2019

Hybrid Life Cycle Sustainability Assessment-based Multi-objective Optimization: A Case for Sustainable Fleet Mix

Burak Sen
University of Central Florida

HYBRID LIFE-CYCLE SUSTAINABILITY ASSESSMENT-BASED MULTI-OBJECTIVE OPTIMIZATION: A CASE FOR SUSTAINABLE TRANSIT BUS FLEET MIX

by

BURAK SEN

B.S. Sakarya University, 2011
M.Sc. Karl-Franzens University of Graz/Chalmers University of Technology (Joint Degree)

A thesis submitted in partial fulfillment of the requirements
for the degree of Master of Science
in the Department of Industrial Engineering and Management Systems
in the College of Engineering and Computer Science
at the University of Central Florida
Orlando, Florida

Spring Term

2019

Major Professor: Qipeng Phil Zheng

ABSTRACT

Sustainable transportation idea includes not only switching from conventional energy sources to alternative fuel resources, but also diverging from private vehicle use and shifting to alternative transportation modes. As a part of alternative transportation mode, utilizing alternative fuels in public transportation operation supports sustainable transportation at it full-glance. Given their implications in terms of air quality and sustainable movement of people, transit buses, which provide the primary public transportation service, are considered an ideal domain for the deployment of alternative fuels. An input-output (IO) model is developed based on Eora database – a detailed IO database that consists of national IO tables. Using the Eora-based IO model, this study quantifies and assesses the environmental, economic, and social impacts of alternative fuel buses in Atlanta, GA, and Miami, FL based on 6 macro-level sustainability indicators. The life cycle sustainability performance of these buses are then compared to that of a diesel transit bus as well as a regional comparison is carried out based on the two U.S. metropolitan areas. Based on these results, a multi objective optimization model is constructed to find an optimal transit bus fleet for the studied U.S. regions. It has been found that a transit fleet that is composed of diesel buses operating in Atlanta has 30% more global warming potential than that of a transit fleet operating in Miami. The same bus fleet operating in Atlanta incurs a life cycle cost (LCC) that is more than double the LCC of the fleet operating in Miami. The study presents a way in which transit agencies can strategize their transitioning to a sustainable bus fleet.

To my beloved family and friends

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS (or) ABBREVIATIONS

AFLEET	Alternative Fuel Life-Cycle Environmental and Economic Transportation
APEEP	Air Pollution Emission Experiment and Policy
BEB	Battery Electric Bus
CAV	Connected Autonomous Vehicle
CNG	Compressed Natural Gas
DALY	Disability-Adjusted Life Year
FCB	Fuel-Cell Bus
GDP	Gross Domestic Production
GHG	Greenhouse Gas Emissions
GOS	Gross Operating Surplus
GREET	Greenhouse Gas, Regulated Emissions, and Energy Use in Transportation
GWP	Global Warming Potential
IE	Industrial Ecology
IO	Input-Output
LCA	Life Cycle Assessment
LCSA	Life Cycle Sustainability Assessment
LCC	Life Cycle Costing
LNG	Liquefied Natural Gas
PMFP	Particulate Matter Formation Potential
POFP	Photochemical Oxidant Formation Potential
SDA	Structural Decomposition Analysis
SUT	Supply and Use Tables
TCO	Total Cost of Ownership
VMT	Vehicle Miles Traveled
VOC	Volatile Organic Compound
WF	Water Footprint

CHAPTER 1: INTRODUCTION

1.1 Overview

Today, cities accommodate over 50% of the world's population and contribute substantially to global GDP as well as global energy consumption and greenhouse gas (GHG) emissions (United Nations 2018). Similarly, over 80% of the U.S. population reside in urban areas. Due to their characteristics (e.g. concentration of population and accumulation of socio-economic activities), the sustainability implications of these areas have become a mainstream topic in the scientific community, making cities a focal point for researchers and policy-makers to find ways to improve the efficiency of socio-technical systems that comprise the building blocks of a city, one of which is transportation.

Without a doubt, the availability of a reliable surface transportation infrastructure as well as the accessibility of urban dwellers to transportation services has far-reaching economic, social, and environmental implications. Transportation sector alone consumes a vast amount of energy being responsible for almost 30% of U.S. total energy in 2017 (U.S. Energy Information Administration 2016). The mobility of people and goods relies heavily on petroleum products, which accounted for over 90% of the U.S. transportation sector's total energy use in 2017. Following the health, accommodation, and food items, transportation-related expenditures make up almost 10% of U.S. total personal expenditures, as shown in Figure 1 (U.S. Department of Transportation Bureau of Transportation Statistics 2018). Transportation sector accounts for over 25% of the total greenhouse gas emissions, and is heavily dependent on fossil fuel, which has a polluting production process that also generates considerably large amounts of emissions (U.S. EPA 2019).

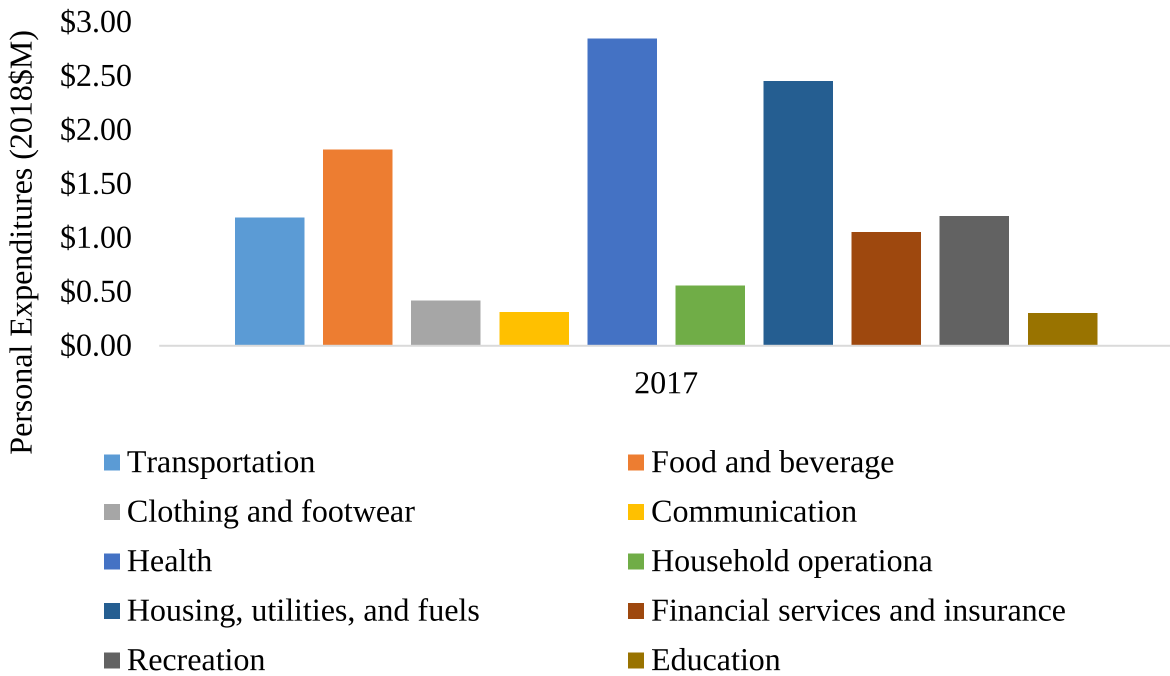

Figure 1-1 Personal expenditures by category (millions of current years)

Within the transportation sector, even though transit buses are responsible for a tiny share of the total U.S. emissions from this sector despite their poor fuel economy (U.S. EPA 2018), increase in transit bus's vehicle miles-travelled (VMT) that is already three to four times the VMT of passenger vehicles causes a concern over (U.S. Department of Transportation Bureau of Transportation Statistics 2018). One of the favorable aspects of transit buses in terms of their sustainability impacts is regarding the large deployment of alternative fuel systems (AFS), which have achieved remarkable improvements in GHG and conventional air pollutant emission, and fuel economy, and hence, fuel expenditures (Bureau of Transportation Statistics 2019). Given the benefits of AFSs, the remaining diesel transit bus fleets should be converted to alternative fuel-powered transit bus fleets. Even though different AFSs have been adopted for transit buses, given the growing population in urban areas and an increasing number of transit ridership, transit buses are considered an ideal vehicle class to improve the sustainability impacts of transportation in urban areas. In this regard, alternative fuels offer remarkable improvements to bus's fuel economy and ultimately, tailpipe emissions as well as emissions at petroleum refineries. Furthermore, zero-emission transit buses produce no tailpipe emissions, thereby improving urban air quality, and reducing air pollution externality (APE) costs (or social cost of air pollution) (Ercan and Tatari 2015).

Transit service authorities will need to respond to increasing demand by growing number of population for public transportation, with convenient service. However, given their operational characteristics (i.e. VMT and fuel economy), an increase in ridership will likely result in an increased amount of greenhouse gas (GHG) and tailpipe emissions, especially if transit bus fleets that still comprise of diesel buses do not consider deploying alternative fuel buses in their fleets. This would help reduce the U.S. dependence on imported petroleum products used for buses while improving air quality at urban centers. Therefore, not only does such a transition have environmental applications, but also significant economic and social implications through increased energy security and reduced social cost of carbon. In this regard, transition to sustainable transit bus fleet mix would be an effective strategy that transit authorities can adopt.

In recent years, a dramatic shift from diesel fuel to alternative fuel has been experienced in the makeup of transit bus fleets. The early adopters of alternative fuels deployed biofuels and Compressed Natural Gas (CNG) as oppose to diesel (Baker et al. 2016). Due to reported benefits from various transit agencies, CNG was rapidly adopted by many U.S. public transportation agencies [Ercan and Tatari, 2015-LCA paper]. The hybrid technology, which significantly improved the fuel economy of conventional diesel buses, was introduced in early 2000s, followed by the introduction battery electric buses. Hybrid transit buses have achieved a remarkable market penetration so far, while techno-economic circumstances (e.g. battery technology, charging infrastructure, range anxiety etc.) that apply to battery electric transit buses have slowed down the penetration of these type of transit buses. are still in the developmental stage due to the limited number of battery-electric transit buses compared to total number of transit buses in the U.S. However, the rapid developments on energy storage (battery) technology around the globe reduced the high purchase price of battery electric buses and reduced concerns over range anxiety.

As a result, over 50% of the U.S. transit bus fleet currently comprises of alternative fuel buses such as hybrid-electric (over 20%), CNG (almost 30%), and a tiny share of battery electric buses (American Public Transportation Association 2019; Lee et al. 2019). Given distinct socio-cultural and socio-economic characteristics of cities, it is a challenging task for transit authorities to make procurement and planning decisions that can accelerate the deployment of alternative fuel buses. In addition, individual transit agencies may well be subject to different economic and/or regulatory constraints that influence the decision-making process with regard to transit bus fleet management. Holistic and well-established analytical tools should be utilized to assist agencies in making informed decisions (Hanlin et al. 2018). For this purpose, this study applies transit bus activity-based hybrid life cycle sustainability analysis and multi-objective optimization to the case of sustainable transit bus fleet composition in fifteen U.S. metropolitan areas.

1.2 Objectives of the Thesis

As opposed to end-users (i.e. light-duty vehicles) and U.S. trucking industry (e.g. freight trucks), public transportation agencies have been the early adopters of alternative fuels. Today, transit buses that run on alternative fuels outnumber diesel transit buses in the United States. In 2016, U.S. public transportation agencies provided over 10 billion trips, marking a 20% increase in transit ridership during the last two decades (Federal Transit Administration 2019). Different public transportation agencies serve populations, with different socio-cultural and socio-economic backgrounds. Therefore, each public transportation agency has different circumstances and strategize its services depending on the region, in which it serves, as well as the climatic, geographic, and traffic conditions of that region (Xu et al. 2015). For example, while New York's Metropolitan Transportation Authority plans to purchase 60 battery-electric buses through 2020, Los Angeles Metro aims to transform its transit bus fleet to a 100 percent zero emission bus fleet by 2030 (Albert et al. 2014; Los Angeles Metropolitan Transportation Authority 2017). Therefore, environmental and socio-economic impacts associated with transit bus fleets of each public transportation agency also vary just like local conditions that each agency experience. In this regard, it is crucial to get insights into these impacts while making a decision on composing a sustainable transit bus fleet.

For this purpose, one of the main objectives of the thesis is given as the following:

1. Quantify and compare the life cycle sustainability impacts of conventional and alternative-fuel transit buses. The quantification and comparison are based on environmental impacts (e.g. GHG and air pollutant emissions, energy and material consumption, and midpoint impacts such as global warming potential

and photochemical oxidant formation potential), social impacts (e.g. air pollution health damage costs, human health impact (DALY), and employment), and economic impacts (e.g. life cycle costs, taxes, and GDP).

Even though tracking and understanding the sustainability impacts of a transit bus fleet is an important step towards a sustainable fleet composition, it is not sufficient to operationalize this knowledge obtained from an initial life cycle sustainability assessment. Despite having different local conditions, it is a common objective of transit agencies to minimize their negative sustainability impacts and maximize their positive sustainability impacts while making a decision on new bus purchases. Since transit agencies usually have limited available funds, they are likely to transition to a sustainable fleet gradually and hence, they will have to consider multiple factors in their decision-making practices. In order to support transit agencies at informed decision-making, another main objective of the thesis is as follows:

2. Find a Pareto optimal composition of a transit bus fleet mix based on aforementioned sustainability impacts in a way that will minimize the negative impacts while maximizing the positive impacts.

1.3 Organization of the Thesis

This thesis consists of five chapters. The first chapter presents an overview of the sustainability implications of transportation (exclusively public transportation) within the context of urban sustainability. This chapter also states the main objectives of the thesis. The second chapter provides the review of most relevant scientific work in the literature on life cycle assessment and application of the studied optimization method in fleet mix problems. The third chapter presents the methods and materials applied to carry out the analysis, including hybrid life-cycle assessment and multi-objective linear programing. The fourth chapter present the findings of the study, and the fifth chapter draws the conclusions of the study based on these findings.

CHAPTER 2: LITERATURE REVIEW

Given their sustainability implications, i.e. environmental, social, and economic, transit buses have always been a subject of interest for scholars. Furthermore, upon the introduction of *sustainability science*, scholars have adopted various frameworks and methods from the sustainability science toolbox to analyze transit buses' multi-dimensional impacts and conduct policy-relevant syntheses to aid strategic decision-making for public transportation investments. Scholars have applied those frameworks and/or tools either separately (e.g. LCA, LCSA, LCC, life cycle energy analysis etc.) or in combination with other techniques (e.g. LCA-based optimization). There is a large number of studies in the literature that have examined different aspects of public transportation. Therefore, this review of the literature mainly focuses on the studies that have investigated transit bus sphere using life cycle sustainability assessment or life cycle assessment frameworks in combination with multi-objective optimization methods. Given the most commonly accepted lifetime of a transit bus, the studies conducted in 2007 onwards have been included in the literature review.

