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Minimization of Carbon Footprint of Transit Agencies by Adopting Alternative Fuel Technologies

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Minimization of Carbon Footprint of Transit Agencies by Adopting Alternative Fuel Technologies

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B.Sc., Bangladesh University of Engineering and Technology, 2015

A Thesis
Submitted in Partial Fulfillment of the Requirements for the Degree of Masters of Science
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Minimization of Carbon Footprint of Transit Agencies by Adopting Alternative Fuel Technologies

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CHAPTER 1. INTRODUCTION

1.1. Motivation

A greenhouse gas is a gas in an atmosphere that absorbs and emits radiant energy. The increasing trend in carbon dioxide (CO\textsubscript{2}) emission around the globe has been of broad and current interest for the past few decades. It has been estimated that if greenhouse gas emissions continue at their present rate, Earth’s surface temperature could exceed its historical values as early as 2047, leading to global warming, adverse effects on ecosystems, biodiversity and overall livelihoods of people worldwide [Wikipedia, 2018]. Total greenhouse gas (GHG) emissions in 2015 in the U.S. was 6,586.2 million metric tons of CO\textsubscript{2} equivalent (MMT CO\textsubscript{2} e). Combustion of fossil fuels for transportation purposes is the second largest contributor of GHG emission in the U.S., contributing about 27\% of the total GHG [EPA, 2017]. In the state of Connecticut (CT), it is the largest contributor of GHG emission at about 42\% of the total emission of 36.5 MMT CO\textsubscript{2} e [EIA, 2017].

The stark difference between emission sources in the state is more evident when historic data is plotted. Figure 1.1 shows emission in the state of CT by five major sources.

![Figure 1-1: GHG Emission from Major Sectors in CT](image-url)
Until 2004, emission from transportation sector was increasing almost linearly. Since then, although emission trend has started going downwards, the difference between transportation and other sectors in the state of Connecticut is increasing. In order to tackle the emission problems in the state, in 2008, the Connecticut Global Warming Solutions Act set mandatory targets for reducing GHG to at least 10% below 1990 levels by 2020 and 75-85% below 2001 levels by 2050 (CT Gen, 2010). On Earth Day 2015, the Governor’s Council on Climate Change, otherwise known as the GC3 was created for the sole purpose of examining the effectiveness of existing policies and regulations required to reduce GHG emission in the state.

While transit buses account for less than 1% (0.07MMT in 2017) of the total transportation emissions in CT, they are significant sources of several pollutants that lead to ground level ozone formation and smog and eventually may lead to public health hazards (EPA, 1990). On the other hand, while the average single occupant auto emits 0.44 kg of CO2 per passenger mile (PPM), the average public transit bus emitted only 0.29 kg CO2PPM per bus mile; with all seats occupied, it would emit only 0.08 kg CO2PPM (Southworth et al, 2011). By investing in low-carbon mobility models and increasing the market share of public transport, 550 million tons of CO2 equivalent can be reduced by the year 2025 (UITP, 2014). Moreover, if transit agencies all over the country start taking responsibility for their own carbon footprint and reduce it by a noteworthy percentage, there could be a remarkable amount of reduction in total GHG emission from transit buses in the country.

Keeping consistent with the state’s policy around emission reduction, Connecticut Department of Transportation (CTDOT) has requested Connecticut Academy of Science and Engineering (CASE) to take up a study to identify strategies to achieve a vision of pathway to minimize their carbon footprint. This research includes analysis carried out as a part of the study “Sustainability Strategies to Reduce Carbon Footprint from CT Buses” (CASE, 2018).

Diesel combustion engines are still the predominant type of fuel technology for transit buses in the United States. Compressed natural gas (CNG), Liquefied Natural Gas (LNG), and Biodiesel are
examples of alternative fuels which have lower emissions, while hybrid diesel-electric buses that combine internal combustion engine propulsion with an electric is becoming increasingly popular as well. Although they use diesel as their primary fuel, these buses are more fuel efficient and are considered “green” as they emit less GHG. In 2015, 46.9% of U.S. public transportation buses were using alternative fuel or hybrid technology (APTA, 2015) which is a significant change compared to that of 2010 being 33.5% and 2005 is only 16.0%. According to the same resource, in 2015, 16.7% of the transit buses in the U.S. were hybrid electric buses (HEB) which translates to about 12,000 HEBs in operation in the U.S. But in recent years, completely zero-emission buses are becoming progressively more popular and market ready. Plug in Battery Electric Bus (BEB) and Hydrogen Fuel Cell Bus (FCB) are both on-site zero emission options available for transit agencies. Since Foothill Transit in California started the journey with testing BEBs in 2010, many transit agencies have been considering migrating to an all-electric fleet. To date, more than 60 transit agencies in the US have either already taken up a test fleet or plan to deploy electric buses (FTA, 2016). Nonetheless, there exists a lack of research regarding the complete process, economic impact and also optimization of alternative fuel technology adoption into an existing fleet.

This research includes open source emission and economic analysis for replacement of an existing conventional diesel fleet with alternate fuel technologies. It also includes a research on optimization of the bus replacement problem. In this thesis, unless otherwise specified, alternative fuel buses refer to HEB, BEB and FCB.

1.2. Objectives

The overarching objective of this thesis is to help transit agencies make more informed decision regarding reduction of carbon footprint by alternative fuel technology adoption. The key goal can be disintegrated into the following specific objectives.
Document and analyze the current GHG emission footprint from buses and facilities of a transit agency.

- Study the impact on carbon footprint by introducing alternative fuel buses in an existing bus fleet.
- Study the impact of introducing alternative fuel buses in an existing bus fleet on life-cycle cost (LCC).
- To make abovementioned parts of the study open source and readily accessible by the public.
- To optimize the fleet replacement schedule by minimizing the life cycle cost (LCC) of owning and operating a fleet of buses and required infrastructures and reducing GHG emission simultaneously.

1.3. Thesis Organization

The organization of the thesis resembles the objectives mentioned in the previous subsection. Chapter 1 includes an introduction and the motivation behind this research. It also summarizes the objectives of this thesis. Chapter 2 introduces a modified inventory based GHG emission calculator for a transit agency that can be used to quantify their emission. It includes current emission footprint of CTDOT and forms the basis of subsequent chapters. Chapter 3 comprises of emission and economic analysis of adopting alternative fuel technology for CT buses using tentative bus replacement schedule of CTDOT. It introduces a method for estimating future fleet size required by a transit agency depending on ridership variation. Furthermore, it introduces an open source tool for calculating both GHG emission and LCC of a transit agency. Finally, it includes the results of various scenario analysis that was performed using the same tool. Chapter 4 introduces an optimization study on fleet replacement that is an improvement upon the replacement schedule assumed in chapter 3. It also includes various sensitivity analysis to find the optimized replacement schedule for adopting alternative fuel technologies.
CHAPTER 2. GHG EMISSION FOOTPRINT INVENTORY

2.1 Introduction

Transit agencies are recommended to quantify their greenhouse gas emissions by American Public Transportation Association. This is due to a number of reasons, such as reporting to carbon counting organizations, securing future funding for projects, supporting internal efforts for reducing carbon etc. (APTA, 2009). The Connecticut Department of Transportation (CTDOT) is responsible for the development and operation of highways, railroads, mass transit systems, ports, waterways in the U.S. state of Connecticut. Despite being a large transit operator, CTDOT did not have any emission detailed inventory from their bus operation prior to 2017. In order to study the sustainable strategies to minimize carbon footprint from CT buses first an emission inventory of current fleet and facility is required. This chapter includes the data collection and emission calculations for the fleet and facility operating under a transit fleet.

Transportation's contribution to GHG emissions is primarily (96.7%) associated with three GHGs: Carbon Dioxide (CO\textsubscript{2}), Nitrous Oxide (N\textsubscript{2}O), and Methane (CH\textsubscript{4}). Approximately 95% of those transportation GHG emissions are associated with CO\textsubscript{2} alone. The other GHGs can be converted to CO\textsubscript{2} equivalents (CO\textsubscript{2}e) using Global Warming Potential (GWP) factors developed by the IPCC for a 100-year time horizon (APTA, 2009). Carbon dioxide is the baseline unit, and therefore assigned a GWP value of 1. Some typically-used ranges of GWP values for the other GHGs are 21-25 for CH\textsubscript{4} and 298-310 for N\textsubscript{2}O. American Public Transportation Association (APTA) also recommends the reporting of other gases such as Hydrofluorocarbons (HFCs), Perfluorocarbons (PFCs), and Sulfur hexafluoride (SF\textsubscript{6}).
2.2. Literature Review

Emission inventory calculators have three scopes in terms of capturing sources of emissions. Scope 1 includes direct emission from the fleet that is controlled by the agency. These are shown in the graphic (figure 2.1) below.

![Figure 2-1: Scopes of Emission from Transit Agencies](image)

APTA recommends all three scopes to be included in reporting. There are a number of emission calculators available for public usage. EPA's simplified GHG emission calculator (SGEC) and APTA Calculator for Transit Green House Emission are two widely used calculators that follow the industry practice of inventory protocol. Although it provides a comprehensive accounting framework for estimating GHG emissions from both mobile and stationary sources, however, provides very little technical guidance for estimating upstream fuel-cycle, vehicle-cycle, or infrastructure-cycle emissions (Scope 3) ([Weigel, 2010](#)). The Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) model gives a platform for incorporating upstream or downstream of the agency. But these are mostly based off of private vehicles and not specifically designed for the use of a transit agency. A spreadsheet-based calculation tool that incorporates all three scopes that is specially designed for transit agencies was developed by Chicago Transit Authority (CTA) but is not available to the public.

In an effort to incorporate some part of all the scopes into the analysis, a modified Inventory Based GHG Emission Calculator for Transit Agencies was build that will be available for public usage.
2.3. Methodology

The modified inventory based GHG emission calculator uses APTA’s calculator as its basis and design but modifies the emission factors of GHGs using GREET model. Incorporating all measures of scope 3 was out of range for this study. But, the emissions associated with fuel production was taken into consideration. For example, Battery electric buses are zero emission on-site. But there is emission associated with the electricity production (non-renewable) that is used as fuel for those buses. This calculator is essentially a spreadsheet that incorporates different sheets for data entry. It also has help sheets and a summary sheet. Users (transit agencies) can use this to self-report their data and get the results in a summary sheet. Figure 2-2 shows a snapshot of the introduction page.

![Figure 2-2: Snapshot of Introduction Page from the GHG Inventory Calculator](image-url)
2.4. Case Study: Data Collection

CTDOT owns the local bus systems in eight different metropolitan area and operates under the brand name of *CTtransit*. Besides, they have contracts with other private providers for services in New Britain, Bristol, Waterbury, Meriden, and Wallingford. In all of these service areas, the state is fully responsible for all operating deficits and capital costs. Current fleet size for which CTDOT is accountable is 550.

Hartford, New Haven, and Stamford divisions have large facilities for bus storage and maintenance which are under the operation of CTDOT. They also have buildings for administrative works. The facilities use electricity, gas, fire suppressors, heating & cooling systems, refrigerators etc. that are significant contributors of greenhouse gas emissions.

Except for CTtransit, five other transit agencies that operate under CTDOT, don't have a storage and maintenance facility that is operated under CTDOT. So the emission from their bus fleet is the only source of emission that is associated with the DOT. These agencies are,

- The New Britain Transportation Company (NBT)
- Collin Bus
- Dattco Inc.
- Nason Partners LLC
- Peter Pan

First, data regarding fleet and facility was collected from *CTtransit* manually by visiting the Hartford office. These data were later translated into input data with appropriate units for the calculator. Later, data were self-reported by the remaining five operators. Data collected and cleaned for *CTtransit* was used as an example which made it more convenient for other operators to organize their data better.

