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Multi-Objective Optimization Framework For Electrified Vehicle Penetration Based On Life Cycle Assessment And Life Cycle Cost.

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MULTI-OBJECTIVE OPTIMIZATION FRAMEWORK FOR ELECTRIFIED VEHICLE PENETRATION BASED ON LIFE CYCLE ASSESSMENT AND LIFE CYCLE COST

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Dedication

I dedicate this thesis to the most important people in my life - my mom and my sister. Thank you for always believing in me and encouraging me to pursue my dreams. I am forever grateful for the sacrifices you have made and the countless ways you have helped me along the way. This achievement would not have been possible without your constant motivation and inspiration. This thesis is as much yours as it is mine.

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by

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THESIS

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Abstract

This research proposed a novel framework for creating optimal transportation scenarios that consider multiple objectives such as minimum greenhouse gas emissions, air pollutant levels, and cost of ownership. The thesis approach is a multi-objective evolutionary algorithm coupled with the AFEET tool, allowing us to efficiently explore the complex trade-offs between these objectives and identify a diverse set of optimal solutions. Through several case studies and a design of experiments, this demonstrates the effectiveness and practicality in different scenarios. This approach has significant implications for policymakers and industry professionals seeking to make sustainable and cost-effective decisions in the transportation sector.

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Chapter 1: Introduction

Since the mid-20th century, anthropogenic activities have strongly influenced climate change and are attributed to the observed rise in average global warming, resulting in profound disruption to humans and the ecosystem (Allen et al., 2018).

1.1 International Panel on Climate Change

The International Panel on Climate Change (IPCC) is a scientific and intergovernmental committee dedicated to providing the world with the most updated scientific and objective information regarding climate change and its potential economic, social, and political impacts.

The latest IPCC report (2021) presented observations related to the climate changes in every region, such as extreme weather, floods, increases in droughts, sea level rise, and biodiversity loss, all representing an unprecedented risk to susceptible populations (Allen et al., 2018). These risks depend on the magnitude and warming percentage, geographic location, development and vulnerability levels, and decisions and implementation of adaptation and mitigation options (IPCC, 2018).

The greenhouse effect is a million-year-old natural process discovered by Joseph Fourier in 1827. This effect is a primary factor in keeping the earth warm as it helps to prevent heat from escaping from the atmosphere. Thus, the average global temperature would be colder without the greenhouse effect, not allowing life to exist on earth as we know it (Kweku et al., 2018). According to Kweku et al. (2018), the greenhouse gas effect is mainly caused by the interaction of the radiation from the sun and greenhouse gases, trapping heat in the atmosphere.

Between 1880 and 2012 global average surface warming temperature observed was 0.85°C (Allen et al., 2018). However, according to the IPCC report Climate Change: The Physical Science Basis (2021), Greenhouse Gas (GHG) emissions generated by anthropogenic activities caused an increase to approximately 1.1°C of average warming and are projected to reach, or exceed, 1.5°C of the global temperature over the next 20 years, based on datasets to assess historical warming. Still, around 20% to 40% of the worldwide population has experienced over 1.5°C warming above pre-industrial in at least one season (Allen et al., 2018). In addition, the IPCC (2021) report presented new estimates of the chances of surpassing the global warming level of 1.5°C in the following decades. It stated that taking action to reduce GHG emissions on a large scale is essential. Otherwise, warming will be surpassed by 1.5°C or even beyond 2°C, which could take 20 to 30 years to stabilize global temperatures. However, substantial and continuous reductions in GHG emissions would establish a limit for climate change (IPCC, 2021).

The United States Environmental Protection Agency (EPA) (2021b) stated that carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and fluorinated gases are some of the most predominant GHG emissions in the US (Figure 1). Fossil fuels, solid waste, and other biological materials are significant contributors to the formation of (CO_2), in the atmosphere. On the other hand, methane (CH_4) is emitted during the production and transportation of natural gas, coal, and oil, as well as in other agricultural practices and land use. Nitrous oxide (N_2O) is also emitted during agricultural but also industrial activities, combustion of fossil fuels, and solids. Additionally, fluorinated gases are usually cast in smaller quantities, sometimes called high Global Warming Potential (GWP) gases.

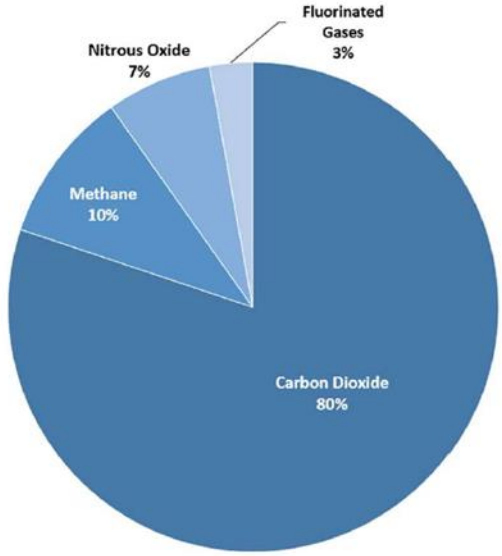


Figure 1.1: Total U.S. Emissions in 2019, 6,558 million metric tons CO_2 equivalent (excludes land sector) (EPA, 2021b).

The rapid increase in atmospheric GHG concentration has caused climate change and the global warming effect, which has motivated international efforts on climate change to monitor, prevent and overturn adverse outcomes. Greenhouse gas in global warming is commonly expressed in GWP, which allows assessing the differences between global warming impact of the gases, typically CO_2 (Kweku et al., 2018).

According to EPA (2021b), the primary greenhouse gas emitted through anthropogenic activities is CO_2, accounting for approximately 80% of all U.S. GHG emissions from anthropogenic activities in 2019, such as CO_2, are present in the atmosphere naturally as part of the earth's carbon cycle. However, the carbon cycle is being affected by human activities by adding more CO_2 to the atmosphere, disrupting the ability of forests and soils to remove and store those CO_2 emissions. According to EPA, the top CO_2 emitters are China, the United States, the European Union, India, the Russian Federation, and Japan (Figure 1.2). The data in figure 2 is based on fossil fuel emissions, as well as cement manufacturing and gas flaring, accounting for a considerable portion of total global CO_2 emissions (EPA, 2022).

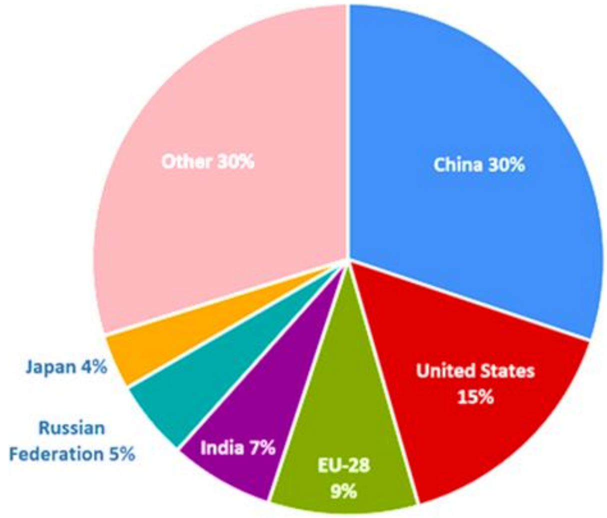


Figure 1.2: 2014 Global CO_2 fossil fuel combustion and industrial processes emissions (EPA, 2022).

The main anthropogenic activity that leads to CO_2 emissions increase in fossil fuel combustion to supply energy, industrial, and transportation systems (Figure 1.3) (Kazancoglu et al., 2021).

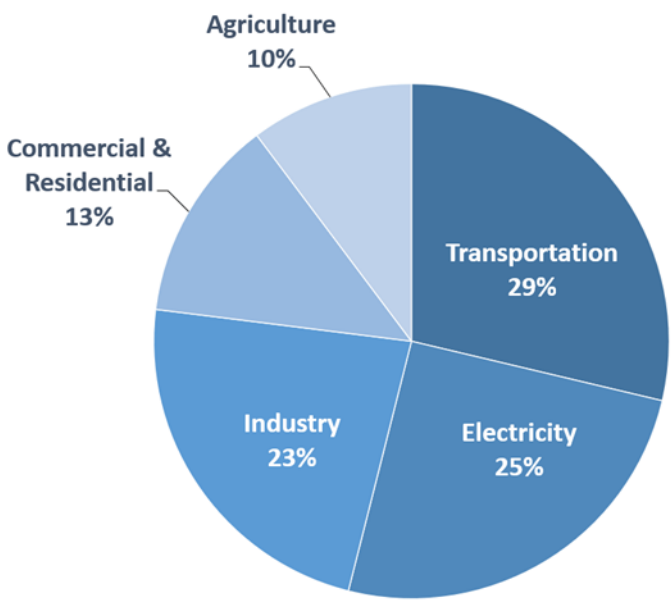


Figure 1.3: 2019 U.S. carbon dioxide emissions by source (EPA, 2021b).

Fossil fuels are the most significant sources of energy to generate electricity in the U.S. In 2020, natural gas accounted for 40% of its electricity generation. Coal was the third largest with 19% of the U.S. electricity generation, and petroleum accounted for 1%, leaving renewable and nuclear energy electricity generation at 20% (EIA, 2019).

1.2 Transportation Sector

Over the past 20 years, the transportation sector accounted for almost a quarter of CO_2 emissions from global energy use (Woodcock et al., 2019). As transportation sector accounted for nearly 29% of GHG emissions and 28% of total energy consumption in the U.S. (Wang et al., 2021). More than 50% of transportation-related GHG emissions result from passenger cars, medium- and heavy-duty trucks, and light-duty trucks, such as sport utility vehicles, pickup trucks, and minivans. On the other hand, commercial aircraft, ships, boats, and trains, as well as pipelines and lubricants, are responsible for the remaining GHG emissions from the transportation sector (EPA, 2021a; Woodcock et al., 2019).

Internal combustion engine vehicles (ICEV) are the source of other climate pollutants, such as CH_4, N_2O, black carbon, and ozone (O_3) (Woodcock et al., 2019). In addition, a small amount of hydrofluorocarbon (HFC) emissions is created in the transportation sector. These emissions result from the increased use of mobile air conditioners and refrigerated transport (EPA, 2021a). Likewise, the number of Vehicle Miles Traveled (VMT) also harms the environment and has increased by 48% from 1990 to 2019. Therefore, sustainable transportation options should be considered to reduce environmental impacts such as climate change, global warming, and other climate change impact categories (EPA, 2021a; Ercan & Tatari, 2015).

Since emissions from transport are increasing faster than from energy-using sectors, and the trend is expected to increase by 80% between 2007 and 2030, significant reductions in GHG emissions are needed to prevent severe climate destabilization (Woodcock et al., 2019). According to McCollum & Yang (2009), scientific studies suggest that global annual GHG emissions should be reduced by 50% to 80% by 205 to avoid destructive climate change impacts.

Furthermore, there are diverse opportunities to decrease GHG emissions related to transportation. Reducing travel demand through urban planning and reducing the number of VMT per individual each day by building public transit, sidewalks, and bike paths are great alternatives to decrease the use of motor vehicles (EPA, 2021a; Woodcock et al., 2019). However, switching to fuels that emit less CO_2, and intensifying alternative sources such as biofuels, renewable electricity, and other renewable sources would significantly reduce transport related GHG emissions (EPA, 2021a).

1.3 Biofuels

To rely less on oil resources, the demand for renewable energy production increases, especially biomass conversion to biofuels. The Energy Independence and Security Act of 2007 (EISA) mandates expanding biofuel volumes and extending target dates to 2022. First, in 2008, the Renewable Fuel Standard required 9 billion gallons of biofuels to be produced and consumed. The target for 2022 is to produce 36 billion gallons of biofuels, where at least 16 billion should be obtained from cellulosic ethanol. Biofuels are considered one of the most influential and low-cost fuels. When diluted with gasoline help decrease harmful pollutants to human health, such as carbon monoxide, benzene, and exhaust hydrocarbons (Cram, 2019). The intensification of renewable energy technologies such as biofuels can meet global energy demand and are essential to reducing GHG emissions. However, their commercial production remains in the process (Girdhar et al., 2017). Generally, biofuels are classified as first-, second-, and third generation.

First-generation biofuels are sourced from crop plants as energy-containing molecules like sugars, oils, and cellulose (Aro, 2016). These biofuels are made through fermentation or chemical processes that convert the biomass's oils, sugars, and starches into liquid fuels. First-generation biofuel markets and technologies are well-established. The most common in the U.S. is corn ethanol, blended into most gasoline sold domestically, providing new economic opportunities by expanding markets for conventional commodity crops (Nagler & Gerace, n.d.). However, there are concerns about the environmental impacts, setting limits in the increasing production of this classification of biofuels, as it is claimed that they are not cost-efficient emission abatement technology. Therefore, it is recommended to have more efficient alternatives (Naik et al., 2010). The main disadvantage of first-generation biofuels is the food versus fuel debate. The rapid expansion of first-generation biofuel production could impact global food production due to the competition of biofuel crops with food crops, decreasing food supply and increasing food prices (Nagler & Gerace, n.d.).

In contrast, second-generation biofuels are manufactured from lignocellulosic biomass such as corn stover, wheat straw, miscanthus, switchgrass, poplar, willow, and wood (Geismar et al., 2022). This type of biofuel is more suited to being grown on land not used for food production (Nagler & Gerace, n.d.; Aro, 2016). Second-generation biofuel's advantages include lower greenhouse gas emissions through their life cycle than grain alcohol. Another advantage is the ability to be produced from grasses that grow on low-quality marginal lands since these fuels have a fundamental non-food nature (Geismar et al., 2022). However, a significant challenge for a biofuel supply chain is the seasonal availability of biomass. Most harvest windows of crops are approximately eight weeks, and none exceed 11 (Hess et al., 2009). Thus, the supply of over 40 weeks must be stored. Therefore, the design and operation of the biomass supply chain are essential for a biorefinery's success (Geismar et al., 2022).

Finally, third-generation biofuels, such as microalgae, are currently considered an ideal biofuel feedstock due to their rapid growth rate, CO_2 fixation ability and high production capacity of lipids can be produced on non-arable land. In addition, microalgae have bioenergy potential as they can be used to produce liquid transportation and heating fuels, such as biodiesel and bioethanol (Dragone et al., 2010). According to Christi et al. (2007), biodiesel production by microalgae will not compromise the production of food, fodder, and other crop products. However, technological developments, including advances in microalgal biomass harvesting, drying, and processing, are significant areas that may lead to enhanced cost-effectiveness. Therefore, effective commercial implementation of the biofuel from microalgae strategy (Dragone et al., 2010).

In 2007, the Low Carbon Fuel Standard (LCFS) aimed to reduce GHG emissions generated by petroleum-based transportation. Using a market-based cap and trade approach by establishing a requirement for fuel producers would reduce the carbon intensity of their products under the LCFT, allowing importers, refiners, and wholesalers to develop low-carbon fuel products (Cram, 2019).

1.4 Fuel Costs

Given the essential role of crude oil in the world economy, the impact of crude oil prices on the economy has been a matter of great concern to economists. Several studies have focused on the U.S. economy since it is the most significant oil importer (Wang et al., 2013). The U.S. produced 20% of the world share total in 2021, almost 18.88 million barrels per day. Saudi Arabia and Russia are the second and third most significant oil importers. They accounted for 10.84 million and 10.78 million barrels per day, respectively, as shown in Table 1.1 (EIA, 2022).

Table 1.1: The ten largest oil producers and share of total world oil production in 2021

Country	Million barrels per day	Share of world total
United States	18.88	20%
Saudi Arabia	10.84	11%
Russia	10.78	11%
Canada	5.54	6%
China	4.99	5%
Iraq	4.15	4%
United Arab Emirates	3.79	4%
Brazil	3.69	4%
Iran	3.46	4%
Kuwait	2.72	3%
Total top 10	68.82	72%
World total	95.57	

(EIA, 2022)

According to West Texas Intermediate (WTI), oil prices have risen from an average of $71 per barrel in December 2021 to $109 in May 2022. U.S. gasoline and diesel inventories are running low, refining capacity is strained, and export demand remains strong (Goolding, 2022). However, according to an article published in the Federal Reserve Bank of Dallas, the monthly national average for regular-grade gasoline, which reached $4.46 per gallon in May, has not reached the 2008 peak of $5.35 realistically. Gasoline prices between 2011 and 2014 were consistently at or above recent (gasoline and diesel prices in the U.S. are at record levels on a nominal (non-inflation-adjusted) basis for Figure 1.4 and Figure 1.5 (Goolding, 2022).

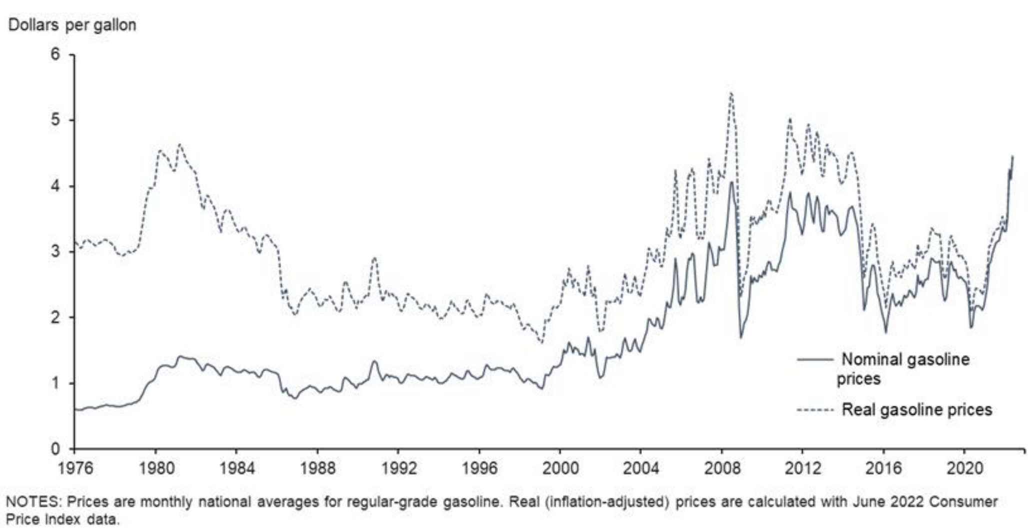
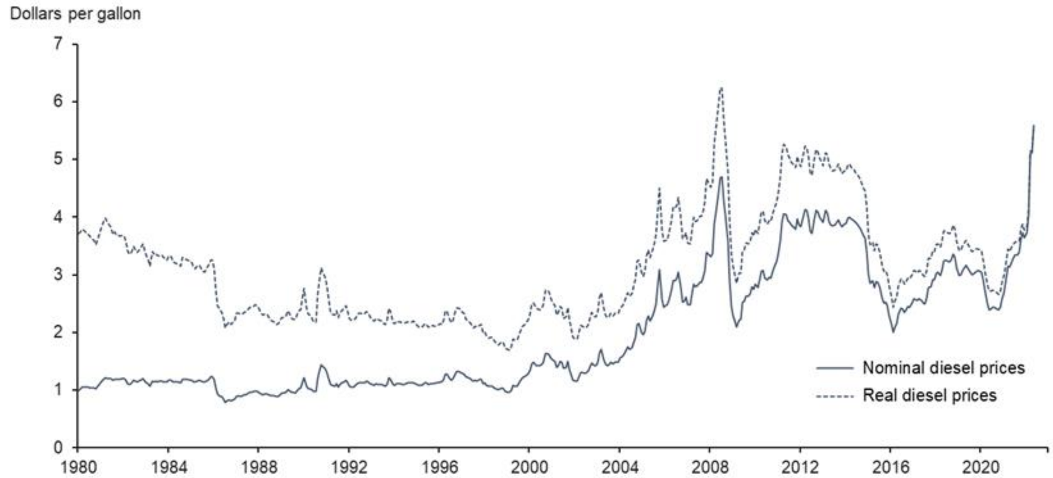


Figure 1.4: Gasoline prices (Goolding, 2022).



NOTES: Prices are monthly national averages for on-highway diesel fuel. Real (inflation-adjusted) prices are calculated with June 2022 Consumer Price Index data.

Figure 1.5: Diesel prices (Goolding, 2022).

Historically, U.S. consumers only slowly reduce fuel consumption when prices increase since most consumers need to drive daily to work, school, grocery stores, and other destinations. Public transportation is an alternative, mainly for those in dense urban areas. Buying a more fuel-efficient or electric vehicle when fuel prices increase is not an option for most people (Goolding, 2022).

1.5 ENERGY-EFFICIENT VEHICLES

The automotive industry is one of the leading worldwide industries, not only in the economic aspect but also in research and development (Sanguesa et al., 2021). The significant growth of today's cities has led to increased transportation use, resulting in increased pollution and severe environmental problems (Hannan et al., 2014). Therefore, with the accelerated increase in the number of vehicles, mitigation of the dependence of vehicles on petroleum to reduce pollutant emissions is becoming one of the main approaches (Xueliang et al. 2015). However, one of the automotive industry's most significant challenges is developing near-zero-emission technologies (Hannan et al., 2014).

Due to the increase in oil and gas usage leading to environmental problems, automotive companies have started developing new technologies to offer more sustainable vehicle options (Prajapati et al., 2014). The development of these new vehicle technologies has focused on total electric traction (Lanzarotto et al. 2018). Battery Electric Vehicles (BEV), Hybrid Electric Vehicles (HEV), and Fuel Cell Vehicles (FCV) are the three typical vehicles that are proposed to replace conventional vehicles with ICEVs (Kebriaei et al., 2015). Table 1.2 shows a comparison of the significant characteristics of EVs, HEVs, and FCVs. Such comparisons are made based on five attributes: (1) Propulsion; (2) Energy Storage Subsystem (ESS); (3) Energy source and infrastructure; (4) Characteristics; and (5) Major issues.

Table 1.2: Characteristics of BEV, HEV, and FCV (Chan et al., 2010).

	BEV	HEV	FCV
Propulsion	• Electric motor drives	• Electric motor drives • Internal combustion engines	• Electric motor drives
Energy storage subsystem (ESS)	• Battery • Supercapacitor	• Battery • Supercapacitor • Fossil or alternative fuels	• Hydrogen tank • Battery / supercapacitor needed to enhance power density.
Energy source & infrastructure	• Electrical grid charging facilities	• Gasoline stations • Electrical grid charging facilities (for Plug-In Hybrid)	• Hydrogen • Hydrogen production and transportation infrastructure
Characteristics	• Zero local emissions • High energy efficiency • Independent of fossil fuel • Relatively short range • High initial cost • Commercially available	• Low local emissions • High fuel economy • Long driving range • Dependence on fossil fuels • Higher cost than ICE vehicles • Commercially available	• Zero low local emissions • High energy efficiency • Independent of fossil fuels (if not using gasoline to produce H2) • High cost • Under development
Major issues	• Battery sizing and management • Charging facilities • Cost • Battery Lifetime	• Battery sizing and management • Control, optimization and management of multiple energy sources.	• Fuel cell cost, life cycle and reliability • Hydrogen production and distribution infrastructure • Cost

1.5.1 Battery Electric Vehicles

BEVs are proposed as a long-term solution to the harmful effects of traditional transportation, especially on the environment (Onat et al., 2019), as BEVs are characterized to be more eco-efficient due to their great potential to minimize the emissions related to transportation (Emadi, 2014). BEVs have only one energy source, namely, an electric battery. BEVs need to be periodically connected to a battery source to replenish the start, which has been the primary subject of ongoing research (Selvakumar, 2021). Because the vehicle is powered only by batteries or other electrical energy sources, zero-emission can be achieved (Figure 6) (Chan, 2010). The typical range of a BEV is estimated to be around 100-150 km on a full charge, but high-end models of the BEV can extend this range to about 300-350 km (Grunditz and Thiringer, 2016).

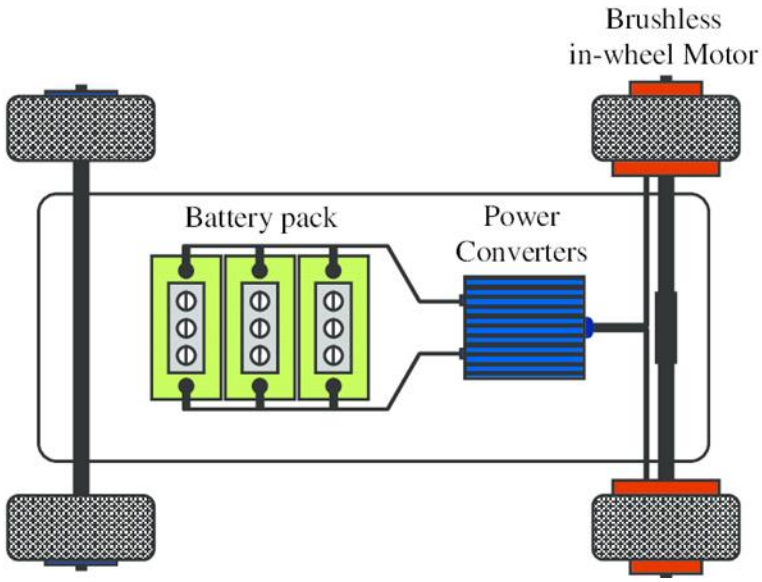


Figure 1.6: BEV configuration (Yousfi et al., 2011).

1.5.2 Hybrid Electric Vehicles

HEVs are experiencing rapid sales growth compared to BEVs and FCVs, as they maintain the advantages of conventional vehicles. Furthermore, HEVs incorporates internal composition engine, electric machines, and power electronic equipment, operating in charging environments of different fuel types, load levels, and weather conditions (Liu, 2013; Kebriaei et al., 2015). Manufacturing HEVs can reduce fuel consumption, lowering GHG and pollutant emissions (Lanzarotto et al. 2018).

An HEV's composition consists of storing energy on board in two or more forms. In a typical HEV, gasoline with an engine is used as a fuel converter. Another form is a bidirectional electrical storage device, reducing the fuel consumption of the HEV by recovering energy during braking, downsizing the engine, operating the engine more efficiently, and shutting the engine off when it is not moving (Kebriaei et al., 2015). More modern HEVs use efficiency-improving technologies, such as regenerative braking, converting the vehicle's kinetic energy into electric energy to charge the battery, avoiding wasting it as heat energy as conventional breaks do (Kebriaei et al., 2015).

Depending on the way the two powertrains are integrated, there are generally three basic HEV architectures: (1) Series hybrid; (2) Parallel hybrid; and (3) Series-parallel hybrid. Describing the Series HEV, the Internal Combustion Engine (ICE) has no mechanical connection with the traction load, never directly powering the vehicle. The traction power is converted to electricity, and the sum of energy from the two power sources is made in an electric node (Figure 1.7) (Chan et al., 2010).

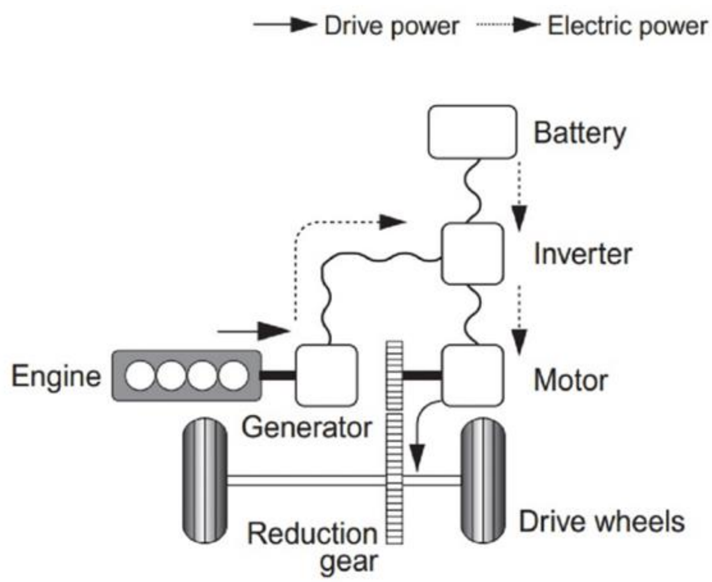


Figure 1.7. Series HEVs configuration (Fayyad et al., 2012).

Parallel hybrid systems have an ICE and electric motor connected to a mechanical transmission, allowing the battery to recharge during regenerative braking and cruising. However, due to a fixed mechanical link between the wheels and the motor, the battery cannot be charged when the car is not moving (Figure 1.8) (Kebriaei et al., 2015).

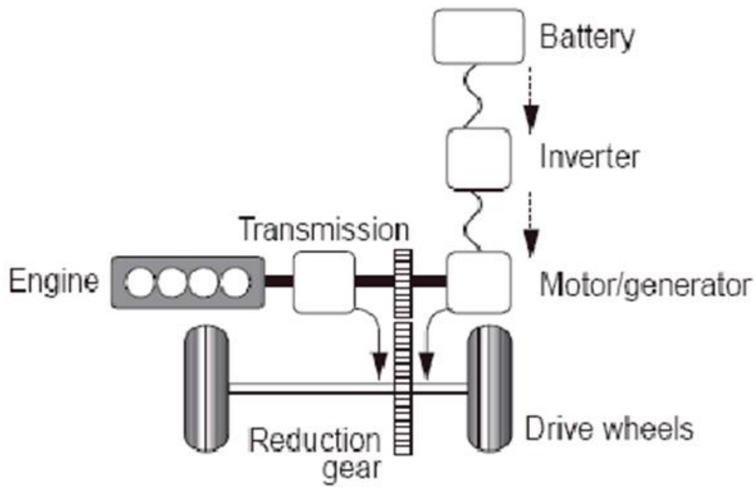


Figure 1.8: Parallel HEV configuration (Fayyad et al., 2012).

