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Research Paper

Forecasting Vehicle Emissions Using an Integrated COPERT- Artificial Neural Network Modeling Framework

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Abstract

Urban vehicle emission modeling has traditionally relied on conventional regression methods that inadequately capture complex non-linear interactions among influencing variables. Moreover, the combined influence of fleet composition and local environmental conditions remains poorly understood. This study integrated COPERT-derived baseline passenger vehicle (PV) emission factors with an Artificial Neural Network (ANN) model to predict Addis Ababa's city-specific PV emission levels. The framework also employed Polynomial Linear Regression (PLR) model to forecast PV fleet growth between 2005 and 2025 and to evaluate the associated environmental impacts from 2018 to 2025. The models utilized climate data, vehicle activity patterns, and PV registration records as key inputs. Results reveal that PV ownership in Addis Ababa has increased more than twentyfold over the past two decades. Baseline emission factors indicated substantial reductions in CO and NO_x emissions with higher Euro classification levels, although CO_2 emissions remain persistently high. The ANN-based predictions show a 25% increase in CO_2 emissions, while NOx emissions rose from 1.89 to 2.08 tons/year for gasoline and from 6.02 to 7.27 tons/year for diesel PVs. CO emissions peaked at 26.25 tons/year in 2021 before declining to 21.10 tons/year by 2025, following the ban on internal combustion engine PVs. The ANN model achieved high predictive accuracy, with R^2 values ranging from 0.96 to 0.99. Overall, the integrated COPERT–ANN framework offers a robust, data-driven approach for urban emission prediction, providing valuable insights to guide sustainable transport planning and emission mitigation in rapidly growing cities.

1. Introduction

The transport sector contributes significantly to air pollutants such as carbon monoxide (CO), nitrogen oxides (NO_x), and particulate matter (PM), which adversely affect air quality and human health (Da Silva Marques et al., 2021; Dejene et al., 2019). Particularly, urban transport emissions have become a major environmental challenge in developing countries due to rapid vehicle growth, aging fleets, and poor traffic management. The European Environment Agency emphasizes that compliance with progressive vehicle emission standards (Euro 1–6) is crucial for reducing such impacts (Singh et al., 2023).

The Ethiopian government has pledged to reduce national greenhouse gas (GHG) emissions by improving transport efficiency and promoting low-emission vehicles (Wang-Helmreich & Mersmann, 2018). However, over the past two decades, Addis Ababa has experienced a sharp increase in motorization, with a fleet composed mainly of buses, commercial vehicles, passenger vehicles, and a growing number of

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motorbikes. Most of the cars are imported second-hand, often characterized by high emission factors and outdated technologies (Lencho et al., 2022). Studies revealed that, in Addis Ababa, vehicle exhaust gases are the dominant source of traffic-related air pollution, exacerbated by rapid urbanization and obsolete vehicle technology (Redi, 2024; Grutter, 2021).

The non-linear dynamics of urban transport systems are often not adequately captured by conventional linear projection models used to estimate vehicle population growth. Artificial Neural Networks (ANNs), however, offer a powerful alternative due to their capacity to model non-linear relationships and learn from historical data (Haykin, 2009). ANN-based models have demonstrated superior predictive performance in emission and traffic studies, outperforming traditional regression techniques (Jaworski et al., 2019; Zhao et al., 2019). ANNs are particularly effective in capturing complex interactions among vehicle activity, meteorological conditions, and fleet composition (Kuo et al., 2020; Zhang et al., 2020).

Standardized drive cycles such as the Worldwide Harmonised Light Vehicles Test Cycle (WLTC) and its predecessor, the New European Driving Cycle (NEDC), are frequently used for emission certification and modeling. These test cycles, however, may not accurately represent traffic conditions in African cities, as they were developed based on driving patterns in other regions (Gruner & Marker, 2016). Thus, localized data that reflect real-world driving behavior are crucial for developing accurate vehicle emission inventories. In agreement with this, Liu et al. (2024) and Lovell & Parry (2024) demonstrated that default European emission factors may not reflect local traffic and environmental conditions in cities such as Addis Ababa. Similarly, Amanuel et al. (2021) highlighted the importance of developing Addis Ababa–specific driving cycles to account for real-world driving patterns and energy consumption characteristics. In response, the Addis Ababa Drive Cycle (AADC) was developed to reflect the city’s unique driving conditions (Amanuel, 2022). Despite this progress, the AADC has not yet been incorporated into urban environmental planning or emission estimation frameworks.

The Computer Programme to Calculate Emissions from Road Transport (COPERT) is one of the most widely used models globally for estimating vehicle emissions. According to Ntziachristos et al. (2009), COPERT estimates emissions of major pollutants, including CO_2, CO, NO_x, PM, and volatile organic compounds (VOCs), based on fuel type, vehicle activity, and operating conditions. It has proven to be an effective tool for evaluating passenger vehicle (PV) emissions and has been applied in numerous studies to assess emissions and fuel consumption under various policy and geographic contexts (Abdulraheem et al., 2023; Ali et al., 2021; Obaid et al., 2021; Singh et al., 2017). The accuracy of COPERT results depends heavily on the quality of input data, including vehicle fleet composition, mileage statistics, and emission factors. Customization and calibration to local driving and environmental conditions are therefore essential. To enhance inventory reliability, the incorporation of local emission factors and driving cycle data is particularly important in developing-country contexts, where default European parameters may not be appropriate (Tsanakas et al., 2020).

According to Chindamo & Gadola (2018), 56.57% of Addis Ababa’s vehicles are diesel-powered, while the remainder use gasoline. Electric vehicles represent a very small share, although their number is gradually increasing. Despite increasing concern over vehicular emissions in the city, a comprehensive and locally calibrated emissions inventory has not been yet developed, underscoring a critical knowledge gap in understanding the city’s transport-related environmental impacts. Thus, understanding the current fleet composition is essential for developing an accurate emissions inventory and implementing targeted mitigation strategies. Furthermore, it is cructial to address the frequently lacking reliable data on future vehicle growth, which can be used in urban planning initiatives.

Thus, in the present study, an integrated ANN-based passenger vehicle (PV) growth forecasting model was developed in combination with COPERT to estimate PV emissions for Addis Ababa from 2018 to 2025. To enhance the models accuracy and contextual relevance, the locally developed AADC was incorporated. The results are expected to provide actionable insights for environmental policymakers, urban planners, and public health authorities, while also offering a replicable analytical framework for other rapidly motorizing cities confronting similar challenges in sustainable urban air quality management.

2. Materials and Methods

2.1 Study area description

This study was conducted in Addis Ababa, the capital and largest city of Ethiopia, located between latitudes 8°50′N and 9°06′N and longitudes 38°40′E and 38°50′E. The city covers an area of approximately 527 km² and lies at an elevation ranging from 2,200 to 3,000 m above sea level. Addis Ababa serves as the political, economic, and cultural center of the country and it serves as Africa's diplomatic and political hub, a symbolic capital for the continent, and the base for key organizations like the AU Commission.

Vehicle flow in Addis Ababa is severely congested, leading to high levels of emissions, including CO, CO_2, NO_x, and PM, particularly during peak hours. The congestion is exacerbated by factors like a high number of old vehicles, especially minibuses, and is a significant contributor to fuel consumption and overall air pollution in the city. Moreover, limited emission control regulations have exacerbated vehicular pollution levels. The city’s rapidly growing urban population has intensified the demand for transport services, making passenger vehicles a dominant mode of urban mobility. Thus, the emission analysis of this study focused on passenger vehicles operating within the city boundaries.