The survey constituted six major parts of the agency essentially consisting of data from its mobile sources or fleet, and its facilities. These included subdivisions which are listed in table 2-1.
Table 2-1: Survey Constitution

<table>
<thead>
<tr>
<th>Survey Divisions</th>
<th>Survey Subdivisions</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Agency Description</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Mobile Sources</strong></td>
<td>1. Number of vehicles operated</td>
</tr>
<tr>
<td></td>
<td>2. Vehicle Specification</td>
</tr>
<tr>
<td></td>
<td>a. Powertrain Type (Diesel or Hybrid Electric)</td>
</tr>
<tr>
<td></td>
<td>b. Vehicle Age</td>
</tr>
<tr>
<td></td>
<td>c. Fuel mix (Ethanol percentage if any)</td>
</tr>
<tr>
<td></td>
<td>3. Vehicle miles traveled in a year</td>
</tr>
<tr>
<td></td>
<td>4. Fuel Consumption (thousand gallons)</td>
</tr>
<tr>
<td><strong>Electricity</strong></td>
<td>1. eGrid Subregion</td>
</tr>
<tr>
<td></td>
<td>2. Electricity Purchased (kWh)</td>
</tr>
<tr>
<td><strong>Refrigeration and AC</strong></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1. Type of gas used as a refrigerant</td>
</tr>
<tr>
<td></td>
<td>2. Amount of gas used (lb)</td>
</tr>
<tr>
<td><strong>Purchased Gases</strong></td>
<td>1. Type of gas purchased</td>
</tr>
<tr>
<td></td>
<td>2. Amount of gas purchased (CCF)</td>
</tr>
<tr>
<td><strong>Fire Suppression</strong></td>
<td>1. Type of fire suppressors used</td>
</tr>
<tr>
<td></td>
<td>2. The gas used in those suppressors</td>
</tr>
<tr>
<td></td>
<td>3. Amount of gas in each suppressor (lb)</td>
</tr>
</tbody>
</table>

2016 data for fleet composition (Diesel/Hybrid), vehicle age, fuel usage per mile, fuel efficiency per mile), and vehicle miles traveled per bus (VMT) of each month was collected. The temporal data was then averaged over a 12 month period to get average fuel usage, fuel efficiency, and VMT.

2.5. CTDOT Fleet and Facility Data Inventory

Most of the buses operated by CODOT are Conventional Diesel (433) and some are Hybrid Diesel Electric buses (117). The metro areas served by CTtransit can be categorized into three, Hartford, New Haven, and Stamford. Of the three major divisions, Hartford has the highest number of buses
It also has the highest VMT and fuel usage in a year (2016). Total fleet size, VMT and fuel usage from *CTtransit* and five other operators are listed below in table 2-2.

**Table 2-2: CTtransit Fleet Inventory**

<table>
<thead>
<tr>
<th>Transit Operators</th>
<th>Fleet Size</th>
<th>Total VMT (Thousand Miles)</th>
<th>Diesel usage (Thousand Gallons)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CTtransit</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hartford Division</td>
<td>298</td>
<td>10,343</td>
<td>2,582</td>
</tr>
<tr>
<td>New Haven Division</td>
<td>129</td>
<td>4,168</td>
<td>1,169</td>
</tr>
<tr>
<td>Stamford Division</td>
<td>59</td>
<td>1,605</td>
<td>371</td>
</tr>
<tr>
<td><strong>Other Operators</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NBTC</td>
<td>16</td>
<td>868</td>
<td>220</td>
</tr>
<tr>
<td>Collin Bus</td>
<td>6</td>
<td>225</td>
<td>47</td>
</tr>
<tr>
<td>Dattco Inc.</td>
<td>26</td>
<td>1,285</td>
<td>292</td>
</tr>
<tr>
<td>Nason Partners LLC</td>
<td>4</td>
<td>80</td>
<td>21</td>
</tr>
<tr>
<td>Peter Pan</td>
<td>21</td>
<td>738</td>
<td>190</td>
</tr>
</tbody>
</table>

Although Hartford has the double the fleet load of New Haven, facility emission from the latter is not much different from the former in terms of electricity usage and purchased gases. This may be due to the fact that the size of the facility is not directly proportional to the size of the fleet. Purchased gases for the facilities are mostly Methane (CH4) that is predominantly used for heating purposes. Different Refrigerants are used in different divisions including CO2, R-22 (Chlorodifluoromethane), R-234aa (2,2-Dichloro-1,1,3,3-tetrafluoropropane), R290 (Propane) and R-1270 (Propylene) which are used for cooling purposes of the fleet and the facility. Non-CO2 producing ABC Dry chemical fire suppressants are used in all three areas. Three different sizes of fire suppressants, 5lbs, 10lbs, and 20lbs are used in the facilities and the buses.
Table 2-3: *CTtransit* Facility Inventory

<table>
<thead>
<tr>
<th>Area</th>
<th>Electricity (kWh)</th>
<th>Purchased Gases (CCF)</th>
<th>A-B-C Fire Suppressant (lb)</th>
<th>Refrigeration and AC (lb)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hartford</td>
<td>3,694,459</td>
<td>578,112</td>
<td>1,455</td>
<td>11,348</td>
</tr>
<tr>
<td>New Haven</td>
<td>3,761,715</td>
<td>543,269</td>
<td>785</td>
<td>2,743</td>
</tr>
<tr>
<td>Stamford</td>
<td>1,256,640</td>
<td>278,536</td>
<td>475</td>
<td>165</td>
</tr>
</tbody>
</table>

2.6. GHG Emission Inventory

The emission inventory is divided into two major parts consisting of emission from mobile sources and from the facility. Non-revenue vehicles were not considered in the analysis. Table 2-4 and 2-5 consist of the emission results obtained from different transit operators in metric tons of CO$_2$ equivalent (MT CO$_2$ e).

Table 2-4: Emission Inventory for Mobile Sources

<table>
<thead>
<tr>
<th></th>
<th>Hartford</th>
<th>New Haven</th>
<th>Stamford</th>
<th>NBTC Bus</th>
<th>Collin Inc.</th>
<th>Dattco Inc.</th>
<th>Nason Partners</th>
<th>Peter Pan</th>
</tr>
</thead>
<tbody>
<tr>
<td>MT CO$_2$ e</td>
<td>26,373</td>
<td>11,938</td>
<td>3,788</td>
<td>2,245</td>
<td>472</td>
<td>2,978</td>
<td>55</td>
<td>1,935</td>
</tr>
</tbody>
</table>

Here an important thing to note is that fire suppressors were not included in the emission inventory as all of them were ABC dry chemical suppressors which do not emit any greenhouse gas.

Table 2-5: Emission Inventory for Facilities

<table>
<thead>
<tr>
<th>Division</th>
<th>MT CO$_2$ equivalent from Facility</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Electricity</td>
<td>Refrigeration &amp; AC</td>
<td>Purchased Gases</td>
<td></td>
</tr>
<tr>
<td>Hartford Division</td>
<td>1,077</td>
<td>2,447</td>
<td>5,506</td>
<td></td>
</tr>
<tr>
<td>New Haven Division</td>
<td>1,097</td>
<td>25</td>
<td>5,174</td>
<td></td>
</tr>
<tr>
<td>Stamford Division</td>
<td>367</td>
<td>2</td>
<td>2,653</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>2,541</td>
<td>2,472</td>
<td>13,334</td>
<td></td>
</tr>
</tbody>
</table>
Total GHG emission (MT CO₂ e) from different sectors of CTDOT is shown in figure 2-3.

![GHG Emission by Sources from CTDOT](image)

**Figure 2-3: GHG Emission by Sources from CTDOT**

From the analysis, total GHG emission from DOT owned buses is 49938.11 Metric Ton of CO₂ equivalent which is almost 73% of the total emission from CTDOT. The other 27% of the emission is from the facility, which is consistent with the calculations that have been done by other agencies.

### 2.7. Conclusion

The inventory based calculator can be used by transit agencies to self-report their data and keep track of their carbon footprint. This calculator is user-friendly and overcomes some of the nuances of existing publicly available calculators. The emission results from this chapter formed the basis for the further study on scenario analysis for reducing the carbon footprint. This calculator however has its limitations. It can be used for inventory purposes only. It is static and there is not much room for introducing different scenarios without incorporating an extensive number of manual iterations.
CHAPTER 3. GHG EMISSION AND ECONOMIC ANALYSIS OF ADOPTING ALTERNATIVE FUEL TECHNOLOGY BUSES

3.1. Introduction

Subsequent to GHG inventory for current fleet and facility, the focus of the study shifted to investigate the effect of replacing diesel buses with alternative fuel buses on the carbon footprint of DOT owned buses. As discussed in chapter 1, many transit agencies are considering shifting their fleet towards alternative technology fuel buses. Connecticut DOT is not much far behind. Hybrid buses have been the major alternate to traditional combustion engine buses for the past few years as they have lower emission rate. But technology related to battery electric buses have rapidly matured, making it one of the most desirable replacements in recent years. A major reason apart from it being zero emission (on-site) is the recent improvement in cost competitiveness of these options. Other zero emission technologies are yet to become viable replacements in terms of cost. Nonetheless, because of their low carbon footprint and availability of Hydrogen as a fuel, Hydrogen fuel cell buses (FCB) are also a popular alternative for transit buses. In this chapter, well-to-wheel GHG emission levels for replacing an existing fleet with either DBs, HEBs, BEBs or FCBs over the design period is studied. Along with GHG emission analysis, a life cycle cost (LCC) analysis was also performed to study the economic impact of adopting alternative fuel technologies. Study horizon was chosen to be 2018 to 2030. This period represents the time required to replace CTDOT fleet.

3.2. Literature Review

Emission studies comparing GHG emission of alternative fuel vehicles are abundant in literature. In most of the studies, electric vehicles have proven to be superior in terms of emissions and cost compared to others (Ou et al., 2010 and Lajunen, 2014). But these studies only include the comparison of single buses. These did not compare the bus fleet as a whole and doesn’t include the effect of replacing the fleet with alternative fuel buses.
In addition to the GHG emissions over the life of a transit system, more traditional formal life-cycle cost analysis (LCCA) are generally performed for comparison of vehicle purchasing options. Life-cycle cost analysis (LCCA) is a tool to determine the most cost-effective option among different competing alternatives to purchase, own, operate, maintain and, finally, dispose of an object or process, when each is equally appropriate to be implemented on technical grounds. LCC of diesel, hybrid and electric vehicles have been studied extensively (Xu et al. 2015, Delucchi et al. 2001). In most of these studies comprise of either studying passenger vehicle or includes comparison buses of different fuel technologies and not an entire fleet. There is also variation in results. Aber, 2016 for New York State performed a study that concluded that BEBs are more cost effective than hybrid buses because of their lower fuel cost and operation & maintenance cost. But this study again was done by comparing single vehicles and not an entire fleet. However, some other study showed that BEBs are only viable option for 8 of the 50 states in the USA (Cooney et al. 2013). This chapter compares the LCC of replacing the bus fleet with alternative fuel buses which helps study the interaction between current and future fleet and also gives a more realistic overall picture.

3.3. Methodology

The overall methodology of the emission and economic analysis in this chapter consists of three steps. First, two static calculators were selected; the modified inventory based GHG emission calculator for emission analysis and Fuelcost2 (TCRP-146) for economic analysis. Both of these are spreadsheet based. These calculators were later translated into a python script. The python based calculator takes the initial conditions (from data collection) and some assumptions as inputs. It can be used for multiple scenario analysis. Variation in emission condition due to public transit ridership changes were studied. Finally sensitivity analysis was performed for many of the assumptions. Finally this python based calculator was translated into a web-application where users can modify the assumptions and run scenarios. The application runs for default data which is data collected and
assumed for CTDOT. But users can modify all the assumptions and compare results. Figure 3-1 shows a flow of the steps.

![Diagram of Methodology for Emission and Economic Analysis]

**Figure 3-1: Methodology for Emission and Economic Analysis**

### 3.4. Transit Ridership Scenarios

Three different future scenarios were considered to study the replacement of diesel buses with alternative fuel technology. Parameter considered to frame the scenarios was transit ridership. The current level of public transit ridership in the state of Connecticut is about 3%. Three possible combinations public transit ridership at 3%, 7%, and 10% were considered. The higher percentages of ridership were considered in order to analyze the possible positive effect of current and future travel demand management (TDM) strategies and transit-oriented development (TOD) strategies.

