accuracy of best-performing machine learning model for GHG emission by road transport in Canada.

Ensemble methods have been used on various occasions, which involved learning techniques and their exploitation. Table 2 shows the domains which have been benefitted by using ensemble techniques:

Table 2. Domains Benefitted By Ensemble Techniques

Domains	Paper Title	Authors
Computer vision (Object detection, recognition, and tracking)	• Robust real-time face detection. Pose invariant face recognition. In Automatic Face and Gesture Recognition.	Viola & Jones (2004), Huang et al. (2000).
Computer security (intrusion detection, Malware detection, etc.)	• Fusion of multiple classifiers for intrusion detection in computer networks. • Data mining methods for detection of new malicious executables.	Giacinto et al. (2003), Schultz et al. (2001).
Computer aided medical diagnosis.	• Medical diagnosis with C4. 5 rule preceded by artificial neural network ensemble. • An ensemble based data fusion approach for early diagnosis of Alzheimer's disease	Zhou & Jiang (2003), Polikar et al. (2008).
Credit card fraud detection	• Distributed data mining in credit card fraud detection. • Credit card fraud detection: A fusion approach using Dempster–Shafer theory and Bayesian learning	Chan et al., (1999), Panigrahi et al.,(2009).
Bankruptcy detection	Neural network ensemble strategies for financial decision applications	West et al., (2005)
Species distribution Forecasting	Ensemble forecasting of species distributions.	Araújo & New (2007)
Weather forecasting	An ensemble of neural networks for weather forecasting	Maqsood et al. (2004)
Aircraft engine fault diagnosis	• Jet engine gas path fault diagnosis using dynamic fusion of multiple classifiers • Diagnostic information fusion: requirements flow down and interface issues.	Yan & Xue (2008), Goebel et al. (2000)
Artist classification	Aggregate features and AdaBoost for music classification.	Bergstra et al. (2006)

3.3.1 Bagging

It is most commonly known as bootstrap aggregation. The two important elements of Bagging algorithm are bootstrap and aggregation (Breiman, 1996).

Table 3 shows Pseudo Code for Bagging algorithm. Bagging deploys bootstrap sampling to obtain the data subsets for training the base learners. Consider a training data set containing m number of training examples, sampling with replacement will generate a sample of m training examples. Some original examples may appear more than once, while some original examples are not present in the sample. Repeating the process T times, T samples of m training examples are obtained. Then, from each sample, a base-learner/classifier can be trained by applying the base-learning/classifier algorithm (Zhou, 2012) (Breiman, 1996).

Pseudo code:

Table 3. Bagging Pseudo Code. Source: (King et al., 2014)

Input:	
Data set $D = [(X_1, y_1), (X_2, y_2), \dots, (X_n, y_n)]$	X_n attribute vectors, n observations, y_n predictions.
Base classification algorithm, d	Define base learning algorithm.
Ensemble size, S	Number of training loops.
For $s = 1$ to S	
D_s = BootstrapSample(D)	Create bootstrap sample from D.
d_s = CreateBaseLearnerModels(D_s)	Create base models from bootstrap samples.
Make model prediction d_s	
Save model prediction d_s	
End	
Output:	
Average S model predictions	Combine model outputs by mean.
Return ensemble prediction	

Each bootstrap replicates contain, on an average 63.2% of the original training set, with multiple repetitions of example from the training set. Additionally, bagging reduces variance (Breiman, 1996) (Dietterich, 2000).

Bagging uses voting for classification and averaging for regression to aggregate the outputs of the base learners (Zhou, 2012). For example in a classification problem, the algorithm inputs an instance to its base learners and collects their outputs. Voting the labels follows this process, and finally, the algorithm chooses the winner label as a prediction. Bagging algorithm is functional with binary as well as multi class problems (Zhou, 2012).

3.3.2 Boosting

Boosting (Freund et al., 1996) incorporates a family of methods. This ensemble method produces a series of classifiers. Based on the performance of the previous classifier(s) in series, the training set used for each member classifier of the series is chosen. According to the logic of Boosting algorithm, it gives less emphasis to correctly classified examples by the classifier in series and give more emphasis on previously misclassified examples by a classifier in series, by choosing them more frequently compared to correctly predicted examples. In general, the Boosting algorithm tries to generate new classifiers that are better able to predict examples for which the current ensemble's performance is poor (Opitz et al., 1999).

The most popular boosting procedure is AdaBoost-M1(Adaptive Boosting). This procedure allows continuing adding weak learners until some desired low training error is achieved.

Adaptive Boosting Algorithm M1 (Freund et al., 1996)**:**

Consider the input to the boosting algorithm takes a training set of m examples.

$S = ((x_1, y_1), .., (x_m, y_m))$ Where, x_i is an instance drawn from some space X and represented in some manner (typically, a vector of attribute values) and, $y_i \in Y$ is the class label associated with x_i.

The boosting algorithm invokes Weak Learner (base algorithm) repeatedly in a series of rounds. On round *t*, the algorithm provides weak learners with a distribution (D_t) over the training set *S*. Following the reception of distribution the weak learners computes a classifier or hypothesis $h_t : X \rightarrow Y$ which should correctly classify a fraction of the training set that has large probability with respect to (D_t).

The weak learner's goal is to find hypothesis h_t, which minimizes the training error.

$$\epsilon_t = Pr_{i \sim D_t} [h_t (x_i) \neq y_i]$$

This error is measured with respect to the distribution (D_t) that was provided to the weak learner. This process continues for T rounds, and at last the boosting algorithm combines the weak hypotheses $h_1, \dots . h_T$ into a single final hypothesis (h_{fin})

Pseudo code (Freund et al., 1996)**:**

Input: Sequence of m examples $((x_1, y_1), .., (x_m, y_m))$ with labels $y_i \in Y = \{1, \dots, K\}$

Weak learning algorithm and integer T specifying number of iterations

Initialize: $D_1(i) = \frac{1}{m}$ for all *i*.

Do for t = 1,2,.., T:

1. Call Weak learning algorithm, providing it with distribution (D_t).
2. Get back a hypothesis $h_t : X \rightarrow Y$.
3. Calculate the error of h_t

   $$h_t: \epsilon_t = \sum_{i:h_t(x_i) \neq y_i} D_t(i).$$

   If $\varepsilon_t > 0.5$, then set $T = t$-1 and abort loop.
4. Set $\beta_t = \frac{\epsilon_t}{(1 - \epsilon_t)}$.
5. Update distribution (D_t):

   $$D_{t+1}(i) = \frac{D_t(i)}{Z_t} \times \beta_t \text{ (if } h_t(x_i) = y_i\text{) or}$$

   $$D_{t+1}(i) = \frac{D_t(i)}{Z_t} \times 1 \text{ (otherwise)}$$

   Where, Z_t is a normalization constant (chosen so that D_{t+1} will be a distribution).

Output the final hypothesis:

$$\boldsymbol{h_{fin}(x) = average\ max_{y \in Y}} \sum_{t:h_t(x) = y} log \frac{1}{\beta_t}.$$

AdaBoost.M1 uses a simple rule for calculating Distribution and final hypothesis as shown below.

Distribution ($\boldsymbol{D_t}$) Calculation (Freund et al., 1996)**:**

The initial distribution D_i is uniform over S so, $D_1(i) = \frac{1}{m}$ for all *i.* To compute distribution D_{t+1} from D_t and last week hypothesis h_t, we multiply the weight of example i by some number $\beta_t \in [0,1]$ if h_t classifies x_i correctly, or else the weight is left unchanged. The weights are then renormalized by dividing by the normalization constant Z_t effectively, "easy" examples that are correctly classified by many of the previous weak hypotheses get lower weight, and "hard" examples which tend often to be misclassified get higher weight. AdaBoost focuses the most weight on the examples, which seem to be hardest for Weak Learners.

Final hypothesis Calculation ($\boldsymbol{h_{fin}}$) (Freund et al., 1996):

The number β_t is calculated as a function of ϵ_t. The final hypothesis ($\boldsymbol{h_{fin}}$) is a weighted vote (i.e., a weighted linear threshold) of the weak hypotheses. That is, for a given instance x, ($\boldsymbol{h_{fin}}$) outputs the label *y* that maximizes the sum of the weights of the weak hypotheses predicting that label. The weight of hypothesis h_t is given by $\log(\frac{1}{\beta_t})$ so that greater weight is given to hypotheses with lower error.

In chapter 4 we will be adapting the data mining techniques mentioned in chapter 3 to perform predictive modeling of GHG emissions caused by road transportation (passenger & freight). Furthermore using the best performing model, a scenario analysis will be conducted to demonstrate the model's applicability in the context of Canadian road transport GHG emissions predictions and component distribution (emissions share of different road vehicle) all the way through the year 2030.

Chapter 4

Research Methodology

Our research methodology is divided into 3 different phases:

Phase 1: Study of GHG Emissions Landscape of Canada

Phase 2: Supervised learning model development (Regression & Classification) and applications for emissions prediction

- Feature Selection
- Multiple Linear Regression
- Logistic regression
- Decision tree (C4.5)
- Multilayer Perceptron (ANN)
- Bagging
- Boosting

Phase 3: Canada GHG emissions scenario analysis

- Business as usual scenario
- Minimum mitigation scenario (M1)
- Maximum mitigation scenario (M2)

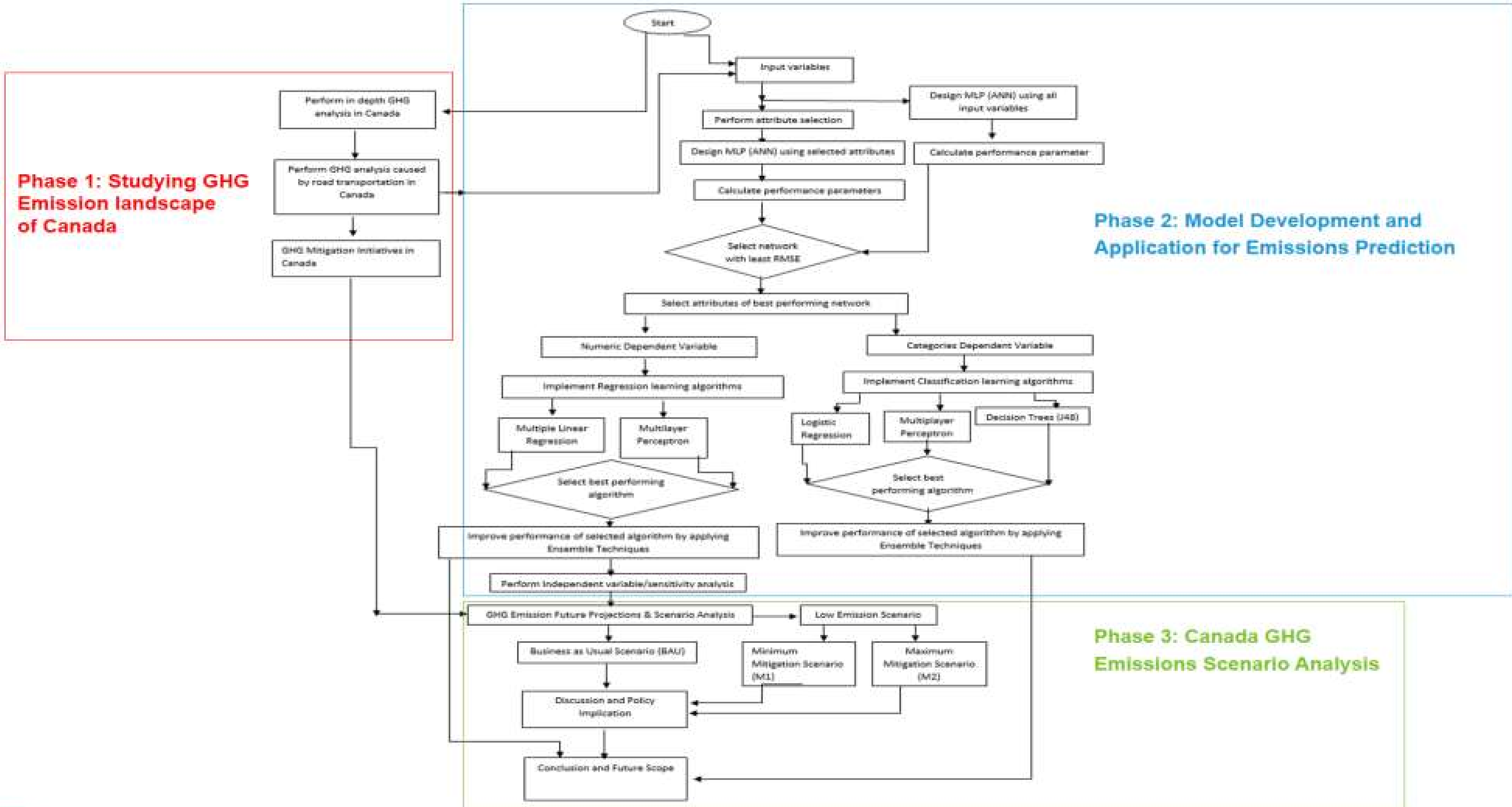


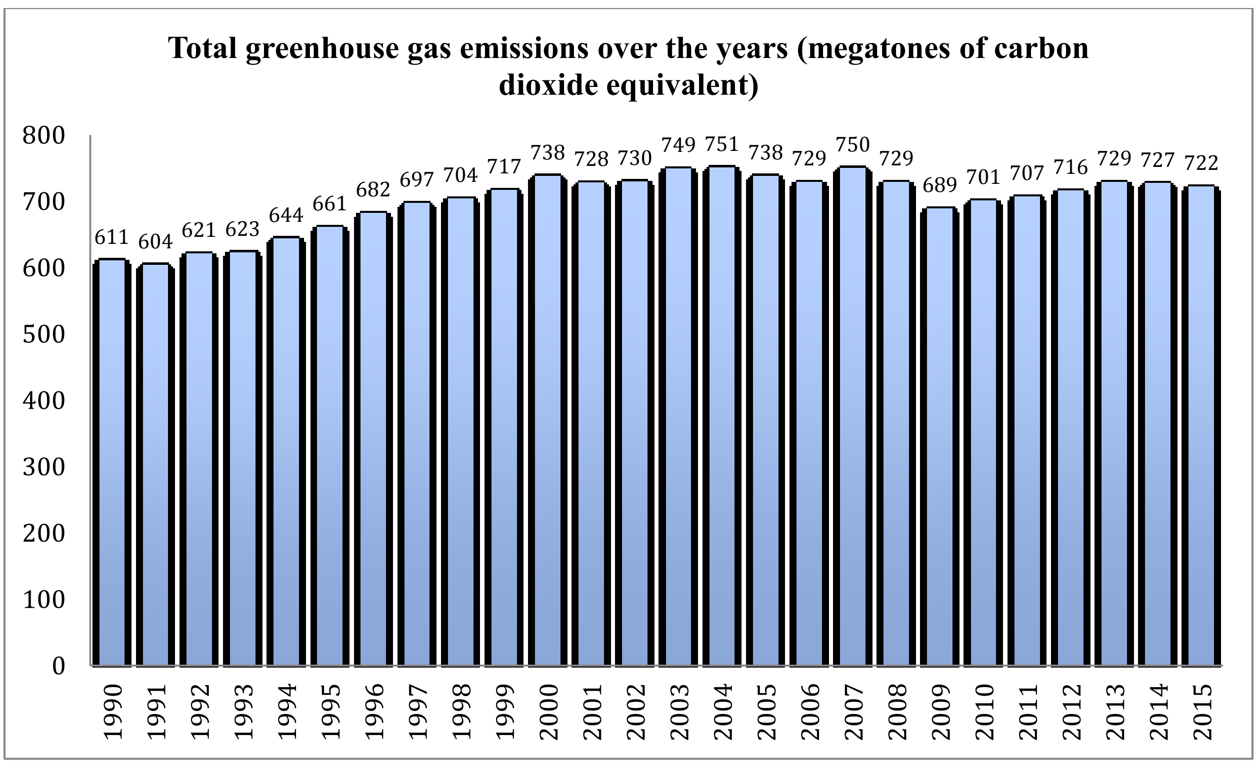
Figure 9 Flowchart of Research steps

Phase 1: GHG Emissions Landscape of Canada

4.1 GHG emissions in Canada

According to (Government of Canada, et al., 2017) as of 2015, Canada's total greenhouse house gas GHG emissions was 722 (MtCo2Eq.) with respect to emission breakdown by economic sector. Figure 10 shows Canada's national greenhouse gas emissions in mega tonnes of carbon dioxide equivalent from 1990 to 2015. Source: Environment and Climate Change Canada (2017) National Inventory Report 1990–2015

Figure 10 Total GHG Emissions over the Years (MtCo2eq.)



According to (Government of Canada, et al., 2017) Canada's emissions growth between 1990 and 2015 was mainly caused by increased emissions from mining and upstream oil and gas production as well as transport. Emission reductions from 2005 to 2015 were results of reduced emissions from public electricity and heat production utilities. The GHG emission given above includes emissions from seven GHG gases namely: carbon dioxide, methane, nitrous oxide, sulfur hexafluoride, perfluorocarbons, hydrofluorocarbons, and nitrogen trifluoride.

4.1.1 GHG analysis in Canada

GHG Emission in Canada are categorized as per the below two sectors (Government of Canada, Canada's GHG Inventory 2017):

Intergovernmental Panel on climate change (IPCC) sector:

GHG emissions are categorized into the following five sectors as per IPCC: Energy, Industrial Processes and Product Use, Agriculture, Waste and Land Use, Land-Use Change and Forestry.

In IPCC a rounding protocol has been developed for the emission and removal estimates presented by activity sectors defined by the Intergovernmental Panel on Climate Change to reflect their uncertainty levels. In rounding Protocols, estimates have been rounded to the nearest 1Mt and 0.1Mt for National-level estimates and provincial/territorial-level estimates. As a result of these procedures, individual values in the emission tables may not add up to the subtotals and overall totals (Government of Canada, Canada's GHG Inventory 2017).

Economic Sector:

To analyze economic trends, GHG emissions are categorized to the economic sector from which they originate. Canada's emission is categorized by following economic sector:

Oil and Gas, Electricity, Transportation, Heavy Industry, Buildings, Agriculture, Waste, and Others. The IPCC rounding protocol does not apply to estimates presented by Canadian Economic Sectors.

4.1.2 Greenhouse gas emissions by Canadian Economic Sector

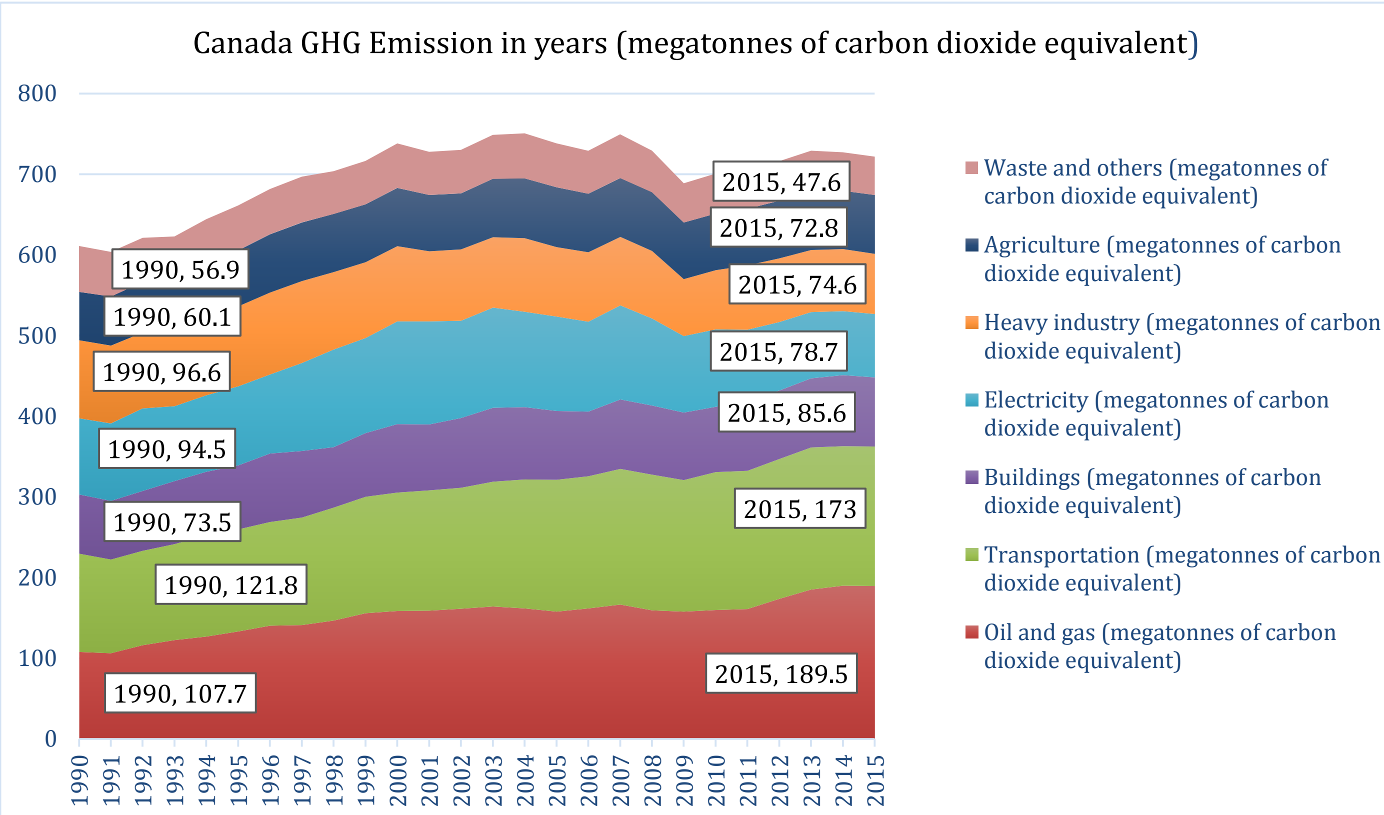


Figure 11. GHG Emission by Canadian Economic Sector

Figure 11 shows GHG emissions increase of 82 MtCo2Eq. and 51 MtCo2Eq between 1990 and 2015 was mostly due to rise in emissions from the oil & gas and the transportation sector. These increases in emissions from the oil & gas and the transportation sector were offset by a 16 MtCo2Eq. decrease in emissions in the electricity sector and a 22 MtCo2Eq. decrease in emissions from heavy industry (Government of Canada, Canada's GHG Inventory 2017). Data Source: Environment and Climate Change Canada (2017) National Inventory Report 1990–2015.

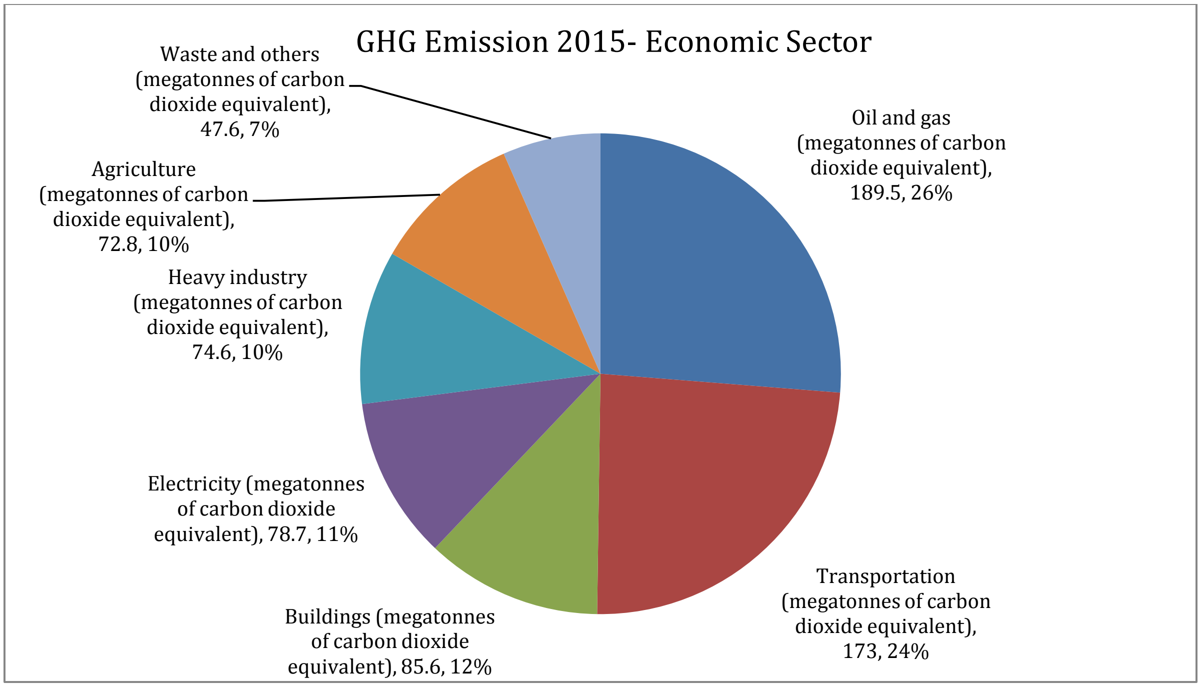


Figure 12. GHG Emission by Canadian Economic Sector in 2015

Figure 12 shows that in 2015, total greenhouse gas (GHG) emissions in Canada were 722 (MtCo2eq). Oil & gas sector was the biggest contributor to GHG emissions emitting 26% of total emissions in 2015, followed by the transportation sector, which emitted 24%. The other Canadian economic sectors (i.e., buildings, electricity, heavy industry, agriculture, and waste and others), each accounted for 12% 11% 10% 10% and 7% respectively of total GHG emissions in Canada.

4.1.3 Provincial GHG Analysis in Canada

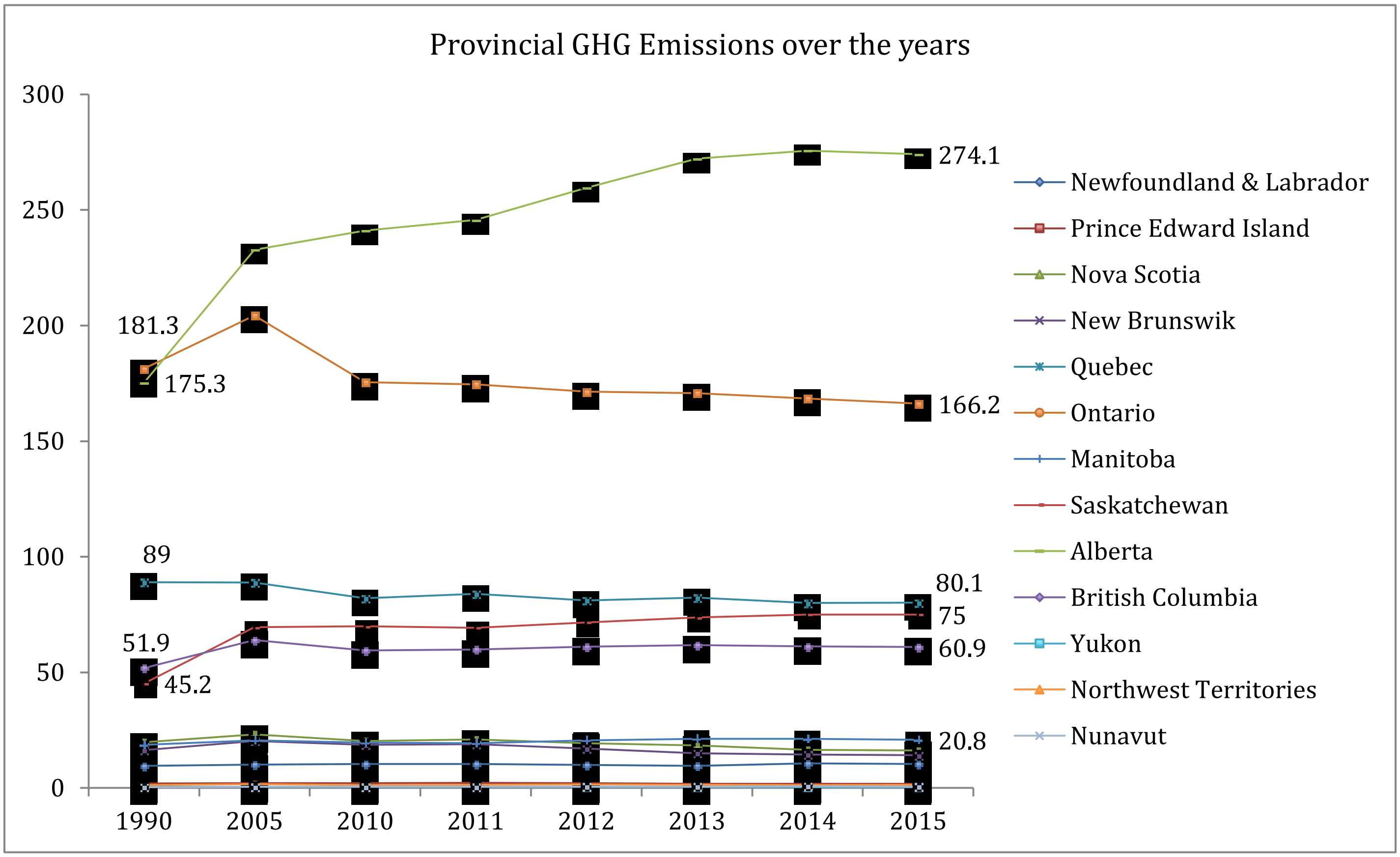


Figure 13 shows Canadian Provincial GHG Emissions over the Years. Each province has different Emission levels. According to (Government of Canada, Environment and Climate Change Canada 2017), this significant difference depends on population, energy sources and economic base. The provincial economies, which are service-based economies had lower emission levels whereas the economies based on natural resource extraction usually had higher emission levels in comparison. The provinces like Ontario, which bank on fossil fuels for their power requirement (electricity generation) had greater emissions share compared to the provinces relying on renewable sources to meet their energy needs like Quebec. The data for the figure 13 is given in Appendix A.

As can be seen in figure 13, in 1990, Alberta's emissions exceeded Ontario by 56% since 1990,

Figure 13. Provincial GHG Emissions over the Years

largely due to the increase in the oil and gas industry for export markets. And because of large manufacturing industry, Ontario's GHG emissions were higher than those from the other provinces. Between 1990 and 2015, Ontario's emissions reduced mostly because of the termination of coal-fired electricity generation plants (Government of Canada, Environment and Climate Change Canada 2017). After adopting Climate Action plan in the year 2008, a steady decrease in BC's emission trend from 63.9 (Mt Co_2 eq.) in 2005 to 60.9 (Mt Co_2 eq.) in 2015 is observed as a result of carbon pricing.

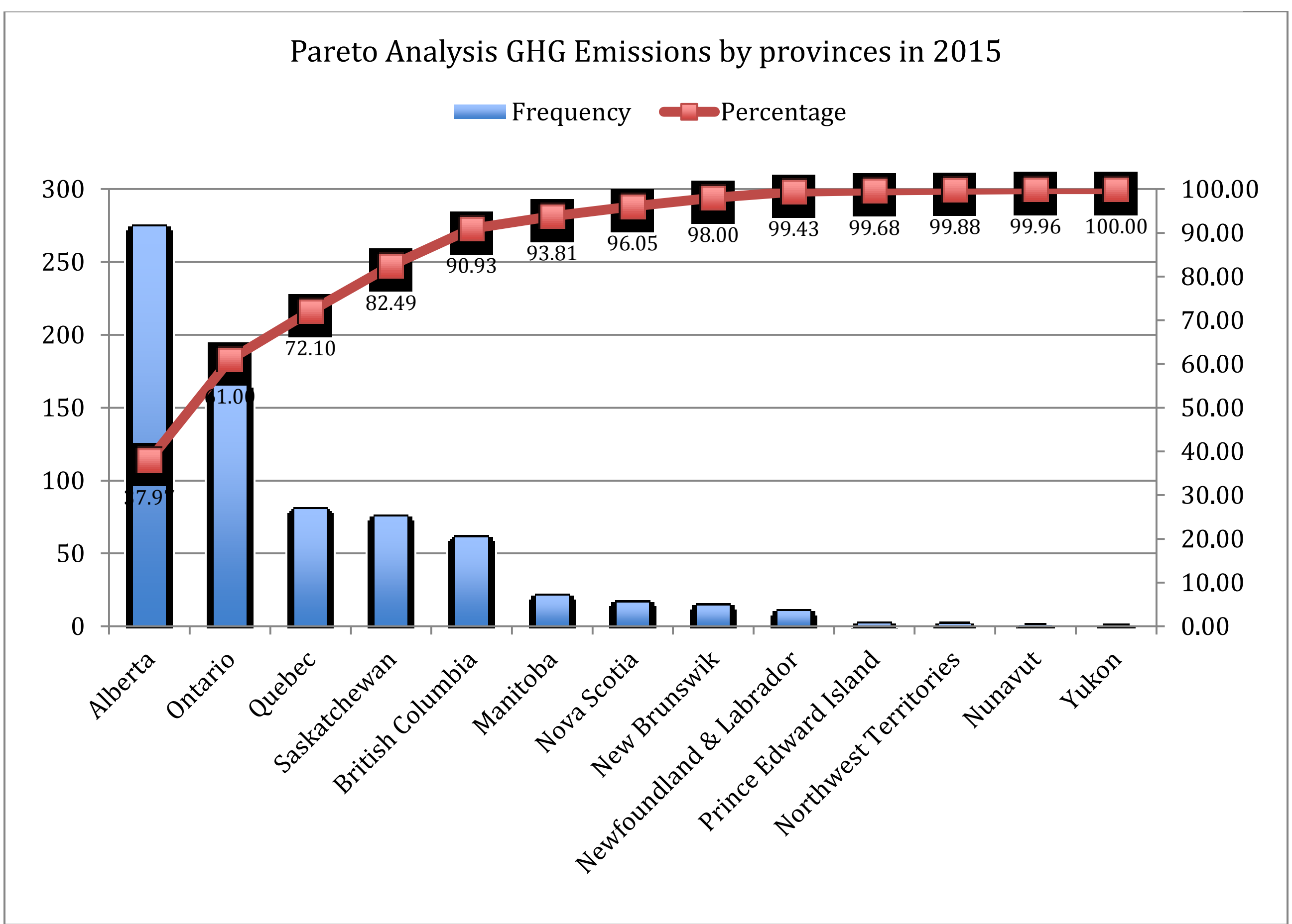
Pareto analysis

Joseph Juran named this technique after an Italian economist Vilfredo Pareto, as he observed that 80% of the effects resulted due to the 20% of the causes (Juran, 1992). A Pareto diagram is a simple histogram of the data entries sorted from largest to lowest frequency, and a cumulative frequency curve is obtained. Pareto analysis is widely used as a statistical tool by employees undertaking improvement projects in numerous organizations to isolate the most impactful problems from a relatively larger number of problems. As a result, the problems, which are most significant, stand out and provide opportunities for improvements.

In the present study, we employed Pareto analysis to identify the provinces, which are major contributors of GHG emissions within Canada, i.e., "vital few" (Canadian provinces) from "Trivial many" (Canada).

To determine contributors of GHG emission from Canadian provinces, we performed Pareto analysis on the Provincial GHG emission data (Appendix B) of 2015. This data was categorized by economic sector.

Figure 14. Pareto Analysis of GHG Emissions by Provinces in 2015



The result of Pareto analysis as shown in Figure 14 shows that Alberta, Ontario, Quebec, and Saskatchewan are the major contributors of GHG emissions in Canada. In the year 2015, Canadian provinces of Alberta, Ontario, Quebec, and Saskatchewan were the major contributors of GHG emissions in Canada. Combined all together these four Canadian provinces contributed 82.49% (595.4 megatons (Mt) of carbon dioxide equivalent (CO2 eq)) in overall GHG emissions (722 megatons (Mt) of carbon dioxide equivalent (CO2 eq).

4.1.4 Major GHG Emitting Provinces (GHG Emission Distribution by Economic Sector)

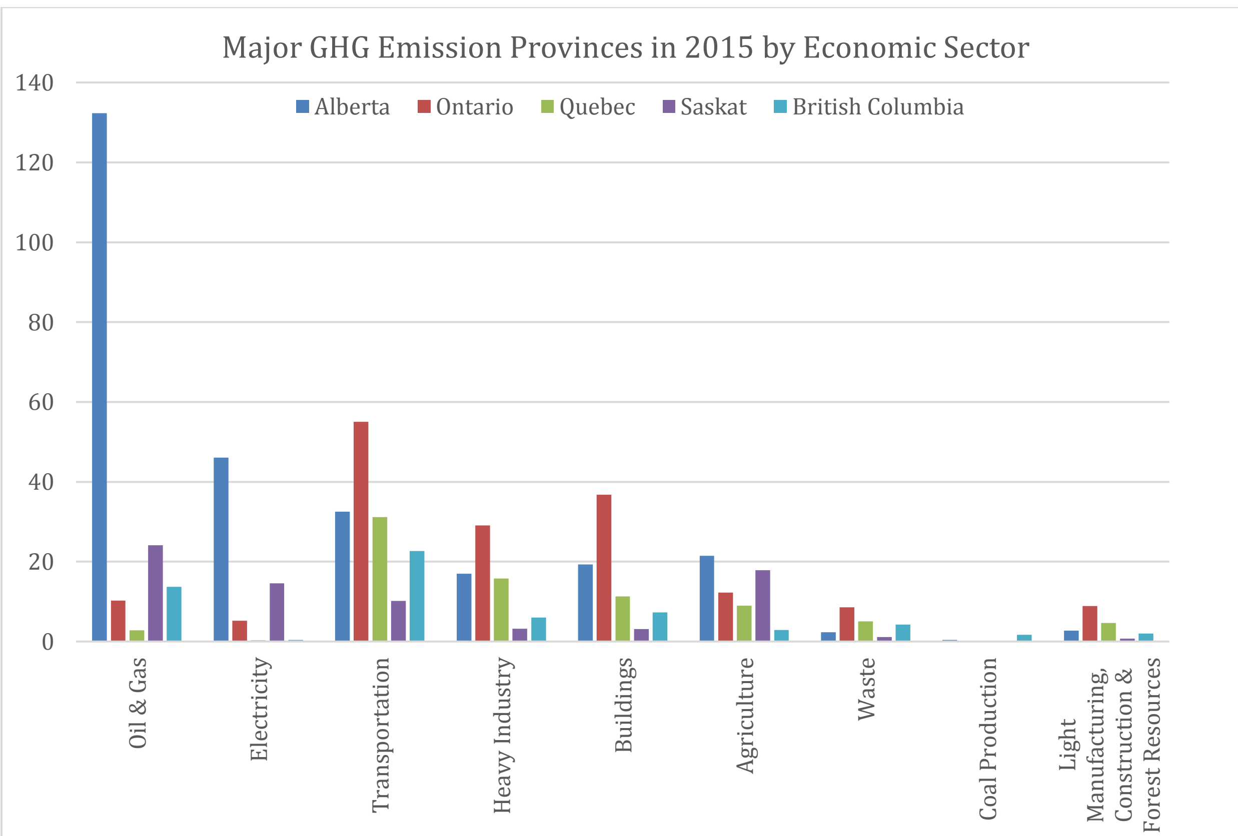


Figure 15. Major GHG Emission Provinces in 2015 Distribution by Economic Sector

Figure 15 shows the GHG distribution of top five major GHG emitting provinces of Canada by economic sector; we considered the province of British Columbia since British Columbia along with top four GHG emitting provinces contributed over 90% in overall GHG emissions in the year 2015 (Appendix C). We further studied the distribution of GHG emissions from each province with respect to economic sectors.

