Machine Learning for Predicting Emissions from Vehicles and Power Plants: Impact Analysis of Increasing Adoption of Electric Vehicles in the United States

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Abstract

While electric vehicles (EVs) are often considered emission-free, increasing adoption of EVs leads to higher air pollutant emissions from vehicles running on fossil fuels due to traffic congestion caused by the induced EV trips, as well as from power plants due to the increased energy consumption of EVs from the grid. This research provides a large-scale analysis of air pollutant emissions from vehicles and power plants with rising EV adoption in Atlanta (GA), Los Angeles (CA), New York (NY), and Seattle (WA) using an integrated model that leverages machine learning. We estimate the vehicle energy consumption and emission rates of CO_2, NO_x, and PM2.5 based on vehicle speed, considering vehicle type, fuel, and age, using a feedforward neural network trained with the Motor Vehicle Emission Simulator (MOVES) inventory. To estimate the mixed traffic composition by vehicle type, fuel, and manufacture year, we have analyzed state vehicle registration data. We capture the impacts of traffic dynamics on EV charging and air pollutant emissions from vehicles using a macroscopic traffic model trained with probe-based traffic data. This model is employed to approximate traffic speed based on volume at the tract level in the downtown areas of Atlanta, Los Angeles, New York, and Seattle. Having energy consumption and emission rates estimated in conjunction with traffic speed and volume profiles, as well as mixed traffic composition, enables the estimation of EV energy consumption and air pollutant emissions of heterogeneous vehicles at a large scale. The increase in emissions of CO_2, CH_4, and N_2O from power plants due to the energy consumption of EVs from the grid is estimated using a machine learning model developed on the Meta Prophet platform, trained with the Cambium database, and incorporating seasonality, pricing, taxation, and energy mix. Integrating the vehicle emission model with the EV charging and power plant emission model facilitates the estimation of air pollutant emissions from both vehicles and power plants with increasing EV adoption and projected changes in traffic conditions. In the final stage of this research, we employ the proposed model to predict changes in greenhouse gas and other air pollutant emissions from vehicles and power plants with the projected increases in EV adoption through 2030 in Atlanta, Los Angeles, New York, and Seattle.

Keywords: vehicle emission; grid emissions; machine learning; MOVES4; NREL Cambium; macroscopic fundamental diagram

1 Introduction

Electric vehicles (EVs) produce significantly fewer emissions compared to conventional vehicles running on fossil fuels. However, the increased adoption of EVs, due to their lower travel and maintenance costs, leads to a rise in total vehicle miles traveled, which in turn exacerbates traffic congestion on highways and urban networks, thereby increasing air pollution emissions from conventional vehicles. Additionally, the electrical energy consumption of EVs from the power grid for charging their batteries increases with their growing adoption and total vehicle miles traveled (VMT), resulting in higher air pollution emissions from power plants. This research leverages machine learning to develop an integrated model for estimating emissions from various classes of vehicles and power plants of different technologies, based on traffic composition and dynamics at a large scale, with increased adoption of EVs in Atlanta (GA), Los Angeles (CA), New York (NY), and Seattle (WA).

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Energy consumption and air pollutant emissions of vehicles depend on various factors, including vehicle design, weight, powertrain technology, and kinematic variables such as acceleration and speed. Numerous models have been developed in the literature to estimate the energy consumption and air pollutant emissions of vehicles at both microscopic and macroscopic scales. Micro-level emission models focus on individual vehicle behaviors, capturing detailed emissions based on driving patterns, engine conditions, and real-time vehicle activity. The Comprehensive Modal Emission Model (CMEM) and its variants estimate emissions by considering instantaneous vehicle speed, acceleration, and engine power, allowing precise calculation of emissions during different driving conditions (Barth et al., 2000; Scora and Barth, 2006). Advanced models incorporate vehicle-specific parameters such as weight, aerodynamics, and powertrain characteristics to improve accuracy (Pathak et al, 2016; Park et al., 2023). Recent developments include machine learning techniques to enhance prediction accuracy by analyzing large datasets of vehicle activity and emissions (Xia et al., 2023; Liu et al. 2023). Simulation-based models like PHEM (Passenger Car and Heavy Duty Emission Model) simulate second-by-second emissions for different driving cycles and vehicle types, providing insights into the effects of driving behavior and traffic conditions on emissions (Hausberger et al., 2015; Abou-Senna et al., 2013; Noland and Quddus, 2006). Incorporating high-resolution GPS and telematics data into these models has further refined their ability to predict emissions in real-world scenarios (Agarwal and Mustafi, 2021; Chen et al., 2022).

Macros-scale emission models aggregate data from numerous vehicles to provide comprehensive assessments at city, regional, or national levels. The COPERT model (Computer Programme to calculate Emissions from Road Transport) uses detailed vehicle fleet information, including vehicle type, age, and fuel type, to estimate emissions over extensive road networks (Ntziachristos et al., 2009; Smit et al., 2022). The EMFAC (Emission Factors Model) developed by the California Air Resources Board offers a robust framework for estimating emissions from all on-road vehicles in California, leveraging extensive traffic data and emission factors (Barth et al., 2001; CARB, 2021). The IVE (International Vehicle Emissions) model provides a versatile tool for estimating emissions in diverse global contexts, incorporating local driving conditions and fleet characteristics (ISSRC, 2008; Hui et al., 2007). Hybrid models that combine traffic simulation and emission estimation, like the EMEP/EEA air pollutant emission inventory guidebook, enable large-scale evaluations while considering the influence of traffic dynamics and congestion (Nielsen, 2013). The MOVES (Motor Vehicle Emission Simulator), developed by the U.S. Environmental Protection Agency (EPA), provides detailed estimates of emissions from various types of vehicles based on vehicle activities by incorporating accurate emission rates and environmental factors, allowing for detailed analysis of air pollutant emissions (U.S. EPA, 2023).

EV energy consumption and emission can be estimated based on the characteristics of electric drivetrains, battery management, and charging behaviors to accurately predict energy use and environmental impacts. Micro-level models, such as the Vehicle Energy Consumption Calculation Tool (VECTO), estimate energy use based on detailed driving cycles, accounting for factors like vehicle weight, aerodynamics, and auxiliary power consumption (European Commission, 2019). Advanced simulation tools like ADVISOR and Autonomie incorporate real-world driving data to enhance the precision of energy consumption predictions and integrate various powertrain configurations (Rousseau et al., 2006; Markel, 2001; Markel et al., 2002; Vijayagopal, 2018). Machine learning algorithms are increasingly applied to improve model accuracy by analyzing large datasets of EV operations and charging patterns (Shahriar et al., 2020; Fescioglu-Unver and Aktaş, 2023). Real-world driving studies leveraging telematics and GPS data provide insights into the energy consumption variations under different driving conditions and help refine these models (Wu et al., 2015; Liu et al., 2017). The Electric Vehicle Routing Problem (EVRP) model considers the impact of route planning and charging infrastructure on energy consumption, enabling more efficient travel and reduced emissions (Wu et al., 2015; Lin et al., 2017). Moreover, models that incorporate battery degradation over time offer a more comprehensive assessment of long-term energy efficiency and emissions (Shirk and Wishart, 2015; Mohammed and Amirgholy, 2023; Amirgholy and Gao, 2023). Macro-scale models aggregate data from numerous EVs to assess the broader impacts of electric mobility on energy consumption and emissions at city, regional, or national levels. The GREET (Greenhouse gases, Regulated Emissions, and Energy use in Technologies) model evaluates the lifecycle emissions of EVs, including manufacturing, operation, and disposal phases (Burnham et al., 2021). The EVI-Pro Lite also provides scenario-based analysis of future EV adoption, estimating impacts on electricity demand and emissions (Wood et al., 2023).

EVs produce significantly fewer emissions compared to conventional vehicles running on fossil fuels. However, the electrical energy consumed to charge their batteries increases with the rise in EV adoption and total vehicle miles traveled. Although EVs are nearly emission-free, the continual increase in energy consumption from the power grid leads to higher air pollutant emissions from power plants over time. The resulting increase in air pollutant emissions from power plants depend on a wide range of factors, including fuel type, technology, age, grid demand, load factors, and operational practices. Different models have been developed to project air pollutant emissions from power plants as electrical energy consumption from the power grid increases, taking into account new investments and advancements in clean energy technology. Studies indicate that in regions heavily reliant on fossil fuels, particularly coal, the increase in electricity demand can lead to higher emissions of pollutants such as NOx, SO2, and particulate matter (Abbas et al., 2015; Liddle and Sadorsky, 2017). The net environmental benefit of EVs, therefore, varies based on the carbon intensity and pollution profile of the grid (Siler-Evans et al., 2013). The Cambium model developed by the National Renewable Energy Laboratory (NREL) provides forward-looking data on electricity generation mix, costs, and emissions, allowing for comprehensive analysis of the future impacts of energy policies and technologies on grid emissions and economic performance (Mai et al., 2021). Comprehensive lifecycle analyses reveal that while EVs can reduce greenhouse gas emissions, their impact on air pollutants may be less straightforward, with potential increases in localized emissions near power plants (Pan et al., 2019; Michalek et al., 2011). Advancements in cleaner energy technologies and stringent emission regulations for power plants are crucial in mitigating these adverse effects (Tamayao et al., 2015). Renewable energy integration into the grid can significantly offset the rise in emissions, highlighting the importance of parallel investments in renewable energy sources (Yuksel et al., 2016). Additionally, smart grid technologies and energy storage solutions can help balance demand and supply, reducing the need for peaking power plants, which are often the most polluting (Sioshansi and Denholm, 2009). Regional studies suggest that the environmental benefits of EVs are maximized in areas with substantial renewable energy penetration and robust regulatory frameworks for power plant emissions (Jochem et al., 2015; McLaren et al., 2016). As the energy sector continues to evolve, the interplay between EV adoption and power generation will remain a critical factor in shaping future air quality outcomes (Holland et al., 2016).

