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Exploring the Feasibility of Introducing Alternative Fuel Vehicles into Fleet

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EXPLORING THE FEASIBILITY OF INTRODUCING ALTERNATIVE FUEL

VEHICLES INTO FLEET

by

Samia Rubaiat

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ABSTRACT

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The transportation sector is one of the most significant contributors to emissions and consequently air pollution. State and private agencies consider alternative fuel vehicle (AFV) as a promising option for reducing vehicle emissions from their fleet. In addition, AFVs typically have lower operating and maintenance costs. The primary barrier of introducing AFVs in the fleet is the high purchasing cost, along with the uncertainty of future fuel costs. This tradeoff between the benefits of AFV and its high purchasing cost makes it challenging to introduce AFV into the fleet.

In this study, the feasibility of introducing AFV into the fleet is determined by optimizing life-cycle costs for the fleet. A mixed-integer linear model has been adapted from the literature and modified, which allows us to determine which type of vehicle needs to be purchased and salvaged in which year to minimize the total costs. This study also implemented the Rolling Horizon (RH) optimization approach for the fleet replacement model. The RH model has been adopted for the first time for such a use case. This RH model allows us to consider the change in fuel price rates and adjust fleet

replacement decisions based on the latest data available.

This study investigated the feasibility of introducing AFVs into the Utah Department of Transportation (UDOT) fleet. A sensitivity analysis was conducted to showcase vehicle replacement decisions for different fuel price scenarios. This study found that the change in fuel prices has a substantial impact on the decisions of introducing AFVs into the fleet. This study shows how the inclusion of AFVs changes with the variations of fuel price and daily activity (driven miles per day) of vehicles. It also demonstrates that the RH model can provide better cost-efficient fleet composition decisions comparing to other models that are currently being utilized.

(91 pages)

PUBLIC ABSTRACT

Exploring the Feasibility of Introducing Alternative Fuel Vehicles into Fleet

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Transportation is one of the most significant contributing sectors to emissions and consequently air pollution in the United States. Many state and private fleet agencies have announced their visions of zero-emission fleet programs. Adopting alternative fuel vehicle (AFV) is a viable option for achieving this objective. AFVs offer lower emissions along with low operating and maintenance costs, and higher fuel economy. The advancement of technologies has provided several AFV options, such as hybrid electric vehicles (HEV), electric vehicles (EV), compressed natural gas vehicles (CNGV), and liquefied petroleum gas vehicles (LPGV). The main challenges in adopting AFVs are the high purchasing cost, lack of adequate infrastructure, and the uncertainty of future fuel cost.

This study aims to introducing AFVs in the fleet while minimizing the life-cycle cost by utilizing an optimization replacement model. To account for the uncertainty of the fuel prices, the rolling horizon (RH) approach has been adopted for the optimization model. This RH approach considers the updated parameters and data while adjusting the vehicle replacement decisions. This study found purchasing price, variations of fuel price and daily activity (miles driven per day) of vehicles as the most significant factors for the vehicle replacement decisions. The study also showed that RH model can provide more cost-efficient fleet composition decisions compared to other models currently being used.

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CHAPTER 1

INTRODUCTION

1.1 Problem Statement

Introducing alternate fuel vehicles (AFVs) into a fleet system offers a variety of benefits, including low fuel and maintenance costs and higher fuel efficiency (LeSage, 2015). AFVs in a fleet system can also contribute to solving environmental issues by lowering greenhouse gas (GHG) emissions. In 2017, approximately 29% of total GHG emissions in the U.S. came from the transportation sector (the highest contributing sector for emissions), to which vehicles (light-duty) and trucks (medium-duty and heavy-duty) contributed 59% and 23%, respectively (U.S. Environmental Protection Agency, 2019). Consequently, the federal and local governments in the U.S. prioritized the introduction of AFVs into fleet systems, especially medium- and heavy-duty vehicles (Baker et al., 2016). The American Public Transportation Agency (APTA) published a statistical report that indicated that there is an increase in the adoption of AFVs for public transit fleets, based on comparisons of data from 2008 to 2019. For example, the proportion of public buses powered by natural gas increased from 18.5% in 2008 to 28.5% in 2018, according to APTA (Cromwick, 2019). AFVs offer higher fuel economy and lower air pollutant emissions, making AFVs a viable option for fighting climatic challenges and achieving air quality policy goals (Baker et al., 2016).