Series–parallel HEVs can take advantage of the positive attributes of both series and parallel HEVs and are dominating the current passenger HEV market, requiring a transmission device to couple the engine and electric machines with the vehicle. For hybrid vehicles, the coupling mechanism must be compact, efficient, easy to control, and low-cost (Figure 1.9) (Chen et al., 2011).

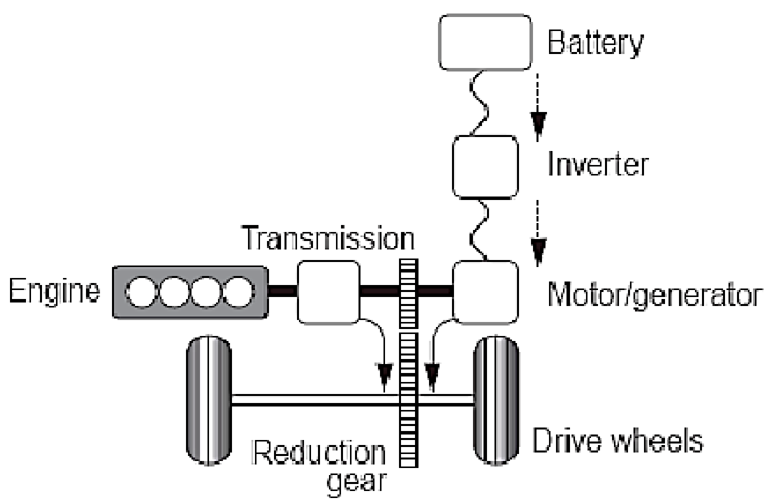


Figure 1.9: Series-parallel HEV configuration (Fayyad et al., 2012).

1.5.3 Fuel Cell Vehicles

An FCV refers to an EV that uses a fuel cell instead of batteries or a supercapacitor to power an electric motor (Figure 1.10) (Das et al., 2017). The fuel cell is a direct chemical converter into electrical energy. The process consists in generating electrical power if fuel and oxidants are provided to the fuel cell in sufficient quantities (Eberle et al., 2012). However, the adoption of FCV is mainly affected by the inflated cost of vehicles and infrastructure distribution, compared to EVs, which are the optimal choice for addressing environmental problems and the energy crisis, as they do not consume oil (Sun et al., 2019).

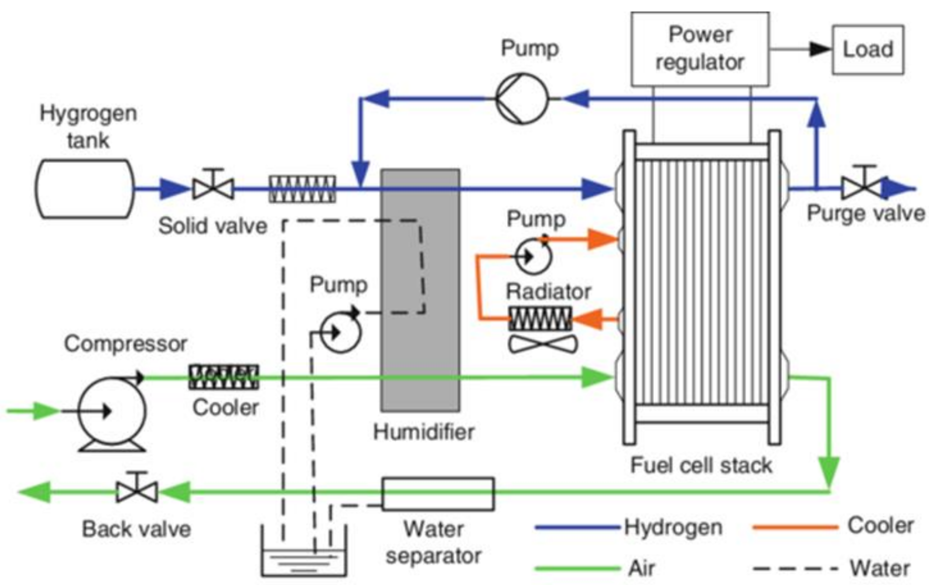


Figure 1.10: FCV configuration (Guo et al., 2013).

Technological measures to reduce vehicle pollutants might reduce emissions, but health effects would be more negligible. Therefore, the combination of reduced reliance on motorized travel, such as hybrid or electric automobiles, with the vigorous implementation of low-emission technology like energy generated from lower-carbon or non-fossil fuels, will offer the best outcomes in terms of climate change mitigation and public health (Woodcock et al., 2019; EPA, 2021a). In addition, according to Ercan & Tatari (2015), electricity as the power source has been suggested as the future primary energy source for most vehicles due to its potential environmental benefits. Some studies show that the electric sector has the lowest marginal emissions reduction costs and, as a result, would provide the bulk of near-term mitigation in an economy-wide policy regime (McCollum & Yang, 2009).

Increased life expectancy and income have accompanied global economic growth. However, environmental degradation and pollution in many regions are related to significant poverty and severe inequality in income distribution and access to resources, amplifying vulnerability to climate change (Allen et al., 2018).

1.6 Vehicle Penetration

As the demand for passenger vehicles and freight transportation rapidly rises, adverse effects such as traffic congestion, traffic accidents, and air pollution increase. Consequently, the demand for fossil fuels is constantly growing while oil self-sufficiency has significantly declined (Shigeru et al., 2020). With the rapid growth of the U.S. economy, ownership of private vehicles has been increasing. According to the Federal Highway Administration, the total number of cars registered in the U.S. reached 276,491,191 in 2019, being 6% higher compared to the number of vehicles registered in 2014 (Paulus et al., 2022). Figure 1.11 shows the number of registered vehicles in the US from 2013 to 2019.

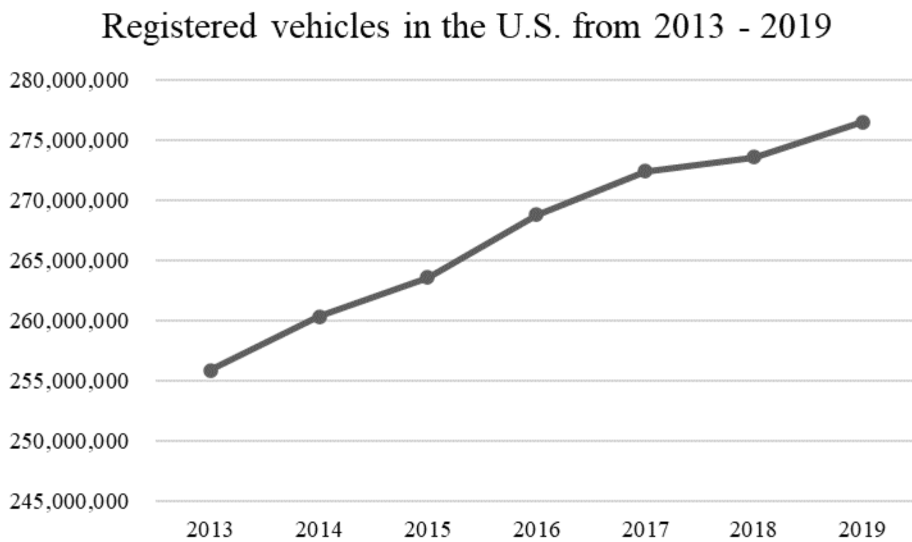


Figure 1.11: Registered vehicles in the U.S. from 2013 - 2019 (Paulus et al., 2022).

BEVs have recently gained tremendous popularity as vehicles that generate fewer carbon emissions, are less polluting, and depend less on fossil fuel, becoming a promising alternative for daily personal transportation. However, adopting this type of transport does not rely solely on demand for BEVs. Still, it is also subject to supply-side restrictions, which include battery performance and cost and the level of access to charging infrastructure (Nemry & Brons, 2011).

The implementation of BEVs is assumed to reduce oil consumption and air pollution. However, it will increase the electricity demand. Depending on the power generation sectors (generation mix, input fuels, etc.), countries might not become energy self-sufficient or solve their environmental problems (Shigeru et al., 2020).

Chapter 2: Literature Review

Over the years, many scientists have studied the life cycle performance related to biofuels, BEVs, HEVs, and fuel costs. The Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) Model and the Alternative Fuel Life-cycle Environmental and Economic Transportation (AFLEET) tool allow stakeholders to consider the variable of cost of ownership have already established comprehensive databases for further studies (Argonne National Laboratory, n.d.).

Based on the GREET database, Hawkins has performed complete life cycle assessments on various kinds of vehicles in Europe, showing results where the life cycle GHG emissions of a BEV was about 200 g CO_2eq/km, about 10–20% lower than that of an ICEV (Hawkins et al., 2013). Thus, BEVs could work for GHG emission reduction if managed with green battery production, low-carbon electricity, and EV recycling (Qiao et al., 2019). China Automotive Technology & Research Center also published a study where an LCA utilized data for vehicle components and the battery material obtained from the GREET2 2017 model. This information was used to calculate and compare the GHG emissions from BEV's and ICEV's life cycle from 2010, 2014, and 2020 under different scenarios, considering different electricity mixes, electricity generation technologies, and combined heat and power scales. The study found the total life cycle's GHG reduction potential of BEVs will progressively improve by up to 13.4% in 2020 relative to ICEVs (Wu et al., 2018).

Conventional diesel medium- and heavy-duty vehicles (MHDVs) contributed 23% to the total GHG emissions in the transportation sector in 2018, which is the most significant GHG emission sector in the United States (EPA, 2021). With the reduction in the cost of batteries and the development of new technologies, BEVs are increasingly attractive options for improving energy efficiency and reducing air emissions of MHDVs (Liu et al., 2020). A Well-to-wheels analysis was conducted utilizing the GREET model, comparing MHD BEVs and conventional MHDVs' air pollutant emissions. It was found that MHD BEVs significantly improve the environmental sustainability of MHDVs by reducing WTW GHGs, nitrogen oxides, volatile organic compounds, and carbon monoxide emissions compared to conventional MHDVs (Liu et al., 2020).

Nevertheless, it is essential to consider the contribution of lithium-ion batteries to the life cycle of BEVs energy consumption and environmental impacts. A study by Dun et al. (2014) stated the significance of lithium-ion batteries in BEVs and the need for reducing battery assembly cradle-to-gate impacts. Recycling metals in cathode materials would help to minimize the total energy and emissions intensity of battery production, primarily when assembly facilities operate at high capacity (Dunn et al., 2014). Additionally, it concluded that BEVs consume less petroleum and emit less GHG than ICEVs on a life-cycle basis. The only scenario in which a BEV generated more GHGs than an ICEV was when it used only coal-derived electricity as a fuel source. However, sulfur oxide (SOx) emissions were up to four times greater for BEVs than ICEVs (Dunn et al., 2014).

Most studies approaching vehicle carbon footprints mainly focus on the vehicle cycle. However, Wong et al. (2021) analyzed the GREET LCA to analyze the fuel cycle, focusing on different hydrogen production pathways for fueling up Hydrogen Fuel Cell Vehicles (HFCV) to compare the product carbon footprint (PCF) of a BEV and an HFCV. The results indicate that the fuel cycle contributed significantly to the PCF and concluded that the cleaner the hydrogen production is, the lower the environmental impact of vehicles' emissions.

Biofuels are the alternative solutions in the fossil fuel family and have been mainly utilized to reduce ICEV emissions (Hira et al., 2022). Biofuels can reduce GHG emissions by converting to 85–100% biofuels without requiring major engine modifications (Ternel et al., 2021). Many pioneer works have been done to improve the accuracy of the climate change impact assessment of biofuels in LCA, such as the consideration of biogenic CO_2 emissions, emissions from land-use practice change, and carbon loss (Liu et al., 2018; Searchinger et al., 2008; Arbault et al., 2014). However, Liu et al. (2020) developed a framework that considers all the components, such as fossil fuel-derived GHG emissions, biogenic CO_2 emissions, emissions from land-use practice change, regrowth for compensation, and differences in carbon storage within the time horizon. Results indicated that fossil fuel produced CO_2 emissions, biogenic CO_2 emissions and regrowth for compensation contributed most of the positive impact. It also suggests that land-use practice changes and differences in carbon sequestration could have adverse effects. Still, biofuels would be attractive due to their sustainability and renewability.

According to Hira et al. (2022), methanol produced by gasification is the best-recommended fuel for combustion with the lowest emission levels. This study showed that using methanol fuel produced by gasification results in the lowest GHG emission value of 11.44 gm using the GREET model compared to fossil fuels. Comparative biofuel production from corn stover fast pyrolysis and subsequent hydrotreating and hydrocracking LCA was conducted based on a GREET model and investigated three different cases of different hydrogen treatments in bio-oil. The results showed an essential net non-renewable energy demand reduction of 147.5% and a net GWP reduction of 119.4% compared to conventional gasoline and diesel (Dang et al., 2014). Another LCA of energy consumption and GHG emissions for various biofuel vehicles has been performed, focusing on four potential fuels for vehicles: switchgrass ethanol, corn ethanol, soybean biodiesel, and bio-hydrogen from corn ethanol with the fuel cycle model developed in GREET, showing that the Flexible Fuel Vehicles (FFVs) ran with an ethanol fuel blend of 85% switchgrass ethanol and 15% gasoline (E85) have the most significant benefits in GHG emission reduction by 59.4% (Chang et al., 2017).

On the other hand, the AFLEET tool allows stakeholders to consider the variable cost of ownership (Argonne National Laboratory, n.d.). Based on that, Ercan et al. performed a study focused on optimizing the economic and sustainability impacts of transit bus fleet operation to reduce CO_2 emissions and other air pollutants related to health and environmental damage costs by utilizing the AFLEET tool to analyze different weight scenarios to provide solutions for decision-makers with various budget constraints or emission reduction requirements (Ercan et al., 2015).

Furthermore, a modeling and analysis method called the Electric Vehicles Regional Optimizer (EVRO) was proposed by Noori et al. (2015) to address the uncertainties and predict the optimal combination of the LCC, Environmental Damage Cost (EDC), and Water Footprint (WFP) of different vehicle types modeled for other U.S. electricity grid regions for the year 2030. Noori et al. (2015) utilized the AFLEET tool to find the LCC of different EVs, concluding that the optimal fleet composition in 2030 is HEVs, EREV (Gasoline Extended Range Electric Vehicles), and BEVs. HEVs dominate most regions since they have better fuel efficiency and less environmental impact. The combined share of EREV and BEVs ranges between 40% and 51% throughout the entire U.S. since electric technology reduces the EDC dramatically, with the lowest EDC. However, BEVs consume the most water, mainly due to electricity generation and battery production, and HEVs have the smallest footprint.

In addition, Plug-in Electric Vehicles (PEVs) are one sustainable solution to reduce emissions from road transportation. Furthermore, a multiple regression model was developed to assess the effect of charging station infrastructure and other cost-related and socio-demographic factors on the PEV adoption rate in 58 California counties. The model's results helped to estimate decreases in life-cycle air pollutants emissions, GHG, and fossil fuel emissions and calculate the benefit-cost ratio that would result from expanding charging stations and growing PEVs across California utilizing the AFLEET tool (Javid et al., 2019). However, the results show that the infrastructure expansion scenario is more advantageous in reducing air pollutants compared to GHGs, as the GHG emission reduction is approximately 0.006% of annual GHG emission in the state, and the air pollutant emission reduction is about 0.17% of the yearly statewide air pollutant emissions tool (Javid et al., 2019).

Moreover, the sustainable energy technology and policies book conducted a lifecycle-based cost-benefit analysis to evaluate the net ownership costs and net external benefits serving as decision-support for policymakers regarding alternative vehicle technologies utilizing the AFLEET and GREET tools (Lopez et al., 2018). The data presented reflected the excellent health and social benefits of BEVs. However, this study also shows high fueling infrastructure investment costs (Lopez et al., 2018). In addition, using a lifecycle-based approach, another analysis was performed to calculate ownership savings and societal benefits for numerous alternative vehicle technologies compared to their baseline vehicle technology, such as diesel and gasoline, utilizing the AFLEET and GREET databases. The results found significant societal benefits from BEVs and FCVs. However, they also lead to high ownership costs (Lopez et al., 2020). Therefore, the diesel hybrid electric vehicle can soon have both favorable societal and operational costs for public transportation if a shift to diesel with 20% biodiesel or 85% methanol is made (Lopez et al., 2020).

Chapter 3: Optimization

The attention to cost minimization, energy saving, environmental protection, and sustainable development issues in different fields, such as engineering or scientific research, is growing. Therefore, a solution to manage our production, manufacturing, experiments, and living activities more efficiently and friendly way.is needed (Cui et al., 2017).

Optimization algorithms are essential in engineering and scientific design activities, which help solve many decision-making problems (Nayak, 2020). A variety of activities can be described as systems, and the efficient operation of these systems often requires the optimization of several indices that measure the system's performance (Foulds, 2012). Optimization techniques are applied to obtain the values of a set of parameters that maximize or minimize the objective function of interest (Everitt, 2012) to find the best combination of activities with the available resources (Schrage, 2009).

The basic procedure of optimization for any problem is shown in figure 3.1. Inputs and resources are necessary information to model the problem mathematically. The problem is formulated with the help of the objective function and the constraints. Then, applying the optimization techniques, the solutions are investigated, creating the output to get optimal solutions (Nayak, 2020).

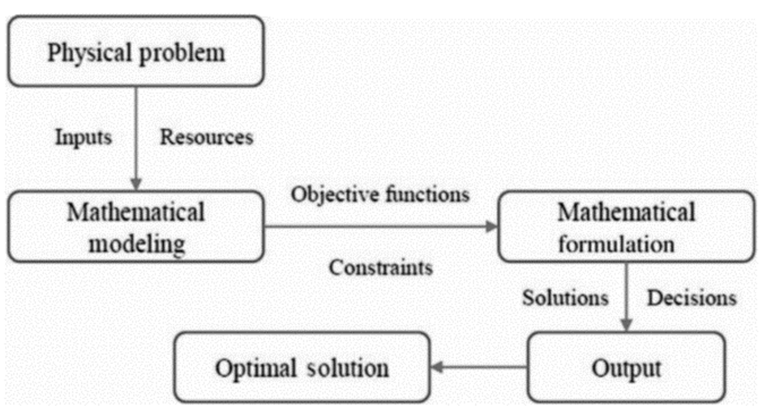


Figure 3.1: Flow chart of modeling physical problems to get an optimal solution (Nayak, 2020).

3.1 LINEAR PROGRAMMING

One particularly important subclass of programming problems is called a linear-programming problem, which can be stated using relationships called "straight-line" or linear (Gass, 2003). Mathematically, these relationships can be expressed in the form:

$$\alpha_1 x_1 + \alpha_2 x_2 + \cdots \alpha_j x_j + \cdots + \alpha_n x_n = b^t$$

(Eq. 3.1)

Where α_j and b are known coefficients and x_j is an unknown variable. To complete a mathematical statement of a linear-programming problem, a set of linear equations representing the conditions of the problem and a linear function expressing the objective of the problem are needed (Gass, 2003).

With the added condition of optimizing an objective function, the linear-programming problem can now select a solution that satisfies all the problem conditions. However, the problem might have multiple answers (Gass, 2003). Combining the optimization of a linear objective function with the linear constraints of the programming problem transforms an undetermined system of linear equations with many viable solutions to a system that can be solved for an optimal solution (Gass, 2003).

The general mathematical model of the linear-programming problem "minimize the objective function" can be expressed in the form:

$$c_1 x_1 + c_2 x_2 + \cdots c_j x_j + \cdots + c_n x_n$$

Subject to the conditions

$$\alpha_{11} x_1 + \alpha_{12} x_2 + \cdots \alpha_{1j} x_j + \cdots + \alpha_{1n} x_n = b_1$$

$$\alpha_{21} x_1 + \alpha_{22} x_2 + \cdots \alpha_{2j} x_j + \cdots + \alpha_{2n} x_n = b_2$$

$$\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots$$

$$\alpha_{i1}x_1 + \alpha_{i2}x_2 + \cdots \alpha_{ij}x_j + \cdots + \alpha_{in}x_n = b_i$$

$$\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots$$

$$\alpha_{m1}x_1 + \alpha_{m2}x_2 + \cdots \alpha_{mj}x_j + \cdots + \alpha_{mn}x_n = b_m$$

And

$$\begin{aligned} x_1 &\geq 0 \\ x_2 &\geq 0 \\ x_j &\geq 0 \\ x_n &\geq 0 \\ x &\neq 0 \end{aligned}$$

(Eq. 3.2)

Were c_j for $j = 1, 2, \ldots, n$; b_j for $i = 1, 2, \ldots, m$; and α_{ij} are all constants and $m < n$ (Gass, 2003).

Every linear-programming problem has either no solution, in terms of nonnegative values of the variables, or a nonnegative solution that yields a finite value to the objective function. A nonnegative solution generates an infinite value to the objective function (Gass, 2003).

3.2 MULTI-OBJECTIVE OPTIMIZATION

The optimal solution can be found through optimization, looking for maximum or minimum value utilizing one objective or multi-objective function (Gunantara, 2018). Multi-objective Optimization Problems (MOPs) or vector optimization problem is the process of optimizing systematically and simultaneously a set of objective functions (Marlet & Arora, 2004). Moreover, the objective functions tend to contradict each other as an optimal solution is suitable for one function, but it may conflict with the others (Cui et al., 2017). Therefore, not all solutions can satisfy all objective functions. Thus, there exists a set of feasible solutions (Cui et al., 2017).

The general mathematical model of the MOP “minimize the objective function” can be expressed in the form:

$$F(x) = (f_1(x), \dots, f_k(x),))^T$$

(Eq. 3.3)

Where k is the number of objective functions in the MOP being solved, and x is an independent variable. Subject to:

$$g_i(x) \leq 0$$

$$x^{lower} \leq x \leq x^{upper}$$

(Eq. 3.4)

Where $g_i(x)$ is the feasible solution space and x^{lower} and x^{upper} are the independent variable's lower and upper bounds (Cram, 2019).

Multi-criterion optimization will have multiple individual optimal solutions for each objective function, creating conflict with each other, which leads to a significant difference between the optimal solutions (Cram, 2019). Thus, there is not a unique solution but a set of solutions. However, those solutions can be found using Pareto Optimality Theory (Coello et al., 2007). Compared to single-criterion optimization, which has only one global optimal solution (Cram, 2019).

3.2.1 Pareto Optimality Theory

In MOPs, there is no single global solution, and it is often necessary to determine a set of points that all fit in a definition of optimum points (Marler & Arora, 2004). Therefore, the concept of Pareto optimality is used to define optimality for MOPs (Schütze & Hernández, 2021), which is defined as follows:

A point, $\boldsymbol{x}^* \epsilon \boldsymbol{X}$, is Pareto optimal if there does not exist another point, $\boldsymbol{x} \epsilon \boldsymbol{X}$, such that $\boldsymbol{F}(\boldsymbol{x}) \leq \boldsymbol{F}(\boldsymbol{x}^*)$, and $\mathbf{F_i}(\mathbf{x}) < \mathbf{F_i}(\mathbf{x}^*)$ for at least one function (Marler & Arora, 2004).

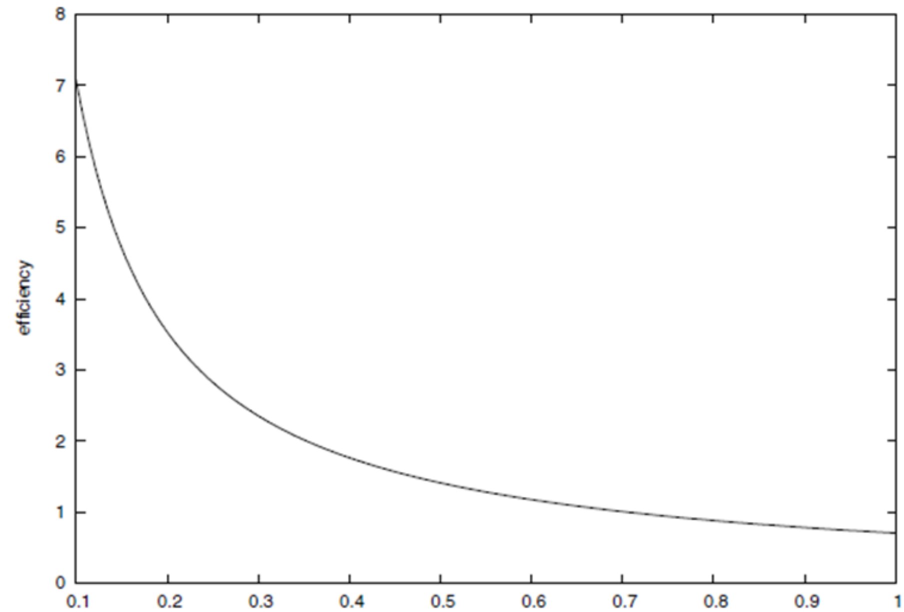


Figure 3.2: An example of a problem with two objective functions: cost and efficiency.

The Pareto front or trade-off surface is delineated by a curved line (Coello et al., 2007). The definition of Pareto optimal states that x* is optimal if no feasible vector x exists, which would decrease some criterion without causing a simultaneous increase in at least one other criterion (assuming minimization) (Coello et al., 2007).

3.3 MOP Evolutionary Algorithm Approaches

Over the past 30 years, MOP Evolutionary Algorithms (MOEA) have attracted much research since MOEAs can estimate the Pareto optimal set in a single run (Zhu et al., 2011). Also, MOEAs generate a trade-off performance such as efficiency and effectiveness for specific systems model objectives such as cost/profit, constraints, and other mutually conflicting objectives (Coello et al., 2007). MOEA approaches have been classified into three major categories described as follows:

- A Priori Techniques: Lexicographic, linear, and nonlinear fitness combination.
- Progressive Techniques: Progressive techniques or interactive computational steering.
- A Posteriori Techniques: Independent sampling, criterion selection, aggregation selection, Pareto-based selection, Pareto rank- and niche-based selection, Pareto deme-based selection, Pareto elitist-based selection, and hybrid selection (Coello et al., 2007).

3.3.1 A Priori Techniques

The a priori techniques require a previous search to the Decision Maker (DM) to define the MOP objective's relative importance, as this is usually reflected in weights related to the aggregated sum of the objectives. Establishing the DM's preferences aims to evaluate and compare solutions to the Multi-Criteria Decision Making (MCDM) problem. Finding the one solution of interest to the DM for real-world problems is essential. Therefore, objective quality prioritization is needed to find all adequate solutions (Coello et al., 2007).

Lexicographic ordering

The DM is asked to classify the objectives in order of importance to obtain the optimum solution by minimizing the objective functions in sequence according to the order of importance assigned to the objectives. When the priority is unknown, selecting an objective randomly to be optimized at each generation is possible. However, randomly choosing an objective equivalent to a weighted combination of objectives (tournament selection) with this approach makes a significant difference compared to other techniques, such as the Vector Evaluated Genetic Algorithm (VEGA), as its main weakness is that it tends to favor more certain objectives when present in the problem due to the randomness involved in the process (Coello et al., 2007).

Linear aggregating functions

The mathematical form for linear aggregation functions to compute fitness is expressed as follows:

$$fitness = min \sum_{i=1}^{k} w_i f_i(x)$$

(Eq. 3.5)

Were $w_i \geq 0$ and $i = 1. . . k$ are the weighting coefficients representing the relative importance of the DM in the k objective functions of the MOP. It is usually assumed for normalization that:

$$\sum_{i=1}^{k} w_i = 1$$

(Eq. 3.6)

Regardless of the simplicity of the linear fitness combination technique, it is a popular approach because of its simplicity. Figure 3.3 shows parallel lines, which indicate when the search finds a single Pareto front point A at a minimum cost when it is on the convex hull of the Pareto front. Even though point B may be found, it is not retained as a smaller aggregate objective function value is found at point A. However, the linear aggregating algorithm does not tend to find all Pareto front points of interest since these points are defined as non-supported points because they are not on the convex hull of the Pareto front (Coello et al., 2007).

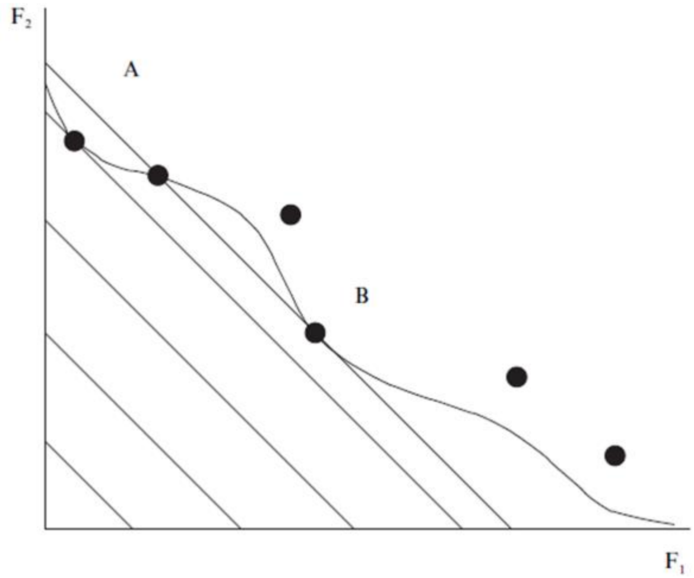


Figure 3.3: Priori weight selection for a bi-objective example in linear aggregating technique, w_1x_1+w_2x_2 (Coello et al., 2007).

Nonlinear aggregating functions

In contrast to linear aggregating functions, nonlinear aggregating functions (multiplicative methods) are uncommon in the literature since it requires overhead to determine the appropriate probability of acceptance or utility functions. However, overhead does not justify the quality of the resulting solutions (Coello et al., 2007).