Ally and Pryor (2007) constructed a process-based life cycle assessment model to assess the life cycle environmental and energy impacts of diesel, CNG, and FC buses throughout their lifetime – assumed to be 16 years –, including in the system boundary the stages such as bus manufacturing, refueling infrastructure, operations, and end-of-life. The researchers found fuel cell bus to be competitive with diesel and CNG options, particularly in terms of their global warming potential. The study showcased an example in the Australian context and lacks the consideration of other commonly-used alternative fuel bus options such as hybrid and battery electric buses in their analysis. Golub et al. (2011) developed a life cycle cost model for transit buses to evaluate hybrid electric bus technology's performance in terms of operating and capital costs. The researchers also carried out a comparison of the results between CNG, diesel, gasoline hybrid electric, and diesel hybrid electric bus (HEB) options. They found the LCCs of diesel and gasoline HEBs to be 3% and 5% to be higher than that of a conventional diesel bus; and the LCC of CNG buses to be 8% higher than that of diesel buses. The developed model was comprehensive but limited to LCC accounting only. Vahdani et al. (2011) employed a fuzzy multiple criteria decision-making (MCDM) method to assist with transit bus fleet composition considering various alternative fuel bus options including conventional diesel, CNG, batter electric, hybrid electric, fuel cell, liquid propane gas (LPG), and methanol buses. The researchers took into account several aspects that influence a bus purchase decision such as energy supply, energy efficiency, air pollutant emissions, noise pollution, industrial relationship, technology implementation cost, maintenance cost, vehicle capability, road facility, speed of traffic flow, and sense of comfort. According to their analysis results, conventional diesel, CNG, and LPG are ranked in top three of the transit bus selection. The study lacked the consideration of life cycle perspective, and not necessarily optimized the transit fleet. Kliucininkas et al. (2012) presented a case study from Kaunas, Lithuania on the life cycle assessment of public transportation in the city that included trolleybuses, transit buses, and taxis/microbuses based on alternative fuel chains. The system boundary included the extraction/production and initial treatment of fuels, their transportation, production, distribution, and combustion. The researchers adopted the ReCiPe method to quantify weighted damage that was caused by five alternative fuel chains, and found the compressed biogas to have the lowest damage value, while diesel and CNG caused the highest damage. The study only focused on the considered fuels' life cycles and excluded other life cycle stages as well as life cycle costs.

Xu et al. (2013b, a, 2015) developed a novel, load-based life cycle fuel and emissions calculator model based on several other models such as AFLEET, MOVES, GREET, and a load surrogate known as *scale tractive power* (SPT). The researchers took into consideration of several parameters in their estimations of the life cycle environmental impacts of transit bus fuel production and consumption, such as terrain roughness, meteorological conditions, duty cycles, and passenger loads. They applied the model to the cases of Atlanta, GA, San Francisco, CA, and Phoenix, AZ, and found that significant differences in emissions depending on geographic and ridership characteristics. The study only focused on fuel cycle emissions and is not considered a complete LCA. The researchers state that low-income households, which usually benefit from transit buses to commute, are disproportionately exposed to emissions from transit bus operations. However, the study lacks the inclusion of health impact costs of air pollutant emissions from transit bus operations. Lajunen (2014) presented a cost-benefit analysis (CBA) of hybrid and battery electric buses in terms of their life cycle costs for the considered operation routes (or duty cycles) based on the cost variables such as capital costs, operating costs, and costs of the energy storage system replacements. The researchers found hybrid buses to have almost the same life cycle cost as conventional buses; and plug-in hybrid and battery electric uses to have the best potential to lower the LCCs of transit bus operations.

Ribau et al. (2014) carried out a life cycle-based optimization study to investigate an optimal powertrain design for plug-in hybrid electric and hybrid electric vehicles based on life cycle cost, life cycle fuel efficiency, and life cycle greenhouse gas emissions (GHG). The researchers set the system boundary of the analysis based on cradle-to-grave, which includes all the life cycle stages from raw material extraction to end-of-life. Furthermore, they based the optimization model on a single-objective generic algorithm (i.e. minimizing LCC, life cycle fuel efficiency, and life cycle GHG), and a multi-objective generic algorithm (i.e. minimizing the objective couples of LCC and life cycle fuel efficiency, LCC and life cycle GHG, and life cycle fuel efficiency and life cycle GHG), which were then linked to a vehicle simulation software. They found hydrogen fuel cell buses to potentially reduce the life cycle energy consumption by almost 60% and emit almost 70% less life cycle GHG emissions relative to diesel buses. Ercan and Tatari (2015) carried out a hybrid life cycle assessment of alternative fuel buses options (i.e. diesel, biodiesel, CNG, liquefied natural gas (LNG), hybrid electric bus, and battery electric bus) that operate on three driving cycles, i.e. Manhattan, Central Business District (CBD), and Orange County Transit Authority (OCTA). The researchers included in their analysis all the life cycle stages except for the end-of-life stage. In addition, regional electricity grid mix differences were also considered in their analysis with regard to power supply for the battery electric bus option. The researchers found CNG and LNG buses to underperform all the other transit bus options operating under all the considered driving cycle conditions. In addition, the researchers found battery electric bus options to cause the highest amount of water withdrawal given the use of the prevailing regional grid mix; however, the use of renewable energy sources to generate power (e.g. solar PV) reversed this result. One of the key shortcoming of this study was that it was based on an old version of an input-output model developed by Carnegie Mellon University Green Design Institute (2008). Li et al. (2015) presented an optimization approach, called remaining life additional benefit-cost analysis, to aid decision-making on when and what kind of actions to take with regard to retiring or retrofitting an existing bus fleet. The optimization model considered cost components such as operating and retrofit costs, and external costs from emissions as well as emissions generated from buses. The analysis results showed that by employing the proposed approach, it was possible to gain over $170 million from emission reduction under a zero inflation rate. As dictated by the study's scope, only those costs and emissions from the remaining lifetime of buses were included in the analysis. Ercan et al. (2015) carried out an LCA-based multi-objective optimization and tradeoff analyses to assist with the decision-making on composing a new transit bus fleet that is relatively sustainable. In their analysis, the researchers only included three driving cycles such as Manhattan, Central Business District (CBD), and Orange County Transit Authority (OCTA), and the model parameters such as life cycle costs, life cycle environmental emissions, and life cycle air externality costs (or social cost of air pollution) that originate from diesel, hybrid, biodiesel, battery electric, CNG, and LNG buses. Their analysis results showed biodiesel buses to perform the worst in terms of conventional air pollution impacts; and battery electric buses to underperform all other transit bus options in terms of life cycle costs. The optimization model developed by the researchers found no diesel bus in any objective weighting scenarios (e.g. cost-dominant, environmental-dominant etc.).

Lajunen and Lipman (2016) developed simulation models of different transit but powertrains using the Autonomie vehicle simulation software to evaluate the life cycle costs and carbon dioxide emissions of different types of city buses based on the driving conditions in Finland and California. The researchers found that alternative transit bus powertrains could significantly improve the energy efficiency and reduce GHG emissions, with battery electric buses potentially reducing these emissions by up to 75%. Ally and Pryor (2016) presented a case study from Australia on life cycle cost accounting of diesel, natural gas, hybrid, and hydrogen fuel cell transit buses. The input parameters for the developed LCC model included the cost components such as bus purchase cost, life cycle maintenance and repair costs, life cycle fuel costs, life cycle AdBlue (i.e. a non-hazardous aqueous urea to tackle diesel tailpipe emissions) consumption, and end-of-life salvage value. The study found the total cost of ownership of diesel hybrid electric transit bus to be 10% higher than that of a conventional diesel bus. Zhou et al. (2016) designed a real-world experiment for three battery electric buses' performances and life cycle fuel benefits with respect to energy consumption and carbon dioxide emissions and presented a case study for Macao, China. The researchers tested the studied battery electric buses under different air-conditioning, passenger loads, and driving conditions (i.e. bus speed). The analysis also included the life cycle energy consumption and environmental impacts of the studied battery electric buses based on the GREET model. The study found that battery electric buses operating in the case city had the potential to reduce well-to-wheel petroleum use by over 85%, well-to-wheel fossil fuel use by over 32%, and well-to-wheel carbon dioxide emissions by as much as 35% relative to conventional diesel buses. The study is confirmatory in that auxiliary loads such as passenger loads and air-conditioning use are significant parameters to consider when constructing a model to analyze the performances of transit buses' operations. Yu et al. (2016) presented another case study concerning China on the influence of passenger load on conventional (Euro III) diesel bus's fuel consumption and emission performances by designing a real-world experiment based on *Vehicle Specific Power*, which was also adopted in the FEC model used by the thesis. The researchers found an inverse correlation between passenger load and per-passenger emission and fuel consumption factors, marking the significance of the inclusion of passenger loads in emission and fuel consumption analysis of transit buses. The study only focused on the activity-based emission, i.e. emissions from transit bus operations, and hence, did not include the life cycle impacts that are associated with fuel production. Even though their study was not complete in that sense, it is confirmatory of the effect of passenger loads on transit bus's operational performance.

Tong et al. (2017) examined the life cycle ownership cost and environmental externality of alternative fuel-powered 40'ft and 60-ft transit bus options, which included conventional bus powered by either diesel or biodiesel, diesel hybrid-electric bus, natural gas-powered bus (either CNG or LNG), and a battery electric bus (rapid or slow charging). Life cycle ownership cost model included the cost parameters such as bus purchase cost, fuel costs, operation and maintenance cost, and infrastructure cost, while environmental externality costs were estimated by monetizing the GHG emissions through the social cost of carbon, and conventional air pollutant emissions through the APEEP model, which is also adopted by the thesis. The study found conventional buses to outperform all the other studied transit bus options in terms of life cycle ownership costs as well as environmental externality costs. The study did not include in the analysis any other life cycle indicator; however, concluded that battery electric buses could provide important performance improvements in regard to the considered indicators. Bi et al. (2015) carried out a comparative analysis, using a process-LCA approach, of plug-in charging (i.e. scenario 1) and wireless charging (i.e. scenario 2) of battery electric transit buses in terms of their life cycle energy consumption and life cycle GHG emissions. The study found wireless charging system to consume slightly less energy and emit slightly less GHG emissions relative to plug-in charging technique. In a follow-up study, Bi et al. (2018) conducted a life cycle-based multi objective optimization for wireless charger deployment for a battery electric transit bus network based upon the results of the researchers' previous study. The objective function solved in the study was to minimize life cycle costs, life cycle GHG emissions, and life cycle energy 2016consumption by selecting bus stops where wireless chargers will be deployed. Through their analysis, the researchers revealed that it was possible through the optimal siting strategies to help reduce the objective function parameters, on average, by 10% relative to a base case scenario, where such a decision-making aid is not present. Lozanovski et al. (2018) carried out a sustainability assessment of fuel cell transit buses under the European context, with environmental LCA, total cost of ownership, and qualitative, open-ended interviews, which represented the three pillars of sustainability (i.e. the environment, society, and the economy), respectively. The researchers found that hydrogen production has an important implications in terms of fuel cell buses' environmental impacts, and that fuel cell buses become competitive enough by 2030 when their benefits to human health and climate change are also taken into account. Emiliano et al. (2018) presented a multi-objective optimization model applying *Weighted Tchebycheff* and *Augmented Weighted Tchebycheff* methods to find Pareto-optimum bus fleet combinations composed of 20 buses based on life cycle GHG emissions and conventional air pollutant emissions that were obtained from Ercan and Tatari (2015), and total costs that originate from transit bus operations in Joinville, Brazil. The analysis included a diesel bus, two types of battery electric buses, and a CNG bus that run on three routes denoted as SN, IT, and ST. The analysis results showed that battery electric buses were the only bus choice for the SN line, whereas IT and ST lines were dominated by diesel and CNG transit buses, respectively. The study confirmed the significance of using multi-objective optimization approaches to tackle life cycle-based optimum transit bus fleet composition problems. Lee et al. (2019) investigated the well-to-wheel environmental implications of fuel economy targets for hydrogen fuel cell electric buses in the United States using the Greenhouse Gases, Regulated Emissions, and Energy Use Transportation (GREET) model. The researchers found that hydrogen fuel cell electric transit buses reach to a break-even point with diesel buses in terms well-to-wheel energy consumption and air pollutant emissions, and start producing net benefits in this regard. Xylia et al. (2019) presented a case study from Stockholm, Sweden on the implications of transit bus electrification in terms of carbon emissions employing an optimization model to find the optimum location of electric bus chargers and estimate the associated life cycle carbon emissions, and eventually the climate change impact of bus electrification. The researchers employed Ecoinvent – a life cycle inventory database – and Intergovernmental Panel on Climate Change (IPCC) 2013 GWP100 impact assessment method. The life cycle environmental impacts from powertrain manufacturing and maintenance, road construction, and the transportation service delivery were excluded from the analysis. The optimization model constructed by the researchers in another study of theirs was utilized for the analysis. The researchers found that GWP of the studied bus type was mainly dominated by the emissions associated with fuels and batteries, and that electricity as a transportation fuel type outperformed first-generation biofuels in terms of GWP. The study concluded that electrification could be beneficial for reducing conventional air pollution reduction; however, that it was hard to offer the same claim for the overall reduction.

CHAPTER 3: METHODOLOGY

3.1 Hybrid Life Cycle Sustainability Assessment

Owing to its ability to provide a comprehensive and analytical framework, life cycle assessment (LCA) is considered as a well-established tool, widely used by scholars from diverse scientific backgrounds to analyze and assess the environmental impacts of production and consumption (Guinée et al. 2002). Through complementary impact methods that may be incorporated in an LCA, it becomes possible to quantify midpoint indicators (e.g. *global warming potential, photochemical oxidant formation potential*, *resource consumption etc.*) and endpoint indicators (e.g. *human health, social assets, biodiversity etc.*) with regard to production or consumption system at hand (Russell et al. 2005).

Different LCA approaches have been proposed by scholars that attempted to broaden the capabilities of the LCA tool. Since its introduction, approaches such as consequential LCA, attributional LCA (Russell et al. 2005), process-LCA, and economic input-output (EIO) LCA (Hendrickson et al. 1997; Lenzen 2000) have been employed to different production and consumption systems. Recently, process LCA – also referred to as process-based LCA (Haes et al. 2004)- and EIO LCA have reached a wider use both in academy and industry. However, LCA is limited in that it mainly focuses on environmental and energy analysis of an economic activity, hence not able to capture social and economic impacts thereof (Sala et al. 2013). Therefore, LCA is extended with the social LCA (SLCA) and life cycle cost (LCC) analysis through the use of EIO analysis. The hybrid life cycle sustainability assessment (LCSA) approach employed in this study is composed of process-based LCA and EIO analysis techniques. Through hybridization, the life cycle sustainability impacts could be more effectively estimated.

Kloepffer (2008) defined the LCSA framework, and Finkbeiner et al. (2010) contributed to formulating and operationalizing the framework. Accordingly, LCSA was defined as the following:

$$LCSA = LCA + LCC + SLCA \quad (1)$$

Input-output analysis method introduced by Leontief (1970) and employed in this study enables the operationalization of the LCSA framework. Previously, similar models were developed based on the IO method for the U.S. (Kucukvar and Tatari 2013), U.K., and Australian economies (Foran et al. 2005). For the purposes of this study, the Eora database developed by Lenzen et al. (2013) is used to construct a single region industry-by-industry IO model for the U.S. economy to assess the studied life cycle sustainability impacts from the considered transit buses. Eora was chosen because of its high consistency and level of sectoral details (Wiedmann et al. 2015). In essence, Eora is composed of national input-output tables that represent the entire global economy (Lenzen et al. 2013).

