Study of Vehicle Emissions Inventory and Energy Consumption from Road Transport Using COPERT Modelling: A Case of Addis Ababa City

Alemayehu Niguse Arsedi

A Thesis Submitted to the Department of Mechanical Engineering,

College of Mechanical, Chemical, and Materials Engineering

Presented in Partial Fulfillment of the Requirement for the Degree of Master's in Automotive Engineering

Office of Graduate Studies

Adama Science and Technology University

July, 2025

Adama, Ethiopia

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I, the advisor of this thesis, hereby certify that I have read the revised version of the thesis entitled "**Study of Vehicle Emissions Inventory and Energy Consumption from Road Transport Using COPERT Modelling: A Case of Addis Ababa City**" prepared under my guidance by **Alemayehu Niguse** submitted in partial fulfillment of the requirements for the degree of Mater's of Science in Automotive Engineering. Therefore, I recommend the submission of a revised version of the thesis to the department following the applicable procedures.

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APPROVAL PAGE

I, the advisors of the thesis entitled "**Study of Vehicle Emissions Inventory and Energy Consumption from Road Transport Using COPERT Modelling: A Case of Addis Ababa City**" and developed by **Alemayehu Nigussie**, hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

Alemayehu Wakjira (PhD)	____________________	______________
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LIST OF ABBREVIATIONS

AA	Addis Ababa
ANN	Artificial Neural Networks
CO	Carbon Monoxide
CO_2	Carbon Dioxide
EC	Energy Consumption
GHG	Greenhouse Gas
HBEFA	Handbook on Emission Factors for Road Transport
IVE	International Vehicle Emissions
NOx	Nitrogen Oxide
ORNL	Oak Ridge National Laboratory
PM	Particulate Matter
UNECE	United Nations Economic Commission for Europe
VOC	Volatile Organic Compounds
WLTC	World Light Duty Test Cycle

ABSTRACT

This study investigates Addis Ababa's passenger car growth after 2005 and its effects on the environment between 2018 and 2024. Predictive Linear Regression and Artificial Neural Networks (ANN) machine learning techniques were used in the study to forecast the growth of the fleet of passenger cars to determine related emissions and energy usage. The study incorporates environmental factors, vehicle activity patterns, and local vehicle registration data into the COPERT model. Vehicle classifications by fuel type (diesel and petrol) and Euro 1 to Euro 6 criteria were taken into account in the analysis. The overall number of passenger vehicles has increased by more than twentyfold during the last 20 years, according to the results. Pollutant emissions have increased as a result, especially from older Euro 1 to Euro 3 vehicles, and include CO_2, NO_x, CO, and VOC. Due to limited adoption of low-emission vehicle technology and growing travel demand, the energy consumption for passenger cars also exhibited steady growth. The results highlighted how policy changes stopped the increase of passenger vehicle emissions after 2024 due to the banning of internal combustion-based passenger vehicles. By offering a data-driven methodology for assessing vehicle-related emissions and guiding mitigation methods, this study supports sustainable transportation planning at the local and national levels.

Keywords: *Addis Ababa, Energy Consumption, Vehicle Emissions, Vehicle Growth*

CHAPTER ONE
INTRODUCTION

1.1. Background of the study

Many cities in sub-Saharan Africa have seen a sharp increase in vehicle ownership as a result of the fast urban population expansion and rising demand for motorised transportation. Addis Ababa, the capital of Ethiopia, is no exception. The city, which is the administrative, political, and economic center of the country, has seen a dramatic increase in motor vehicle activity over the last 20 years. As a result of this expansion, there are now major issues with public health and environmental sustainability due to the rise in urban air pollution, greenhouse gas emissions resulting from the use of petroleum fuels (UNEP, 2016).

Emissions from motor vehicles are a major contributor to both local air pollution and climate change. Internal combustion engine (ICE) vehicles emit carbon monoxide (CO), nitrogen oxides (NOx), particulate matter (PM), hydrocarbons (HC), and carbon dioxide (CO_2) (EEA, 2019). These pollutants contribute to global warming, harm human health, and degrade the overall quality of the air. In developing countries like Ethiopia, where there are few vehicle emissions regulations and enforcement rules, measuring emissions and fuel consumption from motor vehicles is essential for evidence-based planning and policymaking.

Over the past 20 years, Addis Ababa has experienced a notable increase in motorisation, with a fleet of vehicles primarily composed of buses, commercial vehicles, passenger vehicles, and a growing number of motorbikes. Most of these cars are imported used cars, frequently with high emission factors and antiquated technology (Gebreegziabher et al., 2020).

Comprehending the present makeup of the automobile fleet is essential for creating an emission inventory and putting focused mitigation plans into action. Buses, motorbikes, light and heavy trucks, and passenger cars make up 41, 34, 18, and 3.96 percent of all vehicles, respectively. According to Gadola (2018), 56.57% of the city's automobiles are diesel-powered, while 43.43% are gasoline-powered.

Not much attention has been given to Addis Ababa's emissions, despite the city's concerning car expansion. Vehicles by kind in 2021 are depicted in Figure 1.1. It is equally crucial to forecast future vehicle expansion, especially for infrastructure development and urban planning. Although they are helpful for extrapolating trends, traditional linear models frequently fail to capture the intricate, nonlinear interactions present in transportation networks. Because of their ability to learn from past data and represent nonlinear dynamics, Artificial Neural Networks (ANNs) have become highly effective tools for time series prediction and demand forecasting (Haykin et al., 2009).

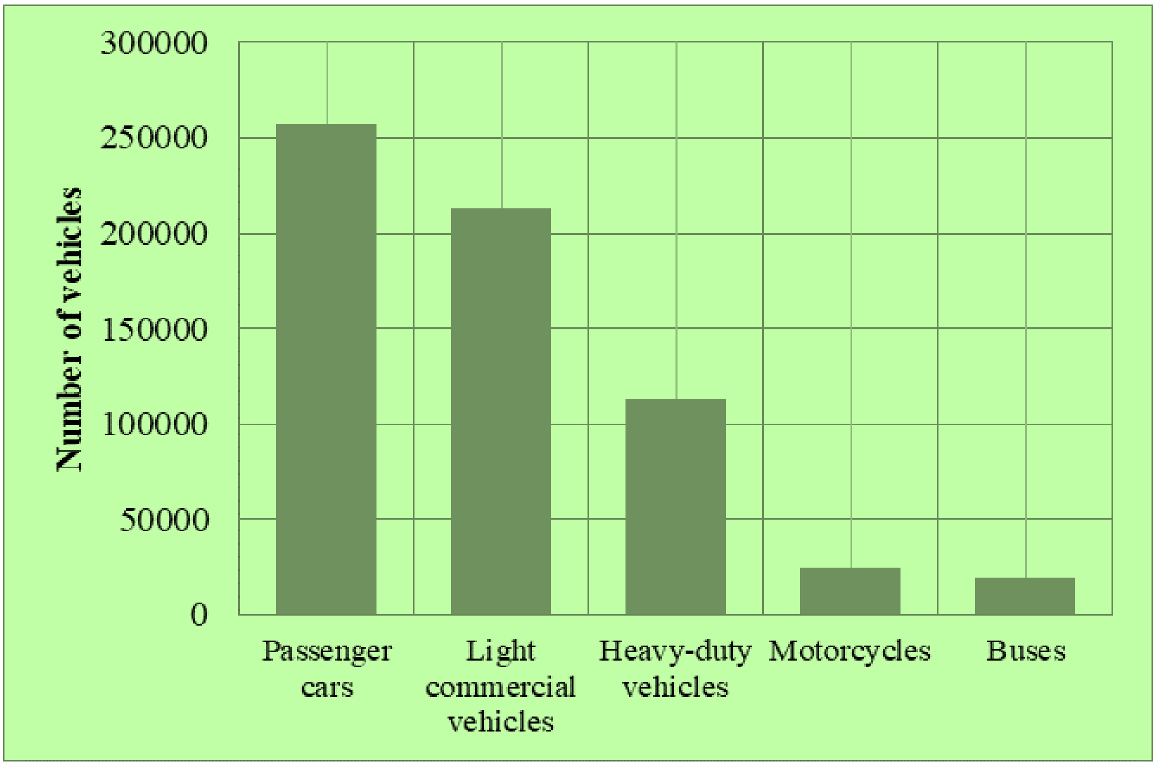

Figure 1.1: Distribution of vehicle categories in 2021

An essential first step in managing urban air quality is quantifying automobile emissions using an inventory approach. Pollutant emissions from various vehicle types under various operating situations are estimated both spatially and temporally using emission inventories. To complete vehicle emissions inventories and calculate emissions and fuel consumption from light-duty vehicles, Europe employs the WLTC. The WLTC was developed by the UNECE and is shown in Figure 1.2. In the EU, it will take the place of the NEDC (Marker et al., 2016). The NEDC for the type-approval testing of light-duty vehicles was replaced in September 2017 by the Euro 6C emission requirements. The WLTC was developed without the inclusion of driving data from African nations. The WLTC might therefore not be a realistic representation of local driving conditions in places like Addis Ababa.

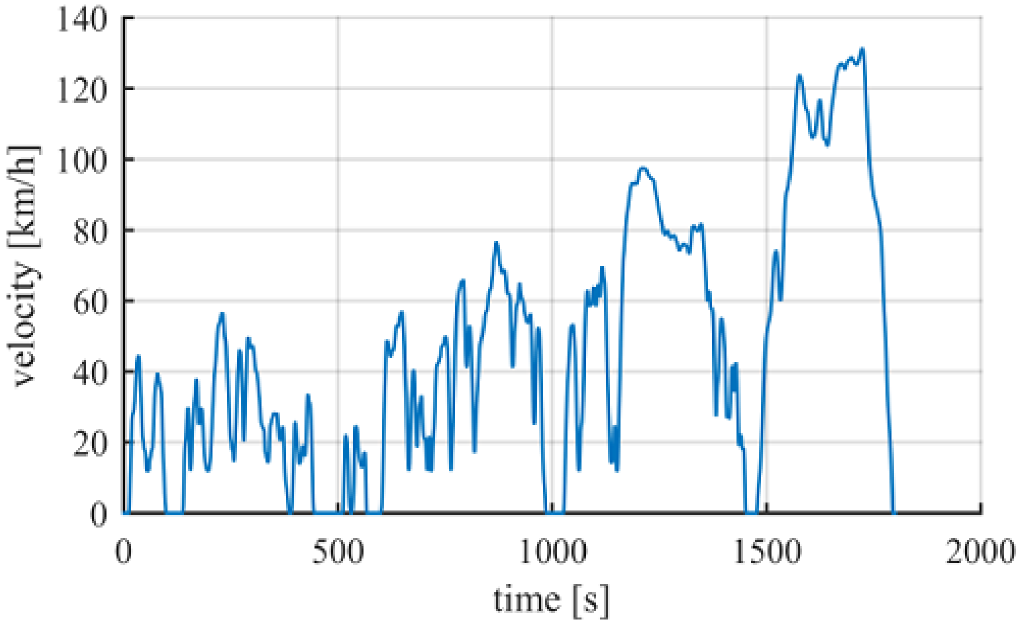

Figure 1.2: WLTC for class 3 vehicles

The Addis Ababa Drive Cycle (AADC), seen in Figure 1.3, was created in 2022 to account for the city's distinct traffic and driving patterns, but it hasn't been applied to assess car emissions and fuel consumption as of yet.

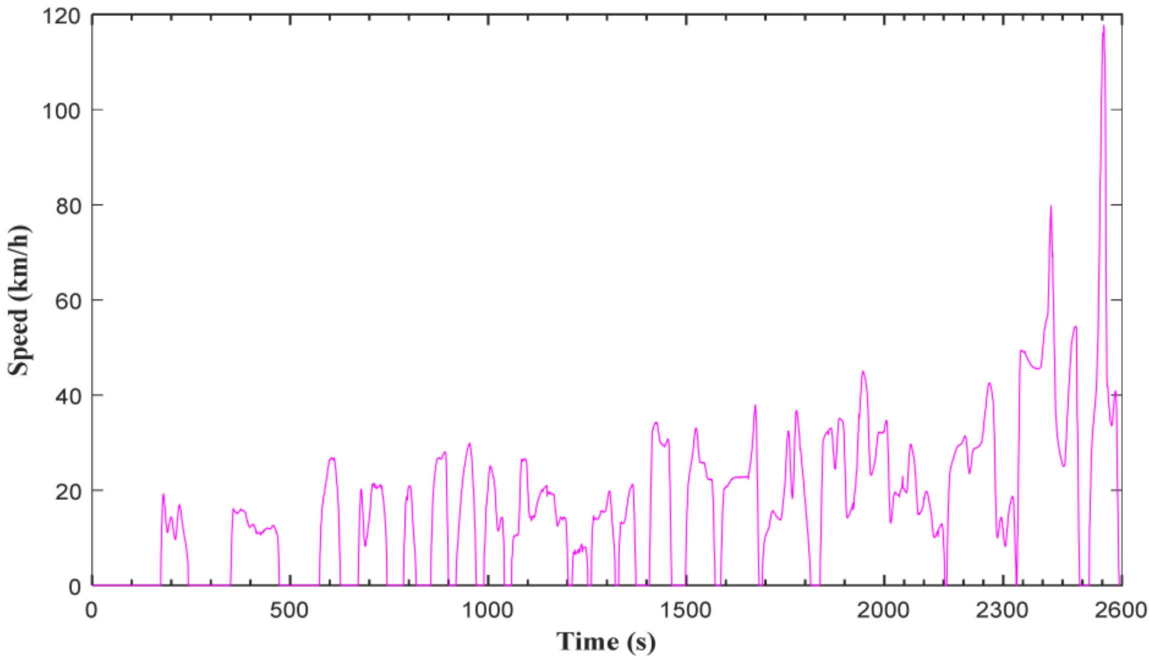

Figure 1.3: Addis Ababa Drive Cycle (A. Gebisa, 2022)

Vehicle emissions inventories are crucial resources for comprehending how the transportation industry contributes to both air pollution and climate change. Over a given period and geographic area, these inventories offer quantitative estimates of the pollutants released by motor vehicles. Modelling air quality, developing policies, evaluating mitigation techniques, and assessing regulations are all based on them. Worldwide, a number of models have been created to aid in the assessment of vehicle emissions. The most popular tools are Handbook Emission Factors for Road Transport (HBEFA), Motor Vehicle Emission Simulator (MOVES), International Vehicle Emissions (IVE) Model, and Computer Programme to Compute Emissions from Road Transport (COPERT).

To estimate the emissions inventory of Addis Ababa's road transport industry, this study employed the COPERT model, a globally recognised instrument created by the European Environment Agency. Based on vehicle activity data, fuel type, and driving behaviour, COPERT is intended to compute emissions of pollutants such as CO_2, CO, NOx, PM, and VOC (Ntziachristos & Samaras, 2018).

In addition to emissions, the energy consumption of road transport is a key indicator of its effectiveness and dependence on fossil fuels. Given the growing concerns regarding sustainability and energy security, it is imperative to understand the amount and trends of fuel usage. In Addis Ababa, almost all road transport is powered by petroleum products, with petrol and diesel being the most commonly used fuels. This reliance makes the transportation industry particularly vulnerable to changes in energy prices and supplies. The COPERT model further integrates fuel consumption estimation modules that allow the integration of vehicle activity data with fuel efficiency metrics to produce precise fuel inventory projections (EEA, 2019).

Generally speaking, this study was driven by the pressing need to assess and manage the energy and environmental impacts of road travel in Addis Ababa. By determining the current fleet of vehicles, projecting future vehicle growth, and estimating emissions and fuel consumption inventories using COPERT, the study hopes to generate valuable insights for environmental stakeholders, policymakers, and urban planners. The findings are expected to support efforts to reduce Addis Ababa's use of fossil fuels and urban air pollution, as well as the development of sustainable transportation policy.

1.2. Statements of the problem

Despite the alarming increase in the number of automobiles in Addis Ababa, the pollution these vehicles emit has received little attention. Ethiopia has no legally mandated ambient air quality regulations, and studies done in Addis Ababa, Ethiopia, revealed significant levels of CO, NOx, HC, and PM emissions. The goal of this study was to look at Addis Ababa's road emissions because air pollution affects society, the economy, and the environment. The overall amount of emissions generated from vehicle transport in numerous nations has been developed.

A local drive cycle has not yet been used to calculate the emission inventory in Addis Ababa, Ethiopia. Furthermore, it is unknown how quickly Addis Ababa's road vehicle population will rise in the future. To predict vehicle growth rates, many studies employed traditional prediction techniques. However, to the best of our knowledge, no study has been conducted on the use of the artificial neural network prediction model to forecast vehicle growth rates.

The purpose of this study is to project the total yearly emissions that Addis Ababa's road cars will emit between 2018 and 2025, following the use of an artificial neural network to forecast the growth rate of the road vehicle. This study will have important implications for science, policy, and practice. The study offers the city's first thorough, localised emission inventory by using the COPERT modelling approach to estimate fuel/energy consumption and vehicle emissions unique to Addis Ababa's traffic and vehicle profile.

1.3. Objectives of the Study

1.3.1. General objective

This study's main aim was to employ COPERT modelling to forecast the energy consumption and vehicle emissions inventory of passenger vehicles in Addis Ababa City, following the use of an artificial neural network to forecast the growth rate of the vehicle population.

1.3.2. Specific objectives

To achieve the aim of the study, the specific objectives were to:

1. Identify the existing vehicles in Addis Ababa.
2. Predict the vehicle growth rate in Addis Ababa using an ANN prediction method.
3. Predict the vehicle’s emissions inventory for the study duration period; and
4. Predict the vehicle's fuel consumption inventory for the study duration period

1.4. Significance of the study

Vehicle emissions have a significant effect on a nation's development. This study's main objectives are to evaluate the fuel consumption and emissions of passenger vehicles in Addis Ababa City, which are important for a number of reasons.

- The emission inventory to be developed for AA city will help researchers and the EPA to quantify pollutants generated (vehicular emissions) and fuel consumption from vehicles.

- In addition to providing large amounts of data and information, this study will assist the city administration, the EPA, and the FTA in identifying how vehicle emissions contribute to air quality problems.
- Policymakers and vehicle manufacturers will use the results of this research to develop future emissions policy/technology strategies and set fuel efficiency standards for transport vehicles.
- It will be a useful reference that provides a theoretical framework for researchers and academicians, those interested in the field of automotive engineering, transportation planning, traffic engineering, environmental, and health.
- This study will be intended to inform Ethiopian policymakers and domestic stakeholders, as well as an interested international audience, on the potential vehicle emissions reduction and fuel savings that could be achieved with the setting of standards.

In general, the findings of this study would be beneficial to the AA city administration, the EPA, FTA, TMA, Researchers, the Automotive industries, and society.

1.5. Scope of the study

Only passenger cars registered in Addis Ababa were the subject of this study. Using the previously created Addis Ababa drive cycle, this analysis forecasted the increase and emissions inventory of vehicles by category between 2018 and 2025. The top 4 emissions that are harmful to the environment and public health, CO_2, CO, NO_X, and VOC, and energy consumption were the focus of this study. Several important aspects remain beyond the scope of the current study, such as particulate matter inventory, the influence of vehicle maintenance status, impact of the operation of air conditioning system were not considered in this study.

1.6. Organization of the Thesis

There are five chapters in this thesis. A thorough analysis of pertinent literature is provided in Chapter Two, which also covers important ideas about vehicle emissions, emissions inventory techniques, and modelling tools like ANNs. The study's methodological framework, data sources, and data gathering techniques are all covered in Chapter 3. The findings and discussion are presented in Chapter Four, along with information on the present state of passenger vehicles in Addis Ababa, anticipated vehicle growth, and the estimated fuel and emissions for the study period. The study's conclusions are presented in Chapter 5, along with helpful recommendations for legislators and urban planners.

CHAPTER TWO

LITERATURE REVIEW

2.1. Overview of vehicle emissions formulation

IC engines, commonly used in industrial and transportation applications, are major sources of air pollution and GHG emissions. The mid-20th century saw an increase in energy consumption, leading to a rise in cars on the road (Ashok et al., 2021). The incomplete combustion, oxygen scarcity, and heterogeneity in the air-fuel mixture all contribute to the formation of toxic gases from vehicles (Adeyanju & Manohar, 2017). High temperatures from complete combustion also generate NOx, as diatomic nitrogen in the air rises (Ashok et al., 2021). Figure 2.1 illustrates the diverse hazardous pollutants produced by CI and SI engines. Vehicle emissions such as CO_2, NOx, CO, PM, and HC contribute to climate change and pose risks to human health and air quality (Fan et al., 2018). Understanding fuel combustion trends is crucial for achieving energy efficiency and optimizing engine performance.