Additionally, combining an evolutionary algorithm and a target-vector approach can minimize the current solution according to the vector difference of the desired goals. Target-vector strategies also require the definition of goals to be achieved and require extra computational effort, which can result in additional problems. However, it is more commonly used than multiplicative methods (Coello et al., 2007).

3.3.2 Progressive Techniques

The progressive technique approach demands the DM’s time and effort at its premium as it requires supporting the search when defining the goals or scheme of preference. It could be assumed that the closer the interaction between the DM and searchers would increase the efficiency of the discovered solutions. However, progressive techniques may be complicated and inefficient when nothing about the problem is known (Coello et al., 2007).

3.3.2 A Posteriori Techniques

The focus of the a posteriori technique is to find P_{true} and PF_{true}. Thus, an extensive search is needed to generate as many elements of the Pareto optimal set as possible since the decision-making process will occur after the search is done (Coello et al., 2007). The a posteriori technique is composed of the following a posteriori sub-techniques:

- Independent sampling techniques
- Criterion selection techniques
- Aggregation techniques (linear, nonlinear)
- ϵ-constraint technique
- Pareto sampling techniques

Independent sampling techniques

Since several independent sampling approaches tend to have reduced effectiveness, the independent sampling technique utilizes fitness combinations where the weights assigned to each objective are varied over several separate MOEA runs, the variability of the difference concerning a priori linear aggregating process. However, not always these points are evenly distributed at the Pareto front. Simplicity and efficiency are what make this approach convenient. However, this approach applies only to specific types of problems. For instance, this method is not very useful when the number of objectives is low (Coello et al., 2007).

Criterion Selection Techniques

The VEGA approach, proposed by David Shaffer, considers the first implementation of the MOEA. This approach randomly selects a fraction of the objectives in every generation based on separate objective performance. VEGA tends to converge to solutions close to local optima regarding each objective (Coello et al., 2007).

For a problem with k objectives, k subpopulations of size M/k each would be generated, and only one of the k objectives will be considered a fitness function. These sub-populations are then rearranged to obtain a new population of size M, on which the Genetic Algorithm (GA) would apply the crossover and mutation operators in the usual way. Shuffling is done before sub-population partitioning to reduce positional population bias (Figure 3.4). The population size is assumed to be M, and there are k objective functions (Coello et al., 2007).

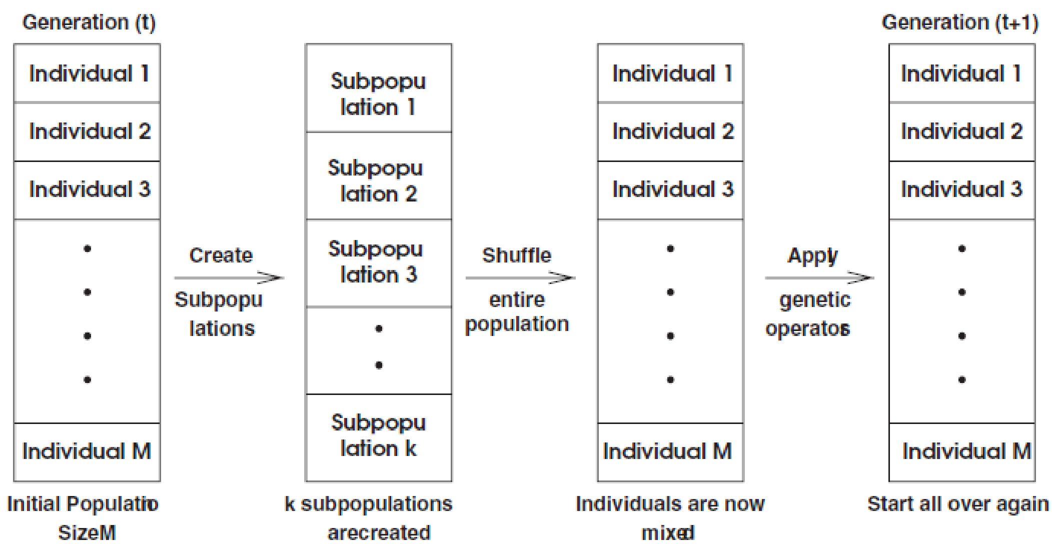


Figure 3.4: Schematic of VEGA's selection mechanism.

The structural representation of the VEGA process is shown in figure 3.5:

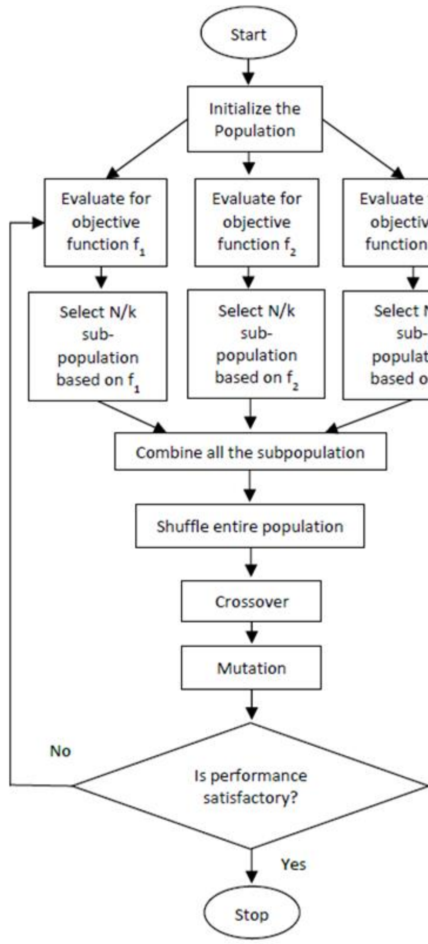


Figure 3.5: Schematic of VEGA's (Coello et al., 2007).

Aggregation techniques

This technique integrates several techniques to solve MOPs, such as hybrid approaches, weighted sums, and constraint and objective combinations. Nevertheless, this approach utilizes different weight combinations between generations and each function evaluation instead of static objective weights (Coello et al., 2007).

Several solutions can be generated utilizing aggregation techniques in a single run of MOEA. However, when the weighted sum approach is employed, individuals of the PF_{true} may be missed. Thus, a meaningful effort is required to use both constraint/objective combination and hybrid search approaches (Coello et al., 2007).

Constraint technique

Selecting a primary objective function followed by bounding the others with different predefined ϵ-constraint values is the base of the constraint technique. To generate another point in the Pareto front (phenotype), the ϵ-constraints are changed, resulting in finding elements in the Pareto optimal set (genotype). The distribution of the Pareto front is usually non-uniform, and the smooth implementation of this technique is their main advantage (Coello et al., 2007).

Pareto sampling techniques

The Pareto sampling technique offers the realistic objective of finding P_{known} and PF_{known}. It refers to techniques that utilize the capability of the MOEA's population to create several elements of the Pareto optimal set in a single stochastic computational run (Coello et al., 2007). Two objective understandings of Pareto optimality are presented in Figure 3.6. Nevertheless, the graphical definition of nondominated and nominated points must be related to the objective space and the solutions corresponding to the variable (Coello et al., 2007).

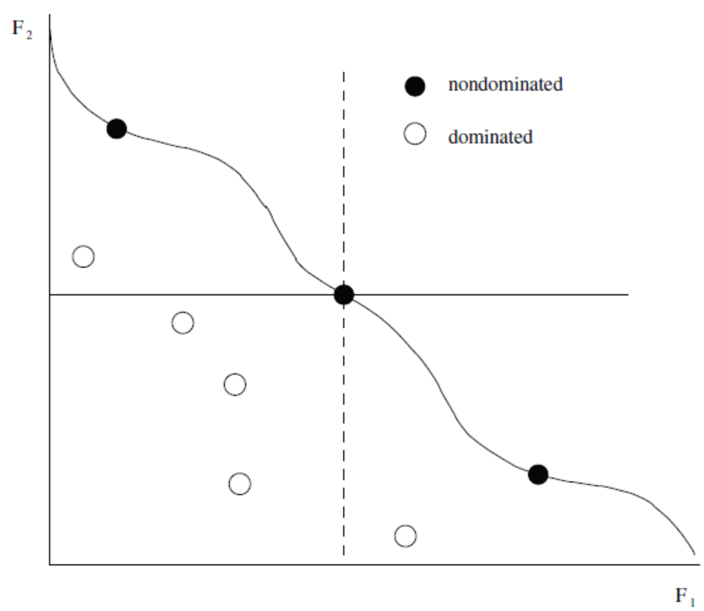


Figure 3.6: The concept of Pareto optimality as related to non-dominance in a maximization MOP (Coello et al., 2007).

3.4 Multi-objective Genetic Algorithms (MOGA)

The “Multi-objective Genetic Algorithm” (MOGA) technique variation was proposed by Carlos M. Fonseca and Peter J. Fleming, in which the rank of a specific individual correlates to the number of chromosomes in the current population by which is dominated (Coello et al., 2007). For example, an individual x_i at t generation, is dominated by $p_i^{(t)}$ Individuals in the current generation. Therefore, a rank is assigned to the individual by the rule: rank (x_i, t) = 1 + $p_i^{(t)}$ (Coello et al., 2007). The pseudo-code of MOGA is shown in figure 3.7.

```
Initialize Population
Evaluate Objective Values
Assign Rank Based on Pareto Dominance
Compute Niche Count
Assign Linearly Scaled Fitness
Assign Shared Fitness
For i = 1 to number of Generations
    Selection via Stochastic Universal Sampling
    Single Point Crossover
    Mutation
    Evaluate Objective Values
    Assign Rank Based on Pareto Dominance
    Compute Niche Count
    Assign Linearly Scaled Fitness
    Assign Shared Fitness
End Loop
```

Figure 3.7: MOGA Pseudo code (Coello et al., 2007).

Fitness is assigned by sorting the population according to a fitness function, from best to worst. This procedure maintains the global population fitness constant (Coello et al., 2007).

, the niche-formation method distributes the population over the Pareto-optimal region, sharing the objective function values instead of the parameter values to avoid premature convergence caused by significant selection pressure (Coello et al., 2007).

Chapter 4: Alternative Fuel Life-Cycle Environmental and Economic Transportation (AFLEET) Tool

The AFLEET Tool was developed by Argonne National Laboratory (Argonne) and co-sponsored by the U.S. Environmental Protection Agency (EPA). It assists metropolitan areas and Clean Cities partnerships in estimating criteria for air pollutant reductions achieved by the near-term introduction of alternative-fueled vehicles (Burnham, 2020). In 2009, the Department of Energy's (DOE's) Clean Cities requested Argonne to create a calculator known as the GREET Fleet Footprint Calculator to measure GHG emissions caused by petroleum displacement of medium and heavy-duty alternative fuel vehicles. This tool was developed for Clean Cities stakeholders to estimate these values utilizing excel spreadsheet inputs (Burnham, 2020).

In compliance with having a tool with the capacity to estimate the benefits of using alternative fuel and advanced vehicles (AFVs) and measure both environmental and economic costs, Argonne Laboratory has developed the AFLEET tool. This tool allows stakeholders to estimate GHG emissions, air pollutant emissions, fossil fuel use, and costs of ownership for light-duty vehicles (LDVs) and heavy-duty vehicles (HDVs) depending on the user's goals (Burnham, 2020).

The AFLEET tool provides six calculation methods according to the user's objectives. The first method is the Simple Payback Calculator, which examines acquisitions and annual operating costs to estimate a payback for buying a new AFV compared to its counterpart, as well as yearly GHGs, air pollutant emissions, and petroleum use. The Total Cost of Ownership (TCO) Calculator is the second option the AFLEET tool provides. This option evaluates the net present value of operating and fixed costs related to the years of planned ownership of a new vehicle and petroleum use, air pollutant emissions, and GHG emissions. The third option is the On-Road Fleet Footprint

Calculator. In this option, the annual petroleum use, GHGs, and air pollutant emissions of new and existing on-road vehicles considering the higher emissions that older vehicles produce. Off-Road Fleet Footprint Calculator is the fourth methodology that can be utilized. This calculator estimates the annual petroleum use, GHGs, and air pollutant emissions of new and existing off-road equipment, considering that typically older equipment produces higher pollutant emissions than the latest equipment. Electric Vehicle Charging Calculator is another option the AFLEET tool provides, which estimates the same emissions as previous calculators. However, the emissions are related to public electric vehicle charging infrastructure benefits. Additionally, the Idle Reduction (IR) Calculator examines the acquisition and annual operating costs to determine the payback for purchasing a new AFV compared to conventional vehicles and their emissions (Burnham, 2020).

Chapter 5: Methodology

This chapter explains the methodology approach, which is to couple a Multi-objective Evolutionary Algorithm (MOEA) with the Alternative Fuel Life-Cycle Environmental and Economic Transportation (AFLEET) Tool to develop an Optimization Framework that can provide optimal BEV penetration scenarios considering minimum emissions, air pollutants, and cost of ownership.

5.1 METHODOLOGY STRUCTURE

In this study, the AFLEET tool was utilized to perform a Life Cycle Assessment to obtain CO, NOx, and GHG emissions produced from passenger cars and passenger trucks, as well as a Life Cycle Cost to get the Total Cost of Ownership depending on the fuel type. The structure followed to collect and input the data into the utilized tool is explained in the next subchapters.

After retrieving the outputs from the AFLEET Tool, a MOEA is performed to create multiple scenarios with different BEV percentages.

5.2 AFLEET TOOL

5.2.1Collect fuel data for passenger cars and passenger trucks

Information related to average gallons per mile of fossil fuel depending on the type of car was retrieved from the official U.S. government source for fuel economy information developed by the Department of Energy is needed to begin with the AFLEET tool. Also, the information related to the Vehicles' Miles Traveled (VMT) was necessary to utilize the On-Road Fleet Footprint Calculator. This study used the same number of VMTs for all vehicles.

ICEVs that utilize regular gasoline, diesel, and E85 were included in this study, along with HEVs, PHEVs, and BEVs. This research considered several types of cylinder capacity and the vehicle's fuel type and model from 2012 to 2022. Lastly, the two categories utilized were passenger cars and passenger trucks. The passenger truck category includes light-duty trucks and SUVs. Tables 5.1 and 5.2 show the gallons per mile and Miles Per Gallon of Gasoline Equivalent (MPGGE) according to the category of cars, fuel type, and model.

Table 5.1: Passenger cars fuel information (ORNL, 2022).

Passenger Cars					
ICEVs - Gasoline			**ICEVs - Diesel**		
Year	**gal/100 miles**	**MPGGE**	**Year**	**gal/100 miles**	**MPGGE**
2012	4.33	23.09	2012	3.40	29.41
2013	4.33	23.08	2013	3.80	26.32
2014	4.03	24.79	2014	2.80	35.71
2015	4.20	23.81	2015	3.75	26.67
2016	4.20	23.81	2016	3.35	29.85
2017	4.27	23.44	2017	3.00	33.33
2018	4.00	25.00	2018	3.40	29.41
2019	3.50	28.57	2019	2.90	34.48
2020	3.97	25.21	2020	2.70	37.10
2021	4.03	24.79	2021	2.70	37.10
2022	4.03	24.79	2022	2.70	37.10
Passenger Cars					
HEVs			**BEVs**		
Year	**gal/100 miles**	**MPGGE**	**Year**	**kWh/100 miles**	**MPkWhE**
2012	2.55	39.22	2012	38.00	2.63
2013	2.65	37.74	2013	38.00	2.63
2014	2.65	37.74	2014	38.00	2.63
2015	2.65	37.74	2015	38.00	2.63
2016	2.55	39.22	2016	38.00	2.63
2017	2.10	47.62	2017	33.00	3.03
2018	2.10	47.62	2018	35.00	2.86
2019	2.85	35.09	2019	33.00	3.03
2020	2.50	40.00	2020	29.00	3.45
2021	2.85	35.09	2021	28.00	3.57
2022	3.20	31.25	2022	28.00	3.57
PHEVs					
Year	**gal/100 miles**	**hWh/100 miles**	**MPGGE**	**MPkWhE**	
2012	2.00	29.00	50.00	3.45	
2013	2.60	37.00	38.46	2.70	
2014	2.60	37.00	38.46	2.70	
2015	2.60	37.00	38.46	2.70	
2016	2.60	37.00	38.46	2.70	
2017	2.40	35.00	41.67	2.86	
2018	2.40	35.00	41.67	2.86	
2019	2.40	33.00	41.67	3.03	
2020	2.40	33.00	41.67	3.03	
2021	2.40	31.00	41.67	3.23	
2022	1.90	28.00	52.63	3.57	

Table 5.1. Passenger cars fuel information continuation (ORNL, 2022).

ICEVs - E85 gasoline		
Year	**gal/100 miles**	**MPGGE**
2012	6.45	15.50
2013	5.20	19.23
2014	5.20	19.23
2015	6.15	16.26
2016	5.75	17.39
2017	5.25	19.05
2018	5.60	17.86
2019	5.85	17.09
2020	5.85	17.09
2021	5.85	17.09
2022	5.85	17.09

Table 5.2: Passenger truck's fuel information (ORNL, 2022).

Passenger Truck					
ICEVs - Gasoline			**ICEVs - Diesel**		
Year	**gal/100 miles**	**MPGGE**	**Year**	**gal/100 miles**	**MPGGE**
2012	5.2	24.00	2012	6.1	16.48
2013	5.3	18.87	2013	6.0	16.67
2014	5.1	25.00	2014	4.0	24.79
2015	5.2	19.08	2015	3.8	26.55
2016	4.9	26.00	2016	3.7	27.40
2017	5.2	19.38	2017	3.5	28.99
2018	4.8	27.00	2018	3.5	28.99
2019	5.1	19.46	2019	3.7	27.27
2020	4.7	28.00	2020	3.33	30.00
2021	4.9	20.49	2021	4.1	24.39
2022	4.8	29.00	2022	4.35	22.99
HEVs			**BEVs**		
Year	**gal/100 miles**	**MPGGE**	**Year**	**kWh/100 miles**	**MPkWhE**
2012	4.80	20.83	2012	49.00	2.04
2013	4.80	20.83	2013	44.00	2.27
2014	4.80	20.83	2014	44.00	2.27
2015	4.80	20.83	2015	44.00	2.27
2016	4.80	20.83	2016	44.00	2.27
2017	4.80	20.83	2017	44.00	2.27
2018	5.60	17.86	2018	30.00	3.33
2019	4.80	20.83	2019	34.00	2.94
2020	5.00	20.00	2020	50.00	2.00
2021	4.00	25.00	2021	54.00	1.85
2022	4.00	25.00	2022	48.00	2.08

Table 5.2: Passenger trucks fuel information continuation (ORNL, 2022).

PHEVs				
Year	gal/100 miles	kWh/100 miles	MPGGE	MPkWhE
2012	2.53	32	39.5	3.13
2013	2.53	32	39.5	3.13
2014	2.53	32	39.5	3.13
2015	2.53	32	39.5	3.13
2016	2.60	29	38.46	3.45
2017	3.80	45	26.32	2.22
2018	5.30	80	18.87	1.25
2019	5.30	80	18.87	1.25
2020	5.30	80	18.87	1.25
2021	5.30	80	18.87	1.25
2022	5.00	63	20.00	1.59

ICEVs - E85 gasoline		
Year	gal/100 miles	MPGGE
2012	7.33	13.65
2013	6.88	14.55
2014	6.98	14.33
2015	7.34	13.62
2016	6.98	14.33
2017	6.86	14.58
2018	6.80	14.71
2019	7.90	12.66
2020	8.00	12.50
2021	4.41	22.70
2022	4.41	22.70

5.2.2 Input data in On-Road Fleet Footprint Calculator

The AFLEET tool On-Road Fleet Footprint Calculator estimates GHGs, air pollutant emissions, and externality costs of existing and new on-road vehicles. The calculator considers that older vehicles cause higher air pollutant emission rates (Burnham, 2020). The critical inputs for this sheet are:

- Vehicle type
- Model year
- Annual vehicle mileage
- Fuel use

The first step in utilizing this calculator is to choose between the two vehicle type categories. In this case, passenger cars and passenger trucks were selected. If the user wants to examine more vehicles than is provided in this sheet, the user can copy and paste the entire row(s) with calculations (Burnham, 2020). Thus, six rows for each year were assigned since there are six types of vehicles. A range of 10 years was utilized for this research from 2012 to 2022. The state of Texas was selected for this study. In compliance with the Federal Highway Administration, an annual vehicle millage of 14,240 miles was standardized for all the models of vehicles based on the average miles driven per year by Americans (Covington, 2022). The data collected for passenger cars and passenger trucks presented in tables 5.1 and 5.2 were also assigned in the fuel use section. One row was utilized for each type of fuel to obtain the emissions of each fuel separately.

On-Road Fleet Footprint Calculator

State

TEXAS

Vehicle Type	Model Year	Annual Vehicle Mileage	Fuel Use: Gasoline (gal)	Diesel (gal)	Gasolin e HEV (gal)	Gasolin e PHEV (gal)	Gasolin e PHEV (kWh)	Electricity (kWh)	E85 (gal)
Passenger Car	2012	14,260	618						
Passenger Car	2012	14,260		485					
Passenger Car	2012	14,260			378				
Passenger Car	2012	14,260				285	4,135		
Passenger Car	2012	14,260						5,420	
Passenger Car	2012	14,260							920
Passenger Car	2013	14,260	618						
Passenger Car	2013	14,260		542					
Passenger Car	2013	14,260			378				
Passenger Car	2013	14,260				285	5,276		
Passenger Car	2013	14,260						5,420	
Passenger Car	2013	14,260							742
Passenger Car	2014	14,260	575						
Passenger Car	2014	14,260		400					
Passenger Car	2014	14,260			378				
Passenger Car	2014	14,260				285	5,276		
Passenger Car	2014	14,260						5,420	
Passenger Car	2014	14,260							742
Passenger Car	2015	14,260	600						
Passenger Car	2015	14,260		535					
Passenger Car	2015	14,260			378				
Passenger Car	2015	14,260				285	5,276		
Passenger Car	2015	14,260						5,420	
Passenger Car	2015	14,260							880
Passenger Car	2016	14,260	600						
Passenger Car	2016	14,260		478					
Passenger Car	2016	14,260			378				
Passenger Car	2016	14,260				285	5,276		
Passenger Car	2016	14,260						5,420	
Passenger Car	2016	14,260							820
Passenger Car	2017	14,260	609						
Passenger Car	2017	14,260		428					
Passenger Car	2017	14,260			300				
Passenger Car	2017	14,260				342	4,991		
Passenger Car	2017	14,260						4,710	
Passenger Car	2017	14,260							750
Passenger Car	2018	14,260	507						
Passenger Car	2018	14,260		485					
Passenger Car	2018	14,260			300				
Passenger Car	2018	14,260				342	4,991		
Passenger Car	2018	14,260						4,990	
Passenger Car	2018	14,260							800
Passenger Car	2019	14,260	523						
Passenger Car	2019	14,260		413					
Passenger Car	2019	14,260			406				
Passenger Car	2019	14,260				342	4,991		
Passenger Car	2019	14,260						4,710	
Passenger Car	2019	14,260							840
Passenger Car	2020	14,260	566						
Passenger Car	2020	14,260		385					
Passenger Car	2020	14,260			360				
Passenger Car	2020	14,260				342	4,991		
Passenger Car	2020	14,260						4,135	
Passenger Car	2020	14,260							840
Passenger Car	2021	14,260	575						
Passenger Car	2021	14,260		385					
Passenger Car	2021	14,260			406				
Passenger Car	2021	14,260				342	4,991		
Passenger Car	2021	14,260						3,990	
Passenger Car	2021	14,260							840
Passenger Car	2022	14,260	575						
Passenger Car	2022	14,260		385					
Passenger Car	2022	14,260			460				
Passenger Car	2022	14,260				271	3,993		
Passenger Car	2022	14,260						3,990	
Passenger Car	2022	14,260							840

Figure 5.1: On-Road Fleet Footprint Calculator for passenger cars (Burnham, 2020).

On-Road Fleet Footprint Calculator

State

TEXAS

Vehicle Type	Model Year	Annual Vehicle Mileage	Fuel Use						
			Gasoline (gal)	Diesel (gal)	Gasoline HEV (gal)	Gasoline PHEV (gal)	Gasoline PHEV (kWh)	Electricity (kWh)	E85 (gal)
Passenger Truck	2012	14,280	739						
Passenger Truck	2012	14,280		885					
Passenger Truck	2012	14,280			685				
Passenger Truck	2012	14,280				0	0		
Passenger Truck	2012	14,280						6,275	
Passenger Truck	2012	14,280							1,033
Passenger Truck	2013	14,280	755						
Passenger Truck	2013	14,280		855					
Passenger Truck	2013	14,280			685				
Passenger Truck	2013	14,280				0	0		
Passenger Truck	2013	14,280						6,275	
Passenger Truck	2013	14,280							980
Passenger Truck	2014	14,280	727						
Passenger Truck	2014	14,280		575					
Passenger Truck	2014	14,280			685				
Passenger Truck	2014	14,280				0	0		
Passenger Truck	2014	14,280						6,275	
Passenger Truck	2014	14,280							995
Passenger Truck	2015	14,280	747						
Passenger Truck	2015	14,280		540					
Passenger Truck	2015	14,280			685				
Passenger Truck	2015	14,280				0	0		
Passenger Truck	2015	14,280						6,275	
Passenger Truck	2015	14,280							1,046
Passenger Truck	2016	14,280	698						
Passenger Truck	2016	14,280		540					
Passenger Truck	2016	14,280			685				
Passenger Truck	2016	14,280				370	4,135		
Passenger Truck	2016	14,280						6,275	
Passenger Truck	2016	14,280							995
Passenger Truck	2017	14,280	736						
Passenger Truck	2017	14,280		540					
Passenger Truck	2017	14,280			685				
Passenger Truck	2017	14,280				540	6,417		
Passenger Truck	2017	14,280						4,278	
Passenger Truck	2017	14,280							980
Passenger Truck	2018	14,280	690						
Passenger Truck	2018	14,280		540					
Passenger Truck	2018	14,280			685				
Passenger Truck	2018	14,280				755	11,408		
Passenger Truck	2018	14,280						4,278	
Passenger Truck	2018	14,280							1,010
Passenger Truck	2019	14,280	733						
Passenger Truck	2019	14,280		525					
Passenger Truck	2019	14,280			685				
Passenger Truck	2019	14,280				755	11,408		
Passenger Truck	2019	14,280						4,850	
Passenger Truck	2019	14,280							1,120
Passenger Truck	2020	14,280	673						
Passenger Truck	2020	14,280		480					
Passenger Truck	2020	14,280			715				
Passenger Truck	2020	14,280				755	11,480		
Passenger Truck	2020	14,280						7,130	
Passenger Truck	2020	14,280							1,140
Passenger Truck	2021	14,280	705						
Passenger Truck	2021	14,280		585					
Passenger Truck	2021	14,280			570				
Passenger Truck	2021	14,280				755	11,480		
Passenger Truck	2021	14,280						7,670	
Passenger Truck	2021	14,280							1,180
Passenger Truck	2022	14,280	690						
Passenger Truck	2022	14,280		620					
Passenger Truck	2022	14,280			570				
Passenger Truck	2022	14,280				713	8,980		
Passenger Truck	2022	14,280						6,845	
Passenger Truck	2022	14,280							1,140

Figure 5.2: On-Road Fleet Footprint Calculator for passenger cars (Burnham, 2020).

5.2.3 Extract and save CO, NOx, and GHG data from the AFLEET tool

Once the On-Road Fleet Footprint Calculator is completed, the GHG, CO, and NOx values will be displayed under the vehicle operation section. Each value will represent the vehicle operation emissions from a specific fuel used in each year of each model. Figure 5.3 and 5.4 shows an example of the emissions of a 2012 gasoline passenger car and a 2012 gasoline passenger truck respectively.

On-Road Fleet Footprint Calculator
State
TEXAS

Vehicle Type	Model Year	Annual Vehicle Mileage	Well-to-Wheels GHGs (short tons)	Vehicle Production GHGs (short tons)	Vehicle Operation Air Pollutants (lb)	
					CO	NOx
Passenger Car	2012	14,260	7.3	0.6	82.7	1.1
Passenger Car	2012	14,260	6.7	0.6	95.6	2.1
Passenger Car	2012	14,260	4.4	0.0	82.7	0.9
Passenger Car	2012	14,260	4.9	0.9	0.0	0.0
Passenger Car	2012	14,260	2.0	0.9	0.0	0.0
Passenger Car	2012	14,260	5.3	0.6	82.7	1.1

Figure 5.3: Example of GHG, CO, and NOx values for a 2012 gasoline passenger car – AFLEET Tool screenshot.

On-Road Fleet Footprint Calculator
State
TEXAS

Vehicle Type	Model Year	Annual Vehicle Mileage	Well-to-Wheels GHGs (short tons)	Vehicle Production GHGs (short tons)	Vehicle Operation Air Pollutants (lb)	
					CO	NOx
Passenger Truck	2012	14,260	8.7	0.7	90.9	1.5
Passenger Truck	2012	14,260	11.9	0.7	34.5	29.9
Passenger Truck	2012	14,260	8.1	0.0	90.9	1.2
Passenger Truck	2012	14,260	0.0	0.0	90.9	1.2
Passenger Truck	2012	14,260	2.4	1.1	0.0	0.0
Passenger Truck	2012	14,260	5.9	0.7	90.9	1.5

Figure 5.4: Example of GHG, CO, and NOx values for a 2012 gasoline passenger truck – AFLEET Tool screenshot.