2.2 Data collection

The COPERT and ANN models were utilized to estimate exhaust emissions from PVs within the city. Based on historical vehicle registration data, predictive models were also developed to forecast PV fleet growth. The key input parameters included vehicle fleet composition, Ethiopian fuel specifications, Addis Ababa’s climate data, vehicle activity patterns, technology classifications, and AADC.

Data for the study were collected using a combination of primary and secondary sources. Secondary data, essential for developing the emission model based on the Addis Ababa driving cycle, were obtained from relevant authorities and offices. These included records on the number of vehicles by type, vehicle-specific parameters from the Addis Ababa Transport Authority, and historical vehicle data for the period 2005–2024. Document analysis was also conducted to identify vehicle categories, technology shares, and related characteristics.

Before modeling, the collected datasets underwent rigorous preprocessing to ensure reliability and accuracy. Missing data were addressed using interpolation for short gaps, while outliers exceeding defined thresholds were adjusted to minimize the influence of erroneous entries. Inconsistent records were cross-checked against secondary sources, such as city transport reports and relevant literature, to verify their validity. These preprocessing steps collectively ensured that the dataset used for training and prediction was consistent, robust, and suitable for accurate modeling.

Average weather data for Addis Ababa (2018–2025) were obtained from the Ethiopian Meteorological Service (Table 1), while fuel specifications (Table 2) were sourced from the Ethiopian Petroleum Enterprise.

Table 1: Environmental data of Addis Ababa

Month	Min Temp. (℃)	Max Temp. (℃)	Humidity (%)
Jan.	9.7	20.5	50.0
Feb.	11.9	22.3	59.0
Mar.	12.5	21.2	53.0
Apr.	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
Aug.	11.5	19.6	82.0
Sep.	11.2	20.7	82.0
Oct.	9.8	21.0	54.0
Nov.	9.4	20.9	57.0
Dec.	9.6	21.2	52.0

Primary data were gathered through quantitative, self-administered questionnaires distributed to vehicle drivers and owners to assess daily, monthly, and annual vehicle activity. A sample size of 416 was determined using the population proportion formula (Equation 1) with a 95% confidence level and a 5% margin of error. A total of 400 valid responses were received, providing comprehensive information on passenger car usage patterns and enabling the estimation of typical vehicle activity levels necessary for energy consumption and emission calculations.

Table 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	-	-
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

Observations, interviews, and document analysis on vehicle activity patterns complemented the random sampling of drivers.

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

where: n = required sample sizes, Zα/2 = 95% (confidence level, Z = 1.96), d = margin of error, and p = proportion of vehicles attending daily activities (0.56).

Based on survey responses, the average daily travel distance for small PVs, typically compact cars used for short-distance travel and personal commuting, was 60 km. Medium PVs, often station wagons or mid-size sedans used for both private and public transport, averaged 80 km/day. Large (executive) passenger cars, commonly used for long-distance travel and business or governmental purposes, recorded a daily average of 100 km.

2.3 Passenger Vehicle growth prediction

This study predicted PVs growth in Addis Ababa from 2005 to 2030 by using ANN and a Predictive Linear Regression (PLR) models. The projections were based on historical data for registered passenger vehicles in Addis Ababa, obtained from official government records. This dataset included annual vehicle registration counts categorized by fuel type, vehicle class, and technology share. The predictors used in the models included Addis Ababa's population, GDP per capita, and time (year) (Table 3).

The ANN model was developed using a Multilayer Perceptron (MLP) architecture (Figure 1). The modeling process began with data cleaning and visualization, followed by the random division of the dataset into training (70%), validation (15%), and testing (15%) subsets. The iterative development process (Figure 2), required continuous monitoring and adjustment to achieve optimal predictive performance.

Table 3: Values of predictors for each considered year

Year	Population	GDP Per Capita (USD)	Year	Population	GDP Per Capita (USD)
2005	2,634,000	181.49	2018	4,400,000	839.86
2006	2,689,000	218.64	2019	4,592,000	948.85
2007	2,750,000	266.89	2020	4,794,000	969.01
2008	2,871,000	350.57	2021	5,228,000	947.10
2009	2,996,000	373.20	2022	5,461,000	1142.93
2010	3,126,000	341.10	2023	5,704,000	1511.36
2011	3,263,000	377.69	2024	5,461,000	1320.16
2012	3,405,000	510.54	2025	5,957,000	1066.36
2013	3,554,000	548.87	2026	6,221,491	1240.49
2014	3,709,000	622.59	2027	6,497,725	1400.70
2015	3,871,000	707.98	2028	6,786,224	1577.53
2016	4,040,000	790.79	2029	7,087,532	1758.49
2017	4,216,000	822.70	2030	7,402,219	1952.45

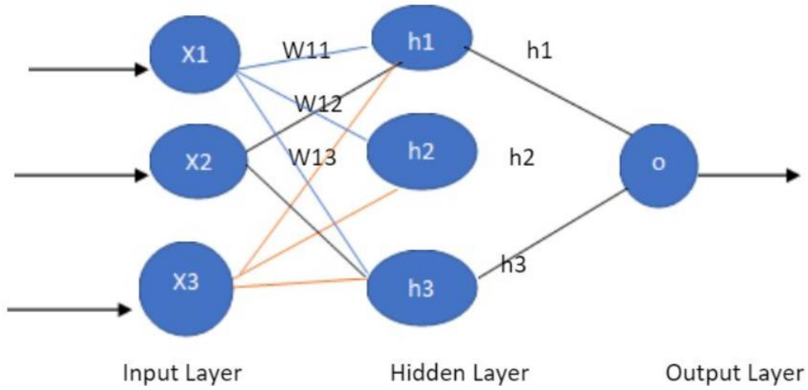

Figure 1: Diagram of MLP-based ANN prediction model

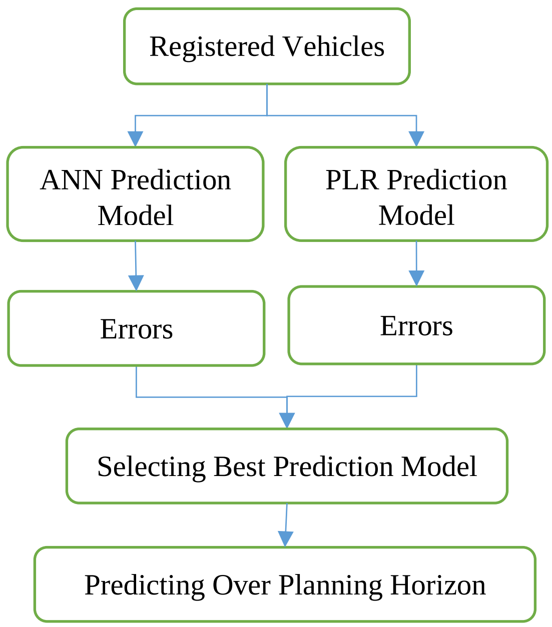

Figure 2: The passenger vehicles prediction process

The ANN model development followed the steps outlined below:

1) Creating a command-line script and specify the target series.
2) Selecting an appropriate training algorithm.
3) Randomly dividing the data into training (70%), validation (15%), and testing (15%) subsets.
4) Adjusting the feedback delays and hidden layer units through a trial-and-error process.
5) Evaluating the final neural network performance.

Model performance was assessed using multiple statistical indicators, including the time-series response plot, Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). The best-performing model was then applied to forecast passenger vehicle growth up to 2030, providing critical insights to support urban transportation planning and environmental impact assessment in Addis Ababa.