While various models have been developed to estimate emissions from vehicles and power plants at various scales, the lack of integration between the modeling components limits the effectiveness of the proposed models in estimating emissions with the projected increase in EV adoption. Therefore, developing an integrated model for the concurrent and consistent estimation of emissions from both vehicles and power plants facilitates accurate assessment of the environmental impacts associated with the projected rise in EV adoption.

This research develops an integrated model for estimating emissions from heterogeneous vehicles based on the dynamics and composition of mixed traffic, as well as the consequent increase in emissions from power plants due to the projected rise in EV adoption. To estimate energy consumption and emissions from vehicles, we develop a feedforward fully connected neural network, trained using the EPA MOVES4 inventory for Atlanta, Los Angeles, New York, and Seattle. The proposed neural network model accurately captures the relationship between vehicle energy consumption and emission rates of CO_2, NO_x, and PM2.5 – from tires and brakes – and vehicle speed, considering vehicle type, fuel, and age. Having the energy consumption and emission rates, the total energy consumption and air pollutant emissions from heterogeneous vehicles can be estimated based on the traffic speed and volume profiles, given the composition of mixed traffic. We estimate the mixed traffic composition for various vehicle classes based on their type, fuel, and manufacture year by analyzing state vehicle registration data. To estimate the relationship between traffic speed and volume, we adopt the concept of the Macroscopic Fundamental Diagram (MFD) to develop a macroscopic traffic model using probe-based traffic data at the tract level for the downtowns of Atlanta, Los Angeles, New York, and Seattle. The increase in air pollutant emissions from power plants due to the rise in EV energy consumption from the power grid is also predicted by the Meta Prophet model trained using the NREL Cambium database. Training the Prophet model using the NREL Cambium database enables capturing seasonal patterns in predicating marginal emission rates of air pollutants from power plants of various technologies in Georgia, California, New York, and Washington. Having estimated the power plant marginal emission rates and the electrical energy consumption of EVs from the power grid over time, the resulting increase in air pollutant emissions from power plants can be estimated at the state level.

Integrating the vehicle emission model with the EV charging and power plant emission model facilitates the estimation of air pollutant emissions from both vehicles and power plants with increasing EV adoption and projected

changes in traffic conditions. In the final stage of this research, we employ the proposed model to predict changes in greenhouse gas and other air pollutant emissions from vehicles and power plants with the projected increases in EV adoption through 2030 in Atlanta, Los Angeles, New York, and Seattle.

2 Vehicle Energy Consumption and Emission Model – Deep Learning

We estimate the energy consumption and air pollutant emissions of vehicles based on their speed, considering their type, fuel, and manufacture year. To this end, we develop a feedforward neural network model, trained using the MOVES4 vehicle emission and energy consumption rate inventory. The proposed model accurately captures the relationship between vehicle energy consumption and emission rates with vehicle speed, based on vehicle type, fuel, and age. The architecture of the feedforward neural network model consists of an input layer followed by five fully connected hidden layers before the output layer, as illustrated in Fig. 1. The model contains a total of 181824 weight and 961 bias parameters that are estimated through the training process. The activation function selected for the feedforward layers is rectified linear unit (ReLU), because of its ability to capture non-linearity and its computational efficiency. The input of the model consists of four primary variables: vehicle type (combination long-haul truck, combination short-haul truck, light commercial truck, motorhome (recreational vehicle), motorcycle, other buses, passenger truck, refuse truck, school bus, single unit long-haul truck, single unit short-haul truck, transit bus), fuel type (compressed natural gas (CNG), diesel fuel, electricity, ethanol (E-85), gasoline), vehicle age (years), and speed (mph). The output of the model is either the vehicle energy consumption rate (kJ/mile) or one of the following air pollutant emission rates: CO_2 (gr/mile), NO_x (gr/mile), and PM2.5 (gr/mile) – from tires (T) brakes (B) and. The proposed model is trained using the MOVES4 inventory for Atlanta, Los Angeles, New York, and Seattle to provide accurate and efficient estimation of energy consumption and air pollutant emission rates of heterogeneous vehicles under varying traffic dynamics.

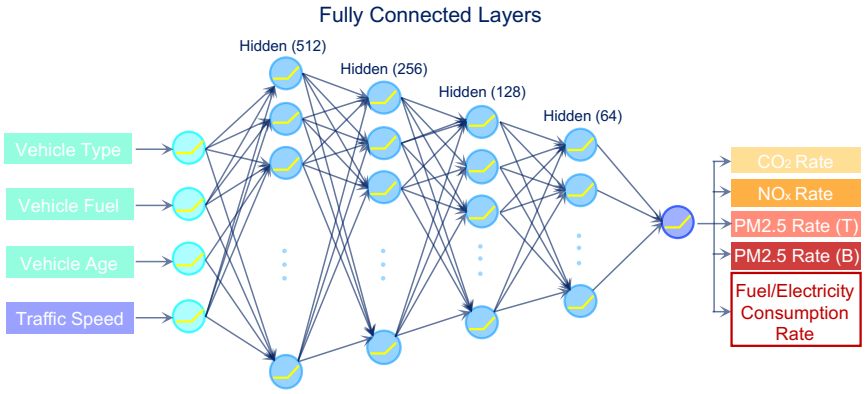


Fig. 1. Feedforward Neural Network Model Architecture

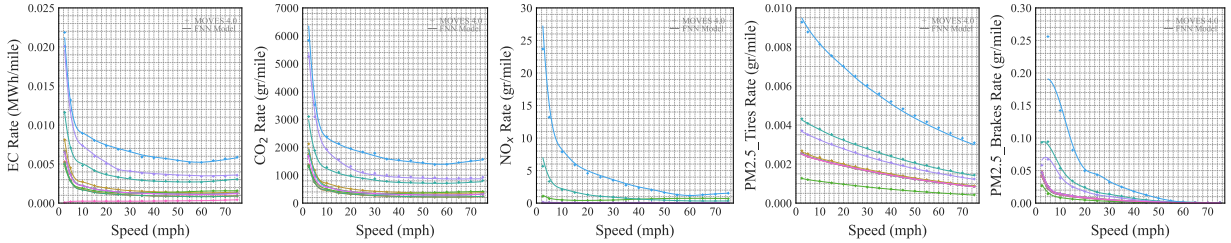
The training data consists of energy consumption and emission rates at various speeds, from 2.5 mph to 75 mph (in 5 mph increments), for all existing combinations of vehicle type, fuel, and age in the state vehicle registration database. In preparation of the training data, we encode the categorical variables of the model, i.e., vehicle type and fuel, using the one-hot approach. We also apply the Yeo-Johnson (YJ) transformation to enhance the normality and homoscedasticity of the data (Yeo and Johnson, 2000). To train the proposed feedforward neural network model, we use backpropagation with the Adaptive Moment Estimation (ADAM) algorithm (Kingma and Ba, 2015) with a learning rate of 0.001, to optimize the model parameters. Training the proposed model using the MOVES4 inventory enables bypassing the need for numerous runs of simulation models, which can be time-consuming and computationally expensive, for estimating the energy consumption and emissions of heterogeneous vehicles based on traffic speed, considering their type, fuel, and age. The results of the training process for estimating vehicle energy

consumption and air pollutant emission rates in Atlanta, Los Angeles, New York, and Seattle are summarized in Tab 1.

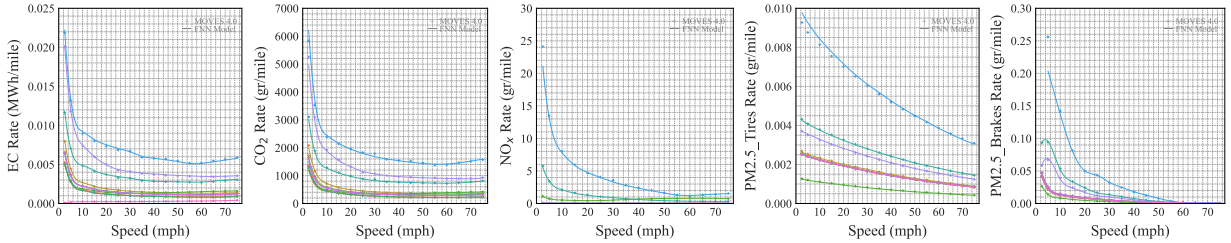
Tab. 1. Feedforward Neural Network Model Accuracy Measures