5.2.4 Input Light-duty vehicle information in AFLEET Tool

The AFLEET tool provides default data for the calculator inputs (Burnham, 2020). However, for more accurate results, the number of vehicles to be compared, the amount of time in years, annual vehicle mileage, fuel economy values on a mile-per-gasoline gallon equivalent (MPGGE), and the purchase price were modified. Table 5.3 represents the average cost of purchasing a specific model in 2022. Prices of 4-cylinder, 6-cylinder, and 8-cylinder models from 2012 to 2022 were collected to generate an average cost for the three prices in the simulation.

Table 5.3: Average cost of vehicles (Edmunds, 2022).

Vehicle Type - Passenger Cars			
ICEVs - Gasoline		**ICEVs - Diesel**	
Year	**Purchase Price ($/vehicle)**	**Year**	**Purchase Price ($/vehicle)**
2012	$10,500.00	2012	$14,000.00
2013	$11,500.00	2013	$15,750.00
2014	$13,666.67	2014	$17,000.00
2015	$14,833.33	2015	$19,500.00
2016	$16,000.00	2016	$21,750.00
2017	$17,100.00	2017	$23,500.00
2018	$18,266.67	2018	$28,000.00
2019	$19,633.33	2019	$25,000.00
2020	$21,166.67	2020	$27,000.00
2021	$23,500.00	2021	$27,000.00
2022	$27,966.67	2022	$27,000.00
HEVs		**BEVs**	
Year	**Purchase Price ($/vehicle)**	**Year**	**Purchase Price ($/vehicle)**
2012	$8,950.00	2012	$29,000.00
2013	$10,100.00	2013	$31,000.00
2014	$13,000.00	2014	$33,000.00
2015	$14,000.00	2015	$36,000.00
2016	$18,500.00	2016	$40,000.00
2017	$22,000.00	2017	$43,000.00
2018	$24,000.00	2018	$50,000.00
2019	$26,500.00	2019	$65,000.00
2020	$28,500.00	2020	$75,000.00
2021	$32,250.00	2021	$80,000.00
2022	$40,000.00	2022	$100,000.00
PHEVs		**ICEVs - E85 gasoline**	
Year	**Purchase Price ($/vehicle)**	**Year**	**Purchase Price ($/vehicle)**
2012	$16,000.00	2012	$11,250.00
2013	$17,000.00	2013	$11,500.00
2014	$18,000.00	2014	$16,000.00
2015	$19,000.00	2015	$19,250.00
2016	$20,000.00	2016	$19,750.00
2017	$21,000.00	2017	$19,750.00
2018	$22,000.00	2018	$21,500.00
2019	$23,000.00	2019	$22,200.00
2020	$25,000.00	2020	$20,000.00
2021	$28,000.00	2021	$20,000.00
2022	$29,000.00	2022	$20,000.00

Table 5.3: Average cost of vehicles (Edmunds, 2022).

Vehicle Type - Passenger Trucks			
ICEVs - Gasoline		ICEVs - Diesel	
Year	Purchase Price ($/vehicle)	Year	Purchase Price ($/vehicle)
2012	$13,166.67	2012	$17,500.00
2013	$14,266.67	2013	$18,500.00
2014	$16,666.67	2014	$21,000.00
2015	$18,000.00	2015	$22,000.00
2016	$19,666.67	2016	$24,500.00
2017	$22,833.33	2017	$27,500.00
2018	$25,166.67	2018	$32,500.00
2019	$30,333.33	2019	$34,500.00
2020	$36,666.67	2020	$41,500.00
2021	$39,666.67	2021	$50,000.00
2022	$48,100.00	2022	$57,000.00
HEVs		BEVs	
Year	Purchase Price ($/vehicle)	Year	Purchase Price ($/vehicle)
2012	$15,000.00	2012	$18,000.00
2013	$16,000.00	2013	$19,000.00
2014	$16,500.00	2014	$19,000.00
2015	$17,000.00	2015	$19,800.00
2016	$18,000.00	2016	$21,000.00
2017	$18,500.00	2017	$22,000.00
2018	$20,000.00	2018	$26,000.00
2019	$30,000.00	2019	$35,000.00
2020	$40,000.00	2020	$39,000.00
2021	$50,000.00	2021	$49,000.00
2022	$60,000.00	2022	$50,000.00
PHEVs		ICEVs - E85 gasoline	
Year	Purchase Price ($/vehicle)	Year	Purchase Price ($/vehicle)
2012	$38,500.00	2012	$13,166.67
2013	$38,500.00	2013	$14,266.67
2014	$38,500.00	2014	$16,666.67
2015	$38,500.00	2015	$18,000.00
2016	$21,800.00	2016	$19,666.67
2017	$46,000.00	2017	$22,833.33
2018	$59,000.00	2018	$25,166.67
2019	$62,000.00	2019	$30,333.33
2020	$68,000.00	2020	$36,666.67
2021	$80,000.00	2021	$39,666.67
2022	$85,000.00	2022	$48,100.00

In addition, figure 5.5 shows the key vehicle and fuel inputs required in the Total Cost of Ownership Calculator. First, the primary vehicle location selected was El Paso County in Texas. For the "vehicle type," passenger car and passenger truck were selected once at a time. Under the column "number of light-duty vehicles," light-duty fuel types such as gasoline, diesel, gasoline HEV, gasoline PHEV, All-EV, and Ethanol (E85) were selected with the number 1 since that will only account for the emissions of one vehicle of each. The "annual vehicle mileage" was the same for all types of vehicles. However, the "fuel economy (MPGGE)" and the "purchase price" were modified with the data presented in Tables 5.1 and 5.2, and 5.3. Figure 5.6 illustrates the Simple Payback Calculator. Since BEVs and PHEVs utilizes electricity, the kWh/mi must be accounted for. Thus, the red numbers represent an example of the data modified to obtain an accurate Total Cost of Ownership.

Key Vehicle and Fuel Inputs					
Primary Vehicle Location					
State	TEXAS				
County	EL PASO				
Light-Duty Vehicle Information					
Vehicle Type	Passenger Car				
Vocation Type	Car				
Light-Duty Fuel Type	**Number of Light-Duty Vehicles**	**Annual Vehicle Mileage**	**Fuel Economy (MPGGE)**	**Purchase Price ($/vehicle)**	**Maintenance & Repair ($/mi)**
Gasoline	1	14,260	23.0	$20,000	$0.15
Diesel	1	14,260	29.4	$27,000	$0.23
Gasoline Hybrid Electric Vehicle (HEV)	1	14,260	39.2	$22,000	$0.14
Gasoline Plug-in Hybrid Electric Vehicle (PHEV)	1	14,260	50.0	$27,000	$0.13
Gasoline Extended Range Electric Vehicle (EREV)	0	14,260	44.4	$33,000	$0.13
All-Electric Vehicle (EV)	1	14,260	106.0	$37,000	$0.09
Gaseous Hydrogen (G.H2) Fuel Cell Vehicle (FCV)	0	14,260	73.5	$50,000	$0.09
Biodiesel (B20)	0	14,260	37.1	$27,000	$0.23
Biodiesel (B100)	0	14,260	37.1	$27,000	$0.23
Renewable Diesel (RD20)	0	14,260	37.1	$27,000	$0.23
Renewable Diesel (RD100)	0	14,260	37.1	$27,000	$0.23
Ethanol (E85)	1	14,260	15.5	$20,000	$0.15
Propane (LPG)	0	14,260	30.9	$26,000	$0.15
Compressed Natural Gas (CNG)	0	14,260	29.4	$27,000	$0.15

Figure 5.5: Example of the key vehicle and fuel inputs for Passenger Cars - AFLEET Tool screenshot.

On-Road Vehicle Inputs						
Light-Duty Vehicle Inputs						
Vehicle Type	Passenger Truck					
Number of LDVs	1	1	1	1	0	1
Annual Mileage	14,260	14,260	14,260	14,260	14,260	14,260
Fuel Economy (MPGGE)	29.0	23.0	25.0	18.9	27.4	69.5
CD Electricity Use (kWh/100mi)				80.0	57.7	38.0
CD Electricity Use (GGE/100mi)				2.4	1.8	
CD Gasoline Use (GGE/100mi)				5.3	0.0	
PHEV CD Range (miles)				22.6	46.0	
Charges/day				1.0	1.0	
Days driven/week				5	5	
Share of CD miles				41%	84%	

Figure 5.6: Representation of the Simple Payback Calculator - AFLEET Tool screenshot.

5.2.5 Extract and save Total Cost of Ownership Calculator results

This sheet summarizes the output of the Total Cost of Ownership (TCO) Calculator (Burnham, 2020). This study considers the depreciation, fuel, maintenance, repair, insurance, license, and registration to generate the TCO for the vehicles.

Total Cost of Ownership Calculator Output

Lifetime Cost of Ownership Calculator Output - Costs

	Gasoline	Diesel	Gasoline HEV	Gasoline PHEV	EV	E85
Light-Duty Passenger Truck Fleet and Infrastructure						
	$0	$0	$0	$0	$0	$0
	$13,949	$16,530	$17,400	$24,650	$14,500	$13,949
	$1,618	$2,435	$1,877	$3,041	$793	$2,269
	$0	$35	$0	$0	$0	$0
	$1,084	$1,647	$991	$946	$683	$1,084
	$2,631	$3,003	$3,128	$4,172	$2,711	$2,631
	$51	$51	$51	$51	$51	$51
T	**$19,332**	**$23,699**	**$23,446**	**$32,859**	**$18,738**	**$19,984**

Figure 5.7: Example of the TCO calculator - AFLEET tool screenshot.

5.2.6 Result Tables

After utilizing the data in the AFLEET tool, a result table for the LCA and LCC is created. The table size is a 132x5 matrix, where the 132 columns identify the type of vehicle (Table 5.3). Table 5.4, 5.5, 5.6, and 5.7 shows the GHGs, CO, NOx, and TCO output data, which will conform to the result table. Figure 5.8 shows an example of one result table for a simulation with 132 types of vehicles. The first row saves the number of vehicles in the simulation. Rows 2, 3, and 4 keep the results in lbs. of GHG, CO, and NOx emissions generated by the number of vehicles in each column, respectively, and the TCO is accounted for in row 5.

Table 5.3: Type of vehicles

Vehicle Type - Passenger Cars				Vehicle Type - Passenger Trucks			
1	2012 - Gasoline	**34**	2017 - PHEV	**67**	2012 - Gasoline	**100**	2017 - PHEV
2	2012 - Diesel	**35**	2017 - EV	**68**	2012 - Diesel	**101**	2017 - EV
3	2012 - HEV	**36**	2017 - E85	**69**	2012 - HEV	**102**	2017 - E85
4	2012 - PHEV	**37**	2018 - Gasoline	**70**	2012 - PHEV	**103**	2018 - Gasoline
5	2012 - EV	**38**	2018 - Diesel	**71**	2012 - EV	**104**	2018 - Diesel
6	2012 - E85	**39**	2018 - HEV	**72**	2012 - E85	**105**	2018 - HEV
7	2013 - Gasoline	**40**	2018 - PHEV	**73**	2013 - Gasoline	**106**	2018 - PHEV
8	2013 - Diesel	**41**	2018 - EV	**74**	2013 - Diesel	**107**	2018 - EV
9	2013 - HEV	**42**	2018 - E85	**75**	2013 - HEV	**108**	2018 - E85
10	2013 - PHEV	**43**	2019 - Gasoline	**76**	2013 - PHEV	**109**	2019 - Gasoline
11	2013 - EV	**44**	2019 - Diesel	**77**	2013 - EV	**110**	2019 - Diesel
12	2013 - E85	**45**	2019 - HEV	**78**	2013 - E85	**111**	2019 - HEV
13	2014 - Gasoline	**46**	2019 - PHEV	**79**	2014 - Gasoline	**112**	2019 - PHEV
14	2014 - Diesel	**47**	2019 - EV	**80**	2014 - Diesel	**113**	2019 - EV
15	2014 - HEV	**48**	2019 - E85	**81**	2014 - HEV	**114**	2019 - E85
16	2014 - PHEV	**49**	2020 - Gasoline	**82**	2014 - PHEV	**115**	2020 - Gasoline
17	2014 - EV	**50**	2020 - Diesel	**83**	2014 - EV	**116**	2020 - Diesel
18	2014 - E85	**51**	2020 - HEV	**84**	2014 - E85	**117**	2020 - HEV
19	2015 - Gasoline	**52**	2020 - PHEV	**85**	2015 - Gasoline	**118**	2020 - PHEV
20	2015 - Diesel	**53**	2020 - EV	**86**	2015 - Diesel	**119**	2020 - EV
21	2015 - HEV	**54**	2020 - E85	**87**	2015 - HEV	**120**	2020 - E85
22	2015 - PHEV	**55**	2021 - Gasoline	**88**	2015 - PHEV	**121**	2021 - Gasoline
23	2015 - EV	**56**	2021 - Diesel	**89**	2015 - EV	**122**	2021 - Diesel
24	2015 - E85	**57**	2021 - HEV	**90**	2015 - E85	**123**	2021 - HEV
25	2016 - Gasoline	**58**	2021 - PHEV	**91**	2016 - Gasoline	**124**	2021 - PHEV
26	2016 - Diesel	**59**	2021 - EV	**92**	2016 - Diesel	**125**	2021 - EV
27	2016 - HEV	**60**	2021 - E85	**93**	2016 - HEV	**126**	2021 - E85
28	2016 - PHEV	**61**	2022 - Gasoline	**94**	2016 - PHEV	**127**	2022 - Gasoline
29	2016 - EV	**62**	2022 - Diesel	**95**	2016 - EV	**128**	2022 - Diesel
30	2016 - E85	**63**	2022 - HEV	**96**	2016 - E85	**129**	2022 - HEV
31	2017 - Gasoline	**64**	2022 - PHEV	**97**	2017 - Gasoline	**130**	2022 - PHEV
32	2017 - Diesel	**65**	2022 - EV	**98**	2017 - Diesel	**131**	2022 - EV
33	2017 - HEV	**66**	2022 - E85	**99**	2017 - HEV	**132**	2022 - E85

Table 5.4: GHG output values

Vehicle Type - Passenger Cars					
No.	**Year and Fuel**	**Tons**	**No.**	**Year and Fuel**	**Tons**
1	2012 - Gasoline	7.2685	**34**	2017 - PHEV	5.9034
2	2012 - Diesel	6.6532	**35**	2017 - EV	1.7751
3	2012 - HEV	4.4458	**36**	2017 - E85	4.2895
4	2012 - PHEV	4.9104	**37**	2018 - Gasoline	5.9630
5	2012 - EV	2.0427	**38**	2018 - Diesel	6.6532
6	2012 - E85	5.2618	**39**	2018 - HEV	3.5284
7	2013 - Gasoline	7.2685	**40**	2018 - PHEV	5.9034
8	2013 - Diesel	7.4351	**41**	2018 - EV	1.8806
9	2013 - HEV	4.4458	**42**	2018 - E85	4.5755
10	2013 - PHEV	5.3404	**43**	2019 - Gasoline	6.1512
11	2013 - EV	2.0427	**44**	2019 - Diesel	5.6655
12	2013 - E85	4.2438	**45**	2019 - HEV	4.7751
13	2014 - Gasoline	6.7628	**46**	2019 - PHEV	5.9034
14	2014 - Diesel	5.4872	**47**	2019 - EV	1.7751
15	2014 - HEV	4.4458	**48**	2019 - E85	4.8043
16	2014 - PHEV	5.3404	**49**	2020 - Gasoline	6.6569
17	2014 - EV	2.0427	**50**	2020 - Diesel	5.2814
18	2014 - E85	4.2438	**51**	2020 - HEV	4.2341
19	2015 - Gasoline	7.0568	**52**	2020 - PHEV	5.9034
20	2015 - Diesel	7.3391	**53**	2020 - EV	1.5584
21	2015 - HEV	4.4458	**54**	2020 - E85	4.8043
22	2015 - PHEV	5.3404	**55**	2021 - Gasoline	6.7628
23	2015 - EV	2.0427	**56**	2021 - Diesel	5.2814
24	2015 - E85	5.0331	**57**	2021 - HEV	4.7751
25	2016 - Gasoline	7.0568	**58**	2021 - PHEV	5.9034
26	2016 - Diesel	6.5571	**59**	2021 - EV	1.5037
27	2016 - HEV	4.4458	**60**	2021 - E85	4.8043
28	2016 - PHEV	5.3404	**61**	2022 - Gasoline	6.7628
29	2016 - EV	2.0427	**62**	2022 - Diesel	5.2814
30	2016 - E85	4.6899	**63**	2022 - HEV	5.4102
31	2017 - Gasoline	7.1626	**64**	2022 - PHEV	4.6922
32	2017 - Diesel	5.8713	**65**	2022 - EV	1.5037
33	2017 - HEV	3.5284	**66**	2022 - E85	4.8043

Table 5.4: GHG output values (continuation).

Vehicle Type - Passenger Trucks					
No.	**Year and Fuel**	**Tons**	**No.**	**Year and Fuel**	**Tons**
67	2012 - Gasoline	8.6916	**100**	2017 - PHEV	8.7695
68	2012 - Diesel	11.8660	**101**	2017 - EV	1.6123
69	2012 - HEV	8.0565	**102**	2017 - E85	5.6050
70	2012 - PHEV	0.0000	**103**	2018 - Gasoline	8.1153
71	2012 - EV	2.3649	**104**	2018 - Diesel	7.4077
72	2012 - E85	5.9081	**105**	2018 - HEV	8.0565
73	2013 - Gasoline	8.8798	**106**	2018 - PHEV	13.1792
74	2013 - Diesel	11.7288	**107**	2018 - EV	1.6123
75	2013 - HEV	8.0565	**108**	2018 - E85	5.7766
76	2013 - PHEV	0.0000	**109**	2019 - Gasoline	8.6210
77	2013 - EV	2.3649	**110**	2019 - Diesel	7.2019
78	2013 - E85	5.6050	**111**	2019 - HEV	8.0565
79	2014 - Gasoline	8.5505	**112**	2019 - PHEV	13.1792
80	2014 - Diesel	7.8878	**113**	2019 - EV	1.8278
81	2014 - HEV	8.0565	**114**	2019 - E85	6.4057
82	2014 - PHEV	0.0000	**115**	2020 - Gasoline	7.9154
83	2014 - EV	2.3649	**116**	2020 - Diesel	6.5846
84	2014 - E85	5.6908	**117**	2020 - HEV	8.4093
85	2015 - Gasoline	8.7857	**118**	2020 - PHEV	13.2063
86	2015 - Diesel	7.4077	**119**	2020 - EV	2.6871
87	2015 - HEV	8.0565	**120**	2020 - E85	6.5201
88	2015 - PHEV	0.0000	**121**	2021 - Gasoline	8.2917
89	2015 - EV	2.3649	**122**	2021 - Diesel	8.0250
90	2015 - E85	5.9825	**123**	2021 - HEV	6.7039
91	2016 - Gasoline	8.1859	**124**	2021 - PHEV	13.2063
92	2016 - Diesel	7.4077	**125**	2021 - EV	2.8906
93	2016 - HEV	8.0565	**126**	2021 - E85	6.7489
94	2016 - PHEV	5.9101	**127**	2022 - Gasoline	8.1153
95	2016 - EV	2.3649	**128**	2022 - Diesel	8.5051
96	2016 - E85	5.6908	**129**	2022 - HEV	6.7039
97	2017 - Gasoline	8.6563	**130**	2022 - PHEV	11.7702
98	2017 - Diesel	7.4077	**131**	2022 - EV	2.5797
99	2017 - HEV	8.0565	**132**	2022 - E85	6.5201

Table 5.5: CO output values

Vehicle Type - Passenger Cars					
No.	**Year and Fuel**	**lb.**	**No.**	**Year and Fuel**	**lb.**
1	2012 - Gasoline	82.7132	**34**	2017 - PHEV	0.0000
2	2012 - Diesel	95.5713	**35**	2017 - EV	0.0000
3	2012 - HEV	82.7132	**36**	2017 - E85	28.0741
4	2012 - PHEV	0.0000	**37**	2018 - Gasoline	26.4707
5	2012 - EV	0.0000	**38**	2018 - Diesel	28.9858
6	2012 - E85	82.7132	**39**	2018 - HEV	26.4707
7	2013 - Gasoline	70.3581	**40**	2018 - PHEV	0.0000
8	2013 - Diesel	81.8015	**41**	2018 - EV	0.0000
9	2013 - HEV	70.3581	**42**	2018 - E85	26.4707
10	2013 - PHEV	0.0000	**43**	2019 - Gasoline	25.8105
11	2013 - EV	0.0000	**44**	2019 - Diesel	27.2252
12	2013 - E85	70.3581	**45**	2019 - HEV	25.8105
13	2014 - Gasoline	70.4000	**46**	2019 - PHEV	0.0000
14	2014 - Diesel	81.8000	**47**	2019 - EV	0.0000
15	2014 - HEV	70.4000	**48**	2019 - E85	25.8105
16	2014 - PHEV	0.0000	**49**	2020 - Gasoline	24.1758
17	2014 - EV	0.0000	**50**	2020 - Diesel	25.4647
18	2014 - E85	70.4000	**51**	2020 - HEV	24.1758
19	2015 - Gasoline	58.9000	**52**	2020 - PHEV	0.0000
20	2015 - Diesel	67.0000	**53**	2020 - EV	0.0000
21	2015 - HEV	58.9000	**54**	2020 - E85	24.1758
22	2015 - PHEV	0.0000	**55**	2021 - Gasoline	22.6923
23	2015 - EV	0.0000	**56**	2021 - Diesel	23.7458
24	2015 - E85	58.9000	**57**	2021 - HEV	22.6923
25	2016 - Gasoline	58.9000	**58**	2021 - PHEV	0.0000
26	2016 - Diesel	67.0000	**59**	2021 - EV	0.0000
27	2016 - HEV	58.9000	**60**	2021 - E85	22.6923
28	2016 - PHEV	0.0000	**61**	2022 - Gasoline	21.2088
29	2016 - EV	0.0000	**62**	2022 - Diesel	22.0270
30	2016 - E85	58.9000	**63**	2022 - HEV	21.2088
31	2017 - Gasoline	28.0741	**64**	2022 - PHEV	0.0000
32	2017 - Diesel	30.7148	**65**	2022 - EV	0.0000
33	2017 - HEV	28.0741	**66**	2022 - E85	21.2088

Table 5.5: CO output values (continuation).

Vehicle Type - Passenger Trucks					
No.	**Year and Fuel**	**lb.**	**No.**	**Year and Fuel**	**lb.**
67	2012 - Gasoline	90.9499	**100**	2017 - PHEV	0.0000
68	2012 - Diesel	34.4874	**101**	2017 - EV	0.0000
69	2012 - HEV	90.9499	**102**	2017 - E85	43.1328
70	2012 - PHEV	90.9499	**103**	2018 - Gasoline	31.3122
71	2012 - EV	0.0000	**104**	2018 - Diesel	23.6099
72	2012 - E85	90.9499	**105**	2018 - HEV	31.3122
73	2013 - Gasoline	79.0349	**106**	2018 - PHEV	0.0000
74	2013 - Diesel	34.0158	**107**	2018 - EV	0.0000
75	2013 - HEV	79.0349	**108**	2018 - E85	31.3122
76	2013 - PHEV	79.0349	**109**	2019 - Gasoline	30.3062
77	2013 - EV	0.0000	**110**	2019 - Diesel	22.6667
78	2013 - E85	79.0349	**111**	2019 - HEV	30.3062
79	2014 - Gasoline	79.0349	**112**	2019 - PHEV	0.0000
80	2014 - Diesel	48.1629	**113**	2019 - EV	0.0000
81	2014 - HEV	79.0349	**114**	2019 - E85	30.3062
82	2014 - PHEV	79.0349	**115**	2020 - Gasoline	28.0112
83	2014 - EV	0.0000	**116**	2020 - Diesel	21.7550
84	2014 - E85	79.0349	**117**	2020 - HEV	28.0112
85	2015 - Gasoline	66.9942	**118**	2020 - PHEV	0.0000
86	2015 - Diesel	42.2211	**119**	2020 - EV	0.0000
87	2015 - HEV	66.9942	**120**	2020 - E85	28.0112
88	2015 - PHEV	66.9942	**121**	2021 - Gasoline	26.0119
89	2015 - EV	0.0000	**122**	2021 - Diesel	20.8413
90	2015 - E85	66.9942	**123**	2021 - HEV	26.0119
91	2016 - Gasoline	66.9942	**124**	2021 - PHEV	0.0000
92	2016 - Diesel	42.2211	**125**	2021 - EV	0.0000
93	2016 - HEV	66.9942	**126**	2021 - E85	26.0119
94	2016 - PHEV	0.0000	**127**	2022 - Gasoline	24.0126
95	2016 - EV	0.0000	**128**	2022 - Diesel	19.9275
96	2016 - E85	66.9942	**129**	2022 - HEV	24.0126
97	2017 - Gasoline	43.1328	**130**	2022 - PHEV	0.0000
98	2017 - Diesel	28.6714	**131**	2022 - EV	0.0000
99	2017 - HEV	43.1328	**132**	2022 - E85	24.0126

Table 5.6: NOx output values

Vehicle Type - Passenger Cars					
No.	**Year and Fuel**	**lb.**	**No.**	**Year and Fuel**	**lb.**
1	2012 - Gasoline	1.0689	**34**	2017 - PHEV	0.0000
2	2012 - Diesel	2.1378	**35**	2017 - EV	0.0000
3	2012 - HEV	0.8979	**36**	2017 - E85	0.6602
4	2012 - PHEV	0.0000	**37**	2018 - Gasoline	0.5973
5	2012 - EV	0.0000	**38**	2018 - Diesel	0.6288
6	2012 - E85	1.0689	**39**	2018 - HEV	0.5017
7	2013 - Gasoline	0.9746	**40**	2018 - PHEV	0.0000
8	2013 - Diesel	1.9806	**41**	2018 - EV	0.0000
9	2013 - HEV	0.8186	**42**	2018 - E85	0.5973
10	2013 - PHEV	0.0000	**43**	2019 - Gasoline	0.5344
11	2013 - EV	0.0000	**44**	2019 - Diesel	0.5344
12	2013 - E85	0.9746	**45**	2019 - HEV	0.4489
13	2014 - Gasoline	1.0000	**46**	2019 - PHEV	0.0000
14	2014 - Diesel	2.0000	**47**	2019 - EV	0.0000
15	2014 - HEV	0.8000	**48**	2019 - E85	0.5344
16	2014 - PHEV	0.0000	**49**	2020 - Gasoline	0.4716
17	2014 - EV	0.0000	**50**	2020 - Diesel	0.4716
18	2014 - E85	0.8000	**51**	2020 - HEV	0.3961
19	2015 - Gasoline	0.9000	**52**	2020 - PHEV	0.0000
20	2015 - Diesel	1.8000	**53**	2020 - EV	0.0000
21	2015 - HEV	0.8000	**54**	2020 - E85	0.4716
22	2015 - PHEV	0.0000	**55**	2021 - Gasoline	0.4272
23	2015 - EV	0.0000	**56**	2021 - Diesel	0.4157
24	2015 - E85	0.9000	**57**	2021 - HEV	0.3588
25	2016 - Gasoline	0.9000	**58**	2021 - PHEV	0.0000
26	2016 - Diesel	1.8000	**59**	2021 - EV	0.0000
27	2016 - HEV	0.8000	**60**	2021 - E85	0.4272
28	2016 - PHEV	0.0000	**61**	2022 - Gasoline	0.3828
29	2016 - EV	0.0000	**62**	2022 - Diesel	0.3598
30	2016 - E85	0.9000	**63**	2022 - HEV	0.3216
31	2017 - Gasoline	0.6602	**64**	2022 - PHEV	0.0000
32	2017 - Diesel	0.6916	**65**	2022 - EV	0.0000
33	2017 - HEV	0.5546	**66**	2022 - E85	0.3828

Table 5.6: NOx output values (continuation).