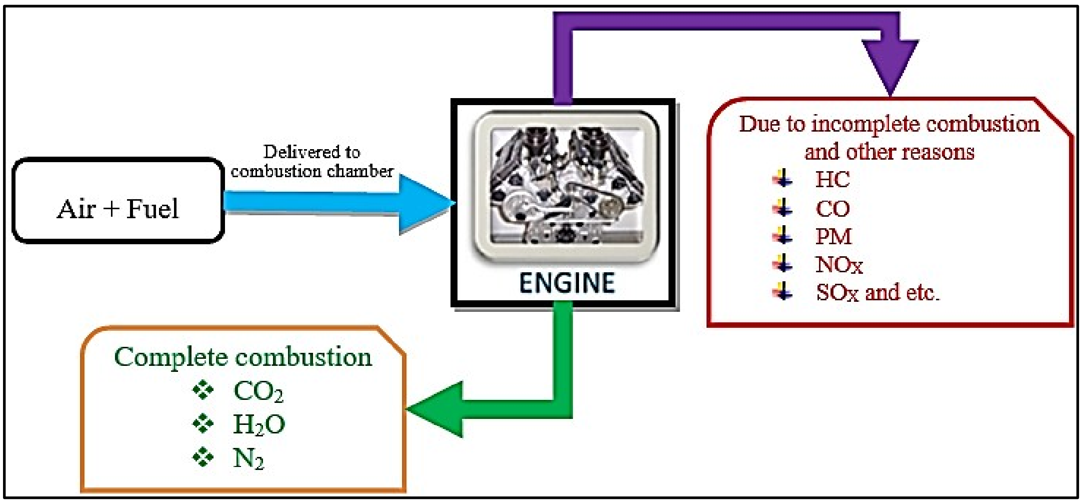

Figure 2.1: Emissions produced from IC engines

Since the growing global population increases demand for transportation, which impacts air quality and climate change, estimating vehicle emissions is essential for environmental assessment and sustainable transportation planning (Wang et al., 2018). Understanding the environmental impact of transportation systems, developing effective plans for managing air quality, and draughting legislation to lessen the effects on the environment and public health are all made easier with the help of estimates of pollutants released by vehicles, including CO_2, CO, NOx, PM, and HC. Emission estimates are used by academics, decision-makers, and urban planners to evaluate emissions standards, reduce emissions, and create environmentally friendly transportation infrastructure (Cedillo et al., 2023). The accuracy of these estimations has improved with real-world data, modelling, and simulation approaches.

2.2. Formation of emissions from the tailpipe

Moving cars emit a variety of hazardous substances, including aromatics in petroleum-based fuel, all of which have the potential to cause harm or cancer. Air pollution can result in acute health reactions like asthma attacks, angina attacks, strokes, and early mortality, according to Ramprasanna et al. (2020). The most hazardous emissions are produced by inefficient engines. The majority of problems stem from incomplete combustion, which is impacted by engine efficiency parameters such as volumetric, thermal, mechanical, and frictional (Ashok et al., 2021). Insufficient air and rich mixes both contribute to the generation of CO and HC during combustion (Lairenlakpam et al., 2018). High combustion chamber temperatures and quick exhaust gas cooling during combustion produce NOx (Triantafyllopoulos et al., 2019).

The air–fuel ratio and combustion quality have a direct impact on hydrocarbon (HC) emissions (Mei et al., 2021). They come from oil desorption, incomplete combustion, and cracks, and they change depending on the engine's temperature. Defects in the fuel seal cause short-chain HCs to be released by petrol engines (Ashok et al., 2021). In addition to being impacted by quench layers, porous deposits, and injector effects, HC emissions happen throughout the diurnal, hot soak, and operating phases (Kawsar et al., 2023).

Although CO is released by both gasoline and diesel engines, the gas's makeup changes based on the system. Diesel engines emit far less CO than gasoline-powered engines (Ashok et al., 2021). Because of the tremendous oxygen circulation in diesel engines, complete combustion is almost always possible. However, when the combustion reaction moves towards lower conversion in petrol systems, the fuel's heterogeneity changes (Adeyanju & Manohar, 2017). Additionally, the architecture of the combustion chamber plays a crucial role in the production of CO in petrol engines. Partial fuel oxidation is promoted in some areas with low oxygen concentrations (Ashok et al., 2021).

Oxygen shortages brought on by driver demands during engine acceleration can reduce combustion efficiency (Adeyanju & Manohar, 2017). This is especially important when the air-fuel ratio becomes unstable during short-term operations like gear shifting, acceleration, and deceleration (Yakın & Behçet, 2021). High CO emissions may result from a combination of insufficient oxygen under cold-start conditions (Wu et al., 2022). Three key reasons contribute to CO emissions in petrol engines, according to Ashok et al. (2021): short residence time, inadequate air-fuel mixing that creates rich zones, and heat loss to cool walls that extinguishes the flame. Even though the high oxygen concentration of diesel engines usually results in lower CO emissions, some CO is nevertheless created in the combustion chamber's oxygen-deficient areas.

Early combustion in ICEs produces nitrogen oxides ($NOx = NO + NO_2$) at high temperatures (Wang et al., 2021; Ren et al., 2014). Human oxidative stress and respiratory ailments are associated with NOx exposure (Ashok et al., 2021; Jonson et al., 2017). In addition to contributing to ozone generation, acid rain, and climate change, it decreases blood oxygen transport (Mei et al., 2021). Ozone is 2000 times more powerful than CO_2 (Ashok et al., 2021).

In order to counteract the greenhouse effect, which was first described by Arrhenius in the 19th century, the EU has implemented policies to lower CO_2 and fuel consumption from vehicles (Tsokolis et al., 2020; Fontaras & Ciuffo, 2017). Wu et al. (2018) highlight the impact of fossil fuel use on CO_2 levels and global warming.

2.3. Methods for estimating vehicle emissions

Regular monitoring is necessary to evaluate changes in air conditions and emission levels. It is commonly acknowledged that vehicle emissions contribute significantly to environmental deterioration and public health issues, especially in urban areas where they are a significant source of air pollutants. Prolonged exposure to vehicle exhaust pollutants has been linked to increased mortality rates and a higher risk of respiratory and cardiovascular disorders (Crossani et al., 2021). The public is more susceptible to air pollution from traffic because fossil fuel-powered vehicles are more common in urban areas (Tarekegn & Gulilat, 2018).

There are several methods for estimating vehicle emissions, and each one offers a different way to account for the many relationships and factors that affect emissions. Emission models, on-road emissions testing, and chassis dynamometers are examples of common techniques.

A chassis dynamometer is used to measure vehicle emissions in a controlled laboratory environment (Adamiak et al., 2023). Emissions models integrate data on vehicle activity, traffic flow, and emissions parameters with mathematical models to simulate and forecast vehicle emissions in specific regions (Fan et al., 2018). By directly measuring emissions from moving vehicles, the on-road emissions test yields more accurate and useful data (Karimipour et al., 2021). Portable emissions measuring devices are used for this test. Furthermore, roadside measurements of exhaust emissions from vehicles on public roads can be made with remote sensing equipment (Shi et al., 2023). Which approach is taken will depend on the study's goals, the resources at hand, and the degree of accuracy needed. The overall accuracy of the vehicle emissions estimate can be increased by combining several techniques.

2.4. Prior research on the inventory of vehicle emissions

Ahn and Rakha (2002) developed mathematical models to predict vehicle emissions and energy consumption using acceleration and instantaneous velocity as explanatory factors. They utilise data collected at Oak Ridge National Laboratory (ORNL), which comprised assessments of the CO, HC, and NOx emission rates and fuel consumption on a chassis dynamometer for three light-duty trucks and five light-duty cars. The fuel consumption and emission models they found have coefficients of determination ranging from 0.92 to 0.99 when compared to the ORNL data. Since the models employ the vehicle's instantaneous velocity and acceleration values as independent parameters, they conclude that they can evaluate the environmental implications.

Ho et al. (2014) developed the Singapore DC, which is responsible for 64% of Singaporean automobiles. On 12 roads, speed-time data were gathered in the morning, evening, and off-peak hours using the chase-car technique. A random collection of microtrips was used to generate the 2400-second Singapore DC. Vehicle exhaust emissions were estimated using a comprehensive modal emission model (CMEM). The results showed that although the mean velocity between Singapore and Europe was very close, the maximum velocity, the proportion of idle mode, and fluctuations in velocity were significantly different between the two driving cycles. The CMEM results show that car emissions in Singapore's DC are higher than those in the European DC. In comparison to the European DC, the Singapore DC consumed 5% more fuel and emitted 5%, 8%, 22%, and 47% more emissions, CO_2, CO, CO, and NO_X emissions, respectively. Most models use mean velocity to assess emissions and energy consumption. The Singapore DC's results showed that mean velocity is not a good way to measure fuel consumption and pollutants.

Amin et al. (2018) used micro-trip data gathered over two weeks via GPS to create a driving cycle (DC) for Mashhad's principal highways. The cycle's average speed differed significantly from that of the European and American cycles, according to 10 evaluation metrics. Mashhad was shown to release 10.5–30.69% more CO than Beijing, Pune, and Mexico using the IVE model. VOC emissions were lower than those in Beijing and Pune, but 18.45% greater than those in Mexico. NOx levels were lower than those in Pune but greater than those in Beijing and Mexico. The study did not distinguish between different vehicle kinds and only looked at major metropolitan routes.

Using micro-trip data collected over seven days, Syafrizal et al. (2014) created a Jakarta DC to evaluate emissions and fuel consumption at the Semanggi intersection. The DC was determined by mean speed, cruising, idling, and acceleration. Using a chassis dynamometer, emissions from passenger automobiles running on petrol and diesel (both Euro-2 and non-Euro) were monitored at different speeds. Mean speed and emission variables (g/km) were connected by a regression model. The theory of planned behaviour was also used in the study to evaluate changes in the use of public transport. Buses had more emissions per vehicle than cars, but because they could carry more passengers, overall emissions decreased.

Tamsanya and Chungpaibulpatana (2009) examined the impact of the DC on vehicle exhaust emissions and the rate of fuel consumption of gasoline-powered passenger cars in Bangkok using a chassis dynamometer. The average speed, the proportion of microtrips, and the percentage of microtrip times distributed throughout the different speed ranges were the three driving factors they considered. CO, CO_2, THC, and NOx exhaust emissions were monitored using a chassis dynamometer and CVS with a hot start after the DC for Bangkok was created. The DC found that short trips in Bangkok were done at slow speeds and that stops were common. The vehicle's low speed, frequent stops, and abrupt speed changes resulted in higher pollutants and fuel consumption.

In order to simulate fuel consumption, Ma et al. (2019) created typical driving cycles for light-duty cars in Beijing, China, using an iterative Markov Chain technique. The off-peak and peak driving cycles were designed with mean speeds of 28.8 km/h and 23.9 km/h, respectively, which were lower than those of NEDC, WLTC, and CLTC. The median fuel consumption during the off-peak and peak cycles was 29.3% and 37.5% higher than the standard NEDC limit, respectively, based on the fuel consumption simulation results.

Using micro-trip data and statistical techniques like PCA and clustering, Yang et al. (2019) created a local driving cycle (LDC) for Nanjing. A Nissan passenger automobile was put through both peak and off-peak emission tests. The average speed and driving characteristics of Nanjing's LDC were higher than those of other Chinese cities. According to emission studies, LDC displayed the highest NOx when idling but the lowest CO_2 when cruising. The NEDC has the greatest HC emissions. According to the study's findings, the LDC gave Nanjing's small passenger cars more precise emission estimations.

2.5. Fuel and energy consumption

The largest factor influencing an automobile's fuel consumption is its engine. Among the variables that can be taken into account when calculating fuel/energy consumption are the engine, driving cycle, and vehicle parameters (Muhammad Ali, 2021).

Fuel/energy consumption can be estimated through experimentation and analysis of the independent variables. This can be further ascertained using the carbon balance methods. The experimental assessment is a more accurate method for estimating vehicle fuel/energy consumption (Zhang, 2020).

2.6. Classification of vehicles and emission requirements of EU

The European Union (EU) employs stringent emission regulations and a systematic vehicle classification system to regulate and reduce pollution from road transport. These consist of two and three-wheelers (L), light commercial vehicles (N1), heavy-duty vehicles (N2, N3, M2, and M3), and passenger cars (M1) (European Commission, 2020). The application of particular emission standards that take into account the functional and technical variations among vehicle classes is made possible by these classifications.

Passenger vehicle classification is crucial for vehicle laws, taxes, insurance, and pollution control policies. Worldwide, and particularly in regulatory frameworks such as those of the US Environmental Protection Agency (US EPA) and the European Union (EU), passenger cars are categorised based on parameters such as engine displacement, vehicle weight, seating capacity, and intended use (European Commission, 2020; USEPA, 2021). In the meantime, the EU uses interior volume as the primary criterion for classifying passenger cars into small, medium, and large (executive) size categories (USEPA, 2021).

The European Union created the European emission standards (Table 2.1), a set of increasingly strict rules that began with Euro 1 in 1992 and are currently in effect, to combat vehicle emissions. Carbon monoxide (CO), nitrogen oxides (NOx), hydrocarbons (HC), particulate matter (PM), and particle number (PN) are among the major pollutants that are limited by these criteria (European Environment Agency, 2022). Using real driving emissions (RDE) and laboratory testing under the Worldwide Harmonised Light Vehicles Test Procedure (WLTP), Euro 6 for light-duty vehicles, for example, requires that NOx emissions from diesel cars not exceed 80 mg/km and PM be below 4.5 mg/km (Fontaras et al., 2017). This regulation was put into effect in 2014.

Table 2.1: European emission standards for passenger cars (Category M*), g/km

Tier	Date	CO	THC	NMHC	NO_x	$HC+NO_x$	PM	PN
Diesel								
Euro 4	Jan. 2005	0.50	-	-	0.25	0.30	0.025	-
Euro 5a	Sept. 2009	0.50	-	-	0.180	0.230	0.005	-
Euro 5b	Sept. 2011	0.50	-	-	0.180	0.230	0.005	6×10^{11}
Euro 6	Sept. 2014	0.50	-	-	0.080	0.170	0.005	6×10^{11}
Gasoline								
Euro 4	Jan. 2005	1.0	0.10	-	0.08	-	-	-
Euro 5	Sept. 2009	1.0	0.10	0.068	0.060	-	0.005**	-
Euro 6	Sept. 2014	1.0	0.10	0.068	0.060	-	0.005**	6×10^{11}***

Additionally, Euro VI sets significantly stricter criteria for heavy-duty vehicles. Stricter on-board diagnostics (OBD) regulations and portable emissions measurement systems (PEMS) for real-world testing are among its features (Giechaskiel et al., 2019). The classification and standards have a major impact on global fuel technology and car manufacture, and they are the cornerstone of EU efforts to meet climate targets and reduce urban air pollution.

2.7. Vehicular emissions in Addis Ababa

Toxic emissions from car exhaust pipes include HC, CO, NOx, SOx, PM, and CO_2. The consequences of these pollutants include smog, acid rain, liver damage, cancer, heart disease, and accelerated global warming. About 0.3% of global emissions came from Ethiopia, which was identified as the 22nd most climate change vulnerable country and the 31st least prepared to increase resilience in the 2017 ND-GAIN country index, indicating the urgent need for action (Wang-Helmreich, 2018). 6.1% of all energy is used in the transportation sector, and between 2015 and 2035, FC is expected to grow by almost 285%. "From 1990 to 2017, emission intensity increased from 2.46 to 3.22 $MtCO_2$ per ktone of fossil fuels, indicating higher emissions being released". "Ethiopia pledges to cap its 2030 GHG emissions at 145 $MtCO_2e$, which equates to a 64% (255$MtCO_2e$) reduction from projected emission levels in 2030, 10$MtCO_2$ reduction is expected from the transport sector" (Federal Democratic Republic of Ethiopia, 2015).

According to COPERT's emissions estimates for 97,873 vehicles, passenger cars in AA city are responsible for 40.12% of CO_2 (0.543 Mtons), 76.59% of CO (6.025 Ktons), 14.33% of

NOx (0.88 Ktons), and 33% of PM (0.152 Ktons) emissions. Assuming a 10% annual gain in fuel efficiency, passenger automobile GHG emissions will reach 13.1MtCO_2e in 2030. The overall (mean±SD) concentration levels of CO, VOC, NO_2, and SO_2 were 4.82±3.60 ppm, 317.52±221.52μg/m^3, 0.12±0.16 ppm, and 0.23±0.20 ppm, respectively, based on data collected in AA roadsides between June and August 2016. The researcher suggests that the pollutants were high and require ongoing monitoring and the investigation of mitigation techniques (D. Tsegaye, 2019).

Ethiopia imported 135,457 vehicles in the fiscal year ending July 7, 2019, which was 30,834 more than the previous year (Federal Ministry of Transport). Although the government has begun to restrict the import of used cars, the sudden imposition of high excise taxes without stakeholder input has raised concerns. Notably, 53.5% of Addis Ababa's vehicles are over 20 years old, and 29.3% exceed 30 years, indicating that most are beyond their intended service life (Fekadu, 2017). More than 51% of Ethiopia's vehicles are concentrated in Addis Ababa, with used imports accounting for 80% of total vehicle sales.

Table 2.2: Review of Vehicular emissions in AA city

Reference	Obtained results
Wondifraw (2018)	In Addis Ababa, passenger vehicles were responsible for 40.12% of CO_2 (0.543 million tons), 76.59% of CO (6.025 thousand tons), 14.33% of NOx (0.88 thousand tons), and 33% of PM (0.152 thousand tons) emissions.
Tsegaye et al. (2019)	Average concentrations were measured as follows: CO – 4.82±3.60 ppm, VOC – 317.52±221.52 μg/m³, NO_2 – 0.12±0.16 ppm, and SO_2 – 0.23±0.20 ppm.
Embiale et al. (2019)	Average PM_{10} readings ranged between 206 and 308 μg/m³. The Addis Ketema area showed the highest pollution levels, while Arada sub-city exhibited the lowest.
Bikis & Pandey (2021)	Most locations of Addis Ababa recorded CO_2 concentrations under 700 ppm, though two sites reached up to 1307 ppm in 30-minute measurements. During rush hours, $PM_{2.5}$ levels at bus and taxi stations surpassed 65 μg/m³ and 150 AQI. PM_{10} peaked at 1700 μg/m³ during peak hours and dropped to 970 μg/m³ off-peak. $PM_{2.5}$ also spiked to 560 μg/m³, with the lowest recorded value being 51 μg/m³.
Kebede et al. (2022)	Emissions testing of 358 diesel vehicles in Addis Ababa showed that 67.9% exceeded the U.S. EPA's smoke opacity limit of 41%. Minibuses were identified as the dominant source of urban air pollution, outpacing mid-sized and large buses.
Bizualem et al. (2023)	The study observed significant spatial variation in SO_2, NO_2, $PM_{2.5}$, and PM_{10} levels across Addis Ababa, with SO_2 concentrations in some areas surpassing acceptable limits.

The severity of Addis Ababa's vehicle emissions is continuously highlighted in the evaluated studies presented in Table 2.2, posing a serious risk to human health and urban air quality. According to Moges and Alemu (2024), significant pollutants like CO, SO_2, and PM can increase by up to 51.61% during peak traffic periods, demonstrating how congestion worsens emissions. This implies that air pollution levels and traffic density are directly correlated.

According to Bizualem et al. (2023), SO_2 levels exceed allowable norms in several locations, indicating local hotspots that are likely influenced by vehicle types and traffic patterns. This further emphasises the spatial heterogeneity in pollutant concentrations. Kebede et al.'s (2022) findings that approximately 68% of diesel vehicles exceed emission limits, with minibuses being highlighted as major pollutants, further support the need for targeted regulation and fleet modernisation.

Particulate matter concentrations ($PM_{2.5}$ and PM_{10}) regularly exceed World Health

Organisation (WHO) and Air Quality Index (AQI) standards, sometimes by more than double, posing serious health hazards, according to Jida et al. (2020) and Tefera et al. (2020).

Bizualem et al. (2023) further emphasise the spatial heterogeneity in pollutant concentrations by pointing out that SO_2 levels exceed allowable norms in several locations, hinting at local hotspots that are likely influenced by traffic patterns and vehicle types. The findings by Kebede et al. (2022) that approximately 68% of diesel vehicles surpass emission limits, with minibuses being identified as major pollutants, further support the need for targeted regulation and fleet modernisation.

At transport terminals, peak-hour $PM_{2.5}$ and PM_{10} concentrations are dangerously high, with PM_{10} levels spiking up to 1700 µg/m³, many times over acceptable norms, according to real-time insights provided by Bikis and Pandey (2021). This illustrates the high dangers of short-term exposure for both traffic workers and passengers.

According to Wondifraw (2018), passenger cars are primarily responsible for urban air pollution, accounting for more than 76% of CO and 40% of CO_2 emissions from total vehicular emissions in the city. High concentrations of NO_2 and volatile organic compounds (VOCs) are also reported by Tsegaye et al. (2019), contributing to the mix of dangerous urban pollutants. This suggests inefficiencies in combustion technologies and a lack of emission mitigation.

2.8. Summary of literature review

With a focus on urban environments, this chapter offered a comprehensive analysis of the literature review on vehicle emissions and how to determine them. This chapter provided the formation of tailpipe emissions, various techniques for estimating vehicle emissions, and previous studies on vehicle emission inventory, and Addis Ababa's vehicle emissions.

According to the literature review, localised approaches are still lacking in the Addis Ababa, Ethiopia, context, despite significant global advancements in modelling and estimating vehicle emissions. This highlights how supporting urban air quality management and policy-making requires data-driven driven that are tailored to local conditions.

In summary, the combined data from these studies highlight the serious and complex issues Addis Ababa faces with regard to vehicle emissions. To reduce the increasing air pollution and its negative health effects, critical measures, including fleet replacement, improved urban transportation planning, enforcement of emission regulations, and infrastructure for air quality monitoring, must be implemented immediately.

2.9. Research gap

In Addis Ababa, there are still few systematic and localised studies on vehicle emissions and related energy consumption, despite the city's increasing urbanisation and vehicle population. While COPERT is frequently used to create comprehensive emission inventories in Europe and some African nations, prior research has found little use of the tool in Ethiopian cities, especially Addis Ababa. The majority of Ethiopia's current emission assessments are based on the European driving cycle and use general emission factors, which ignore regional driving habits, road conditions, and variations in fuel quality.

Even though ANN models have demonstrated great promise in forecasting approaches. However, no thorough study has yet integrated ANN-based vehicle growth forecasting with COPERT-based emission modelling customised for the Addis Ababa city context, despite the city's rapidly expanding vehicle fleet and growing air quality concerns. This suggests a serious flaw in the methodology as well as the use of local data.

Therefore, a locally contextualised, data-driven emission inventory framework that uses COPERT for emission estimation based on the Addis Ababa driving cycle while incorporating current traffic and vehicle registration data, and ANN for vehicle growth prediction, is desperately needed. By addressing this, policymakers will receive evidence-based insights for creating emission control and sustainable transportation plans.

