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Original Paper

Assessing the Environmental, Economic, and Route Optimization Impacts of Implementing a Green Bus System in Urban Areas

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Abstract
The proliferation of e-bus has swept the globe. Many countries have begun the transformation of electric buses. Electric buses are embraced worldwide for their environmental and low-cost advantages. This work will help local governments establish a complete e-bus system.
The first question mainly addresses the ecological impact that would be brought by the impact. In this work, ***the Ecological Impact Quantification Model (EIQM)*** *is developed to address gaseous pollution including Greenhouse gas carbon dioxide, pollutants nitric oxide and PM2.5. The ecological effect enhancement with e-bus system is presented, and especially, the gaseous pollution caused by electricity production is approximated by the Monte Carlo simulation method. As a result, this team figures out that with the development of e-bus system, the average CO_2 emission per person decreases, having a reduction of 11391g at first, and 14039g after five years.*
The second question mainly addresses the financial problem that the government needs to face. In this work, ***the Quantification of Financial Impact Model (QFIM)*** *is developed. This team utilizes the differential equation to obtain the exact varying rate of diesel fuel and electricity fee, and finally determined the possible range of the government deficit. By synthesizing these data, this team discovers that the government could start reducing its deficit after 8 years of the transformation from diesel bus to e-bus, having deficit from* **$***-88,412,180 to* **$***-64,182,722.*
The third question addresses the 10-year plan for the selected city and 2 additional cities. This team develops ***Optimized Deployment Model based on Greedy Algorithm (ODGA)*** *to optimize the transformation plan over 10 years of existing bus routes and the number of e-bus to be constructed per year. Monetary and time utility is considered and Greedy Algorithm is introduced to find out the best travelling route for e-buses. This team successfully figures out the best transformation plan of*

travelling routes and number of e-bus to be constructed per year to maximize the efficiency, including 5-min interval departure time and 867 buses are required to run the proposed route in Chicago.
Finally, the team writes a piece of letter to Chicago Transit Authority and proposes the 10-year plan of e-bus system construction to guarantee the steady implementation of e-bus.

Keywords
E-bus, Contamination, Budget, Arrangement, Optimization

1. Introduction

In 2018, the UN reported that 55% of the global population resides in cities, totaling 4.2 billion people. By 2050, urban dwellers are expected to make up 68% of the world population. Coping with population growth and urbanization necessitates sustainable cities, fostering social and economic development while mitigating environmental impacts. Public transport is vital for urban sustainability, improving mobility through safe and efficient services. A sustainable transport system mitigates traffic congestion, accidents, and pollution (Perumal, Shyam, Richard, & Jesper, 2022).
China, as the largest bus manufacturer globally (Heid, 2018), has assumed a pioneering role in the electric bus industry. Mahmoud et al. contend that e-buses offer a more effective solution compared to other powertrains for achieving net zero emissions (Mahmoud, Moataz, Ryan, Mark, & Pavlos, 2016). The electric car market has matured significantly, with manufacturers offering vehicles that match conventional ones in functionality and cost. E-buses have made up 90 percent of the total sales of new urban buses in 2017, out of the 97,000 urban buses sold in China in the previous year, a significant 87,000 of them were equipped with electric power systems, while the entire European urban bus market, including both electric and traditional buses, accounted for around 13,000 units (Heid, 2018).

1.1 Problem Restatement

In the first question, this team is assigned to develop a model to aid the city in understanding what ecological impact would be brought by the e-bus system.
In the second question, this team is required to develop a financial model to concentrate on the financial influence of the e-bus system on the government. This team builds up the differential equation to calculate the range of the possible government new deficit.
In the third question, this team would mainly focus on how to optimize the bus system. This team focuses on monetary and ridership efficiency optimization. Additionally, this team considers the departure interval, frequency, and quantity of departures.

1.2 Our work

For question 1, this team develops a model to quantify the ecological impacts and qualify the results. It will mainly focus on three indicators that are related to ecological quality: emission of nitrogen oxide (NO_x), carbon dioxide (CO_2), and lung-accessible particulate matter (PM2.5). To make it closer to reality, this team will also consider the acceptance rate of people riding electric vehicles, as this will affect the government's efforts to build electric vehicle systems.

For question 2, this team develops a differential equation model to quantify the financial impact on the local government in the process of completing the electric vehicle system. This means that the model can quantify financial impacts over time. The financial impact is divided into 3 segments: construction (transformation) costs, battery abrasion cost, and delta quantity between traditional diesel fuel fees and current electric fees.

For question 3, this team develops an e-bus roadmap model to optimize the ten-year e-bus system construction. It considers the annual construction numbers of e-buses and charging posts, aiming to minimize financial stress. Additionally, the model determines the optimal running track by factoring in futuristic development centers and densely populated areas, assigning different weights for calculation. This team applies this model to two other large urban areas to derive the best ten-year roadmap.

The thought process map for this article is shown below.

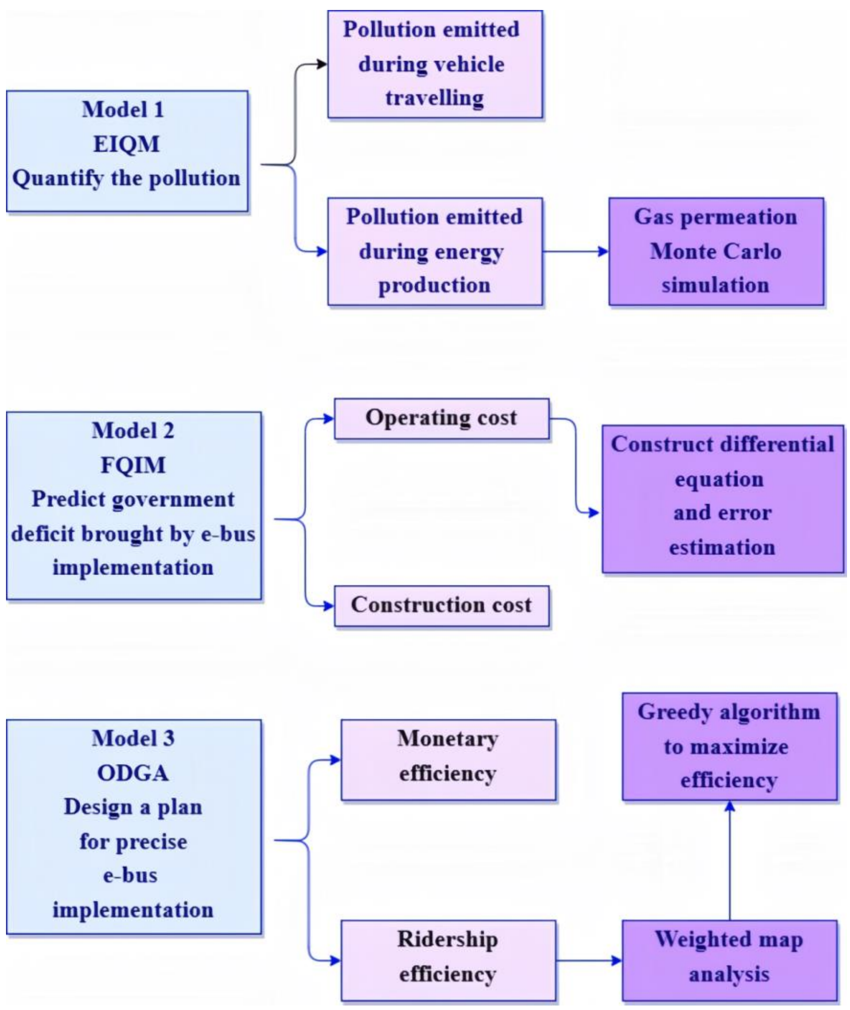


Figure1. The Flow Chart of this Paper

2. Assumptions and Justifications

Assumption 1: Leakage of e-bus batteries will have no ecological impact on the metropolitan area.