Technology development has provided several viable AFV options for fleet purchase choices, such as hybrid electric vehicles (HEV), plug-in hybrid electric vehicles

(PHEV), battery electric vehicles (BEV), compressed natural gas vehicles (CNGV), and liquefied petroleum gas vehicles (LPGV). Although AFVs ensure reduced GHG emissions, the lack of sufficient infrastructure and the necessity of high initial funding to purchase AFVs are challenging issues for transportation agencies and make it difficult to arrive at swift decisions regarding the adoption of AFVs (Stephan and Sullivan, 2004; Schwoon, 2007; Kang and Recker, 2014). A complex trade-off exists between adopting AFVs and coping with their financial and technical issues, which leads to an intricate decision-making process that is crucial for the fleet management system. The lack of data regarding new and upcoming technologies renders assumptions of future scenarios even more complicated in the case of adopting a few AFVs, such as EV and HEV (Li et al., 2019).

It is common practice for fleet management agencies to introduce AFVs into their fleet systems when purchasing replacement vehicles. Different fleet management agencies use different replacement methods based on their goals, budgets, and policies. The replacement method is one of the key measures for cost-effective and efficient fleet management operations for any organization, according to the AASHTO Maintenance Subcommittee. Planned replacement ensures vehicle safety, minimized maintenance costs, and minimized operating costs. Each organization has its own replacement guidelines that ensure an efficient fleet management system. Some organizations make replacement decisions based on factors such as vehicle age, mileage, life-cycle cost, and maintenance cost. However, the ultimate objective of a fleet replacement system is to introduce AFVs into a fleet while optimizing the total ownership cost of the fleet. In general, most transit agencies replace their vehicles either after the vehicles reach a fixed age (12 to 15 years), cross a certain maintenance cost threshold, or cross a certain mileage limit (Sarwar and

Beg, 2019). A few replacement methods analyze life-cycle costs to make replacement decisions.

Selecting AFVs for introduction into a fleet is a crucial decision because the purchasing price of AFVs is typically higher than conventional vehicles. A fleet replacement model (FRM) was developed in the form of a linear optimization program that can yield the best composition of vehicles to be introduced into the fleet. The FRM optimizes the total cost of ownership in terms of purchasing cost, fuel cost, maintenance cost, and emission rate. The FRM was utilized in this project to evaluate the feasibility of introducing AFVs into UDOT's fleet. To account for uncertainties revolving around fuel prices, AFV purchase prices, and technological developments, a Rolling Horizon (RH)-based approach was proposed and used to further improve the FRM. The RH approach allows agencies to consider the change in prices/costs and to modify the replacement decisions based on the updated prices/costs.

1.2 Research Objectives

To achieve the research goal of this study, the following objectives have been identified:

- To conduct a literature review and study fleet replacement practices in the literature as well as practices adopted by DOTs
- To check the feasibility of introducing AFVs into the fleet of UDOT utilizing an FRM which replaces vehicles minimizing the total cost of ownership over a certain time horizon
- To utilize the RH optimization approach for different fuel price scenarios and compare the fleet composition decisions for UDOT's fleet

- To conduct a sensitivity analysis based on fuel price
- To compare results of FRM and current practices (by DOTs)

1.3 Organization of the Article

The rest of the article is organized as follows. Chapter 2, Research Methods, discusses the models and methodologies reported in the literature that are used by DOTs as current practices. Chapter 3, Data Collection, includes the collection and categorization of UDOT's vehicle data, and description of other used parameters such as purchasing price, energy cost, maintenance cost, salvage price etc. Chapter 4, Replacement Model, is dedicated to the formulation of the model and introduction of the RH algorithm. Section 4 also contains descriptions of the scenarios used for sensitivity analysis. Chapter 5, Results, contains the numerical results and cost analyses generated by different approaches. Finally, chapter 6, Conclusions, concludes the thesis and discuss future research directions.