	Energy Consumption and Emission Estimation Model																			
	Energy Consumption				CO_2				Nox				PM2.5_Brakes				PM2.5_Tires			
City	RMSE	MAE	MAPE	R^2	RMSE	MAE	MAPE	R^2	RMSE	MAE	MAPE	R^2	RMSE	MAE	MAPE	R^2	RMSE	MAE	MAPE	R^2
Atlanta	0.054	0.03	0.252	0.997	0.063	0.04	0.26	0.996	0.039	0.025	0.083	0.999	0.064	0.025	0.168	0.996	0.051	0.023	0.277	0.997
Los Angeles	0.044	0.026	0.213	0.998	0.067	0.044	0.333	0.996	0.038	0.025	0.096	0.999	0.045	0.017	0.067	0.998	0.042	0.017	2.586	0.998
New York	0.064	0.038	0.335	0.996	0.048	0.029	0.168	0.998	0.03	0.02	0.086	0.999	0.06	0.025	0.18	0.996	0.055	0.025	0.373	0.997
Seattle	0.045	0.027	0.206	0.998	0.038	0.025	0.126	0.999	0.023	0.017	0.096	1	0.051	0.023	0.084	0.997	0.038	0.018	2.034	0.999

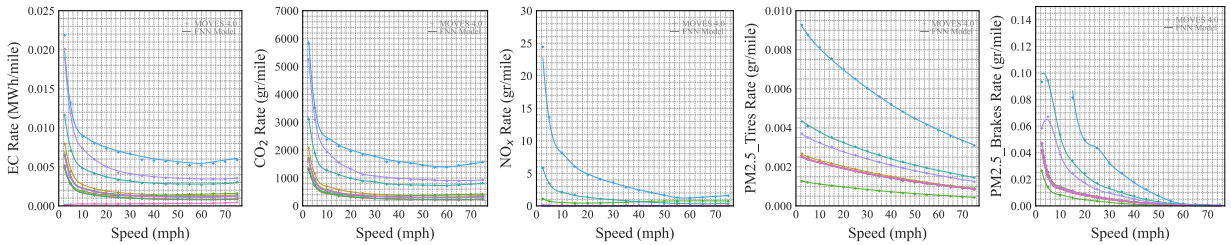
Fig. 2a-d plot the simulated and estimated rates of energy consumption (kJ/mile) and emissions of CO_2 (gr/mile), NO_x (gr/mile), and PM2.5 (gr/mile) – from tires and brakes – for a selected subset of 2024 vehicles (Gasoline Passenger Car, E-85 Passenger Car, Gasoline Light Commercial Truck, Gasoline Passenger Truck, Gasoline Motorcycle, Diesel Passenger Car, Diesel Short-Haul Truck, , E-85 Passenger Truck, Diesel Long-Haul Truck, Gasoline Short -Haul Truck, E-85 Commercial Truck, Electric Passenger Car) at various speeds in Atlanta, Los Angeles, New York, and Seattle. Note that the energy consumption and air pollutant emission rates of vehicles vary slightly with humidity, temperature, altitude, and other exogenous factors in different locations. The impacts of these exogenous factors on energy consumption and air pollutant emission rates, varying with vehicle type, fuel, and age, are captured in the MOVES4 inventory data. The proposed feedforward neural network model provides a continuous and accurate estimation of energy consumption and air pollutant emission rates with speed for all existing combinations of vehicle type, fuel, and age in different locations. As shown in Fig. 2a-d, the energy consumption and emission rates are minimized at an optimal speed that varies with vehicle type, fuel, and age in different locations.



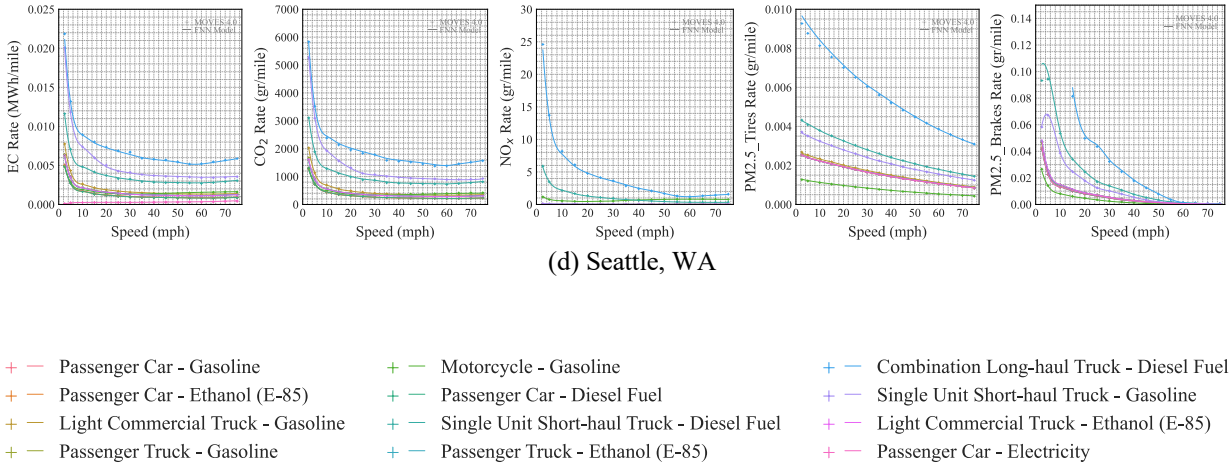
(a) Atlanta, GA



(b) Los Angeles, CA



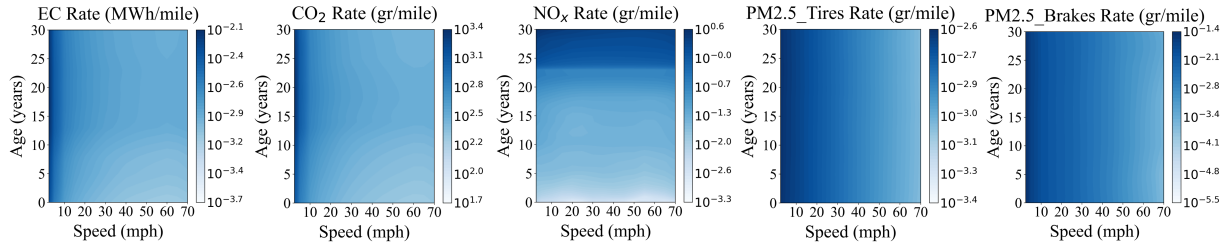
(c) New York, NY



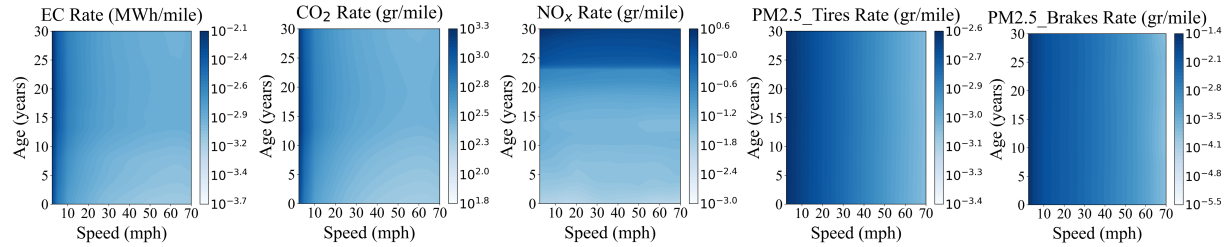
(d) Seattle, WA

Fig. 2. Simulated and Estimated Energy Consumption and Air Pollutant Emission Rates of 2024 Vehicles with Speed in Atlanta, Los Angeles, New York, and Seattle.

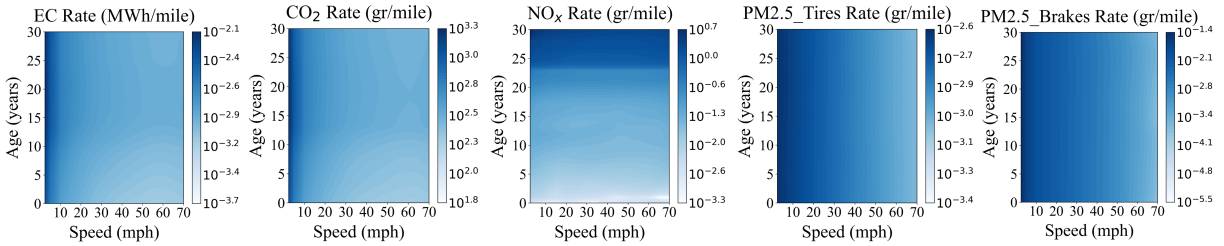
The energy consumption and air pollutant emission rates increase with vehicle age depending on the powertrain technology. Fig. 3a-d plot the energy consumption and emission rates of CO_2, NO_x, and PM2.5 for a typical passenger-gas vehicle at various speeds and ages in the year 2024 in Atlanta, Los Angeles, New York, and Seattle. Note that the emission rate of PM2.5 from tires and brakes directly depends on vehicle speed, as well as vehicle weight, tire type, and braking technology, and does not significantly change over the course of the vehicle's lifetime. However, the energy consumption and CO_2 and NO_x emission rates decrease in newer vehicles due to their higher efficiency and improved powertrain technology.