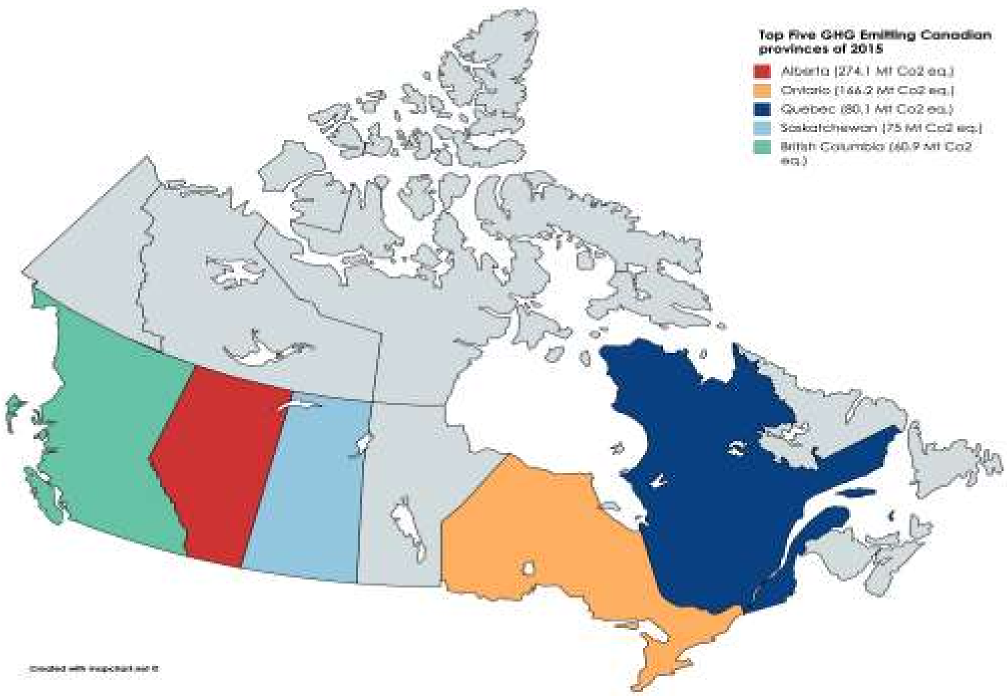


Figure 16. Top Five GHG Emitting Canadian Provinces of 2015

4.1.5 GHG Distribution of Top Five High Emission Provinces in 2015

Figure 17 shows Alberta's 2015 GHG Emission Distribution by Economic Sector. In the year

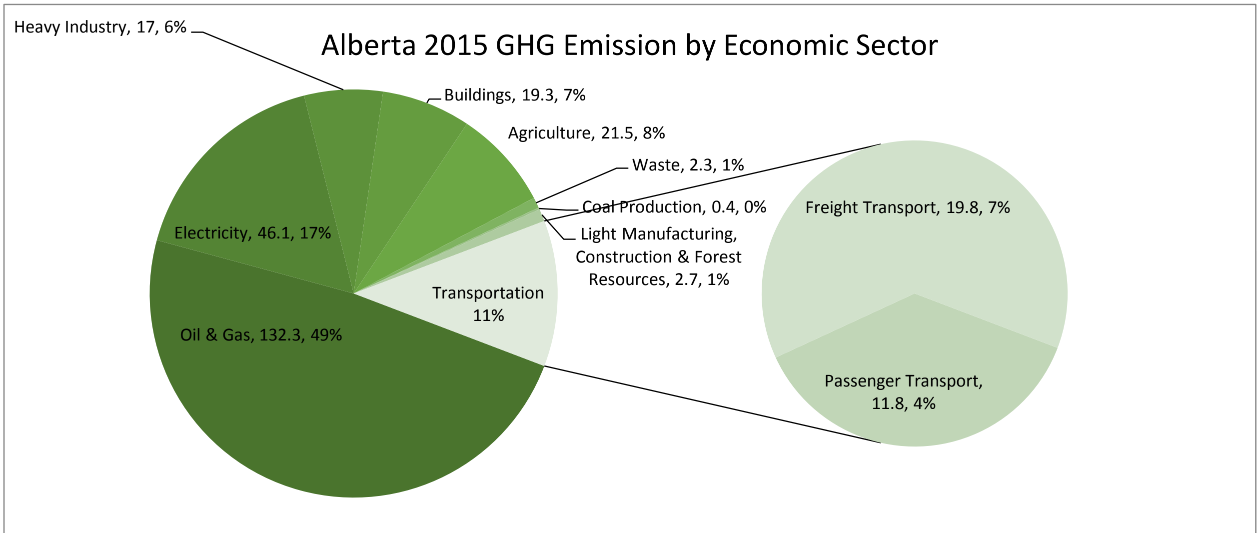
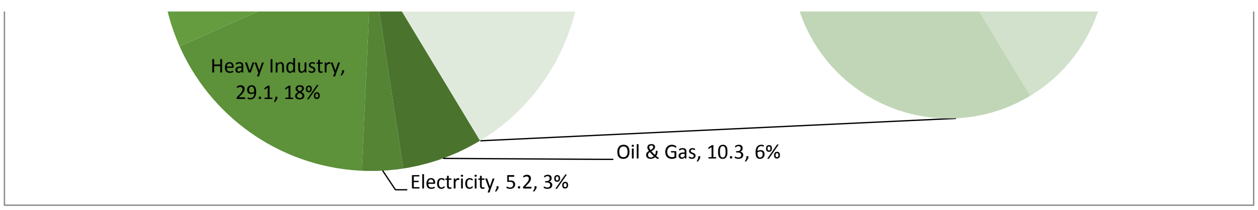


Figure 17. Alberta 2015 GHG Emission Distribution by Economic Sector



2015, Alberta was the highest contributor of GHG emission (i.e., it contributed 274.1 Mt Co2 eq.). On further analyzing the economic sectors contributing to this number of GHG emissions within Alberta, it was found that Oil & gas sector is responsible for emitting 49% of the total GHG emitted by Alberta. Followed by Electricity and Transportation, which contributed 17% and 11% respectively. Furthermore, within the transportation sector, freight transport contributes by 7% in Alberta's GHG emissions, and passenger transport contributes 4%.

Figure 18 shows Ontario's 2015 GHG Emission Distribution by Economic Sector. In the year 2015, Ontario was the second highest contributor in Canadian GHG emission (i.e., it contributed 166.2 Mt Co2 eq.).

Figure 18. Ontario 2015 GHG Emission Distribution by Economic Sector

The major economic sectors contributing to this number of GHG emissions within Ontario were Transportation, Heavy Industry, and Building sector. Transportation sector emits 32% of total GHG from Ontario followed by Heavy Industry and Building sector, i.e., 18% and 22% respectively.

Furthermore, within the transportation sector, passenger transport contributes 21%, and freight transport contributes 11% to Ontario's GHG emissions.

Figure 19 shows Quebec's 2015 GHG Emission Distribution by Economic Sector. Quebec was the third highest contributor in overall Canadian GHG emission (i.e., it contributed 80.1 Mt Co2 eq.). The major economic sectors contributing to this number of GHG emissions within Quebec were Transportation, Heavy Industry, and Building sector.

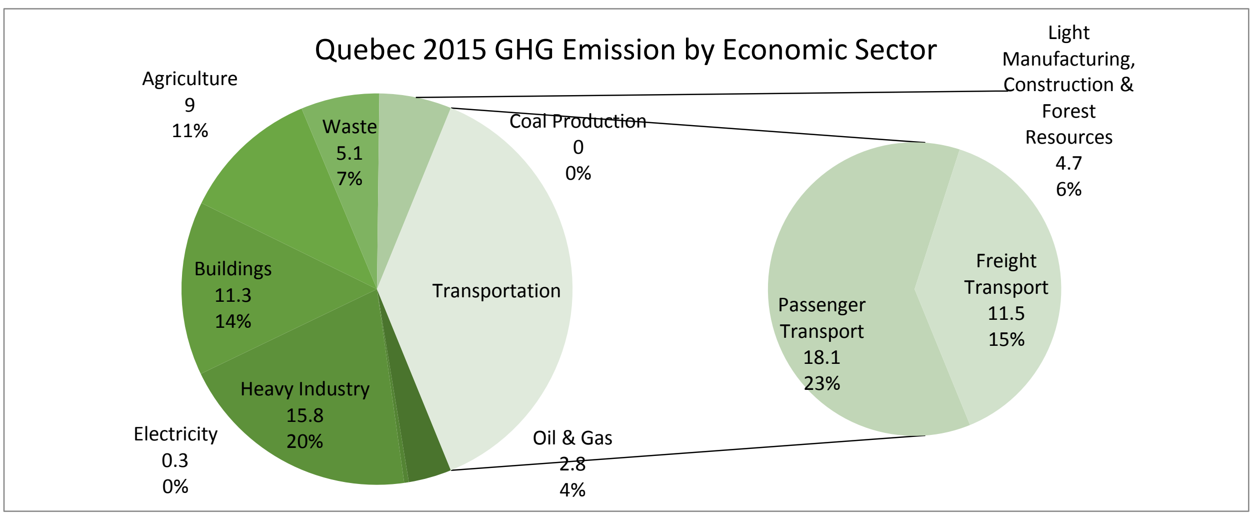


Figure 19 Quebec 2015 GHG Emission Distribution by Economic Sector

Transportation sector emits 38% of total GHG from Quebec followed by Heavy Industry, Building sector and Agriculture, i.e., 20%, 14%, and 11% respectively. Furthermore, the passenger transport within the transportation sector contributes 23%, and freight transport contributes 15% to Quebec's GHG emissions.

Figure 20 shows Saskatchewan's 2015 GHG Emission Distribution by Economic Sector. Saskatchewan contributed 75 Mt Co2 eq. of GHG emission in the year 2015. The major economic sectors contributing to this number of GHG emissions within Saskatchewan was Oil & Gas, Agriculture, and Electricity sector. The Oil & gas sector is responsible for emitting 32% of the total GHG emitted by Saskatchewan. Followed by Agriculture, Electricity, and transportation, which contributed 24%, 20%, and 13% respectively.

Furthermore, within the transportation sector, freight transport contributes by 7% in Saskatchewan's GHG emissions, and passenger transport contributes 6%.

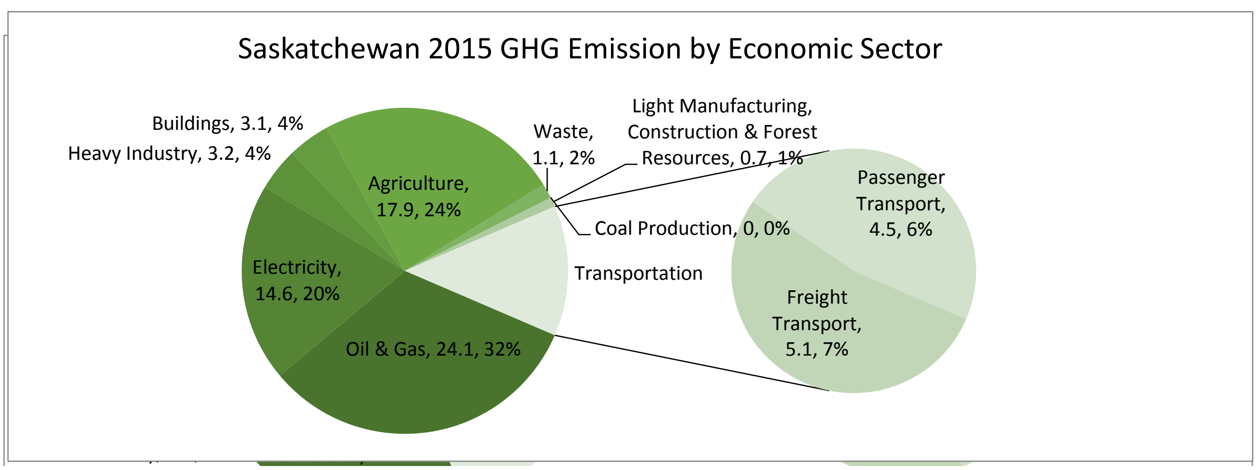


Figure 20. Saskatchewan 2015 GHG Emission Distribution by Economic Sector

Figure 21. British Columbia 2015 GHG Emission Distribution by Economic Sector

Figure 21 shows British Columbia's 2015 GHG Emission Distribution by Economic Sector. British Columbia contributed 60.9 Mt Co2 eq. of GHG emission in the year 2015.

The major economic sectors contributing to this number of GHG emissions within British Columbia were Transportation, Oil & Gas, Building and Heavy Industry sector. Transportation sector emits 37% of total GHG from British Columbia followed by Oil & Gas, Building and Heavy Industry, i.e., 22%, 12%, and 10% respectively. Furthermore, the freight transport within the transportation sector contributes 19%, and passenger transport contributes 18% of British Columbia's GHG emissions. In British Columbia, Transportation sector emits 37% of total GHG from BC followed by Oil & Gas and Building sector, i.e., 22% and 12% respectively.

4.1.6 GHG emission by Transportation Sector

In this thesis, we used the data categorized by IPCC to analyze the GHG emission trend by the Transportation sector. Concerning the IPCC data, the below graph represents GHG emission by transportation sector in Canada.

The transportation sector was the second largest source of GHG emission accounting 24% of total Canadian emission in the year 2014 (Appendix D).

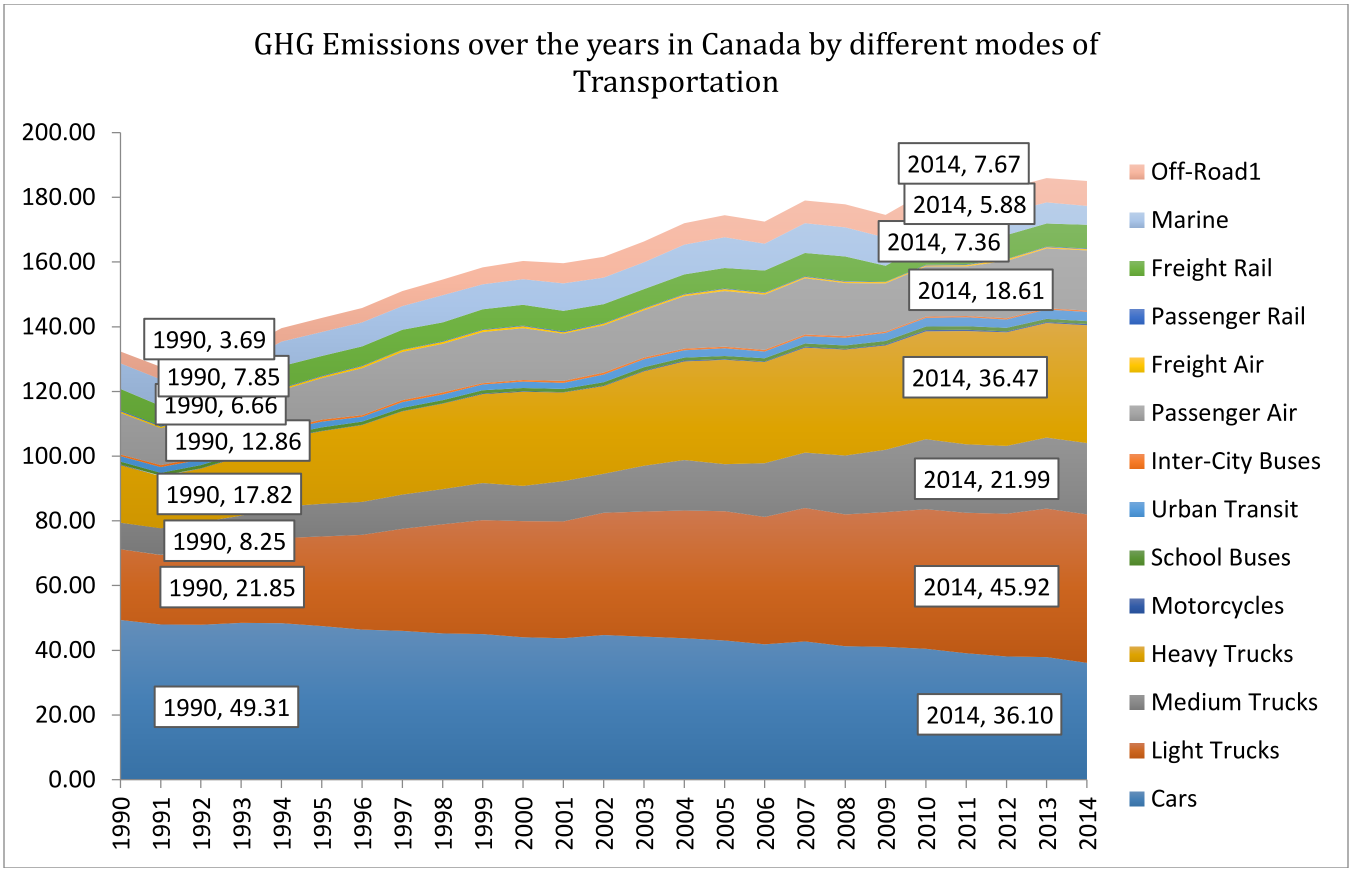
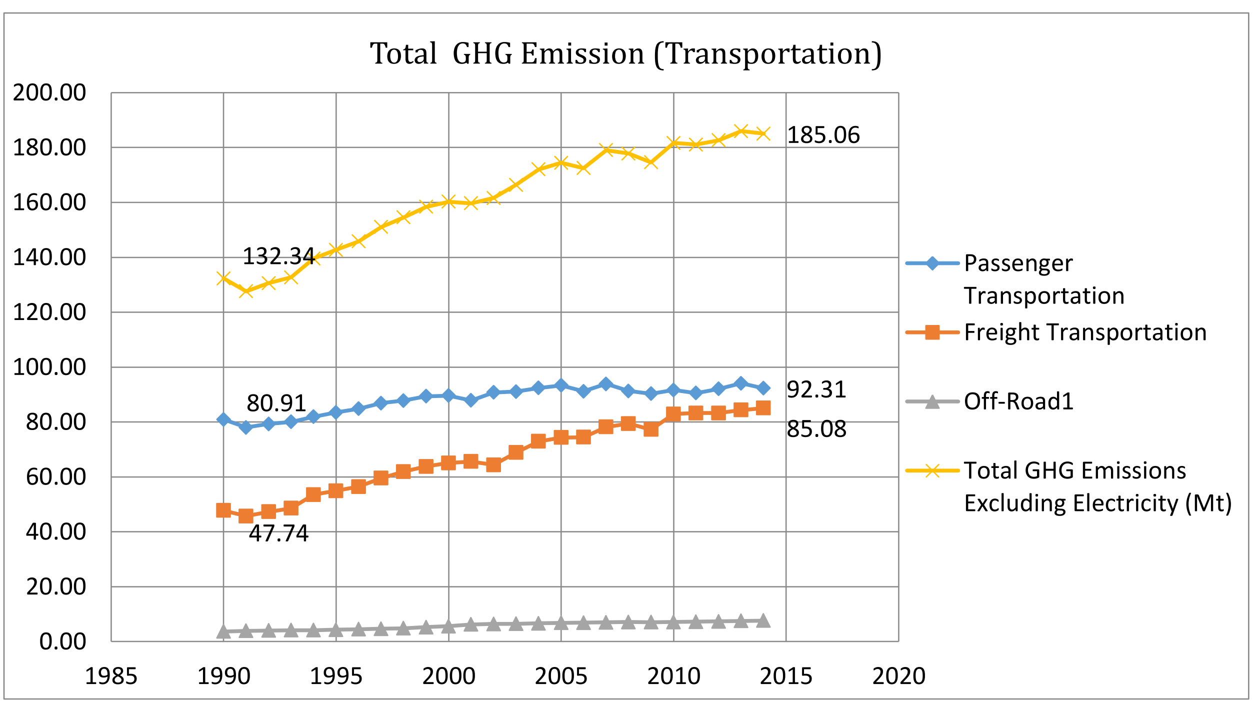


Figure 22. GHG Emissions over the years in Canada by different modes of Transportation

Figure 22 portrays GHG Emissions over the years in Canada by different modes of Transportation. Emissions from cars over the years declined whereas emission from light trucks and Freight trucks almost doubled. Also, the minute decrease has been observed in GHG



emissions from Marine, Passenger rail, Freight Air and Inter-city Buses.

Figure 23. Represents the trend of GHG emission by broad categories of transportation sector (Appendix E). It can be seen that GHG emissions from freight transportation are showing an increasing trend since 2009. In general, compared to emissions from 1990 there has been a steady increment of 14% in GHG emission from passenger transport whereas, on the other hand, emission from freight transport increased by 78%.

Figure 23. Total GHG Emission by Transportation Sector

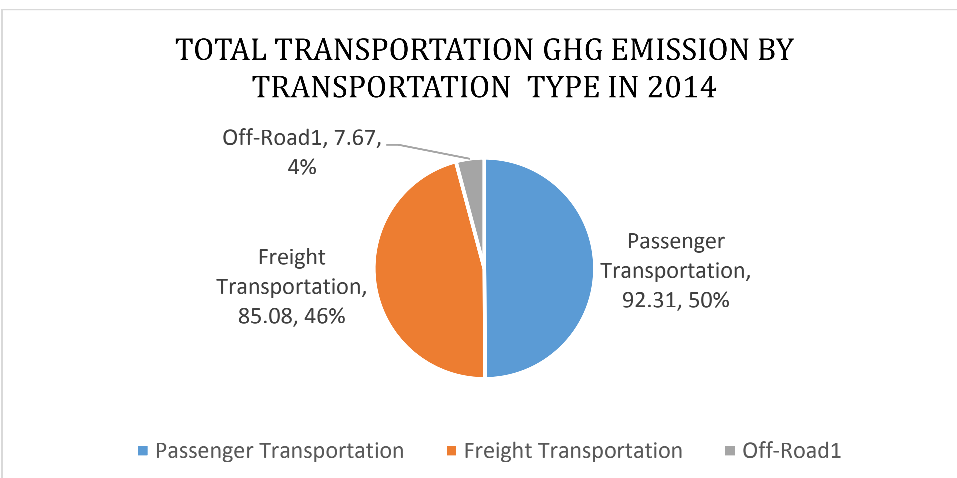


Figure 24. Total Transportation GHG Emission by Transportation in 2014

According to the recent IPCC data for the year 2014. Passenger Transportation emitted 92.31 Mt of Co2 eq GHG, i.e., 50% of the total GHG emissions caused by transportation and Freight Transportation emitted 85.08 Mt of Co2 eq GHG, i.e., 46% in total (Appendix E).

4.1.7 GHG Emission by Road Transport

Over the years from 1990, the contribution of GHG emissions from Transportation sector grew by 52.72 Mt Co2 eq. (39.8%) By the year 2014 (figure 23). As shown in figure 25. Emission from cars declined by 26% while emission from light trucks increased by 110%, emission from Heavy trucks increased by 104% and emission from Medium trucks increased by 161% with respect to 1990 emissions (Appendix F).

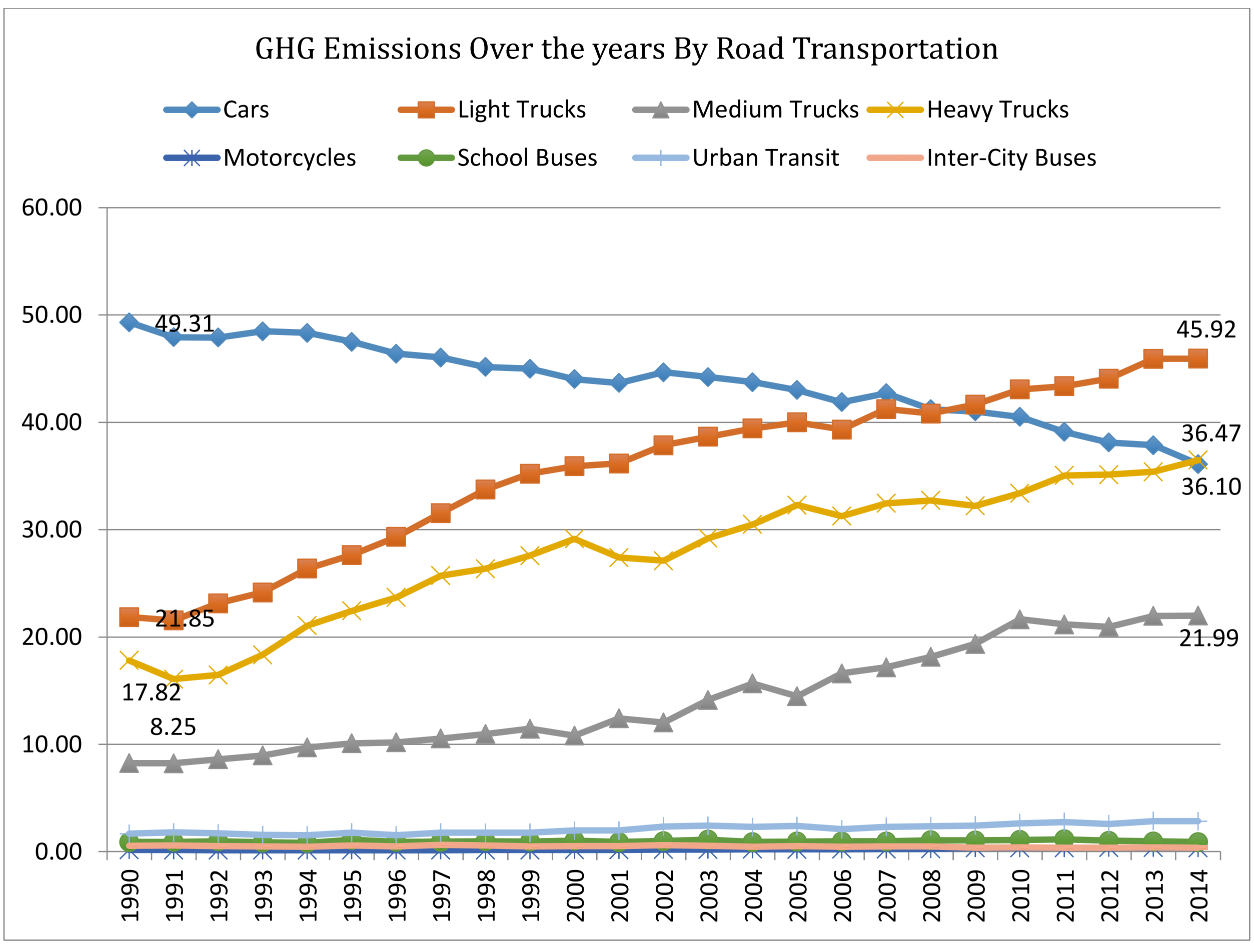


Figure 25. GHG Emissions Over the years By Road Transportation

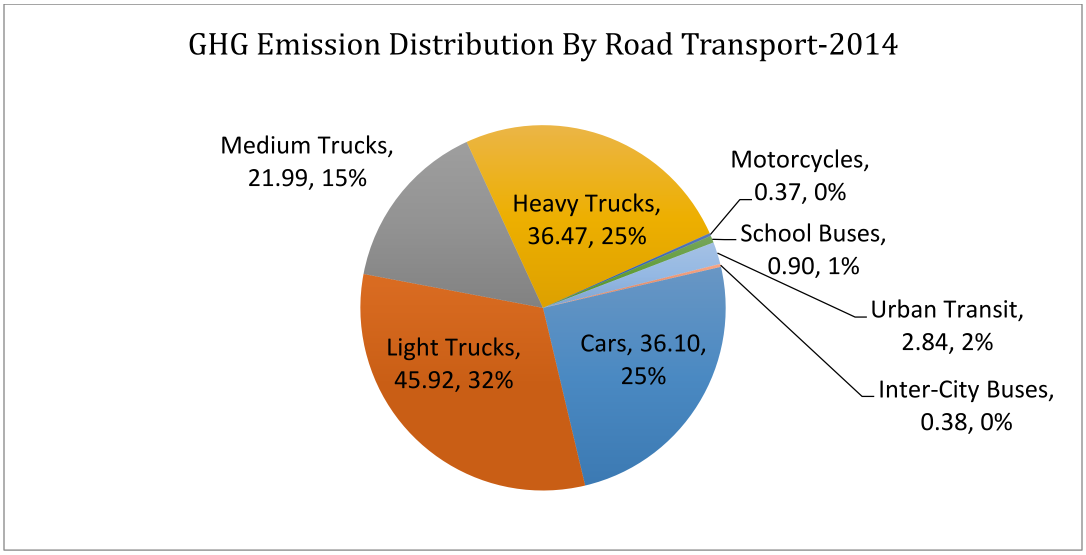


Figure 26. GHG Emission Distribution by Road Transport-2014

Figure 26. represents GHG Emission Distribution for 2014 by Road Transport. According to the latest IPCC GHG emission data for the year 2014 (Appendix F), Trucks (Light, Medium, and Heavy) emitted 92.91 Mt Co2 eq. i.e., 72% of GHG emissions caused by road transportation (144.97 Mt c02 eq.).

Within the category of trucks, Light Trucks (trucks, vans and sport utility vehicles) emitted 45.92 Mt co2 eq.; Heavy trucks emitted 36.47 Mt Co2 eq. And medium trucks emitted 21.99 Mt Co2 eq. of GHG emissions. Furthermore, Cars emitted 36.10 Mt co2 eq. of GHG emissions in 2014.

4.2 GHG Mitigation Initiatives in Canada

In last one decade, the Canadian government is paying more focus towards sustainable GHG emission reductions. Harper government (conservative) in the year 2015 submitted Intended National determined Contribution (INDC) to United Nations Framework Convention on Climate Change with a willingness to target GHG reduction by 30% below 2005 levels by 2030 (Canada,

G. O. 2015). The conservatives proposed this initiative with a perspective of economy wide GHG reduction. Later in the year 2015 Liberal government came into power and took a positive, aggressive approach towards a reduction in GHG emissions. Trudeau's led liberal party indicated that in the further coming year the federal government would engage in a consultation process with the provinces to propose even more concrete & ambitious reduction target levels.

Following up on the intention to propose even more aggressive GHG emission reduction targets, on December 9, 2016, the Liberal government adopted Pan-Canadian Framework on Clean Growth and Climate Change. The Framework is a broad plan to reduce emissions across all sectors of Canada's economy. The framework will also boost to stimulate clean economic growth, and build resilience to the impacts of climate change. The activities outlined in the Pan-Canadian Framework will enable Canada to meet or exceed its target to reduce emissions to 30% below 2005 levels by 2030 (Canada, S. 2016)

In recent years few Canadian provinces took proactive measures before the federal government by adopting policies to mitigate GHG emissions. For example, the policies proposed by Alberta include a hybrid system which combines carbon levy with a performance based system for large industrial emitters. Quebec and Ontario have cap and trade system (Canada, S. 2016). The below table 4 summarizes the provincial commitments, policy measures and plans to mitigate GHG emissions as of early 2016

Table 4 Canada provincial commitments, policy measures and plans

PROVINCE	2013 EMISSIONS PER CAPITA	MEASURES	2020 TARGET	2030 TARGET
Quebec	82.6 Mt	In 2013, Climate Change Action Plan and Adaptation Strategy (2013-2020) (Government du Québec. 2012). proposed to operate Cap and Trade system for GHG emission reduction and proposed higher allowances to large GHG emitters. In 2014, Quebec linked up with California's carbon market.	20% below 1990	37.5% below 1990

Ontario	171.0 Mt	Ontario's Climate Change Strategy (2015) (Government of Ontario 2016). The report highlights the results of the Green Energy Act of 2009 that effectively phased out the use of coal and introduced a feed-in-tariff program to promote renewable energy. On January 2016, Ontario joined the cap-and-trade system along with Quebec and California.	15% below 1990	37% below 1990
British Columbia	62.8 Mt	According to Climate Action Plan (BC Government. 2008). It Introduces short, medium and long-term targets as well as some provincial legislations, including the Carbon Tax Act.	33% below 2007	40% below 2007 (target has been proposed but not adopted)
Alberta	267.0 Mt	Alberta's Climate leadership plan (Alberta Government. 2015). It focuses on new strategy presents the new strategy on climate change to covers four key areas: 1. Phasing out coal-generated electricity 2. Developing more renewable energy 3. Implementing a new carbon price, legislated oil sands emission limit, and 4. Implementing a new methane emission reduction plan.	Upon implementation, it is expected to reduce emissions by 20Mt from business-as-usual scenario (297Mt).	Upon implementation, it is expected to reduce emissions by 50Mt from business-as-usual scenario (320Mt).
Saskatchewan	74.8 Mt	(Government of Saskatchewan. 2013). The government introduced a climate change legislation setting out the province's plan to meet its target in 2009. However, the legislation was never enacted due to delays of federal plan and elections	20% below 2006	40% below 2005 level
Manitoba	21.4 Mt	Climate Change and Green Economy Action Plan (Government of Manitoba, Conservation, Wildlife Branch. 2015). Indicates the government's plan to join the cap-and-trade system established by Quebec. Introduced some policy measures in the transportation, agriculture, and energy efficiency sectors.	No 2020 target but had a 2012 target of 6% below 1990	33% below 2005
Newfoundland and Labrador	8.6 Mt	Climate Change Action Plan (Newfoundland and Labrador 2011). Focus on hydroelectricity with the support of Lower Churchill Hydroelectric project. It also Introduces progressive action into its policy, planning, and programs.	10% below 1990	NA
Prince Edward Island	1.8 Mt	Strategy for Reducing the Impacts of Global Warming (Prince Edward Island. 2008). Outlines 35 actions to mitigate and adapt to climate change.	10% below 1990	NA

Nova Scotia	18.3 Mt	Toward a Greener Future (Nova Scotia. 2009). Indicated the government's plan to address climate change by notably establishing a cap on Nova Scotia Power Inc.'s emissions by 2010. Further, Nova Scotia introduced the Environmental Goals and Sustainable Prosperity Act.	10% below 1990	NA
New Brunswick	15.7 Mt	Climate Change Action Plan 2014–2020 (Brunswick, C. G. 2017) includes actions in various areas, including renewable energy, transportation, industrial sources, etc. mainly through voluntary measures.	10% below 1990	NA
Canada	722Mt	PAN Canadian Frame Work (Government of Canada, et al., 2017)	NA	30% below 2005

Carbon pricing: Carbon pricing is recognized as most transparent, effective & operational approach towards GHG reduction (Parry et al., 2015). Baranzini (Baranzini et al., 2015) laid out seven reasons to use carbon pricing for GHG emission policies. Carbon pollution pricing is central to Pan-Canadian Framework. In the framework the Government of Canada has outlined a benchmark for pricing carbon pollution that will build on existing provincial GHG mitigation policies and ensure a minimum price of CAD 10 per tonne is in place across Canada by 2018, rising to CAD 50 per tonne by 2022 (Canada, S. 2016). Carbon pricing will help influence investment and purchase decisions towards less carbon-intensive options (Canada, S. 2016).

Phase 2: Model development and applications for emissions predictions

4.3 Data collection

Sources

Canadian GHG emissions are categorized as an economic sector and IPCC sector activities which lead to their production. As we are focusing our interest on GHG emissions from Road transport, we needed detailed vehicular emission values. Since transport sector emissions are well categorized under IPCC sector emission values, we considered the data from IPCC sector activities. Figure 25 represents contribution in GHG emission by road vehicle type and the figure 26 presents the share contribution of GHG emissions by each road vehicle type for the year 2014. We also selected various socioeconomic indicators in our dataset.

The respective data was collected from GHG inventory sink of Canada, Statistics Canada, CAFC targets & fleet average website and trading economics. GHG inventory sink reports emission figures by vehicle type, Statistics Canada, and trading economics reports values for socioeconomic indicators, and we used transport policy.net for Fleet average reports for fleet fuel efficiency values for passenger cars and Light duty trucks.

Attributes

In this section, the attributes given in Appendix G are described.

Consumer Price Index: According to (Canada, G. O. 2017) this index is used to quantify changes in expenditures necessary for consumers to maintain a constant standard of living. The notion is that consumers would normally switch between products as the price relationship of goods changes. The goods & services that make up the Consumer Price Index (CPI) are hierarchical structure with the "all-items CPI" as the top level. Eight major components of goods and services make up the "all-items CPI." They are: "food", "shelter", "household operations, furnishings and equipment", "clothing and footwear", "transportation", "health and personal care", "recreation, education and reading", and "alcoholic beverages and tobacco products". These eight components are broken down into a varying number of subgroups which are further broken down into other sub-groups. Indents are used to identify the components that make up each level of aggregation. We considered CPI values with respect to Transportation in our research

Gasoline Price: (Canada, G. O. 2017) retail prices for gasoline and fuel oil, by the urban center (Canada), annual (Canadian cents per liter).

