

Charging Ahead with E-Buses: Benefits, Costs, and Transition Roadmap

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Abstract

This paper reaches a recommendation for the 10-year e-bus transition roadmap for New York City. The lifecycle model of emission reduction demonstrates the ecological and financial impacts of a complete transition from the current diesel bus fleet to an all-electric bus fleet in New York City by 2033. This study focuses on the NO_x pollution, which is the highest among all major cities by Environmental Protection Agency (EPA) and greenhouse gases (GHG) with annual emissions of over five million tons. Our model predicts that switching to an all-electric bus fleet will cut GHG emissions by over 390,000 tons and NO_x emissions by over 1300 tons annually, in addition to other pollutants such as VOCs and PM 2.5. yielding an annual economic benefit of over 75.94 million USD. This aligns with the city mayor office's initiative of achieving total carbon neutrality. We further model an optimized transition roadmap that balances ecological and long-term benefits against the costs of the transition, emphasizing feasibility and alignment with the natural replacement cycle of existing buses, ensuring a steady budgeting pattern to minimize interruptions and resistance. Finally, we advocate for collaboration between government agencies, public transportation authorities, and private sectors, including electric buses and charging facility manufacturers, which is essential for fostering innovation and reducing the costs associated with the transition to e-buses.

Keywords

City, Electric Bus, Greenhouse Gas, Emission Reduction, Economic Analysis, Optimization Model, Total Cost of Ownership

1. Introduction

1.1. Background

The growing recognition of environmental sustainability's significance and the

pressing imperative to address climate change have spurred a worldwide shift towards eco-conscious practices and policies [1]. This trend is particularly evident in urban transportation, where there's a marked surge in the use of battery-operated vehicles [2]. Governments worldwide are promoting green commuting options, like metro systems, to their citizens. Despite these strides, further steps are essential. A critical initiative in this direction is the replacement of diesel buses with their electric counterparts. E-buses offer the dual benefits of being both environmentally friendlier and potentially more cost-effective. Thus, formulating a thorough strategy for this transition is vital.

1.2. Problem Statement and Analysis Process

This report is to outline a comprehensive 10-year transition roadmap for the adoption of e-buses in metropolitan areas. Our approach is described in three phases, as illustrated in Figure 1. We chose New York City, the largest urban hub in the U.S., as a primary case study to demonstrate our model. Task 1 focuses on assessing the environmental benefits of transitioning to a fully electric bus fleet. Task 2 delves into the financial implications of this shift. Building on the findings of the first two tasks, Task 3 employs a constrained optimization model to formulate an optimal 10-year transition plan. The model is applied to three diverse U.S. cities—New York City, Chicago, and San Diego, to evaluate its efficacy across different geographic contexts.

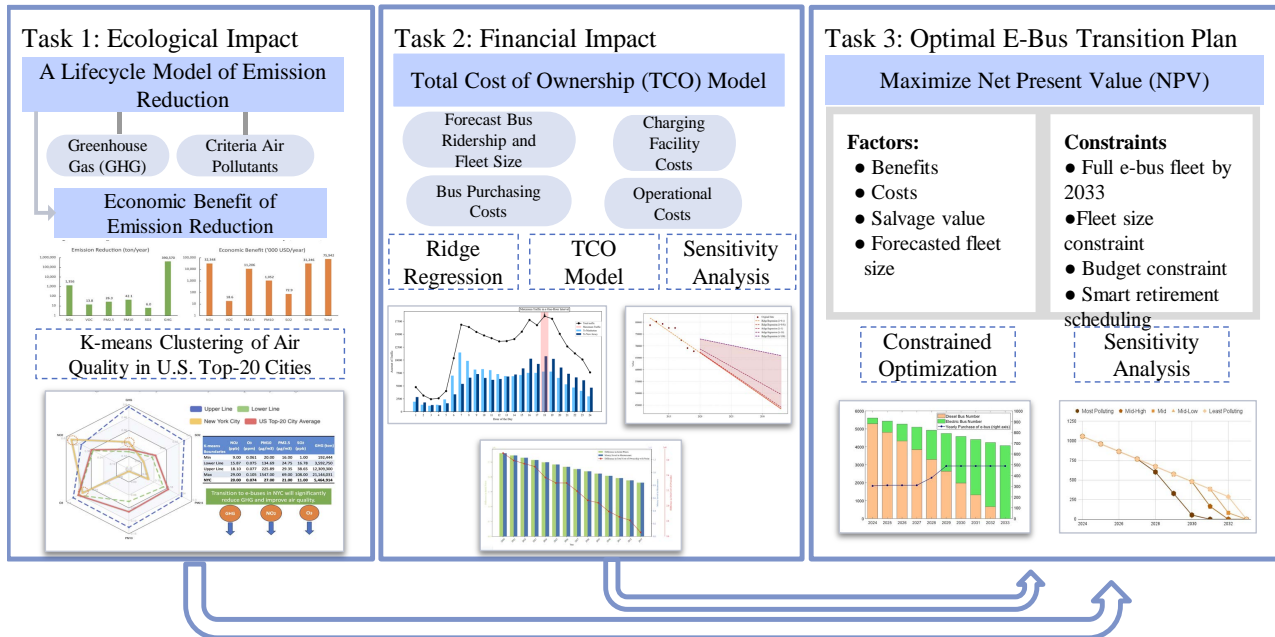


Figure 1. Flow chart of analysis process.

Our research adopts a data-driven approach. To estimate the ecological and financial outcomes of transitioning to e-buses, we gather a diverse array of data sets. These include emissions statistics for greenhouse gases and other key air pollutants

from both diesel buses and e-buses, urban bus ridership figures, bus procurement costs, and expenses related to charging infrastructure. To analyze this data, we utilize various mathematical models and algorithms. For instance, we employ the K-means clustering algorithm to benchmark air quality in the top 20 U.S. cities. In addition, ridge regression is used to forecast future trends of model variables.

2. Task 1: Ecological Benefits of Transitioning to E-Buses

To create a model to estimate the ecological consequences of transitioning to an all-electric bus fleet, we proceed in two steps: 1) Estimate the **emission reduction** of air pollutants, which include greenhouse gases and five other major air pollutants; 2) Estimate the **economic value of emission reduction** in terms of US dollars.

2.1. A Lifecycle Model of Emission Reduction

To estimate the emission reduction from bus electrification, we develop a lifecycle model by comparing emissions from both the production and the operation phases of e-buses and diesel buses. Specifically,

$$\begin{aligned} &\text{Emission Reduction} \\ &= \text{Diesel Bus Lifecycle Emissions} - \text{E-Bus Lifecycle Emissions} \end{aligned} \quad (1)$$

The essence of this framework can be seen in **Figure 2**. This figure demonstrates that although e-buses have zero emission during their operation phase, their total life cycle emission is not zero. This is because emissions exist during the electricity generation and battery production phases. Because emissions from vehicle production (excluding battery production) are common to both e-buses and diesel buses, they cancel out when calculating the emission reduction. Finally, we need to include emissions from diesel bus operation and diesel production to derive the emission reduction.

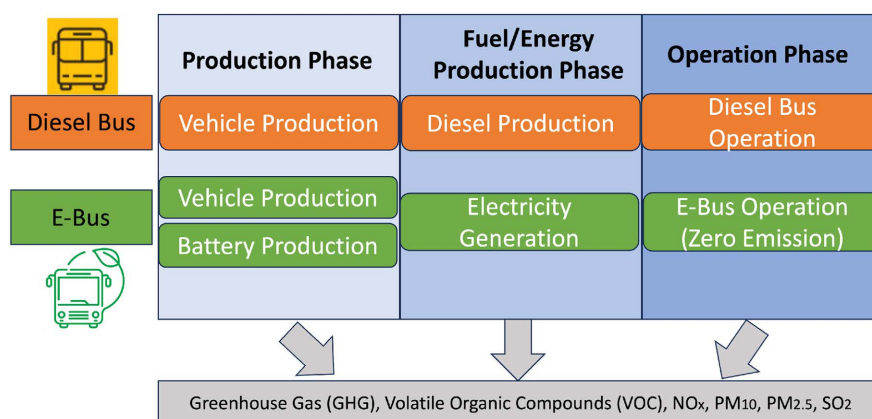


Figure 2. A lifecycle model of emission reduction.

2.1.1. Model Assumptions and Variable Definition

Before we specify our model, here are the key assumptions and their justifications:

Assumption 1. Lifecycle emissions from diesel buses and e-buses include those emitted during the following three phases: 1) The production phase (vehicle

production for both diesel buses and e-buses, but battery production for e-buses only); 2) The fuel or energy production phase (either diesel production for diesel buses or electricity generation for e-buses); 3) the operation phase. This is the most critical assumption of this lifecycle model of emission reduction. Emissions from both operation and non-operation phases of buses are both important contributions of the total emission. It is particularly important to consider non-operation emissions of e-buses because they typically generate zero emissions when in use. Such lifecycle emission assessment approach has been adopted in previous research on bus electrification (see [3]).

Assumption 2. Emissions from vehicle production for a diesel bus is identical to emissions from vehicle production for an e-bus.

The major steps in producing a bus involves chassis production, body production, powertrain production. They are fairly similar in the overall production process if the same size and materials are used [4], and therefore are often assumed to be identical when assessing emission reduction of e-buses (e.g., see [3]).

Assumption 3. Emissions from e-bus operation is zero.

E-buses are often referred to as zero-emission buses because they are run on batteries. The electricity used to charge e-buses may not be generated with zero emission, but they are already included in the electricity generation emissions in this model.

Assumption 4. Lifecycle emissions of buses include the following six major emissions: Green-house Gases (GHG), NO_x , Volatile Organic Compounds (VOC), PM_{10} , $PM_{2.5}$, and SO_2 .

To evaluate the ecological impact of bus electrification, we consider these six major contributors of emissions. GHGs are gases in the earth's atmosphere that trap heat. Scientific studies have shown that greenhouse gases are the cause of global warming and climate change. GHGs include carbon dioxide CO_2 , Methane CH_4 , Nitrous oxide N_2O , and fluorinated gases (See the definition of GHG on EPA's website: <https://www.epa.gov/ghgemissions/overview-greenhouse-gases>). In environmental studies, GHG emission factors are often expressed as **Carbon Dioxide Equivalent**, *i.e.*, CO_{2eq} to capture the fact that there exist multiple greenhouse gases. Note that CO_2 contributes to 79% of GHG emissions from human activities in the U.S. in 2021 (EPA website).

In addition to GHG, we also consider five major criteria air pollutants associated with vehicle production and operations: NO_x , Volatile Organic Compounds (VOC), PM_{10} , $PM_{2.5}$, and SO_2 . According to EPA's website, air pollution emitted from transportation contributes to poor air quality, leading to negative impacts on the health and welfare of people. Major pollutants include particulate matters (PM), nitrogen oxides (NO_x), and volatile organic compounds (VOC). Most notably, the transportation sector is responsible for about 45% of NO_x total emissions inventory in the U.S. We also include sulfur dioxide (SO_2) because it is an additional major air pollutant from coal-fired electricity generation.

The variables used in Problem 1's model are listed in **Table 1**.

Table 1. Variable definition.

Notation	Description
R_i	Reduction of emission i
D_i	Diesel bus emission i
E_i	E-bus emission i
$D_{p,i}$	Diesel bus emission i during diesel production
$D_{o,i}$	Diesel bus emission i during operation
$E_{e,i}$	E-bus emission i during electricity generation
$E_{b,i}$	E-bus emission i during battery production
C_i	Economic cost of emission i

2.1.2. Model Specification

Our lifecycle model of emission reduction can be expressed as:

$$R_i = D_i - E_i = D_{p,i} + D_{o,i} - E_{e,i} - E_{b,i} \quad (2)$$

As shown in **Figure 2**, the emission reduction comes from four components: 1) Diesel production emission; 2) Diesel bus operation; 3) Electricity generation for e-bus; 4) Battery production for e-bus.

$$\text{Economic Benefit of Emission Reduction} = \sum_i^6 R_i C_i \quad (3)$$

where i indicates six emissions shown in **Figure 2**. Next, we conduct analysis by splitting the six emissions into two groups: GHG and criteria air pollutants.