These assumptions are consistent with goals established in statewide programs such as *Let’s Go CT!*, which evaluates and seeks to improve the statewide bus transit system [CTDOT, 2015]. The 30-year plan includes expansion of bus service by 25%, providing residents in urbanized areas access to a bus within half-mile, integrating real-time information, extending CTfastrak to increase access to
jobs and education, targeting University students with U-pass etc. (CTDOT, 2015). Connecticut is one of the very few states where transit ridership has steadily increased. CTFastrak alone has seen 23% increase in total corridor passenger trips in July 2016 compared to that of July 2015. Looking at the data of 33.25 million passenger trips in 2006 and 42.16 million in 2014 and taking into account state’s effort to become more sustainable it can be forecasted that the ridership will keep increasing in the coming years. An appropriate fleet turnover strategy is required to meet the increased demand.

3.5. Fleet Size Estimation

In order to build the scenarios for different transit ridership, the relationship between ridership, unlinked passenger trips, and fleet size was studied. A detailed analysis of fleet size estimation as a function of multiple variables including ridership was outside of the scope of this study. However, a linear regression was adopted in order to quantify the fleet size requirement at the system level.

Connecticut State Data Center (CtSDC, 2017) has published population projections through 2040. Figure 3.1 shows historic population data (Census, 2016) and CtSDC projections.

![Figure 3-2: Connecticut Population: Historic and Projected](image-url)
From the total population in the state, the number of people using public transit can be inferred. For example, for the year 2018, ridership from a population of approximately 3.6 million produces an estimate of 107,294 persons using public transit.

Number of people using public transportation (PT) is highly correlated unlinked passenger trips (UPT). Using the data for all the states in the U.S., a linear relationship between numbers of people using PT to work (NTD, Table 19, 2015) and UPTs (NTD, Table 4-4, 2015) can be established. So for changes in the percentage of people using public transportation, UPT for a state can be calculated.

![Figure 3-3: Unlinked Passenger Trips as a Function of Persons Using PT to Work](image)

**Figure 3-3: Unlinked Passenger Trips as a Function of Persons Using PT to Work**

Using the linear relationship from figure 3.2, total number of UPTs for CT can be estimated. For 2018,

\[
\text{Unlinked passenger trips} = (227.22 \times 0.107294) + 18.11 = 42.5 \text{ million}
\]

UPT for a state is again, linearly related to size bus fleet required to serve that population. Using the data for all the states in the U.S. (NTD, Appendix A, 2015), a linear relationship for UPT and fleet size estimated.
Again, using the relationship shown in figure 3.3, the fleet size required by CTDOT can be calculated. It should be noted that a percentage of statewide operating buses is owned by DOT. For 2015 this was 64.5% which is assumed to be constant throughout the analysis period. So, for 2018,

\[
\text{Statewide Fleet Size} = (15.71 \times 42.5) + 178.98 = 845 \text{ vehicles}
\]

\[
\text{CTDOT Owned Fleet Size} = 845 \times 0.645 = 545 \text{ vehicles}
\]

An important thing to note here is that due to the lack of a single dataset, an intermediate variable was used to define the relationship between fleet size and ridership estimates. If there was a single source available, the intermediate variable (unlinked passenger trips) could be simply removed to give a straightforward relationship between ridership and fleet size.

Table 3-1 represents the fleet size values for upcoming years for different ridership percentages. In other words, this table shows the fleet size required to do the GHG emission and economic calculations for the scenarios.

---

**Figure 3-4: Fleet Size as a Function of Unlinked Passenger Trips**

![Graph showing fleet size as a function of unlinked passenger trips with the equation $y = 15.71x + 178.98$ and $R^2 = 0.8863$.](image-url)
Table 3-1: Estimated Fleet Size

<table>
<thead>
<tr>
<th>Year</th>
<th>Transit Ridership</th>
<th>CT Population</th>
<th>#of People Using PT</th>
<th>UPT (millions)</th>
<th>Statewide Fleet Size</th>
<th>CTDOT Fleet Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015</td>
<td>~3%</td>
<td>3,574,000</td>
<td></td>
<td>41.6</td>
<td>853</td>
<td>550</td>
</tr>
<tr>
<td>2018</td>
<td>3%</td>
<td>3,576,452</td>
<td>107,294</td>
<td>42.5</td>
<td>845</td>
<td>545</td>
</tr>
<tr>
<td>2030</td>
<td>3%</td>
<td>3,705,041</td>
<td>111,152</td>
<td>43.4</td>
<td>859</td>
<td>554</td>
</tr>
<tr>
<td></td>
<td>7%</td>
<td>3,705,041</td>
<td>259,353</td>
<td>77.0</td>
<td>1,388</td>
<td>895</td>
</tr>
<tr>
<td></td>
<td>10%</td>
<td>3,705,041</td>
<td>370,505</td>
<td>102.3</td>
<td>1,784</td>
<td>1,150</td>
</tr>
</tbody>
</table>

The first row represents the latest available current data (2015) for Connecticut. There are 41.6 million annual unlinked passenger trips in the state which requires a fleet of 550(DOT). The following rows represent the estimate for different years using the relationships established in this section. 2015 actual data for 3% ridership and 2018 estimates for 3% ridership are very similar. This was assumed to be an indication of model validation.

3.5. Emission Analysis

The Inventory Based GHG Emission calculator built for the earlier study (discussed in chapter 2) was modified to accommodate the alternative fuel technology analysis. The same sources as before were taken as standards for emission factors and global warming potential values for different fuels. But performing scenario analysis in an excel sheet is difficult and inefficient. So using Python™ programming language, a script was written for doing emission analysis. It is an open source calculator that can be used to determine GHG emission resulting from adopting alternative fuel technology transit buses and for performing scenario analysis within a specified design period. By simply changing the input values, different scenario analysis can be done using this calculator which is much more interactive, proficient and more comprehensible than an excel sheet.

Replacement of CTDOT buses were used as a case study for this analysis.
3.5.1. Assumptions for Emission Analysis

CTDOT’s tentative fleet replacement schedule was used to calculate the emission from mobile sources over the analysis period due to shifting towards alternative fuel technology buses. A typical service life of a bus is 12 years which may be extended 2-3 years depending on budgetary and procurement conditions. Figure 3-4 shows the plausible fleet turnover schedule of CTDOT as of 2017. It is shown as a as a percentage of total buses required at the end of analysis period which accommodates the flexibility to analyze transit ridership variation. For initial scenario analysis, it was assumed that by the end of 2030, a single technology buses will be in operation. Assumptions about the fuel economy, vehicle miles traveled (VMT) by DOT buses, and percentages of renewable electricity (RE) in 2018, 2030, and 2050 were made. Table 3-2 shows all the assumptions related to emission analysis.

![Figure 3-5: Percentage of the CTDOT Bus Fleet Turnover](image-url)
Table 3-2: Assumptions for Emission Analysis

<table>
<thead>
<tr>
<th>Input Data</th>
<th>Values</th>
<th>Sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuel Economy</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Conventional Diesel Bus</td>
<td>3.67mi/gal</td>
<td>CTDOT data</td>
</tr>
<tr>
<td>Hybrid Electric Bus</td>
<td>5.13 mi/gal</td>
<td>CTDOT data</td>
</tr>
<tr>
<td>Battery Electric Bus</td>
<td>0.47 mi/kWh</td>
<td>L. Eudy, et.al. (2017)</td>
</tr>
<tr>
<td>Hydrogen Fuel Cell Bus</td>
<td>7.01 mi/DGE</td>
<td>L. Eudy &amp; M. Post (2017)</td>
</tr>
<tr>
<td>Vehicle Miles Travelled (Miles)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2018</td>
<td>19,306,997</td>
<td>CTDOT data</td>
</tr>
<tr>
<td>2030 - Ridership 3%</td>
<td>19,447,412</td>
<td>Calculated using fleet size estimates</td>
</tr>
<tr>
<td>2030 - Ridership 7%</td>
<td>31,417,750</td>
<td>Calculated using fleet size estimates</td>
</tr>
<tr>
<td>2030 - Ridership 10%</td>
<td>40,369,176</td>
<td>Calculated using fleet size estimates</td>
</tr>
<tr>
<td>Renewable Electricity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2018</td>
<td>17%</td>
<td>DEEP, Renewables (2017)</td>
</tr>
<tr>
<td>2030</td>
<td>30%</td>
<td>Comprehensive Energy Strategy (Draft 2017)</td>
</tr>
<tr>
<td>2050</td>
<td>85%</td>
<td>DEEP, GC3 (2017)</td>
</tr>
</tbody>
</table>

3.5.2. Results

Cumulative GHG emission from each type of fuel technology adoption scenarios was calculated using the calculator. It should be noted that these analysis does not include the emission from facilities. It is acknowledged that for scenario 2 and 3, where fleet size increases momentously compared to scenario 1, facility demand and therefore, emission will also increase. But those emissions are assumed to remain same for each type of fuel technology and so were not included in the results. The results are shown in table 3-3.
### Table 3-3: Cumulative GHG Emission from Alternative Fuel Buses

<table>
<thead>
<tr>
<th>Ridership</th>
<th>All DB</th>
<th>All HEB</th>
<th>All BEB</th>
<th>All FCB</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MMT CO₂ e</td>
<td>MMT CO₂ e</td>
<td>MMT CO₂ e</td>
<td>MMT CO₂ e</td>
</tr>
<tr>
<td>3%</td>
<td>0.669</td>
<td>0.616</td>
<td>0.350</td>
<td>0.499</td>
</tr>
<tr>
<td>7%</td>
<td>0.894</td>
<td>0.812</td>
<td>0.385</td>
<td>0.624</td>
</tr>
<tr>
<td>10%</td>
<td>1.062</td>
<td>0.958</td>
<td>0.410</td>
<td>0.717</td>
</tr>
</tbody>
</table>

In all scenarios that battery electric buses result in lowest greenhouse gas emission values. Whereas diesel buses produce maximum emissions. For example, for 3% ridership, GHG emission over the 12 year analysis period for BEB adoption is 0.350 million metric tons of CO₂ equivalent (MMT CO₂ e) which is 47% less than that of Diesel Buses. The following three figures show a breakdown of the results by year which gives a better understanding of emission reduction due to technology adoption.

![Figure 3-6: Emission from Alternative Fuel Technology Buses in Scenario 1](image-url)
Figure 3-8: Emission from Alternative Fuel Technology Buses in Scenario 2

Figure 3-7: Emission from Alternative Fuel Technology Buses in Scenario 3
In all three scenarios, BEBs prove to be predominantly better in terms of reducing GHG emission from buses.

3.6. Economic Analysis

The subsequent part of this study includes economic analysis of adopting alternative fuel bus technologies. Several cost analyses alternatives were considered for this study: benefit-cost analysis (BCA), cost-effectiveness analysis (CEA), and life-cycle cost (LCC) analysis. LCC analysis was identified as the preferred approach in the context of GHGs.

Life-cycle costs, in generic terms mean the cost of owning, operating and disposing a single product over its life span. But this approach has some nuances when considering an entire fleet. A fleet of buses cannot be completely replaced by a newer technology in a single purchase. Instead, newer technologies are slowly integrated into the fleet. If only a single vehicle is considered for comparison, the interactions between older and newer vehicles is lost. Moreover, factors such as learning cost, cost variation over time, changes in cost due to aging of buses is ignored. So, instead of the traditional approach, the LCC in this thesis refers to total cost of owning, operating and disposing of an entire bus fleet over the design period.