Justification 1: The government will properly dispose of discarded e-bus batteries so that they will not have an ecological impact on the urban area, which will be severe and irreversible.

Assumption 2: Highly consistent performance across all e-bus.

Justification 2: It has been researched that buses of different ages would discharge different amounts of pollution. However, the team considers the average emission data, balancing the impact of ages.

Assumption 3: The government would issue the Treasury bond to the public for the funds to be raised.

Justification 3: Treasury bond is used when new infrastructure or futuristic plans are proposed. This team does not plan to borrow money from banks, since the interest rate varies over the periods; this team does not plan to borrow money from foreign countries since this strategy needs the inclusion of the foreign currency consideration not related to this topic.

Assumption 4: E-bus uses a secondary charger to charge. Every time e-bus would run out of battery to charge before recharging.

Justification 4: The quick charger would wear out the battery, meaning it will shorten the battery's longevity. Additionally, because this team's model takes into account the scenario where the one-time rechargeable capacity of the battery decreases with aging.

3. Notation

Table 1. Symbols and Description

Notations	Definitions
Lp	Travelling miles per person
Ep	Pollutant emission per mile
r	E-bus utility rate
t	Time
Pop	Population
D_{total}	Total distance travelled by bus annually
ER	Pollutant emitted running vehicle
EP	Pollutant emitted producing fuel
ECM	kWh of electricity consumed per mile
DCM	kWh of diesel fuel consumed per mile
CEK	Carbon dioxide emitted per kWh
F	Financial deficit
C	Construction cost
p_e	Price of electricity
p_d	Price of diesel fuel

BC	Battery capacity
CPC	Charging pole capacity
SOH	State of health of battery according to time
CKE	Cost per kWh of electricity
CGD	Cost per gallon of diesel fuel
CMM	Cost per mile of maintenance
p_{rd}	Price of diesel bus repairing
$N(t)$	Number of e-bus according to time

4. Ecological Impact Quantification Model

To address question one, this paper develops an **Ecological Impact Quantification Model (EIQM)**. The calculations for this model are based on three basic data: emission of transportation, people's willingness to use e-bus over time, and emissions from electricity generation. The model can quantitatively calculate three ecological quality indicators to help qualitatively analyze ecological impacts. This question is considered in 2 phases: the traditional diesel bus era and the complete transition of the e-bus. Two timelines for the complete transformation of traditional buses and electric buses. These timelines are important since this team would calculate the specific gasoline bus pollution value before the start of the transition and the end of the transition.

4.1 Gasoline Bus Pollution

Considering air pollution, an average citizen could use the following three transportations: gasoline car, diesel bus, and e-bus. This is because the other means of transportation like biking creates little pollution, and the ridership is comparatively fixed. In this work, the average miles ran using cars, buses, and e-buses of an average person is calculated, and the CO_2 emission caused by a certain mean is miles run times CO_2 emitted per mile.

So, the carbon dioxide emission equals to:

$$E_{CO_2} = \sum_{i \in \{e,b,c\}} L(i) \cdot E(i) \tag{1}$$

where L represents length run by vehicles, E represents emission, c represents car, b represents bus and e represents e-bus. Specifically, $L(e) = 0$ at first, $L(b) = 0$ at last, and $L(c) + L(b) + L(e)$ is a fixed number because one has an almost fixed distance to travel in everyday life.

Since all buses are replaced by e-buses, this team needs to consider the relative change between $L(e)$ and $L(b)$. The difference is caused by variation of the acceptance rate of citizens, *r*, which is the proportion of citizens' willingness to use e-buses as their means of transportation compared to buses. According to data provided by Wang et al, *r* can be calculated as follows (Wang, Pei, & Wang, 2022).

$$r = \frac{1}{kt + b} + \varepsilon \quad (2)$$

After the precise calculation, the parameter k is -1.5, b is -1.5 and ε is 1.67 and t represents time. The reason the willingness is inversely proportional to the time is that the e-bus is not propagated enough initially. But with the propagation and other forms of spread, the utility of e-bus would finally rise. Notice that citizens' willingness to use buses as their transportation to use buses as transportation is already indicated by the proportion of $L(e)$ to $L(c)$), so there is no need to conclude this, especially.

Therefore, the distance traveled by an average person using e-bus can be expressed as

$L(e) = L(b) \cdot r$,

As above, the variation according to time,

$$\Delta_t = \sum_{i=a,b,c} L(i)' \cdot E(i) - \sum_{i=a,b,c} L(i) \cdot E(i) \quad (3)$$

where $L(i)'$ represents distance after transformation. And to make it clearer, this team sets $L(b') = 0, L(e) = 0, L(c)' - L(c) = L(b) - L(e')$. Notice that $L(b) = D_{total}/Pop$, and the calculated result is 21.8 miles per person. As to CO_2 emission of cars and diesel fuel buses, it can be calculated as follows.

$$E(c) = ER(c) + EP(c) \quad (4)$$

$$E(b) = ER(b) + EP(b) \quad (5)$$

The pollutant emitted running vehicle *ER* is 400g and 299g, with respect to car and bus; the pollutant emitted producing fuel *EP* is 120g and 71.71g, with respect to car and bus. Thus $E(c)$ is 520.00g/mile and $E(b)$ is 370.71g/mile. *ECM* represents kWh of electricity consumed per mile, and *CEK* represents Carbon dioxide emitted per kWh, so $E(e)$ can be calculated as follows.

$$E(e) = EP(e) = ECM \times CEK \quad (6)$$

Noticing that in Chicago, 21.5% of electricity is produced by coal, 12.8% is produced by natural gas, about 2.36 kWh is consumed per mile, 950 g of gas is generated per kWh using coal, and 350 g of gas is generated per kWh using gas thus *E(e)* is 587g/mile.

4.2 E-bus Pollution

The value above is greater than that of gasoline vehicles so it seems paradoxical. However, electricity power stations are located away from the center of Chicago, and the carbon dioxide emitted will permeate to all directions, so the air pollution of the city center is lower in terms of density than that of the power station. The density of the CO_2 gas as well as NOx and PM2.5 needs to be calculated to quantify the impact.

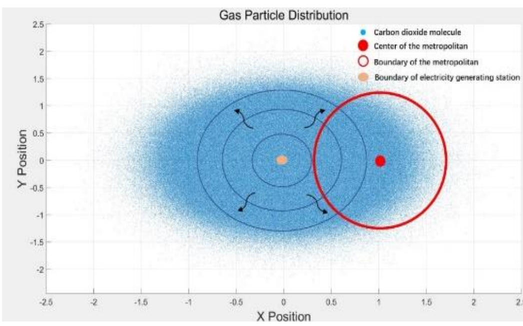
First, for CO_2, as it permeates as a gas, a gas permeation prediction model, the Monte Carlo Model, is applied to find the density of the pollutant in the city. According to Kwak and Ingall (2007), the Monte Carlo method simulates the full system many times, each time randomly choosing each variable from its probability distribution. The outcome is a distribution of the overall value of the system calculated through iterations of the model (Kwak, Young, & Lisa, 2007). With the help of MATLAB, this model uses points on a two-dimensional plane to simulate the CO_2 molecules, and every time the points move, their x and y labels go a distance randomly obeying normal distribution. In this way, after many steps, the allocation of the points assembles the CO_2 molecule permeation.