2.1.3. Greenhouse Gas (GHG) Emission Reduction

The GHG emission reduction is calculated by

$$R_{GHG} = D_{GHG} - E_{GHG} = D_{p,GHG} + D_{o,GHG} - E_{e,GHG} - E_{b,GHG} \quad (4)$$

The equation models the difference between the green house gas emission of diesel bus and electric bus. There are 2 main factors that will affect the emission of greenhouse gas of a diesel bus: the operation of the bus and the diesel production. On the other hand, the electrical bus produce green house gas mainly through production of batteries and the GHG emitted while generating electricity. Therefore, we can substitute the variables above to have a more detailed formula for the amount of green house gas emission.

In the following calculation, GHG emission is calculated as the number of grams of **Carbon Dioxide Equivalent**, *i.e.*, CO_{2eq} .

- **Diesel production** The diesel production GHG emission takes the medium of the green-house gas emissions from three European studies, which is 15.8 grams per mega joule per bus [5]-[7]. We convert it to 385.26 grams per mile per bus by assuming that 1 mega joule produces 1 gallon of diesel, which in turn supports 6 miles of bus operating distance.
- **Diesel Operation** The diesel operation GHG emission is 2680 grams per mile per bus [8].
- **Battery Production** The battery that New York City currently is using for its

15 electric bus is LiNiCoMn Lithium ion batteries. These batteries produce an average of 85,000 carbon dioxide equivalent gram per Kilowatt hour (KWh). We further assume that e-buses adopted in New York City has a lifetime of 12 years with an estimated annual mileage of 36,500 miles. Over the 12 years, three batteries need to be used because a typical battery life is 4 years. After conversion, an e-bus produces about 174.66 grams per mile per bus.

- **Electricity Generation** To calculate the electricity generation emission per bus in a city, we need to know the component of powers that generate electricity and their corresponding air pollutant emissions. Given the data from US Energy Information Administration, we can calculate the CO₂ equivalent emission gram per kilowatt per hour.

$$E_{e,GHG} = \sum_j \text{GHG Emission Factor}_j \cdot \text{percentage of Electricity Generation Source } j \quad (5)$$

where j = electricity generation source, $j \in \{\text{coal, natural gas, nuclear, renewables}\}$. These four sources contribute to over 99% of U.S. total electricity generation (see **Table 2**). We further assume that 1KWh runs an electric bus for 1 mile. This is a reasonable assumption as the typical range is between 0.67 miles to 2 - 3 miles. In the end, we get that the electricity generation emission is 257.59 grams per mile per bus in New York City. GHG emissions from electricity generation are also calculated for Chicago, San Diego, and US Average using their corresponding electricity power grid mix. The results are displayed in **Table 2**.

Table 2. GHG emission from electricity generation.

Electricity Generation Source	GHG Emission (g/mile)	US Average	New York City	Chicago	San Diego
Coal	820	16.20%	0.00%	14.20%	0.10%
Natural Gas	490	45.30%	50.40%	19.60%	27.30%
Nuclear	12	18.20%	22.60%	55.60%	9.40%
Renewables	30	19.60%	26.40%	10.20%	62.50%
Total Emission (g/mile)	--	362.87	257.59	222.21	154.47

In the end, we plug in the amount of GHG emission of the four categories into Equation (4) and the amount of GHG emission reduction is 2633.01 grams per mile per e-bus.

2.1.4. Criteria Air Pollutant Emission Reduction

Next we consider criteria air pollutant emission reduction for the aforementioned five air pollutants: NO_x , VOC , $PM_{2.5}$, PM_{10} , and SO_2 . Following [3], pollutant emissions are mostly from diesel bus operation and electricity generation, while the emissions from vehicle production and battery production are ignorable for the five key air pollutants studied here. Therefore, the equation we will use to calculate emission reduction becomes

$$R_i = D_{o,i} - E_{e,i} \quad (6)$$

According to [3], the emission factors of the five major air pollutants during the phase of diesel bus operation are listed in the first column of the right panel in **Table 3**. The emission factors of e-buses depend on the electricity generation sources. Among the four major sources listed in **Table 3**, coal is the only one that leads to pollutant emission. In contrast, natural gas, nuclear, and renewables have ignorable emissions of air pollutants [3]. Therefore, we can calculate pollutant emissions by taking into account of the electricity power grid mix in a city (from **Table 2**) according to the following equation:

$$E_{e,i} = \sum_j \text{Pollutant } i\text{'s Emission Factor}_j \cdot \text{percentage of Electricity Generation Source } j \quad (7)$$

where j = electricity generation source, $j \in \{\text{coal, natural gas, nuclear, renewables}\}$.

Table 3. Criteria air pollutant emission from bus operations.

Pollutant (g/mile)	Electricity Generation Source				Diesel Bus	Bus Type and Location		
	Coal	Natural Gas	Nuclear	Renewables		E-Bus in New York City	E-Bus in Chicago	E-Bus in San Diego
NOx	0.35	0	0	0	9.14	0	0.05	0.0004
VOC	0	0	0	0	0.09	0	0	0
PM2.5	0	0	0	0	0.18	0	0	0
PM10	0	0	0	0	0.28	0	0	0
SO2	0.37	0	0	0	0.04	0	0.05	0.0004

The results are displayed in **Table 3**.

2.1.5. Economic Benefit of Emission Reduction

In this section, we translate the emission reduction of GHG and air pollutants obtained earlier into economic benefit, specifically, into US Dollars (USD) according to the following equation:

$$\text{Economic Benefit of Emission Reduction} = \sum_{i=1}^6 R_i C_i \quad (8)$$

where i indicates six major emission components shown in **Figure 2**.

According to a World Bank report [9], the shadow prices of GHG (CO_{2eq}) in the next ten years will be increasing. Both low and high estimates are displayed in **Table 4**.

Table 4. Shadow price of GHG from world bank 2017 guidance (USD/ton).

Year	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033
Low Estimate	44	45	46	47	48	49	50	51	52	53
High Estimate	87	89	91	94	96	98	100	102	105	107

Economic damages of air pollution is estimated based on a data source from European Commission [10], which is shown in **Table 5**. These pollutant prices are calculated as the average of EU 28 countries with the currency converted from

Euro to USD.

Table 5. Pollutant price from EU 28 countries in 2019 (USD/ton).

Pollutant	NO _x	VOC	PM _{2.5}	PM ₁₀	SO ₂
Average	23,856	1344	426,720	24,976	12,208

Plugging in the amount of GHG and pollutant emission reduction (in g/mile) obtained earlier, we then use Equation (8) to calculate the economic value an e-bus would generate per mile of driving. The detailed results will be illustrated in the next section.

2.2. Results and Analysis

2.2.1. Ecological Benefits of Transitioning to an All-Electric Bus Fleet

According to our earlier calculations in Section 2.1, we have the ecological implications of transitioning to e-buses in the unit of per mile per e-bus. Now further assuming that the annual mileage of buses is 365,000 miles (=10 hours per day × 10 miles/hour × 365 days), we can calculate the annual ecological implications of converting a diesel bus to an e-bus. The estimated ecological benefits per e-bus conversion are displayed in **Table 6**.

Table 6. Ecological benefits of NYC bus electrification (per e-bus per year).

Pollutant	NO _x	VOC	PM _{2.5}	PM ₁₀	SO ₂	GHG	Total
Emission Reduction (ton/year)	0.334	0.003	0.006	0.010	0.001	96.10	--
Economic Benefit (USD/year)	7959.5	4.6	2757.3	258.8	17.9	7688.4	18,686.5

According to **Table 6**, the annual GHG reduction per e-bus is 96.10 tons. With the GHG price increasing over the 10 years from 2024 to 2033 (see **Table 4**), the average annual economic benefit of GHG reduction will increase to \$7688.4 per e-bus by year 2033. The annual pollutant reduction per e-bus is 0.355 ton, and the annual economic benefit of pollutant reduction is \$10,998.1 per e-bus, bringing the total economic benefit of emission reduction to \$18,686.5 per e-bus per year by 2033 (see **Figure 3**). Among the five air pollutants, *NO_x* emission reduction contributes most to the overall emission reduction both in terms of weight and economic benefit as shown in **Table 6**.

Finally, we are ready to evaluate the total ecological benefits of transitioning to an all-electric bus fleet in New York City. To do so, we assume the fleet size is 4064 (according to our prediction of bus ridership in 2033, see Section 3 for details). The total emission reduction and economic benefit are shown in **Figure 4**.

Figure 4 shows that the total annual GHG emission reduction is **390,570 tons** after transition to an all-electric bus fleet in New York City by 2033 and the associated economic benefit is over **\$31.25 million**. Benefits from pollutant reduction are also huge, making the total economic benefit to be over **\$75.94 million**. Among the five air pollutants, *NO_x* reduction contributes to over **\$32.35 million**

economic benefit.

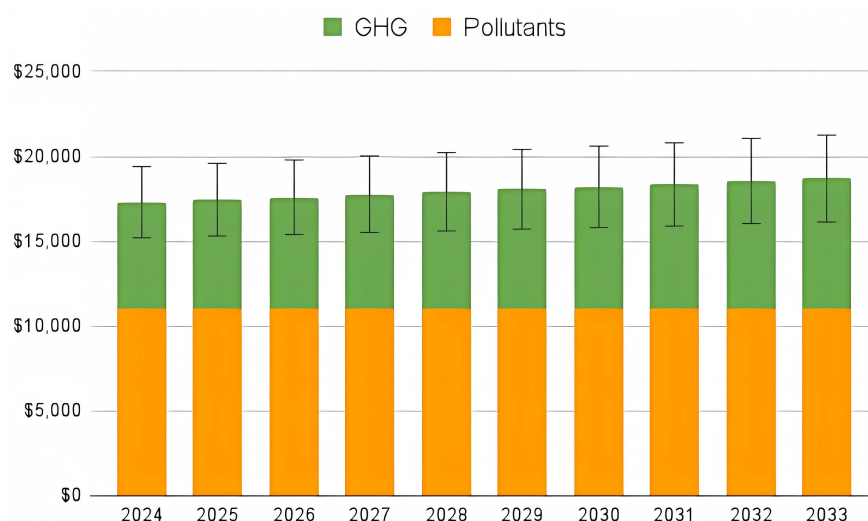


Figure 3. Estimated ecological benefits of NYC bus electrification in year 2024-2033 (USD/bus). The error bars indicate the high and low ranges of GHG benefit estimation.