Python™ programming language was used to develop code to perform the calculations for LCC as well. This code allows a user running an analysis to change a number of parameters, including level of ridership, VMT options, the fleet mix (i.e., percentage of alternative fuel buses and diesel buses), discount rate and rate of general price increases, decline in capital costs due to technological improvements, as well as other options. LCC for each scenario context can be calculated using the following expression:

\[
LCC = \sum_{t=1}^{T} \sum_{k=0}^{K} P_{t,k} \cdot e_{t,k} + \sum_{k=0}^{K} \left( A_{t,k} \cdot f_{k} + A_{t,k} \cdot j_{k} \right) \cdot m + Q_{t} \cdot l + C_{t} \cdot n \cdot \frac{(1 + \alpha)^t}{(1 + \beta)^t}
\]
Where,

\[ k \in \{1,2,3...K\} \] Types of fuel technology

\[ t \in \{2018,2019 ... T\} \] Analysis period

\[ d \in \{1,2 ... D\} \] Ridership Scenarios

\[ P_{kt} \] Number of \( k \) type vehicle purchased at year \( t \) for scenario \( d \)

\[ Q_t \] No. of charging infrastructure installed at year \( t \) for scenario \( d \)

\[ A_{kt} \] No. of \( k \) type vehicle in operation at year \( t \) for scenario \( d \)

\[ C_t \] No. of charging infrastructure in operation at year \( t \) for scenario \( d \)

\[ B \] Total annual budget

\[ e_{kt} \] Capital cost of \( k \) type vehicle at year \( t \) (bus cost + warranty cost)

\[ f_k \] Operation and maintenance cost per mile for \( k \) type vehicle

\[ j_k \] Fuel cost per mile for \( k \)-type vehicle

\[ l \] Capital cost of charging infrastructure

\[ n \] O&M cost of charging infrastructure

\[ m \] Average annual mileage in year \( t \)

\[ \alpha \] Discount rate

\[ \beta \] Rate of price increase

3.6.1. Assumptions for Economic Analysis

In order to calculate the life cycle cost of owning and operating different fuel technology fleets, various assumptions were made. Similar to the previous analysis, DOT’s tentative replacement schedule was used to find the number of buses to purchase each year. Diesel, Hybrid electric, Battery Electric and Fuel cell buses were the fuel technologies \( (k) \) considered. Analysis period \( (t) \) and ridership scenarios \( (d) \) were also the same as emission analysis. Since there was no age information incorporated in the analysis, some coarse assumptions about bus salvaging were made. It was
assumed that diesel buses will be salvaged at the beginning of the analysis period and then hybrid buses will be salvaged. This may not hold true if the age of bus is taken into consideration. Assumptions about the capital and O&M costs for buses and fueling infrastructures and other input values are shown in the following table.

**Table 3-4: Assumptions for Economic Analysis**

<table>
<thead>
<tr>
<th>Input Data</th>
<th>Conventional Diesel Bus</th>
<th>Hybrid Electric Bus</th>
<th>Battery Electric Bus</th>
<th>Hydrogen Fuel Cell Bus</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimated Capital Bus Cost</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2018</td>
<td>$450K (a)</td>
<td>$600K (a)</td>
<td>$800K (a)</td>
<td>$1.356M (b)</td>
</tr>
<tr>
<td>2030</td>
<td>$450K</td>
<td>$600K</td>
<td>$700K (c)</td>
<td>$1.356M</td>
</tr>
<tr>
<td>Fuel Price</td>
<td></td>
<td>$2.50/gal (a)</td>
<td>$0.12/kwh (d)</td>
<td>$7.81/DGE (a)</td>
</tr>
<tr>
<td>Fuel Cost ($/mile) (calculated)</td>
<td></td>
<td>$0.68/mile</td>
<td>$0.49</td>
<td>$0.25</td>
</tr>
<tr>
<td>Bus Maintenance Cost ($/mile)</td>
<td></td>
<td>$0.45(a)</td>
<td>$0.47(a)</td>
<td>$0.16 (e)</td>
</tr>
<tr>
<td>Fueling infrastructure capital cost</td>
<td></td>
<td>-</td>
<td>$50K/bus (e)</td>
<td>$2.8M/28 buses (f)</td>
</tr>
<tr>
<td>Annual Fueling Infrastructure Operating and Maintenance Cost</td>
<td>$189/bus (g)</td>
<td>$163/bus (g)</td>
<td>$38/bus (h)</td>
<td>$140K/unit (h)</td>
</tr>
<tr>
<td>Learning Cost Multiplier (a)</td>
<td>Year 1 -</td>
<td>-</td>
<td>1.1</td>
<td>1.1</td>
</tr>
<tr>
<td></td>
<td>Year 2 -</td>
<td>-</td>
<td>1.2</td>
<td>1.2</td>
</tr>
<tr>
<td>Annual Mileage of Bus (miles)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Annual Discount Rate – 3% (assumed)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annual Rate of Price Increase – 3% (assumed)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

3.6.2. Results

When single vehicles are considered for comparison, a static calculator is sufficient for doing the analysis. A comparison of LCC for single diesel, hybrid, BEB and FCB vehicles were done for 2017 values. Then, the calculator was run using all the assumed base input values to get the initial results for the entire fleet replacement. As mentioned before these results are based on the cumulative cost of owning and operating a bus fleet and required fueling infrastructures over the analysis period of 12 years. Table 3-5 shows the summary of the results.

Table 3-5: Life-Cycle Cost over Analysis Period for Alternative Fuel Buses

<table>
<thead>
<tr>
<th>Approach</th>
<th>All DB ($ millions)</th>
<th>All HEB ($ millions)</th>
<th>All BEB ($ millions)</th>
<th>All FCB ($ millions)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single Vehicle</td>
<td>0.96</td>
<td>1.04</td>
<td>1.01</td>
<td>2.09</td>
</tr>
<tr>
<td>Entire Fleet</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ridership 3%</td>
<td>539</td>
<td>622</td>
<td>626</td>
<td>1,123</td>
</tr>
<tr>
<td>Ridership 7%</td>
<td>789</td>
<td>926</td>
<td>936</td>
<td>1,738</td>
</tr>
<tr>
<td>Ridership 10%</td>
<td>977</td>
<td>1,153</td>
<td>1,167</td>
<td>2,198</td>
</tr>
</tbody>
</table>

When we consider single vehicles, owning and operating a single HEB is more expensive than BEB or FCB. But when we are considering entire fleet replacement, we can see that replacing the fleet with BEB is somewhat more expensive than HEBs. This validates the line of reasoning for selecting comparison of entire fleet replacement rather than single vehicles.

In each of the scenarios, Diesel buses are most cost-effective. But their emission profile, as discussed in emission analysis, makes them a poor choice for transit buses. BEBs, despite having a much higher capital cost, has a life cycle cost that is almost similar to hybrid buses due to their low operation and maintenance costs. Fuel cell buses in all scenarios failed to be cost competitive compared to other fuel technologies.
3.7. **Sensitivity Analysis**

A series of sensitivity analysis was conducted for different scenarios. Baseline assumptions were relaxed using various combinations of input parameters to determine their impact on the result. The purpose of this was also to find if any combination of interest rates, price declines, light-duty vehicle electrification, and other assumptions exits where life-cycle cost and GHG impacts of the fuel technologies change relative to each other. The following subsections describe the base assumptions that were modified to do sensitivity analysis and summary tables of those on GHG emissions and LCC of alternative fuel technology bus adoption.

3.7.1. **Sensitivity Results of GHG Emission**

**Renewable Electricity (RE) Portfolio:** As shown in Table 3-2, renewable electricity requirement for the state of Connecticut in 2030 is at least 30% Class I RE. A modified assumption for 20% RE was made to see the impact on GHG emission of BEBs as a lower percentage of RE will result in higher emission on the production side of this fuel technology. Table 3-6 summarizes the results.

**Bus Fleet Fuel Technology Mix:** A fleet mix sensitivity was performed to see the impact of replacing a percentage of the fleet with greener technology and keeping the rest either diesel or diesel hybrid. This scenario analysis also serves the purpose of finding emission footprint for an emergency response fleet that may be accessible in case of a natural calamity when BEBs or FCBs may not be functional. Modified assumption includes 75% of the fleet being replaced by alternative fuel technology over the analysis period and 25% of the fleet remaining diesel.

As expected, this modified assumption for class I RE significantly impacts the GHG emissions reduction potential of battery electric buses. However, for all ridership scenarios, battery electric buses still outperform other fuel technologies.
### Table 3-6: Sensitivity Results of Total GHG Emissions for Modified Assumptions

<table>
<thead>
<tr>
<th>Assumptions</th>
<th>All DB MT CO2 e</th>
<th>All HEB MT CO2 e</th>
<th>All BEB MT CO2 e</th>
<th>All FCB MT CO2 e</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ridership 3%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>669,466</td>
<td>615,722</td>
<td>350,456</td>
<td>499,234</td>
</tr>
<tr>
<td>Modified: Class I RE - 20%</td>
<td>669,466</td>
<td>615,722</td>
<td>359,630</td>
<td>499,234</td>
</tr>
<tr>
<td>Modified Fleet mix 25%-75%</td>
<td>-</td>
<td>628,000</td>
<td>425,000</td>
<td>537,000</td>
</tr>
<tr>
<td>Ridership 7%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>893,844</td>
<td>811,727</td>
<td>384,778</td>
<td>624,307</td>
</tr>
<tr>
<td>Modified: Class I RE-20%</td>
<td>893,844</td>
<td>811,727</td>
<td>403,703</td>
<td>630,948</td>
</tr>
<tr>
<td>Modified: Fleet mix 25%-75%</td>
<td>-</td>
<td>830,000</td>
<td>507,000</td>
<td>687,000</td>
</tr>
<tr>
<td>Ridership 10%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>1,061,632</td>
<td>958,218</td>
<td>409,624</td>
<td>717,398</td>
</tr>
<tr>
<td>Modified: Class I RE-20%</td>
<td>1,061,632</td>
<td>958,218</td>
<td>435,054</td>
<td>723,833</td>
</tr>
<tr>
<td>Modified: Fleet mix 25%-75%</td>
<td>-</td>
<td>982,000</td>
<td>567,000</td>
<td>798,000</td>
</tr>
</tbody>
</table>

The 25%-75% modified sensitivity also shows results that have similar trends to the baseline scenario. However, 25%-75% may not be the optimum percentage but finding the optimum percentage was out of scope at this point of the study.

#### 3.7.2. Sensitivity Results of Life Cycle Cost

A series of sensitivity analysis was also performed to find the sensitivity of the LCC to inputs and also to find alternative results to base scenarios. Three major inputs were modified to get these sensitivity results.

**BEB & FCB cost reduction:** Initial assumption for capital costs were that BEB costs will decline by 12.5% and FCB costs will remain the same. Literature suggests that increase in BEB market share and the decline in battery pack costs have led to the assumption that cost of BEBs will reduce.
significantly in the coming years [McKinsey, 2017]. Sensitivity analysis was run for scenarios where neither of the fuel technologies incurs cost reductions and where both the technologies experience 25% of the reduction in their capital costs.

**Inflation & Discount Rate:** Initial assumption for the discount rate and rate of price increase was that they will remain the same at 3%. This was based on the fact that the Federal Reserve tends to target interest rates based on the rates of price increase of goods and services in the economy. But in reality, there could be some divergence between these. So sensitivity analysis was done where inflation is 2% and the discount rate is 4% and vice versa.

**Bus Fleet Fuel Technology Mix:** Similar to the sensitivity of GHG emission, fleet mix sensitivity of 25%-75% was performed for economic analysis as well. Table 3-7 summarizes the LCCs for different scenarios and modified assumptions.