2.4 Baseline PV emissions factor determination

The COPERT approach was employed in this study to estimate emissions and fuel consumption (FC) from PVs by accounting for hot, cold-start, and evaporative emissions. The collected data were entered into the COPERT model after incorporating the necessary climatic data for Addis Ababa and the average distance traveled by each vehicle category. The model was then used to quantify three major pollutant emissions from PVs over the study period, categorized by vehicle type.

Among these, the three most dominant pollutants, namely CO_2, CO, and NO_x, pose significant risks to both the environment and public health. In this study, COPERT version 5.6.1 was applied to estimate emission levels based on vehicle category. The emissions of different vehicle types were computed in tons per year using Equations (2) – (5) (Ntziachristos et al., 2009).

Cold start emissions (E_{cold}) was determined by equations (2) and (3).

$$E_{cold} = \beta * bc * N * M * e_{hot} * \left(\frac{e_{cold}}{e_{hot}} - 1\right) \quad (2)$$

$$\frac{e_{cold}}{e_{hot}} = A * V + B * T + C \quad (3)$$

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 (4) and expressed as the total km driven by vehicles during the time considered for a given activity level (NM).

$$E_{hot} = NM \times e_{hot} \quad (4)$$

COPERT takes into account evaporation from diurnal fuel losses ($E_{diurnal}$), after-use (E_{soak}), and running losses ($E_{running}$), as shown in Equation (5).

$$E_{evap} = E_{diurnal} + E_{soak} + R_{running} \quad (5)$$

2.5 PV Emissions estimation

The hybrid modeling approach integrates the COPERT and ANN models to estimate PV emissions. Baseline emission factors were derived using the COPERT model based on PV and fuel type, as described earlier. These emission factors were subsequently used as input features for the artificial neural network (ANN) model, which was trained to predict Addis Ababa–specific PV emission levels under the conditions represented by the AADC. The integration of COPERT and ANN combines empirically derived emission factors with data-driven prediction capabilities, enhancing the robustness of the emission estimates.

2.6 Model performance evaluation

While the hybrid COPERT–ANN approach enhances prediction accuracy, it also has certain limitations. The COPERT model may not fully capture local fleet heterogeneity or variations in road conditions, and the ANN predictions are influenced by the quality and completeness of the training data. In addition, uncertainties in emission factors and drive cycle representation may affect the model's performance. Therefore, to ensure the reliability of the predictions, the model was validated using a combination of a 70–30% train–test split and cross-validation techniques. Moreover, the model performance was enhanced through calibration with localized parameters to improve prediction accuracy.

3. Results and Discussion

3.1 Existing passenger vehicles data

The total number of registered gasoline and diesel PVs in Addis Ababa is presented in Figure 3. The dataset includes only vehicles officially registered with the city's transport authority, excluding unregistered vehicles and those powered by alternative fuels such as electric or hybrid vehicles. Between 2005 and 2024, the number of registered PVs in Addis Ababa increased sharply, as illustrated in Figure 3, with notable implications for air quality, traffic management, and urban planning. Over this two-decade period, the total number of registered PVs expanded more than twentyfold, from 15,232 in 2005 to 312,372 in 2024. Following the Ethiopian government's ban on the importation of second-hand vehicles older than five years, the city's automobile market began to show signs of saturation after 2021, suggesting that these regulatory measures have begun to take effect. Moreover, in 2024, the Ethiopian government introduced a ban on the importation of internal combustion engine PVs to encourage electric vehicle adoption and accelerate the transition toward sustainable transport systems.

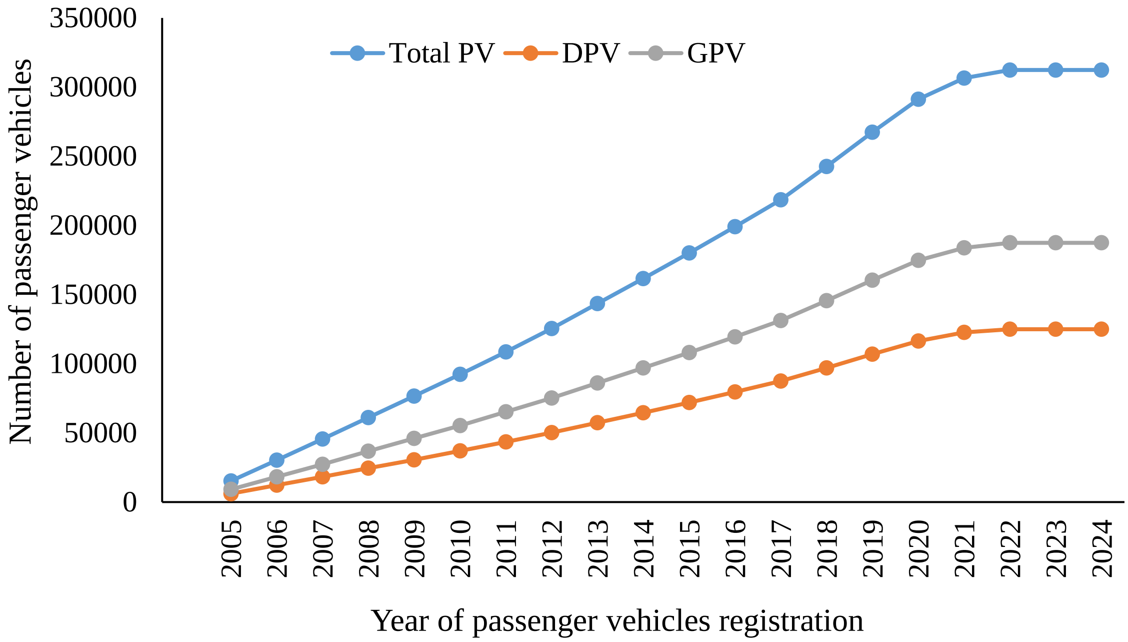

Figure 3: Registered number of passenger vehicles in Addis Ababa based on fuel type

3.2 Predicted passenger vehicle growth

Figure 4 presents the historical and projected passenger car registrations in Addis Ababa from 2005 to 2030, as estimated using ANN and PLR models. During the historical period (2005–2024), the ANN model demonstrated superior performance compared to the PLR model when evaluated against actual car registration data, effectively capturing the nonlinear growth trends and fluctuations. In contrast, the PLR model's rigid linear structure led to noticeable deviations from the observed data during periods of irregular growth. These results indicate that the ANN model provides higher forecasting accuracy and greater adaptability to the complex dynamics of urban vehicle growth.

Both models predict continued growth in PV registrations between 2025 and 2030; however, the PLR model anticipates a steeper increase, likely due to its inherent linear assumptions and reliance on historical data patterns. Overall, the ANN model appears more suitable for forecasting in dynamic, data-driven urban environments, whereas the PLR model may serve complementary purposes in long-term trend analysis and policy planning.

Table 4 compares the prediction performance metrics of the ANN and PLR models. The mean error of the ANN model is –132.025, while that of the PLR model is 71.164. The Mean Absolute Error (MAE) is considerably lower in the ANN model (362.024) than in the PLR model (882.502). Similarly, the standard deviation of prediction errors, reflecting consistency and variability in predictive performance, is substantially smaller for the ANN model (591.391) compared to the PLR model (1123.423). Finally, the ANN model exhibits a higher correlation coefficient (R^2 = 0.992) between predicted and actual values than the PLR model (R^2 = 0.970). Overall, the ANN model aligns more closely with the observed data trend, suggesting a more reliable representation of the underlying vehicle growth pattern, despite both models showing strong positive correlations.