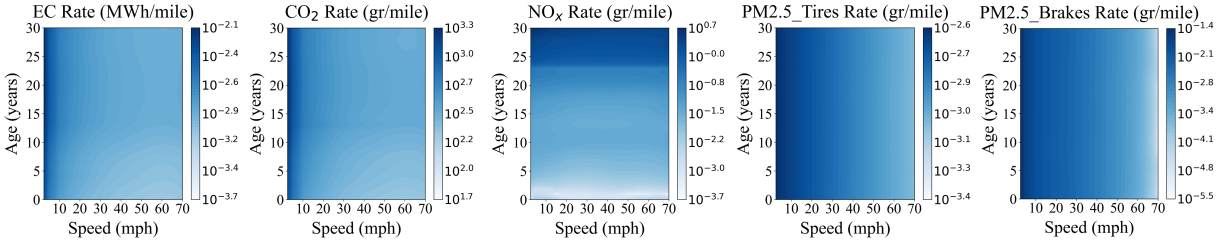
(a) Atlanta, GA



(b) Los Angeles, CA



(c) New York, NY



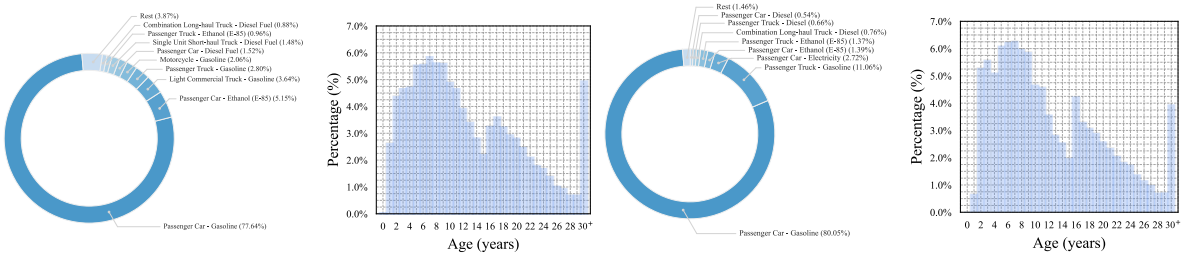
(d) Seattle, WA

FIGURE 3. Energy Consumption and Air Pollutant Emission Rates of a Passenger-Gas Vehicle by Speed and Age in 2024 in Atlanta, Los Angeles, New York, and Seattle.

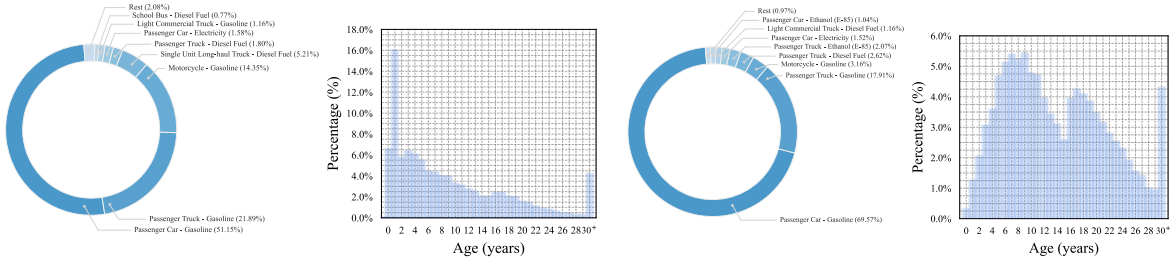
The proposed feedforward neural network model enables estimating the energy consumption and emission rates of vehicles with traffic speed based on vehicle type, fuel, and age in different locations. However, the total energy consumption and air pollutant emissions of vehicles depend on the composition of mixed traffic, which varies across different locations. In the following section, we use state vehicle registration data to capture the composition of mixed traffic in Atlanta, Los Angeles, New York, and Seattle.

3 Mixed Traffic Composition

We estimate the composition of mixed traffic in Atlanta, Los Angeles, New York, and Seattle using the 2024 state vehicle registration data provided by the Georgia Department of Driver Services (GA DDS), California Department of Motor Vehicles (CA DMV), New York State Department of Motor Vehicles (NY DMV), and Washington State Department of Licensing (WA DOL). To estimate the mixed traffic composition, we classify vehicles from the state registration data based on their type, fuel, and age. The ring charts in figures 4a-d depict the composition of mixed traffic based on vehicle type and fuel in Georgia, California, Ney York, and Washington. The age distribution of vehicles in these cities is also presented in the histograms in Fig. 4a-d.



(a) Georgia (b) California



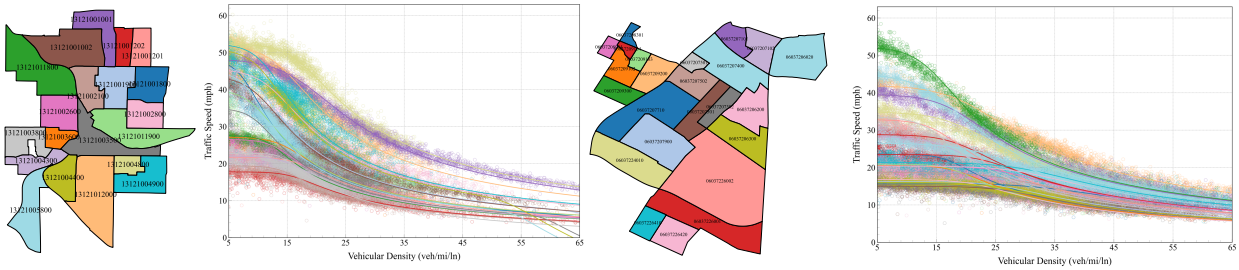
(c) New York (d) Washington

Fig. 4. Distribution of Vehicles Based on Their Type, Fuel, and Age in Georgia, California, New York, and Washington.

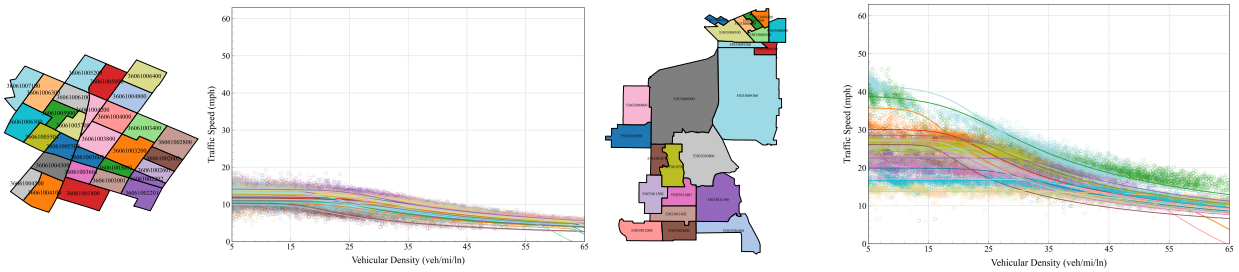
In addition to traffic composition, the total energy consumption and emissions of heterogeneous vehicles in mixed traffic depend on traffic volumes and speed. To estimate the relationship between traffic volume and speed on a large scale, we use probe-based traffic data to develop a macroscopic traffic model for the downtowns of Atlanta, Los Angeles, New York, and Seattle in the following section.

4 Macroscopic Traffic Model

The relationship between traffic volume and speed in urban networks can be captured on a large scale using the concept of the Macroscopic Fundamental Diagram (MFD) (Daganzo, 2007; Daganzo and Geroliminis, 2008; Aboudolas and Geroliminis, 2013; Ramezani et al., 2015; Knoop et al., 2015, Amirgholy and Gao, 2017). MFD is an analytical framework for macroscopic traffic modeling that leverages traffic data from road networks to provide an accurate and efficient estimation of the relationship between traffic volume, speed, and vehicular density at a large scale (Saberi and Mahmassani, 2013; Ampountolas, and Kouvelas, 2015; Castrillon and Laval, 2018; Ambühl et al, 2019; Mousavizadeh and Keyvan-Ekbatani (2024); Ma et al., 2024; Jin et al, 2024). In this research, we adopt the concept of MFD to estimate traffic speed based on traffic volume in the downtowns of Atlanta, Los Angeles, New York, and Seattle. To this end, we use traffic data estimated using a deep learning approach that leverages vehicle probe and road sensor data, as described in Sekuła et al. (2018). The traffic data is estimated over 15-minute intervals based on vehicle probe data provided by HERE Technologies and aggregated at the census tract level. Fig. 5a-d plot traffic speed against vehicular density at the census tract level in the downtowns of Atlanta, Los Angeles, New York, and Seattle.



(a) Atlanta, GA (b) Los Angeles, CA



(c) New York, NY (d) Seattle, WA

Fig. 5. Macroscopic Relationship of Traffic Speed with Vehicular

The traffic data, estimated over 15-minute intervals, is used to model the relationship between traffic speed, volume, and vehicular density at the census tract level. We employ a modified version of the log-sum-exp model proposed in Ambühl et al. (2020) to estimate traffic speed (v) based on vehicular density (k) with a high level of accuracy:

$$v = -\frac{\lambda_1 \ln\left(e^{-\frac{v_f(k+\lambda_2)}{\lambda_1}} + e^{-\frac{Q_m}{\lambda_1}} + e^{-\frac{(k_j-k)w}{\lambda_1}}\right)}{k}, \tag{1}$$

where v_f denotes the free flow speed, Q_m is the network capacity, k_j represents the jam density, and λ_1 and λ_2 are the shape parameter of the model, all of which are estimated through calibration using traffic data. Leveraging the macroscopic flow equation, which formulates traffic volume (q) as the product of vehicular density and traffic speed, $q = kv$, the volume-speed relationship can be equivalently derived from the speed-density relationship estimated by the log-sum-exp regression model (1). Tab. 2 presents the accuracy measure (R^2) and model parameters estimated at the census tract level for the downtowns of Atlanta, Los Angeles, New York, and Seattle.