CHAPTER 2

RESEARCH METHODS

2.1 Literature Review

Several types of models for a fleet replacement system have been described in previous studies. Optimization models are widely used to model vehicle or equipment replacement. Table 2.1 includes a summary of some of the studies that had the same objective. Simms et al. (1984) developed a dynamic linear programming (DLP) model and conducted a case study of an urban bus fleet that spanned different ages and mileage. This model was constructed based on detailed data, i.e., varying capacity constraints, acquisition, operating, and salvage cost functions for varying ages and mileages. The model generated an optimal policy for buying, operating, and selling vehicles. Hartman (1999) proposed a linear programming (LP) model for minimizing costs associated with an equipment replacement schedule in which the utilization of vehicles is considered to be a decision variable. The proposed model merged replacement and utilization decisions. The formulation considered operating costs as a function of utilization, where utilization is dependent on deterministic demand. Subsequently, Hartman (2004) proposed a Stochastic Dynamic Programming (SDP) model that can be used to determine an optimal equipment replacement schedule, along with an optimal utilization level for two equipment units.

A Deterministic Dynamic Programming (DDP) model was presented that was used to solve the Equipment Replacement Optimization (ERO) problem for the vehicle fleet of

the Texas Department of Transportation (Fan et al., 2012). The model was programmed based on both Bellman and Wanger formulation. Bellman formulation decides to either keep or replace a vehicle, and Wanger formulation fixes the number of years that a vehicle is utilized. The vehicle replacement decision was made based on a comparison of the vehicles' utilization costs. However, this approach did not consider the optimization of heterogeneous vehicles. Arifin et al. (2017) applied the same approach to the development of a city bus replacement model.

Another popular approach involves the computation of the economic life for a fleet vehicle in order to calculate life-cycle cost, which is known as Life-cycle Cost Analysis (LCCA). LCCA modeling generally follows a nonlinear programming (NLP) approach. LCCA provides only one criterion for vehicle replacement: the "economic life". Economic life includes purchasing price, operating costs, and salvage price (Eilon et al., 1966; Chee, 1975; Weissmann et al., 2003). A vehicle is replaced either when it reaches its economic life limit or it crosses the maintenance cost threshold. LCCA combined with the multi-attribute ranking method provides more cost-efficient replacement plans than a single age limit (economic life) (Weissmann et al., 2003).

2.2 Procedures Used in the Real World

In practice, fleet management agencies typically adopt simpler approaches when making vehicle replacement decisions. The National Academies of Sciences, Engineering, and Medicine (NASEM, 2014) surveyed the fleet replacement practices of 38 different DOTs. The book classified the methodologies into six groups, including:

1. Replacement cycle policies based on formal analysis of life-cycle costs

Table 2.1 Literature review summary

Literature Source	**Model**	**Case Study**	**Purpose**
Eilon, S., King, J.R. and Hutchinson D.E. (1966)	NLP	Fork lift truck	LCCA
Chee, P.C.F. (1975)	No mathematical model	Ontario Hydro fleet	LCCA
Simms, B.W., Lamarre, B.G., and Jardine, A.K.K. (1984)	DLP	Urban Transit bus fleet	Total cost minimization
Hartman, J.C. (1999)	LP	Multi asset case	Total cost minimization
Weissmann J., Weissmann A.J. and Gona S. (2003)	NLP	Texas Department of Transportation (TxDOT) fleet	LCCA along with multi-attribute ranking method
Hartman, J.C. (2004)	SDP	Two asset case	Total cost minimization
Fan, W., Machemehl, R.B., and Gemar, M.D. (2012)	DDP	TxDOT fleet	Total cost minimization
Arifin, D., Yusuf, E. (2017)	DDP	City bus of Bandung, Indonesia	Total cost minimization