In the simulation process, the number of molecules this team adopted is 1000000 to be sufficiently large to simulate reality more accurately; The steps this team took is 10000 since this also needs to be sufficiently large and simulate the distance from Chicago center to the nearest power plant, which is approximately 10000 meters. To simplify the calculation, the length of each step is 1. And Diffusion Coefficient (*DC*) is selected from $8 \cdot 10^{-6}, 6 \cdot 10^{-6}, 4 \cdot 10^{-6}, 2 \cdot 10^{-6}$ as the DC value depends on various unknown variables, varying unpredictably.

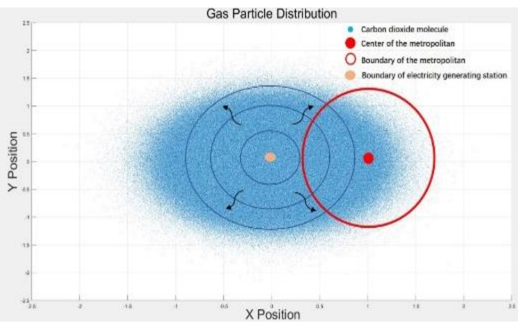
Second, for NO*x* and PM2.5, according to Allen, Marques, and Michelini (2022), one diesel bus would produce 245,000 grams of NO*x* into the atmosphere. According to the Commission (2019), the electric buses approved today will eliminate nearly 57,000 pounds of nitrogen oxides and nearly 550 pounds of fine particulate matter (PM2.5). Similarly, this team can gain the predicted variation of NO*x* emission and PM2.5 emission.

4.3 Result

Scatter graphs of Monte Carlo simulation for distribution of CO_2 are shown in Figure 2.



(a)



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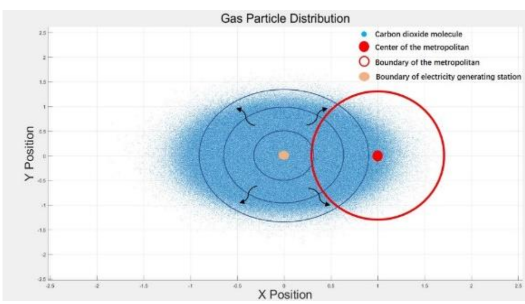

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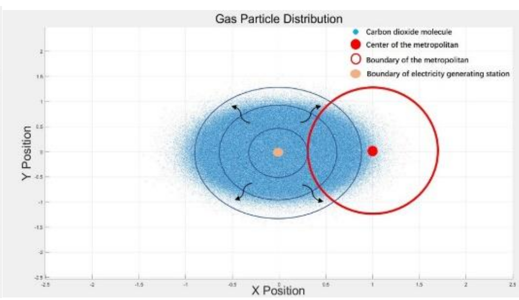


(d)

Figure 2. CO_2 Molecules Distribution (a): DC is 0.000008 (b): DC is 0.000006 (c): DC is 0.000004 (d): DC is 0.000002

The shape of the metropolitan is a circle since this team believes that in such a shape, the CO_2 molecules would spread most easily in a circular model. Specifically, this team puts a red dot, the metropolitan center, at the place *x*=1. As the decline of the *DC*, the CO_2 molecules also decrease over time.

To simulate the gas density of different areas in the graph, the number of spots in every block with a width of 0.02 and length of 0.04 is counted in Figure 3 shown below, so that the rate of the density of CO_2 is deducted. In the following graphs, the x-axis is the distance (km) from the origin of the CO_2 emission to the city center. The Y-axis represents the number of molecules.

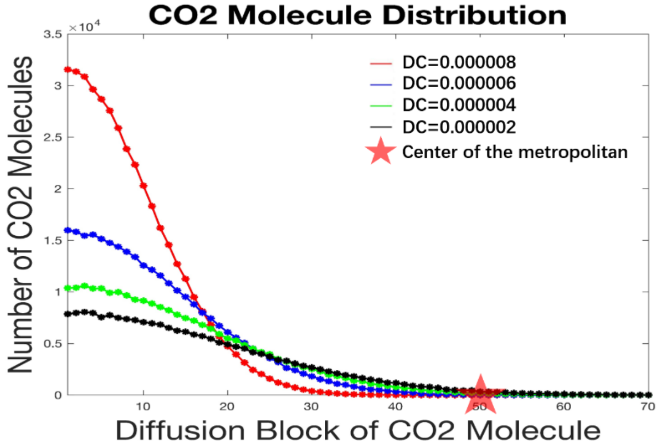


Figure 3. Variation of the Number of CO_2 Molecules Concerning the Area of the Blocks

Table 1. The CO_2 Molecule Density Concerning the Variation of Diffusion Coefficient

DC	0.000002	0.000004	0.000006	0.000008
The Number at the center	31738	15768	10644	8048
The Number at the 50th block	0	33	165	420

The CO2 molecule density concerning the variation of diffusion coefficient is displayed in Table 2. The number of CO_2 molecules at the 50th cube (also the red star) is examined as it assembles the distance from the power plant to the Chicago city center (10000m). After examining the 4 results above, the third result is chosen. This is because the first two results have a too-small ratio (0 and 33 compared to 31378 and 15768) due to the limited number of points and limited number of steps. The ratio of the density of CO_2 in the city center and the power plant is approximately 0.016. Thus, the equivalent effect of the power plant CO_2 emission is 9.39g according to formula (6). In conclusion, the predicted CO_2, NO_x and PM2.5 emission change per person is shown in Figure 4, Figure 5 and Figure 6.