Tab. 2. Macroscopic traffic model parameters and the accuracy measure

Atlanta, GA

TractID	Model Parameters						R^2
	v_f	Q_m	k_j	w	λ_1	λ_2	
13121001800	37.05	412.44	102.53	61.62	60.00	0.43	0.91
13121001900	34.59	496.51	70.40	150.82	60.00	0.76	0.93
13121003600	22.86	429.21	118.32	8.69	60.00	0.34	0.77
13121012000	46.21	734.77	202.87	177.55	60.00	0.37	0.92
13121001202	15.55	314.04	97.52	8.35	60.00	0.28	0.67
13121001201	19.85	386.84	111.79	9.86	60.00	0.17	0.59
13121001001	41.96	826.93	138.08	98.93	60.00	0.65	0.91
13121004300	19.72	368.46	93.80	15.88	60.00	0.27	0.66
13121001002	34.20	482.90	384.11	264.26	60.00	0.67	0.93
13121002100	17.79	298.53	90.31	38.15	60.00	0.19	0.71
13121002600	22.41	378.54	129.50	24.41	60.00	0.25	0.79
13121002800	36.60	585.36	538.82	461.14	60.00	0.61	0.91
13121003800	21.76	341.83	148.86	54.75	30.00	0.00	0.58
13121004400	40.48	587.17	264.32	55.81	60.00	0.49	0.87
13121004800	49.91	869.74	731.13	592.92	59.96	0.16	0.82
13121004900	42.61	629.95	127.98	212.87	60.00	0.45	0.88

Los Angeles, CA

TractID	Model Parameters						R^2
	v_f	Q_m	k_j	w	λ_1	λ_2	
6037208301	21.60	421.20	134.97	51.39	50.00	0.12	0.56
6037207710	13.64	568.69	105.17	233.67	50.00	1.22	0.60
6037207900	14.40	462.18	134.98	136.73	50.00	0.41	0.40
6037209102	18.50	395.01	210.07	3.51	50.00	0.23	0.57
6037209200	35.45	845.73	267.45	226.06	50.00	0.88	0.79
6037209300	44.63	721.06	106.21	100.60	50.00	0.54	0.87
6037209103	19.09	394.42	394.28	95.57	50.00	0.12	0.54
6037209104	21.07	596.10	237.47	5.44	50.00	0.25	0.56
6037207101	32.71	725.33	98.43	173.24	50.00	0.72	0.87
6037207102	23.30	494.68	86.49	486.83	50.00	0.70	0.82
6037207301	13.47	419.54	434.49	246.99	50.00	0.39	0.60
6037207502	15.88	541.17	108.36	57.02	50.00	0.88	0.53
6037208904	18.04	581.64	182.74	115.14	50.00	0.33	0.54
6037206200	14.71	395.73	85.97	117.35	50.00	0.42	0.61
6037226420	17.74	636.62	126.85	173.84	50.00	0.57	0.59
6037207302	13.91	420.09	974.44	79.31	50.00	0.38	0.61
6037206300	14.24	435.55	121.51	8.27	50.00	0.52	0.46
6037224010	27.97	695.43	93.02	234.84	50.00	1.02	0.85
6037226410	18.45	677.56	157.61	125.50	50.00	0.58	0.64
6037206020	37.67	682.49	155.43	810.79	50.00	0.69	0.92
6037207400	21.97	631.45	145.23	305.61	50.00	0.90	0.78

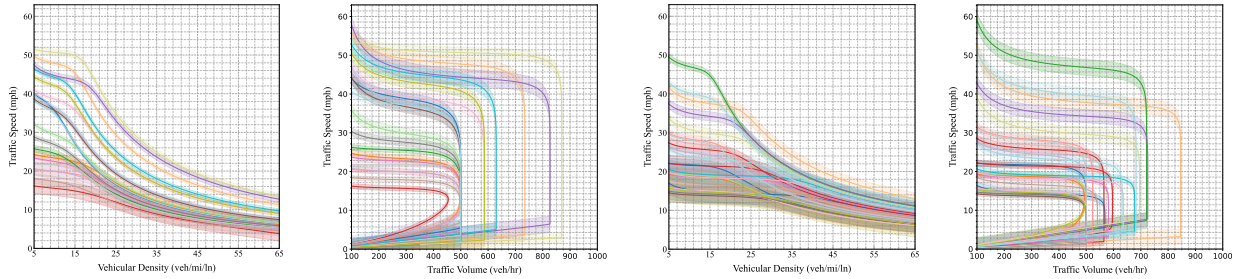
New York, NY

TractID	Model Parameters						R^2
	v_f	Q_m	k_j	w	λ_1	λ_2	
36061003602	11.67	371.27	84.74	227.36	50.00	0.54	0.31
36061005502	11.00	350.11	88.95	13.95	50.00	0.64	0.41
36061004800	12.38	335.52	172.30	184.84	50.00	0.76	0.50
36061003200	9.15	614.12	114.05	3.00	30.00	0.69	0.37
36061004100	9.31	342.44	130.83	47.77	50.00	1.01	0.62
36061006300	11.52	335.89	94.89	10.82	50.00	1.19	0.55
36061005900	11.50	268.27	114.77	7.93	50.00	0.56	0.55
36061003002	10.85	345.36	119.82	6.31	33.30	0.47	0.24
36061003400	9.81	744.16	84.39	4.93	30.00	0.47	0.28
36061005000	10.53	343.26	98.59	16.17	50.00	0.92	0.54
36061001800	10.38	348.48	98.64	156.81	50.00	0.94	0.57
36061004000	12.32	385.12	96.85	8.32	50.00	0.63	0.27
36061002201	13.39	282.32	106.93	6.11	50.00	0.27	0.43
36061002202	13.23	362.07	106.14	7.39	35.69	0.30	0.28
36061002601	9.76	199.64	73.06	5.84	50.00	0.34	0.38
36061002602	10.21	202.97	97.87	4.25	50.00	0.32	0.37
36061002800	10.45	696.71	100.46	3.10	43.22	0.20	0.31
36061003001	11.63	347.95	115.41	8.38	50.00	0.46	0.40
36061003601	10.76	347.24	169.32	44.58	50.00	0.39	0.41
36061003800	11.85	361.70	72.57	22.47	50.00	0.59	0.27
36061004200	11.01	360.46	148.85	3.75	50.00	0.70	0.39
36061004300	10.07	314.58	106.27	14.65	50.00	0.73	0.48
36061006100	11.21	358.88	104.90	11.60	50.00	1.06	0.52
36061004500	9.81	340.44	135.77	103.24	50.00	1.09	0.66
36061005501	11.56	328.31	96.66	51.31	50.00	0.61	0.53
36061005700	11.55	356.64	124.19	7.42	50.00	0.89	0.48
36061006400	12.04	348.00	106.07	58.93	50.00	0.80	0.52
36061006500	9.83	303.66	84.79	10.87	46.40	0.73	0.45
36061007100	11.27	308.40	85.51	10.45	50.00	1.08	0.57
36061005200	10.03	292.24	115.02	10.98	50.00	0.91	0.55

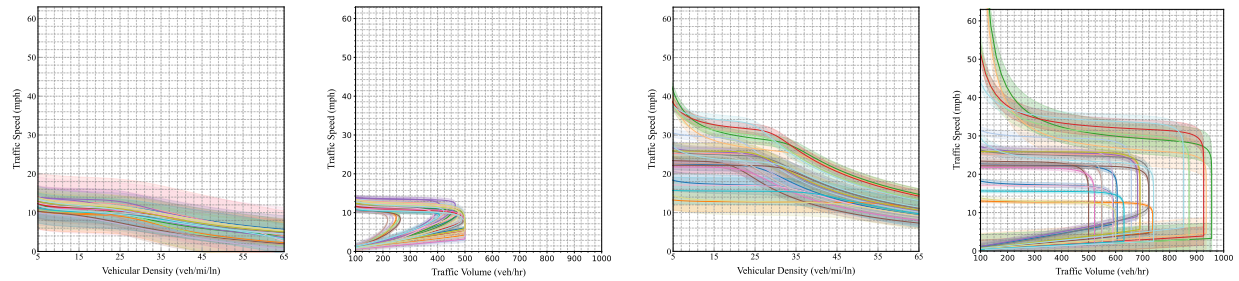
Seattle, WA

TractID	Model Parameters						R^2
	v_f	Q_m	k_j	w	λ_1	λ_2	
53033008002	16.85	592.54	92.82	81.31	50.00	0.44	0.61
53033026500	28.96	658.17	169.65	142.55	50.00	0.27	0.86
53033008400	12.64	737.50	158.10	94.10	50.00	0.24	0.82
53033008200	23.39	935.33	214.89	96.49	50.00	3.35	0.87
53033008300	26.11	955.61	686.30	216.01	50.00	2.94	0.91
53033008500	28.18	871.74	455.19	577.04	50.00	1.67	0.89
53033009100	29.88	926.06	244.43	150.18	50.00	1.40	0.90
53033012000	25.26	688.84	271.29	53.09	48.12	0.00	0.50
53033011300	25.16	681.50	85.09	83.34	50.00	0.30	0.79
53033011500	26.64	589.06	157.42	73.98	50.00	0.01	0.58
53033026600	22.18	722.56	168.60	64.27	49.91	0.00	0.56
53033011401	21.70	521.92	744.19	85.59	50.00	0.03	0.61
53033009800	17.02	590.19	347.17	112.34	49.99	0.04	0.74
53033009900	24.44	724.20	114.98	16.46	50.00	0.29	0.71
53033010701	25.82	690.45	140.27	46.45	50.00	0.02	0.53
53033008100	12.49	600.25	188.51	241.02	49.99	0.78	0.56
53033008600	15.51	631.07	257.87	115.33	50.00	0.06	0.43
53033009200	22.28	740.58	372.56	286.52	50.00	1.09	0.87
53033009300	32.34	852.04	147.67	116.35	50.00	0.82	0.85

Fig. 6a-d depict the relationship between traffic speed, volume, and vehicular density, with their 95% confidence intervals, at the census tract level in the downtowns of Atlanta, Los Angeles, New York, and Seattle.