2. Replacement cycle policies based on judgment, experience, rules of thumb, etc.
3. Multiyear fleet replacement plans showing future replacement dates and costs by asset

4. Replacement lists that identify assets meeting pre-defined criteria (e.g., age or mileage)
5. Methods for prioritizing specific assets for replacement when funds are insufficient to replace every asset that should be replaced
6. Repair versus replace tools or policies that target specific assets needing expensive repairs

Among the 38 DOTS, a significant proportion of them (17 of 38) follow "decision criteria-based replacement eligibility lists", where criteria of different features (i.e., age, mileage, etc.) are pre-defined. Nine DOTs replace their fleet vehicles based on past practice, such as judgment and rules of thumb. Other DOTS replace their fleets by calculating life-cycle costs and comparing repair costs with replacement costs, resulting in multiyear replacement plans.

Zhu et al. (2017) investigated the fleet replacement methodology of 50 states of the U.S. and eight Canadian provinces and identified 17 replacement decision-making factors. The most common factors were found to be age/equipment life, usage, repair cost, and manual evaluation. This study categorized fleet replacement practices into three classes: Life-cycle Cost Analysis (LCCA), Pre-defined Threshold (PDT) Method, and Mathematical Ranking Model (MRM).

DOTs use different tools and approaches for the fleet replacement problem based on their own criterion and budget. Fleet replacement practices of different DOTs are discussed in the following subsections.

FDOT

The Florida Department of Transportation (FDOT) developed an Equipment Replacement Criteria and used it as the basis for their creation of the Replacement Eligibility Factor (REF) calculator. A point is calculated for each vehicle using the REF calculator considering age, odometer reading, vehicle condition, activity for the last one year, lifetime maintenance cost, maintenance cost within the last 12 months, and the cost per mile. For each class of fleet, threshold values are different for different factors (e.g., age and cost). For instance, if the total points exceed 300, then the vehicle is eligible for replacement (Florida Fish and Wildlife Conservation Commission, 2011; Florida Department of Management Services, 2009). Mercury (2011) made a business proposal in which they proposed a method to use LCA to replace fleet vehicles (Florida Fish and Wildlife Conservation Commission, 2011).

TxDOT

The Texas Department of Transportation (TxDOT) utilizes a uniform approach to determine equipment (i.e., vehicle, machine, etc.) replacement criteria. With the collaboration of the University of Texas, TxDOT developed a model named the Texas Equipment Replacement Model (TERM), which was developed in the SAS environment as a Statistical Model. TERM generates an equipment replacement priority list using two types of modules: 1) the Life-cycle Cost (LCC) Ranking Module and 2) the Multi-Attribute Priority Ranking Module, both of which provide a similar interpretation (Weissmann and Weissmann, 2003).

The LCC model utilizes life-cycle cost analysis (LCCA) and trendscore function to develop a replacement priority list. LCCA can generate the most economic life for any

vehicle based on purchasing, resale value, life repair cost, fuel cost, mileage/hours of usage, age, data variables, equipment status, and other indirect costs. Through trendscore, which is a new concept developed for TERM, the life-cycle cost history/trend is used to prioritize any vehicle whose life-cycle cost has been increasing. Then, the model calculates the duration of this increase and which vehicle has the longest increase duration. The steeper the cost slope, the higher the trendscore for any vehicle.

The second module in TERM is the Multi-Attribute Priority Ranking Module. This module provides the percentile for any piece of equipment in the fleet that shows the percentage of the fleet that is in the worse condition. This priority rank is calculated by a weighted method where weights are defined by the TxDOT. The four attributes used in calculations of priority rank are trendscore (life-cycle cost trend), repair cost, cumulative usage, and cumulative downtime. Any equipment with a higher percentile in the module gets a higher priority replacement.