In Eora, an IO table is constructed converting Supply and Use Tables (SUTs) of 190 countries that are merged with environmental, social, and economic satellite accounts such as GHG emissions, labor inputs, energy use, water requirements, etc., into Make and Use Matrixes for the purposes of this study (Lenzen et al. 2013).

The Use matrix, denoted as U, gives information on the consumption of commodities by other industries or final demand categories (i.e. households, government, investment, and export).

In this matrix, the columns show commodities purchased by industries, whereas the rows show industries that use those commodities. As a component of U, u_{ij} denotes the value of the purchase of commodity *i* by industry *j*. Using the information provided by U, the technical coefficient matrix B is computed through the following equation (Miller and Blair 2009):

$$B = \left[b_{ij}\right] = \left[\frac{u_{ij}}{x_j}\right] \tag{2}$$

where b_{ij} denotes the amount of commodity *i* required to produce a dollar-worth output of industry *j*, and x_j denotes the total amount of industry *j* including imports.

The Make matrix – the transposed supply table -, denoted as V, provides information on the production of commodities by industries. In this matrix, the rows show the amount of commodities used by industries, whereas the columns show industries. Using information given by the V matrix, the industry-based technology coefficient matrix D (also referred to as market share matrix) can be formed as the following (Miller and Blair 2009):

$$D = \left[d_{ij}\right] = \left[\frac{v_{ij}}{q_i}\right] \tag{3}$$

where v_{ij} denotes the value of the output of commodity *i* by industry *j*; q_i denotes the total output of commodity *i*, and d_{ij} denotes the fraction of total commodity *i*'s output produced by industries.

After defining B and D matrixes, an industry-by-industry IO model can be formulated as the following (Miller and Blair 2009):

$$x = [(I - DB)^{-1}]f \tag{4}$$

where x denotes the total industry output vector, I denotes the identity matrix, DB denotes the direct requirement matrix, and f denotes the total final demand vector.

Once the IO model is constructed, the LCSA impacts can be estimated by multiplying the final demand of an industry j with the multiplier matrix. A vector of total LCSA impacts is formulated as the following (Miller and Blair 2009):

$$r = E_{dim}x = E_{dim}[(I - DB)^{-1}]f \tag{5}$$

where r denotes the total impact vector that gives the estimations of LCSA impacts per unit of final demand, and E_{dim} represents a diagonal matrix, consisting of LCSA impact values per dollar-worth output of each industry. The multiplier matrix consists of the product of E_{dim} and $(I - DB)^{-1}$, values of which are provided in Table 1. These multipliers are used to quantify the LCS indicators considered in the analysis. These LCS indicators are presented in Table 1.

Table 3-1 Life cycle sustainability indicators analyzed

Impact Area	Impact/Indicator	Unit	Description
Environmental	Global Warming Potential (GWP)	tCO2-eq.	Total GHG emissions based on IPCC's factors for GWP100
Social	Employment	person	Number of jobs based on Bureau of Labor Statistics (BLS) data for total employment for each sector
	Income	$M	The compensation of employees, wages, and salaries
Economic	Gross Domestic Product		Economic value added by the U.S. sectors
	Life Cycle Cost	$M	Cost of an automated heavy-duty truck throughout its life cycle
	Social Cost of Air Pollution		Health damage cost of air pollution

Almost all of the upstream environmental impacts stemming from the manufacturing phase are obtained the Eora-based EIO model developed for the purposes of the study. The EIO model developed for the U.S. economy uses the economic input-output tables based on the transactions executed 2015. As for the downstream environmental impacts, which are caused by the use phase, both the EIO model and process-based models such as the *Greenhouse gases, Regulated Emissions, and Energy use in Transportation (GREET)* (Center for Transportation Research 2016), *Alternative Fuel Life-Cycle Environmental and Economic Transportation (AFLEET)* (Burnham 2017), and *Motor Vehicle Emission Simulator (MOVES)* (EPA 2014) models are used. For the categorization of the data used in the model North American Industry

Classification System (NAICS) is employed (Green Design Institute 2006). Therefore, the input values to account for the upstream environmental impacts of the life cycle phases are the purchase prices of each of the studied transit buses and their additional parts, if any.

The tailpipe emissions that stem from the fuel consumption during the use phase are obtained from FEC Bus model developed by Xu et al. (2015), which is built upon vehicle specific function that uses second-by-second vehicle speed data. The reason why an activity-based approach, i.e. the use of vehicle specific power (VSP), has been adopted is because fuel consumption and associated emissions rates are better explained by VSP (Frey et al. 2007). In turn, there are other parameters that affect the VSP required for efficient bus operations. Road grades and passenger loads, which have been proven to significantly affect fuel consumption and, ultimately, the associated emissions, are among these parameters (Frey et al. 2007; Khan and Clark 2010). The AFLEET tool enables the examination of indicators such as petroleum use, GHGs and air pollutant emissions, and cost of ownership of both light-duty and heavy-duty vehicles (Burnham 2017). The AFLEET tool also uses the U.S. EPA's Motor Vehicle Emissions Simulator (MOVES) database to trace air pollutant emissions since the MOVES model was developed to reflect the air pollutants produced from vehicle operating processes (EPA 2014).

Just like LCA framework, LCSA framework consists of four consecutive steps, namely *goal and scope definition*, *life cycle inventory analysis*, *life cycle impacts assessment*, and *interpretation* (International Organization for Standardization 2006). According to this framework, firstly, the goal and scope of the study is defined. This includes system boundary, level of aggregation, and the midpoint and endpoint impact categories that are to be analyzed at the end of the assessment. Secondly, the inputs and outputs, e.g. raw materials used, water, energy, and emissions, of the defined system boundary are documented. In the following stage, the impacts of the inputs used and the outputs obtained are assessed by using a specific impact method. The ReCiPe methodology provided by Huijbregts et al. (2017) has been employed for life cycle impact assessment. Finally, the assessment results are interpreted and reported for effectively communicating the LCS impacts of the studied system.

3.1.1 Life Cycle Inventory

A conventional (diesel) transit bus is considered the baseline truck, composed of the essential truck components such as truck's body, shell, engine, other miscellaneous parts, and a trailer. Alternative fuel buses require the installation of additional parts, and these additional parts come along with additional costs to the baseline truck manufacturing. For example, a hybrid bus is equipped with a battery pack and an electric motor, while a battery electric bus (BEB) requires glider and power electronics, in addition to a battery pack and an electric motor. Similarly, a compressed natural gas-fueled (CNG) bus uses a metal tank to store its fuel.

In addition to the differences in physical characteristics of the studied buses, infrastructural needs of the studied buses are also reflected in the analysis. For diesel and hybrid buses. the diesel station construction cost per gallon is first calculated based on the infrastructure cost model provided by AFLEET (Burnham 2017). Then, to account for the parts of the station construction costs that belong to the studied buses, the obtained value is then multiplied by the amount of fuel consumed by the relevant buses throughout their life cycles. For CNG bus type, the construction cost per mile is calculated based on the AFLEET; and the estimated value is then multiplied by vehicle-miles-travelled (VMT) of CNG bus to account for their causes of the examined life cycle sustainability impacts associated with the construction of a natural gas refueling station. As for BE bus type, electric vehicle suppy equipment (EVSE) station cost that pertains to a battery electric bus throughout its lifetime is estimated based on the total cost of constructing a station provided by the AFLEET model (Burnham, 2017). The lifetimes of these infrastructures are assumed to be 30 years as provided by the AFLEET model (Burnham, 2017). The considerations (e.g. fuel prices, refueling stations, and air pollution costs) regarding the inputs for LCSA are presented.

The life cycle fuel consumption of each studied transit bus type is calculated by the division of a bus's vehicle-miles-travelled by its fuel economy. Therefore, fuel economy of the studied transit buses are significant for the LCSA results. The fuel economies of each studied transit bus type has been obtained from the activity-based FECBUS model developed by Xu et al. (2015), which are provided in Table 2 below.

Table 3-2 Fuel economy (fuel consumption for BE transit bus) values for the studied bus options in the studied cities

	Fuel Economy/Fuel Consumption	
	Atlanta	**Miami**
Diesel (mpdg)[a]	3.74	4.10
Battery Eelectric (kWh/mile)	3.47	2.58
Hybrid (mpdg)[a]	4.85	5.88
CNG (mpdge)[b]	2.73	3.14

Table 3-3 Life cycle sustainability impact multipliers relevant for the sectors included in the system boundary

	Heavy-duty vehicle mnfg.	*Motor vehicle parts mnfg.*	*Motor and generator mnfg.*	*Metal tank, heavy gauge mnfg.*	*Natural gas mnfg.*	*Miscellaneous electrical equipment and component mnfg.*
Carbon dioxide (CO2) (Kt/$M)	0.353065	0.358746	0.254780	0.285574	0.849641	0.163091
Methane (CH4) (Kt/$M)	0.001076	0.001332	0.001140	0.001758	0.003568	0.000846
HFC-134a (Kt/$M)	0.000300	0.000186	0.000400	0.000723	0.000476	0.000490
HFC-143a (Kt/$M)	0.000312	0.000195	0.000414	0.000750	0.000493	0.000503
HFC-125 (Kt/$M)	0.000309	0.000192	0.000407	0.000736	0.000484	0.000501
Dinitrogen oxide (N20) (Kt/$M)	0.000285	0.000193	0.000371	0.000660	0.000563	0.000441
Employment (person/$M)	3.680948	3.795739	3.888803	5.640225	3.062494	4.739971
Income (000 USD / $M)	405.066068	290.581238	447.575874	543.375575	323.424383	492.736376
GDP ($M/$M)	0.680973	0.718459	0.806596	0.830981	0.856103	0.790236

The inputs that are entered to the developed EIO model are the unit costs of each component related to the manufacturing and operations of the studied buses. Accordingly, once life cycle fuel costs, life cycle maintenance costs, and life cycle battery replacement (i.e. for hybrid and BE buses) are calculated, it is then possible to estimate the values of the examined life cycle sustainability indicators utilizing the multipliers, shown in Table 1, which are obtained from the developed EIO model.

3.2 Multi-Objective Linear Programing

The multi objective linear programming (MOLP) approach has been employed for the analysis. The LCS impacts of transit buses are categorized into three main category in accordance with the LCSA framework, i.e. environmental, social, and economic, based on the studied LCSA indicators. These three sustainability dimensions are considered as the multiple objectives which, depending on the indicator that belongs to each dimension, a transit agency seeks to minimize or maximize the impact. The life cycle sustainability indicators assumed in the analysis are *global warming potential (GWP)* for environmental dimension, *employment* and *income* for social dimension, and *gross domestic product (GDP), social cost of air pollution (SCAP),* and *life cycle costs (LCCs)* for economic dimension.

An optimal transit bus fleet mix for Atlanta, GA, and Miami, FL is found by using the MOLP approach, in which constraints with regard to transit agencies' circumstances (e.g. budget constraints, emission reduction goals or the like, etc.). The approach employed in this study is suited to type of decision-making cases, in which there are multiple objectives to be considered, and an infinite number of possible decisions (Eiselt and Sandblom 2012). The optimization model constructed for the purposes of this study is formulated by using a MINIMAX function. The decision variables included in the model are the number of the studied buses (i.e. diesel, hybrid, BE, CNG, and FC) in a transit bus fleet, hypothetically assuming that the fleets in both cities are composed of 100 buses for the purposes of the study, like in (Ercan et al. 2015).

The multi objective optimization (MOO) model has been constructed as it applies to the transit bus fleets in two U.S. metropolitan areas, namely Atlanta, GA and Miami, FL, which are indexed on *j*, composed of four transit buses, which are indexed on *i*. Accordingly, the sets included in the optimization model are *set J*, which is composed of the studied metropolitan areas and given as J = {1(Atlanta), 2(Miami)}; and *set A*, which is composed of the studied bus types and given as A = {1(diesel), 2(hybrid electric bus), 3(compressed natural gas bus), 4(battery electric bus)}. Decision variables are Z_{ij}, the number of bus type *i* given a city *j*, and Q_j, objective function values' maximum weighted deviations from their target values for a city *j*. According to this setting, the purchase decision on each studied bus type *i* by each city *j* is denoted by the variable P_{ij}. For example, P_{22} represents *hybrid electric bus* that may potentially be purchased by *Miami transit fleet.* The model *parameters* are obtained from the hybrid life cycle sustainability analysis carried out in the first part of the thesis and defined as *global warming potential (GWP)* (i.e. based on life cycle carbon dioxide equivalent emissions) as environmental impact indicator, *employment* and *income* as social impact indicators, and *gross domestic product (GDP), life cycle cost (LCC)* and *social cost of air pollution (SCAP)* as economic indicators. Accordingly, Z_{ij}^{1} denotes the GWP of transit bus type *i* in city *j*, Z_{ij}^{2} denotes the employment, Z_{ij}^{3} denotes the income, Z_{ij}^{4} denotes the GDP, Z_{ij}^{5} the LCC, and Z_{ij}^{6} denotes the SCAP, all in the same manner as the GWP.

In addition, to find the target values of each model parameters for the application of the MINIMAX function-based optimization model, six single minimization models have been developed, which are given as the followings:

G_j = The minimum *GWP* value resulting from a fleet of 100 transit buses in city *j*,

E_j = The maximum number of *employment* resulting from a fleet of 100 transit buses in city *j*,

I_j = The maximum amount of *income* resulting from a fleet of 100 transit buses in city *j*,

D_j = The maximum amount of *GDP* resulting from a fleet of 100 transit buses in city *j*,

L_j = The minimum amount of *LCC* incurred by a fleet of 100 transit buses in city *j*, and

S_j = The minimum amount of *SCAP* incurred by a fleet of 100 transit buses in city *j*.

Since some of the model parameters such as employment, income, and GDP are positive indicators, meaning that the higher their values are, the more benefits a transit bus fleet provides. Therefore, to include these in the developed optimization model, their objective function values have been multiplied by -1, which are given as the followings:

$$\mathrm{G_j} = \mathrm{MIN} \sum_{i=1}^{4} \mathrm{P_{ij}} \times \mathrm{Z_{ij}^1} \quad (6)$$

$$\mathrm{E_j} = \mathrm{MIN} \sum_{i=1}^{4} \mathrm{P_{ij}} \times \mathrm{Z_{ij}^2} \quad (7)$$

$$\mathrm{I_j} = \mathrm{MIN} \sum_{i=1}^{4} \mathrm{P_{ij}} \times \mathrm{Z_{ij}^3} \quad (8)$$

$$\mathrm{D_j} = \mathrm{MIN} \sum_{i=1}^{4} \mathrm{P_{ij}} \times \mathrm{Z_{ij}^4} \quad (9)$$

$$\mathrm{L_j} = \mathrm{MIN} \sum_{i=1}^{4} \mathrm{P_{ij}} \times \mathrm{Z_{ij}^5} \quad (10)$$

$$\mathrm{S_j} = \mathrm{MIN} \sum_{i=1}^{4} \mathrm{P_{ij}} \times \mathrm{Z_{ij}^6} \quad (11)$$

Subject to

$$\sum_{i=1}^{4} P_{ij} = 100 \quad (12)$$

$$P_{ij} \geq 0, \forall\, i \in A, \;\; j = 1,2 \quad (13)$$

$$P_{ij} \in \text{INTEGER}, \forall\, i \in A \quad (14)$$

As mentioned previously, the optimization model constructed for the analysis will eventually find an optimum number of buses in a transit bus fleet minimizing costs and negative impacts (i.e. GWPs, LCCs, and SCAP) and maximize positive impacts (i.e. employment, income, and GDP). These indicators are essentially the model parameters used in the optimization model. Because these model parameters have different units, the objective function of the model will be composed of the weighted percentage deviations of these parameters, as also applied in (Ercan et al. 2015). Four weighting scenarios have been examined in the thesis. These scenarios include *equal weights* ($\beta_{ENV} = \beta_{SOC} = \beta_{ECO} = 1$), *environmental-dominant* ($\beta_{ENV} = 2, \beta_{SOC} = \beta_{ECO} = 1$), *social-dominant* ($\beta_{SOC} = 2, \beta_{ENV} = \beta_{ECO} = 1$, *economic-dominant* ($\beta_{ENV} = \beta_{SOC} = 1, \beta_{ECO} = 1$).