CHAPTER THREE

MATERIALS AND METHODS

3.1. Introduction

This chapter outlines the methodology employed by employing COPERT modelling to examine the fuel consumption (FC) and vehicle emissions inventory from Addis Ababa's passenger vehicles. The approach, which is customised to the city's local transportation and environmental context, combines emission inventory tools with predictive modelling techniques. After assessing Addis Ababa's present fleet of vehicles, the methodological framework predicts vehicle growth using an ANN prediction model. This predicted growth is coupled with a number of localised input parameters, including Ethiopian fuel specifications, Addis Ababa-specific climate conditions, vehicle activity data and technology, and the Addis Ababa Driving Cycle (AADC), to model emissions and fuel consumption.

The COPERT model, which is based on the input data, is then used to estimate the FC and emission factors. Policy recommendations and sustainable transport planning are based on the simulation outputs, which are used to evaluate energy demands and pollution levels. This chapter provides a detailed description of each step in this methodological flow, including the collection of vehicle data, ANN-based growth modelling, emission simulation using COPERT, and the final analysis and interpretation of the results. Vehicle exhaust emissions and FC were calculated for this study using the framework in Figure 3.1.

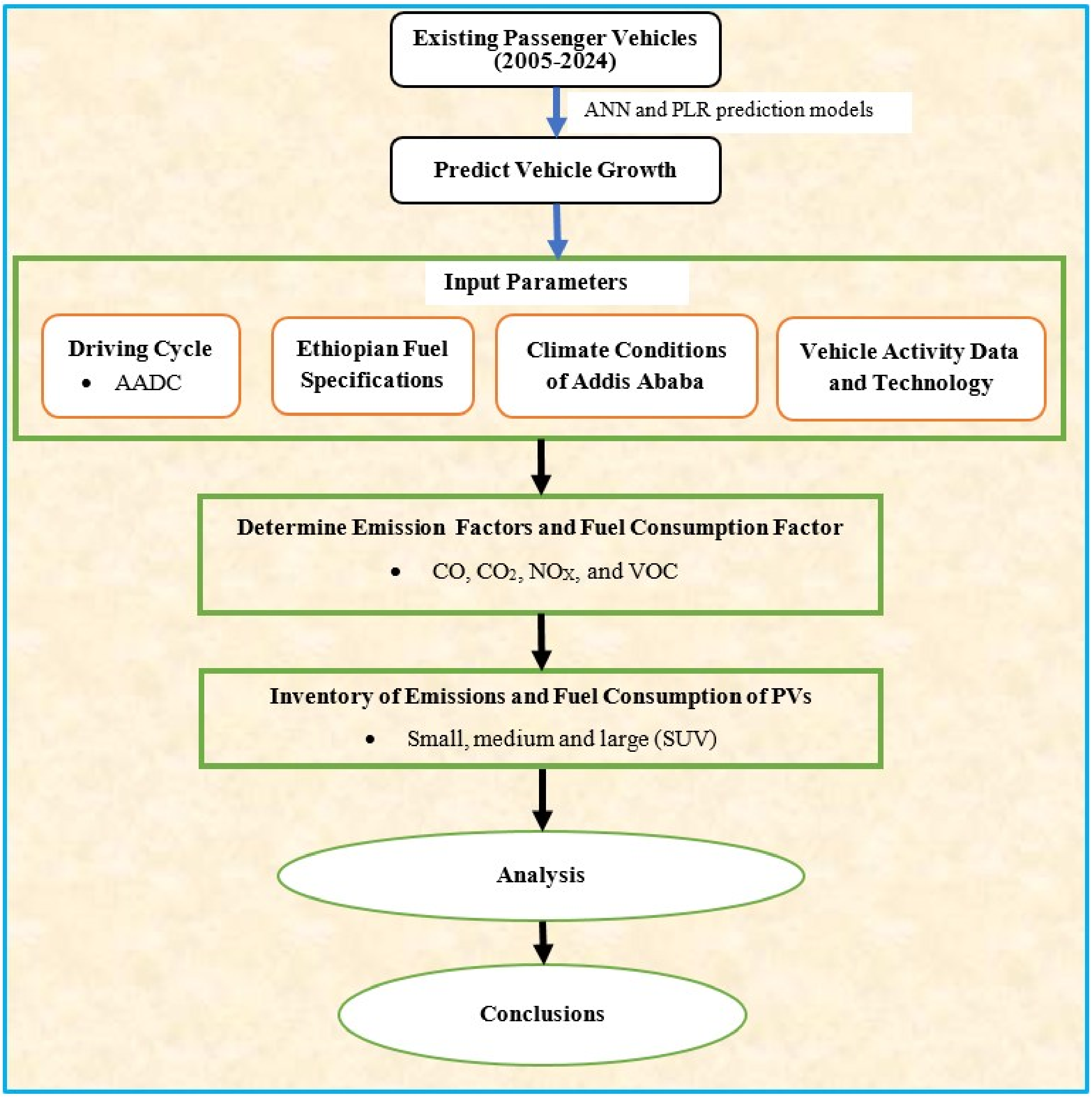

Figure 3.1: Workflow of the present investigation

3.2. Study area

Ethiopia's capital and largest city, Addis Ababa, served as the study's location (Figure 3.2). The city occupies an area of roughly 527 square kilometres and is situated at an elevation of 2,200 to 3,000 meters above sea level. The headquarters of numerous national and international organisations, including the African Union, are located in Addis Ababa, the nation's political, economic, and cultural centre. The urban population of Addis Ababa is expanding quickly, which has raised demand for transport services. A large percentage of the city's traffic is made up of passenger vehicles, which are essential to urban mobility and include private automobiles, taxis, buses, and low-speed train services.

Particularly, passenger cars that are driven inside city borders are the subject of the investigation. Because of traffic jams, ageing fleets, and poor emission control laws, these cars are a significant source of energy use and local air pollution. Developing evidence-based transport and environmental policies in Addis Ababa requires an understanding of the emission and FC trends of these vehicles.

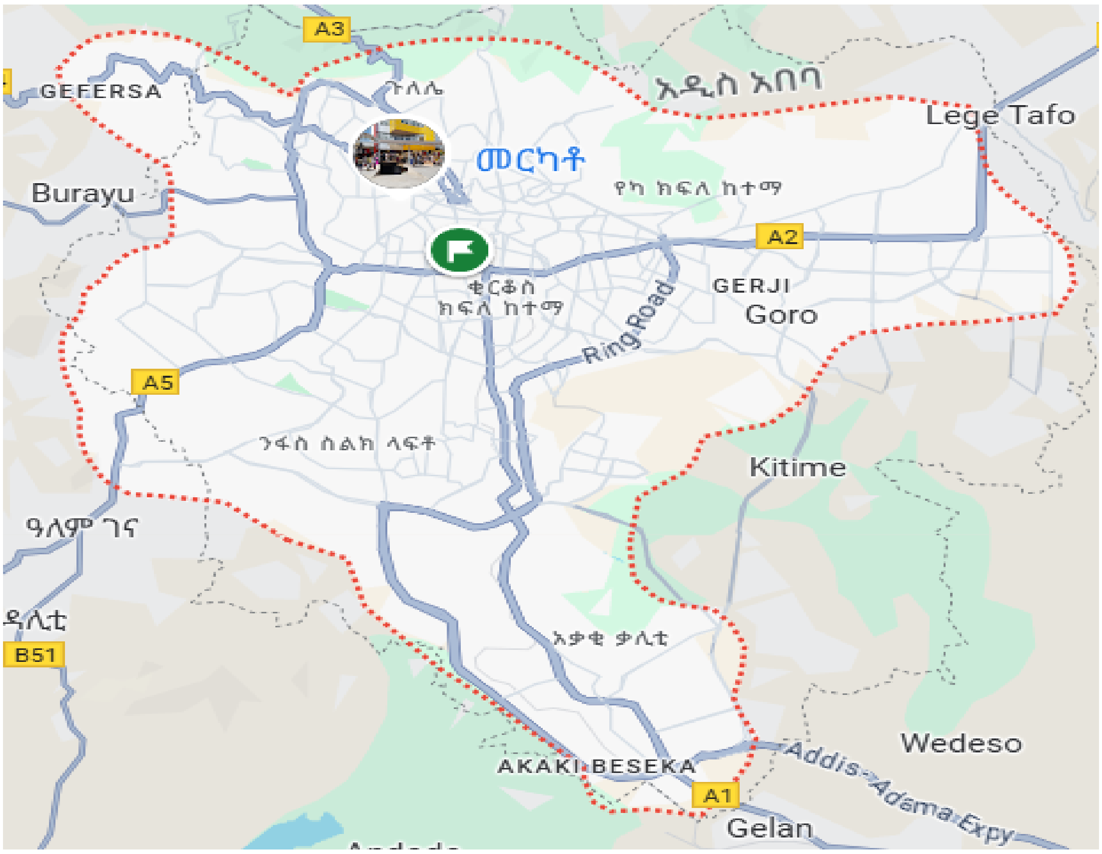

Figure 3.2: Study area map

3.3. Data collection

3.3.1. Sampling procedure

A sample is a portion of a population that has been chosen for investigation. The complete population of interest is meant to be represented by this sample size. Due to variables like time limits and insufficient resources, it is typically difficult to consider the complete population in research. As a result, it is always appropriate to choose some subset of the population that can accurately reflect the population under study. For this study, the vehicles under consideration offer a variety of activities every day, making it impossible to take into account every single vehicle, especially in urban areas like Addis Ababa. Data for this study were gathered by random sampling from quantitative surveys of drivers and were complemented by observations, interviews, and document analysis on patterns of vehicle activity.

3.3.2. Source of data

To analyze the emission inventory for different pollutants and fuel consumption of the Addis Ababa driving cycle, emissions and FC models were developed. Secondary data were collected from the respective authorities and offices.

Secondary data collection includes the number of vehicles for each type and vehicle-specific parameters from the AA transport authority. Document analysis was done to identify the vehicle category, their technology share, and related information. The average weather data for Addis Ababa for the years 2018 to 2025 was obtained from the Ethiopian Meteorological Service, and specifications of fuels used in Addis Ababa were collected from the Ethiopian Petroleum Enterprise. The historical vehicle data of Addis Ababa for 2005-2024, vehicle activities data, vehicle technology, fuel specification, and weather data were the information needed for this study.

Primary data collection includes a quantitative self-administered questionnaire that was used to assess the vehicle's activity per day, month, and year from vehicle drivers or owners. To assess vehicle activity data each vehicle category in AA, Ethiopia, the sample size is determined by means of the population proportion equation as shown in equation 3.1.

$$n = \frac{(Z\frac{\alpha}{2})^2 \times P \times (1-P)}{d^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.1$$

$$n = \frac{(1.96)^2 \times 0.56 \times (1-0.56)}{0.05^2} = 416 \text{ with a } 10\% \text{ non}-\text{response rate}$$

Where: n = required sample sizes, $Z\alpha/2$ = 95% (confidence level (Z = 1.96)), d = 5% (degree of margin of error), and p = proportion of vehicles attending daily activities

However, only 400 drivers responded to the structured questionnaire used in this study to gauge vehicle activity. The survey collected comprehensive data on passenger car usage patterns on a daily, monthly, and annual basis, including frequency of operation and distance travelled. Typical vehicle activity levels, which are crucial inputs for figuring out energy consumption and emissions, were estimated using this sample size.

3.4. Prediction of vehicle growth

One of the goals of this study was to create and evaluate prediction models in order to project Addis Ababa's passenger car growth between 2005 and 2030. Using IBM SPSS Modeller software, two modelling techniques were used: an ANN model and a Predictive Linear Regression (PLR) model. The official government provided historical data on the number of passenger cars registered in Addis Ababa. Annual vehicle registration counts, broken down by fuel type, vehicle class, and technology share, are included in the dataset, which spans the years 2005–2024. Performance metrics were evaluated after the test set was used to validate both models. The model that performed the best was chosen to predict vehicle raising until 2030. Forecasts for 2024 through 2030 were produced using the completed models. In addition to serving as the foundation for Addis Ababa's urban transportation planning and environmental impact assessments, the forecasts offer insights into future passenger vehicle patterns. The models employed in this study used predictors such as the Addis Ababa population, GDP per capita, and time series (year).

Contrary to quantitative forecasting algorithms, ANN can learn to recognize relationships between data, even when these are challenging to articulate. ANNs are computational modelling methods for difficult issues. Artificial intelligence is a field that has recently gained widespread attention (M. A. Hoffmann, 2020). Time series forecasting is one of the major applications of artificial neural networks. The backpropagation network, also known as a multilayer perceptron, has shown itself to be an effective substitute for quantitative methods. The ANN prediction model to be developed consists of an input-output system that is made up of neurons. The forces that connect the neurons in each phase are referred to as synaptic weights, and the signals that the neurons produce are a function of the total of their inputs. Each processing unit of the hidden layer and output layer is connected via a slant neuron in addition to the processing neuron (Y.H et al., 2020)

The three primary phases in prediction are data collection and analysis, evaluation of forecasting methods, and derivation and comparison of prediction findings. Historical vehicle data that have been collected from the Addis Ababa transport authority were initially cleaned and graphed. Vehicle growth rate information for each vehicle classification was collected on a yearly basis from 2005 to 2024. An ANN model is developed for the prediction of vehicle growth rate using SPSS Modeler. A Multilayer Perceptron (MLP) model was applied to predict the output as shown in Figures 3.3 and 4.4.

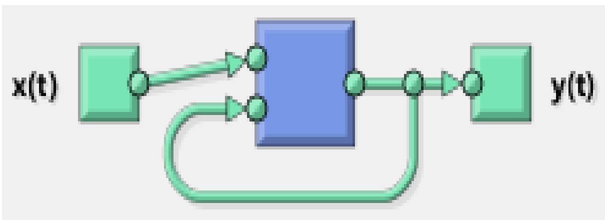

Figure 3.3: NARX diagram

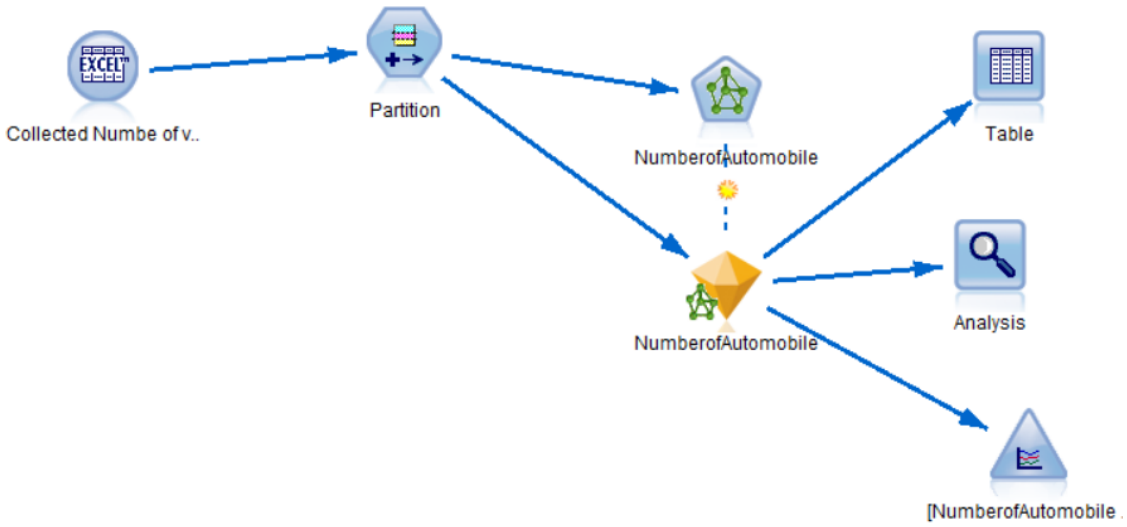

Figure 3.4: ANN model developed using SPSS Modeler

The phases in Figure 3.5 show how the continuous process needs ongoing observation and modification to forecast the vehicle's growth rate.

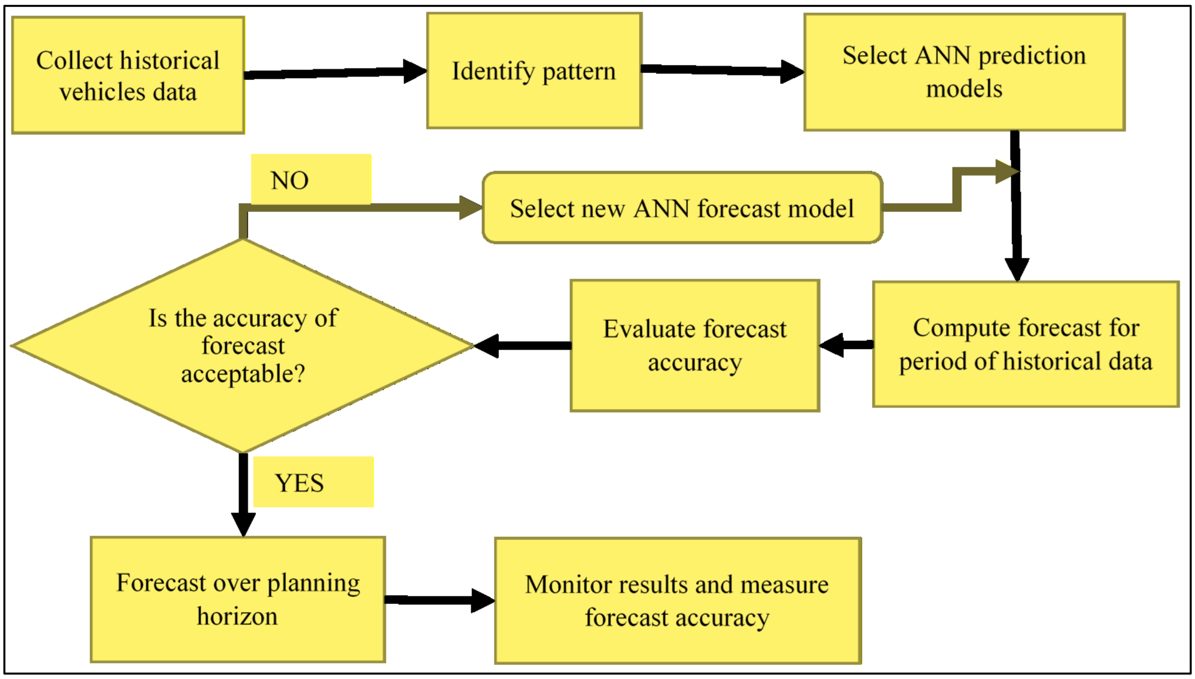

Figure 3.5: The prediction process

The ANN model development process is outlined in the following sections.

- ✓ Create a command-line script, and enter the target series.
- ✓ Select the training algorithm.
- ✓ Divide the data at random into training, validation, and testing subsets. Set the ratios to 70% training, 15% validation, and 15% testing.
- ✓ By using trial and error, adjust the argumentation feedback delays and hidden units.

- ✓ The accuracy of prediction is the most crucial metric for evaluating the performance of a neural network. There are various ways to evaluate how accurate a prediction is, and this study employed the time series response plot, MSE, RMSE, MAPE, and R-squared.
- ✓ Input the network's targets for multi-step ahead prediction following feedback delays.

3.5. Model performance evaluation

Performance measurements are used to assess the model's stability and output. Errors that cannot be isolated by the forecasting method are factors that must be taken into account. The accuracy of the forecast will improve if the error value decreases (N. Nurhamidah, 2020). The status of time series data in the future can be predicted using time series data, and future planning activities can be organized using time series data as a foundation. RMSE, MSE, and MAPE have all been employed by various authors to estimate forecast errors as shown in equations 3.2 to 3.4.

Root mean squared error (RMSE)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \quad \text{......} 3.2$$

Mean absolute error (MAE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \quad \text{......} 3.3$$

Mean absolute percentage error (MAPE)

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \quad \text{......} 3.4$$

Where $\hat{y}_i$ is the forecast value, y_i is the observed value, and n is the sample number

The network was trained using a back-propagation training technique and Bayesian regularisation. Even though it takes longer, this method offered robust generalisation for difficult, small, or noisy datasets. Based on adaptive weight minimization, training stops were applied. To forecast future emissions inventory, the ANN estimated vehicle growth value for each vehicle type was used.

3.6. Determination of emissions and FC inventory

The COPERT approach was utilized in this study to calculate the emissions and FC from PV by considering hot, cold, and evaporation emissions. The collected data were entered into the COPERT model after evaluating the necessary Addis Ababa climate data and the distance covered by each category of vehicle. Then, the COPERT model was used to quantify results on the four most significant pollutant emissions from PVs within the considered period according to vehicle category. These top 4 emissions, such as CO_2, CO, NO_X, and VOC, pose a threat to both the environment and public health. In this study, COPERT 5.6.1 was used to study the emission levels and FC based on vehicle category. The emissions of various vehicle types were determined in tons per year using Equations 3.5 to 3.8 (L. Ntziachristos, 2009).

Cold start emissions (E_{cold}) will be determined by equations 3.5 and 3.6.

$$E_{cold} = \beta \times bc \times N \times M \times e_{hot} \times \left(\frac{e_{cold}}{e_{hot}} - 1\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. 3.5$$

$$\frac{e_{cold}}{e_{hot}} = A \times V + B \times T + C \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.6$$

Where β is the fraction of distance driven in cold engine mode, bc is the beta reduction factor, N is the number of vehicles in stock, M is distance travelled per vehicle, e_{hot} is the hot emission factor, e_{cold}/e_{hot} is over-emission level compared to hot emissions, V is vehicle velocity in km/h and T is the temperature in ºC.