Vehicle Type - Passenger Trucks					
No.	**Year and Fuel**	**lb.**	**No.**	**Year and Fuel**	**lb.**
67	2012 - Gasoline	1.4776	**100**	2017 - PHEV	0.0000
68	2012 - Diesel	29.8975	**101**	2017 - EV	0.0000
69	2012 - HEV	1.2412	**102**	2017 - E85	0.5973
70	2012 - PHEV	1.2412	**103**	2018 - Gasoline	0.5659
71	2012 - EV	0.0000	**104**	2018 - Diesel	4.9043
72	2012 - E85	1.4776	**105**	2018 - HEV	0.4753
73	2013 - Gasoline	1.2890	**106**	2018 - PHEV	0.0000
74	2013 - Diesel	38.7001	**107**	2018 - EV	0.0000
75	2013 - HEV	1.0827	**108**	2018 - E85	0.5659
76	2013 - PHEV	1.0827	**109**	2019 - Gasoline	0.5344
77	2013 - EV	0.0000	**110**	2019 - Diesel	4.3384
78	2013 - E85	1.2890	**111**	2019 - HEV	0.4489
79	2014 - Gasoline	1.2890	**112**	2019 - PHEV	0.0000
80	2014 - Diesel	14.7444	**113**	2019 - EV	0.0000
81	2014 - HEV	1.0827	**114**	2019 - E85	0.5344
82	2014 - PHEV	1.0827	**115**	2020 - Gasoline	0.4401
83	2014 - EV	0.0000	**116**	2020 - Diesel	3.7726
84	2014 - E85	1.2890	**117**	2020 - HEV	0.3697
85	2015 - Gasoline	1.0375	**118**	2020 - PHEV	0.0000
86	2015 - Diesel	11.3491	**119**	2020 - EV	0.0000
87	2015 - HEV	0.8715	**120**	2020 - E85	0.4401
88	2015 - PHEV	0.8715	**121**	2021 - Gasoline	0.3975
89	2015 - EV	0.0000	**122**	2021 - Diesel	3.6325
90	2015 - E85	1.0375	**123**	2021 - HEV	0.3339
91	2016 - Gasoline	1.0375	**124**	2021 - PHEV	0.0000
92	2016 - Diesel	11.3491	**125**	2021 - EV	0.0000
93	2016 - HEV	0.8715	**126**	2021 - E85	0.3975
94	2016 - PHEV	0.0000	**127**	2022 - Gasoline	0.3548
95	2016 - EV	0.0000	**128**	2022 - Diesel	3.4924
96	2016 - E85	1.0375	**129**	2022 - HEV	0.2980
97	2017 - Gasoline	0.5973	**130**	2022 - PHEV	0.0000
98	2017 - Diesel	7.1050	**131**	2022 - EV	0.0000
99	2017 - HEV	0.5017	**132**	2022 - E85	0.3548

Table 5.7: TCO output values

Vehicle Type - Passenger Cars					
No.	**Year and Fuel**	**Average cost**	**No.**	**Year and Fuel**	**Average cost**
1	2012 - Gasoline	$ 7,101.61	**34**	2017 - PHEV	$ 66,862.00
2	2012 - Diesel	$ 8,635.18	**35**	2017 - EV	$ 62,600.00
3	2012 - HEV	$ 5,673.44	**36**	2017 - E85	$ 77,603.00
4	2012 - PHEV	$ 7,922.90	**37**	2018 - Gasoline	$ 66,641.00
5	2012 - EV	$ 11,390.08	**38**	2018 - Diesel	$ 86,865.00
6	2012 - E85	$ 8,641.35	**39**	2018 - HEV	$ 58,566.00
7	2013 - Gasoline	$ 7,433.36	**40**	2018 - PHEV	$ 66,862.00
8	2013 - Diesel	$ 9,442.36	**41**	2018 - EV	$ 62,600.00
9	2013 - HEV	$ 6,101.86	**42**	2018 - E85	$ 79,615.00
10	2013 - PHEV	$ 8,593.07	**43**	2019 - Gasoline	$ 65,584.00
11	2013 - EV	$ 12,053.58	**44**	2019 - Diesel	$ 83,683.00
12	2013 - E85	$ 8,079.77	**45**	2019 - HEV	$ 62,459.00
13	2014 - Gasoline	$ 68,179.00	**46**	2019 - PHEV	$ 66,714.00
14	2014 - Diesel	$ 83,054.00	**47**	2019 - EV	$ 62,600.00
15	2014 - HEV	$ 61,420.00	**48**	2019 - E85	$ 81,066.00
16	2014 - PHEV	$ 68,048.00	**49**	2020 - Gasoline	$ 65,954.00
17	2014 - EV	$ 62,600.00	**50**	2020 - Diesel	$ 83,942.00
18	2014 - E85	$ 77,320.00	**51**	2020 - HEV	$ 60,643.00
19	2015 - Gasoline	$ 69,217.00	**52**	2020 - PHEV	$ 66,714.00
20	2015 - Diesel	$ 89,038.00	**53**	2020 - EV	$ 62,600.00
21	2015 - HEV	$ 61,420.00	**54**	2020 - E85	$ 81,066.00
22	2015 - PHEV	$ 68,048.00	**55**	2021 - Gasoline	$ 68,355.00
23	2015 - EV	$ 62,600.00	**56**	2021 - Diesel	$ 82,392.00
24	2015 - E85	$ 82,783.00	**57**	2021 - HEV	$ 62,497.00
25	2016 - Gasoline	$ 67,380.00	**58**	2021 - PHEV	$ 66,567.00
26	2016 - Diesel	$ 86,519.00	**59**	2021 - EV	$ 62,600.00
27	2016 - HEV	$ 60,901.00	**60**	2021 - E85	$ 81,066.00
28	2016 - PHEV	$ 68,048.00	**61**	2022 - Gasoline	$ 65,315.00
29	2016 - EV	$ 62,600.00	**62**	2022 - Diesel	$ 82,392.00
30	2016 - E85	$ 80,485.00	**63**	2022 - HEV	$ 64,277.00
31	2017 - Gasoline	$ 69,561.00	**64**	2022 - PHEV	$ 63,751.00
32	2017 - Diesel	$ 84,314.00	**65**	2022 - EV	$ 62,600.00
33	2017 - HEV	$ 58,566.00	**66**	2022 - E85	$ 81,066.00

Table 5.7: TCO output values (continuation).

Vehicle Type - Passenger Trucks					
No.	**Year and Fuel**	**Average cost**	**No.**	**Year and Fuel**	**Average cost**
67	2012 - Gasoline	$ 89,893.00	**100**	2017 - PHEV	$ 51,081.00
68	2012 - Diesel	$ 126,560.00	**101**	2017 - EV	$ 105,066.00
69	2012 - HEV	$ 54,055.00	**102**	2017 - E85	$ 107,708.00
70	2012 - PHEV	$ 40,709.00	**103**	2018 - Gasoline	$ 87,489.00
71	2012 - EV	$ 105,066.00	**104**	2018 - Diesel	$ 110,053.00
72	2012 - E85	$ 110,395.00	**105**	2018 - HEV	$ 58,200.00
73	2013 - Gasoline	$ 95,774.00	**106**	2018 - PHEV	$ 61,378.00
74	2013 - Diesel	$ 126,124.00	**107**	2018 - EV	$ 105,066.00
75	2013 - HEV	$ 54,055.00	**108**	2018 - E85	$ 107,359.00
76	2013 - PHEV	$ 40,709.00	**109**	2019 - Gasoline	$ 94,940.00
77	2013 - EV	$ 105,066.00	**110**	2019 - Diesel	$ 111,425.00
78	2013 - E85	$ 107,789.00	**111**	2019 - HEV	$ 54,055.00
79	2014 - Gasoline	$ 89,028.00	**112**	2019 - PHEV	$ 61,378.00
80	2014 - Diesel	$ 113,737.00	**113**	2019 - EV	$ 105,066.00
81	2014 - HEV	$ 54,055.00	**114**	2019 - E85	$ 113,690.00
82	2014 - PHEV	$ 40,709.00	**115**	2020 - Gasoline	$ 86,802.00
83	2014 - EV	$ 105,066.00	**116**	2020 - Diesel	$ 109,321.00
84	2014 - E85	$ 108,396.00	**117**	2020 - HEV	$ 55,090.00
85	2015 - Gasoline	$ 95,471.00	**118**	2020 - PHEV	$ 61,378.00
86	2015 - Diesel	$ 112,051.00	**119**	2020 - EV	$ 105,066.00
87	2015 - HEV	$ 54,055.00	**120**	2020 - E85	$ 114,272.00
88	2015 - PHEV	$ 40,709.00	**121**	2021 - Gasoline	$ 93,599.00
89	2015 - EV	$ 105,066.00	**122**	2021 - Diesel	$ 114,154.00
90	2015 - E85	$ 110,488.00	**123**	2021 - HEV	$ 49,898.00
91	2016 - Gasoline	$ 88,229.00	**124**	2021 - PHEV	$ 61,378.00
92	2016 - Diesel	$ 111,315.00	**125**	2021 - EV	$ 105,066.00
93	2016 - HEV	$ 54,055.00	**126**	2021 - E85	$ 99,016.00
94	2016 - PHEV	$ 43,706.00	**127**	2022 - Gasoline	$ 86,163.00
95	2016 - EV	$ 105,066.00	**128**	2022 - Diesel	$ 115,728.00
96	2016 - E85	$ 108,396.00	**129**	2022 - HEV	$ 49,898.00
97	2017 - Gasoline	$ 95,050.00	**130**	2022 - PHEV	$ 58,603.00
98	2017 - Diesel	$ 110,053.00	**131**	2022 - EV	$ 105,066.00
99	2017 - HEV	$ 54,055.00	**132**	2022 - E85	$ 99,016.00

Vehicle Type	1	2	3	4	5	6	7	8	6	…	132
Random number of vehicles	1	1	1	1	1	1	1	1	1	…	1
GHGs	7.26	6.65	4.44	4.91	2.04	5.26	7.26	7.43	4.44	…	6.52
CO	82.71	95.57	82.71	3.9	3.9	82.71	70.35	81.80	70.35	…	24.01
NOx	1.06	2.13	0.89	2.3	2.3	1.06	0.97	1.98	0.81	…	0.35
Cost	7101.61	8635.18	5673.44	7922.90	11390	8641.35	9442.36	9442.36	6101.86	…	19983.5

Figure 5.8: Example of the result table.

5.3 MOEA

This study adjusts four different fitness functions to guarantee that multiple objectives are considered when searching for an optimal solution. The MOEA flowchart is presented in figure 5.9.

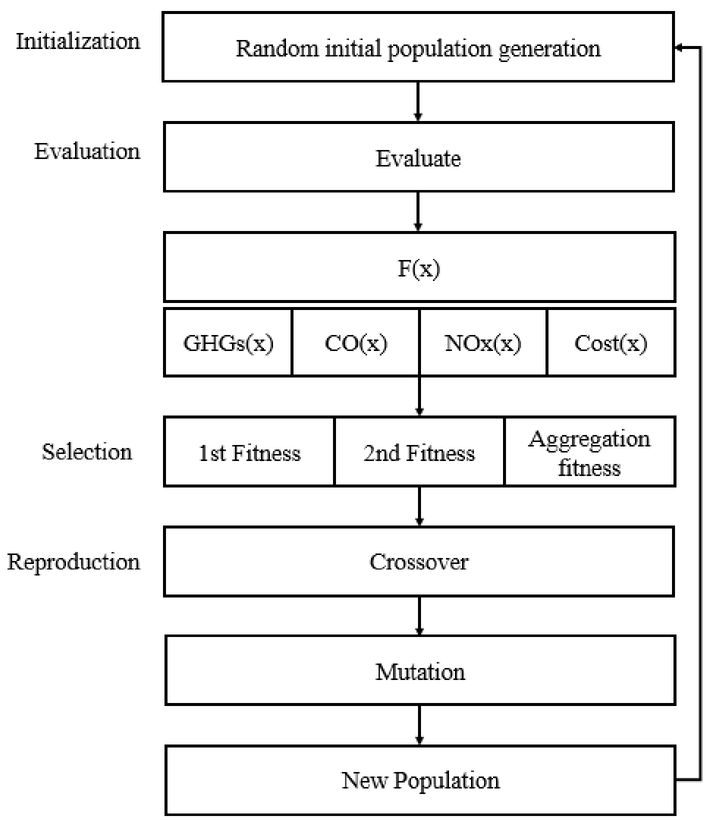


Figure 5.9: MOEA

The MOEA creates a random initial population where the individuals are evaluated to rank their environmental performance and life cost. Later, the individuals are assessed under the metric functions utilized in this algorithm. When creating new populations, the best-fitted individuals from the current population are selected. The process repeatedly runs until the optimal solution is found, given by Pareto optimality.

5.3.1 Initialization

At the beginning of the algorithm, a set of possible solutions called individuals is produced. These individuals are differentiated from others by the structure of their genes, better known as chromosome encoding. In this study, the number of vehicles is equal to the number of genes of an individual. The individuals represent possible scenarios and are produced by combining the outputs of CO, NOx, GHG, and TCO generated by the AFLEET tool presented in the result table. Maintaining a diverse population is essential to ensure the search space's efficiency. Figure 5.10 shows a representation of the process of how an individual is created. For this study, the individuals are created by assigning a random number of each type of vehicle corresponding to the first row. However, the total number of vehicles could not be greater or less than the number of vehicles assigned for the simulation, corresponding to the number of vehicles registered in the region under study. One restriction to be considered is setting a percentage of the total number of vehicles to BEVs.

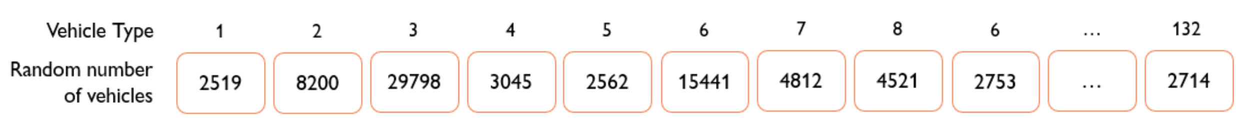


Figure 5.10: Example of the initial individual.

After generating the first random row, the algorithm multiplies each random number of vehicles by the lbs. of GHG, CO, and NOx emissions caused by just one vehicle, as well as the TCO, as shown in figure 5.11. After the multiplication, a new 132x5 matrix is generated, corresponding to the new individual shown in figure 5.12.

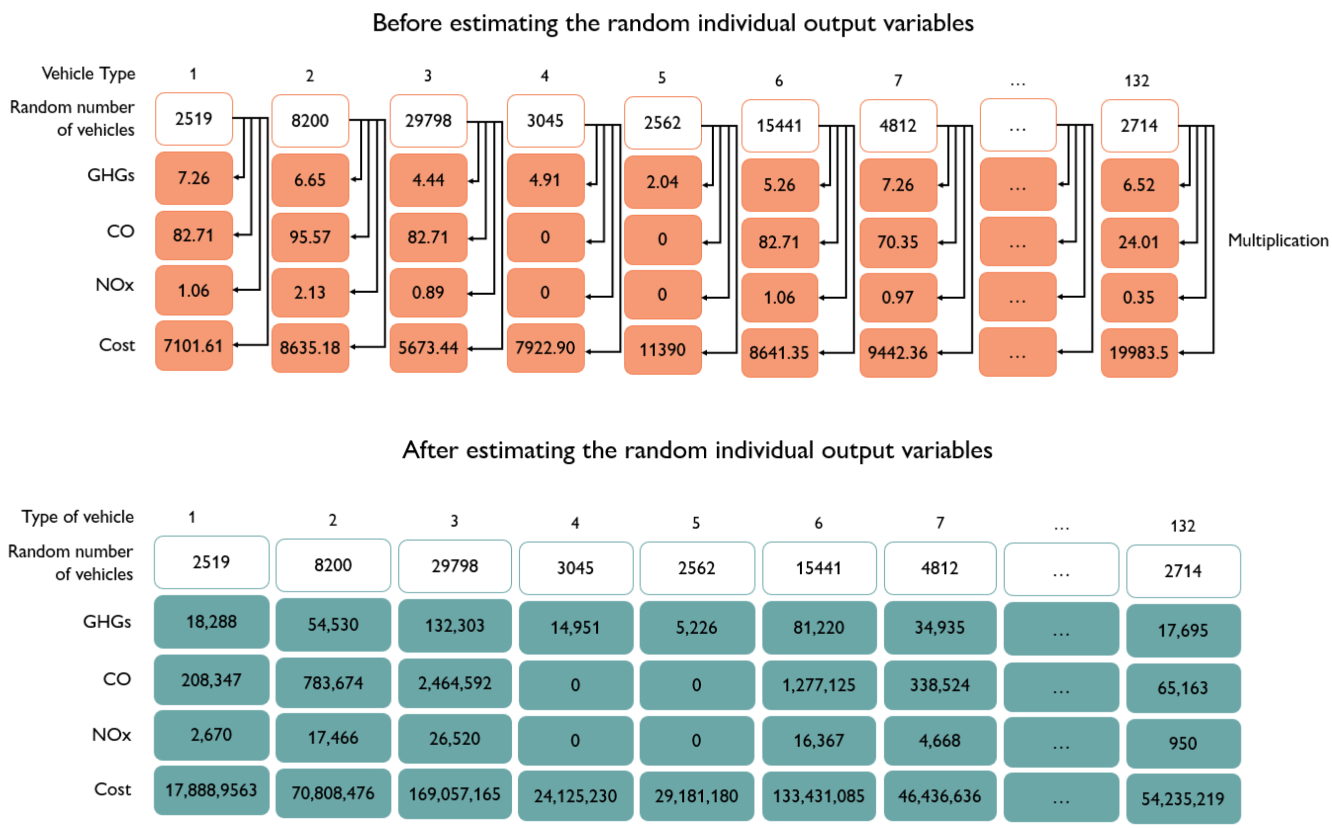


Figure 5.12: Generation of the new individual.

The variable assigned to the initial population corresponding to a set of random individuals is given at the beginning of the algorithm. This variable constantly persists throughout the entire algorithm, helping the MOEA towards the Pareto optimal front by providing a base for succeeding populations. Figure 5.13 shows an example of an initial population of 10 individuals.

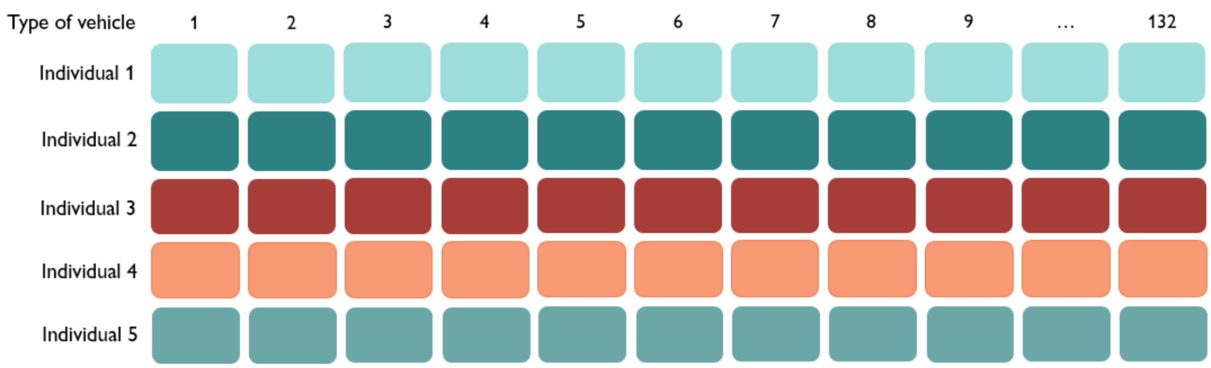


Figure 5.13: Example of the initial population

5.3.2 Evaluation

In this phase of the MOEA, four objective functions evaluate each individual in the current generation. It is essential to mention that the algorithm considers the concept of Pareto dominance; only the nondominated individuals survive, while the dominated individuals are removed. By applying the Pareto criterion, a count of the individuals dominated by a single solution is performed.

5.3.3 Fitness assignment

Diversity of population and proximity to the Pareto front are the two main objectives to be evaluated in this MOEA. The evaluation is performed according to the following fitness metrics:

- First Fitness Metric: Distance-based $f_1(i)$

The purpose of the distance-based metric is to maintain the variety of the solutions given by the Pareto optimal front by assigning higher fitness to individuals farther away from others. There are two steps to measure the individuals: normalization and distances. Normalization refers to removing unit inconsistencies. The equation to normalize every result of the objective is expressed as shown in equation 5.1.

$$\frac{f_i(x) - f_i^{min}}{f_i^{max} - f_i^{min}} \qquad \text{(Eq. 5.1)}$$

Were $f_i(x)$ corresponds to the value in the nondominated set, f_i^{min} belongs to the minimum value in the nondominated set, and f_i^{max} is the maximum value in the nondominated set (Cram, 2019).

- Second Fitness Metric: Dominance count-based $f_2(i)$

This fitness metric aims to approximate the Pareto front by choosing the more dominating individuals. The dominance count concept is the base of this metric (Cram, 2019).

- Aggregated Fitness Metric

This fitness metric aims to find the two most common desirable characteristics in the MOEA, which correspond to proximity and diversity. Equal weights for individuals in the two previous fitness metrics are aggregated (Cram, 2019).

5.3.4 Selection

Some of the most fitted individuals survive into the next generation during selection. This process is called elitism. Individuals with the greatest fittest value have the highest probability of reproducing, filling the remaining spots by reproduction. Secondly, tournament selection is applied, where two individuals are randomly selected. The fittest individual selected is chosen to be parent 1, and the tournament selection process is repeated to find parent 2. The new parents are intended to produce new individuals through a crossover process, which will be explained in the following subsection.

5.3.5 Crossover

In the MOEAs, there exist different types of ways to achieve the reproduction of parents through a crossover. Knowing the type of chromosome encoding of the problem will help to achieve effectiveness during the crossover method. For this research, the technique utilized was the random single-point crossover. However, the MOEA needs to fulfill the constraint assigned to the individual, which consists of having a sum equal to the number of vehicles the user selects for a specific scenario. Figure 5.14 shows a graphic representation of the crossover technique. First, a random point through the 132 genes is chosen to divide the chromosomes into two segments. Once the chromosomes are divided, segment 1 of the first parent is joined with segment 2 of the second parent. Likewise, segment 2 of the first parent is joint with segment 1 of the second parent. This way, two new children will serve as new parents to populate the next generation.

It is essential to mention that to satisfy the constraint, a MATLAB code evaluates the sum of all the types of vehicles in one individual, as shown in figure 5.15. If the sum of the child equals the total number of vehicles the user selects, it will satisfy the constraint. In contrast, if the child's sum is less than the total number of vehicles assigned, the code will choose a random gene and sum the remaining vehicles' number to that gene to achieve the desired sum. However, a possible scenario would be that the selected gene's number of vehicles and the difference number surpass the desired sum. In that case, the code will re-evaluate the sum, select another random gene, and rest the surplus. This process will repeat itself until we achieve the desired number of vehicles.

Nevertheless, the code will not choose any gene corresponding to the BEVs since another constraint is that 10% of the total vehicles will be destined for BEVs. Additionally, suppose the individual's sum exceeds the total number of vehicles. In that case, the code will perform the same operation, select a random gene to rest the surplus, and re-evaluate the new sum until the constraints are satisfied.

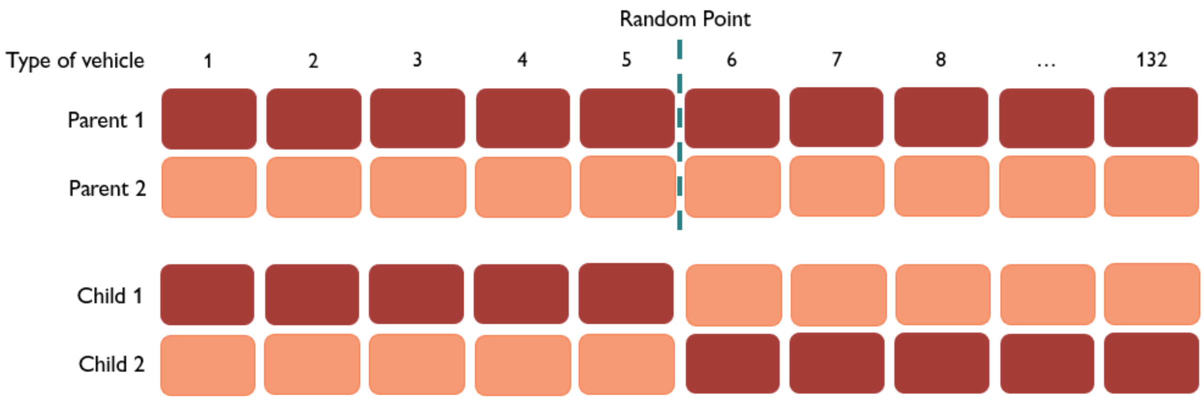


Figure 5.14: Single-point crossover process.

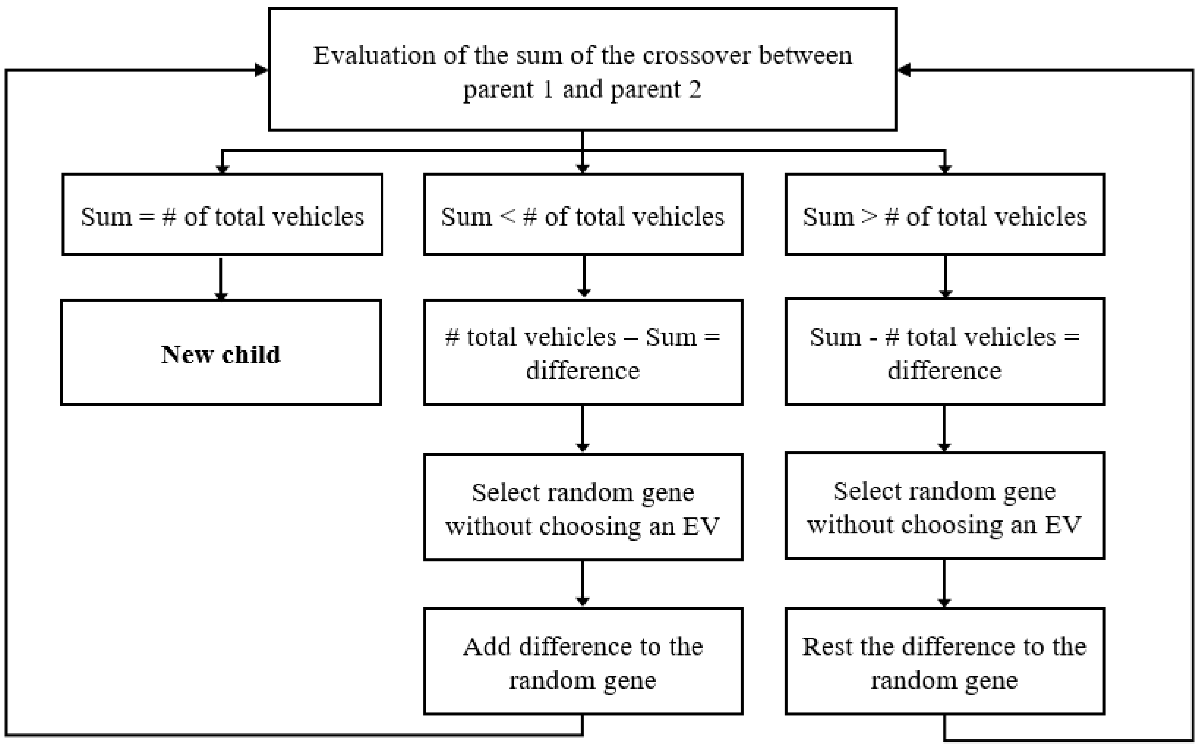


Figure 5.15: Evaluation of the crossover constraints.

5.3.6 Mutation

In the mutation step, the new individuals have a 0.01% chance of mutation, which will increase the variation of solutions to avoid falling into the local optimum (Cram, 2019). If new individuals mutate, genes will be swapped, as shown in figure 5.16.

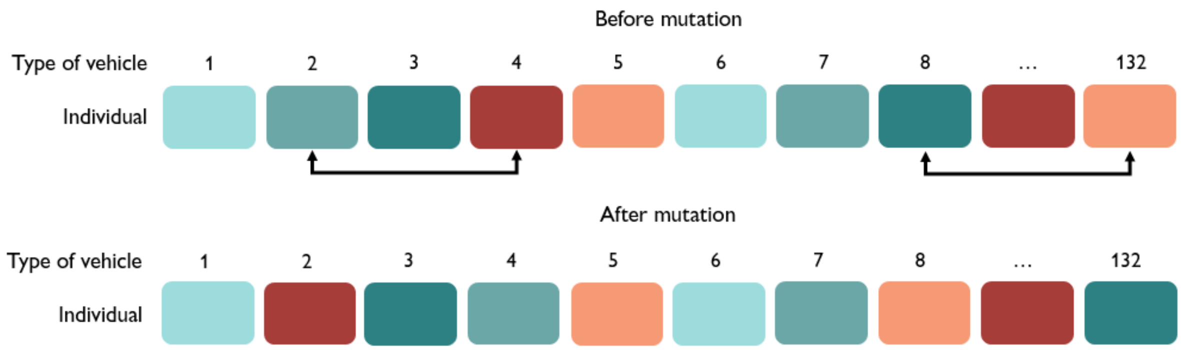


Figure 5.16: Mutation process

5.3.7 Termination

Depending on the study's objectives, MOEAs have multiple ways to terminate the iterative process. For this research, reaching the predetermined number of generations and the predetermined number of generations assigned at the beginning of the MOEA will stop the iterative process. The algorithm will re-evaluate the non-dominated solutions to find the solution closes to the objective vector [0 0 0]. The closest solution will be the most optimal solution.

Chapter 6: Case Studies

This chapter presents four case studies utilizing the developed optimization model explained in chapter 5. Additionally, these case studies demonstrate that the percentage of BEVs can be modified to simulate different scenarios.

6.1 Case Studies

The following subsections utilized MATLAB code to run a MOEA simulation. The four case studies are based on the data obtained from the Texas region. The total number of vehicles used to run the MOEA is 704,274, which is the number of vehicles registered in the City of El Paso, TX., in 2021, according to El Paso District Statistics (cite). The simulation parameters must be defined at the beginning of the algorithm shown in table 6.1. Each of these parameters is going to be explained in the following subsections.

Table 6.1: MOEA Parameters

Number of individuals	100
Number of generations	100
Elitism	0.25
Crossover	0.75
Mutation	0.01

6.2 Case Study 1

According to the Edison Electric Institute, in 2030, the projected number of BEVs will make up nearly 10% of the 259 million light-duty vehicles (cars and light trucks) expected to be on U.S. roads (2022). Therefore, the percentage established in this case study for BEVs was 10%, equal to 70,425 EVs. The number of individuals utilized in this MOEA is 1000, along with 1000 iterations. In each iteration, the most fitted 25% of individuals were selected for reproduction, with a 75% crossover and a 1% chance of mutation. The AFLEET tool calculations were performed in a Lenovo computer, with an 11th Gen Intel® Core™ i7-1165G7 processor operating at 2.80 GHz and 16 GB of RAM. The MOEA was run with an Intel® Xeon® W-2195 CPU processor operating at 2.30 GHz and 256 GB of RAM.