3.3 Pareto Optimum

To make more informed decisions, it is very useful to have a knowledge of the trade-offs between multiple objectives that are considered in the decision-making process. Trade-offs, as found in this analysis, are nothing but the conditions, with which an objective gets worse while another objective is improved. This state, where such a condition applies to, is called *Pareto optimality*. Following the methodology presented by Winston and Albright (2008), the trade-off curves for the assumed multiple objectives were determined. Accordingly, it is possible for a transit agency (or a decision-maker, in this regard) to understand the changes in the objective function value when a decision is altered. The parameters included in the trade-off analysis are the life cycle costs (LCCs) and global warming potentials (GWPs) of the studied transit bus options.

To generate the trade-off curves, a single objective optimization model (i.e. a minimization problem) has been constructed using linear programming method. The parameters that have been used in this optimization model remain the same as those used in the multi-objective optimization problem defined in the previous section. Accordingly, the maximum GWP and LCC values are first calculated using the following model:

$$\mathrm{H_j} = \mathrm{MAX} \sum_{i=1}^{4} P_{ij} \times Z_{ij}^{1} \qquad (15)$$

$$\mathrm{O_j} = \mathrm{MAX} \sum_{i=1}^{4} P_{ij} \times Z_{ij}^{3} \qquad (16)$$

where H_j denotes the maximum GWP that can result from a fleet of any combination of 100 transit buses for city *j*; and O_j denotes the maximum LCC that can result from a fleet of any combination of 100 transit buses. Once these maximum values are calculated, the boundary values of GWP and LCC could be determined since the minimum values are obtained from G_j and L_j. Pareto optimal solutions are determined at every 20 thousand tons of CO_2 intervals using the following single objective optimization model:

$$\mathrm{L_j} = \mathrm{MIN} \sum_{i=1}^{4} \mathrm{P_{ij}} \times \mathrm{Z_{ij}^{5}} \qquad (17)$$

Subject to

$$\sum_{i=1}^{4} \mathrm{P_{ij}} = 100 \qquad (18)$$

$$\mathrm{P_{ij}} \geq 0, \forall \mathrm{i} \in \mathrm{A}, \quad \mathrm{j} = 1,2 \qquad (19)$$

$$\mathrm{P_{ij}} \in \mathrm{INTEGER}, \forall \mathrm{i} \in \mathrm{A} \qquad (20)$$

$$\mathrm{G_j} \leq \sum_{i=1}^{4} \mathrm{P_{ij}} \times \mathrm{Z_{ij}^{1}} \leq \mathrm{H_j} \qquad (21)$$

The constraint (20) is repeated for each predetermined GWP interval, which was 20,000 ton $C0_2$ in this case by changing L_j.

CHAPTER 4: FINGINGS

4.1 Hybrid Lice Cycle Sustainability Assessment Results

4.1.1 Environmental Impacts

The environmental impacts are reported based on the global warming potentials of the studied transit buses operating in the examined metropolitan areas. The overall results are presented in Figure 2. Accordingly, the total GWP of all the studied transit buses are significantly higher in Atlanta relative to Miami; however, the GWP intensities (i.e. CO_2-eq. per life cycle vehicle-miles-traveled) of the transit buses are higher in Miami than in Atlanta. A CNG bus has been observed to be the worst performing transit bus type studied in terms of the GWP in Atlanta. In Miami, while a battery electric bus has been observed to cause the biggest harm with regard to the GWP, a CNG bus operating in Miami has been estimated to cause only 3% less GWP than its battery electric counterpart.

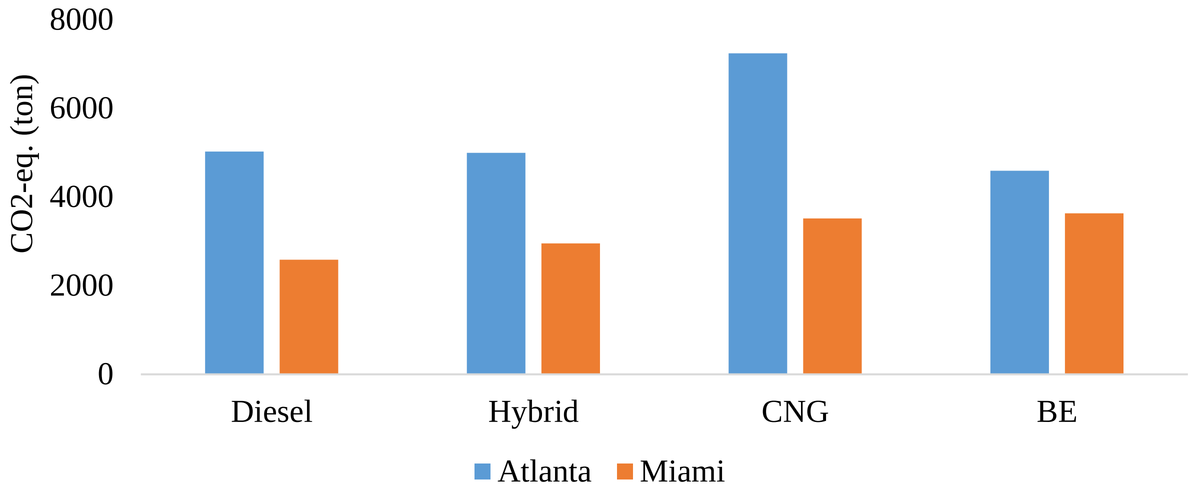

Figure 4-1 Global warming potentials of transit bus options in the studied areas

The underlying reason behind this picture is the heavy burden that the production of natural gas as a transportation fuel places on the total GWP of a CNG bus. Another factor that plays a significant role in this result is the CNG bus's fuel economy obtained from the activity-based FECBUS model, which is the lowest in comparison to all the other bus options considered in the analysis.

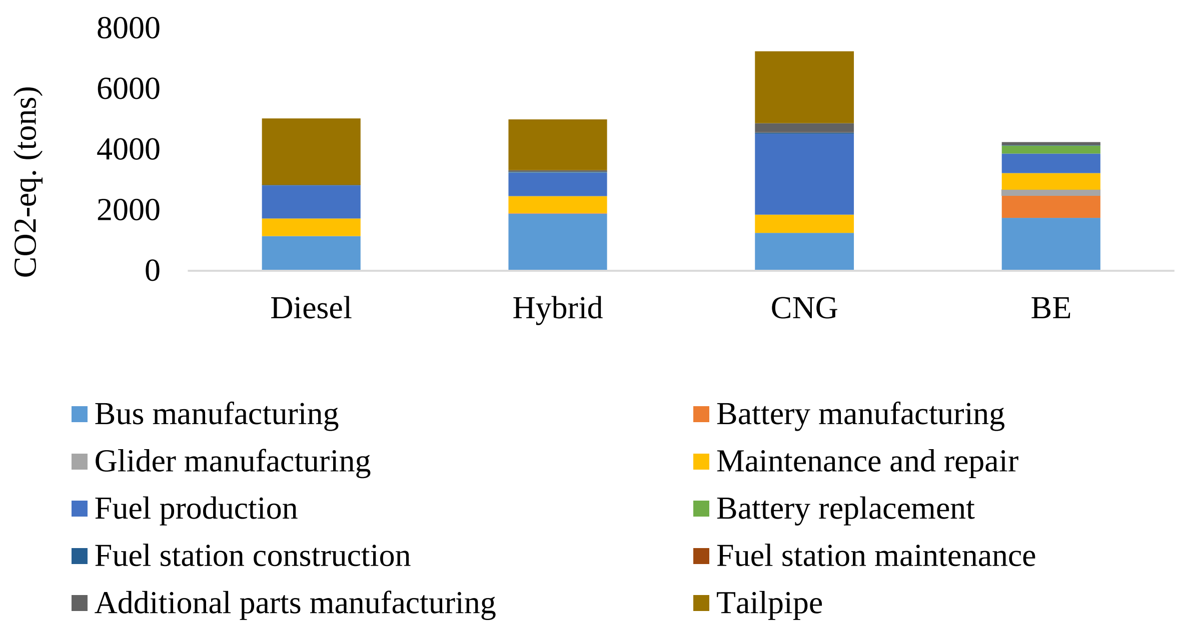

Figure 4-2 Global warming potential of individual life cycle phases for Atlanta

A diesel bus operating in Atlanta has a GWP of 5025 ton CO_2-eq., which is almost two times that of a diesel bus operating in Miami. The activities associated with vehicle manufacturing, and fuel production and consumption have been observed to be responsible for the great majority of the GWP impacts of this type of bus in both metropolitan areas examined. While tailpipe emissions make up almost 30% of the GWP potential of a diesel bus operating in Miami, it is almost 45% for the same bus in Atlanta. In addition, the GWP attributable to fuel production activities for a diesel bus in Atlanta is 22% of the total GWP, it is less than 20% for a diesel bus operating in Miami. On the other hand, vehicle manufacturing-related impacts have been observed to be responsible for almost 45% of the GWP of a diesel bus in Miami, while it has been estimated to account for 23% of the total impact in Atlanta. As can be seen in Figure 3 and Figure 4, the manufacturing of battery electric bus causes the largest GWP, among other life cycle components. It has been observed that CNG bus underperforms all the other studied transit bus types both in Atlanta and Miami.

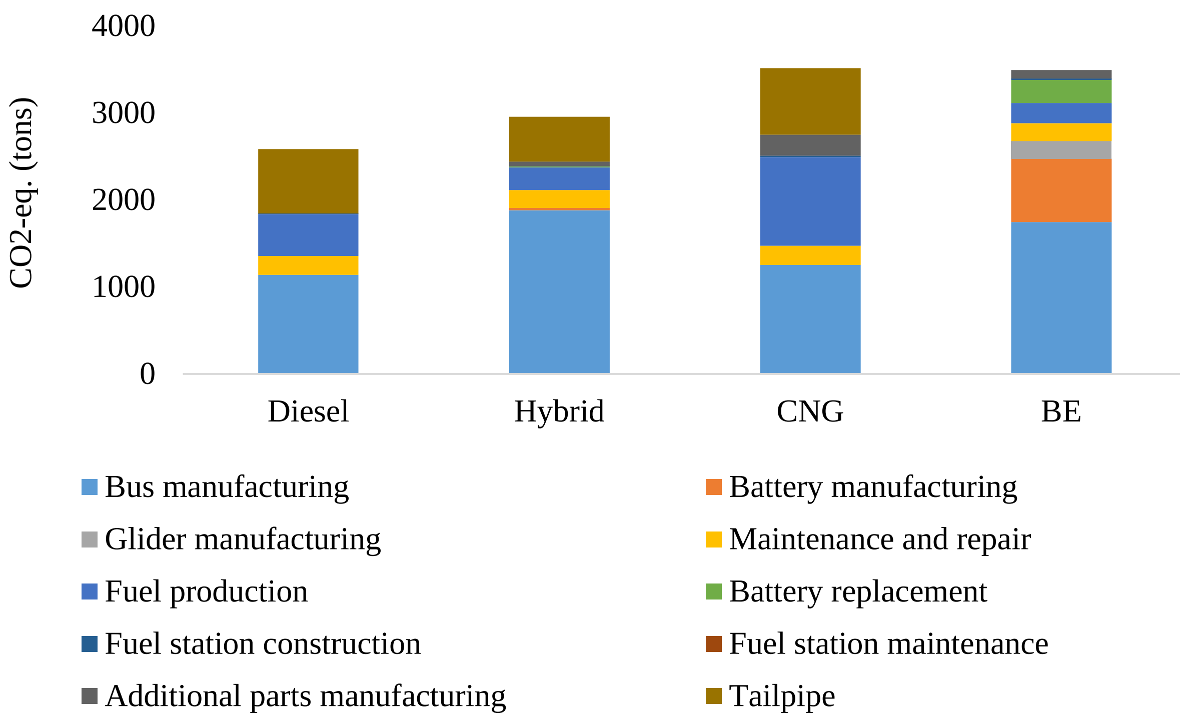

Figure 4-3 Global warming potential of individual life cycle phases for Miami

Given the role of vehicle-miles-travelled in fuel economy profiles (and fuel production as a result of the consumption) of the studied transit bus options, the studied transit bus options operating in Miami have caused lesser amounts of GWPs relative to those in Atlanta. Therefore, to better understand the efficiency of these bus options, it is useful to take a look at the GWP intensity of each bus options running in both cities, as shown in Figure 5.

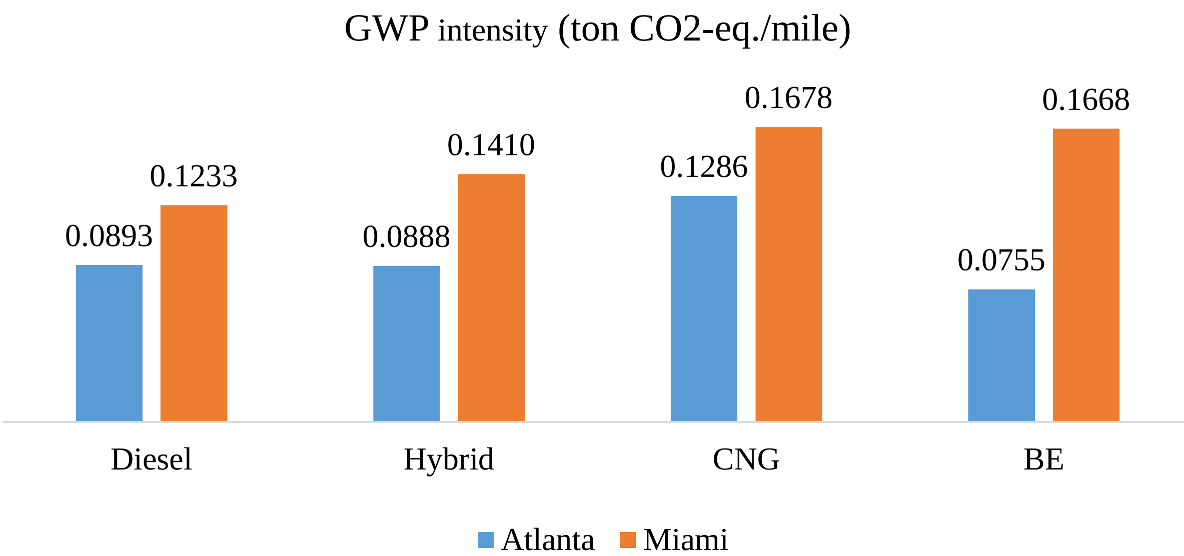

Figure 4-4 Global warming potential intensities of transit bus options in the studied areas

Battery electric bus has been found to be the most efficient bus option for operations in Atlanta, whereas it is conventional bus that has been found to be the most efficient bus option for operations in Miami.