Hot emissions (E_{hot}) were calculated using Equation 3.7 and expressed as the total kilometers driven by vehicles during the considered time for a given activity level (NM).

$$E_{hot} = NM \times e_{hot} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. 3.7$$

Equation 3.8 states that COPERT takes into account evaporation from diurnal fuel losses ($E_{diurnal}$), after-use (E_{soak}), and running losses ($E_{running}$).

$$E_{evap} = E_{diurnal} + E_{soak} + R_{running} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. 3.8$$

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1. Results

4.1.1. Existing Passenger Vehicles Data

The total number of registered petrol and diesel passenger cars in Addis Ababa is shown in Figure 4.1, which only includes cars that are officially registered with the city's transport authority and does not include unregistered or other fuel-type vehicles like electric or hybrid cars. Between 2005 and 2024, Addis Ababa's registered passenger vehicle (PV) count increased significantly, as illustrated in Figure 4.1, with noteworthy ramifications for air quality, traffic control, and urban planning. The overall number of registered PVs grew by more than 20 times throughout the two-decade period, from 15,232 in 2005 to 312,372 in 2024, as indicated in Figure 4.1.

The fast rate of urbanisation, economic expansion, and rising car ownership among locals, all made possible by the importation of mostly old automobiles, are reflected in this pattern. According to the data, from 2006 and 2021, there was an average yearly growth of 15,000 to 25,000 automobiles. The private transport industry is seeing exponential growth at this time. The biggest increases happened after 2010, coinciding with policy-driven incentives and economic liberalisation. The overall number of registered PVs, however, stays steady at 312,372 starting in 2022, indicating an abrupt halt in vehicle registration.

The decline could have been the result of government policies such as import bans, increased excise taxes on used cars, or foreign exchange restrictions on auto imports. Furthermore, the data distinguishes between diesel passenger vehicles (DPVs) and petrol passenger vehicles (GPVs). In 2005, there were 6,093 DPVs and 9,139 GPVs. By 2024, these figures rose to 124,949 and 187,423, respectively. Given that government cars make up nearly 60% of all PVs in Addis Ababa, this indicates a large investment in public-sector transportation fleets. The higher percentage of GPVs could be due to vehicle classification standards, institutional fleet upgrades, or administrative preferences.

The number of electric cars and hybrid electric vehicles registered in Addis Ababa increased steadily and significantly between 2021 and 2024, according to the data collected from the transport authority. As a result of a rapid adoption rate, the total number doubled from 10,000 in 2021 to 20,000 in 2022. In the following years, the numbers still increased, rising to

27,016 in 2023 and 28,809 in 2024. This upward trend shows that cleaner transportation options are becoming more popular and supported by policymakers. This is due to the government's ban on fuel-based passenger vehicles in 2023 and the provision of incentives that promote sustainable mobility.

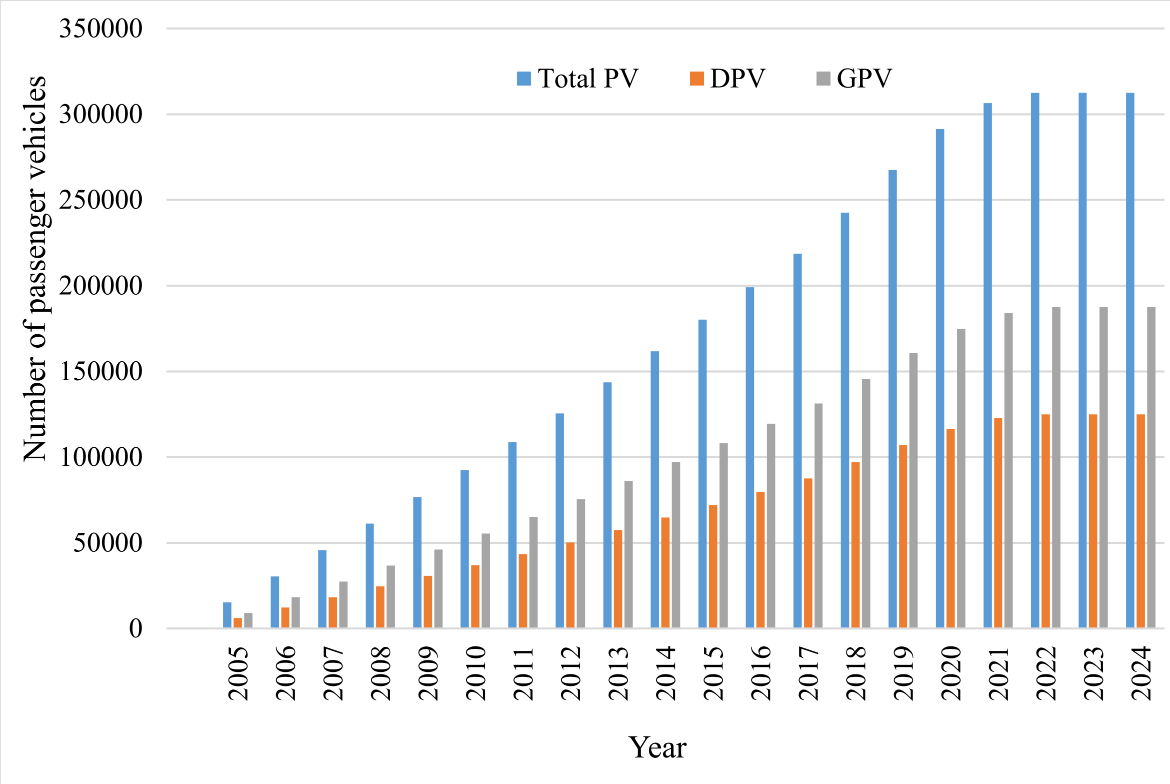

Figure 4.1: Registered number of passenger vehicles in Addis Ababa based on fuel type

Particularly in the absence of strict pollution regulations or widespread adoption of electric vehicles, the ongoing rise in vehicle numbers through 2021 is probably going to have made urban traffic congestion, road infrastructure strain, and vehicular emissions worse. According to earlier research, the increase in vehicles suggests a corresponding growth in the use of fossil fuels and emissions of pollutants (such as CO, NOx, and PM2.5), which exacerbates the decline in Addis Ababa's air quality (Tefera et al., 2020; Wondifraw, 2018).

Due to the Ethiopian government's ban on the import of second-hand vehicles aged more than 5 years, the automobile market in Addis Ababa approached saturation after 2021, which indicated that restrictive policies are starting to have an impact. Furthermore, in 2024, the Ethiopian government banned the import of internal combustion-based passenger vehicles to encourage electric vehicles and ensure that sustainable transport alternatives.

The way that Addis Ababa's GPVs are categorised based on EU emission regulations provides important information about the city's transportation sector's environmental quality and regulatory development. Globally, automobiles are categorised according to their allowed pollutant emissions using the EU vehicle emission standards, which range from Euro 1 (adopted in 1992) to Euro 6 (implemented in the EU in 2014) (EC, 2020). The number of GPVs in Addis Ababa increased steadily between 2005 and 2024 for all Euro categories as depicted in Figure 4.2.

The fleet only included Euro 1 to Euro 3 cars in 2005; there were no Euro 4 or higher vehicles represented, suggesting that older, high-emission cars were probably imported as used cars. In particular, there were 4,570 Euro 1, 3,656 Euro 2, and 914 Euro 3 cars in 2005. Even though there were only 914 Euro 4 cars on the road in 2007, their numbers steadily increased till they reached 43,081 by 2021 and stayed there. The Euro 5 and Euro 6 vehicles show a similar pattern, with the former entering the fleet in 2010 (942 units) and rising sharply to 34,776 by 2021, while the latter joined in 2015 (1,107 units) and reached 15,436 by 2022, staying at that level in the following years. Although the rate of transition seems gradual and unfinished, the gradual move from Euro 1–3 to Euro 4–6 vehicles indicates a gradual adoption of cleaner vehicle technology. Significantly, Euro 1 vehicles stayed steady at 21,890 units starting in 2014, suggesting that older, more polluting cars are still in use, most likely as a result of lax enforcement of vehicle scrappage regulations.

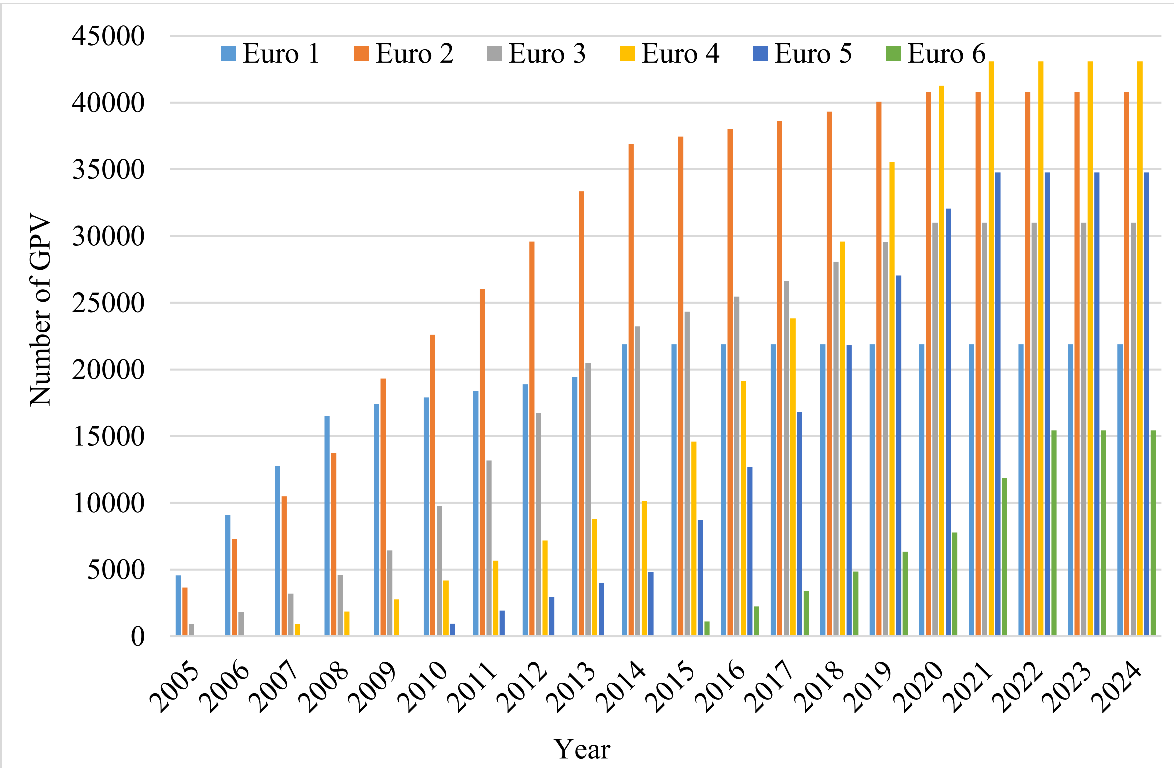

Figure 4.2: Registered number of GPVs in Addis Ababa based on EU classification

Important information about the changes in fleet composition and the gaps in environmental policy related to diesel-powered transportation can be found in the European emission standard classification of diesel passenger vehicles (DPVs) in Addis Ababa over the previous 20 years, as shown in Figure 4.3. According to the data, Addis Ababa's diesel fleet grew gradually between 2005 and 2024, with the largest increases seen in cars classified as Euro 3 to Euro 5. The fleet consisted of only older cars in 2005: 3,046 Euro 1, 2,437 Euro 2, and 609 Euro 3.

The employment of high-emission, pre-2000 technology automobiles was shown by the absence of Euro 4 or more recent models at the time. Beginning with 609 units in 2007, the number of Euro 4 vehicles registered increased dramatically to 28,903 units by 2021 and stayed steady after that. Likewise, Euro 5 cars, which started to appear in 2010 (628 units) and reached 23,366 units by 2021, demonstrate a certain level of adoption of comparatively cleaner technologies. The cleanest class of vehicles according to EU criteria, Euro 6-compliant vehicles, first debuted in 2015 (738 units) and grew steadily to 10,594 units by 2022, with no additional rise recorded until 2024.

The data shows that a sizable number of Euro 1 to Euro 3 vehicles continue to be used even with the implementation of newer emission criteria. In 2024, there were still 13,319 Euro 1, 27,375 Euro 2, and 21,392 Euro 3 vehicles in use. An ineffective vehicle retirement or scrappage strategy may be the cause of the continued usage of high-emission diesel vehicles, as seen by the stagnation in these categories starting in 2020. A gradual and unequal shift towards cleaner technologies is seen in the fact that, despite the adoption of Euro 4 to Euro 6 cars starting in 2010, their combined total by 2024 (Euro 4: 28,903; Euro 5: 23,366; Euro 6: 10,594) represents less than 50% of the diesel fleet. The scenario in Addis Ababa suggests delayed adoption and loose import limits in comparison to global benchmarks, especially in Europe, where Euro 6 vehicles dominate the market.

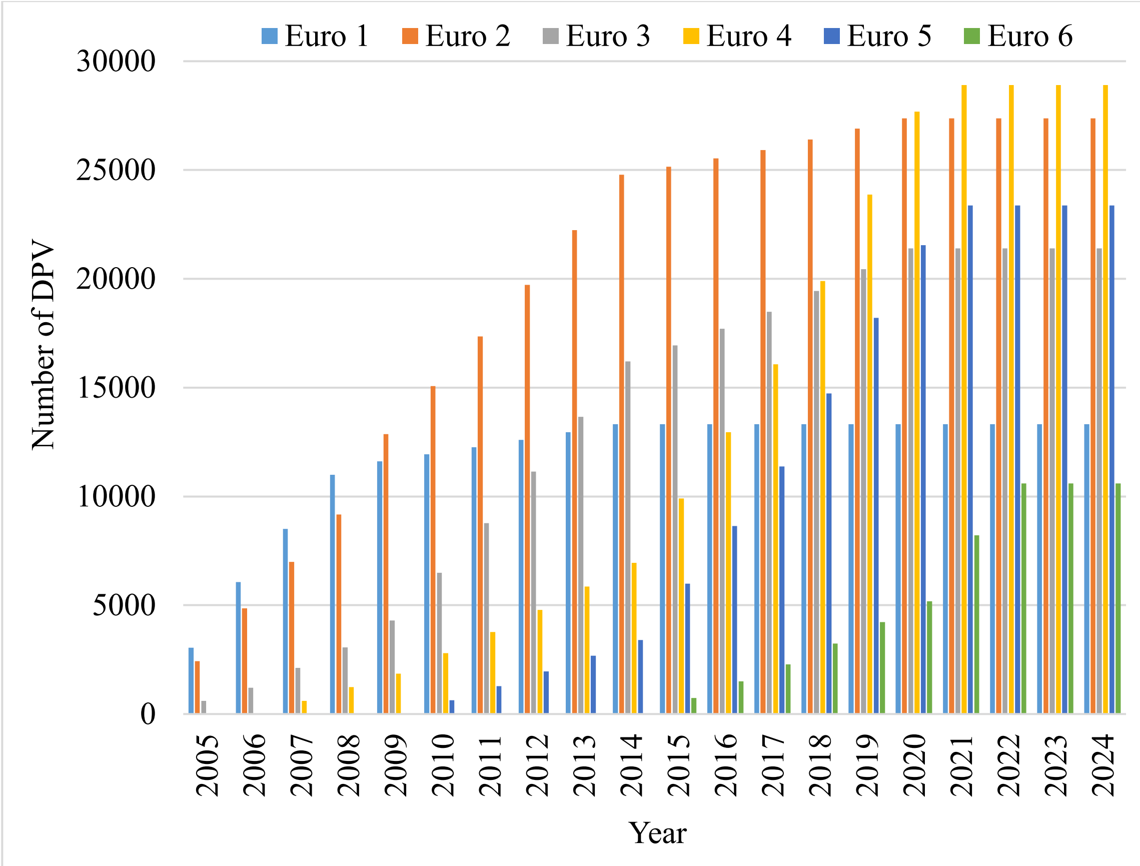

Figure 4.3: Registered number of DPVs in Addis Ababa based on EU classification

4.1.3. Environmental data of Addis Ababa

The Ethiopian Meteorology Authority provided the Addis Ababa environmental data for the years 2018–2024. The environmental data for 2018 are specifically shown in Table 4.1 and include key meteorological variables like air pressure, humidity, and ambient temperature. For precise estimation of vehicle emissions and fuel consumption, these environmental factors are essential. In order to simulate and measure the emissions and energy consumption related to passenger car operation in the city, the data were used as input parameters in the COPERT model.

Table 4.1: Environmental data of Addis Ababa in 2018

Month	Min Temperature (°C)	Max Temperature (°C)	Humidity (%)
January	9.7	20.5	50.0%
February	11.9	22.3	59.0%
March	12.5	21.2	53.0%
April	13.5	21.5	66.0%
May	13.1	22.2	71.0%
June	13.5	20.3	78.0%
July	12.1	19.9	82.0%
August	11.5	19.6	82.0%
September	11.2	20.7	82.0%
October	9.8	21.0	54.0%
November	9.4	20.9	57.0%
December	9.6	21.2	52.0%

4.1.4. Fuel specifications

The other input required for the COPERT model is fuel specification. In this study, the fuel specifications used in Addis Ababa were collected from the Ethiopian Petroleum Enterprise, and its specification is shown in Table 4.2.

Table 4.2: Fuel specifications of Addis Ababa

Parameters	Petrol	Diesel
Energy Content [MJ/kg]	43.774	42.695
H: C Ratio [-]	1.86	1.86
O: C Ratio [-]	0.00	0.00
Density [kg/m^3]	720-740	820-860.
S Content [% wt]	Max 0.05	Max 0.05
Pb Content [g/l]	Max 0.013	Not specified
Cd Content [ppm wt]	0.0002	0.00005
Cu Content [ppm wt]	0.0045	0.0057
Cr Content [ppm wt]	0.0063	0.0085
Ni Content [ppm wt]	0.0023	0.0002
Se Content [ppm wt]	0.0002	0.0001
Zn Content [ppm wt]	0.033	0.018
Hg Content [ppm wt]	0.0087	0.0053
As Content [% wt]	Not specified	Max 0.01
RON/ Cetane index	Min 92	Min 48

4.1.5. Vehicle activity data

Vehicle activity data is essential for assessing fuel consumption and emissions, especially the average daily trip distance. In order to comprehend utilisation trends across various vehicle types, primary data was gathered from Addis Ababa passenger vehicle drivers via surveys and interviews. According to the findings, the average daily travel distance for small passenger vehicles, usually small cars used for short-distance travel and personal commuting, was 60 km. The average daily mileage of medium passenger cars, which frequently included station wagons and mid-size sedans for both private and public transportation, was 80 km. The average daily travel distance for large (executive) passenger cars, which are typically used for long-distance travel and are typically used for business or governmental purposes, was 100 kilometres.

4.2. Prediction of PVs growth for Addis Ababa

Figure 4.4 displays the historical and projected passenger car registrations in Addis Ababa from 2005 to 2030 using two predictive models: an ANN and a PLR model. For the historical period (2005–2024), the ANN model performed better than the actual car registration data, accurately capturing the nonlinear trends and fluctuations of the growth pattern. In contrast, the PLR model's more rigid linear trend resulted in noticeable deviations from the actual data during years with irregular growth. This implies that the ANN model offers enhanced forecast accuracy and adaptability to the complex dynamics of urban vehicle growth. Both models predict that car registrations will continue to rise between 2025 and 2030, but the PLR model predicts faster growth, which is probably due to linear patterns and interactions in the historical data. Generally, the ANN model is more suited for forecasting in dynamic, data-driven urban settings, whilst the PLR model can have complementary uses in long-term planning and policy assessment.

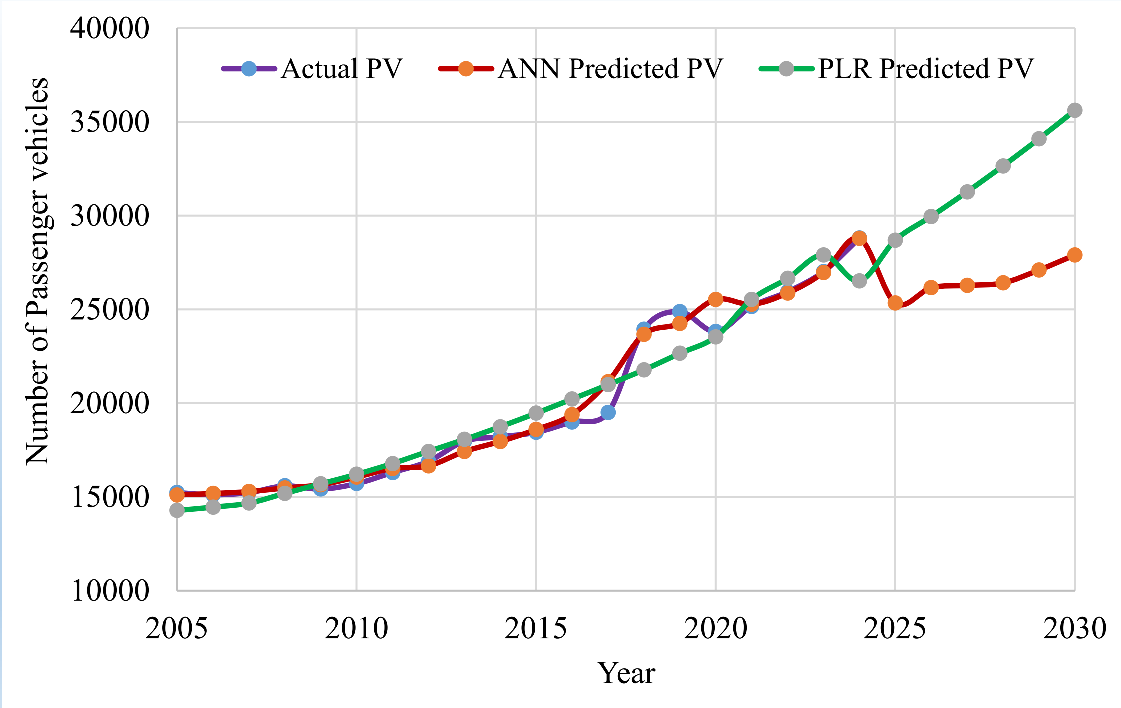

Figure 4.4: Vehicle growth prediction

Prediction error evaluation

Table 4.3 compares the prediction performance metrics for the ANN and PLR models. The evaluation is based on four statistical indicators that give information about the accuracy and reliability of the model: mean error, mean absolute error (MAE), standard deviation of the error, and linear correlation coefficient. The mean error of the ANN model is -132.025, whereas that of the PLR model is 71.164. The ANN model's negative value indicates a slight tendency to underpredict, whereas the PLR model's positive mean error shows a tiny overprediction on average. Nevertheless, it appears that both models have very little systematic bias because these mean errors are so tiny when compared to the prediction scale.