Table 4: 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

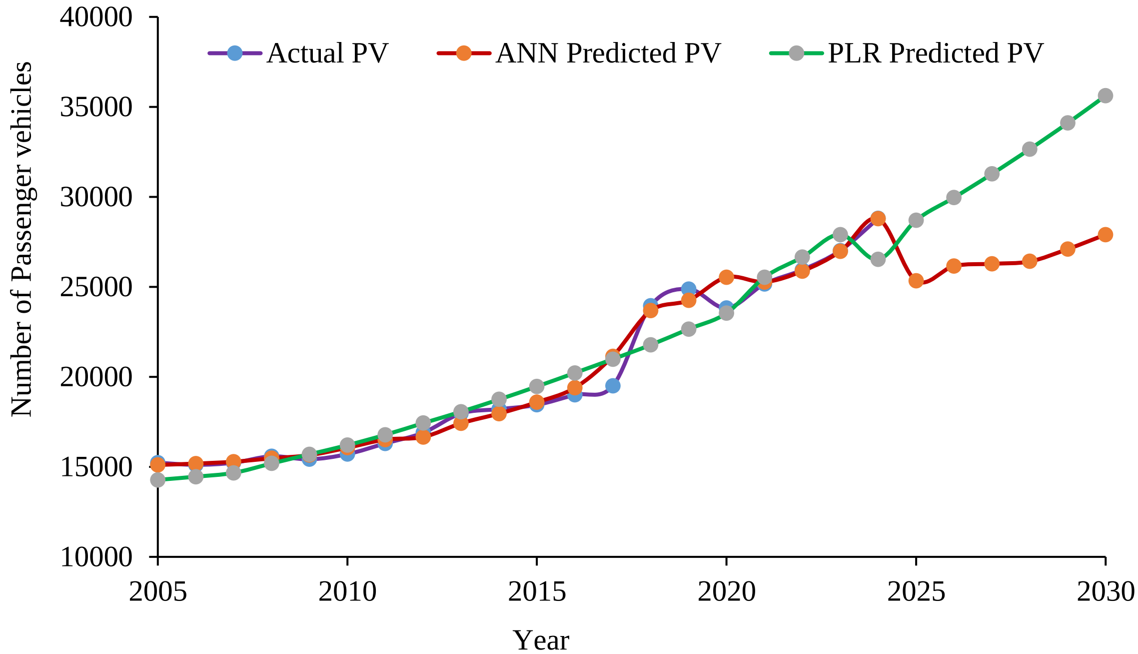

Figure 4: Projected PV registrations in Addis Ababa from 2005 to 2030

3.3 PV emission factors using the COPERT model

The model estimated emission factors for key pollutants, including CO, NO_x, and CO_2, which served as reference values representing the average emissions per kilometer for each PV class. The baseline factors provide a critical foundation for assessing the city's vehicular emissions profile, enabling comparisons with model-based forecasts and supporting the calibration of subsequent machine learning (ANN) predictions tailored to local traffic and environmental conditions.

3.3.1 CO emission factor

CO emission factors for gasoline passenger vehicles (GPVs) consistently decreased with advancing Euro emission standards (Figure 5(a)). This trend shows a substantial reduction from Euro 1 to Euro 6 across all the three vehicle types. For example, small GPVs exhibited a marked decline in CO emission factors from 5.6559 g/km under Euro 1 to 0.3449 g/km under Euro 6. Similar reductions were observed for medium and executive GPVs. The convergence of the values to 0.3449 g/km for all vehicle sizes under Euro 6 underscores the stringent emission limits imposed on manufacturers. On average, small GPVs recorded the highest CO emissions, followed by medium and then large GPVs. The relatively higher emissions of smaller vehicles in the earlier Euro stages can be attributed to less advanced emission control technologies. Additionally, a slight increase in CO levels from Euro 4 to Euro 5 in some categories may reflect variations in real-world vehicle performance.

For diesel passenger vehicles (DPVs), CO emission factors in Addis Ababa also exhibit a clear declining trend with successive Euro classifications, confirming the effectiveness of manufacturers' CO-reduction strategies (Figure 5(b)). For instance, Euro 1 vehicles have an average CO emission factor of 0.6811 g/km, which sharply decreases to 0.0569 g/km for Euro 5-compliant vehicles, largely due to improved fuel combustion efficiency and the adoption of advanced catalytic converter technologies. However, slightly elevated CO emissions in Euro 3 and Euro 4 DPVs may be attributed to factors such as lean-burn engine operation under urban driving conditions, discrepancies between test cycles and real-world performance, and the degradation of emission control systems over time. The average CO emission factor for all DPV categories in Addis Ababa is 0.3408 g/km, which remains relatively high compared to contemporary European city fleets. This suggests the continued operation of older Euro 1 and Euro 2 DPVs (with emissions exceeding 0.59 g/km) contributes significantly to urban air pollution.