4.1.2 Social Impacts

The social impacts are reported based on the *employment* and *income* indicators. The overall results with regard to employment are presented Figure 6 and Figure 7. Accordingly, the total employment created by each studied truck type in Atlanta is about two times the employment created by the studied transit buses in Miami. This is due largely to the daily VMT of the buses driven in Atlanta being greater relative to that of Miami. Employment associated with CNG bus type has been observed to be the highest in Atlanta, followed by battery electric bus type. Of the total employment created, almost 65% is attributable to maintenance and repair (M&R) activities. This is mainly to the fact that average daily mileage (or VMT) of the studied transit bus options in Atlanta is higher than the daily VMT of the studied transit bus options operating under the Miami conditions. This higher VMT results in relatively more maintenance and repair activities of a diesel bus in Atlanta. When it comes to employment, M&R activities also play a significant role in Miami; however, employment related to bus manufacturing has also been found significant as such activities are responsible for almost 35% of the total employment created by a diesel bus in Miami.

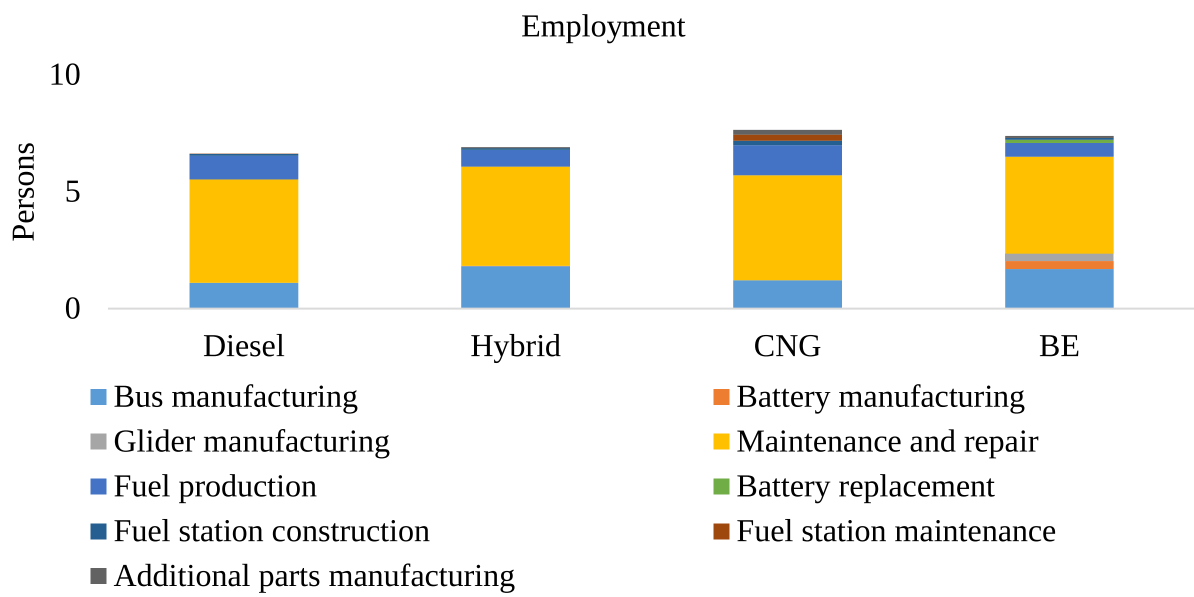

Figure 4-5 Employment created by the studied bus types in Atlanta (persons)

In Atlanta, the activities related to maintenance and repair have been observed to contribute to employment creation the most for all the studied bus types. In Miami, given relatively shorter VMT, the activities related to the manufacturing of hybrid and battery electric bus types contribute the most to employment creation, with 49% and 38.5% of the total employment, respectively, while it is the activities related to maintenance and repair that contribute the most to employment creation by diesel (51%) and CNG (45%) buses. In Atlanta, a CNG bus type has been observed to create the highest number of employment, whereas it is the battery electric bus type in Miami.

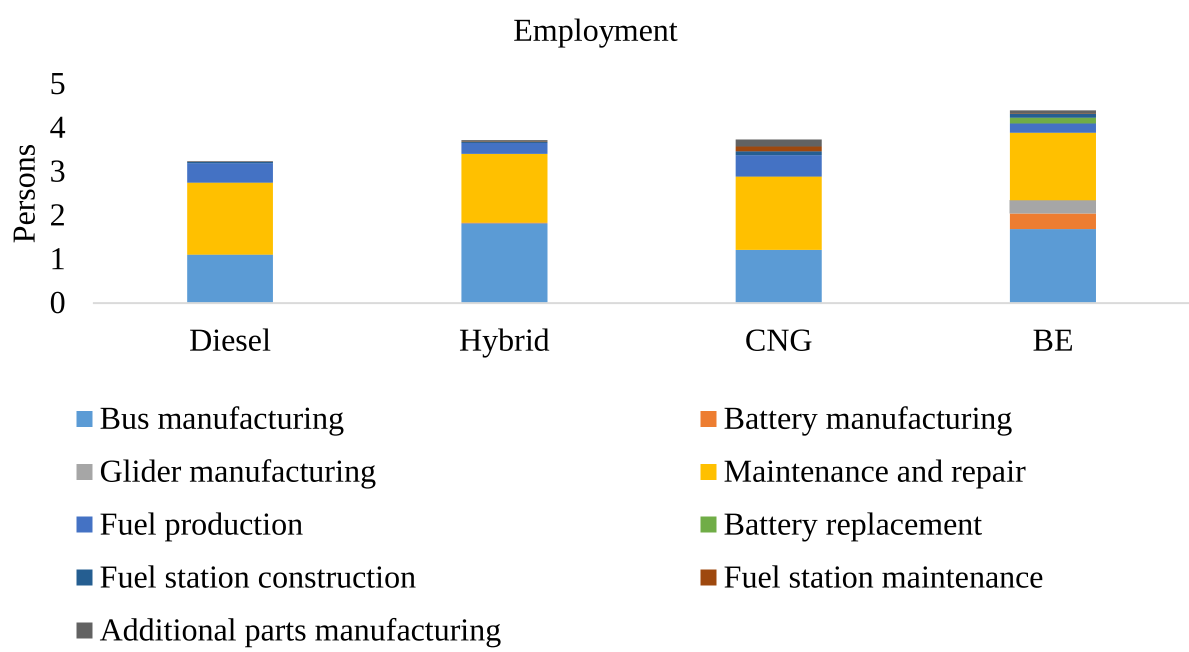

Figure 4-6 Employment created by the studied bus types in Miami (persons)

Overall, employment associated with battery electric bus type has been observed to be the highest in Miami, followed by CNG bus type. As mentioned previously, this is also the case in Atlanta. The reason behind the effect of CNG bus type on employment is likely to be attributable to natural gas supply (i.e. natural gas refueling station). The findings related to employment are consistent with the data provided by Hughes-Cromwick et al. (2018) in American Public Transportation Association (APTA)'s recent report. The data in this report revealed that vehicle operations and maintenance account for the great majority of the employment in public transit industry. Furthermore, the APTA's report stated that each $1 billion investment in public transit industry resulted in 50,000 jobs. When it is assumed that the same amount of investment is done in the transit bus system, the amount of employment generated by the transit bus system has been estimated to be around 6 to 9 thousands in Atlanta, and 3 to 5 thousands in Miami. Considering the fact that these results only reflect the transit bus systems in these cities, the numbers are aligning with that of the APTA's report.

Income is another indicator that represents the social dimension. As shown in Figure 8, the battery electric bus type has been estimated to generate the highest income ($610K), followed by CNG bus type ($595K) in Atlanta. For all the studied bus types in Atlanta, the activities associated with maintenance and repair activities have been observed to generate the majority of the total income generated. This is followed by the activities related to the manufacturing of each bus type. These results align with the rate of employment created through these activities, which are consistent with the data provided by APTA's report. The lowest income generating transit bus options in Atlanta have been found to be conventional ($455K) and hybrid transit buses ($510K). The difference stems from the income generated through hybrid bus manufacturing activities.

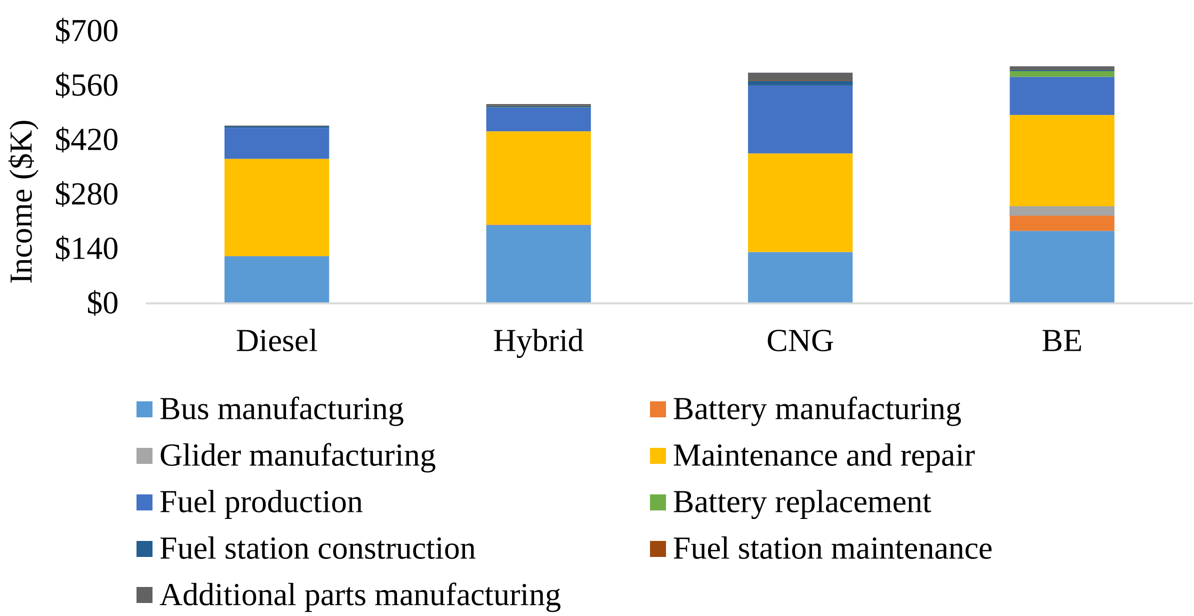

Figure 4-7 Income ($K) generated through the studied buses in Atlanta

As for Miami, the picture is slightly different in that the income generated through the activities associated with bus manufacturing is almost the same as those stemming from fuel production and M&R related activities combined. Unlike the case of Atlanta, battery electric and hybrid bus types have been estimated to generate the highest income, with almost $390K and $315K of income, respectively. In Miami as well, there seems to be a consistent relation between the rate of employment and the income generated. Another difference observed in Miami relative to Atlanta is that the incomes generated through bus manufacturing activities have been found to be higher than any other life cycle component. This is followed by maintenance-and-repair-related activities and fuel production-related activities. This is mainly due to the relatively lower VMT and the relatively better fuel economy/fuel consumption experienced in Miami.

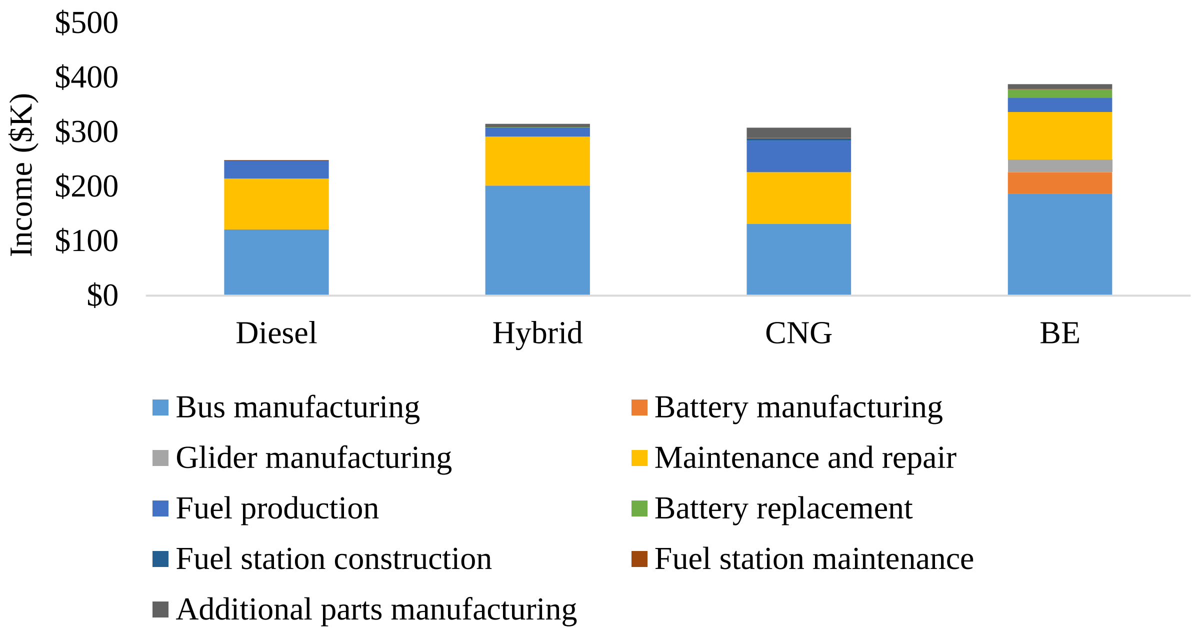

Figure 4-8 Income ($K) generated through the studied buses in Miami

In Atlanta, the manufacturing of battery (including battery replacement) for battery electric transit bus has been estimated to account for 9% of the total income generated through this bus type; whereas the income generated through battery manufacturing has been estimated to be almost 15% of the total income in Miami.

4.1.3 Economic Impacts

One of the economic sustainability indicators that represent the economic dimension is *social cost of air pollution (SCAP)*. Figure 10 presents the overall social cost of air pollution caused by each of the studied bus types operating in Atlanta. Tailpipe emissions have been observed to cause the greatest health damage in Atlanta due to relatively higher VMT. This is followed by the health damage costs incurred by the activities associated with fuel production in Atlanta; on average, over one fourth of the SCAP of the studied buses, except for the battery electric bus type, is caused by the production of diesel or natural gas as a transportation fuel. On the other hand, the activities related to power generation for the battery electric bus type is responsible for over 70% of the SCAP in Atlanta.