The mean absolute error (MAE), a critical indicator of average prediction accuracy, is significantly lower in the ANN model (362.024) than in the PLR model (882.502). Given that its predictions are, on average, much closer to actual values, this implies that the ANN model has higher predictive accuracy. Similarly, the standard deviation of prediction errors in the ANN model, which measures the consistency or variability of prediction performance, is substantially lower at 591.391 than in the PLR model (1123.423). This implies that the ANN model not only performs better overall but also more consistently and with less variation across the dataset. Finally, compared to the PLR model (0.970), the ANN model exhibits a higher linear correlation coefficient (0.992) between expected and actual values.

The ANN model exhibits a closer alignment with the real data trend, suggesting a more trustworthy reproduction of the underlying vehicle growth pattern, even if both models exhibit substantial positive correlations.

Table 4.3: Summary of prediction model errors

Parameters	ANN model	PLR model
Mean Error	-132.025	71.164
Mean Absolute Error	362.024	882.502
Standard Deviation	591.391	1123.423
Linear Correlation	0.992	0.97

Importance of Predictors

The numerical values of the input predictor variables used in the PLR and ANN models are shown in Table 4.5. The accuracy and dependability of the anticipated results are greatly influenced by these predictors, which are the primary inputs for model training and analysis.

Table 4.5: Values of predictors for each considered year

Year	Population	GDP Per Capita (USD)	Year	Population	GDP Per Capita (USD)
2005	2634000	181.49	2018	4,400,000	839.86
2006	2689000	218.64	2019	4,592,000	948.85
2007	2750000	266.89	2020	4,794,000	969.01
2008	2871000	350.57	2021	5,228,000	947.1
2009	2996000	373.2	2022	5,461,000	1142.93
2010	3126000	341.1	2023	5,704,000	1511.36
2011	3263000	377.69	2024	5,461,000	1320.16
2012	3405000	510.54	2025	5,957,000	1066.36
2013	3554000	548.87	2026	6,221,491	1240.49
2014	3709000	622.59	2027	6,497,725	1400.7
2015	3871000	707.98	2028	6,786,224	1577.53
2016	4040000	790.79	2029	7,087,532	1758.49
2017	4216000	822.7	2030	7,402,219	1952.45

Figures 4.5 and 4.6, respectively, illustrate the relative importance of the input predictors used by the ANN and PLR models to predict passenger car registrations in Addis Ababa.

This analysis clarifies the basic factors influencing vehicle growth and demonstrates the substantial impact of each input variable on the forecast accuracy of the model. The feature importance scores are obtained from the internal structure of the ANN model, which is often based on the weights assigned to input nodes during training. The output of the model is more affected by a predictor with a higher significance score. The figures make it evident that the factors with the highest relevance values are population growth, vehicle registration year, and gross domestic product. This implies that these factors are identified by the ANN and PLR models as the primary forces behind vehicle growth.

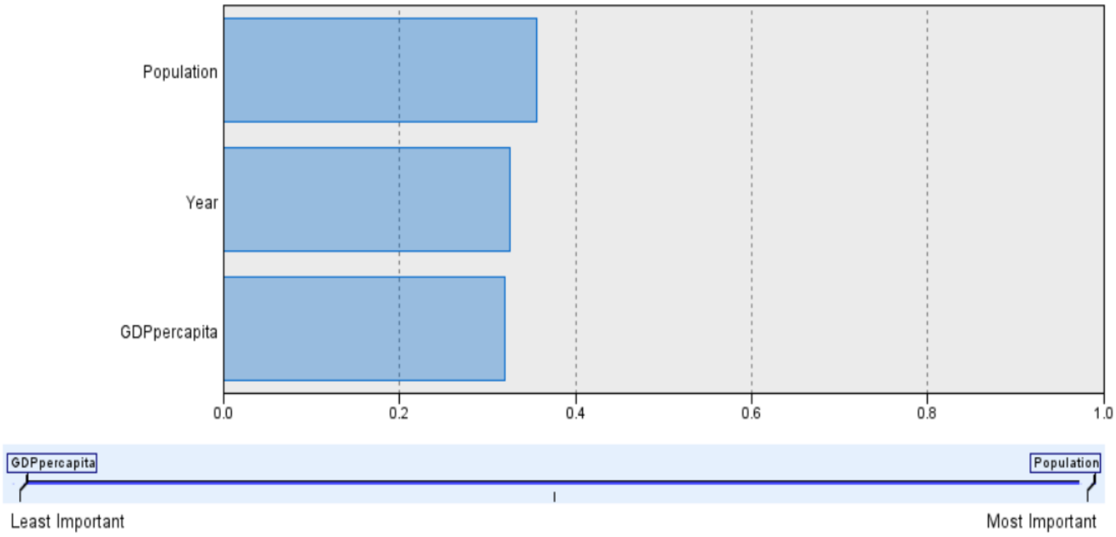

Figure 4.5: Predictors importance of ANN prediction model

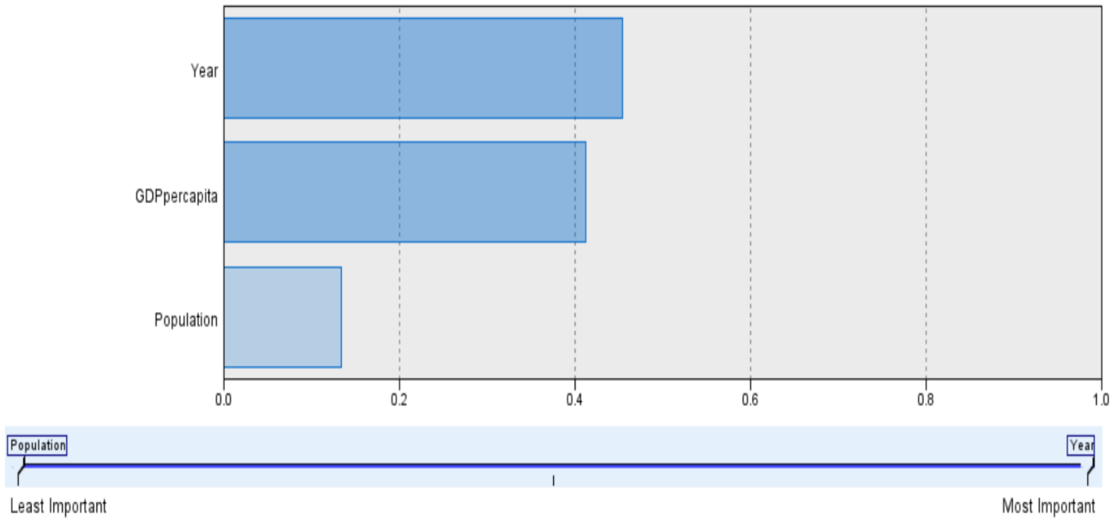

Figure 4.6: Predictors' importance PLR prediction model

Figure 4.7 shows the accuracy of two prediction models for Addis Ababa's vehicle growth, comparing the performance of an Ensemble Model and a Reference Model. The Ensemble Model achieved a remarkable accuracy rating of 99.7%, while the Reference Model came in second with an accuracy of 99.6%. These results show that both models are very good at predicting trends in vehicle growth, which is crucial for informing politicians and urban planners about the needs of mobility in the future. Given that the Ensemble Model outperformed the Reference Model by 0.1%, it is plausible that the ensemble approach, which typically integrates multiple algorithms, could be more effective at spotting complex patterns in the data.

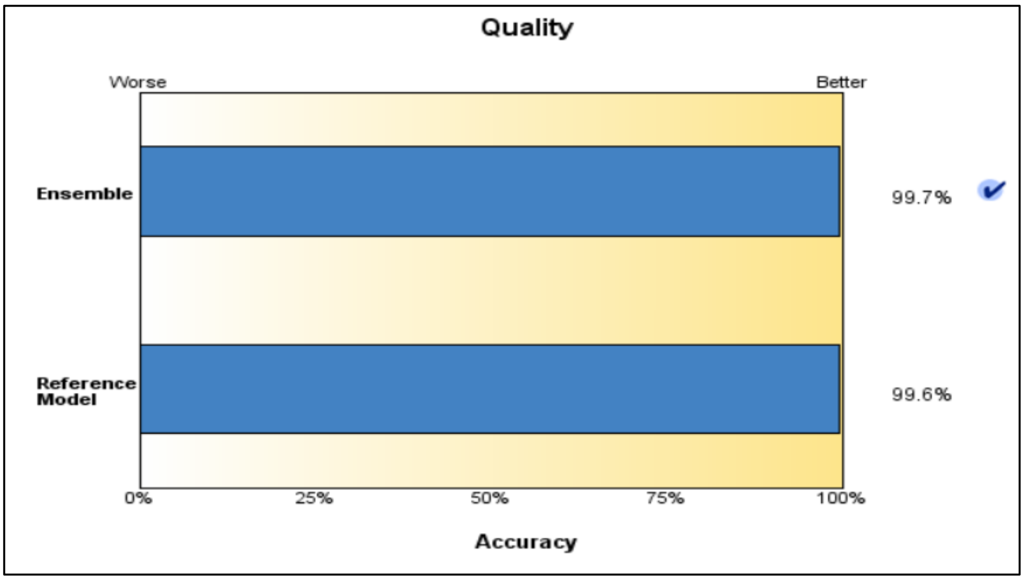

Figure 4.7: ANN prediction model accuracy

Finally, based on the evaluation of prediction accuracy and error metrics, the ANN model demonstrated superior performance compared to the PLR model. As a result, the ANN prediction model was used for estimating the future passenger vehicles expected to be registered in Addis Ababa.

4.3. Estimated PV Emissions

In order to estimate the annual emissions and energy consumption, this study took into account gasoline and diesel passenger cars that were registered in Addis Ababa in 2005 and later. This choice was selected to represent the features of the comparatively more recent fleet of vehicles, which are more pertinent to the emission profiles and urban mobility patterns of today.

Annual CO emissions

The annual CO emissions from GPV in Addis Ababa, split by Euro vehicle classification, are shown in Figure 4.8 for the years 2018 through 2025. According to the data, overall CO emissions peaked in 2021 at 26.25 tons/year, which also happened to be the year with the most registered passenger cars (306,427). The primary cause of the dramatic increase in emissions between 2018 and 2021 is the increasing number of older cars without pollution emissions control systems, especially those categorised as Euro 1 to Euro 3. Small GPVs of the Euro 1 to Euro 3 classes account for more than 43% of the fleet in 2021 and contributed considerably to the total amount of CO produced. However, starting in 2022, CO emissions decreased to 19.11 tons/year in 2023 and then slightly increased to 21.10 tons/year in 2025, even though the total number of GPVs (~312,000) remained relatively consistent. Due to Ethiopian government banned the importation of ICE PVs in 2023.

With the number of Euro 6 vehicles rising from 2,427 in 2018 to 7,946 by 2025, this trend illustrates the fleet's progressive transition to cleaner vehicles (Euro 5 and Euro 6). However, the rate of fleet modernisation seems inadequate, as the advantages of newer, low-emitting models are still outweighed by the continued dominance of Euro 1 to Euro 3 vehicles, which include a sizable share of small, medium, and executive GPVs. The need for more aggressive policy measures, like the early retirement of high-emitting GPVs, and incentives for adopting electric vehicles. Since the government banned the import of ICE PVs in 2023 and permitted electric and hybrid vehicles, the trend of CO emissions has been stabilized. This marks a significant shift compared to previous years, during which CO emissions were on the rise. The new policies have likely contributed to this stabilization by promoting cleaner transportation options.

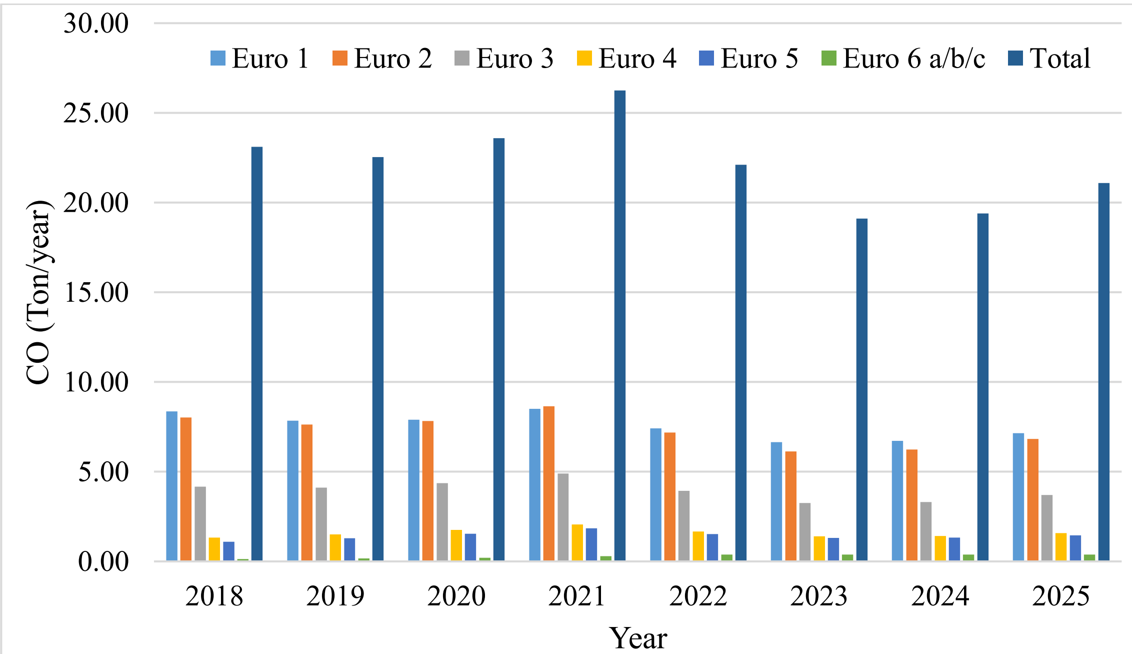

Figure 4.8: GPV annual CO emissions from 2018 to 2025

According to this study, the estimated CO emissions from Addis Ababa's DPVs from 2018 to 2025 are shown in Figure 4.9. Overall, CO emissions from DPVs generally varied significantly, rising from 2.45 tons/year in 2018 to a peak of 2.61 tons/year in 2021, then slightly declining and stabilising at 2.54 tons/year by 2025. Due to their significant proportion in the ageing vehicle fleet and the increasing number of electric vehicles, Euro 2 DPVs were consistently the largest contributors, making up about half of the total CO emissions annually (1.15 tons/year in 2021). Due to its smaller population, the Euro 4 category's relative impact remained secondary even though its emissions increased significantly, from 0.28 ton/year in 2018 to 0.39 ton/year in 2021.

Throughout the study period, the combined emissions of Euro 1 and Euro 3 vehicles were moderate but consistent, coming to about 0.9 tonnes annually. It is encouraging that emissions from Euro 6 vehicles showed the largest relative growth, indicating a steady adoption of newer, cleaner diesel technology, even though their magnitude was still small (from 0.018 tons/year in 2018 to 0.056 tons/year in 2025). Fleet replacement dynamics and slight policy changes in favour of lower-emitting vehicle regulations contributed to the slight drop in emissions seen after 2021. The continued prevalence of high-emission Euro 1 to Euro 3 automobiles highlights the urgent need for legislative measures, including age-based vehicle retirement incentives and stricter emissions regulations on DPV.

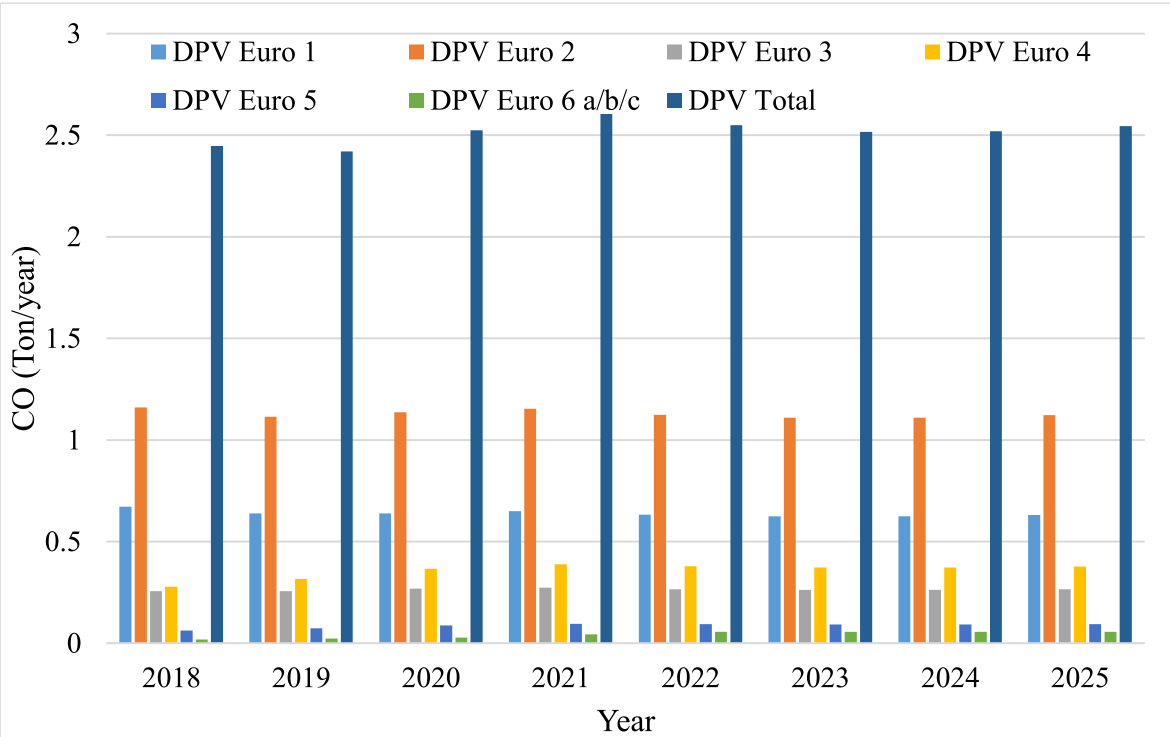

Figure 4.9: DPV annual CO emissions from 2018 to 2025

Annual CO_2 emissions

The CO_2 emissions from GPVs considered in this study from 2018 to 2025 are illustrated in Figure 4.10. The overall CO_2 emissions from GPVs showed a consistent upward trend, increasing by about 25.2% from 3,063.77 tons/year in 2018 to 3,835.49 tons/year in 2025. This upward trend primarily happened due to the rising number of high CO_2-emitting (older) vehicles in the Addis Ababa area. The increase in these cars contributes significantly to overall CO_2 emissions. With yearly values ranging from 836 to 849 tons/year throughout the investigation, Euro 2 GPVs consistently contributed the most to CO_2 emissions. Euro 2 cars are still widely used in the fleet, even though they are an older standard, which has a significant cumulative effect on emissions.

Emissions from Euro 4 GPVs in particular increased dramatically, from 646.11 tons/year in 2018 to 920.57 tons/year by 2021. This increase is a result of the fleet's composition shifting towards medium passenger cars, which nevertheless emit a lot of CO_2, even though they are cleaner than older models. Similar trends were seen in Euro 5 vehicles, whose emissions nearly doubled from 477.23 tonnes per year in 2018 to 736.05 tonnes per year in 2025. The most recent standard, Euro 6 vehicles, has the largest relative growth, increasing more than three times from 105.72 tons/year in 2018 to 322.50 tons/year in 2025. The overall rise in GPV CO_2 emissions, despite the increasing penetration of newer standards, highlights the cumulative effect of growing vehicle numbers.