Gross Domestic Product (Transportation): According to (Canada, G. O. 2017) Gross domestic product (GDP) value we used is at basic prices, according to North American Industry Classification System (NAICS), annual (dollars x 1,000,000). We considered GDP by transportation and warehousing which includes GDP by sub groups Air Transportation, Rail Transportation, Water Transportation, Truck Transportation, Transit, ground passenger and scenic and sightseeing transportation, Urban transit systems, Taxi and limousine service Other transit and ground passenger transportation and scenic and sightseeing transportation

Support activities for transportation, Pipeline Transportation, Pipeline transportation of natural gas, Crude oil, and other pipeline transportation, Postal service, couriers and messengers, Postal service, Couriers and Messengers, Warehousing and storage.

Interest Rate (Overnight): Benchmark interest rate is set by the Bank of Canada's (BOC) Governing Council. Overnight Rate is the the official interest rate. The overnight rate is the interest rate at which major financial institutions borrow and lend one-day (or "overnight") funds among themselves; the Bank sets a target level for that rate. This target for the overnight rate is often referred to as the Bank's policy interest rate (Canada Interest Rate 2017) (Bank of Canada 2017).

Car Sales: The number of new Car registration in Canada over the years (Canada New Motor Vehicle Sales 2017).

The population of Canada in Million: We collected the data on the population of Canada over the years (Canada, G. O. 2016).

Emissions Data: Emission data from cars, Light Trucks ((0 to 3,855 kg [0 to 8,500 lb.]), Medium Trucks (3,856 to 14,969 kg [8,501 to 33,000 lb.]), Heavy-Trucks (14,970 kg [33,001 lb.] or more) and Bus Transit was collected from (Government of Canada, Natural Resources Canada 2017).

Passenger Car Fuel efficiency & Light Duty Truck Efficiency: The Motor Vehicle Fuel Consumption Standards Act (MVFCSA) of 1982 attempted to make Company Average Fuel Consumption (CAFC) targets mandatory, but the government did not formally implement MVFCSA until 2007. The targets remained stagnant at 8.6 l/100km between 1985 and 2010. The Fleet average data was collected from (Canada: Light-duty: Fuel Consumption and GHG 2016).

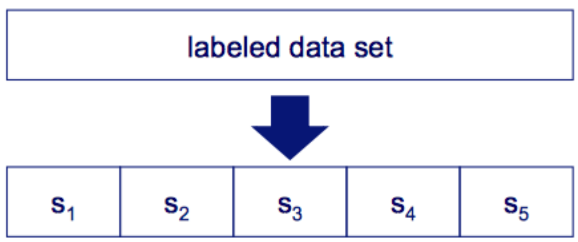
Application

For the implementation of learning algorithms mentioned in methodology, we used WEKA. In this section, we will outline the algorithm performance measures and results of, attribute selection, algorithm application & improvement on Numeric data, algorithm application & improvement on Nominal data and variable importance analysis on MLP model using Numeric data in IBM SPSS Statistics.

4.4 K-fold cross validation

In machine learning methods over fitting is a well-known problem (Weigend et al., 1990). To avoid vagaries in selecting a particular training and testing set, it is recommended to utilize cross validation technique since entire data set will be used for training and validation.

In K fold cross validation the data set is partitioned into K equal (or nearly equal) folds. K iterations of training and validation are performed and within each iteration a different fold of data is held out for validation while remaining K-1 folds are used for learning (Kohavi 1995). The learned models are subsequently asked for predicting the validation set. The performance of each algorithm on each fold is determined by accuracy metric. K samples of performance metric will be available for each algorithm, which later can be averaged to derive an aggregate measure (Refaeilzadeh et al., 2009). In our research, since we have 25 instances, it is better to recycle them and additionally to avoid the problem of overfitting, we used 10 fold cross validation technique on the input data.



iteration	train on	test on
1	s_2 s_3 s_4 s_5	s_1
2	s_1 s_3 s_4 s_5	s_2
3	s_1 s_2 s_4 s_5	s_3
4	s_1 s_2 s_3 s_5	s_4
5	s_1 s_2 s_3 s_4	s_5

Figure 27. Five Fold Cross Validation Example. Source: (Refaeilzadeh et al., 2009).

Figure 27 demonstrates an example with k = 5. The data is partitioned into five equal folds/subsamples. Five iterations of training and validation are performed. In iteration one, subsample S1 is held out for validation, and remaining subsamples S2, S3, S4, and S5 are used for learning. Following in the next iteration, the next fold, i.e., S2 is held out for validation, and the remaining subsamples are used for training. The iteration continues until training and validation are done on all subsample/folds. In data mining and machine learning, 10-fold cross-validation (k = 10) is the most common (Refaeilzadeh et al., 2009).

4.5 Performance Evaluation Metrics

In this thesis, the performance of algorithms was assessed by the below-mentioned metrics.

Root Mean square Error

RMSE measures the average magnitude of the error. It's the square root of the average of squared differences between prediction and observation. RMSE indicates the error in the similar units as the parameter, thus, providing more information about the efficiency and accuracy of the model (Legates et al., 1999) (Niu et al., 2017) (Amirkhani et al., 2015). The value of RMSE is always positive and in the ideal case is equal to zero. The lower the RMSE, the more accurate is the performance of the model. For ideal data modeling, the value of RMSE should be closer to zero (Ma et al., 1983). The RMSE metrics is calculated as below:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}}$$

Where:

y_i = Observed Value

$\hat{y}_i$ = Predicted Value

n = Number of observations.

Mean Absolute Error

MAE calculates the average magnitude of the errors in a set of predictions. It's the average of the absolute differences between prediction and observation. It differs with RMSE because RMSE increases as the variance associated with the frequency distribution of error magnitudes increases; on the contrary, MAE remains steady (Chai et al., 2014). The MAE metrics is calculated as below: (Niu et al., 2017) (Amirkhani et al., 2015)

$$MAE = \frac{\sum_{i=1}^{n} |y_i - \hat{y}_i|}{n}$$

Where:

y_i = Observed Value

$\hat{y}_i$ = Predicted Value

n = Number of observations.

Sum of Square Error (SSE)

To understand SSE, We need to understand the terms used for the goodness of fit analysis in a regression problem. The below figure 28 shows an estimated regression line with an observation *x1* (Cottrell 2003).

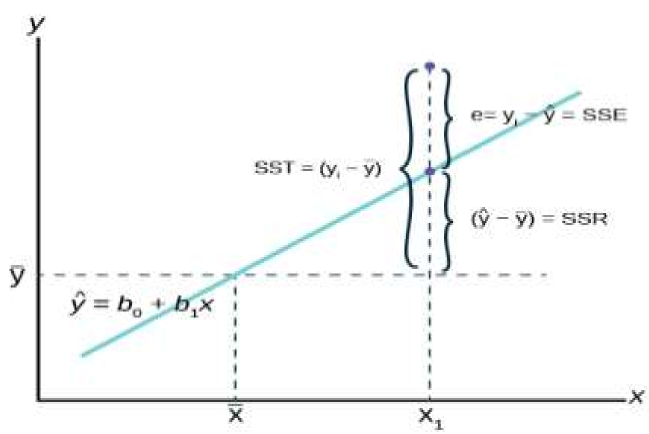


Figure 28. Estimated Regression Line with Observations. Source: (Alexander 2015)

The above parameters are defined as follows (Crawley 2005):

SST is the **total sum of squares**; it measures the total squared deviation of the dependent variable *y*, from its mean value.

$$SST = \sum (y_i - \bar{y})^2$$

SSR is the **total sum of square regressions**; it measures the squared deviation from the predicted value of y from the mean value of y.

$$SSR = \sum (\hat{y} - \bar{y})^2$$

SSE is the **total sum of squared errors**; it measures the difference between actual and estimated value.

$$SSE = \sum (y_i - \hat{y})^2$$

R square/Coefficient of Determination

R^2 Calculates the degree of correlation among the observed and predicted values with values close to 1.0 demonstrating good model performance (Mashaly et al., 2016). For ideal data modeling, R^2 should approach to 1.0 as closely as possible (Niu et al., 2017) (Amirkhani et al., 2015).

The performance parameter is calculated as below:

$$R^2 = \frac{\left(n \sum_{i=1}^{n} y_i \hat{y}_i - \sum_{i=1}^{n} y_i \sum_{i=1}^{n} \hat{y}_i\right)^2}{\left(n \sum_{i=1}^{n} {y_i}^2 - \left(\sum_{i=1}^{n} y_i\right)^2\right)\left(n \sum_{i=1}^{n} {\hat{y}_i}^2 - \left(\sum_{i=1}^{n} \hat{y}_i\right)^2\right)}$$

Where:

y_i = Observed Value

$\hat{y}_i$ = Predicted Value

n = Number of observations.

Confusion matrix

Confusion matrix summarizes classification performance of a classifier with respect to test data. It is a two-dimensional matrix, indexed in one dimension by the true class of an object and in the other by the predicted class (the one that the classifier assigns) (Ting 2011).

Consider for a two-class classification problem, as shown in figure 29 columns represents actual class and rows represent predicted class.

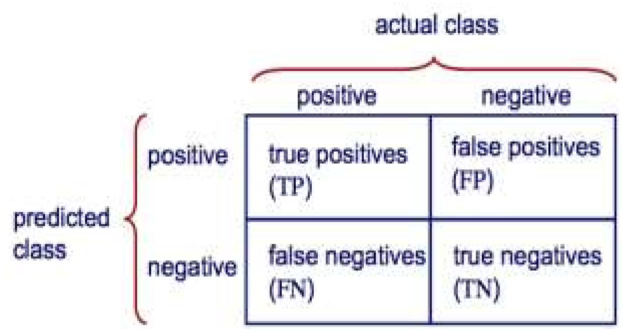


Figure 29. Two Class Confusion Matrix. Source: (Ting 2011).

Precision:

It denotes the proportion of positive predicted cases that are correctly real positives.

$$Precision = \frac{TP}{TP + FP}$$

Recall /Sensitivity/ True Positive Rate:

The sensitivity is defined as the ability of a model to find positive answers.

$$Sensitivity = \frac{TP}{TP+FN} \ i.e. \ \frac{TP}{Actual\ Positives}$$

Where *TP* is the number of true positives and *FN* is the number of false negative predicted by the model.

Specificity: The specificity is defined as the ability of a model to find negative answers.

$$Specificity = \frac{TN}{TN + FP}$$

Where *TN* is the number of true negatives and *FP* is the number of false positives predicted by the model.

False Positive Rate:

It is the ratio of negatives cases that were incorrectly classified as positive

$$False\ Positive\ Rate = \frac{FP}{TN+FP}\ \ i.e.\ \ \frac{FP}{Actual\ Negetives}$$

Accuracy

It measures the capacity of the predictive model to classify correctly; it is the proportion of the total number of predictions that were correct.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

Cohen's Kappa Statistics

It evaluates the portion of hits that can be credited to the classifier itself relative to all the classifications that cannot be credited to chance alone (Carletta 1996). In other words, it measures how well the classifier performed as compared to how well it would have performed simply by chance.

Kappa statistics is given by:

$$\frac{n\sum_{i=1}^{m} TP - \sum_{i=1}^{m} T_{ri}T_{ci}}{n^2 - \sum_{i=1}^{m} T_{ri}T_{ci}}$$

Where *TP* is the number of True Positives for each class, *n* is a total number of examples, *m* is a number of class labels. T_{ri} is row count and T_{ci} is column count.

Cohen's Kappa ranges from -1 through 0 to 1. These values indicate total disagreement, random classification, and perfect agreement respectively (Viera et al., 2005). For ideal data modeling, the value Kappa statistics will approach to 1.

F measure

It is harmonic mean of Precision and Recalls, i.e.; it can be interpreted as a weighted average of Precision and Recall, F measure calculates the accuracy of a test (Sasaki 2007).

$$F\ measure = 2 \times \left(\frac{Precision \times Recall}{Precision + Recall}\right)$$

For ideal data modeling, the F measure value should approach 1.

Receiver Operating Characteristic Curve (ROC curve):

A receiver operating characteristics (ROC) graph is a technique for visualizing, organizing and selecting classifiers based on their performance over all possible thresholds. It plots the *sensitivity* (proportion of true positives) of the predictive model versus the complement of the *specificity* (i.e., the proportion of false positives), in a series of thresholds for a positive result (de Menezes et al., 2017). Figure 30 represents an example of ROC curve. The point (0,1) is the perfect classifier: it classifies all positive cases and negative cases correctly. It is (0,1) because the false positive rate is 0 (none), and the true positive rate is 1 (all). The point (0,0) represents a classifier that predicts all cases to be negative, while the point (1,1) corresponds to a classifier that predicts every case to be positive (Fawcett 2006) (DBD 2014).

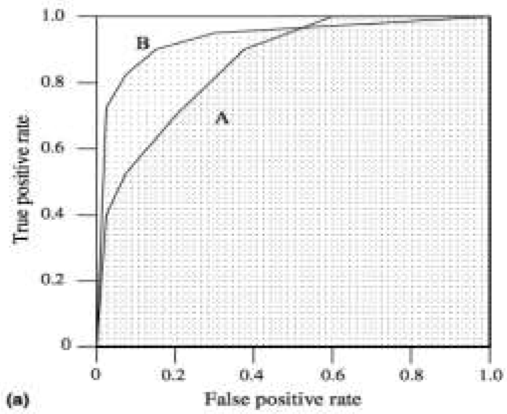


Figure 30. ROC Curve Example. Source: (Fawcett 2006).

The area under the curve:

To compare classifiers have to reduce the two-dimensional representation of classifier performance into a single scalar value. The most common method is to calculate the area under the ROC curve, abbreviated AUC (Hanley et el., 1982). The AUC is a portion of the area of the unit square; hence its value will always be between 0 and 1. The diagonal line between (0,0) and (1,1) produced by random guessing has an area of 0.5. In general, no credible classifier should have an AUC less than 0.5. In the figure 30 Classifier B has greater area and therefore better average performance (Fawcett 2006).

The area under the ROC curve (AUC - *area under the curve*) is calculated by the trapezoid rule, (de Menezes et al., 2017).

$$AUC = \sum_{i=1}^{n} (x_{i+1} - x_i) \left(\frac{y_{i+1} + y_i}{2}\right)$$

Where i is the threshold of the curve from which the pair of points (x_i, y_i) are taken.

The AUC measures the success of the model in correctly classifying TP and TN. Usually as a general rule as stated by (Zhou et al., 2009), If AUC ≥0.8, the discrimination is said to be excellent.

4.6 Attribute selection (Ranking)

The performance of any predictive model depends on data representation and a number of input variables (Cherkassky et al., 1992). Poor generalization performance can occur if a number of attributes are large (Freitag 2017). In attribute selection, most relevant input attributes from the collected set have to be selected for modeling GHG emission by road transport.

To perform Attribute selection, we implemented RRelief Algorithm in WEKA (capable of performing RReliefF). We used an input vector X [Year, Carsales, Gasoline Price CAD Later, GDP transportation, Interest Rate, CPI, Car Emission, Light Trucks Emission, Medium Trucks Emission, Heavy Trucks Emission, Buses Transit Emission, Population(million), Passenger Car Fuel Efficiency, Light Duty Truck Fuel Efficiency, Total GHG (only Road)] 25*15. In WEKA Explorer we chose attribute evaluator and search method and observed the rank of input attributes. The below table 5 shows the rank of attributes as determined by WEKA for GHG emission prediction.

Table 5. Attribute Rank by Relief Algorithm

Attribute	Rank
HeavyTrucksemission	0.10452
LightTrucksEmission	0.09533
GDPtransportation	0.08615
CPI	0.06161
Year	0.05956
Population(million)	0.05457
CarsEmission	0.04721
MediumTrucksEmission	0.03853
InterestRate(Overnight)	0.02853
Passengercarfuelefficiency	0.02109
BusesTransitEmission	0.0125
Lightdutytruckfueleffi	0.00931
GasolinePriceCADLiter	0.00594
Carsales	-0.01398

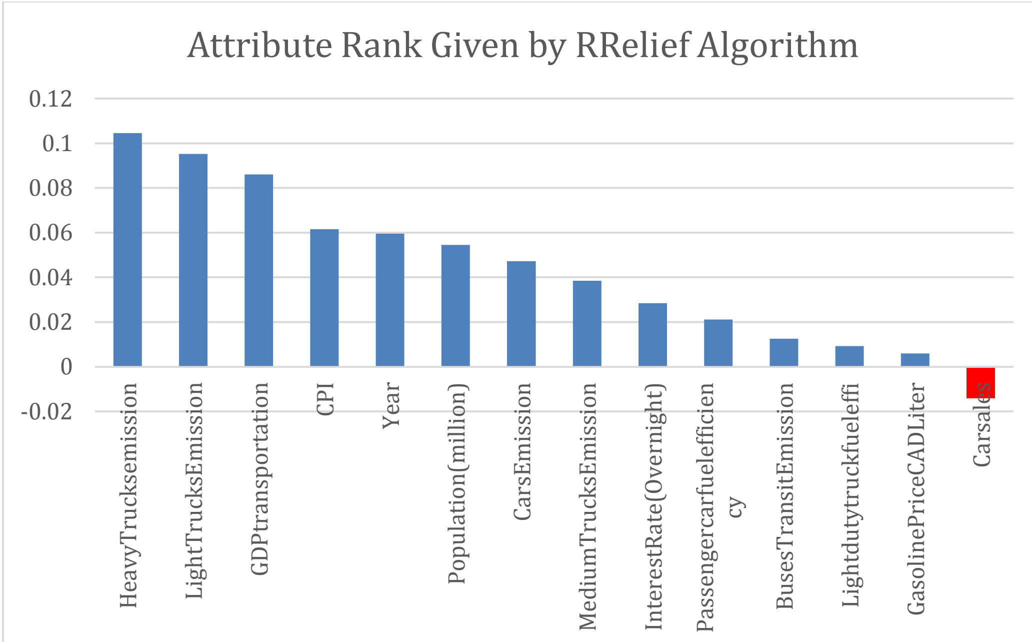


Figure 31. Attribute Rank Given by Relief Algorithm

Figure 31 shows Car sales to have a negative ranking. In the following section using different attributes as inputs, two predictive models will be designed, and their performance will be evaluated. In below section, verification of selected attributes will be performed. “Car sales” will be omitted as an input attribute from one of the two models and performance parameters for each model will be assessed.

Verification of Selected Attributes

For authentication and to analyze the performance improvement (in case) by utilizing the selected relevant input variables given by RReliefF Algorithm, in predictive modeling, we developed two Multilayer perceptron models. Model MLP1 with all input attributes and Model MLP2 with Relief algorithm selected attributes (excluding car sales). To further implement various learning algorithm and to have the good generalizing performance, we want to keep the most relevant attributes as inputs.

The MLP models are developed in WEKA. Total numeric values of GHG emission by road transport were selected as the dependent variable, and remaining attributes were used as covariates.

The created Multilayer perceptron is a two-layered feed forward network with back propagation setting. The training is done using gradient descent algorithm. We utilized 10-fold cross validation technique to avoid the problem of over fitting and to check the generalization by the model when applied to the independent/unknown data set.

The model performance was analyzed using performance indicators like Root Mean Square Error, Correlation coefficient and Mean Absolute Error.

Modeling MLP1 using all attributes:

We used all the available 14 input attributes to analyze the prediction performance of the model MLP1. As can be seen in figure 32 it's a three layer network, input layer, hidden layer, and output layer. The weights are given for each attribute that feeds into each sigmoid node plus the threshold (bias) weight. The output nodes have a feed of weight and threshold from the seven hidden neurons.

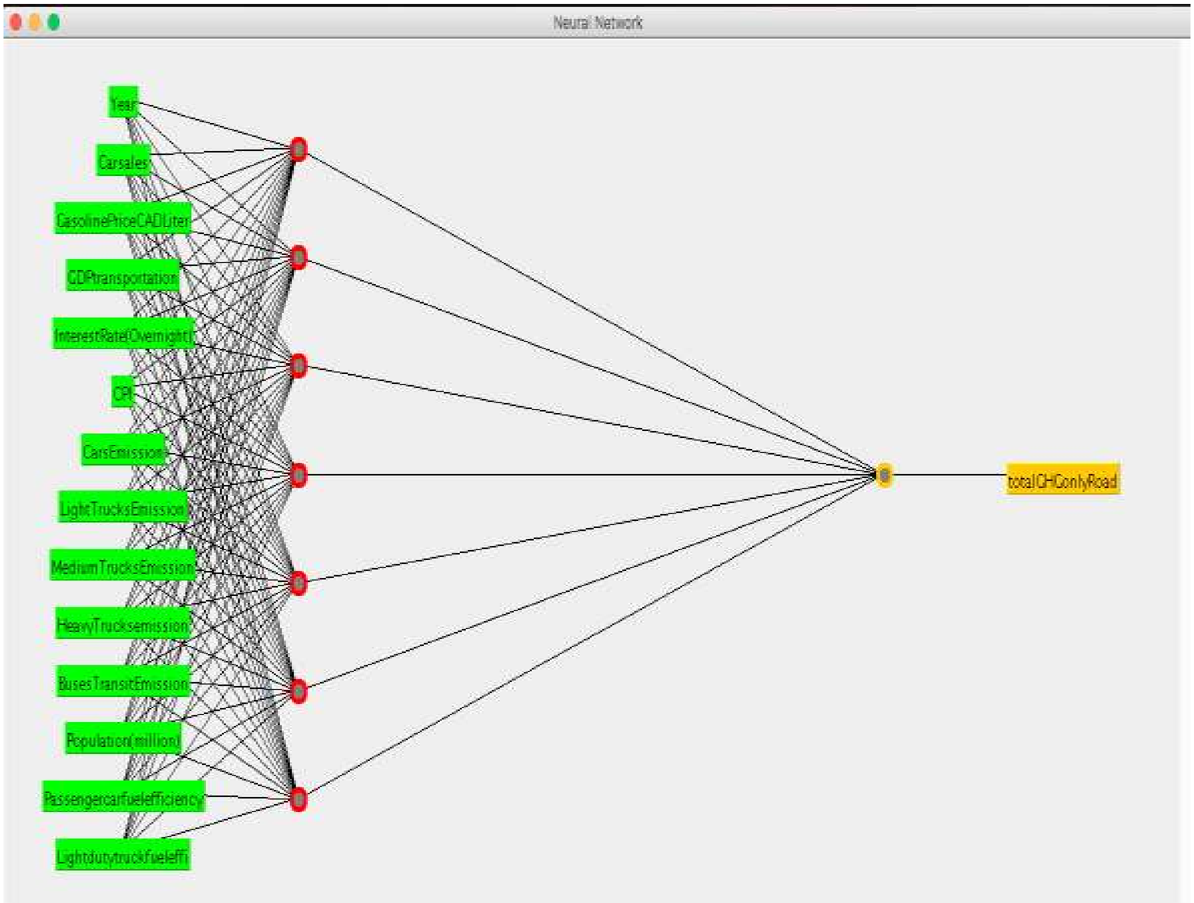


Figure 32. MLP1 Neural Network Model

Performance Indicators of MLP1:

Root mean squared error	0.5776
Correlation coefficient	0.9993
Mean absolute error	0.5148

Modeling MLP2 using attributes selected by Relief algorithm

We excluded car sales, which got negative ranking in input selection and designed the model with same gradient decent back propagation algorithm, learning rate, momentum and the same number of hidden layers as MLP1.

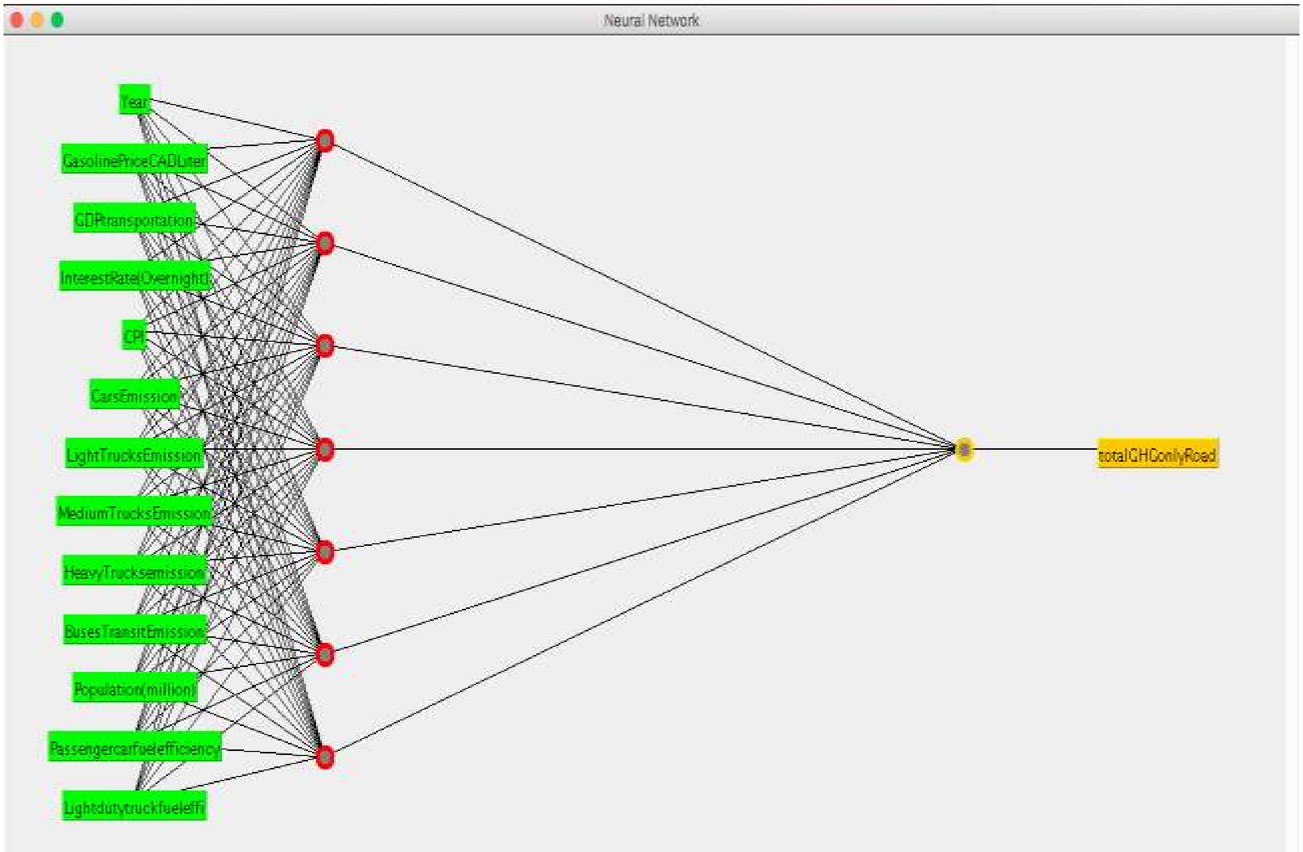


Figure 33. MLP2 Neural Network Model

Performance Indicators of MLP2:

Root mean squared error 0.442

Correlation coefficient 0.9996

Mean absolute error 0.3471

Results of Selected Attribute Verification

The prediction accuracy of numeric GHG emission was evaluated with the help of performance indicators. MLP2 with attributes selected by Relief algorithm performs better compared to MLP1 with all available inputs as attributes. Table 6 represents the results of both model's performance indicators:

Table 6. MLP1 vs MLP2 Performance Indicators

Model	RMSE	R Square	MAE
MLP1	0.5776	0.9993	0.5148
MLP2	0.442	0.9996	0.3471

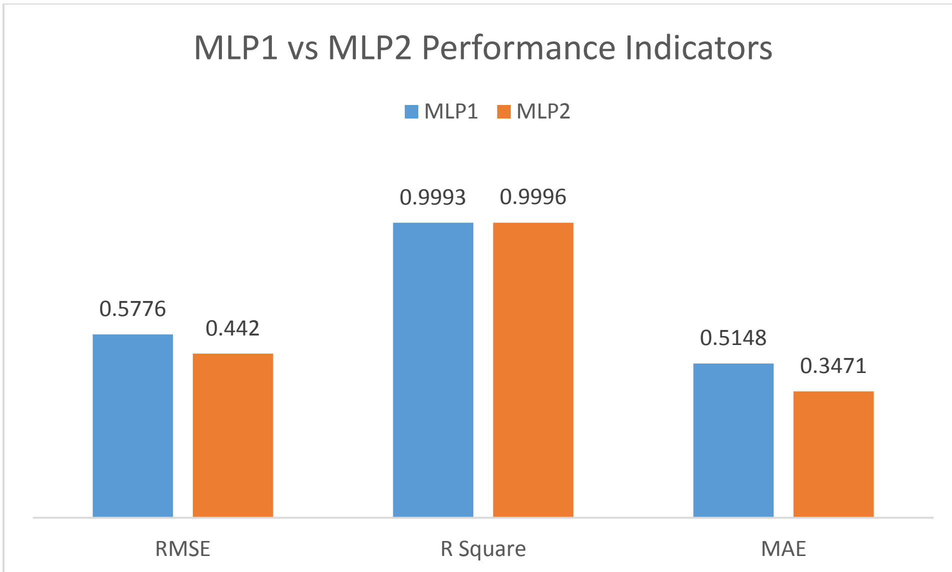


Figure 34. MLP1 vs. MLP2 Performance Indicators

Figure 34 shows the results that after removing less influencing attribute (Car sales) the model MLP2 error rates RMSE & MAE decreased to 0.442 & 0.3471 respectively and correlation coefficient value slightly increased to 0.9996 proving that generalizing performance of machine learning models will improve with relevant input attributes.

4.7 Algorithm Application on Numeric Data

In this study, we implemented supervised Regression algorithms to fit a linear model for GHG emissions by Road Transportation in Canada using socio-economic, emission and fuel efficiency data as independent variables. Considering the data obtained by Attribute selection given in Appendix H. In below section, we implemented Multiple Linear Regression and Multilayer perceptron. Furthermore, we implemented Bagging algorithm (ensemble technique) on the best performing model.

In this section, for application of the Regression supervised learning algorithms, we utilized WEKA (Wakaito Environment of Knowledge Analysis) tool. The model performance was evaluated by the Error Estimated by the Cross Validation technique using performance indicators like Root Mean Square Error, Correlation coefficient and Mean Absolute Error.

Multiple Linear Regression

The MLR model is developed in WEKA. Classified socio-economic, emissions and fuel efficiency data was selected with 10-fold cross validation technique to avoid the problem of over fitting and to check the generalization by the model when applied to independent/unknown data set. The averaged evaluation results after 10 fold cross validation were given by WEKA under cross validation summary results. On the 11th run WEKA runs the Multiple Linear Regression algorithm on the data set and provide MLR model (figure 35). Total numeric values of GHG emission by road transport were selected as the dependent variable, and remaining attributes were used as covariates.

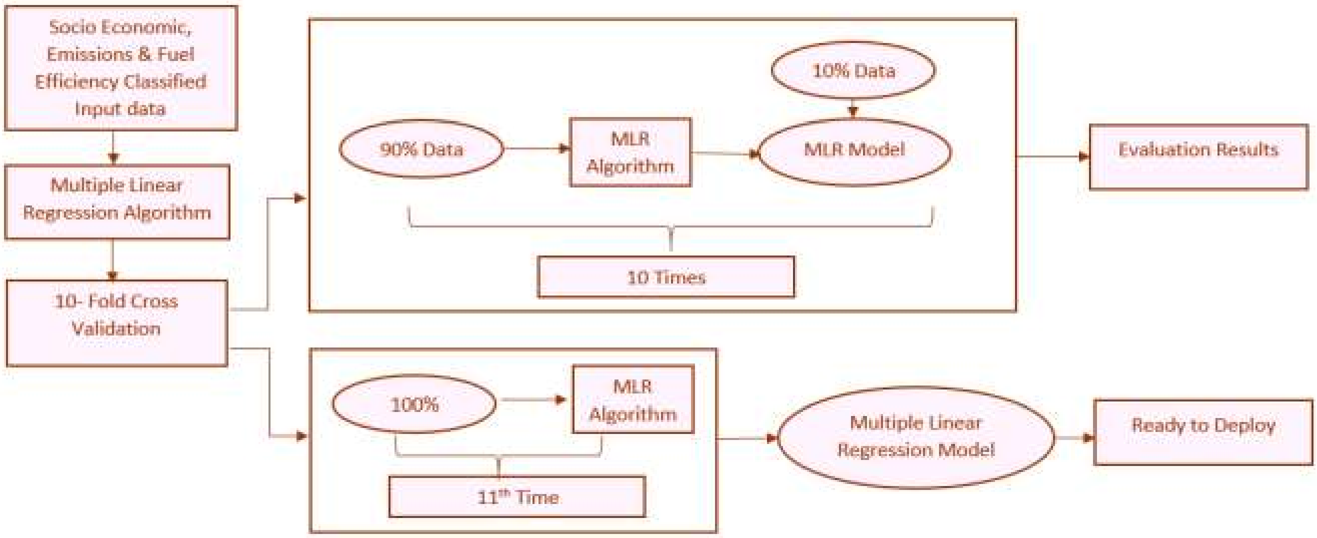


Figure 35 Multiple Linear Regression model development

The following is the Regression model given by WEKA.

Linear Regression Model:

Total GHG by Road = 0.0063 * Year + 0.0734 * Gasoline Price CAD Liter +0* GDP transportation -0.0024 * Interest Rate(Overnight) -0.0016 * CPI +1.0005 * Cars Emission + 0.9984 * Light Trucks Emission +1.0012 * Medium Trucks Emission + 1.0019 * Heavy Trucks emission + 0.9986 * Buses Transit Emission + 0.0008 * Population(million) + 0.0044 * Passenger car fuel efficiency + 0.0187 * Light duty truck fuel efficiency -12.6902

Cross-validation

Summary

Correlation coefficient	0.9973
Mean absolute error	0.7223
Root mean squared error	1.301
Total Number of Instances	25

Multilayer Perceptron

The MLP model is developed in WEKA. Classified socio-economic, emissions and fuel efficiency data was selected with 10-fold cross validation technique to avoid the problem of over fitting and to check the generalization by the model when applied to independent/unknown data set. The averaged evaluation results after 10 fold cross validation were given by WEKA under cross validation summary results.

Learning parameters plays a vital role in fine tuning of Multilayer Perceptron model, In case the performance parameters given by cross validation are not satisfactory, the network can be fine tuned by changing Learning rate, momentum and number of epochs (or training time). Therefore cross validation is an important validation technique as its results impact the network training.

The MLP model development is shown in figure 36. On the 11th run WEKA develops the Multilayer perceptron network which is shown is a two-layered feed forward network with back propagation setting in figure 37. The training is done using gradient descent algorithm. We utilized 10-fold cross validation technique to avoid the problem of over fitting and to check the generalization by the model when applied to independent/unknown data set.

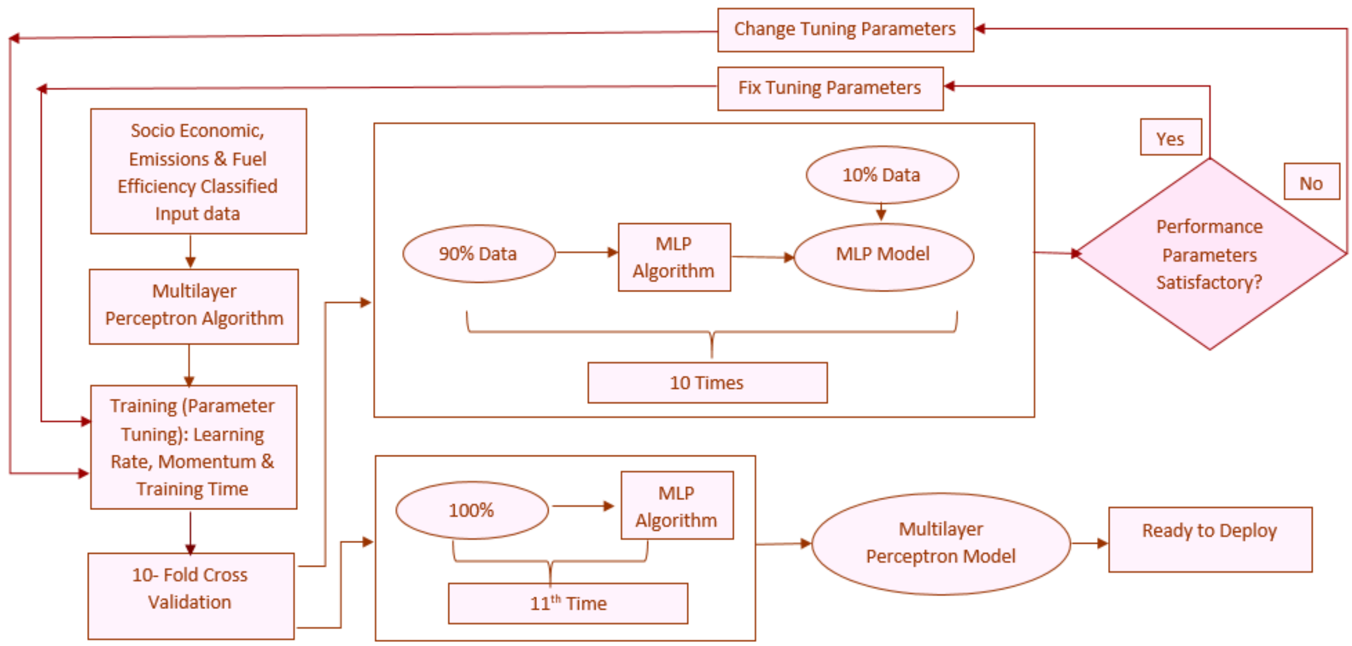


Figure 36 Multi layer Perceptron model development

Cross-validation

Summary

Correlation coefficient	0.9996
Mean absolute error	0.3471
Root mean squared error	0.442
Total Number of Instances	25

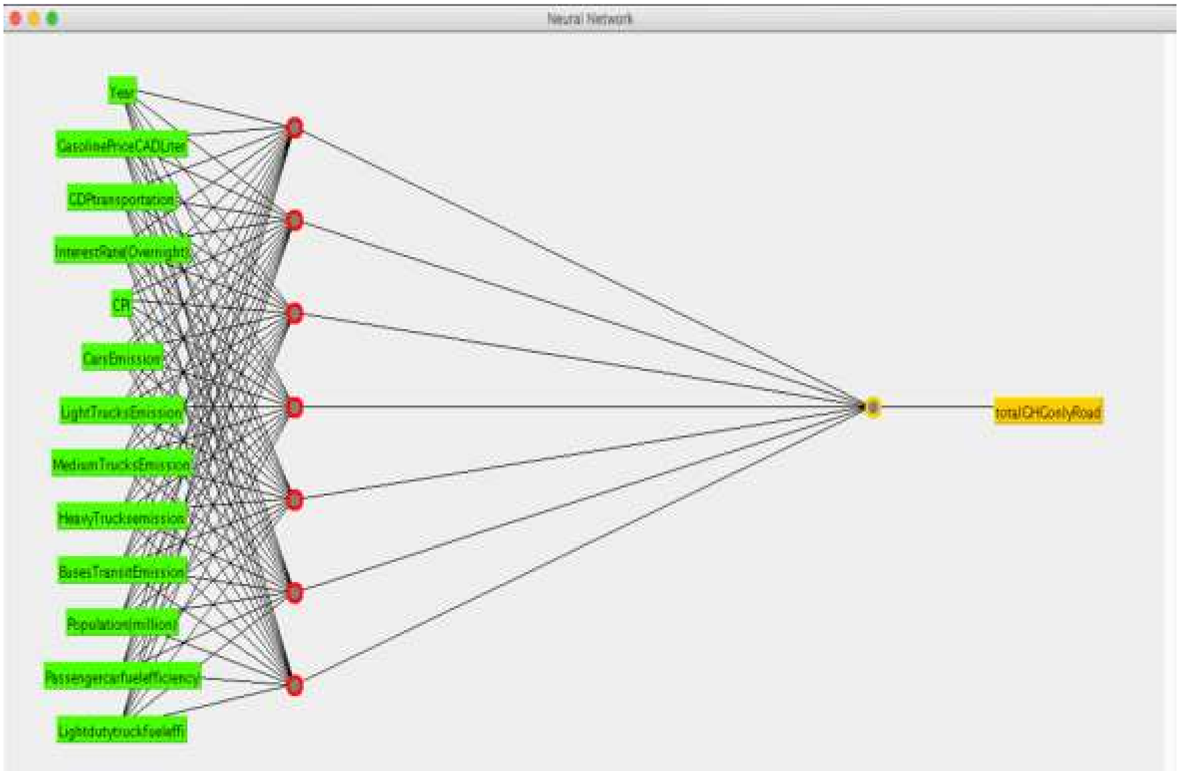


Figure 37 Multilayer Perceptron Model

4.7.1 Algorithm Improvement for Numeric Data

We tabulated the performance parameters of the above-implemented algorithms. The primary performance parameter we considered is Root Mean Square Error (RMSE).