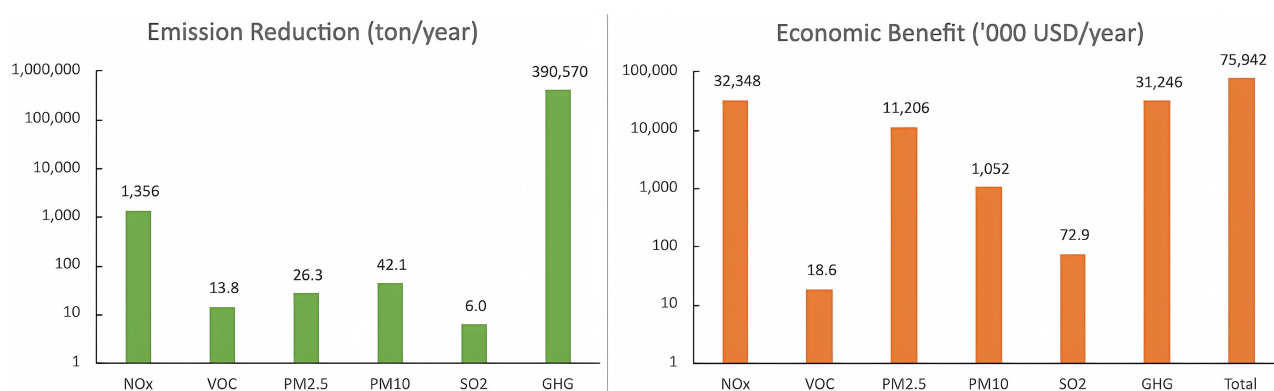


Figure 4. Ecological benefits of an all-electric bus fleet in New York City (Year 2033).

2.2.2. Impact on Air Quality: K-Means Clustering of U.S. Top-20 Metropolitan Areas

After establishing evaluations of the impact of emission reduction in New York City, a standardized model is needed to assess the impact of bus electrification on the overall air quality. We adopted the K -means clustering algorithm to compare air quality and GHG emissions across top-20 metropolitan areas in the U.S. in 2022 (see **Table 7** for the data). By doing this, we will understand how New York City's air pollution and GHG emission compare to other cities before and after e-bus transition.

K -means clustering is an iterative, data-partitioning algorithm that assigns observations X to exactly one of K clusters defined by centroids, where K is chosen before the algorithm starts. In this algorithm, the data set X includes the air quality indexes of NO_2 , O_3 , PM10, PM2.5, SO_2 , and GHG of top-20 cities in the U.S. K is set to be 3 so that the algorithm will cluster these 20 cities into three groups. Let μ_k denote the centroids of the partitions and C_k denote cluster k . Then, the sum of

squares of the distances from the centroid is represented by

Table 7. Air quality in U.S. top-20 metropolitan areas (2022, data source: EPA).

Core Based Statistical Area (CBSA)	2010 Population	NO ₂ (ppb)	O ₃ (ppm)	PM10 (µg/m ³)	PM2.5 (µg/m ³)	SO ₂ (ppb)	GHG (ton)
New York-Newark-Jersey City, NY-NJ-PA	19,567,410	20	0.074	27	21	11	5,464,914
Los Angeles-Long Beach-Anaheim, CA	12,828,837	25	0.095	92	33	4	10,543,740
Chicago-Naperville-Elgin, IL-IN-WI	9,461,105	17	0.074	134	30	45	1,910,900
Dallas-Fort Worth-Arlington, TX	6,426,214	14	0.082	82	27	16	3,745,116
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	5,965,343	14	0.07	50	23	7	1,408,892
Houston-The Woodlands-Sugar Land, TX	5,920,416	18	0.084	140	27	14	192,444
Washington-Arlington-Alexandria, DC-VA-MD-WV	5,636,232	15	0.066	36	17	3	291,407
Miami-Fort Lauderdale-West Palm Beach, FL	5,564,635	13	0.068	104	22	2	4,656,432
Atlanta-Sandy Springs-Roswell, GA	5,286,728	16	0.069	48	19	4	323,653
Boston-Cambridge-Newton, MA-NH	4,552,402	12	0.07	36	17	9	524,680
San Francisco-Oakland-Hayward, CA	4,335,391	13	0.068	38	24	15	410,374
Detroit-Warren-Dearborn, MI	4,296,250	14	0.071	77	33	108	21,144,031
Riverside-San Bernardino-Ontario, CA	4,224,851	29	0.105	1547	32	3	1,349,415
Phoenix-Mesa-Scottsdale, AZ	4,192,887	26	0.081	431	33	5	15,842,569
Seattle-Tacoma-Bellevue, WA	3,439,809	16	0.075	33	69	3	1,002,377
Minneapolis-St. Paul-Bloomington, MN-WI	3,348,859	12	0.061	118	19	15	1,459,487
San Diego-Carlsbad, CA	3,095,313	15	0.079	196	17	1	3,130,578
St. Louis, MO-IL	2,787,701	10	0.076	175	24	44	771,495
Tampa-St. Petersburg-Clearwater, FL	2,783,243	9	0.067	53	16	71	6,217,739
Baltimore-Columbia-Towson, MD	2,710,489	15	0.069	20	16	3	1,002,377
US Top-20 City Average	5,821,206	16.15	0.0752	171.85	25.95	19.15	4,069,631

$$J(C_k) = \sum_{x_i \in C_k} \|x_i - \mu_k\|^2 \tag{9}$$

where $J(C_k)$ denotes the sum of squares of the distances from the centroid. The goal of the algorithm is to solve the following optimization problem:

$$\min_{d_{ki}} \sum_{k=1}^3 \sum_{i=1}^{20} \|d_{ki} x_i - \mu_k\|^2 \tag{10}$$

$$\text{s.t. } d_{ki} = \begin{cases} 1, & x_i \in C_i \\ 0, & x_i \notin C_i \end{cases} \tag{11}$$

The solution algorithm for K -Means is defined as follows:

- **Standardize the original data.** Formalize the given data with Equation (12) to make their mean as zero and variance as one:

$$x_{ij}^* = \frac{x_{ij} - \bar{x}_j}{\sqrt{Var(x_j)}} \quad (i = 1, 2, \dots, n; j = 1, 2, \dots, p) \tag{12}$$

where $\bar{x}_j = \frac{1}{n} \sum_{i=1}^n x_{ij}$, $Var(x_j) = \frac{1}{n-1} \sum_{i=1}^n (x_{ij} - \bar{x}_j)^2$

- **Initialize k centroids.** Initially, randomly choose k observations as centroids.

$$c_1^{(0)}, c_2^{(0)}, \dots, c_k^{(0)} \tag{13}$$

- **Assign given points.** For a given cluster assignment C of the data points, compute each point's distance to each centroid. Assign these points according to their least distance to the nearest centroid.

$$v_j = \arg \min_{1 \leq j \leq k} \|x_i - c_j\|^2 \tag{14}$$

- **Update Centroid.** Recalculate each cluster's mean value and replace the centroid with this mean value until every centroid does not change.

$$c_j = \frac{\sum_{i=1}^n I(v_j = j) x_i}{\sum_{i=1}^n I(v_j = j)} \tag{15}$$

Otherwise, repeat the Assign Step and Update Step until the convergence condition is satisfied.

The K-means clustering algorithm gives us the following three levels of air pollution in comparison within the top-20 metropolitan areas, as shown in the right panel of Figure 5. The minimum, the lower line, the upper line, and the maximum are calculated for each of the six air pollutants. The lower line and the upper line are calculated as the mean of the pollutant indicators of the centroids. Falling below the lower line, between the lower line and the upper line, and above the upper line represent low, medium, and high level of air pollution.

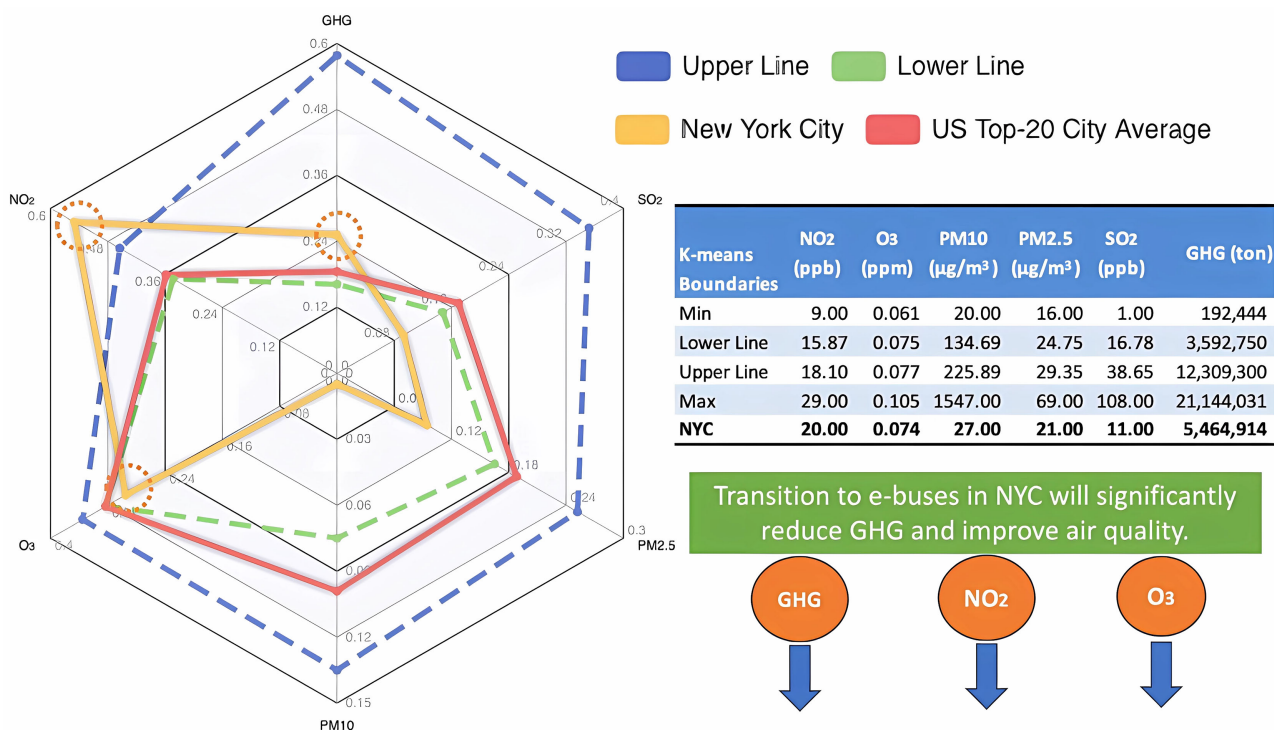


Figure 5. Air quality: New York City vs. US top-20 city average.

In order to visualize the air quality comparison between New York City and other cities, we plot a radar chart. Because the six air quality measures have highly different ranges, we scale all measures into a common interval of [0, 1] with the minimum being 0 and the maximum being 1. The left panel of **Figure 5** indicates that New York City has low levels of O_3 , PM_{10} , $PM_{2.5}$, and SO_2 as they fall under the lower line. This is likely due to the lack of coal-fired electric generation in the region (as indicated in **Table 2**). However, New York City has **the highest level of NO_2 pollution** (above the upper line) and **second highest emission of GHG** (above the lower line).

According to our earlier analysis, a complete bus electrification in New York City will generate an annual reduction of 1356 tons of NO_x emission, 13.8 tons of VOC emission, as well as 390,570 tons of GHG emission. Because O_3 , known as ozone, is a secondary air pollutant formed as a result of photochemical reactions between primary pollutants, such as nitrogen oxides (NO_x) and volatile organic compounds (VOC), reduction of NO_x and VOC will lead to reduced O_3 .

3. Task 2: Financial Implications of Transitioning to E-Buses

Task 2 requires us to construct a model to predict the financial implications of transitioning to e-buses. We model a 10-year horizon to estimate the cost increase needed to acquire and maintain an e-bus fleet compared to the current diesel bus fleet.

In order to make these calculations, we separated the considerations into two categories: Initial and operational prices. Initial prices refer to variables such as the capital cost of one electric bus, or the price of purchasing one electric charger. Operational prices refer to costs such as the annual electricity and diesel for a bus, or the maintenance of the electric chargers.

3.1. A Total Cost of Ownership (TCO) Model

3.1.1. Variable Definition

The variables that will be used in Task 2 are listed in **Table 8**.

Table 8. Variable definition.