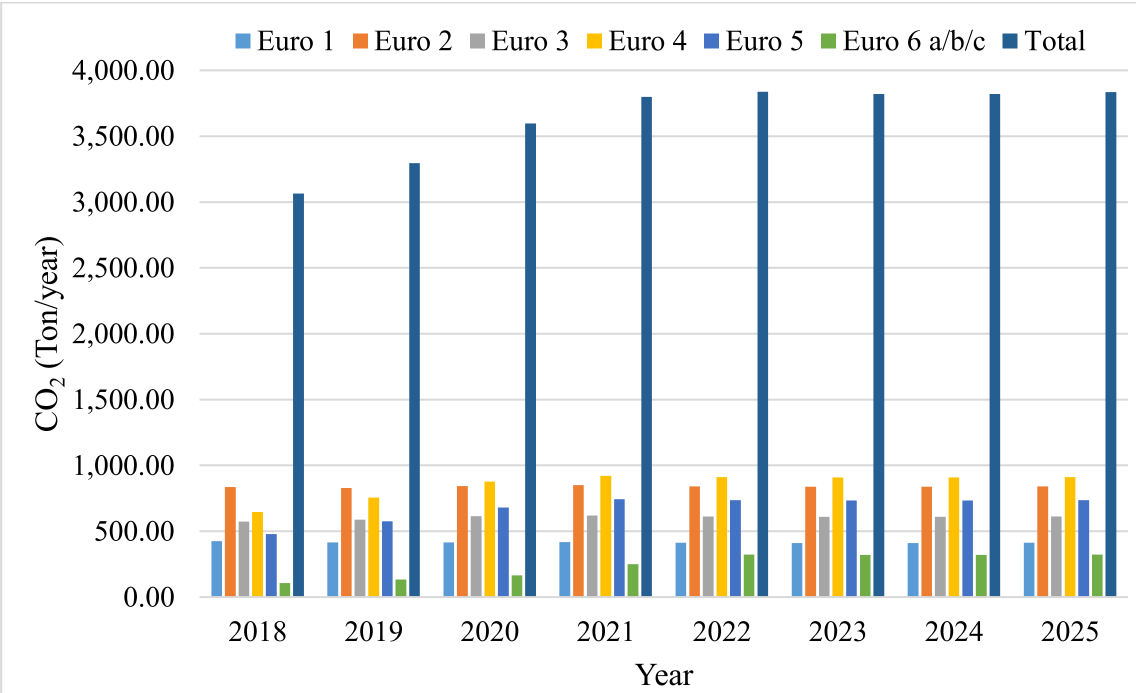

Figure 4.10: GPV annual CO_2 emissions from 2018 to 2025

Between 2018 and 2025, the annual CO_2 emissions from DPVs considered in this study are depicted in Figure 4.11. Total CO_2 emissions from DPVs grew from 1,682.82 tons/year in 2018 to 2,103.28 tons/year in 2025. With emissions ranging from 471.97 to 482.95 tons/year, Euro 2 vehicles were the top contributors over the considered period. Their persistently high emissions indicate that old, high-emitting cars still make up the majority of the urban fleet. Likewise, Euro 3 and Euro 4 cars showed steady rises in emissions, with Euro 4 emissions going up from 339.46 tons/year in 2018 to 484.75 tons/year by 2021 and then staying at about 480 tons/year after that. This increase is in line with the increasing proportion of middle-aged DPVs.

Between 2018 and 2020, Euro 5 vehicle CO_2 emissions increased by more than double, and they continued to rise rapidly until 2025, when they reached 388.49 tonnes annually. Comparatively speaking, Euro 6 vehicles grew at the fastest rate, rising from 55.21 tonnes annually in 2018 to 176.14 tonnes annually by 2025. The overall contribution from Euro 6 vehicles remained relatively low because of their lesser presence in the vehicle population, even though this growth suggests a shift towards cleaner technology. In general, older and mid-aged vehicles continue to dominate in terms of overall CO_2 emissions, even if newer vehicles are progressively making their way onto the market.

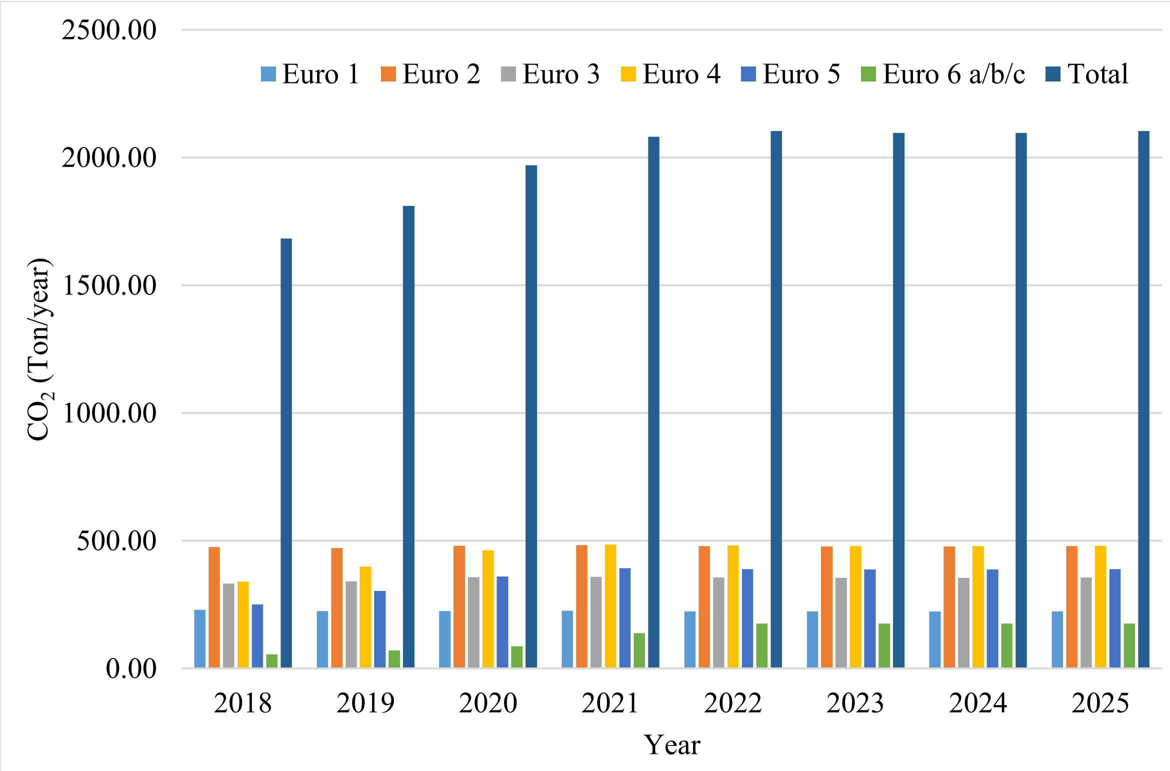

Figure 4.11: DPV annual CO_2 emissions from 2018 to 2025

Annual NOx emissions

In this study, the estimated annual NO_x emissions released by GPVs from 2018 to 2025 in the Addis Ababa area are depicted in Figure 4.12. By 2025, GPVs were responsible for 2.08 tonnes of NO_x emissions annually, growing from 1.89 tonnes in 2018. Over the course of the eight-year timeframe, NOx emissions increased gradually before steadying in 2021. With NOx ranging from 0.74 to 0.76 tonnes annually, Euro 2 vehicles were the biggest emitters among the Euro categories during this time. A slight but discernible rise was observed in emissions from Euro 3 and Euro 4 automobiles. Emissions of Euro 3 increased from 0.22 tonnes annually in 2018 to 0.24 tonnes annually in 2020 and thereafter stayed constant.

Emissions of Euro 4 rose from 0.18 tonnes annually in 2018 to 0.26 tonnes annually in 2021, where they remained until 2025. This pattern points to a rising percentage of electric vehicles in Addis Ababa, which make up a moderate amount of the total NO_x emissions. The NO_x emissions of Euro 5 cars, which are of a more modern generation, showed a gradual increase from 0.08 tons/year in 2018 to 0.12 tons/year starting in 2022. Despite being built with better pollution controls, their increasing numbers have caused a slight rise in this group's overall emissions. The most notable relative rise over the research period was seen in Euro 6 vehicles, despite having the lowest emissions (going from 0.02 to 0.05 tons/year). This is a reflection of the fleet's growing adoption of more recent, low-emission technologies.

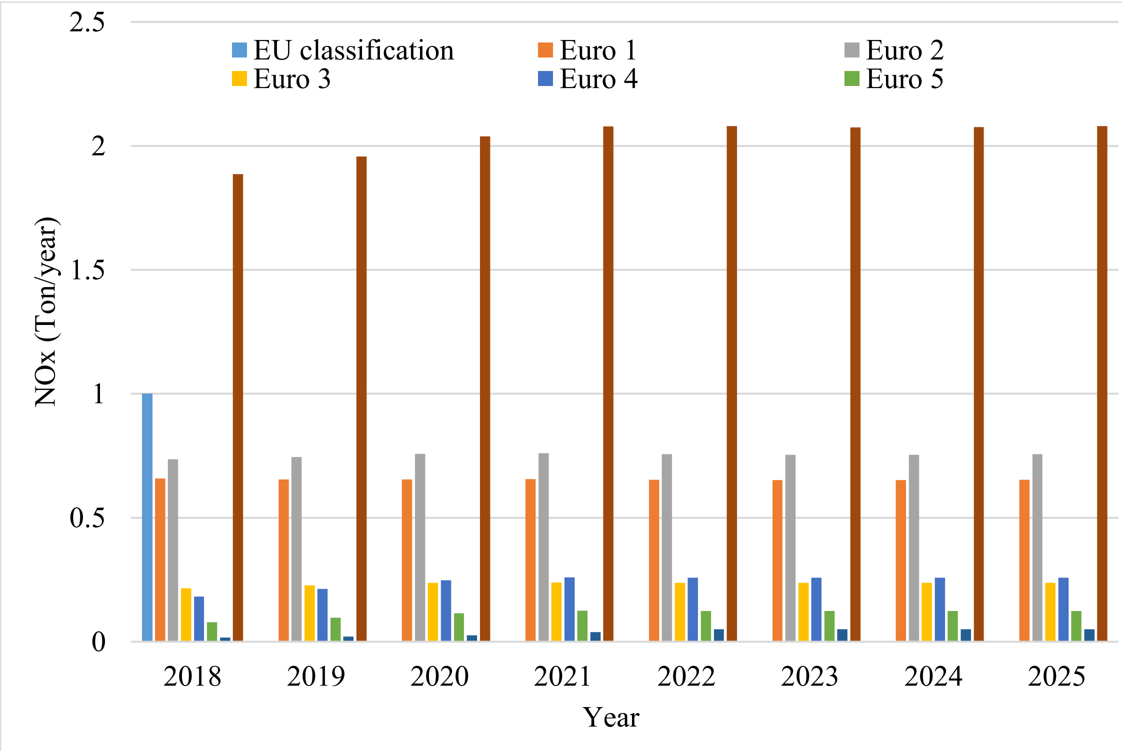

Figure 4.12: GPV annual NOx emissions from 2018 to 2025

The NO_x emissions from DPVs throughout Euro emission categories from 2018 to 2025 are illustrated in Figure 4.13. The total NO_x emissions from DPVs grew from 6.02 tons/year in 2018 to 7.27 tons/year in 2025, demonstrating a persistent and considerable contribution of diesel cars to ambient NO_x levels. With annual NO_x emissions ranging from 1.81 to 1.86 tonnes over the study period, Euro 2 cars continued to be the largest source of NO_x emissions among the categories. The second biggest contributors were Euro 3 cars, whose emissions steadily increased from 1.31 tonnes per year in 2018 to a plateau of 1.41 tonnes per year by 2021.

In the same manner, the number of Euro 4 vehicles increased more sharply, and the NOx emissions also rose from 1.08 tonnes annually in 2018 to 1.52 tonnes annually by 2021 and remained almost constant until 2025. From 0.77 tons/year in 2018 to 1.18 tons/year in 2025, the emissions from Euro 5 cars also demonstrated a notable rising trend, indicating that even while these vehicles adhere to more recent regulations, their larger fleet size has resulted in a higher overall emission burden. Euro 6 vehicles began with the lowest contribution (0.16 tons/year in 2018), which are built to comply with the tightest emission limits. These vehicles showed a significant relative increase in NOx emissions to 0.50 tons/year by 2022, and they continued to do so until 2025. This rise corresponds with the market's increasing proportion of Euro 6-compliant automobiles. In general, the total NO_x emissions from DPVs increased gradually between 2018 and 2021, peaking at 7.24 tons/year, and then stayed largely unchanged.

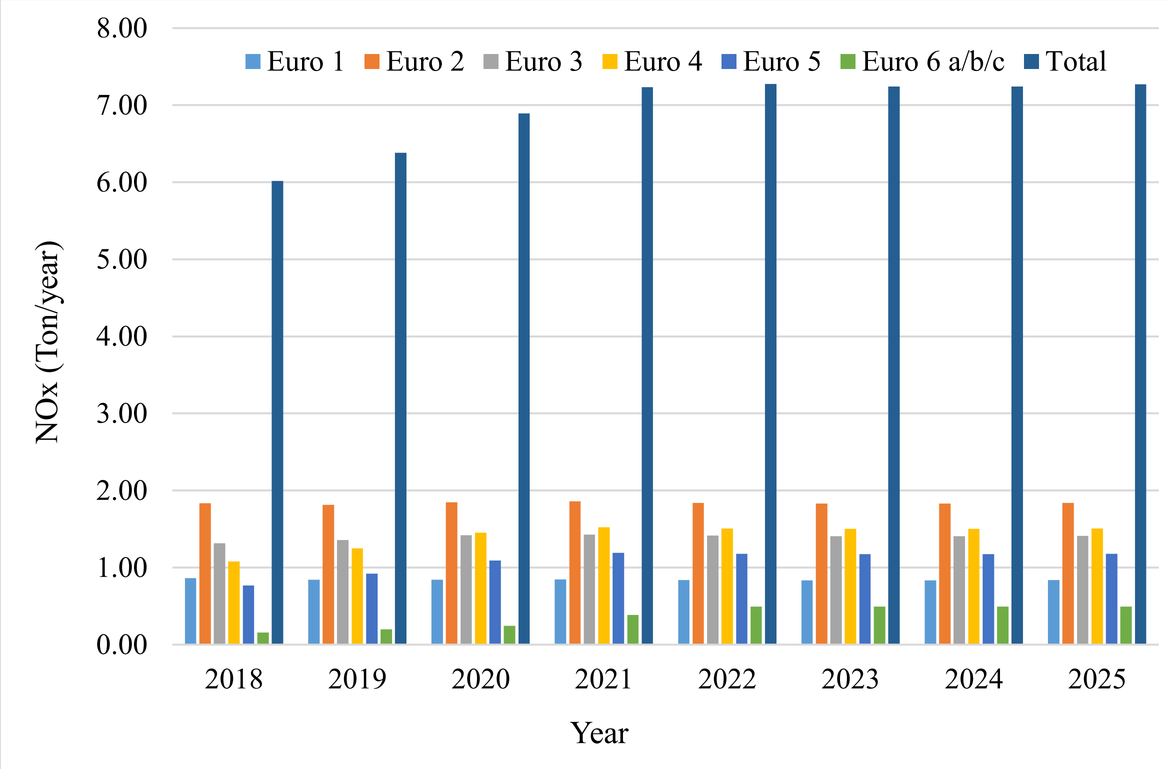

Figure 4.13: DPV annual NOx emissions from 2018 to 2025

Annual volatile organic compounds emissions

The findings in Figure 4.14 show the emissions of volatile organic compounds (VOCs) from gasoline passenger cars in Addis Ababa from 2018 to 2025, according to European vehicle classification criteria (Euro 1 to Euro 6). From 151.77 tonnes in 2018 to a peak of 212.70 tonnes in 2023, the total VOC emissions exhibit a definite increasing tendency. By 2025, they have somewhat decreased to 204.47 tonnes. As shown in Table 4.6, which groups the PV according to their individual Euro standards, this development is a reflection of the increasing number of cars on the road. Different patterns in VOC emissions over time can be seen in each Euro class. The higher percentage of older vehicles remaining in use is highlighted by the fact that Euro 1 emissions exhibit a modest increase, peaking at 28.04 tonnes in 2023, whereas Euro 2 emissions grow dramatically from 42.87 tonnes in 2018 to 49.53 tonnes in 2023.

On the other hand, Euro 6 emissions, which were initially low at 4.75 tonnes in 2018, gradually rose to 16.82 tonnes by 2023, indicating a fleet shift towards cleaner, newer vehicles. Concerningly, VOC emissions have been rising with time, which suggests that more laws and incentives are required to support cleaner car technology. According to the data, older models (Euro 1 and 2) continue to contribute considerably to overall emissions, even while newer models (Euro 4, 5, and 6) are being adopted gradually. This emphasises how crucial it is to put laws into place that phase out older, more polluting cars and encourage the use of cleaner ones. All things considered, the findings point to an increasing environmental problem in Addis Ababa as the number of vehicles rises and older models continue to be widely used. Improving the city's public health and air quality will require addressing these problems with focused actions.

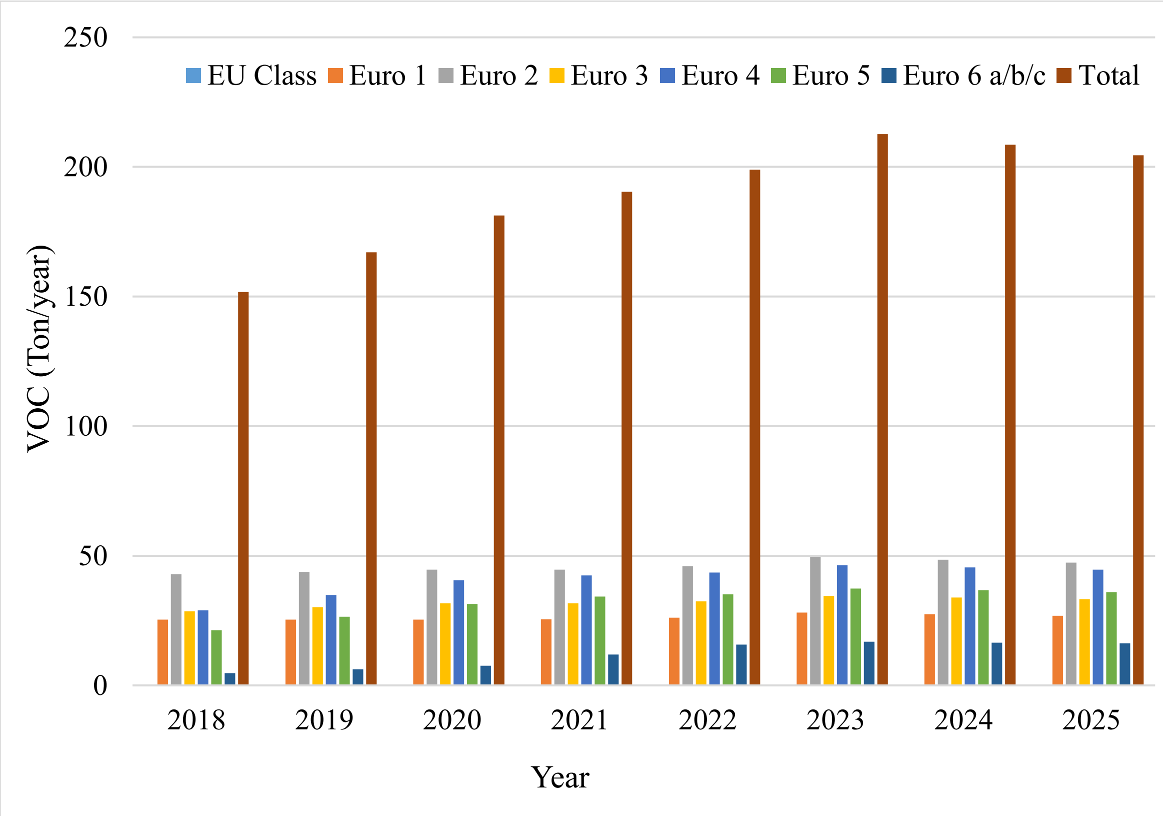

Figure 4.14: GPV annual NOx emissions from 2018 to 2025

Annual Energy Consumption

In this study, only passenger cars with petrol and diesel engines were used to estimate the annual energy use. Because of their relatively small percentage of the present vehicle fleet and the unique characteristics of their energy consumption patterns, which call for a separate analytical technique, hybrid and electric vehicles were not included in the analysis. More precise estimation based on the most common conventional fuel types in Addis Ababa is ensured by this approach.

Figure 4.15 displays the EC data for GPVs in Addis Ababa. These results highlight significant patterns in energy consumption across various passenger vehicle classifications between 2018 and 2025. Between 2018 and 2023, the overall energy consumption increased steadily from 49.35 terajoules (TJ) to 62.67 TJ, then stabilised at 62.49 TJ in 2024 and 2025 due to the Ethiopian government banning the import of IC-based vehicles in 2024. The increasing number of passenger cars is correlated with this higher trend in energy use. The energy consumption of Euro 1 vehicles is comparatively steady, declining little from 7.01 TJ in 2018 to 6.95 TJ in 2023, according to an analysis of energy consumption by Euro classification.

Euro 2 cars, on the other hand, use energy consistently, reaching a peak of 13.85 TJ in 2023. This suggests that even if older cars are still widely used, they still use a lot of energy. Energy consumption has increased significantly over time for both the Euro 4 and Euro 5 categories, especially for Euro 4, which went from 10.28 TJ in 2018 to 14.72 TJ in 2023. This implies that energy usage is rising as the fleet moves towards newer vehicle norms, maybe as a result of more cars fulfilling these requirements. Despite starting with a low energy consumption of 1.68 TJ in 2018, Euro 6 vehicles exhibit a significant growth to 5.23 TJ by 2023. Although their overall contribution to total energy consumption is still quite small when compared to previous Euro classes, this shows a slow transition towards more efficient vehicles. The real number of passenger cars increased significantly from 242,561 in 2018 to 312,372 by 2025, according to the figures in Table 4.6. Because more cars on the road generally result in higher aggregate energy use, independent of the efficiency of individual vehicles, this increase in the number of vehicles has a direct impact on total energy consumption.