Caltrans

The California Department of Transportation (Caltrans) previously used Vehicles Meets Criteria (VMC), where they considered equipment age, usage, and life-to-date repair costs. Threshold values were assigned based on historical data to identify replacement candidates. Later, they started using Fleet Utilization Score. This score consists of four digits, which represent the equipment’s age, total usage (mileage/hours), usage over the previous one year, and the amount of repair costs spent as compared to its repair standard that is half of its capital cost. The score is the percentage of the actual utilization of the pre-

defined standard. This approach helps to prioritize the equipment that needs to be replaced. Equipment with higher percentages are prioritized for replacement (Scora, 2017).

PennDOT

The Pennsylvania Department of Transportation (PennDOT) uses a Microsoft Access-based tool named Equipment Life-cycle Prediction Tool. The ultimate goal of this tool can be divided into three parts: 1) Maintenance Cost Prediction, 2) Prioritized Equipment Replacement, and 3) Equipment Budget Allocation. Data is imported from the SAP Plant Maintenance Tool for further analysis (Vance et al., 2014). SAP is a data processing and managing tool that also performs the task of resource planning. Equipment information, equipment fuel usage, equipment hours, and individual equipment maintenance costs are used as the inputs. This tool defines two cost ratios that are used to compare the efficiency of the equipment's life-cycles. Cost ratio 1 is the summation of the cumulative maintenance costs and repair costs divided by the cumulative personnel hours charged to any piece of equipment. Cost ratio 2 is the summation of the cumulative maintenance costs and repair costs divided by the cumulative fuel usage of the equipment. For the life-cycle prediction tool, PennDOT used data recorded from July 2007 to September 2012. Hence, the tool was predicted to lose its predictive value accuracy in the future due to changing practices. To address this issue, data and equations involved in the different steps need to be reanalyzed periodically.

MnDOT

The Minnesota Department of Transportation (MnDOT) is currently using M5 software from AssetWorks (an assistance-providing fleet management company) to manage their fleet. However, the M5 fleet replacement tool was found to not be useful for MnDOT. Hence, they developed a Microsoft Excel-based life-cycle calculation tool. This tool uses predetermined life-cycles and available funds allocated to the replacement of equipment. As the pre-defined life-cycles were developed a long time ago, MnDOT is currently re-evaluating this tool. This tool utilizes data from M5, captures only ownership costs, and anticipates a replacement cost at the end of the lifecycle using a 3% inflationary factor. Monthly and annual ownership expenses for the equipment are also predicted by this tool.

NCDOT

The North Carolina Department of Transportation (NCDOT) developed “Fleet Analysis & Economic Modeling”, which is a Microsoft Excel-based application that is used to manage their fleet. This model was developed based on engineering economics. Therefore, this model contains market value modeling parameters (i.e., depreciation rate, minimum resale value, vehicle’s life), CPI (Consumer Price Index) data, and data from SAP and the Business Warehouse database. Raw data that are analyzed based on vehicle classification and economic factors (i.e., Time Value of Money, Inflation Rate) need to be updated according to the base year. The data analysis section considers annual use (mileage/hours), age, total operating cost, and many other factors. The application analyzes the NCDOT fleet data in terms of depreciation rate, cost, and usage trends. Then, the optimal life for a fleet of different classes is calculated based on life-to-date equivalent

uniform annual cost (LTD EUAC) and life-to-date (LTD) cost per mile (Kauffmann et al., 2013).

ODOT

The Oregon Department of Transportation (ODOT), along with Oregon State University, completed a study in 2009 in which they investigated different fleet replacement methodologies. They designed a simulation-based model in Visual Basic. This model was used to analyze data of all vehicles separately. The simulation was designed as a three-dimensional matrix: 1) time, 2) identification of each vehicle, and 3) data regarding mileage, repair cost, maintenance cost, energy cost, and many other direct and indirect costs were considered as the third dimension. This simulation used ten different replacement priority ranking methods. The best method was determined based on a comparison among all methods. Based on the simulation, the interaction between replacement methods and replacement age was found to be significant. Subsequently, the study proposed a logic model where replacement ranking was made based on age, cost, and usage (Kim and Porter, 2009).