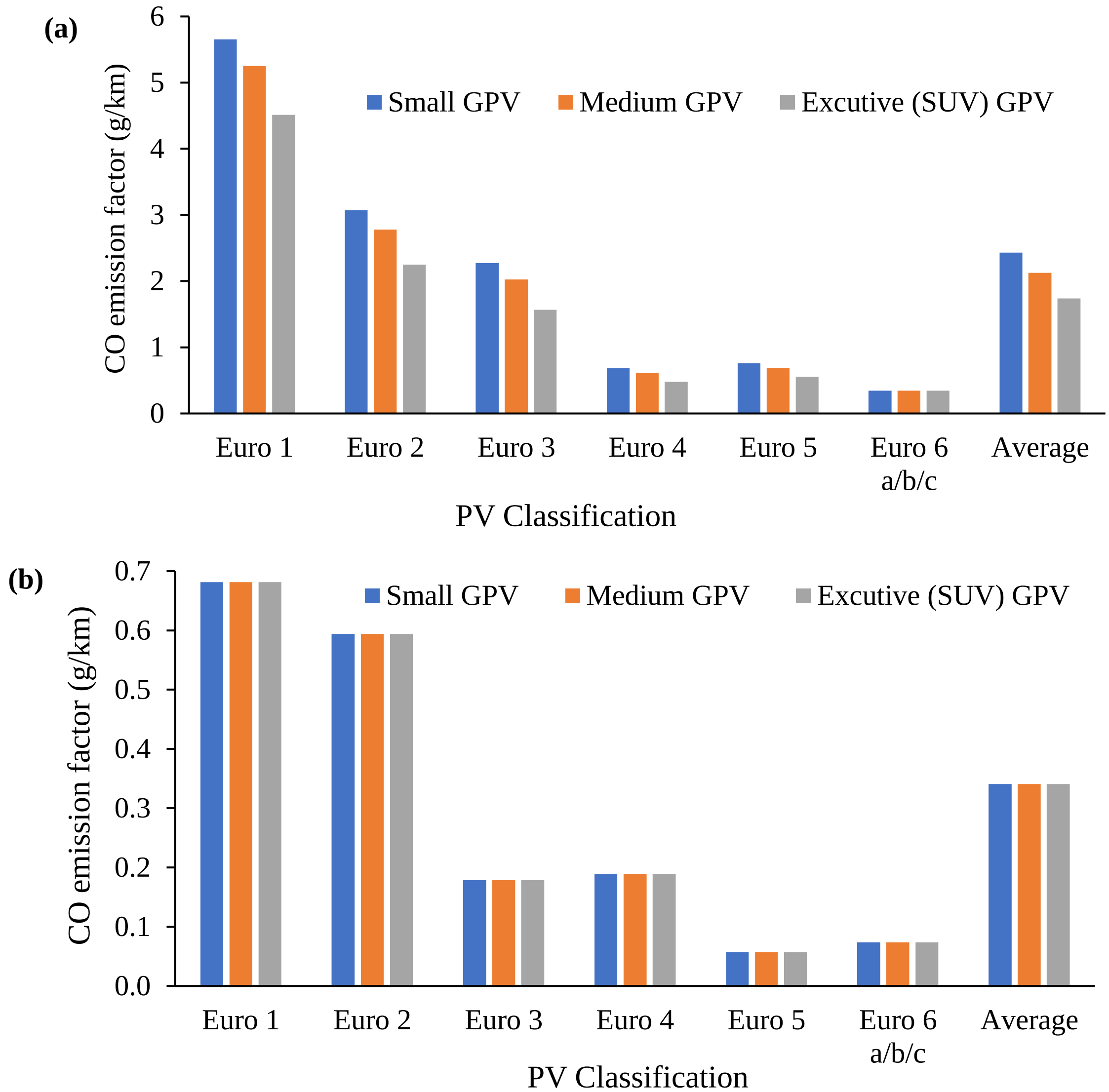

Figure 5: CO emissions factor of 9a) GPVs and (b) DPVs, in Addis Ababa

3.3.2 CO_2 emission factor

As shown in Figure 6(a), the average CO_2 emission factors are significantly high: 230.73, 273.73, and 378.01 g/km for small, medium, and large GPVs, respectively. While stricter Euro regulations have successfully reduced pollutants like CO, HC, and NOx, their impact on CO_2 emissions for GPVs has been minimal, with no consistent or noteworthy decrease across newer Euro standards (Euro 4-6). For instance, large (SUV) GPVs show a constant CO_2 emission value of 404.64 g/km from Euro 4 to 6. This suggests that gains in combustion efficiency are often offset by increases in engine size, power demand, or vehicle weight, as CO_2 emissions are directly tied to fuel consumption. The urban fleet's average CO_2 emissions are significantly above current EU regulation standards, indicating a considerable carbon footprint.

DPVs also show increased CO_2 emissions in larger vehicle categories, with little variation across Euro standards for SUVs, as illustrated in Figure 6(b). While slight improvements in CO_2 emissions are observed for small and medium-sized diesel cars from Euro 3 to 6, SUVs do not show significant improvement. This is likely because contemporary diesel engines prioritize the reduction of PM and NOx over CO_2 management.

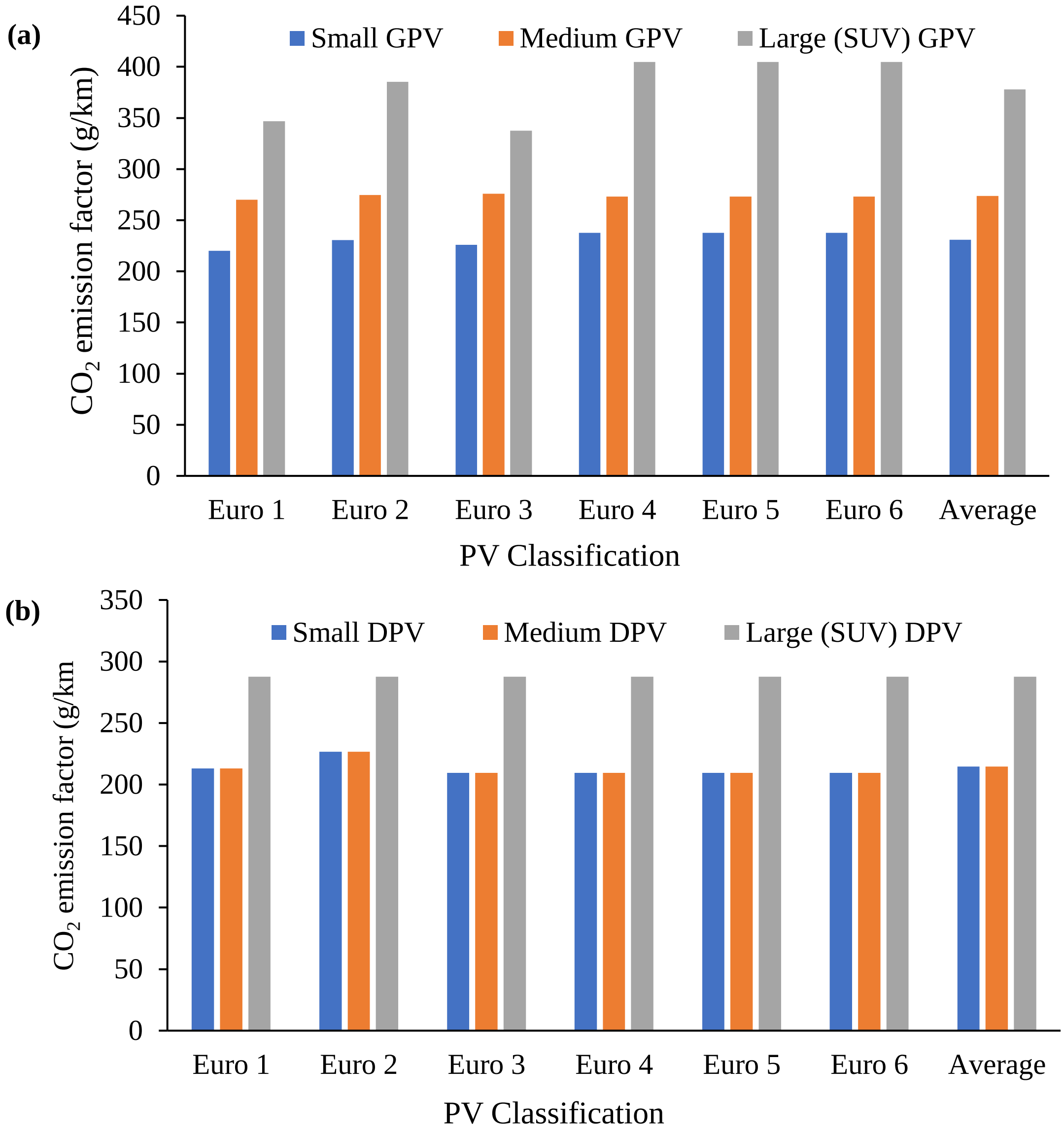

Figure 6: CO_2 emissions factor of (a) GPVs and (b) DPVs, in Addis Ababa

A key finding is the trade-off between CO and CO_2 emissions: while severe Euro requirements have led to a significant fall in CO emissions, CO_2 reductions have plateaued or even grown, particularly in larger cars. This highlights a technical compromise where increased combustion efficiency reduces CO but not equally CO_2, largely due to variations in fuel type and engine size. The high and constant CO_2 emission levels from diesel SUVs pose a unique problem, despite their perception as more fuel-efficient. This underscores the urgent need for robust policy interventions, such as regulations addressing emissions related to engine displacement and weight, phase-outs of diesel vehicles, and the establishment of low-emission zones.

3.3.3 NO_x emission factor

The NO_x emission factors (g/km) of passenger cars that run on petrol are shown in Figure 7(a). 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.

