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An Investigation of Life Cycle Sustainability Implications of Emerging Heavy-Duty Truck Technologies in the Age of Autonomy

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AN INVESTIGATION OF LIFE CYCLE SUSTAINABILITY IMPLICATIONS OF EMERGING HEAVY-DUTY TRUCK TECHNOLOGIES IN THE AGE OF AUTONOMY

by

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ABSTRACT

Heavy-duty trucks (HDTs) play a central role in the U.S. freight transportation, carrying most of the goods across the country. The projected increase in freight activity (e.g. truck-miles-traveled) raises concerns regarding the potential sustainability impacts of the U.S. freight industry, marking HDTs as an ideal domain for improving the sustainability performance of U.S. freight transportation. However, the transition to sustainable trucking is a challenging task, for which multiple sustainability objectives must be considered and addressed under a variety of emerging HDT technologies while composing a sustainable HDT fleet. To gain insights into the sustainability implications of emerging HDT technologies as well as how they can be adopted by freight organizations, given their implications, this research employed an integrated approach composed of methods and techniques, grounded in sustainability science, operations research, and statistical learning theory, to provide a scientific means with public and private organizations to increase the effectiveness of policies and strategies. The research has contributed to the scientific body of knowledge in three useful ways; (1) by comprehensively analyzing HDT electrification based on regional differences in power generation practices and price forecasts, (2) by conducting the first life cycle sustainability assessment (LCSA) on HDT automation and electrification, and (3) providing a case study of an unsupervised machine learning application for sustainability science. Consequently, the research has found that, given the transformation of the U.S. energy system towards renewables, automation and electrification of HDTs offer significant potential for improving the sustainability performance of these vehicles, especially in terms of global warming potential, life cycle costs, gross domestic product, import independence, and income generation. The research has also found that, under the prevailing techno-economic circumstances and except for energy security reasons, natural gas as a transportation fuel option for freight trucks is by almost no means a viable alternative to diesel.

To my family…

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LIST OF ACRONYMS/ABBREVIATION

AFLEET	Alternative Fuel Life-Cycle Environmental and Economic Transportation
AHP	Analytic Hierarchy Process
APEEP	Air Pollution Emission Experiments and Policy Analysis
ATRI	American Truck Research Institute
AV	Autonomous Vehicle
B20	Biodiesel with the blend of 20% bio and 80% conventional diesel
BAU	Business As Usual
BE	Battery Electric
BRT	Bus Rapid Transit
CLD	Causal Loop Diagram
CNG	Compressed Natural Gas
DALY	Disability-Adjusted Lost Years
EIO-LCA	Economic Input-Output based Life Cycle Assessment
EMA	Exploratory Modelling Analysis
EPA	Environmental Protection Agency
EU	European Union
FHWA	Federal Highway Administration
GDP	Gross Domestic Product
GHG	Greenhouse Gas
GOS	Gross Operating Surplus

GREET	Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation
HDT	Heavy-Duty Truck
HDV	Heavy-Duty Vehicle
IEA	International Energy Agency
LCA	Life Cycle Assessment
LCC	Life Cycle Cost
LCSA	Life Cycle Sustainability Analysis
LDV	Light Duty Vehicle
LNG	Liquefied Natural Gas
MOLP	Multi Objective Linear Programming
MOVES	Motor Vehicle Emission Simulation
MSE	Mean Square Error
RPO	Robust Pareto Optimal
SD	System Dynamics
TBL	Triple Bottom Line
VMT	Vehicle-Miles Travelled

CHAPTER ONE: INTRODUCTION

Overview

One of the major questions that sustainability science seeks an answer for is how to establish sustainable production and consumption by transforming the underlying socio-technical systems such as energy, water, food, sanity and waste management, and transportation (Sala et al. 2013a). Within the transportation sector, freight transportation lies in the intersection of these two essential socio-economic processes (i.e. production and consumption) connecting them and enabling their proper functioning. However, transportation itself is a complex and dynamic system intertwined with other socio-technical systems that support it.

The current state of the U.S. freight transportation (especially heavy-duty trucking) raise critical concerns regarding the environmental quality, macroeconomic stability, and energy security (Bureau of Transportation Statistics 2017), but is also believed to present a window of opportunities for economic benefits through investments in alternative fuel options (e.g. electricity, compressed natural gas (CNG), biodiesel, and hydrogen) and advanced vehicle technologies (e.g. automated HDTs) (Williams and Haley 2015). However, these technological alterations applied to heavy-duty trucks (HDTs), be it an alternative fuel system or an advanced driving technology, come along with an additional need for socio-economic re-structuring (e.g. infrastructure, and new social and professional skills). These, in turn, bring about an additional cost and complexity for the freight transportation network, along with the associated (negative or positive) consequences for the three pillars of sustainability, namely the environment, society, and economy, which must be improved in an optimum way.

Therefore, the sustainability of the freight transportation system must be ensured to transition toward sustainable production and consumption, given the interconnectedness of socio-technical systems and the role of HDTs in this regard (Quiros et al. 2017). However, this is a challenging task that cannot be overcome solely by the regulatory efforts of governmental agencies but calls for a holistic and transdisciplinary approach. In this regard, companies that utilize HDTs for their daily operations also play an important role in gearing these efforts toward the direction of sustainable freight transportation. Therefore, it would not be an exaggeration to claim that the actors regarded within the *triple helix* concept – a key to innovation in a knowledge-based society –, wherein academia, government, and industry act upon overcoming societal challenges together (Jofre and Andersen 2009). Hence, in harmony with governmental and academic efforts, and based on the relevant scientific findings, companies should also act upon this challenge by incorporating sustainability into their strategic decision-making processes. To this end, it becomes crucial to grasp a clear understanding of the sustainability implications of HDTs with alternative fuel systems and advanced driving technologies from the life cycle thinking perspective.

Problem and Hypothesis Statement and Research Objectives

The economic recovery after the 2008 recession brought substantial growth in freight activity across the United States (U.S.). Compared to the year 2012, the amount of goods moved by the U.S. freight transportation system rose by 10 percent, reaching to 18.6 billion tons in 2018. Furthermore, the projections on the demand for goods indicate that the amount of goods to be moved by the U.S. freight transportation system will increase up to nearly 25 billion tons by 2045 (U.S. Department of Transportation Bureau of Transportation Statistics 2020), which is likely to result in increased energy consumption as well as the emissions of greenhouse gases (GHGs) and air pollutants (U.S. Department of Energy 2013; U.S. EPA 2016a). One major source of impact is heavy-duty vehicles or long haul commercial trucks (HDVs or HDTs), where substantial reductions (nearly 40 percent) in the sector's greenhouse gas (GHG) emissions are expected for model year (MY) 2027 vehicles compared to MY 2014 reference year (U.S. EPA 2015a).

HDTs comprise a significant part of today's U.S. trucking industry and therefore have crucial implications related to sustainability. Long-haul HDTs have carried 65 percent of the total U.S. freight in

2018 (U.S. Department of Transportation Bureau of Transportation Statistics 2020), while the trucking industry employed 11 percent of the total transportation-related labor force in 2014 (U.S. Department of Transportation Bureau of Transportation Statistics 2018). In addition, HDTs accounted for 23 percent of the total GHG emissions from the U.S. transportation sector in 2016 (U.S. Environmental Protection Agency 2018). HDTs were also responsible for 18 percent of the U.S. transportation-related energy consumption in the same year (Davis et al. 2016).

Huge efforts and investments have been made in technology development and commercialization of different types of HDTs (National Petroleum Council 2012; National Academies of Sciences Engineering and Medicine 2015). Hence, one part of the concerns with respect to the overall sustainability of U.S. HDTs should be regarding the identification of where in the system's unsustainability originates from. Gaining insights into the problematic parts of the system is undoubtedly an important first step; however, insufficient to act upon. Any scientific effort made in that regard should also be able to provide solutions applicable to real-life trucking operations.

This can be achieved by the comprehensive analysis of different types of HDTs. Thus, the potential of any policy measure or technological development aimed at improving the efficiency of HDTs can be better interpreted in terms of their sustainability performances. Hence, in the light of the characteristics of the sustainability science, such an analysis should at least include the following two features (Sala et al. 2013a):

- Having a holistic approach based on life cycle thinking in assessing their environmental and socioeconomic implications of new technologies in a resource-constrained world, and
- Capability to provide direction addressing strategic and operational questions with regard to viable pathways under both prevailing techno-economic circumstances and possible alternative scenarios.

The main objective of this research is to comprehend the implications of emerging heavy-duty truck technologies within the domain of sustainability science, hypothesizing that alternative fuel-powered HDTs could provide a viable option for, at least, transitioning to a more sustainable freight trucking, and hence, shedding light on their potential impacts and benefits in this context. This research particularly seeks answers for the following questions:

1- How do alternative fuel HDTs perform relative to conventional/diesel HDTs and each other in terms of their life cycle emissions and costs? What are the health impacts of BE HDTs given the fact that these HDTs generate no tailpipe emissions? Do different techno-economic circumstances influence the life cycle performances of these HDTs? If so, how are their performances influenced?
2- Given companies' varying operational needs as well as environmental, social, and economic priorities and strategies, what is the optimal composition of an HDT fleet for companies under the current techno-economic circumstances? What are the overall improvements that come along with considering sustainability in composing an HDT fleet?
3- Given the limited understanding of how autonomous driving technology due to its infancy, what are the potential triple bottom line sustainability impacts of U.S. automated HDTs (A-HDTs)?

Organization of the Dissertation

This dissertation is comprised of five chapters, as shown in Figure 1. Chapter One presents a brief overview of the current state of U.S. freight transportation as well as heavy-duty trucking within the context of sustainability science, along with the questions that this research seeks answers for. Chapter Two assesses the life cycle environmental and cost impacts of alternative fuel-powered HDTs and compares these impacts to those of a conventional HDT. Chapter Three builds upon Chapter Two by *broadening* the scope of the analysis and hence, examines the life cycle sustainability impacts (also referred to as *triple-bottom-line analysis*) of conventional and electrified automated heavy-duty trucks (HDTs). This advanced driving technology is taken under investigation based on several sustainability indicators from environmental, social, and economic perspectives

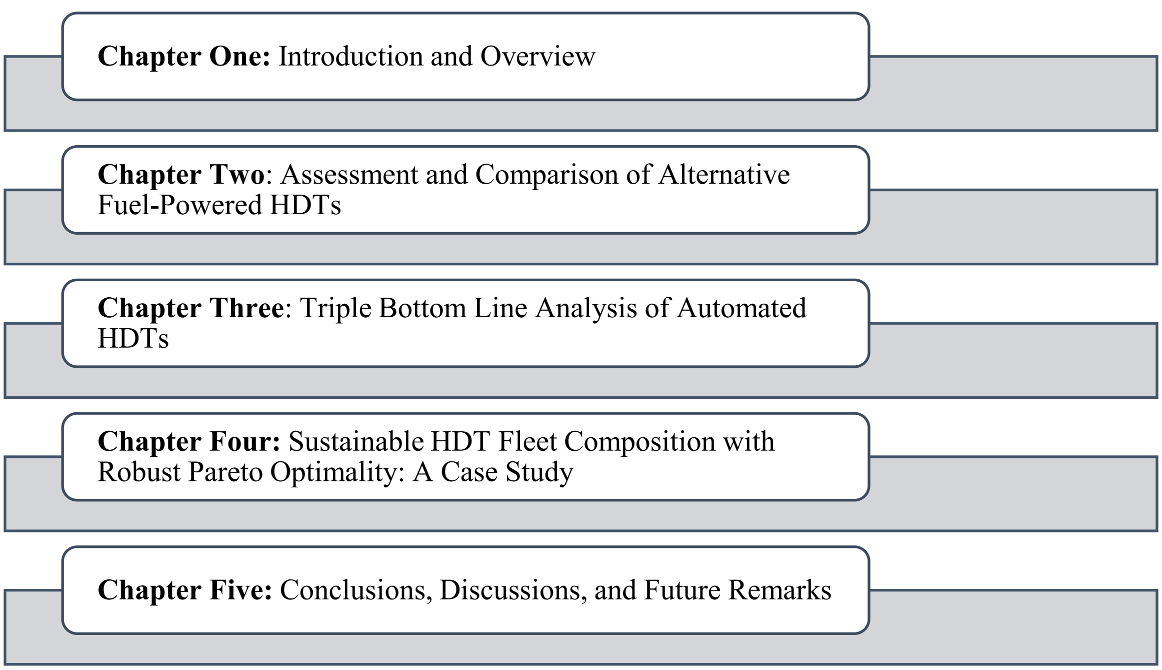


Figure 1: Organization of the dissertation

Chapter Four *deepens* the analysis carried in the previous chapters by employing a hybrid life cycle assessment-based robust Pareto optimization that aims to provide decision support for companies in their efforts to compose a more sustainable HDT fleet and presents a case study for five U.S. sectors. Additionally, freight routes, originating from Miami FL, that are readier for alternative fuel-powered HDTs have been also investigated under Chapter Four. Finally, Chapter Five presents the conclusions of the research and provides a number of suggestions that will be useful for policy- and decision-makers in public and private organizations to better strategize efforts made towards more sustainable HDTs, overall.

CHAPTER TWO: HYBRID LIFE CYCLE EMISSION, COST, AND EXTERNALITY ANALYSIS OF ALTERNATIVE FUEL-POWERED CLASS 8 HEAVY-DUTY TRUCKS

A partial work of this chapter has been published in the Journal of Cleaner Production, with the title "Does a battery-electric truck make a difference? Life cycle emissions, costs, and externality analysis of alternative fuel-powered Class 8 heavy-duty trucks in the United States" (Sen et al. 2017)

Introduction

Diesel has been the dominant fuel of choice for HDTs for decades around the world, and HDTs on U.S. highways have likewise been highly dependent on fossil fuels (TIAX 2008). In this regard, a recent study by the American Transportation Research Institute (ATRI) showed that more than 92 percent of trucks currently run on fossil fuels (Torrey and Murray 2015a). Furthermore, despite accounting for only approximately 1 percent of on-road vehicles in 2013 (U.S. Department of Transportation 2015) and a relatively tiny share of the total national vehicle-miles-travelled (VMT) at slightly more than 5 percent in 2015 (Oak Ridge National Laboratory 2018), HDTs consumed nearly 29 billion gallons of fuel (17 percent of the total fuel consumption by highway vehicles) in 2015 (U.S. Department of Transportation Bureau of Transportation Statistics 2018). Additionally, including distributed energy-related emissions, HDTs were responsible for almost one-fourth of the U.S. transportation sector's GHGs emissions in 2013 (U.S. EPA 2016b).

On one hand, the total global market share of hybrid electric, plug-in hybrid electric, and battery-electric (BE) trucks was predicted to be ten times larger in volume by 2020 compared to 2013 (Navigant Consulting Inc. 2013). Furthermore, the U.S. EPA projected that 3 percent of U.S. HDTs would be electrified by 2025 (Fairley 2015). On the other hand, the forecasts carried out by the U.S. Energy Information Administration (EIA) (2014) have estimated that the growth in the U.S. economy between 2013 and 2040 will cause an increase in diesel consumption with an annual average rate of 0.8 percent until

2040, with trucking responsible for a large share of this increase. Hence, emissions from HDTs are expected to substantially increase by 2040. Therefore, HDTs must be considered more thoroughly, taking into account the current status and future predictions related to the U.S. HDTs (National Research Council 2010). Furthermore, alternative fuel technology must be given special consideration for HDTs, given the potential emissions from their upstream, downstream, and use activities as well as life-cycle costs (LCCs), including externalities.

Literature Review and Objectives of the Study

Numerous articles have been recently published in the literature addressing the future of alternative fuel-powered vehicles from all of the classes defined by the U.S. Federal Highway Administration (FHWA), and made comparative life cycle environmental and cost analyses that have applied either process-based life cycle assessment (process-LCA), economic input-output-based LCA (EIO-LCA), or a combination of these two, known as hybrid LCA. Some of these studies focused on analyzing and comparing alternative fuel technologies in passenger vehicles and in light-duty vehicles (LDVs) with respect to their environmental and cost impacts, whereas some other studies analyzed medium-duty vehicles (MDVs) and heavy-duty vehicles such as buses, delivery trucks, and refuse trucks (see Table 1). Many studies are also available that address the environmental and cost performances of alternative fuel-powered trucks as shown in Table 1 below.

Table 1: Review of the related literature

Type of the study	**Reference**	**Short description of the article**
Passenger and Light-Duty Vehicles (LDVs)	Aguirre et al., 2012	Comparing BE and gasoline vehicle, using LCA
	Nigro and Jiang, 2013	Analyzing life-cycle GHGs emissions from different LDVs using different fuels

Type of the study	Reference	Short description of the article
	Sharma et al., 2013	Comparing life-cycle GHGs emissions from hybrid and electric vehicles to conventional vehicles in Australia
	Joseck and Ward, 2014	Conducting a total LCA analysis for LDVs with different fuel options
	Onat et al., 2014	Analyzing social, economic, and environmental impacts of alternative vehicle technologies
	Onat et al., 2016	Estimating the optimal distribution of alternative passenger cars based on their sustainability impacts
Medium- and Heavy-Duty Vehicles (M-&HDVs)	Clark et al., 1995a	Comparing the emissions performance of natural gas and diesel buses
	Feng and Figliozzi, 2012	Evaluation of the competitiveness of diesel and electric commercial vehicles.
	MJB&A, 2012	Comparative analysis of CNG and diesel buses with respect to their economic, and air quality and climate impacts
	MJB&A, 2013	Comparing the efficiency and environmental performance of CNG and Hybrid-Electric transit buses to diesel buses
	Cooney et al., 2013	Assessing the cradle-to-grave life cycle impacts of diesel and electric public buses
	California Hybrid Efficient and Advanced Truck Research Center, 2013	Assessing the performance of BE parcel delivery trucks, and comparing them to conventional counterparts
	Sandhu et al., 2014	Analyzing the real-world fuel use rates of diesel and CNG refuse trucks

Type of the study	Reference	Short description of the article
	Zhao and Tatari, 2015	Hybrid life-cycle assessment approach to analyzing vehicle-to-grid application in light-duty commercial fleet
Class 8 Heavy-Duty Trucks (HDTs)	Wang et al., 1993	Analyzing the performances of CNG, methanol, and diesel trucks with respect to their emissions
	Clark et al., 1995b	Evaluating the emissions from conventional and ethanol-powered Class 8 trucks
	Clark et al., 1998	Comparing the fuel use of liquefied natural gas (LNG) trucks to conventional trucks
	Norton et al., 1998	Comparing Fischer-Tropsch (F-T) diesel-truck to a diesel-truck, with respect to their emission production
	Gaines et al., 1998	Analyzing the life cycle impacts of alternative fuel-powered Class 8 heavy trucks
	Wang et al., 2000	Comparing emissions from biodiesel heavy trucks to diesel heavy trucks
	Beer et al., 2000	Analyzing GHGs and air pollutants emissions from low- and ultra-low sulfur diesel, and alternative fuel-powered trucks
	Beer et al., 2002	Applying LCA to examining fuel-cycle GHG emissions from alternative-fuel HDTs
	Hofstetter and Müller-Wenk, 2005	Monetizing externalities from transportation
	Muller and Mendelsohn, 2007a	Measuring the damages caused by air pollution
	Graham et al., 2008	Comparing biodiesel, CNG, hybrid, and LNG HDTs to diesel HDTs
	Meyer et al., 2011	Analyzing the total fuel-cycle of HDTs
	Michalek et al., 2011	Evaluating the impacts of air emissions and oil consumption from passenger vehicles

Type of the study	Reference	Short description of the article
	Gao et al., 2012	Comparing diesel and natural gas-powered HDTs
	Zhao et al., 2013	Examining of fuel savings potential of Class 8 trucks
	Zhu et al., 2013	Analyzing the fuel economy of alternative fuels in HDTs
	Tong et al., 2015	Examining the use of natural gas in both MDVs and HDVs, including tractor-trailers

As evident from the literature reviewed, given the slow pace of deployment of alternative fuel HDTs in the U.S., and the infancy of some alternative fuel-powered vehicle technologies such as battery electric (BE) HDTs, there has not been a sufficiently thorough comparison between conventional and alternative fuel-powered HDTs with respect to their life cycle emissions, costs, and externalities. This chapter attempts to contribute to the scientific body of knowledge in this particular domain by investigating alternative fuel-powered HDTs from a life cycle perspective and to provide insights into the sustainability-related implications of emerging HDT technologies. The HDT technologies considered in the analysis are hybrid electric truck, compressed natural gas (CNG)-powered truck, biodiesel truck, and battery-electric truck.

Hybrid electric and BE HDTs have been considered separately based on the battery sizes they employ such as mild hybrid trucks and full hybrid trucks, and BE HDTs with 270 kWh and 400 kWh motor sizes. The studied alternative fuel-powered HDTs have all been compared to conventional HDTs with respect to their life cycle greenhouse gas (GHG) emissions, life cycle costs (LCC), air pollutant emissions, and air pollution externalities (APE). The emissions estimated by the analysis are carbon dioxide (CO_2), carbon monoxide (CO), nitrous oxides (NO_x), particulate matter (PM10 and PM2.5), sulfur dioxide (SO_2), and volatile organic compound (VOC).

In addition, the regional differences in power generation have been incorporated into the life cycle assessment based on the grid characteristics defined by North American Electric Reliability Corporation (NERC). Accordingly, the life cycle impacts caused by BE HDTs operating in each of the U.S. NERC regions have been analyzed separately. The system boundary of the life cycle analysis essentially includes the manufacturing and use phases. The study described in this chapter contributes to the scientific body of knowledge in two ways; firstly, by comprehensively analyzing BE HDTs based on regional power generation and electricity price forecasts, and secondly, by incorporating into the analysis the cost of air pollution incurred by the studied trucks through their life cycle.

Methods and Materials

Hybrid Life-Cycle Assessment

Life cycle assessment (LCA) is a well-known, well-established tool (International Organization for Standardization 2006) to analyze the direct and indirect upstream and downstream environmental, social, and economic impacts of processes and products that previously could not be accounted for, using complementary impact assessment methods. Process-LCA, coined by Haes et al. (2004), and EIO-based LCA have recently become more widely used in academia and industrial practices (Park et al. 2015; Onat et al. 2016a). For the analysis of this research, both EIO-based LCA and process-based LCA are hybridized to account for both the upstream and the downstream environmental impacts of HDTs.

Almost all of the upstream environmental impacts are obtained using the Carnegie Mellon University Green Design Institute's publicly available online EIO-LCA tool (Carnegie Mellon University Green Design Institute 2008). The EIO-LCA tool uses EIO tables based on transactions in 2002 (Noori et al., 2015). Downstream environmental impacts are obtained using the EIO model and a variety of process-based models and databases, such as the *Greenhouse gases, Regulated Emissions, and Energy use in*

Transportation (GREET), *Alternative Fuel Life-Cycle Environmental and Economic Transportation (AFLEET)*, and the U.S. EPA's *Motor Vehicle Emissions Simulator (MOVES)*. The EIO-LCA tool uses a linear model based on the EIO matrix developed by Leontief (1970). The monetary value of the product in question, in 2002 dollars, is used as input into the model embedded in the tool. The matrix used in this model is composed of economic transactions between 428 industries in the U.S. economy. The North American Industry Classification System (NAICS) is used to categorize the data used in the model (Green Design Institute 2006). Hence, the input values needed to calculate the upstream life cycle environmental impacts are the purchase prices of each HDT and, if any, those of their additional parts. As for the downstream emissions from fuel consumption during the use phase, the AFLEET (Burnham 2016) and GREET (Center for Transportation Research 2016) models are used, both of which were developed by the Argonne National Laboratory.

The LCA method has been widely used by many scientific fields, although hybridization has not yet been applied as widely. Egilmez et al. (2013) and Egilmez et al. (2016) used the EIO-LCA method to assess the sustainability of 53 U.S. manufacturing industries and 33 U.S. food manufacturing industries, respectively. Using the EIO-LCA method, Kucukvar et al. (2014a) carried out an analysis with regard to the sustainability of U.S. consumption and investment activities. Similarly, Kucukvar et al. (2014) and Kucukvar et al. (2014b) incorporated the EIO-LCA method into their studies to assess the sustainability of different asphalt pavement systems. Onat et al. (2014b) identified sustainability hotspots of U.S. residential and commercial buildings throughout their life cycle, using hybrid LCA. Furthermore, Onat et al. (2014b) also analyzed the carbon footprint of U.S. buildings, using the same method. Facanha and Horvath (2006) applied a hybrid LCA method to analyze air pollutant emissions from freight transportation in the U.S. Jiang et al. (2014) likewise conducted an hybrid LCA study for the manufacturing of a diesel engine. Ercan and Tatari (2015) analyzed the life cycle emissions, LCCs, and total water withdrawal rates for alternative fuel-powered transit buses in the U.S., while Zhao and Tatari (2015) performed a hybrid LCA of the vehicle-to-grid applications for LDVs.

Monte Carlo Analysis

HDTs have a wide range of configurations, and thus a wide variety of possible life cycle inventory (LCI) components. Furthermore, as previously discussed in Section 1, the currently limited degree of deployment for alternative-fuel HDTs means that the number of available data points for such HDTs is limited. A probabilistic method should be integrated with the LCA methods in order to accommodate this uncertainty and the applicable value ranges. One such probabilistic method is the Monte Carlo method, which simulates point values with variable distributions, allowing the LCA analysis results to be presented within a range instead of being limited to only using average values (Kucukvar and Tatari 2012; Noori et al. 2015c; Tatari et al. 2012). The Monte Carlo simulation method is widely utilized in many scientific areas, and numerous examples of combining LCA with Monte Carlo uncertainty analyses are available from the literature (McCleese and LaPuma 2002; Finkel 1995; Peters 2007). Within the considered ranges, inputs are regenerated for one thousand iterations and linked with their corresponding hybrid LCA components.

Materials: Life-Cycle Inventory

In the inventory analysis phase of a typical LCA, inputs to and outputs from a production system are quantified to assess the impacts in the subsequent step. Process-based LCA requires data inputs specific to each unit process included in the product manufacturing system under investigation, while EIO-based LCA requires the monetary values of products as inputs. The vehicle characteristics of the HDT considered in this study are presented in Table 2. Based on the goal and scope of the study, the life cycle assessment phases included in the system boundary are divided into two primary parts, as shown in Figure 2.

Table 2: Vehicle characteristics and battery specifications

Characteristics	**Value**	**Source**
Lifetime	6.6 – 10 years	(Torrey and Murray 2014; CALSTART 2013)
Average annual mileage	109,226 – 170,000 miles	(Torrey and Murray 2015b; CALSTART 2013)
Physical features	Class 8 heavy-duty trucks with 53' truck-trailer; >33,001 lbs.	(U.S. Department of Energy 2011)
Battery specifications (BE)	270kWh, 400kWh, 150Wh/kg, Li-ion batteries	(California Air Resources Board 2015)
Battery specifications (Hybrid)	5 kWh, 25 kWh, 150Wh/kg, Li-ion batteries	(TRB and NRC 2010)

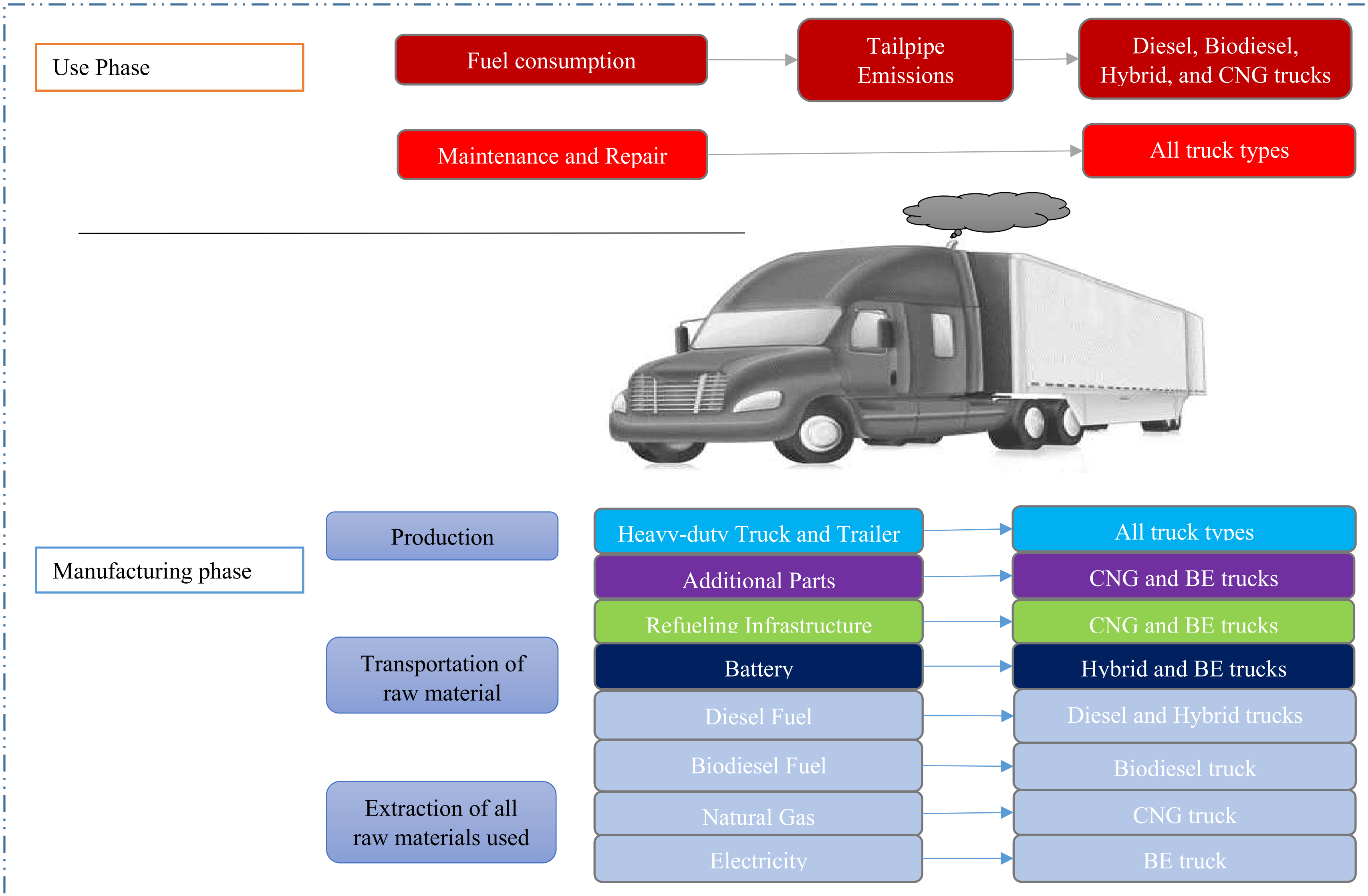


Figure 2: System boundary for hybrid-life cycle assessment

The baseline truck has been assumed to be made of the essential truck components such as the truck's body, shell, engine, other required miscellaneous parts, and a trailer. The purchase price for such a truck is converted to 2002 US dollars using the U.S. Bureau of Labor Statistics' CPI Inflation Calculator and used as an input to run the EIO-based LCA model and obtain the environmental impact results from the relevant NAICS economic sector. The hybrid electric, CNG, and BE trucks each require additional parts during the manufacturing phases, and these additional parts come with additional costs to the baseline truck manufacturing.

According to the California Air Resources Board (2015), BE trucks additionally require power electronics, an electric motor, and a battery system. Likewise, CNG trucks require the installation of a metal tank and a heavy gauge (Burnham 2013). For battery system manufacturing, the GREET tool's Vehicle-Cycle Model has been used to calculate the environmental impacts of battery manufacturing based on the battery specifications from Table 2.

CNG and BE trucks also necessitate the construction of refueling/recharging stations. The U.S. Department of Energy estimates the cost of a natural gas refueling station (NGRS) with the daily supply capacity of 1,500-2,000 gasoline-gallon-equivalents of fuel to range between $910K and $1,365K (both in 2002 dollars) (Smith et al. 2014). As in the study conducted by Ercan and Tatari (2015), it has been assumed that 46 percent, 39 percent, and 15 percent of the total cost of a unit of NGRS consists of investment, labor, and installation costs for miscellaneous electrical equipment installed in the NGRS, respectively. The relevant NAICS sectors for the environmental impacts of the CNG refueling infrastructure are provided in Table 3.

Based on the study conducted by De Filippo et al. (2014) as well as a report published by NREL (2012), charging stations used for HDTs have been assumed to adopt a conductive charging technique. Therefore, like in the study conducted by Ercan and Tatari (2015), and also based on additional cost information from Proterra, it has been assumed that BE HDTs are charged using Level 3 charging stations, each with a charging capacity of 250 kW. Furthermore, it has been assumed based on Kempton et al. (2001), that each charging station has an efficiency of 90 percent. It has been also assumed that the existing diesel infrastructure is suitable to refuel hybrid electric and B20 trucks (i.e. a fuel blend composed of 20 percent of biodiesel and 80 percent of conventional diesel).

In this research, the load-specific fuel economy (LSFE) has been taken into account, thereby assuming that a truck's fuel economy decreases by 1 percent for each 1,000-pound increase in the payload (TRB and NRC 2010). The truck fuel economy values have been assumed to be for trucks with empty trailers, and that the maximum payload capacity of truck-trailers is 54,000 pounds. (TRB and NRC 2010). Based on these assumptions, the fuel economies of each truck type relative to their payload has been first calculated in decreasing order, and the resultant fuel economies are normally distributed for each truck type. The load-specific fuel consumption of each type of truck has been then randomized based on the relevant statistical parameters (e.g. mean and standard deviation). To calculate the environmental impacts of biodiesel production, the emissions generated by a biodiesel HDT per gallon of B20 have been taken from the GREET tool's process-LCA model.

Changing diesel prices have been also reflected in the analysis, as have been the various environmental impacts of regional electricity production and electricity prices. Based on a study conducted by U.S. EIA (2015), it has been assumed that diesel prices follow a steady 30 percent increase from 2015 to 2025. Additionally, the MOVES analysis results for HDTs indicate that tailpipe emissions deteriorate over the HDT lifetime for each emission type. These deterioration factors have been considered in the analysis, and the values of these factors for the overall impacts and costs of tailpipe emissions have been taken from the AFLEET database (Burnham 2016).

As for battery manufacturing and replacement, it has been assumed that lithium-ion batteries are used in BE and hybrid electric HDTs, based on Transportation Research Board (2010). Based on Zhao et al. (2013), it has been assumed that the battery of a hybrid electric truck lasts for 3 years. Therefore, this truck type has been assumed to replace its battery 2 or 3 times during its entire lifespan, depending on its average lifetime, which is randomized between 6.6 and 10 years. It has been also assumed, based on a study conducted by Ozdemir (2012), that BE truck batteries are replaced approximately every 4 years. The GREET tool's Vehicle-Cycle Model is used to obtain the emissions from battery replacement (Burnham 2012). The future projections of battery price declines have been reflected, applying a 2 percent annual inflation rate to this initial battery price, based on data from the EIA (2015).

With regard to the maintenance and repair of trucks, it is possible to assume based on NREL (2012), that hybrid electric and BE trucks have lower M&R costs than conventional trucks because conventional trucks have more fluids to change and far more moving parts. Based on M&R cost and relevant NAICS Sector data for each of the studied truck types, given in Table 3, the environmental impacts of M&R activities have been calculated, using the applicable M&R LCCs as inputs in the EIO-based LCA tool. The details of the specific data for each of the aforementioned tools as applicable to each relevant part are presented in Table 3. The emissions factors used for the calculations can be found in Appendix A.

Table 3: Inputs for hybrid life-cycle assessment

Vehicle technology	LCA component		Cost (2015$)	EIO-LCA tool NAICS sector	Process-LCA data	Source
Common for all types of trucks	Truck manufacturing		$107,362	#336120	n.a.	(California Air Resources Board 2015) (Commercial Truck Trader 2016)
	Trailer manufacturing		$32,500	#336212	n.a.	
Diesel	Diesel fuel production		$1,030,445	#324110	n.a.	(U.S. Department of Energy 2015)
	Maintenance		$224,873	#81111	n.a.	(Burnham 2013)
Biodiesel (B20)	Biodiesel fuel production		$867,976	#324110	GREET's biodiesel production	(Burnham 2013; U.S. Department of Energy 2015)
	Maintenance		$223,020	#81111	n.a.	(Burnham 2013)
CNG	Natural gas manufacturing		$855,785	#325120	n.a.	
	Metal tank, Heavy gauge manufacturing		$60,495	#332420	n.a.	(Burnham 2013)
	Infrastructure		$58,278	#332420, #237100, #335999	n.a.	(Smith et al. 2014)
	Maintenance		$224,873	#81111	n.a.	(Burnham 2013)
Hybrid	Diesel fuel production	Mild	$757,262	#324110	n.a.	(U.S. Department of Energy 2015)
		Full	$803,928			
	Battery system manufacturing	Mild	$3,000	n.a.	GREET's Battery Model based on specifications.	(TRB and NRC 2010; Burnham 2013)
		Full	$15,000			
	Battery replacement	Mild	$4,960	n.a.		
		Full	$24,802			
	Maintenance		$211,314	#81111	n.a.	(Burnham 2013)

Vehicle technology	LCA component		Cost (2015$)	EIO-LCA tool NAICS sector	Process-LCA data	Source
BE	Power generation		$380,211	#221110	n.a.	(California Air Resources Board 2015)
	Battery system manufacturing	270kWh	$162,000	n.a.	GREET's Battery Model based on Table 2.	(California Air Resources Board 2015; Burnham 2013)
		400kWh	$240,000			
	Battery replacement	270kWh	$160,885	n.a.	GREET's Battery Model based on Table 2.	(California Air Resources Board 2015; Burnham 2013)
		400kWh	$238,350			
	Motor		$9,290	#335212	n.a.	(California Air Resources Board 2015)
	Power electronics		$12, 388			
	Maintenance		$202,715	#81111	n.a.	(Burnham 2013)

Regional Electricity Generation and Prices

A regional approach has been adopted to evaluate electricity generation-related environmental impacts of BE HDTs. More specifically, the North American Electric Reliability Corporation (NERC) regions have been considered for further analysis, as listed below:

1. Texas Regional Entity – TRE
2. Florida Reliability Coordinating Council – FRCC
3. Midwest Reliability Organization – MRO
4. Northeast Power Coordinating Council – NPCC
5. Reliability First Corporation – RFC
6. SERC Reliability Corporation – SERC
7. Southwest Power Pool – SPP
8. Western Electricity Coordinating Council - WECC

Similarly, the regional variations in electricity generation and prices have been also considered in the fuel life cycle costs (LCCs) of BE HDTs, based on data from the EVRO tool (Noori, 2015; Noori et al., 2015a). To account for electricity price projections, the commercial electricity rate has been assumed to be equal to the levelized cost of electricity. More detailed information on regional electricity prices and on the environmental impacts of power generation can be found in Ercan et al. (2016).

Air Pollution Externality Costs

A few studies have included the externalities from a vehicle's emissions during operation (Muller and Mendelsohn 2007; Michalek et al. 2011; Onat et al. 2014a). In general, the estimation of operation and maintenance costs for trucks typically do not include these externalities (NESCCAF/ICCT 2009). With this in mind, the externality costs considered in this study have been estimated based on the Air Pollution Emission Experiments and Policy Analysis (APEEP) model developed by Muller and Mendelsohn (2007b).

Air pollution externality (APE) costs of electricity generation have been accounted for to cover the total externality costs of BE HDTs. The energy consumption of a CNG truck has been calculated to be 0.028 GJ/mile, and the total APE costs of natural gas have been obtained based on this value. Regarding the externality costs of fuel consumption for conventional, hybrid, and B20 HDTs, the APE costs provided for diesel production (in $/ton) have been used. APE costs related to manufacturing, including the manufacturing of batteries, and maintenance have been considered within the same category, and have been likewise applied to each truck type on a dollar-per-ton basis. Finally, the APE costs of tailpipe emissions have been obtained for each type of truck on a dollar-per-ton basis, except for BE HDTs as these types of HDTs do not generate tailpipe emissions.

Results

Life-Cycle Cost (LCC) Analysis Results

The use phase has been observed to be the main driver of the life cycle costs (LCCs) of HDTs. As shown in Figure 3, BE and mild hybrid electric HDTs have been found to have the best overall performances out of all of the considered truck types in terms of their LCC impacts. The dominant contributor to the LCCs of all types of HDTs is the cost of fuel consumption followed by their maintenance and repair (M&R) costs, except for BE HDTs. Although there has been found a slight difference between the LCCs of conventional and CNG trucks, there is a noticeable difference between the life cycle fuel costs (LCFC) of these two truck types. The LCFC of a B20 truck has been estimated to be slightly higher than that of a CNG truck; however, a B20 truck performs better overall in terms of economic impacts.

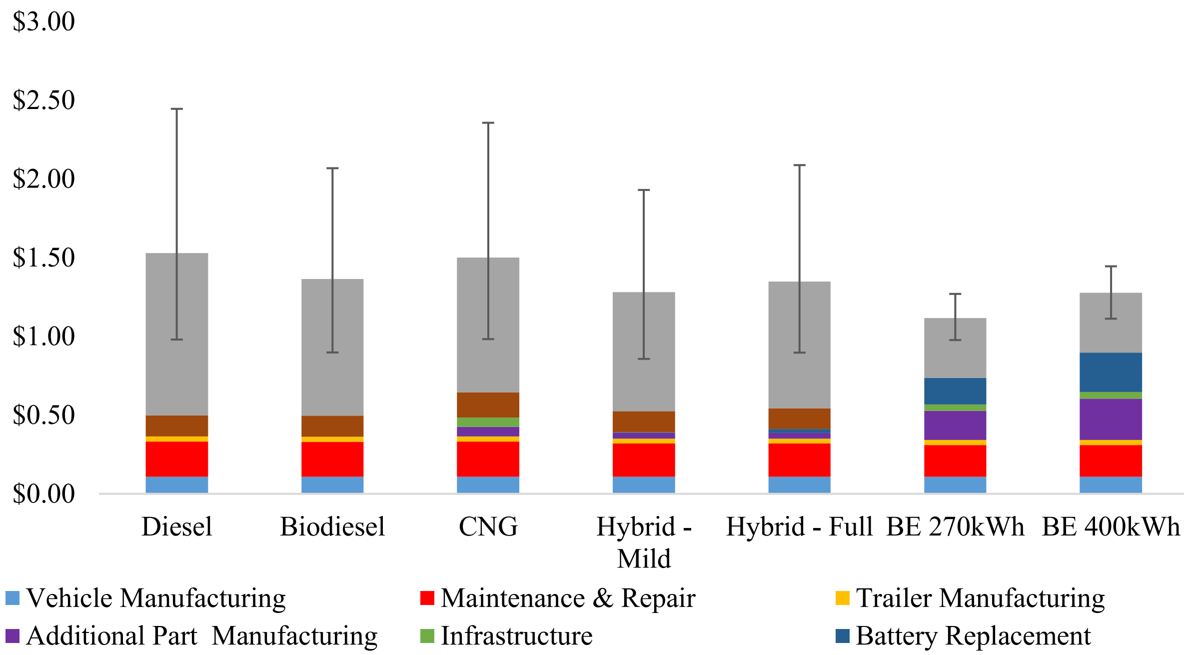


Figure 3: Life cycle costs of heavy-duty trucks (2015$M)

Unlike the study conducted by Lajunen (2014), which found hybrid electric buses to be performing almost the same as a diesel city bus with respect to LCCs, the results of this research have indicated that hybrid electric HDT might have moderately less LCC than that of a conventional truck, and therefore, favor the hybrid electric configuration for HDTs. Individual LCFCs and battery replacement costs have been the two primary differences in the respective LCCs of both hybrid electric HDT types. The fuel economy of mild hybrid electric HDTs has been observed to be better than that of full hybrid electric HDTs, resulting in lower LCFC for mild hybrid electric HDTs. For BE HDTs, additional part manufacturing has been found to be the second largest driver of the LCCs of BE HDTs. The greatest portion of these incremental costs of BE HDTs stems from battery system manufacturing.