Table 7 MLR & MLP Performance Evaluation

Performance Evaluation Metric	Multiple Linear Regression	Multilayer Perceptron
Root mean squared error	1.301	0.442
Correlation coefficient	0.9973	0.9996
Mean absolute error	0.7223	0.3471

Table 7 gives performance evaluation of MLR and MLP models; Multilayer Perceptron algorithm outperforms Multiple Linear Regression. Hence, in this section, we implemented ensemble technique, i.e., Bagging algorithm on Multilayer Perceptron Regression model to enhance the predictive modeling capacity of this neural network. In Multilayer perceptron algorithm we kept the same learning parameters, i.e., learning rate, momentum and the same number of hidden layers and used gradient descent back propagation algorithm.

Bagging

Bagging performs better on the unstable base classifier, where minor changes in the training set can lead to major changes in the classifier output. A multilayer perceptron is an example of the unstable classifier. The bagging algorithm with 10 iterations/bags was also evaluated using 10 fold cross validation technique. So for each bag, 10 Multilayer perceptron classifiers were trained and combined. To aggregate the outputs of the base learner, Bagging algorithm use averaging for Regression.

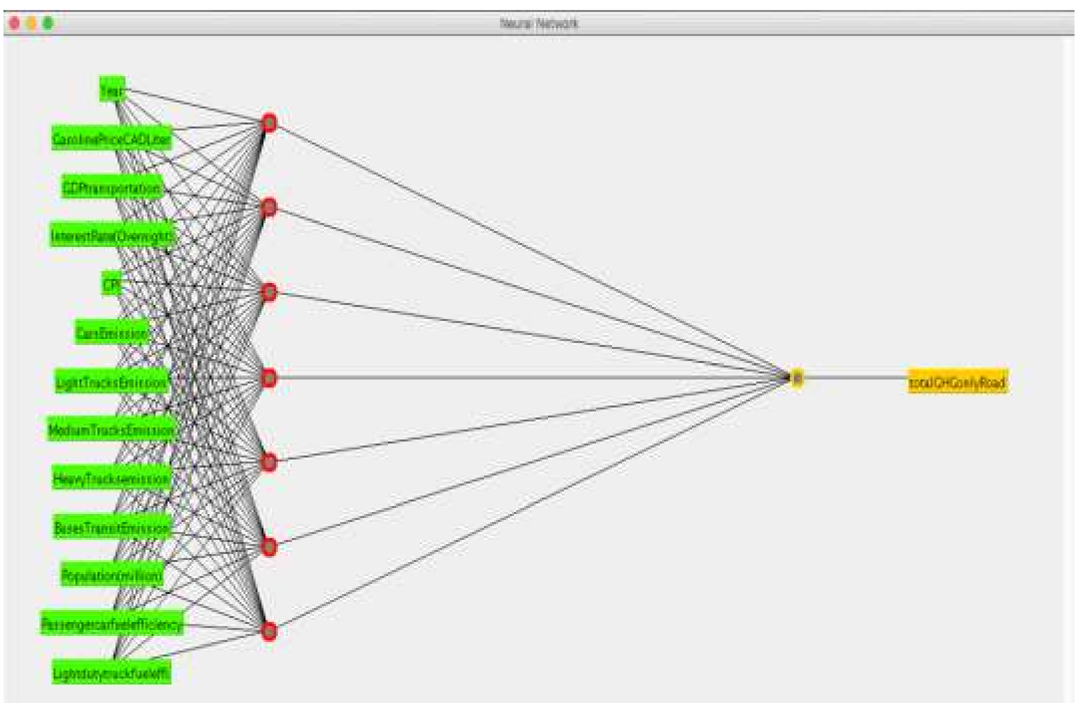


Figure 38 Bagging Multilayer Perceptron Model

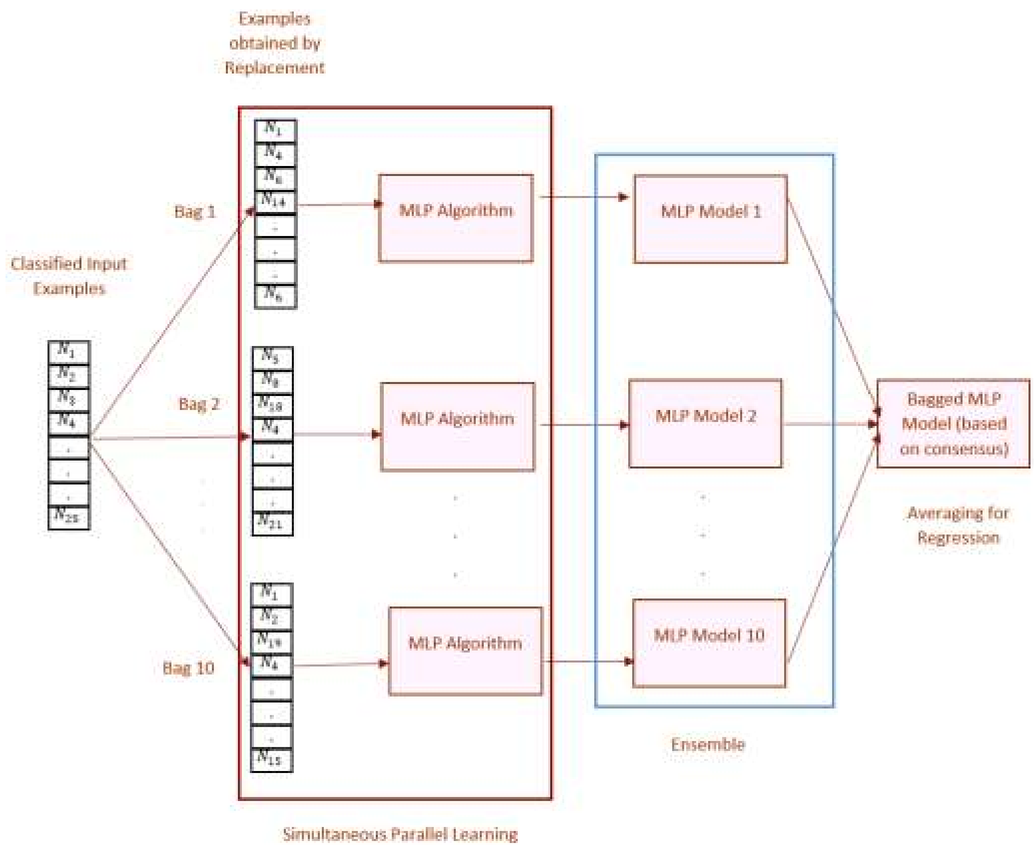


Figure 39 Bagging algorithm

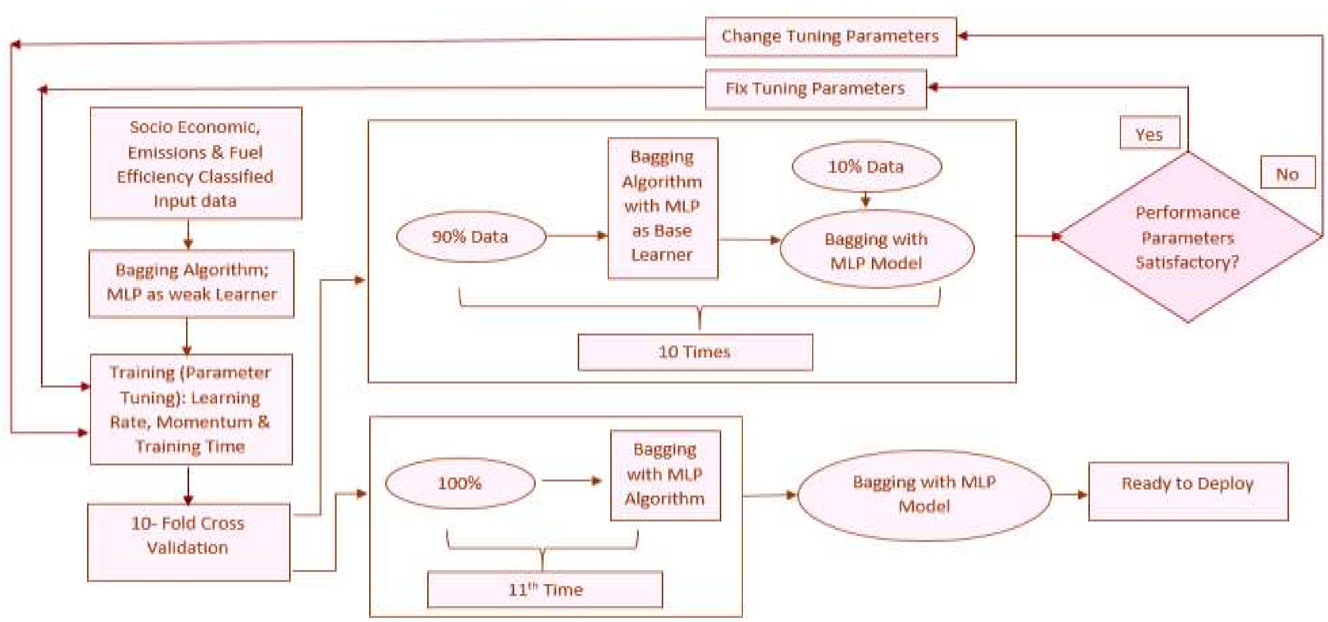


Figure 40 Bagging with MLP Model development for Numeric data

The MLP model development is shown in figure 40 and as it can be seen in figure 39 we used 10 iteration for bagging algorithm and we used 10 fold cross validation, which means for each bag 10 MLP classifiers were trained and combined using averaging. Finally for regression averaging is done for all 10 bags and the model is selected. The final developed Multilayer perceptron with Bagging network is shown in figure 38 is a two-layered feed forward network with back propagation setting. The training is done using gradient descent algorithm.

Cross-validation

Summary

Correlation coefficient	0.9997
Mean absolute error	0.265
Root mean squared error	0.3805
Total Number of Instances	25

4.7.2 Results & comparison of Algorithm Improvement on Numeric Data

Table 8 Results of Algorithm Improvement on Numeric Data

Performance Evaluation Metric	Multiple Linear Regression	Multilayer Perceptron	Bagged Multilayer Perceptron
Root mean squared error	1.301	0.442	0.3805
Correlation coefficient	0.9973	0.9996	0.9997
Mean absolute error	0.7223	0.3471	0.265

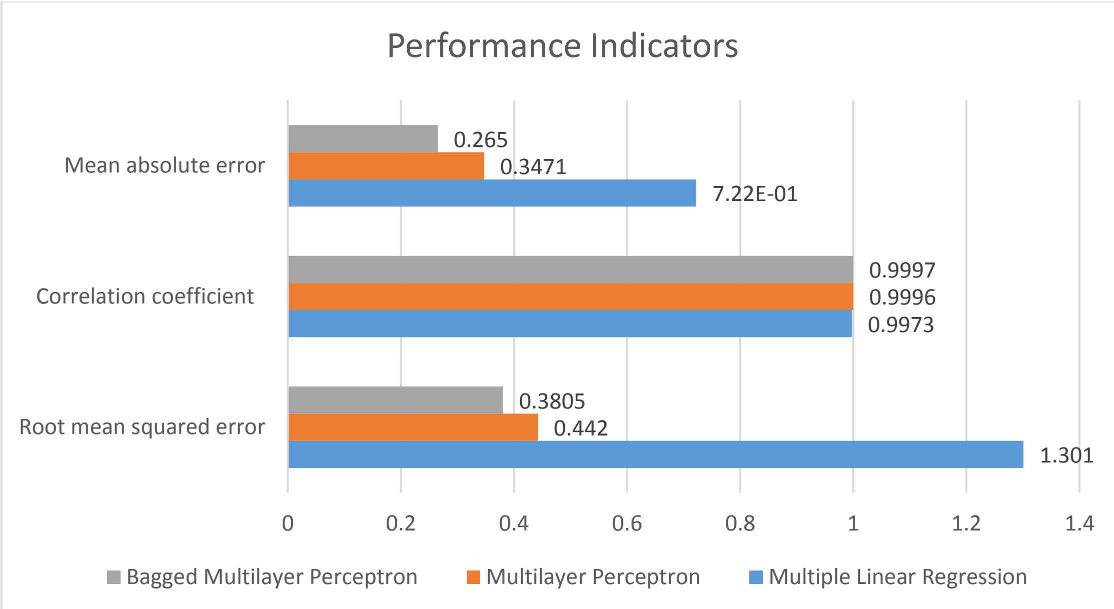


Figure 41 Performance Indicators of Algorithms on Numeric Data

Figure 41 shows, that the model developed by Multilayer Perceptron with Bagging algorithm outperforms the models given by Multiple Linear Regression and Multilayer Perceptron. That is, for Bagged Multilayer Perceptron the value of errors are minimum and Correlation coefficient is high.

Data for Implementing Supervised Classification Algorithms:

The available attribute data sources contain all numeric values. We further wanted to implement supervised classification algorithm and algorithm improvement (bagging & boosting) hence, we categorized the numerical values of GHG emissions by road transport into six category bins. The bin width is 10 Mt CO2 eq. GHG emission value and the bin values start from 90 Mt CO2 eq. to 150 Mt Co2 eq. values.

4.8 Algorithm Application on Nominal Data

We converted our numeric dependent variable into a nominal variable to implement classification algorithm (Appendix I). Hence, we have a multiclass problem in this research. There are two approaches to deal with the multi class problem for classifiers one-vs-one (OVO) and one-vs-all (OVA) (Galar et al., 2011). OVO approach for multiclass problem builds ${}^{m}C_{2}$ base classifiers for m classes, hence dividing a multiclass problem into many possible binary problems. In OVO the cost of resources are high as more number of classifiers are required. On the contrary, the OVA approach forms one classifier for each target class and hence requiring only m classifiers. In OVA the classifier discriminates the target class from other $(m-1)$ classes (Galar, M. et el., 2011).

In this section, for application of the classification learning algorithms, we utilized WEKA (Wakaito Environment of Knowledge Analysis) tool, as it can handle multi-class classification automatically by using the OVA approach.

The performance of the classifiers and ensemble techniques were evaluated by the Error Estimated by the 10 Fold Cross Validation technique.

Multinomial Logistic Regression

We implemented multinomial logistic regression on our categorized GHG emission by road transport data set. The data given in Appendix I, has been categorized into six different classes; the Multinomial logistic regression algorithm chose the last category as the reference category. Coefficients and Odd ratios are determined for all independent attributes for each class of dependent variable except the reference class.

Classified socio-economic, emissions and fuel efficiency data was selected with 10-fold cross validation technique to avoid the problem of over fitting and to check the generalization by the model when applied to independent/unknown data set. The voted averaged evaluation results after 10 fold cross validation were given by WEKA under cross validation summary results. The exponential of coefficient values represents the odds ratio. Figure 42 shows Multinomial Logistic regression model development. The model run information is given in Appendix J.

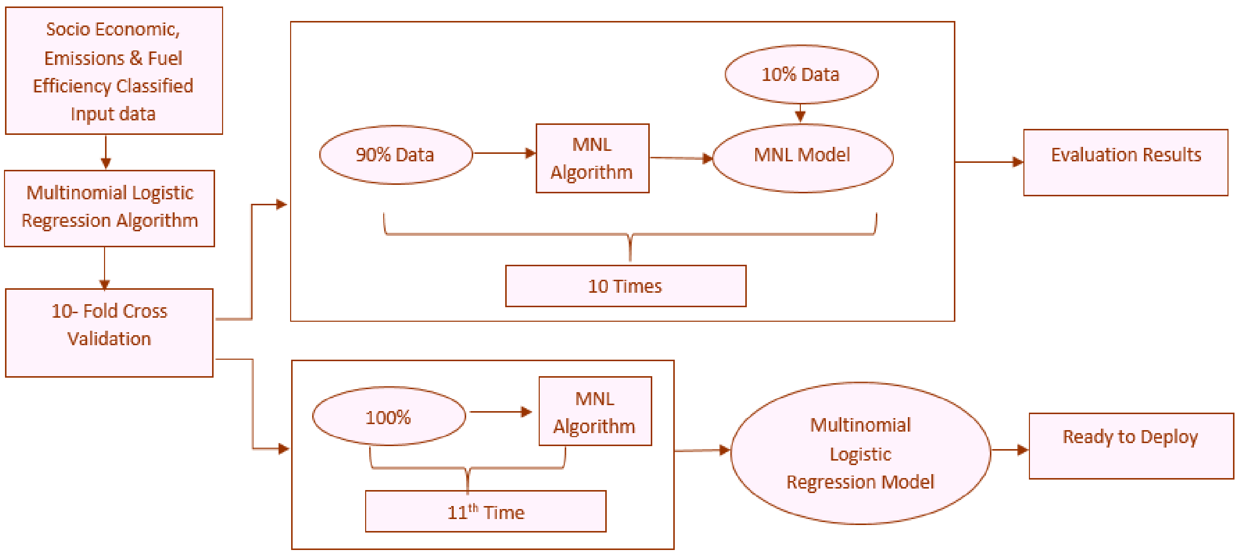


Figure 42 Multinomial Logistic regression model development

Coefficients are weights that are applied to each attribute before adding them together. The result is the probability that new instance belong to the given class (the threshold is 0.5). Odds ratio examines how large the influence of the value of the independent variable will be on prediction for an independent variable to be in a particular category with respect to the reference category.

For example, The high value of 201493152.4827 “passenger car fuel efficiency” represents that the odds for passenger car efficiency are extremely favorable to the class being predicted as “bet 100 &110” with respect to reference class “bet 140 &110”.

Similarly, the high value of 2017456.5082 “GasolinePriceCADLiter” represents that the odds for GasolinePriceCADLiter are extremely favorable to the class being predicted as “bet 110 &120” with respect to reference class “bet 140 &150”.

Cross-validation

Summary

Correctly Classified Instances	15	62.5	%
Incorrectly Classified Instances	9	37.5	%
Kappa statistic	0.5394		
Mean absolute error	0.1217		
Root mean squared error	0.3445		
Total Number of Instances	24		

Detailed Accuracy by Class

Table 9. Multinomial Logistic Regression Detailed Accuracy by Class

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.333	0.048	0.5	0.333	0.4	0.651	bet 100 & 110
	1	0.091	0.5	1	0.667	0.955	bet 90 & 100
	0.5	0.05	0.667	0.5	0.571	0.963	bet 110 & 120
	0.5	0.1	0.5	0.5	0.5	0.9	bet 120 & 130
	0.714	0.118	0.714	0.714	0.714	0.916	bet 130 & 140
	0.75	0.05	0.75	0.75	0.75	0.988	bet 140 & 150
Weighted Avg.	0.625	0.081	0.632	0.625	0.617	0.903	

Confusion Matrix

Table 10. Multinomial Logistic Regression Confusion Matrix

a	b	c	d	e	f	<-- classified as
1	2	0	0	0	0	| a = bet 100 & 110
0	2	0	0	0	0	| b = bet 90 & 100
1	0	2	1	0	0	| c = bet 110 & 120
0	0	1	2	1	0	| d = bet 120 & 130
0	0	0	1	5	1	| e = bet 130 & 140
0	0	0	0	1	3	| f = bet 140 & 150

In our data set, we have total 24 instances and 6 classes. As per the confusion matrix given in table 10, the following were the classifications given by Multinomial logistic regression classifier:

- Out of 3 actual instances which belong to class "bet 100 & 110", the classifier correctly predicted 1 instance and predicted that two instances belong to class "bet 90 & 100".
- Out of 2 actual instances which belong to class "bet 90 & 100", the classifier correctly predicted all instances.
- Out of 4 actual instances which belong to class "bet 110 & 120", the classifier correctly predicted 2 instances and predicted the other two instances belong to class "bet 100 & 110" and to class "bet 120 & 130" respectively.
- Out of 4 actual instances which belong to class "bet 120 & 130", the classifier correctly predicted 2 instances and predicted the other two instances belong to class "bet 110 & 120" and to class "bet 130 & 140" respectively.
- Out of 7 actual instances which belong to class "bet 130 & 140", the classifier correctly predicted 5 instances and predicted the other two instances belong to class "bet 120 & 130" and to class "bet 140 & 150" respectively.
- Out of 4 actual instances which belong to class "bet 140 & 150", the classifier correctly predicted 3 instances and predicted the other 1 instance belong to class "bet 130 & 140".

Decision Tree

As can be seen in figure 43, Light duty truck efficiency has been choosing as the root node. It has the highest information gain and gain ratio compared to other attributes and hence was selected as the best splitting attribute. Analyzing the below C4.5 Decision Tree given by WEKA we can see that the algorithm calculates a threshold 10.8, in this case, it has two branches, i.e., the values less than 10.8 and values greater than 10.8

Later the algorithm will consider the subset of GHG by road transport data which contains only the object with attribute Lightdutytruckfuelefficiency<=10.8 and will calculate the information gain and gain ration of this subset. After analyzing the algorithm finds out that information gain and gain ratio for the attribute "Interest rate (overnight)" is higher compared to other attributes and hence the second node is split on "Interest rate (overnight)." And the algorithm recurs until all data is classified into available classes.

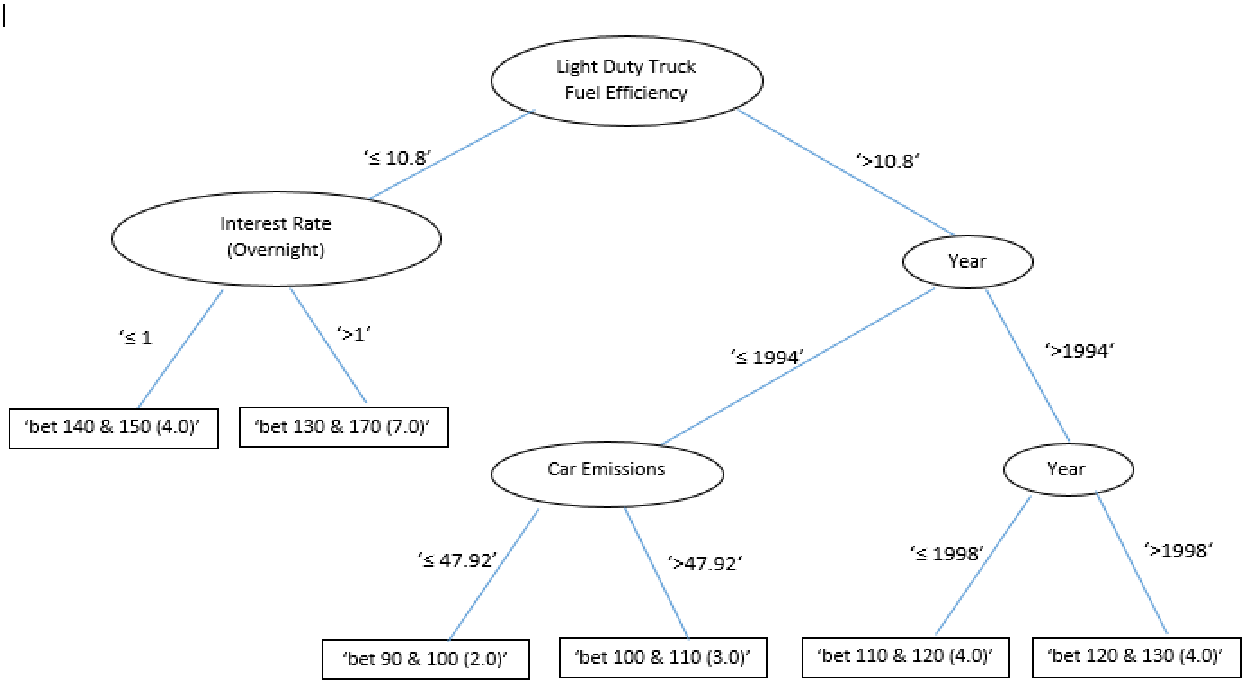


Figure 43. C4.5 Decision Tree

So, if the value Lightdutytruckfuelefficiency<=10.8 and the value of "Interest rate(overnight)" is <= 1, 4 out of 24 instances are classified to belong to class "bet 140 & 150" and in the same branch if the value of "Interest rate(overnight)" is >1, 7 out of 24 instances are classified to belong to class "bet 130 & 140".

Cross-validation

Summary

Correctly Classified Instances 17 70.8333 %

Incorrectly Classified Instances 7 29.1667 %

Kappa statistic 0.6403

Mean absolute error 0.1019

Root mean squared error 0.3143

Total Number of Instances 24

Number of Leaves: 6

Size of the tree: 11

Detailed Accuracy by Class

Table 11. C4.5 Decision Tree Detailed Accuracy by Class

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.667	0.048	0.667	0.667	0.667	0.802	bet 100 & 110
	0	0.045	0	0	0	0.455	bet 90 & 100
	0.5	0.15	0.4	0.5	0.444	0.675	bet 110 & 120
	0.75	0.1	0.6	0.75	0.667	0.825	bet 120 & 130
	0.857	0	1	0.857	0.923	0.929	bet 130 & 140
	1	0	1	1	1	1	bet 140 & 150
Weighted Avg.	0.708	0.051	0.708	0.708	0.704	0.826	

Confusion matrix

Table 12. C4.5 Decision Tree Confusion matrix

a	b	c	d	e	f	<-- classified as
2	0	1	0	0	0	| a = bet 100 & 110
1	0	1	0	0	0	| b = bet 90 & 100
0	1	2	1	0	0	| c = bet 110 & 120
0	0	1	3	0	0	| d = bet 120 & 130
0	0	0	1	6	0	| e = bet 130 & 140
0	0	0	0	0	4	| f = bet 140 & 150

The data set has total 24 instances and 6 classes. As per the confusion matrix from table 12, the following were the classifications given by C4.5 (J48) classifier:

- Out of 3 actual instances which belong to class "bet 100 & 110", the classifier correctly predicted 2 instances and predicted one instance belong to class "bet 110 & 120.
- Out of 2 actual instances which belong to class "bet 90 & 100", the classifier predicted all instances wrong.
- Out of 4 actual instances which belong to class "bet 110 & 120", the classifier correctly predicted 2 instances and predicted the other two instances belong to class "bet 90 & 100" and to class "bet 120 & 130" respectively.
- Out of 4 actual instances which belong to class "bet 120 & 130", the classifier correctly predicted 3 instances and predicted that the other instance belongs to class "bet 110 & 120".
- Out of 7 actual instances which belong to class "bet 130 & 140", the classifier correctly predicted 6 instances and predicted that the other instance belongs to class "bet 120 & 130".
- Out of 4 actual instances which belong to class "bet 140 & 150", the classifier correctly predicted all 4 instances.

Multilayer Perceptron

The neural network is using 24 instances each with 13 variables to predict 6 class bin value of GHG emission by road transport. The training of the network is done using Back propagation algorithm to adjust the internal weights to get as close as possible to the known class category. Classified socio-economic, emissions and fuel efficiency data was selected with 10-fold cross validation technique to avoid the problem of over fitting and to check the generalization by the model when applied to independent/unknown data set. The averaged evaluation results after 10 fold cross validation were given by WEKA under cross validation summary results.

Learning parameters plays a vital role in fine tuning of Multilayer Perceptron model, In case the performance parameters given by cross validation are not satisfactory, the network can be fine tunes by changing Learning rate, momentum and number of epochs (or training time). Therefore cross validation is an important validation technique as its results impact the network training.

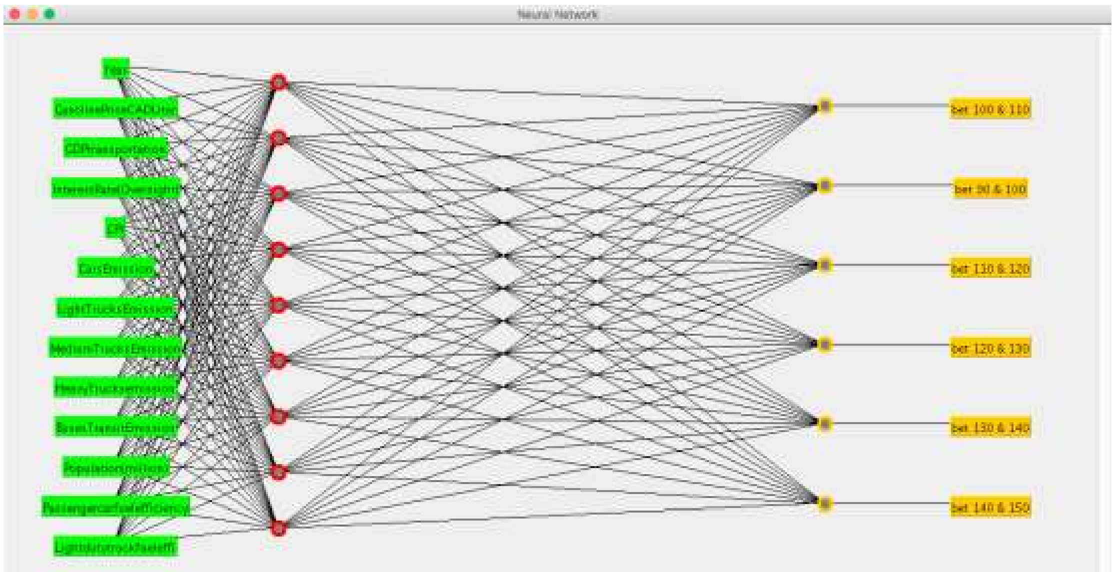


Figure 44. Multilayer Perceptron Neural Network Model

Figure 45 shows MLP model development. On the 11th run WEKA develops the Multilayer perceptron network which is shown in figure 44. Multilayer Perceptron Neural Network for categorical dependent data, it's a three layer network, input layer, hidden layer, and output layer. The weights are given for each attribute that feeds into each sigmoid node plus the threshold (bias) weight. The output nodes have a feed of weight and threshold from the 9 hidden neurons.

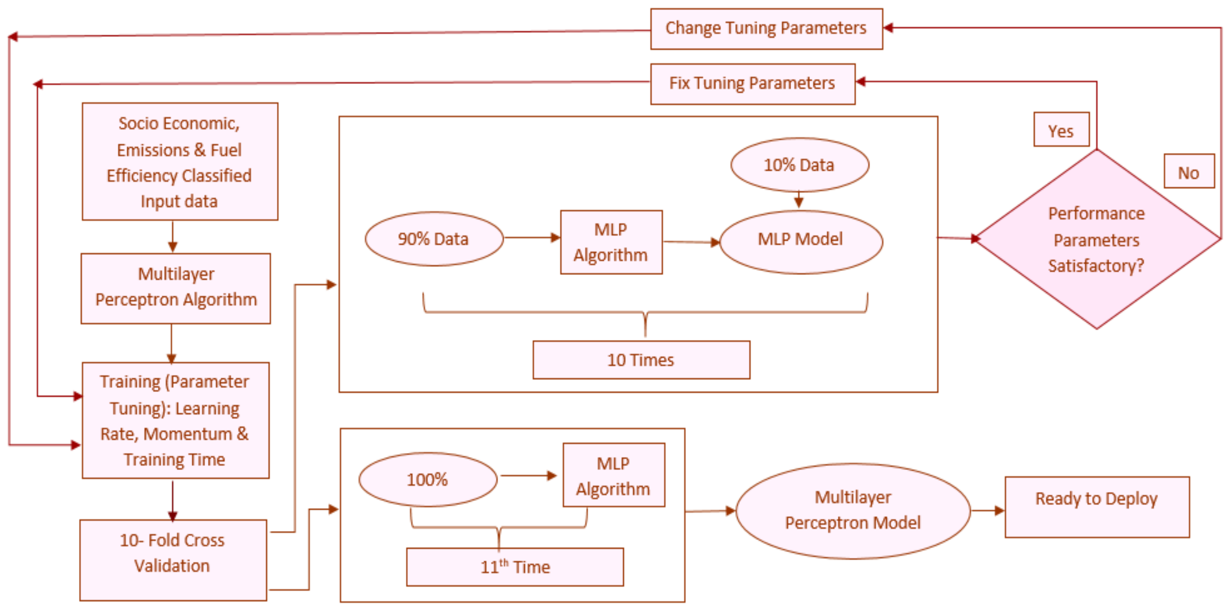


Figure 45 The Multilayer Perceptron model development for Nominal data

Cross-validation

Summary

Correctly Classified Instances 15 62.5 %

Incorrectly Classified Instances 9 37.5 %

Kappa statistic 0.5375

Mean absolute error 0.1236

Root mean squared error 0.2676

Total Number of Instances 24

Detailed Accuracy by Class

Table 13. Multilayer Perceptron Detailed Accuracy by Class

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0	0.048	0	0	0	0.857	bet 100 & 110
	0.5	0.045	0.5	0.5	0.5	0.932	bet 90 & 100
	0.75	0.2	0.429	0.75	0.545	0.875	bet 110 & 120
	0.5	0.05	0.667	0.5	0.571	0.95	bet 120 & 130
	0.714	0.059	0.833	0.714	0.769	0.966	bet 130 & 140
	1	0.05	0.8	1	0.889	0.988	bet 140 & 150
Weighted Avg.	0.625	0.077	0.601	0.625	0.6	0.935	

Confusion matrix

Table 14. Multilayer Perceptron Confusion matrix

a	b	c	d	e	f	<-- classified as
0	1	2	0	0	0	| a = bet 100 & 110
0	1	1	0	0	0	| b = bet 90 & 100
1	0	3	0	0	0	| c = bet 110 & 120
0	0	1	2	1	0	| d = bet 120 & 130
0	0	0	1	5	1	| e = bet 130 & 140
0	0	0	0	0	4	| f = bet 140 & 150

The data set has total 24 instances and 6 classes. As per the confusion matrix given in table 14, the following were the classifications given by Multilayer Perceptron classifier:

- Out of 3 actual instances which belong to class "bet 100 & 110", the classifier predicted all instances wrong.
- Out of 2 actual instances which belong to class "bet 90 & 100", the classifier correctly predicted 1 instance and incorrectly predicted other instance as belonging to the class "bet 110 & 120".
- Out of 4 actual instances which belong to class "bet 110 & 120", the classifier correctly predicted 3 instances and predicted that the other instance belongs to class "bet 100 & 110".
- Out of 4 actual instances which belong to class "bet 120 & 130", the classifier correctly predicted 2 instances and predicted the other two instances belong to class "bet 110 & 120" and to class "bet 130 & 140" respectively.
- Out of 7 actual instances which belong to class "bet 130 & 140", the classifier correctly predicted 5 instances and the other two instances belong to class "bet 120 & 130" and to class "bet 140 & 150" respectively.

- Out of 4 actual instances which belong to class “bet 140 & 150”, the classifier correctly predicted all 4 instances.

4.8.1 Algorithm Improvement for Nominal Data

We tabulated the important performance parameters of the above-implemented algorithms. The primary performance parameter we considered is Root Mean Square Error (RMSE).

Table 15. MNL, C4.5 & MLP Algorithm Performance Evaluation

Performance Evaluation Metric	Multinomial Logistic Regression	Decision Tree	Multilayer Perceptron
Root mean squared error	0.3445	0.3143	0.2676
Kappa statistic	0.5394	0.6403	0.5375
Wt. Avg. ROC Area	0.903	0.826	0.935

As can be seen from the table 15, performance indicators for Multilayer Perceptron model outperforms Decision tree and Multinomial logistic regression models. Hence, in this section, we implemented ensemble techniques, i.e., Bagging and Boosting algorithm on Multilayer Perceptron classifier to enhance the predictive modeling capacity of this neural network. In Multilayer perceptron algorithm we kept the same learning parameters, i.e., learning rate, momentum and the same number of hidden layers and used gradient descent back propagation algorithm.