Notations	Descriptions	Notations	Descriptions
t	Set of years 2024-2033	F_t	Fleet size in year t
P_E	Purchase price of an e-bus	O_E	Operation price of an e-bus
P_C	Purchase price of a charger	P_d	Purchase price of a diesel bus
O_D	Operation price of a diesel bus	N_t	Ridership in year t
P_b	Current amount of buses in NYC	P_L	Price of electricity annually needed
M_e	Maintenance price of electric bus	M_c	Maintenance price of chargers
C_m	Cost of materials	C_l	Cost of labor
P_d	Price of diesel annually needed	M_d	Maintenance price of diesel bus
P_{max}	Maximum ridership of bus in a day	T_{max}	Maximum traffic in a day
L_e	Maximum service years of electric buses	L_d	Maximum service years of diesel buses

3.1.2. Model Creation

We construct a **Total Cost of Ownership, TCO** model to analyze the increased capital needed to maintain and transition to a fully electric bus system. Various factors are considered, including the price of purchasing and maintaining chargers, the slow decrease in the popularity of public transportation, and the prices of electricity and diesel. We calculated the difference between the TCO of a fully electric bus model and the TCO of a fully diesel bus model to analyze this increased capital. This difference can be summarized as

$$\Delta TCO_t = TCO_{et} - TCO_{dt} \quad (16)$$

where ΔTCO_t represents the difference in TCOs of the electric and diesel bus models, TCO_{et} and TCO_{dt} are the electric bus model's TCO and the diesel bus model's TCO in year t , respectively. Furthermore,

$$TCO_{et} = F_t \cdot P_E + F_t \cdot O_E + \frac{F_{max,t}}{F_{max,2023}} \cdot P_C \quad (17)$$

where F_t is the fleet number in year t , $F_{max,t}$ is the possible max fleet charging at the same time in year t , P_E is the purchase price of an e-bus, O_E is the operation price of an e-bus, and P_C is the purchase price of the charger. Similarly,

$$TCO_{dt} = F_t \cdot P_D + F_t \cdot O_D \quad (18)$$

where P_D is the purchase price of a diesel bus and O_D is the operation price of a diesel bus.

3.1.3. Bus Fleet Size Needed

In order to create this model, we analyzed the number of people who used the MTA bus system in years 2012 to 2019. We noticed an overall decrease in the popularity of using buses, which means in the future, it would not be necessary to purchase as many electric buses as the current fleet of buses. We were then able to predict the ridership in **Table 9**:

Table 9. Predicted amount of people taking buses.

Year	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033
Ridership (N_t)	616,639	598,368	580,098	561,827	543,556	525,286	507,015	488,745	470,474	452,203	433,933

We can express the fleet of buses needed as the amount of people decreases as

$$F_t = \frac{N_t}{N_{2023}} \cdot P_b \quad (19)$$

where N_t is the ridership of year t and P_b is the current amount of buses in NYC. As of 2021, there were 5780 buses in the MTA fleet, and due to the aftermath of Covid-19 and lack of public transportation usage we feel it is safe to assume there would be little change in the fleet size as the city finishes its recovery from the pandemic [11]. Applying the above data to this formula provides the predicted bus fleet in **Table 10**:

Table 10. Predicted amount of people taking buses.

Year	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033
Bus Fleet	5780	5603	5432	5261	5090	4919	4748	4577	4406	4235	4064

3.1.4. Operational Costs E-Bus

We consider both the operational costs of diesel and e-buses in this model. In order to calculate the operational costs for a year of operation for the e-bus system, we use the following equation:

$$O_E = P_L + M_e + M_c \quad (20)$$

where P_L refers to the price of electricity, M_e refers to the price of maintaining an electric buses, and M_c refers to the price of maintaining chargers.

- **Annual cost of electricity:** In order to find the price of electricity per year, we will need to find the total mileage of a NYC bus every year. At its highest usual speed, an NYC bus travels at 10 miles per hour, and bus operators work on a 10 hour shift [11]. Therefore, we can extrapolate that annually, we can expect an NYC bus to have $10 \text{ mph} \times 10 \text{ hours} \times 365 \text{ days} = 36,500$ miles of mileage every year.

Electricity averages around 0.08 cents per kilowatt, and an electric bus uses approximately 2.8 kilowatts per mile. Therefore, the cost of electricity for one electric bus on average can be represented as $2.8 \times 0.08 \times 36,500 \approx 8000$ dollars per year [12].

- **Maintenance of Chargers:** The price of maintaining one charger can be written as

$$M_c = C_m + C_l \quad (21)$$

where C_m is the cost of materials, and C_l is the cost of labor. The material per charger will cost 11,500 dollars and require 72 hours of labor, which with a fully-loaded electrician salary of 87.85 dollars per hour results that the maintenance per charger is approximately 17,825 dollars. However, each charger can supply electricity to multiple buses around the clock. We assume one charger is needed for every four electric buses. The average cost for charger maintenance is 4456 dollars per bus [12]. Therefore,

$$O_E = 4456(\text{Charger cost}) + 8000(\text{Electricity cost}) + M_e \quad (22)$$

Diesel Buses

The operational costs of a diesel bus per year can be expressed as

$$O_D = P_d + M_d \quad (23)$$

where P_d represents the price of diesel, and M_d represents the price of maintaining a diesel bus.

Price of diesel: From our calculations that a bus travels an annual 36,500 miles, we can write that. given today's rates, the total cost of diesel evaluates to about 28,000 dollars per year [12]. Therefore,

$$O_D = 28000 + M_d \quad (24)$$

3.1.5. Purchasing Cost

E-bus The MTA lists the price of a standard E-bus as 1,033,000 dollars. Therefore, the price of purchasing the needed E-buses in year t can simply be written as

$$Pe_{net} = F_t \cdot 1033000 \tag{25}$$

Diesel Bus The MTA lists the price of a standard diesel bus as 635,000 dollars. Therefore, the price of purchasing the needed diesel buses in year t can simply be written as

$$Pd_{net} = F_t \cdot 635000 \tag{26}$$

3.1.6. Maximum Fleet Size Needed

Clearly, having the chargers necessary to charge every single one of the buses in our fleet would be far too costly and illogical. We use data from the George Washington Bridge to extrapolate the total bus needs of the city. On the George Washington Bridge, the maximum amount of people on the bridge is 18,500 at 5 p.m., as seen in the following **Figure 6**:

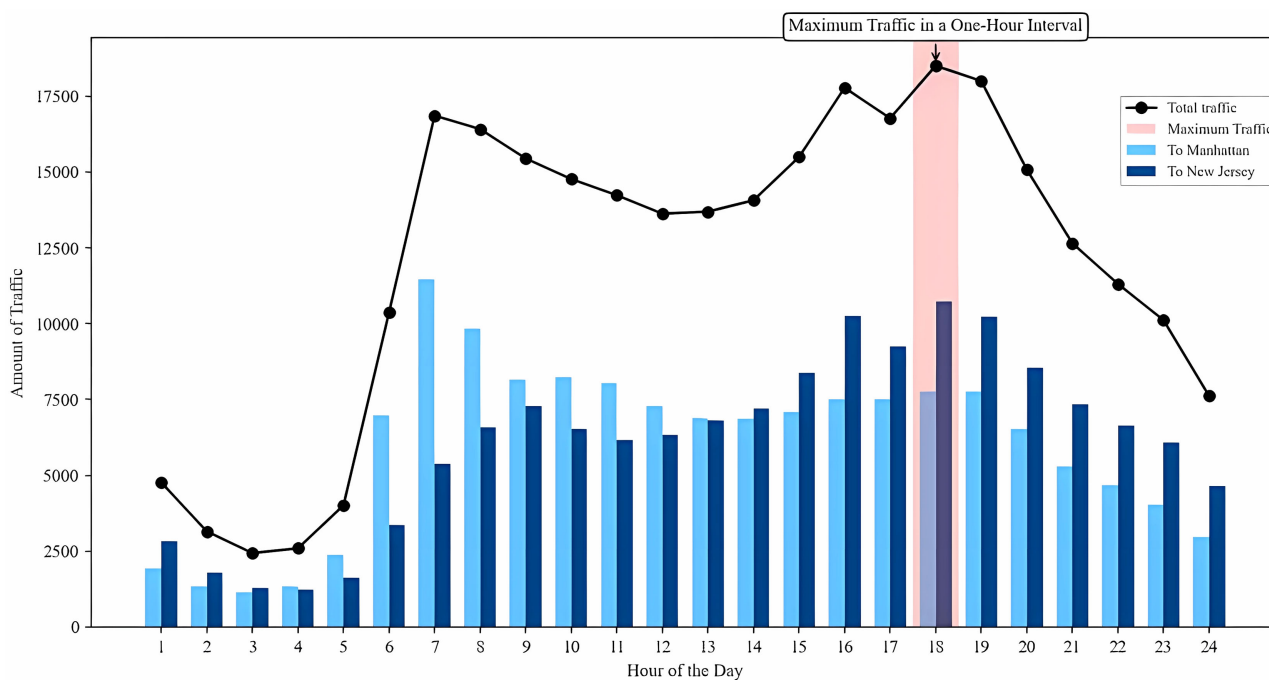


Figure 6. Hourly traffic on George Washington Bridge.

As the bridge reportedly accounts for 8 percent of the traffic in the city, we can calculate the total traffic in NYC. Furthermore, a reported 12 percent of vehicles in the city are buses, so we can calculate the maximum amount of people in buses in one hour in NYC as

$$P_{max} = \frac{T_{max}}{0.08} \cdot 0.12 \tag{27}$$

where T_{max} represents the maximum traffic recorded and P_{max} represents the maximum ridership of buses at the same time. From this, we evaluate that a

maximum of 345 buses will be needed at one time since a standard NYC bus has a limit of 80 people [12].

3.1.7. Cost of Charging Facilities

An MTA report stated that it costed them 50 million dollars for their purchase of charging facilities needed for 60 electric buses [13]. Therefore, the cost of purchasing a charger per bus is approximated at $50,000,000/60 \approx 833,000$ dollars. We then conclude that given the current maximum number of buses that need to be charged at once, *i.e.*, 345 from above estimation, purchasing chargers will cost 287,385,000 dollars.

3.1.8. Future Prediction

The general formula of polynomial fitting can be represented with this equation:

$$y = f(x) = a_k x^k + a_{k-1} x^{k-1} + \dots + a_1 x + a_0 + \epsilon \tag{28}$$

where x is the predictor variable, y is the response variable, $a_i (i = 0, 1, 2, \dots, k)$ is the coefficient, and k is the order of the polynomial.

Finding the best parameters of this polynomial function aims to minimize the residual error between the value $f(x_i)$ estimated by the polynomial and the actual data y_i . L_2 norm of this residual error is then optimized by n training samples:

$$\min_{a_i} R^2 = \min \sum_{j=1}^n \|y_j - f(x_j)\|_2^2 = \min \sum_{j=1}^n \left[y_j - \sum_{i=1}^k a_i x_j^i \right]^2 \tag{29}$$

To obtain the minimum of this objective function, the partial derivatives of R^2 with respect to the coefficients a_i is derived:

$$\frac{\partial(R^2)}{\partial a_i} = -2 \sum_{i=1}^n \left[y - (a_0 + a_1 x + \dots + a_k x^k) \right] x^i = 0 \tag{30}$$

which is expressed in matrix form as:

$$\begin{bmatrix} n & \sum_{i=1}^n x_i & \dots & \sum_{i=1}^n x_i^k \\ \sum_{i=1}^n x_i & \sum_{i=1}^n x_i^2 & \dots & \sum_{i=1}^n x_i^{k+1} \\ \vdots & \vdots & \ddots & \vdots \\ \sum_{i=1}^n x_i^k & \sum_{i=1}^n x_i^{k+1} & \dots & \sum_{i=1}^n x_i^{2k} \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_k \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^n y_i \\ \sum_{i=1}^n x_i y_i \\ \vdots \\ \sum_{i=1}^n x_i^k y_i \end{bmatrix} \tag{31}$$

This is a Vandermonde matrix and can be rewritten as:

$$\begin{bmatrix} 1 & x_1 & \dots & x_1^k \\ 1 & x_2 & \dots & x_2^k \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_n & \dots & x_n^k \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_k \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \tag{32}$$

which is $\mathbf{Xa} = \mathbf{y}$ Solving this equation yields

$$\mathbf{a} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y} \tag{33}$$

The regularization term is applied to avoid the over-fitting problem. Here we use the L_2 norm of the coefficient as the penalty:

$$\min \sum_{j=1}^n \|y_j - f(x_j)\|_2^2 + \lambda \|a\|_2^2 \quad (34)$$

where λ is inferred by sensitivity analysis to control the effects of regularization.