The simulation model was a product of the "Access System" program, which was providing management services for the ODOT fleet system. In 2013, "AssetWorks" was assigned the responsibility of managing the ODOT fleet system. Hence, ODOT can no longer utilize the simulation. "AssestWorks" introduced a new model that follows the methodology of the simulation-based model developed by "Access System". ODOT is currently using a Microsoft Excel-based approach, which was designed based on repair

costs, age, and utilization. Table 2.2 summarizes the tools and methodologies used by different DOTs.

Table 2.2 Methodology adopted by DOTs

State DOT	Tool Name	Software/App/Tool	Methodology
Florida	Replacement Eligibility Factor (R EF) Calculator	Manual	PDT
Texas	TERM (Texas Equipment Replacement Model)	SAS	LCCA & MRM
California	Vehicles Meets Criteria (VMC)	Unknown	PDT
Pennsylvania	Equipment Life Cycle Prediction Tool	Microsoft Access	MRM
Minnesota	Unknown	Microsoft Excel	PDT
North Carolina	Fleet Analysis & Economic Modeling	Microsoft Excel	LCCA
Oregon	Unknown	Microsoft Excel	MRM

2.3 Future Technologies, Opportunities, and Challenges

Various technologies have provided numerous opportunities for AFVs over the last few years. EVs have been one of the most attractive additions to AFV options. Other new

additions, such as hybrid pickups and hydrogen fuel cell trucks, are on their way of entering the market. Fleet agencies are already prioritizing new technologies and are planning to convert their fleet into a fleet with zero-emissions. The South Coast Air Quality Management District (SCAQMD) was awarded $23.6 million by the state of California for a zero-emission truck development and demonstration study in 2016. They have included 43 electric and hybrid plug-in hybrid trucks in their fleet. This was the first large-scale demonstration of zero-emission Class 8 trucks that involved major manufacturers, including BYD, Kenworth, Peterbilt, and Volvo (BYD, 2016).

In the truck industry, payload capacity is a decisive factor in the adoption of AFV. The weight of the battery pack is a challenge to the adoption of an electric truck. The empty truck weight is generally in the range of 6,000-8,000 kg without the weight of the battery pack. The required battery pack is 1,000 kWh and 2,000 kWh for 300 and 600 miles of driving, respectively. The weights of battery packs are 17,000 and 25,000 kg for 600- and 900-miles driving ranges, respectively. Large battery weights challenge the payload capacity of electric trucks. However, research on battery capacity is addressing this challenge. The transition of Li-ion battery density from 350 wh/kg to 260 wh/kg reduces battery pack weight by one-third. Adopting a more advanced battery option (beyond Li-ion) will significantly reduce the battery pack weight. Researchers are also working on more advanced batteries with increased density and decreased cost (Sripad and Viswanathan, 2017). A few companies, including Tesla, BYD, and Toyota, are trying to improve the batteries of EVs. Additionally, deploying new technologies such as dynamic wireless power transfer may reduce the demand of EVs placed on their batteries. Feasibility

analyses of such deployments have already been done by Caltrans for certain major transit corridors (Esfahani, and Song, 2019).

Hydrogen fuel cell technology is another emerging technology that represents an additional AFV option. Nikola Motor is aiming to bring this technology to market via their Class-8 trucks. Nikola Motor company is planning to create a network of 700 fuel stations across the U.S. and Canada by 2028 that will provide enough fueling options for users. They have received more than 13,000 orders in advance for this type of truck (O'Dell, 2019). The challenging part of hydrogen fuel cell technology is the hydrogen gas itself. It ignites more easily as compared to any other fuel at both high and low concentrations of the gas. The storage of hydrogen in liquid form demands extra preparation due to its features. It has a very low boiling temperature (20 degrees Kelvin), which is why it boils off very quickly when spilled. In contrast, overly cold fuel can embrittle and break metal equipment and cause cold burn damage to people. Hydrogen-powered vehicles can also cause an electric shock due to the chemical reaction of hydrogen and oxygen with the surrounding air while powering the vehicles (The International Consortium for Fire Safety, Health & The Environment). Nikola is preparing to handle all types of safety issues for hydrogen cells according to national and international guidelines (Park, 2019). They plan to build a hydrogen gas plant at the refueling stations, so that transporting gas to the refueling station will not be necessary (Park, 2019). The future of AFV options appears to be very promising as manufacturers have already announced upcoming products. These products appear to address all of the challenges identified to date. Thus, there will be better opportunities for adopting AFVs in the future.