An important portion of the LCCs of HDTs comes from M&R activities, with conventional trucks being costlier, as expected. Overall, the M&R LCCs of BE HDTs are the lowest out of all truck types, which is consistent with the findings from the NREL (2012), which clearly highlights the lower maintenance requirements of battery-electric vehicles due to fewer fluids to change and fewer moving parts in such vehicles.

Life-Cycle Environmental Emissions Results

According to the analysis results presented in Figure 4, fuel consumption and tailpipe emissions have been found to be the predominant contributors to total life cycle GHGs emissions, to the point where all other factors are practically negligible. Overall, CNG trucks produced the largest amount of life cycle GHGs emissions compared to other trucks, with BE trucks emitting the least amount of GHGs emissions at 53 percent less than the GHGs emissions from CNG truck's life cycle. This is mainly because BE HDT does not generate any tailpipe emissions, while CNG HDT has been found to emit as much tailpipe emissions as conventional HDT. Like in the LCC results, fuel consumption played a major role in the life cycle GHGs emissions from each truck type. In terms of GHGs emissions associated with fuel consumption, mild hybrid electric trucks were found to outperform full hybrid electric trucks and CNG-powered trucks by more than 6 percent and 121 percent, respectively, due to their better fuel economy.

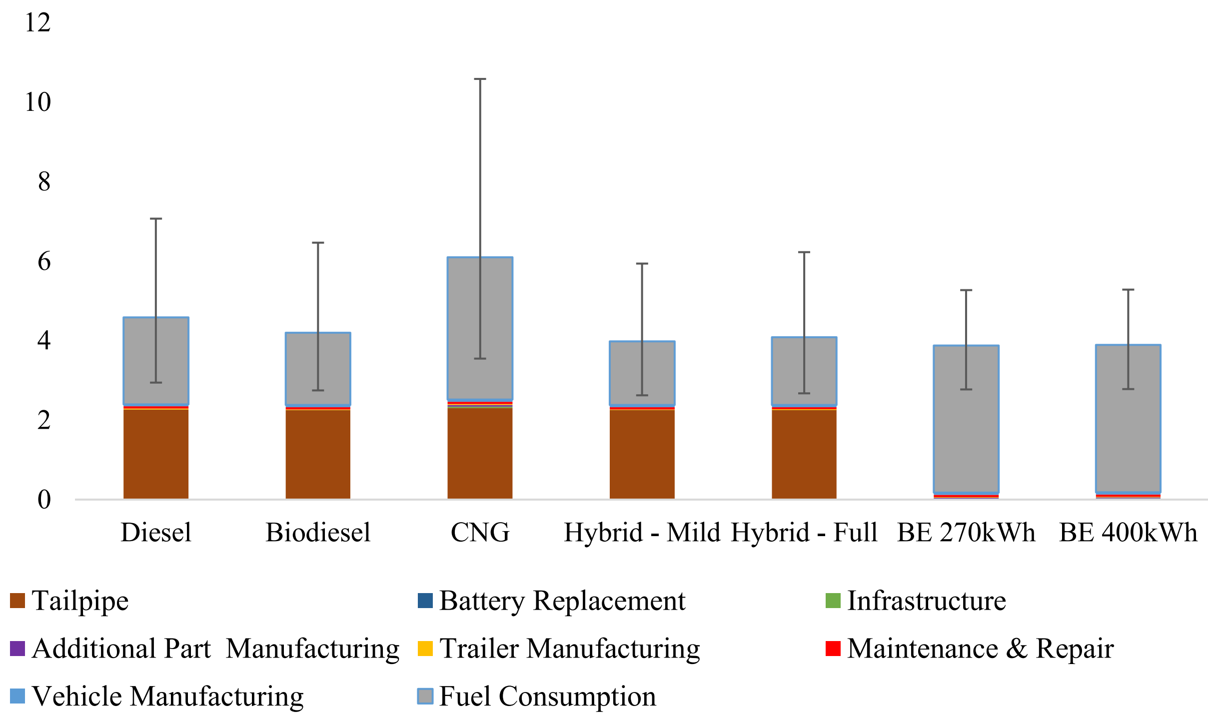


Figure 4: Life-cycle greenhouse gas emissions of heavy-duty trucks (thousand-tons of CO2-eq.)

Unlike the findings of Sharma et al. (2013), in which BE passenger vehicles were found to have higher life cycle CO_2 emissions than diesel passenger vehicles, the results of this research found that BE HDTs perform better, albeit slightly, than conventional HDTs in terms of life cycle GHGs emissions. An immense amount of GHGs emissions from electricity generation negated the zero tailpipe emission advantage of BE HDTs. In fact, the analysis results have shown that the amount of GHGs emissions from electricity generation are 70 percent and almost 5 percent greater, compared to the two largest GHGs emitters out of the considered truck types (i.e. conventional and CNG trucks), respectively.

Similarly, conventional and CNG HDTs have yielded the greatest amounts of air pollutant emissions compared to other HDTs, as shown in Figure 5. Air pollutants emissions from CNG HDTs are twice as much as those from conventional HDTs. This is consistent with the findings in Tong et al. (2015), which also found that CNG HDTs did not yield any emission improvements compared to diesel HDTs. The main driver of this significant difference has been observed to CO emissions, which have been estimated to account for 68 percent of the tailpipe emissions from CNG HDTs. According to the results, NO_x and SO_x emissions are also significant contributors to the total air pollutant emissions, largely due to fuel consumption and tailpipe emissions. Natural gas manufacturing has been observed to be the biggest contributor to SO_x emissions, followed by electricity generation and diesel manufacturing. Mild hybrid electric trucks had the lowest SO_x emissions at nearly 90 percent less than those of CNG trucks.

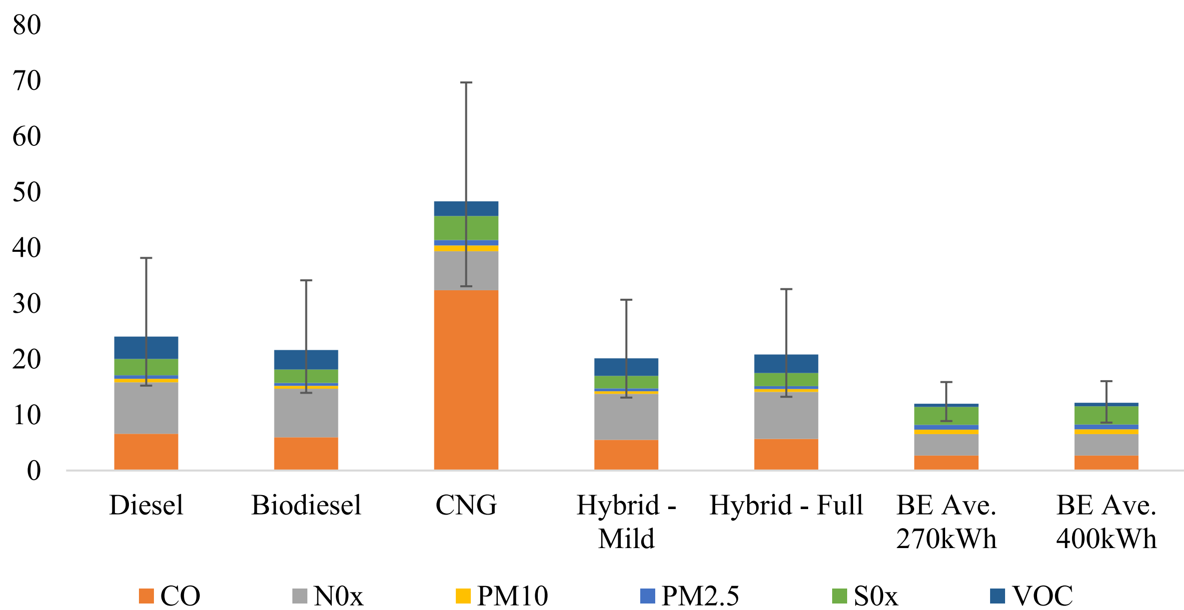


Figure 5: Life-cycle air pollutants emissions of heavy-duty trucks (tons)

From a life cycle perspective, this research has found that biodiesel trucks cause almost as much PM, CO, VOC, and NO_x emissions as do diesel HDTs. The main reason behind this difference between these emissions produced by biodiesel HDTs and diesel HDTs is that the emissions from maintenance and repair-related, fuel consumption-related , and tailpipe emissions of biodiesel trucks are slightly less than diesel trucks.

Life-Cycle Air Pollution Externality Costs Results

Compared to the baseline HDT, all the studied alternative fuel-powered HDT types, except CNG HDT, performed better with respect to APE LCCs. Fuel consumption and tailpipe emissions have been found to be the two main contributors to APE LCCs, respectively, yielding the largest and second largest APE damages out of all the analyzed modules. According to the results presented in Figure 6, the life cycle externalities for each HDT type (except for BE trucks) ranged between \$280,000 and \$340,000 (in 2015 dollars), with GHGs and SO_x emissions as the main drivers of APE LCCs for such HDTs.

Contrary to the results found by Michalek et al. (2011) regarding BE vehicles' APE costs, the results of this research have shown that BE HDTs significantly outperformed all other HDT types in spite of the U.S. electricity generation sector's high dependency on fossil fuels. This is mainly because BE HDTs have no tailpipe emissions, thereby eliminating one of the two main drivers of APE costs. This result is consistent with the study conducted by Feng and Figliozzi (2013) in that BE trucks have been found to be more competitive when indirect costs are taken into account. On the other hand, CNG trucks have been found to have the highest overall APE costs, with BE trucks' APE LCCs at 85 percent less than those of CNG trucks.

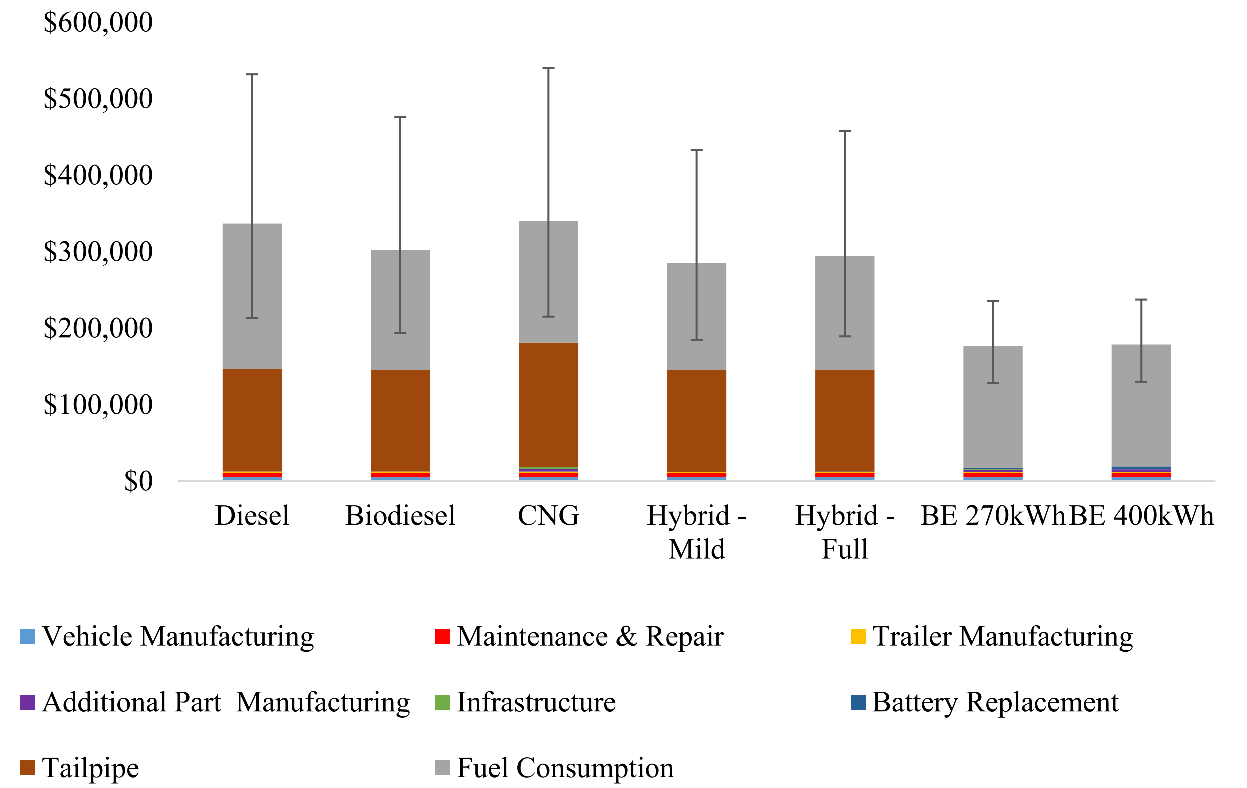


Figure 6: Life-cycle air pollution externalities (2015$)

The life cycle fuel consumption-related APE costs of alternative-fuel HDTs ranged between $140,000 and $160,000 (in 2015 dollars). Both hybridization and electrification of HDTs lowered the APE LCCs by 36 percent and 20 percent compared to conventional HDTs, respectively. This is to a large extent due to three factors, including a projected increase in diesel prices over the lifetime of an HDT, hybrid electric HDT's (especially mild hybrid electric HDT) relatively improved fuel economy, and a predicted decrease in electricity prices. Conventional, B20, and hybrid electric HDTs all produced nearly the same amount of APE costs from tailpipe emissions, mainly because these trucks still run largely on diesel fuel, and because the tailpipe emission values collected from the AFLEET tool's database and the tailpipe-related APE cost values collected from the APEEP model for these HDTs are identical. In terms of damages from tailpipe emissions, CNG HDTs incurred 22 percent higher APE costs than conventional HDTs, largely because of the additional APE costs from tailpipe CO emissions from CNG HDTs, as well as the higher SO_x emissions from natural gas manufacturing.

Cost and GHG Emissions Results for Regional Electricity Consumption

The regional analysis for BE HDTs is based only on the electricity consumption of such vehicles, which varies significantly among regions. Special emphasis is placed on electricity generation, and thus fuel consumption, taking into account the regional differences in life cycle emissions and costs. Although BE HDTs generally produced lower amounts of GHGs emissions than all other HDT types, electricity generation alone was still responsible for a considerable amount of GHGs emissions. The results from the previous sections for BE HDTs are based on a national average of the regional electricity grid mixes calculated based on NERC regions, but it must not be forgotten that different regions made varying contributions to this average. With respect to regional GHGs emissions from fuel consumption, the NPCC region produced substantially less emissions than all the other regions. The NPCC region's emissions from electricity generation were found to be 106 percent less than those of the SPP region. This difference is so significant that, if BE HDTs, nationwide, are to be charged using the electricity grid mix of NPCC region, the fuel consumption-related GHGs emissions of BE HDT type would be reduced by over 70 percent, and overall GHGs emissions would be reduced by over 63 percent. As previously noted in Ercan and Tatari (2015), this is due in large part to the relatively small share of coal use in the electricity grid mix of the NPCC region.

According to the results, another significant impact driven largely by fuel consumption is the overall LCCs. That said, with respect to the LCCs of electricity generation-related activities, the differences in LCCs are still considerable, though not as vastly different from region to region as GHGs emissions are. The electricity grid mix of the SERC region has been found to have the greatest fuel LCCs for BE HDTs at almost 30 percent higher than the LCCs for the U.S. national average grid mix. On the other hand, it has been observed that the use of the electricity grid mix in the NPCC region would improve the fuel LCCs of BE HDT by 12 percent compared to the U.S. national average grid mix (see Figure 7 and Figure 8).

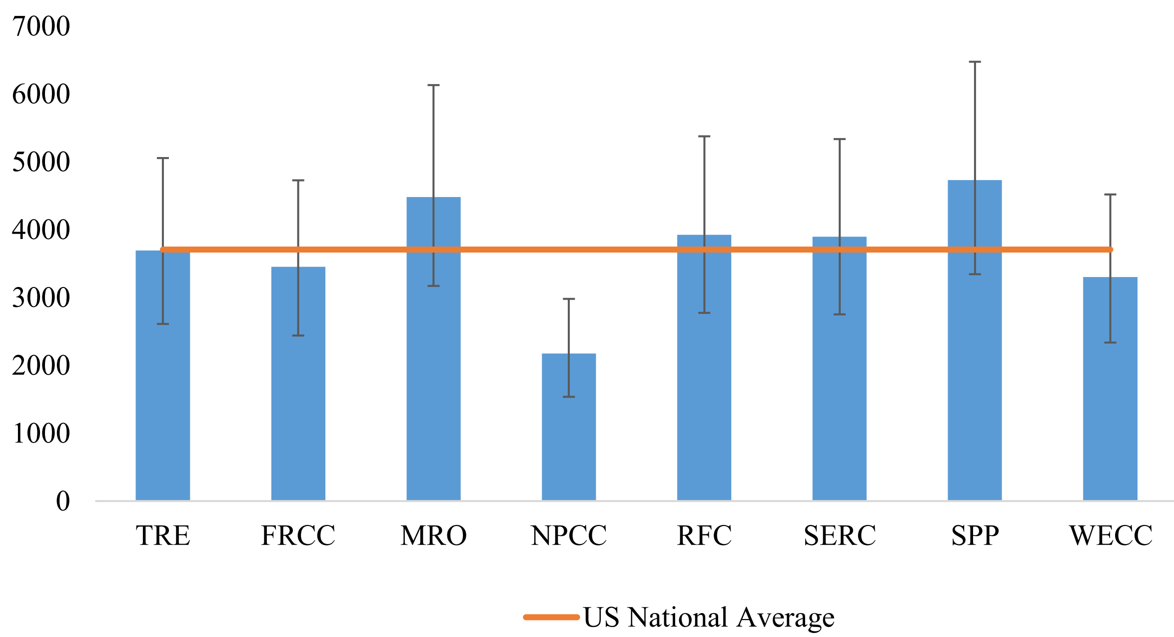


Figure 7: Regional electricity-consumption-related greenhouse gas emissions for 400 kWh electricity (ton of CO2-eq.)

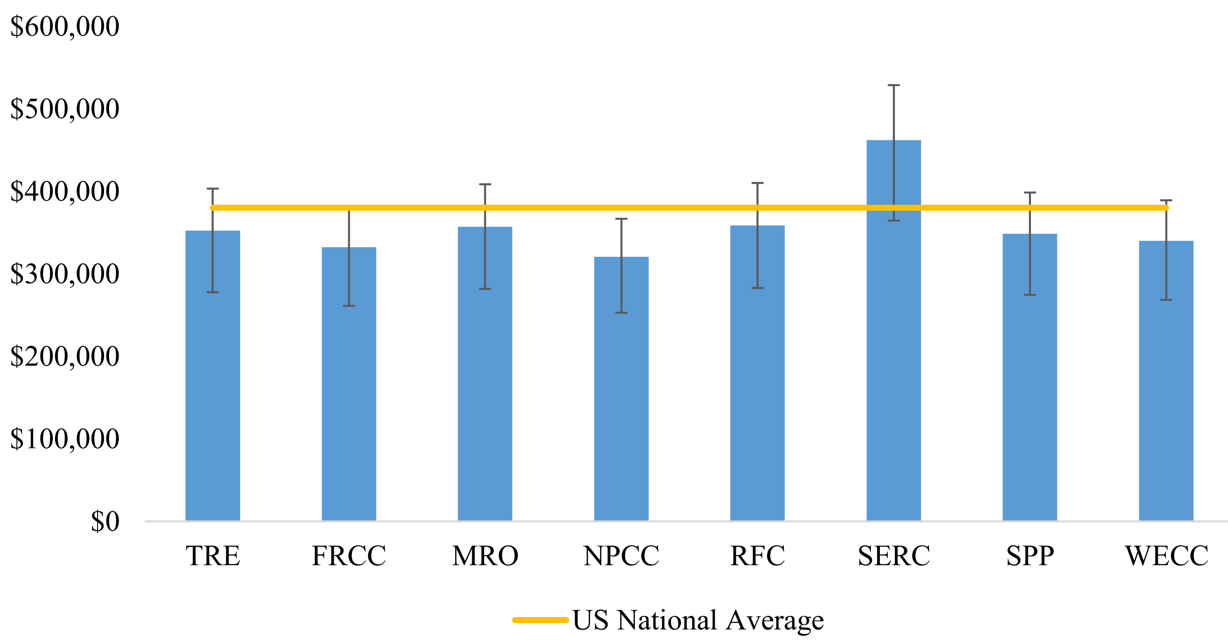


Figure 8: Regional life cycle cost of electricity consumption for 400 kWh electricity (2015$)

CHAPTER THREE: TRIPLE BOTTOM LINE SUSTAINABILITY ASSESSMENT OF AUTONOMOUS HEAVY-DUTY TRUCKS

A partial work of this chapter has been published in the special issue of Journal of Industrial Ecology on 'Life Cycle Assessment of Emerging Technologies', with the title "Life Cycle Sustainability Assessment of Autonomous Heavy-Duty Trucks" (Sen et al. 2019b)

Introduction

Connected and automated vehicle (CAV) technology is expected to herald a new era for transportation system increasing the system's efficiency and revolutionizing the way that goods move around the world. The CAV technology essentially provides means of communication among vehicles as well as between vehicles and infrastructure. Once vehicles are in the range of communication, they become connected to each other as well as infrastructure, and this vehicular connectivity facilitates automated driving. Given their potential socioeconomic and environmental implications as well as the potential of the CAV technology for operational cost savings and environmental improvement (U.S. Energy Information Administration 2017), heavy-duty trucks (HDTs) are considered an ideal vehicle segment for early adoption of this emerging technology - possibly earlier than passenger vehicles (Shanker et al. 2013). On one hand, it is deemed possible that the use of fully automated HDTs will reduce these costs by as much as 30 percent (International Transport Forum 2017), including driver costs approaching zero (Wadud et al. 2016). In addition to costs, the introduction of automated trucking is also expected to bring improvements in terms of energy use and associated emissions owing to greater fuel efficiency and increased operational efficiency (Slowik and Sharpe 2018; Collingwood 2018; Greenblatt and Shaheen 2015; Barth et al. 2014). On the other hand, some researchers argue that the CAV technology may cause a rebound effect, increasing both travel demand and freight demand, which are likely to result in increased energy consumption and public health problems (Wadud et al. 2016; Crayton and Meier 2017; Ross and Guhathakurta 2017).

Overall, the CAV technology has a potential to alleviate the impacts of environmental and socioeconomic issues, caused by freight transportation and trucking in particular, with the implications of automated HDTs going beyond the trucking industry to include cybersecurity (Van Meldert and De Boeck 2016), public health, public policy (Slowik and Sharpe 2018), urban planning and ethics (Alessandrini et al. 2015). However, a great deal of uncertainty remains in how these impacts will be experienced in terms of sustainability (Fitzpatrick et al. 2017).

This chapter attempts to contribute to the efforts made for shedding light on some of the uncertainties in CAV technology implementation in the U.S. trucking industry by exploring the sustainability impacts of automated HDTs (A-HDTs). Going beyond life cycle assessment (LCA), which mainly focuses on environmental and energy analysis of an economic activity, life cycle sustainability assessment (LCSA) framework presents an effective means to broaden the impact analysis by capturing social and economic impacts of such an activity, in addition to its environmental impacts (Sala et al. 2013b). In this regards, input-output (IO) analysis is regarded as an effective method to carry out LCSA studies (Guinee et al. 2011). Jeswani et al. (2010) underline the usefulness of combining input-output (IO) analysis with LCA to create hybrid models that can capture the LCS impacts of intra- and inter-sectoral activities. Hence, IO-based LCSA has been employed to investigate the potential LCS impacts of truck automation.

Consequently, the primary objective of this chapter is to quantify, assess, and compare the macro-level LCS impacts of automated HDTs taking the environmental, social, and economic dimensions into account based on current techno-economic circumstances. With these objectives, this chapter specifically aims to contribute to:

- The general body of scientific knowledge on potential sustainability impacts of A-HDTs based on the system boundary defined; and
- The LCSA literature on CAVs by providing another example of the integration of IO analysis for LCSA; and

Literature Review

Several studies have employed IO modeling based on the Eora database developed by Lenzen et al. (2012a) and the LCSA framework. The reader interested in the publications that are excluded from the review but apply Eora-based IO modeling and the LCSA framework in a wider scientific spectrum is kindly referred to Lenzen et al. (2012b) and Onat et al. (2017).

In recent years, the research on the application of CAV technology in passenger vehicles has attracted relatively more attention from researchers (Fitzpatrick et al. 2017). Hence, even though LCSA has been previously applied to different types of production systems (Zamagni et al. 2013), the literature on automated HDTs is not as abundant as the literature on automated passenger vehicles and LCA of alternative fuel HDTs. Using Argonne National Laboratory's process LCA model – *Greenhouse Gas, Regulated Emissions, and Energy Use in Transportation (GREET)* (Center for Transportation Research 2016), Gaines et al. (1998) conducted one of the first life cycle analysis of alternative fuel-powered Class 8 heavy trucks to investigate energy use and emissions from Fischer-Tropsch diesel and liquefied natural gas (LNG) powered trucks and their manufacturing as well as recycling. The study found the vehicle operation (e.g. fuel economy, payload, and vehicle-miles-traveled [VMT]) to dominate energy consumption and emissions. It was concluded that natural gas-powered trucks did not perform better than conventional trucks with respect to energy or emission. Beer et al. (2002) applied a process LCA method to examine life cycle tailpipe emissions, fuel cycle greenhouse gas (GHG) emissions, and fuel production-related emissions from diesel, compressed natural gas (CNG), LNG, liquefied petroleum gas (LPG), and biodiesel heavy-duty vehicles. Biodiesel was found to outperform other fuels given that emissions from renewable carbon stocks are not counted and highlighted the sensitivity of results to energy type used in the fuel production process. The study lacked the consideration of the complete life cycle assessment. Graham et al. (2008) study compared GHG emissions from trucks fueled with diesel, biodiesel, CNG, hythane (20 percent hydrogen, 80 percent CNG), and LNG, and concluded that GHG emissions varied depending on the choice of fuel, revealing that the use of natural gas only moderately improved the tailpipe emissions compared to conventional truck. Meyer et al. (2011) conducted a comparative total fuel cycle analysis of diesel and alternative fuel (i.e. diesel and its variations, biodiesel, CNG, and LNG) HDTs, carrying 20 tons of cargo, based on the GREET model. The researchers found tailpipe emissions to be the main contributor to total GHG emissions, concluding that fuel economy and truck payload are two key variables that affect operational emissions. Tong et al. (2015) made a comparative analysis of natural gas pathways for medium- and heavy-duty trucks, including Class 8 tractor-trailers and refuse trucks, and found that, compared to diesel trucks; the use of natural gas did not reduce emissions per unit of freight-distance moved. It was further concluded that current technologies do not provide good opportunities to achieve desired reductions in emissions from natural gas-fueled Class 8 trucks. Nahlik et al. (2015) estimated GHG and conventional air pollutant emissions from diesel, LNG, and hybrid electric HDT freight activities inside and associated with California using process LCA method considering vehicle and fuel manufacturing, vehicle operation and maintenance, including roadway infrastructure and maintenance. It was found that switching to LNG, with 1 percent annual fuel economy improvement, offers short-term reductions, but long-term increases. The study concluded that electric-propulsion trucks can lead to additional GHG emission reductions and that higher deployment of zero-emission vehicles is needed for California to meet emission reduction goals. Gruel and Stanford (2016) developed a system dynamics simulation model to examine the impacts of autonomous vehicles on traveling behavior, mode choice, and broader transportation system based on various scenarios. The researchers concluded that VMT is likely to increase resulting in increased energy consumption and associated emissions; however, have not reported any estimation in this regard. They also confirmed the potential of AV technology to improve mobility and traffic safety. Wadud et al. (2016) examined travel related energy consumption and emissions of both light- and heavy-duty vehicle automation based on an extensive literature review. They underlined the significance of automated vehicle operation for the sustainability profile of these vehicles and found that different levels of vehicle automation result in different energy outcomes and travel impacts, with a high level of automation potentially increasing travel activities and associated energy consumption. They concluded highlighting the importance of further research on how mobility models, vehicle design, fuel choices, and driver's behavior will change the implications of vehicle automation to improve our understanding of these responses. Harper et al. (2016) conducted a cost-benefit analysis of partially automated vehicle collision avoidance technologies used in U.S. light-duty vehicles. The researchers only considered the social cost of crashes and estimated that over 130 thousand injury crashes and over 10 thousand fatal crashes could be avoided through the use of such technologies resulting in $20 billion net benefits. They did not, however, include the social cost of air pollution, and suggested that VMT is an important parameter to incorporate in economic analysis.

To and Lee (2017) used a triple-bottom-line approach to assess the sustainability performance of Hong Kong's logistics sector based on three non-linear equations representing environmental, economic, and social performances. They considered GHG emissions to be the only environmental performance indicator; value-added values and R&D expenditures to be the only economic indicators; and education, health, housing, public safety, employment, and income to be the social indicators. The sector's environmental performance was found to remain steady, and economic and social performances to show a downward trend. The researchers did not include various indicators included in this study and did not report any result on the social indicators except for employment. Ross and Guhathakurta (2017) quantified the impact of AVs on energy use under three autonomous vehicle dominance scenarios based on literature review. Like Wadud et al. (2016), they found a great variation in energy consumption rates for different automation levels, with full automation generally resulting in more energy consumption through the induced increase in travel demand, and ultimately, higher VMT. Bösch et al. (2017) conducted a cost-based analysis of fully autonomous mobility services for different operational modes such as ride-sharing and taxis, public transportation, and private vehicle. Vehicle automation was found to bring substantial decreases in taxis and public transportation services, while the cost of private vehicle and rail services changed only marginally. It was concluded based on the study result and ongoing developments, that electric vehicles will be the prevailing choice by the time autonomous vehicles are introduced. Heard et al. (2018) examined the sustainability implications of CAVs for the food supply without employing an analytical approach. The researchers pointed out the criticality of evaluating the environmental performance of the CAV technology and highlighted the importance of the inclusion of social aspects of the technology in assessing its economic impacts. A recent review study concluded that developing quantitative social and economic life cycle indicators and life cycle-based approaches to investigate various product development scenarios and practical ways to cope with uncertainties still remain as the main challenges of the LCSA framework for sustainability assessment of emerging technologies (Guinée 2016).

Different approaches such as deterministic models, econometric models, and dynamic simulation models have been employed to answer important questions and generate valuable knowledge on a likely future under the dominance of CAVs. Even though several projects on automated HDTs – particularly on platooning of A-HDTs (Tsugawa et al. 2016) – exist, it has been also observed that the research on connected automated HDTs is quite limited and most of these studies focused primarily on full-market existing systems rather than new technologies. Cucurachi et al. (2018) concluded that, to achieve a more sustainable society, new technologies and their life cycle sustainability impacts need to be proven with sound and systematic methodologies. As observed, there are many studies in the literature that investigate environmental and economic impacts of alternative vehicle technologies; the sustainability impacts (i.e. encompassing environmental, social, and economic dimensions) of emerging vehicle technologies such as connected automated vehicles have not been investigated sufficiently. These make those calls made by several researchers for additional research reasonable (Bechtsis et al. 2017; Slowik and Sharpe 2018; Gruel and Stanford 2016; Barth et al. 2014).

The literature review has also shown that the social cost of emissions has not been included in most of the studies. Therefore, Wadud et al. (2016) are agreed with on the level of uncertainty in the environmental and energy impacts of AVs (especially of A-HDTs), and that it is difficult to truly predict these impacts under the current circumstances. However, it is crucial to "take a snapshot" of the potential life cycle sustainability impacts of A-HDTs based on possible A-HDT specifications given by the literature and relevant reports. To this end, the research presented in this chapter is the first attempt to conduct an assessment of the life cycle environmental, economic and social impacts of U.S. connected automated trucks.

Objectives of the Study

The scholars that engage in the research related to the CAV technology seem to agree on the potential benefits of the technology with respect to traffic safety. However, it does not seem possible to claim such a consensus on the potential environmental and other socioeconomic impacts of automation of HDTs. This is a good indication for the need to diversify the research conducted so far regarding this emerging technology to grasp a better understanding of its multi-dimensional implications from a holistic perspective, which is also evident from the reviewed literature.

The primary objective of the research conducted in this chapter is to quantify, assess, and compare the macro-level LCS impacts of automated HDTs taking the environmental, social, and economic dimensions into account based on current techno-economic circumstances. The use table within the input-output framework not only gives information on primary inputs into industries' production systems but also on the cost structures of industries and their activities (Eurostat 2008). Current technological and economic circumstances are important determinants of these cost structures, which, in turn, have a significant influence on the multiplier matrix values used to estimate impacts. As known, the main inputs to an economic input-output-based LCSA model are the unit costs of variables that are included in the system boundary under examination (Kucukvar and Tatari 2013). These unit costs are influenced by vehicle types and their technical specifications (Rogge et al. 2018). For example, truck platooning is regarded as a new mode in terms of cost structure (Meersman et al. 2016). In another example, user cost structures are defined as those costs related to vehicle ownership and vehicle use such as purchase, insurance, and fuel (U.S. Department of Transportation 2018). Accordingly, several considerations underlying the research conducted in this chapter, e.g. changing diesel prices, changing electricity prices, deterioration of tailpipe emissions over time (which affect the overall health damage costs), changing battery prices, fuel economies of HDTs, etc., have been taken into account these circumstances. The research conducted in this chapter investigates these dimensions based on the indicators that are presented in the following section specifically for U.S. Class 8 diesel and battery electric (BE) automated HDTs with a truck-trailer as defined by the U.S. Department of Energy (2011). The developed IO model focuses on the United States for the year 2015 – the latest data year in the Eora database at the time of the research conducted (Fry et al. 2018).

Industrial ecology (IE) is concerned with the sustainability of resources (e.g. materials and energy) used in producing goods and services as well as the analysis of the impacts of consumption on the environment, society, and economy, i.e. the three pillars of sustainability (Clift and Druckman 2016). In doing so, IE adopts a system perspective to operationalize forward-looking research and practice taking into account the role of technological change (Lifset and Graedel 2002). LCSA, which is viewed either as an analytical framework (Guinée et al. 2011) or a holistic method (Kloepffer 2008), is an IE tool widely used to investigate the sustainability of production and consumption activities (Gloria et al. 2017). Within this context, this chapter also aims to contribute to 1) advancing the understanding of sustainability implications of automated HDTs based on the system boundary shown in Figure 9 and the studied sustainability indicators, and 2) advancing the LCSA literature on CAVs by providing another example of the integration of IO analysis for LCSA.

Methods and Materials

Triple Bottom Line Life Cycle Sustainability Assessment Model

Triple bottom line (TBL) is a construct within the ontology of sustainability science that provides a framework used to measure the sustainability performance of organizational activities (Goel 2010; Rogers and Hudson 2011). Since the term sustainability is equivocally used to refer to the environmental performance of products, processes, or organizations, the TBL framework, coined by Elkington (1997), expands this sole environmental consideration to integrate economic and social aspects into the sustainability agenda (Alhaddi 2015). Hence, the TBL framework has been adopted in this research and operationalized with the application of the economic input-output (EIO) modeling technique, introduced by Leontief (1970), which is used to assess the sustainability impacts of A-HDTs at the triple bottom line.

EIO modeling has been widely used to analyze a wide variety of policy-relevant issues, including the sustainability impacts of products, infrastructures, international trade, and households (Lettenmeier et al. 2014; Giljum et al. 2008a; Tukker et al. 2014; Kucukvar and Tatari 2013; Weber and Matthews 2007; Kucukvar et al. 2017; Giljum et al. 2008b; Zhang et al. 2015; Caron et al. 2014). EIO models are constructed based on sectoral monetary transaction matrices (e.g. supply and use tables, which are the building blocks of EIO models representing the data on financial flows between sectors) encompassing the economic interactions between industries within national economies (Onat et al. 2017a). In this research, the supply and use tables, provided by Eora National IO Tables constructed by Lenzen et al. (2012), have been merged along with a number of environmental, social, and economic sustainability metrics to construct an EIO model capable of analyzing the TBL sustainability impacts of the studied A-HDTs.

The Use matrix, denoted as U, provides data on the consumption of each commodity by each industry or by final demand categories, i.e. households, government, investment, and export, whereas the Make table, denoted as V, provides data on the production of each commodity by each industry included in these tables. Accordingly, u_{ij} represents the value of commodity i purchased by industry j; and v_{ij} represents the value of commodity i produced by industry j. Using these two tables, it is then possible to calculate the direct requirements table, also referred to as *technical coefficient matrix*, denoted as B, and the market share matrix, denoted as D, given in Eqs. 1 and 2.

$$B = [b_{ij}] = \left[\frac{u_{ij}}{x_j}\right] \tag{1}$$

$$D = [d_{ij}] = \left[\frac{v_{ij}}{q_i}\right] \tag{2}$$

In Equations (1) and (2), B refers to the amount of input of commodity i used by industry j to produce one dollar of output of that industry; D refers to the proportion of the total output of commodity i produced in each industry; and x_j and q_i represent the total output of industry j, and the total output of commodity i, respectively (Horowitz and Planting 2006). After the direct requirement and market share matrices are defined, an industry-by-industry IO model can be formulated as the following (Miller and Blair 2009):

$$x = [(I - DB)^{-1}]f \tag{3}$$

In this equation;
x: Total industry output vector
I: The identity matrix
f: Total final demand vector
DB: Direct requirement matrix
$[(I - DB)^{-1}]$: Total requirement matrix (also referred to as *multiplier matrix*)

Following the construction of the foundation of industry-by-industry IO model, a diagonal matrix E_{sus}, referring to triple bottom line impacts per dollar of output of each industry is integrated in Eq. 3, as shown in Eq. 4. This matrix is constructed by dividing the total direct impact of industry j, e.g. GHG emissions, GDP, income etc., by the total output of that industry. It is then possible to estimate total sustainability impacts per unit of final demand, denoted as r, by pre-multiplying the total industry output vector as the following:

$$r = E_{sus}x = E_{sus}[(I - DB)^{-1}]f \qquad (4)$$

Here, 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 B.18. These multipliers are used to quantify the LCS indicators considered in the analysis. These LCS indicators are presented under the following section.

Scope and Goal

Life cycle phases such as material extraction, procurement, manufacturing, and operation phases have been included in the analysis. While the vehicle characteristics of the studied HDTs are presented in Table 4, Figure 9 shows the system boundary assumed for the LCSA analyses of automate diesel HDT and automated electric HDT. The functional unit of the analysis can be given as a commercial truck manufactured and operated until its end of lifetime, like in Sen et al. (2017). Therefore, the results will be presented based on unit of indicator per truck (e.g. GWP100/truck).

Table 4: Vehicle characteristics

Characteristics	**Value**	**Source**
Lifetime	19 years	(CALSTART 2013; Burnham 2017)
Average annual mileage	137,000	(Trego and Vice 2017; Burnham 2017)
Physical features	Class 8 heavy-duty truck with 53’ (16 meter) truck-trailer; >33,001 lbs. (15 tons)	(U.S. Department of Energy 2011)
Battery Energy	400 kWh of Li-ion battery	(California Air Resources Board 2015)

Characteristics	Value	Source
Fuel Economy (Diesel)	7.03 mpg	(Slowik and Sharpe 2018;
Fuel Economy (BE)	17.9 mpgge	Burnham 2017)

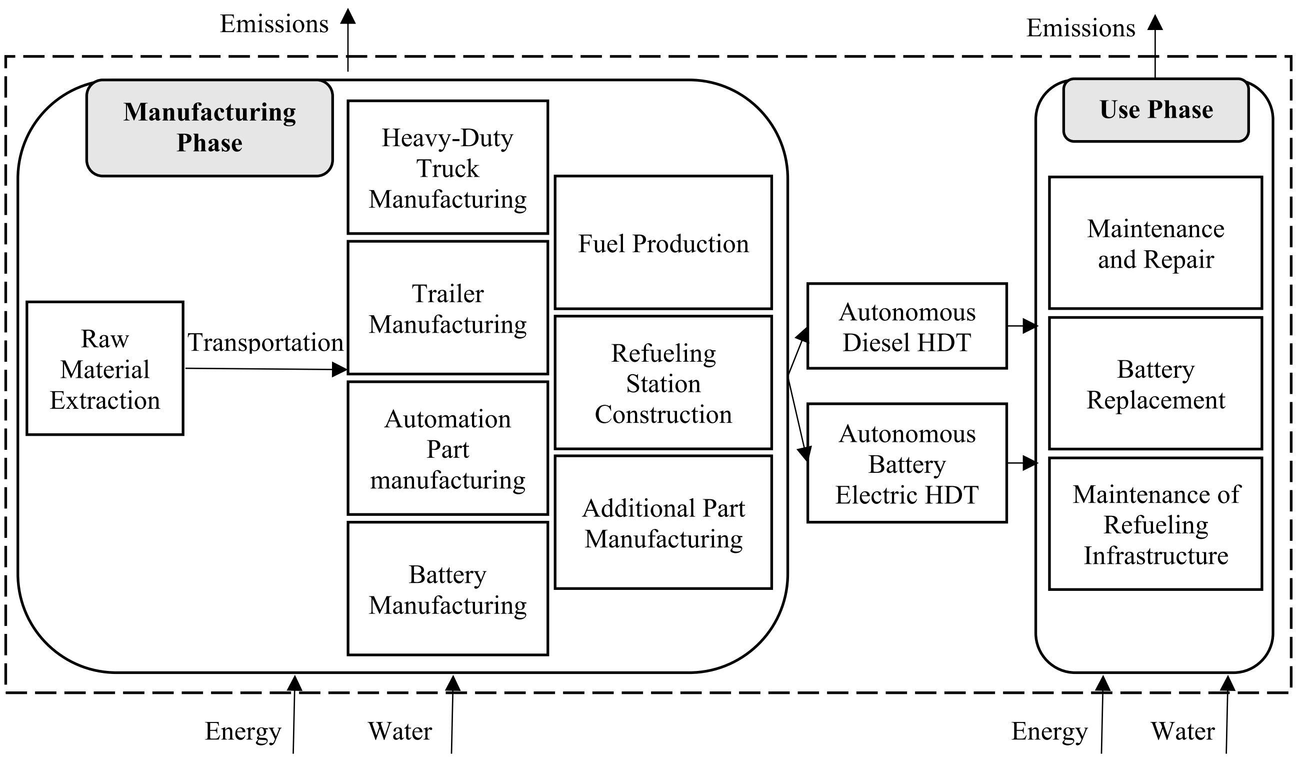


Figure 9: System boundary for the life cycle sustainability assessment

Selected Sustainability Indicators

Given the importance of indicators used gain insights into the sustainability implications of products and processes, scholars involved in scientific research within the domain of sustainability science have sought to develop and improve indicators that can enhance society's understanding of the consequences of anthropogenic activities (Ramani 2018). Because the sustainability science deals with multi-faceted multi-dimensional dynamic interactions between the nature and society (Sala et al. 2013a), the evolution of indicators and the efforts to include different insightful indicators in sustainability impact analysis continue (Malik et al. 2018). To this end, the inclusion (i.e. selection and quantification) of indicators – especially when it comes to the social dimension of the triple bottom line – is one of the major challenges in making use of a triple bottom line analysis (Onat et al. 2014a). A predetermined set of social indicators does not exist, and there is still a need for further research in developing social and economic indicators that go beyond traditional indicators such as employment or life cycle cost (Onat et al. 2014a; Wood and Hertwich 2013; Finkbeiner et al. 2010; Valdivia et al. 2013). The TBL LCS indicators considered in the analysis, as shown in Table 5, have been selected based on the literature, availability of relevant data, and ease of integration of the data with current TBL LCS analysis.