In **Figure 7**, it is evident that when $\lambda = 0.1$, decreasing λ further by factors of 10 has very little impact on the resulting regression line. Even when λ is increased by a factor of 10 several times, the mode is still relatively insensitive to this change. We found that λ is obtained to be 0.1.

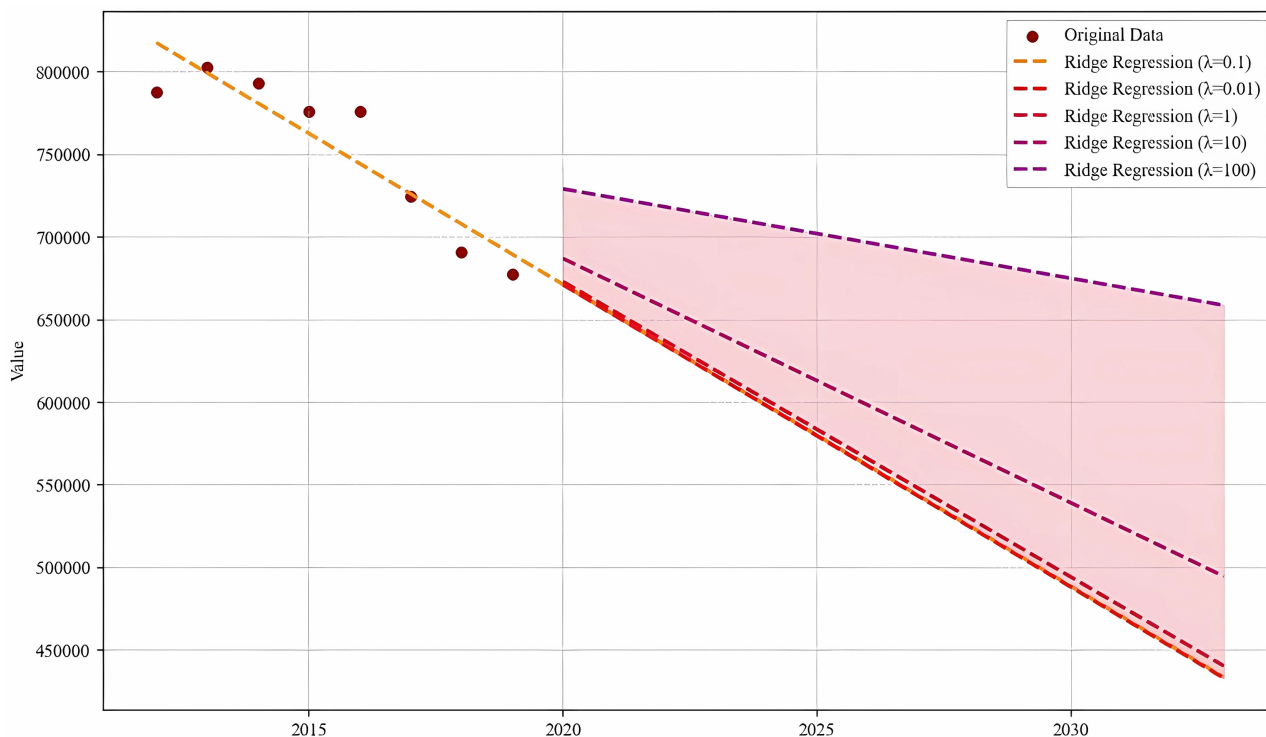


Figure 7. Prediction of future volume.

The solution to the optimization is calculated by

$$a = (X^T X + \lambda k I)^{-1} X^T y \quad (35)$$

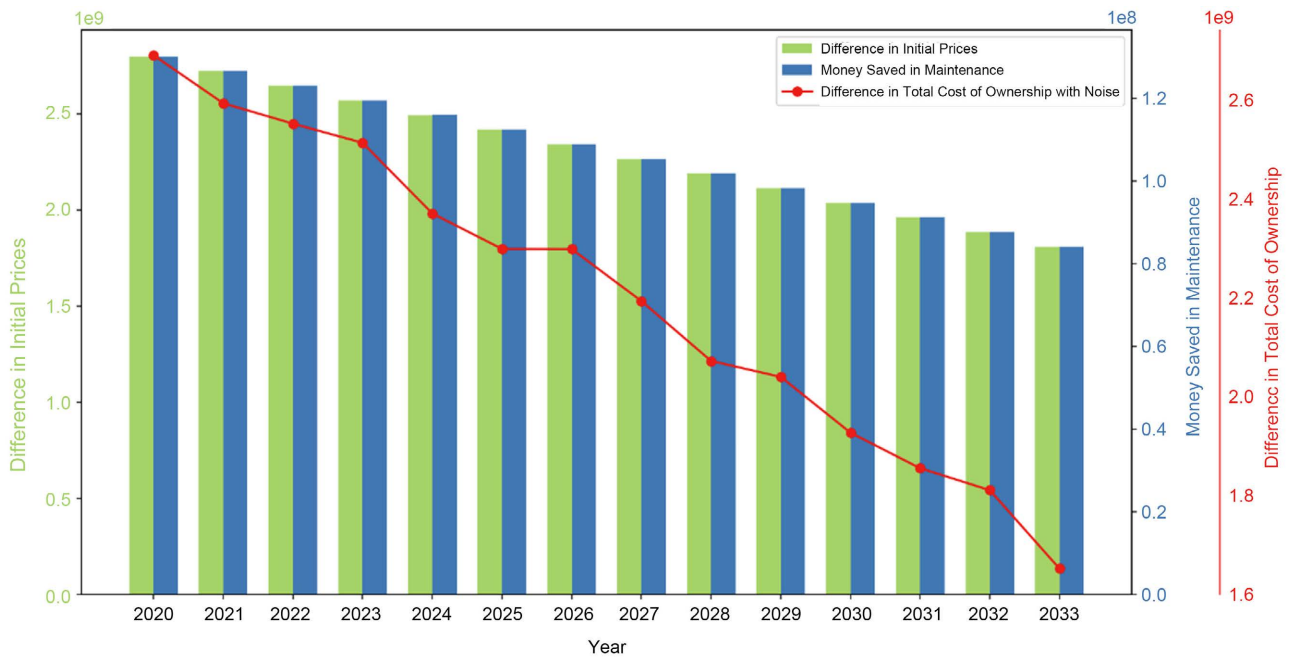
3.2. Results and Analysis

3.2.1. Solution of the TCO Model

In our data, we found that the cost of maintaining a diesel bus and an electric bus were extremely similar. Therefore, it will not impact our calculation of the difference in TCOs. By substituting the values we found into the original TCO model, our findings are summarized in **Figure 8**.

Because of the decrease in popularity of buses, the difference in cost of ownership will decrease further every year. While buses may be losing popularity in New York City, we firmly believe that the introduction of completely net-zero emission

buses will promote and give New Yorkers a reason to ride.



Years	ΔTCO (\$/year)
2023	2,471,930,084
2024	2,398,958,688
2025	2,325,987,291
2026	2,253,015,895
2027	2,179,193,674
2028	2,106,222,277
2029	2,033,250,881
2030	1,960,279,485
2031	1,886,475,088
2032	1,813,503,692
2033	1,740,532,296

Figure 8. TCO difference and components.

3.2.2. Net Benefits in the Long Run

By joining the ecological benefits and economical costs together, our findings support the conclusion that, after the initial investment of charging facility construction is made, switching to electric bus fleet is more beneficial in the long run. For New York City, the post-transition yearly-average net gain per bus is estimated to be

$$E_{co} + \frac{P_D}{L_d} + O_D - \frac{P_E}{L_e} - O_E = \$1064 \tag{36}$$

where E_{co} is the estimated ecological benefits per e-bus in year 2033 (Table 6).

This estimation is based on the current purchase price of e-buses and charger maintenance costs. In the long term, we expect these costs will drop significantly with the technological advances and economy of scale following the broader adoption of electric buses. Therefore, we expect the positive gains of future e-bus fleet can only be larger.

4. Task 3: Optimizing the 10-Year E-Bus Transition Roadmap

Given the ecological benefits and financial feasibility of switching from traditional diesel vehicles to electric buses, we build a mathematical model that can aid to craft transition roadmaps for different cities. The plan aims to transition into a fully e-bus fleet by the end of year 2033. It aligns closely with the natural replenishment process of the existing bus fleet. As illustrated in Figure 9, the model optimizes the transitional process to balance the dual objectives of increasing ecological benefits and lowering the associated financial costs. It also takes the practicality of government budgeting into consideration by spreading the purchases of new buses into more years and mitigating large budget variation from year to year.

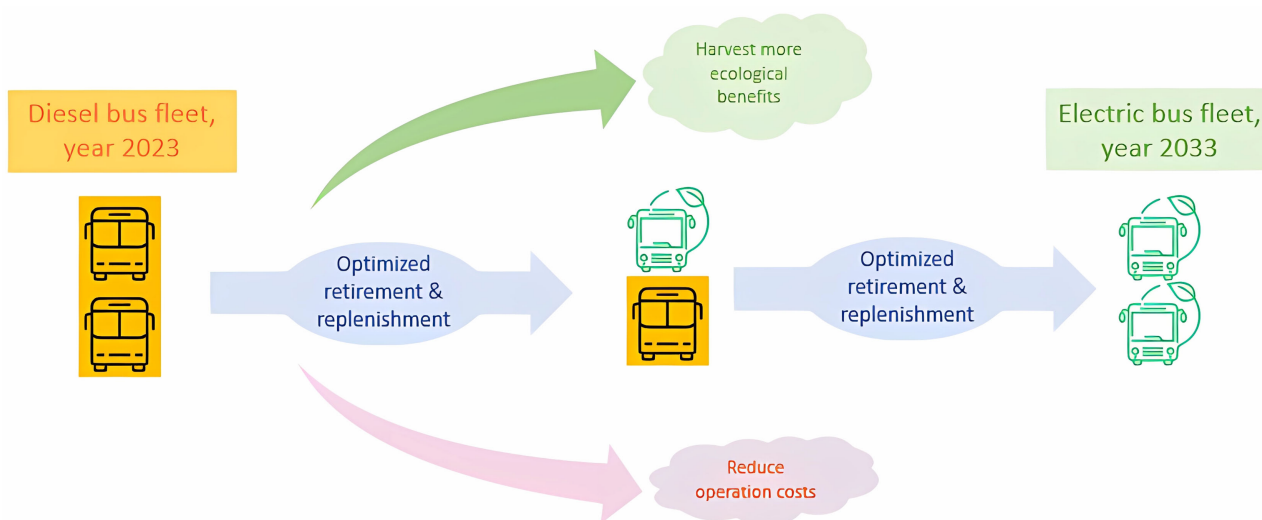


Figure 9. Optimization model aligns with the replenishment process of the existing bus fleet and harvests the benefits at controlled cost. The e-bus icon is downloaded from Adobe.