In all the scenarios except where BEB capital cost doesn’t decline (highlighted), BEB adoption results in lower LCC values than other technologies (HEB and FCBs). Even though there is a significant variation in total LCCA values over the analysis period for different discount and inflation rates, the results follow the same pattern as the baseline scenario. 25-75 fleet mix also result in similar overall results as the base case. But this estimation is somewhat crude as the analysis in this chapter does not account for bus age and so assumptions were made about when and what part of the fleet will be replaced by which technology bus.
Table 3-7: Sensitivity Results of LCCA for Modified Assumptions

<table>
<thead>
<tr>
<th>Assumptions</th>
<th>All DB ($ millions)</th>
<th>All HEB ($ millions)</th>
<th>All BEB ($ millions)</th>
<th>All FCB ($ millions)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Ridership – 3%</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>539</td>
<td>622</td>
<td>627</td>
<td>1,123</td>
</tr>
<tr>
<td>BEB/FCB cost reduction: 0%</td>
<td>539</td>
<td>622</td>
<td>654</td>
<td>1,123</td>
</tr>
<tr>
<td>BEB/FCB cost reduction: 25%</td>
<td>539</td>
<td>622</td>
<td>627</td>
<td>1,069</td>
</tr>
<tr>
<td>Inflation 2%; Discount 4%</td>
<td>472</td>
<td>546</td>
<td>555</td>
<td>984</td>
</tr>
<tr>
<td>Inflation 4%; Discount 2%</td>
<td>619</td>
<td>712</td>
<td>714</td>
<td>1,289</td>
</tr>
<tr>
<td>Fleet mix 25%—75%</td>
<td>-</td>
<td>601</td>
<td>604</td>
<td>977</td>
</tr>
<tr>
<td><strong>Ridership – 7%</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>790</td>
<td>926</td>
<td>937</td>
<td>1,738</td>
</tr>
<tr>
<td>BEB/FCB cost reduction: 0%</td>
<td>790</td>
<td>926</td>
<td>980</td>
<td>1,738</td>
</tr>
<tr>
<td>BEB/FCB cost reduction: 25%</td>
<td>790</td>
<td>926</td>
<td>937</td>
<td>1,650</td>
</tr>
<tr>
<td>Inflation 2%; Discount 4%</td>
<td>689</td>
<td>810</td>
<td>827</td>
<td>1,520</td>
</tr>
<tr>
<td>Inflation 4%; Discount 2%</td>
<td>911</td>
<td>1,065</td>
<td>1,071</td>
<td>1,999</td>
</tr>
<tr>
<td>Fleet mix 25%—75%</td>
<td>-</td>
<td>892</td>
<td>900</td>
<td>1,501</td>
</tr>
<tr>
<td><strong>Ridership – 10%</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>977</td>
<td>1,154</td>
<td>1,167</td>
<td>2,199</td>
</tr>
<tr>
<td>BEB/FCB cost reduction: 0%</td>
<td>977</td>
<td>1,154</td>
<td>1,224</td>
<td>2,199</td>
</tr>
<tr>
<td>BEB/FCB cost reduction: 25%</td>
<td>977</td>
<td>1,154</td>
<td>1,167</td>
<td>2,084</td>
</tr>
<tr>
<td>Inflation 2%; Discount 4%</td>
<td>850</td>
<td>1,007</td>
<td>1,029</td>
<td>1,920</td>
</tr>
<tr>
<td>Inflation 4%; Discount 2%</td>
<td>1,129</td>
<td>1,329</td>
<td>1,337</td>
<td>2,531</td>
</tr>
<tr>
<td>Fleet mix 25%—75%</td>
<td>-</td>
<td>1,109</td>
<td>1,119</td>
<td>1,893</td>
</tr>
</tbody>
</table>

3.8. GHG Emission and LCC Analysis Summary

Although in one of the scenarios Battery Electric Buses were less economical than Hybrid buses, the difference remains very minimal. In all other scenarios, BEBs outperformed Hybrid Electric Buses and Hydrogen Fuel Cell buses in both emission analysis and Life Cycle Cost analysis. In other words, adopting BEB technology always results in lower cost of GHG emission reduction from CT buses.
Table 3-8 summarizes the additional cost (in dollars) of reducing GHG emission by 1 metric tons (MT) of CO₂ equivalent over the 12 year period compared to diesel bus adoption.

### Table 3-8: Cost of Reducing 1 MT CO₂ e

<table>
<thead>
<tr>
<th>Ridership</th>
<th>All DB</th>
<th>All HEB</th>
<th>All BEB</th>
<th>All FCB</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>3%</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total GHG (MMTCO₂e)</td>
<td>0.669</td>
<td>0.616</td>
<td>0.350</td>
<td>0.499</td>
</tr>
<tr>
<td>GHG Reduction (MMTCO₂e)</td>
<td>-</td>
<td>0.054</td>
<td>0.319</td>
<td>0.170</td>
</tr>
<tr>
<td>Total LCC ($ millions)</td>
<td>539</td>
<td>622</td>
<td>626</td>
<td>1,123</td>
</tr>
<tr>
<td>LCC/ton GHG Reduction ($/MTCO₂e)</td>
<td>N/A</td>
<td>1,537</td>
<td>273</td>
<td>3,435</td>
</tr>
<tr>
<td><strong>7%</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total GHG (MMTCO₂e)</td>
<td>0.894</td>
<td>0.812</td>
<td>0.385</td>
<td>0.624</td>
</tr>
<tr>
<td>GHG Reduction (MMTCO₂e)</td>
<td>-</td>
<td>0.082</td>
<td>0.509</td>
<td>0.270</td>
</tr>
<tr>
<td>Total LCC ($ millions)</td>
<td>789</td>
<td>926</td>
<td>936</td>
<td>1,738</td>
</tr>
<tr>
<td>LCC/ton GHG Reduction ($/MTCO₂e)</td>
<td>N/A</td>
<td>1,671</td>
<td>289</td>
<td>3,515</td>
</tr>
<tr>
<td><strong>10%</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total GHG (MMTCO₂e)</td>
<td>1.062</td>
<td>0.958</td>
<td>0.410</td>
<td>0.717</td>
</tr>
<tr>
<td>GHG Reduction (MMTCO₂e)</td>
<td>-</td>
<td>0.103</td>
<td>0.652</td>
<td>0.344</td>
</tr>
<tr>
<td>Total LCC ($ millions)</td>
<td>977</td>
<td>1,153</td>
<td>1,167</td>
<td>2,198</td>
</tr>
<tr>
<td>LCC/ton GHG Reduction ($/MTCO₂e)</td>
<td>N/A</td>
<td>1,709</td>
<td>291</td>
<td>3,549</td>
</tr>
</tbody>
</table>

It can be seen from the table that when replacing the fleet with BEBs, $ spent/ MT CO₂ e reduction compared to diesel buses is lowest. It is much lower than HEBs and FCBs in all three ridership scenarios. So when considering fleet replacement, BEBs are superior in both emission and economic perspective.
3.9. **Web-Calculator**

As a final part of this part of the research, the Python script was translated into a web-based calculator that can be used to do emission and economic analysis of transit fleet for alternative fuel technology adoption. Users can choose to do the analysis with default data that has been documented in this study or they can input different parameters. The calculator is accessible to the public at [t-HUB GHG Emission and LCC calculator](#).

3.10. **Conclusion and Limitations**

The analysis included in this chapter reflects the importance of replacing diesel buses with alternative technology buses in order to reduce carbon footprint from a transit agency. Based on the results in can be suggested that battery electric buses are cost and emission effective alternative for replacing a diesel fleet under presumed conditions.

A number of limitations are associated with this step of the study. First, as mentioned before, the replacement schedule adopted in this part of the study does not represent true or optimized numbers. This schedule does not have any age restriction on the buses and so, doesn't specify which type of the buses are needed to be replaced in which year. This affects the accuracy of both the emission and economic analysis results.

Additionally, LCCA performed in this step of the study does not incorporate carbon costs. In an effort to quantify the emission in terms of dollar value, the social cost of carbon (SCC) can be incorporated into the study to make it more intuitive.

Finally, studying full variations of fleet mix sensitivity was out of the scope at this step of the study without performing numerous iterations. So the question regarding if there is indeed an optimum fleet mix where a shift in technology may result in a better solution or an optimum fleet mix of two or more technologies where lowest LCC can be achieved still upholds.
CHAPTER 4. OPTIMIZING BUS FLEET REPLACEMENT

4.1 Introduction

When switching the entire fleet or most part of it to a different technology, transit agencies must consider two important tradeoffs; Cost of owning and operating the buses and emission produced by the buses. Besides, the cost of operation and maintenance (O&M) increases with the age of the bus. Which indicates that replacing older buses comes with a higher capital cost but the lower O&M cost (Feng and Figliozzi, 2012). These costs also vary across powertrain type of the buses.

The focus of this chapter is to find an optimum bus replacement strategy and provide an optimum fleet mix consisting of hybrid electric and battery electric vehicles including the required charging infrastructure under budget and demand constraints using data from the CTDOT. Hydrogen fuel cell buses were not considered in this study as the cost structure related to them (discussed in chapter 3) indicate that they are not economically viable option to this date. Although BEBs have proven in the previous analysis to be suitable solution for emission reduction, HEBs, however, have lower capital costs and can prove to be a suitable alternative if emission goals have been reached. Not one of these two technologies can said to be "truly superior" compared to other. So the model gives the option for selecting either HEB or BEBs.

The model built in this chapter is transferable to other transit agencies wishing to find an optimum replacement schedule for any type of fleet mix under any budget or demand limitations. This model aims to minimize the cumulative life-cycle cost of owning and operating a fleet mix along with GHG emissions, taking into account economic factors, environmental factors, characteristics of vehicles, demand and initial fleet mix over a design period.

The subsequent parts of this chapter are organized as follows. Section 4.2 comprises of literature reviews, section 4.3 describes the methodology for developing this model, section 4.4 contains the model formulation, section 4.5 describes the case study performed using CTDOT data, section 4.6
describes the different scenarios and sensitivity analysis that was done as a part of the case study, section 4.7 presents the results of the scenarios and sensitivity analysis of the case study and finally section 4.8 includes some discussion about the implication of this research.

### 4.2 Literature Review

Studies including both life-cycle cost and emission consideration of transit buses are very rare (Lajunen, 2014). Most HEB or BEB fleet adoption models focus on purchasing process rather than replacement process. The effect of replacing the fleet of buses with alternative fuel technology buses have not been studied thoroughly.

Equipment replacement or product replacement studies have been performed comprehensively in the fields of operations research (Eilon et al. 1966), Industrial Engineering (Bellman, 1955) and management science (Meyer, 1971). A parallel replacement problem is considered when multiple assets are required to be replaced in a finite time horizon. In this context, assets themselves are independent of each other (Parthanadee, 2012) as they satisfy a common demand, consume a common budget and have similar costs associated with them. Depending on the types of product in the fleet in consideration, replacement problems can either be homogeneous or heterogeneous. Homogenous models assume that the products of same age and type must be replaced together whereas Heterogeneous models don’t. Heterogeneous models are more appropriate when solving real-world fleet replacements where the budget constraints are of concern. These models generally apply integer programming (IP) (Simms et al 1984, Hartman 2004). This chapter includes a heterogeneous study which considers three fuel types of buses that, although serve same demand and utilize common budgets, have different cost structure associated with them. The basic dynamic framework developed by Hartman (2004) and Feng et al. (2012) although is an IP problem but assumes some of the dynamic frameworks was adopted in this study. Both of these studies, however, utilize discrete time replacement, which means an unknown lifetime of the product. This study uses
finite time horizon optimization which is more complex but is more practical when considering federal or state planning procedures and that transit vehicles have a documented expected lifetime.

Two relevant studies were executed for commercial electric trucks (Feng and Figliozzi 2012) and personal vehicles (He et al. 2017; Figliozzi et al. 2011) which investigated the phasing out of conventional diesel vehicles and replacing them with electric but did not consider life-cycle cost in the model. Parthanadee et al. also studied the parallel replacement with alternative fuel consideration for vehicle fleet but that study was for personal automobile and it didn't include cost related to transit bus infrastructure. Feng and Figliozzi (2012) conducted one of the most extensive studies with real-world data considering both LCC and emission factors of hybrid and diesel buses to find an optimum replacement scheduling. That study, however only incorporated diesel and hybrid electric buses, excluding more recent technologies such as battery electric and hydrogen fuel cell buses.

In this study, a cumulative ownership, operation, maintenance, and emission cost over the design period was used to calculate the LCC of the fleet instead of the more conventional analysis method which is performed at a certain point of a product's life (Riechi et al. 2017). This method yields an optimum replacement timing cycle and a corresponding equivalent annual cost (O'Connor, 2015). Moreover, this study incorporates a more detailed GHG emission calculation instead of a per mile based calculation used in prior work (e.g., Feng and Figliozzi, 2012).

To summarize, this study aims to find the optimum schedule for replacing diesel transit buses with a mix of HEB and BEB for DOT, considering the cost of building and maintaining charging infrastructure for BEB. Also, the dynamic nature of the transit system is considered where the demand for transit changes due to either population increase or changes in travel behavior. Mixed-Integer Programming (MIP) is used to model the fleet replacement problem as described above.
4.3 Methodology

For this study, a mixed integer program is formulated to find the optimum replacement schedule for buses. The model is deterministic in nature which means that all the input values must be known apriori. The input values include economic factors, vehicle characteristics, environmental factors and available resources. The model was formulated in GAMS and solved using CPLEX solver. Figure 4-1 shows the model flow.