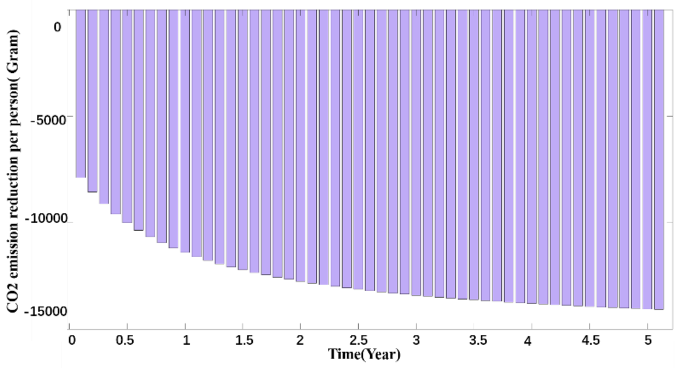


Figure 4. CO_2 Emission Reduction per Person over Time

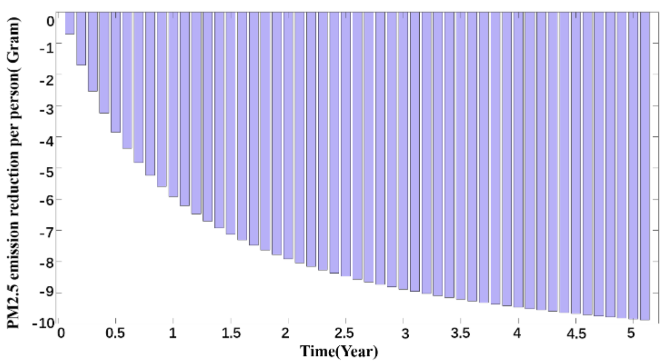


Figure 5. NOx Emission Reduction per Person over Time

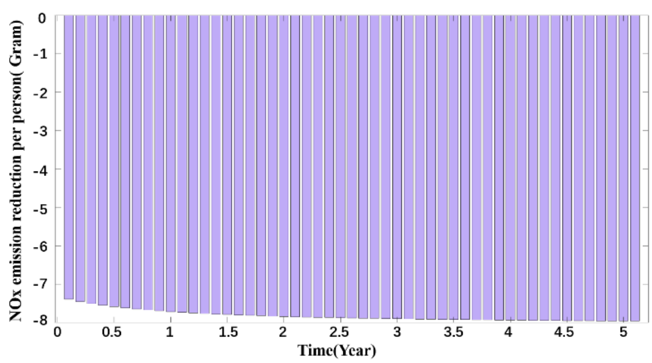


Figure 6. PM2.5 Emission Change per Person over Time

Table 2. Predicted Emission of CO_2, NOx and PM2.5 over the Next Five Years

	After 1 year	**After 2 years**	**After 3 years**	**After 4 years**	**After 5 years**
Variation of CO_2 emission(g)	-11391	-12738	-13394	-13783	-14039
Variation of NO_x emission(g)	-5.914	-7.911	-8.884	-9.460	-9.841
Variation of PM2.5 emission(g)	-7.713	-7.837	-7.898	-7.933	-7.957

NO_x and PM2.5 follow the same procedure as CO_2's calculation. Therefore, to avoid the prolix formula presentation, this team just directly places the final data in Table 3. It can be concluded that within five years of the introduction of electric vehicles, there was a significant reduction in CO2 emissions in the metropolitan area, as well as a yearly reduction in NO*x* and PM2.5 emissions, which had a very positive impact on the ecology of the urban area.

5. Financial Quantification Impact Model

The Financial Quantification Impact Model (FQIM) is developed to quantify how much the transition cost impacts society. This model is constituted of three elements: fixed cost, battery degradation, and the delta quantity between traditional diesel fuel fees and current electric fees**.** This model successfully measures the amount of difference in the financial deficit that the government needs to face, including 3 aspects: the construction cost, battery abrasion cost, and the variation of operating fees.

Financial deficit is a delta quantity that includes fixed cost, battery abrasion, and the difference between diesel fuel price and electricity fee, *C* represents construction cost.

$$\frac{dF}{dt} = \frac{dp_e}{dt} - \frac{dp_d}{dt} - \frac{dp_{rd}}{dt} \tag{7}$$

F represents the financial deficit, p_e represents the price of electricity, p_d represents the price of the price of diesel fuels and p_{rd} represents the price for repairing the diesel bus.

5.1 Construction Cost

Fixed cost includes the fees that transform the diesel bus into e-bus. The transition preparation fee before putting e-buses in use to replace the fuel buses contains the cost of the purchase and implementation of charging poles, and the cost of attaining e-buses. According to research, the cost of purchasing one e-bus is about **$**350000, while the cost of transforming a fuel bus into an e-bus is critically lower, with about **$**150000, so the second choice is the wiser one. Different types of charging poles are considered and the type CCS2 160kW IEC 62196 DC Bus Fast Electric Vehicle Car EV Charging Station is chosen due to its high efficiency and relatively acceptable price, costing **$**3000 each, and having a capacity of *CPC*=160 kW. The buses are designed to be long-range battery electric buses (BEBs) that have a battery capacity of BC=450 kWh on average, and they need only one charge every day. The number of buses needed is 1800, the same as the buses in Chicago right now. The time that one bus needs to get fully charged is:

$$T_{charge} = \frac{BC}{CPC} \tag{8}$$

and it is approximately 3 hours after adding the time needed to switch the buses to get charged, and the time available for charging is 8 p.m. to 5 a.m. Therefore, a charging pole can charge three buses in one day, which means that a total of 600 poles are needed. To sum up, the money needed for pole purchasing is 1.8 million dollars. In conclusion, the fixed money needed for preparation is 271.8 million dollars.

5.2 Operational Cost

5.2.1 Battery Degradation

As a natural process, battery degradation decreases the electricity capacity of the batteries and the energy provided by the battery. Therefore, a utility percentage needs to be calculated to determine how much electricity is needed for an aged bus and a new bus.

According to Argue (2020), the State of Health (*SOH*) is studied and corresponds with time, vehicle age, temperature, and charging level. Under the insufficient data situation, this team fitted the graphs one by one. Specifically, the formulas are fitted and weighted due to the preceding coefficients. The fitted equation is listed below.

The relationship between SOH and time is not linear, and it can be calculated as follows.

$$S_0 = p_3 t^3 + p_2 t^2 + p_1 t + p_0 \tag{9}$$

where p_3=-0.00119, p_2=0.01429, p_1=-0.0631, p_0=1.

The relationship between SOH and time affected by temperature level is linear, and it can be calculated as follows.

$$S_1 = -0.0025t + 1 \tag{10}$$

The relationship between SOH and time affected by charging type is linear, and it can be calculated as follows.

$$S_2 = -0.0075t + 1 \tag{11}$$

The relationship between SOH and time affected by utility level is linear, and it can be calculated as follows.

$$S_3 = -0.0075t + 1 \tag{12}$$

Considering all these factors are conducive to battery degradation, our team utilizes the entropy method to weigh each state of health affected by the factors separately. Calculating the derivative of each influencing factor ($S_1, S_2, S_3, and\ S_4$) as $a_1, a_2, a_3, and\ a_4$), weight coefficient $b_1, b_2, b_3, and\ b_4$ can be calculated using the equation below.

$$b_n = \frac{a_n}{a_1 + a_2 + a_3 + a_4} \tag{13}$$

With independent variable *t* changing from 1 to 10, $b_1, b_2, b_3, and\ b_4$ can be calculated according to Table 4.

Table 3. Weight Coefficient of Influencing Factors

t	$b1$	$b2$	$b3$	$b4$
1	0.4006	0.2629	0.2629	0.0736
2	0.2618	0.3238	0.3238	0.0907

3	0.1427	0.376	0.376	0.1053
4	0.0938	0.3975	0.3975	0.1113
5	0.1422	0.3762	0.3762	0.1053
6	0.2611	0.3241	0.3241	0.0907
7	0.3998	0.2632	0.2632	0.0737
8	0.5248	0.2084	0.2084	0.0584
9	0.6251	0.1644	0.1644	0.0461
10	0.702	0.1307	0.1307	0.0366

Combining the four factors, the Battery State of Health over time can be calculated as formula (14). The function of battery health condition according to three different factors time, type and utility level, and temperature and the combined function are shown in Figure 7. The x-axis is time, and y-axis is battery health condition with 1 representing the highest.

$$SOH = 0.35539(-0.00119t^3 + 0.01429t^2 - 0.0631t + 1) + 0.56544(-0.025t + 1) + 0.07917(-0.0075t + 1) \tag{14}$$

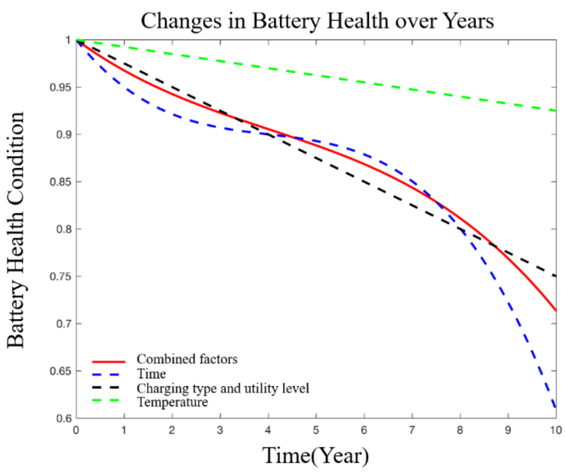


Figure 7. Battery State of Health

The blue line represents the battery health condition varies along time when other conditions stay the same. The black line represents that varies along charging type and utility level. The green line represents that varies along temperature. The red line represents that varies along combined factors.