Bagging

Bagging performs better on the unstable base classifier, where minor changes in the training set can lead to major changes in the classifier output. A multilayer perceptron is an example of the unstable classifier. The bagging algorithm with 10 iterations/bags was also evaluated using 10 fold cross validation technique. So for each iteration/bags, 10 Multilayer perceptron classifiers were trained and combined. Following the 10 iterations, bagging algorithm picks the winner Label.

The bagging MLP model development is shown in figure 47 and as it can be seen in figure 46 we used 10 iteration for bagging algorithm and we used 10 fold cross validation, which means for each bag 10 MLP classifiers were trained and combined using averaging. Finally for classification majority voting is done for all 10 bags and the model is selected. Figure 48 shows Multilayer Perceptron for Bagging network.

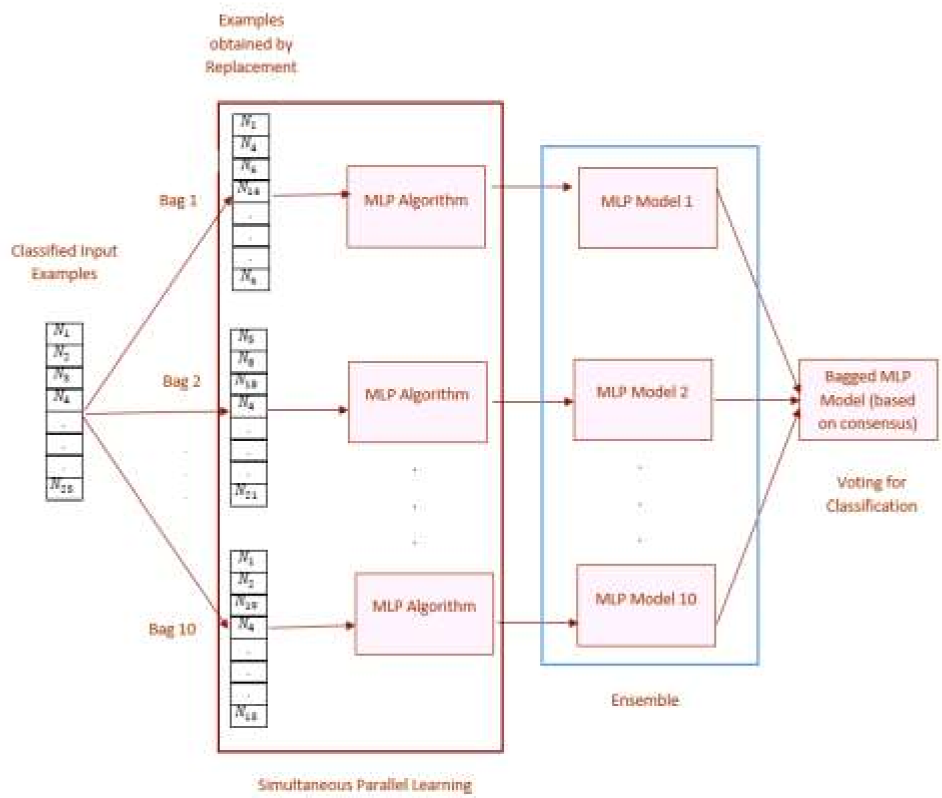


Figure 46 Bagging algorithm

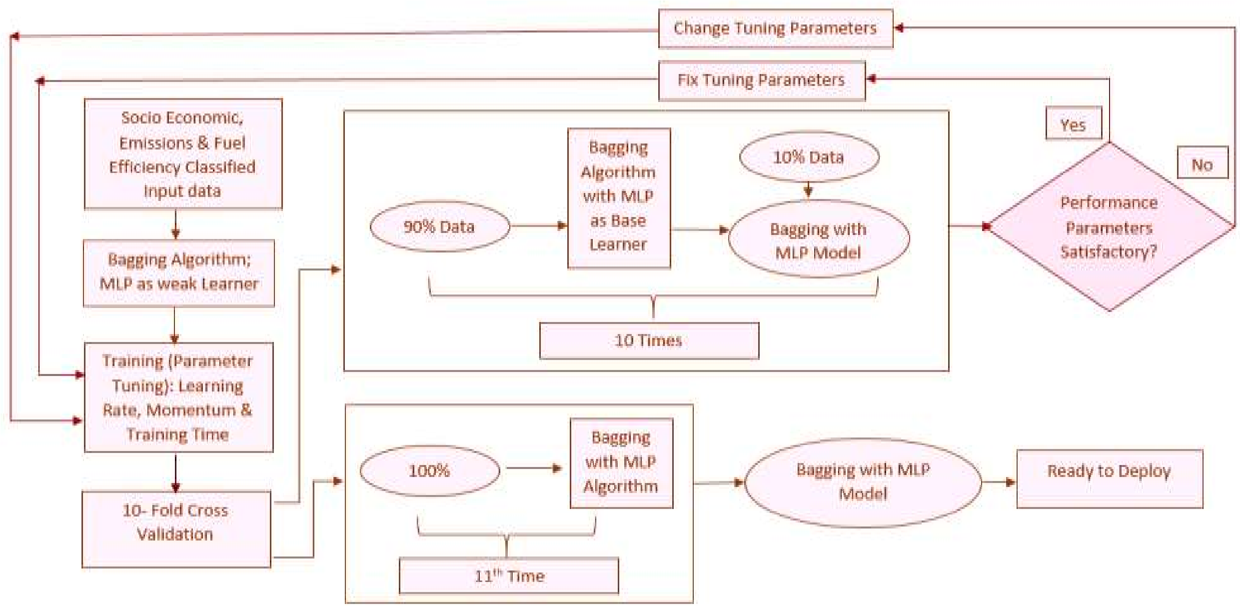


Figure 47 Bagging with MLP Model development for Nominal data

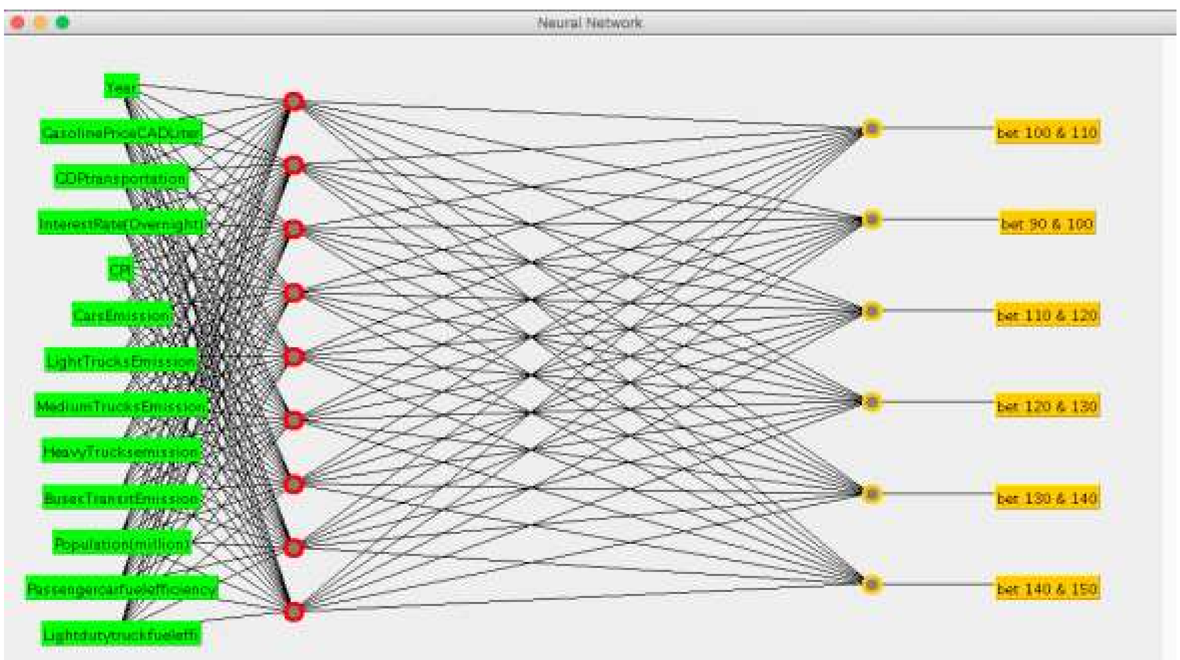


Figure 48. Multilayer Perceptron for Bagging

Cross-validation Summary

Correctly Classified Instances	16	66.6667 %
Incorrectly Classified Instances	8	33.3333 %
Kappa statistic	0.5906	

Mean absolute error 0.1331

Root mean squared error 0.2562

Total Number of Instances 24

Detailed Accuracy by Class

Table 16. Bagging Detailed Accuracy by Class

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0	0.048	0	0	0	0.873	bet 100 & 110
	0.5	0.091	0.333	0.5	0.4	0.955	bet 90 & 100
	1	0.1	0.667	1	0.8	0.975	bet 110 & 120
	0.5	0.05	0.667	0.5	0.571	0.963	bet 120 & 130
	0.714	0.059	0.833	0.714	0.769	0.966	bet 130 & 140
	1	0.05	0.8	1	0.889	0.975	bet 140 & 150
Weighted Avg.	0.667	0.064	0.626	0.667	0.634	0.956	

Confusion Matrix

Table 17. Bagging Confusion Matrix

<table>
<tr><th>a</th><th>b</th><th>c</th><th>d</th><th>e</th><th>f</th><th><-- classified as</th></tr>
<tr><td>0</td><td>2</td><td>1</td><td>0</td><td>0</td><td>0</td><td>| a = bet 100 & 110</td></tr>
<tr><td>1</td><td>1</td><td>0</td><td>0</td><td>0</td><td>0</td><td>| b = bet 90 & 100</td></tr>
<tr><td>0</td><td>0</td><td>4</td><td>0</td><td>0</td><td>0</td><td>| c = bet 110 & 120</td></tr>
<tr><td>0</td><td>0</td><td>1</td><td>2</td><td>1</td><td>0</td><td>| d = bet 120 & 130</td></tr>
<tr><td>0</td><td>0</td><td>0</td><td>1</td><td>5</td><td>1</td><td>| e = bet 130 & 140</td></tr>
<tr><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td><td>4</td><td>| f = bet 140 & 150</td></tr>
</table>

As per the confusion matrix given in Table 17, the following were the classifications given by Bagged Multilayer Perceptron classifier:

- Out of 3 actual instances which belong to class “bet 100 & 110”, the classifier correctly predicted 2 instances and incorrectly predicted other instance as belonging to the class “bet 110 & 120”.
- Out of 2 actual instances which belong to class “bet 90 & 100”, the classifier correctly predicted 1 instance and incorrectly predicted other instance as belonging to the class “bet 100 & 110”.

- Out of 4 actual instances which belong to class “bet 110 & 120”, the classifier correctly predicted all 4 instances.
- Out of 4 actual instances which belong to class “bet 120 & 130”, the classifier correctly predicted 2 instances and predicted the other two instances belong to class “bet 110 & 120” and to class “bet 130 & 140” respectively.
- Out of 7 actual instances which belong to class “bet 130 & 140”, the classifier correctly predicted 5 instances and the other two instances belong to class “bet 120 & 130” and to class “bet 140 & 150” respectively.
- Out of 4 actual instances which belong to class “bet 140 & 150”, the classifier correctly predicted all 4 instances.

Boosting

The boosting algorithm with 10 iterations was also evaluated using 10 fold cross validation technique. The boosting algorithm invokes Weak Learner (base algorithm) repeatedly in a series of rounds. The summary discusses the results of Boosting algorithm. The Boosting MLP model

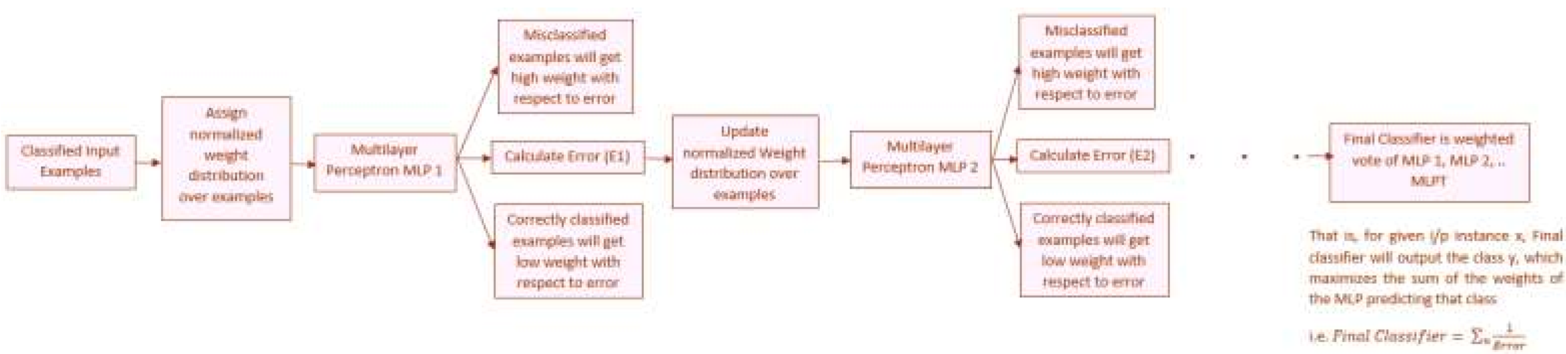


Figure 49 Boosting algorithm

development is shown in figure 50 and as it can be seen in figure 49 we used 10 iteration for bagging algorithm and we used 10 fold cross validation, which means for each boosting iteration 10 MLP classifiers were trained and combined using averaging. Finally for classification majority voting is done for all 10 bags and the model is selected. That is for a given input *x*, final classifier will output the class *y*, which maximizes the sum of weights of MLP predicting that class. Figure 51 shows Multilayer Perceptron with Boosting network.

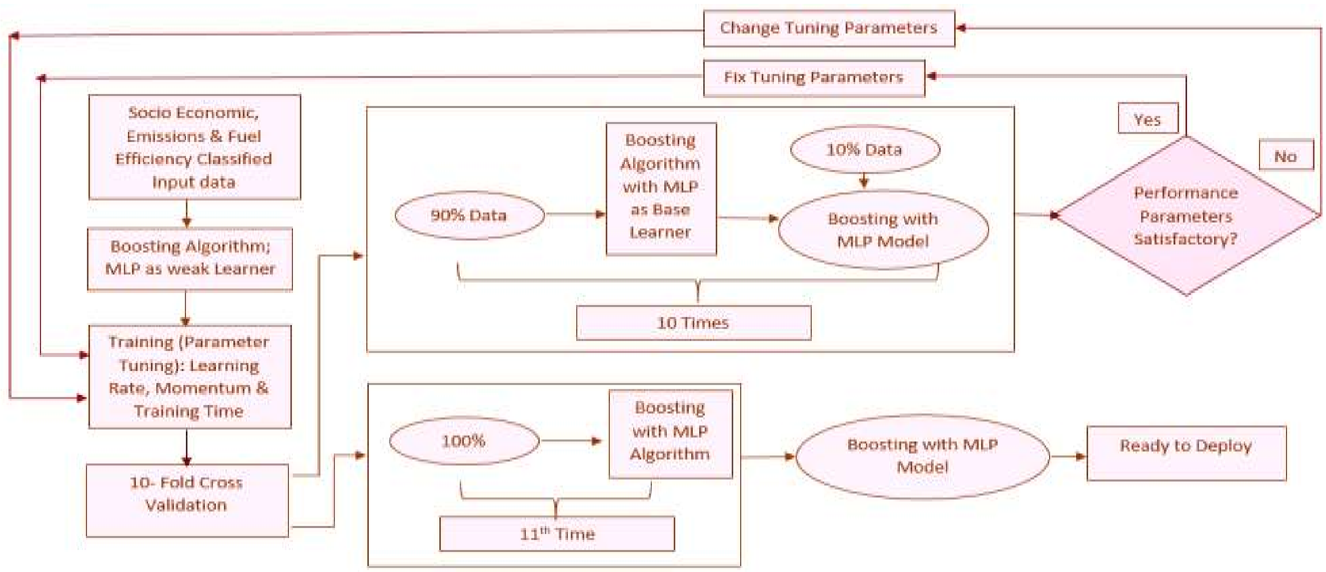


Figure 50 Boosting with MLP Model development for Nominal data

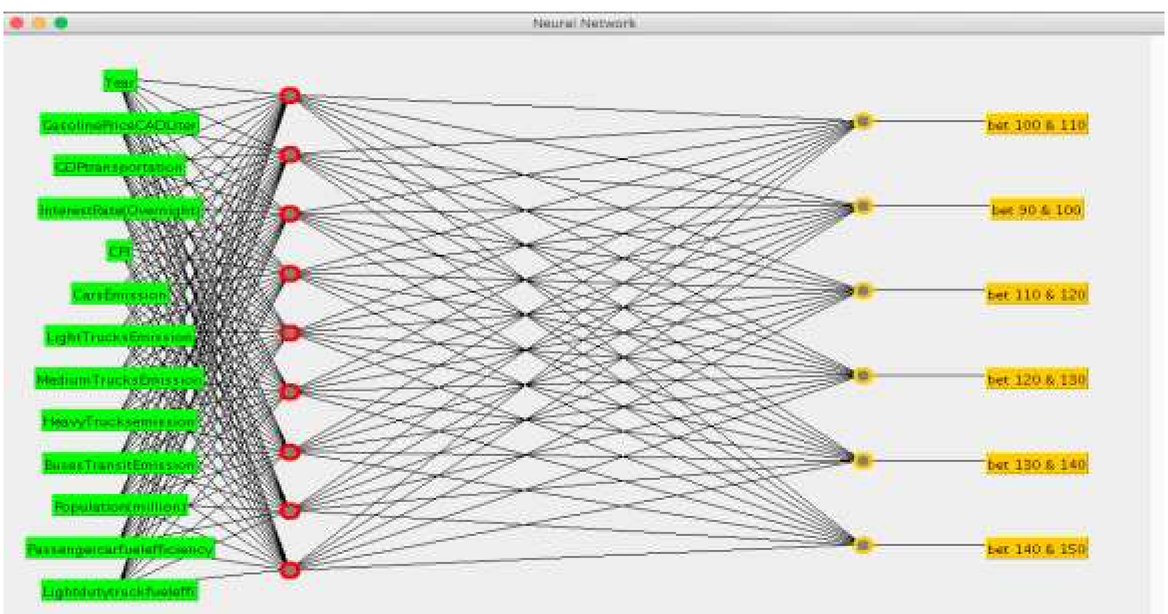


Figure 51. Multilayer Perceptron Model for Boosting

Cross-validation Summary

Correctly Classified Instances 18 75 %

Incorrectly Classified Instances 6 25 %

Kappa statistic 0.693

Mean absolute error 0.103

Root mean squared error 0.2302

Total Number of Instances 24

Detailed Accuracy by Class

Table 18. Boosting Detailed Accuracy by Class

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.333	0	1	0.333	0.5	0.921	bet 100 & 110
	1	0.045	0.667	1	0.8	0.977	bet 90 & 100
	1	0.1	0.667	1	0.8	0.925	bet 110 & 120
	0.5	0.05	0.667	0.5	0.571	0.963	bet 120 & 130
	0.714	0.059	0.833	0.714	0.769	0.966	bet 130 & 140
	1	0.05	0.8	1	0.889	0.988	bet 140 & 150
Weighted Avg.	0.75	0.054	0.779	0.75	0.73	0.958	

Confusion Matrix

Table 19. Boosting Confusion Matrix

a	b	c	d	e	f	<-- classified as
1	1	1	0	0	0	| a = bet 100 & 110
0	2	0	0	0	0	| b = bet 90 & 100
0	0	4	0	0	0	| c = bet 110 & 120
0	0	1	2	1	0	| d = bet 120 & 130
0	0	0	1	5	1	| e = bet 130 & 140
0	0	0	0	0	4	| f = bet 140 & 150

As per the above confusion matrix in table 19, the following were the classifications given by Boosted Multilayer Perceptron classifier:

- Out of 3 actual instances which belong to class “bet 100 & 110”, the classifier correctly predicted 1 instance and incorrectly predicted other two instances as belonging to the class “bet 100 & 110” and “bet 110 & 120” respectively.
- Out of 2 actual instances which belong to class “bet 90 & 100”, the classifier correctly predicted all 2 instances.
- Out of 4 actual instances which belong to class “bet 110 & 120”, the classifier correctly predicted all 4 instances.
- Out of 4 actual instances which belong to class “bet 120 & 130”, the classifier correctly predicted 2 instances and predicted the other two instances belong to class “bet 110 & 120” and to class “bet 130 & 140” respectively.
- Out of 7 actual instances which belong to class “bet 130 & 140”, the classifier correctly predicted 5 instances and the other two instances belong to class “bet 120 & 130” and to class “bet 140 & 150” respectively.
- Out of 4 actual instances which belong to class “bet 140 & 150”, the classifier correctly predicted all 4 instances.

4.8.2 Results & comparison of Algorithm Improvement on Nominal Data

Table 20. Results of Algorithm Improvement

Performance Evaluation Metric	Multilayer Perceptron	Multilayer Perceptron Bagging	Multilayer Perceptron Boosting
Root mean squared error	0.2676	0.2562	0.2302
Mean absolute error	0.1236	0.1331	0.103
Kappa statistic	0.5375	0.5906	0.693
Wt. Avg. ROC Area	0.935	0.956	0.958
Wt. Avg. F-measure	0.6	0.634	0.73
Accuracy	62.5%	66.66%	75%

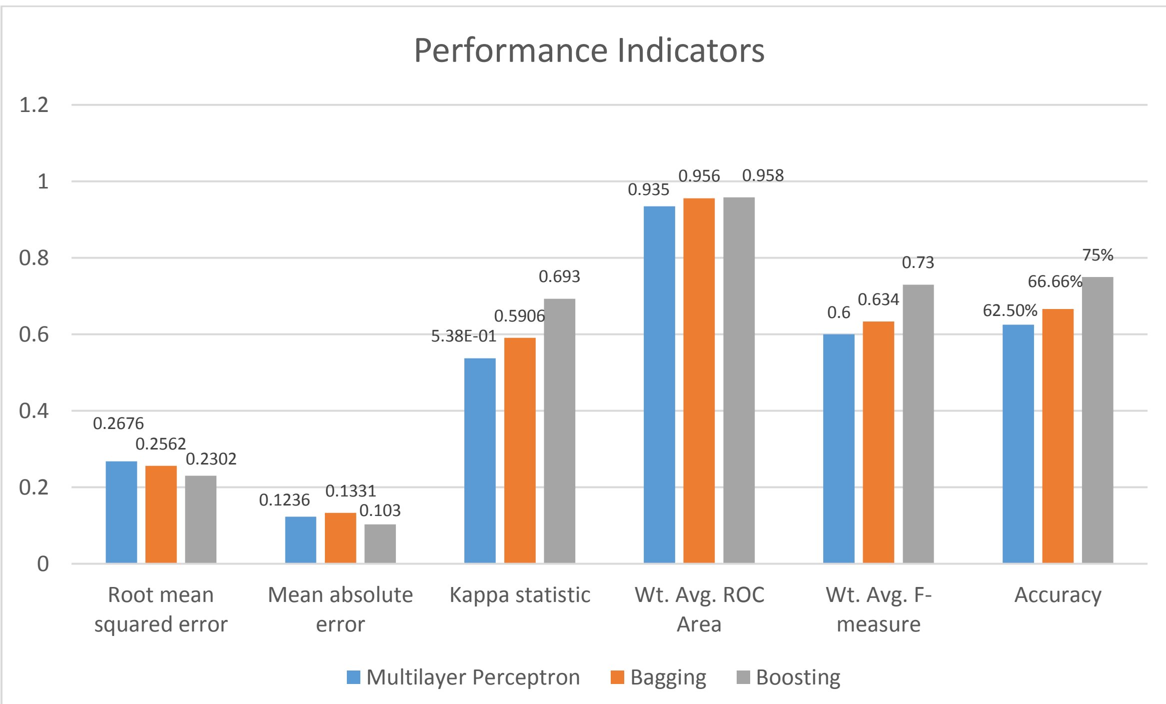


Figure 52 Performance Indicators of Algorithms on Nominal Data

Figure 52 shows Performance Indicators of Algorithms on nominal data, the model developed by Multilayer Perceptron with Boosting algorithm outperforms the models developed by Multilayer Perceptron and Multilayer Perceptron with Bagging for nominal data. In Multilayer perceptron algorithm we kept the same learning parameters, i.e., learning rate, momentum and the same number of hidden layers and used gradient descent back propagation.

4.9 Neural Network modeling & Sensitivity Analysis on Numerical Data

We used IBM SPSS software to conduct independent variable importance analysis on the numerical data for GHG emissions by road transport.

Using the positive ranked variables given by Relief algorithm we modeled a neural network (Multilayer Perceptron) with back propagation (gradient descent) algorithm and sigmoid activation function. The data was divided into a training set (66%) and test set (34%). The best predictive model was observed with one hidden layer, learning rate 0.4 with a momentum of 0.3.

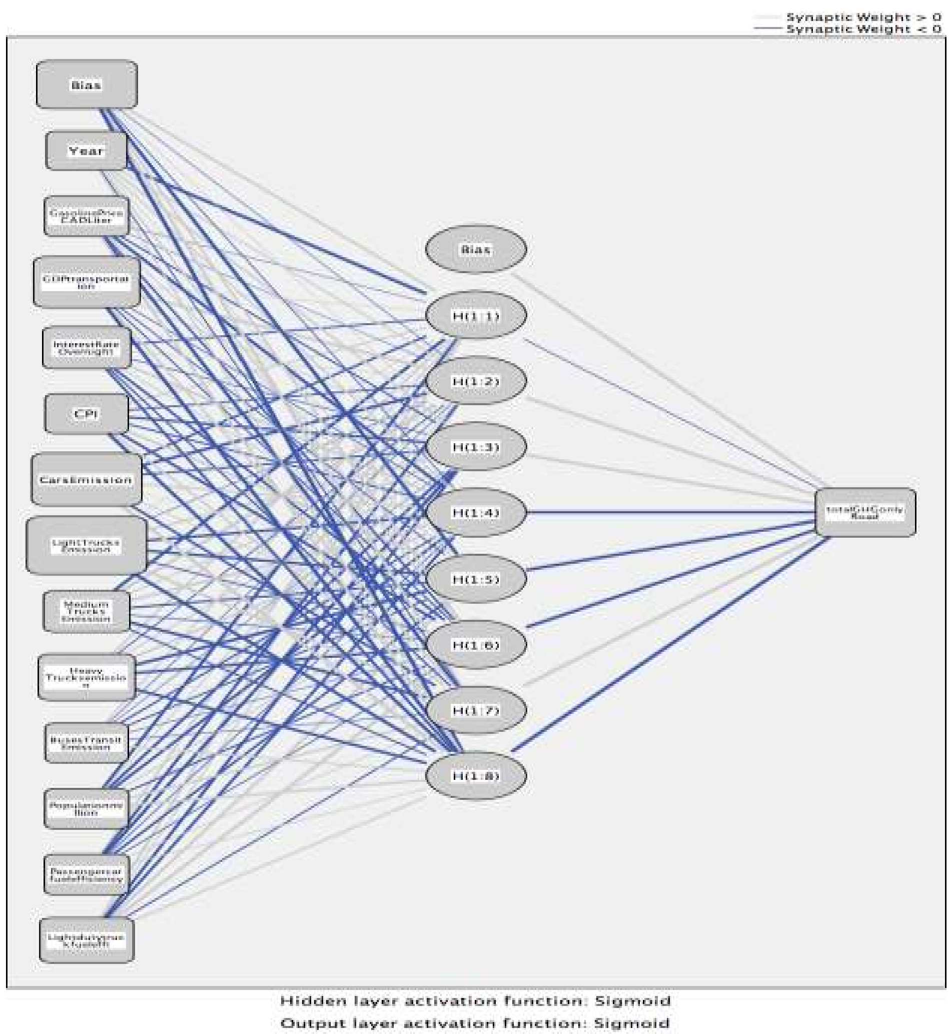


Figure 53. MLP Model for Numeric GHG Emission Values developed in SPSS

Network Information

Table 21.SPSS Network Information

Input Layer	Covariates	1	Year
		2	GasolinePriceCADLiter
		3	GDPtransportation
		4	InterestRateOvernight
		5	CPI
		6	CarsEmission
		7	LightTrucksEmission
		8	MediumTrucksEmission
		9	HeavyTrucksemission
		10	BusesTransitEmission
		11	Populationmillion
		12	Passengercarfuelefficien cy
		13	Lightdutytruckfueleffi
	Number of Units[a]		13
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		8
	Activation Function		Sigmoid
Output Layer	Dependent Variables	1	totalGHGonlyRoad
	Number of Units		1
	Rescaling Method for Scale Dependents		Normalized
	Activation Function		Sigmoid
	Error Function		Sum of Squares

a. Excluding the bias unit

Model Summary

Table 22. Summary of Model Developed in SPSS

Training	Sum of Squares Error	.016
	Relative Error	.023
	Stopping Rule Used	1 consecutive step(s) with no decrease in error
	Training Time	0:00:00.00
Testing	Sum of Squares Error	.012
	Relative Error	.027

Dependent Variable: totalGHGonlyRoad

a. Error computations are based on the testing sample.

As can be seen from the model summary the Sum of Square error for testing is 0.012 which is close to zero, and the value of Correlation coefficient (R square) as shown in figure 54 is 0.979 which is close to 1 indicating a good performing Multilayer Perceptron model given by SPSS.

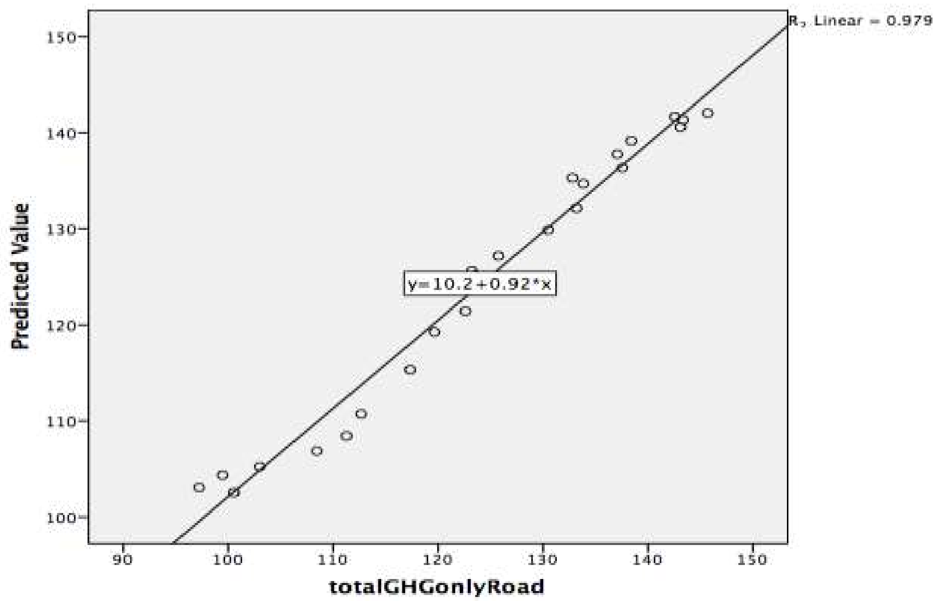


Figure 54. SPSS Predicted GHG Emission Regression line

4.9.1 Independent Variable Importance Analysis

Sensitivity analysis computes the importance of each predictor attribute in determining the neural network. Sensitivity analysis helps in understanding the relationship between input and output and aids in testing the robustness of the developed Multilayer perceptron model.

As per the Literature from IBM SPSS Knowledge center, in this analysis, both data samples (training & testing) or only training samples, in case of absence of the testing sample, are/is used. SPSS gives out a table and a chart displaying importance and normalized importance for each predictor.

Normalized importance is measured by dividing importance values by the largest importance values and expressed it as percentages.

Independent Variable Importance

Table 23. Independent Variable Importance

Parameters	Importance	Normalized Importance
Year	0.004	1.70%
GasolinePriceCADLiter	0.027	10.70%
GDPtransportation	0.163	65.70%
InterestRateOvernight	0.05	20.10%
CPI	0.02	7.90%
CarsEmission	0.187	75.20%
LightTrucksEmission	0.249	100.00%
MediumTrucksEmission	0.038	15.30%
HeavyTrucksemission	0.105	42.10%
BusesTransitEmission	0.019	7.50%
Populationmillion	0.025	10.00%
Passengercarfuelefficiency	0.029	11.80%
Lightdutytruckfueleffi	0.085	34.10%

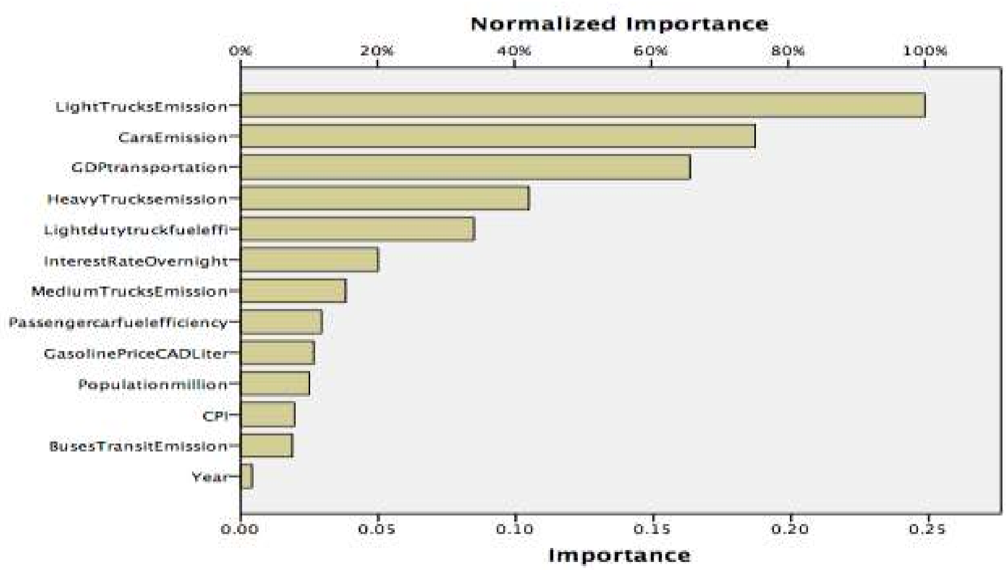


Figure 55MLP Attribute Normalized Importance

Figure 55 disclose the results of independent variable importance analysis. The attributes Light truck emissions, Car emissions, GDP transportation, Heavy truck emission, Light duty truck fuel efficiency, Interest rate (over night), Medium Trucks Emission, Passenger car fuel efficiency and

Gasoline Price has higher sensitivity for the Multilayer perceptron predictive model of GHG emissions by road transport respectively.

Phase 3: Canada GHG emissions scenario analysis

4.10 GHG Emission Future Projections and Scenario Analysis

From the results of section 4.7.2 Algorithm application on GHG emission by road transport numeric data, it was found that Multilayer Perceptron with Bagging model performs better compared to Multiple Linear Regression and Multilayer perceptron. In this section, we projected the numeric GHG emission values by road transport till the year 2030 using Multilayer Perceptron with bagging model.

We Designed three different scenarios namely Business as usual (BAU), Minimum mitigation emission scenario and Maximum emission mitigation scenario, with an **optimistic belief of reduction in GHG emissions in future**, using the historical data of socioeconomic, emission and fuel efficiency as input data. The model's predictions were analyzed and plotted along with the target projection of 2030 for Canadian Road transport emissions.

According to Canada's 2016 greenhouse gas emissions Reference Case (Government of Canada, Environment and Climate Change Canada 2017) which presents the future impacts of policies and measures taken by federal, provincial and territorial governments as of November 1st, 2016, the projected 2030 value for emissions from over all transportation (Road, Air and Marine) is 5.4% below than 2014 emission values. As we are focusing on emissions by Road transportation in our thesis, we utilized the same negative 5.4% of 144.96 Mt Co2 eq. (Emission by road transportation value in 2014). Hence, the 2030 projection for emissions from Road Transport is estimated as 137.13 Mt Co2 eq.

The results of Independent variable importance/sensitivity analysis of Multilayer perceptron model from the section 4.7.1, indicates that the Light truck emissions, Car emissions, GDP transportation, Heavy truck emission, Light duty truck fuel efficiency, Interest rate (overnight), Medium Trucks Emission, Passenger car fuel efficiency and Gasoline Price has higher sensitivity for the predictive modeling of numeric GHG emission values by road transport. Hence, the assumption of the values for this attributes will play an important role in scenario analysis.

4.11 Scenario Analysis

Significant potential of GHG emission reduction endures in Road transportation sector by introducing various policy measures and technological improvement. The key drivers of GHG emissions by road transport are the emissions from freight and passenger transport, which are subjected to Economic (GDP) growth, Fuel price and Fuel efficiencies (Government of Canada, Environment and Climate Change Canada 2017). For Future projection of GHG till 2030 by road transportation, we developed one Business As Usual (BAU) scenario and two Low emission scenarios M1 and M2.

Under BAU scenario we assumed historic trend of attributes and the impact of current mitigation policies and technological trend for projecting GHG emissions. On the other hand for Low emission scenario, aggressive measures are assumed for optimistic mitigation of GHG emissions. In scenario analysis, we considered different realistic rates of the year over year percentage change in input attributes. The average rate of technological improvement in terms of fuel efficiencies (the year over year) percentage change from 2014 is assumed to be 1%, 2% & 3% for BAU, M1, and M2 respectively. According to oil price forecast (Knoema 2017), the equivalent gasoline price is expected to rise between 2% to 2.5% yearly with respect to 2014 till 2030. Hence, the average year over year rate of growth in Gasoline price from 2014 as a base reference is assumed 2%, 2.3% and 2.5% for BAU, M1, and M2 respectively. According to Canada's 2016 greenhouse gas emissions Reference Case (Government of Canada, Environment and Climate Change Canada 2017) faster the GDP growth (economic growth) rate, higher is the GHG emission contribution. We assumed slower GDP and CPI growth rates, i.e., 2.5%, 1.8% and 1.4% for BAU, M1, and M2 respectively for GDP and 1.9%, 1.7% and 1.4% for CPI. Additionally, for each different scenario, the percentage year over year change for vehicles emission values are roughly quantified in such a way to reflect impact of historical data trend, policies and technological improvement resonating with the assumptions of that scenario. Further, we assumed higher interest rate growth rate Positive 3%, 5% & 7% for BAU, M1 & M2 scenarios.