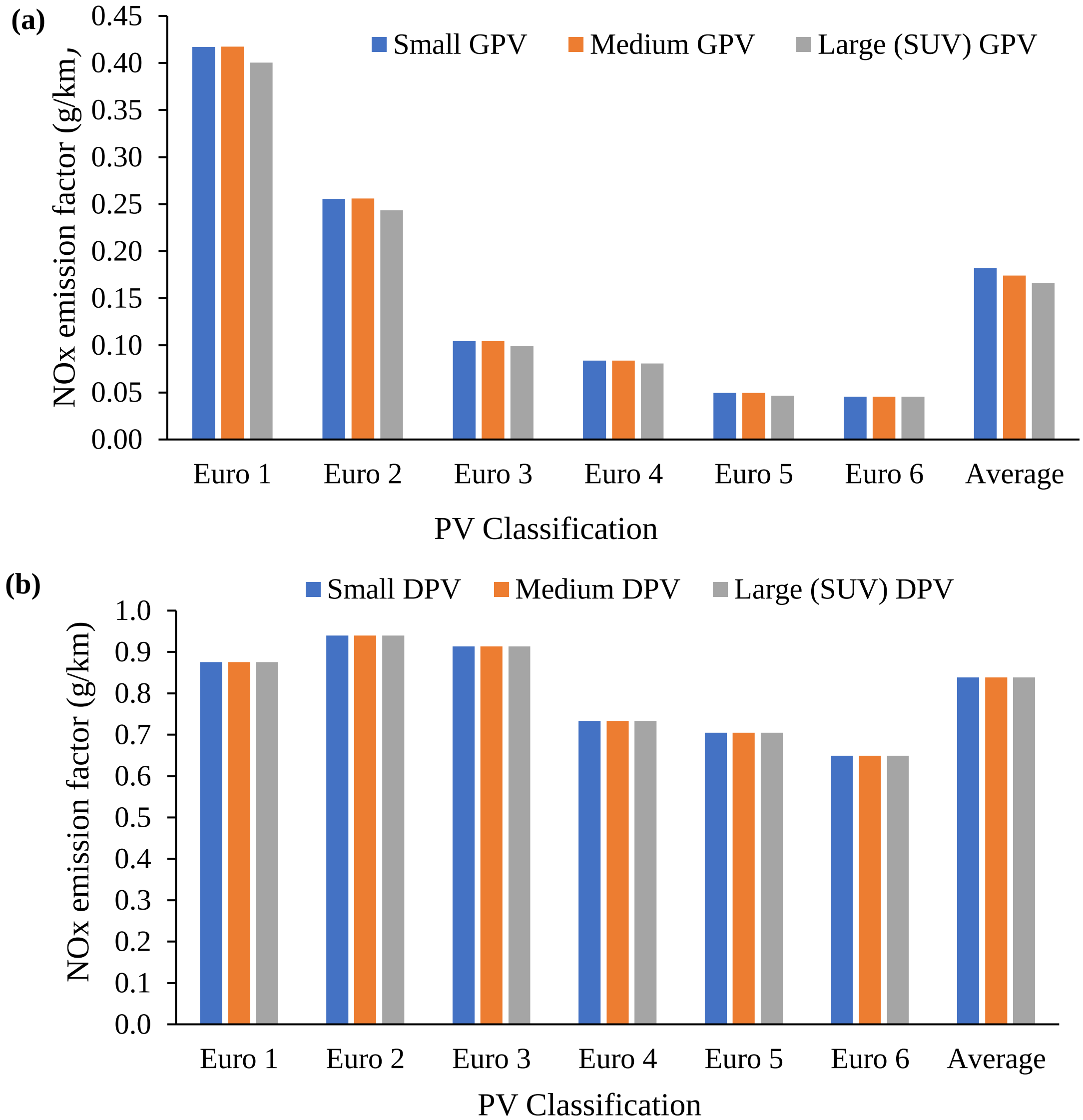

Figure 7: NOx emissions factor of (a) GPVs and (b) DPVs, in Addis Ababa

NO_x emissions for passenger cars with diesel engines are shown in Figure 7(b). 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 NO_x 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.

3.4 Predicted PV emission levels using ANN

The integration of COPERT-derived empirical data with ANN model enabled a more accurate estimation of emissions under Addis Ababa's driving conditions. The results revealed that small PVs consistently exhibited lower emission levels across all Euro standards, reflecting improvements in fuel efficiency and emission control technologies. Medium PVs demonstrated moderate emission outputs, while large PVs recorded the highest emission levels, particularly in pre-Euro and Euro I categories. As the Euro standard advanced, a clear reduction in emissions was observed for all vehicle classes, highlighting the effectiveness of newer vehicle technologies and regulatory measures in mitigating vehicular pollution. The detailed annual prediction of PV emissions for CO, CO_2 and NO_x is presented in the below to show the trends quantitatively.

3.4.1. Annual CO emissions

CO emissions from GPVs in Addis Ababa showed a clear trend, peaking at 26.25 tons/year in 2021, as shown in Figure 8(a). This surge was primarily attributed to the predominance of older Euro 1 to Euro 3 vehicles, which comprised over 43% of the fleet and significantly contributed to the total emissions. Following 2021, emissions declined, reaching 19.11 tons/year by 2023, and then slightly rose to 21.10 tons/year by 2025, even with consistent vehicle numbers. This decrease was largely influenced by the Ethiopian government's 2023 ban on ICE PV imports and a progressive transition towards cleaner Euro 5 and Euro 6 vehicles, though the rate of fleet modernization remains insufficient to fully counteract the impact of older models.

CO emissions from DPVs exhibited significant annual variation as shown in Figure 8(b), reaching a peak of 2.61 tons/year in 2021 before stabilizing around 2.54 tons/year by 2025. Euro 2 DPVs were consistently the largest contributors, accounting for roughly half of the total annual CO emissions due to their substantial presence in the aging fleet. While Euro 4 emissions increased, their overall impact was less significant. Notably, emissions from Euro 6 vehicles demonstrated the largest relative growth, indicating a steady adoption of newer, cleaner diesel technology, despite their currently small overall contribution.