5.2.2 Variation of Operating Cost

The variation of operating cost is the cost of electricity minus the cost of diesel fuel, minus the cost of the repairing of diesel fuel buses. Since the charging poles are implemented gradually, and e-buses cannot function without a charging pole, the speed at which the government adds new e-buses into the transportation system needs to be proportional to the number of charging poles, which increases linearly. Therefore, considering the function $y = N(t)$ of y, the number of e-buses, to t, the time, the differential of function y is a linear expression of t, which means that $y = N(t)$ has a degree of two. Furthermore, at the beginning, there is no charging pole, which means that the speed of the implementation at the beginning is 0 thus $N(0)' = 0$, $N(t) = a \cdot t^2$. And it can be calculated as follows.

$$N(t) = \frac{225}{8} \cdot t^2 \tag{15}$$

The useful data is collected below: kWh of electricity consumed per mile (ECM); cost per kWh of electricity (CKE); gallon of diesel fuel consumed per mile:(DCM); cost per gallon of fuel (CGD); cost per mile of maintenance (CMM).

The cost for electricity per bus is calculated below:

$$\frac{dp_e}{dt} = CKE \times D_{total} \times ECM/1800 \tag{16}$$

However, the estimation above is an ideal situation, in which a bus will never age. The fact is that as a bus ages, its battery will age, which results in the reducing charging efficiency. As calculated above, the state of health of the battery represents the efficiency of the utility of electricity. Therefore, when calculating the actual cost of electricity, *SOH*, as well as the efficiency, need to be divided.

The cost of diesel fuel per bus is also calculated considering a bias caused by vehicle aging. And as the price of diesel fuel varies in normal distribution, this team believes that there is a price fluctuation in the cost of diesel fuel per bus and it can be calculated as follows.

$$\frac{dp_d}{dt} = CGD \times D_{total} \times DCM/1800 \tag{17}$$

The cost of diesel bus maintenance per bus can be can be calculated as follows.

$$\frac{dp_{rd}}{dt} = CMM \times D_{total}/1800 \tag{18}$$

The variation of operational cost can be calculated as follows.

$$\int N(t) \cdot (\frac{dp_e}{dt}/SOH - \frac{dp_d}{dt}) - (1800 - N(t)) \cdot \frac{dp_{rd}}{dt} \tag{19}$$

5.3 Result

This team depicts Figure 8 above to demonstrate the varying maintenance cost when the variable is in normal distribution. The numerical value includes the mean, max value, and min value. The operating cost decreases from **$**-52,000,000 to **$**-28,000,000. Total transition cost of the eight years is calculated according to formula(19) and the result varies from **$**-88,412,180 to **$**-64,182,722. In assumption 3, this team considers using the government bond to raise at least half of the fixed cost, which is **$**135,900,000, and this is the amount of money that the government needs to afford due to the question requirement. However, due to our numerical analysis above, the government not only could cover up **$**135,900,000, but also could earn **$**88,412,180, and this profit will continuously increase as time passes by.

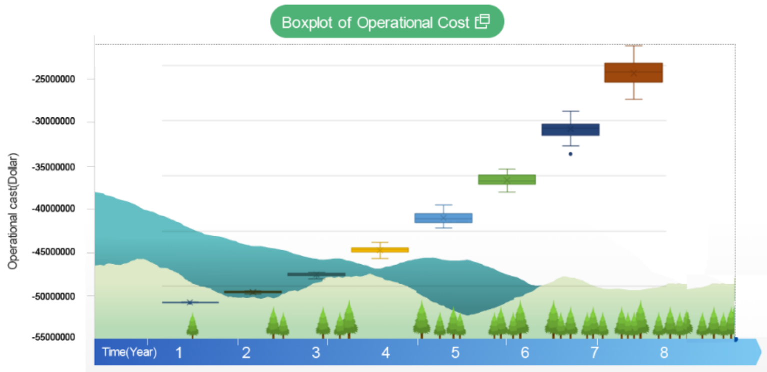


Figure 8. Predicted Operating Costs of the Chicago E-bus System over the Next Eight Years

6. Optimized Deployment Model Based on Greedy Algorithm

This team selects other 2 cities based on the utility of e-bus status quo and latitude. This team firstly selects Chicago city as a model to further reflect the other 2 cities. This is because Chicago has a transparent future development plan and plenty of data. Toronto and Miami are also selected since these 2 cities resemble Chicago, where e-bus is not sufficient but both are ambitious to replace the diesel cars with e-buses.

This team designs the Optimized Deployment Model based on Greedy Algorithm to optimize the ridership efficiency and monetary efficiency. The model, ODGA, is established to can find the optimized options. With the data about the location of highly populous areas, the model gives an optimized design of e-bus routes using greedy algorithms, so that every route can satisfy most people's need of e-bus. According to Barron et al. (2008), greedy algorithm does not only help the optimization, but also help to address the approximation (Barron, Albert, Wolfgang, & Ronald, 2008).

6.1 Monetary efficiency

For the monetary efficiency part, this team considers the profit maximization. Initially, as question 2 suggested, a great amount of money is needed to transform the diesel bus to the e-bus. Therefore, this team needs to address the issue of where the government can get the funding? How much money could be lent?

This team concerns the relationship between the tax revenue and the number of e-bus that are intended to be produced. Therefore, this team determines that when there is a high tax revenue, there is more bus transformation; when there is a low tax revenue, there is less bus transformation.

$$R(t) = p_1 \cdot t^3 + p_2 \cdot t^2 + p_3 \cdot t + p_4 \tag{20}$$

where the accurate calculation, the coefficients p_1 is 1.522, p_2 is -88.92, p_3 is 1757 and p_4 is -11230. This is based on the Chicago data for annual government annual tax revenue. According to UChicago Medicine (2023), the ratio of tax revenue and expenditure on traffic is 25 to 1. Since the cost for the e-bus is fixed as shown in question 2, if the tax revenue could be determined, the number of buses that need to be transformed could also be determined.

6.2 Ridership Efficiency

This plan mainly concerns the population flow in one metropolis. Newly established bus routes can be more aligned with areas of dense population flow. The dense areas are determined by the weights that how many dense population areas there are in one block.

6.2.1 Weight Allocation of the Map

Fig.8 below is the map of Chicago. To attain a countable overall data representing the allocation of the routes, the following method is used: First, the whole Chicago city is divided into 8 columns and 12 rows, which totally counted as 96 blocks. In each part a square, and the red lines below show the divide. Second, in every separated district, the team evaluates the urgency of the need of e-bus based on whether there are or will be places that have a large population flow and in need of more e-buses. The e-buses have a priority to pass these districts that have more places in need of the traffic to alleviate the burden of transportation.