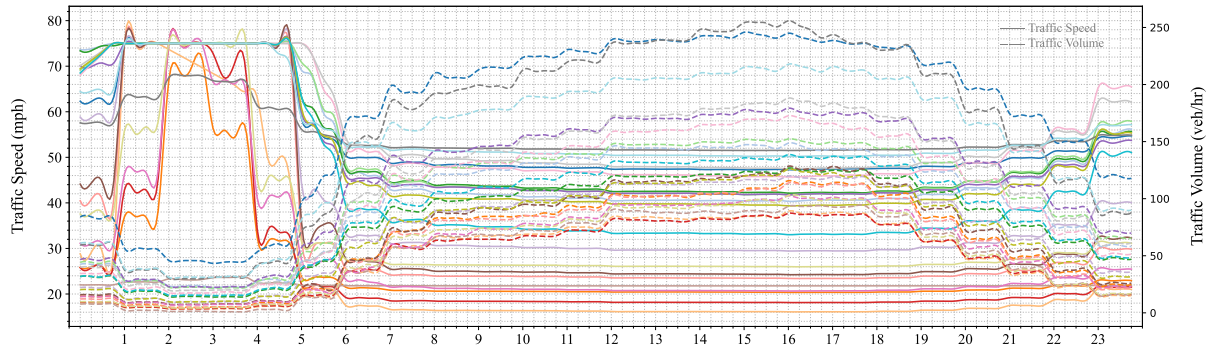
(a) Atlanta, GA (b) Los Angeles, CA



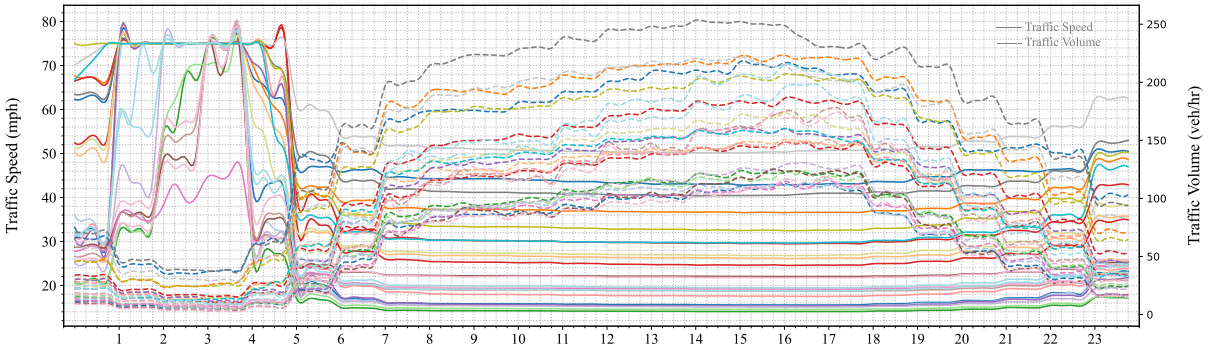
(c) New York, NY (d) Seattle, WA

Fig. 6. Macroscopic Network Fundamental Diagram – Relationship of Traffic Speed with Vehicular Density and Traffic Volume, Including Their 95% Confidence Intervals

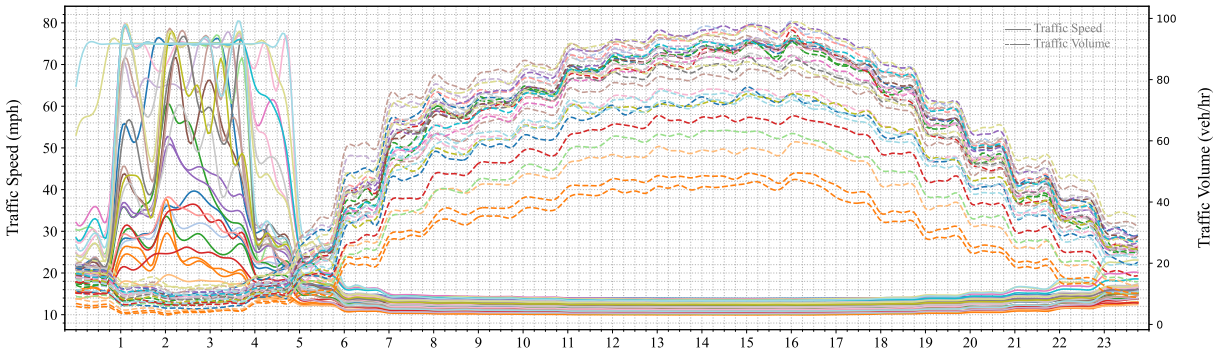
The proposed macroscopic traffic model enables the estimation of traffic speed as volumes increase over the years in urban networks. Fig. 7a-d plot the average traffic speed and volume profiles on workdays in 2024, estimated using probe-based traffic data at the tract level in the downtowns of Atlanta, Los Angeles, New York, and Seattle.



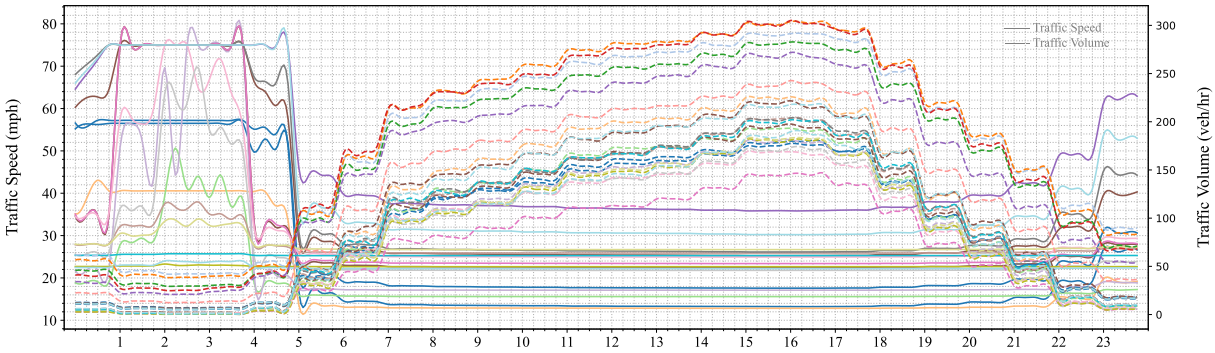
(a) Atlanta, GA



(b) Los Angeles, CA



(c) New York, NY



(d) Seattle, WA

Fig. 7. Average Daily Traffic Speed and Volume Profiles in 2024 in Atlanta, Los Angeles, New York, and Seattle.

Having the macroscopic traffic model and mixed traffic composition, we estimate the energy consumption and air pollutant emissions of various classes of vehicles, including electric vehicles. To estimate the increase in air pollutant emissions from power plants due to the electricity consumed by EVs from the grid to charge their batteries, we employ the Meta Prophet model, trained using the NREL Cambium database, in the following section

5 Power Plant Emission Model – Meta Prophet

With the rise in the adoption and VMT of EVs, the electrical energy consumption of EVs for charging their batteries also increases, thereby raising the air pollutant emissions from power plants. Integrating the vehicle energy consumption model with the macroscopic traffic model and traffic composition data enables the estimation of the total electrical energy consumption of EVs for charging their batteries from the power grid. To estimate the resulting increase in emissions from power plants, we develop a machine learning model on the Meta Prophet platform, trained using the NREL Cambium database. The Cambium database provides precise estimations of marginal air pollutant emission rates[2] (i.e., Additional emissions of air pollutants from power plants with a 1 MWh increase in electrical energy consumption from the grid) for increases in the electrical energy consumption from the grid over months and years, taking into account various power generation technologies across different states. The Cambium model also projects air pollutant emission rates for the coming years under various development, taxation, and pricing scenarios. Training the proposed model using the Cambium database enables efficient and accurate prediction of the emission rates of CO_2 (kg/MWh), CH_4 (g/MWh), and N_2O (g/MWh) from power plants over days, months, and years until 2050, by accounting for various power generation technologies in Georgia, California, New York, and Washington. After successful training, the Prophet model enables bypassing the critical need for detailed data in predicting the marginal emission rates for the additional energy consumption of EVs from the power grid.