![Model Flow Diagram](image)

**Figure 4-1: Optimization Model Flow**

The economic factors include annual budget, fuel prices, discount rate, the rate of price increase, and the social cost of CO₂. The environmental factors include emission factors and global warming potentials (GWP) for different GHGs. Vehicle-specific factors include capital costs and O&M costs of different bus types and infrastructure, salvage value, fuel economy, and maximum life. Demand is the
annual requirement of fleet size considering changes in transit ridership and population changes. Lastly, the initial fleet mix includes the age of all current vehicles in the fleet.

The cost function has two major components consisting of life cycle cost and GHG emission cost for the entire fleet over the lifespan of the project. The output of the model consists of a number of buses purchased in a year, number of buses salvaged in a year, charging infrastructure built, the existing number of buses and infrastructure, and cost breakdown in a year.

4.4 Model formulation

The framework for the mathematical model for a fleet replacement used in this study is similar to Feng and Figliozi (2012). The primary difference is the finite time structure nature of this study. As discussed earlier, another major difference is that this study aims to meet the target GHG level at the end of the analysis period.

4.4.1 Indices

\[ i \in \{0,1,2 \ldots ,I\} \quad \text{Age of vehicle} \]
\[ k \in \{1,2,\ldots K\} \quad \text{Types of fuel technology} \]
\[ t \in \{2018,2019,\ldots T\} \quad \text{Number of years} \]
\[ g \in \{1,2,\ldots G\} \quad \text{Type of greenhouse gas} \]

4.4.2 Decision Variable

\[ P_{kt} \quad \text{Number of} \ k \ \text{type vehicle purchased at year} \ t \]
\[ Q_t \quad \text{Number of charging infrastructure installed at year} \ t \]
\[ R_{kti} \quad \text{Number of} \ i \ \text{-year old} \ k \ \text{type vehicle salvaged at year} \ t \]
\[ A_{kti} \quad \text{Number of} \ i \ \text{-year old} \ k \ \text{type vehicle in operation at year} \ t \]
\[ C_t \quad \text{Number of charging infrastructure in operation at year} \ t \]
### 4.4.3 Parameters

- **\( B \)**: Total annual budget
- **\( e_{kt} \)**: Capital cost of \( k \) type vehicle at year \( t \) (bus cost + warranty cost)
- **\( f_{ki} \)**: Operation and maintenance cost per mile for \( i \)-year old \( k \) type vehicle
- **\( j_k \)**: Fuel cost per mile for \( k \)-type vehicle
- **\( l \)**: Capital cost of charging infrastructure
- **\( n \)**: O&M cost of charging infrastructure
- **\( s_k \)**: Salvage value of \( k \)-type bus
- **\( \delta_t \)**: Social cost of \( CO_2 \) at year \( t \)
- **\( \pi_{k,t} \)**: Renewable fuel percentage of \( k \)-type bus in year \( t \)
- **\( \gamma_t \)**: Expected GHG level at year \( t \)
- **\( \theta_{kg} \)**: Emission factor for \( g \)-type GHG by \( k \) type vehicle (kg/mile)
- **\( \varphi_{kg} \)**: Emission factor for \( g \)-type GHG (kg/mile)
- **\( d_t \)**: Demand of vehicle at year \( t \)
- **\( m \)**: Average annual mileage in year \( t \)
- **\( \alpha \)**: Discount rate
- **\( \beta \)**: Rate of price increase
- **\( \varphi \)**: Maximum age of a bus in operation
- **\( \rho \)**: Minimum age of a bus in operation
- **\( \omega \)**: Minimum percentage of Battery Electric bus at the end of the analysis period
- **\( h_{kt} \)**: Number of \( k \) type \( i \) year old vehicle available at time 0 (*Initial Condition*)
4.4.4 **Objective Function**

\[
\min z = \sum_{t=0}^{T} LCC_t = \sum_{t=0}^{T} \left[ \sum_{k=0}^{K} P_{t,k} e_{t,k} + \sum_{k=0}^{K} \sum_{i=1}^{l} (A_{t,k,i,f_{k,i}} + A_{t,k,i,j_{k,i}}) m \right] \left[ (1 + \alpha)^t \right] \left(1 + \beta\right)^t \\
+ \sum_{t=0}^{T} \sum_{k=0}^{K} \sum_{i=1}^{l} \sum_{g=1}^{g} A_{k,t,i} \theta_{k,g} \theta_{g} \delta_{t} m (1 - \pi_{k,t}) \frac{1}{1000} \]

\[\ldots (1)\]

4.4.5 **Constraints**

\[
\sum_{k=1}^{K} (P_{t,k} \cdot e_{t,k} + Q_{t} \cdot l) \leq B_t \quad \forall t \quad \ldots (2)
\]

\[
\sum_{k=0}^{K} \sum_{i=1}^{l} A_{t,k,i} \geq d_t \quad \forall t \quad \ldots (3)
\]

\[
R_{0,k,i} + A_{0,k,i} + P_{0,k} = h_{k,i} \quad \forall k, t \quad \ldots (4)
\]

\[
P_{t,k} = A_{t,k,0} \quad \forall k, t \quad \ldots (5)
\]

\[
A_{t,k,i} = A_{(t-1),k,(i-1)} - R_{t,k,i} \quad \forall k, t, i \quad \ldots (6)
\]

\[
R_{t,k,i} = 0 \quad \forall t, i \in \{0, 1, \ldots, \rho\} \quad \ldots (7)
\]

\[
A_{t,k,i} = 0 \quad \forall t, i \in \{\varphi, \varphi + 1, \ldots, l\} \quad \ldots (8)
\]

\[
P_{t,1} = 0 \quad \forall k, t \quad \ldots (9)
\]

\[
C_t \geq \sum_{i=1}^{l} A_{t,k,i} \quad \forall t \quad \ldots (10)
\]

\[
C_0 = Q_0 \quad \forall t \quad \ldots (11)
\]

\[
C_t = C_{(t-1)} + Q_t \quad \forall t \quad \ldots (12)
\]
\[
\sum_{k=1}^{K} \sum_{i=1}^{I} \sum_{g=1}^{G} (\theta_{k,g} m A_{t,k,i} \star \vartheta_{g} \star (1 - \pi_{t,k})) \leq \gamma_{t} \quad \forall t \quad \text{... (13)}
\]

\[
\sum_{i=0}^{I} A_{T,k,i} \leq \omega \star \sum_{k=1}^{K} \sum_{i=0}^{I} A_{T,k,i} \quad \text{... (14)}
\]

\[
P_{t,k,R_{t,k,i},A_{t,k,i},Q_{t},C_{t}} \in \mathbb{Z}^{+} \quad \text{... (15)}
\]

The objective function, equation (1), minimizes the sum of purchasing, operating and maintaining of the entire fleet of buses including charging infrastructure, fuel cost, salvage value, and emission costs over the design period.

Equation (2) ensures that annual expenditures do not exceed the available annual budget, based on the CTDOT’s published budget for the next 5 fiscal years (CTDOT, 2017). The study an average capital budget each year, though the model could accommodate distinct annual budget amounts if those numbers were known with certainty. Expression (3) ensures that a total number of buses in operation at any given year satisfies the demand. Expression (4) establishes the initial fleet mix. Expression (5) satisfies the purchase new vehicle only rule (PNOR). Which mathematically translates to - in any given year, the number of any type of bus purchased sets the value of zero-year-old buses. Expression (6) increments the age of a bus by one year at the end of every year. Expression (7) ensures that the buses must be in operation for at least 12 years before they can be salvaged, in accordance with state and federal requirements (FTA, 2007). Expression (8) requires that when a bus reaches its maximum age, it cannot be in operation anymore. Federal law mandates that vehicles at the end of their service life must be salvaged due to safety and environmental hazard (FTA, 2007). For Connecticut, the state of practice is 15 years, based on data describing the existing fleet. This also satisfies the older vehicle selling rule (OVSR) which is adapted from an optimal rule called the “older cluster replacement rule” (OCRR) in PMRP, which states that a machine of age \( i \) is replaced only if all machines of greater age have been replaced (Hopp et al., 1993). Expression (9) indicates that
purchase of diesel buses is restricted for this study. As mentioned earlier, a major aim of this study is to reduce GHG emissions in a cost-effective manner. As replacing diesel buses does not accomplish this goal, the purchasing of new diesel buses is disallowed. Expression (10) satisfies the required number of charging infrastructure in any given year for the battery electric bus fleet. According to current practices in battery electric buses, the transit agency must have one depot charger to charge each bus. Expression (11) specifies the initial condition for charging infrastructure. Expression (12) ensures that charging infrastructures remains in use in the following years until the design year is reached. Also, newer stations are in operation immediately after construction. Expression (13) ensures that the GHG emission from the existing bus fleet in any given year is less than the emission goal set by CTDOT. Emission targets in each year are projected linearly from the emission goal set at the end of the analysis period. Expression (14) ensures that at least some percentage of the total fleet at the end of design year is battery electric. This may take any value from zero to one hundred. Expression (15) satisfies the MIP structure that says all the decision variables must be non-negative integers.

4.5. Case Study

From chapter 3 of this thesis, it can be concluded that DOT should replace their diesel bus fleets with alternative fuel technology buses to achieve their emissions reduction goals. So buses owned and operated under CTDOT were used as a case study for the parallel fleet replacement problem. Figure 4.2 shows the age and number of Diesel Buses (DB) and Hybrid Electric Buses (HEB) in operation for CTDOT in 2017. This was used as the initial condition of the data ($h_{kl}$).
4.6. Scenarios

The base case in this chapter refers to the scenario where transit ridership remains constant throughout the analysis period. Here, the total bus fleet is replaced completely with battery electric buses ($\omega = 100\%$) by 2030. The GHG level in 2030 is expected to be 35% below the level in a base year. A base assumption in cost declination of battery electric bus is 12.5% in 2030 from 2018 (discussed in chapter 3). Discount rate and rate of price increase are both assumed to be 3%. Renewable electricity (zero carbon) is assumed as 30% of the total state energy portfolio in the end year 2030. The social cost of carbon is taken as $36$/Metric Ton of CO$_2$-equivalent (EPA, 2016). The results for base case is discussed in the results section. Sensitivity analysis is performed for multiple other scenarios consisting of different combinations of the above mentioned parameters.

- BEB technology adoption percentage at the end of analysis period is varied from 45% to 100%.

  Increased in percentage adoption of BEB means a further reduction in GHG emission. This model was tested for the sensitivity to different levels of BEB adoption.
Cost declination of BEBs is used from 0% to 25% of that of the base year. Literature suggests that increase in BEB market share and the decline in battery pack costs have led to the assumption that cost of BEBs will reduce significantly in the coming years (McKinsey, 2017).

The expected GHG level in 2030 is varied from 15% to 95% of that of the base year. As there is no hard GHG level target set for 2030, the model was tested for several different scenarios.

SCC is varied from $0 to $350/ Metric Tons (MT) of CO$_2$Equivalent. The base social cost of carbon ($36) takes into account economic damage due to climate change. But there has been a variety of studies showing different levels of SCC. One study suggests a lower bound of $125/tons of Carbon (tC) for lower discount rates (Van Den Bregh and Botzen). Others suggest an unweighted value of $51.4 and a value of $329/tC weighted for equity (Anthoff & Richard, 2013). If temperature change is taken into account then under a business-as-usual emissions scenario, an average SCC value of US$96/tC if a discount rate of 3% is applied (Hanemann, 2008). Ackerman and Stanton reported values between US$241 and US$445/tC. For this analysis, values are varied between $36 and $350.

Fleet size and therefore total bus VMT and fuel usage are a function of transit ridership, accordingly, the percentage of workers using public transportation is subjected to a sensitivity analysis similar to the scenario discussed in chapter 3.