4.1. Assumptions

Assumption 1. The city has an active diesel bus fleet serving the current public transportation needs. The operational capacity of the bus program and its future growth are exogenous to our transition plan. The in-transition fleet and the eventual fully electric one run the same pre-determined bus program in terms of bus number and capacity, except in a more eco-friendly way.

Justification: Our model targets to build a transition roadmap for an established metropolitan area with a population over half million people. Public bus

programs are usually determined by people's transportation needs and city's budget constraints. This report does not have the scope of completely redesigning the capacity and routes of the metropolitan's bus program.

Assumption 2. Each bus has a limit of maximum service year, after which it must be retired and does not have further redemption value. The existing bus fleet has distributed ages that warrants a natural replenishment procedure.

Justification: The decommissioning and replenishing is mandatory for safety and liability reasons.

Assumption 3. The transition plan can early-retire some diesel buses before they reach maximum service year.

Justification: Early retirement on selected buses is necessary to achieve the targeted full transition by the end of 10 years. Early-retired diesel buses are replenished with e-buses. Within the existing fleet, the model can early-retire those worst polluting buses.

Assumption 4. The full electric bus fleet has salvage value at the end of 10-year transition period. The salvage value of each bus, after an initial 10% discount, is assumed to be linearly proportional to its remaining service life and purchase cost.

Justification: Even though this planning model focuses on the 10-year transition period, it needs to incorporate the salvage value into consideration as part of the long-term planning. The linear depreciation model is one common method in financial accounting.

Assumption 5. The purchase of new electric buses are spread into years. The purchase in any year cannot be 20% more than the yearly average of the eventual target.

Justification: A practical roadmap needs to smooth the purchase and update into multiple years. The gradual transition helps to mitigate any potential resistance from stakeholders, and gives all teams more time to overcome the learning curves in operation and management.

4.2. Optimization Model

Optimization Objective and Constraints

The model runs constrained optimization with the aid of MATLAB [14] [15]. The concept of constrained optimization is demonstrated in **Figure 10**. The variables of the optimization model are summarized in **Table 11**. This model optimizes the decision variables X_t , which are the numbers of new e-buses purchased in the coming 10 years.

The optimization objective is to minimize the net present value of the financial and environmental costs in next 10 years, net of the salvage value of the full e-bus fleet at the end of the period.

The optimization is subject to following constraints:

- 1) Mandatory target of full e-bus fleet at the end of 10 years.
- 2) Purchase in any year cannot be 20% more than the yearly average of the eventual target.

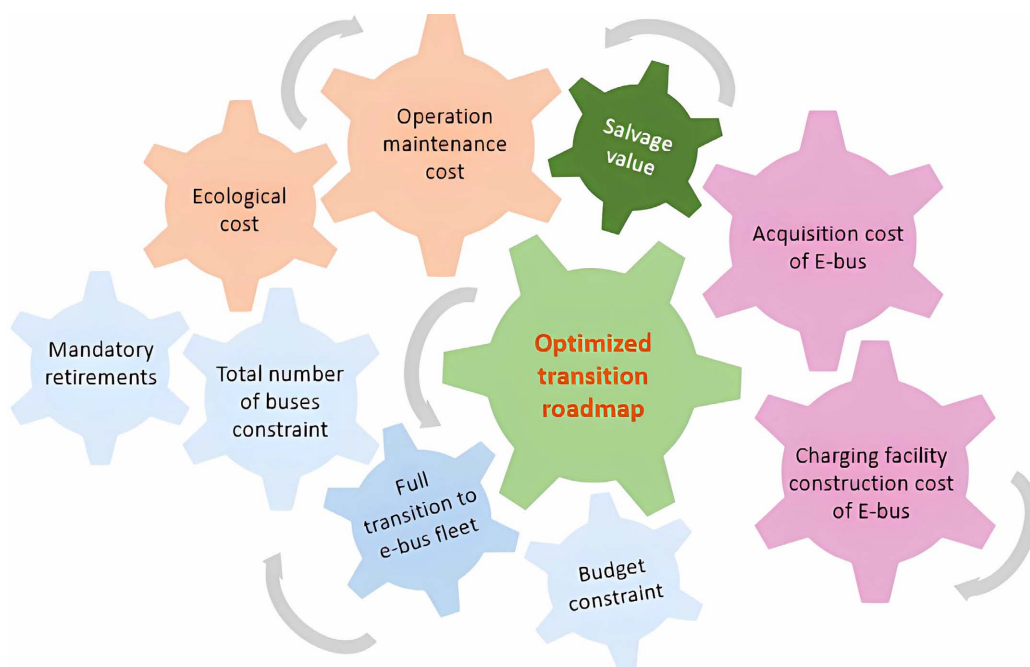


Figure 10. Constrained optimization model has objectives to maximize benefits and minimizes costs.

Table 11. Variable definitions.

Notation	Description	Notation	Description
t	1 to 10, representing year 2024-2033	N_{e0}	Initial number of electric buses
N_{d0}	Initial number of diesel buses	N_t	Total number of vehicles, including both diesel and electric buses
L_e	Maximum service years of electric buses	L_d	Maximum service years of diesel buses
ND_t	Number of buses at maximum service year	P_{et}	Forecasted purchase price of one e-bus
P_{dt}	Forecasted purchase price of one diesel bus	C_{et}	Yearly operation and maintenance cost of each electric bus, including electricity cost
C_{dt}	Yearly operation and maintenance cost of each diesel bus, including fuel cost	F_t	Average cost of building new charging facilities for each newly purchased electric bus.
E_{et}	Yearly ecological cost of one e-bus.	E_{dt}	Yearly ecological cost of one diesel bus.
G_t	Government subsidies, modeled as the percentage of $(P_{et} + F_t)$.	r	Annual discount rate, 5%
N_{rt}	Number of buses retired each year	N_{et}, N_{dt}	Number of active electric, diesel buses

$$\max \sum_t (-C_t - P_t) + S_{10} \tag{37}$$

$$\text{s.t.} \begin{cases} \sum_t X_t = N_{10} \\ X_t \leq \frac{N_{10}}{10} * 1.2 \end{cases} \text{ for } t \in [1,10] \tag{38}$$

where **operation, maintenance and ecological costs of active fleet**

$$C_t = \frac{1}{(1+r)^{t-1}} * ((Ce_t + Ee_t) * Ne_t + (Cd_t + Ed_t) * Nd_t) \tag{39}$$

acquisition costs of new buses, including the construction costs of new charging facilities

$$P_t = \frac{1}{(1+r)^t} * (Pe_t + Ft) * X_t * (1 - G_t) \tag{40}$$

and salvage value at the end of year 2033

$$S_{10} = \frac{1}{(1+r)^{10}} * Pe_t * X_t * (1 - G_t) * 0.9 * \left(1 - \frac{10-t}{L_e}\right) \tag{41}$$

4.3. Transition Roadmap for New York City

With the aid of this optimization model, we craft a roadmap to transition the mostly combustion engine bus fleet to a fully electric one in 10 years.

In this gradual transition plan, diesel buses retire, which are replenished by electric buses over years. The mix of buses in the fleet is illustrated in **Figure 11** and **Table 12**. The downward trend of total fleet size is extrapolated from the shrinking trend of NYC bus ridership in years 2012 to 2019.

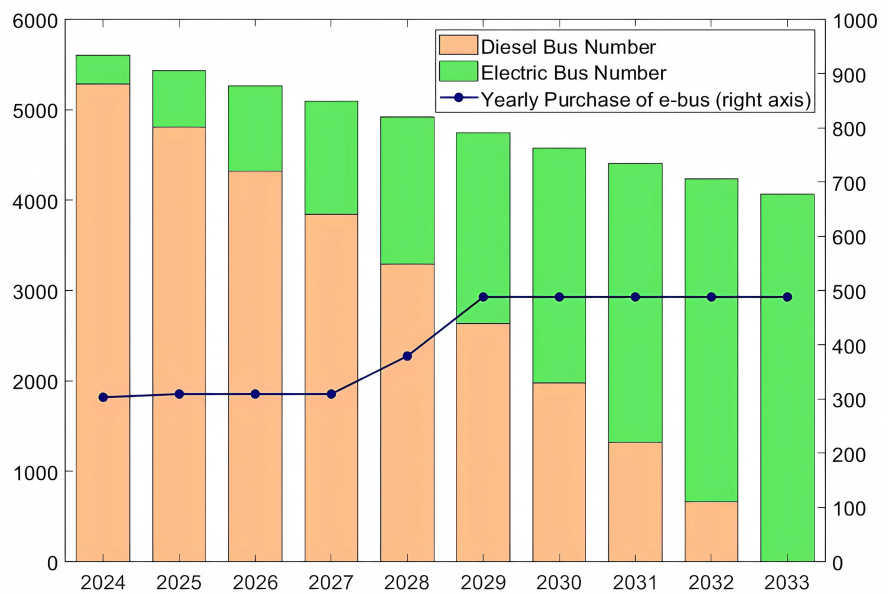


Figure 11. E-bus transition roadmap (left axis) and e-bus purchase schedule (right axis).

Table 12. 10-year roadmap: transition from a mostly diesel bus fleet to a fully e-bus fleet.

Year	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033
Diesel Buses	5285	4804	4324	3843	3293	2635	1976	1317	659	0
Electric Buses	318	628	937	1247	1626	2113	2601	3089	3576	4064

4.3.1. Transition Schedule

Purchase of new electric buses (**Figure 11**) started at a relatively lower rate of

around 309 vehicles per year in the first four years. They are allocated to partially replenish the retired vehicles as the total fleet size is shrinking.

In these first several years, no buses are retired before their maximum service age. This is due to the expensive purchase price of e-buses available to US cities as well as the high construction cost of charging facilities, which we will analyze in more details in later chapter.

The purchase will accelerate in year 2028 and stabilize at 488 e-buses per year in the last five years. This acceleration is necessary to achieve our target of full transition by year 2033, and it is bounded by our constraint to smooth the purchase budgeting over years.

4.3.2. Net Cost and Ecological Benefits

In this transition period, the metropolitan needs to make additional investment due to the relatively higher prices of e-buses and the extra cost of building charging facilities (Figure 12). This cost increases in year 2028 and 2029 when the purchases accelerate. On the other hand, the lower operation and maintenance cost of e-bus contributes to the downward trend of net cost in the other years when the new purchases are stable.

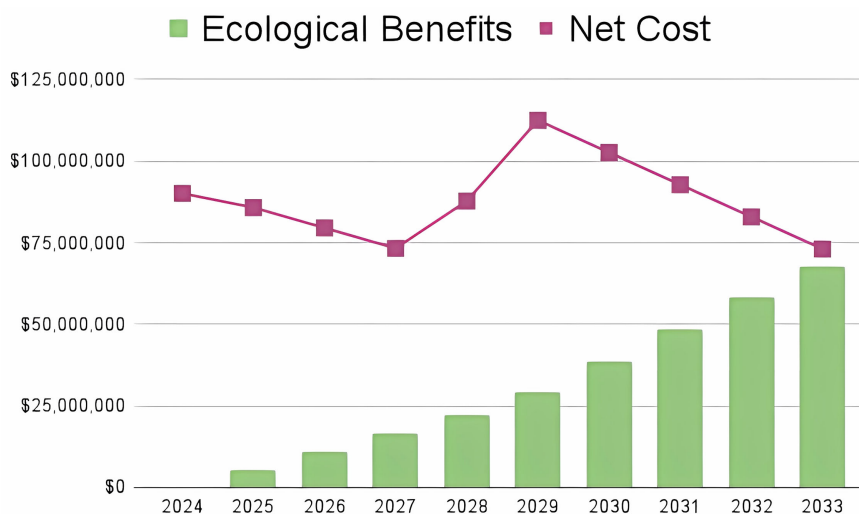


Figure 12. Net cost of the transition and the increasing ecological benefits.