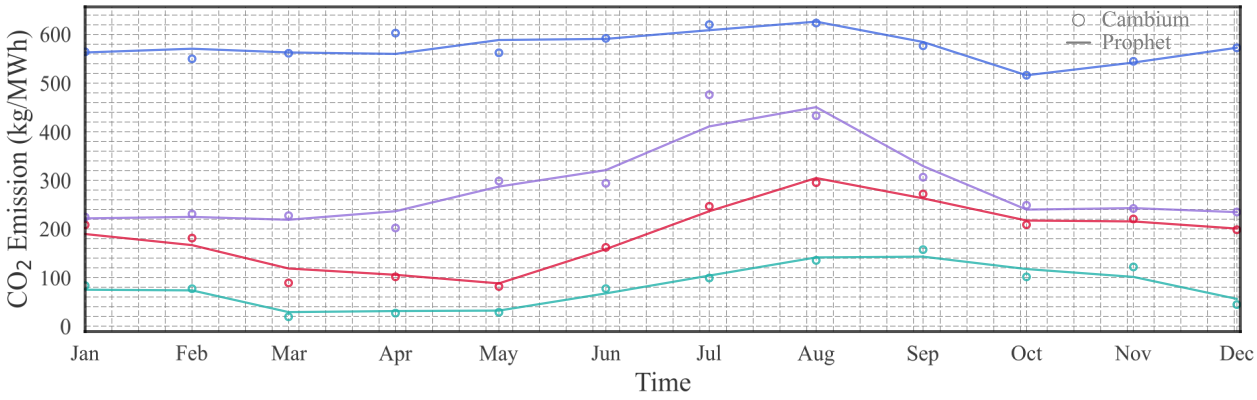
Tab. 3 summarizes the error measures describing the accuracy of the proposed machine learning model in estimating the marginal emission rates of power plants under the mid-case scenario in Georgia, California, New York, and Washington.

[2] Additional emissions of air pollutants from power plants with a 1 MWh increase in electrical energy consumption from the grid.

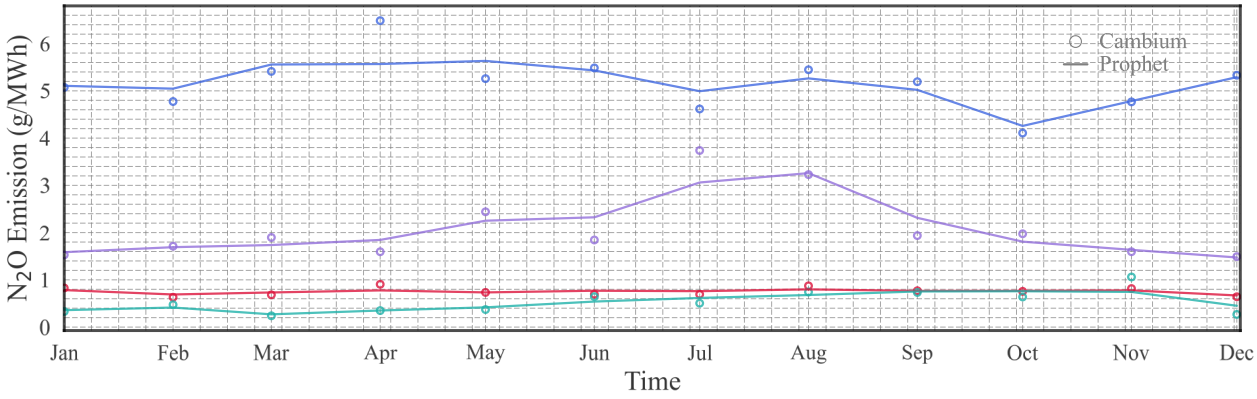
Tab. 3. Power Plant Marginal Emission Rate Model Accuracy – Mid-case Scenario

City	Emission Model											
	CO_2				N_2O				CH_4			
	RMSE	MAE	MAPE	R^2	RMSE	MAE	MAPE	R^2	RMSE	MAE	MAPE	R^2
Georgia	36.85	29.36	19.20	0.95	0.30	0.23	24.67	0.96	166.47	113.91	11.42	0.96
California	11.91	9.30	74.21	0.98	0.08	0.06	37.27	0.92	69.96	53.60	118.19	0.98
New York	14.73	9.00	5.98	0.98	0.17	0.11	15.94	0.95	54.14	33.79	4.30	0.99
Washington	11.51	9.51	45.94	0.95	0.08	0.05	32.42	0.98	72.42	58.67	54.07	0.92

Fig. 8a-c present the scatter plots of CO_2 (kg/MWh), CH_4 (g/MWh), and N_2O (g/MWh) marginal emission rates from the Cambium database, along with their estimated profiles generated by the Prophet model for the base year 2022 in Georgia, California, New York, and Washington. Fig. 9 also plots the predicted marginal emission rates of power plants for the additional energy consumption of EVs from the power grid through 2050 under the mid-case scenario in Georgia, California, New York, and Washington.



(a) CO_2 Emission Rate Profile



(b) N_2O Emission Rate Profile

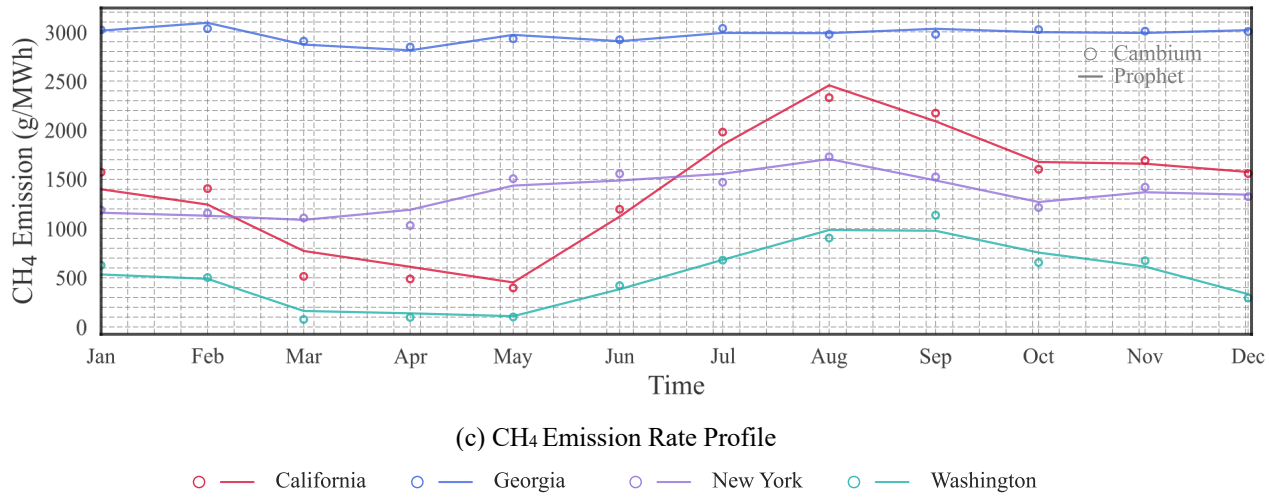


Fig. 8. Power Plant Marginal Emission Rate in 2024 in Georgia, California, New York, and Washington

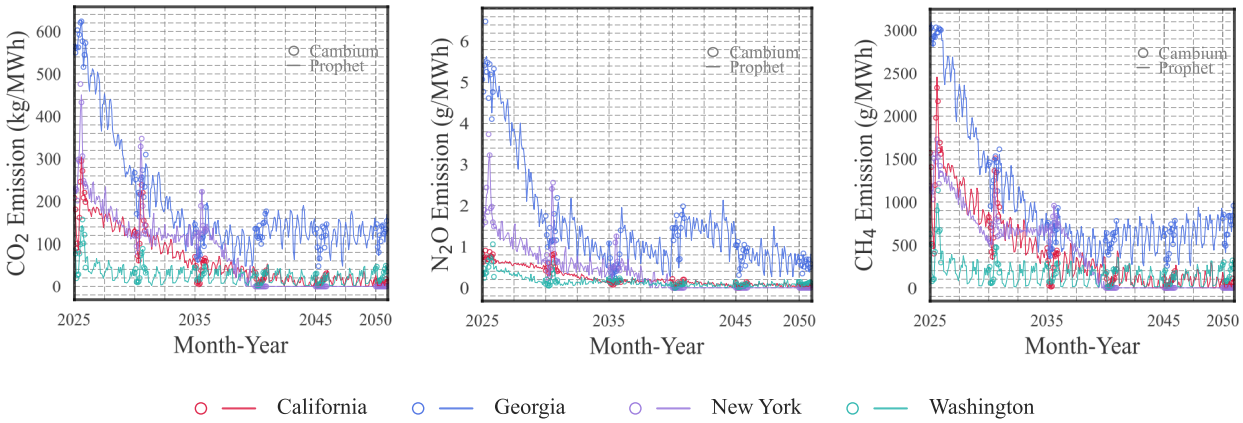


Fig. 9. Power Plant Marginal Emission Rate Through 2050 in Georgia, California, New York, and Washington – Mid-case Scenario.

The proposed machine learning model, trained using the Cambium data, enables estimating power plant marginal emission rates for the additional energy consumption of EVs from the power grid. However, predicting the increase in air pollutant emissions from power plants with the rising adoption of EVs requires integrating the Prophet model with the vehicle energy consumption model and macroscopic traffic model to estimate the energy consumption of EVs based on traffic speed and volume in urban networks, as described in the following section.