Environmental Indicators

Water scarcity, global warming, and fossil and mineral depletion have been among the most important emerging environmental concerns for the present century (UNEP 2012). In addition, several scholars regarded energy consumption as one of the most important aspects of environmental consequences of vehicle automation (Morrow et al. 2014; Greenblatt and Shaheen 2015; Wadud et al. 2016). Furthermore, Crayton and Meier (2017) emphasized the significance of particulate matter and ozone – a photochemical oxidant – in developing a public health research agenda for the future of transportation, wherein CAVs are dominant. The environmental indicators considered in the analysis have been estimated based on the characterization factors obtained from the ReCiPe impact assessment method developed by Huijbregts et al. (2016) and Goedkoop et al. (2013).

- *Global Warming Potential (GWP100)* has been estimated based on the emissions of carbon dioxide (CO_2), methane (CH_4), hydrofluorocarbons (HFC-134A, HFC-143a, and HFC-125), and nitrous oxide (NOx). The multipliers for each of these emissions are provided in Table B.17. The GWP100 is a midpoint impact category, whose characterization factors are provided in Table B.24.

- *Total Water Footprint (TWF)* is included in the satellite accounts provided by the Eora database used to construct the IO model. The uses of green, blue, and grey waters are included in the estimation of TWF. Thus, the TWF estimation has been calculated as a model output for each TBL component considered in the analysis, with the relevant multipliers provided in Table B.18.
- *Mineral Resource Scarcity (MRS)* has a characterization factor called Surplus Ore Potential (SOP), which is defined by Huijbregts et al. (2016) as the average extra amount of ore that is needed to be produced in the future due to the extraction of 1 kg of a mineral resource. To estimate the MRS in this study, the estimated use of copper (Cu), lead (Pb), Zinc (Zn), Iron (Fe), and miscellaneous minerals, including sand, stone, gravel, clay, and ceramic (as provided by the Eora database as *Mining and quarrying industry*). The MRS is a midpoint impact category, whose characterization factors are provided in Table B.21.
- *Fossil Resource Scarcity (FRS)*'s characterization factor is given by Huijbregts et al. (2016) as the Fossil Fuel Potential of a fossil resource, which is defined as the ratio between the energy content of a fossil resource (higher heating value) and the energy content of crude oil. In this research, the FRS has been estimated based on the consumption of coal, natural gas, and oil. The FRS is a midpoint impact category, whose characterization factors are provided in Table B.21.
- *Particulate Matter Formation Potential (PMFP)* is related to the potential of air pollutant emissions such as sulfur dioxide (SO2), ammonia (NH3), nitrogen oxides (NOx), and particulate matter (PM) to cause primary and secondary aerosols in the atmosphere (Huijbregts et al. 2016). PMFP has been estimated based on the PM10, SO_2, and NH_3 emissions. PMFP is a midpoint impact category, whose characterization factors are provided in Table B.24.
- *Photochemical Oxidant Formation Potential (POFP)* is related to the potential of air pollutants such as non-methane volatile organic compounds (NMVOC), NO_2, SO_2, and carbon monoxide (CO) to form oxidants – particularly ozone (O_3) – that are harmful to human health. POFP has been

estimated and reported based on these emissions, like in Fugiel et al. (2017). POFP is a midpoint impact category, whose characterization factors are provided in Table B.24.

Social Indicators

The inclusion of social indicators is not as straightforward as the environmental indicators, since, as Malik et al. (2018) states, it is challenging to establish causal mathematical relationship between socio-economic activities and social consequences. Therefore, the authors were inclined more to including the traditional, macro-level indicators such as the followings:

- *Income* is considered an important indicator in this regard given its contributions to societal welfare, like in (Onat et al. 2014a). Since income is an internal component of the Eora database used in the form of compensation of employees, its estimate refers to the total income, including wages and salaries.
- *Employment* has been one of the main concerns when it comes vehicle automation, particularly heavy-duty long-haul trucks. Several scholars have brought up this topic of employment and raised important concerns over whether and to what extent the CAV technology will influence employment. Therefore, employment is considered another social indicator. The data on employment was obtained from the U.S. EPA's Environmental Dataset Gateway database (U.S. EPA 2017).
- *Occupational health and safety* is another critical social indicator, which has important implications in terms of quality of life. Therefore, *fatal* and *non-fatal injuries* at industrial facilities are included in the analysis. The data on fatal and non-fatal injuries were obtained from the census of fatal occupational injuries provided by the U.S. Department of Labor Bureau of Labor Statistics (Bureau of Labor Statistics 2015).

- As mentioned by (Crayton and Meier 2017), the public health implications of the CAV technology have been given relatively less attention. However, without a doubt, it is, maybe, the most important aspect to be considered, since any technology is expected to serve the public good first. *Human Health Impact* (HHI) has been included in the analysis based on the health impacts arising from GWP, POFP, and PMFP. The health impact characterization factors of each of these midpoint impacts are provided in Table B.26.

Economic Indicators

- *Gross Operating Surplus (GOS), Import, and Gross Domestic Product (GDP)* are internal parts of the Eora database used in the analysis as they are key economic indicators considered in several studies (Alises and Vassallo 2016; Wood and Hertwich 2013; Onat et al. 2014a; Kucukvar and Tatari 2013). GOS refers to the capital available to industries after total intermediate inputs, compensation of employees, and taxes subtracted from the total industry output. GDP refers to the market value of goods and services produced within a country, and includes compensation of employees, GOS, and net taxes on production and imports (Lenzen and Dey 2002; Kucukvar and Tatari 2013). Imports refers to the value of goods and services purchased from foreign countries to produce domestic commodities. Imports are considered a negative economic indicator as increased imports results in an increase in the current deficit through the outflow of money from a country.
- *Tax* is another component of value added through consumption and production, and considered a relevant indicator for the economic dimension of triple bottom line (Wood and Hertwich 2013). Tax is another internal component of the Eora database; hence its estimate has been obtained as a model output.

- As the life cycle thinking necessitates and given the aforementioned importance of human health implications of the CAV technology, the economic costs of externality damages due to emissions of CO_2, CO, NO_x, PM10, SO_2, and VOC have been included in the analysis.
- Finally, yet importantly, *Life Cycle Cost (LCC)* has been included as an indicator and reported as per-mile basis so that the performance of the studied truck configurations can be assessed in a better way.

Table 5: Life cycle sustainability indicators considered in the analysis

Impact Area	Impact/Indicator	Unit	Description
Environmental	Global Warming Potential	tCO_2-eq.	Total GHG emissions based on IPCC's factors for GWP100
	Particulate Matter Formation Potential	kg PM10-eq.	Total criteria air pollutant emissions
	Photochemical Oxidant Formation Potential (	kg NMVOC-eq.	Amount of airborne substances able to form atmospheric oxidants
	Mineral Resource Scarcity	t Cu-eq.	Extra amount of ore mined per additional unit of resource extracted
	Fossil Resource Scarcity	t Oil-eq.	Total decrease in fossil fuel potential of oil
	Total Water Footprint	mm^3/yr.	Amount of water polluted or consumed to produce goods and services
Social	Employment	person	Number of jobs based on Bureau of Labor Statistics (BLS) data for total employment for each sector
	Fatal Injuries	person	Number of fatal occupational injuries (FOI) based on BLS Census of FOI
	Non=Fatal Injuries	thousand-person	Number of non-FOI by industry based on BLS Industry Injury and Illness Data

Impact Area	Impact/Indicator	Unit	Description
	Income	$M	The compensation of employees, wages, and salaries
	Human Health	DALY	The number of years lost due to disability, illness, or early death
Economic	Import	$M	Purchase of product and/or service from foreign countries
	Gross Operating Surplus	$M	The amount of capital available to corporations to maintain business
	Gross Domestic Product	$M	Economic added value by the U.S. industries
	Tax	$M	Taxes collected from production and imports
	Life Cycle Cost	$M	Cost of a product throughout its life cycle based on the system boundary defined
	Mineral Depletion Potential	$M	Total additional future cost to the global society of producing one unit of mineral resource
	Fossil Depletion Potential	$M	Total additional future cost of the global society of producing one unit of fossil resource
	Air Pollution Cost	$M	Health damage cost of air pollution

Life Cycle Inventory

Since the foundation of an IO modeling is the matrices that contain monetary transactions between industries within a nation's economy, the inputs required to carry out an IO-based TBL LCS analysis are the unit costs of each activity that takes place within the system boundary. After obtaining the relevant unit costs, the TBL LCS impact multipliers have been used to estimate the indicators considered in the analysis. These multipliers associated with emissions, energy consumption, mineral use, and some internal indicators (e.g. TWF, income, GOS, and GDP) are provided in Table B.17, Table B.19, Table B.20, Table B.21, Table B.22, Table B.23. Furthermore, the characterization factors for each of the midpoint and endpoint impact categories considered in the analysis are provided in Table B.24, Table B.25, Table B.26.

The additional parts assumed to be used in automating and electrifying an HDT are provided in Table 6. In addition to these parts, the construction of a new, private (i.e. having only one dispenser) diesel refueling station and battery recharging infrastructure has been included in the analysis. In addition to the installation costs, annual maintenance costs for refueling and recharging stations have been considered in the analysis to be $6K and $2.3K, respectively, based on the AFLEET2017 database (Burnham 2017). The unit costs of each of these parts are the inputs for the constructed IO model, which are presented in Table 6, along with their sources and corresponding module (e.g. truck manufacturing) and industry (e.g. Heavy-Duty Truck Manufacturing).

Table 6: Inputs for life cycle sustainability assessment

Truck type	LCSA module	LCSA component	Eora industry	Cost (2015$)	Source
Common for both types of trucks	Vehicle manufacturing	Truck manufacturing	Heavy Duty Truck Manufacturing	$107K	California Air Resources Board (2015)
		Truck trailer manufacturing	Truck trailer manufacturing	$32.5K	Commercial Truck Trader (2016)
		LIDAR (A)[b]	Search, detection, and navigation instruments manufacturing	$7.5K	Slowik and Sharpe (2018)
		DSRC (A)	Telecommunications	$200	Slowik and Sharpe (2018)
		V2V communication (A)	Broadcast and wireless communications equipment	$350	Slowik and Sharpe (2018)
		Automated manual transmission (A)	Mechanical power transmission equipment manufacturing	$3.75K	Slowik and Sharpe (2018)
		Blind spot detection system (A)	Search, detection, and navigation instruments manufacturing	$850	Slowik and Sharpe (2018)
		Mobile eye advanced driver assistance (A)	Search, detection, and navigation instruments manufacturing	$1.1K	Slowik and Sharpe (2018)
		Adaptive cruise control (A)	Relay and industrial control manufacturing	$2K	Slowik and Sharpe (2018)
		Predictive cruise control (A)	Relay and industrial control manufacturing	$1K	Slowik and Sharpe (2018)
		Other miscellaneous hardware (A)[b]	Hardware manufacturing	$6.7K	Slowik and Sharpe (2018)
Diesel truck	Vehicle operation	Diesel fuel production[a]	Petroleum refineries		Burnham (2017)
		Maintenance[c]	Automotive maintenance and repair	$0.199	Burnham (2017)

Truck type	LCSA module	LCSA component	Eora industry	Cost (2015$)	Source
		Refueling station	Retail trade	$91K	Burnham (2017)
Battery-Electric truck	Vehicle manufacturing	Power electronics and electric motor	Motor and generator manufacturing	$20K	California Air Resources Board (2015)
		Glider	Motor and generator manufacturing	$80K	California Air Resources Board (2015)
		Battery system manufacturing	Storage battery manufacturing	$109K	California Air Resources Board (2015)
	Vehicle operation	Battery replacement[d]	Storage battery manufacturing		Wang et al. (2016)
		Power generation[a]	Electric power generation, transmission, and distribution		California Air Resources Board (2015)
		Maintenance[c]	Automotive maintenance and repair	$0.181	Burnham (2017)
		Recharging station	All other miscellaneous electrical equipment and component manufacturing	$59K	Burnham (2017)

[a] The cost values for these inputs are not given in the table because the changing diesel and electricity prices are considered in the analysis.

[b](A) stands for *automation*, meaning that those additional parts are used to manufacture an automated HDT.

[c] The values represent per mile cost

[d] The battery replacement is assumed to be once in every 10 years. Hence, the cost value for battery replacement varies depending on HDT lifetime. Based on Curry (2017) and Berckmans et al. (2017), it is assumed that the initial cost of a battery pack per kWh is $273, which goes down to $100/kWh by 2025 (i.e. the first battery replacement), and then further down to $75/kWh by 2035 (i.e. the second battery replacement). Given these considerations, these values were not included in the table.

A fuel economy of 6.3 mpg for a diesel HDT and 16.1 mpgge for a BE HDT has been assumed based on the AFLEET2017 database (Burnham 2017). Based on the report published by (Slowik and Sharpe 2018). HDT automation has been assumed to bring 10 percent improvement in fuel economy. Changing diesel prices have been reflected based on the diesel price and the price escalation rate for the period between 2015 and 2045 given by (Burnham 2016). Changing electricity prices have been also reflected. The projected electricity prices have been acquired from Annual Energy Outlook 2018 report published annually by U.S. Energy Information Administration (2018) and converted to 2015$. Additionally, increasing tailpipe emissions due to deterioration of vehicle fuel systems have been taken into account based on the Motor Vehicle Emission Simulator (MOVES) analysis results for HDTs (EPA 2014). The cost values of tailpipe emissions to calculate the air pollution externality (APE) costs have been obtained from the AFLEET2017 database (Burnham 2016).

An electric HDT has been assumed to replace its battery once in every 10 years (Wang et al. 2016). Based on the estimation done by Curry (2017), the unit cost of battery has been assumed to be currently $273/kWh, going down to $100/kWh by 2025, and $75/kWh by 2035. These projections on battery costs have been reflected in the battery replacement cost of a BE HDT. There are different approaches concerning the maintenance of automated HDTs. Bösch et al. (2017) assumed no additional maintenance cost for autonomous trucks since the automation is likely to cancel out the benefit stemming from more considerate automatic driving. Nowak et al. (2016) stated that automation, e.g. remote diagnostics, will provide significant savings in maintenance of trucks, which supports Bösch et al. (2017)'s assumption. Bösch et al. (2017)'s assumption has been deemed to be agreed upon by some other scholars as well, hence has been followed in the analysis.

Additionally, the air pollution externality (APE) costs from electricity generation and diesel HDT's tailpipe emissions have been estimated based on the health damage cost coefficient per ton of emission provided by (Michalek et al. 2011). (Michalek et al. 2011) used the Air Pollution Emission Experiment and

Policy (APEEP) model developed by Muller and Mendelsohn (2007) to evaluate these impacts in terms of dollars per ton of emissions. The APEEP model quantifies the impacts of air pollutants using county-level marginal costs of human health and environmental damages, with said damages consisting of mortality, morbidity, crop loss, timber loss, etc. (Michalek et al. 2011). Accordingly, the APE cost coefficients provided by Michalek et al. (2011) for diesel fuel production, vehicle manufacturing (including batteries), and vehicle maintenance on dollar-per-ton basis have been used, whereas for power generation, the coefficients on dollar-per-megawatt hours have been used. The tailpipe emissions of PM10 from tire and brake wear (i.e. PM10 TBW) have been also considered in the calculation of the life cycle tailpipe emissions of automated diesel HDTs. Average values of the coefficients have been used in the analysis, though the APEEP model quantifies these externalities on a county basis.

Sensitivity Analysis

In addition to vehicle characteristics, the life cycle sustainability impacts of HDTs are also significantly dependent on how these vehicles are used, e.g. annual mileage and lifetime. Given different plausible sources such as (Hooper et al. (2018) and Burnham (2017) that report different values for these two variables, a sensitivity analysis has been performed to primarily determine how a variation from -10 percent to +10 percent in the values of these variables would influence the selected LCS indicators.

Results

The TBL sustainability assessment results are presented in the following subsections based on the quantified environmental, social, and economic impacts associated with each life cycle phase for each of the studied HDTs. Additionally, the TBL analysis of a conventional HDT is also studied and presented in a separate subsection to enable a clearer picture as to where the efforts are likely to land and a comparison with respect to the TBL sustainability performance of an A-HDT, since this is also regarded essential in the literature (Flämig 2016).

Environmental Impacts

Life cycle water footprint (WF) of automated diesel HDT and automated electric HDT has been estimated to amount to 116 thousand cubic meters and 72 thousand cubic meters, respectively. Fuel consumption is the primary contributor to the total WF of an automated diesel HDT, being responsible for over 70 percent of the total WF, whereas it represents slightly less than 20 percent of the total WF of automated electric HDT (see Figure 10). The main driver of automated electric HDT's total WF is the total truck manufacturing (more than 45 percent) due to the manufacturing of battery, including battery replacement, (almost 30 percent) and incremental parts such as glider and power electronics (almost 15 percent). Overall, these values translate into a water intensity of 0.044 m3 per mile for an automated diesel

HDT and 0.027 m3 per mile for an automated electric HTD; and an energy intensity of 7.75 MJ per mile for a diesel A-HDT and 10.4 MJ per mile for a BE A-HDT.

As shown in Figure 10, Global warming potential (GWP) of automated diesel HDT is estimated to be 11.6 thousand-tons CO2-eq.; 4.7 thousand-tons CO2-eq. higher than that of automated electric HDT. As shown in Figure 10, almost 90 percent of automated diesel HDT's GWP is driven by tailpipe emissions (65 percent) and fuel consumption (23.5 percent), whereas the contributors to automated electric HDT's GWP are fuel production, representing 35 percent of the GWP, followed by BE truck manufacturing, accounting for 28 percent. Battery-related activities, i.e. manufacturing and replacement, have been found to cause 30 percent of an automated electric HDT. An automated diesel HDT and an automated electric HDT have been found to reduce GHG emissions by 10 percent and over 60 percent, respectively, relative to a conventional HDT. Nahlik et al. (2015) found similar results, reporting that switching to hybrid or LNG truck technologies could reduce GHG emissions by 5 percent and 9 percent, respectively. The difference between the numbers may well be attributed to automation given the expected increase in driving efficiency.

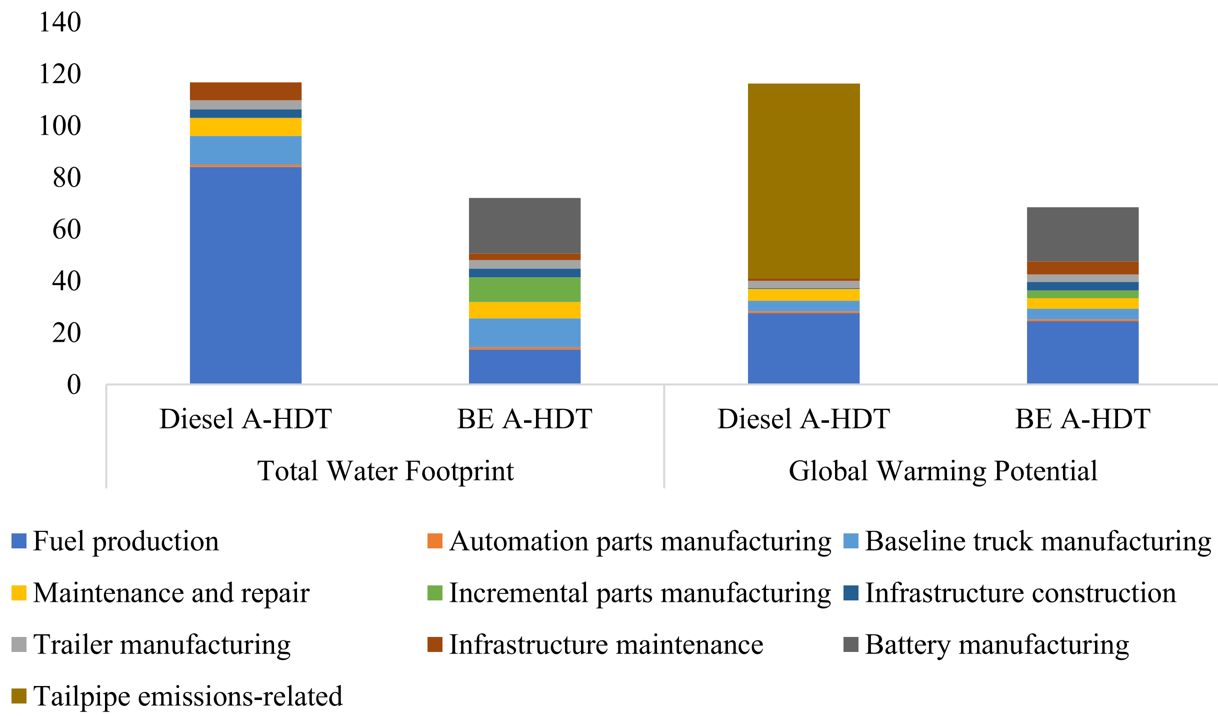


Figure 10: Environmental impact results of the LCSA per truck: Total water footprint (thousand m3) and Global warming potential (ton CO2-eq.)

According to the analysis results, fuel consumption is by far the greatest contributor to fossil resource scarcity (FRS) for both truck types, as shown in Figure 11 and Figure 12. Mineral resource scarcity (MRS) impact of an automate electric HDT has been estimated to be 45 tons Cu-eq., which is significantly larger than that of an automated diesel HDT (10 tons Cu-eq.). This difference appears to be stemming from battery manufacturing (including battery replacement), which has been estimated to account for over 75 percent of this impact due to the use of copper in the battery manufacturing process. This finding aligns with the findings of Notter et al. (2010), stating that the supply of copper is a major contributor to the environmental burden caused by battery manufacturing. Additionally, the results have shown that fuel consumption is responsible 65 percent of the MRS impact caused by an automated diesel HDT, followed by the truck manufacturing process, which accounts for 18 percent of the MRS impact.

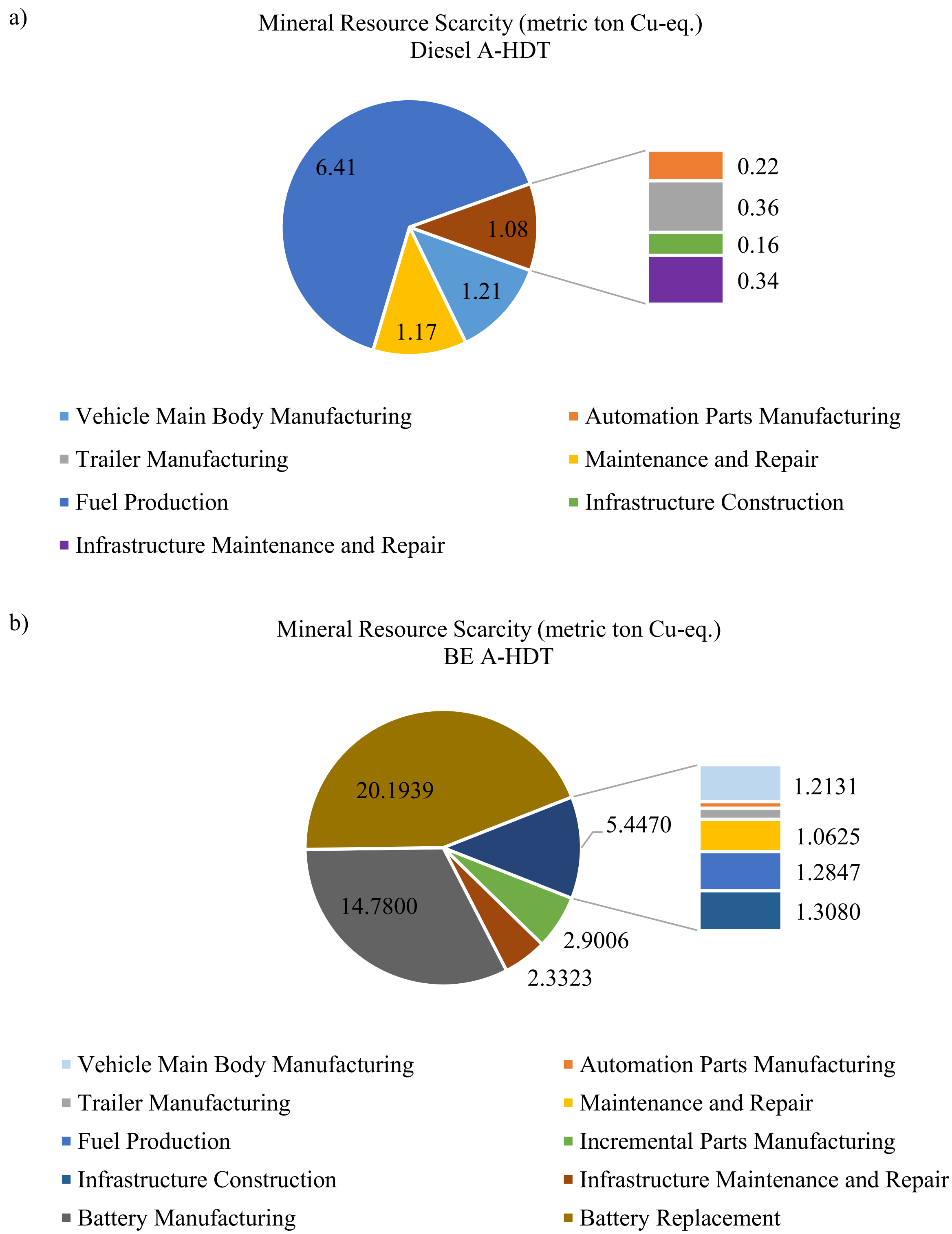
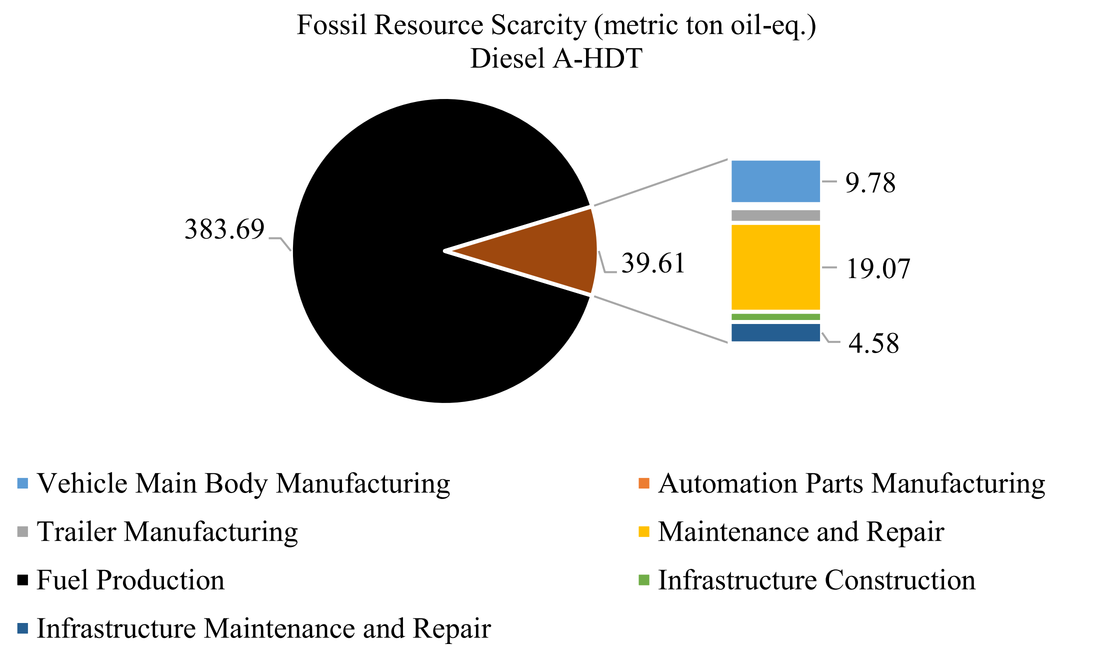


Figure 11 Impacts on mineral resource scarcity (ton Cu-eq.) for (a) diesel A-HDT and (b) BE A-HDT

The manufacturing of automation parts has been observed to have a negligible impact on both mineral resource scarcity and fossil resource scarcity indicators. The results showed that automating a heavy-duty truck with the automation parts considered in the analysis is less costly than manufacturing a trailer in terms of these two scarcity related indicators. It has been estimated that the manufacturing of automation parts results in less than a ton oil-eq. of fossil resource scarcity and 0.2 metric ton Cu-eq. of mineral resource scarcity. On the other hand, the MRS value for trailer manufacturing has been estimated to be around 0.35 metric ton Cu-eq.

Even though automated electric HDT's fuel economy is more than two times that of automated diesel HDT, the use of coal in the average U.S. electricity grid mix is the primary cause for automated electric HDT to have a relatively larger impact on fossil resources, as shown in Figure 12. Fossil resource scarcity caused by an automated electric HDT is found to be 45 tons oil-eq. higher than that of an automated diesel HDT. As in mineral resource scarcity, both the manufacturing of automation parts (0.2 percent) and of trailer (0.7 percent) has been estimated to make up a tiny fraction of the overall fossil resource scarcity caused by both HDT types (see Figure 12). Both diesel and charging infrastructures have been observed to cause approximately the same fossil resource scarcity, with 2 and 2.5 metric tons oil-eq., respectively.

a)



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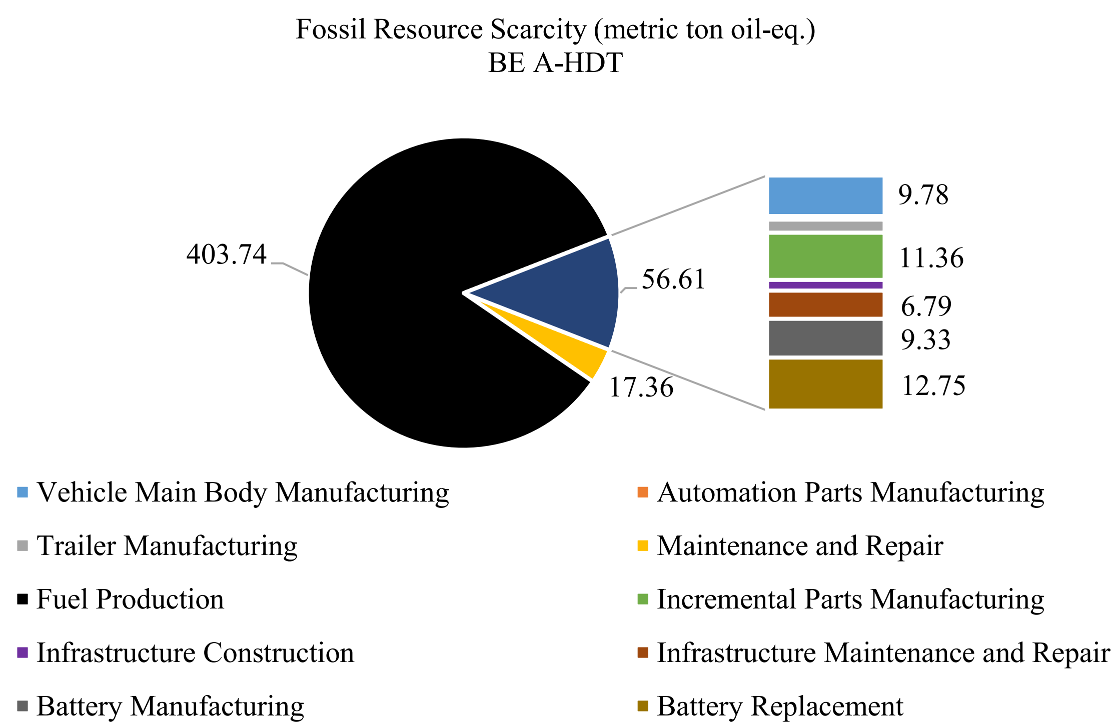


Figure 12 Impacts on fossil resource scarcity (ton oil-eq.) for (a) diesel A-HDT and (b) BE A-HDT

Particulate matter formation potential (PMFP) of an automated diesel HDT has been estimated to be almost two times that of an automated electric HDT, as shown in Figure 13. According to the results, as expected, tailpipe emissions with over 75 percent contribution are the primary driver of the PMFP of an automated diesel HDT due to nitrogen oxides emissions, followed by fuel production (17 percent). The PMFP of an automated electric HDT is driven largely by fuel production/electricity generation (70 percent) due to sulfur dioxide (SO_2) emissions at power plants, while the manufacturing of incremental parts and battery has accounted for 13 percent of an automated electric HDT's PMFP. The manufacturing of automation parts and of trailer caused only 0.5 percent and 2 percent of an automated electric HDT's PMFP, respectively, while the PMFP impacts of these components in an automated diesel HDT have been estimated to be half the impacts from an automated electric HDT. It can be also seen from Figure 13, that diesel fuel production has resulted in relatively greater particulate matter formation potential than power generation. Overall, electrification and automation of heavy-duty trucks has been estimated to reduce particulate matter formation potential from these vehicles by 45 percent.

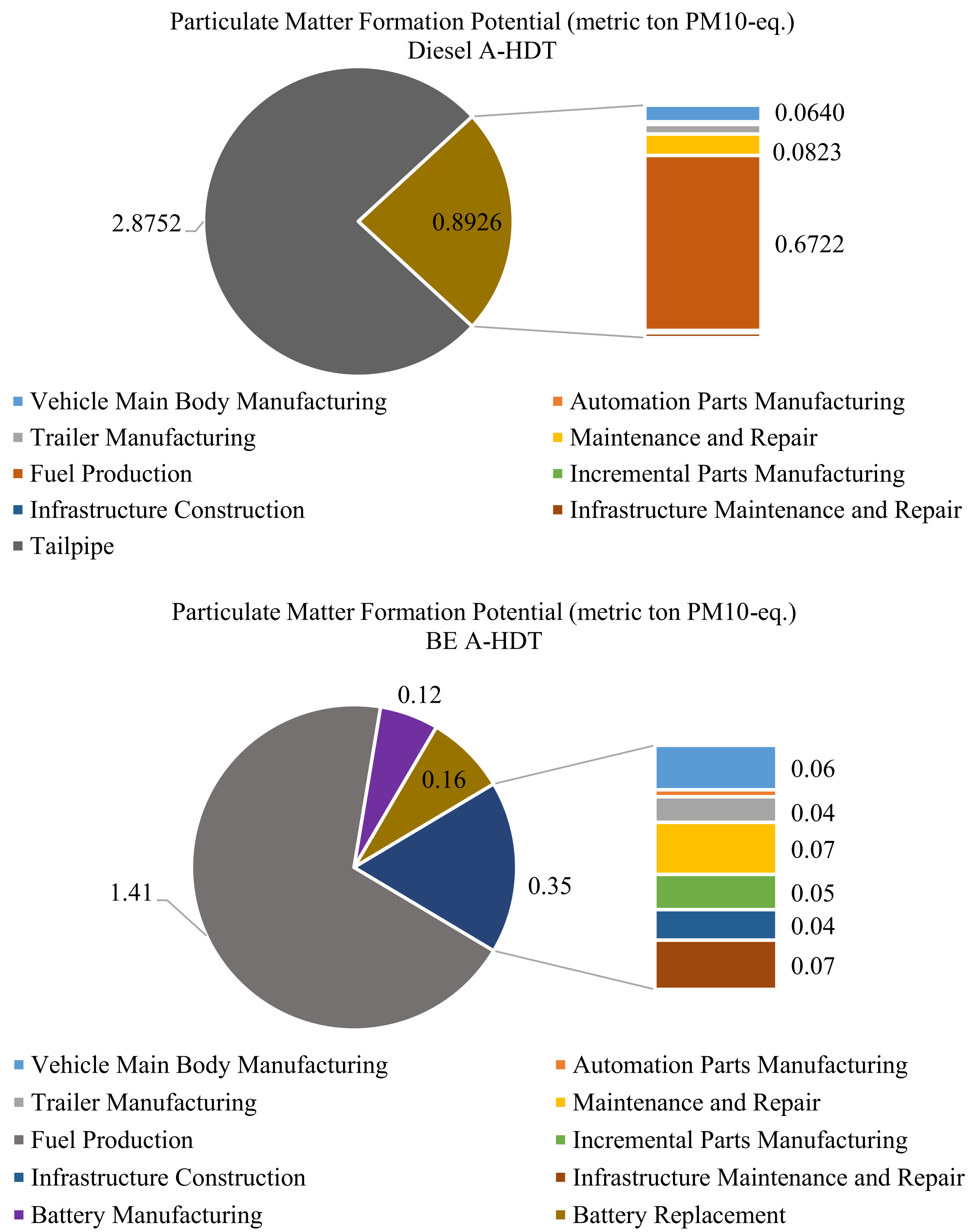
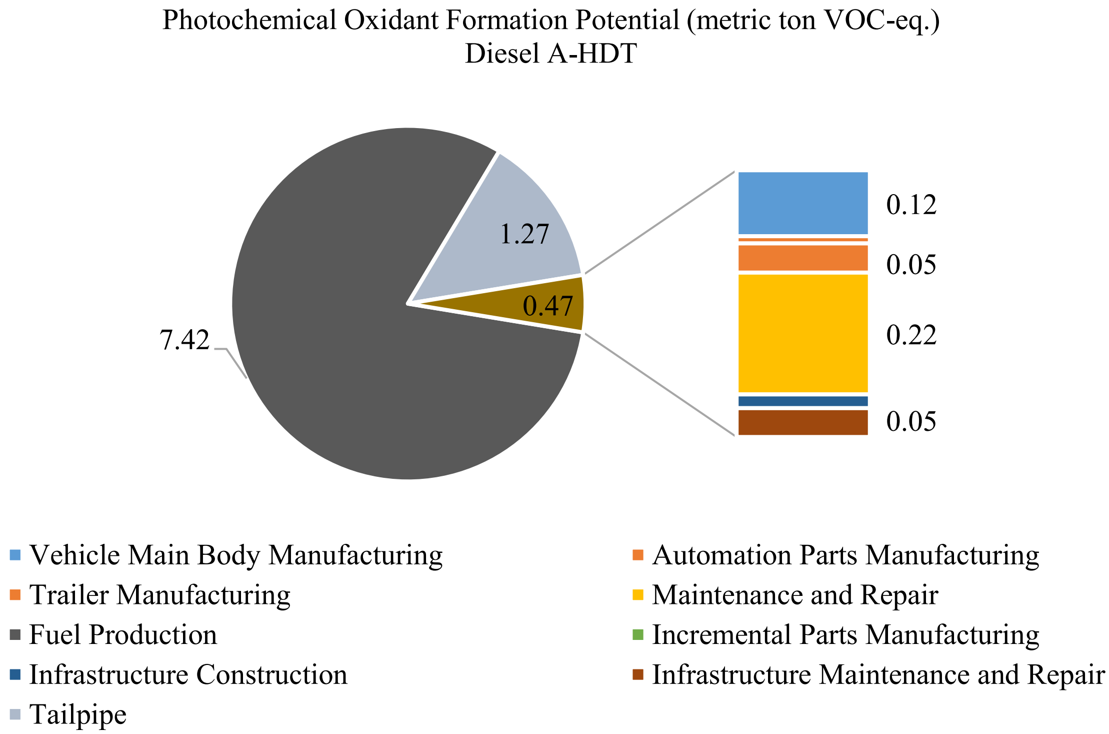


Figure 13 Particulate matter formation potential of the studied HDTs (metric ton PM10-eq.)

As presented in Figure 14, the photochemical oxidant formation potential (POFP) of an automated diesel HDT has been estimated to be almost three times that of an automated electric HDT. Due primarily to methane (CH_4) and volatile organic compound (VOC) emissions at diesel production facilities, fuel production is responsible for slightly over 80 percent of an automated diesel HDT's POFP impact, followed by the impact from tailpipe emissions (14 percent), according to the results. The rest of the processes accounted for 5 percent of automated diesel HDT's photochemical oxidant formation potential. Within this 5 percent, almost half of the POFP impacts is attributed to the impacts stemming from activities related to maintenance and repair (0.22 metric ton VOC-eq.) of an automated diesel HDT, while the process of vehicle body manufacturing, including trailer accounted for over 35 percent of the POFP impacts from the processes other than operation (i.e. tailpipe) and fuel production). The manufacturing of automation parts has been estimated to make up only a tiny fraction (i.e. less than 1 percent) of automated diesel HDT's POFP.

Similarly, automated electric HDT's POFP impact has been found to be also driven by fuel production (i.e. power generation), which accounted for 71 percent of the impacts in this category, due largely to VOC and SO_2 emissions. Fuel production is followed by the battery replacement, and maintenance and repair processes, accounting for almost 6 percent and 5.50 percent of the total POFP impacts, respectively, due to VOC and CO emissions. Overall, the total POFP impact caused by an automated diesel HDT has been estimated to be almost three times that of an automated electric HDT.