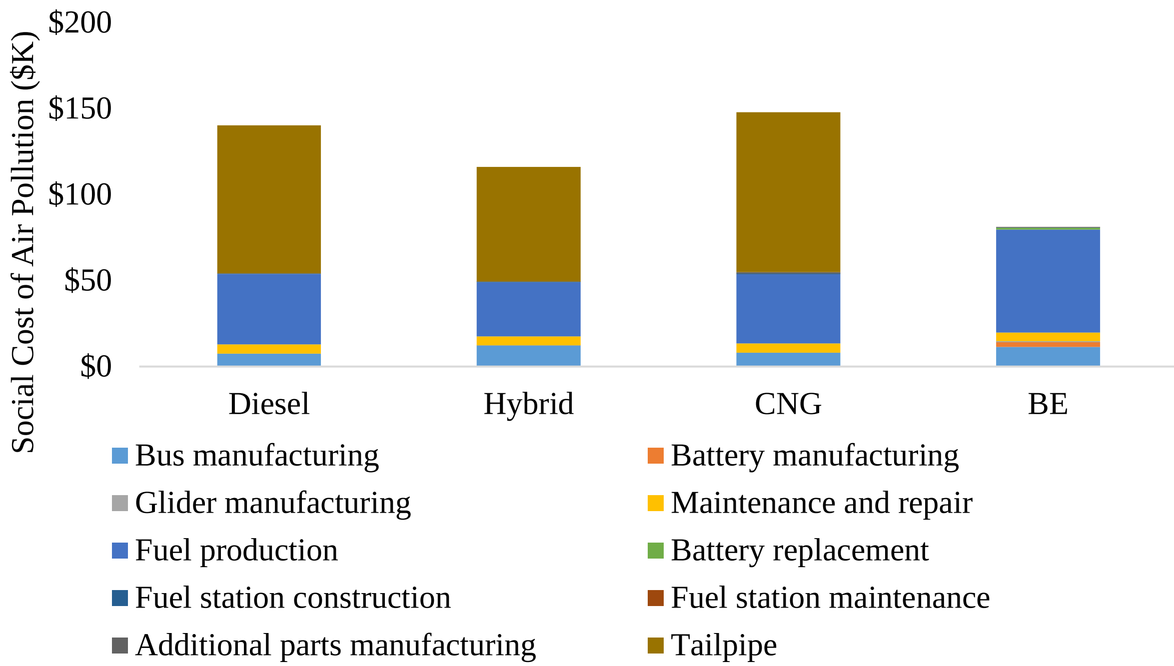

Figure 4-9 Social cost of air pollution caused by the studied buses in Atlanta

As shown in Figure 10 and Figure 11, the battery electric bus type incurs the least amount of SCAP in both of the analyzed metropolitan areas. In Atlanta, with $147K of SCAP, CNG bus type has been found to incur the highest social cost of air pollution, followed by conventional bus. Unlike in Atlanta, due to the activities related to diesel production, the diesel bus causes the highest amount ($57K) of SCAP in Miami, even though the SCAP incurred by the CNG bus's tailpipe emissions is slightly higher than that of a diesel bus in Miami, where CNG bus type has been estimated to cause a SCAP of $55K.

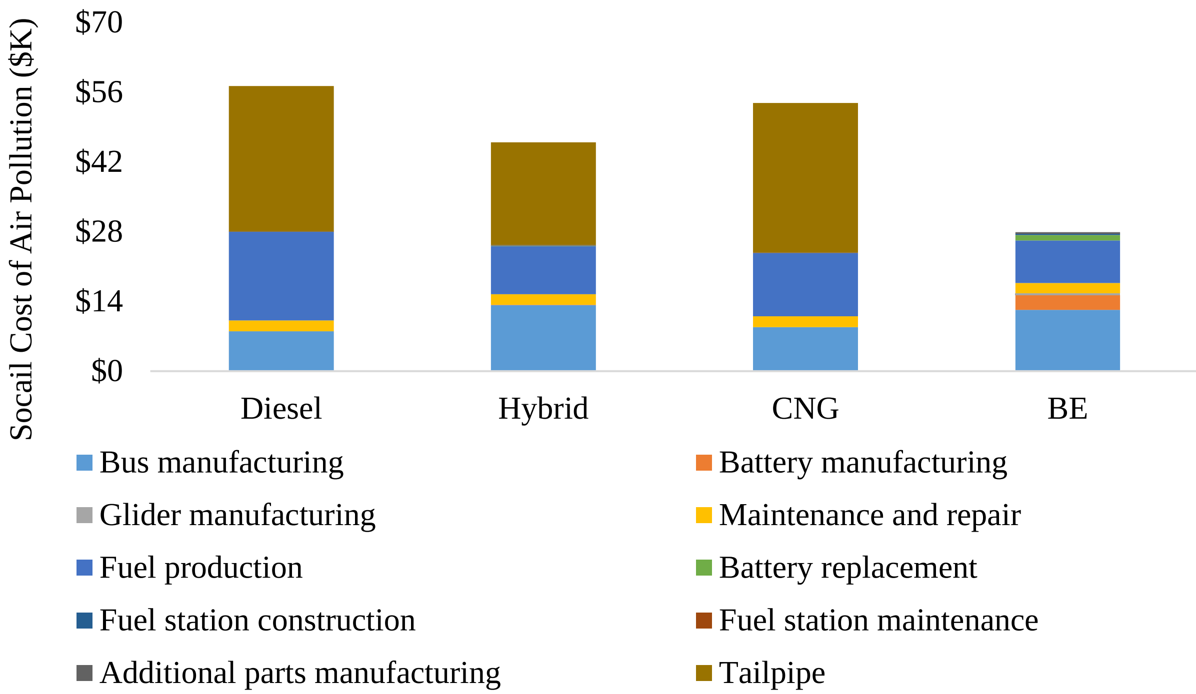

Figure 4-10 Social cost of air pollution caused by the studied buses in Miami

Health impact costs resulting from a diesel bus operating in Atlanta and Miami are estimated to be $140K and $57K, respectively. The total health impact cost of a diesel bus in Miami is largely driven by the conventional air pollutants coming from bus's tailpipe, which is estimated to be responsible for 77% of the total SCAP, whereas fuel production related activities (15%) and bus manufacturing related activities (7%) are the two other major drivers of the total social cost of air pollution from a diesel bus in Miami. Since the VMTs of the studied transit bus types are different in Atlanta than in Miami, it is useful to take a look at the SCAP intensity of the studied transit buses, as shown in Figure 12. Accordingly, the SCAP intensity of CNG bus type has been estimated to be almost identical, whereas for the remainder of the transit bus options has been found to run more efficiently in Atlanta than in Miami despite their higher fuel economies under the conditions in Miami. The underlying reason why this has been the case is that the conventional air pollutants in Miami cause greater health impact relative to those in Atlanta.

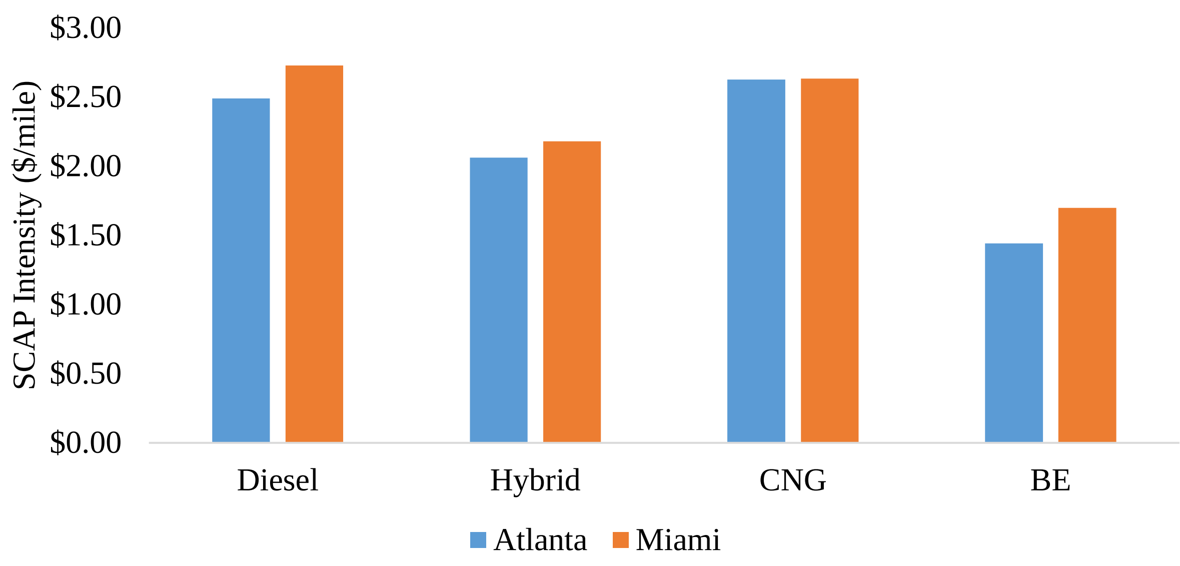

Figure 4-11 Social cost of air pollution (SCAP) intensities ($/mile) of the studied transit bus options in both metropolitan areas

Another indicator that is representative of the economic dimension is *gross domestic product (GDP)*. Figure 13 presents the results with regard to GDP generated by the studied transit bus types in Atlanta. One of the first observations that can be made from the figure is that the rate of employment, income generation, and the GDP generated are consistent with each other, reflecting the significance of the accumulation of economic activity (i.e. maintenance and repair related activities). Even though the GDP generated through the manufacturing of hybrid and battery electric bus types are highest in Atlanta, the CNG bus type has been observed to produce the highest total GDP, owning to the activities associated with bus maintenance and repair (44%), and fuel production (28.5%). Accordingly, CNG bus type has been estimated to generate $1.33 million in Atlanta, followed by battery electric transit bus, generating $1.29 million.

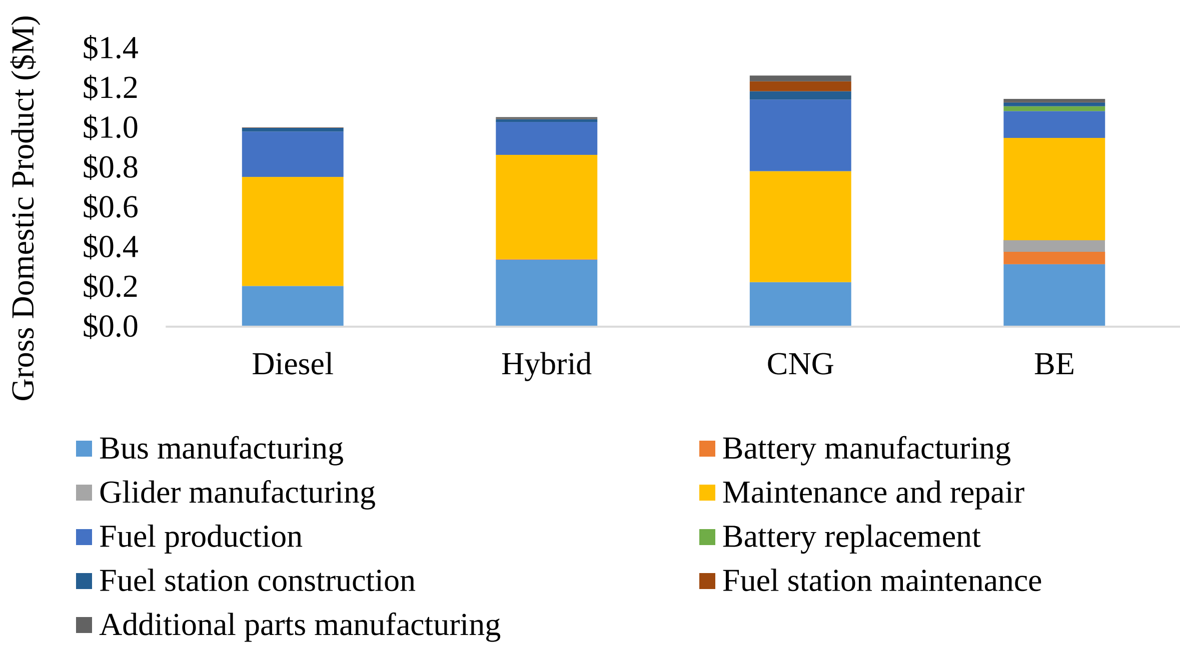

Figure 4-12 Gross domestic product (GDP) ($M) generated in Atlanta

In Miami, the battery electric bus has been observed to generate the highest GDP ($747K), owning to the activities associated with the manufacturing of this bus type, as shown in Figure 14. The CNG bus follows, generating $632K of GDP. Almost 70% of total GDP generated by these bus types are accounted for by the activities related to the manufacturing of this bus type and maintenance and repair. The additional parts installed on a battery electric bus accounted for 13% of the GDP generated from this bus type, while the additional parts installed on a CNG bus has been observed to be responsible for only 4% of the total GDP from this bus type.

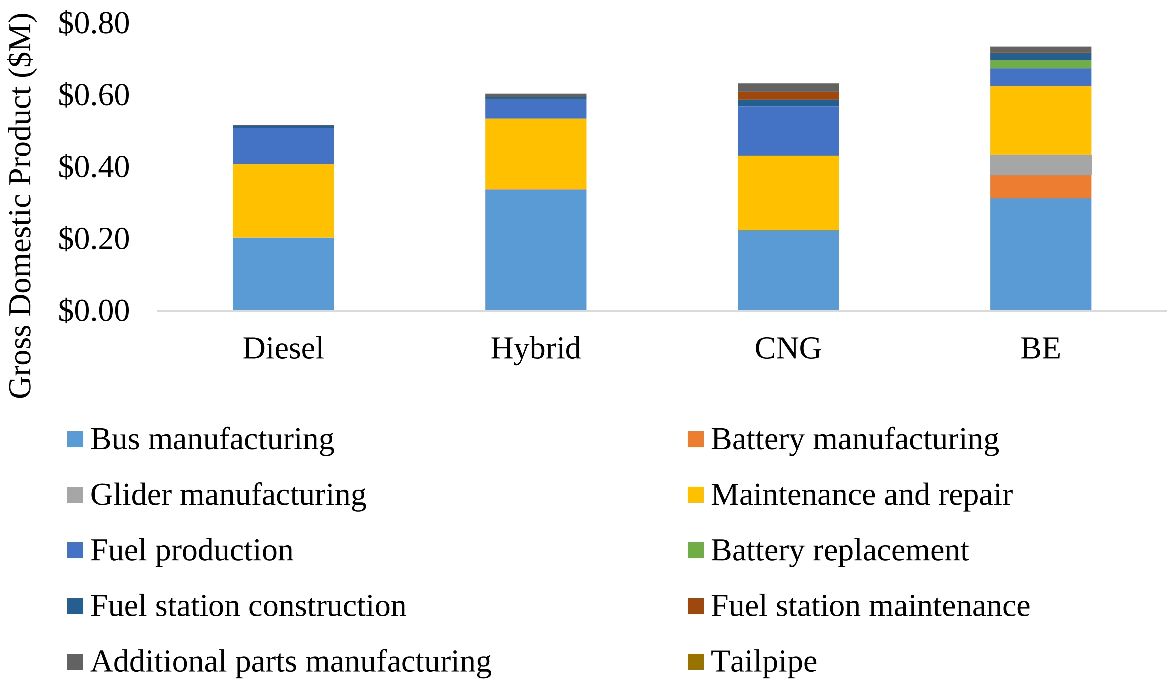

Figure 4-13 Gross domestic product (GDP) ($M) generated in Miami

The last economic sustainability indicator analyzed is the *life cycle cost* of the studied bus types. As evident from Figure 15, the battery electric bus type has been estimated to have the highest LCC, among the other bus options. Accordingly, the biggest LCC component of the battery electric bus in Miami is the initial bus cost, while the costs associated with the battery electric bus maintenance and repair activities have been observed to account for the biggest share of the LCC of this bus type in Atlanta. It has been also observed that, due to relatively higher VMT in Atlanta, the costs associated with the fuel consumption account for a significant part of the LCC difference between the two studied metropolitan areas with respect to the BEB operations.