Here are three places this team focuses on. Hospitals are places that the most population enter and leave, especially those weak or old. As a result, hospitals are considered a place urgently in need of clean, safe, and comfortable e-buses. The team tried to consider all the schools but found that the population of other schools is too small compared to that of the universities. Thus, only universities with an unignorable population are considered. Every local government has its own plans, which include the places that it will focus on to construct a commercial center. These places are also the important factors to consider while designing our routes. Then the number of hospitals, universities, and future development centers in each district is counted and recorded in Figure 10 using three-dimensional number lists.

Figure 9. Map of Chicago

(1,0,0)	(1,0,0)	(0,0,0)	(1,0,0)	(1,0,0)	(0,0,0)	(0,0,0)	(0,0,0)
(1,0,0)	(1,0,0)	(0,0,0)	(0,0,0)	(1,0,0)	(0,0,0)	(0,0,0)	(0,0,0)
(0,0,0)	(0,0,0)	(1,0,0)	(0,0,0)	(1,0,0)	(0,0,0)	(0,0,0)	(0,0,0)
(0,0,0)	(0,0,0)	(0,0,0)	(2,0,0)	(2,0,0)	(4,0,0)	(0,0,0)	(0,0,0)
(2,0,0)	(1,0,0)	(1,0,0)	(0,0,0)	(2,0,0)	(4,2,1)	(0,0,0)	(0,0,0)
(0,0,0)	(1,0,0)	(2,0,0)	(1,0,0)	(4,0,0)	(3,6,1)	(2,0,0)	(0,0,0)
(0,0,0)	(2,0,0)	(1,0,0)	(0,0,0)	(3,0,1)	(0,0,0)	(2,0,1)	(0,0,0)
(2,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(1,1,0)	(0,0,0)
(1,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(1,0,0)	(1,0,0)	(2,0,1)	(0,0,0)
(0,0,0)	(0,0,0)	(0,0,0)	(1,0,0)	(1,0,0)	(0,0,0)	(0,0,0)	(2,0,0)
(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(1,0,0)	(0,0,0)
(0,0,0)	(0,0,0)	(1,0,0)	(0,0,0)	(1,0,0)	(0,0,0)	(0,0,0)	(0,0,0)

Figure 10. Hospital, University, and Center Distribution Graph

To calculate the importance of every district in terms of bus route, hospitals, universities, and future centers are each given a weight, and the values in corresponding blocks of the three graphs are added together to get an overall evaluation of the districts shown in Figure 11 below. Weight of the three places is evaluated according to predicted population flow ratio: population flow per day of hospitals is around 50000, population flow of universities is around 20000, and predicted population flow of commercial centers is around 100000. The weight of the hospital, university, and future center are 5, 2, 10, respectively. Bigger number and darker color mean greater urban significance. For instance, 0 represents the lightest purple color, and 34 is the darkest purple one. Noticeably, the blue 0 is an oceanic area.

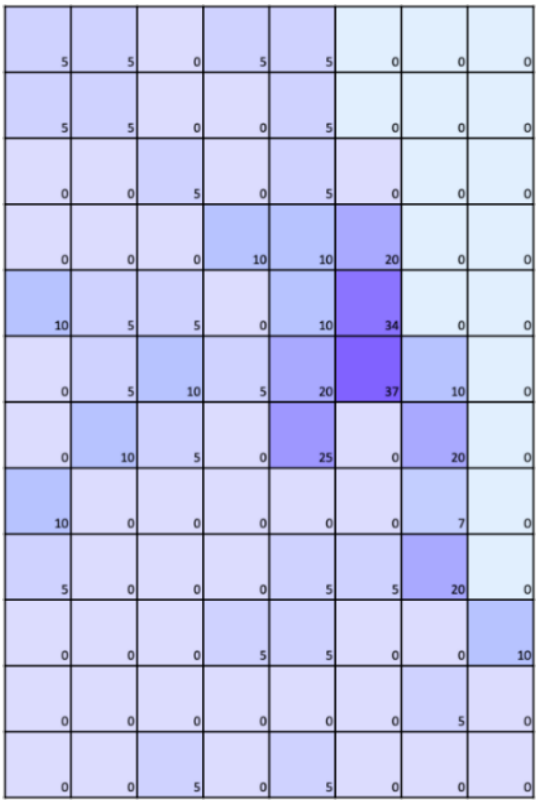


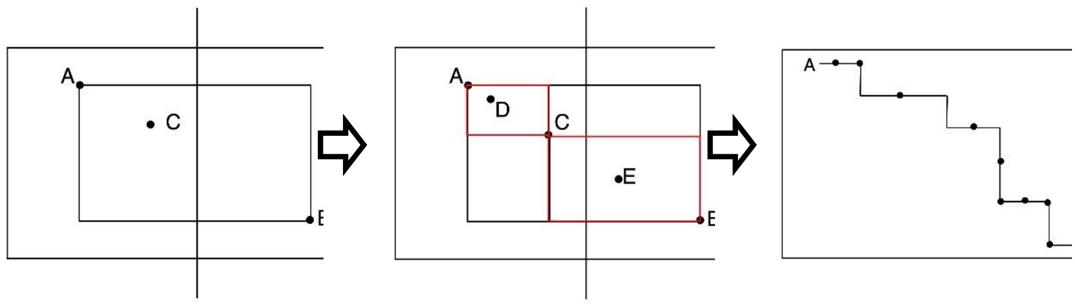
Figure 11. Chicago Weight Distribution Chart

6.2.2 Implementation of the Greedy Algorithm

Greedy algorithm is the strategy that during each step of a whole series of processes, the best choice for this simple step is made regardless of steps following. The target of using greedy algorithm in this question is to optimize the number of routes and the number of e-buses and charging posts deployed by the government each year to minimize money costs and maximize ridership efficiency.

To achieve the target, it is necessary to create a list of routes, each passing the points that are the most urgent to use the e-bus and has not been passed by routes in the list before, to maximize the ridership efficiency as much as possible each time a new route is constructed. The detailed process of the greedy algorithm is shown in Figure 12. There are two major types of roads, one type crosses the city horizontally, another vertically. For horizontal ones (same as vertical ones), one of the calculation loop can be described as follows.

- This team divides the whole graph into two parts with a vertical line. During each turn, the points that have the largest weight are chosen, 1 from each side. These two points, A and B, are the starting and ending points of the route.
- Then consider the rectangle that these two points encompass and the points inside it: choose a point C in the rectangle that has the largest weight and has not been deleted yet. Then the route will pass A, C, and B.
- Then the point with the largest weight that has not been deleted, D and E, is taken from the rectangle encompassed by A and C, and C and B.
- Then continuously repeat this process until there is no point with a weight bigger than 0 to choose.
- If two continuous points chosen by the program are adjacent, the route simply needs to go directly from one to another. If not, the route needs to pass through these two points so that it also passes the points encompassed by the two points. After this procedure, delete all the points on this route. So far, this turn is complete, and the loop is repeated until all non-zero points are deleted.



(a) (b) (c)

Figure 12. Schematic of the Greedy Algorithm

However, after the program above, the route design is still flawed. Notice that the algorithm above completely ignores the districts with a weight 0 which results in these districts not passed by the route. Therefore, it is necessary for the team to add those districts into the routes by hand. The rule is to link most of the 0 districts to its adjacent non-zero districts with the routes that already exist.

6.3 Result

6.3.1 Result of Chicago

After accurate calculation according to section 6.1 and 6.2, the route of Chicago's e-bus system is shown in Figure 13.