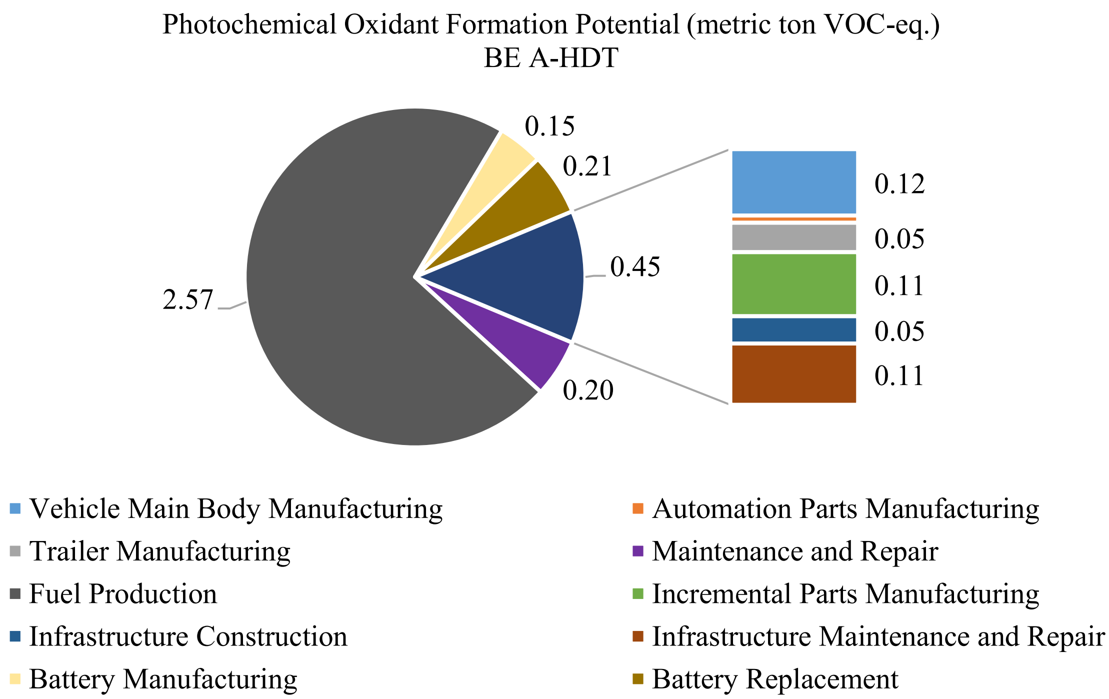


Figure 14 Photochemical oxidant formation potential of the studied HDTs (metric ton VOC-eq.)

Social Impacts

As shown in Figure 15, the results on the social impact categories have shown that automated electric HDT generates more employment than its diesel counterpart. Maintenance and repair, and fuel production-related activities make the major contributions to the employment rate from an automated diesel HDT accounting for 47 percent and 35 percent of the total employment, respectively. While 14 percent of an automated diesel HDT's employment rate is attributable to truck manufacturing, it accounts for almost 20 percent of an automated electric HDT's employment rate given the manufacturing of additional parts. Maintenance and repair related activities represent almost 40 percent of an automated electric HDT's employment rate, followed by truck manufacturing related activities (18 percent).

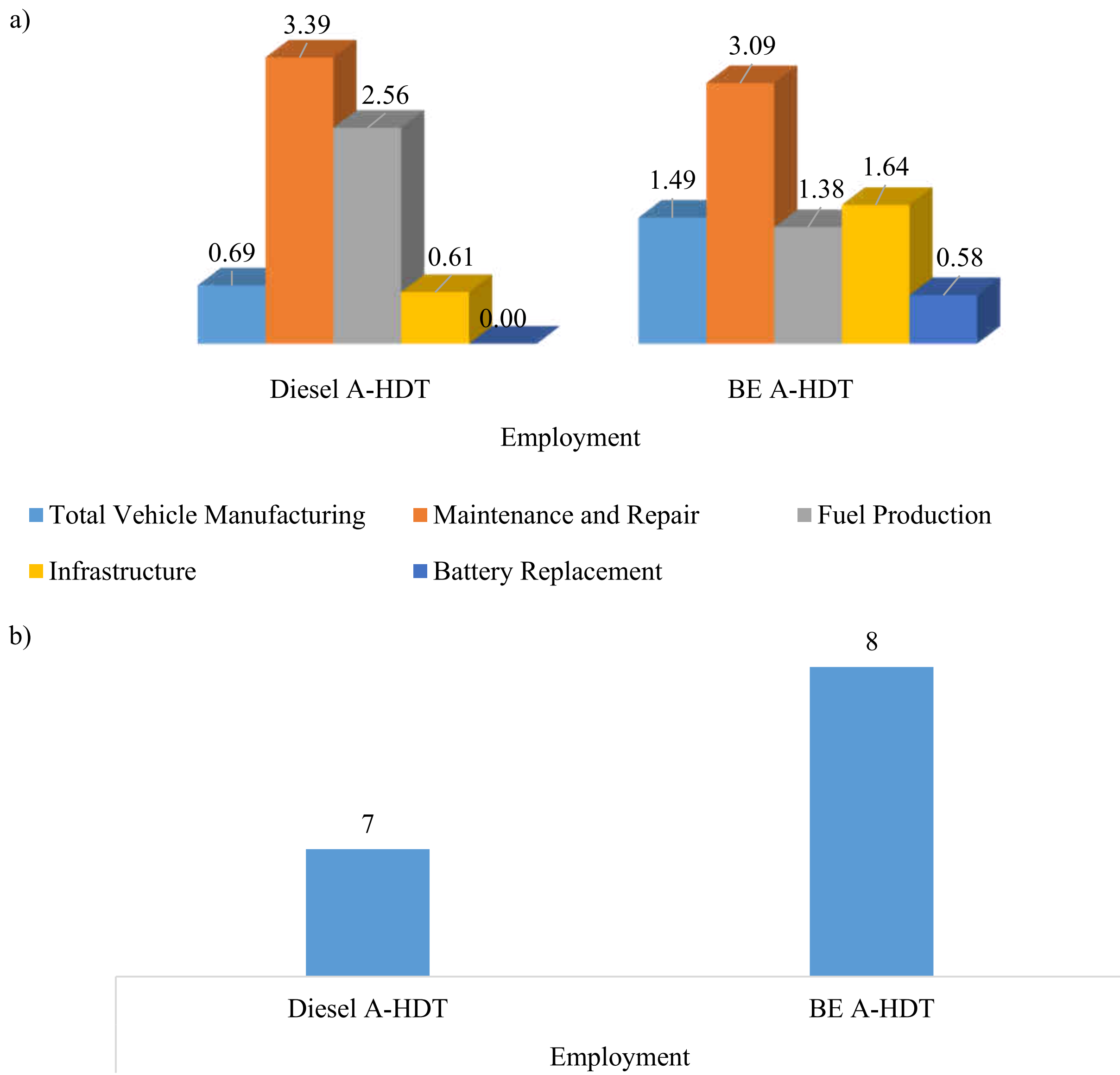


Figure 15: Estimated impact of automating a HDT on employment in person: a) Impacts from individual processes and b) Total employment generated (Note: The values in (a) have been left in two decimals in order to avoid the rounding error.)

As shown Figure 16, the results have indicated that income is generated largely through activities related to fuel production (39 percent), M&R (40 percent), and truck manufacturing (14 percent) for automated diesel HDT. The results have also shown a more diverse distribution of income generation for automated electric HDT, with truck manufacturing (21 percent) and fuel production (22 percent) related activities having the two largest shares owing to additional parts required for automated electric HDT. The income from M&R related activities have represented 25 percent of the total income generated by an automated electric HDT.

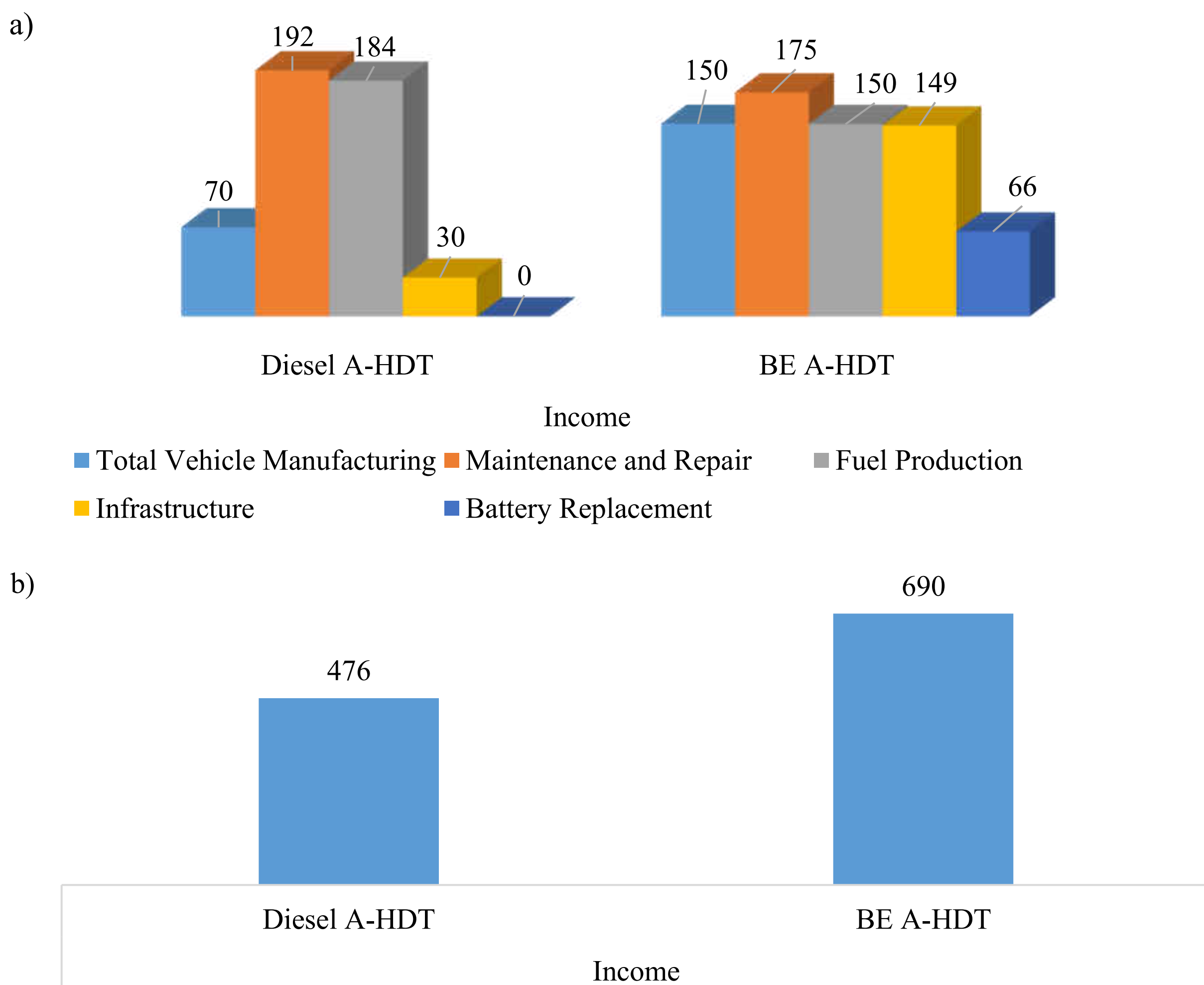


Figure 16: Estimated impact of automating a HDT on income (K$): a) Impacts from individual processes and b) Total income generated

According to the results presented in Figure 17, the human health impact (HHI) of automated diesel HDT is estimated to be 11 DALY – four units higher than that of automated electric HDT. Tailpipe emissions are the primary cause of this impact, accounting for 65 percent of automated diesel HDT's HHI total. The estimates have shown that the manufacturing of additional parts, including battery manufacturing and replacement, is responsible for almost 35 percent of the total HHI caused by automated electric HDT. It has been estimated that diesel production results in slightly higher HHI than power generation. Similarly, automated diesel HDT maintenance and repair has been estimated to cause higher HHI than that of automated electric HDT, as the former is equipped with more parts and fluids.

Figure 17 Human health impact (HHI) (DALY) from (a) diesel A-HDT and (b) BE A-HDT

According to the results, while automated electric HDT causes noticeably higher fatal injuries, automated diesel HDT has been observed to cause higher non-fatal injuries, as shown in Figure 18. Overall, the differences in both injury categories have been observed to be small. Aligning with the rate of employment for both truck types, most of the injuries have been observed to occur in truck and refueling station M&R, fuel production, and truck manufacturing (including additional parts for automated electric HDT) related activities. The results indicate that 85 percent of the fatal injuries caused by an automated diesel HDT occurs due to M&R (65 percent) and fuel production (20 percent) related activities, whereas truck M&R, refueling station M&R, and truck manufacturing related activities cause 52 percent, 25 percent, and 10 percent of the fatal injuries caused by an automated electric HDT, respectively. According to the results on non-fatal injury impact category, a great majority of non-fatal injuries caused by automated diesel HDT stems from activities related to M&R (42 percent), fuel production (24 percent), and refueling station M&R (17 percent). The activities related to truck M&R, truck manufacturing, and power generation have been found to be responsible for over 40 percent, 15 percent, and almost 20 percent of non-fatal injuries caused by automated electric HDT, respectively.

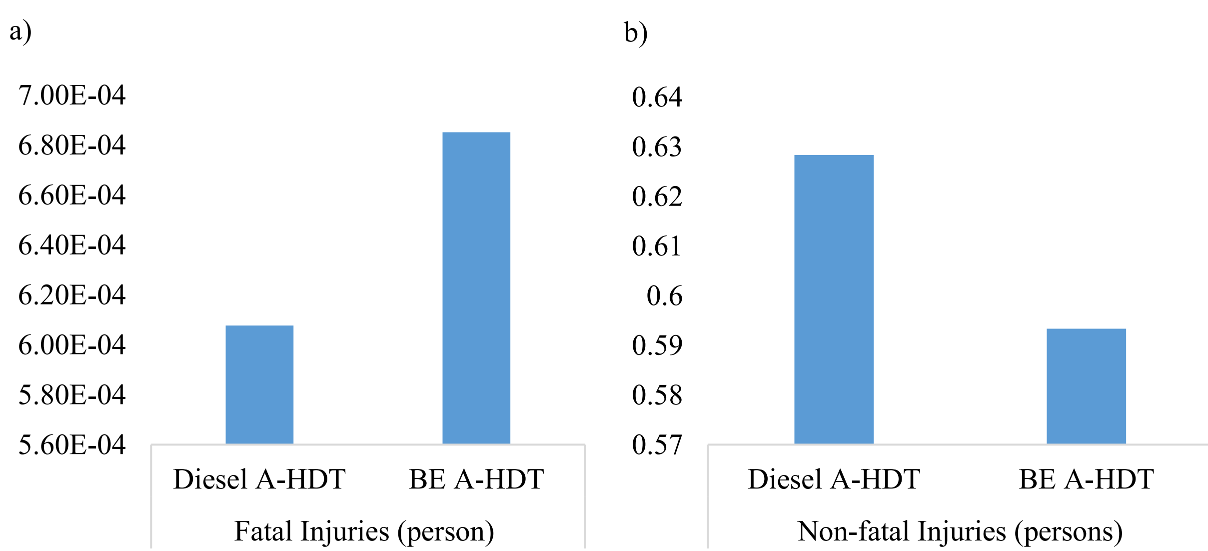


Figure 18 Total fatal and non-fatal injuries caused by the studied HDTs (person)

Economic Impacts

The total import of goods and services used for an automated diesel HDT have been estimated to amount to slightly less than $1M – almost four times higher than that of an automated electric HDT. As provided in Figure 19, the results showed that more than 85 percent of this import is associated with fuel production, while imports related to power generation represent only 12 percent of the total imports caused by an automated electric HDT. This finding is consistent with several others such as Larson et al. (2013), Pontau et al. (2015), U.S. EPA (2015), and Goldin et al. (2014), confirming the U.S. dependence on foreign oil. The largest import item for an automated electric HDT has been found to be the manufacturing of additional parts (including battery), accounting for almost 35 percent of the imports, followed by the imports associated with M&R activities (26.5 percent). Gross operating surplus (GOS) and gross domestic product (GDP) indicators show an identical pattern for both truck types, with fuel production and M&R related activities generating the major share of the GOS and GDP, as shown in Figure 19.

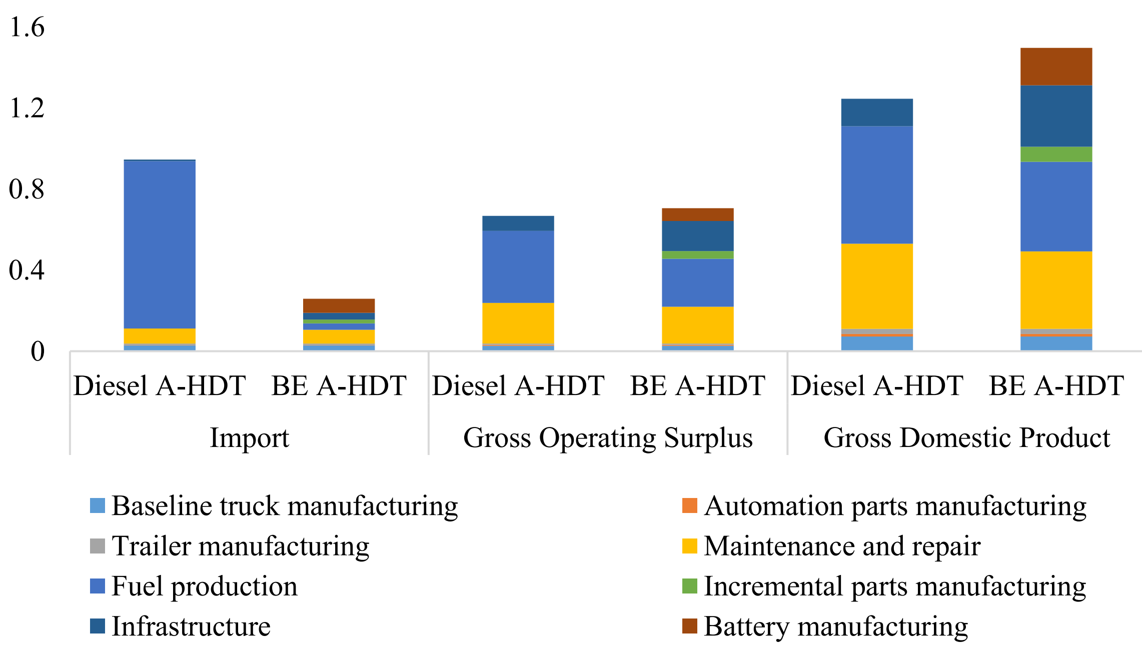


Figure 19: Economic impact results of the LCSA per truck: Import ($K), Gross Domestic Product ($M), Gross Operating Surplus ($M)

Total health impact cost (or the cost of air pollution) of an automated electric HDT has been observed to be almost entirely driven by fuel production related activities, estimated to be responsible for 90 percent of this impact category, whereas activities related to fuel production (32 percent) and fuel combustion (i.e. tailpipe emissions) (65 percent) have been found as the two major drivers of the total health impact cost of an automated diesel HDT, as presented in Table 7. Hence, an automated diesel HDT causes a per-mile health cost of \$0.14, whereas an automated electric HDT causes a per-mile health cost of \$0.10. Based on the cost assumptions considered in the analysis, the air pollution cost of automation-related parts may be regarded as negligible for the studied HDTs. LCC of an automated diesel HDT is largely driven by the expenditures on fuel, accounting for almost 65 percent of the total cost, whereas, for an automated electric HDT, life cycle fuel cost (27 percent), M&R cost (26 percent), and battery replacement cost (8 percent) have been found to be the main drivers of the LCC. Hence, an automated diesel HDT's per-mile cost has been estimated to be \$0.88, while an automated electric HDT's per-mile cost is estimated to be \$0.71. Overall, electrification and automation of HDTs brings significant improvements in terms of both externality costs caused by air pollution and HDT's life cycle costs.

Table 7 Life cycle air pollution costs and life cycle costs associated with each process caused by HDTs

	Air Pollution Cost ($)		Life Cycle Cost ($)	
	Diesel A-HDT	**BE A-HDT**	**Diesel A-HDT**	**BE A-HDT**
Vehicle Main Body Manufacturing	0.86%	1.26%	4.66%	5.83%
Automation Parts Manufacturing	0.09%	0.14%	1.02%	1.27%
Trailer Manufacturing	0.32%	0.47%	1.41%	1.77%
Maintenance and Repair	1.33%	1.77%	22.54%	25.68%
Fuel Production	32.28%	90.36%	63.12%	27.38%
Incremental Parts Manufacturing	0.00%	1.10%	0.00%	5.44%
Infrastructure Construction	0.34%	0.51%	2.34%	3.25%
Infrastructure Maintenance and Repair	n/a	n/a	4.91%	15.31%
Battery Manufacturing	n/a	1.86%	n/a	5.95%
Battery Replacement	n/a	2.54%	n/a	8.12%
Tailpipe	64.77%	n/a	n/a	n/a
Total Impacts	373,500	255,000	230,000	184,000

Aligning with the mineral resource scarcity results, mineral resource depletion (MDP) caused by an automated electric HDT ($13K) has been estimated to be four times that of an automated diesel HDT, as shown in Figure 20. This is due largely to additional part manufacturing, including battery, which has been estimated to account for more than 75 percent of the total MDP. Automated diesel HDT's MDP is caused largely by fuel consumption related activities (65 percent), followed by truck manufacturing, accounting for 18 percent of the total MDP of an automated diesel HDT. Of this 16 percent, the manufacturing of automation related parts has been estimated to account for about 2 percent-point. Accordingly, an automated diesel HDT have caused an MDP of $0.001 per mile, whereas it has been estimated to be $0.005 for an automated electric HDT. Similarly, fossil resource depletion impacts of both truck types have been found to be largely caused by fuel production related activities, accounting for 91 percent and 78 percent of the total FDP for an automated diesel HDT and an automated electric HDT, respectively. This means that every mile driven by an automated diesel HDT brings an additional cost of fossil resource production of about $0.11, whereas it is $0.08 for an automated electric HDT.

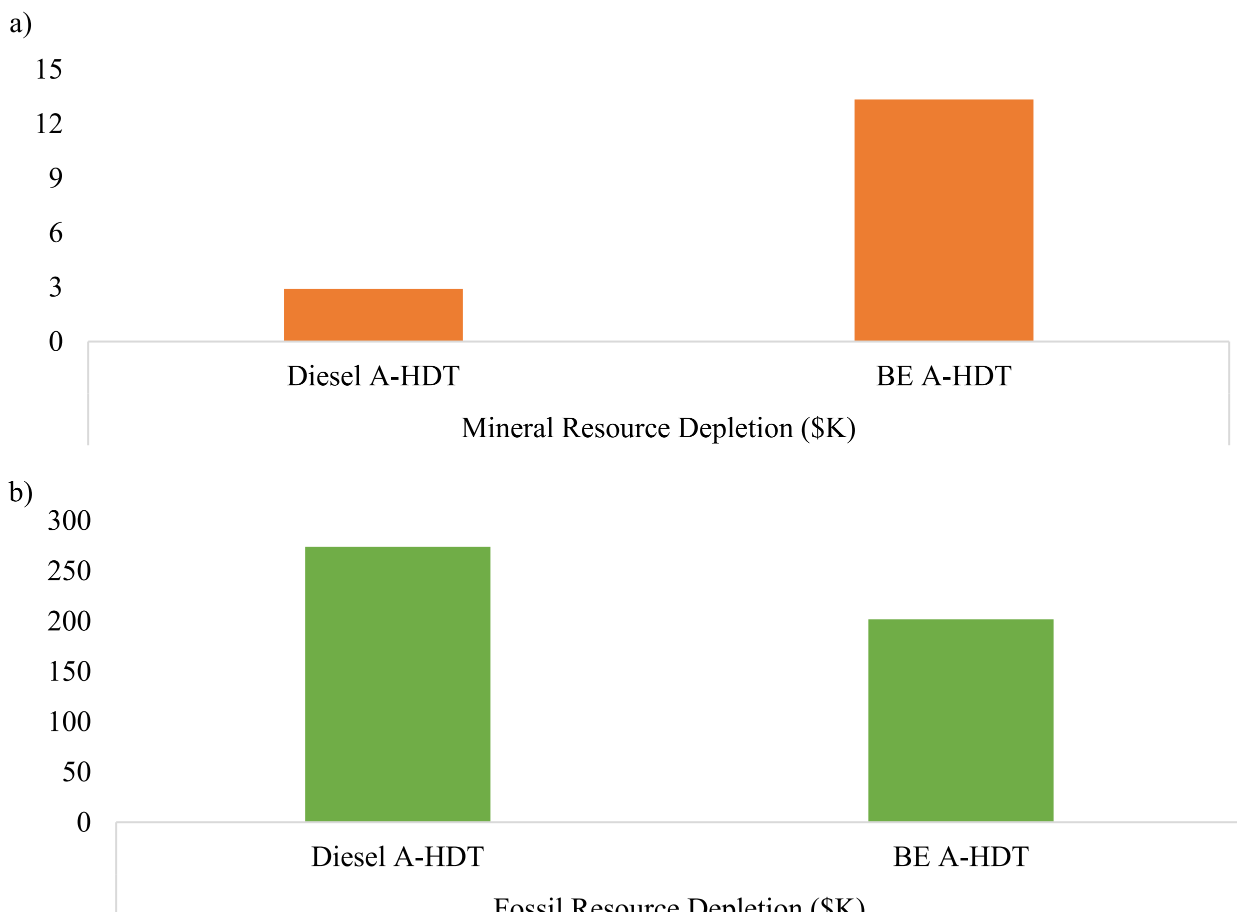


Figure 20 Estimated impacts of the studied HDTs on (a) Mineral resource deplition ($K) and (b) Fossil resource depletion ($K)

The amount of tax generated through an automated electric HDT has been estimated to be slightly over $100K, which is only almost $2K less than that of an automated diesel HDT, as shown in Figure 21. This translates into a per mile tax of $0.038 for an automated electric HDT and $0.039 for an automated diesel HDT. According to the results, the tax generated from fuel consumption and M&R related activities account for over 65 percent of the total tax from an automated diesel HDT, followed by the tax associated with refueling infrastructure (29.5 percent). Because the rate of tax generation through electric power generation, transmission, and distribution is higher than that of diesel fuel production and distribution, an automated electric HDT generated more tax through fuel production activities than that of an automated diesel HDT. Furthermore, since an automated electric HDT requires less M&R than that of an automated diesel HDT, which may be attributed to an automated electric HDT's less sophisticated powertrain, it generates less M&R-related tax than an automated diesel HDT. Of the total tax generated through an automated electric HDT, 80 percent can be attributed to electricity production and M&R activities, with truck manufacturing accounting for 9 percent of the total tax.

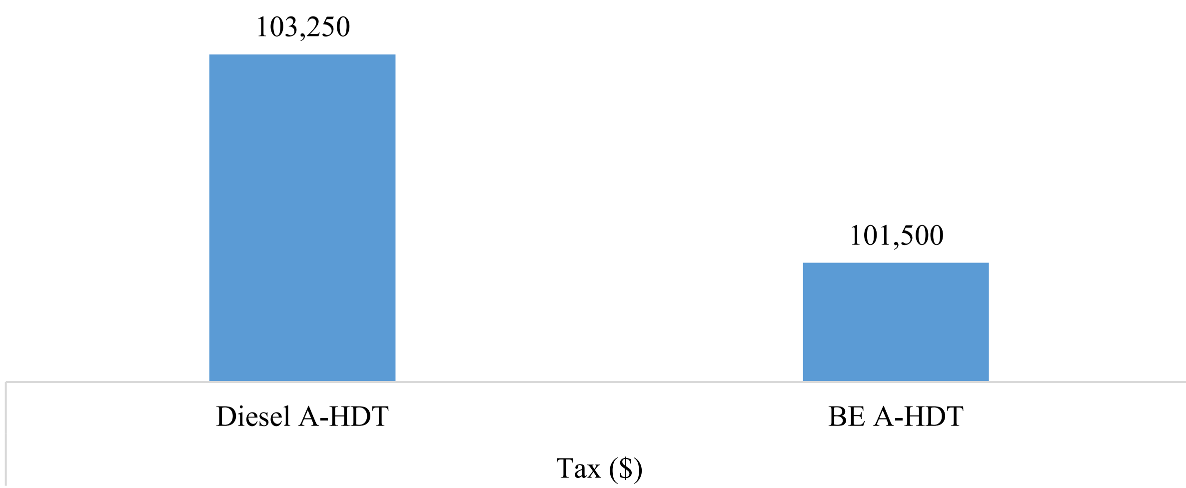


Figure 21 Estimated tax generated by each of the studied HDTs ($)

Sensitivity Analysis Results

The results have shown that the life cycle sustainability impacts of the studied HDTs are fairly sensitive to the variations in assuming values for truck's annual mileage and lifetime, which were entered as input variables for the sensitivity analysis. The analysis has also revealed parameters other than annual mileage and lifetime, to which the life cycle sustainability impacts are sensitive as well, even though such variables were not considered in the sensitivity analysis as variables. In this regard, HDT's fuel economy has been observed to influence various impact categories to an important extent, as shown in Figure 22. For example, a 10 percent increase in automated diesel HDT's fuel economy results in 600 tons CO2-eq. emission reduction and brings imports down to below $880K per HDT, and the LCC of automated diesel HDT down to below $2.2M.

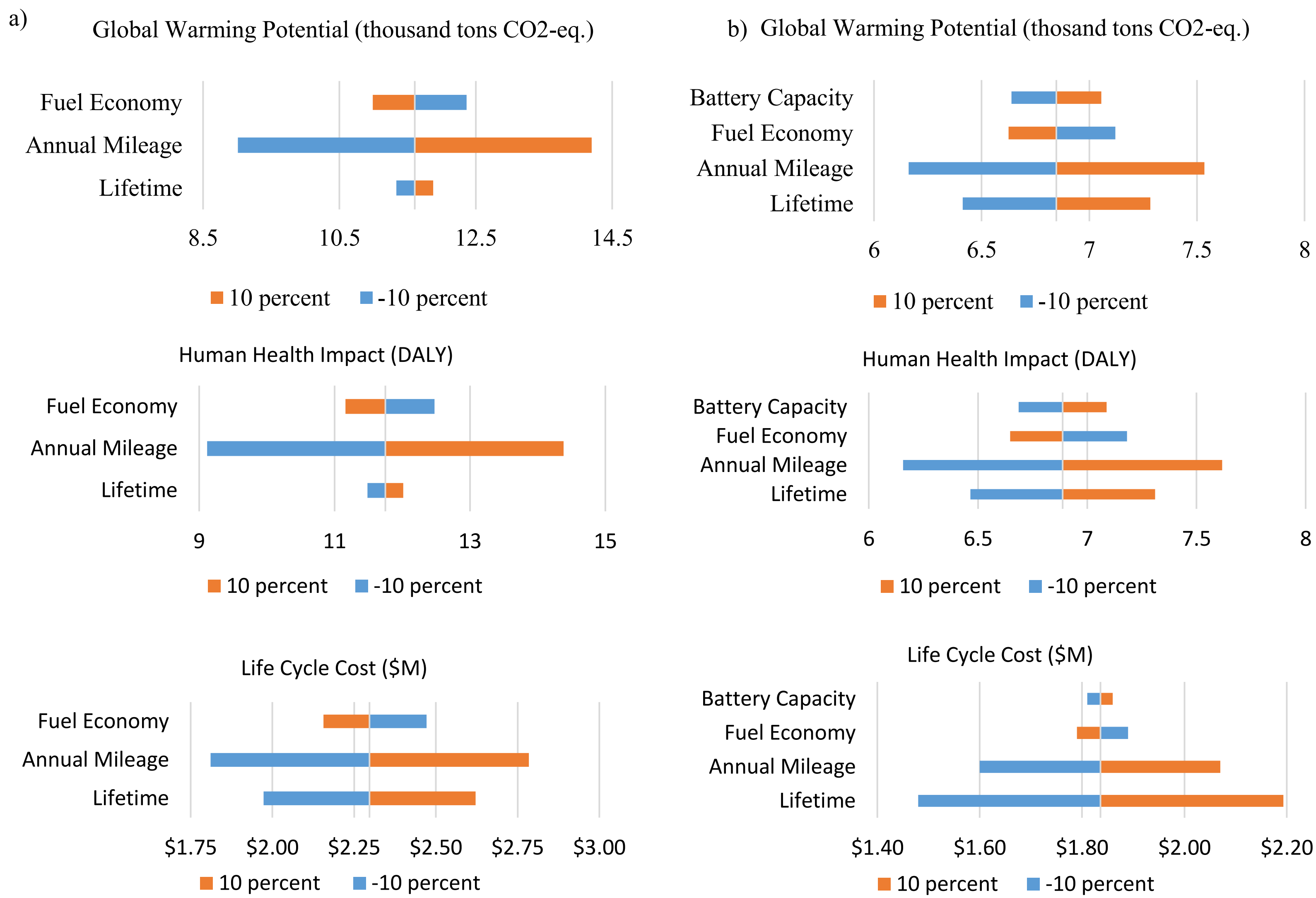


Figure 22: Sensitivity analysis results for the selected parameters

Similarly, the sensitivity analysis for automated electric HDT was initially run for two variables, i.e. annual mileage and lifetime. However, the software (Frontline Systems's (2019) Analytic Solver) used to carry out the sensitivity analysis revealed battery capacity and fuel economy as other primary variables that influence the results. Therefore, these parameters have been also included in the sensitivity analysis. Accordingly, annual mileage, which is an indication of vehicle usage, has been observed to bring the greatest improvement in the global warming potential and human health impact categories for automated electric HDT, as shown in Figure 22. As for the LCC of automated electric HDT, lifetime has been observed to bring the highest variation, as expected.

Comparison of Triple Bottom Line Impacts Between an Automated HDT and Conventional HDT

Total water footprint of a conventional HDT has been estimated to be 126 Mm^3, corresponding to a water intensity of 0.048 m^3 per mile. This corresponds to a reduction in water intensity of 8 percent for an automated diesel HDT, and 43% for an automated electric HDT. Fossil resource scarcity impact of a conventional HDT is estimated to be 468 tons oil-eq., with the total energy consumptions of conventional HDT being 22 TJ, corresponding to an energy intensity of 8.5 MJ per mile. Hence, automation of a diesel HDT is estimated to reduce its energy intensity by 10 percent, while an automated electric HDT’s energy intensity is 22 percent higher than that of a conventional HDT.

Based on the assumed techno-economic circumstances, an automated diesel HDT and an automated electric HDT bring about a reduction in GWP of about 6 percent and 45 percent, respectively. The reduction in particulate matter formation potential (PMFP) through automation of a conventional HDT has been observed to be quite conservative, with only 2 percent reduction; however, automation and electrification of a HDT brings about 46 percent reduction in PMFP, as shown in Figure 23. Similarly, reduction in photochemical oxidant formation potential (POFP) through only automation is less than 10 percent, while when an HDT is both automated and electrified, the reduction in POFP goes almost up to 65 percent. Given automated electric HDT's configuration (i.e. need for additional parts and battery), the impact on MRS of an HDT is estimated to increase by over 75 percent relative to a conventional HDT; however, an automated diesel HDT's MRS impact is found to be 7 percent less than that of a conventional HDT.

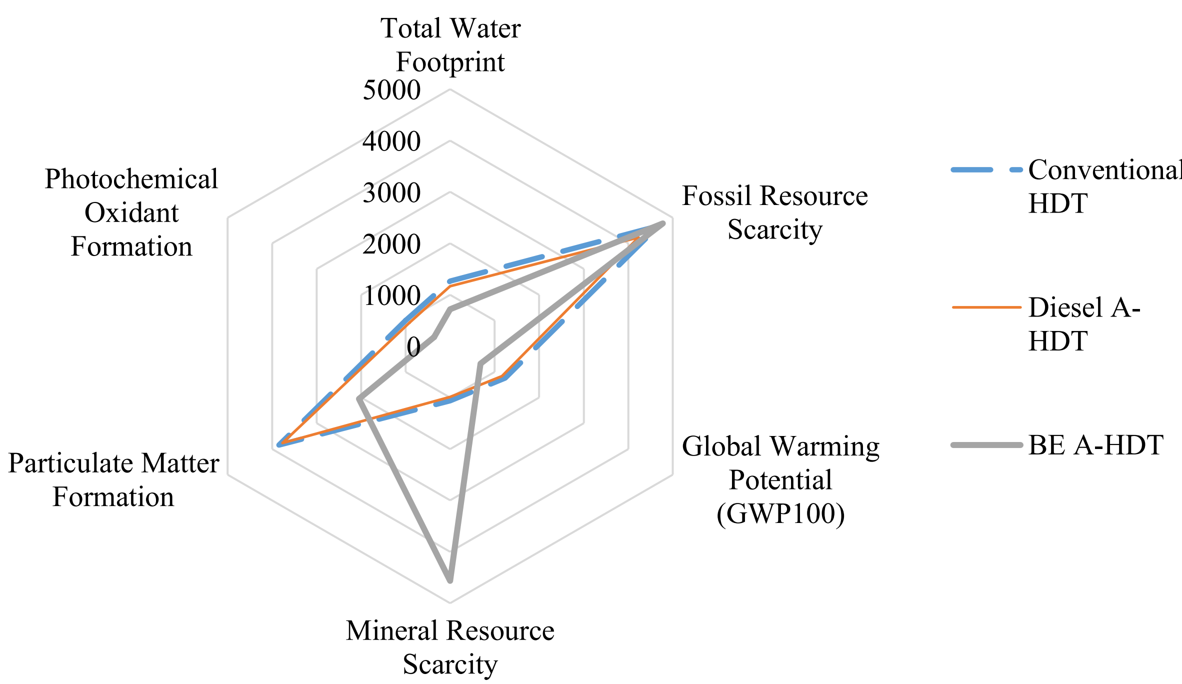


Figure 23: Comparison of environmental impacts between the studied HDTs and a conventional HDT

While an automated diesel HDT has been estimated to generate 3 percent less employment than a conventional HDT, an automated electric HDT has been observed to generate 8 percent more employment relative to a conventional HDT. The decrease has been observed to result largely from the improved operation of an automated diesel HDT (e.g. fuel consumption and M&R activities), and the increase brought by automated electric HDT can be attributed to the manufacturing of additional parts, including battery and power train-related parts. An automated diesel HDT brought reductions of 2 percent and 3 percent in the number of fatal and non-fatal injuries, respectively. When automation and electrification combined, the number of fatal injuries has been observed to increase by 9 percent, due to activities related to charging infrastructure maintenance. However, the number of non-fatal injuries caused by an automated electric HDT has been estimated to decrease by 8 percent compared to that of a conventional HDT. The income generated through an automated diesel HDT has been estimated to decrease by 2.5 percent, largely due to improved fuel consumption and maintenance through automation; however, an automated electric HDT has been estimated to generate 30 percent more income than a conventional HDT owing to activities related to the manufacturing of additional parts, including battery, and refueling infrastructure. Finally, human health impact has been estimated to decline by 5 percent through automation of an HDT, and by almost 45 percent through automation and electrification of an HDT, as shown in Figure 24.