The optimal solution given with the parameters selected is shown in table 6.2. The well-to-wheel analysis of the fuel and vehicle production produced 4,506,356.86 tons of GHG emissions, while the air pollutants such as CO and NOx produced 22,576,079.51 lbs. and 872,636.58 lbs., respectively, along with a TCO of $8,748,478,084.31 US dollars. In this MOEA, the number of non-dominated solutions found was 44, shown in figure 6.1. Non-dominated solutions are represented by blue dots, while the optimal solution found is represented by a red dot.

Table 6.2: Solutions for Case Study 1.

2012 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	**2942**	**891**	**11489**	**30055**	**3301**	**12079**
COx	243342.13	85154.00	950291.54	117214.50	12873.90	999092.31
NOx	3144.67	1904.76	10315.59	69126.50	7592.30	12911.11
GHGs	23063.57	6450.60	51077.53	175991.81	9863.28	70433.28
TCO	$ 20,892,936.62	$ 7,693,945.38	$ 65,182,152.16	$ 238,122,759.50	$ 37,598,654.08	$ 104,378,866.65
2013 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	**1864**	**8984**	**4817**	**381**	**3464**	**5628**
COx	131147.43	734904.35	338914.78	1485.90	13509.60	395975.17
NOx	1816.61	17793.61	3943.41	876.30	7967.20	5484.91
GHGs	14612.68	72066.54	21415.31	2394.84	10350.32	27087.58
TCO	$ 13,855,783.04	$ 84,830,162.24	$ 29,392,659.62	$ 3,273,959.67	$ 41,753,601.12	$ 45,472,945.56
2014 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	**592**	**22284**	**273**	**5274**	**3880**	**8555**
COx	41676.80	1822831.20	19219.20	20568.60	15132.00	602272.00
NOx	592.00	44568.00	218.40	12130.20	8924.00	6844.00
GHGs	4341.54	135346.68	1213.70	33150.64	11593.31	41175.24
TCO	$ 4,743,459.20	$ 207,016,131.60	$ 1,928,455.62	$ 47,069,500.68	$ 49,342,270.40	$ 81,894,020.75
2015 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	**11131**	**4125**	**3030**	**4083**	**5134**	**2802**
COx	655615.90	276375.00	178467.00	15923.70	20022.60	165037.80
NOx	10017.90	7425.00	2424.00	9390.90	11808.20	2521.80
GHGs	84904.10	32693.22	13470.71	25664.40	15340.23	15697.58
TCO	$ 94,364,722.15	$ 43,964,745.00	$ 22,408,940.70	$ 37,794,575.31	$ 70,399,102.22	$ 31,214,392.08

2016 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	**3730**	**2563**	**10143**	**3102**	**2146**	**4863**
COx	219697.00	171721.00	597422.70	12097.80	8369.40	286430.70
NOx	3357.00	4613.40	8114.40	7134.60	4935.80	4376.70
GHGs	28451.38	18309.33	45093.52	19498.16	6412.18	25575.07
TCO	$ 33,065,704.00	$ 28,648,675.77	$ 89,680,855.95	$ 29,742,968.64	$ 32,274,402.18	$ 53,979,737.67
2017 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	**5624**	**4416**	**869**	**27542**	**370**	**14001**
COx	157888.52	135636.76	24396.36	107413.80	1443.00	393064.93
NOx	3712.94	3054.26	481.92	63346.60	851.00	9243.41
GHGs	43493.58	28517.72	3066.17	188625.74	1006.54	68027.46
TCO	$ 52,082,907.92	$ 51,048,032.64	$ 8,509,048.13	$ 270,240,176.06	$ 5,932,794.60	$ 151,799,122.02
2018 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	**16804**	**7856**	**12693**	**1033**	**4382**	**1848**
COx	444814.10	227712.14	335992.94	4028.70	17089.80	48917.90
NOx	10037.37	4939.53	6368.70	2375.90	10078.60	1103.85
GHGs	109795.87	56875.36	44785.91	7074.66	12383.14	9507.45
TCO	$ 160,020,291.00	$ 104,325,166.08	$ 137,174,139.51	$ 10,478,421.44	$ 80,439,629.06	$ 21,441,826.56
2019 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	**6828**	**5505**	**63**	**5425**	**1018**	**6239**
COx	176234.31	149874.93	1626.06	21157.50	3970.20	161031.90
NOx	3649.19	2942.12	28.28	12477.50	2341.40	3334.40
GHGs	45898.46	34417.53	300.83	37153.97	2769.35	33525.28
TCO	$ 66,516,737.28	$ 164,762,448.00	$ 733,095.72	$ 56,829,207.75	$ 23,753,075.44	$ 74,648,823.93
2020 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	**12385**	**1139**	**11656**	**17489**	**4041**	**7264**
COx	299416.78	29004.31	281792.65	68207.10	15759.90	175612.72
NOx	5840.38	537.12	4617.15	40224.70	9294.30	3425.48
GHGs	89516.68	6683.59	49352.36	119776.18	10117.38	39033.12
TCO	$ 129,660,918.15	$ 14,291,989.76	$ 141,455,234.48	$ 183,204,795.27	$ 107,694,993.78	$ 81,611,185.28
2021 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	**13115**	**3249**	**2031**	**7130**	**5147**	**1502**
COx	297609.57	77150.25	46088.07	27807.00	20073.30	34083.84
NOx	5602.54	1350.54	728.80	16399.00	11838.10	641.63
GHGs	96181.25	19064.96	9698.22	48830.93	12605.19	8071.00
TCO	$ 147,872,018.45	$ 40,767,932.16	$ 27,507,864.00	$ 86,516,703.40	$ 145,708,121.51	$ 16,875,000.04
2022 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	**78**	**58**	**2121**	**9019**	**40**	**10593**
COx	1654.29	1277.56	44983.97	35174.10	156.00	224665.34
NOx	29.86	20.87	682.02	20743.70	92.00	4055.03
GHGs	572.03	340.34	11475.05	50844.46	97.96	56921.51
TCO	$ 995,016.36	$ 727,774.72	$ 34,528,522.56	$ 111,212,567.48	$ 1,397,773.20	$ 119,012,566.86
2012 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	**1131**	**5145**	**1199**	**615**	**708**	**2732**
COx	102864.34	177437.66	109048.93	55934.19	3256.80	248475.12
NOx	1671.15	153822.43	1488.16	763.32	1982.40	4036.75
GHGs	10611.83	64640.87	9659.74	0.00	2485.36	18025.34
TCO	$ 9,119,875.05	$ 59,531,560.20	$ 10,662,766.95	$ 9,715,013.55	$ 5,750,312.28	$ 26,997,214.20

2013 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	**5646**	**592**	**3012**	**6048**	**4571**	**1365**
COx	446231.20	20137.37	238053.20	478003.24	21026.60	107882.68
NOx	7277.44	22910.45	3261.16	6548.30	12798.80	1759.42
GHGs	54037.18	7356.57	24266.18	0.00	16046.01	8592.30
TCO	$ 50,681,319.00	$ 7,023,044.00	$ 27,785,097.60	$ 95,538,864.96	$ 38,641,679.86	$ 13,690,922.70
2014 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	**4975**	**2718**	**4408**	**8044**	**9772**	**6181**
COx	393198.76	130906.74	348385.96	635756.96	44951.20	488514.89
NOx	6412.55	40075.24	4772.64	8709.42	27361.60	7967.03
GHGs	45976.77	23335.77	35513.06	0.00	34303.56	39437.97
TCO	$ 45,586,273.25	$ 31,466,748.06	$ 41,394,073.36	$ 127,069,217.88	$ 82,609,165.52	$ 67,252,494.12
2015 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	**863**	**2767**	**10367**	**2100**	**654**	**559**
COx	57816.00	116825.85	694528.92	140687.83	3008.40	37449.76
NOx	895.32	31402.93	9034.42	1830.06	1831.20	579.94
GHGs	8178.47	22427.96	83521.75	0.00	2295.80	3729.76
TCO	$ 8,792,149.07	$ 32,531,951.04	$ 99,072,753.85	$ 33,173,217.00	$ 5,702,265.24	$ 6,434,330.37
2016 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	**2180**	**9981**	**596**	**3068**	**4955**	**4415**
COx	146047.37	421409.05	39928.55	14112.80	22793.00	295779.41
NOx	2261.64	113275.25	519.39	8590.40	13874.00	4580.35
GHGs	19351.78	80901.14	4801.67	21646.48	17394.00	28169.98
TCO	$ 21,940,065.00	$ 124,963,716.96	$ 5,893,426.80	$ 31,516,306.12	$ 45,175,527.80	$ 52,334,836.05
2017 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	**945**	**1005**	**10992**	**6301**	**5738**	**6742**
COx	40760.52	28814.74	474116.00	28984.60	26394.80	290801.50
NOx	564.47	7140.49	5515.23	17642.80	16066.40	4027.13
GHGs	8833.31	8146.04	88557.06	62474.54	15824.11	42439.04
TCO	$ 11,106,745.65	$ 13,695,949.05	$ 110,515,436.64	$ 119,558,891.59	$ 54,217,845.58	$ 86,734,481.60
2018 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	**759**	**13951**	**2669**	**8415**	**2569**	**15244**
COx	23765.93	329381.39	83572.17	38709.00	11817.40	477322.67
NOx	429.50	68420.10	1268.69	23562.00	7193.20	8626.31
GHGs	6684.05	113080.03	21502.80	120542.23	7084.72	98572.39
TCO	$ 8,989,550.46	$ 210,109,454.03	$ 29,162,401.46	$ 203,925,659.85	$ 27,683,312.79	$ 207,433,492.20
2019 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	**1770**	**12105**	**3263**	**2074**	**2195**	**934**
COx	53641.89	274380.88	98888.98	9540.40	10097.00	28305.95
NOx	945.97	52516.73	1464.87	5807.20	6146.00	499.17
GHGs	16482.47	95626.43	26288.36	29709.40	6526.50	6627.14
TCO	$ 25,189,489.50	$ 191,834,471.70	$ 45,255,525.90	$ 52,324,614.16	$ 30,206,843.70	$ 14,839,999.10
2020 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	**2730**	**145**	**11245**	**2575**	**788**	**8823**
COx	76470.54	3154.48	314985.78	11845.00	3624.80	247142.69
NOx	1201.56	547.02	4157.39	7210.00	2206.40	3883.27
GHGs	23495.61	1055.95	94563.03	36955.94	3020.11	63612.31
TCO	$ 42,579,837.30	$ 2,607,150.75	$ 194,316,636.15	$ 70,089,800.50	$ 11,889,864.08	$ 159,181,830.87

2021 Passenger Trucks						
Type of fuel						
	Gasoline	Diesel	HEV	PHEV	EV	E85
# of vehicles	**1799**	**1470**	**7159**	**1844**	**3010**	**8236**
COx	46795.40	30636.66	186219.15	8482.40	13846.00	214233.96
NOx	715.02	5339.73	2390.10	5163.20	8428.00	3273.41
GHGs	16160.08	12822.54	47993.58	26464.76	12148.76	61264.33
TCO	$ 30,954,277.62	$ 31,216,140.90	$ 144,100,790.58	$ 57,533,426.96	$ 55,402,541.60	$ 141,540,272.16

2022 Passenger Trucks						
Type of fuel						
	Gasoline	Diesel	HEV	PHEV	EV	E85
# of vehicles	**5807**	**8044**	**1219**	**866**	**2544**	**12754**
COx	139441.18	160296.77	29271.36	3983.60	11702.40	306256.72
NOx	2060.16	28092.82	363.27	2424.80	7123.20	4524.76
GHGs	51138.73	74028.48	8172.11	11184.96	9476.94	91954.14
TCO	$ 112,263,595.22	$ 190,638,456.24	$ 28,580,820.28	$ 28,455,971.94	$ 47,669,243.04	$ 254,870,069.16

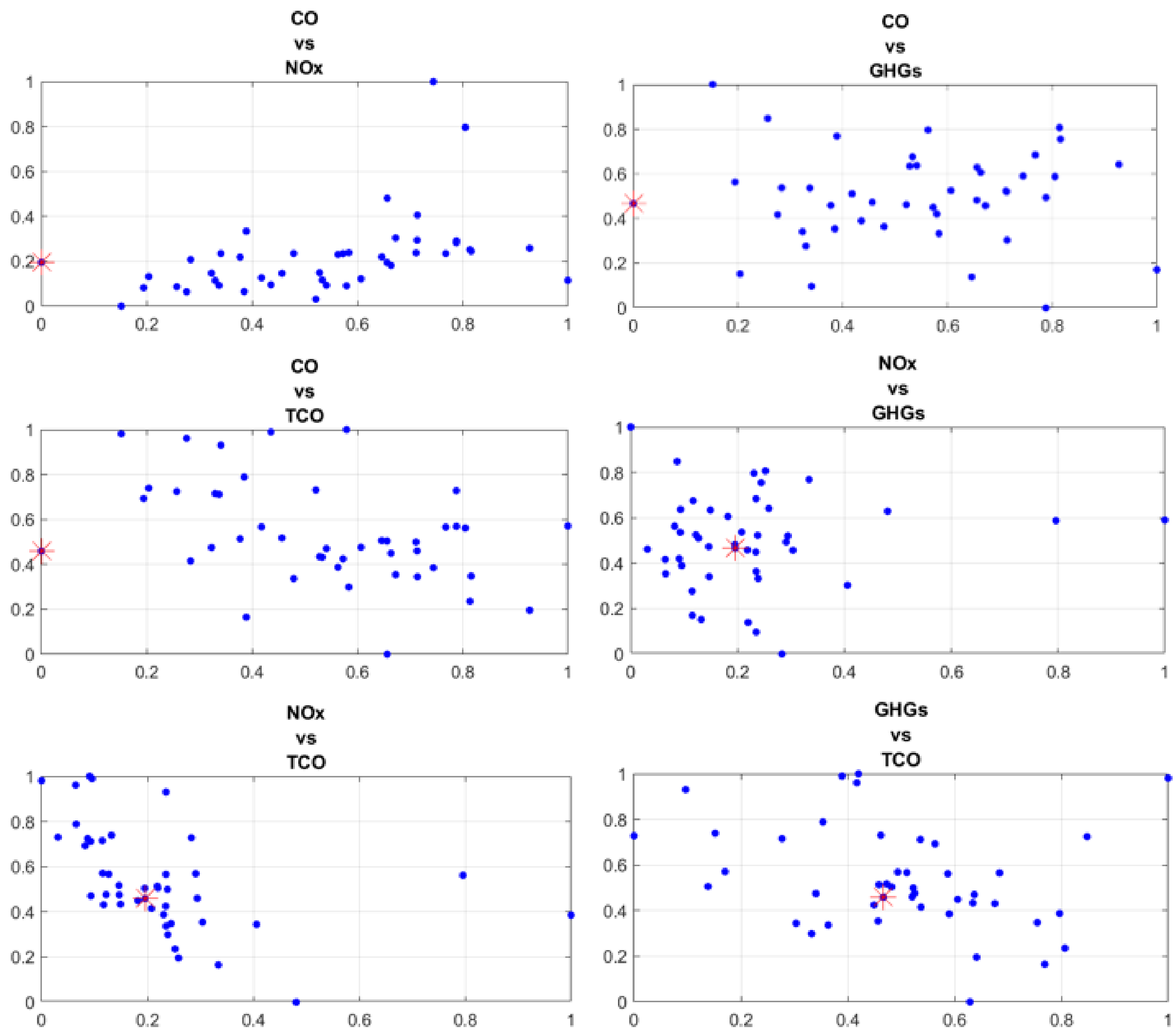


Figure 6.1: Pareto Optimality for Case Study 1.

The computational time used to run this MOEA to find the optimal solution shown in Case Study 1 was 2 hours 9 mins.

6.3 CASE STUDY 2

The percentage established in this case study for EVs was 8%, equal to 56,342 vehicles. The number of individuals utilized in this MOEA is 1000, along with 1000 iterations. In each iteration, the most fitted 25% of individuals were selected for reproduction, with a 75% crossover and a 1% chance of mutation. The AFLEET tool calculations were performed in a Lenovo computer, with an 11th Gen Intel® Core™ i7-1165G7 processor operating at 2.80 GHz and 16 GB of RAM. The MOEA was run with an Intel® Xeon® W-2195 CPU processor operating at 2.30 GHz and 256 GB of RAM.

The optimal solution given with the parameters selected is shown in table 6.2. The well-to-wheel analysis of the fuel and vehicle production produced 4,479,447.05 tons of GHG emissions, while the air pollutants such as CO and NOx produced 22,164,602.89 lbs. and 563,440.09 lbs., respectively, along with a TCO of $8,966,197,155.59 US dollars. In this MOEA, the number of non-dominated solutions found was 48, shown in figure 6.1. Non-dominated solutions are represented by blue dots, while the optimal solution found is represented by a red dot.

Table 6.3: Solutions for Case Study 2.

2012 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	1694	5989	3155	11913	409	14355
COx	140116.10	572376.35	260960.03	46460.70	1595.10	1187347.47
NOx	1810.70	12803.16	2832.77	27399.90	940.70	15343.90
GHGs	13279.98	43358.77	14026.43	69758.46	1222.08	83704.76
TCO	$ 12,030,127.34	$ 51,716,093.02	$ 17,899,703.20	$ 94,385,507.70	$ 4,658,542.72	$ 124,046,579.25
2013 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	3072	7857	3197	26	1231	5613
COx	216139.97	642714.10	224934.72	101.40	4800.90	394919.80
NOx	2993.90	15561.49	2617.20	59.80	2831.30	5470.29
GHGs	24082.70	63026.14	14213.15	163.43	3678.19	27015.38
TCO	$ 22,835,281.92	$ 74,188,622.52	$ 19,507,646.42	$ 223,419.82	$ 14,837,956.98	$ 45,351,749.01
2014 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	2163	11807	2203	85	4422	1268
COx	152275.20	965812.60	155091.20	331.50	17245.80	89267.20
NOx	2163.00	23614.00	1762.40	195.50	10170.60	1014.40
GHGs	15862.76	71712.36	9794.05	534.28	13212.79	6102.89
TCO	$ 17,331,253.80	$ 109,685,849.30	$ 15,561,859.82	$ 758,609.70	$ 56,234,927.76	$ 12,138,120.20
2015 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	6273	9125	11841	8601	4969	130
COx	369479.70	611375.00	697434.90	33543.90	19379.10	7657.00
NOx	5645.70	16425.00	9472.80	22362.60	12919.40	117.00
GHGs	47848.66	72321.37	52642.45	54063.07	14847.21	728.30
TCO	$ 53,180,298.45	$ 97,255,345.00	$ 87,572,365.29	$ 79,615,758.57	$ 68,136,567.77	$ 1,448,205.20
2016 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	2160	305	1463	288	731	16786
COx	127224.00	20435.00	86170.70	1123.20	2850.90	988695.40
NOx	1944.00	549.00	1170.40	662.40	1681.30	15107.40
GHGs	16475.87	2178.83	6504.17	1810.27	2184.20	88279.49
TCO	$ 19,147,968.00	$ 3,409,225.95	$ 12,935,333.95	$ 2,761,436.16	$ 10,993,750.23	$ 186,326,110.74
2017 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	4718	10615	3955	22706	3967	18473
COx	132453.42	326038.10	111032.91	88553.40	15471.30	518612.13
NOx	3114.81	7341.70	2193.30	52223.80	9124.10	12195.81
GHGs	36486.97	68549.72	13954.80	155505.63	10791.77	89755.83
TCO	$ 43,692,595.94	$ 122,707,170.85	$ 38,726,450.35	$ 222,789,682.58	$ 63,609,178.86	$ 200,284,635.46
2018 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	20119	1396	3809	555	2184	15721
COx	532564.57	40464.12	100827.00	2164.50	8517.60	416146.31
NOx	12017.49	877.75	1911.16	1276.50	5023.20	9390.47
GHGs	131455.80	10106.67	13439.66	3801.01	6171.79	80880.25
TCO	$ 191,588,207.25	$ 18,538,433.28	$ 41,164,129.63	$ 5,629,742.40	$ 40,091,316.72	$ 182,406,361.12

2019 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	4633	1062	20975	15942	829	2782
COx	119580.19	28913.20	541375.89	62173.80	3233.10	71804.90
NOx	2476.08	567.58	9416.38	36666.60	1906.70	1486.82
GHGs	31143.46	6639.68	100157.60	109181.31	2255.20	14949.08
TCO	$ 45,133,574.08	$ 31,785,235.20	$ 244,074,329.00	$ 166,999,305.06	$ 19,343,123.32	$ 33,286,268.34
2020 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	1784	5284	6071	18597	3196	1505
COx	43129.55	134555.55	146771.04	72528.30	12464.40	36384.52
NOx	841.28	2491.77	2404.83	42773.10	7350.80	709.71
GHGs	12894.45	31006.24	25705.06	127364.49	8001.77	8087.12
TCO	$ 18,677,034.96	$ 66,302,786.56	$ 73,676,623.93	$ 194,811,571.71	$ 85,175,253.68	$ 16,908,705.10
2021 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	8475	24570	7845	748	345	1682
COx	192317.28	583435.43	178021.13	2917.20	1345.50	38168.46
NOx	3620.40	10213.24	2815.07	1720.40	793.50	718.53
GHGs	62152.96	144175.47	37460.61	5122.80	844.92	9038.23
TCO	$ 95,555,879.25	$ 308,300,428.80	$ 106,252,680.00	$ 9,076,366.64	$ 9,766,718.85	$ 18,897,303.64
2022 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	9798	362	3944	12817	3861	11812
COx	207804.31	7973.77	83647.70	49986.30	15057.90	250518.93
NOx	3750.70	130.24	1268.21	29479.10	8880.30	4521.67
GHGs	71855.42	2124.20	21337.85	72255.63	9455.73	63471.80
TCO	$ 124,989,362.76	$ 4,542,318.08	$ 64,205,795.84	$ 158,045,401.64	$ 134,920,058.13	$ 132,708,056.24
2012 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	1773	148	6833	934	964	7251
COx	161254.17	5104.13	621460.66	84947.21	4434.40	659477.71
NOx	2619.75	4424.82	8480.91	1159.25	2699.20	10713.95
GHGs	16635.52	1859.45	55050.07	0.00	3384.02	47841.04
TCO	$ 14,296,674.15	$ 1,712,472.48	$ 60,766,210.65	$ 14,754,183.18	$ 7,829,521.24	$ 71,653,294.35
2013 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	37	621	6611	7639	830	1349
COx	2924.29	21123.83	522499.90	603747.81	3818.00	106618.12
NOx	47.69	24032.75	7157.87	8270.91	2324.00	1738.80
GHGs	354.12	7716.95	53261.53	0.00	2913.63	8491.59
TCO	$ 332,130.50	$ 7,367,078.25	$ 60,985,152.80	$ 120,671,526.03	$ 7,016,537.80	$ 13,530,443.02
2014 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	292	2559	460	2154	4680	308
COx	23078.20	123248.84	36356.07	170241.23	21528.00	24342.76
NOx	376.37	37730.88	498.05	2332.18	13104.00	397.00
GHGs	2698.54	21970.65	3705.99	0.00	16428.64	1965.20
TCO	$ 2,675,616.44	$ 29,625,978.03	$ 4,319,708.20	$ 34,026,242.58	$ 39,563,128.80	$ 3,351,200.16
2015 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	6703	86	858	7672	1950	4079
COx	449062.15	3631.02	57481.03	513979.54	8970.00	273269.36
NOx	6954.04	976.02	747.71	6685.83	5460.00	4231.76
GHGs	63522.91	697.07	6912.48	0.00	6845.27	27215.93
TCO	$ 68,289,426.67	$ 1,011,112.32	$ 8,199,519.90	$ 121,192,819.44	$ 17,002,167.00	$ 46,951,043.97

2016 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	13260	623	3653	9399	7060	756
COx	888343.15	26303.76	244729.83	43235.40	32476.00	50647.62
NOx	13756.60	7070.48	3183.44	26317.20	19768.00	784.31
GHGs	117708.51	5049.74	29430.40	66315.28	24783.38	4823.67
TCO	$ 133,451,955.00	$ 7,800,059.68	$ 36,121,959.90	$ 96,552,073.41	$ 64,367,149.60	$ 8,961,525.72
2017 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	161	6552	3101	16460	126	391
COx	6944.38	187854.89	133754.89	75716.00	579.60	16864.93
NOx	96.17	46551.76	1555.92	46088.00	352.80	233.55
GHGs	1504.93	53107.33	24983.21	163201.23	347.48	2461.24
TCO	$ 1,892,260.37	$ 89,289,411.12	$ 31,177,981.17	$ 312,321,751.40	$ 1,190,562.66	$ 5,030,136.80
2018 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	786	8805	13131	2889	13233	1238
COx	24611.36	207884.97	411160.06	13549.41	62062.77	38764.46
NOx	444.78	43182.50	6241.71	8089.20	37052.40	700.56
GHGs	6921.83	71369.05	105789.92	41384.02	36493.63	8005.29
TCO	$ 9,309,336.84	$ 132,607,966.65	$ 143,473,770.54	$ 70,010,841.51	$ 142,597,617.03	$ 16,846,146.90
2019 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	1707	2627	1365	3902	414	6409
COx	51732.60	59545.52	41367.90	17949.20	1904.40	194232.14
NOx	912.30	11397.06	612.79	10925.60	1159.20	3425.26
GHGs	15895.81	20752.63	10997.12	55894.92	1230.97	45474.67
TCO	$ 24,292,914.45	$ 41,631,487.58	$ 18,931,594.50	$ 98,442,933.68	$ 5,697,327.24	$ 101,830,357.85
2020 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	2537	4839	2389	4989	748	35167
COx	71064.38	105272.64	66918.72	22949.40	3440.80	985069.36
NOx	1116.61	18255.37	883.24	13969.20	2094.40	15478.08
GHGs	21834.57	35239.74	20089.91	71601.23	2866.80	253548.00
TCO	$ 39,569,614.37	$ 87,006,913.65	$ 41,282,565.03	$ 135,797,287.26	$ 11,286,317.68	$ 634,472,112.23
2021 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	363	25	14958	66	10	234
COx	9442.32	521.03	389085.91	303.60	46.00	6086.78
NOx	144.27	90.81	4993.87	184.80	28.00	93.00
GHGs	3260.76	218.07	100277.68	947.22	40.36	1740.63
TCO	$ 6,245,915.94	$ 530,886.75	$ 301,083,897.96	$ 2,059,222.44	$ 184,061.60	$ 4,021,421.04
2022 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	14949	2296	6275	1885	183	7254
COx	358964.39	45753.53	150679.08	8671.00	841.80	174187.41
NOx	5303.49	8018.54	1870.00	5278.00	512.40	2573.52
GHGs	131646.77	21129.96	42067.28	24346.01	681.71	52300.09
TCO	$ 289,000,944.54	$ 54,413,960.16	$ 147,124,403.00	$ 61,939,384.65	$ 3,429,037.53	$ 144,960,599.16

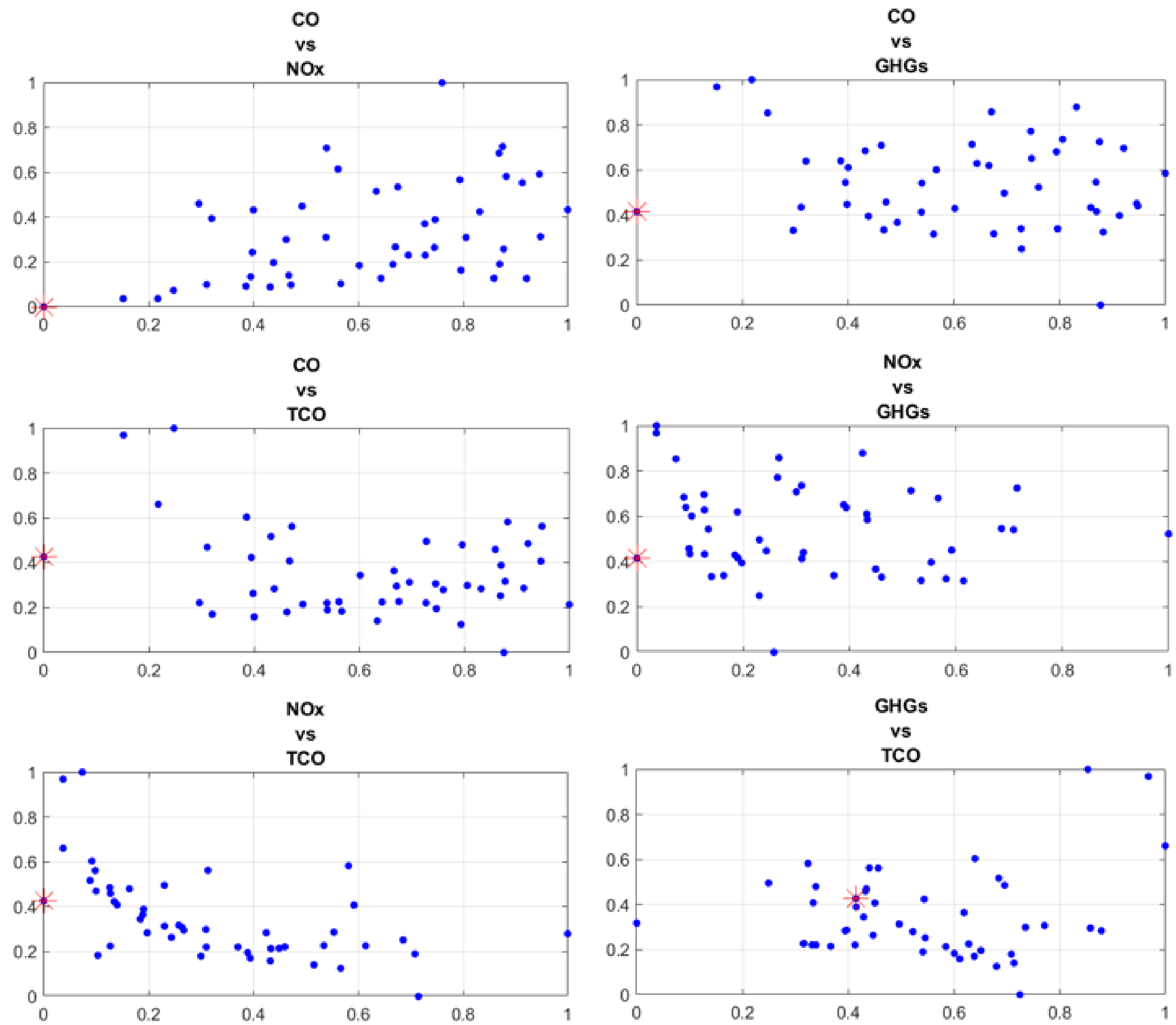


Figure 6.2: Pareto Optimality for Case Study 2.