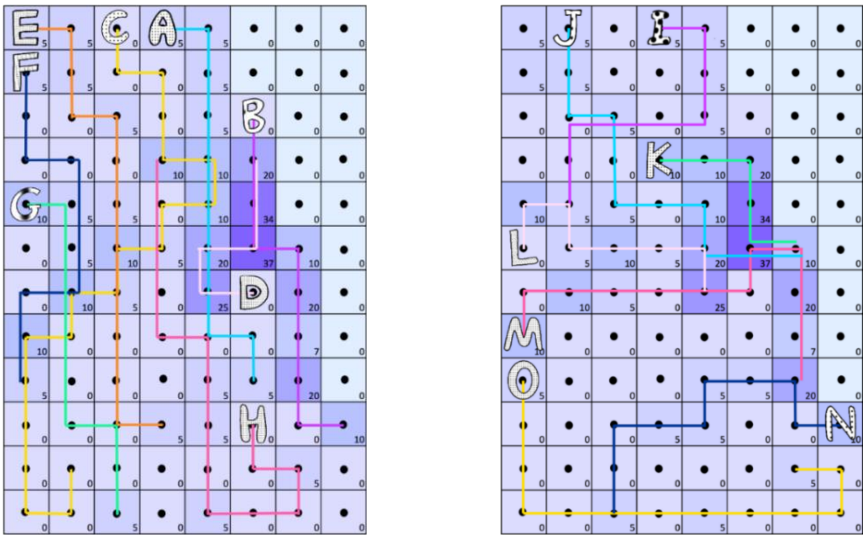


Figure 13. Bus route of Chicago

Then the time sequence of constructing these routes is decided according to the sequence that each route is created by the computer. And the program decides the order based on the largest weighted districts not covered yet, which means that by following this order of construction, the government can cover areas that need e-bus most economically and efficiently. Construction sequence of e-bus route, number of e-bus to be built per year and total cost in transforming e-bus and building charging pole are displayed in Table 5. The configuration of buses along each route is primarily determined by the departure interval and distance. This team determined the side length of these city squares, along with the scale of the actual paths. Then this team estimated the total path length from the graphical representation. After consulting the average car travel speed of around 25 kilometers per hour, the team adjusted departure intervals to five minutes. Since buses typically operate round trips, the team ensured a continuous presence within the given time frame for a bus round trip. Additionally, this team reserved extra vehicles corresponding to the route length to mitigate disruptions caused by factors such as driver breaks and vehicle breakdowns.

According to solution for question 2, in generally, each e-bus would cost **$**150,000 and each charging pole would cost **$**3,000. The team recommends that the Chicago government build the D and K bus lines in the first year at a total cost of **$**3,000,000 for 20 new e-buses and **$**21,000 for 7 new charging poles, respectively. In the seventh year, the largest number of buses would be built, with 110 new buses at a cost of **$**10,500,000 and 37 new charging poles at a cost of **$**1,117,000. By adhering to this ten-year plan, the Chicago government will complete the construction of the e-bus system at the lowest possible cost and improve the efficiency of travel for its citizens.

Table 4. The Estimated Number of Electric Buses Needed to Operate Annually in Chicago

Time (Year)	E-bus route	E-bus number	Cost in e-bus($1m)	Charging pole number	Cost in charging pole($)
1	D	20	3	7	21000
1	K	20	3	7	21000
2	B	55	8.25	18	54000
2	J	55	8.25	18	54000
3	A	55	8.25	18	54000
3	M	65	9.75	22	66000
4	F	68	10.2	23	69000
4	L	40	6	13	39000
5	E	70	10.5	23	69000
6	N	50	7.5	17	51000
7	C	110	16.5	37	117000
8	I	50	7.5	17	51000
9	G	55	8.25	18	54000
10	O	55	8.25	18	54000

6.3.1 Result of Miami and Toronto

The new routes are centered on the most crowded districts, and evenly spread to other blocks, creating an efficient and low-cost public transportation network. By using the similar strategy, the maps of Miami and Toronto are divided into square districts, the weights are added, and the bus routes are designed with a time order. After the same accurate calculation as in Chicago, the route of Miami and Toronto e-bus system is shown in Figure 15 and Figure 16. Comparing the maps of the two cities separately, it can be seen that the e-bus routes cover the main streets and population centers of the two cities reasonably well.

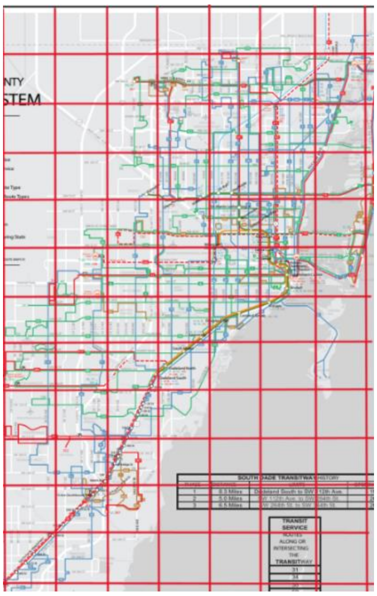


Figure 14. Map of Miami

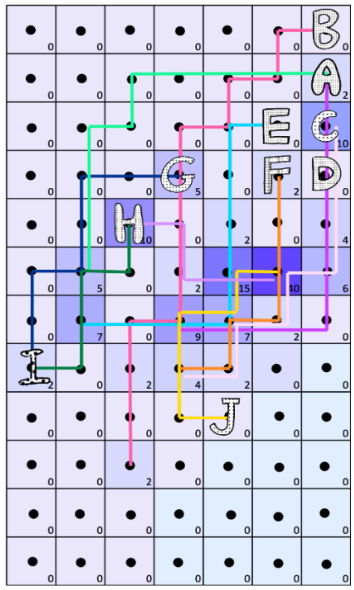


Figure 15. Bus Route of Miami

Figure 16. Toronto Map

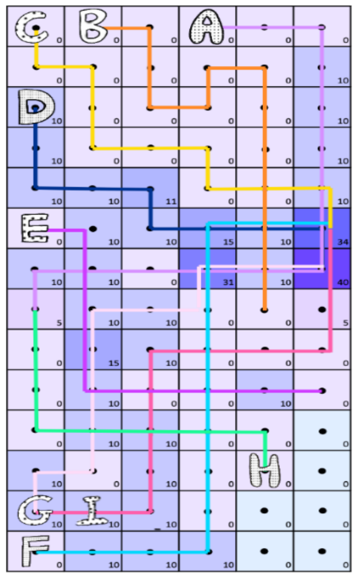


Figure 17. Bus Route Design of Toronto

Construction sequence of e-bus route, number of e-bus to be built per year and total cost in transforming e-bus and building charging pole for Miami and Toronto are displayed in Table 6. If the two municipalities follow the transition plan below, the e-bus system will also be built at the lowest possible construction cost and Toronto city will only need nine years to complete the full plan.

Table 5. The Estimated Number of Electric Buses Needed to Operate Normally in Miami and Toronto

Time (Year)	Bus route	E-bus number	Cost in bus($ 1m)	Charging pole number	Cost in charging pole($)	Time (Year)	Bus route	E-bus number	Cost in bus($ 1m)	Charging pole number	Cost in charging pole($)
1	J	55	8.25	18	54000	1	D	30	4.5	10	30000
2	H	30	4.5	10	30000	2	A	48	7.2	16	48000
3	F	35	5.25	12	36000	3	G	38	5.7	13	39000
4	D	40	6	13	39000	4	I	40	6	13	39000
5	C	35	5.25	12	36000	5	C	35	5.25	12	36000
6	E	40	6	13	39000	6	F	45	6.75	15	45000
7	B	70	10.5	23	69000	7	E	36	5.4	12	36000
8	I	30	4.5	10	30000	8	H	30	4.5	10	30000
9	G	35	5.25	12	36000	9	B	40	6	13	39000
10	A	50	7.5	17	51000	\	\	\	\	\	\

7. Model Testing

7.1 FQIM Robustness Test

To test the robustness of FQIM, this team put the model into Miami to see its robustness. This team would use the same requirement as question 2 to test the model. Miami-Dade Transit has 817 buses, construction cost is the cost of bus transformation added to the cost of charging poles, which equals 123.4 million dollars. The calculated result p_e, p_d, p_{rd} is \$4230, \$25,989 and \$31,236 per bus, respectively. The variation of operational cost shows in Figure 18.