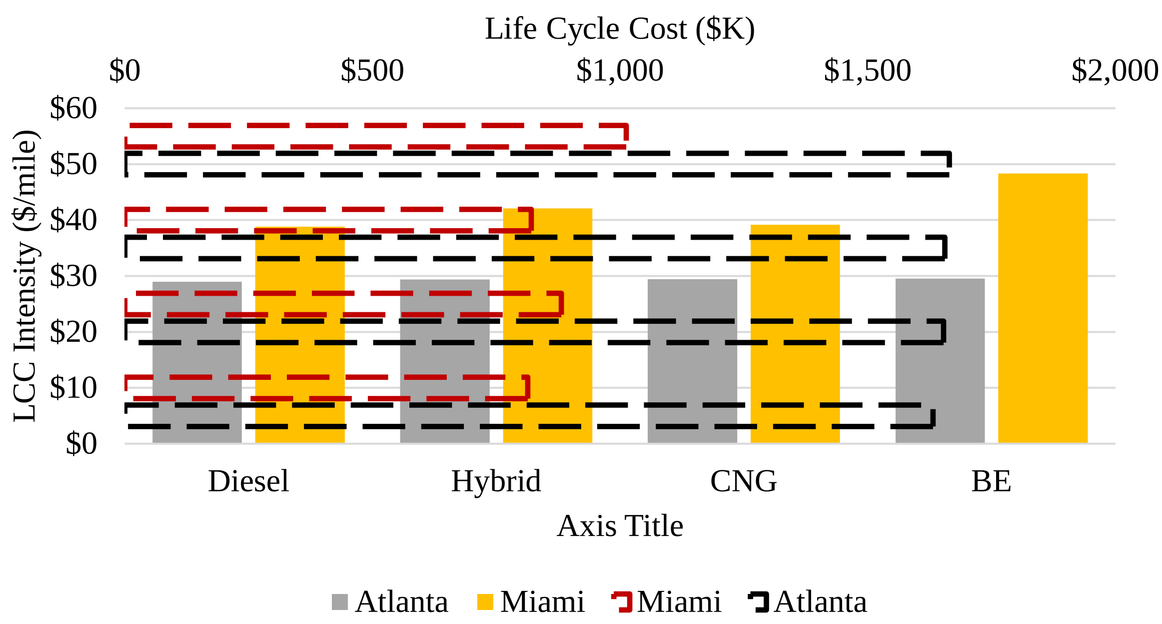

Figure 4-14 Comparison of the life cycle costs and LCC intensities of the studied bus types in the studied areas

As can be seen from Figure 15, even though the studied bus types operating in Atlanta incurred higher LCCs (mainly due to the activities related to fuel consumption and production) relative to those operating in Miami, the LCC intensity, given as incurred LCC per mile, is higher in Miami than in Atlanta. This provides an overall understanding that a transit bus fleet operating in Atlanta is economically more efficient than that of Miami.

4.2 Multi Objective Linear Programing Results

One of the main objectives of the thesis is to find an optimum transit bus fleet mix for the analyzed metropolitan areas based on the life cycle sustainability performances of each of the studied transit bus options, which have been investigated considering the geographic and social characteristics of the two cities. According to the analysis results, when a transit bus fleet composition decision is to be made based upon the investigated life cycle sustainability indicators, the newly composed fleet mix does not include a diesel or a CNG bus. According to the *equal weights* scenario, the Atlanta transit bus fleet is composed of 90 battery electric buses and 10 diesel hybrid-electric buses. As shown in Figure 14, the *LCC*- and *socio-economic dominant* scenarios resulted in the same transit bus fleet mix, composed of 67 battery electric bus and 33 diesel hybrid-electric bus types. Lastly, the Atlanta transit bus fleet mix has been observed to include 97 battery electric bus and only 3 diesel hybrid-electric bus options under the *environmental-dominant* scenario.

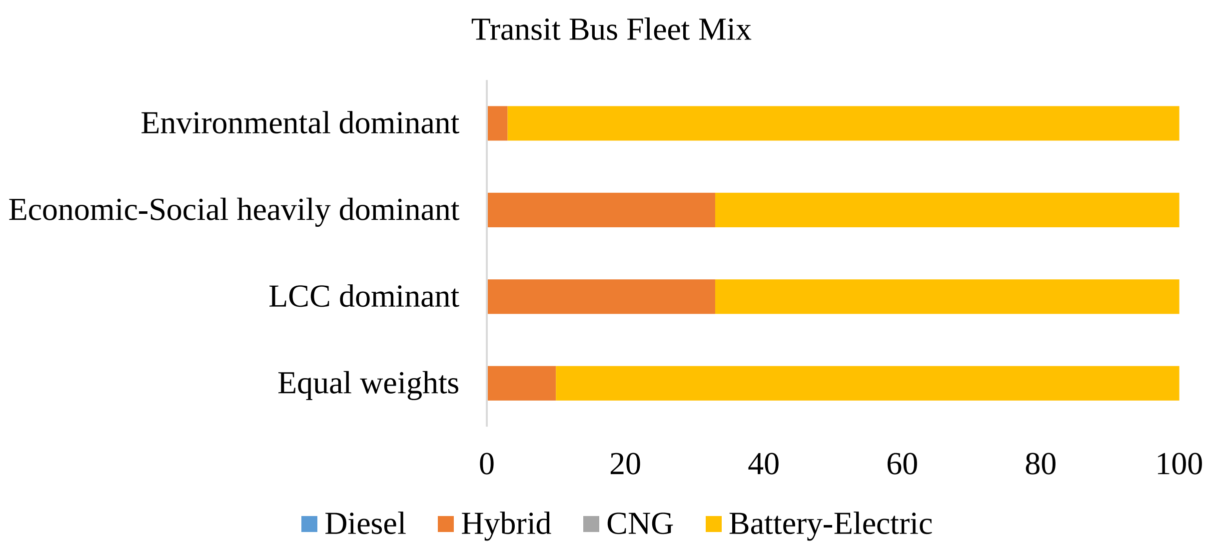

Figure 4-15 Optimal transit bus fleet mix results for Atlanta

According to these results, the Atlanta transit bus fleet will cost an extra $7.2 million for a fleet of 100 buses, while saving almost 53 thousand tons of CO_2-eq. and $7 million of SCAP, relative to a fleet of 100 conventional diesel buses. As shown in Figure 15, the optimization resulted in different outcomes for Miami.

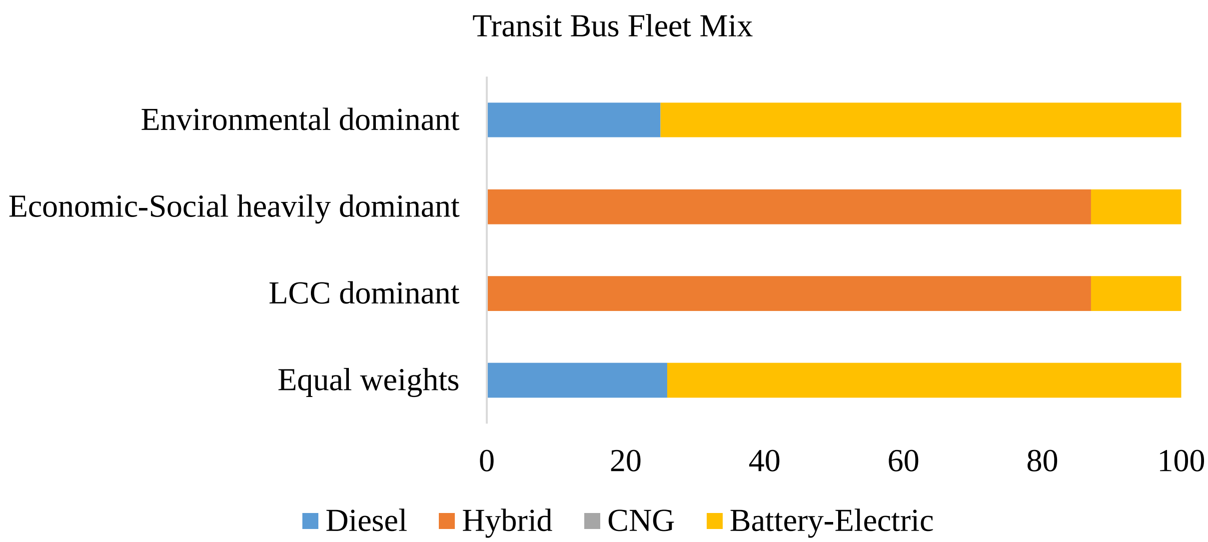

Figure 4-16 Optimal transit bus fleet mix results for Miami

Accordingly, the *environmental-dominant* scenario and the *equal weights* scenario results provided similar outcomes with respect to the Miami transit bus fleet, with the former being composed of 75 battery electric bus and 25 conventional diesel bus, and the latter being composed of 76 battery electric bus and 24 conventional diesel bus options. The remaining two scenarios have resulted in the same outcomes, with the fleet mix composed of 87 diesel hybrid-electric bus and 13 battery electric bus options. This is largely due to the relatively lower vehicle-miles-traveled by the bus options in Miami. Another likely reason is the lower ridership in Miami, relative to Atlanta, since, as the thesis shows, passenger load is a significant factor in the vehicle specific power required and hence, bus's fuel consumption. The newly composed transit bus fleet would results in an SCAP reduction of over $2 million, and generating $16 million more GDP relative to a fleet of 100 conventional diesel buses.

4.3 Trade-off Results

Based on the results obtained from the hybrid life cycle sustainability assessment and multi-objective optimization analysis, a tradeoff has been observed between the global warming potential and life cycle costs of the studied bus types. As presented in Figure 16, the Atlanta transit bus mix shows a drastically linear decrease reaching the highest reduction in the LCC between $155 and $160 million, and its GWP follows a much slower linear decrease peaking at 750 thousand tons of CO_2-eq. emissions.

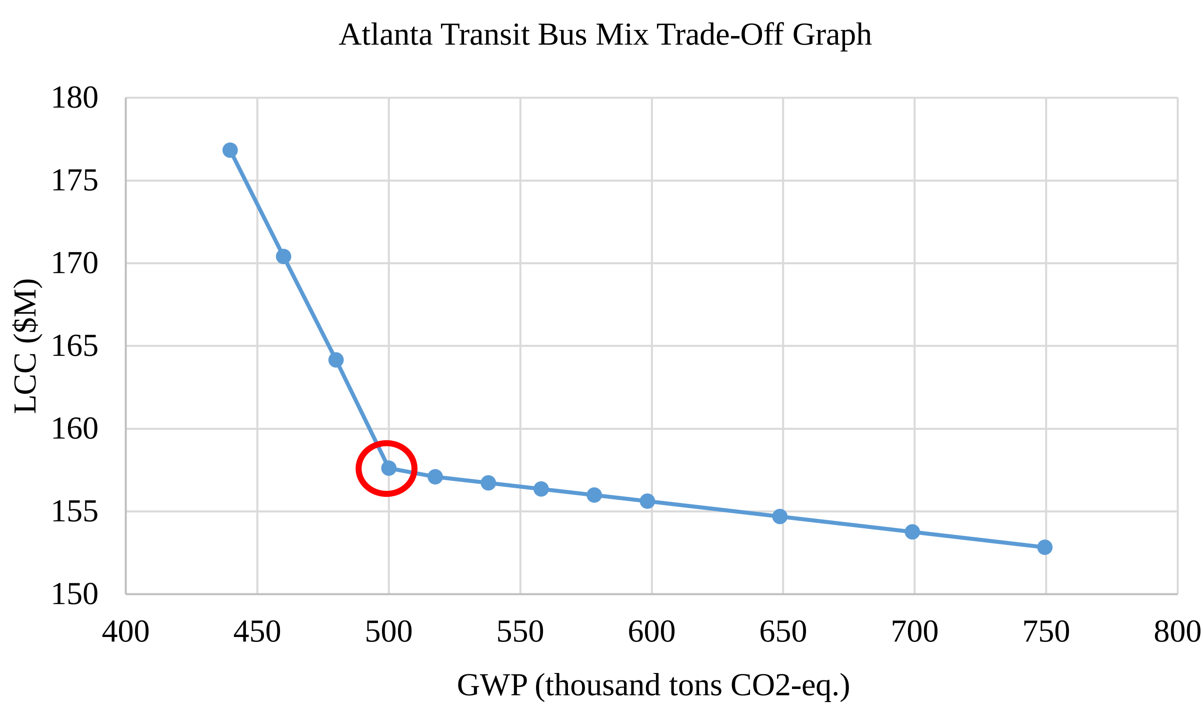

Figure 4-17 Trade-off analysis between global warming potential and life cycle costs for the Atlanta transit bus mix

The boundary of the trade-off presented in the figure above is determined by the highest and lowest data values. Essentially, this trade-off graph indicates that, for the optimum bus choice considering all the six indicators included in the analysis, the cost of reducing the GWP of the Atlanta transit bus mix increases substantially after 500 thousand tons of CO_2-eq. emissions. In contrast to the case of Atlanta, no trade-off has been found for the Miami transit bus mix when the Pareto optimality has been searched for based only on the GWP and LCC indicators. This is likely because the hybrid LCSA results showed that the conventional diesel bus type has the lowest GWP and LCC under Miami driving conditions. Therefore, in every iteration the optimization model presented with the equation (17) subject to the constrains (18) through (21) was run, another diesel transit bus was added given their lowest LCC and lowest GWP under the operating conditions in Miami.

CHAPTER 5: CONCLUSIONS

Transit buses are claimed to have important implications in terms of mitigating global warming, reducing the social cost of air pollution owning to its ability to lower private vehicle use and hence, fuel consumption, and contributing to the national economy through employment creation, and GDP and income generation. However, different cities have different geographic and social characteristics, which in turn affect the costs and benefits of transit buses. Taking into consideration these factors, this thesis has first analyzed the life cycle sustainability implications of alternative transit bus options based on six sustainability indicators and compared the results with that of a conventional diesel bus. Secondly, the results of the hybrid LCSA have been used in a multi-objective optimization model constructed by using the MINIMAX function – a multi-objective linear programming method – to find an optimal transit bus fleet mix.