2.4 Chapter Summary

In this chapter, the previous studies on the replacement models described in the literature have been reviewed. In literature, deterministic and stochastic linear and nonlinear models have been used widely. LCCA is also a very popular approach in fleet replacement modeling. Also, real-life practices by different DOTs, future technologies and challenges regarding AFVs are discussed. DOTs mainly develop their own easy-to-use tools and software to analyze their present vehicle data, and to decide which vehicles are more prioritized to get replaced.

CHAPTER 3

DATA COLLECTION

3.1 Data from UDOT's Fleet Tracking Website

Detailed data regarding all used and unused vehicles can be found on the UDOT Fleet Tracking Website (verizonconnect.com). Heavy-duty truck and pickup truck data has 578 and 51 data points (rows) respectively, each of which represents a certain truck and associated truck model, production year, registration number, monthly mileage from October 2018 to September 2019, and the average active days per month (between October 2018-September 2019).

3.1.1 Heavy-duty Truck in UDOT's Fleet

The UDOT fleet system has 578 heavy-duty trucks (Class 7 & 8 trucks; based on classification of commercial trucks by Federal Highway Administration) with their full profile information. Profile information includes the vehicle's model information, exterior description, date of inclusion into the fleet, utilization data (driven mileage), idle time, fuel information, current location, type of use (heavy/medium duty), and device condition. Among 578 trucks, 551 trucks are identified as utilized vehicles, which refers to vehicles that are driven for more than or equal to one-mile during the data collection period (October 2018 to September 2019). Among the 27 unused trucks, 15 trucks were new additions to the fleet. The remaining unused trucks (12 trucks) have not been used, possibly due to maintenance or technical issues. Among all trucks, 55% are less than ten-years old, and the

rest are between 11 and 24-years old. Figure 3.1 shows the frequency plot of the vehicles' age.

Trucks are categorized based on their mileage via the following two approaches:

I. Average mile per active day (AMAD)

II. Month-wise mile per active day (MMAD)

The fleet agencies will make the decision of applying any vehicle classification approach based on the utilization rate of the vehicles. If the vehicles are utilized at a similar rate throughout the year, then both AMAD and MMAD classification approach will categorize the vehicles in a similar way. On the other hand, if there is seasonal variation in utilization, then MMAD classification approach will categorize the vehicles in a more representative way. For example, snowplows are only used during the winter season. MMAD classification approach is more suitable for the classification of snowplows in the fleet.

In the first approach, the total annual mileage of each truck is divided by the total active days within a year to calculate AMAD.

$$\text{AMAD} = \frac{\Sigma \text{ Vehicle Mileage Traveled in a year}}{\Sigma \text{ Active days within a year}}$$

Active days refers to the days when the vehicle was driven. The AMAD can be used to categorize vehicles into different groups. In this study, four groups are considered as follows: 1) 1-51, 2) 51-101, 3) 101-150, and 4) 151- 201 miles/active day. Figure 3.2 represents the number and the percentage of heavy-duty trucks based on their AMADs.