Figure 24: Comparison of social impacts between the studied HDTs and a conventional HDT

Mainly due to improved fuel consumption, the value of imports has been estimated to decrease almost 10 percent and 75 percent with an automated diesel HDT and an automated electric HDT relative to their conventional counterpart. However, improved fuel consumption and maintenance have been also observed to result in a decrease in GOS from an automated diesel HDT and an automated electric HDT by 5 percent and 0.3 percent, respectively. Relative to a conventional HDT, GDP generated through an automated diesel HDT has been estimated to decline by 4.5 percent, while an automated electric HDT has been estimated to increase by 12 percent. Similar to the GOS results, the amount of tax generated through an automated diesel HDT has been estimated to decrease by 5 percent due to improved fuel consumption and maintenance, while an automated electric HDT has been estimated to generate 6.5 percent less tax relative to a conventional HDT. Even though additional minerals and materials are used to manufacture automation related parts, an automated diesel HDT has been estimated to decrease the mineral depletion potential of HDTs by 5 percent, thanks to improved fuel consumption; however, due to battery need of an automated electric HDT, the mineral depletion potential has been estimated to be 77 percent higher than that of a conventional HDT. Thanks solely to improved fuel consumption, the fossil depletion potential of a conventional HDT has been estimated to decrease by almost 10 percent through automation, and almost 35 percent through automation and electrification. With conventional HDT estimated to have a health impact cost of $0.16 per mile, an automated diesel HDT and an automated electric HDT achieves a reduction in health impact cost of about 10 percent and more than 35 percent, respectively. Finally, as shown in Figure 25, the LCCs of a n automated diesel HDT and an automated electric HDT have been estimated to be 6 percent and 25 percent less than that of a conventional HDT, which incurred a LCC of $3.1M. The LCC results correspond to an average decrease of $7,900 and $36,000 per truck per year in the LCCs of an automated diesel HDT and an automated electric HDT relative to a conventional HDT, respectively. These results align with the findings of Bishop et al. (2015), who reported only the fuel savings from two-diesel truck platooning to be $14,000 per truck per year.

c)

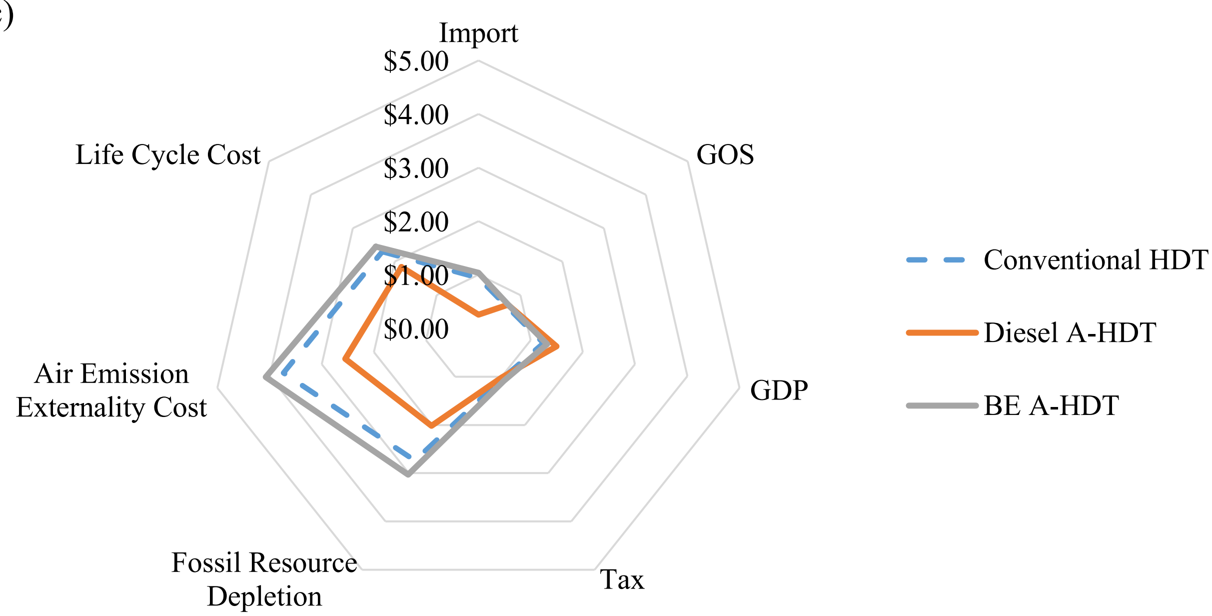
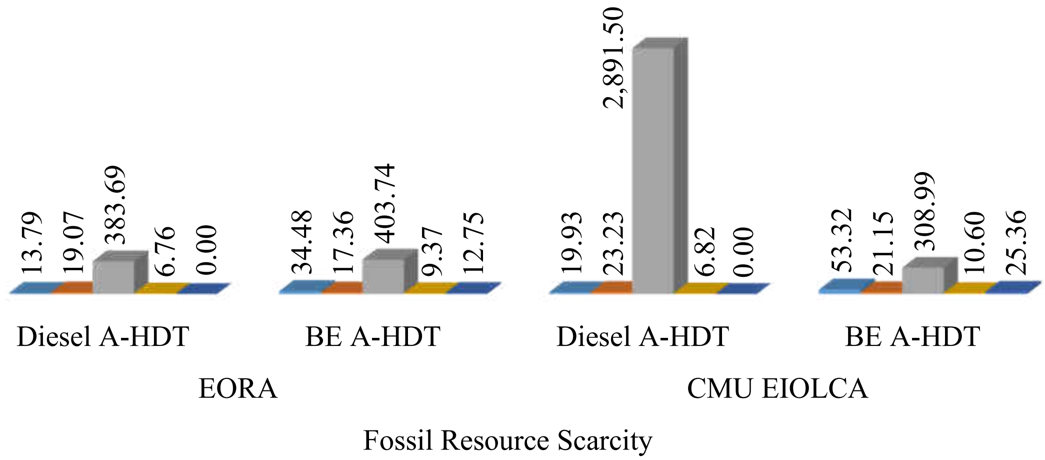


Figure 25: Comparison of economic impact indicators between the studied HDTs and a conventional HDT

Comparison of the LCSA Results with EORA and Carnegie Mellon University's EIO-LCA Tool

The Eora database based on the year 2015 has been used in constructing the IO model to conduct the present study, instead of the EIO LCA tool developed by Carnegie Mellon University Green Design Institute (2008). The most recent version (i.e. the model based on the year 2007) of CMU's EIO-LCA tool covers only limited end-point impact categories and does not allow one to report on some of the sustainability indicators such as total water footprint, mineral resource scarcity, and none of the social and economic indicators. On the other hand, Eora is a high-resolution global MRIO database and provides one of the most up-to-date data, including social and material satellite accounts, in addition to all that are provided by EIO-LCA, for the base year of 2015 (Malik et al. 2018; Wiedmann et al. 2015). Hence, the CMU's EIO-LCA model is not suitable for LCSA, and the comparison between the two models could not be adequately reported. It is evident from Figure 26 that there is a discrepancy between the results obtained from two different models. This is consistent with the findings of other scholars such as Eisenmenger et al. (2016), Moran and Wood (2014), and Kucukvar et al. (2019).

a)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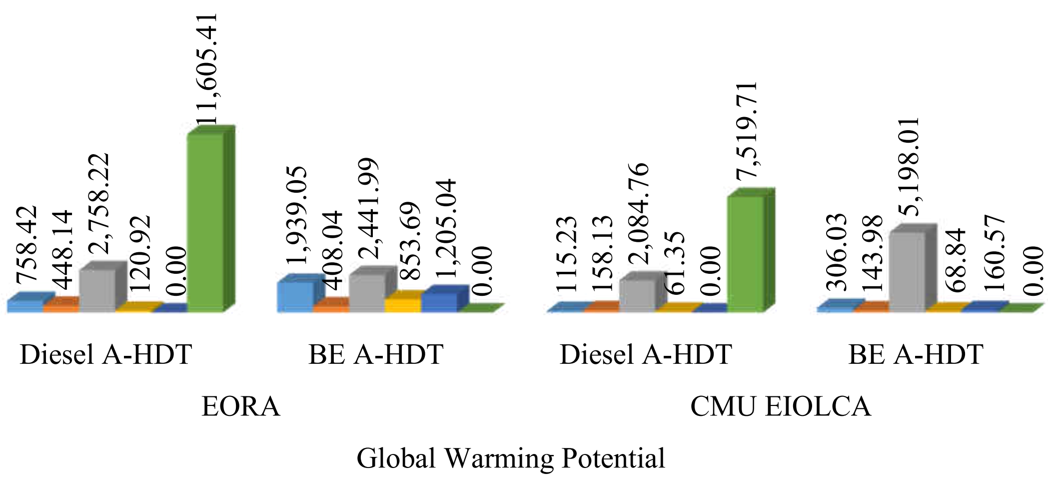
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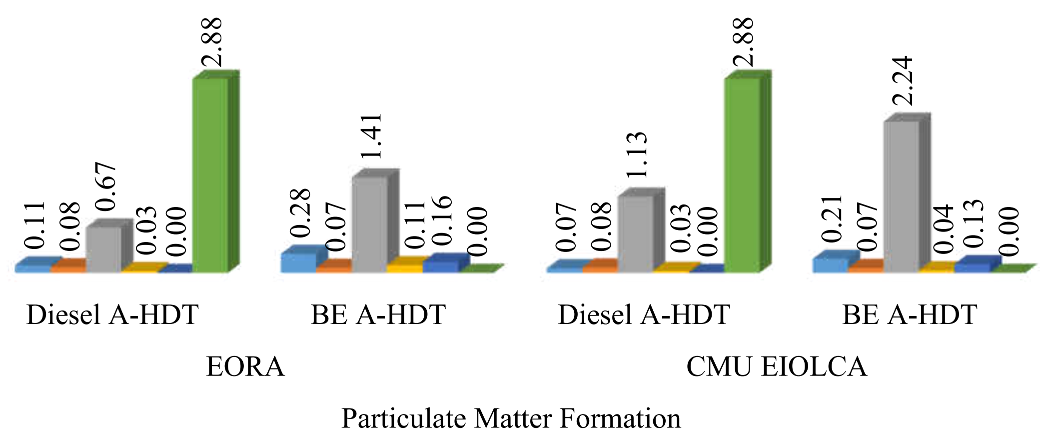
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Particulate Matter Formation

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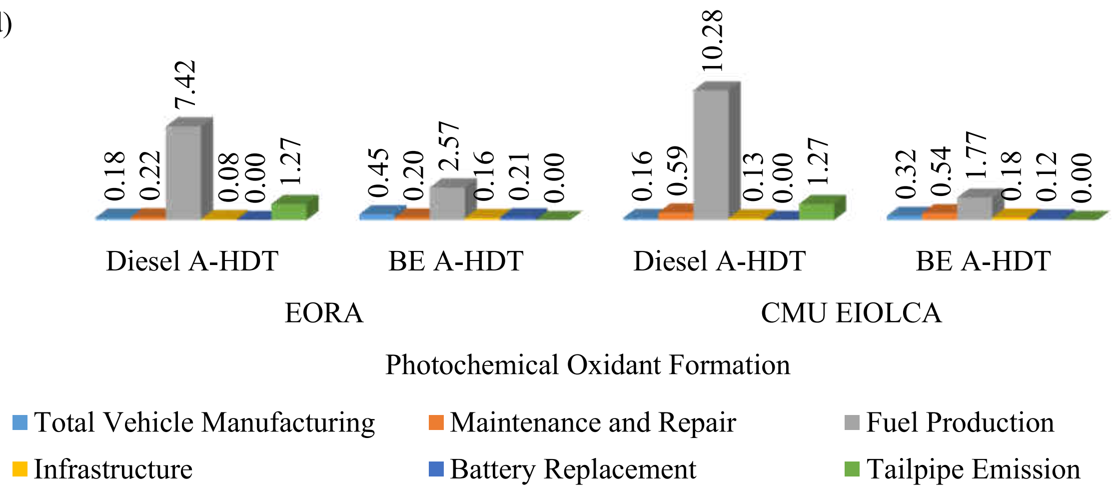

Figure 26: Comparison of some of the environmental endpoint impacts between Eora and Carnegie Mellon University's EIO-LCA tool: a) Fossil resource scarcity (ton oil-eq.), b) Global warming potential (ton CO2-eq.), c) Particulate matter formation potential (ton PM10-eq.), and d) Photochemical oxidant formation potential (ton VOC-eq.)

CHAPTER FOUR: PARETO-OPTIMAL APPROACH TO SECTOR SPECIFIC LOAD SPECIFIC SUSTAINABLE FLEET COMPOSITION OF HEAVY-DUTY TRUCKS

A partial work of this chapter has been published in the Journal of Resources, Conservation, and Recycling, with the title "Robust Pareto Optimal Approach to Sustainable Heavy-Duty Truck Fleet Composition" (Sen et al. 2019a)

Introduction

The circumstances and projections mentioned in the overview regarding freight transportation – especially heavy-duty trucks – in the U.S. raise critical concerns regarding the sustainability of the U.S. freight industry (Williams and Haley 2015), making it an ideal target to improve the sustainability performance of U.S. freight transportation system as a whole (Boriboonsomsin 2015; Nealer et al. 2012). To this end, companies can make a difference by making strategic decisions towards reducing their HDT fleets' fuel consumption, thereby reducing fleet costs, life cycle GHG emissions, and air pollutant-borne externalities while also achieving sustainable growth (U.S. EPA 2016a).

However, freight transportation cost is a particularly important factor for determining trade activities, making the transition to sustainable trucking a challenging task (Hummels 2007) that would require HDT fleet owners to meet multiple sustainability objectives, including minimizing the LCCs, life cycle GHG (LCGHGs) emissions, and life-cycle air pollution externality costs (LCAPECs) of trucks, while composing a sustainable truck fleet relative to a conventional truck fleet composed of diesel trucks only. The main challenge in this task is to develop a fleet mix that can meet the given sustainability objectives to be addressed, optimizing their resulting costs and impacts while also taking national and global sustainability goals into account. An effective approach to addressing this difficulty is to apply multi-objective decision-making methods, which take multiple conflicting objectives into account, such as socio-economic benefits versus environmental impacts (Kucukvar et al. 2014c; Onat et al. 2016b). Therefore, in this chapter, a robust multi-objective optimization model has been developed based on the hybrid life cycle assessment results from Chapter Two in an effort to provide decision support with companies for transitioning to alternative fuel-powered HDT fleet for their operations.

The environmental and socioeconomic implications of deploying alternative fuel-powered heavy-duty trucks such as biodiesel, natural gas (e.g. compressed natural gas (CNG)), and electricity, have been investigated by many scholars such as Wang et al. (2000), Lipman and Delucchi (2002),(Frey and Kuo (2007), Graham et al. (2008), Gao et al. (2012), and Sen et al. (2017). Despite these scientific findings, alternative fuels have not been adopted in freight transportation as much as in public transportation (U.S. Energy Information Administration 2020). A significant barrier to wider deployment of alternative fuels by U.S. trucking industry appears to be stemming from a ‘chicken and egg’ conundrum, creating a vicious circle, in which truck fleet owners are reluctant to procure alternative fuel-powered heavy-duty trucks (AF-HDTs), unless there is no infrastructure, and agencies and/or truck providers are hesitant to investing in infrastructure for vehicles that are not in the market yet (Browne et al. 2012).

However, the deployment of alternative fuel HDTs is still a critical issue that requires an effective coordination and cooperation between relevant stakeholders (e.g. government agencies, truck manufacturers, infrastructure technology providers, etc.) (Melaina et al. 2017). This is also evident on the government end as the lawmakers in the U.S. Senate Environment and Public Works Committee recently approved a $1 billion in funding for various transportation programs, including the expansion of alternative fuel stations such as electricity, hydrogen, and natural gas (Barrasso 2020). Such a policy is expected to recreate a momentum for paving the way for alternative fuel-powered surface transportation, including freight. To that end, Ko et al. (2017) stated that, given flourishing research in this particular domain in recent years, clustering refueling facilities to expedite policy design for early deployment could be a reasonable strategy. In fact, He et al. (2015) mentioned a typical approach, in which clustering techniques could be used to group demands for alternative fuel stations (AFSs), which, in turn, provides reasonable locations (e.g. centers of formed clusters) for AFS deployment.

Hence, in an effort to contribute to the ongoing discussions on and planning efforts for building sustainable freight network in the U.S., the research conducted in this chapter also attempts to provide useful insights into freight routes that are readier for alternative fuel truck deployment by industries that transport goods through these routes by clustering U.S. domestic freight routes based on the number of alternative fuel refueling stations (AFSs) (i.e. electricity, biodiesel, hydrogen, and compressed natural gas). The present article is expected to provide a decision support with HDT fleet owners for planning on alternative fuel-powered HDT deployment. Given their important role in the development and deployment of alternative fuel vehicles (Melaina et al. 2017), this chapter is also expected to contribute to aiding transportation agencies (e.g. state Departments of Transportation) in prioritizing investments on alternative fuel station infrastructure that will increase the market penetration of emerging HDT truck technologies and facilitate the transition to sustainable freight transportation. Additionally, this chapter presents a simple but practical and effective case study of an application of data mining for sustainable transportation.

Literature Review

Despite the data constraints that are mainly due to the heterogeneous structure of HDT sector (Askin et al. 2015), several studies existing in the literature have used various multiple-objective optimization (MOO) approaches to study the subject of fleet management with varying focuses and techniques. However, to the authors' knowledge, the number of studies that have adopted a robust Pareto optimal approach is limited in the literature. For example, Dessouky et al. (2003) integrated the economic input-output (EIO) LCA method into the MOO model, with an objective to maximize environmental and economic improvements in fleet scheduling. Leung et al. (2002) and Leung et al. (2006) each studied optimal fleet management solutions for cross-border logistics from two different approaches, i.e. a robust optimization model and a goal programming model, respectively, to aid the development of a long-term transportation strategy, i.e. optimal delivery routes and vehicle fleet compositions; the objectives of these two studies (minimizing trip costs, hiring costs, inventory costs, and fixed costs) were both kept constant for two different approaches. Similarly, List et al. (2003) developed a robust optimization model to determine an optimal truck fleet size, which would optimize a combination of objectives that involved minimizing fleet ownership costs, operating costs, and service quality penalties.

Gouge et al. (2013) built a MOO model for transit bus fleet scheduling to find an optimal solution that would minimize the operational costs, and climate and health impacts of the operation of a public bus on the Central Business District drive cycle, although Gouge et al.'s study included only a part of a bus's life cycle, i.e. operation phase. Mishra et al. (2014) developed a branch-and-bound algorithm-based optimization model for transit fleet resource allocation to find Pareto-optimal solutions that will maximize the fleet's lifetime while also minimizing its maintenance costs. Ercan et al. (2015) utilized a different MOO technique (combined with a life cycle assessment method) to find an optimal solution for a transit bus fleet of 100 buses that would minimize the fleet's LCGHGs, air-pollutant-related health damage costs, and total LCCs under three different drive-cycles, as well as the trade-off relationship (the Pareto optimality) among the multiple objectives being considered. Zhao et al. (2016a) conducted a more recent study with a similar approach to sustainable fleet management problem, focusing on minimizing LCGHGs, LCCs, and health externality costs for a heterogeneous delivery truck fleet. Like in Ercan et al.'s (2015) study, Zhao et al. (2016a) approximated to the Pareto optimal solution, taking into account the maximum weighted deviations of three objective function values from the best-case values of their respective objectives.

Noori et al. (2015a) developed a MOO model using the compromise programming technique combined with a LCA method to find an optimal, region-specific combination of passenger vehicle types that would minimize LCCs, environmental damage costs, and water footprint; instead of using a robust optimization technique, they applied Exploratory Modeling and Analysis (EMA) to account for uncertainties in the input parameters. Likewise, Onat et al. (2016) presented a novel example for a combined application of MOO and life cycle sustainability assessment to find a Pareto optimal passenger vehicle fleet distribution that will meet several environmental and socio-economic objectives, using distance-based compromise programming to approximate to the ideal solution.

Numerous other studies in the literature have combined multi-objective optimization (MOO) methods with LCA in an effort to strengthen decisions geared towards improving the sustainability of the transportation sector and other socio-technical systems such as construction (Kucukvar et al. 2016b, 2014d; Antipova et al. 2014), energy (Cambero et al. 2016; Páez et al. 2016; Rentizelas and Georgakellos 2014), and water (Ahmadi and Tiruta-Barna 2015).

In addition, several studies in the literature have provided estimations for alternative fuel infrastructure availability and/or location, relying either on simple metrics such as number of existing refueling stations or on mathematical models to provide optimum deployment and locations of AFSs (Tong et al. 2019). For example, Melaina and Bremson (2008) constructed a statistical model to partition refueling stations into two groups as “urban” and “rural” to provide an estimate for the number of refueling stations contained in an unspecified area, basing their study on the assumption that the number (i.e. counts) of stations in a given region is a function of population of that region. It was shown that some cities contained more refueling availability than it was economically sufficient. Ip et al. (2010) employed a two-step approach, consisting of hierarchical clustering and linear programing to identify similar roads based on traffic information and allocate optimum number of charging stations for electric vehicles. It was concluded that the approach implemented was useful for designing a refueling infrastructure. Momtazpour et al. (2014) employed a similar approach, implementing the K-Spectral Centroid (K-SC) algorithm to determine candidate locations for charging stations, followed by an optimization model to maximize user benefits in assigning appropriate charging stations to electric vehicle users. In doing so, Momtazpour and colleagues based their modeling approach on two fundamental assumptions, which are (1) that users prefer the cheapest charging option, and (2) that users desire to minimize their detour and waiting time for charging. It was concluded that the adopted approach was useful for identifying locations to place charging infrastructure. Andrenacci et al. (2016) applied the Fuzzy K-means clustering method to determine the suitable locations of electric vehicle charging infrastructure represented by the centroids of formed clusters. The researchers then assigned each trip, represented as a row in the dataset, to one of the formed clusters. It was concluded that although important factors cannot be taken into account, clustering-based approach is a reasonable first step to helping solve optimum recharging station allocation problem based on trip energy profiles.

It appears that the limited number of studies that exist in the literature have focused on first identifying potentially ideal locations of alternative fuel stations using clustering techniques, and then allocating either the optimum number of charging stations to those locations using mathematical models or assigning trips to clusters formed based on the number of charging stations. Hence, investigating alternative fuel infrastructure availability for alternative fuel-powered heavy-duty trucks provides valuable insights into the topic. Furthermore, Melaina and Bremson (2008) stated that refining estimates for alternative fuel infrastructure availability would facilitate more effective policy design for the deployment of alternative fuel-powered vehicles as well as provide insights useful for managing investment risks possibly faced by both transportation agencies and businesses pursuing alternative fuel vehicle technologies.

Research Motivation and Objectives of the Study

There are several important considerations that decision makers should take into account when composing a fleet suitable for their sectoral needs. However, different sectors have different logistical needs for their sector-related activities. For example, TRB and NRC (2010) illustrated the differences in the average payload of various commodities that are each attributed to different sectors. This results in variations in operational costs and the associated environmental and social impacts, especially those due to fuel consumption that differs based on the payload. Furthermore, each sector has varying priorities in terms of its environmental and socio-economic performances depending on sectoral activities and regulatory environments.

Given the current circumstances faced by the U.S. trucking industry, and the explicit research need pointed out by Gorissen et al. (2015), this chapter aims to contribute to the scientific body of knowledge in the multi-objective optimization literature (particularly with respect to HDT fleet composition problem) by proposing a combined application of a robust Pareto optimal (RPO) solution and a hybrid LCA method. The Executive Order 13693 by The White House (2015) has been considered another indication of a research need in this regard as well as a point of departure, from which to arrive at more realistic model assumptions, thus yielding practical as well as policy-relevant results.

The main objective of the study conducted in this chapter is to develop a RPO solution model that will be used to find an optimum HDT fleet composition for the studied U.S. sectors (i.e. Food Products, Beverages (e.g. alcoholic beverages), Household Durables, Oil and Gas, and Automotive), minimizing the life cycle greenhouse gas emissions (LCGHGs), life cycle costs (LCC), and life cycle air pollution externality costs (LCAPEs). Several aspects distinguish the research conducted in this chapter from previous efforts. Firstly, since costs and emissions incurred by HDT fleets are dependent on vehicle characteristics (Ranaiefar and Regan 2011), the analysis incorporates a hybrid life cycle model into the multi-objective optimization modeling framework, including in the analysis a variety of alternative fuel HDTs (i.e. hybrid, biodiesel, CNG, and BE HDTs), in addition to diesel HDT. Secondly, sector-specific load-specific operational costs (i.e. fuel costs, emissions associated with fuel consumption and production, and APEs) based on varying average payloads of commodities carried by HDTs within the studied sectors have been considered, given the impact of payload on fuel consumption. Finally, the uncertainties in objective optimization by sectors, e.g. changing weighting factors assigned by each sector to each objective under different socio-economic circumstances, have been considered using the robust Pareto optimal approach.

Additionally, another objective of this chapter is essentially to examine the AFS availability over the freight routes selected according to the origins and destinations provided in the Freight Analysis Framework 4 database. The analysis focuses particularly on the routes originating from Miami FL, given its significance for freight transportation as a U.S. freight hub. For that purpose, a clustering algorithm defined within the subject of unsupervised machine learning have been applied to cluster alternative fuel stations such battery recharging, compressed natural gas refueling, and biodiesel refueling stations. Such an examination over the selected routes will provide useful insights into the readiness of AFSs in order for freight industry to better plan transition to sustainable trucking.

Methods and Materials

Hybrid Life Cycle Assessment

The hybrid LCA approach proposed in this study consists of the combined application of the process-based LCA and economic input-output (EIO) LCA methods (Kucukvar et al. 2014d; Tatari and Kucukvar 2012). Through this hybridization, the impacts from the upstream activities, used to produce a HDT (i.e. manufacturing phase, consisting of the extraction and transportation of raw materials) and from the downstream activities corresponding to HDT use (i.e. use phase consisting of HDT maintenance and repair (M&R) and fuel consumption) can both be more effectively accounted for and analyzed.

The process-based LCA method attempts to capture the overall environmental impacts of a product over the course of its entire lifetime, evaluating individual unit process flows that comprise an overall cradle-to-grave manufacturing system (Onat et al. 2014a). However, the complexity of supply chains is a serious drawback for the process-based LCA method in terms of the time, resources, and boundary selection required for a sufficiently plausible analysis (Onat 2015a; Kucukvar and Samadi 2015).

The EIO-based LCA modeling, on the other hand, is based on national input-output (IO) tables representing monetary transactions within or between entire economies, and enables the quantification of environmental impacts from complex supply chains, integrating the environmental loads associated with these transactions accordingly (Onat 2015b; Kucukvar et al. 2014b). Hence, the EIO-based LCA method eliminates some of the key drawbacks of the process-based LCA method, such as the aforementioned issues with boundary cutoff, and higher data requirements (Noori et al. 2015c). However, the EIO-based LCA method also suffers from a serious drawback due to the level of uncertainty inherent in the level of product aggregation found in the EIO-based LCA method (Facanha and Horvath 2006; Mattila et al. 2010; Hendrickson et al. 1997; Zhao et al. 2016b; Onat et al. 2015, 2014a, 2014b; Kucukvar et al. 2015; Kucukvar and Samadi 2015; Kucukvar et al. 2016a; Noori et al. 2015b; Yue et al. 2016; Onat et al. 2014c). Therefore, both these methods have been integrated into a single hybrid methodology in this chapter as hybridization reduces overall disadvantages of using these techniques individually as previously mentioned.

Life Cycle Inventory

The life-cycle inventory analysis phase of a typical LCA is where the inputs and outputs of a product system are quantified with respect to the system boundary in order to assess the impacts arising from the overall system (Onat et al. 2017b). The LCA phases considered in this study are divided into two primary parts:

1) The manufacturing phase, i.e. raw material extraction and procurement, and vehicle, battery manufacturing, and miscellaneous equipment manufacturing, and
2) The operation phase, i.e. fuel consumption and associated tailpipe emissions, and maintenance and repair.

Figure 27 illustrates the overall system boundary to be considered in this study. Furthermore, vehicle characteristics based on CALSTART (2013), Torrey and Murray (2015), TRB and NRC (2010), California Air Resources Board (2015), and Alternative Fuel Life-Cycle Environmental and Economic Transportation (AFLEET) model (Burnham 2013) are given in Table 8.

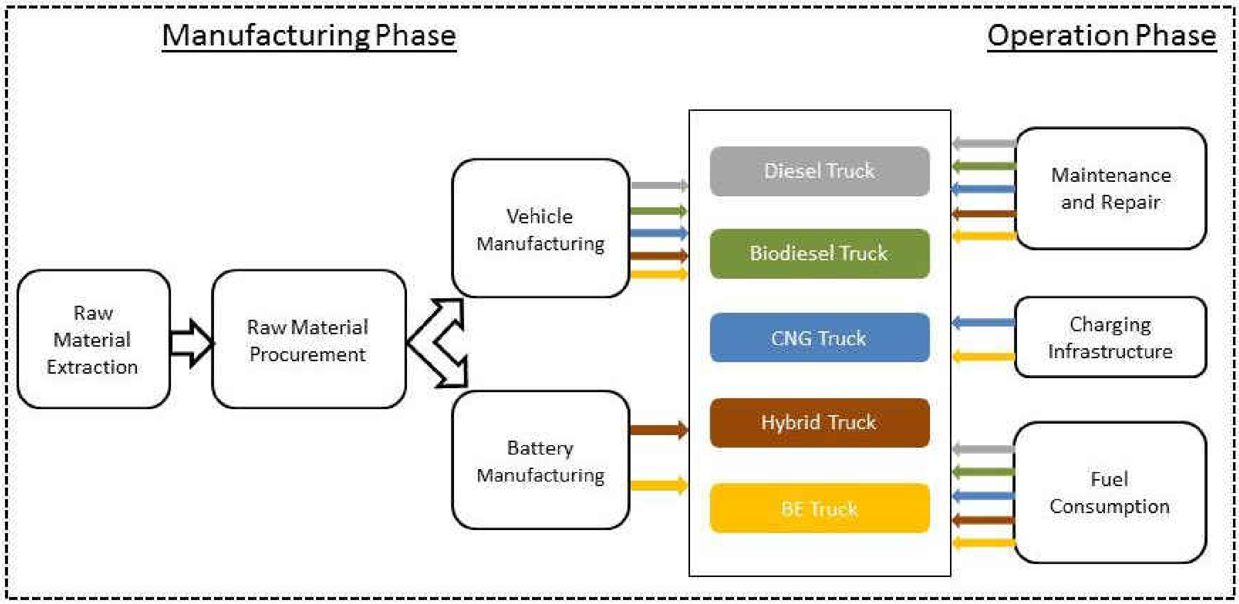

Figure 27: System boundary for hybrid life-cycle assessment

Data on the majority of the upstream environmental impacts of the studied HDTs have been obtained from the Carnegie Mellon University Green Design Institute's publicly available online EIO-LCA tool (Carnegie Mellon University Green Design Institute 2008). The downstream environmental impacts, on the other hand, have been acquired from both the EIO model which consists of 428 U.S. sectors, and various process models and databases such as *Greenhouse gases, Regulated Emissions, and Energy Use in Transportation (GREET)*, *AFLEET*, and the U.S. EPA's *Motor Vehicle Emissions Simulator (MOVES)*. More details on the data sources of the LCA indicators, the inputs of the LCA model, and the relevant calculations can be found in the authors' earlier study by Sen et al. (2017).

Table 8: Assumptions regarding vehicle characteristics

Characteristics	Value
Lifetime	10 years
Average annual mileage	140,000 miles
Physical features	Class 8 heavy-duty trucks with 53' truck-trailer; >33,001 lbs.
Battery specifications (BE)	400 kWh, 150 Wh/kg Li-ion battery
Battery specifications (Hybrid)	25 kWh, 150 Wh/kg Li-ion battery

The baseline truck (i.e. a diesel HDT) includes all essential truck parts, including the truck's body, shell, engine, and relevant miscellaneous parts, as well as a trailer. In addition to these parts, which are all assumed to be common for any type of truck considered in this study, additional parts for a CNG HDT (e.g. a metal tank and a heavy gauge), and for hybrid electric and BE HDTs (e.g. power electronics, an electric motor, and a battery system) have been also considered (California Air Resources Board 2015; Burnham 2013). Data on the environmental impacts of battery system manufacturing has been derived from GREET's Vehicle-Cycle Model (Center for Transportation Research 2016). Furthermore, the additional infrastructural needs of CNG and BE HDTs have been considered in the LCAs of each of these HDTs, as well. Based on studies conducted by Ercan and Tatari (2015) and by Smith et al. (2014), a natural gas refueling station (NGRS) has been assumed to have a daily supply capacity of 1500 to 2000 gasoline-gallon equivalents of fuel, and the investment, labor, and installation costs respectively take up 46 percent, 39 percent, and 15 percent of the total infrastructure cost of a NGRS. Likewise, based on studies conducted by De Filippo et al. (2014), Ercan and Tatari (2015), Kempton et al. (2001), and NREL (2012), it has been assumed that BE HDTs are charged using a Level 3 conductive battery charging station (BCS), which has a charging efficiency of 90 percent and a charging capacity of 250 kW. Lastly, the existing refueling infrastructure has been assumed to be sufficient for all other HDTs.

The life-cycle impacts caused by fuel consumption take into account the load-specific fuel economy (LSFE) specific to each of the 5 sectors considered in this study. Therefore, based on TRB and NRC (2010), it has been assumed that each 1000-pound increase in a HDT's payload results in a 1 percent decrease in its fuel economy. The payloads assumed in the analysis have been derived from data from a report published by the Transportation Research Board and National Research Council (2010), and are all listed in Table 9. The fuel prices used in the LCA calculations for diesel and hybrid, biodiesel, CNG, and BE HDTs have all been obtained from the databases of the U.S. EIA (2017a, 2017b) and the U.S. Department of Energy (2015). The environmental impacts and APE costs incurred by tailpipe emissions have been derived from the AFLEET database, and based on the results of the MOVES analysis, these externalities also include the relevant deterioration factors, which can subsequently affect tailpipe emissions. Additionally, based on studies conducted by Zhao et al. (2013) and by Ozdemir (2012), it has been assumed that hybrid electric HDTs and BE HDTs replace their batteries 3 times, and 2 times during their individual lifetimes, respectively. The emissions from battery replacement have been derived from GREET's Vehicle-Cycle Model. The LCA conducted in this chapter also reflects battery price projections, which estimate a 2 percent annual inflation in battery prices (U.S. EIA, 2015).

Table 9: Payloads and load-specific fuel economy (LSFE) values of heavy-duty trucks considered in hybrid life-cycle analysis

Sectors	**Average Payload (lbs.)**	**LSFEs for each HDT type**				
		Diesel miles/gal	Biodiesel miles/gal	CNG miles/gal	Hybrid miles/gal	BE kWh/mile
Food Products	40,000	4.21	4.21	3.81	4.48	2.77
Beverages	36,000	4.38	4.38	3.96	4.66	2.67
Household Durables	23,000	4.99	4.99	4.52	5.31	2.34
Oil and Gas	40,000	4.21	4.56	3.81	4.48	2.77
Automotive	32,000	4.56	4.21	4.13	4.85	2.56

The data used to calculate the LCGHGs and LCCs caused by the M&R of HDTs during operation have been taken from the AFLEET model (Burnham 2013), and the LCAPEs caused by the operation of HDTs have been also reflected in their respective LCA phases. Since the fuel consumption behavior of HDTs is a key factor in the magnitudes of the corresponding LCAPECs, sector-specific LSFE factors have been taken into account to calculate individual LCAPEs. It is important to note that the LCAPEs incurred by each HDT have ben considered differently from the LCCs of these HDTs, the latter of which are composed of cost components, such as initial capital costs i.e. the cost of a baseline truck and trailer, the costs of additional parts i.e. parts for alternative HDTs, and infrastructure costs, i.e. NGRS, BCS, fuel, and M&R.

Robust Pareto Optimal Fleet Composition

The three objectives of the optimization analysis conducted in this research consist of three LCA indicators, i.e. LCGHGs, LCCs, and LCAPECs, all of which have been quantified using the hybrid LCA method. All the three indicators are functions of the fleet portfolio mixes composed of different types of trucks, making fleet composition the basic decision to be made in this research. Regarding the multi-objective optimization (MOO) method used in this study, because multiple objectives almost certainly do not all achieve their optima in the same solution, it is usually useful to find the Pareto efficient frontier, on which all of the possible non-dominated points in terms of the multiple objectives lie.

However, there could be infinitely many points on this efficient frontier and finding analytical closed-form functions of this frontier might be difficult, if not impossible; in practice, it is sufficient to find many representative Pareto points or an important subset of the frontier. Under relatively mild conditions, a Pareto optimal solution (corresponding to a point in the Pareto efficient frontier) can be obtained by solving a single-objective optimization problem and thereby optimizing the weighted sum of the multiple-objectives (Miettinen 1999). Hence, many effective and successful MOO applications have used the weighted-sum-single-objective approach (Li et al. 2016; Onat et al. 2016a), and assigning appropriate weights to each of the multiple objectives is therefore an important step in finding the right Pareto optimum solutions. Many research efforts have been devoted to defining effective and meaningful weights, including tradeoff weighting (Keeney and Raiffa 1976), swing weighting (von Winterfeldt and Edwards 1986), and worst-case weighting (Hu and Mehrotra 2012).

The main challenge encountered in the weighting approach lies in its subjectivity in assessing and determining decision-makers' priorities with respect to each objective, particularly in terms of which objective(s) should be prioritized over other objectives (Kucukvar et al. 2014d). This inherent subjectivity in the weighting approach is due largely to potential biases in judgements with respect to each objective (Seppälä et al. 2016) as well as different value structures and differences in values, which is also referred to as value plurality (Bengtsson 2001; Finnveden 1997). Finnveden (1997) mentions that these differences in values can lead to different views on market economy, the environment, and society, leading to variations and/or disagreements as well as subjective uncertainties in weighting factors as they apply to the organizational objectives of each decision-maker. In addition to design variables, uncontrollable parameters such as those corresponding to key environmental and socio-economic factors (e.g. noise factors) also exist, thus affecting the feasibility of a solution for "real-world" optimization problems causing differentiations and uncertainties in the weighting factors of objectives (Gaspar-Cunha and Covas 2008; Gorissen et al. 2015; Gabrel et al. 2014; Onat et al. 2016a).

This research takes these considerations into account while also characterizing the uncertainty set to be used in the model, based on a survey conducted by RobecoSAM AG (2016). This survey is annually conducted and asks thousands of companies, each operating in different sectors around the world, various questions that focus on the environmental, social, and economic dimensions relevant to their organizational objectives. Hence, in this research, a Robust Pareto Optimal (RPO) approach has been employed to find the optimal composition of future HDT fleets in different sectors under varying level of priorities (i.e. weights).

First, the MOO model has been introduced as it applies to the fleet composition problem, focusing on the five U.S. sectors previously discussed (i.e. Food Products, Beverages, Household Durables, Oil and Gas, and Automotive), which are indexed on $j = 1,2,3,4,5$. Each sector has five truck types available, all indexed on i with respect to the set given as the following:

$$A = \{1(\text{diesel}), 2(\text{biodiesel}), 3(\text{CNG}), 4(\text{hybrid}), 5(\text{BE})\}$$

The investment decision on each type of truck i by each sector j is denoted by the variable h_{ij}. Three major LCA indicators are considered as previously mentioned, and the parameters used to estimate these three indicators have been obtained from the life cycle inventory. LCGHG parameters include CO_2 emissions from various life cycle activities, including:

a) Truck manufacturing, M&R, infrastructure (NGRS and BCS), and battery manufacturing and replacement, collectively denoted by e_i;

b) Fuel production (supply), denoted by n_{ij}^1; and

c) Downstream activities, i.e. fuel consumption (tailpipe), denoted by t_{ij}^1.

LCAPE parameters are determined in a similar manner and are converted into the LCAPECs as described previously; these parameters are denoted as y_i, n_{ij}^2, and t_{ij}^2, respectively. Lastly, the three main constituents of the LCC parameters are:

a) The initial truck cost, denoted by m_i;

b) The life-cycle operation costs (consisting of M&R, battery replacement, and refueling infrastructure costs), denoted by q_{ij}; and

c) Fuel expenditures, denoted by n_{ij}^3.

It is worth noting that these costs may vary from sector to sector, depending on the relevant LSFE factors.

Denoting the values of the indicators for each sector j as f_{1j}, f_{2j}, f_{3j} for LCGHGs, LCAPECs, and LCCs, respectively, these three indicators are calculated using the following three equations:

$$f_{1j} = \sum_{i=1}^{5} h_{ij} \times (e_i + n_{ij}^1 + t_{ij}^1), \qquad j = 1,2,3,4,5$$

$$f_{2j} = \sum_{i=1}^{5} h_{ij} \times \left(y_i + n_{ij}^2 + t_{ij}^2\right), \qquad j = 1,2,3,4,5$$

$$f_{3j} = \sum_{i=1}^{5} h_{ij} \times \left(m_i + n_{ij}^3 + q_{ij}\right), \qquad j = 1,2,3,4,5$$

Without loss of generality, it has been assumed that each sector has a total of 30 trucks, for which the optimal selection of truck types is to be determined, as modeled in the constraint shown as Eq. (3). In reality, many restrictions exist when selecting which type of truck to invest on. Based on the fleet requirement scenarios set forth by Executive Order 13693 from The White House (2015), it has been assumed that 50 percent of a HDT fleet comprises of zero-emission vehicles, as represented in Constraint (4). Likewise, alternative fuel HDTs have been assumed to comprise 50 percent to 75 percent of the truck fleet, as represented by Constraints (5) and (6). Additionally, the constraints that observe potential GHG reductions, life-cycle fuel costs (LCFCs), LCAPECs, and LCCs of a newly composed HDT fleet relative to conventional fleet (i.e. a truck fleet composed of 30 diesel HDTs) have been also included in the MOO model, and are each represented in Eqs. (7), (8), (9), and (10), respectively.

In summary, the MOO problem is presented as follows:

[MOO]: Minimize $[f_1, f_2, f_3]^T$ (1)

Subject to $f_k = \sum_{j=1}^{5} f_{kj}\,,\ k = 1,2,3$ (2)

$\sum_{i=1}^{5} h_{ij} = 30,\ j = 1,2,3,4,5$ (3)

$h_{5j} \geq 30 \times 50\%,\ \ j = 1,2,3,4,5$ (4)

$\sum_{i=2}^{5} h_{ij}\ \geq 30 \times 50\%,\ \ j = 1,2,3,4,5$ (5)

$\sum_{i=2}^{5} h_{ij}\ \leq 30 \times 75\%,\ j = 1,2,3,4,5$ (6)

$\sum_{i=1}^{5} h_{ij} \times \left(e_i + n_{ij}^1 + t_{ij}^1\right) \leq 30 \times \left(e_1 + n_{1j}^1 + t_{1j}^1\right),\ j = 1,2,3,4,5$ (7)

$\sum_{i=1}^{5} h_{ij} \times n_{ij}^3 \leq 30 \times n_{1j}^3,\ \ j = 1,2,3,4,5$ (8)

$\sum_{i=1}^{5} h_{ij} \times \left(y_i + n_{ij}^2 + t_{ij}^2\right) \leq 30 \times \left(y_1 + n_{1j}^2 + t_{1j}^2\right),\ j = 1,2,3,4,5$ (9)

$$\sum_{i=1}^{5} h_{ij} \times \left(m_i + n_{ij}^3 + q_{ij}^1\right) \geq 30 \times \left(m_1 + n_{1j}^3 + q_{1j}^1\right),\ j = 1,2,3,4,5 \tag{10}$$

$$h_{ij} \geq 0 \ and\ integers, \quad \forall\, i \in A,\ \ j = 1,2,3,4,5 \tag{11}$$

Here, the model [MOO] tries to minimize the multiple indicators of the aggregated cost/impact of all sectors as calculated in Eq. (2). By taking the weighted average of the three objectives, this problem has been transformed into a single-objective minimization problem. Because most of the sectors perceive the objective weights differently and independently, five different problems for each sector can be solved separately because Constraints (3) through (11) are separable with respect to each sector. For each sector j, let the weights be modeled by α_{kj}, $k = 1,2,3$. Hence the single objective optimization problem for each sector j can be presented as follows:

$$[\text{SOO}_j]\text{: Minimize} \left\{\sum_{k=1}^{3} \alpha_{kj} f_{kj} \mid (3)_j - (11)_j\right\}$$

Here, the equations with subscript j denote the constraints in the MOO model above with respect to index j only individually, and α_{kj} has been assumed to be a deterministic parameter. As previously mentioned, the weights on each of the three indicators represent the perceptions of the decision-makers regarding their corresponding importance, which are subject to expert opinions and future socio-economic uncertainties. This means that, for each sector j, the weighting factors α_{kj} ($k = 1,2,3$) are no longer fixed or deterministic but may instead vary within an uncertainty set (Ω_j). The lower and upper weighting factors (also referred to as the lower and upper bounds and denoted as b_{kj} and a_{kj}, respectively) for each sector and objective have been acquired from the survey conducted by RobecoSAM AG (2016). As also mentioned previously, the companies included in the survey are asked to assign weights to economic, social, and environmental dimensions of sustainability, each of which comprises of certain number of criteria. The sum of the assigned weights is 1. For example, for the Household Durables sector, the sum of the weighting factors for the economic, environmental, and social dimensions is 0.48, 0.23, and 0.29, respectively. Furthermore, the Household Durables sector assigns the minimum weight of 0.2 to materiality criteria; this minimum weight assigned by a sector to a certain criterion has been used as the lower bound (b_{kj}), and the sum of the weights assigned to a certain dimension is then used as the upper bound (a_{kj}). Hence, it is very valuable to find the Robust Pareto Optimal solutions, which can be obtained by solving the following bi-level optimization problem:

$$[\mathrm{RPO}_j]: \quad \text{Minimize} \quad \text{Maximize} \left\{ \sum_{k=1}^{3} \alpha_{kj} f_{kj} \mid \alpha_j \in \Omega_j \right\}$$

$$\text{Subject to} \quad f_{kj}, h_{ij} \in \{(3)_j - (11)_j\}$$

Here, $\boldsymbol{\alpha_j}$ is a vector composed of α_{kj} $(k = 1,2,3)$. Based on the survey by RobecoSAM AG (2016), the uncertainty set Ω_j can be set up as $\left\{ \boldsymbol{\alpha_j} | \sum_k^3 \alpha_{kj} = 1,\ b_{kj} \leq \alpha_{kj} \leq a_{kj}, k = 1,2,3 \right\}$. When Ω_j is a compact and convex set (which is the case in this study), the bi-level optimization problem is equivalent to a single-level optimization problem as shown below:

$$[\mathrm{SRP}_j]: \quad \text{Minimize} \quad z_j$$

$$\text{Subject to} \quad z_j \geq \sum_{k=1}^{3} \hat{\alpha}_{kj}^{l} f_{kj}, \forall l \in E_j$$

$$f_{kj}, h_{ij} \in \{(3)_j - (11)_j\}$$

Here, z_j is an unrestricted continuous variable, E_j is the extreme point set of Ω_j, and $\hat{\alpha}_{kj}^{l}$ $(k = 1,2,3)$ is the l^{th} extreme point in the set. The uncertainty set Ω_j is a closed 2-dimensional polyhedral set, because the three weight factors sum up to 1. In the case where there are only bounds (upper and lower) on each factor, all possible extreme points can be easily enumerated. By choosing two factors at either their upper or their lower bounds (4 combinations), the other factor can then be determined, since these three factors sum up to 1. The solution (of all factors) is then treated as an extreme point if the third factor is within its bounds; if not, the solution is simply discarded. The MATLAB software, developed by The Mathworks Inc. (2017), has been used for the computations needed to determine the extreme points. In the case of three weighting factors, only $\binom{3}{2} \times 4 = 12$ possible combinations are to be checked. For general cases, the following cutting plane algorithm is suggested to find robust Pareto optimal solutions:

Step 0: Initialize the Extreme Point Set E_j^n and $n = 0$.