The computational time used to run this MOEA to find the optimal solution shown in Case Study 2 was 2 hours 18 mins.

6.4 Case Study 3

The percentage established in this case study for EVs was 12%, equal to 84,513 vehicles. The number of individuals utilized in this MOEA is 1000, along with 1000 iterations. In each iteration, the most fitted 25% of individuals were selected for reproduction, with a 75% crossover and a 1% chance of mutation. The AFLEET tool calculations were performed in a Lenovo computer, with an 11th Gen Intel® Core™ i7-1165G7 processor operating at 2.80 GHz and 16 GB of RAM. The MOEA was run with an Intel® Xeon® W-2195 CPU processor operating at 2.30 GHz and 256 GB of RAM.

The optimal solution given with the parameters selected is shown in table 6.2. The well-to-wheel analysis of the fuel and vehicle production produced 4,182,367.31 tons of GHG emissions, while the air pollutants such as CO and NOx produced 25,202,901.06 lbs. and 845,978.86 lbs., respectively, along with a TCO of $8,727,315,002.87 US dollars. In this MOEA, the number of non-dominated solutions found was 41, shown in figure 6.1. Non-dominated solutions are represented by blue dots, while the optimal solution found is represented by a red dot.

Table 6.4: Solutions for Case Study 3.

2012 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	2519	8200	29798	3045	2562	15441
COx	208354.46	783684.43	2464686.85	11875.50	9991.80	1277173.96
NOx	2692.53	17529.78	26754.64	7003.50	5892.60	16504.72
GHGs	19747.50	59365.83	132475.27	17830.48	7655.17	90037.28
TCO	$ 17,888,955.59	$ 70,808,476.00	$ 169,057,165.12	$ 24,125,230.50	$ 29,181,384.96	$ 133,431,085.35
2013 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	4812	4521	2753	4766	2714	4498
COx	338562.99	369824.42	193695.74	18587.40	10584.60	316470.56
NOx	4689.66	8954.24	2253.73	10961.80	6242.20	4383.64
GHGs	37723.28	36265.90	12239.22	29957.51	8109.34	21648.88
TCO	$ 35,769,328.32	$ 42,688,909.56	$ 16,798,420.58	$ 40,954,571.62	$ 32,713,416.12	$ 36,342,805.46
2014 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	14492	2266	2008	1941	4244	2031
COx	1020236.80	185358.80	141363.20	7569.90	16551.60	142982.40
NOx	14492.00	4532.00	1606.40	4464.30	9761.20	1624.80
GHGs	106279.73	13763.04	8927.12	12200.49	12680.93	9775.21
TCO	$ 116,118,599.20	$ 21,050,913.40	$ 14,184,391.52	$ 17,323,075.62	$ 53,971,287.52	$ 19,442,052.15
2015 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	11861	1117	9107	18960	903	4132
COx	698612.90	74839.00	536402.30	73944.00	3521.70	243374.80
NOx	10674.90	2010.60	7285.60	43608.00	2076.90	3718.80
GHGs	90472.33	8852.93	40487.69	119176.35	2698.13	23148.61
TCO	$ 100,553,406.65	$ 11,905,120.04	$ 67,352,548.83	$ 175,504,567.20	$ 12,382,233.99	$ 46,030,645.28

2016 Passenger Cars						
Type of fuel						
	Gasoline	Diesel	HEV	PHEV	EV	E85
# of vehicles	732	101	8609	4874	14234	4879
COx	43114.80	6767.00	507070.10	19008.60	55512.60	287373.10
NOx	658.80	181.80	6887.20	11210.20	32738.20	4391.10
GHGs	5583.49	721.51	38273.70	30636.37	42530.73	25659.22
TCO	$ 6,489,033.60	$ 1,128,956.79	$ 76,117,764.85	$ 46,733,471.68	$ 214,069,823.22	$ 54,157,339.11

2017 Passenger Cars						
Type of fuel						
	Gasoline	Diesel	HEV	PHEV	EV	E85
# of vehicles	3377	4401	9798	2106	1266	23760
COx	94806.11	135176.04	275069.65	8213.40	4937.40	667039.70
NOx	2229.48	3043.88	5433.63	4843.80	2911.80	15686.26
GHGs	26116.26	28420.85	34571.21	14423.27	3444.01	115444.08
TCO	$ 31,273,822.91	$ 50,874,635.79	$ 95,939,762.46	$ 20,663,924.58	$ 20,299,778.28	$ 257,606,395.20

2018 Passenger Cars						
Type of fuel						
	Gasoline	Diesel	HEV	PHEV	EV	E85
# of vehicles	711	6011	741	8409	1723	6427
COx	18820.69	174233.41	19614.81	32795.10	6719.70	170127.37
NOx	424.69	3779.47	371.80	19340.70	3962.90	3838.98
GHGs	4645.61	43518.05	2614.54	57590.37	4869.05	33065.16
TCO	$ 6,770,675.25	$ 79,824,156.48	$ 8,008,038.87	$ 85,298,205.12	$ 31,628,818.09	$ 74,570,681.44

2019 Passenger Cars						
Type of fuel						
	Gasoline	Diesel	HEV	PHEV	EV	E85
# of vehicles	3140	2384	3239	6780	3174	2079
COx	81045.07	64904.97	83600.31	26442.00	12378.60	53660.09
NOx	1678.16	1274.12	1454.10	15594.00	7300.20	1111.11
GHGs	21107.38	14904.88	15466.53	46433.90	8634.51	11171.51
TCO	$ 30,589,126.40	$ 71,352,166.40	$ 37,690,429.16	$ 71,023,415.40	$ 74,059,195.92	$ 24,874,964.73

2020 Passenger Cars						
Type of fuel						
	Gasoline	Diesel	HEV	PHEV	EV	E85
# of vehicles	2638	259	9703	10326	3337	8272
COx	63775.65	6595.36	234577.39	40271.40	13014.30	199981.88
NOx	1244.00	122.14	3843.53	23749.80	7675.10	3900.82
GHGs	19067.02	1519.80	41083.22	70719.24	8354.79	44449.61
TCO	$ 27,617,723.22	$ 3,249,890.56	$ 117,753,958.49	$ 108,169,290.18	$ 88,932,985.46	$ 92,936,085.44

2021 Passenger Cars						
Type of fuel						
	Gasoline	Diesel	HEV	PHEV	EV	E85
# of vehicles	1636	16161	5995	14391	5954	3440
COx	37124.61	383756.61	136040.36	56124.90	23220.60	78061.53
NOx	698.88	6717.79	2151.22	33099.30	13694.20	1469.52
GHGs	11997.90	94831.90	28626.69	98559.04	14581.56	18484.85
TCO	$ 18,445,949.08	$ 202,785,642.24	$ 81,196,280.00	$ 174,622,984.38	$ 168,553,750.82	$ 38,648,468.80

2022 Passenger Cars						
Type of fuel						
	Gasoline	Diesel	HEV	PHEV	EV	E85
# of vehicles	1593	1871	8506	3624	2422	25473
COx	33785.70	41212.48	180402.47	14133.60	9445.80	540253.02
NOx	609.81	673.17	2735.14	8335.20	5570.60	9751.14
GHGs	11682.56	10978.93	46019.20	20430.24	5931.57	136879.21
TCO	$ 20,321,295.66	$ 23,477,008.64	$ 138,472,236.16	$ 44,687,254.08	$ 84,635,167.26	$ 286,189,664.46

2012 Passenger Trucks						
Type of fuel						
	Gasoline	Diesel	HEV	PHEV	EV	E85
# of vehicles	3199	5112	3867	281	4549	4345
COx	290948.73	176299.57	351703.26	25556.92	20925.40	395177.31
NOx	4726.79	152835.82	4799.60	348.77	12737.20	6420.09
GHGs	30015.25	64226.27	31154.49	0.00	15968.78	28667.67
TCO	$ 25,795,296.45	$ 59,149,725.12	$ 34,389,424.35	$ 4,438,892.37	$ 36,946,568.59	$ 42,936,638.25

2013 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	3107	2594	1792	601	1458	2998
COx	245561.52	88237.06	141630.59	47499.99	6706.80	236946.71
NOx	4004.78	100388.00	1940.24	650.72	4082.40	3864.29
GHGs	29736.72	32234.72	14437.25	0.00	5118.15	18871.59
TCO	$ 27,889,985.50	$ 30,773,270.50	$ 16,530,841.60	$ 9,493,858.77	$ 12,325,436.28	$ 30,069,880.04

2014 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	1576	6438	1911	8885	768	2885
COx	124559.05	310072.69	151035.75	702225.33	3532.80	228015.77
NOx	2031.39	94924.34	2069.08	9619.98	2150.40	3718.63
GHGs	14564.70	55274.35	15395.97	0.00	2695.98	18407.79
TCO	$ 14,440,998.32	$ 74,533,820.46	$ 17,945,570.37	$ 140,354,301.45	$ 6,492,410.88	$ 31,390,300.20

2015 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	3669	6747	3639	40779	5527	174
COx	245801.74	284865.93	243791.91	2731956.67	25424.20	11656.99
NOx	3806.41	76572.30	3171.24	35537.23	15475.60	180.52
GHGs	34770.34	54687.91	29317.61	0.00	19401.94	1160.96
TCO	$ 37,379,368.41	$ 79,325,288.64	$ 34,776,285.45	$ 644,176,483.83	$ 48,190,244.62	$ 2,002,814.82

2016 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	18816	9	3164	8148	2037	2358
COx	1260562.95	379.99	211969.66	37480.80	9370.20	157972.33
NOx	19520.68	102.14	2757.30	22814.40	5703.60	2446.31
GHGs	167028.90	72.95	25490.77	57488.77	7150.67	15045.26
TCO	$ 189,368,928.00	$ 112,681.44	$ 31,286,581.20	$ 83,701,063.32	$ 18,571,654.92	$ 27,951,425.46

2017 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	13195	710	349	8702	1483	5461
COx	569137.62	20356.68	15053.36	40029.20	6821.80	235548.35
NOx	7881.64	5044.53	175.11	24365.60	4152.40	3261.97
GHGs	123339.13	5754.92	2811.72	86280.50	4089.78	34375.50
TCO	$ 155,083,078.15	$ 9,675,745.10	$ 3,508,905.33	$ 165,116,882.18	$ 14,012,733.53	$ 70,254,672.80

2018 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	19559	5219	161	5012	4339	775
COx	612434.67	123219.95	5041.26	23055.20	19959.40	24266.93
NOx	11068.10	25595.62	76.53	14033.60	12149.20	438.56
GHGs	172244.25	42302.68	1297.10	71795.32	11965.98	5011.39
TCO	$ 231,655,622.46	$ 78,600,906.07	$ 1,759,140.74	$ 121,458,753.08	$ 46,756,673.49	$ 10,545,851.25

2019 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	7749	1062	3255	382	14588	3304
COx	234842.38	24072.08	98646.53	1757.20	67104.80	100131.53
NOx	4141.41	4607.42	1461.28	1069.60	40846.40	1765.81
GHGs	72159.69	8389.53	26223.91	5472.03	43375.18	23443.33
TCO	$ 110,278,731.15	$ 16,830,087.48	$ 45,144,571.50	$ 9,637,416.88	$ 200,755,096.08	$ 52,496,099.60

2020 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	1097	147	8200	893	363	5254
COx	30728.27	3197.99	229691.72	4107.80	1669.80	147170.77
NOx	482.82	554.56	3031.62	2500.40	1016.40	2312.45
GHGs	9441.28	1070.52	68956.59	12816.18	1391.24	37880.43
TCO	$ 17,109,919.97	$ 2,643,111.45	$ 141,698,214.00	$ 24,306,870.62	$ 5,477,183.58	$ 94,791,039.26

2021 Passenger Trucks						
Type of fuel						
	Gasoline	Diesel	HEV	PHEV	EV	E85
# of vehicles	97	669	434	2341	146	6770
COx	2523.15	13942.81	11289.16	10768.60	671.60	176100.52
NOx	38.55	2430.12	144.89	6554.80	408.80	2690.75
GHGs	871.33	5835.57	2909.51	33597.61	589.28	50359.34
TCO	$ 1,669,018.86	$ 14,206,529.43	$ 8,735,821.08	$ 73,039,995.94	$ 2,687,299.36	$ 116,346,241.20
2022 Passenger Trucks						
Type of fuel						
	Gasoline	Diesel	HEV	PHEV	EV	E85
# of vehicles	1082	3988	2483	6172	6722	3431
COx	25981.64	79470.85	59623.29	28391.20	30921.20	82387.24
NOx	383.86	13927.67	739.96	17281.60	18821.60	1217.22
GHGs	9528.52	36701.34	16645.91	79715.44	25040.87	24736.92
TCO	$ 20,917,721.72	$ 94,513,446.48	$ 58,216,715.96	$ 202,806,303.48	$ 125,956,231.02	$ 68,563,525.74

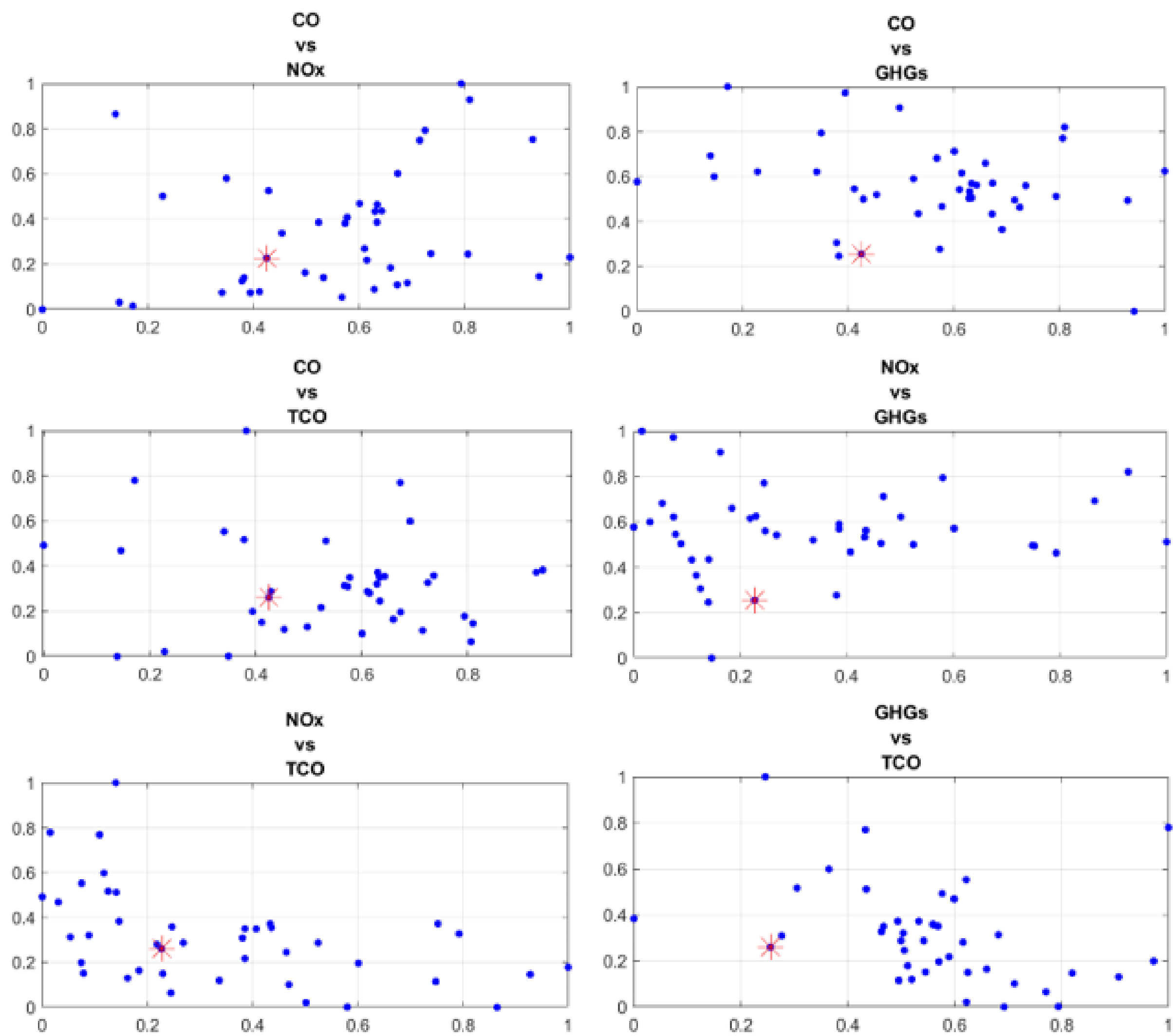


Figure 6.3: Pareto Optimality for Case Study 3.

The computational time used to run this MOEA to find the optimal solution shown in Case Study 3 was 2 hours 6 mins.

6.5 Case Study 4

The percentage established in this case study for EVs was 15%, equal to 105,641 vehicles. The number of individuals utilized in this MOEA is 1000, along with 1000 iterations. In each iteration, the most fitted 25% of individuals were selected for reproduction, with a 75% crossover and a 1% chance of mutation. The AFLEET tool calculations were performed in a Lenovo computer, with an 11th Gen Intel® Core™ i7-1165G7 processor operating at 2.80 GHz and 16 GB of RAM. The MOEA was run with an Intel® Xeon® W-2195 CPU processor operating at 2.30 GHz and 256 GB of RAM.

The optimal solution given with the parameters selected is shown in table 6.2. The well-to-wheel analysis of the fuel and vehicle production produced 4,260,865.66 tons of GHG emissions, while the air pollutants such as CO and NOx produced 26,224,903 and 563,795.37 lbs., respectively, along with a TCO of $8,611,203,464.81. In this MOEA, the number of non-dominated solutions found was 23, shown in figure 6.1. Non-dominated solutions are represented by blue dots, while the optimal solution found is represented by a red dot.

Table 6.5: Solutions for Case Study 4.

2012 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	5196	22936	2181	365	4649	3387
COx	429777.60	2192022.71	180397.41	1423.50	18131.10	280149.49
NOx	5553.95	49032.09	1958.25	839.50	10692.70	3620.33
GHGs	40733.62	166050.57	9696.24	2137.32	13891.06	19749.78
TCO	$ 36,899,965.56	$ 198,056,488.48	$ 12,373,772.64	$ 2,891,858.50	$ 52,952,481.92	$ 29,268,252.45
2013 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	4926	931	3078	1084	8142	8610
COx	346583.81	76157.16	216562.11	4227.60	31753.80	605782.91
NOx	4800.76	1843.93	2519.78	2493.20	18726.60	8391.09
GHGs	38616.98	7468.16	13684.10	6813.67	24328.03	41439.95
TCO	$ 36,616,731.36	$ 8,790,837.16	$ 18,781,525.08	$ 9,314,887.88	$ 98,140,248.36	$ 69,566,819.70

2014 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	14486	713	2331	13109	1882	29843
COx	1019814.40	58323.40	164102.40	51125.10	7339.80	2100947.20
NOx	14486.00	1426.00	1864.80	30150.70	4328.60	23874.40
GHGs	106235.72	4330.56	10363.11	82398.88	5623.35	143634.43
TCO	$ 116,070,523.60	$ 6,623,698.70	$ 16,466,044.14	$ 116,995,465.38	$ 23,933,544.56	$ 285,676,593.95
2015 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	7973	1403	10165	30654	1161	3659
COx	469609.70	94001.00	598718.50	119550.60	4527.90	215515.10
NOx	7175.70	2525.40	8132.00	70504.20	2670.30	3293.10
GHGs	60815.77	11119.66	45191.33	192681.00	3469.03	20498.73
TCO	$ 67,592,303.45	$ 14,953,342.36	$ 75,177,188.85	$ 283,750,896.78	$ 15,920,015.13	$ 40,761,406.36
2016 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	1572	2117	2610	2699	11529	16990
COx	92590.80	141839.00	153729.00	10526.10	44963.10	1000711.00
NOx	1414.80	3810.60	2088.00	6207.70	26516.70	15291.00
GHGs	11990.77	15123.23	11603.48	16965.03	34448.28	89352.35
TCO	$ 13,935,465.60	$ 23,663,381.43	$ 23,076,706.50	$ 25,878,875.68	$ 173,388,435.57	$ 188,590,529.10
2017 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	3195	9924	1588	2584	1157	2911
COx	89696.63	304814.14	44581.61	10077.60	4512.30	81723.59
NOx	2109.33	6863.78	880.65	5943.20	2661.10	1921.83
GHGs	24708.75	64087.37	5603.09	17696.93	3147.49	14143.84
TCO	$ 29,588,351.85	$ 114,719,355.96	$ 15,549,330.76	$ 25,354,027.12	$ 18,552,009.06	$ 31,561,120.22
2018 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	10365	339	1310	10364	10250	26324
COx	274369.09	9826.17	34676.65	40419.60	39975.00	696815.43
NOx	6191.23	213.15	657.29	23837.20	23575.00	15723.86
GHGs	67724.01	2454.27	4622.20	70979.49	28965.59	135429.78
TCO	$ 98,703,303.75	$ 4,501,811.52	$ 14,157,261.70	$ 105,129,099.52	$ 188,157,507.50	$ 305,430,001.28
2019 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	3588	1533	3696	1519	5806	2458
COx	92608.19	41736.29	95395.72	5924.10	22643.40	63442.29
NOx	1917.59	819.30	1659.26	3493.70	13353.80	1313.66
GHGs	24118.87	9584.39	17648.75	10403.11	15794.56	13208.07
TCO	$ 34,953,434.88	$ 45,882,076.80	$ 43,008,282.24	$ 15,912,178.17	$ 135,471,862.48	$ 29,409,650.46
2020 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	8466	1651	16544	6793	1497	4362
COx	204671.98	42042.24	399963.76	26492.70	5838.30	105454.66
NOx	3992.30	778.56	6553.37	15623.90	3443.10	2056.98
GHGs	61190.81	9687.98	70048.51	46522.93	3748.01	23439.22
TCO	$ 88,632,162.54	$ 20,716,483.84	$ 200,775,171.52	$ 71,159,595.99	$ 39,895,918.26	$ 49,007,157.24
2021 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	16971	728	4768	7868	2807	9149
COx	385111.10	17286.98	108196.91	30685.20	10947.30	207611.89
NOx	7249.77	302.61	1710.93	18096.40	6456.10	3908.32
GHGs	124459.92	4271.87	22767.65	53885.24	6874.45	49162.17
TCO	$ 191,348,534.13	$ 9,134,827.52	$ 64,577,792.00	$ 95,471,728.24	$ 79,464,289.31	$ 102,789,197.98

2022 Passenger Cars						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	550	2802	7096	4608	3049	8762
COx	11664.87	61719.59	150498.00	17971.20	11891.10	185831.94
NOx	210.54	1008.13	2281.75	10598.40	7012.70	3354.12
GHGs	4033.53	16441.99	38390.82	25977.52	7467.11	47082.62
TCO	$ 7,016,141.00	$ 35,159,047.68	$ 115,518,338.56	$ 56,820,879.36	$ 106,545,262.17	$ 98,441,245.24
2012 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	8926	1650	763	9365	2280	12512
COx	811818.79	56904.20	69394.77	851745.80	10488.00	1137965.13
NOx	13188.90	49330.81	947.01	11623.55	6384.00	18487.51
GHGs	83749.96	20730.31	6147.11	0.00	8003.70	82552.34
TCO	$ 71,975,247.30	$ 19,091,754.00	$ 6,785,397.15	$ 147,936,751.05	$ 18,517,954.80	$ 123,641,707.20
2013 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	500	77	4890	572	3067	7996
COx	39517.46	2619.22	386480.79	45207.98	14108.20	631963.28
NOx	644.48	2979.91	5294.51	619.32	8587.60	10306.48
GHGs	4785.44	956.85	39396.29	0.00	10766.38	50332.63
TCO	$ 4,488,250.00	$ 913,470.25	$ 45,109,272.00	$ 9,035,752.44	$ 25,927,375.22	$ 80,199,720.08
2014 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	5545	1936	48	3880	631	5060
COx	438248.67	93243.36	3793.68	306655.52	2902.60	399916.73
NOx	7147.25	28545.13	51.97	4200.96	1766.80	6522.11
GHGs	51244.46	16621.80	386.71	0.00	2215.06	32285.42
TCO	$ 50,809,223.15	$ 22,413,401.12	$ 450,752.16	$ 61,291,467.60	$ 5,334,259.46	$ 55,055,431.20
2015 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	14498	1532	1102	2065	460	11394
COx	971281.98	64682.76	73827.61	138343.03	2116.00	763331.97
NOx	15040.97	17386.80	960.35	1799.56	1288.00	11820.72
GHGs	137394.48	12417.65	8878.26	0.00	1614.78	76023.11
TCO	$ 147,704,029.22	$ 18,011,907.84	$ 10,531,318.10	$ 32,620,330.05	$ 4,010,767.60	$ 131,149,839.42
2016 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	17757	1536	13755	1928	7644	7070
COx	1189616.09	64851.65	921505.28	8868.80	35162.40	473649.03
NOx	18422.02	17432.20	11986.92	5398.40	21403.20	7334.78
GHGs	157628.20	12450.07	110817.17	13603.13	26833.45	45110.25
TCO	$ 178,710,887.25	$ 19,230,965.76	$ 136,013,566.50	$ 19,805,553.52	$ 69,691,571.04	$ 83,806,860.90
2017 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	773	2547	122	2669	2896	628
COx	33341.67	73026.01	5262.20	12277.40	13321.60	27087.41
NOx	461.73	18096.36	61.21	7473.20	8108.80	375.12
GHGs	7225.55	20644.75	982.89	26463.19	7986.51	3953.09
TCO	$ 9,085,200.41	$ 34,710,032.07	$ 1,226,608.74	$ 50,643,180.71	$ 27,364,043.36	$ 8,079,094.40
2018 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	992	1007	1616	890	257	3544
COx	31061.67	23775.15	50600.46	4094.00	1182.20	110970.32
NOx	561.36	4938.65	768.15	2492.00	719.60	2005.49
GHGs	8735.94	8162.25	13019.31	12748.97	708.75	22916.59
TCO	$ 11,749,188.48	$ 15,165,953.71	$ 17,656,965.44	$ 21,567,895.10	$ 2,769,408.87	$ 48,225,157.20

2019 Passenger Trucks						
	Type of fuel					
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	340	576	1667	982	6907	1060
COx	10304.09	13056.04	50520.36	4517.20	31772.20	32124.52
NOx	181.71	2498.94	748.37	2749.60	19339.60	566.51
GHGs	3166.12	4550.25	13430.19	14066.84	20536.90	7521.17
TCO	$ 4,838,659.00	$ 9,128,183.04	$ 23,120,123.10	$ 24,774,720.88	$ 95,051,785.62	$ 16,841,969.00
2020 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	8043	1314	13029	1367	4092	17777
COx	225293.96	28586.12	364957.74	6288.20	18823.20	497954.84
NOx	3539.97	4957.13	4816.95	3827.60	11457.60	7824.21
GHGs	69221.68	9569.13	109565.30	19618.94	15683.09	128169.10
TCO	$ 125,446,751.43	$ 23,626,179.90	$ 225,144,637.83	$ 37,208,837.78	$ 61,742,796.72	$ 320,727,123.13
2021 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	1378	91	8230	1315	8993	2571
COx	35844.39	1896.56	214077.89	6049.00	41367.80	66876.58
NOx	547.69	330.55	2747.66	3682.00	25180.40	1021.85
GHGs	12378.32	793.78	55173.51	18872.64	36296.95	19124.65
TCO	$ 23,710,391.64	$ 1,932,427.77	$ 165,658,542.60	$ 41,028,447.10	$ 165,526,596.88	$ 44,184,074.76
2022 Passenger Trucks						
Type of fuel						
	Gasoline	**Diesel**	**HEV**	**PHEV**	**EV**	**E85**
# of vehicles	1915	1380	2404	1491	16485	4724
COx	45984.13	27499.94	57726.30	6858.60	75831.00	113435.53
NOx	679.39	4819.50	716.41	4174.80	46158.00	1675.94
GHGs	16864.24	12700.06	16116.30	19257.25	61410.12	34059.22
TCO	$ 37,021,660.90	$ 32,705,254.80	$ 56,364,472.48	$ 48,992,903.19	$ 308,894,446.35	$ 94,402,242.96

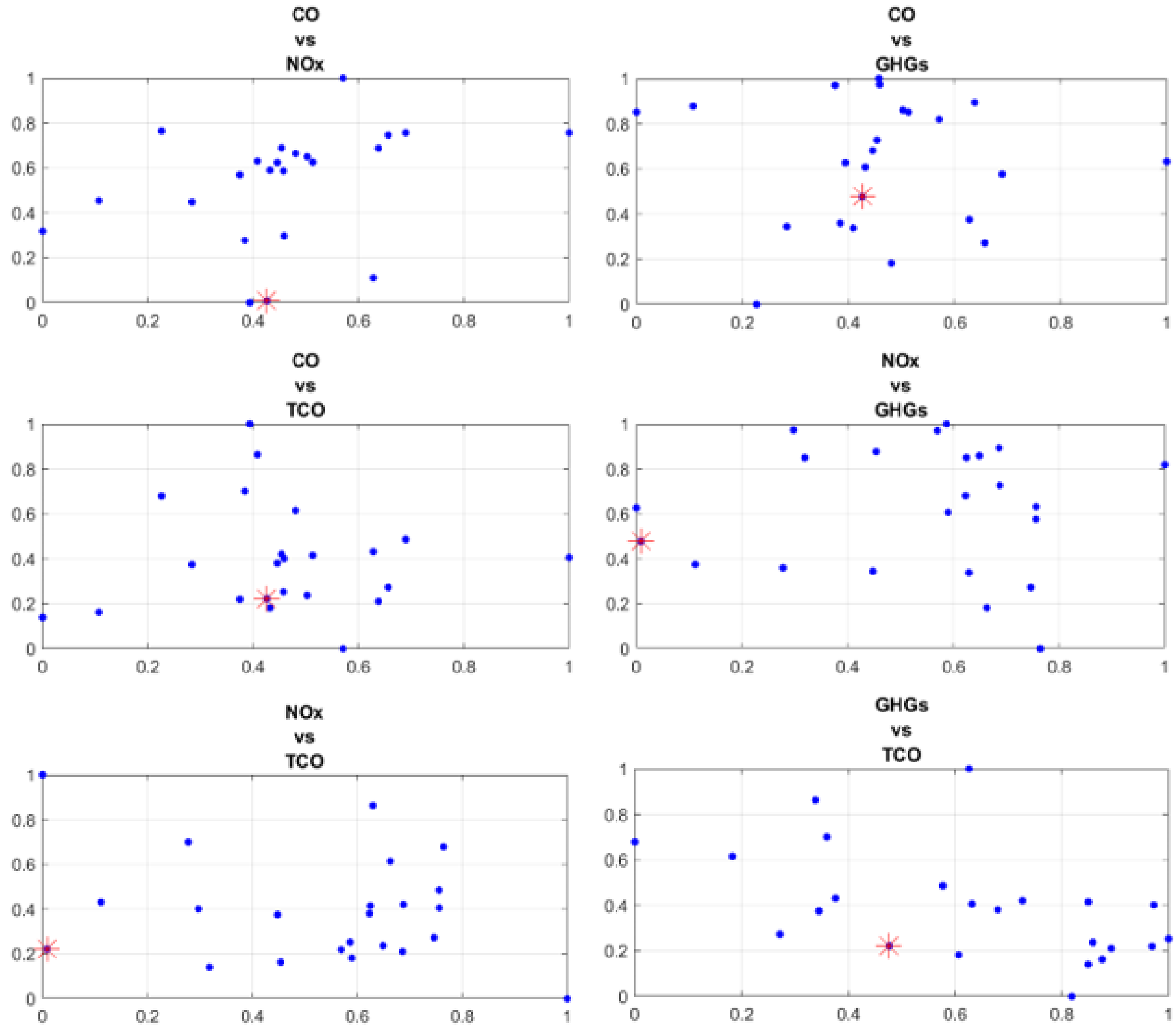


Figure 6.4: Pareto Optimality for Case Study 4.