More importantly, with the expansion of e-buses, the fleet will realize more ecological benefits year over year which is illustrated in the same Figure 12.

4.3.3. Smart Scheduling: Prioritized Decommissioning of the Worst Polluting Diesel Buses

The transition plan takes the working condition of buses and polluting situation of the city into consideration. It manages smart retirement-scheduling among buses of various polluting situations and city boroughs of different polluting levels (Figure 13). Starting from year 2028, it expedites the decommissioning of the heaviest pollution generating group. After its completion in year 2031, the second group is expedited. And then in year 2032, the third group is expedited.

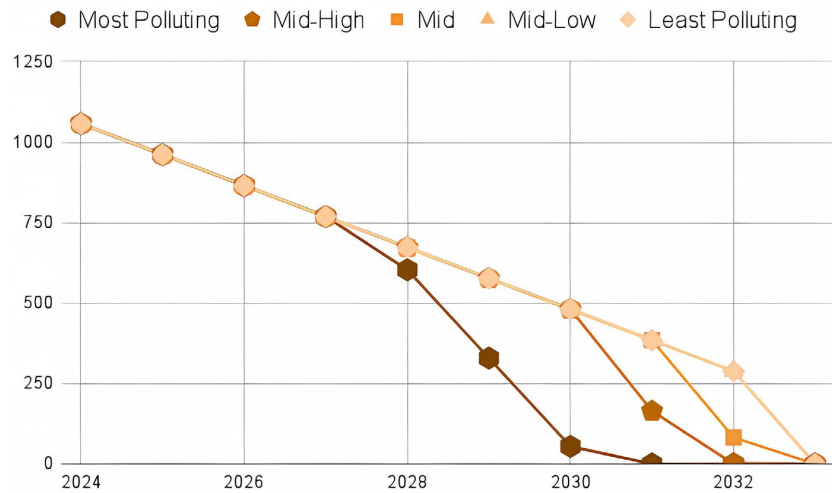


Figure 13. Smart scheduling: worst pollution-generators are decommissioned earlier.

4.3.4. Government Funding as a Crucial Factor to the Transition

Government subsidies, such as the allocation to e-bus projects from the 2023 US Bipartisan Infrastructure Law will be crucial for the successful transition to an e-bus future. In the 10-year roadmap for New York City, we expected 50% of the transition cost will be shouldered by various government funding. This kind of government support is common among the cities that have been successful in achieving the transition to electric bus fleet, such as Shenzhen, China.

Without the needed government support, the transition cost can become prohibitively high for the transportation enterprise. Figure 14 shows the net cost could be as high as \$567M in the peak year of 2029 if there was no extra government support.

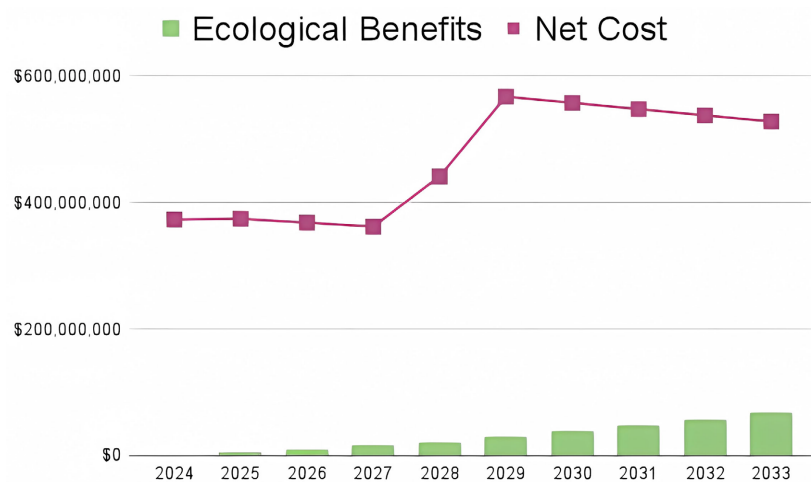


Figure 14. Without extra government support, the net cost for transition can be prohibitively high.

4.3.5. Lower Cost Could Help to Realize Ecological Benefits Earlier

Compared with Shenzhen, China, the transition to the e-bus future is financially more challenging for US cities. The main concern will be the significantly higher

e-bus purchase price and construction cost of charging facilities.

We encourage transportation officials and private enterprises to be more innovative and competitive in lowering these costs. For instance, cities can import lower-priced e-buses, such as BYD, to reduce the cost and encourage domestic manufacturers to be more competitive. US government can provide more synchronized support to cities and bus manufacturers so that it is easier to achieve economy of scale and lowered costs for all stakeholders.

With the optimistic expectation of this success, by assuming the e-bus prices can be lowered by 30% and the charging facility cost can be cut to \$150K per new bus, we use the same optimization model to construct an alternative 10-year roadmap, which significantly expedites the transition in the first several years (**Figure 15**). The purchase of e-bus is not only unequal over years, it is not monotonic. Instead, it started by purchasing 488 new e-buses in the first two years and then slows down to 200+ per year for another three years. Afterwards, it accelerates again to 488 buses per year in the last five years.

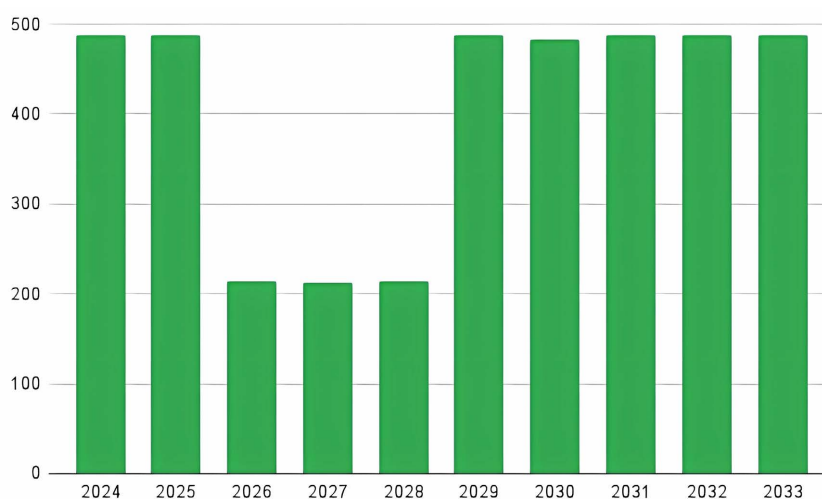


Figure 15. U-shaped purchase schedule: if the adoption cost can be reduced, the transition process can be expedited.

The accelerated purchase in the first two years is justified by the fact that the ecological benefits and operation savings can be harvested perennially after the one-time investment is made. As long as the cost is justified, it is beneficial to invest earlier. Meanwhile there is financial incentive to preserve the cash and utilize the existing bus fleet till the end of their service life. These two competing drivers lead to the U-shaped purchasing schedule in this alternative roadmap. The expedited replacement in the early years helps to decommission the worst polluting maker earlier (**Figure 16**).

Cities have different needs in their bus programs. Each city also has its unique mix of power sources, which contribute to varying ecological benefits from the transition to the e-bus future. Nevertheless, the same analytical methodology can be applied to other metropolitan areas, such as San Diego, CA and Chicago, IL. The roadmap of e-bus transition of each city is driven by its own unique situation

of multiple factors (Figure 17 and Table 13)

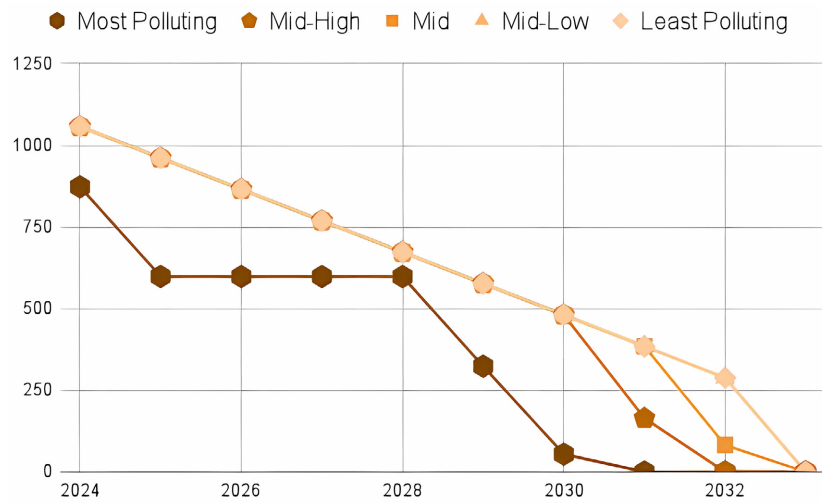


Figure 16. With lower adoption cost and expedited transition, the worst pollution makers are decommissioned even earlier. Transition roadmaps for San Diego, CA and Chicago, IL.

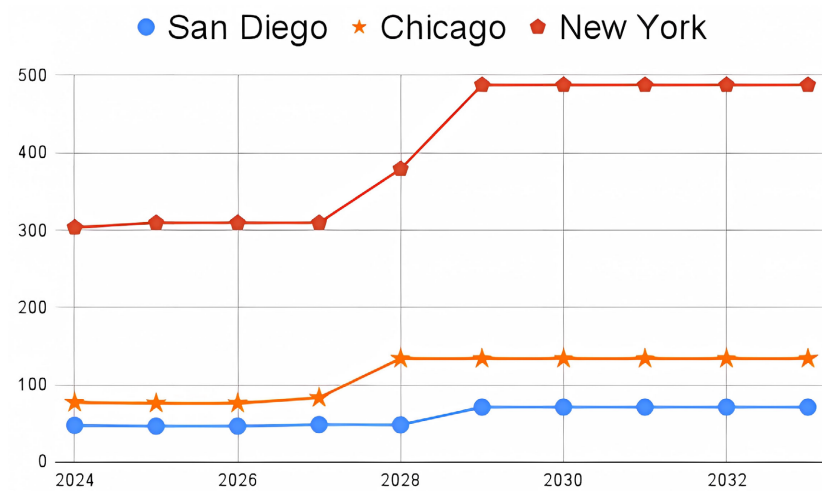


Figure 17. E-bus purchase schedule for San Diego, Chicago, and New York City. Each city has its own transition roadmap, which is determined by the varying factors.

Table 13. 10-year roadmap of transition for San Diego, CA and Chicago, IL

Year	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033
San Diego Diesel Buses	688	625	563	499	435	348	260	174	87	0
San Diego Electric Buses	48	94	141	189	237	308	380	451	522	593
Chicago Diesel Buses	1937	1761	1585	1403	1169	935	701	468	234	0
Chicago Electric Buses	77	153	229	312	446	580	714	848	982	1116

5. Model Evaluation and Discussion

5.1. Sensitivity Analysis

5.1.1. Roadmap Sensitivity to Future Ridership Trend

The baseline plan for New York City was built on a decreasing bus ridership trend,

which was extrapolated from the surveyed data in years 2012 to 2019. On the other hand, one major benefit of transition to e-bus would be the reduction of air pollution. It is possible that cleaner and more eco-friendly electric buses might attract more bus riders, and reduce the need of private transportation and further reduce greenhouse gas emission and other air pollution. Shenzhen's data shows, after transition to a full e-bus fleet, the bus ridership increased by 2% [3].