4.7. Results

4.7.1. Base Case

For the base case, the results of optimized purchasing schedule are shown in table 2. The total life-cycle cost for the base case is $666.1 million and the total GHG emissions are 0.198 million MT CO$_2$equivalent. Total allocated capital budget is not utilized completely in all the years. The first three years are the ones with the highest capital cost associated with them.
Table 4-1 Purchasing Schedule for Base Case

<table>
<thead>
<tr>
<th></th>
<th>2018</th>
<th>2019</th>
<th>2020</th>
<th>2021</th>
<th>2022</th>
<th>2023</th>
<th>2024</th>
<th>2025</th>
<th>2026</th>
<th>2027</th>
<th>2028</th>
</tr>
</thead>
<tbody>
<tr>
<td>HEB</td>
<td>27</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>BEB</td>
<td>100</td>
<td>100</td>
<td>52</td>
<td>68</td>
<td>8</td>
<td>1</td>
<td>81</td>
<td>14</td>
<td>1</td>
<td>27</td>
<td></td>
</tr>
</tbody>
</table>

Installation Schedule: Charging Infrastructure

<table>
<thead>
<tr>
<th></th>
<th>2018</th>
<th>2019</th>
<th>2020</th>
<th>2021</th>
<th>2022</th>
<th>2023</th>
<th>2024</th>
<th>2025</th>
<th>2026</th>
<th>2027</th>
<th>2028</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>9</td>
<td>8</td>
<td>8</td>
<td>1</td>
<td>4</td>
<td>6</td>
<td>0</td>
<td>0</td>
<td>7</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 3 shows the salvaging schedule for the base case. The initial fleet composition included many older diesel buses. From the salvaging schedule, it can be seen that the model is disposing of them due to the high cost associated with operating and maintenance of older buses and the maximum age constraint. These are being replaced by battery electric buses in all years of the analysis period with the exception of the initial year where a number of hybrid buses are being purchased due to the available capital budget.

Table 4-2: Salvaging Schedule for Base Case

<table>
<thead>
<tr>
<th></th>
<th>Age</th>
<th>2018</th>
<th>2019</th>
<th>2020</th>
<th>2021</th>
<th>2022</th>
<th>2023</th>
<th>2024</th>
<th>2025</th>
<th>2026</th>
<th>2027</th>
<th>2028</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diesel Bus Salvaged</td>
<td>12</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>2</td>
<td>37</td>
<td>58</td>
<td>0</td>
<td>0</td>
<td>11</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td></td>
<td>13</td>
<td>0</td>
<td>0</td>
<td>65</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td></td>
<td>14</td>
<td>0</td>
<td>15</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td></td>
<td>15</td>
<td>62</td>
<td>84</td>
<td>33</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td></td>
<td>16</td>
<td>41</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td></td>
<td>17</td>
<td>23</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Hybrid Bus Salvaged</td>
<td>12</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>14</td>
<td>10</td>
<td>8</td>
<td>81</td>
<td>3</td>
<td>27</td>
<td></td>
</tr>
<tr>
<td></td>
<td>15</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Total Bus Salvaged</td>
<td>127</td>
<td>99</td>
<td>100</td>
<td>2</td>
<td>51</td>
<td>68</td>
<td>8</td>
<td>81</td>
<td>14</td>
<td>27</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 2 is a graphical representation of the table that shows a gradual declination in a number of diesel and hybrid buses and increases in BEBs as the final year of analysis period is approached.

![Figure 4-3: Buses in Operation over Analysis Period of Base Case](image)

4.7.2. BEB Adoption Percentage

For the base case, it was assumed that the total fleet will be replaced completely by low emission battery electric buses by 2030. Obviously, a higher percentage of BEB will result in lower emission and hence lower carbon cost. But the high purchase cost associated with BEBs may lead to the belief that this is not the most cost-effective solution. The model was rerun for different percentage of BEBs in operation at the end of the analysis period. In other words, the $\omega$ in expression 14 was given a value of 0.0 – 1.0 to analyze the sensitivity of the model to BEB adoption percentage. Figure 3 shows the variation in life cycle cost and carbon cost for different percentage of BEB adoption.

The change in the color of the markers represents the different percentage of BEB adoption. Starting from the left, the darkest blue represents 100% adoption. As the color shade changes to light blue, reduction of 5% in BEB adoption is represented by each point. The lightest shade ends in 45%. Below 45% adoption of BEBs, the model becomes infeasible due to the emission constraint.
From the figure, one can infer that at about 80% BEB adoption by 2030, the LCC is the lowest which is 646.6 million dollars. This is 2.92% lower than the base cost which represents 100% BEB adoption. But this 19.5 million reduction of the cost comes at a price of 19.25% increase in greenhouse gas emissions over the 12 year period. In other words, in this scenario, $510 is saved by not reducing each MT of CO$_2$ equivalent. The figure also shows very interesting results where the costs are fluctuating with the change in BEB adoption. This is because the model is very restrictive and in order to meet this constraint, buses are either being purchased or salvaged when it may not be necessary. If we relax this constraint we can modify the equation as follows, allowing

$$\sum_{i=1}^{18} A(2030,3, i) \leq \omega \sum_{k=1}^{3} \sum_{i=1}^{18} A(2030, k, i) \quad \ldots \ldots (16)$$

With this constraint, the model restricts the most cost-effective BEB fleet mix using an inequality rather than a fixed percentage value. The least cost solution is 78% BEB adoption ($645.9 million). It is possible to save $20.2 million dollars by retaining 21% of the fleet as Hybrid Diesel Electric. This constraint also eliminates the general hypothesis that higher percentage of BEB will result in higher
cost. For example, the cost of replacing 78% vehicles with battery electric buses is 7.18 million dollars lower than 65%. But this 78% replacement comes at a cost of 21.9% increase in GHG emission than the base case. Table 4 shows the replacement schedule for 78% BEB adoption by 2030.

Table 4-3: Replacement Schedule for 78% BEB adoption

<table>
<thead>
<tr>
<th></th>
<th>2018</th>
<th>2019</th>
<th>2020</th>
<th>2021</th>
<th>2022</th>
<th>2023</th>
<th>2024</th>
<th>2025</th>
<th>2026</th>
<th>2027</th>
<th>2028</th>
<th>2029</th>
<th>2030</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Purchasing Schedule: Buses</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HEB</td>
<td>27</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>81</td>
<td>14</td>
<td>1</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BEB</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>2</td>
<td>52</td>
<td>68</td>
<td>8</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Installation Schedule: Charging Infrastructure</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>8</td>
<td>8</td>
<td>1</td>
<td>4</td>
<td>6</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 5 shows the graphical representation of existing buses in the analysis period with 78% BEB adoption. The results are very similar to the base case except for the later few years.

Figure 4-5: Buses in Operation over Analysis Period for 78% BEB Adoption
4.7.3. **BEB Cost Decline**

Although decline in the cost of the battery pack for an electric vehicle, and hence the declination of the overall capital cost of BEBs is supported by several recent studies (McKinsey, 2017), a sensitivity analysis was conducted for the pessimistic case in which BEB capital cost remains constant. With no decrease in the cost of BEBs, the base case replacement schedule doesn’t hold. The life cycle cost for the optimized replacement schedule is $682.9 million which is about 2.4% higher than the base case. But the replacement schedule remains the same as the base case.

For the relaxed constraint (Expression 16), it can be found that the least cost solution occurs at 76% BEB adoption for no decline in BEB cost over the analysis period. The cost is 1.2% higher than that of 78% BEB adoption in the baseline BEB cost decline scenario. But the GHG level at this replacement schedule is also 2.3% higher than that at 0.2474 MMT of CO$_2$ equivalent. Table 4 shows the purchasing schedule for no declination in BEB cost for 76% BEB adoption. The purchasing schedule up to 2023 is identical to the 78% BEB adoption at base cost decline scenario. This is due to the fact that there is a high number of older diesel buses in the DOT fleet in the earlier years of the analysis period which are required to be replaced due to the age constraint and also the GHG level constraints. When the minimum GHG levels are satisfied, hybrid bus purchase prevails as the best choice over battery electric buses due to lower purchasing cost.

For a 25% reduction in BEB capital cost by 2030, i.e., the cost becomes $600,000, the replacement schedule remains the same as the base case (Table 2). But the life cycle cost becomes $649.3 million resulting in a 4.9% decrease in cost. But for the relaxed constraint, the least cost solution occurs at 95% BEB adoption. In that case, LCC becomes $632.5 million resulting in a 1.5% decrease in cost compared to 78% adoption of BEB with base cost decline scenario. In this scenario, the emission is also 17% less than the former scenario at 0.2004 million metric tons of CO$_2$ equivalent. Table 5 shows the schedule for both 0% decrease and 25% decrease of BEB purchase cost for the relaxed constraint scenario.
Table 4-4: Purchasing Schedule for variation in Decline in BEB Cost

<table>
<thead>
<tr>
<th></th>
<th>2018</th>
<th>2019</th>
<th>2020</th>
<th>2021</th>
<th>2022</th>
<th>2023</th>
<th>2024</th>
<th>2025</th>
<th>2026</th>
<th>2027</th>
<th>2029</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Decline in Cost: Purchasing Schedule of Buses (76% Adoption)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HEB</td>
<td>27</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>8</td>
<td>1</td>
<td>81</td>
<td>14</td>
<td>1</td>
</tr>
<tr>
<td>BEB</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>2</td>
<td>52</td>
<td>68</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>25% Decline in Cost: Purchasing Schedule of Buses (95% Adoption)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HEB</td>
<td>27</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>BEB</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>2</td>
<td>52</td>
<td>68</td>
<td>8</td>
<td>1</td>
<td>81</td>
<td>14</td>
<td>1</td>
</tr>
</tbody>
</table>

4.7.4. Social Cost of Carbon

Changes in the value of the social cost of carbon have an impact on life-cycle cost and carbon cost. For higher SCC, the life cycle cost increases significantly. Table 6 shows the results for a few different SCC.

Table 4-5: Sensitivity to Social Cost of Carbon

<table>
<thead>
<tr>
<th>SCC in 2030 ($/Ton CO₂)</th>
<th>BEB Adoption (%)</th>
<th>Life Cycle Cost (Million $)</th>
<th>GHG Level (MMT CO₂ eqv.)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Restricted Model</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>100</td>
<td>658.2</td>
<td>0.1980</td>
</tr>
<tr>
<td>125</td>
<td>100</td>
<td>685.4</td>
<td>0.1980</td>
</tr>
<tr>
<td>360</td>
<td>100</td>
<td>734.3</td>
<td>0.1980</td>
</tr>
<tr>
<td><strong>Relaxed Model</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>78</td>
<td>636.9</td>
<td>0.2424</td>
</tr>
<tr>
<td>125</td>
<td>95</td>
<td>666.3</td>
<td>0.2006</td>
</tr>
<tr>
<td>360</td>
<td>95</td>
<td>715.9</td>
<td>0.2004</td>
</tr>
</tbody>
</table>
The overall replacement schedule remains the same for restricted constraint (expression 14) regardless of the SCC. In this scenario, the only portion of this particular model that is sensitive to SCC changes is the carbon cost. This may not hold true for any other set of initial condition inputs. For the relaxed constraint, when higher SCC values are considered compared to the base case of $36/Metric Ton CO\textsubscript{2}, BEB adoption percentage changes to 96% and follows the replacement schedule as 25% cost decline in BEB (Table 5). This is because, with the higher social cost of carbon, diesel and hybrid buses are now costlier to operate. A sensitivity analysis for zero dollars SCC was also considered. The replacement schedule unsurprisingly remains same for the restricted constraint (expression 14). But an interesting result is found when the model is run for relaxed constraint (expression 16). It can be seen that even without considering any SCC value, the model results in 78% BEB adoption being the most optimal solution for this problem.

4.7.5. The GHG level in 2030

The base case assumption starts enforces a 35% reduction in GHG level by 2030. A sensitivity analysis was done for a few other cases by lowering and increasing the reduction in GHG levels by 2030. Table 4-6 shows the results of the analysis.