The computational time used to run this MOEA to find the optimal solution shown in Case Study 4 was 1 hour 35 mins.

Chapter 7: Design of Experiments

A Design of Experiments (DOE) was performed in Minitab® to identify the effect of the selected parameters over the optimal solutions. The parameters under the statistical analysis were the number of individuals, number of generations, percentage of elitism, percentage of crossover, and percentage of mutation. Thus, a factorial design of two levels was created with two responses of 32 runs and resolution V. Tables 7.1 shows the low and high parameters selected for this DOE. Table 7.2 presents the full factorial DOE with the parameters chosen previously. The first response corresponds to the normalized solution utilizing the formula provided in chapter 5 (eq. 5.1) for the optimal solutions of the four objectives in this research. The second response is the MATLAB code's computational time to find an optimal solution.

Table 7.1: MOEA parameters for the Design of Experiments.

Parameters	**Low**	**High**
Number of Individuals	50	300
Number of generations	100	350
Elitism	0.10	0.30
Crossover	0.50	0.80
Mutation	0.001	0.05

Table 7.2: Design of experiments full factorial.

Number of individuals	Number of generations	Elitism	Crossover	Mutation	Solution	Time
50	100	0.1	0.5	0.001	0.58068904	6.407
300	100	0.1	0.5	0.001	1.34810947	59.463
50	350	0.1	0.5	0.001	1.18087205	36.821
300	350	0.1	0.5	0.001	1.14235544	952.795
50	100	0.3	0.5	0.001	0.8506811	5.427
300	100	0.3	0.5	0.001	1.14235544	125.6874
50	350	0.3	0.5	0.001	1.18087205	62.841
300	350	0.3	0.5	0.001	0.76382746	275.628
50	100	0.1	0.8	0.001	1.40263332	4.72
300	100	0.1	0.8	0.001	1.38061218	185.329
50	350	0.1	0.8	0.001	1.39813104	73.027
300	350	0.1	0.8	0.001	0.94668508	483.901
50	100	0.3	0.8	0.001	1.30285794	5.359
300	100	0.3	0.8	0.001	1.54323554	126.314
50	350	0.3	0.8	0.001	1.18087205	44.394
300	350	0.3	0.8	0.001	1.37080013	750.658
50	100	0.1	0.5	0.05	1.59898134	4.796
300	100	0.1	0.5	0.05	0.79398404	190.789
50	350	0.1	0.5	0.05	1.01184567	19.566
300	350	0.1	0.5	0.05	0.91331399	262.468
50	100	0.3	0.5	0.05	0.75238112	3.479
300	100	0.3	0.5	0.05	1.17798008	49.178
50	350	0.3	0.5	0.05	1.07941666	137.17
300	350	0.3	0.5	0.05	0.71835295	162.48
50	100	0.1	0.8	0.05	0.91969843	5.333
300	100	0.1	0.8	0.05	0.7043893	54.972
50	350	0.1	0.8	0.05	1.39813104	18.839
300	350	0.1	0.8	0.05	1.03873899	443.69
50	100	0.3	0.8	0.05	1.37341832	4.576
300	100	0.3	0.8	0.05	0.5758879	48.945
50	350	0.3	0.8	0.05	1.28739128	20.234
300	350	0.3	0.8	0.05	0.70636142	300.025

7.1 RESULTS

After analyzing the full factorial design, according to the Analysis of Variance (ANOVA) presented in table 7.3, for the normalized solution and the computational time, a P-value of 0.005

and an F-value of 18.48 corresponding to the "number of individuals," a P-value of 0.015 and an F-value of 11.45 corresponding to the "number of generations," and a P-value of 0.041 and an F-value of 6.69 corresponding to the 2 way interaction of the factors "number of individuals*number of generations," with a significance level of 0.05, proves that the means are statistically significant to the responses.

Table 7.3: Analysis of variance for Solution and computational time

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	25	1388276	55531	2.03	0.192
Linear	5	901293	180259	6.6	0.02
Number of individuals	1	504845	504845	18.48	0.005
Number of generations	1	312794	312794	11.45	0.015
Elitism	1	14472	14472	0.53	0.494
Crossover	1	1449	1449	0.05	0.826
Mutation	1	67733	67733	2.48	0.166
2-Way Interactions	10	343649	34365	1.26	0.405
Number of individuals*Number of generations	1	182736	182736	6.69	0.041
Number of individuals*Elitism	1	25791	25791	0.94	0.369
Number of individuals*Crossover	1	5392	5392	0.2	0.672
Number of individuals*Mutation	1	63210	63210	2.31	0.179
Number of generations*Elitism	1	4872	4872	0.18	0.688
Number of generations*Crossover	1	1721	1721	0.06	0.81
Number of generations*Mutation	1	41974	41974	1.54	0.261
Elitism*Crossover	1	17201	17201	0.63	0.458
Elitism*Mutation	1	543	543	0.02	0.893
Crossover*Mutation	1	210	210	0.01	0.933

The normal plot of the standardized effects and the Pareto chart of the standardized effects are shown in figure 7.1 and figure 7.2, respectively. The two factors significant to the normalized solution and the computational time are the number of individuals utilized in the algorithm and the number of generations. The factors that are not significant to the responses include Elitism, crossover, and mutation rates. On the other hand, the only significant iteration for the responses is the number of individuals*number of generations.

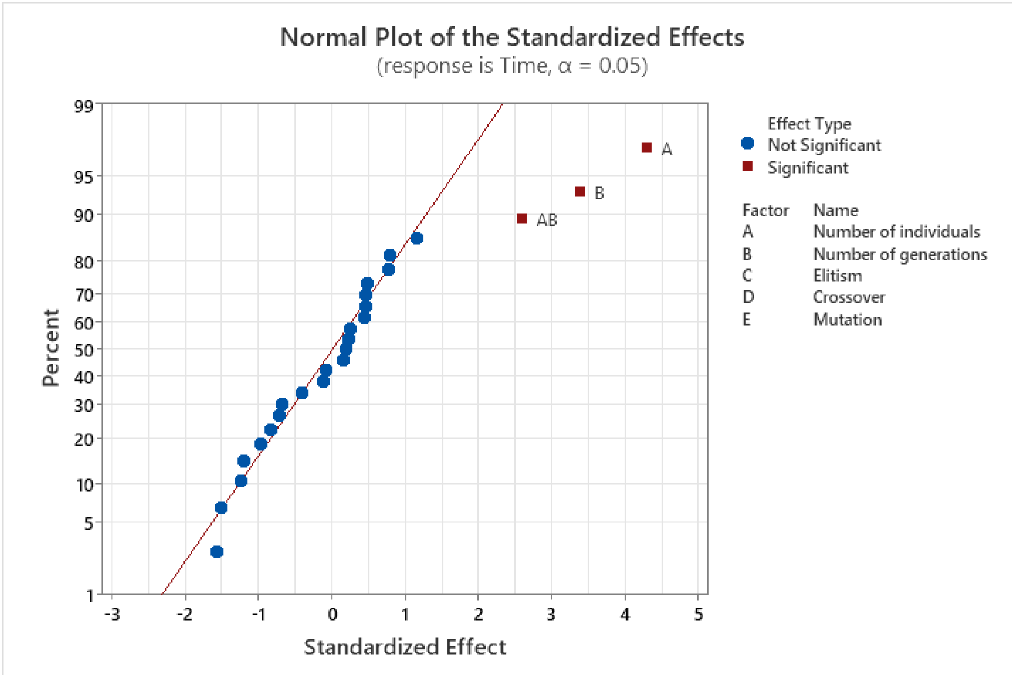


Figure 7.1: Normal plot of the effects for the normalized solution and computational time.

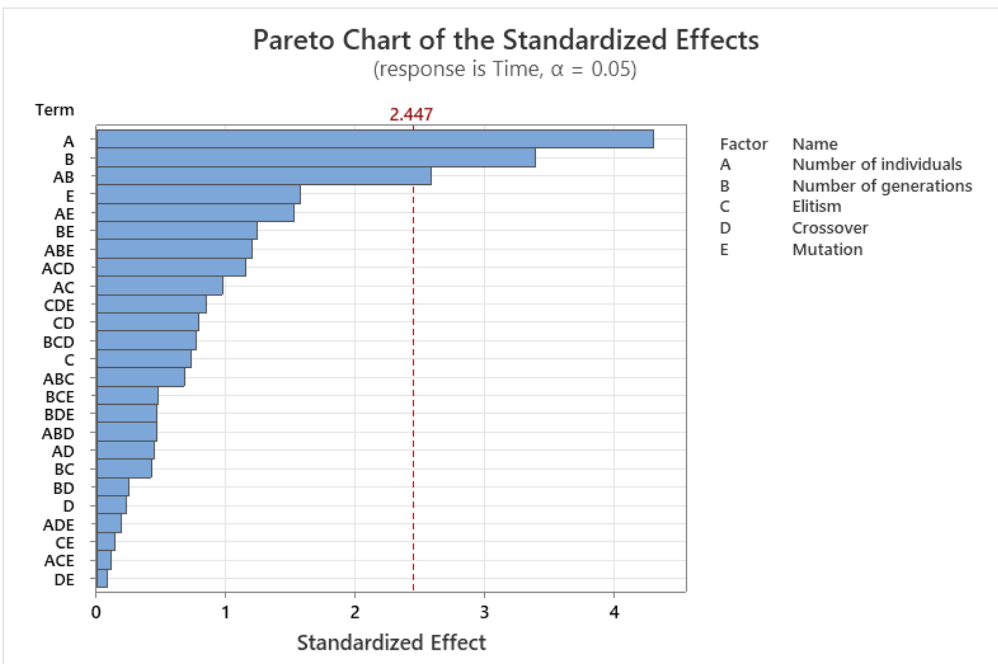


Figure 7.2. Pareto chart of the standardized effects for the normalized solution and computational time.

The ANOVA for the normalized solution response, presented in table 7.3, and a P-value of 0.046 and an F-value of 4.68 corresponding to the 2-way interaction of the factors "number of individuals*mutation," with a significance level of 0.05, proves that the mean is statistically significant to the response.

Table 7.3: Analysis of variance for a normalized solution.

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	15	1.39471	0.092981	1.24	0.338
Linear	5	0.56031	0.112062	1.49	0.247
Number of individuals	1	0.15567	0.155666	2.07	0.169
Number of generations	1	0.00053	0.000528	0.01	0.934
Elitism	1	0.01769	0.017695	0.24	0.634
Crossover	1	0.16443	0.164426	2.19	0.158
Mutation	1	0.222	0.221997	2.95	0.105
2-Way Interactions	10	0.8344	0.08344	1.11	0.411
Number of individuals*Number of generations	1	0.12529	0.125289	1.67	0.215
Number of individuals*Elitism	1	0.00143	0.001427	0.02	0.892
Number of individuals*Crossover	1	0.09691	0.096906	1.29	0.273
Number of individuals*Mutation	1	0.35125	0.351253	4.68	0.046
Number of generations*Elitism	1	0.01674	0.016739	0.22	0.643
Number of generations*Crossover	1	0.00448	0.004481	0.06	0.81
Number of generations*Mutation	1	0.01294	0.012944	0.17	0.684
Elitism*Crossover	1	0.03485	0.034854	0.46	0.506
Elitism*Mutation	1	0.01375	0.013749	0.18	0.675
Crossover*Mutation	1	0.17676	0.17676	2.35	0.145

The normal plot of the standardized effects and the Pareto chart of the standardized effects are shown in figure 7.3 and figure 7.4, respectively. There is just one significant factor to the normalized solution, which is the 2-way interaction between the number of individuals*mutation rate. The factors that are not significant to the responses include Elitism rate, crossover rate, mutation rate, and the 2-way interactions: number of individuals*number of generations, number of individuals*elitism, number of individuals*crossover, number of generations*elitism, number of generations*crossover, number of generations*mutation, elitism*crossover, elitism*mutation, and crossover*mutation.

Figure 7.3: Normal plot of the effects for the normalized solution.

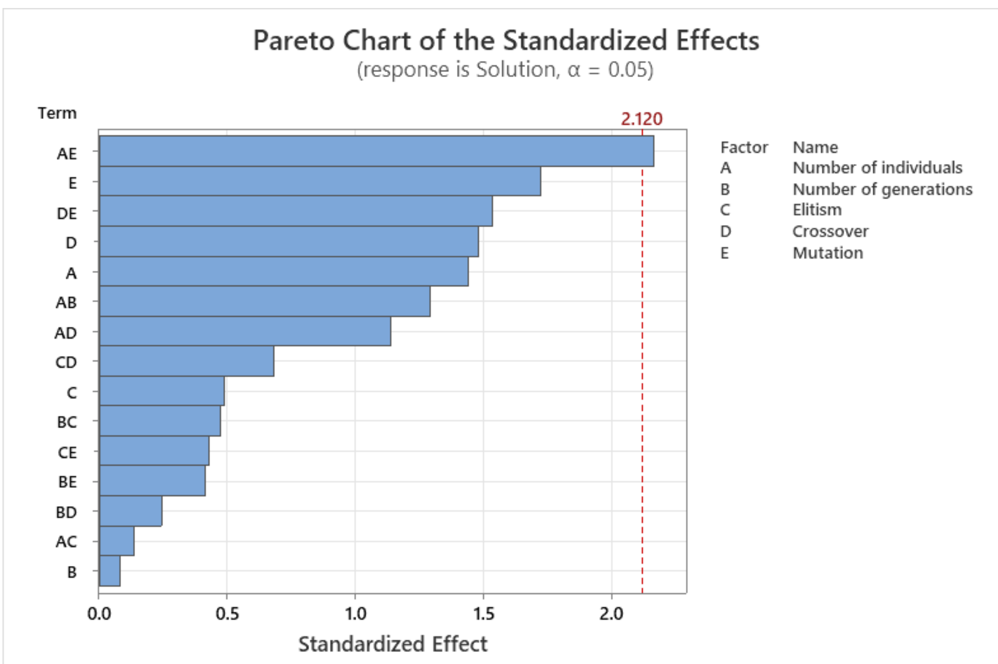


Figure 7.4: Pareto chart of the standardized effects for the normalized solution.

The ANOVA conducted for the computational time response, presented in table 7.4, has a P-value of 0.000 and an F-value of 26.29 corresponding to the "number of individuals," a P-value of 0.000 and an F-value of 16.29 corresponding to the "number of generations," and a P-value of

0.007 and an F-value of 9.52 corresponding to the 2 way interaction of the factors "number of individuals*number of generations," with a significance level of 0.05, proves that the means are statistically significant to the responses.

Table 7.4: Analysis of variance for computational time.

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	15	1244942	82996	4.32	0.003
Linear	5	901293	180259	9.39	0.000
Number of individuals	1	504845	504845	26.29	0.000
Number of generations	1	312794	312794	16.29	0.001
Elitism	1	14472	14472	0.75	0.398
Crossover	1	1449	1449	0.08	0.787
Mutation	1	67733	67733	3.53	0.079
2-Way Interactions	10	343649	34365	1.79	0.144
Number of individuals*Number of generations	1	182736	182736	9.52	0.007
Number of individuals*Elitism	1	25791	25791	1.34	0.263
Number of individuals*Crossover	1	5392	5392	0.28	0.603
Number of individuals*Mutation	1	63210	63210	3.29	0.088
Number of generations*Elitism	1	4872	4872	0.25	0.621
Number of generations*Crossover	1	1721	1721	0.09	0.769
Number of generations*Mutation	1	41974	41974	2.19	0.159
Elitism*Crossover	1	17201	17201	0.9	0.358
Elitism*Mutation	1	543	543	0.03	0.869
Crossover*Mutation	1	210	210	0.01	0.918

The normal plot of the standardized effects and the Pareto chart of the standardized effects are shown in figure 7.5 and figure 7.6, respectively. The two significant factors in computational time are the number of individuals utilized in the algorithm and the number of generations. The factors that are not significant to the responses include Elitism, crossover, and mutation rates. On the other hand, the only significant iteration for the responses is number of individuals*number of generations.

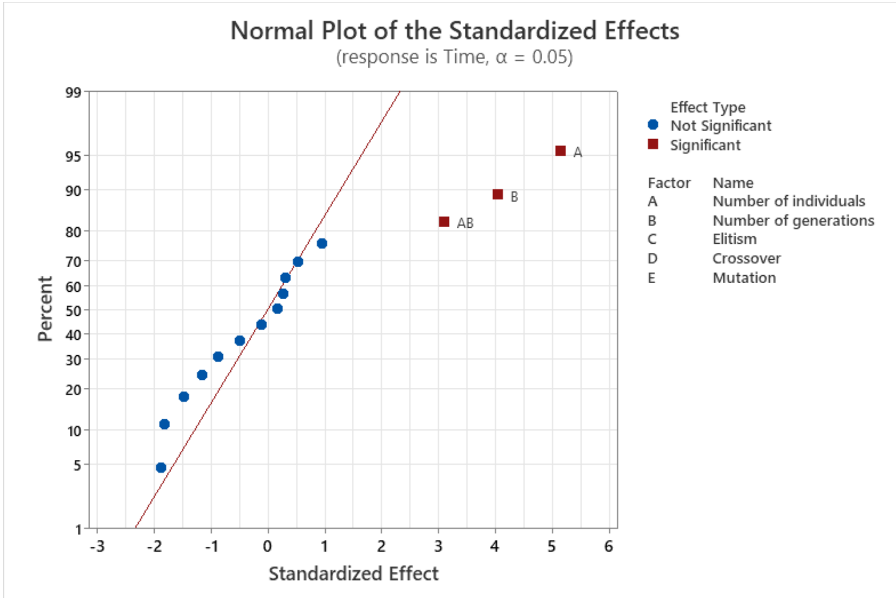


Figure 7.5: Normal plot of the effects for computational time.

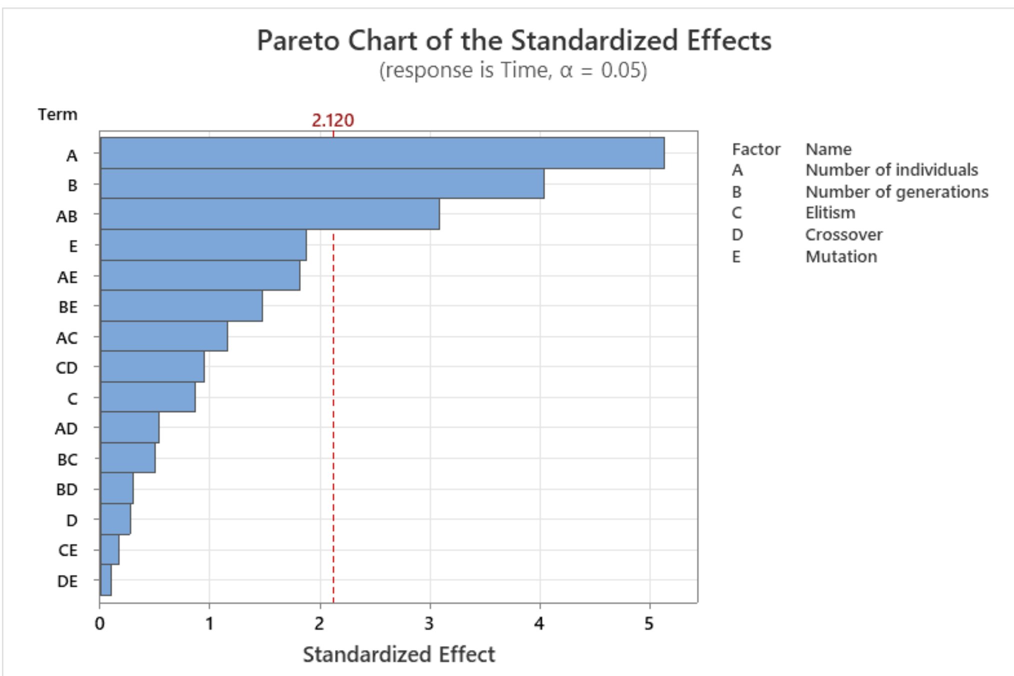


Figure 7.6: Pareto chart of the standardized effects for computational time.

The Main Effects Plot for the response Solution is shown in figure 7.7. The best parameters to utilize in the MOEA to minimize the solution would be 300 individuals with 350 generations, using an elitism rate of 30% and a crossover rate of 50% combined with a 5% of mutation.

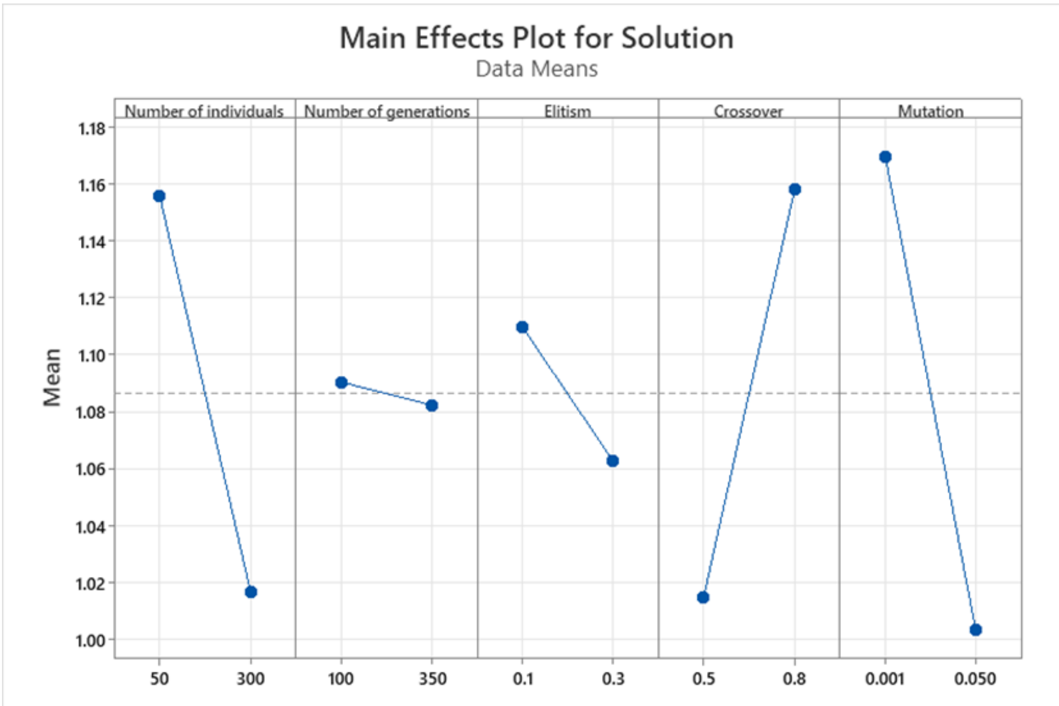


Figure 7.7: The Main Effects Plot for the response Solution

The response optimizer graph in figure 7.8 presents the optimal combination of parameters and the best possible solution to minimize the response. The number of individuals selected was 300 and 350 for the number of generations. For elitism, crossover, and mutation, the values of 0.3, 0.8, and 0.05 were selected.

Figure 7.8: Response Optimization

Chapter 8: Conclusions and Future Work

8.1 Conclusion

The transportation sector accounts for almost a third of the total CO2 U.S. emissions, with ICEVs being the primary source. Therefore, there has been a growing push towards transitioning to BEVs as a more sustainable way of transportation since BEVs produce fewer GHGs while operating. However, there are challenges related to infrastructure and production of BEVs. Effective policy and regulatory frameworks are needed to support this shift to a more sustainable future, considering the significant reduction in emissions, potential for substantial long-term cost savings, and improved air quality that BEVs offer.

The rising urge to achieve a more sustainable way of transportation has pushed the need for more suitable tools to analyze alternative scenarios and their respective emissions, considering long-term cost savings. Coupling life cycle assessments and life cycle costs with heuristic multiple objective evolutionary algorithms is a feasible approach to recognizing the optimal scenario that can potentially decrease emissions and cost for the transportation system.

This thesis proposed a coupled modeling framework to create optimal scenarios to minimize GHGs, air pollutants, and total cost of ownership. This framework Alternative Fuel Life-Cycle Environmental and Economic Transportation (AFLEET) Tool with a Multi-Objective Optimization Algorithm to simulate and compare different BEV penetration scenarios by minimizing the objective functions. This algorithm takes into account GHGs, air pollutants such as CO and NOx, and TCO generated by different vehicle types depending on their fuel type and model year.

This optimization approach can be applied to analyze and simulate different scenarios for decision-makers when exploring resources to reduce emissions and costs caused by transportation systems. Additionally, it was demonstrated the proposed methodology is flexible since it can be applied in other regions with similar data available.

8.2 Future Work

For future research, considering weights in the objective functions is essential in prospective studies to ensure better decision-making. For this research, the objective functions are to minimize GHGs, air pollutants, and vehicle ownership costs. Each of these objectives is equally important for this research. Thus, assigning the same weight to all objective functions may not result in an optimal solution that satisfies, in totality, all objectives. However, giving weights according to the importance of the objective will help the decision-maker to emphasize the need to minimize objectives over others. This approach will help achieve informed decisions more aligned with the user's goals.

The proposed model considers six different fuel types (gasoline, diesel, HEV, PHEV, BEV, E85%) that can be used to analyze the current transportation system. However, the AFLEET tool can include Gasoline Extended Range Electric Vehicle (EREV), Gaseous Hydrogen (G.H2) Fuel Cell Vehicles (FCV), Diesel Hybrid Electric Vehicles (HEV), Diesel Hydraulic Hybrid Vehicles (HHV), Biodiesel (B20) and (B100), Renewable Diesel (RD20) and (RD100), Propane (LPG), Compressed Natural Gas (CNG), Liquefied Natural Gas (LNG) and LNG / Diesel Pilot Ignition vehicles, to expand the analysis in the current framework.

Moreover, this modeling approach can be utilized in other areas with similar data inputs. Since the AFLEET tool can be adapted to any region of the U.S. Applying the methodology to different areas can lead to sustainable transportation solutions.

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Vita

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