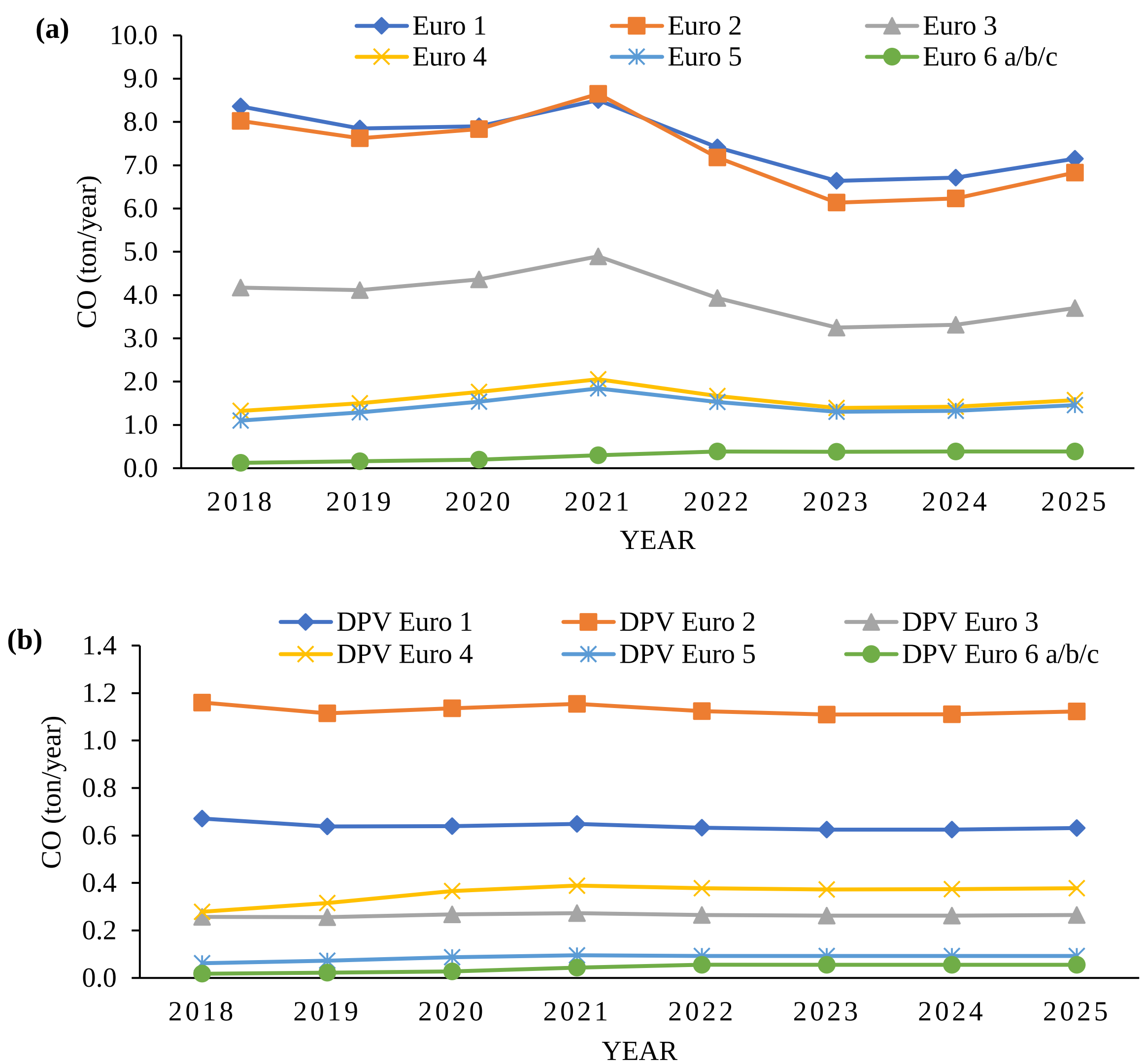

Figure 8: Annual CO emissions from 2018 to 2025 of (a) GPV and (b) DPV

3.4.2. Annual CO_2 emissions

CO_2 emissions from GPVs displayed a consistent upward trend (Figure 9(a)), increasing by ~25.2%. This increase was primarily driven by the rising number of older, high-emitting vehicles within the fleet. Specifically, Euro 2 GPVs consistently contributed the most to CO_2 emissions (836-849 tons/year), reflecting their significant presence and cumulative impact. While newer Euro 4, Euro 5, and particularly Euro 6 vehicles showed increasing emissions, with Euro 6 experiencing the largest relative growth (more than tripling from 105.72 to 322.50 tons/year), the overall rise highlights the cumulative effect of growing vehicle numbers despite the gradual adoption of cleaner standards.

Figure 9(b) shows that total CO_2 emissions from DPVs also increased, from 1,682.82 tons/year in 2018 to 2,103.28 tons/year in 2025. Euro 2 DPVs remained the top contributors, indicating that older, high-emitting vehicles still form the majority of the urban diesel fleet. Although Euro 3 and Euro 4 vehicles also saw steady emission increases due to their growing proportion, and Euro 5 and Euro 6 vehicles exhibited significant relative growth (Euro 6 from 55.21 to 176.14 tons/year), their overall contribution remained comparatively low. This underscores that older and mid-aged DPVs continue to dominate total CO_2 emissions, despite the market entry of cleaner technologies.

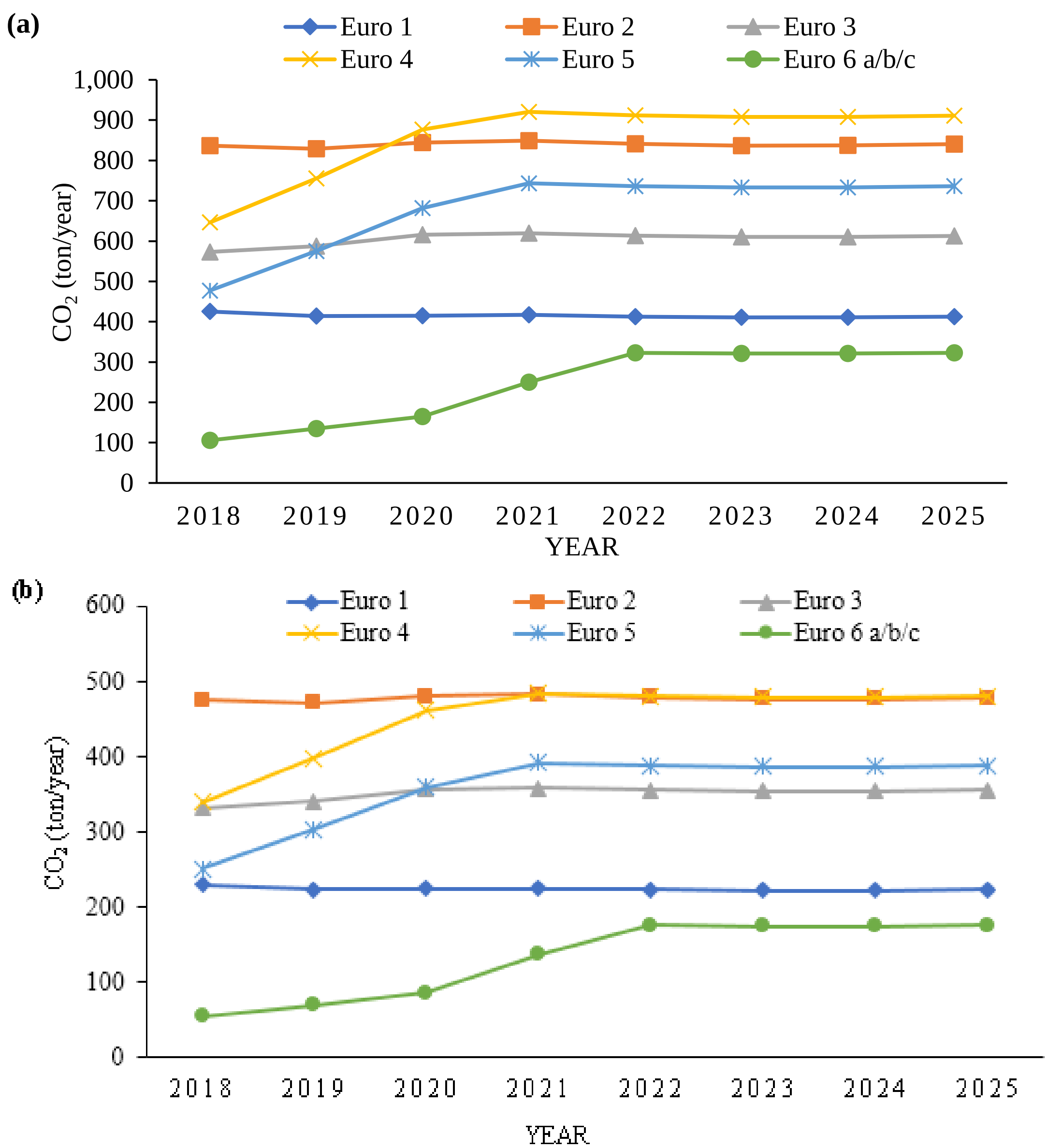

Figure 9: Annual CO_2 emissions from 2018 to 2025 of (a) GPV and (b) DPV

3.4.3. Annual NOx emissions

In this study, NOx emissions from GPVs in Addis Ababa exhibited a gradual increase from 1.89 tonnes/year in 2018 to 2.08 tonnes/year by 2025, as depicted in Figure 10(a), stabilizing around 2021. Euro 2 vehicles were consistently the largest emitters, contributing 0.74 to 0.76 tonnes annually. While Euro 3 and Euro 4 emissions showed slight rises and then plateaued, Euro 5 emissions also increased, despite these vehicles having better pollution controls, due to their growing numbers. The most notable relative rise was observed in Euro 6 vehicles, which, despite having the lowest emissions overall (0.02 to 0.05 tons/year), reflect the fleet's increasing adoption of more recent, low-emission technologies.