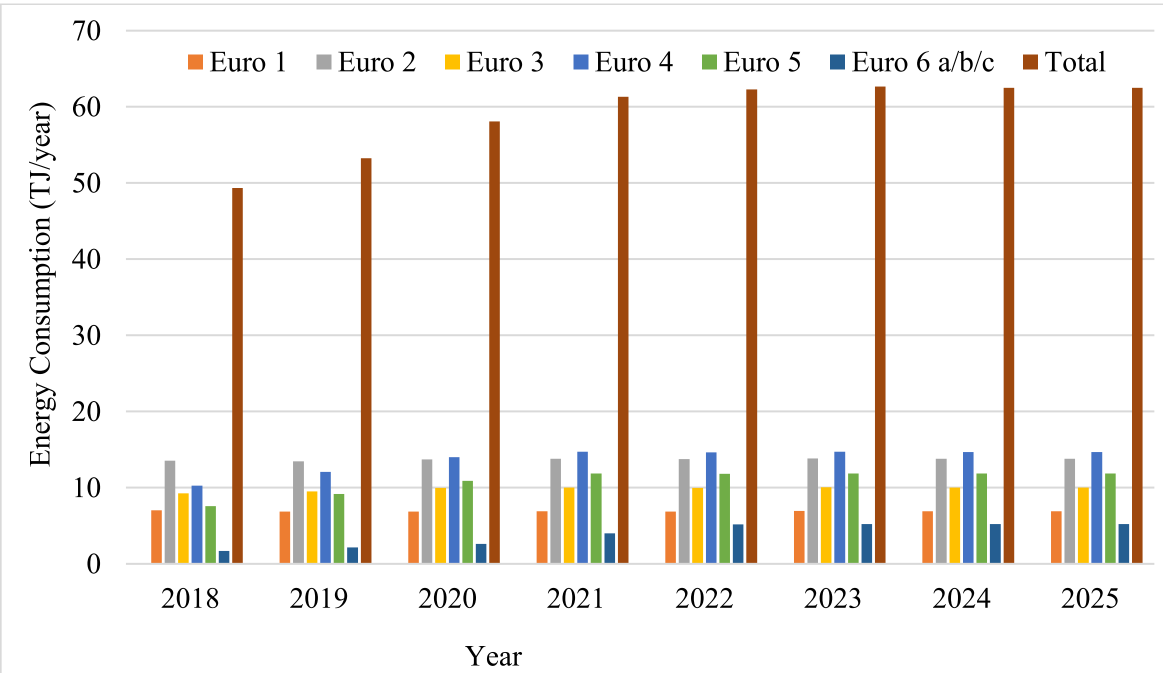

Figure 4.15: GPV annual energy consumption from 2018 to 2025

Figure 4.16 displays the EC figures for diesel passenger cars in Addis Ababa. These results offer important information about the patterns of energy use for various DPV categories between 2018 and 2025. From 22.67 TJ in 2018 to a peak of 28.34 TJ in 2022, the overall energy consumption of diesel vehicles rose. It then declined slightly to 28.24 TJ in 2024 and stabilised at 28.33 TJ in 2025. Figure 4.12 shows a steady rise in energy consumption, which is probably caused by the increasing number of DPVs on the road. Different patterns emerge when the energy use is analysed by Euro categorisation. With values ranging from roughly 3.00 to 3.10 TJ over time, Euro 1 vehicles retain rather constant energy usage. Conversely, Euro 2 cars show a modest increasing trend, using 6.40 TJ in 2018 and 6.43 TJ in 2023, suggesting that older, more polluting vehicles will continue to be a part of the fleet.

Energy usage has also increased under the Euro 3 and Euro 4 classes, especially Euro 4, which increased from 4.57 TJ in 2018 to 6.45 TJ in 2023. This implies that the energy usage of newer models may not completely counteract the general rise in diesel vehicles when older models are phased out, leading to increased aggregate energy use. Notably, the energy consumption of Euro 6 vehicles adhere to the most recent international emissions regulations, rose from 0.74 TJ in 2018 to 2.36 TJ in 2023. The growth indicates a slow shift towards cleaner, more energy-efficient automobiles, even though their share of overall energy use is still small. In 2025, there were 124,949 diesel passenger cars overall, up from 97,024 in 2018, suggesting that the city's transport system is becoming more and more dependent on diesel technology.

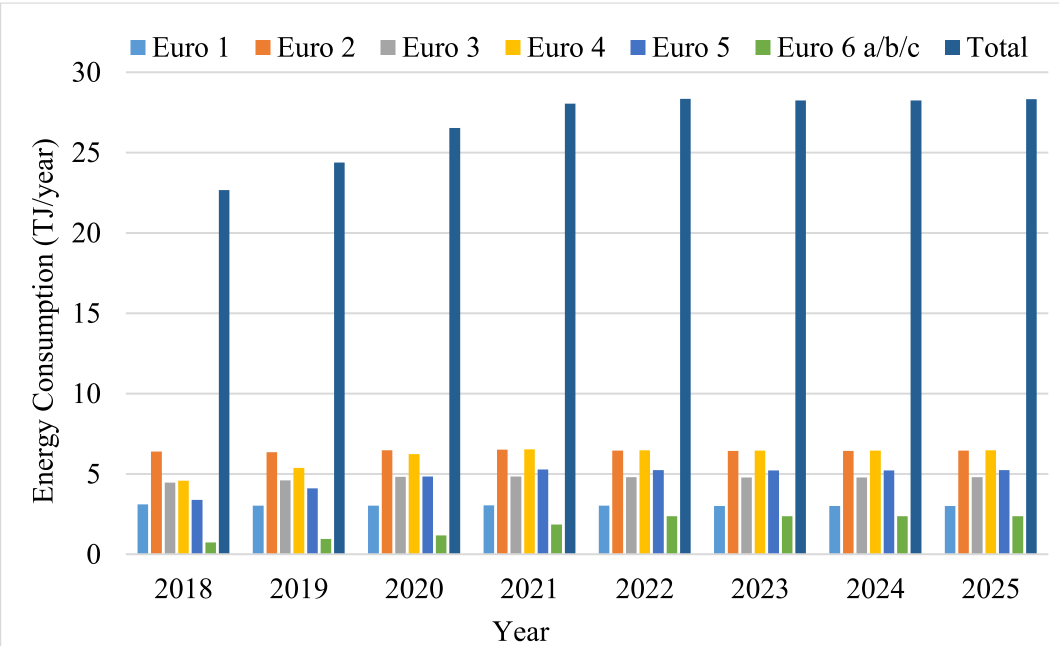

Figure 4.16: DPV annual energy consumption from 2018 to 2025

4.4. Emissions and Energy Consumption Factors

In order to evaluate emission patterns across standards and vehicle types and to shed light on their effects on the environment, the emission factors were examined. The CO, CO_2, and NOx emission factors for passenger cars in Addis Ababa were analysed in this section according to EU emission levels (Euro 1 to Euro 6) and vehicle types, including small, medium, and large (SUV) vehicles with gasoline and diesel engines.

4.4.1. CO emission factor

The results in Figure 4.17 show that CO emission factors for petrol passenger vehicles consistently decrease across various EU classifications. From the Euro 1 to the Euro 6 classes, CO emissions dramatically dropped for all three vehicle types: small, medium, and executive (SUV). Under Euro 1, small GPVs had the greatest CO emission factor (5.6559 g/km), which gradually decreased to 0.3449 g/km under Euro 6. The same pattern was observed for medium GPVs, which decreased from 5.2519 g/km (Euro 1) to 0.3449 g/km (Euro 6). Similarly, executive GPVs began at 4.5149 g/km and reached 0.3449 g/km by Euro 6. This convergence of results under Euro 6 across all vehicle sizes reflects the strict emission limitations followed by most vehicle manufacturers.

Large GPVs (1.7399 g/km), medium GPVs (2.1242 g/km), and small GPVs (2.4326 g/km) had the highest CO emissions on average. During the early Euro stages, the adoption of less advanced emission control systems was what caused the somewhat higher emissions in smaller cars. Additionally, a small increase in CO levels from Euro 4 to Euro 5 in some categories suggests potential variations in actual vehicle performance.

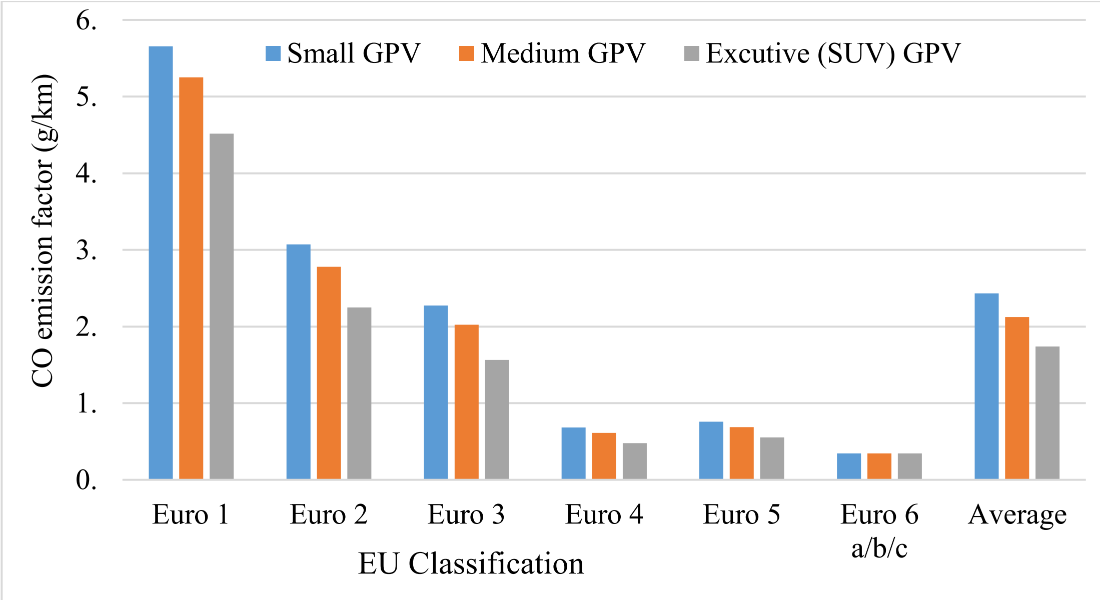

Figure 4.17: CO emissions factor of GPVs in Addis Ababa

CO emission factors from diesel passenger vehicles operating in Addis Ababa were analysed and interpreted based on the results presented in Figure 4.18. These cars are grouped by vehicle class (small, medium, and large diesel passenger vehicles, or DPVs) and classified by EU vehicle classification. When compared to the more recent Euro level, the measured CO emission factors, given in g/km, clearly show a falling trend. In particular, Euro 1 vehicles have an average CO emission factor of 0.6811 g/km, whereas Euro 5-compliant vehicles have an average CO emission factor of 0.0569 g/km. The effectiveness of vehicle manufacturers' gradual adoption of CO-reducing tactics, such as better fuel combustion, electronic fuel injection systems, and catalytic converter technology, in lowering CO emissions is confirmed by this pattern.

The CO emissions of Euro 3 (0.1784 g/km) and Euro 4 (0.1893 g/km) DPV, however, are slightly higher. There are a number of reasons for this phenomenon, including: some Euro 4 vehicles now have lean-burn engines, which could result in incomplete combustion and higher CO emissions when driving in cities, differences between test cycle representation and actual driving circumstances, and the impact of vehicle ageing and emission control system degradation. According to EU standards, the average CO emission factor calculated for all vehicle categories is 0.3408 g/km. When compared to contemporary European city fleets, this level is relatively high, suggesting that older generation DPVs significantly contribute to urban air pollution. Specifically, the continued use of Euro 1 and Euro 2 cars (emissions higher than 0.59 g/km) worsens the negative effects of CO on the environment and human health in crowded places.

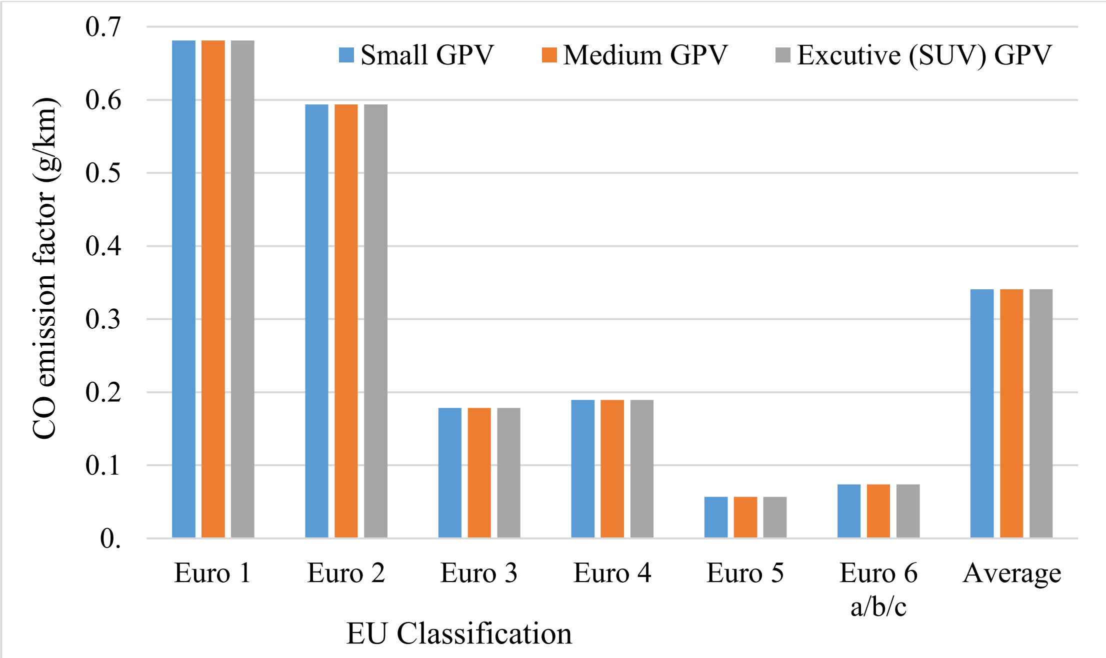

Figure 4.18: CO emissions factor of DPVs in Addis Ababa

4.4.2. CO_2 emission factor

The CO_2 emission factors (in g/km) for passenger cars in Addis Ababa were analysed in this section. They are divided into three vehicle classes: small, medium, and large (SUVs), as well as by Euro level (Euro 1 to Euro 6). According to the findings illustrated in Figure 4.19, CO_2 emission factors often rise as vehicle size increases. For Small, Medium, and Large GPVs, the corresponding average emission factors were 230.73 g/km, 273.73 g/km, and 378.01 g/km. This hierarchy is in line with the well-established knowledge that larger cars often use more fuel and emit more CO_2 because of their larger bulk and engine displacement.

Figure 4.19 shows that although CO_2 emissions differ within EU classes, the trend of decrease is neither constant nor noteworthy across more recent criteria. Under Euros 4 through 6, CO_2 emissions in Small GPVs rise from 220.18 g/km under Euro 1 to 237.63 g/km under Euro 6. Medium GPVs exhibit a similar plateau, with values peaking at 275.95 g/km under Euro 3 and barely decreasing under later standards. Interestingly, there is no discernible improvement in the CO_2 emission value of Large GPVs (SUVs) from Euro 4 to Euro 6, which remains constant at 404.64 g/km. These findings suggest that although subsequent EU regulations have been successful in lowering pollutants, including CO, HC, and NOx, their influence on CO_2 emissions has been minimal. This is mostly because fuel consumption directly affects CO_2 emissions, and increases in engine size, power demand, or vehicle weight may cancel out gains in combustion efficiency. The high CO_2 emission factors found in the fleet of cars in Addis Ababa point to significant local and worldwide environmental problems. A considerable carbon footprint is indicated by the urban fleet's average emissions, which are greatly above existing EU regulation standards (such as the 95 g/km fleet average under Euro 6).

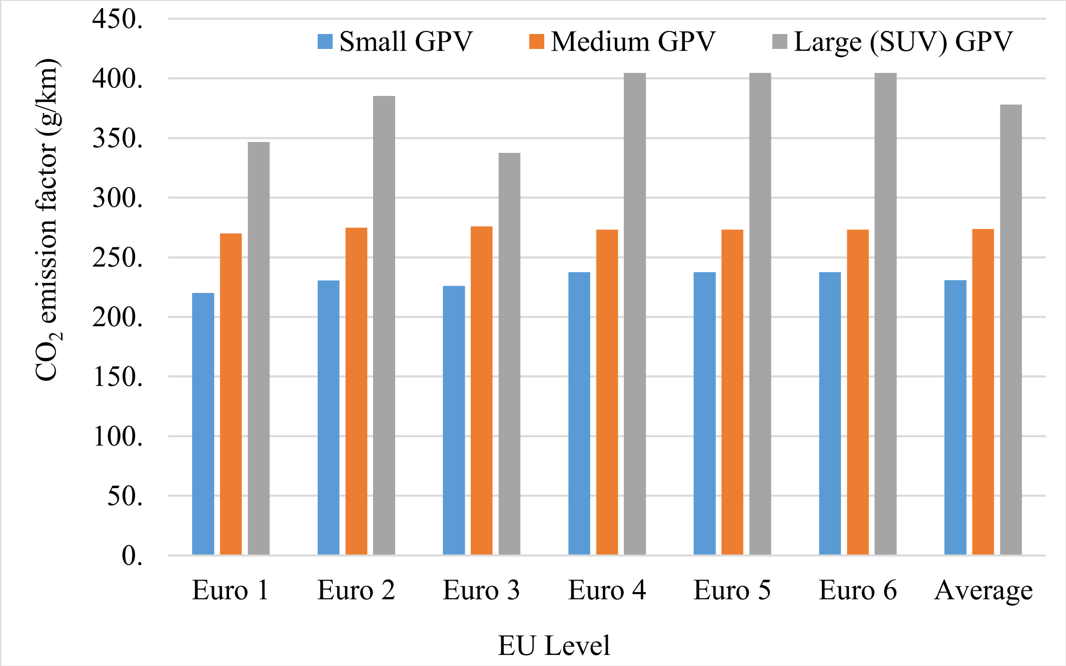

Figure 4.19: CO_2 emissions factor of GPVs in Addis Ababa

Figure 4.20 shows the CO_2 emission profile of cars with diesel engines. With little variation across Euro standards for SUVs, a general tendency indicates increased emissions in larger vehicle categories. From Euro 3 to Euro 6, there are very slight improvements in CO_2 emissions, particularly for small and medium-sized diesel cars. Large DPVs, however, do not move at high emission levels. This could be explained by the fact that contemporary diesel engines prioritise particulate matter and NOx reduction technologies over CO_2 management.

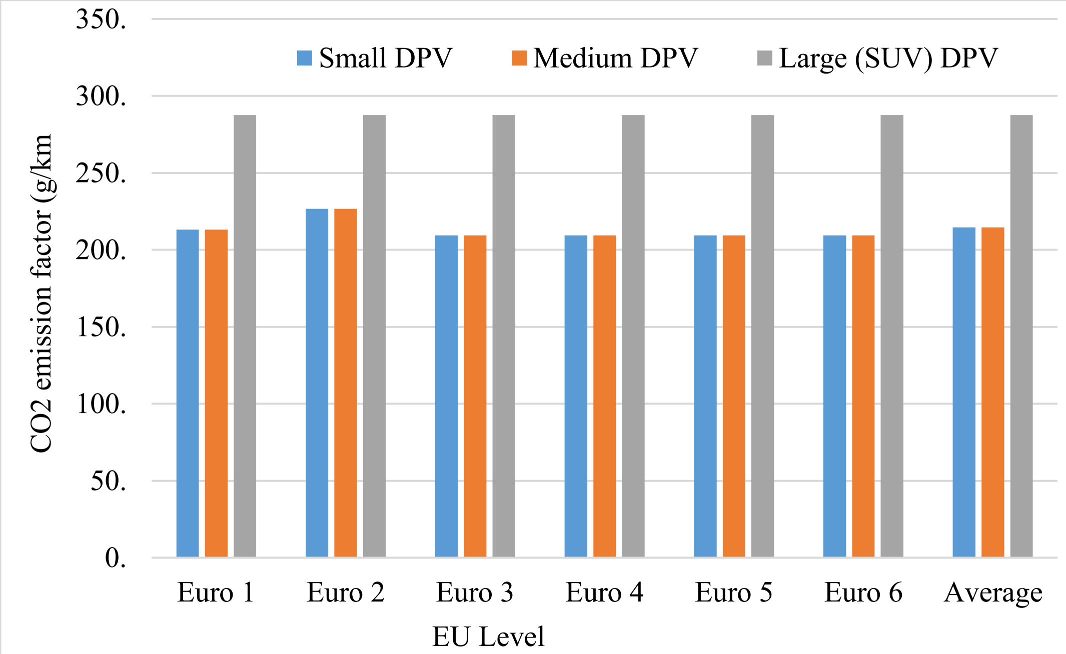

Figure 4.20: CO_2 emissions factor of DPVs in Addis Ababa

Several important decisions can be drawn from a comparison of petrol and diesel passenger vehicles. The trade-off between emissions of CO and CO_2 is one important finding. Severe Euro requirements have resulted in a significant fall in CO emissions; however, CO_2 reductions have plateaued or even grown, especially in larger cars. Due in large part to variations in fuel type and engine size, this points to a technical compromise whereby increases in combustion efficiency successfully reduce CO but do not equally lower CO_2 emissions.

There is a noticeable difference in emissions according to the size of the vehicle. Regardless of the fuel source, sport utility vehicles (SUVs) continuously emit more CO_2, highlighting the urgent need for regulations addressing emissions related to engine displacement and weight. Diesel SUVs provide a unique problem because, despite their widespread perception as being more fuel-efficient, their CO_2 emissions levels remain constant across a range of standards. The need for more robust policy interventions, such as phase-outs of diesel vehicles and the establishment of low-emission zones, is highlighted by this standstill. Furthermore, the realities of on-road emissions in African urban areas are not well captured by the dependence on laboratory-based Euro regulations. Therefore, for efficient environmental management, real-world emissions data must be incorporated into the creation of policies and laws governing the importation of vehicles.

4.4.3. NOx emission factor

The NOx emission factors (g/km) of passenger cars that run on petrol are shown in Figure 4.21. As pollution rules were tightened over time, the data shows a noticeable and steady decline in NOx levels from Euro 1 to Euro 6. The most significant decrease in NOx emissions, which is nearly 50% lower between Euro 2 and Euro 3, shows how effective strict legal restrictions are. Improvements continue, albeit more slowly, after Euro 3. This indicates the necessity for hybrid or zero-emission solutions for upcoming reductions and illustrates the declining returns from conventional technology.