Step 1: Solve [SRP$_j$] using E_j^n instead of E_j.

Step 2: Let the optimal solution be $\hat{f}_{kj}, \hat{h}_{kj}, \forall k, j$.

Step 3: Solve Maximize$\left\{\sum_{k=1}^{K} \hat{f}_{kj}\alpha_{kj} \mid \boldsymbol{\alpha_j} \in \Omega_j\right\}$.

Step 4: Let its optimal solution be $\widehat{\boldsymbol{\alpha}}_j^{n+1}$. If $\widehat{\boldsymbol{\alpha}}_j^{n+1}$ is already in E_j^n, stop; the current solution $\hat{f}_{kj}, \hat{h}_{kj}, \forall k, j$ is the robust Pareto optimal solution.

Step 5: Let $E_j^{n+1} = E_j^n \cup \left\{\widehat{\boldsymbol{\alpha}}_j^{n+1}\right\}$, and $n = n + 1$, and proceed accordingly to Step 1.

The algorithm above is an iterative method that adds cutting planes (a.k.a. extreme points) at each step, where K is the number of indicators (in general cases) and n is the iteration count. This algorithm avoids the complete enumeration of the extreme point set E_j. To initialize the extreme point set, one or a few feasible points from the uncertainty set Ω_j are to be found. The algorithm stops when a newly found extreme point already exists in the set E_j^n, and at the same time, the upper and lower bounds of $[RPO_j]$ match each other. All programs have been coded in GAMS (General Algebraic Modeling System), which was developed by GAMS Development Corporation (2013) to solve the Robust Pareto Optimal Fleet Mix problem.

K-Means Clustering

Regarded as an important unsupervised learning technique for exploratory data analysis, clustering is a well-established approach widely studied in the statistical learning and data mining literature to unveil hidden patterns and information in a dataset (James et al. 2007). The main aim of clustering is to segment data points (or observations) into a number of nonpredetermined and homogenous groups, called clusters, such that each cluster formed as a result contains those observations that are similar to each other but dissimilar to observations in other clusters based on a predetermined similarity function. For this very reason, a clustering problem can be approached as an optimization problem such that the predetermined similarity function is minimized for observations within the same cluster but maximized between observations in different clusters (Bandyopadhyay and Saha 2013). Given its applications found in a wide spectrum of scientific disciplines, a great number of clustering algorithms have been introduced and applied (James et al. 2007). The least squares quantization algorithm introduced by Lloyd (1982)– also famously known as *K*-means algorithm – is by far the most widely used clustering algorithm in the scientific and industrial applications (Reddy and Vinzamuri 2014), given its simplicity and computational convenience, with a time complexity of O(n), where n is the number of observations (Jain et al. 1999). Another reason why the *K*-means algorithm has been very popular among others is that the algorithm can be applied to almost any dataset and guarantees to converge, though not to the global optima (Aggarwal and Reddy 2014), and provide useful solutions in many practical applications (Rodriguez et al. 2019).

The *K*-means algorithm partitions a dataset into predetermined number (k) of distinct, non-overlapping clusters based on the Euclidean distance and assigns each of the n data points to one of the k clusters. Hence, as mathematically described by James et al. (2007), there are two properties that are satisfied by the $C_1, \dots, C_k$ sets of data points in each cluster:

1. $C_1 \cup C_2 \cup \dots\ C_k = \{1, \dots, n\}$. In words, because each data point is assigned to only one cluster, the total number of data points in each set C equal the number of data points in the dataset.

2. $C_k \cap C_{k'} = 0$ for all $k \neq k'$. In words, clusters formed as a result of partitioning does not overlap.

The *K*-means algorithm employs a squared error criterion and thus, it generates clusters such that the within-cluster variation, or in other words the sum of squared errors (SSE) defined as squared distances from the cluster centroids, is minimized. Given this information, the objective function for the *K*-means clustering method can be written as the following:

$$\min_{C,\{m_k\}_1^K} \sum_{k=1}^{K} \|x_i - c_k\|^2$$

Here, c_k is the mean vector $c_k = (x_{1k}, \dots, c_{pk)}$ associated with the k^{th} cluster (C_k) and denotes the center of cluster k; and x_i is a data point in cluster C_k. As explained by Bandyopadhyay and Saha (2013), supposing k is the number of predetermined clusters and the similarity function is the Euclidean distance, the process of the algorithm starts with arbitrarily selecting k points from the dataset as initial cluster centroids. Then, each point in the data set is assigned to a cluster, the centroid of which it is closest to, determined based on the similarity function. Once the clusters are formed, the cluster centers are updated to the means of newly formed clusters and the within-cluster variation for each cluster is computed. These two steps are repeated until a convergence criterion is met, i.e. either the data point assignment to clusters do not change or the within-cluster variations are minimized.

Step 1: Randomly select *k* points from the dataset ($x_1, x_2, \dots, x_3$) as initial cluster centroids, $c_1, \dots, c_k$.

repeat

Step 2: Assign point x_i to the closest cluster $c_j, j \in 1, 2, \dots, K$.

Step 3: Recompute new cluster centers $c_1^*, c_2^*, \dots, c_k^*$ as follows:

$c_i^* = \frac{\sum_{x_j \in c_i} x_j}{n_i}, i = 1, 2, \dots, K.$, where n_j denotes the number of data points in cluster C_i.

until

Step 4: Convergence criterion is met.

According to the *K*-means algorithm provided above, there are two major parameters that significantly impact the performance of the *K*-means clustering algorithm: (1) Choosing the initial centroids, and (2) Selecting the most appropriate number of clusters k to partition a dataset into. These parameters are significant because, unless the lengths of K and n are quite small, there are usually so many ways (i.e. K^n) to group n observations into k number of clusters, which is why the *K*-means algorithm converges at a local optima providing a good solution. Because the *K*-means algorithm find a local optimum, cluster initialization becomes crucial, as the shape of clusters formed would change depending on the assumed initialization (James et al. 2007). Therefore, to assume more effective cluster initialization, the *K*-means++ algorithm introduced by Arthur and Vassilvitskii (2007) has been employed in this study. Different from the *K*-means algorithm is the probabilistic approach used in the *K*-means++ algorithm, which adds two more steps before assigning data points to clusters. Accordingly, in between Step 1 and Step 2 in Algorithm 1 shown above, the *K*-means++ algorithm adds the following steps, as laid out by Arthur and Vassilvitskii (2007):

Step 1b: Take a new cluster centroid c_i, selecting $x \in X$ with the probability $\frac{D_{(x)}^2}{\sum_{x \in X} D_{(x)}^2}$.

Step 1c: Repeat Step 1b until k cluster centroids have been taken altogether

Here, $D_{(x)}$ denotes the shortest distance from a data point in the data space to the closest center that has been already chosen. After the initialization is made, the *K*-means++ algorithm follows the *K*-means algorithm in the remainder of the steps. Since selecting a right number of clusters k is dealt within the subject of cluster validation, it will be explained under the relevant section.

To carry out a cluster analysis, the steps outlined in Figure 28 have been followed. The steps were adopted from Ogbuabor and Ugwoke (2018).

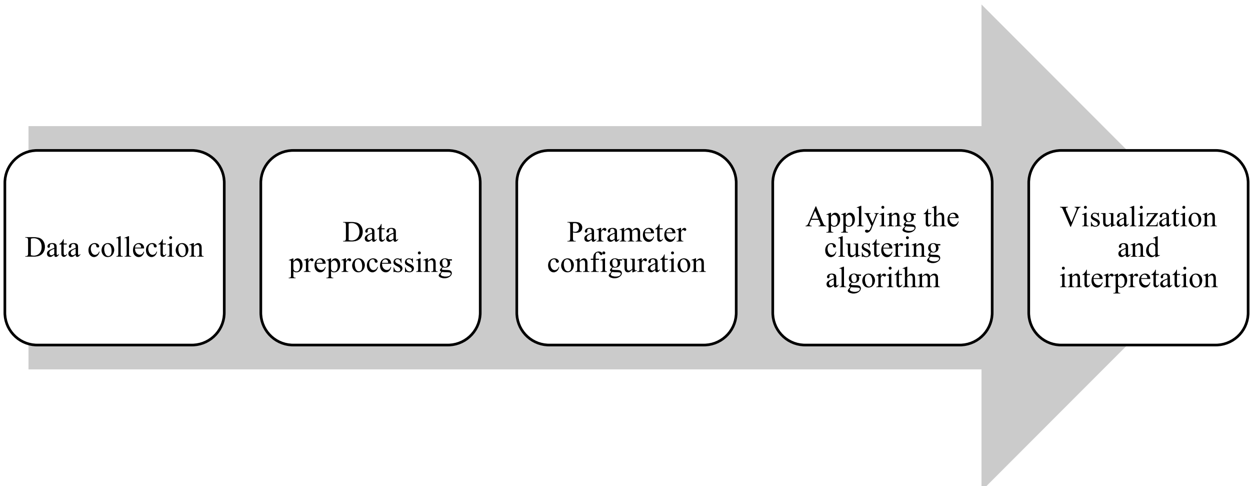

Figure 28 Steps taken for the cluster analysis

Data Collection and Preprocessing

The data used for the analysis is the count of public alternative fuel stations (AFSs), i.e. electric vehicle direct-current (DC) fast charging, (compressed) natural gas refueling station, and biodiesel (B20 and above) refueling station, over the selected routes. The count data of the studied AFSs has been acquired from Alternative Fuel Data Center provided by U.S. Department of Energy (2020) using a simple data mining technique, called web scraping – an automated process of collecting useful information from a certain webpage. Accordingly, a Python script was implemented, which opened the alternative fuel station locator webpage, selected the studied AFSs, typed the names of the origins and destinations, and retrieved the count of AFSs within 5 miles distance from the route between the given origin-destination pair. A sample route selection, with existing fast recharging stations scattered throughout the route, presented in Figure 29, shows the route between Miami FL as the origin, and Atlanta GA as the destination. The routes selected in this fashion for each pair of origin and destination provided by the Freight Analysis Framework 4 (FAF4) database has been checked for consistency with the National Freight Highway Network map generated by (U.S. Department of Transportation 2020).

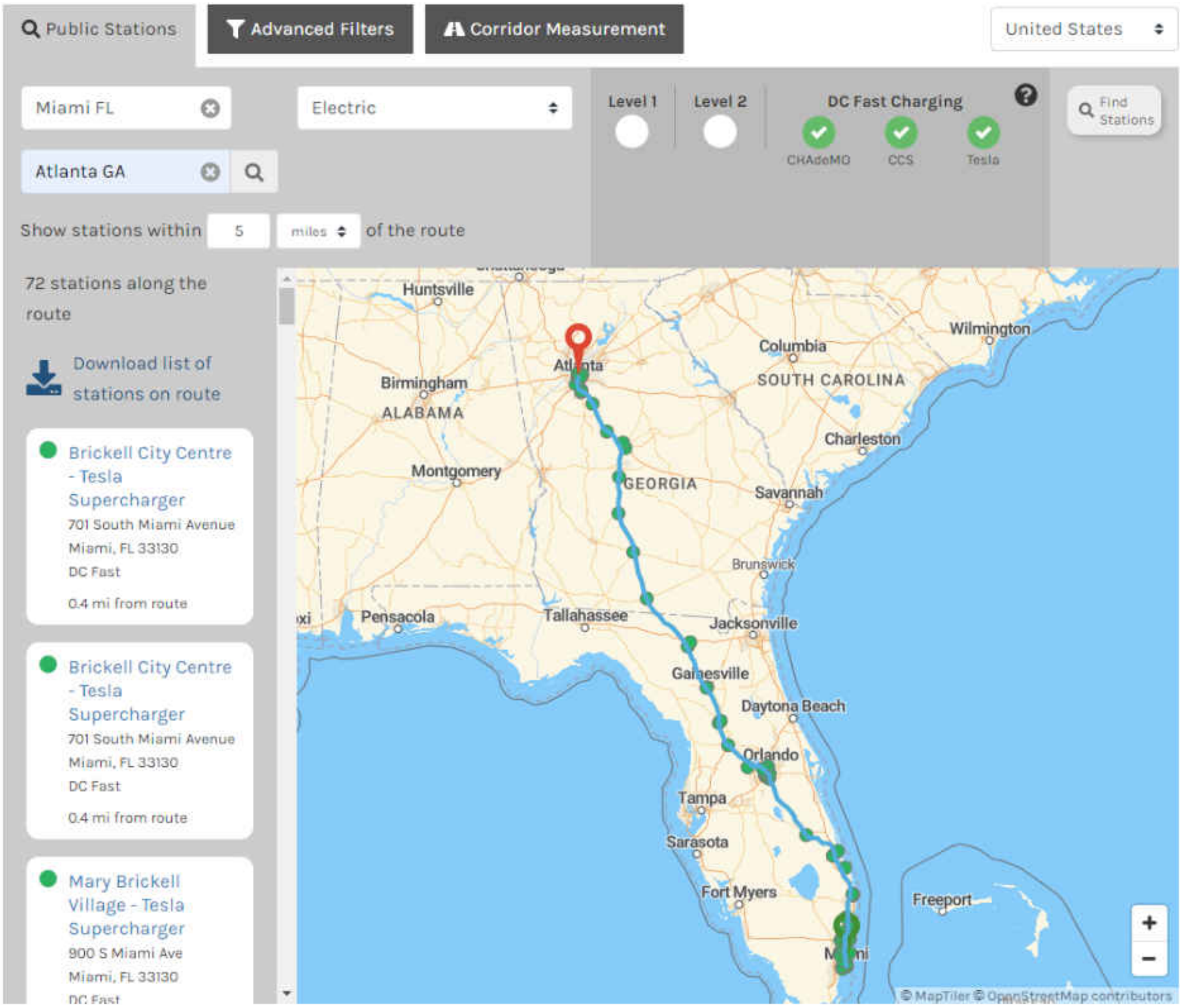

Figure 29 A sample route selection between Miami FL and Atlanta GA with existing fast recharging stations

The routes and transported goods analyzed are freight origins and destinations, and goods carried over those routes, defined in the FAF4 database (Center for Transportation Analysis 2015). All the routes but those to and from Alaska and Hawaii have been excluded from the analysis, given the scope of the study encompassing the contiguous United States. The FAF4 database contains origins and destinations that were specified as states (i.e. Idaho, Iowa, Maine, New Mexico, Montana, Mississippi, North Dakota, South Dakota, Vermont, West Virginia, Wyoming, and Arkansas), metropolitan statistical areas, and combined statistical areas. Hence, for those state origins and destinations, state capitals have been considered in collecting the count data of AFSs over the routes to and from those state capitals. The dictionary and characteristics of the data collected are provided in Table 10.

Table 10 Characteristics and description of the data used in the analysis

Field	Description	N statistic	Maximum	Minimum	Standard Deviation	Skewness		Kurtosis	
						Statistic	Std. Error	Statistic	Std. Error
od_pair	Origin-destination pair, indicating FAF region or state where a freight movement begins (o) and ends (d)	6414	-	-	-	-	-	-	-
sctg2_updated	Types of goods/commodity carried according to the Standard Classification of Transportation Goods (SCTG)	6414	-	-	-	-	-	-	-
bio_station	Biodiesel stations over the course of the route between an OD pair	6414	275	0	27.69201	0.983	0.031	2.47	0.061
cng_station	Compressed natural gas stations over the course of the route between an OD pair	6414	33	0	3.54418	3.500	0.031	17.388	0.061
ev_station	Electric vehicle charging stations over the course of the route between an OD pair	6414	69	0	15.14097	1.219	0.031	1.408	0.061
orig_lat	Latitude of the origin	6414	-	-	-	-	-	-	-
orig_lon	Longitude of the origin	6414	-	-	-	-	-	-	-
dest_lat	Latitude of the destination	6414	-	-	-	-	-	-	-
dest_lon	Longitude of the destination	6414	-	-	-	-	-	-	-

After collecting the data, it has been observed that the existing electric vehicle charging stations and CNG refueling stations remarkably outnumbered the existing biodiesel stations as of January 2020, having greater variability, as well. Because a distance-based clustering has been employed and because it has been unwanted that large numbers in some features (e.g. ev_sta) dominate the clustering of the data space, the z-score scaling has been applied to the collected count data. The z-score scaling is one of the data preprocessing steps recommended to attempt to give all variables an equal weight, in the hope of achieving objectivity (Kaufman and Rousseeuw 1990). Furthermore, in their study, in which the effects of different scaling approaches on the *K*-means clustering were investigated, Johor Bahru et al. (2013) concluded that the z-score standardization was more effective and efficient than the min-max and decimal scaling methods. The data after the z-score scaling is shown in Figure 30.

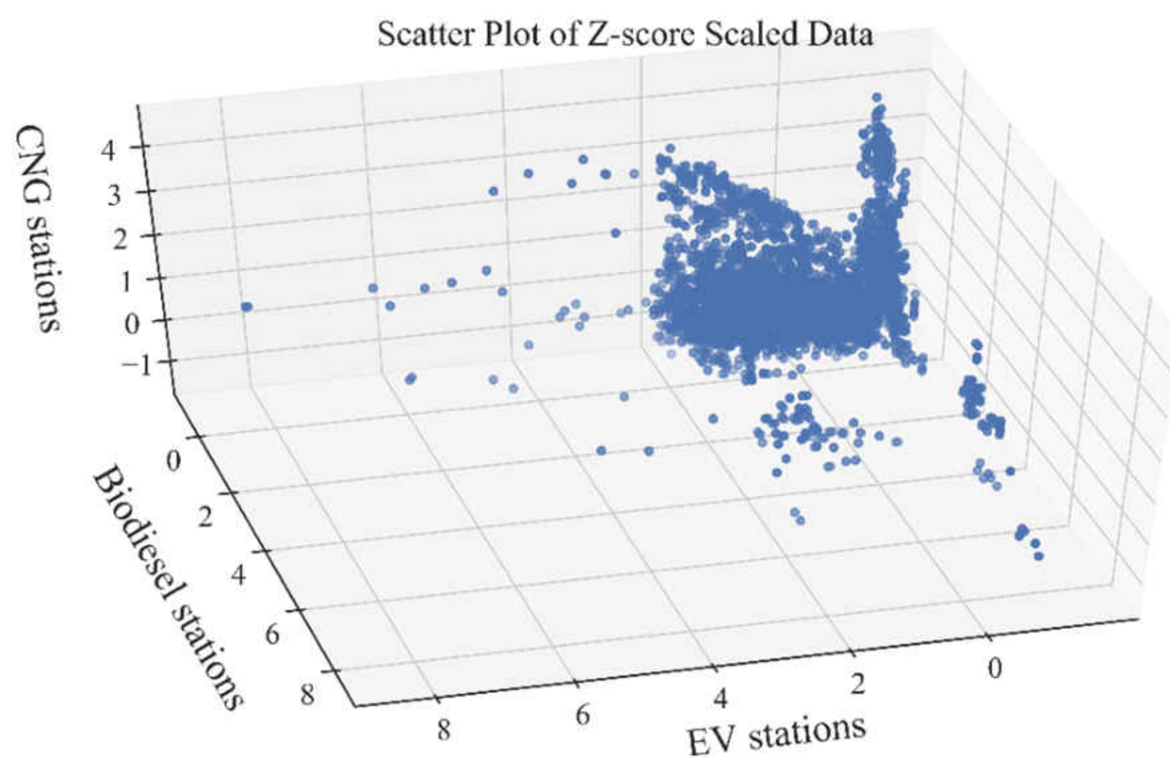

Figure 30 A scatter plot showing the z-score scaled data for the studied alternative fuel refueling stations

Because the *K*-means algorithm is known to be sensitive to outliers, given its use of the mean of squared Euclidean distances, the analysis has been carried out using the data both with outliers and without outlies. The interquartile range (IQR) rule has been applied to detect the outliers in each feature. In total, 499 data points have been detected as outliers (see Figure 31), and thus, removed from the data set. The scatter plot of the data, from which the outliers were removed, is presented in Figure 32.

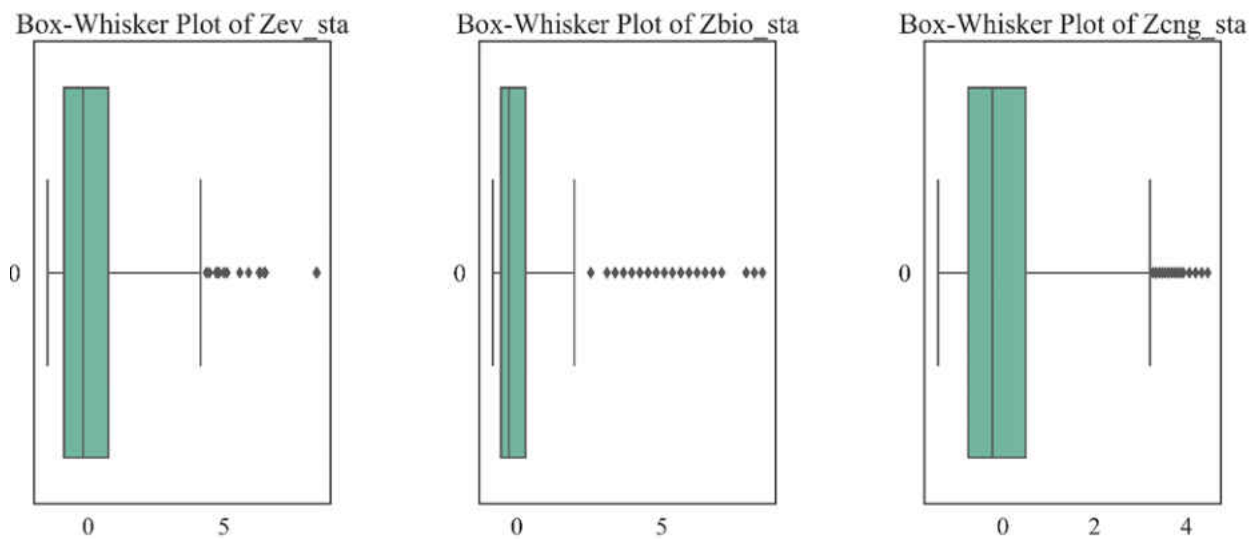

Figure 31 Outlier detection based on the interquartile range (IQR) rule

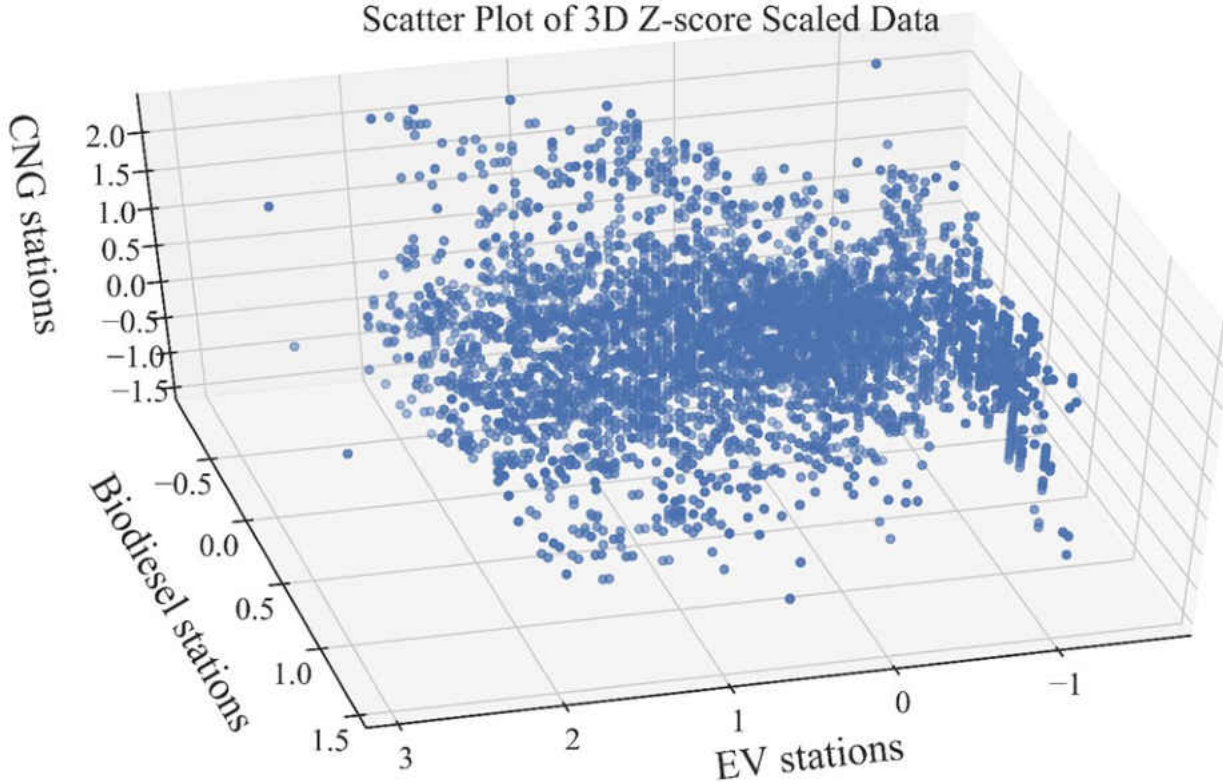

Figure 32 A scatter plot showing the z-score scaled data for the studied alternative fuel refueling stations

Parameter Configuration and Cluster Validation

There are two major factors such as initialization of cluster centroids and selecting the number of clusters k, that affect the performance and validity of clustering a data space using the *K*-means algorithm (Reddy and Vinzamuri 2014). The latter also leads to two crucial questions to be addressed for insightful cluster analysis: (1) How many clusters naturally exist in the data and (2) how good is the clustering? Therefore, one must also take into account the validity of the clusters formed as a result of implementing a clustering algorithm (Bandyopadhyay and Saha 2013). As mentioned previously, the cluster initialization was done using *K*-means++ initialization method because it performs reasonably well in providing an effective initialization (Fränti and Sieranoja 2019).

As for determining the right number of clusters k, one of the widely adopted approaches to selecting an appropriate number of clusters in a data set is the Elbow method used in various clustering applications. The Elbow method, as a variance-based approach (Mirkin 2011). relies on the within-cluster sum of squared errors (SSE), also referred to as inertia, as a performance indicator (Yuan and Yang 2019). Intuitively, as the number of clusters increases, the inertia of clusters decreases; when the number of naturally occurring clusters is reached, a rapid decline in the value of inertia becomes apparent. The Elbow method has been implemented for the data both with and without outliers. Though a valid method, the Elbow graph does not provide a measure in terms of the separation of the formed clusters. That is, it is not possible to gain insights into how well the clusters are separated from each other. Therefore, the cluster validation metrics introduced previously have been also implemented.

There are two categories of cluster validation approaches such as external cluster validation and internal cluster validation. The difference between these two approaches is that the former validates the clusters formed with respect to external information not present in the data, e.g. the ground truth, whereas in the latter, the clustering validation relies on metrics measured based on the structure of the data (Liu et al. 2010). In addition to measuring the goodness and quality of clusters formed, internal validation techniques can be also used to determine the number of naturally occurring clusters k in the data space (Baarsch and Celebi 2012). To that end, in an effort to ensure that the most appropriate number of clusters is selected, the following internal cluster validation indices have been implemented: Silhouette coefficient, Calinski-Harabasz score, and Davies-Bouldin score, which were previously adopted by others, as well (Vogel et al. 2011; Rendón et al. 2011; Hasnat and Hasan 2018). The main reason behind the selection of these metrics is their performances in providing a good indication of an appropriate number of clusters (Sharman and Roorda 2011) as well as good cluster validation (Baarsch and Celebi 2012; Mirkin 2011). In fact, Rendón et al. (2011) carried out a study, comparing the internal cluster validation indexes to the external cluster validation indexes on a number of different datasets. It was concluded based on the comparative analysis results, that, when the *K*-means algorithm, along with internal cluster validation indexes, is used, the DB index and Silhouette scores provide more accurate partitioning.

Silhouette coefficient is a metric that provides insights into the cohesion and separation of clusters, thereby considering both the average distance of data point i in cluster C_k to all other data points in the same cluster, denoted as (a_i), and the average distance (b_i) of data point i in cluster C_k to all other data points in other clusters $C \neq A$. One of the most important characteristics of the Silhouette coefficient is that it only depends on the actual partition of the data space, regardless of the clustering algorithm used (Kaufman and Rousseeuw 1990). The Silhouette coefficient varies between -1 and +1, and values less than 0.25 indicate the inexistence of a substantial cluster structure, values between 0.26 and 0.50 indicate a weak structure, and values above 0.50 indicate an existence of reasonable to strong cluster structure. Therefore, higher Silhouette coefficient indicates a better separation as well as compactness of the cluster formed. In case the average Silhouette coefficient is between 0.26 and 0.50, the implementation of additional methods is recommended (Kaufman and Rousseeuw 1990). Accordingly, the average Silhouette coefficient for cluster C_k is computed as the following:

$$s_{C_k} \frac{b_i - a_i}{max\,\{a_i, b_i\}}$$

Calinski-Harabasz (CH) score, also known as the Variance Ratio Criterion, evaluates the clusters formed based on the ratio of between-cluster sum of square errors (SSB) to within-cluster sum of squared errors (SSW). Given a dataset D consisting of n data points to be partitioned into k number of mutually exclusive clusters, with c_q denoting its cluster centroid, the CH index can be computed as the followings, as provided by Scikit-Learn Developers (2019):

$$\mathrm{CH} = \frac{\mathrm{trace}(\frac{\mathrm{SSB}}{\mathrm{k}-1})}{\mathrm{trace}(\frac{\mathrm{SSW}}{\mathrm{n}-\mathrm{k}})}$$

Therefore, a higher CH score indicates a better separation of clusters and the k value, for which the CH index is at its maximum should be considered the most appropriate value for the number of clusters. Given Equation 3, the SSB and SSW must be computed using the following formulas as provided by Scikit-Learn Developers (2019):

$$SSW = \sum_{q=1}^{k} \sum_{n \in C_q} \left\| n - c_q \right\|^2$$

$$\mathrm{SSB} = \sum_{\mathrm{q}=1}^{\mathrm{k}} \mathrm{n_q} \times \left\| \mathrm{c_q} - \mathrm{c} \right\|$$

Davies-Bouldin (DB score is a commonly used dispersion-based cluster validation measure, which evaluates clusters based on between-cluster distances and the dispersion of clusters. According to the DB score, the most appropriate number of clusters is the one that minimizes the average similarity, while having distant clusters with constant dispersion. This can be mathematically expressed in the following way, as introduced by Davies and Bouldin (1979) and provided by Scikit-Learn Developers (2019):

$$DB = \frac{1}{n}\sum_{i=1}^{N}\frac{\max(S_i + S_j)}{d_{ij}}$$

Here, $S_i$denotes the average distance between each data point x_i in cluster $C_i$and the centroid of C_i; S_j denotes the distance between each point x_j in cluster C_j and the centroid of C_j; and d_{ij} denotes the distances between the centroids of C_i and C_j. Given the equation above, the k value, for which the DB score is at its maximum, should be considered an appropriate number of clusters to form. Consequently, all these techniques of determining the most appropriate number of clusters based on the data structure have been applied to the data, both with and without outliers. The results of these measures as well as the clustering analysis are presented in the following section.

Python 3.6 has been used to run both the *K*-means algorithm and the scripts associated with the cluster validation metrics mentioned in this section. The values for the Elbow graphs have been obtained for each k, where $k = [1, 30]$, whereas the values for the cluster validation metrics have been obtained for each k, where $k = [2, 30]$.

Results

This section presents the results of the hybrid LCA and RPO solution analysis. The tables presented for the hybrid life cycle analysis results constitute the foundation of the optimization analysis. Furthermore, two scenarios regarding the constraints on the number of BE HDTs have been considered in the RPO solution analysis, based on the document authored by Gore and Kurien (2017). These scenarios examine the composition of the HDT fleets in question, in that the number of BE HDTs must be no more than 50 percent (Scenario 1) or no less than 50 percent (Scenario 2) of the composed HDT fleet. Additionally, the fuel cost savings, and the reductions in GHG emissions and LCAPECs achieved by the new fleet composition have been analyzed and compared against the emissions produced, LCAPECs, and fuel costs incurred by a conventional fleet.

Hybrid Life Cycle Analysis Results

Table 11 presents the results of the hybrid LCA regarding the life cycle GHG and tailpipe emissions from the manufacturing and operation of the studied HDTs for each sector analyzed. The results confirm that fuel consumption plays a major role in the life cycle emissions from HDTs, and show that tailpipe emissions are the largest individual contributor to the life cycle GHG and air pollutant emissions of each HDT, except for CNG and BE HDTs. For these two HDT tpes, the fuel supply has been observed to be the largest contributor to these emissions instead. However, the fact that BE HDTs do not produce any tailpipe emissions means that these HDT types produce the least amount of emissions. According to the results, CNG and BE HDTs produce 51 percent and 53 percent more fuel supply-related emissions than conventional HDTs for each of the studied sectors.

Table 11: Life-cycle greenhouse gas (GHG) (tone CO2 eq.) and tailpipe emissions from each heavy-duty truck (HDT) in each sector

Sector	**GHG emissions from HDT types (tone)**					**Tailpipe emissions from HDT types (tone)**				
	Diesel	*Biodiesel*	*CNG*	*Hybrid*	*BE*	*Diesel*	*Biodiesel*	*CNG*	*Hybrid*	*BE*
Food Products	5590	5575	6900	5265	4620	3390	3340	2470	3185	0
Beverages	5375	5360	6640	5060	4445	3255	3205	2375	3060	0
Household Durables	4735	4720	5850	4460	3925	2855	2815	3080	2685	0
Oil and Gas	5590	5575	6905	5265	4620	3390	3340	2470	3185	0
Automotive	5170	5155	6380	4870	4280	3125	3080	2280	2939	0

According to the results, the manufacturing of a CNG HDT produces 37 percent more emissions than the manufacturing of a conventional HDT and 11 percent more emissions than the manufacturing of a BE HDT, due mainly to the manufacturing of additional parts installed on these trucks. As can also be seen in Table 11, the sectors with higher average payloads produce higher magnitude of emissions due primarily to the effect of payload on fuel consumption.

Likewise, the results have shown that CNG and BE HDTs incur the greatest amount of LCCs (excluding LCAPECs) due to additional parts and infrastructural needs. The LCC of BE HDTs has been observed to be 12 percent higher than that of conventional HDTs, as shown in Table 12. The analysis reveals that fuel expenditures comprise the largest cost component for most of the studied HDTs, the sole exception being the BE HDT. Given current fuel prices, biodiesel HDTs incur the highest fuel costs, followed by those of CNG HDTs. Consequently, for each of the sectors studied, the life cycle fuel cost (LCFC) of a biodiesel HDT is over 15 percent more than that of a conventional HDT and almost 60 percent higher than that of a BE HDT. Conversely, the LCFC of a BE HDT is 50 percent less than that of a conventional HDT.

Table 12: Life-cycle costs and life-cycle health costs from each HDT in each sector

Sectors	**Diesel**		**Biodiesel**		**CNG**		**Hybrid**		**BE**	
	LCC	LCAPEC	LCC	LCAPEC	LCC	LCAPEC	LCC	LCAPEC	LCC	LCAPEC
Food products	\$1.1M	\$694K	\$1.24M	\$695K	\$1.25M	\$936K	\$1.1M	\$651K	\$1.26M	\$210K
Beverages	\$1M	\$682K	\$1.21M	\$683K	\$1.22M	\$927K	\$1M	\$640K	\$1.25M	\$202K
Household durables	\$991K	\$645K	\$1.1M	\$683K	\$1.13M	\$889K	\$1M	\$608K	\$1.2M	\$180K
Oil and gas	\$1.1M	\$694K	\$1.24M	\$695K	\$1.25M	\$936K	\$1.1M	\$651K	\$1.26M	\$210K
Automotive	\$1M	\$670K	\$1.1M	\$671K	\$1.1M	\$918K	\$1M	\$630K	\$1.2M	\$195K

Regarding LCAPECs results, the costs incurred by the health impacts of tailpipe emissions are the major cost component for each HDT in each studied sector. Similarly, the average payloads carried by each of the sectors are positively correlated with the magnitude of LCAPECs from the HDTs considered in this study. Hence, sectors with higher average payloads caused higher tailpipe emissions, resulting in higher LCAPECs.

CNG HDTs incur the highest LCAPECs, owing mainly to their high carbon-monoxide (CO) tailpipe emissions. The LCAPECs of diesel, biodiesel, and hybrid HDTs differ only slightly from each other, with conventional HDTs incurring the highest LCAPECs. On the other hand, the only LCAPEC source for BE HDTs is the air pollutant emissions emitted during electricity generation, making them the least LCAPECs incurring HDT option. Being 70 percent less costly than conventional HDTs in terms of LCAPECs, BE HDTs have been observed to be the cleanest truck type for a truck fleet for each studied sector.

Robust Pareto Optimal Solution Analysis Results

The sector-specific weight ranges, on which the EPs are based, are presented in Table 13. As shown in Figure 33, the HDT fleets for each studied sector are almost always composed only of diesel, hybrid electric, and BE HDTs; conversely, given the constraints and the hybrid LCA data, no optimal fleet composition was found that includes biodiesel and/or CNG HDTs.

Table 13: Sector-specific weighting factors

Sector	**Economic**		**Environmental**		**Social**	
	Lower	Upper	Lower	Upper	Lower	Upper
Food Products	0.388	0.588	0.192	0.392	0.22	0.42
Beverages	0.486	0.686	0.164	0.364	0.15	0.35
Household Durables	0.472	0.672	0.138	0.322	0.206	0.406
Oil and Gas	0.388	0.588	0.164	0.364	0.248	0.448

Sector	Economic		Environmental		Social	
	Lower	Upper	Lower	Upper	Lower	Upper
Automotive	0.318	0.518	0.234	0.434	0.248	0.448

Figure 33 presents the results of the first scenario analysis. Accordingly, it has been observed that BE HDTs are dominant in the majority of the sectors being considered, even when the allocation of BE HDTs was not dictated by the *constraint2* shown in Table C.30. The fleet compositions of all sectors have been observed to change depending on the constraint related to the number of BE HDTs to be considered in the fleet. For the Food Products, Automotive, and Oil and Gas sectors in Scenario 1 (where the number of BE HDTs must make up no more than 50 percent of the fleet), the truck distribution in the fleet has been observed to be 8 diesel, 7 hybrid, and 15 BE HDTs. However, in Scenario 2 (where no less than 50 percent of the fleet must consist of BE HDTs), the truck distribution has been observed to change to 8 diesel and 22 BE HDTs for these same three sectors. The underlying reason for such distributions is the relatively higher level of significance of environmental and social concerns for those three sectors. Another reason in this regard is that there is no significant difference between the LCCs of BE HDTs and those of other HDT types, while the LCAPEC of BE HDTs is considerably lower than those of other HDT types. Therefore, the HDT fleet in those sectors include BE HDTs regardless of any constraints on the number of BE HDTs.

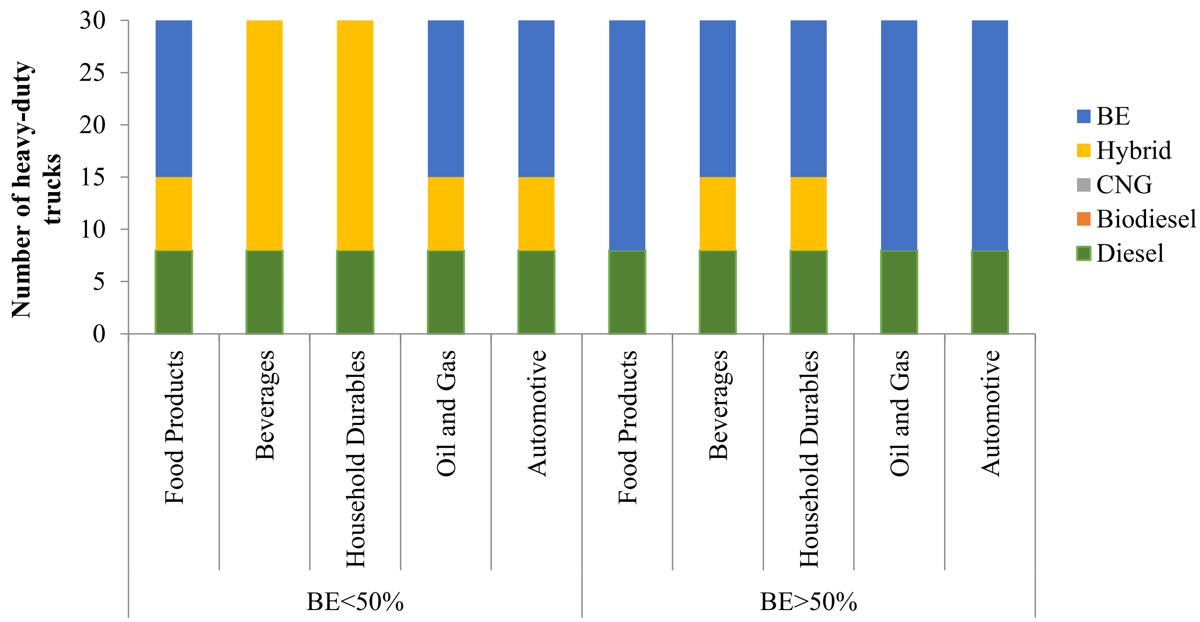

Figure 33: Fleet compositions for each sector under each scenario

On the other hand, as for the Beverages and Household Durables sectors, neither of the HDT fleets includes any BE HDTs; instead, in Scenario 1, both fleets consist of 8 diesel HDTs and 22 hybrid electric HDTs, mainly because, unlike in the other studied sectors, the level of significance of economic concerns is relatively higher for the Beverages and Household Durables sectors. In Scenario 2, the truck distribution for both the Beverages sector and the Household Durables sector has been observed to be 8 diesel, 7 hybrid electric, and 15 BE HDTs. Here, the underlying reason for this distribution is the constraint specified in Scenario 2, under which the HDT fleet must consist of no less than 15 BE HDTs.