The results of the study confirm the significance of taking into consideration regional differences (e.g. terrain characteristics, transit ridership, driving cycle characteristics, and auxiliary loads such as an air conditioner etc.) when analyzing the life cycle impacts of transit buses. This indicates that different efforts may be necessary for each public transportation agency to improve the overall sustainability of their transit bus fleets. This is also supported by the trade-off analysis. Based on the GWP intensity analysis results, the CNG bus option has been found to underperform all the other bus options from the environmental sustainability standpoint. Therefore, even though CNG-powered transit buses have been the first choice of transit agencies to adopt in their transit bus fleets ((Hughes-Cromwick et al. 2018), it is the worst transit bus options, especially in terms of its environmental impacts due mainly to higher hydrofloro carbons (HFCs) and nitrogen oxides from natural gas production, and higher tailpipe emissions due to the worst fuel economy.

As evident from the LCC and GWP intensity results, the Atlanta transit bus fleet is likely to be more efficient relative to the Miami transit bus fleet, despite better fuel economies of the studied transit bus types in Miami. Similarly, battery electric bus has been found to be more suitable and sustainabl for the Atlanta transit bus fleet relative to that of Miami. This is likely to be because of the differences between the electricity grid mix in Florida Reliability Coordinating Council (FRCC) and in SERC Reliability Corporation (SERC). The electricity supply in Florida is dominated largely by natural gas, whereas the electricity supply in Georgia is domintated largely by nuclear and renewable energy sources.

Diesel transit bus has been found in an optimum transit bus fleet in Miami under the equal weights and environmentally-dominant scenarios. Given the modeling technique employed in this study, relatively better fuel economy of diesel transit bus operating in Miami, which is one of the significant determinants of fuel consumption, and relatively lower diesel prices are the main reasons behind that optimization result. This result is consistent with the findings from others such as Allcott and Wozny (2012) and Jeihani and Sibdari (2010) in that consumers take into account either lower fuel prices or better fuel economy when purchasing a vehicle. With these findings in mind, the inclusion of diesel transit bus in an optimal transit bus fleet can be explained. Another reason therefor is likely to be the impact of the effect of electricity generation mix on battery electric vehicle adoption, as revealed by Choi et al. (2018). Based on the multi-objective optimization results, it can be concluded.

These findings reveal that public transportation agencies would be better off taking into account geographic and socio-economic circumstances, under which each agency operates. Furthermore, regulatory environment is likely to be significant in composing a transit bus fleet that would outperform an old transit bus fleet in terms of sustainability impacts. However, constraints that may arise from state-wide rules, regulations, or laws have not been taken into account in the multi-objective optimization analyses.

There are a few aspects that should be considered for a future study that will investigate the sustainability impacts of transit bus sphere. Firstly, a future study should broaden the life cycle sustainability impact analysis by including more indicators, if possible. Secondly, given their environmental performance and abundance of fuel, hydrogen fuel cell (FCB) or hydrogen fuel cell-electric transit buses (FCEB) could be included in the analysis. However, a sensitivity analysis should be better applied in that case because the relevant literature contains studies on FCB and FCEB that assumed varying values for fuel economy of this transit bus type as well as hydrogen fuel prices. Laslty, Eora database does not contain enough information on the impacts of the construction industry. This is likely to have resulted in underestimating the sustainability impacts of constructing the infrastructure required to supply fuel to the studied transit bus options. Therefore, it is recommended that another IO database be used by researchers and/or decision-makers to conduct a LCSA of alternative fuel-powered transit buses.

LIST OF REFERENCES

Albert A, Bickford R, Cappelli A, et al (2014) Capital Program Oversight Committee Meeting

Allcott H, Wozny N (2012) Gasoline Prices, Fuel Economy, and the Energy Paradox. Cambridge, MA

Ally J, Pryor T (2007) Life-cycle assessment of diesel, natural gas and hydrogen fuel cell bus transportation systems. J Power Sources 170:401–411. doi: 10.1016/j.jpowsour.2007.04.036

Ally J, Pryor T (2016) Life cycle costing of diesel, natural gas, hybrid and hydrogen fuel cell bus systems: An Australian case study. Energy Policy 94:285–294. doi: 10.1016/J.ENPOL.2016.03.039

American Public Transportation Association (2019) Public Transit Leading in Transition to Clean Technology Key Takeaways

Baker R, Cochran L, Norboge N, et al (2016) Alternative Fuel Vehicle Forecasts Final report

Bi Z, Keoleian GA, Ersal T (2018) Wireless charger deployment for an electric bus network: A multi-objective life cycle optimization. Appl Energy 225:1090–1101. doi: 10.1016/J.APENERGY.2018.05.070

Bi Z, Song L, De Kleine R, et al (2015) Plug-in vs. wireless charging: Life cycle energy and greenhouse gas emissions for an electric bus system. Appl Energy 146:11–19. doi: 10.1016/J.APENERGY.2015.02.031

Bureau of Transportation Statistics (2019) Transportation Statistics Annual Report 2018.

Washington, D.C.

Burnham A (2017) User Guide for AFLEET Tool 2017. 45

Carnegie Mellon University Green Design Institute (2008) Economic Input-Output Life Cycle Assessment (EIO-LCA), US 1997 Industry Benchmark model [Internet]

Center for Transportation Research (2016) GREET Life-Cycle Model User Guide

Choi H, Shin J, Woo J (2018) Effect of electricity generation mix on battery electric vehicle adoption and its environmental impact. Energy Policy 121:13–24. doi: 10.1016/j.enpol.2018.06.013

Eiselt HA, Sandblom CL (2012) Operations Research - A Model-Based Approach, 2nd edn. Springer-Verlag Berlin Heidelberg

Emiliano WM, Costa L, Maria Carvalho S, et al (2018) Multiobjective optimization of transit bus fleets with alternative fuel options: The case of Joinville, Brazil. Int J Sustain Transp ISSN. doi: 10.1080/15568318.2018.1518500

EPA (2014) MOVES2014a User Guide

Ercan T, Tatari O (2015) A hybrid life cycle assessment of public transportation buses with alternative fuel options. Int J Life Cycle Assess 20:1213–1231. doi: 10.1007/s11367-015-0927-2

Ercan T, Zhao Y, Tatari O, Pazour JA (2015) Optimization of transit bus fleet’s life cycle assessment impacts with alternative fuel options. Energy 93:323–334. doi: 10.1016/j.energy.2015.09.018

Federal Transit Administration (2019) National Transit Database Provides Key Stats on Public Transportation in the U.S. | US Department of Transportation. In: Connections. https://www.transportation.gov/connections/national-transit-database-provides-key-stats-public-transportation-us. Accessed 22 Mar 2019

Finkbeiner M, Schau EM, Lehmann A, Traverso M (2010) Towards Life Cycle Sustainability Assessment. Sustainability 2:3309–3322. doi: 10.3390/su2103309

Foran B, Lenzen M, Dey C, Bilek M (2005) Integrating sustainable chain management with triple bottom line accounting. Ecol Econ 52:143–157. doi: 10.1016/j.ecolecon.2004.06.024

Frey HC, Rouphail NM, Zhai H, et al (2007) Comparing real-world fuel consumption for diesel- and hydrogen-fueled transit buses and implication for emissions. Transp Res Part D 12:281–291. doi: 10.1016/j.trd.2007.03.003

Golub A, Zhen F, Clark N, et al (2011) Creation of life-cycle cost tool for transit buses to evaluate hybrid electric bus technologies in real- world operation. Transp Res Rec J Transp Res Board 19–26. doi: 10.3141/2218-03

Green Design Institute (2006) The EIO-LCA Method. http://www.eiolca.net/Method/index.html. Accessed 23 Mar 2016

Guinée J, Gorrée M, Heijungs R (2002) Handbook on life cycle assessment - Operational Guide to the ISO Standards. Kluwer Academic Publishers, Dordrecht

Haes H a. U, Heijungs R, Suh S, Huppes G (2004) Three Strategies to Overcome the Limitations of Life-Cycle Assessment. J Ind Ecol 8:19–32. doi: 10.1162/1088198042442351

Hanlin J, Reddaway D, Lane J (2018) Battery Electric Buses State of the Practice

Hendrickson CT, Horvath A, Joshi S, et al (1997) Comparing Two Life Cycle Assessment Approaches: A Process Model-vs. Economic Input-Output-Based Assessment. IEEE 176–181

Hughes-Cromwick M, Analyst P, Dickens M, Skoutelas PP (2018) 2018 Public Transportation Fact Book. Washington, D.C.

Huijbregts MAJ, Steinmann ZJN, Elshout PMF, et al (2017) ReCiPe2016: a harmonised life cycle impact assessment method at midpoint and endpoint level. Int J Life Cycle Assess 22:138–147. doi: 10.1007/s11367-016-1246-y

International Organization for Standardization (2006) ISO 14040:2006 Environmental management -- Life cycle assessment -- Principles and framework

Jeihani M, Sibdari S (2010) The Impact of Gas Price Trends on Vehicle Type Choice. J Econ Econ Educ Res 11:

Khan AS, Clark N (2010) An Empirical Approach in Determining the Effect of Road Grade on Fuel Consumption from Transit Buses. SAE Int J Commer Veh 3:2010-01-1950. doi: 10.4271/2010-01-1950

Kliucininkas L, Matulevicius J, Martuzevicius D (2012) The life cycle assessment of alternative fuel chains for urban buses and trolleybuses. J Environ Manage 99:98–103. doi: 10.1016/j.jenvman.2012.01.012

Kloepffer W (2008) Life Cycle Sustainability Assessment of Products. Int J LCA 13:89–95. doi:

10.1065/lca2008.02.376

Kucukvar M, Tatari O (2013) Towards a triple bottom-line sustainability assessment of the U.S. construction industry. Int J Life Cycle Assess 18:958–972. doi: 10.1007/s11367-013-0545-9

Lajunen A (2014) Energy consumption and cost-benefit analysis of hybrid and electric city buses. Transp Res Part C Emerg Technol 38:1–15. doi: 10.1016/J.TRC.2013.10.008

Lajunen A, Lipman T (2016) Lifecycle cost assessment and carbon dioxide emissions of diesel, natural gas, hybrid electric, fuel cell hybrid and electric transit buses. Energy 106:329–342. doi: 10.1016/J.ENERGY.2016.03.075

Lee DY, Elgowainy A, Vijayagopal R (2019) Well-to-wheel environmental implications of fuel economy targets for hydrogen fuel cell electric buses in the United States. Energy Policy 128:565–583. doi: 10.1016/j.enpol.2019.01.021

Lenzen M (2000) Errors in Conventional and Input-Output—based Life—Cycle Inventories. J Ind Ecol 4:127–148. doi: 10.1162/10881980052541981

Lenzen M, Moran D, Kanemoto K, Geschke A (2013) Building EORA: A Global Multi-Region Input–Output Database at High Country and Sector Resolution. Econ Syst Res 25:20–49. doi: 10.1080/09535314.2013.769938

Leontief W (1970) Environmental Repercussions and the Economic Structure: An Input-Output Approach. Rev Econ Stat 52:262–271

Li L, Lo HK, Cen X (2015) Optimal bus fleet management strategy for emissions reduction. Transp Res Part D Transp Environ 41:330–347. doi: 10.1016/j.trd.2015.10.007

Los Angeles Metropolitan Transportation Authority (2017) Metro Leads the Nation in Setting Ambitious 2030 Zero Emission Bus Goal; Takes First Step with Purchase of 100 Electric Buses. In: Public Relations. https://www.metro.net/news/simple_pr/metro-leads-setting-2030-zero-emission-bus-goal/. Accessed 22 Mar 2019

Lozanovski A, Whitehouse N, Ko N, et al (2018) Sustainability Assessment of Fuel Cell Buses in Public Transport. Sustainability 10:1480. doi: 10.3390/su10051480

Miller RE, Blair PD (2009) Input-output analysis: foundations and extensions, Second. Cambridge University Press, Cambridge

Ribau JP, Silva CM, Sousa JMC (2014) Efficiency, cost and life cycle CO 2 optimization of fuel cell hybrid and plug-in hybrid urban buses. Appl Energy 129:320–335. doi: 10.1016/j.apenergy.2014.05.015

Russell A, Ekvall T, Baumann H (2005) Life cycle assessment – introduction and overview. J Clean Prod 13:1207–1210. doi: 10.1016/j.jclepro.2005.05.008

Sala S, Farioli F, Zamagni A (2013) Life cycle sustainability assessment in the context of sustainability science progress (part 2). Int J Life Cycle Assess 18:1686–1697. doi: 10.1007/s11367-012-0509-5

Tong F, Hendrickson C, Biehler A, et al (2017) Life cycle ownership cost and environmental externality of alternative fuel options for transit buses. Transp Res Part D Transp Environ 57:287–302. doi: 10.1016/j.trd.2017.09.023

U.S. Department of Transportation Bureau of Transportation Statistics (2018) National

Transportation Statistics 2018. Washington, D.C.

U.S. Energy Information Administration (2016) Monthly Energy Review. Washington, DC

U.S. EPA (2019) Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2017

U.S. EPA (2018) Fast Facts on Transportation Greenhouse Gas Emissions. Washington, D.C.

United Nations (2018) SDG 11 Syenthesis Report 2018: Tracking Progress Towards Inclusive, Safe, Resilient and Sustainable Cities and Human Settlements. Nairobi, Kenya

Vahdani B, Zandieh M, Tavakkoli-Moghaddam R (2011) Two novel FMCDM methods for alternative-fuel buses selection. Appl Math Model 35:1396–1412. doi: 10.1016/j.apm.2010.09.018

Wiedmann TO, Schandl H, Moran D (2015) The footprint of using metals: new metrics of consumption and productivity. Environ Econ Policy Stud 17:369–388. doi: 10.1007/s10018-014-0085-y

Winston LW, Albright SC (2008) Practical Management Science, 3rd edn. South-Western Cengage Learning

Xu Y, Gbologah F, Cernjul G, et al (2013a) Comparison of Fuel-Cycle Emissions per Passenger Mile from Multiple Bus and Rail Technologies. 204–216. doi: doi:10.1061/9780784413210.019

Xu Y, Gbologah FE, Lee D-Y, et al (2015) Assessment of alternative fuel and powertrain transit bus options using real-world operations data: Life-cycle fuel and emissions modeling. Appl Energy 154:143–159. doi: 10.1016/j.apenergy.2015.04.112

Xu Y, Lee D-Y, Gbologah F, et al (2013b) Load-Based Life Cycle Greenhouse Gas Emissions Calculator for Transit Buses: An Atlanta, GA, Case Study. In: Green Streets, Highways, and Development 2013. American Society of Civil Engineers, Austin, TX, pp 284–294

Xylia M, Leduc S, Laurent A-B, et al (2019) Impact of bus electrification on carbon emissions: The case of Stockholm. J Clean Prod 209:74–87. doi: 10.1016/J.JCLEPRO.2018.10.085

Yu Q, Li T, Li H (2016) Improving urban bus emission and fuel consumption modeling by incorporating passenger load factor for real world driving. Appl Energy 161:101–111. doi: 10.1016/j.apenergy.2015.09.096

Zhou B, Wu Y, Zhou B, et al (2016) Real-world performance of battery electric buses and their life-cycle benefits with respect to energy consumption and carbon dioxide emissions. Energy 96:603–613. doi: 10.1016/j.energy.2015.12.041