Table 24 represents different scenarios and average year over year percentage change assumed for input attributes. The rationale behind different rate assumptions will be discussed in following sections.

Table 24 GHG Projection Scenarios assumptions & Avg. Year over Year % change

Scenario	**Inputs**	**2015-2020 (2014 base reference)**	**2020-2025 (2019 base reference)**	**2025-2030 (2024 base reference)**	**Avg. Year over year change**
BAU	Passenger car fuel Efficiency	-0.5%	-1%	-1.5%	- 1%
	Light duty truck fuel efficiency	-0.5%	- 1%	-1.5%	-1%
	Car Emission	-0.5	- 1	- 1.5%	-1%
	Light Trucks Emission	+ 1.5%	+ 0.5%	- 0.2%	+ 0.7%
	Medium Trucks Emission	+ 5%	+ 4%	- 0.5%	+ 2.8%
	Heavy Trucks emission	+ 4%	+ 3%	-1%	+ 2%
	Buses & Transit Emission	+ 3.5%	+ 2.5%	- 0.5%	+ 1.8%
	GDP transportation	+ 2.5%	+ 2.5%	+ 2.5%	+ 2.5%
	Interest Rate (Overnight)	BOC	+ 3% BOC (2020)	+ 3%	+ 3%

	Gasoline Price CAD Liter	+ 1%	+ 2%	+ 3%	+ 2%
	CPI	+ 1.9%	+ 1.9%	+ 1.9%	+ 1.9%
	Population (million)	+ 1.01%	+ 1.01%	+ 1.01%	+ 1.01%
M1	Passenger car fuel Efficiency	- 1%	-2%	-3%	- 2%
	Light duty truck fuel efficiency	- 1%	- 2%	- 3%	- 2%
	Car Emission	-1%	- 2%	- 3%	- 2%
	Light Trucks Emission	+ 0.75%	+ 0.25%	-0.1%	+ 0.3%
	Medium Trucks Emission	+ 2.5%	+ 2%	- 0.25%	+ 1.4%
	Heavy Trucks emission	+ 2%	+ 1.5%	-0.5%	+ 1%
	Buses & Transit Emission	+ 1.75%	+ 1.25%	- 0.25%	+ 0.9%
	GDP transportation	+ 1.8%	+ 1.8%	+ 1.8%	+ 1.8%
	Interest Rate (Overnight)	BOC	+ 5% BOC (2020)	+ 5%	+ 5%
	Gasoline Price CAD Liter	+ 1.3%	+ 2.3%	+ 3.3%	+ 2.3%
	CPI	+ 1.7%	+ 1.7%	+ 1.7%	+ 1.7%
	Population (million)	+ 1.01%	+ 1.01%	+ 1.01%	BAU
M2	Passenger car fuel Efficiency	- 2%	-3%	- 4%	- 3%
	Light duty truck fuel efficiency	- 2%	- 3%	- 4%	- 3%
	Car Emission	- 2%	- 3%	- 4%	- 3%
	Light Trucks Emission	+ 0.7%	+ 0.1%	- 2%	- 0.4%
	Medium Trucks Emission	+ 2%	+ 0.5%	- 3%	- 0.15%
	Heavy Trucks emission	+ 2%	+ 0.5%	-3%	-0.15%
	Buses & Transit Emission	+ 1%	+ 0.5%	-2%	-0.15%
	GDP transportation	+ 1.4%	+ 1.4%	+ 1.4%	+ 1.4%
	Interest Rate (Overnight)	BOC	+ 7% BOC (2020)	+ 7%	+ 7%
	Gasoline Price CAD Liter	+ 1.5%	+ 3%	+ 3%	+ 2.5%
	CPI	+ 1.4%	+ 1.4%	+ 1.4%	+ 1.4%
	Population (million)	+ 1.01%	+ 1.01%	+ 1.01%	BAU

Future output projections from different scenarios will be analyzed, and impact from each mitigation scenario on total GHG emissions by road transport will be assessed. Further, mitigation policies will be discussed in Scenario analysis results.

4.11.1 Business as Usual Scenario (BAU)

Under BAU scenarios the future projections till the year 2030 are based on historical data trend and the impact of current trends of technology and policies. In BAU scenario we assumed the minimal impact of carbon pricing adopted by British Columbia and cap and trade policy adopted by Quebec (2012) recently adopted by Ontario (2016). Although these policies along with current technological improvement alone will not have enough impact to meet 2030 target projection of GHG emissions by road transport (137.13 Mt Co2 eq.) we assume as a result of current technological improvement and carbon pricing policies after the year 2024 a small declining trend of 0.2%, 0.5%, and 1% will be observed in emissions from Light Trucks, Medium Trucks, and Heavy Trucks respectively. Referring to BAU scenario in table 24 Emissions from cars will have a steady decline of average 1% year over year from 2014 till 2030. Additionally, with reference to Bank of Canada 2020 Interest rate projection (Trading Economics 2017). We assumed a 3% year over year increase in interest rate from 2020 to 2030, i.e., 35% increase with respect to 2020. GDP will grow at rate of average 2.5%, and CPI will grow at a rate of average 1.9% year over year from 2014 to 2030, i.e., increase by 52% and 29.2% with respect to 2014 levels. The fuel efficiencies for Cars and Light duty trucks will improve by average 1% year over year from 2014 to 2030, i.e., 15.2% with respect to 2014 level. The Gasoline price will increase by average 2% year over year from 2014 to 2030, i.e., 38.2% with respect to 2014 level.

In summary under BAU scenario, the following were the assumptions considered for 2030 projections:

- Economic growth will be higher, i.e., GDP will increase by 52%, and CPI will increase by 29.2% with respect to 2014 levels

- Fuel efficiency will improve by 15.2% from 2014
- Gasoline price will increase by 38.2%
- Interest rate will increase by 35% after 2020
- Emissions from Light, Medium & Heavy truck will increase by 9%, 50% & 32.7% respectively and emissions from cars will decline by 15.2% with respect to 2014 level.
- The population will increase by 15.2% with respect to 2016.

The attribute values obtained from BAU was used to obtain the projections of GHG emission by road transport till the year 2030 using Multilayer Perceptron with Bagging model. BAU Scenario projections are given in appendix K.

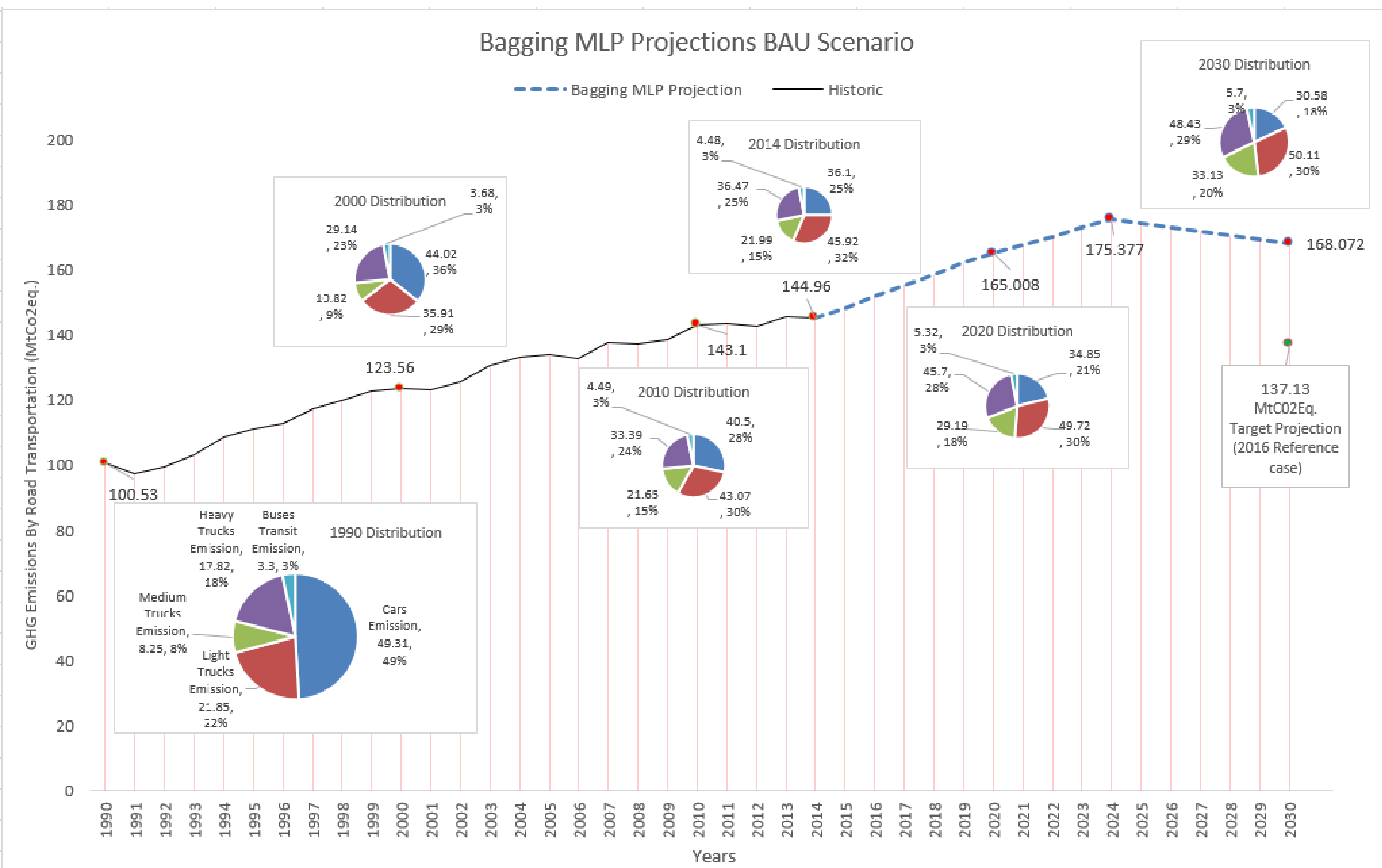


Figure 56 BAU Scenario GHG Projections & Yearly GHG Distribution till 2030

Figure 56 presents GHG emissions by road transport projected till the year 2030 under Business As Usual scenario. Few highlights from figure 46 are mentioned below:

1. Total GHG Emissions will increase by 16% with respect to 2014 level, i.e., from 144.96 Mt Co2 eq. (2014) reaching to **168.07 Mt Co2eq.** by the year 2030.
2. GHG emissions will appear to reach the highest peak value of 175.37 MtCo2Eq.in the year 2024 which is approximately 21% with respect to 2014 level.
3. Under BAU scenario the 2030 projection seems very ambitious. Between target projection 137.13 MtCo2eq. And projections given by the model for BAU scenario for the year 2030, there is a difference of 30.94 Mt Co2 eq.
4. Emissions from Light trucks hold a major share of GHG emissions all the way through 2030. The percentage share will decrease slightly over the years from 32% in 2014 to 30% in 2030. The share of emissions from cars will decrease by from 25% in 2014 to 18% in 2030.
5. On the contrary, emission share of Medium trucks will increase from 15% in 2014 to 20% in 2030 and emission share of Heavy trucks will increase from 25% 2014 to 29% in 2030 respectively.

4.11.2 Low Emission Scenarios

In low emission scenario considering the uncertainty in key factors of GHG emissions, we considered different scenarios of all input factors with potential mitigation measures implemented. As the future technological developments, economic growth and Fuel prices do not hold certainty, in low emission scenarios we assumed aggressive measures for a year over year rates in progression on available input. We designed two mitigation measure scenarios Minimum

Mitigation scenario (M1), and Maximum Mitigation scenario (M2), each of these scenarios, will represent the different extent of mitigation measures, M2 representing the maximum mitigation measures implemented on the inputs as shown in table 24.

Minimum mitigation scenario (M1)

In minimum mitigation scenario, the future projections are based on historical data and the potential average impact of new technological improvement and policies. As it can be seen in table 24 regarding technological improvement and carbon pricing policies, we considered the improvement to be twice as of BAU scenario and further assumed that the impact of technological improvement (including fuel efficiencies improvement) and policy measures will penetrate deeper after the year 2024.

The fuel efficiency for cars and Light Trucks will improve by 2% average year over year from 2014, i.e., 27.6% & 28% respectively. Along with the average impact of carbon pricing adopted by British Columbia and cap and trade policy adopted by Quebec (2012) recently adopted by Ontario (2016), Under M1 scenario we assumed, steady increase in economic growth, positive 1.8% and positive 1.7% average year over year from 2014 i.e. 37.5% & 24.15% for GDP and CPI respectively, steady 2.3% average year over year from 2014 increase in Gasoline price i.e. 45.3% with respect to 2014 level and average 5% year over year increase in interest rate i.e. 65% from 2020 level, emissions from cars will decline steadily by 2% average year over year with respect to 2014 and average year over year change with respect to 2014 for Light, Medium & Heavy Trucks emissions will be reduced by half as compared to BAU scenario, i.e., positive 0.3%, positive 1.4%, and positive 1% respectively.

In summary under the M1 scenario, the following were the assumptions considered for 2030 projections:

1. The impact of technological improvement and carbon pricing is considered to be twice as of BAU scenario and penetration of impact will be deeper after the year 2024
2. Economic growth will be slower in comparison with BAU scenario, i.e., GDP will increase by 37.5%, and CPI will increase by 24.15% with respect to 2014 levels.
3. Fuel efficiency will improve by on an average 28% from 2014 (almost twice of BAU)
4. Gasoline price will increase by 45.3%
5. Interest rate will increase by 65% after 2020
6. Emissions from Light, Medium & Heavy truck will increase by 4.4%, 23% & 15.4% respectively and emissions from cars will decline by 28.3% with respect to 2014 level.
7. The population will increase by 15.2% with respect to 2016.

The attribute values obtained from M1 was used to obtain the projections of GHG emission by road transport till the year 2030 using Multilayer Perceptron with Bagging model. M1 Scenario projections are given in appendix L.

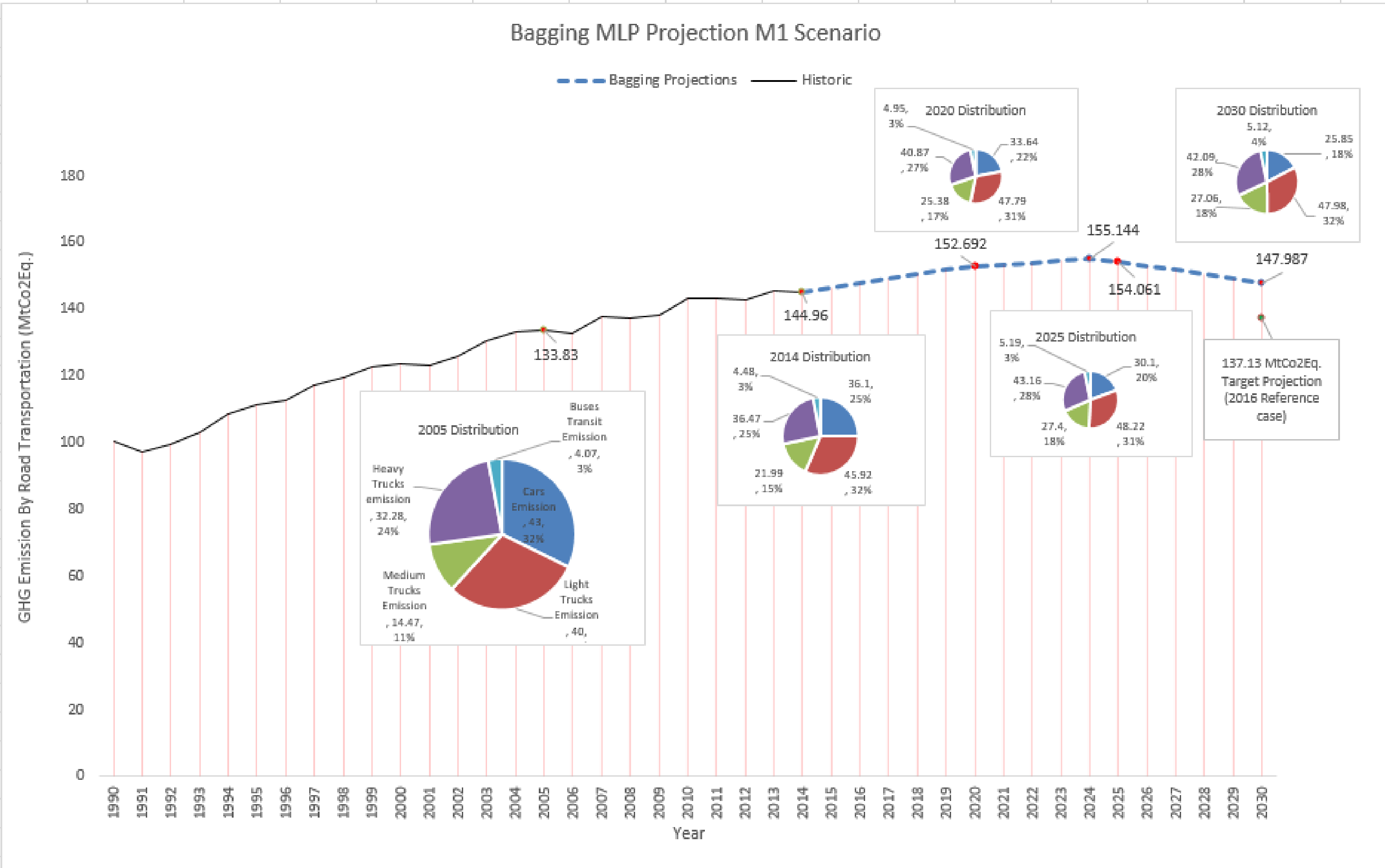


Figure 57 M1 Scenario GHG Projections & Yearly GHG Distribution till 2030

Figure 57 presents GHG emissions by road transport projected till the year 2030 under Minimum Mitigation scenario (M1). Few highlights from figure 47 are summarized below:

1. The emissions from road transportation will slightly increase by 2.08% with respect to 2014 level, i.e., from 144.96 Mt Co2 eq. (2014) reaching to **147.98 Mt Co2 eq.** By the year 2030.
2. Under the M1 scenario, GHG emissions by road transport tend to decline more after attaining its peak value of 155.144 Mt Co2 eq. in 2024 which is 7% higher with respect to 2014 level.

3. The projections given by the M1 scenario for the year 2030 still falls short to meet the target projection 137.13 MtCo2eq. (2016 reference case). To meet the targets, the GHG emission given by M1 scenario should be reduced by 10.85 Mt Co2 eq.
4. Under the M1 scenario, emissions from Light trucks hold a major share of GHG emissions all the way through 2030 Similarly, the share of emissions from cars will decrease from 25% in 2014 to 18% in 2030.
5. The emission share of Medium trucks will increase from 15% in 2014 to 18% in 2030 and emission share of Heavy trucks will increase from 25% 2014 to 28% in 2030 respectively.

Maximum Mitigation Scenario (M2)

Under Maximum mitigation scenario, we considered more aggressive potential possible measures for GHG emission mitigation by assuming along with historical data, the impact of Federal Governments Pan Canadian framework (adopted on December 9, 2016) which along with other endeavours also intends to develop Canada wide strategy for Zero emission by road vehicle (potentially to be in effect by the end of 2018) i.e. introduction of new fuel efficiency standards for passenger cars and specifically for Light, Medium and Heavy Trucks, technological improvement, investment towards zero emission vehicles, Investment in Public transit, Shifting from high to low emitting transportation modes, and a pricing carbon pollution which will build on existing provincial GHG mitigation policies and ensure a minimum price of $10 CAD per tonne in place across Canada by 2018, rising to $50 CAD per tonne by 2022 (Canada, S. 2016).

From Table 24 In terms of technological improvement we considered the improvement to be thrice as of BAU scenario and assumed that fuel efficiencies would improve almost three times

(40%) as BAU scenario with respect to 2014 & will penetrate more deeper after the year 2024 i.e. 4% year over year after 2024. Under the M2 scenario we assumed slower increase in economic growth i.e. positive 1.4% average year over year from 2014 i.e. 30.1% & 19.2% for GDP and CPI respectively, 2.5% average a year over year increase in Gasoline price (potential impact of Carbon pricing) i.e. 49.2% from 2014 and 7% year over year increase in interest rate i.e. 95% with respect to 2020, emissions from cars will decline steadily by 3% average year over year with respect to 2014.

Additionally, under the M2 scenario there will be a slower rate of year over year change in emissions from Light (positive 0.1), Medium and Heavy Truck (positive 0.5%) after year 2019 (potential impact of Canada wide carbon pricing) followed by declining trend in emissions after 2024 (potential impact of deeper improvement in technology). As a result, the average year over year change in emissions with respect to 2014 for Light trucks will be negative 0.4% and 0.15% for Medium & Heavy trucks.

In summary under the M2 scenario, the following were the assumptions considered for 2030 projections:

1. The impact of Pan Canadian Framework (potentially to be in effect by the end of 2018) along with provincial policies and technological improvement.
2. The impact of technological improvement and carbon pricing is considered to be thrice as of BAU scenario and penetration of impact will be deeper after the year 2024
3. Economic growth will be slower in comparison with M1 scenario, i.e., GDP will increase by 30.1%, and CPI will increase by 19.2% with respect to 2014 levels
4. Fuel efficiency will improve by on an average 40% from 2014

5. Gasoline price will increase by 49.2% (potential impact of Carbon pricing)

6. Interest rate will increase by 95% after 2020

7. Emissions from Light, Medium & Heavy truck will decrease by 7.8% 5.7% & 5.7% respectively, and emissions from cars will decline by 39.2% with respect to 2014 level.

8. The population will increase by 15.2% with respect to 2016.

The attribute values obtained from M2 scenario was used to obtain the projections of GHG emission by road transport till the year 2030 using Multilayer Perceptron with Bagging model. M2 Scenario projections are given in appendix M.

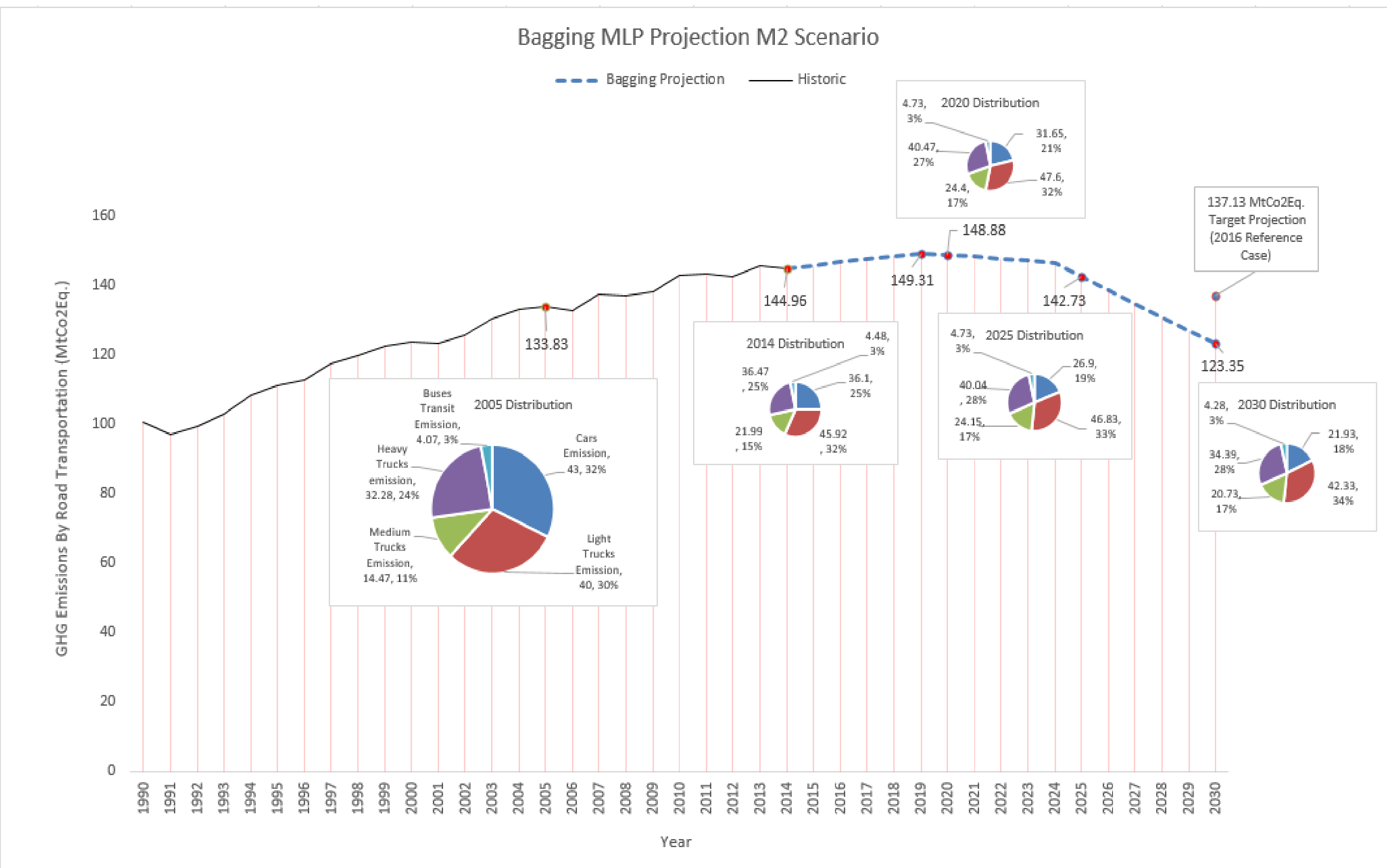


Figure 58 M2 Scenario GHG Projections & Yearly GHG Distribution till 2030

Figure 58 presents GHG emissions by road transport projected till the year 2030 under Maximum Mitigation scenario (M2). Few highlights from figure 48 are summarized below:

1. With the equivalent measures adopted, under the M2 scenario, the emissions from road transport will decrease by 14.9% with respect to 2014 level, i.e., from 144.96 Mt Co2 eq. (2014) reaching to **123.35 Mt Co2 eq**. by the year 2030.
2. Under the M2 scenario, GHG emissions from road transport are likely to decline more after attaining an early peak value of 149.31 Mt Co2 eq. in 2019 which is 3% higher with respect to 2014 level.
3. The ambitious target projection value of 137.13 MtCo2eq. (2016 reference case) is certain to be achieved under the M2 scenario. Further, the projections given by the M2 scenario for the year 2030 well pass beyond the target projection value of 137.13 MtCo2eq. and is projected to reach to 123.35 Mt Co2 eq**.** Which is 10% lower than 2016 target projection value, i.e., 137.13 Mt Co2 eq. and is 14.9% lower than 2014 level.
4. Emissions from Light trucks hold major share of GHG emissions all the way through 2030 Similarly, the share of emissions from cars will decrease from 25% in 2014 to 18% in 2030
5. The emission share of Medium trucks will increase from 15% in 2014 to 17% in 2030 and emission share of Heavy trucks will increase from 25% 2014 to 28% in 2030 respectively.

4.12 Discussion & Policy Implications

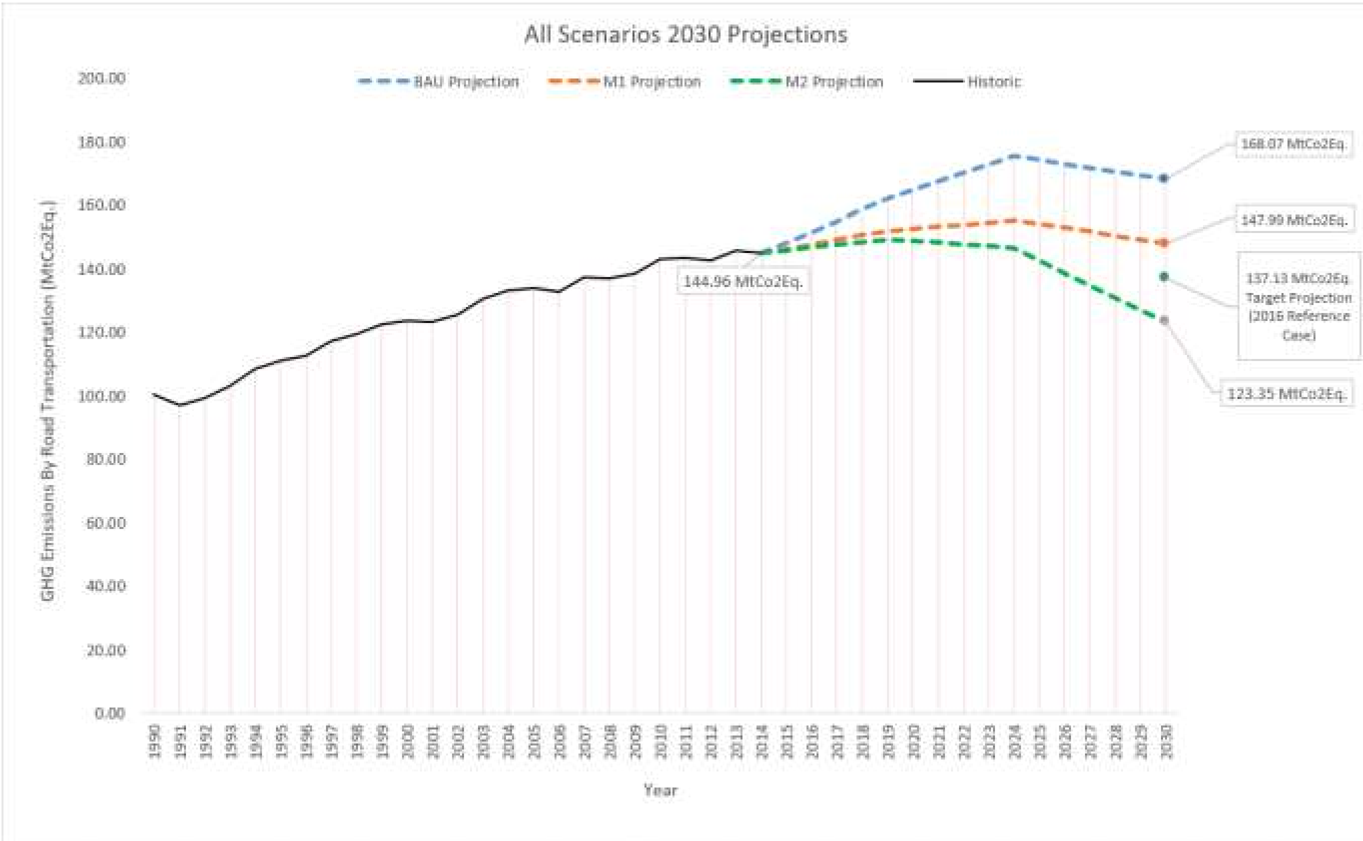


Figure 59 All Scenario Projections till 2030

Discussion:

Figure 59 represents the comparison of GHG emissions projections, given by Bagged Multilayer Perceptron model until the year 2030, caused by road transportation in Canada under BAU, M1 and M2 scenario along with Target projection as per 2016 Reference case (Appendix N). As can be seen with more mitigation measures implemented in incremental order for each scenario, the GHG emission projections will decline to a great degree. In the year 2030, the GHG emissions will range between 168.07 MtCo2Eq. To 123.35 MtCo2Eq. which is 15.9% above 2014 level and 14.9% below 2014 level. In comparison with BAU scenario, the GHG emissions in 2030 under M1 and the M2 scenario will reduce by 11.9% and 26.6% respectively.

We further observed, that emissions from passenger cars will continuously decline to different extents under different scenarios as a result of adoption of rigorous technological improvement (fuel efficiency improvement) and policies (Carbon Tax, Rebate on purchase of Hybrid and electric vehicles, constraining fuel vehicle ownership by increasing the interest rate for its purchase etc.) in place to mitigate the emissions. In general, the mitigation measures for Passenger cars are currently more abundant and likely to increase in future.

On the contrary, in all scenarios emissions from Light trucks (SUV's, Mini vans, etc.) holds a major share of GHG emissions followed by Heavy and Medium trucks all the way through 2030. This reflects the lack of mitigation measures in freight transport sector, and hence it will face more challenges, compared to passenger cars, to mitigate GHG emissions. This highlights the opportunity that policies focusing on mitigating GHG emissions from Light, Medium and Heavy Trucks should be given more focus and should be adopted.

Policy Implication:

Technological improvement in terms of fuel efficiencies and the introduction of low emission to zero emission vehicles are alone not enough to mitigate GHG emissions by road Transportation. The inclusion of robust and realistic policies and their serious adoptions by the provincial and federal government and their timely revisions are vital for effective mitigation of GHG emissions. For example referring to figure 13. In case of British Columbia, implementation of carbon tax helped to mitigate the GHG emissions after adoption of Climate Action plan in the year 2008 by the provincial government, a steady decrease in BC's emission trend from 63.9 (Mt Co2 eq.) in 2005 to 60.9 (Mt Co2 eq.) in 2015 is observed. The selection of which form of carbon taxing policy to be adopted should be open for debate and discussion by the provincial and federal government. Usually, it has been observed that the provincial economies relying on fossil fuel to meet their energy needs adopt Cap and trade and other prefer carbon pricing.

The projections given by Bagged Multilayer Perceptron model for Maximum mitigation Scenario (M2), confirms the potential impact of approaches outlined in Pan Canadian Framework in mitigating GHG emissions by road transport and will surpass the 2016 reference case target. The federal and provincial policy makers along with approaches outlined in Pan Canadian Framework should consider giving higher priority to the following actions mentioned below:

1. Improving Vehicle Emission standards including passenger cars and with a special focus on improving emissions from Light Trucks, Medium & Heavy Trucks.
2. Investment in Alternate fueled vehicle technologies like Electric vehicles, Natural gas, and Hydrogen fuel.
3. Rebates for Electric Vehicles purchase:

   Following the lead of Quebec (Quebec Government 2017), Ontario (Government of Ontario, Ministry of Transportation 2013) and British Columbia (BC Hydro 2016) in providing rebates up to $8000, $14000 & $5000 respectively on the purchase of Electric vehicle, the federal government should introduce some rebates encouraging the purchase of electric vehicles and also should provide incentives to encourage installation of charging stations.
4. Public transport:

   The Federal government should make more investment towards greening the public transport. Recently, STM (Société de transport de Montréal 2017) launched a pilot program by launching three electric buses in service.

5. Higher interest rate on ICE purchase:

   Policies focusing on charging higher interest rate should be adopted to limit the purchase of Internal Combustion Engine (ICE) vehicles.

6. Mode shift:

   Potential opportunities should be explored for the intermodal switch from Road transport to either Railway or Marine to mitigate GHG emissions from road freight transport.

4.13 Sensitivity Analysis of Model

To analyze the sensitivity of the model, we ran Multilayer Perceptron Bagging model and observed the changes in the values of GHG emission projections (output), by replacing values of a single attribute while keeping the values of remaining attributes constant in each single experiment. We run the model for each input attribute and measured the difference in emission values.

We conducted the experiments on BAU scenario projections (Appendix K) by replacing input values of every single attribute once at a time with its M2 scenario values (Appendix M) while keeping the rest attributes values constant, i.e., same as BAU scenario values. For example, Gasoline price values from (Appendix K) were replaced by Gasoline price values from (Appendix M) while keeping the values of remaining attributes constant (same as Appendix K) in each single experiment.

It was observed that the Multilayer Perceptron Bagging model has the same sensitivity behavior to the input attributes, as Multilayer Perceptron model (section 4.9.1). That is, Multilayer Perceptron Bagging model showed higher sensitivity for the attributes Light truck emissions, Car emissions, GDP transportation, Heavy truck emission, Light duty truck fuel efficiency, Interest rate (over night), Medium Trucks Emission, Passenger car fuel efficiency and Gasoline Price.

Chapter 5

Conclusion and Future Works

Prediction of greenhouse gas (GHG) emissions is vital to minimize their negative impact on climate change and global warming. In this thesis, we presented new models based on data mining/supervised learning techniques (Regression and classification) for predicting GHG emissions arising from passenger and freight road transport in Canada. Removing less influencing attribute improved the generalizing performance of machine learning models. We developed four categories of models namely Artificial Neural Network Multilayer perceptron, Multiple Linear Regression, Multinomial Logistic Regression and Decision tree and evaluated their performances by the error estimated by the Cross Validation technique using performance indicators. Ensemble technique (Bagging & Boosting) was applied on the developed Multilayer Perceptron model which significantly improved the model's predictive performance. For numeric GHG emissions attribute values, the Artificial Neural Network Multilayer perceptron model with bagging ensemble technique outperformed other models and was deployed to predict future GHG emission values and scenario analysis for Canadian Road transport GHG emissions all the way through the year 2030. To analyze the strengths, weaknesses, opportunities, and threats of the proposed approaches, we conducted the SWOT analysis.

Strengths

- An alternative method for modeling and predicting GHG Emissions specifically from Road transportation
- The models are developed using machine learning modelling approach hence, compared to traditional inventory based models are less complex, need a small number of inputs, minimal in depth field knowledge and most notably inputs are not predetermined as compared to traditional emission inventory models.
- The developed artificial neural network model is dynamic in nature meaning, the input parameters can be changed or modified for investigation of the given emissions projection problem
- Multilayer perceptron model in association with an ensemble learning technique gives better performing predictive model for GHG emissions by road transportation
- Compared with traditional emission inventory based models like COPERT, MOVES and GAINS, which use precisely defined input parameters and needs significant in depth field study and time, the inputs to Bagged/Boosted Multilayer perceptron model are not predefined and can be efficiently applied by case by case

Weakness

- The synergies and trade-off between inputs and emissions projection for a given scenario/simulation should be given attention and if needed statistical intervention should be considered on input attributes to reflect the impact of scenario under consideration.