The load-specific fuel economy (LSFE) has been found to be the greatest determinant in the variations in the magnitude of GHG emissions released by the HDT fleets evaluated in this study. Also, as shown in Figure 34, the HDT fleet of the Household Durables sector has been observed to produce the least amount of GHG emissions under both of the scenarios considered.

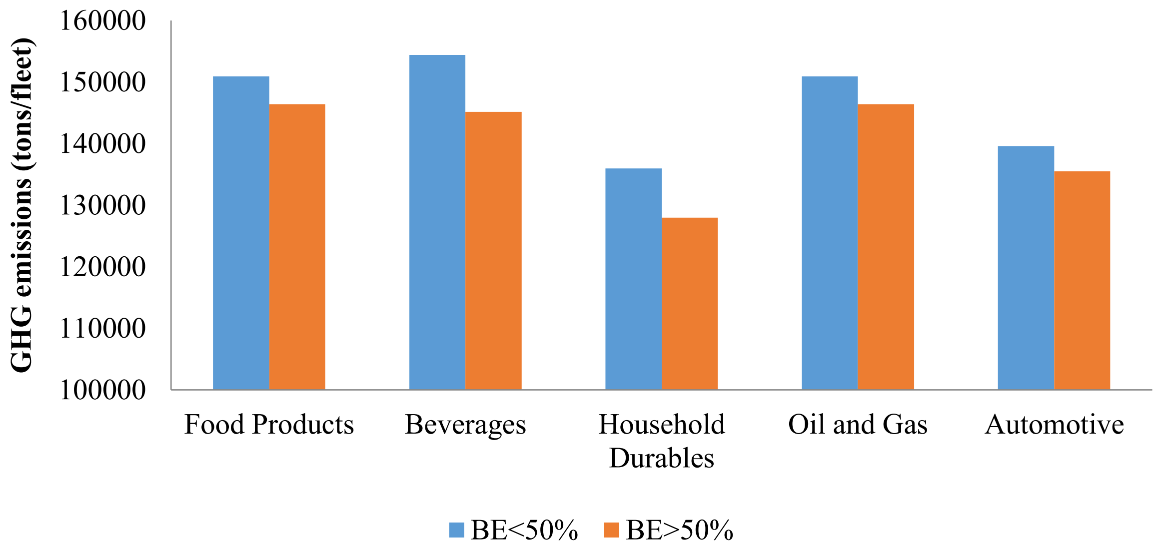

Figure 34: Total amounts of greenhouse gas emissions from each sector's HDT fleet under each scenario

Furthermore, the results have shown that the fleets of the Food Products and Oil and Gas sectors emit approximately the same amount of GHGs, as indicated by their fleets having the same LSFE. Under Scenario 1, the GHG emissions exceed 150K tons CO_2-eq. for both sectors, whereas the Automotive sector has been found to have GHG emissions of slightly less than 140K tons CO_2-eq, despite having the same fleet. According to the results of Scenario 1, the GHG emissions from the fleets of the Food Products and Oil and Gas sectors decrease by 8 percent relative to those of an all-diesel HDT fleet, whereas the corresponding GHG emission reduction from the Automotive sector's fleet has been observed to be slightly over 7.5 percent compared to this same conventional fleet.

Under Scenario 2, it has been estimated that the magnitudes of the GHG emissions from the fleets of these same sectors are further reduced by 3 percent compared to the corresponding Scenario 1 results, which decrease to 146K for the Food Products and Oil and Gas sectors and 135K for the Automotive sector. Likewise, under Scenario 2, these fleets achieved a 10 percent reduction in GHG emissions compared to a conventional fleet under Scenario 2.

The amount of GHG emissions produced in Scenario 1 by the fleets of the Beverages and Household Durables sectors have been observed to be 154K and 136K tons CO_2-eq., respectively. The Beverages sector's fleet emits the largest amount of GHG emissions, owing mainly to the exclusion of BE HDTs from its HDT fleet due to its prioritization of socio-economic factors in terms of its sector-specific environmental and social weighting factors. The results also show that the fleets of the Beverages and Household Durables sectors composed under the Scenario 1 only achieve 2 percent and slightly over 1.5 percent GHG emission reductions, respectively, compared to the GHG emissions of a conventional HDT fleet. Under Scenario 2, the HDT fleets of the Beverages and Household Durables sectors emit 145K and 127K tons CO_2-eq., respectively, resulting in a 6 percent reduction in GHG emissions compared to Scenario 1 and, on average, a GHG emission reduction of 7.5 percent compared to the GHG emissions of a conventional fleet.

Figure 35 presents the fuel costs (LCFCs) (Figure 35a) and total LCCs (Figure 35b) incurred by each sector's fleet throughout its life cycle under each of the two scenarios being considered. Accordingly, despite their relatively lower average payloads, and the higher level of significance of economic concerns with respect to these sectors in terms of weighting factors, the fleets of the Beverages and Household Durables sectors have been observed to incur the highest fuel expenditures. It has been also observed that the LCFCs of the fleets of these two sectors are 23 percent higher under Scenario 1 than under Scenario 2. Under Scenario 1, the LCFCs of the fleets of the Beverages and Household Durables sectors exceed \$20 million and \$17 million, respectively, resulting in LCFC reductions of over 4 percent relative to the corresponding LCFC of a conventional fleet, whereas these same LCFCs under Scenario 2 are approximately \$15 million for the Beverages sector and approximately \$13 million for the Household Durables sector, each decreasing by over 26 percent compared to the LCFC of a conventional fleet.

This looks contradictory at first glance, but the total LCCs incurred by each sector fleet disprove this contradiction because, as shown in Figure 35a, the fleets of the Beverages and Household Durables sectors are the two fleets with the lowest total LCCs. These results show that the fleets of the Food Products and Oil and Gas sectors both incur LCFCs of approximately \$16 million under Scenario 1 and approximately \$14 million under Scenario 2, indicating a LCFC reduction of almost 15 percent from Scenario 1 to Scenario 2. The LCFCs of the Automotive sector fleet, on the other hand, decrease from \$15 million under Scenario 1 to \$13 million under Scenario 2. Overall, compared to a conventional fleet, the LCFC reductions achieved by the HDT fleets of these three sectors amount to 26 percent under Scenario 1 and 37 percent under Scenario 2, due primarily to the inclusion of BE HDTs in the composed fleets in Scenario 2.

a)

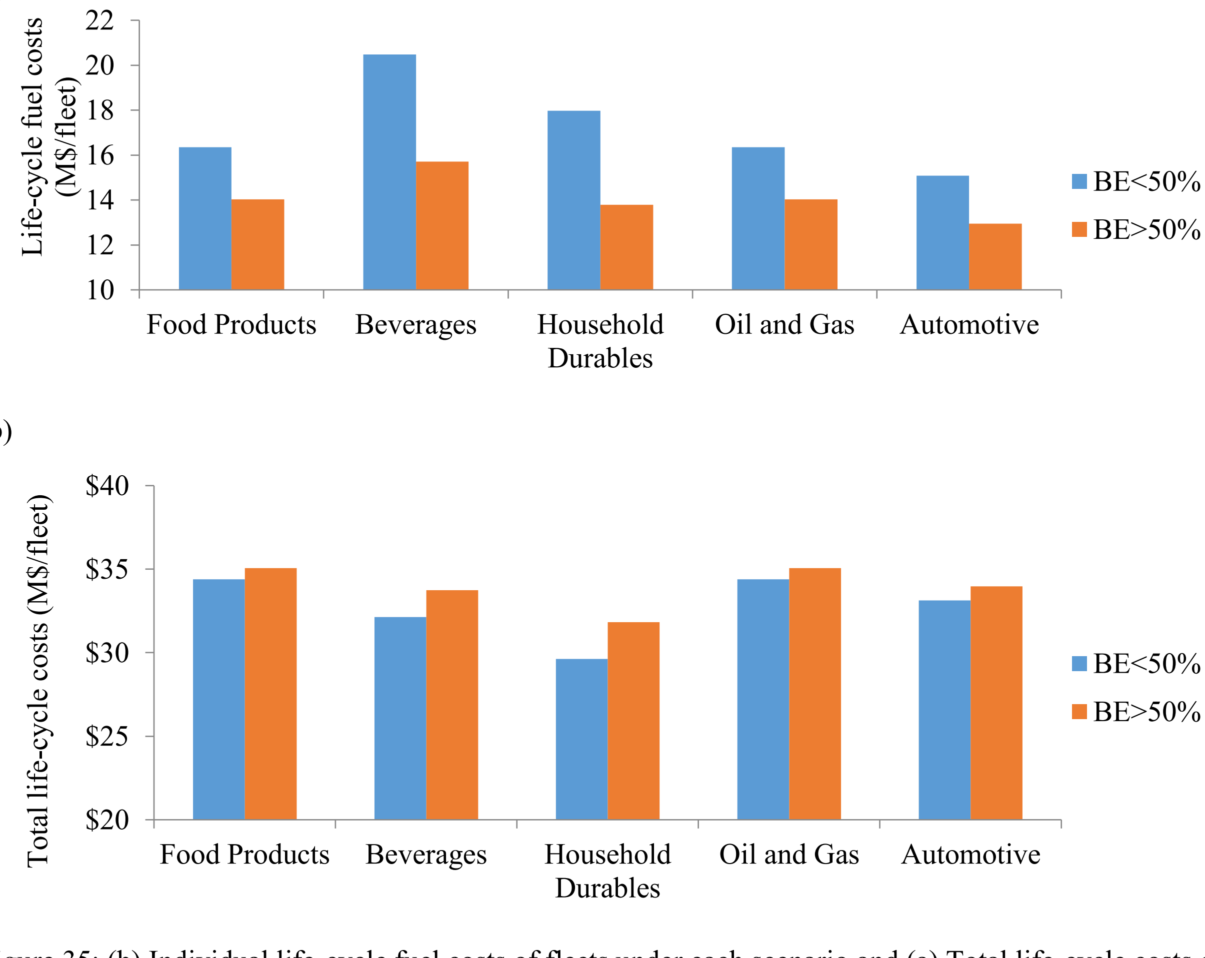

Figure 35: (b) Individual life-cycle fuel costs of fleets under each scenario and (a) Total life-cycle costs of each sector

It has been observed that the LCCs of newly composed fleets exceed the LCCs of a conventional fleet in each sector under each of the two scenarios considered. Under Scenario 1, the LCCs of the fleets of the Food Products and Oil and Gas sectors have been each found to reach approximately $35 million, whereas the Automotive sector's fleet incurs a LCC of roughly $34 million; on the other hand, under Scenario 2, the LCCs of the fleets of Food Products and Oil and Gas sectors each increase by 3 percent, whereas the LCC of the Automotive sector's HDT fleet increases by 3.5 percent. This means that the LCCs of a newly composed HDT fleet in each of these sectors (respectively) are 6 percent, 6 percent, and 8 percent higher than that of a conventional fleet under Scenario 1, and 9 percent, 9 percent, and 11.5 percent higher than that of a conventional fleet under Scenario 2. Likewise, the fleets of the Beverages and Household Durables sectors incur LCCs of $32 million and almost $30 million, respectively, under Scenario 1, whereas the LCCs of these same fleets under Scenario 2 increase to $35 million for the Beverages sector and $33 million for the Household Durables sector. According to these results, the increases in the LCCs of the fleets in these sectors are negligible compared to the LCC of a conventional fleet. However, the HDT fleets in the Beverages and Household Durables sectors under Scenario 2 have been estimated to incur 7 percent and 10 percent higher LCCs, respectively, relative to those of a conventional fleet.

The LCAPECs observed in this analysis are shown in Figure 36 for the HDT fleets of each of the studied sectors under both of the scenarios being considered. The fleets in the Beverages and Household Durables sectors have incurred the highest LCAPECs, given the relative lack of BE HDTs (the only HDT type among those considered in this study that has zero tailpipe emissions) in their fleets under each scenario. Under Scenario 1, the LCAPECs of the fleets in these sectors exceed $19 million for the Beverages sector and $18 million for the Household Durables sector, although these LCAPECs decrease in Scenario 2 to $12.9 million for the Beverages sector and $12.1 million for the Household Durables sector, resulting in 33 percent and 34 percent reductions in their LCAPECs, respectively, in Scenario 2 compared to their corresponding LCAPECs in Scenario 1.

The HDT fleets of the Food Products and Oil and Gas sectors incur LCAPECs of slightly over $13 million under Scenario 1, and slightly over $10 million under Scenario 2, achieving a LCAPEC reduction of 23 percent from Scenario 1 to Scenario 2. This LCAPEC reduction is even higher when compared to the LCAPEC of a conventional fleet, with reductions of 36 percent under Scenario 1 and over 50 percent under Scenario 2. As can be seen in Figure 36, the HDT fleet of the Automotive sector has the lowest LCAPEC in both scenarios, mainly because of this sector's relatively lower payload and the higher number of BE HDTs in its fleet compared to other sectors, such as the Household Durables sector, which has the lowest payload. As a result, the LCAPEC of the Automotive sector fleet amounts to $15 million under Scenario 1 and $9 million under Scenario 2, indicating a decrease of 24 percent from Scenario 1 to Scenario 2. Compared to a conventional fleet in the Automotive sector, the newly composed fleet in this sector achieves the same reduction levels as those previously cited for the Beverages and Household Durables sectors under each scenario.

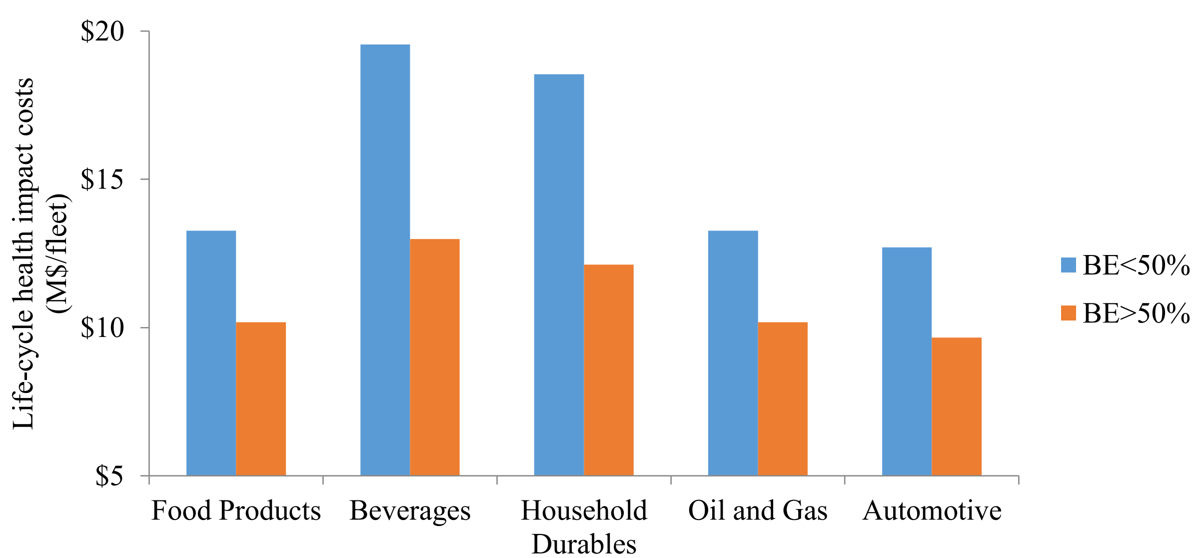

Figure 36: Life-cycle health impact costs of each sector fleet under each scenario

i

Parameter Selection and Cluster Validation

Figure 37 shows the Elbow graph for the dataset with outliers analyzed. As mentioned previously, the Elbow graph has been created based on cluster inertia, defined as the within-cluster sum of squared errors. Accordingly, the cluster inertia for $k = 1$ has been observed to be 22,794.58 – the highest value, as expected-, and then it went down drastically to 15,273.71 for $k = 2$; 7,131 for $k = 3$; and 5,954.76 for $k = 4$. After this point, the change in cluster inertia has been observed to be relatively slightly, going down to 5,281.14 for $k = 5$, which marked the "elbow" of the Elbow graph. This indicated that the appropriate number of k is 4 for the Z-score scaled dataset, with outliers, and 3 for the Z-score scaled dataset, without outliers.

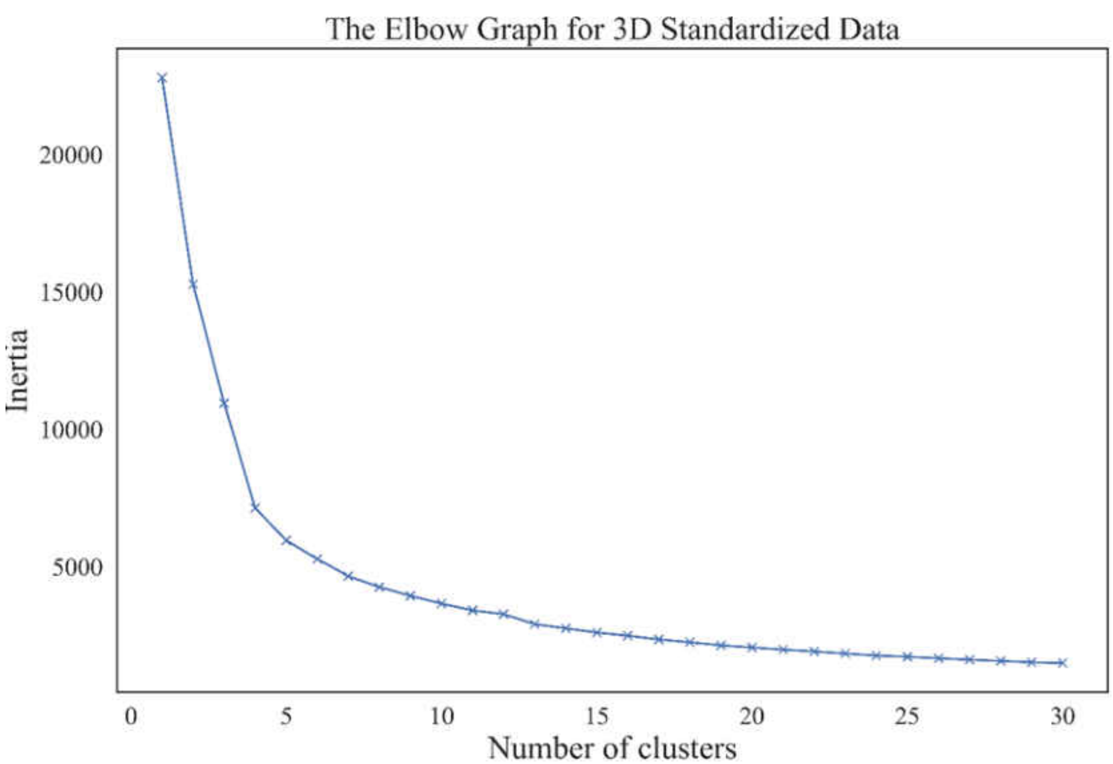

Figure 37 The Elbow curves for the data with outliers

The estimation of the cluster validation metrics (i.e. Silhouette coefficient, CH score, and DB score) for each cluster k has followed the creation of the Elbow graph. Accordingly, for the data with outliers, the silhouette coefficient has been observed to be 0.403, reaching the maximum value for $k = 4$. However, according to the subjective interpretation of the silhouette coefficients defined by Kaufman and Rousseeuw (1990), the maximum value found for the Silhouette coefficient lies in the range of 0.26 and 0.50, which may indicate that the clustering structure may be weak or artificial, suggesting the implementation of other metrics to ensure the result. To that end, CH and DB scores have been estimated to ensure the naturality of the 4 clusters formed. Accordingly, the maximum value for the CH score has been estimated to be 3710.72 for $k = 5$, and the value closest to its maximum has been estimated to be 3628.056 for $k = 4$. On the other hand, the DB score has been observed to reach at its minimum value, which has been estimated to be 0.863, at $k = 4$. Figure 38 presents the plots for all these cluster validation metrics for the data, with outliers included.

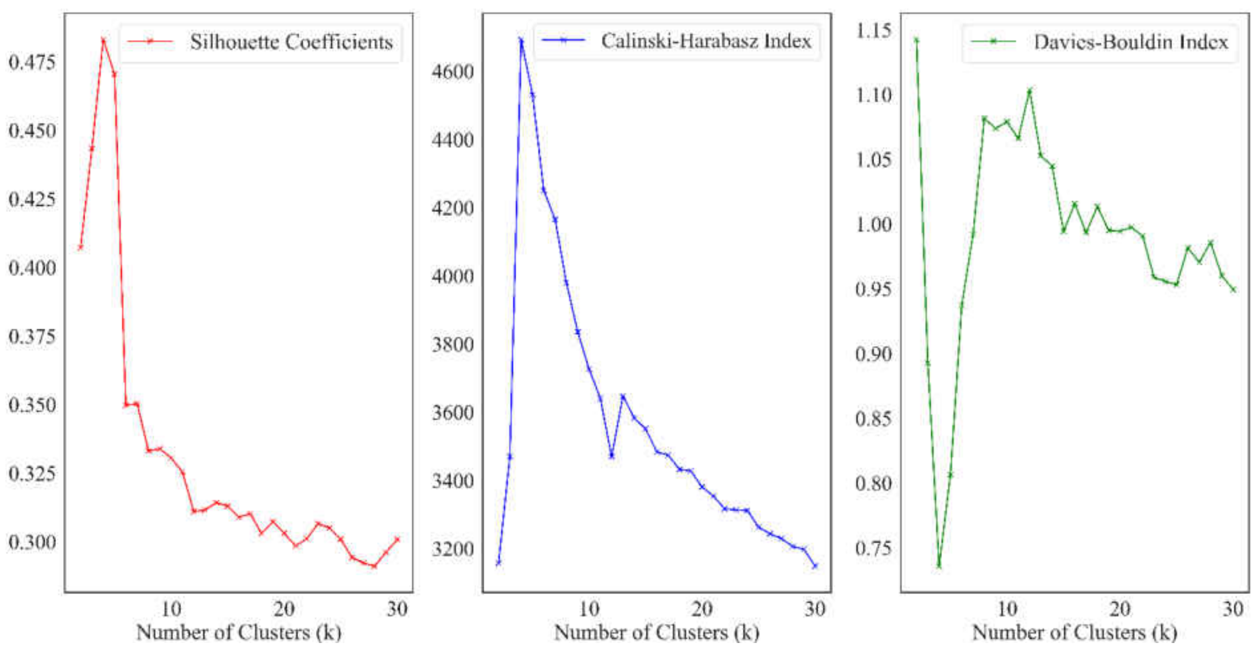

Figure 38 Silhouette coefficient, Calinski-Harabasz score, and Davies-Bouldin score for the Z-score scaled data (with outliers)

The same procedure as the one explained above has been applied to the Z-score scaled data, without outliers. The value of inertia for $k = 1$ has been estimated to be 13793.758, and decreased to 7694.125 for

$k = 2$, and 4395.775 for $k = 3$. After this point, the relative change in inertia has not shown a substantial change, going further down to 3719.354 for $k = 4$. According to the estimation of inertias for each cluster, Figure 39 has been plotted, clearly revealing the "elbow" to appear at $k = 3$, indicating the most appropriate value for k to be 3 for this dataset.

For this dataset, without outliers, all three cluster validation metrics have been estimated to reach their maximum at $k = 3$, as shown in Figure 39, and the separation was clearer. At the point where $k = 3$, the maximum Silhouette score has been estimated to be 0.516 – 0.04 unit higher than the second highest value, while the maximum CH score and the minimum DB score have been estimated to be 6409.252 and 0.803, respectively. Unlike the metrics for the data, with outliers, it has been observed looking at the cluster validation metrics estimated for the data, without outliers, that a better cluster structure and separation were achieved (Figure 40). This is also supported by the subjective interpretation of the estimated Silhouette coefficient, as defined by Kaufman and Rousseeuw (1990). Accordingly, the Silhouette coefficient estimated for the data set, without outliers, lies in the range of 0.51 and 0.70, which indicates the existence of a reasonable cluster structure.

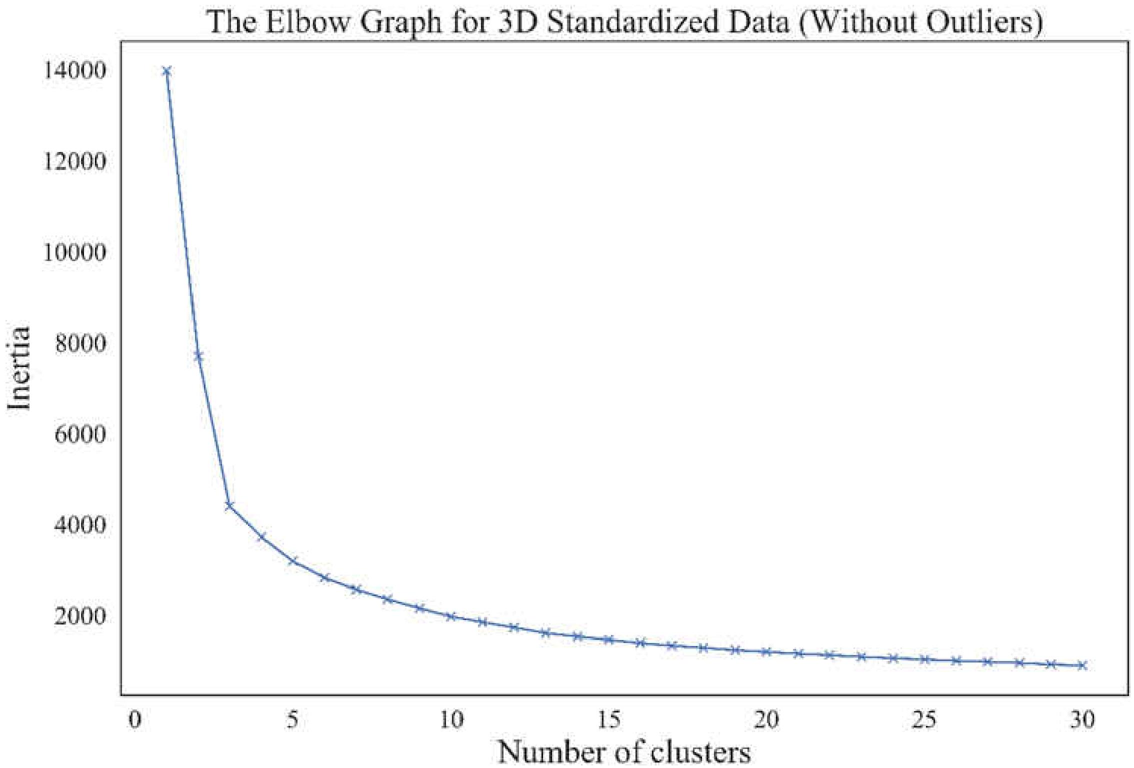

Figure 39 The Elbow curves for the data without outliers

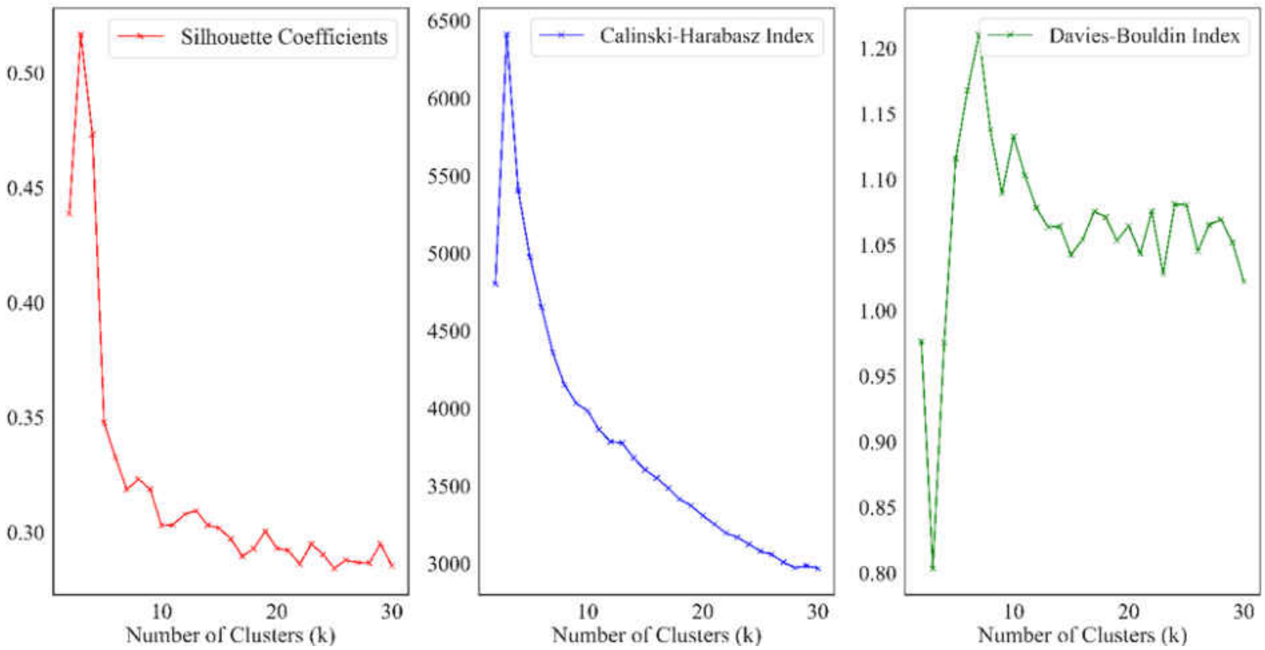

Figure 40 Silhouette coefficient, Calinski-Harabasz score, and Davies-Bouldin score for the Z-score scaled data (without outliers)

Clusters of Freight Routes

Following the analysis regarding the parameter selection and cluster validation analysis, the K-means algorithm has been run again for $k = 4$ for the dataset, with outliers included, and for $k = 3$ for the dataset, with outliers removed. As shown in Figure 41, the final cluster centers, indicated by the mean value of all the data points belonging to each cluster formed, show the same pattern. It has been observed based on these results, that the treatment of the potential outliers in the data resulted in the removal of a cluster that provided information regarding the routes ready for deployment of biodiesel HDTs. Therefore, to include in the analysis the information obtained from this cluster, the further analysis has been conducted based on the dataset, with outliers.

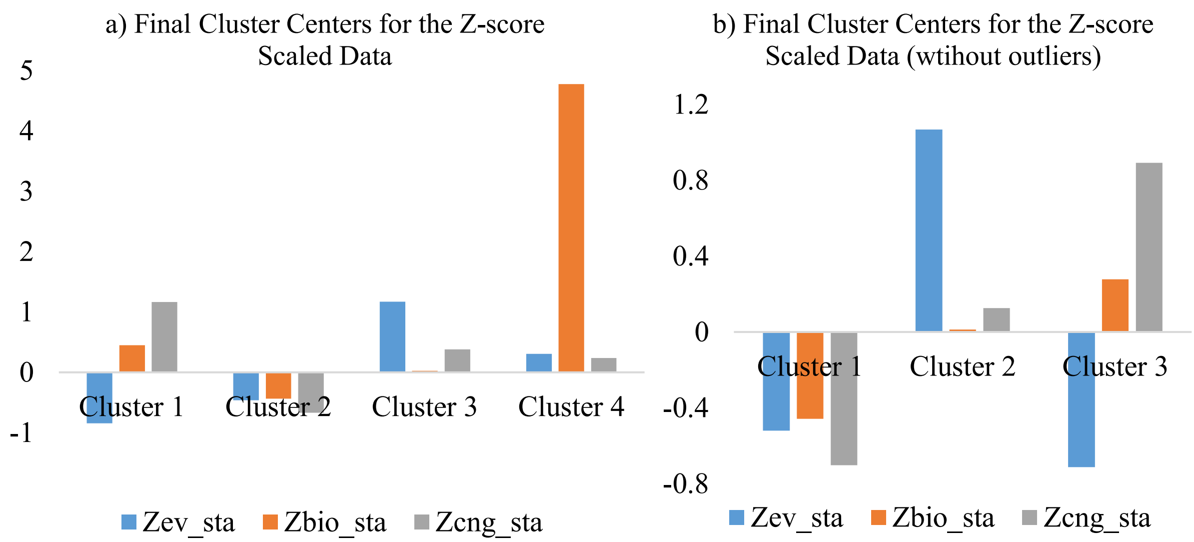

Figure 41 Final cluster centers for (a) dataset with outliers and (b) dataset without outliers

Based on the cluster analysis results, it has been observed that Cluster 1 consists of 1108 routes, while Cluster 2 and Cluster 3 consist of 3134 and 2002 routes, respectively. On the other hand, Cluster 4 consisted of only 170 routes. Cluster 1 has been observed to have the lowest electric HDT recharging stations and the highest number of CNG refueling stations relative to the other clusters. Cluster 2 has been observed to consist of the lowest number of biodiesel refueling stations and CNG refueling stations relative to all other clusters, while the number of electric HDT recharging has been higher relative to Cluster 1, though substantially lower than Cluster 3 and Cluster 4. The number of electric HDT recharging stations dominated Cluster 3, with moderate number of CNG refueling stations existing, as well. Cluster 4, on the other hand, has been observed to contain the highest number of biodiesel stations relative to the other clusters, with moderate numbers of electric HDT recharging and CNG HDT refueling stations existing, as well. The formed clusters are presented in Figure 42.

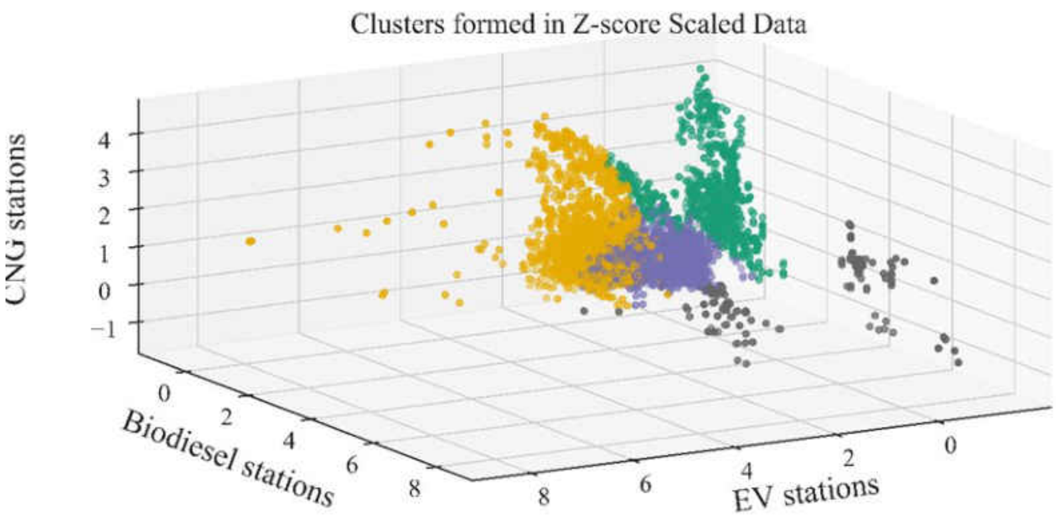

Figure 42 Clusters formed in the Z-score scaled data with outliers

To ease the interpretation of the results, it has been assumed that battery electric HDT consumes 240 kWh of energy per 100 miles and has a battery capacity of 700 kWh (Phadke et al. 2019), that a biodiesel HDT can fuel up to 120 gallons of biodiesel and has a fuel economy of 6 mile per gallon (Burnham 2017), and that a CNG HDT has a range of 400 miles, on average (Tong et al. 2019). Accordingly, the ranges of a battery electric HDT and a biodiesel HDT have been assumed to be approximately 300 miles and 720 miles, respectively. Based on these assumptions, it has been observed that the routes included in Cluster 1, Cluster 3, and Cluster 4 can support either one of the alternative fuel-powered HDT type considered in the analysis. Therefore, Cluster 2 should be paid an extra attention as it contains the routes, on which lack of infrastructure has been identified.

The distances over the routes originating from Miami, FL vary between 1,000 and 3,050 miles, with the latter being the distance between Miami FL and San Jose CA. As shown in Figure 43, Cluster 1 included mostly the routes destined to the west and mid-west of the country, while the routes destined to the east and south of the country are mostly included in Cluster 3. On the other hand, the only route included in Cluster 4 has been observed to be Miami FL and Portland OR, indicating that the availability of biodiesel

HDT refueling stations is higher relative to other routes. Accordingly, despite their sustainability performance similar to conventional HDTs, CNG HDTs can be an option for the freight originating from Miami FL and reaching at FAF destinations in California. As opposed to the FAF destination in California, the most viable alternative fuel option has been observed to be electricity for the routes originating from Miami FL and reaching at the FAF destinations in Texas, as all of these destinations appeared to be clustered in Cluster 3. It has been observed that the number of the longest routes (i.e.2,000+ miles) are mostly clustered in Cluster 1, where the number of CNG stations is higher relative to other clusters. The analysis has shown no route, originating from Miami FL, that has less than 10 charging stations. The longest route among these ones are Miami FL – Tucson AZ, with 2,200 miles, and Miami FL and Las Vegas NV, with 2,600 miles.

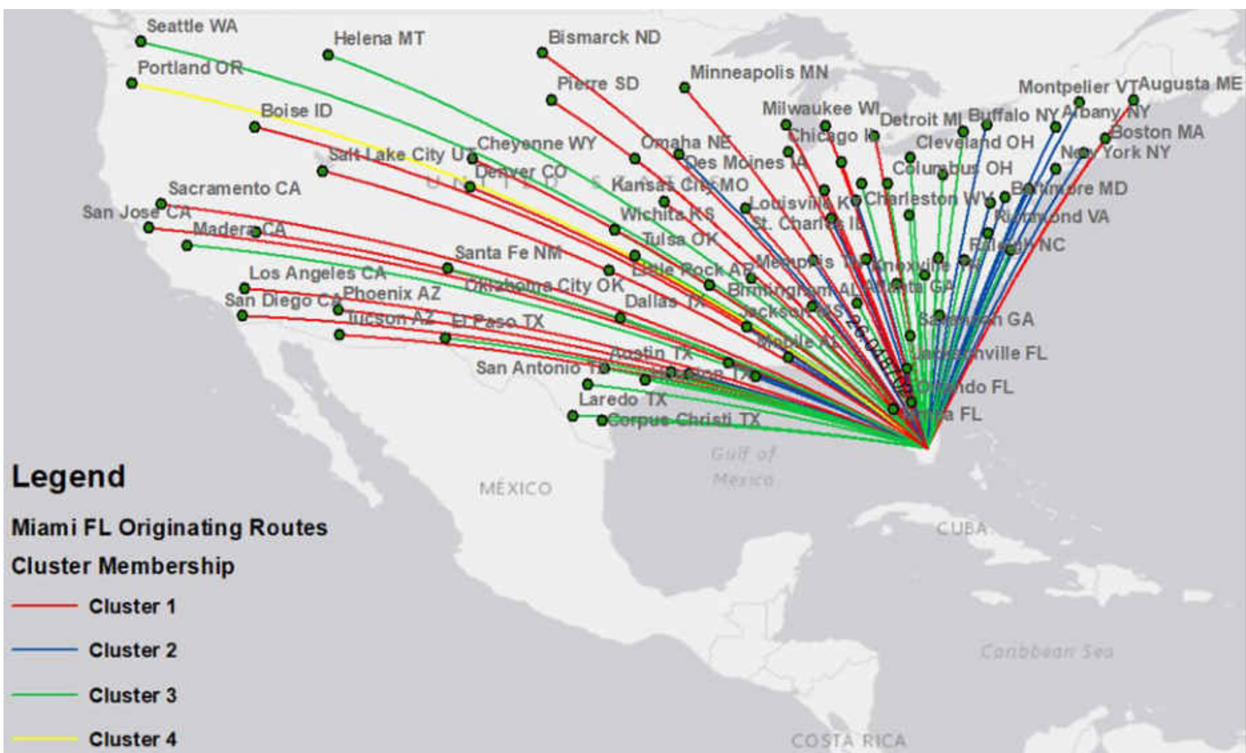

Figure 43 Clusters of the routes originating from Miami FL

CHAPTER FIVE: CONCLUSIONS, DISCUSSIONS, LIMITATIONS, AND FUTURE REMARKS

In Chapter Two, a holistic analysis and comparison of the life cycle emissions and costs, and air pollution externality costs of different types of alternative-fuel heavy-duty trucks have been presented. The HDT types analyzed in this research were biodiesel (B20) HDT, compressed natural gas (CNG) HDT, hybrid electric HDT, and battery electric BE HDT, with special attention paid to BE HDTs as an emerging technology. To that end, the life cycle performance of BE HDTs has been found to be heavily dependent on electricity generation-related activities. The changing circumstances of HDTs, i.e. projections for future diesel and electricity prices, the effect of payload on the fuel economy of a truck, and of tailpipe emissions deterioration factors, throughout their lifetimes have been also reflected.

This research has been the first comprehensive study that, in addition to the LCA of alternative fuel-powered HDTs, accounted for air pollution externalities in the form of APE costs incurred from the life cycle of a HDT. The inclusion of APE costs for different HDTs in LCA is an important consideration and a valuable contribution to the scientific body of knowledge in this particular domain. Another important consideration has been the inclusion of a specific analysis and comparison of BE HDTs based on the regional differences in electricity grid mixes and in the cost of electricity. Major differences have been observed between different NERC regions with respect to the emissions and costs from electricity generation.