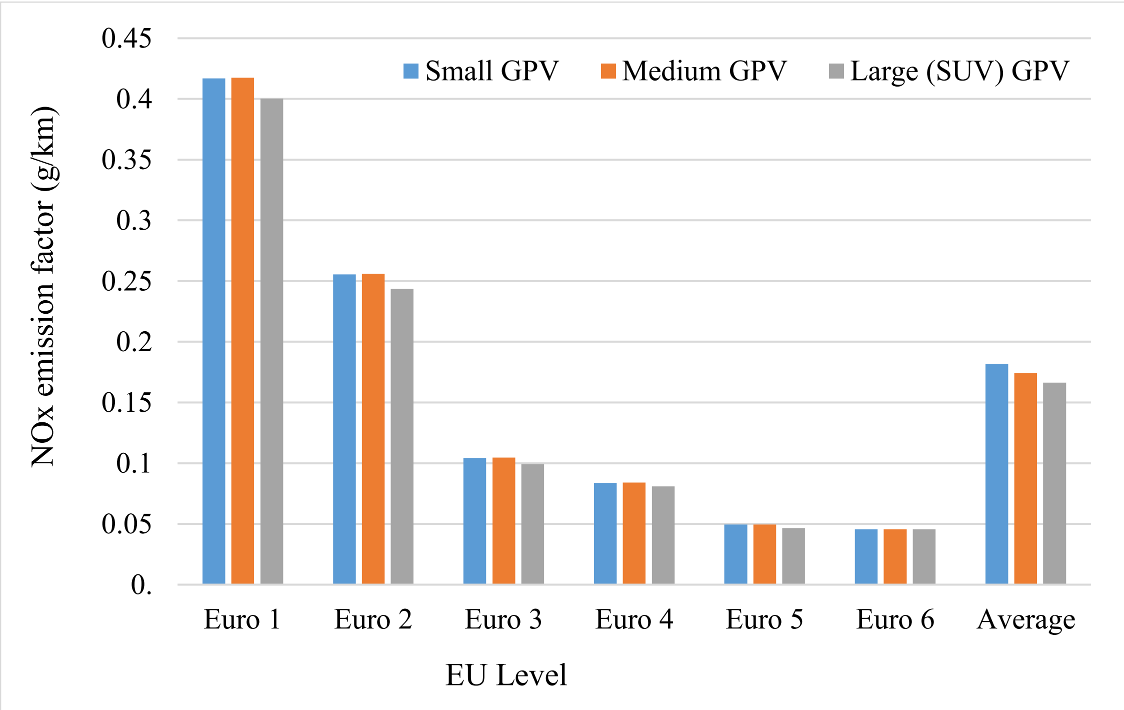

Figure 4.21: NOx emissions factor of GPVs in Addis Ababa

NOx emissions for passenger cars with diesel engines are shown in Figure 4.22. Diesel vehicles have much greater NOx emissions across all Euro criteria than their gasoline-powered counterparts. Despite a noticeable slowdown in NOx emissions starting with Euro 3, total levels are still high when compared to gasoline-powered vehicles. Diesel NOx levels are over four times higher than those of comparable gasoline-powered vehicles, even at Euro 6. These findings highlight the shortcomings of diesel pollution restrictions and support the case for cities like Addis Ababa to move away from fleets that run on diesel.

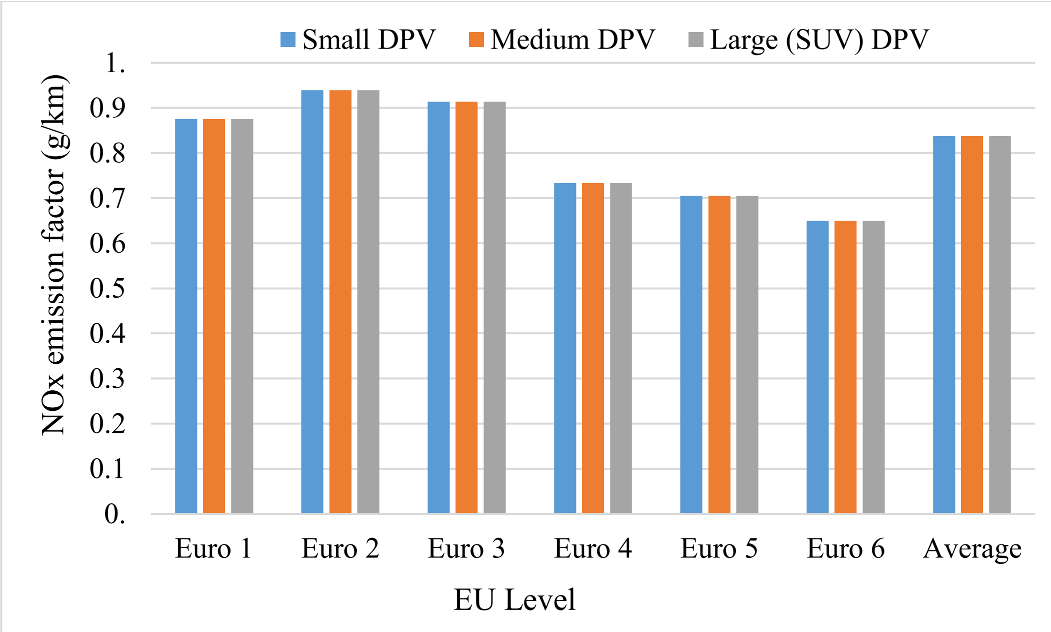

Figure 4.22: NOx emissions factor of DPVs in Addis Ababa

4.4.4. Energy Consumption Factor

Vehicle fuel economy is largely determined by energy consumption (EC), which is commonly measured in MJ/km and is directly related to CO_2 emissions and operating expenses. Although the current dataset uses CO_2 emissions as a stand-in for fuel efficiency, trends in CO_2 can be used to deduce or debate EC emission parameters. According to the data in Figure 4.23, EC decreased somewhat between Euro 1 and Euro 3 standards before stagnating or even rising between Euro 4 and Euro 6. Larger vehicle classes, like SUVs, which continuously exhibit rising pollution levels, are where this tendency is most noticeable.

Improvements in engine efficiency, better fuel injection technology, and lighter vehicles are responsible for the first drop in CO_2 emissions. The subsequent increase in ECs under later Euro standards, however, points to a shift in regulation away from energy efficiency and towards the management of harmful pollutants, including NOx and particulate matter. SUVs' consistently increased energy consumption emphasises the impact of engine displacement and vehicle mass, which naturally require more fuel each kilometre driven, raising CO_2 and EC measurements. These results imply that improvements in tailpipe pollutant management may unintentionally impair overall fuel economy if there is no concomitant regulatory focus on EC. Promoting electric cars or hybrid alternatives could have a significant positive impact on lowering both EC and CO_2 emissions in cities like Addis Ababa, where fuel prices and carbon emissions are becoming increasingly problematic.

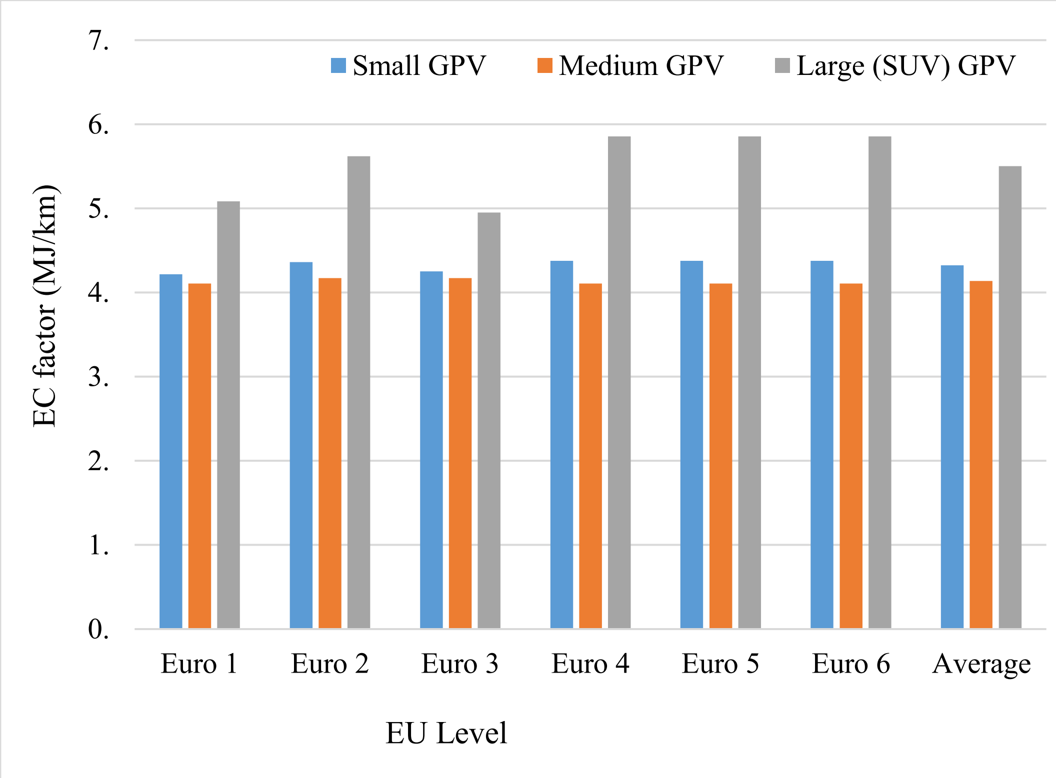

Figure 4.23: EC factor of GPVs in Addis Ababa

The EC factors (in MJ/km) for passenger cars with diesel engines are displayed in Figure 4.24. For small and medium DPVs, the data shows constant values across Euro levels; however, the numbers for large (SUV) diesel vehicles are noticeably higher. Three important findings were shown by this study. First, there is no discernible increase in energy usage from Euro 3 to Euro 6 for small and medium-sized DPVs. This plateau implies that newer pollution regulations do not always improve fuel efficiency, even though they may target NOx and particulate matter. Second, compared to small and medium-sized cars, huge diesel SUVs regularly use more energy approcimetly 35%. This emphasises how engine size and vehicle weight affect fuel requirements. Third, Euro 2 cars use the most energy, probably as a result of their less effective engines and weaker combustion control. Under the current fuel quality and maintenance regulations in Addis Ababa, technological advancements appear to have reached a performance ceiling, based on the small advances in Euro 3 and stability that followed. According to these results, local fuel economy regulations and incentives are necessary to gradually phase out high-consumption diesel SUVs from urban driving.

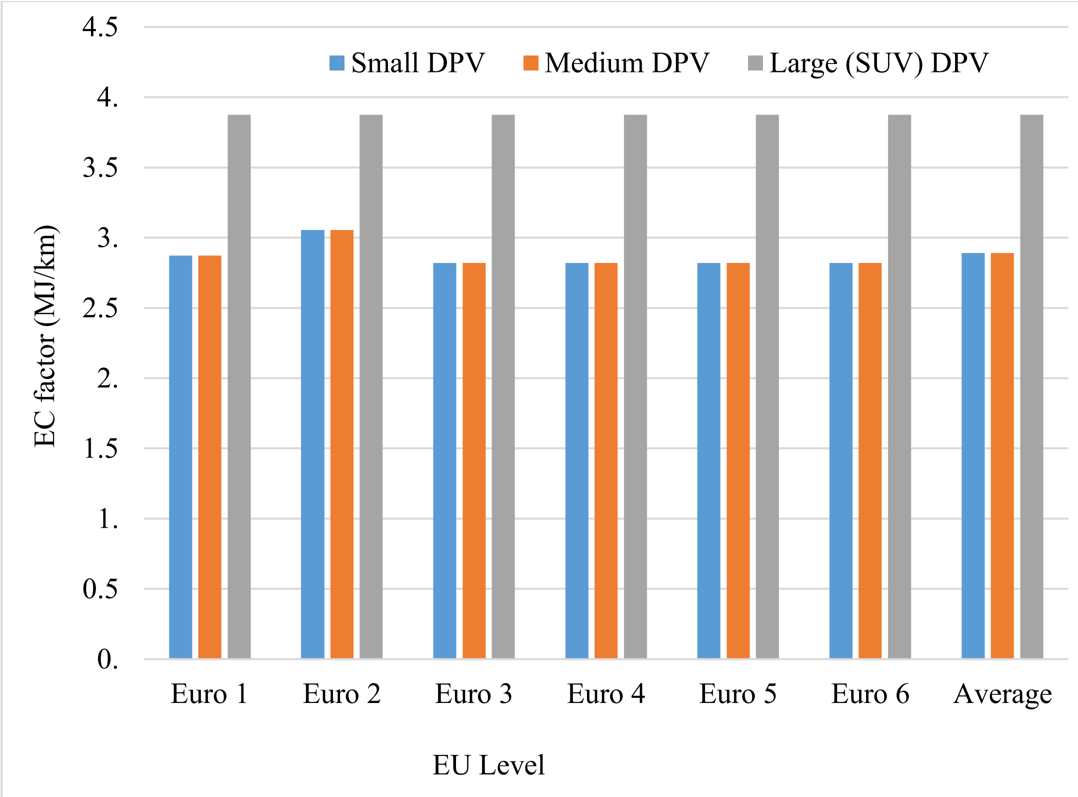

Figure 4.24: EC factor of DPVs in Addis Ababa

4.4.5. A comparative analysis between GPVs and DPVs

Several significant findings with immediate policy implications are shown by comparing petrol and diesel automobiles. The trade-off between emissions of CO and CO_2 is one important finding. Under more stringent Euro regulations, CO emissions have drastically decreased, but CO_2 reductions have stagnated or even grown, especially in bigger vehicle categories. Due in large part to variations in fuel type and engine size, this trend points to a technical compromise whereby increases in combustion efficiency effectively lower CO levels but do not produce proportionate reductions in CO_2.

The persistent difference in emissions between vehicle size classes is another important discovery. Regardless of fuel source, SUVs exhibit increased CO_2 emissions, underscoring the necessity of regulatory attention to vehicle weight and engine displacement. A persistent problem with diesel vehicles is that, although being thought of as more fuel-efficient, diesel SUVs nevertheless have the highest EC values, increasing NOx emissions, and static CO_2 levels. These problems highlight the need for more robust legislative measures, like phase-out plans for diesel vehicles and the establishment of low-emission zones.

On the other hand, gasoline-powered vehicles have demonstrated a considerable decrease in NOx, particularly with the introduction of Euro 2 regulations. However, because Euro standards rely on laboratory testing, which is not a reliable indicator of on-road emissions behaviour in African urban areas, their efficacy is restricted. Therefore, it is crucial to incorporate real-world emissions data into national policy frameworks and car import laws to guarantee that emission control tactics are both environmentally sound and contextually appropriate.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusions

Using cutting-edge modelling and simulation tools, this study provided a comprehensive assessment of Addis Ababa's passenger car fleet expansion, exhaust emissions, and energy consumption patterns from 2008 to 2024. The city's future passenger vehicle registration trends might be reliably predicted thanks to the combination of PLR and ANN models. Both strategies showed good prediction performance by using historical vehicle registration data to train the models; however, ANN outperformed PLR by a small margin in terms of accuracy and flexibility in responding to non-linear growth trends.

With total passenger vehicle registrations increasing from 15,232 in 2005 to over 312,000 in 2024, more than a 20-fold increase, the analysis showed a dramatic rise in the number of registered passenger cars. Rapid urbanisation, rising motorisation, economic expansion, and a lack of viable public transit options are all major contributors to this exponential rise. Although petrol cars made up the majority of the fleet during this time, both DPVs and GPVs demonstrated notable gains.

The COPERT model was used to estimate annual fuel consumption and tailpipe emissions for the years 2008–2024 based on this vehicle growth. Important controlled pollutants like CO, HC, NOx, and CO_2 were included in the emissions inventory. In addition to environmental and technological aspects, the simulation included data on local vehicle activity, such as average daily distances and the driving cycle unique to Addis Ababa. The findings show that overall vehicle emissions have significantly increased in tandem with fleet growth.

The rise of private automobiles and the dominance of internal combustion engine vehicles (ICEVs) resulted in a sharp increase in CO_2 emissions, the main cause of climate change. Significant increases were also seen in NOx and CO emissions, which are linked to urban air pollution and health problems, notably from older Euro standard cars, especially those that are less than Euro 4. Notably, the dominance of older vehicles continues to compromise emission performance, and even if Euro 5 and Euro 6 vehicles started to appear after 2015, their percentage is still small.

The analysis of the fleet of PVs' emissions factor in Addis Ababa highlights how inconsistently EU emission rules reduce emissions of CO, CO_2, NOx, and energy consumption. Even though CO and NOx have significantly decreased, particularly since

Euro 3, CO_2 and EC levels in larger passenger vehicle classes were still very high. This indicates that in order to accomplish climate targets and enhance urban air quality, complementary solutions are required, such as electrification, the adoption of hybrid vehicles, fuel quality improvement, and local policy interventions.

Patterns of EC also increased, which was a result of both the rise in the number of vehicles and the need for travel by each car. The energy burden of Addis Ababa's transport industry is further highlighted by fuel consumption data showing a consistent rise in the demand for petroleum. The city's energy security and environmental sustainability are threatened by this reliance on fossil fuels in the absence of fuel efficiency regulations or a switch to alternative powertrains.

5.2. Recommendations

The following suggestions are put forth to direct policymakers, urban planners, and transportation regulators towards more environmentally conscious and sustainable outcomes in light of the observed sharp rise in passenger vehicle ownership, the corresponding rise in tailpipe emissions, and the rising energy consumption in Addis Ababa:

- Adopt and Implement Tougher Vehicle Emission Regulations
- Quicken Programs for Vehicle Fleet Renewal
- Encourage the use of electric vehicles and other fuels.
- Enhance and Extend Systems of Public Transportation

Although this study uses ANN, PLR models, and COPERT simulation to provide useful insights into the growth, emissions, and energy consumption patterns of passenger vehicles in Addis Ababa, there are still a number of areas that need more research to support evidence-based policymaking and sustainable urban transport planning. These domains consist of:

- Combining Traffic Flow Models with Real-Time Emissions Monitoring
- Assessment of Passenger Vehicle Life Cycles (LCA)
- Creation of a Database on Local Emission Factors
- Assessment of the Effects of Vehicle Emissions on Public Health

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APPENDIX

Appendix A: Data Collection Tool Regarding Vehicle Activity

I. Personal Information:

1. Date: _______________
2. Gender: ☐ Male ☐ Female
3. Age: _____
4. Location: ____________________

II. Vehicle Information:

5. Vehicle category:

   ☐Tax I ☐Tax II ☐Passenger cars

   ☐Light commercial vehicles ☐Heavy-duty vehicles ☐Buses

   ☐Motorcycles ☐Bajaj

6. Fuel Type: ☐Gasoline ☐Diesel ☐Hybrid ☐Electric
7. Make and Model of Vehicle: _________________________________
8. Year of Manufacture: _______
9. Odometer reading or mileage (km): ____________________
10. Engine technology: ☐Conventional engine ☐Computer controlled engine
11. Number of engine cylinders: __________
12. Emissions control devices: _________, __________, ______________, _________
13. Transmission shift method: _____________
14. Air conditioning (AC): ☐ Not AC-equipped vehicle ☐ AC-equipped vehicle

III. Driving Habits:

15. What is the average distance of your typical trip per day? ________ Kms.
16. How often do you drive your vehicle per week? ________ times.
17. What is the average distance covered during your usual trip annually? ________ Kms.
18. Do you primarily utilize your vehicle for: ☐Traveling to work/school ☐Shopping

    ☐Recreational activities ☐Other: ______

19. What time of day do you usually drive? ☐Morning ☐Afternoon ☐Evening

IV. Vehicle Usage Patterns:

20. What percentage of your typical driving occurs in:

    Urban Off Peak Hours [%]: __________ Urban Peak Hours [%]: _________

    Rural road [%]: ________ Ring road [%]: _______ Expressway [%]: ________

21. What is your average driving speed at:

    Urban Off Peak Hours: _____ km/h

    Urban Peak Hours: _____ km/h

    Rural road: _____ km/h

    Ring road: _____ km/h

    Expressway: _____ km/h

22. How do you rate your driving style? (Please circle one):

    (Eco-friendly) 1 2 3 4 5 (Aggressive)

23. Do you frequently engage in the following driving behaviors? (Check all that apply)

    ☐Idling for extended periods ☐Rapid acceleration ☐Harsh braking

    ☐Driving at high speeds ☐Other: _________

24. Are you aware of eco-friendly driving practices that can reduce fuel consumption and emissions? ☐Yes ☐No

25. What is the average fuel consumption of your vehicle per kilometer? _______ liter.

26. What percentage of the time do you typically use the AC during your driving? ______%. (if the vehicle has air conditioning system)

V. Additional Comments or Suggestions:

27. Please use this space to provide any additional comments, suggestions, or feedback related to vehicle usage, fuel consumption and emissions:

    ____

    ____

    ____

    ____

    ____

    ____

    ____.

Appendix B: Environmental Information Data Collection Tool

Year: __________

Month	Min Temperature [°C]	Max Temperature [°C]	Humidity [%]
January			
February			
March			
April			
May			
June			
July			
August			
September			
October			
November			
December			

Appendix C: Sample PVs inventory data collected from Addis Ababa

S/N	Type of Fuel	Engine Capacity (CC)	Year of Manufacturing	Dateof Registration	Model No
1	17	13798	2004	03/03/2005	260E31H
2	17	2488	2004	10/05/2005	BSRE
3	17	12503	2005	05/03/2006	CWB450PPLA
4	17	13798	1990	5/24/2006	330-36
5	17	4334	2006	07/06/2006	NPR-66
6	17	12503	2006	10/12/2006	CWB4504
7	17	1198	2006	02/01/2007	VERYCA
8	17	4334	2005	05/03/2007	NPR66
9	17	2446	2002	07/09/2007	LN145L-PRM03
10	61	171	2000	1/15/2008	DT175