Figure 18. Predicted Operating Costs of the Miami E-bus System over the Next Eight Years

The total transition cost after 8 years is **$-**267,785,586. The result also shows that after 8 years, the construction cost will be completely covered by the money saved from diesel fuel consumption, let alone the 50% cover of the transition cost, showing a similar result with the model applied to Chicago. In addition, the profit is even larger, due to comparatively small number of buses in Miami, and its heavy public traffic because of tourism.

7.2 ODGA Sensitivity Test

To test the sensitivity of the ODGA model, the team decides to assign random values from 1 to 10 to the three kinds of areas to test the sensitivity of the model to parameters. Using computer to generate random numbers, the team allocates two groups of weights to hospitals, universities, and future development centers: 5, 8, 3 and 2, 7, 6 respectively.

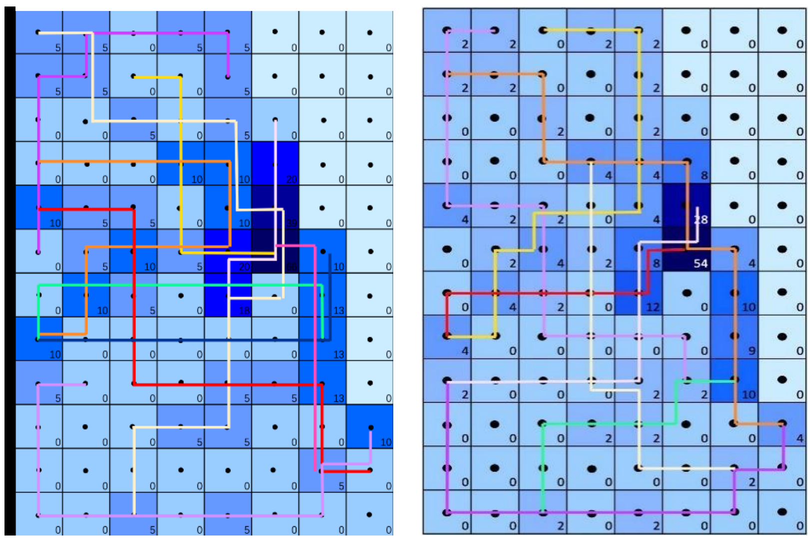


Figure 19. Bus Route Design of Chicago with Different Weights

The outcome after the arbitrary weight giving shares both similarities and differences with the original one. The similarity is that the routes are still largely focusing on few points with the deepest color and largest weight. These points are passed by the largest number of routes. Moreover, the annual and overall cost of bus transformation and charging pole purchase is still in an acceptable range with a similar pattern to the previous outcome. Thus, the design still guarantees minimum cost and maximum efficiency.

Table 7. The Estimated Number of Electric Buses Needed to Operate Normally in Sensitivity Test

Color	E-bus number	Cost in e-bus($1m)	Charging pole number	Cost in charging pole($)
Rose red	85	12.75	29	87000
Red	50	7.5	17	51000
Light green	43	6.45	15	45000
Light purple	32	4.8	11	33000
Orange	24	3.6	8	24000
Yellow	35	5.25	12	36000
Black	52	7.8	18	54000
White	35	5.25	12	36000
Dark green	55	8.25	19	57000
Dark purple	35	5.25	12	36000

The difference is obvious on the design of marginal areas as the weight of these areas differ largely due to the arbitrary weight giving. Comparative weights of some marginal points alter and lead to a change in route point choosing in the loop.

This analysis shows that the algorithm is highly sensitive to the allocation of high-density areas, namely hospitals, universities, and future development centers on the map, which decide the whole weighting trend of the map and the whole trend of route design. However, it is less sensitive to reasonable adjustment on allocation of weights as the most weighted districts encompass nearly all three kinds of populous places, which guarantees their dominant status in the whole map. Also, it is stable in terms of financial performance as the cost per year varies under complete expectation and control.

This property adds to the reliability and promotability of the model, as the precise weight allocation may vary in various cities. That is to say even if bias exists in the weighting process, the final outcome of the route design can still be applied to the real situation.

8. Strengths and Weaknesses

8.1 Strengths

1. The Ecological Impact Quantification Model considers sources of pollution comprehensively with a varying acceptance rate of e-bus to simulate the reality precisely. Also, the Monte Carlo model guarantees the reliability of pollutant permeation simulation.

2. The Quantification of Financial Impact Model uses a differential equation and takes an acceptable error caused by normal distribution of diesel bus aging into consideration, which adds to its scientific rigor and authenticity.

3. The Optimized Deployment Model based on Greedy Algorithm makes use of greedy algorithm,

which ascertains the highest efficiency constructing every new bus route by passing the most districts in need of e-bus.

8.2 Weaknesses

1. The disadvantage of EIQM is that it ignores the period that is between the start of e-bus implementation and end of it.
2. The disadvantage of QFIM is that inflation is not considered, due to the difficulty of prediction.
3. The shortcoming of ODGA is that because of the greedy algorithm, the final whole route system may not be the best among all designs.

9. Conclusion

In the first question, this team applies EIQM to quantify the ecological impact to Chicago. When an error occurs, this team utilizes the Monte Carlo Model to simulate the real gas spread situation. The result is explicit when the diffusion coefficient decreases. In the second question, this team applies FQM to measure the quantitative influence to the government administration. The result is promising and optimistic since the government deficit would decrease after 8 years and even earn profits since then. In the third question, this team adopts optimized deployment model to simultaneously maximize monetary and ridership efficiency. The feasibility is tested and solidified.

10. Post of Assignment

Sparkling Chi-E Proposal

November 12, 2023

The Honorable Dorval R. Carter
President
Chicago Transit Authority
3112 W Foster Ave
Chicago, IL 60625

Dear Dorval R. Carter,

As the proliferation of the green energy vehicle, the team congratulates the Proterra 600-Series. This type of electric bus is currently operational on the thoroughfares of Chicago. This is a huge leap in Chicago's transportation history.

This team strongly proposes that the CTA should operate the e-bus system in future years. As you anticipate, the e-bus system holds the promise of delivering significant advantages to both government administration and the public. Specifically, the e-bus could simultaneously reduce air pollution and decrease government deficit by a great magnitude.

Additionally, this team proposes an e-bus 10-year plan to maximize the efficiency of the construction of e-bus and the crowd flow. In the map the team proposed, massive crowd-gathering spots are considered. By using the data from the *City of Chicago*, this team predicts the future crowded places and through weights comparison finally offers the futuristic e-bus routes that traverse Chicago metropolitan to the CTA.

Thank you for your consideration of our suggestions. We look forward to your response and the opportunity to work with you to achieve success for the e-bus plan and ensure it serves its designated purpose with appropriate participation.

Sincerely,
Team 13909

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