Similarly, total NOx emissions from Diesel Passenger Vehicles (DPVs) consistently increased from 6.02 tons/year in 2018 to 7.27 tons/year in 2025, peaking around 7.24 tons/year in 2021 before largely stabilizing as depicted in Figure 10(b). Euro 2 DPVs remained the primary source of NOx, contributing 1.81 to 1.86 tonnes annually. Euro 3 and Euro 4 vehicles were also significant contributors, showing steady increases. Emissions from Euro 5 cars likewise rose, indicating that their larger fleet size resulted in a higher overall burden despite adherence to newer regulations. Euro 6 vehicles, though starting with the lowest contribution, demonstrated a significant relative increase in NOx emissions (from 0.16 to 0.50 tons/year), corresponding with their growing proportion in the market and reflecting the increasing presence of cleaner diesel technologies.

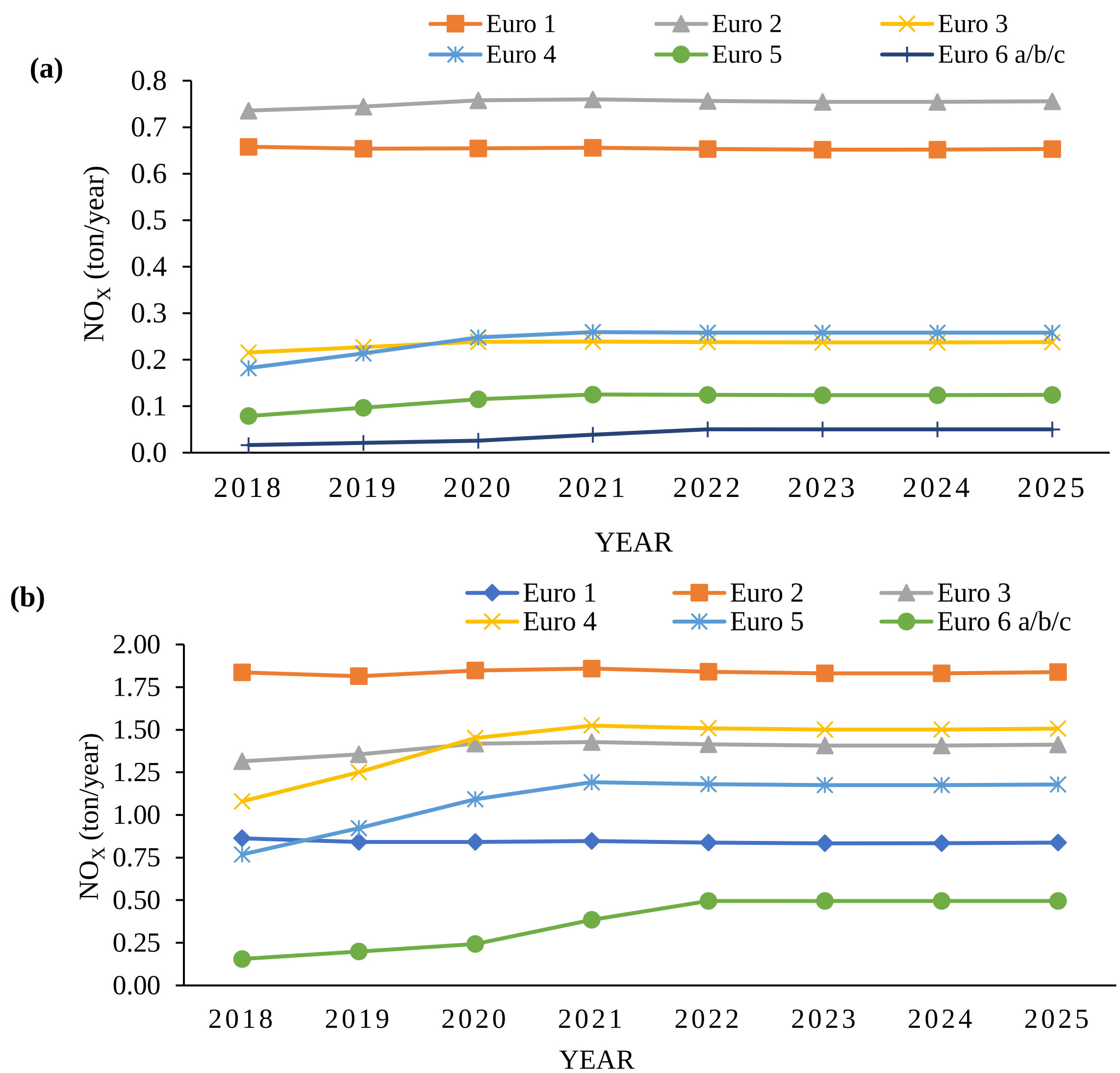

Figure 10: Annual NOx emissions from 2018 to 2025 of (a) GPV and (b) DPV

3.5 Performance of the ANN Model

The performance of the ANN model in predicting Addis Ababa's city-specific PV emissions was evaluated using standard statistical metrics, including R^2, MAE, and RMSE. The model demonstrated excellent predictive capability, with R^2 values ranging from 0.96 to 0.99 across CO, CO_2, and NO_x emissions for both gasoline- and diesel-powered vehicles. This indicates that the ANN model captured over 95% of the variance in the observed emissions data. The MAE values ranged from 0.05 to 0.38 tons/year, indicating a low average deviation between predicted and observed emissions, while RMSE values ranged from 0.08 to 0.55 tons/year, confirming the model's robustness and accuracy in capturing temporal variations across vehicle types, sizes, and Euro classification levels. Overall, the metrics validate the effectiveness of integrating COPERT-derived baseline emission factors with ANN modeling to reliably predict annual emissions for small, medium, and large PVs under Addis Ababa's driving conditions.

4. Conclusions

This study combined COPERT-derived baseline emission factors with an ANN model to forecast Addis Ababa's PV emissions, considering fleet growth across Euro classes. The ANN model outperformed the PLR model, accurately capturing PV growth (R = 0.992, MAE = 362 vehicles). Results show that PV numbers increased over twentyfold from 2005 to 2024, with older Euro 1–3 vehicles remaining dominant.

Annual CO and NO_x emissions from both gasoline and diesel-powered vehicles varied with fleet composition, while total CO_2 emissions rose by about 25% between 2018 and 2025. Euro 2 vehicles were the largest contributors to emissions, whereas Euro 6 vehicles showed the highest relative growth, reflecting gradual adoption of cleaner technologies.

Overall, the findings indicate that aging fleets are key sources of urban air pollution in Addis Ababa. Strengthening vehicle emission standards, promoting cleaner and electric vehicles, enhancing fuel quality, and improving public transport are critical to achieving sustainable mobility and air quality goals. Despite some limitations, such as simplified road condition representation and emission factor uncertainties, the proposed COPERT–ANN framework offers a robust tool for urban emission forecasting and policy analysis applicable to other Ethiopian cities.

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