EIO-LCA model used has been based on matrixes of transactions between sectors of a single country. The use of single-region I-O model leads to the fact that the impacts that are embedded in the domestic trade are better reflected in the results. However, a future study can extend the scope of this study including the environmental impacts of U.S. HDTs embedded in international trade using multi-regional input-output model as a complementary method in order to see the role of economic globalization, and minimize related uncertainties (Hertwich and Peters 2009; Kucukvar and Samadi 2015; Kucukvar et al. 2015, 2016a; Zhao et al. 2016b). An important limitation in Chapter Two is that the analysis did not present any estimation on potential impacts of the studied HDTs on midpoint or endpoint sustainability indicators. In fact, the research conducted in Chapter Three accounted for such indicators; however, it only accounted for automated diesel HDT and automated electric HDT, rather than including other HDT technologies such as hybrid electric, biodiesel, and CNG HDTs. Therefore, a future study could also broaden the analysis by including those HDT types left out and estimating the potential impacts of those HDTs on sustainability indicators (i.e. environmental, economic, and social indicators) such as global warming potential, water footprint, income and tax generation, and contribution to gross domestic product, as well.

As observed during the literature review, the data regarding BE HDTs is currently more limited than that of other alternative-fuel HDTs. For example, specific data on recharging infrastructure for BE HDTs could not be found and was therefore assumed to be the same as that for BE bus charging infrastructure. The lack of data on APE costs per gram of emissions from electricity generation meant that the authors could not compare the APE costs of BE trucks on a regional basis. Under the light of this research, it can be therefore stated that there is a dire need for improving the data collection regarding the alternative fuel-powered HDTs.

In Chapter Three, automation and electrification of HDTs, as an emerging technology, has been put under the spotlight to investigate its potential life cycle sustainability implications. Automating HDTs is certainly a multi-faceted, multi-dimensional task, necessitating the involvement of multiple stakeholders in developing, commercializing, and regulating the technology. Hence, focusing solely on one aspect or one dimension of the sustainability implications of the technology may mislead stakeholders involved in policymaking. To that end, the application of an input-output-based LCSA has been found useful for quantifying and encompassing several aspects and three dimensions of sustainability of automated and electrified HDTs. However, it should still be noted that the analysis carried out based on a different IO database, e.g. EXIOBASE, WIOD, or GTAP, would have likely shown some discrepancies in the results, as revealed in the studies such as Eisenmenger et al. (2016) and Moran and Wood (2014). There may be several reasons such as different approaches taken to construct an IO data, different standards used by countries to publish relevant data, and variation in sectoral resolution, that explain such a discrepancy between results obtained from using different databases (Wood et al. 2014).

Almost all of the considered aspects of the environmental dimension have been improved through automation and electrification, with the exception of mineral resource scarcity, which is a crucial point given the growing demand for minerals around the world (Ali et al. 2017). The improvement in mineral intensity brought by an automated diesel HDT is small, and an automated and electrified HDT increases mineral intensity significantly due to battery manufacturing. Activities associated with battery is an important driver of life cycle sustainability (LCS) impacts for BE HDTs, in general. In fact, the sensitivity analysis results have shown that the battery capacity has indeed a remarkable impact on LCSA results. Therefore, battery technology is a significant factor to be considered in assessing the sustainability impacts of HDTs. Given the method used in the analysis, the impact of battery technology and battery chemistry, e.g. Li-ion, NiMH, Lithium polymer, etc., would have been more visible, if an EIO-based LCSA method hybridized with process-based LCA for battery's impacts were used to analyze the LCS impacts of the studied vehicles.

The same holds for energy intensity, which decreases through automation, but increases due to the prevailing practice of power generation when an automated HDT is electrified. This means that, while automation is likely to lead to a decreased global warming potential of HDTs, it may result in an increase in the global warming potential of power generation, which may outweigh the benefits gained through automation in HDTs. The validation of the results can be better realized as more studies that examine the life cycle impacts of connected automated trucks are carried out. However, to the author's best knowledge, there is no study that has investigated the LCSI of automated trucks. Therefore, it is difficult to make an “apple-to-apple” comparison of this research’s results with those of another study. Nonetheless, some examples can be given. A automated diesel HDT and an automated electric HDT have been found to reduce GHG emissions by 10 percent and more than 60 percent, respectively, relative to a conventional HDT. Nahlik et al. (2015) reported similar results. They found that switching to hybrid or LNG truck technologies could reduce GHG emissions by 5 percent and 9 percent, respectively. The difference between the numbers may well be attributed to automation given the expected increase in driving efficiency. The LCC results correspond to an average decrease of $7,900 and $36,000 per truck per year in the LCCs of an automated diesel HDT and an automated electric HDT relative to a conventional HDT, respectively. These results align with the findings of Bishop et al. (2015), who reported only the fuel savings from two-diesel truck platooning to be $14,000 per truck per year.

As brought up by several scholars such as Clements and Kockelman (2017), Heard et al. (2018), and Crayton and Meier (2017), the findings of this research also show a decline in the rate of employment due to automation of diesel HDTs. Automated electric HDT has been observed to increase employment; however, this increase is not due to the automation but is attributed to charging infrastructure-related activities. The author agrees with Heard et al. (2018), stating that the negative effects of the decrease in employment (e.g. physical and mental health (Crayton and Meier 2017)) must be mitigated while seeking improvements in the overall sustainability performance. When the human health impact (HHI) due to tailpipe emissions are taken into consideration, the HHI has been observed to decline by 45 percent owing to electrification and automation, despite the health impacts of current electricity generation. In case the HHI due to tailpipe emissions are not taken into account, automation and electrification of HDTs have been observed to increase the risk on public health due to the indirect health impact caused by power generation. An analysis of an alternative power generation scenario, e.g. power generation from renewable energy resources, was out of the scope of this research. However, as also concluded in Chapter Two, the power generation phase is an important driver of HDT electrification. Therefore, if the power used to propel a BE

HDT is generated from a sustainable energy resource or an environmentally friendly grid mix, the impact profile of this truck type is highly likely to be positively different.

On the economic front, the decreases in the values of gross operating surplus (GOS) and gross domestic product (GDP) may look alarming at the first glance. However, the gains through the decreased import of materials – especially oil – as well as decreased cost of air pollution outweigh the loss resulting from decreased GOS and GDP combined. Fuel economy is a significant determinant for many aspects of sustainable HDTs. Therefore, interpreting the impacts of HDT automation on imports by focusing only on fuel may lead to overlooking the impacts of other system components. To this end, when fuel is removed from the picture, the impact of truck manufacturing as well as maintenance and repair of trucks can be seen better. In this regard, the application of sustainable design practices, e.g. switching to light-weighting materials, as suggested by Center for Automotive Research (2015), may further decrease the cost burden of imports going into automated HDTs. Such an application may have implications beyond imports by improving the mineral intensity of HDTs, which negligibly change through automation but increases due to automation and electrification of HDTs. Overall, given fuel economy's significant role in the LCS impacts of HDTs, the behavior of consumers and the market, and possible rebound effects that are likely to come along with automation should all be taken under scrutiny.

Several limitations exist due to the infancy of the technology and the lack of data associated with it on some important considerations. An important limitation arises from the year (i.e. 2015) of the IO tables used. The connected automated vehicle technology is a rapidly emerging technology that bears a certain level of uncertainties especially with regard to vehicle operation, including maintenance and fuel consumption, which are important considerations when making a vehicle purchase decision. In case of a large deployment of automated HDTs, the cost and technology structure of the industries included in IO tables may well change, leading to different results. Therefore, the estimated LCS impacts are limited only to the industry structure of the year 2015.

As stated by Greenblatt and Shaheen (2015), several other environmental impacts are worth investigating such as land use change (e.g. how the introduction of automated HDTs will affect roadway capacity) and impacts on biodiversity (e.g. urban ecosystems). The results were limited to the reported LCSA indicators due to a lack of data in this respect. In addition, as applied in Onat, Kucukvar, & Tatari (2016), multivariate uncertainty analysis can be applied to estimate the likelihood of the behavioral limits of sustainability potentials of each truck type.

Since the automated HDTs are likely to require a new set of skills for their maintenance and repair, a new industry (or industries), with its own price and technology structure, may be born, which could not be included in the analysis as existing IO databases, including the Eora database, do not currently contain such industry (or industries). As stated by Miller and Blair (2009), impacts associated with the introduction of a new industry into a regional or a national economy is possible within the IO modeling framework. In order to be able to assess such impacts, estimation of the input coefficients for the new sector, i.e. inputs from all other sectors per dollar output of the new sector, is required. However, the lack of data in this regard did not make it possible for this research to report the impact of the introduction of a potential new sector. Similarly, since the Eora database does not have data on the PM2.5 pollutions, the sustainability impacts of this pollutant could not be reported. However, the author acknowledges that PM2.5 is an air pollutant that has significant public health implications. Another aspect that was left out of the scope is the end-of-life of the studied automated HDTs. Given more data availability, the author will attempt to include this phase, as well, and report an HDT's cradle-to-grave life cycle sustainability impacts in a future study.

The impact of connected automated vehicle technology on employment should be further scrutinized. The IO modeling framework alone does not provide a means to identify the driving factors of impacts on employment. Structural decomposition analysis (SDA) could be applied to identify these factors of what has caused the reported decrease in employment and analyze how employment related to transporting goods (i.e. truck drivers) is affected by the introduction of the technology. Such an analysis will be applied in a follow-up study, which will employ a dynamic multi-regional IO modeling. However, its impact on the overall employment was put under the spotlight, which is still an important insight provided by this research. Furthermore, while the CAV technology's impact on the employment of truck drivers is an important point of discussion regarding the adoption of autonomous trucks among researchers, American Trucking Association stated that the impact of driver-assist automation technologies installed in HDTs may even have a positive impact on the driver shortage experienced by the industry (Costello 2017). Similarly, a recent report published by Viscelli (2018) concluded that, while the jobs that might be lost to automated HDTs could reach as much 300,000, there would be enough jobs to replace the displaced drivers, thanks to the growth of e-commerce and significance of local delivery. The results of the research conducted in Chapter Two reported with respect to employment align with these viewpoints to a certain extent.

Another important aspect that has been left out but will be scrutinized in a future study is the examination of likely LCS profiles of automated HDTs under potential renewable energy transition scenarios. To increase the benefits of this research or similar ones focusing on emerging technologies in transportation, the implications of the social impacts from public policy perspective should be further investigated by experts that can evaluate these implications from such a perspective (e.g. a political scientist). However, the author humbly believes that any aspect that improves the public's standards of living, starting from human health, should be prioritized.

Furthermore, the author has encountered some difficulties in assessing some of these impacts more thoroughly given methodological and data limitations. It is also quite difficult to make a scientific inference regarding the changes in the sustainability impacts overall in the future, given the pace of technological developments as well as the level of uncertainty in the on-going transformation in transportation. Nevertheless, the author expects a rapid change towards automation and connectivity in the near future, particularly in surface transportation. The budgetary actions realized both by governments and by automotive industry giants are a good indication of this tendency. Remarkable improvements may be expected in the sustainability performance of HDTs; however, there are always questions that remain problematic such as how the demand for transportation will evolve, which will have an important influence on the likely future.

Another aspect that may be regarded as a limitation is that other fuel technologies such as compressed natural gas (CNG)-powered HDTs have not been included in the analysis, as mentioned previously. There are two main reasons that explain this exclusion. Firstly, the research conducted in Chapter Two on the life cycle analysis of alternative fuel-powered Class 8 heavy-duty vehicles showed that CNG HDTs remarkably underperform BE HDTs, and only slightly outperforms diesel HDTs. Secondly, transforming the transportation system is planned to be fully autonomous and connected. Such a smart concept of vehicles of the future is deemed to be generally inherently including the use of electricity, which may be due to a realization that fossil fuels cannot be a smart choice anymore.

Coupled with pressures currently arising from various social-ecological circumstances, today's competitive market environment necessitates the consideration of multiple objectives while designing an HDT fleet for any sector. Chapter Four addressed this necessity by conducting a hybrid LCA-based robust Pareto optimal analysis. This research presented an adaptive and applicable model that can be modified based on each sector's fleet requirements in order to find an optimal fleet mix for each application.

Overall, it can be concluded that hybrid electric and BE HDTs are both viable options for a transition to a robust Pareto optimal, more sustainable HDT fleet for each of the studied sectors. This holds despite the relatively higher initial cost (including per-truck infrastructure cost) of BE HDTs. BE HDTs were included in the RPO solution in a vast majority of the considered sector/scenario combinations, even when the constraint on GHGs emissions was soft. The viability of BE HDTs holds from the perspective of infrastructure readiness, as well. Despite its several limitations, the cluster analysis showed that the alternative fuel infrastructure is, in fact, relatively readier for BE HDT deployment than other alternative fuel types. The fleets composed based on the robust Pareto optimal solution lead to important reductions, particularly in both LCFCs and LCAPECs compared to those of a conventional fleet. Since LCAPEs are related to air pollutants, to which communities are exposed to, and regarded as a parameter representative of the social aspect in the analysis, the relative reduction in these costs indicate improved social well-being through cleaner air. However, LCGHG emissions reductions were relatively unsatisfactory, not exceeding 10 percent compared to the LCGHG emissions of a conventional HDT fleet, due to the high GHG emissions associated with the current form of electricity generation as well as the current fuel economy of HDTs. This means that additional efforts are necessary to be made in order to contribute to mitigating negative consequences of HDTs' global warming potential, which has been estimated to pose serious concerns for societal well-being. One of these efforts may be to reform energy policies that currently favor the use of fossil resources in supplying energy as well as internalize sustainability strategies as a part of policymaking and governance at all levels, including corporate, regional, national, and international. When the newly composed fleet was required to achieve a 30 percent reduction in GHG emissions (i.e. the primary aim of Executive Order 13693 issued by the White House (2015)), the GAMS software could not find any feasible solution under neither of the two scenarios analyzed. Furthermore, LCC reductions do not seem possible under the current techno-economic circumstances and given the constraints on the number of alternative-fuel HDts.

Biodiesel- or CNG-fueled HDTs were not included in any fleet mix. The reason is likely to be that these two types of HDTs do not bring any significant life cycle environmental, social (i.e. LCAPE costs), or economic improvements relative to conventional HDTs. One measure that can explain this result is that the emission intensity of natural gas production and use is greater than that of diesel production and use. Additionally, CNG-fueled HDTs require the construction of a natural gas refueling station, which increases the life cycle costs of this truck type higher than that of diesel HDT. Similarly, even though the cost of biodiesel HDT operation is less than that of diesel HDT, the former incurs relatively higher LCCs. Based on the cluster analysis conducted in Chapter Four, the inclusion of biodiesel is not recommended under the current circumstances, as several freight routes have been found lacking the appropriate infrastructure. On the other hand, even though CNG HDTs do not significantly change the "picture" in terms of the sustainability performance of freight transportation, it can be considered a deployment option alternative to diesel HDTs from the perspective of energy security.

Technological advancements in HDTs and their improvements in the sustainability performance of these vehicles are sensitive to socio-political circumstances, meaning that different policy-making approaches are likely to result in different optimal solutions when composing a heavy-duty truck fleet in any economic sector. The environmental burdens arising from the national electricity generation can be decreased through cleaner means of power generation. The efforts made by governmental institutions to improve the fuel economy of HDTs should be continued (and/or strengthened, wherever possible) if U.S. HDT freight fleets are to meet the given objectives by 2025. Otherwise, the GHG emissions reduction objectives set forth in the Executive Order 13693 cannot be achieved.

The sector-specific goal prioritizations tempered the effect of the load-specificity on the fleet composition as a factor. This explains why, for instance, the Beverages sector fleet produced more GHG emissions than the Food Products sector fleet despite having a lower average payload. Even though this research was conducted for 5 sectors only, it considered ordinary operation conditions with relatively soft constraints on LCCs, LCAPECs, and LCGHG emissions as shown in Table C.30. Therefore, the applications of this study are not restricted to these sectors but can include the optimization of HDT fleets in all U.S. sectors.

It is possible to mention several limitations that hindered to an extent drawing more effective conclusions in Chapter Four. One of these limitations is the lack of constraints with respect to HDTs. The author believes that this is due mainly to the fact that, even though policy-makers and scientists have recently put significant amounts of effort into improving the sustainability of heavy-duty vehicles, such vehicles have not yet been studied or regulated as much as light-duty vehicles have been. Therefore, to add more value to this analysis, a future study should attempt to apply more constraints, if necessary, to the RPO solution model (e.g. air pollutant constraints) that are plausible and representative of real-world operational conditions.

Given the existence of several plausible data sources, assumptions are an intrinsic part of the studies that incorporate sustainability implications of economic activities (e.g. production and consumption). The values assumed for model variables, e.g. fuel prices, annual mileage, battery capacity, etc., may well change from region to region and fleet to fleet, and companies may have different sensitivities to any one of these variables. Additionally, fleets may be subjected to different constraints depending on regulatory and techno-economic circumstances, under which they operate. Therefore, the results of the study conducted in Chapter Four represent only the cases that have been showcased.

Another important limitation is that the cluster analysis conducted following the optimization problem considered a single route for each origin-destination pair. Although the routes were checked for consistency with respect to the National Freight Highway Network map, the real-world traffic conditions may well affect the routing of freight trucks, causing them to divert from their usual routes. Furthermore, the cluster analysis did not consider the freight traffic flow over these routes, which would give an idea regarding the demand for an alternative fuel option and help make use of alternative fuel station capacities. The assumption made for the cluster analysis, that alternative fuel stations would be readily available for immediate refill, may not hold at all times and this would obviously imply a reduction in infrastructure availability.

The research conducted in Chapter Four is also limited by the lack of consideration of different means of electricity generation (e.g. renewable electricity). This is especially important given the fact that variations in electricity generation sources can and will have a significant impact on the overall efficiency and sustainability of BE HDTs (Mai et al. 2018). The inclusion of different electricity sources (especially renewable electricity) is likely to change the HDT fleet distribution. Furthermore, a future study could carry out a sector-specific survey investigating more robust weighting factors for study objectives. This is particularly important because of two primary reasons:

1) The literature lacks data with regard to sector-specific weighting factors, and
2) The weighting factors, which determine the sector-specific prioritization of objectives, are as significant as LSFE of HDTs in determining a robust Pareto optimal solution to composing a sustainable HDT fleet.

APPENDIX A
SUPPLEMENTARY INFORMATION FOR CHAPTER 2

Table A.14: Emission factors obtained from GREET

LCI component	GHGs (t)	CO (t)	NO_X (t)	PM10 (t)	PM2.5 (t)	SO_X (t)	VOC (t)
Battery Manufacturing and Replacement (400 kWh)	13.0008	0.00852	0.0223	0.00993	0.00597	0.10733	0.00411
Battery Manufacturing and Replacement (270 kWh)	8.79426	0.00576	0.0151	0.00671	0.00403	0.07248	0.00277
Battery Manufacturing and Replacement (25 kWh)	0.866242	0.00055	0.0014	0.00063	0.00038	0.00680	0.00026
Battery Manufacturing and Replacement (5 kWh)	0.219172	0.00013	0.0003	0.00013	0.000082	0.00144	0.00005
Biodiesel (B100) production	0.002018	5.58E-6	4.81E-6	3.70E-7	3.10E-7	0	2.97E-6

Table A.15: Tailpipe emission factors obtained from AFLEET

LCI component	CO (g/mile)	NO_X (g/mile)	PM10 (g/mile)	PM2.5 (g/mile)	VOC (g/mile)
Diesel – B20 – Hybrid	1.574	4.2967	0.0284	0.0276	0.4015
CNG	24.2396	2.57892	0.0284	0.0276	1.304875

Table A.16: CO emission factors (ton per $1 million) for Diesel and CNG fuels

Phase	NAICS Sector	Diesel	CNG
Vehicle Manufacturing and Refueling Infrastructure	Heavy Duty Vehicle Manufacturing	3.27	3.27
	Trailer Manufacturing	4.5	4.5
	Metal Tank, Heavy Gauge Manufacturing (additional part for CNG trucks)	n.a.	4.22
	Metal Tank, Heavy Gauge Manufacturing (material necessary for CNG infrastructure)	n.a.	4.22
	Other nonresidential construction equipment	n.a.	4.21
	All miscellaneous electrical equipment manufacturing (for CNG infrastructure)	n.a.	1.72
Fuel Production (based on fuel consumption)	Natural (industrial) Gas Manufacturing	n.a.	3.37
	Petroleum Refineries	5.22	n.a.

Phase	NAICS Sector	Diesel	CNG
Operation/Use	Automotive Mechanical and Electrical Repair and Maintenance	1.38	1.38
	Tailpipe (g/mile)	1.574	24.2396

APPENDIX B
SUPPLEMENTARY INFORMATION FOR CHAPTER 3

Table B.17: Life cycle sustainability impact multipliers related to greenhouse gas emissions (tons) per $M output of each industry

	Eora Sectors	*CO2*	*CH4*	*NOx*	*HFC-134a*	*HFC-143a*	*HFC-125*
Manufacturing Phase, including manufacturing of automation related parts, battery, trailer, and fuel production	*Truck trailer manufacturing*	301.43	1.52	0.67	0.72	0.75	0.74
	HDT manufacturing	353.06	1.07	0.28	0.30	0.31	0.31
	Motor vehicle parts manufacturing	358.74	1.33	0.19	0.18	0.19	0.19
	All other miscellaneous electrical equipment and component manufacturing	163.09	0.84	0.44	0.49	0.50	0.50
	Search, detection, and navigation instruments manufacturing	178.88	0.58	0.17	0.18	0.19	0.19
	Telecommunications	121.18	0.62	0.06	0.06	0.06	0.06
	Broadcast and wireless communications equipment manufacturing	184.88	0.54	0.17	0.18	0.19	0.19
	Mechanical power transmission equipment manufacturing	268.39	1.78	0.88	0.97	1.01	0.99
	Hardware manufacturing	234.54	1.09	0.34	0.36	0.38	0.37
	Relay and industrial control manufacturing	153.48	0.69	0.37	0.40	0.42	0.42
	Storage battery manufacturing	324.15	1.47	0.63	0.68	0.71	0.69
	Electric power generation, transmission, and distribution	3,734.25	11.51	0.13	0.06	0.06	0.06
	Petroleum refineries	942.12	9.49	0.22	0.05	0.05	0.053
Operation Phase, including M&R, infrastructure	*Electronic and precision equipment repair and maintenance*	73.43	0.42	0.15	0.16	0.17	0.165
	Automotive repair and maintenance	130.68	0.58	0.07	0.06	0.06	0.064
	Storage battery manufacturing	324.15	1.47	0.63	0.68	0.71	0.69
	Retail trade	159.07	0.75	0.07	0.04	0.05	0.048

	Eora Sectors	*CO2*	*CH4*	*NOx*	*HFC-134a*	*HFC-143a*	*HFC-125*
construction, and battery replacement	*Commercial and industrial machinery and equipment repair and maintenance*	83.48	0.57	0.14	0.15	0.15	0.15

Table B.18: Life cycle sustainability impact multipliers related to criteria pollutant emissions and Total Water Footprint (TWF)

		Impact Multipliers*				
	Eora Sectors	*CO*	*PM10*	*VOC*	*SO2*	*TWF*
Manufacturing Phase, including manufacturing of automation related parts, battery, trailer, and fuel production	*Truck trailer manufacturing*	3.85	0.73	1.30	1.26	104.69
	HDT manufacturing	2.79	0.33	0.87	1.02	104.80
	Motor vehicle parts manufacturing	3.56	0.24	0.89	0.92	103.37
	All other miscellaneous electrical equipment and component manufacturing	2.82	0.42	0.85	0.92	60.15
	Search, detection, and navigation instruments manufacturing	1.63	0.48	0.66	0.78	55.82
	Telecommunications	0.79	0.09	0.28	0.27	11.55
	Broadcast and wireless communications equipment manufacturing	1.38	0.20	0.42	0.55	55.07
	Mechanical power transmission equipment manufacturing	3.22	0.95	1.27	1.47	79.46
	Hardware manufacturing	2.59	0.38	0.77	0.83	54.10
	Relay and industrial control manufacturing	1.63	0.40	0.60	0.67	52.55
	Storage battery manufacturing	3.07	0.69	1.15	1.35	82.54
	Electric power generation, transmission, and distribution	3.16	0.60	3.98	10.88	26.88
	Petroleum refineries	1.13	0.16	4.87	1.25	57.95
Operation Phase, including M&R, infrastructure construction, and battery replacement	*Electronic and precision equipment repair and maintenance*	0.68	0.17	0.29	0.27	6.92
	Automotive repair and maintenance	1.14	0.09	0.34	0.28	13.41
	Storage battery manufacturing	3.07	0.69	1.15	1.34	82.54
	Retail trade	1.50	0.08	0.35	0.33	61.55
	Commercial and industrial machinery and equipment repair and maintenance	0.72	0.162	0.32	0.28	9.23

* The unit for emissions is *ton/$M*, whereas it is *$m^3$/$M* for TWF.

Table B.19: Life cycle sustainability impact multipliers related to criteria pollutant emissions and Total Water Footprint (TWF)

		Impact Multipliers*				
	Eora Sectors	*CO*	*PM10*	*VOC*	*SO2*	*TWF*
Manufacturing Phase, including manufacturing of automation related parts, battery, trailer, and fuel production	*Truck trailer manufacturing*	3.85	0.73	1.30	1.26	104.69
	HDT manufacturing	2.79	0.33	0.87	1.02	104.80
	Motor vehicle parts manufacturing	3.56	0.24	0.89	0.92	103.37
	All other miscellaneous electrical equipment and component manufacturing	2.82	0.42	0.85	0.92	60.15
	Search, detection, and navigation instruments manufacturing	1.63	0.48	0.66	0.78	55.82
	Telecommunications	0.79	0.09	0.28	0.27	11.55
	Broadcast and wireless communications equipment manufacturing	1.38	0.20	0.42	0.55	55.07
	Mechanical power transmission equipment manufacturing	3.22	0.95	1.27	1.47	79.46
	Hardware manufacturing	2.59	0.38	0.77	0.83	54.10
	Relay and industrial control manufacturing	1.63	0.40	0.60	0.67	52.55
	Storage battery manufacturing	3.07	0.69	1.15	1.35	82.54
	Electric power generation, transmission, and distribution	3.16	0.60	3.98	10.88	26.88
	Petroleum refineries	1.13	0.16	4.87	1.25	57.95
Operation Phase, including M&R, infrastructure construction, and battery replacement	*Electronic and precision equipment repair and maintenance*	0.68	0.17	0.29	0.27	6.92
	Automotive repair and maintenance	1.14	0.09	0.34	0.28	13.41
	Storage battery manufacturing	3.07	0.69	1.15	1.34	82.54
	Retail trade	1.50	0.08	0.35	0.33	61.55
	Commercial and industrial machinery and equipment repair and maintenance	0.72	0.162	0.32	0.28	9.23

Table B.20: Life cycle sustainability impact multipliers related to energy consumption per $M output of each sector (TJ)

	Eora Sectors	Impact Multipliers*		
		Coal	**Natural Gas**	**Oil**
Manufacturing Phase, including manufacturing of automation related parts, battery, trailer, and fuel production	*Truck trailer manufacturing*	965.47	1,209.61	2,519.59
	Heavy duty truck manufacturing	1,331.64	1,243.04	2,003.46
	Motor vehicle parts manufacturing	1,347.11	1,740.69	2,885.60
	Motor and generator manufacturing	964.05	1,022.04	1,882.23
	All other miscellaneous electrical equipment and component manufacturing	507.90	626.43	991.85
	Search, detection, and navigation instruments manufacturing	638.97	774.03	945.57
	Telecommunications	514.80	629.53	855.88
	Broadcast and wireless communications equipment	447.18	681.95	936.87
	Mechanical power transmission equipment manufacturing	1,156.53	985.05	1,751.36
	Hardware manufacturing	877.17	900.77	1,681.57
	Relay and industrial control manufacturing	481.36	681.87	1,010.38
	Storage battery manufacturing	1,420.85	1,189.41	1,735.71
	Electric power generation, transmission, and distribution	29,492.78	10,681.96	6,506.98
	Petroleum refineries	1,514.61	6,385.66	4,606.11
Operation Phase, including M&R, infrastructure construction, and battery replacement	*Electronic and precision equipment repair and maintenance*	304.90	348.17	414.30
	Automotive repair and maintenance, except car washes	551.40	548.05	751.74
	Storage battery manufacturing	1,420.85	1,189.41	1,735.71
	Retail trade	681.81	605.37	781.50

Table B.21: Life cycle sustainability impact multipliers related to mineral use per $M output of each sector (tons)

	Eora Sectors	Impact Multipliers				
		Copper	Lead	Zinc	Min. Qu.*	Iron
Manufacturing Phase, including manufacturing of automation related parts, battery, trailer, and fuel production	*Truck trailer manufacturing*	9,583.39	383.04	381.76	26.92	21,231.08
	Heavy duty truck manufacturing	10,476.69	418.74	417.35	24.86	9541.06
	Motor vehicle parts manufacturing	23,108.98	923.64	920.56	36.04	27,305.35
	Motor and generator manufacturing	40,919.33	1,635.49	1,630.05	21.06	23,804.15
	All other miscellaneous electrical equipment and component manufacturing	21,152.53	845.44	842.63	12.87	3427.93
	Search, detection, and navigation instruments manufacturing	10,296.97	411.56	410.19	13.27	2,248.73
	Telecommunications	4,339.19	173.43	172.86	23.02	665.60
	Broadcast and wireless communications equipment	11,386.00	455.08	453.57	14.92	2,255.96
	Mechanical power transmission equipment manufacturing	8,770.31	350.54	349.37	23.16	25,196.53
	Hardware manufacturing	12,394.80	495.40	493.76	18.65	22,480.64
	Relay and industrial control manufacturing	32,841.07	1,312.62	1,308.25	10.59	4,988.92
	Storage battery manufacturing	131,662.00	5,262.37	5,244.86	35.07	4,792.81
	Electric power generation, transmission, and distribution	2,434.54	97.31	96.98	79.07	913.87
	Petroleum refineries	4,251.19	169.91	169.35	28.11	948.06
Operation Phase, including M&R, infrastructure construction, and battery replacement	*Electronic and precision equipment repair and maintenance*	12,276.59	490.68	489.05	5.82	558.84
	Automotive repair and maintenance, except car washes	2,153.67	86.08	85.79	8.17	707.10
	Storage battery manufacturing	131,662.00	5,262.37	5,244.86	35.07	4,792.81
	Retail trade	2,914.39	116.48	116.10	10.60	754.94

Table B.22: Life cycle sustainability impact multipliers related to social indicators per $M output of each sector

Eora Sectors		Impact Multipliers			
		Employment[a]	Fatal Injuries[a]	Non-Fatal Injuries[b]	Income[c]
Manufacturing Phase, including manufacturing of automation related parts, battery, trailer, and fuel production	*Truck trailer manufacturing*	6,808.26	0.82	0.60	$502,293.78
	Heavy duty truck manufacturing	3,680.95	0.12	0.29	$405,066.07
	Motor vehicle parts manufacturing	3,795.74	0.18	0.36	$290,581.24
	Motor and generator manufacturing	3,888.80	0.09	0.27	$447,575.87
	All other miscellaneous electrical equipment and component manufacturing	4,739.97	0.07	0.37	$492,736.38
	Search, detection, and navigation instruments manufacturing	5,082.56	0.07	0.31	$556,919.22
	Telecommunications	2,675.77	0.10	0.44	$211,352.11
	Broadcast and wireless communications equipment	3,990.95	0.08	0.34	$458,386.65
	Mechanical power transmission equipment manufacturing	4,266.62	0.10	0.33	$574,124.49
	Hardware manufacturing	3,493.68	0.09	0.29	$460,321.04
	Relay and industrial control manufacturing	4,733.90	0.06	0.25	$455,389.68
	Storage battery manufacturing	3,858.33	0.11	0.23	$443,892.89
	Electric power generation, transmission, and distribution	2,743.11	0.12	0.18	$298,521.54
	Petroleum refineries	1,763.35	0.08	0.10	$126,817.27
Operation Phase, including M&R, infrastructure construction, and battery replacement	*Electronic and precision equipment repair and maintenance*	4,232.35	0.15	0.21	$476,658.30
	Automotive repair and maintenance, except car washes	6,544.75	0.76	0.52	$370,479.75
	Storage battery manufacturing	3,858.33	0.11	0.23	$443,892.89
	Retail trade	3,672.04	0.30	0.93	$181,413.95

Table B.23: Life cycle sustainability impact multipliers related to economic indicators per $M output of each sector ('000 USD)

Eora Sectors		Impact Multipliers			
		Import	GOS	GDP	Tax
Manufacturing Phase, including manufacturing of automation related parts, battery, trailer, and fuel production	*Truck trailer manufacturing*	217.79	210.88	739.12	25.95
	Heavy duty truck manufacturing	264.93	249.46	680.97	26.45
	Motor vehicle parts manufacturing	202.97	391.16	718.46	36.72
	Motor and generator manufacturing	167.88	339.29	806.60	19.73
	All other miscellaneous electrical equipment and component manufacturing	184.96	277.08	790.24	20.42
	Search, detection, and navigation instruments manufacturing	135.42	233.42	812.49	22.15
	Telecommunications	56.68	407.44	791.28	172.49
	Broadcast and wireless communications equipment	227.84	231.99	717.04	26.66
	Mechanical power transmission equipment manufacturing	115.34	259.46	855.97	22.39
	Hardware manufacturing	125.37	366.37	846.40	19.70466
	Relay and industrial control manufacturing	158.28	347.75	821.88	18.74201
	Storage battery manufacturing	264.63	244.73	712.00	23.38033
	Electric power generation, transmission, and distribution	61.22	470.40	877.60	108.6796
	Petroleum refineries	568.87	244.92	399.47	27.73358
Operation Phase, including M&R, infrastructure construction, and battery replacement	*Electronic and precision equipment repair and maintenance*	96.57	396.42	896.00	22.93053
	Automotive repair and maintenance, except car washes	144.93	385.70	811.62	55.43569
	Storage battery manufacturing	264.63	244.73	712.00	23.38033
	Retail trade	40.55	452.50	815.58	181.6691

Table B.24: Emissions characterization factors (CFs) for Global Warming Potential (GWP), Particulate Matter Formation Potential (PMFP), and Photochemical Oxidant Formation Potential (POFP)

Emissions	GWP CFs (kg CO_2 eq. per kg of emission)	PMFP CFs (kg PM10-eq. per kg emission)	POFP CFs (kg NMVOC-eq. per kg emission)
CO_2	1	-	
CH_4	34	-	0.01
CO	-	-	0.046
NO_x	298	0.22	-
PM10	-	1	-
SO2	-	0.2	0.081
VOC			1
HFC-134a	1549	-	-
HFC-125	3691	-	-
HFC-143a	5508	-	-

Table B.25: Characterization factors for Mineral Resource Scarcity (kg Cu-eq. per kg of resource) and Fossil Resource Scarcity (kg oil-eq per kg of resource)

Mineral and Energy Sources	**Mineral Resource Scarcity CFs**	**Fossil Resource Scarcity**
Copper	1	-
Lead (t)	0.490962827	-
Zinc (Zn) (t)	0.153471592	-
Gold (t)	3734.1494	-
Mining and quarrying (t)	0.0104398	-
Iron (Fe) (t)	0.061936591	-
Coal	-	0.32
Natural Gas	-	0.84
Oil	-	1

Table B.26: Characterization factors for endpoint impacts of each of the midpoint impacts

	Human Health Impact (DALY/kg midpoint impact)	**Mineral Resource Depletion ($/kg Cu-eq.)**	**Fossil Resource Depletion ($/kg) or ($/Nm^3)**
Global Warming Potential	9.28E-07	-	-
Particulate Matter Formation Potential	2.60E-04	-	-
Photochemical Oxidant Formation Potential	3.90E-08	-	-
Mineral Resource Scarcity	-	2.31E-01	-
Oil	-	-	0.46
Coal	-	-	0.03
Natural Gas	-	-	0.30

APPENDIX C
DETAILS OF THE MULTIOBJECTIVE OPTIMIZATION MODEL

Sets:

The set i consists of the studied heavy-duty truck types, and is indexed as shown in Table C.27.

Table C.27: Index for the set of heavy-duty truck types

Fuel alternative for heavy-duty trucks (HDTs)	Index
Diesel	$i = 1$
Biodiesel	$i = 2$
CNG	$i = 3$
Hybrid	$i = 4$
Battery-electric	$i = 5$

The set j consists of the studied sectors, and is defined as shown in Table C.28.

Table C.28: Index for the set of sectors

Sectors	Index
Food Products	$j = 1$
Beverages	$j = 2$
Household Durables	$j = 3$
Oil and Gas	$j = 4$
Automotive	$j = 5$

The set r consists of the objectives, and is defined as shown in Table C.29.

Table C.29: Index for the set of objectives

Objectives	Index
Environmental (LCGHG)	$r = 1$
Social (LCAPE)	$r = 2$
Economic (LCC)	$r = 3$

Table C.30: Description and indexing of decision variables, parameters, and constraints

	Index	Description
Decision variables	h_{ij}	Integer variable denoting the number of heavy duty truck type i in sector j
	Z	Weighted objective function variable
Parameters	e_i	CO_2 emissions from manufacturing, maintenance and repair, infrastructure, and battery manufacturing (and replacement) for truck type i
	f^{I}_{ij}	CO_2 emissions from life-cycle fuel supply for truck type i in sector j

	t^{1}_{ij}	CO_2 emissions from operation of truck type *i* in sector *j* throughout its life-cycle
	y_i	APE cost of manufacturing, maintenance and repair, infrastructure, and battery manufacturing (and replacement) for truck type *i*
	f^{2}_{ij}	APE cost of life-cycle fuel supply for truck type *i* in sector *j*
	t^{2}_{ij}	APE cost of tailpipe emissions from truck type *i* in sector *j*
	m_i	LCC of manufacturing of truck type *i*
	oc_{ij}	LCC of operation cost of truck type *i* in sector *j*
	f^{3}_{ij}	LCC of life-cycle fuel supply for truck type *i* in sector *j*
Constraints	Constr1	The constraint on the fleet size
	Constr2	The constraint on the first set of EPs
	Constr3	The constraint on the second set of EPs
	Constr4	The constraint on the third set of EPs
	Constr5	The constraint on the number of BE HDTs in a fleet (BE HDTs<50% or BE HDTs>50%)
	Constr6	The constraint on the number of alternative-fuel HDTs (the number of alternative-fuel HDTs is at least 50% of the fleet)
	Constr7	The constraint on the number of alternative-fuel HDTs (the number of alternative-fuel HDTs is at most 75% of the fleet)
	Constr8	The constraint observing the magnitude of GHG emissions
	Constr9	The constraint observing the magnitude of life-cycle fuel cost expenditures
	Constr10	The constraint observing the magnitude of LCAPECs
	Constr11	The constraint observing the magnitude of LCCs

APPENDIX D
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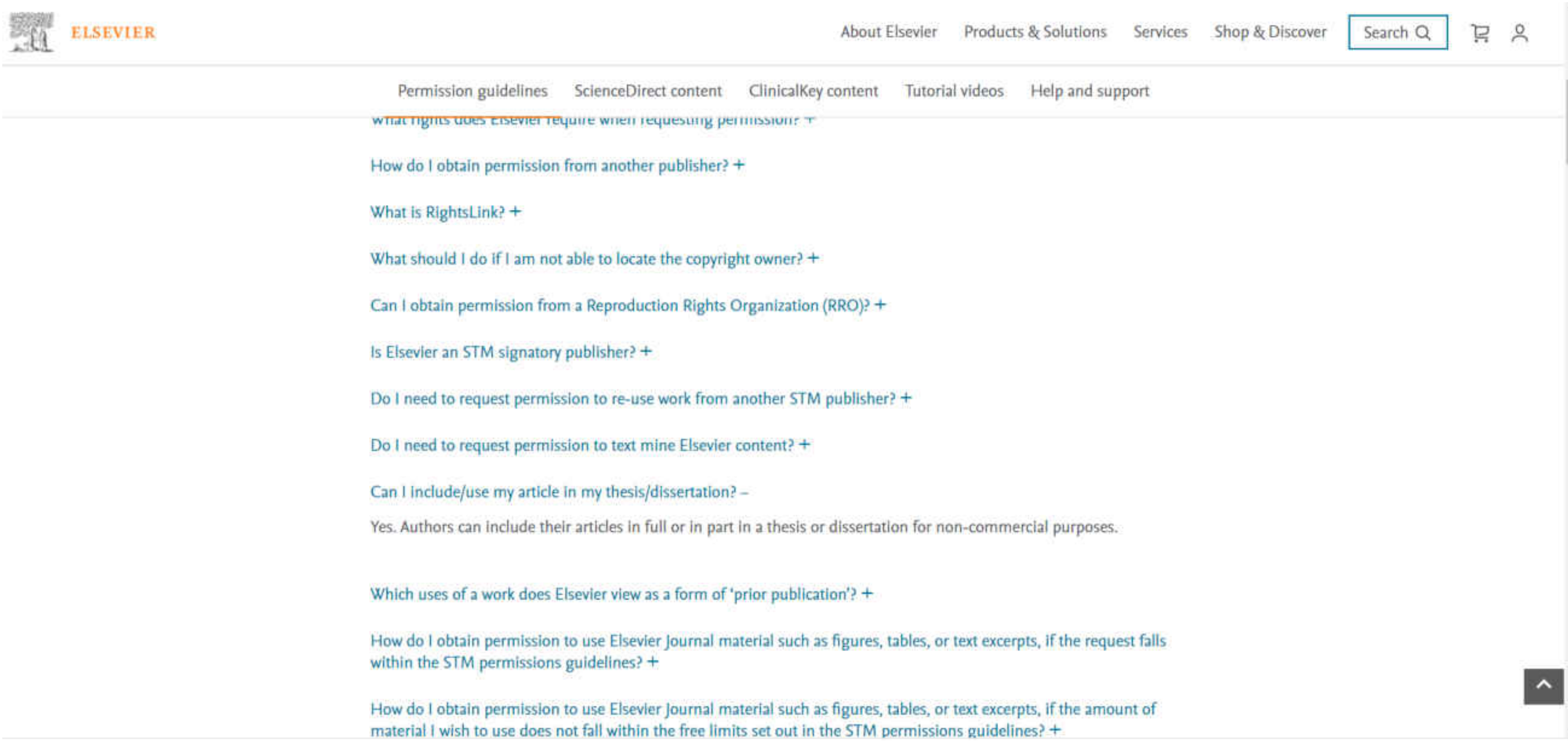

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