- Artificil neuaral network Multilayer perceptron model is non linear in nature and it learns from underlying functional relationship between input & output and historical data trend. Hence, the appropriate input attributes should be mined and their relevance should be analyzed by attribute filtering process before modeling for emissions projection.

- There is a need to conduct senstivity analysis before performing simulations on the developed model in order to better understand the effect of input attributes on the emissions projection

Opportunities

- The model can play a significant role for entities having less or no access to accurate relevant inputs for analysis and understanding the road transport emissions projection.

Threats

- The dynamic capability of the machine learning model is a threat, meaning the selection of irrelevant or random input attributes for emissions modelling can provide misleading and non comprehensive results.

- Uncertainity in the key drivers of GHG emissions by road transportion like Economic (GDP) growth, Fuel price and Fuel efficiencies etc. will effect the predicted data, hence one should take this into account when implementing this model.

Figure 60 SWOT Analysis

Based on the proposed work, several future research works are possible. Firstly**,** detailed study on most relevant and influential parameters to further improve the prediction accuracy of Multilayer Perceptron model with Bagging can be done. Secondly, the model can be expanded further, by including energy, sustainable and environmental indicator for GHG emission projections. Lastly, different GHG emissions scenarios can be projected by performing simulations on the developed model to analyze changes in future projections by introducing relevant changes in inputs (policy implications)

References

1. Anderson, B., Bartlett, K. B., Frolking, S., Hayhoe, K., Jenkins, J. C., & Salas, W. A. (2010). Methane and nitrous oxide emissions from natural sources.
2. Ayodele, T. O. (2010). Types of machine learning algorithms. INTECH Open Access Publisher.
3. Amirkhani, S., Nasirivatan, S. H., Kasaeian, A. B., & Hajinezhad, A. (2015). ANN and ANFIS models to predict the performance of solar chimney power plants. Renewable Energy, 83, 597-607.
4. Alberta Government. (2015). Alberta's Climate leadership plan. Retrieved June 15, 2017, from https://www.alberta.ca/documents/climate/climate-leadership-report-to-minister.pdf
5. Amann, M., Bertok, I., Borken-Kleefeld, J., Cofala, J., Heyes, C., Höglund-Isaksson, L., ... & Sandler, R. (2011). Cost-effective control of air quality and greenhouse gases in Europe: Modeling and policy applications. Environmental Modelling & Software, 26(12), 1489-1501.
6. Amjady, N., & Daraeepour, A. (2008, May). Day-ahead electricity price forecasting using the relief algorithm and neural networks. In Electricity Market, 2008. EEM 2008. 5th International Conference on European (pp. 1-7). IEEE.
7. Araújo, M. B., & New, M. (2007). Ensemble forecasting of species distributions. Trends in ecology & evolution, 22(1), 42-47.
8. Alexander Holmes. (2015). The Regression Equation. Retrieved July 23, 2017, from https://cnx.org/contents/8EtejTNd@7/The-Regression-Equation

9. Breidenich, C., Magraw, D., Rowley, A., & Rubin, J. W. (1998). The Kyoto protocol to the United Nations framework convention on climate change. The American Journal of International Law, 92(2), 315-331.
10. Bank of Canada (2017). Policy Interest Rate, Retrieved June 13, 2017, From http://www.bankofcanada.ca/core-functions/monetary-policy/key-interest-rate/
11. Baranzini, A., Van den Bergh, J. C., Carattini, S., Howarth, R. B., Padilla, E., & Roca, J. (2015). Seven reasons to use carbon pricing in climate policy.
12. BC Government. (2008). Climate Action Plan. Retrieved June 15, 2017, from http://www.gov.bc.ca/premier/attachments/climate_action_plan.pdf
13. Brunswick, C. G. (2017, April 24). Climate Change Action Plan 2014-2020. Retrieved June15,2017,from http://www2.gnb.ca/content/gnb/en/news/news_release.2014.06.0630.html
14. Burón, J. M., López, J. M., Aparicio, F., Martín, M. Á., & García, A. (2004). Estimation of road transportation emissions in Spain from 1988 to 1999 using COPERT III program. Atmospheric Environment, 38(5), 715-724.
15. Barakat, M., Lefebvre, D., Khalil, M., Druaux, F., & Mustapha, O. (2013). Parameter selection algorithm with self adaptive growing neural network classifier for diagnosis issues. International journal of machine learning and cybernetics, 4(3), 217-233.
16. Breiman, L. (1996). Bagging predictors. Machine learning, 24(2), 123-140.
17. Breiman, L., Friedman, J. H., Olshen, R. A., & Stone, C. J. (1984). Wadsworth international group. Classification and Regression Trees.
18. Bergstra, J., Casagrande, N., Erhan, D., Eck, D., & Kégl, B. (2006). Aggregate features and AdaBoost for music classification. Machine learning, 65(2-3), 473-484.

19. BC Hydro. (2016). Incentives for electric vehicles. Retrieved August 11, 2017, from https://www.bchydro.com/powersmart/electric-vehicles/owning-an-electric-vehicle/rebates-and-incentives.html
20. CANSIM - 379-0031 - Gross domestic product (GDP) at basic prices, by North American Industry Classification System (NAICS). Retrieved June 13, 2017, from http://www5.statcan.gc.ca/cansim/a05?lang=eng&id=3790031
21. Canada, G. O. (2017, May 19). CANSIM - 326-0009 Average retail prices for gasoline and fuel oil, by urban centre. Retrieved June 13, 2017, from http://www5.statcan.gc.ca/cansim/a05?lang=eng&id=3260009
22. Canada, S. (2016, December 14). Complementary actions to reduce emissions. Retrieved June 15, 2017, from https://www.canada.ca/en/services/environment/weather/climatechange/pan-canadian-framework/complementary-actions-reduce-emissions.html#3_3
23. Canada Interest Rate 1990-2017 | Data | Chart | Calendar | Forecast. (n.d.). Retrieved June 13, 2017, from https://tradingeconomics.com/canada/interest-rate
24. Canada New Motor Vehicle Sales 1950-2017 | Data | Chart | Calendar. (2017). Retrieved June 13, 2017, from https://tradingeconomics.com/canada/car-registrations
25. Canada, G. O. (2016, September 28). Population by year, by province and territory (Number). Retrieved June 13, 2017, from http://www.statcan.gc.ca/tables-tableaux/sum-som/l01/cst01/demo02a-eng.htm
26. Canada: Light-duty: Fuel Consumption and GHG. (2016). Retrieved June 13, 2017, from http://www.transportpolicy.net/standard/canada-light-duty-fuel-consumption-and ghg/

27. Canada, G. O. (2017, January 20). Consumer Price Index, historical summary (1997 to 2016). Retrieved June 13, 2017, from http://www.statcan.gc.ca/tables-tableaux/sum-som/l01/cst01/econ46a-eng.htm

28. Canada, G. O. (2015). CANADA'S INDC SUBMISSION TO THE UNFCCC. Retrieved June 15, 2017, from http://www4.unfccc.int/submissions/INDC/Published%20Documents/Canada/1/INDC%20-%20Canada%20-%20English.pdf

29. Chan, P. K., Fan, W., Prodromidis, A. L., & Stolfo, S. J. (1999). Distributed data mining in credit card fraud detection. IEEE Intelligent Systems and Their Applications, 14(6), 67-74.

30. Chai, T., & Draxler, R. R. (2014). Root mean square error (RMSE) or mean absolute error (MAE)?–Arguments against avoiding RMSE in the literature. Geoscientific Model Development, 7(3), 1247-1250.

31. Cherkassky, V., & Lari-Najafi, H. (1992). Data representation for diagnostic neural networks. IEEE Expert, 7(5), 43-53.

32. Carletta, J. (1996). Assessing agreement on classification tasks: the kappa statistic. Computational linguistics, 22(2), 249-254.

33. Crawley, M. J. (2005). Statistics: An Introduction using R, ed.

34. Cottrell, A. (2003). Regression analysis: basic concepts. Regression. pdf.

35. Delmas, R. J., Ascencio, J. M., & Legrand, M. (1980). Polar ice evidence that atmospheric CO2 20,000 yr BP was 50% of present. Nature, 284(5752), 155-157.

36. Dimitrios Gkatzoflias, Chariton Kouridis, Leonidas Ntziachristos and Zissis Samaras. (2012). COPERT User Manual. Retrieved June 16, 2017, from http://emisia.com/sites/default/files/COPERT4v9_manual.pdf
37. Dietterich, T. G. (1997). Machine-learning research. AI magazine, 18(4), 97.
38. Dawson, C. W., & Wilby, R. (1998). An artificial neural network approach to rainfall-runoff modelling. Hydrological Sciences Journal, 43(1), 47-66.
39. DBD, U. O. (2014). ROC Graph. Retrieved September 09, 2017, from http://www2.cs.uregina.ca/~dbd/cs831/notes/ROC/ROC.html
40. de Pina, A. A., da Fonseca Monteiro, B., Albrecht, C. H., de Lima, B. S. L. P., & Jacob, B. P. (2016). Artificial Neural Networks for the analysis of spread mooring configurations for floating production systems. Applied Ocean Research, 59, 254-264.
41. Dietterich, T. G. (2000, June). Ensemble methods in machine learning. In International workshop on multiple classifier systems (pp. 1-15). Springer Berlin Heidelberg.
42. de Menezes, F. S., Liska, G. R., Cirillo, M. A., & Vivanco, M. J. (2017). Data classification with binary response through the Boosting algorithm and logistic regression. Expert Systems with Applications, 69, 62-73.
43. Environment and Climate Change Canada (2016) Canadian Environmental Sustainability Indicators: Greenhouse Gas Emissions. Retrieved April 1, 2017 from www.ec.gc.ca/indicateurs-indicators/default.asp?lang=en&n=FBF8455E-1.
44. Freund, Y., & Schapire, R. E. (1996, July). Experiments with a new boosting algorithm. In icml (Vol. 96, pp. 148-156).
45. Fine, T. L. (2006). Feedforward neural network methodology. Springer Science & Business Media.

46. Frias-Martinez, E., Sanchez, A., & Velez, J. (2006). Support vector machines versus multi-layer perceptrons for efficient off-line signature recognition. Engineering Applications of Artificial Intelligence, 19(6), 693-704.

47. Fawcett, T. (2006). An introduction to ROC analysis. Pattern recognition letters, 27(8), 861-874.

48. Freitag, D. (2017, January). Greedy attribute selection. In Machine Learning Proceedings 1994: Proceedings of the Eighth International Conference (p. 28). Morgan Kaufmann.

49. Griggs, D. J., & Noguer, M. (2002). Climate change 2001: the scientific basis. Contribution of working group I to the third assessment report of the intergovernmental panel on climate change. Weather, 57(8), 267-269.

50. Government of Canada, Environment and Climate Change Canada. (2017, April 13). Environment and Climate Change Canada - Environmental Indicators - Data Sources and Methods for the Greenhouse Gas Emissions Indicators. Retrieved July 09, 2017, from https://www.ec.gc.ca/indicateurs-indicators/default.asp?lang=En&n=391052E4-1&offset=4&toc=show

51. Government of Canada, Environment and Climate Change Canada. (2017, April 13). Environment and Climate Change Canada - Environmental Indicators - Greenhouse Gas Emissions by Province and Territory. Retrieved June 11, 2017, from https://www.ec.gc.ca/indicateurs-indicators/default.asp?lang=en&n=18F3BB9C-1

52. Government of Canada, Environment and Climate Change Canada. (2016, May 25). Environment and Climate Change Canada - Environmental Indicators - Drivers and

Impacts of Greenhouse Gas Emissions. Retrieved April 02, 2017, from https://www.ec.gc.ca/indicateurs-indicators/default.asp?lang=en&n=D4C4DBAB-1

53. Government of Canada, Environment and Climate Change Canada. (2017, April 13). Environment and Climate Change Canada - Environmental Indicators - Greenhouse Gas Emissions. Retrieved May 29, 2017, from http://www.ec.gc.ca/indicateurs-indicators/default.asp?lang=En&n=FBF8455E-1

54. Government of Canada, Canada's GHG Inventory (2017, April 13). Environment and Climate Change Canada - Canada's GHG Inventory. Retrieved May 29, 2017, from http://www.ec.gc.ca/ges-ghg/default.asp?lang=En&n=83A34A7A-1

55. Gouvernement du Québec. (2012). Climate Change Action Plan. Retrieved June 15, 2017, from http://www.mddelcc.gouv.qc.ca/changements/plan_action/pacc2020-en.pdf

56. Government of Ontario. (2016). Climate change strategy. Retrieved June 15, 2017, from https://www.ontario.ca/page/climate-change-strategy

57. Government of Saskatchewan. (2013). Climate Change Legislation. Retrieved June 15, 2017, from http://environment.gov.sk.ca/climatechange

58. Government of Manitoba, Conservation, Wildlife Branch. (2015). Climate Change and Air Quality Branch. Retrieved June 15, 2017, from http://www.gov.mb.ca/sd/climate/

59. GAINS EUROPE. (2013). The GAINS Model. Retrieved June 17, 2017, from http://www.iiasa.ac.at/web/home/research/researchPrograms/air/GAINS.en.html

60. Guo, Z. X., Wong, W. K., & Li, M. (2012). Sparsely connected neural network-based time series forecasting. Information Sciences, 193, 54-71.

61. Gardner, M. W., & Dorling, S. R. (1998). Artificial neural networks (the multilayer perceptron)—a review of applications in the atmospheric sciences. Atmospheric environment, 32(14), 2627-2636.

62. Government of Canada, Natural Resources Canada. (2017, March 02). Transportation Sector – GHG Emissions. Retrieved June 13, 2017, from http://oee.nrcan.gc.ca/corporate/statistics/neud/dpa/showTable.cfm?type=AN&sector=aaa&juris=00&rn=5&page=0

63. Giacinto, G., Roli, F., & Didaci, L. (2003). Fusion of multiple classifiers for intrusion detection in computer networks. Pattern recognition letters, 24(12), 1795-1803.

64. Goebel, K., Krok, M., & Sutherland, H. (2000). Diagnostic information fusion: requirements flowdown and interface issues. In Aerospace Conference Proceedings, 2000 IEEE (Vol. 6, pp. 155-162). IEEE.

65. Galar, M., Fernández, A., Barrenechea, E., Bustince, H., & Herrera, F. (2011). An overview of ensemble methods for binary classifiers in multi-class problems: Experimental study on one-vs-one and one-vs-all schemes. Pattern Recognition, 44(8), 1761-1776.

66. Government of Canada, Environment and Climate Change Canada. (2017, January 05). Environment and Climate Change Canada - Climate Change - Canada's 2016 greenhouse gas emissions Reference Case. Retrieved July 27, 2017, from https://www.ec.gc.ca/GES-GHG/default.asp?lang=En&n=1F24D9EE-1&offset=2&toc=show

67. Government of Ontario, Ministry of Transportation. (2013, October 25). Electric Vehicle Incentive Program (EVIP). Retrieved August 11, 2017, from

http://www.mto.gov.on.ca/english/vehicles/electric/electric-vehicle-incentive-program.shtml

68. Houghton, J. T., Ding, Y. D. J. G., Griggs, D. J., Noguer, M., van der Linden, P. J., Dai, X., ... & Johnson, C. A. (2001). Climate change 2001: the scientific basis. The Press Syndicate of the University of Cambridge.
69. Hosmer, D. W., & Lemeshow, S. (2000). Special topics. Applied Logistic Regression, Second Edition, 260-351.
70. Hosmer Jr, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). Applied logistic regression (Vol. 398). John Wiley & Sons.
71. Hssina, B., Merbouha, A., Ezzikouri, H., & Erritali, M. (2014).A comparative study of decision tree ID3 and C4. 5. International Journal of Advanced Computer Science and Applications, 4(2), 13-19.
72. Hunt, E. B., & Martin, J. S. P.(1966). Experiments in Induction.
73. Hansen, L. K., & Salamon, P. (1990). Neural network ensembles. IEEE transactions on pattern analysis and machine intelligence, 12(10), 993-1001.
74. Huang, F. J., Zhou, Z., Zhang, H. J., & Chen, T. (2000). Pose invariant face recognition. In Automatic Face and Gesture Recognition, 2000. Proceedings. Fourth IEEE International Conference on (pp. 245-250). IEEE.
75. Hanley, J. A., & McNeil, B. J. (1982). The meaning and use of the area under a receiver operating characteristic (ROC) curve. Radiology, 143(1), 29-36.
76. Indermühle, A., Stocker, T. F., Joos, F., Fischer, H., Smith, H. J., Wahlen, M., ... & Meyer, R. (1999). Holocene carbon-cycle dynamics based on CO2 trapped in ice at Taylor Dome, Antarctica. Nature, 398(6723), 121-126.

77. IPCCEggleston, H. S., Buendia, L., Miwa, K., Ngara, T., & Tanabe, K. (2006). IPCC guidelines for national greenhouse gas inventories, prepared by the National Greenhouse Gas Inventories Programme. Institute for Global Environmental Strategies, Hayama.

78. Juran, J. M. (1992). Juran on quality by design: the new steps for planning quality into goods and services. Simon and Schuster.

79. Kotsiantis, S. B. (2007). Supervised Machine Learning: A Review of Classification Techniques. Informatica, 31, 249-268.

80. Kota, S. H., Zhang, H., Chen, G., Schade, G. W., & Ying, Q. (2014). Evaluation of on-road vehicle CO and NO x National Emission Inventories using an urban-scale source-oriented air quality model. Atmospheric environment, 85, 99-108.

81. Kononenko, I. (1994, April). Estimating attributes: analysis and extensions of RELIEF. In European conference on machine learning (pp. 171-182). Springer Berlin Heidelberg.

82. Kira, K., & Rendell, L. A. (1992, July). A practical approach to feature selection. In Proceedings of the ninth international workshop on Machine learning (pp. 249-256).

83. Kalousis, A., Prados, J., & Hilario, M. (2007). Stability of feature selection algorithms: a study on high-dimensional spaces. Knowledge and information systems, 12(1), 95-116.

84. King, M. A., Abrahams, A. S., & Ragsdale, C. T. (2014). Ensemble methods for advanced skier days prediction. Expert Systems with Applications, 41(4), 1176-1188.

85. Kohavi, R. (1995, August). A study of cross-validation and bootstrap for accuracy estimation and model selection. In Ijcai (Vol. 14, No. 2, pp. 1137-1145).

86. Knoema. (2017, May 29). Crude Oil Price Forecast: Long Term 2017 to 2030 | Data and Charts. Retrieved August 02, 2017, from https://knoema.com/yxptpab/crude-oil-price-forecast-long-term-2017-to-2030-data-and-charts

87. Kennedy, P. (2008). A guide to modern econometric.

88. Liu, H. B., Wang, Y., Chen, X., & Han, S. (2013). Vehicle emission and near-road air quality modeling in Shanghai, China, based on taxi GPS data and MOVES revised emission inventory. Transp Res Rec J Transp Res Board, 2340, 33-48.

89. Legates, D. R., & McCabe, G. J. (1999). Evaluating the use of “goodness- of- fit” measures in hydrologic and hydroclimatic model validation. Water resources research, 35(1), 233-241.

90. Lang, H. (2013). Topics on Applied Mathematical Statistics. KTH Teknikvetenskap, version 0.97.

91. Marland, G., Boden, T. A., Andres, R. J., Brenkert, A. L., & Johnston, C. A. (2003). Global, regional, and national fossil fuel CO2 emissions. Trends: A compendium of data on global change, 34-43.

92. Metz, B., Davidson, O. R., Bosch, P. R., & Dave, R. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, 2007.

93. Manikandan, P., & Venkateswaran, C. J. (2015). Feature Selection Algorithms: Literature Review. International Journal, 5(3).

94. Murata, A., Fujii, Y., & Naitoh, K. (2015). Multinomial Logistic Regression Model for Predicting Driver's Drowsiness Using Behavioral Measures. Procedia Manufacturing, 3, 2426-2433.

95. McCulloch, W. S., & Pitts, W. (1943). A logical calculus of the ideas immanent in nervous activity. The bulletin of mathematical biophysics, 5(4), 115-133.

96. Mirjalili, S., Mirjalili, S. M., & Lewis, A. (2014). Let a biogeography-based optimizer train your multi-layer perceptron. Information Sciences, 269, 188-209.

97. Melin, P., Sánchez, D., & Castillo, O. (2012). Genetic optimization of modular neural networks with fuzzy response integration for human recognition. Information Sciences, 197, 1-19.

98. Maqsood, I., Khan, M. R., & Abraham, A. (2004). An ensemble of neural networks for weather forecasting. Neural Computing & Applications, 13(2), 112-122.

99. Ma, C. C. Y., & Iqbal, M. (1983). Statistical comparison of models for estimating solar radiation on inclined surgaces. Solar Energy, 31(3), 313-317.

100. Mashaly, A. F., & Alazba, A. A. (2016). MLP and MLR models for instantaneous thermal efficiency prediction of solar still under hyper-arid environment. Computers and Electronics in Agriculture, 122, 146-155.

101. National Inventory Submissions. (2017, May 22). Retrieved September 09, 2017, from http://unfccc.int/national_reports/annex_i_ghg_inventories/national_inventories_submissions/items/9492.php

102. Niu, X., Yang, C., Wang, H., & Wang, Y. (2017). Investigation of ANN and SVM based on limited samples for performance and emissions prediction of a CRDI-assisted marine diesel engine. Applied Thermal Engineering, 111, 1353-1364.

103. Newfoundland and Labrador . (2011). Climate Change Action Plan. Retrieved June 15, 2017, from http://www.exec.gov.nl.ca/exec/occ/publications/climate_change.pdf

104. Nova Scotia. (2009). Toward a Greener Future . Retrieved June 15, 2017, from https://climatechange.novascotia.ca/sites/default/files/uploads/ccap.pdf

105. Opitz, D. W., & Maclin, R. (1999). Popular ensemble methods: An empirical study. J. Artif. Intell. Res.(JAIR), 11, 169-198.

106. Parry, I., Veung, C., & Heine, D. (2015). HOW MUCH CARBON PRICING IS IN COUNTRIES'OWN INTERESTS? THE CRITICAL ROLE OF CO-BENEFITS. Climate Change Economics, 6(04), 1550019.

107. Prince Edward Island. (2008). Strategy for Reducing the Impacts of Global Warming. Retrieved June 15, 2017, from http://www.gov.pe.ca/photos/original/env_globalstr.pdf

108. Park, H. (2013). An introduction to logistic regression: from basic concepts to interpretation with particular attention to nursing domain. Journal of Korean Academy of Nursing, 43(2), 154-164.

109. Peng, C. Y. J., Lee, K. L., & Ingersoll, G. M. (2002). An introduction to logistic regression analysis and reporting. The journal of educational research, 96(1), 3-14.

110. Polikar, R., Topalis, A., Parikh, D., Green, D., Frymiare, J., Kounios, J., & Clark, C. M. (2008).

An ensemble based data fusion approach for early diagnosis of Alzheimer's disease. Information Fusion, 9(1), 83-95.

111. Panigrahi, S., Kundu, A., Sural, S., & Majumdar, A. K. (2009).

Credit card fraud detection: A fusion approach using Dempster–Shafer theory and Bayesian learning. Information Fusion, 10(4), 354-363.

112. Quinlan, J. R. (1996). Improved use of continuous attributes in C4. 5. Journal of artificial intelligence research, 4, 77-90.

113. Quinlan, J. R. (1993). C4. 5: Programming for machine learning. Morgan Kauffmann, 38.

114. Quinlan, J. R. (1986). Induction of decision trees. Machine learning, 1(1), 81-106.

115. Quebec Government. (2017). Purchase or Lease Rebate Program. Retrieved August 11, 2017, from http://vehiculeselectriques.gouv.qc.ca/english/particuliers/rabais.asp

116. Ren, W., Xue, B., Geng, Y., Lu, C., Zhang, Y., Zhang, L., ... & Hao, H. (2016). Inter-city passenger transport in larger urban agglomeration area: emissions and health impacts. Journal of Cleaner Production, 114, 412-419.

117. Rosario, S. F., & Thangadurai, K. (2015). RELIEF: Feature Selection Approach. International Journal of Innovative Research and Development|| ISSN 2278–0211, 4(11).

118. Robnik-Šikonja, M., & Kononenko, I. (2003). Theoretical and empirical analysis of ReliefF and RReliefF. Machine learning, 53(1-2), 23-69.

119. Robnik-Šikonja, M., & Kononenko, I. (1997, July). An adaptation of Relief for attribute estimation in regression. In Machine Learning: Proceedings of the Fourteenth International Conference (ICML'97) (pp. 296-304).

120. Rosenblatt, F. (1957). The perceptron, a perceiving and recognizing automaton Project Para. Cornell Aeronautical Laboratory.

121. Refaeilzadeh, P., Tang, L., & Liu, H. (2009). Cross-validation. In Encyclopedia of database systems (pp. 532-538). Springer US.

122. Sayad, S. (2011). *Real time data mining*. Canada: Self-Help Publishers.

123. Sathya, R., & Abraham, A. (2013). Comparison of supervised and unsupervised learning algorithms for pattern classification. International Journal of Advanced Research in Artificial Intelligence, 2(2), 34-38.

124. Setsirichok, D., Piroonratana, T., Wongseree, W., Usavanarong, T., Paulkhaolarn, N., Kanjanakorn, C., ... & Chaiyaratana, N. (2012). Classification of complete blood count and haemoglobin typing data by a C4. 5 decision tree, a naïve Bayes classifier and a multilayer perceptron for thalassaemia screening. Biomedical Signal Processing and Control, 7(2), 202-212.

125. Sugumaran, V., Muralidharan, V., & Ramachandran, K. I. (2007). Feature selection using decision tree and classification through proximal support vector machine for fault diagnostics of roller bearing. Mechanical systems and signal processing, 21(2), 930-942.

126. Schwenk, H., & Bengio, Y. (2000). Boosting neural networks. Neural Computation, 12(8), 1869-1887.

127. Sun, S., Jiang, W., & Gao, W. (2016). Vehicle emission trends and spatial distribution in Shandong province, China, from 2000 to 2014. Atmospheric Environment, 147, 190-199.

128. Soylu, S. (2007). Estimation of Turkish road transport emissions. Energy Policy, 35(8), 4088-4094.

129. Song, X., Hao, Y., Zhang, C., Peng, J., & Zhu, X. (2016). Vehicular emission trends in the Pan-Yangtze River Delta in China between 1999 and 2013. Journal of Cleaner Production, 137, 1045-1054.

130. Song, X., Hao, Y., Zhang, C., Peng, J., & Zhu, X. (2016). Vehicular emission trends in the Pan-Yangtze River Delta in China between 1999 and 2013. Journal of Cleaner Production, 137, 1045-1054.

131. Shardlow, M. (2016). An analysis of feature selection techniques. The University of Manchester.

132. Saija, S., & Romano, D. (2002). A methodology for the estimation of road transport air emissions in urban areas of Italy. Atmospheric Environment, 36(34), 5377-5383.

133. S Lek Y S Park. (2008). Encyclopedia of Ecology | Multilayer Perceptron. Retrieved July 10, 2017, from https://books.google.ca/books?id=6IQY8Uh1aA0C&pg=PA2455&lpg=PA2455&dq=Ecological%2BInformatics%2B%7C%2BMultilayer%2BPerceptron%2Bs%2Blek&source=bl&ots=sHcEkaag3p&sig=Z30tMpRv9k9Q85Xp-2KwEJe-KVU&hl=en&sa=X&ved=0ahUKEwjLzd6t9f_UAhXj6YMKHcWFCF8Q6AEIJzAA#v=onepage&q=Ecological%20Informatics%20%7C%20Multilayer%20Perceptron%20s%20lek&f=false

134. Sasaki, Y. (2007). The truth of the F-measure. Teach Tutor mater, 1(5).

135. Schultz, M. G., Eskin, E., Zadok, F., & Stolfo, S. J. (2001). Data mining methods for detection of new malicious executables. In Security and Privacy, 2001. S&P 2001. Proceedings. 2001 IEEE Symposium on (pp. 38-49). IEEE.

136. Société de transport de Montréal. (2017).Electric bus. Retrieved August 11, 2017, from http://www.stm.info/en/about/major_projects/bus-network-electrification/electric-bus

137. Ting, K. M. (2011). Confusion matrix. In Encyclopedia of machine learning(pp. 209-209). Springer US.

138. Trading Economics. (2017). Canada Interest Rate Forecast 2016-2020. Retrieved August 01, 2017, from https://tradingeconomics.com/canada/interest-rate/forecast

139. United Nations Framework Convention on Climate Change (2017, April 13). Canada GHG Inventory. Retrieved June 13, 2017, from http://unfccc.int/national_reports/annex_i_ghg_inventories/national_inventories_submissions/items/10116.php

140. United States Environmental Protection Agency. (2016, September 27). Basic Information of Air Emissions Factors and Quantification. Retrieved September 09, 2017, from https://www.epa.gov/air-emissions-factors-and-quantification/basic-information-air-emissions-factors-and-quantification

141. U.S. Environmental Protection Agency, 2012. Motor Vehicle Emission Simulator (MOVES) User Guide for MOVES2010b. EPA report EPA-420-B-12-001b, Office of Transportation and Air Quality.

142. Vallamsundar, S., & Lin, J. (2011). MOVES versus MOBILE: comparison of greenhouse gas and criterion pollutant emissions. Transportation Research Record: Journal of the Transportation Research Board, (2233), 27-35.

143. Viola, P., & Jones, M. J. (2004). Robust real-time face detection. International journal of computer vision, 57(2), 137-154.

144. Viera, A. J., & Garrett, J. M. (2005). Understanding interobserver agreement: the kappa statistic. Fam Med, 37(5), 360-363.

145. Wang, W. C., Yung, Y. L., Lacis, A. A., Mo, T. A., & Hansen, J. E. (1976). Greenhouse effects due to man-made perturbations of trace gases. Science, 194(4266), 685-690.

146. Winiwarter, W., & Rypdal, K. (2001). Assessing the uncertainty associated with national greenhouse gas emission inventories:: a case study for Austria. Atmospheric environment, 35(32), 5425-5440.

147. Wettschereck, D., Aha, D. W., & Mohri, T. (1997). A review and empirical evaluation of feature weighting methods for a class of lazy learning algorithms. In Lazy learning (pp. 273-314). Springer Netherlands.

148. Witten, I. H., Frank, E., Hall, M. A., & Pal, C. J. (2016). Data Mining: Practical machine learning tools and techniques. Morgan Kaufmann.

149. Wang, Y. (2005). A multinomial logistic regression modeling approach for anomaly intrusion detection. Computers & Security, 24(8), 662-674.

150. Wattimena, R. K. (2014). Predicting the stability of hard rock pillars using multinomial logistic regression. International journal of rock mechanics and mining sciences, 71, 33-40.

151. Werbos, P. J. (1974). Beyond regression: New tools for prediction and analysis in the behavioral sciences. Doctoral Dissertation, Applied Mathematics, Harvard University, MA.

152. Weigend, A. S., Huberman, B. A., & Rumelhart, D. E. (1990) Predicting the future: A connectionist approach. International journal of neural systems, 1(03), 193-209.

153. Weigend, A. S., Huberman, B. A., & Rumelhart, D. E. (1990) Predicting the future: A connectionist approach. International journal of neural systems, 1(03), 193-209.

154. XIE, S. D., SONG, X. Y., & SHEN, X. H. (2006). Calculating Vehicular Emission Factors with COPERTⅢMode in China [J]. Environmental Science, 3, 002.

155. Yan, W., & Xue, F. (2008, June). Jet engine gas path fault diagnosis using dynamic fusion of multiple classifiers. In Neural Networks, 2008. IJCNN 2008.(IEEE World Congress on Computational Intelligence). IEEE International Joint Conference on (pp. 1585-1591). IEEE.

156. Yan, X., & Su, X. (2009). Linear regression analysis: theory and computing. World Scientific.

157. Yadav, A. K., & Chandel, S. S. (2015). Solar energy potential assessment of western Himalayan Indian state of Himachal Pradesh using J48 algorithm of WEKA in ANN based prediction model. Renewable Energy, 75, 675-693.

158. Zhou, X. H., McClish, D. K., & Obuchowski, N. A. (2009). Statistical methods in diagnostic medicine (Vol. 569). John Wiley & Sons.

159. Zhou, Z. H. (2012). Ensemble methods: foundations and algorithms. CRC press.

160. Zhou, Z. H., & Jiang, Y. (2003). Medical diagnosis with C4. 5 rule preceded by artificial neural network ensemble. IEEE Transactions on information Technology in Biomedicine, 7(1), 37-42.

161. Zou, K. H., Tuncali, K., & Silverman, S. G. (2003). Correlation and simple linear regression. Radiology, 227(3), 617-628.

Appendices

Appendix A Provincial GHG emission Data by Canadian economic sector MT CO2 eq

Year	Newfoundland & Labrador	Prince Edward Island	Nova Scotia	New Brunswik	Quebec	Ontario	Manitoba	Saskatchewan	Alberta	British Columbia	Yukon	Northwest Territories	Nunavut
1990	9.5	1.9	19.8	16.3	89	181.3	18.6	45.2	175.3	51.9	0.5	1.2	0.3
2005	10.1	2.1	23.2	20.3	88.9	204.4	20.6	69.5	232.8	63.9	0.4	1.6	0.5
2010	10.3	2	20.3	18.6	82	175.5	19.6	69.9	241.1	59.4	0.4	1.3	0.5
2011	10.3	2.2	21	18.9	83.9	174.6	19.4	69.3	245.7	59.9	0.4	1.4	0.5
2012	9.9	2.1	19.4	17	81.1	171.4	20.6	71.6	259.6	61.1	0.4	1.5	0.6
2013	9.6	1.8	18.4	15	82.3	170.8	21.3	73.7	272.2	61.8	0.4	1.4	0.6
2014	10.6	1.8	16.5	14.5	80	168.5	21.2	75	275.7	61.2	0.3	1.3	0.7
2015	10.3	1.8	16.2	14.1	80.1	166.2	20.8	75	274.1	60.9	0.3	1.4	0.6

Appendix B Pareto Analysis Calculation for GHG Emissions by provinces in 2015

	Frequency	Cum.Frequency	Percentage
Alberta	274.1	274.1	37.97
Ontario	166.2	440.3	61.00
Quebec	80.1	520.4	72.10
Saskatchewan	75	595.4	82.49
British Columbia	60.9	656.3	90.93
Manitoba	20.8	677.1	93.81
Nova Scotia	16.2	693.3	96.05
New Brunswik	14.1	707.4	98.00
Newfoundland & Labrador	10.3	717.7	99.43
Prince Edward Island	1.8	719.5	99.68
Northwest Territories	1.4	720.9	99.88
Nunavut	0.6	721.5	99.96
Yukon	0.3	721.8	100.00
	721.8		

Appendix C Sector wise (Economic) Division of Major GHG Emitting Provinces

Economic Sector	Alberta	Ontario	Quebec	Saskatchewan	British Columbia
Oil & Gas	132.3	10.3	2.8	24.1	13.7
Electricity	46.1	5.2	0.3	14.6	0.4
Transportation	32.5	55	31.2	10.2	22.7
Heavy Industry	17	29.1	15.8	3.2	6
Buildings	19.3	36.8	11.3	3.1	7.3
Agriculture	21.5	12.3	9	17.9	2.9
Waste	2.3	8.6	5.1	1.1	4.3
Coal Production	0.4	0	0	0	1.7
Light Manufacturing, Construction & Forest Resources	2.7	8.9	4.7	0.7	2

Appendix D GHG Emissions distribution by various Transportation modes over the years in Canada

Year	Cars	Light Trucks	Medium Trucks	Heavy Trucks	Motor cycles	School Buses	Urban Transit	Inter-City Buses	Passenger Air	Freigh t Air	Passeng er Rail	Freight Rail	Marine	Off-Road[1]
1990	49.31	21.85	8.25	17.82	0.16	0.91	1.67	0.56	12.86	0.46	0.29	6.66	7.85	3.69
1991	47.92	21.55	8.23	16.07	0.15	0.91	1.80	0.57	11.46	0.44	0.24	6.19	8.17	3.89
1992	47.90	23.13	8.61	16.47	0.15	0.98	1.70	0.52	11.86	0.41	0.23	6.50	8.11	4.04
1993	48.47	24.15	8.97	18.33	0.15	0.88	1.55	0.48	11.31	0.45	0.25	6.45	7.14	4.12
1994	48.33	26.38	9.71	21.06	0.15	0.82	1.52	0.46	11.92	0.48	0.22	6.72	7.67	4.16
1995	47.49	27.64	10.10	22.43	0.14	1.11	1.78	0.57	12.85	0.52	0.18	6.10	7.49	4.30
1996	46.38	29.33	10.18	23.69	0.14	0.92	1.52	0.49	14.55	0.58	0.22	5.93	7.36	4.49
1997	46.03	31.54	10.55	25.71	0.15	0.93	1.79	0.64	14.87	0.59	0.19	6.04	7.38	4.67
1998	45.15	33.73	10.96	26.35	0.15	0.97	1.76	0.57	15.11	0.54	0.20	5.87	8.34	4.86
1999	44.98	35.21	11.45	27.58	0.16	0.95	1.77	0.49	15.78	0.58	0.22	6.20	7.79	5.23
2000	44.02	35.91	10.82	29.14	0.17	1.04	1.97	0.51	16.03	0.56	0.23	6.39	7.93	5.59
2001	43.67	36.17	12.42	27.39	0.17	0.90	1.97	0.51	14.65	0.47	0.23	6.33	8.56	6.24
2002	44.66	37.86	12.03	27.10	0.19	0.98	2.34	0.60	14.70	0.51	0.22	5.76	8.21	6.41
2003	44.22	38.65	14.13	29.20	0.21	1.13	2.42	0.55	14.59	0.47	0.20	5.83	8.31	6.50
2004	43.73	39.42	15.67	30.48	0.22	0.89	2.30	0.46	16.28	0.50	0.20	6.01	9.19	6.66
2005	43.00	40.00	14.47	32.28	0.22	0.94	2.40	0.51	17.21	0.54	0.21	6.40	9.42	6.81
2006	41.87	39.32	16.61	31.26	0.23	0.96	2.09	0.46	17.10	0.49	0.21	6.71	8.30	6.91
2007	42.71	41.23	17.17	32.45	0.25	0.97	2.31	0.50	17.37	0.40	0.22	7.20	9.26	7.00
2008	41.22	40.82	18.14	32.72	0.25	1.06	2.37	0.50	16.42	0.34	0.25	7.61	9.01	7.09
2009	41.00	41.65	19.35	32.21	0.34	1.04	2.44	0.38	15.03	0.31	0.18	4.91	8.72	7.06
2010	40.50	43.07	21.65	33.39	0.36	1.10	2.64	0.39	15.51	0.36	0.19	6.37	9.03	7.11
2011	39.09	43.36	21.17	35.05	0.36	1.16	2.76	0.38	15.34	0.37	0.22	7.29	7.24	7.26
2012	38.11	44.06	20.95	35.11	0.38	1.02	2.57	0.37	17.78	0.42	0.19	7.39	6.95	7.36
2013	37.87	45.91	21.95	35.38	0.38	0.96	2.85	0.40	18.49	0.43	0.16	7.13	6.55	7.53
2014	36.10	45.92	21.99	36.47	0.37	0.90	2.84	0.38	18.61	0.42	0.16	7.36	5.88	7.67

Appendix E GHG Emission over the years by Passenger, Freight Transportation mode and Off Road activities.