6 Integrated Emission Model

Integrating the vehicle energy consumption and emission models with the power plant emission model, along with the macroscopic traffic model and mixed traffic composition data, enables accurate yet efficient assessment of the impact of increasing EV adoption on energy consumption and air pollutant emissions at a large scale. In the proposed integrated model, the macroscopic traffic model predicts traffic speed with increasing traffic volumes in urban networks. Having the mixed traffic composition estimated, the vehicle energy consumption and emission model can be used to predict the total energy consumption and emissions of CO_2, NO_x, and PM2.5 from various vehicle classes (Type×Fuel×Age) in mixed traffic based on traffic volume and speed:

$$E_{i,t}^{V,c} = e_i^c\big(v(q_t)\big)v(q_t)q_t\rho^c\tau^2 \tag{2}$$

Here, $E_{i,t}^{V,c}$ denotes the energy consumption and air pollutant emission of vehicle class c in time step t where i denotes the type, $i \in \{\mathrm{EC}, \mathrm{CO_2}, \mathrm{NO_x}, \mathrm{PM2.5_T}, \mathrm{PM2.5_B}\}$, and $e_i^c(\cdot)$ denotes the corresponding energy consumption and emission rate estimated based on traffic speed, $v(\cdot)$. Traffic speed, $v(\cdot)$ is also approximated based on traffic volume in each time step t at the tract level using the equation derived by substituting $k = q/v$ in (1), with the parameters estimated as presented in TABLE 2. In our analysis, the time step length, τ, is 15 minutes ($\tau = 0.25$ hr), and fraction of each vehicle class c in mixed traffic, ρ^c, is estimated using the state vehicle registration data. The total energy consumption and air pollutant emissions of all vehicle classes over the study period T can be expressed as:

$$E_i^V = \sum\nolimits_{c\in C}\sum\nolimits_{t\in T} E_{i,t}^{v,c} \tag{3}$$

where i denotes the type, $i \in \{\mathrm{EC}, \mathrm{CO_2}, \mathrm{NO_x}, \mathrm{PM2.5_Brakes}, \mathrm{PM2.5_Tires}\}$, and C represents the set of all vehicle classes defined based on the state vehicle registration data. Having the energy consumption of EVs from the power grid estimated, the power plant emission model is used predict the expected increase in air pollutant emissions from power plants:

$$\Delta E_{j,t}^P = e_{j,t}^P E_{EC,t}^{V,EV} \tag{4}$$

where $\Delta E_{j,t}^P$ denotes the expected increase in air pollutant emissions of type $j \in \{\mathrm{CO_2}, \mathrm{N_2O}, \mathrm{CH_4}\}$, from power plants due to the total energy consumption of EVs from the grid in time step t. Here, $e_{j,t}^P$ is the corresponding power plant average marginal emission rate in time step t and $E_{EC,t}^{V,EV}$ is the electrical energy consumption of EVs from the grid in time step t. Note that the Meta Prophet power plant emission model, trained using the Cambium database, captures the variations in the average marginal emission rate from power plants over the months and years until 2050. The total expected increase in air pollutant emissions of type $j \in \{\mathrm{CO_2}, \mathrm{N_2O}, \mathrm{CH_4}\}$, from power plants due to the increase in electrical energy consumption of vehicles from power plants can be expressed as:

$$\Delta E_j^P = \sum\nolimits_{t\in T} \Delta E_{j,t}^P \tag{5}$$

Fig.10 presents the integration of modeling modules for assessing the impacts of increasing EV adoption on energy consumption and air pollutant emissions at a large scale.

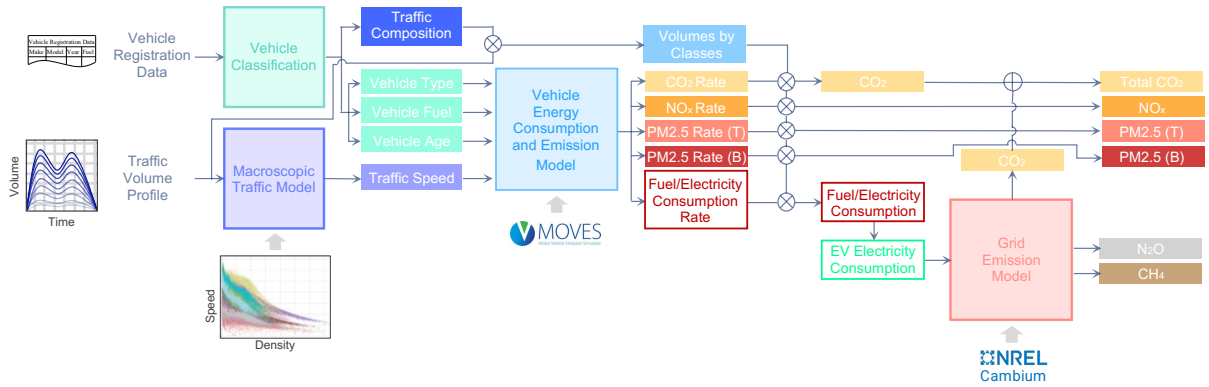


Fig. 10. Integrated Emission Model Pipeline

To assess energy consumption and air pollutant emissions from vehicles and power plants, we consider an estimation of the projected increase in EV adoption and traffic volumes. Fig.11 plots the relative growth in EV adoption compared to 2023, projected through 2030, in California, Georgia, New York, and Washington (US DOE, 2024a). These projections are based on several key factors, including historical EV registration trends, the expansion of charging

infrastructure, and state-level policies aimed at promoting electrification. These projections also account for the development of public and private charging networks, alongside incentives such as rebates and stricter emissions standards designed to accelerate EV adoption. Fig. 12 also presents an estimation of the projected rise in total traffic volumes, along with the lower and upper bounds, in Atlanta, Los Angeles, New York, and Seattle over the coming years through 2030 (US DOT, 2024).

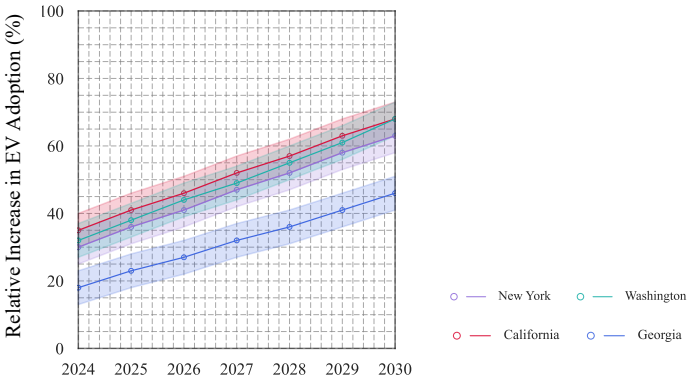


Fig 11. Relative Increase in EV Adoption Compared to 2023 Through 2030

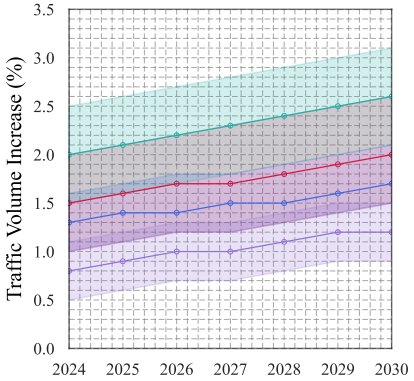


Fig. 12. Projected Increase in the Traffic Volumes Compared to 2023 Through 2030

With the projected increase in EV adoption and the estimated traffic volume, changes in energy consumption and air pollutant emissions from vehicles and power plants can be predicted using the proposed integrated emission model. In the final stage of this research, we employ the proposed integrated emission model presented in the paper to conduct a predictive analysis of the resulting changes in the daily EV charging and the emission of CO_2 (from vehicles and power plants), NO_x, PM2.5 (from tires and brakes and CH_4, and N_2O with the projected rise in the adoption of EVs and traffic volumes in downtown Atlanta, Los Angeles, New York, and Seattle.

Conclusion

Increasing adoption of EVs leads to higher air pollutant emissions from vehicles running on fossil fuels, as well as from non-renewable energy power plants. EVs' lower travel and maintenance costs compared to traditional vehicles can induce users to travel more frequently and over longer distances. The resulting increase in total VMT exacerbates traffic congestion and reduces traffic speeds in urban networks. Consequently, traditional vehicles running on fossil fuels produce higher emissions as traffic speeds decrease with the increased VMT of EVs. Additionally, air pollutant emissions from non-renewable energy power plants rise due to the higher electrical energy consumption required for charging EV batteries from the power grid. This research provides a large-scale analysis of air pollutant emissions from vehicles and power plants with increased EV adoption in Atlanta, Los Angeles, New York, and Seattle using an integrated emission model leveraging machine learning. To estimate the energy consumption and emission rates of heterogeneous vehicles, we develop a feedforward neural network trained using the EPA MOVES4 inventory. The mixed traffic composition is also estimated using state vehicle registration data. We capture the impacts of traffic dynamics on EV energy consumption and emissions from heterogeneous vehicles using a macroscopic traffic model developed based on the concept of MFD, utilizing probe-based traffic data for the downtowns of Atlanta, Los Angeles, New York, and Seattle. Emissions from power plants are also predicted based on the energy consumption of EVs from the grid, accounting for power generation technology, pricing, taxation, and energy mix in Georgia, California, New York, and Washington, using a machine learning model developed on the Meta Prophet platform, trained with the NREL Cambium database. Integrating these modeling components in a comprehensive framework enables the analysis of greenhouse gas and other air pollutant emissions from vehicles based on traffic volume and composition, as well as air pollutant emissions from power plants based on the estimated energy consumption of EVs. In the final stage of this research, we apply the proposed integrated emission model presented in the paper to predict changes in greenhouse gas emissions and other air pollutants from vehicles and power plants with the projected increases in EV adoption through 2030 in Atlanta, Los Angeles, New York, and Seattle.

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