If the trend of bus ridership deviates from the historical trend, the implementation plan needs to have certain level of flexibility to adapt to the new reality. We analyze the NYC's transition plan by modelling two different future scenarios of constant ridership and another one with 1% increase per year. The results (Table 14; Figure 18 for constant ridership & Figure 19 for increasing ridership) show that the transition roadmap can be easily adjusted and adapt to potential evolution of bus ridership.

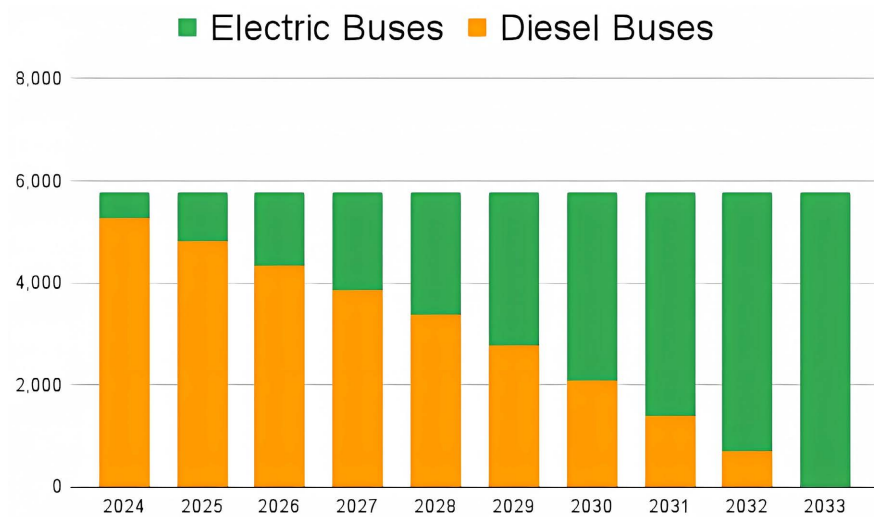


Figure 18. Alternative roadmap for the scenario of constant ridership.

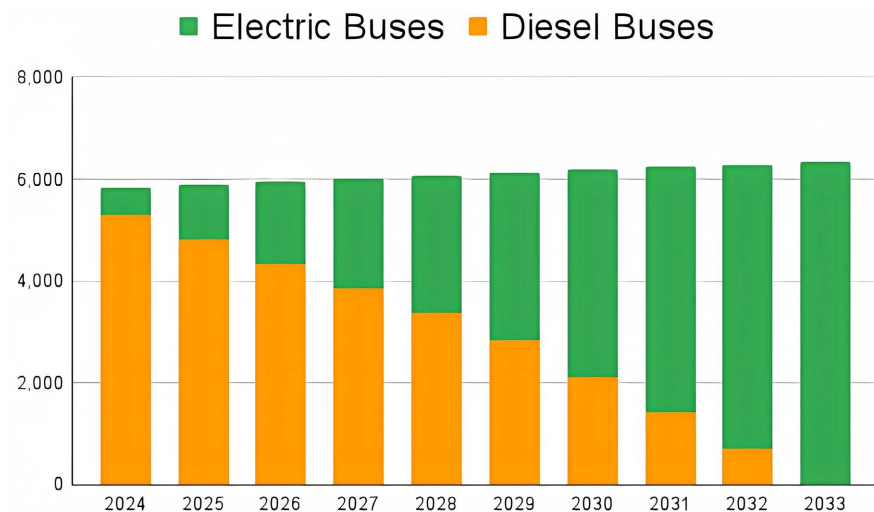


Figure 19. Alternative roadmap for the scenario of increasing ridership.

Table 14. Alternative roadmaps for the scenarios of constant and increasing ridership.

Year	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033
Constant Ridership Diesel Buses	5278	4804	4324	3843	3363	2774	2081	1387	694	0
Constant Ridership Electric Buses	502	976	1456	1937	2417	3006	3699	4393	5086	5780
Increasing Ridership Diesel Buses	5285	4804	4324	3843	3363	2821	2115	1410	705	0
Increasing Ridership Electric Buses	553	1092	1630	2168	2706	3306	4069	4832	5595	6358

5.1.2. Sensitivity to Other Model Assumptions

The optimization model assumes one budget smoothing constraint that new purchase in any year cannot be 20% more than the average of the eventual target. This constraint turns out to be binding in the planning. Without this constraint, the model would tend to concentrate more of the purchase to the last year for most US cities. This is mainly driven by the high purchase price of e-bus, the expensive charging-facility construction cost, the preference to utilize existing buses to their maximum service year, as well as the time value of money. On the other hand, we believe this constraint is practically reasonable because significant variations in project budgeting might cause more resistance from stakeholders and even interruption in future execution. We test the sensitivity and robustness of this constraint by varying its tightness to 10% and 30%, which do lead to different roadmaps from the model (Figure 20). For a tightened constraint of 10% on budget variation, the e-bus purchases are spread to more and earlier years. For a relaxed constraint of 30%, the purchase schedule is concentrated more to the later years. These differences are expected and consistent with the intention of the constraint itself.

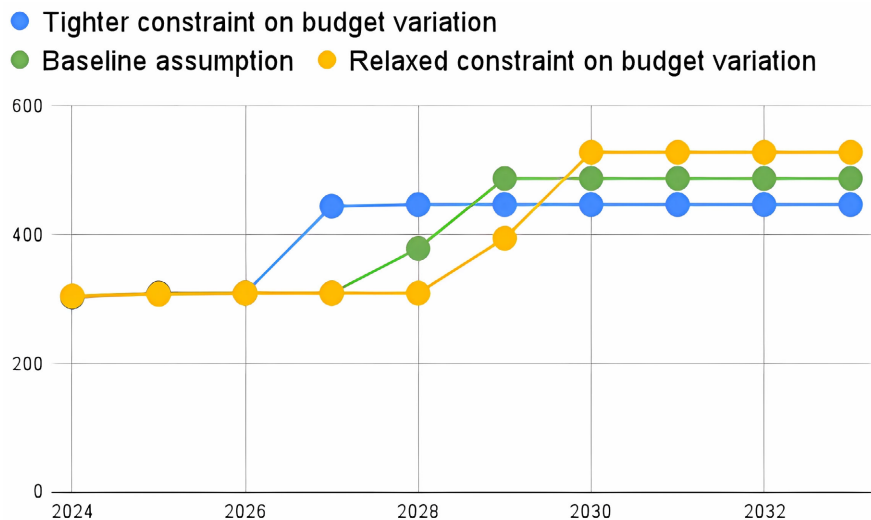


Figure 20. E-bus purchase schedule at different budget constraints.

The model assumes 5% yearly discount rate, which is based on the current interest rate in the US. The mandatory discount rate for public transportation projects may

vary according to local laws and drift over time. Our testing of the model with discount rate from 3% to 12% barely yields any difference in the transition roadmap. The tested range covers most reasonable scenarios in foreseeable future.

5.2. Model Strengths

Our models are built with live logic and data from industry reports and research papers. They are highly relevant to the topic. It helps transportation officials, government planning entities, and general public to gain in-depth understanding of the topic and get guidance on the transition process.

The transition model is highly practical. It optimizes the balance between ecological benefits and net financial costs. The roadmap generally aligns with the natural replenishment process of existing bus fleet. For the purpose of long-term planning, it takes the salvage value into modelling formula. It also mitigates the variation in budgeting over 10 years.

The transition model is robust under various scenarios of analysis and sensitivity tests. This is rooted in the practical approach of the modelling that aligns with the natural replenishment process and constrains on fleet size and budget variation.

5.3. Model Weaknesses

We built our models with current data from environmental research and transportation industry reports, and conducted near-term forecasting. On the other hand, we recognize that the design and manufacturing of electric vehicles and charging facilities are at the frontier of technology innovation. The progress in this field can be fast and potentially interrupting. More in-depth and comprehensive investigations into the technological perspective of this subject could further strengthen the report.

6. Conclusion

The model includes a detailed transition roadmap for New York City, analyzing ecological benefits and financial costs, and outlines a step-by-step procedure for decommissioning old buses. It highlights the importance of government incentives in successful transitions for U.S. metropolitan areas. The model also addresses the challenges of acquisition costs and charging facility construction, calling for collaboration and innovation to reduce these costs and enhance financial feasibility. Similarly, we have developed practical and optimized roadmaps tailored to the unique public transportation needs and electricity sources of San Diego, CA, and Chicago, IL. The model's robustness was also validated through sensitivity analyses across various scenarios involving bus ridership trends, budget constraints, and financial discount rates, with consistent results.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendix. A Report on Use of AI

OpenAI ChatGPT (Nov 5, 2023 version, ChatGPT-4)

Query1: Where can I find data on air pollutants for big cities in the U.S.?

Output: There are several sources where you can find data on air pollutants for big cities in the U.S.: The United States Environmental Protection Agency (EPA): The EPA's Air Quality System (AQS) database contains data on ambient air quality monitoring from thousands of monitoring stations around the country. It includes data on criteria pollutants, such as particulate matter (PM_{2.5} and PM₁₀), ozone (O₃), sulfur dioxide (SO₂), nitrogen dioxide (NO₂), and carbon monoxide (CO). AIRNow is another EPA website that provides real-time air quality information. The American Lung Association: Publishes an annual "State of the Air" report which provides information about air quality in the U.S., including data on various pollutants for cities across the country. Local Environmental Agencies: State or city environmental protection agencies often have their own monitoring systems and publish data on local air quality. For example, the California Air Resources Board (CARB) provides detailed reports on air quality for California cities. International Organizations: The World Health Organization (WHO) collects and provides data on air quality, including measures from cities around the world. Scientific Data Repositories: There are various scientific data repositories such as the National Oceanic and Atmospheric Administration (NOAA) and NASA that provide atmospheric data which can be used to study air quality. Remember to check the date of the last data update to ensure the information is current. When using data for research or analysis, it's also important to verify the data's accuracy, completeness, and methodology to ensure it meets your needs.

OpenAI ChatGPT (Nov 5, 2023 version, ChatGPT-4)

Query2: What's the relationship between ozone and VOC?

Output: Ozone (O₃) at ground level, also known as tropospheric ozone, is not emitted directly into the air but is created by chemical reactions between oxides of nitrogen (NO_x) and volatile organic compounds (VOC) in the presence of sunlight. Non-Methane Volatile Organic Compounds (NMVOCs) are a subset of VOCs that, as the name suggests, exclude methane (which is relatively less reactive) and are significant precursors to the formation of tropospheric ozone.

OpenAI ChatGPT (Nov 5, 2023 version, ChatGPT-4)

Query3: How many miles does a bus in NYC run on average in a year?

Output: The average annual mileage for a bus can vary based on the specific transit agency, the routes it services, and whether the bus is used for local or express routes. In the case of New York City's Metropolitan Transportation Authority (MTA), which operates one of the largest bus fleets in the United States, a typical transit bus might average anywhere from 25,000 to 50,000 miles per year. Local buses that make frequent stops might be on the lower end of that range, while express buses that travel longer distances with fewer stops might be on the higher end. The MTA also operates 24 hours a day, which means some buses are in near-continuous use, contributing to higher annual mileage. For the most accurate and

updated figures, one would need to refer to MTA's operational statistics or contact them directly. These figures can change over time due to policy changes, changes in service levels, or fleet management practices.

OpenAI ChatGPT (Nov 5, 2023 version, ChatGPT-4)

Query4: How many buses are there in the New York City?

Output: The number of buses operating in New York City can vary based on the latest updates from the Metropolitan Transportation Authority (MTA), which runs the city's public bus system. As of my last update, the MTA operated a fleet of around 5800 buses on more than 300 local and express routes. However, this number may have changed due to updates in the fleet, service changes, or policy decisions. For the most current figures, it's best to refer directly to the MTA latest reports or their official website.