Year	Passenger Transportation	Freight Transportation	Off-Road[1]	**Total GHG Emissions Excluding Electricity (Mt)**
1990	80.91	47.74	3.69	**132.34**
1991	77.99	45.72	3.89	**127.60**
1992	79.31	47.27	4.04	**130.61**
1993	80.02	48.56	4.12	**132.70**
1994	81.91	53.52	4.16	**139.59**
1995	83.50	54.91	4.30	**142.71**
1996	84.86	56.44	4.49	**145.78**
1997	86.86	59.54	4.67	**151.07**
1998	87.78	61.92	4.86	**154.56**
1999	89.38	63.77	5.23	**158.38**
2000	89.61	65.09	5.59	**160.29**
2001	87.88	65.56	6.24	**159.69**
2002	90.80	64.37	6.41	**161.58**
2003	91.04	68.86	6.50	**166.40**
2004	92.41	72.95	6.66	**172.02**
2005	93.31	74.31	6.81	**174.43**
2006	91.16	74.47	6.91	**172.54**
2007	93.87	78.16	7.00	**179.04**
2008	91.32	79.41	7.09	**177.82**
2009	90.32	77.24	7.06	**174.62**
2010	91.64	82.93	7.11	**181.67**
2011	90.56	83.24	7.26	**181.06**
2012	92.07	83.24	7.36	**182.67**
2013	94.08	84.39	7.53	**185.99**
2014	92.31	85.08	7.67	**185.06**

Appendix F Total GHG Emission over the years by various modes of Road Transport in Canada

Year	Cars	Light Trucks	Medium Trucks	Heavy Trucks	Motorcycles	School Buses	Urban Transit	Inter-City Buses
1990	49.31	21.85	8.25	17.82	0.16	0.91	1.67	0.56
1991	47.92	21.55	8.23	16.07	0.15	0.91	1.80	0.57
1992	47.90	23.13	8.61	16.47	0.15	0.98	1.70	0.52
1993	48.47	24.15	8.97	18.33	0.15	0.88	1.55	0.48
1994	48.33	26.38	9.71	21.06	0.15	0.82	1.52	0.46
1995	47.49	27.64	10.10	22.43	0.14	1.11	1.78	0.57
1996	46.38	29.33	10.18	23.69	0.14	0.92	1.52	0.49
1997	46.03	31.54	10.55	25.71	0.15	0.93	1.79	0.64
1998	45.15	33.73	10.96	26.35	0.15	0.97	1.76	0.57
1999	44.98	35.21	11.45	27.58	0.16	0.95	1.77	0.49
2000	44.02	35.91	10.82	29.14	0.17	1.04	1.97	0.51
2001	43.67	36.17	12.42	27.39	0.17	0.90	1.97	0.51
2002	44.66	37.86	12.03	27.10	0.19	0.98	2.34	0.60
2003	44.22	38.65	14.13	29.20	0.21	1.13	2.42	0.55
2004	43.73	39.42	15.67	30.48	0.22	0.89	2.30	0.46
2005	43.00	40.00	14.47	32.28	0.22	0.94	2.40	0.51
2006	41.87	39.32	16.61	31.26	0.23	0.96	2.09	0.46
2007	42.71	41.23	17.17	32.45	0.25	0.97	2.31	0.50
2008	41.22	40.82	18.14	32.72	0.25	1.06	2.37	0.50
2009	41.00	41.65	19.35	32.21	0.34	1.04	2.44	0.38
2010	40.50	43.07	21.65	33.39	0.36	1.10	2.64	0.39
2011	39.09	43.36	21.17	35.05	0.36	1.16	2.76	0.38
2012	38.11	44.06	20.95	35.11	0.38	1.02	2.57	0.37
2013	37.87	45.91	21.95	35.38	0.38	0.96	2.85	0.40
2014	36.10	45.92	21.99	36.47	0.37	0.90	2.84	0.38

Appendix G All Attribute Data for GHG Emission by Road transport

Year	Car sales	Gasoline Price CAD Liter	GDP transportation	Interest Rate (Overnight)	CPI	Cars Emission	Light Trucks Emission	Medium Trucks Emission	Heavy Trucks emission	Buses Transit Emission	Population (million)	Passenger car fuel efficiency	Light duty truck fuel efficiency	Total GHG only Road
1990	850000	0.59	24000	13.7	71.6	49.31	21.85	8.25	17.82	3.3	27.5	8.2	11.3	100.53
1991	710000	0.58	28000	9.3	72.9	47.92	21.55	8.23	16.07	3.43	27.9	8	11.4	97.2
1992	710000	0.55	31000	6.1	74.4	47.9	23.13	8.61	16.47	3.35	28.38	8.1	11.1	99.46
1993	600000	0.54	35000	4.3	76.8	48.47	24.15	8.97	18.33	3.05	28.68	8.1	11.3	102.98
1994	750000	0.54	38000	4.8	80.2	48.33	26.38	9.71	21.06	2.95	29	8.2	11.1	108.43
1995	780000	0.57	41000	5.7	84.3	47.49	27.64	10.1	22.43	3.6	29.3	7.9	11.5	111.27
1996	780000	0.59	43000	6	87.6	46.38	29.33	10.18	23.69	3.07	29.61	7.9	11.5	112.65
1997	800000	0.61	46708	4.3	90.3	46.03	31.54	10.55	25.71	3.51	29.97	8	11.3	117.33
1998	720000	0.56	47640	3.3	89.6	45.15	33.73	10.96	26.35	3.46	30.16	7.9	11.4	119.65
1999	860000	0.6	50566	5.1	92.6	44.98	35.21	11.45	27.58	3.37	30.4	7.9	11.3	122.59
2000	900000	0.73	53087	4.7	97.2	44.02	35.91	10.82	29.14	3.68	30.69	7.8	11.1	123.56
2001	860000	0.72	54448	5.9	97.3	43.67	36.17	12.42	27.39	3.55	31.02	7.8	11	123.2
2002	1000000	0.72	54341	2	100	44.66	37.86	12.03	27.1	4.11	31.36	7.7	11	125.76
2003	900000	0.76	54554	2.9	105.2	44.22	38.65	14.13	29.2	4.3	31.64	7.6	10.8	130.5
2004	800000	0.84	56612	2.7	107.7	43.73	39.42	15.67	30.48	3.88	31.94	7.5	10.7	133.19
2005	800000	0.95	59944	2.4	112	43	40	14.47	32.28	4.07	32.24	7.4	10.5	133.83
2006	860000	1.01	61673	3.2	115.2	41.87	39.32	16.61	31.26	3.75	32.57	7.5	10.4	132.81
2007	850000	1.05	62645	4.2	117.1	42.71	41.23	17.17	32.45	4.03	32.89	7.2	10.1	137.58
2008	1200000	1.18	62314	4.2	119.5	41.22	40.82	18.14	32.72	4.19	33.25	7.1	9.5	137.1
2009	750000	0.96	60049	1.4	113.1	41	41.65	19.35	32.21	4.21	33.63	6.8	9.1	138.42
2010	865000	1.04	62346	0.2	118	40.5	43.07	21.65	33.39	4.49	34.01	6.8	8.5	143.1
2011	850000	1.24	64757	1	125.6	39.09	43.36	21.17	35.05	4.66	34.34	6.6	8.5	143.33
2012	100000	1.27	65623	1	128.1	38.11	44.06	20.95	35.11	4.34	34.75	6.6	8.4	142.58
2013	99000	1.27	66797	1	129	37.87	45.91	21.95	35.38	4.58	35.16	6.5	8.4	145.69
2014	99000	1.28	69812	1	130.4	36.1	45.92	21.99	36.47	4.48	35.55	6.5	8.2	144.96

Appendix H Selected Attribute Data for GHG Emission by Road Transport

Year	Gasoline Price CAD Liter	GDP transportation	Interest Rate (Overnight)	CPI	Cars Emission	Light Trucks Emission	Medium Trucks Emission	Heavy Trucks emission	Buses Transit Emission	Population (million)	Passenger car fuel efficiency	Light duty truck fuel efficiency	Total GHG only Road
1990	0.59	24000	13.7	71.6	49.31	21.85	8.25	17.82	3.3	27.5	8.2	11.3	100.53
1991	0.58	28000	9.3	72.9	47.92	21.55	8.23	16.07	3.43	27.9	8	11.4	97.2
1992	0.55	31000	6.1	74.4	47.9	23.13	8.61	16.47	3.35	28.38	8.1	11.1	99.46
1993	0.54	35000	4.3	76.8	48.47	24.15	8.97	18.33	3.05	28.68	8.1	11.3	102.98
1994	0.54	38000	4.8	80.2	48.33	26.38	9.71	21.06	2.95	29	8.2	11.1	108.43
1995	0.57	41000	5.7	84.3	47.49	27.64	10.1	22.43	3.6	29.3	7.9	11.5	111.27
1996	0.59	43000	6	87.6	46.38	29.33	10.18	23.69	3.07	29.61	7.9	11.5	112.65
1997	0.61	46708	4.3	90.3	46.03	31.54	10.55	25.71	3.51	29.97	8	11.3	117.33
1998	0.56	47640	3.3	89.6	45.15	33.73	10.96	26.35	3.46	30.16	7.9	11.4	119.65
1999	0.6	50566	5.1	92.6	44.98	35.21	11.45	27.58	3.37	30.4	7.9	11.3	122.59
2000	0.73	53087	4.7	97.2	44.02	35.91	10.82	29.14	3.68	30.69	7.8	11.1	123.56
2001	0.72	54448	5.9	97.3	43.67	36.17	12.42	27.39	3.55	31.02	7.8	11	123.2
2002	0.72	54341	2	100	44.66	37.86	12.03	27.1	4.11	31.36	7.7	11	125.76
2003	0.76	54554	2.9	105.2	44.22	38.65	14.13	29.2	4.3	31.64	7.6	10.8	130.5
2004	0.84	56612	2.7	107.7	43.73	39.42	15.67	30.48	3.88	31.94	7.5	10.7	133.19
2005	0.95	59944	2.4	112	43	40	14.47	32.28	4.07	32.24	7.4	10.5	133.83
2006	1.01	61673	3.2	115.2	41.87	39.32	16.61	31.26	3.75	32.57	7.5	10.4	132.81
2007	1.05	62645	4.2	117.1	42.71	41.23	17.17	32.45	4.03	32.89	7.2	10.1	137.58
2008	1.18	62314	4.2	119.5	41.22	40.82	18.14	32.72	4.19	33.25	7.1	9.5	137.1
2009	0.96	60049	1.4	113.1	41	41.65	19.35	32.21	4.21	33.63	6.8	9.1	138.42
2010	1.04	62346	0.2	118	40.5	43.07	21.65	33.39	4.49	34.01	6.8	8.5	143.1
2011	1.24	64757	1	125.6	39.09	43.36	21.17	35.05	4.66	34.34	6.6	8.5	143.33
2012	1.27	65623	1	128.1	38.11	44.06	20.95	35.11	4.34	34.75	6.6	8.4	142.58
2013	1.27	66797	1	129	37.87	45.91	21.95	35.38	4.58	35.16	6.5	8.4	145.69
2014	1.28	69812	1	130.4	36.1	45.92	21.99	36.47	4.48	35.55	6.5	8.2	144.96

Appendix I Categorical data for GHG Emission by Road transport modeling

Year	GasolinePrice CADLiter	GDPtransportation	InterestRate(Overnight)	CPI	CarsEmission	LightTrucksEmission	MediumTrucksEmission	HeavyTrucksemission	BusesTransitEmission	Population(million)	Passengercarfueleffi ciency	Lightdutytruckfueleffi	GHGcatagorical
1990	0.59	24000	13.7	71.6	49.31	21.85	8.25	17.82	3.3	27.5	8.2	11.3	bet 100 & 110
1991	0.58	28000	9.3	72.9	47.92	21.55	8.23	16.07	3.43	27.9	8	11.4	bet 90 & 100
1992	0.55	31000	6.1	74.4	47.9	23.13	8.61	16.47	3.35	28.38	8.1	11.1	bet 90 & 100
1993	0.54	35000	4.3	76.8	48.47	24.15	8.97	18.33	3.05	28.68	8.1	11.3	bet 100 & 110
1994	0.54	38000	4.8	80.2	48.33	26.38	9.71	21.06	2.95	29	8.2	11.1	bet 100 & 110
1995	0.57	41000	5.7	84.3	47.49	27.64	10.1	22.43	3.6	29.3	7.9	11.5	bet 110 & 120
1996	0.59	43000	6	87.6	46.38	29.33	10.18	23.69	3.07	29.61	7.9	11.5	bet 110 & 120
1997	0.61	46708	4.3	90.3	46.03	31.54	10.55	25.71	3.51	29.97	8	11.3	bet 110 & 120
1998	0.56	47640	3.3	89.6	45.15	33.73	10.96	26.35	3.46	30.16	7.9	11.4	bet 110 & 120
1999	0.6	50566	5.1	92.6	44.98	35.21	11.45	27.58	3.37	30.4	7.9	11.3	bet 120 & 130
2000	0.73	53087	4.7	97.2	44.02	35.91	10.82	29.14	3.68	30.69	7.8	11.1	bet 120 & 130
2001	0.72	54448	5.9	97.3	43.67	36.17	12.42	27.39	3.55	31.02	7.8	11	bet 120 & 130
2002	0.72	54341	2	100	44.66	37.86	12.03	27.1	4.11	31.36	7.7	11	bet 120 & 130
2003	0.76	54554	2.9	105.2	44.22	38.65	14.13	29.2	4.3	31.64	7.6	10.8	bet 130 & 140
2004	0.84	56612	2.7	107.7	43.73	39.42	15.67	30.48	3.88	31.94	7.5	10.7	bet 130 & 140
2005	0.95	59944	2.4	112	43	40	14.47	32.28	4.07	32.24	7.4	10.5	bet 130 & 140
2006	1.01	61673	3.2	115.2	41.87	39.32	16.61	31.26	3.75	32.57	7.5	10.4	bet 130 & 140
2007	1.05	62645	4.2	117.1	42.71	41.23	17.17	32.45	4.03	32.89	7.2	10.1	bet 130 & 140
2008	1.18	62314	4.2	119.5	41.22	40.82	18.14	32.72	4.19	33.25	7.1	9.5	bet 130 & 140
2009	0.96	60049	1.4	113.1	41	41.65	19.35	32.21	4.21	33.63	6.8	9.1	bet 130 & 140
2010	1.04	62346	0.2	118	40.5	43.07	21.65	33.39	4.49	34.01	6.8	8.5	bet 140 & 150
2011	1.24	64757	1	125.6	39.09	43.36	21.17	35.05	4.66	34.34	6.6	8.5	bet 140 & 150
2012	1.27	65623	1	128.1	38.11	44.06	20.95	35.11	4.34	34.75	6.6	8.4	bet 140 & 150
2013	1.27	66797	1	129	37.87	45.91	21.95	35.38	4.58	35.16	6.5	8.4	bet 140 & 150

Appendix J Multinomial Logistic Regression Run information For Nominal Data

=== Run information ===

Scheme:weka.classifiers.functions.Logistic -R 1.0E-8 -M -1
Relation: final may 31-weka.filters.unsupervised.attribute.Remove-R15-weka.filters.unsupervised.attribute.Remove-R2
Instances: 24
Attributes: 14
Year
GasolinePriceCADLiter
GDPtransportation
InterestRate(Overnight)
CPI
CarsEmission
LightTrucksEmission
MediumTrucksEmission
HeavyTrucksemission
BusesTransitEmission
Population(million)
Passengercarfuelefficiency
Lightdutytruckfueleffi
GHGcatagorical
Test mode:10-fold cross-validation
=== Classifier model (full training set) ===

Logistic Regression

Coefficients...

	Class				
Variable	bet 100 & 110	bet 90 & 100	bet 110 & 120	bet 120 & 130	bet 130 & 140
Year	0.0856	-1.1374	-2.4338	1.6573	4.0768
GasolinePriceCADLiter	43.9027	14.5173	-114.6092	-98.7884	-19.0271
GDPtransportation	-0.0009	-0.0013	0.0003	0.0036	0.0001
InterestRate(Overnight)	-3.195	-7.6046	-2.4208	10.7267	7.0482
CPI	-0.1985	-0.6136	0.0221	-0.6943	0.8695
CarsEmission	10.0069	-4.7604	-1.5485	-7.1305	10.3866
LightTrucksEmission	-1.0984	-2.6539	-1.7882	6.7494	1.6007
MediumTrucksEmission	3.1254	-1.6718	-1.414	-11.3082	6.9163
HeavyTrucksemission	0.2188	-6.5983	4.802	0.2301	3.3411
BusesTransitEmission	-99.4096	40.2464	-21.2482	7.7169	-13.1961
Population(million)	0.1374	-2.8576	-3.3306	1.6673	6.7079
Passenger carfuelefficiency	19.1213	-12.855	-15.2339	48.636	39.7382
Lightdutytruckfueleffi	-27.0541	-8.1767	34.0729	23.1716	45.6804
Intercept	-62.0019	3046.4388	4939.9123	-3839.2181	-9867.7561

Odds Ratios...

	Class				
Variable	bet 100 & 110	bet 90 & 100	bet 110 & 120	bet 120 & 130	bet 130 & 140
Year	1.0894	0.3206	0.0877	5.2454	58.958
GasolinePriceCADLiter	1.17E+19	2017457	0	0	0

GDPtransportation	0.9991	0.9987	1.0003	1.0036	1.0001
InterestRate(Overnight)	0.041	0.0005	0.0889	45555.72	1150.774
CPI	0.82	0.5414	1.0223	0.4994	2.3858
CarsEmission	22178.04	0.0086	0.2126	0.0008	32422.48
LightTrucksEmission	0.3334	0.0704	0.1673	853.5195	4.9567
MediumTrucksEmission	22.7681	0.1879	0.2432	0	1008.54
HeavyTrucksemission	1.2445	0.0014	121.7495	1.2587	28.249
BusesTransitEmission	0	3.01E+17	0	2245.874	0
Population(million)	1.1472	0.0574	0.0358	5.2978	818.8704
Passengercarfuelefficiency	2.01E+08	0	0	1.33E+21	1.81E+17
Lightdutytruckfueleffi	0	0.0003	6.28E+14	1.16E+10	6.90E+19

Appendix K BAU Scenario Projections

Year	Gasoline Price CADLiter	GDP transportation	Interest Rate (Overnight)	CPI	Cars Emission	Light Trucks Emission	Medium Trucks Emission	Heavy Trucks emission	Buses Transit Emission	Population (million)	Passenger car fuel efficiency	Light duty truck fuel efficiency	Bagging MLP Projection
1990	0.6	24000	13.7	71.6	49.31	21.85	8.25	17.82	3.3	27.5	8.2	11.3	100.53
1991	0.6	28000	9.3	72.9	47.92	21.55	8.23	16.07	3.43	27.9	8	11.4	97.2
1992	0.6	31000	6.1	74.4	47.9	23.13	8.61	16.47	3.35	28.38	8.1	11.1	99.46
1993	0.5	35000	4.3	76.8	48.47	24.15	8.97	18.33	3.05	28.68	8.1	11.3	102.98
1994	0.5	38000	4.8	80.2	48.33	26.38	9.71	21.06	2.95	29	8.2	11.1	108.43
1995	0.6	41000	5.7	84.3	47.49	27.64	10.1	22.43	3.6	29.3	7.9	11.5	111.27
1996	0.6	43000	6	87.6	46.38	29.33	10.18	23.69	3.07	29.61	7.9	11.5	112.65
1997	0.6	46708	4.3	90.3	46.03	31.54	10.55	25.71	3.51	29.97	8	11.3	117.33
1998	0.6	47640	3.3	89.6	45.15	33.73	10.96	26.35	3.46	30.16	7.9	11.4	119.65
1999	0.6	50566	5.1	92.6	44.98	35.21	11.45	27.58	3.37	30.4	7.9	11.3	122.59
2000	0.7	53087	4.7	97.2	44.02	35.91	10.82	29.14	3.68	30.69	7.8	11.1	123.56
2001	0.7	54448	5.9	97.3	43.67	36.17	12.42	27.39	3.55	31.02	7.8	11	123.2
2002	0.7	54341	2	100	44.66	37.86	12.03	27.1	4.11	31.36	7.7	11	125.76
2003	0.8	54554	2.9	105.2	44.22	38.65	14.13	29.2	4.3	31.64	7.6	10.8	130.5
2004	0.8	56612	2.7	107.7	43.73	39.42	15.67	30.48	3.88	31.94	7.5	10.7	133.19
2005	1	59944	2.4	112	43	40	14.47	32.28	4.07	32.24	7.4	10.5	133.83
2006	1	61673	3.2	115.2	41.87	39.32	16.61	31.26	3.75	32.57	7.5	10.4	132.81
2007	1.1	62645	4.2	117.1	42.71	41.23	17.17	32.45	4.03	32.89	7.2	10.1	137.58
2008	1.2	62314	4.2	119.5	41.22	40.82	18.14	32.72	4.19	33.25	7.1	9.5	137.1
2009	1	60049	1.4	113.1	41	41.65	19.35	32.21	4.21	33.63	6.8	9.1	138.42
2010	1	62346	0.2	118	40.5	43.07	21.65	33.39	4.49	34.01	6.8	8.5	143.1
2011	1.2	64757	1	125.6	39.09	43.36	21.17	35.05	4.66	34.34	6.6	8.5	143.33
2012	1.3	65623	1	128.1	38.11	44.06	20.95	35.11	4.34	34.75	6.6	8.4	142.58

2013	1.3	66797	1	129	37.87	45.91	21.95	35.38	4.58	35.16	6.5	8.4	145.69
2014	1.3	69812	1	130.4	36.1	45.92	21.99	36.47	4.48	35.55	6.5	8.2	144.96
2015	1.3	72532	0.8	126.5	35.92	46.61	23.09	37.93	4.61	35.93	6.47	8.16	148.211
2016	1.3	74800	0.5	127.9	35.74	47.31	24.24	39.45	4.75	36.28	6.44	8.12	151.647
2017	1.3	75554	0.8	137.1	35.56	48.02	25.46	41.02	4.9	36.71	6.4	8.08	154.991
2018	1.3	77921	1	139.5	35.38	48.74	26.73	42.66	5.04	37.11	6.37	8.04	158.565
2019	1.3	80289	1.5	141.9	35.21	49.47	28.07	44.37	5.19	37.5	6.34	8	162.335
2020	1.4	82656	2	144.3	34.85	49.72	29.19	45.7	5.32	37.89	6.28	7.92	165.008
2021	1.4	85023	2.1	146.8	34.51	49.96	30.36	47.07	5.46	38.29	6.21	7.84	167.514
2022	1.4	87390	2.1	149.2	34.16	50.21	31.57	48.49	5.59	38.68	6.15	7.76	170.12
2023	1.5	89758	2.2	151.6	33.82	50.47	32.83	49.94	5.73	39.07	6.09	7.68	172.823
2024	1.5	92125	2.3	154	33.48	50.72	34.15	51.44	5.88	39.47	6.03	7.61	175.377
2025	1.5	94492	2.3	156.5	32.98	50.62	33.98	50.92	5.85	39.86	5.94	7.49	174.165
2026	1.6	96859	2.4	158.9	32.48	50.52	33.81	50.41	5.82	40.25	5.85	7.38	172.949
2027	1.6	99227	2.5	161.3	32	50.41	33.64	49.91	5.79	40.65	5.76	7.27	171.788
2028	1.7	101594	2.5	163.7	31.52	50.31	33.47	49.41	5.76	41.04	5.67	7.16	170.503
2029	1.7	103961	2.6	166.2	31.04	50.21	33.3	48.92	5.73	41.43	5.59	7.05	169.286
2030	1.8	106328	2.7	168.6	30.58	50.11	33.13	48.43	5.7	41.83	5.51	6.95	168.072

Appendix L Minimum Mitigation (M1) Scenario Projections

Year	Gasoline Price CADLiter	GDP transportation	Interest Rate (Overnight)	CPI	Cars Emission	Light Trucks Emission	Medium Trucks Emission	Heavy Trucks emission	BusesTransit Emission	Population (million)	Passenger car fuel efficiency	Light duty truck fuel efficiency	Bagging MLP Projections
1990	0.59	24000	13.7	71.6	49.31	21.85	8.25	17.82	3.3	27.5	8.2	11.3	100.119
1991	0.58	28000	9.3	72.9	47.92	21.55	8.23	16.07	3.43	27.9	8	11.4	97.73
1992	0.55	31000	6.1	74.4	47.9	23.13	8.61	16.47	3.35	28.38	8.1	11.1	99.495
1993	0.54	35000	4.3	76.8	48.47	24.15	8.97	18.33	3.05	28.68	8.1	11.3	103.14
1994	0.54	38000	4.8	80.2	48.33	26.38	9.71	21.06	2.95	29	8.2	11.1	108.099
1995	0.57	41000	5.7	84.3	47.49	27.64	10.1	22.43	3.6	29.3	7.9	11.5	111.304
1996	0.59	43000	6	87.6	46.38	29.33	10.18	23.69	3.07	29.61	7.9	11.5	112.528
1997	0.61	46708	4.3	90.3	46.03	31.54	10.55	25.71	3.51	29.97	8	11.3	117.404
1998	0.56	47640	3.3	89.6	45.15	33.73	10.96	26.35	3.46	30.16	7.9	11.4	119.721
1999	0.6	50566	5.1	92.6	44.98	35.21	11.45	27.58	3.37	30.4	7.9	11.3	122.567
2000	0.73	53087	4.7	97.2	44.02	35.91	10.82	29.14	3.68	30.69	7.8	11.1	123.546
2001	0.72	54448	5.9	97.3	43.67	36.17	12.42	27.39	3.55	31.02	7.8	11	123.142
2002	0.72	54341	2	100	44.66	37.86	12.03	27.1	4.11	31.36	7.7	11	125.515
2003	0.76	54554	2.9	105.2	44.22	38.65	14.13	29.2	4.3	31.64	7.6	10.8	131.01
2004	0.84	56612	2.7	107.7	43.73	39.42	15.67	30.48	3.88	31.94	7.5	10.7	133.085
2005	0.95	59944	2.4	112	43	40	14.47	32.28	4.07	32.24	7.4	10.5	133.907
2006	1.01	61673	3.2	115.2	41.87	39.32	16.61	31.26	3.75	32.57	7.5	10.4	133.125
2007	1.05	62645	4.2	117.1	42.71	41.23	17.17	32.45	4.03	32.89	7.2	10.1	137.749
2008	1.18	62314	4.2	119.5	41.22	40.82	18.14	32.72	4.19	33.25	7.1	9.5	137.166
2009	0.96	60049	1.4	113.1	41	41.65	19.35	32.21	4.21	33.63	6.8	9.1	138.499
2010	1.04	62346	0.2	118	40.5	43.07	21.65	33.39	4.49	34.01	6.8	8.5	142.867
2011	1.24	64757	1	125.6	39.09	43.36	21.17	35.05	4.66	34.34	6.6	8.5	143.245
2012	1.27	65623	1	128.1	38.11	44.06	20.95	35.11	4.34	34.75	6.6	8.4	142.328

2013	1.27	66797	1	129	37.87	45.91	21.95	35.38	4.58	35.16	6.5	8.4	145.322
2014	1.28	69812	1	130.4	36.1	45.92	21.99	36.47	4.48	35.55	6.5	8.2	145.271
2015	1.3	72532	0.8	126.5	35.74	46.26	22.54	37.2	4.56	35.93	6.4	8.1	146.267
2016	1.31	74800	0.5	127.9	35.38	46.61	23.1	37.94	4.64	36.28	6.4	8	147.738
2017	1.33	76146	0.8	130.1	35.03	46.96	23.68	38.7	4.72	36.71	6.3	8	149.116
2018	1.35	77517	1	132.3	34.68	47.31	24.27	39.48	4.8	37.11	6.2	7.9	150.546
2019	1.37	78912	1.5	134.5	34.33	47.67	24.88	40.27	4.89	37.5	6.2	7.8	152.05
2020	1.4	80333	2	136.8	33.64	47.79	25.38	40.87	4.95	37.89	6.1	7.6	152.692
2021	1.43	81779	2.1	139.1	32.97	47.91	25.88	41.48	5.01	38.29	5.9	7.5	153.221
2022	1.46	83251	2.2	141.5	32.31	48.03	26.4	42.11	5.07	38.68	5.8	7.3	153.86
2023	1.5	84749	2.3	143.9	31.67	48.15	26.93	42.74	5.13	39.07	5.7	7.2	154.566
2024	1.53	86275	2.4	146.4	31.03	48.27	27.47	43.38	5.2	39.47	5.6	7	155.144
2025	1.58	87828	2.6	148.9	30.1	48.22	27.4	43.16	5.19	39.86	5.4	6.8	154.061
2026	1.63	89409	2.7	151.4	29.2	48.17	27.33	42.95	5.17	40.25	5.3	6.6	152.878
2027	1.69	91018	2.8	154	28.32	48.12	27.26	42.73	5.16	40.65	5.1	6.4	151.699
2028	1.74	92656	3	156.6	27.47	48.07	27.2	42.52	5.15	41.04	4.9	6.2	150.494
2029	1.8	94324	3.1	159.2	26.65	48.03	27.13	42.3	5.13	41.43	4.8	6.1	149.233
2030	1.86	96022	3.3	161.9	25.85	47.98	27.06	42.09	5.12	41.83	4.7	5.9	147.987

Appendix M Maximum Mitigation (M2) Scenario Projections

Year	Gasoline Price CAD Liter	GDPtransportation	Interest Rate (Overnight)	CPI	Cars Emission	Light Trucks Emission	Medium Trucks Emission	Heavy Trucks emission	Buses Transit Emission	Population (million)	Passenger car fuel efficiency	Light duty truck fuel efficiency	Bagging MLP Projection
1990	0.59	24000	13.7	71.6	49.31	21.85	8.25	17.82	3.3	27.5	8.2	11.3	99.687
1991	0.58	28000	9.3	72.9	47.92	21.55	8.23	16.07	3.43	27.9	8	11.4	97.816
1992	0.55	31000	6.1	74.4	47.9	23.13	8.61	16.47	3.35	28.38	8.1	11.1	99.49
1993	0.54	35000	4.3	76.8	48.47	24.15	8.97	18.33	3.05	28.68	8.1	11.3	103.251
1994	0.54	38000	4.8	80.2	48.33	26.38	9.71	21.06	2.95	29	8.2	11.1	108.052
1995	0.57	41000	5.7	84.3	47.49	27.64	10.1	22.43	3.6	29.3	7.9	11.5	111.097
1996	0.59	43000	6	87.6	46.38	29.33	10.18	23.69	3.07	29.61	7.9	11.5	112.576
1997	0.61	46708	4.3	90.3	46.03	31.54	10.55	25.71	3.51	29.97	8	11.3	117.351
1998	0.56	47640	3.3	89.6	45.15	33.73	10.96	26.35	3.46	30.16	7.9	11.4	119.898
1999	0.6	50566	5.1	92.6	44.98	35.21	11.45	27.58	3.37	30.4	7.9	11.3	122.528
2000	0.73	53087	4.7	97.2	44.02	35.91	10.82	29.14	3.68	30.69	7.8	11.1	123.659
2001	0.72	54448	5.9	97.3	43.67	36.17	12.42	27.39	3.55	31.02	7.8	11	123.179
2002	0.72	54341	2	100	44.66	37.86	12.03	27.1	4.11	31.36	7.7	11	125.487
2003	0.76	54554	2.9	105.2	44.22	38.65	14.13	29.2	4.3	31.64	7.6	10.8	131.015
2004	0.84	56612	2.7	107.7	43.73	39.42	15.67	30.48	3.88	31.94	7.5	10.7	133.128
2005	0.95	59944	2.4	112	43	40	14.47	32.28	4.07	32.24	7.4	10.5	133.931
2006	1.01	61673	3.2	115.2	41.87	39.32	16.61	31.26	3.75	32.57	7.5	10.4	133.232
2007	1.05	62645	4.2	117.1	42.71	41.23	17.17	32.45	4.03	32.89	7.2	10.1	137.532
2008	1.18	62314	4.2	119.5	41.22	40.82	18.14	32.72	4.19	33.25	7.1	9.5	137.087
2009	0.96	60049	1.4	113.1	41	41.65	19.35	32.21	4.21	33.63	6.8	9.1	138.551
2010	1.04	62346	0.2	118	40.5	43.07	21.65	33.39	4.49	34.01	6.8	8.5	142.918
2011	1.24	64757	1	125.6	39.09	43.36	21.17	35.05	4.66	34.34	6.6	8.5	143.21
2012	1.27	65623	1	128.1	38.11	44.06	20.95	35.11	4.34	34.75	6.6	8.4	142.394

2013	1.27	66797	1	129	37.87	45.91	21.95	35.38	4.58	35.16	6.5	8.4	145.197
2014	1.28	69812	1	130.4	36.1	45.92	21.99	36.47	4.48	35.55	6.5	8.2	145.295
2015	1.3	72532	0.8	126.5	35.38	46.24	22.43	37.2	4.52	35.93	6.4	8	145.819
2016	1.32	74800	0.5	127.9	34.67	46.57	22.88	37.94	4.57	36.28	6.2	7.9	146.796
2017	1.34	75847	0.8	129.7	33.98	46.89	23.34	38.7	4.62	36.71	6.1	7.7	147.546
2018	1.36	76909	1	131.5	33.3	47.22	23.8	39.48	4.66	37.11	6	7.6	148.432
2019	1.38	77986	1.5	133.3	32.63	47.55	24.28	40.27	4.71	37.5	5.9	7.4	149.307
2020	1.42	79078	2	135.2	31.65	47.6	24.4	40.47	4.73	37.89	5.7	7.2	148.882
2021	1.46	80185	2.1	137.1	30.7	47.65	24.52	40.67	4.76	38.29	5.5	7	148.302
2022	1.51	81307	2.3	139	29.78	47.69	24.64	40.87	4.78	38.68	5.4	6.8	147.759
2023	1.55	82446	2.5	141	28.89	47.74	24.77	41.08	4.8	39.07	5.2	6.6	147.321
2024	1.6	83600	2.6	142.9	28.02	47.79	24.89	41.28	4.83	39.47	5	6.4	146.629
2025	1.65	84770	2.8	144.9	26.9	46.83	24.15	40.04	4.73	39.86	4.8	6.1	142.733
2026	1.7	85957	3	147	25.82	45.9	23.42	38.84	4.64	40.25	4.6	5.9	138.639
2027	1.75	87160	3.2	149	24.79	44.98	22.72	37.68	4.54	40.65	4.5	5.6	134.693
2028	1.8	88381	3.4	151.1	23.8	44.08	22.04	36.55	4.45	41.04	4.3	5.4	130.853
2029	1.85	89618	3.7	153.2	22.85	43.2	21.38	35.45	4.36	41.43	4.1	5.2	126.968
2030	1.91	90873	3.9	155.4	21.93	42.33	20.73	34.39	4.28	41.83	3.9	5	123.345

Appendix N All Scenario Projections

Year	BAU Projection	M1 Projection	M2 Projection	Historic
1990	100.53	100.53	100.53	100.53
1991	97.20	97.20	97.20	97.20
1992	99.46	99.46	99.46	99.46
1993	102.98	102.98	102.98	102.98
1994	108.43	108.43	108.43	108.43
1995	111.27	111.27	111.27	111.27
1996	112.65	112.65	112.65	112.65
1997	117.33	117.33	117.33	117.33
1998	119.65	119.65	119.65	119.65
1999	122.59	122.59	122.59	122.59
2000	123.56	123.56	123.56	123.56
2001	123.20	123.20	123.20	123.20
2002	125.76	125.76	125.76	125.76
2003	130.50	130.50	130.50	130.50
2004	133.19	133.19	133.19	133.19
2005	133.83	133.83	133.83	133.83
2006	132.81	132.81	132.81	132.81
2007	137.58	137.58	137.58	137.58
2008	137.10	137.10	137.10	137.10
2009	138.42	138.42	138.42	138.42
2010	143.10	143.10	143.10	143.10
2011	143.33	143.33	143.33	143.33
2012	142.58	142.58	142.58	142.58
2013	145.69	145.69	145.69	145.69

2014	144.96	144.96	144.96	144.96
2015	148.21	146.27	145.82	
2016	151.65	147.74	146.80	
2017	154.99	149.12	147.55	
2018	158.57	150.55	148.43	
2019	162.34	152.05	149.31	
2020	165.01	152.69	148.88	
2021	167.51	153.22	148.30	
2022	170.12	153.86	147.76	
2023	172.82	154.57	147.32	
2024	175.38	155.14	146.63	
2025	174.17	154.06	142.73	
2026	172.95	152.88	138.64	
2027	171.79	151.70	134.69	
2028	170.50	150.49	130.85	
2029	169.29	149.23	126.97	
2030	168.07	147.99	123.35	