\textbf{Table 4-6: Sensitivity to GHG Level in 2030}

<table>
<thead>
<tr>
<th>Reduction of GHG level in 2030 (%)</th>
<th>BEB Adoption (%)</th>
<th>Life Cycle Cost (Million $)</th>
<th>GHG Level (MMT CO\textsubscript{2} eqv.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-75</td>
<td>79</td>
<td>645.9</td>
<td>0.2419</td>
</tr>
<tr>
<td>85</td>
<td>88</td>
<td>646.2</td>
<td>0.2164</td>
</tr>
<tr>
<td>95</td>
<td>97</td>
<td>654.6</td>
<td>0.1995</td>
</tr>
</tbody>
</table>

For reduction in GHG levels up to 75% by 2030 of 2018 level results in the same replacement schedule as the base case. But as the reduction level increases, the optimum level of BEB adoption
changes. At 95%, the optimized BEB adoption is maximum at 97%. The replacement schedules are identical to the optimized BEB adoption up to the year 2025 but vary in the coming years.

4.7.6. Transit Ridership in 2030

Transit Ridership in 2030 is expected to increase in some statewide planning scenarios. A sensitivity analysis for varying levels of transit ridership is shown in the following table (Table 4-7). From the table, it can be seen that with the increase of transit ridership, optimum BEB adoption percentage decreases. This may be due to budget constraint.

**Table 4-7: Sensitivity to change in Transit Ridership in 2030**

<table>
<thead>
<tr>
<th>Transit Ridership (%)</th>
<th>BEB Adoption (%)</th>
<th>Life Cycle Cost (Million $)</th>
<th>GHG Level (MT CO₂ eqv.)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Restricted Model</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>100</td>
<td>744.7</td>
<td>0.2010</td>
</tr>
<tr>
<td>5</td>
<td>100</td>
<td>823.2</td>
<td>0.2039</td>
</tr>
<tr>
<td>6</td>
<td>100</td>
<td>906.5</td>
<td>0.2118</td>
</tr>
<tr>
<td><strong>Relaxed Model</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>75</td>
<td>723.1</td>
<td>0.2548</td>
</tr>
<tr>
<td>5</td>
<td>74</td>
<td>800.1</td>
<td>0.2669</td>
</tr>
<tr>
<td>6</td>
<td>71</td>
<td>877.7</td>
<td>0.2846</td>
</tr>
</tbody>
</table>

4.7.7. Sensitivity Analysis Summary

The purpose of sensitivity analysis was to find the responsiveness of the model to different constraints and parameters. Optimum solutions under different conditions can be used to aid replacement decisions. A manual calculation was performed to find the life-cycle cost including age
and emissions with the DOT schedule discussed in chapter 3. Total LCC, in this case, was 867.5 million dollars and GHG emission was found to be 0.313 MMT CO₂ equivalent. Comparisons were drawn with this scenario based on cost saved by adopting different optimized schedules. Summary of some of the optimized schedule is shown in the following table (Table 4-7).

Table 4-8: Sensitivity Summary

<table>
<thead>
<tr>
<th>Case</th>
<th>BEB Adoption</th>
<th>LCC ($ Millions)</th>
<th>GHG Emission (MMT CO₂e)</th>
<th>Cost Reduction ($ millions)</th>
<th>% Emission Reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>DOT Replacement Schedule</td>
<td>100%</td>
<td>687.5</td>
<td>0.313</td>
<td>-</td>
<td>36.7%</td>
</tr>
<tr>
<td>% BEB Adoption in 2030</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Restricted</td>
<td>100%</td>
<td>665.1</td>
<td>0.198</td>
<td>22.4</td>
<td>36.7%</td>
</tr>
<tr>
<td>Relaxed</td>
<td>78%</td>
<td>645.9</td>
<td>0.2419</td>
<td>41.6</td>
<td>22.7%</td>
</tr>
<tr>
<td>BEB Cost Decline by 2030 compared to 2018</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No Decline</td>
<td>100%</td>
<td>682.9</td>
<td>0.198</td>
<td>4.6</td>
<td>36.7%</td>
</tr>
<tr>
<td>76%</td>
<td>653.2</td>
<td>0.2474</td>
<td>34.3</td>
<td>21.0%</td>
<td></td>
</tr>
<tr>
<td>25% Decline</td>
<td>100%</td>
<td>649.3</td>
<td>0.198</td>
<td>38.2</td>
<td>36.7%</td>
</tr>
<tr>
<td>95%</td>
<td>623.5</td>
<td>0.2004</td>
<td>64</td>
<td>36.0%</td>
<td></td>
</tr>
</tbody>
</table>

The first two columns of the table represent the different sensitivity scenarios and BEB adoption in those scenarios. The third column shows the LCC cost of different scenarios and BEB adoption percentages. The fourth column is the GHG emission in each scenario. The fifth column represents the decrease in cost compared to the DOT Schedule. The final column shows % of emission reduction by adopting different optimized schedule compared to DOT schedule. For example, in restricted BEB adoption percentage case, about $22.4 million is being saved and about 36.7% of emission is being reduced. Whereas, for the relaxed schedule, cost reduction is $41.6 million but emission reduction is
only 22.7%. Figure 4-6 shows a graphical representation of emission and life cycle cost from unoptimized and optimized replacement schedules.

![Figure 4-6: Comparison of DOT and Optimized Bus Replacement Schedule](image)

4.8. **Discussion**

In order to maintain the health of our cities and the well-being of the environment around us, embracing low emission technologies is essential. But how and when a policy induces the adoption of these are imperative in order to protect the users and service providers from technological and economic shocks. This research showcases bus fleet replacement strategies under different scenarios. It is indeed up to the transit provider to decide which scenario they anticipate and more importantly what they want to achieve. If lowest possible emissions are the primary goal, then a transit agency may wish to adopt 100% BEBs within their analysis period. On the other hand, the results show that cost efficiency can be gained by maintaining a portion of the fleet as diesel hybrid. This mixed fleet has the potential or added resilience benefits should a power source be unavailable during storms or other natural disasters.
CHAPTER 5. CONCLUSION

5.1. Contributions of the Research

Key contributions of this research are divided into a few parts in the succeeding paragraphs.

- As a part of this research, a Modified Inventory based GHG Emission Calculator was built that is exclusively designed for Transit. Users (transit agencies) can self-report data related to their fleet and facility in a very straightforward manner. The results from this calculator can either be used for simply recording carbon footprint of the transit agency or as the starting point for further emission analysis. This calculator is a modification of the existing calculators as it incorporates three scopes of public agency emissions, is specially designed for transit agencies, and also is available for public usage.

- Subsequently, this research introduces a simplified method for calculating future fleet size requirements for a transit agency for changes in transit ridership. There are sophisticated methods available for doing similar calculations which are too data extensive and are not open source. To the author's best knowledge, there is no calculator available for doing a similar analysis using simple and publicly available data sources.

- Furthermore, this research introduces a python based web-calculator that can be used by either researchers or transit agencies to calculate GHG emission and LCC for shifting the entire or a portion of the transit fleet with alternative fuel technology within a design period. The tool produces easily interpretable summaries and figures. Although there have been studies regarding alternative fuel technology adoption or comparisons between alternative fuel technologies, there is no substantial tool or code available for public usage that incorporates both. Moreover, this tool, instead of comparing single vehicles, compares fleet replacement of entire fleet. This GHG emission and LCC Calculator for Alternative Technology Adoption can not only be
used for doing scenario analysis, emission or costs comparisons but also as a tool to facilitate investment decision making process of public agencies.

- Finally, a parallel bus fleet replacement study was performed that aims to optimize the alternative technology adoption for transit agencies. The model is deterministic and gives a quantifiable understanding of the importance of shifting towards alternative fuel technology. The model gives flexibility to the user to introduce input values and also to set the scenarios for the desired outcome. The users can decide what is most important to achieve, be it cost reduction or emission reduction or achieving a certain level of technology adoption, the model can give them the optimum solution to their problem. The model is an improvement over previous studies regarding optimization of transit fleet replacement. One of the reasons is that it includes finite time horizon instead of discrete time frame. This model also incorporates the inclusion of fueling infrastructure demand and costs. This is also an improvement over past studies as this presents the option for including newer technologies into the model as they become prevalent. Finally, as a part of the case study, various scenarios including SCC variation and cost variations were considered in a manner that is more representative of current and future scenarios.

- To sum up, this research satisfies its overarching objective of helping transit agencies make more informed decision regarding alternative technology adoption into their existing fleet. From maintaining a simple but exhaustive GHG emission inventory to optimizing their fleet replacement schedule, this study incorporates

5.2. Future Research

A substantial number of parameter values were assumed for each of the GHG and LCCA approaches based on reliable, published documentation. However, some parameters values had significant variation based on different sources, especially the ones related to BEBs or FCBs. Parameters associated with these newer technologies, are not available through any single source of
input. Moreover, a considerable amount of uncertainty remains regarding future scenarios and parameter values. Although sensitivity analyses were performed in an effort to capture some of the nuances of uncertainty, but studying all possible variations of all input values were out of the scope of the study. For future research, the study could be revisited when more reliable single source data is available. Additionally, sensitivity of other parameters can also be studied.

As an alternative way of incorporating uncertainty into the model, a stochastic model can be studied instead of deterministic one. A stochastic model gives the probability of a potential outcome by incorporating random variation of inputs. It gives the likelihood of an event occurring within a confidence interval. Although deterministic models are more useful when exact solution is desired, they ignore the randomness of input. A stochastic model could overcome some of the uncertainty and risk associated with parameters.

Furthermore, although most part of this research is open source, the optimization problem was formulated using GAMS which is a proprietary software. Some version of the software is available for public usage but the breadth of this optimization problem is much greater than the limit of the free version. In order to make all components of this research fully open source, this problem can be coded with python language as well. Several optimization packages such as Pyomo or DOcplex are available for solving large scale optimization problem using cplex solver.

Finally, as newer technologies become available, this research can be updated for optimizing inclusion of those technologies into fleet mix.
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APPENDIX

Inventory Questions

Organizational Information:
- Organization Name
- Organization Address
- Inventory Reporting Period (Start Date & End Date)
- Name of Preparer
- Phone Number of Preparer
- Date Prepared

Emission Sources Questions. (Y/N)
- Do your facilities use refrigeration or air conditioning equipment?
- Do your facilities use chemical fire suppressants?
- Do you purchase any industrial gases for use in your business? These gases may be purchased for use in manufacturing, testing, or laboratories.
- Does your inventory include facilities that use electricity?
- Do you purchase steam for heating or cooling in your facilities?

Emissions from Mobile Sources
- Source ID
- Source Description (Optional)
- No of Vehicles Operated
- Vehicle Powertrain Type
- Vehicle Miles Traveled in a Year
- Vehicle Purchase Year
- Fuel Usage or Energy consumed

<table>
<thead>
<tr>
<th>Fuel Type</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diesel</td>
<td>Thousand Gallons</td>
</tr>
<tr>
<td>Gasoline</td>
<td>Thousand Gallon Equivalent</td>
</tr>
<tr>
<td>Liquified Petroleum Gas</td>
<td>Thousand Diesel Gallon Equivalent (DGE)</td>
</tr>
<tr>
<td>Liquified Natural Gas</td>
<td>Thousand Diesel Gallon Equivalent (DGE)</td>
</tr>
<tr>
<td>Compressed Natural Gas</td>
<td>Thousand Diesel Gallon Equivalent (DGE)</td>
</tr>
<tr>
<td>Bio-Diesel Fuel</td>
<td>Thousand Diesel Gallon Equivalent (DGE)</td>
</tr>
<tr>
<td>Electricity</td>
<td>Thousand kWh</td>
</tr>
</tbody>
</table>
Emissions from Purchase of Electricity

- Source ID
- Source Description (Optional)
- eGrid Subregion
- Purchased Electricity (kWh) in a Year

Emissions from Refrigeration and Air Conditioning Equipment

- Source ID
- Source Description (Optional)
- Type of Refrigerant
- New Units - Charge & Capacity (lb)
- Existing Units - Charge & Capacity (lb)
- Disposed Units - Recovered (lb)

Emissions from Purchased Gases

- Source ID
- Source Description (Optional)
- Type of Gas
- Amount purchased (CCF)