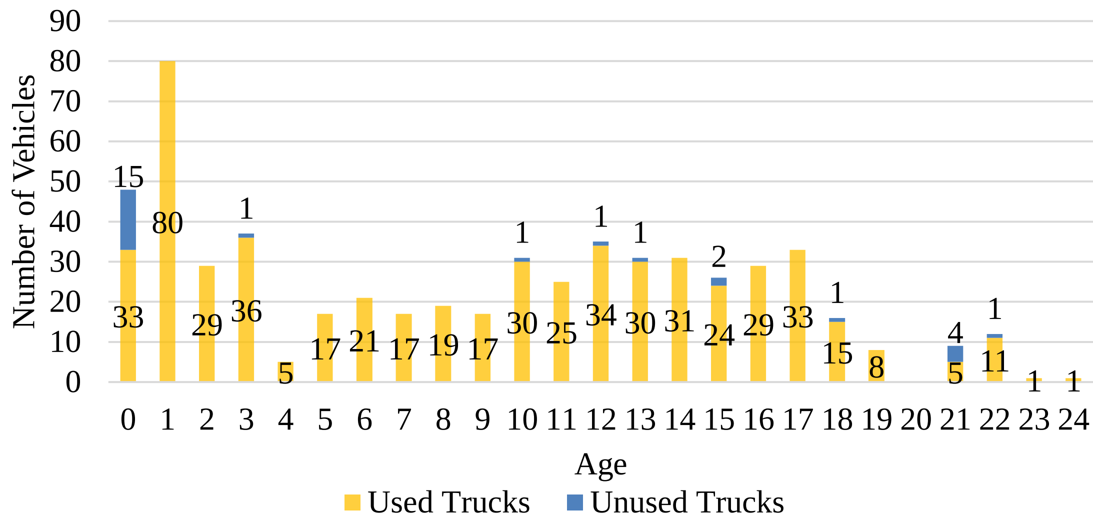


Figure 3.1 Histogram of trucks in UDOT's fleet

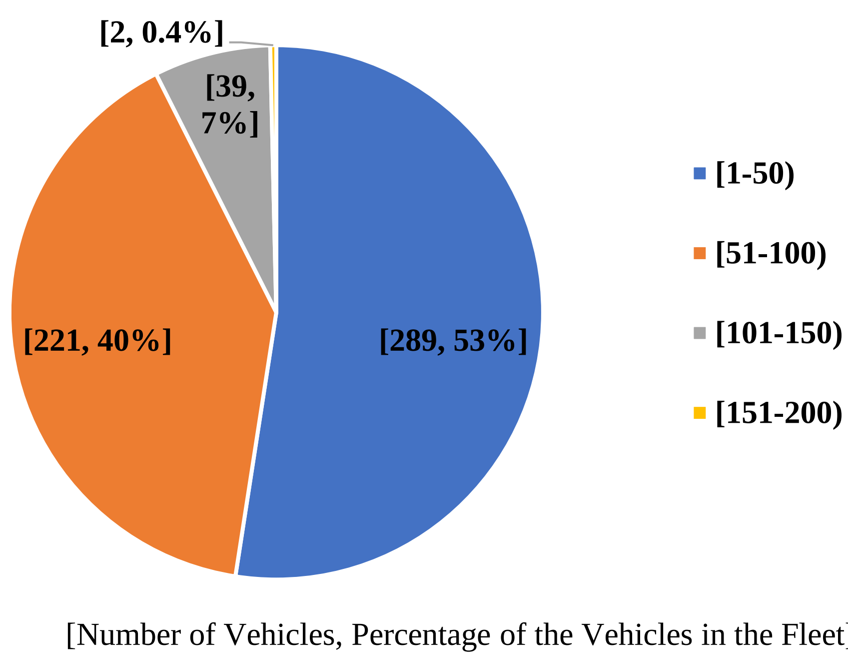


Figure 3.2 Representation of trucks in UDOT's fleet based on AMAD

Following the categorization of all the trucks, the summation of total annual mileage was calculated for each category, and then the summation was divided by the number of trucks assigned to that category to find the average annual mileage traveled by each truck associating with that category. Table 3.1 represents the average annual mileage per vehicle for each category.

$$\text{Average annual mileage per vehicle} = \frac{\text{Mileage Traveled in a year by all the vehicles of a range category}}{\text{Number of vehicles within a range category}}$$

Based on the AMAD approach, the highest number of trucks is in the first category, 1-50 mile/active day. The average annual mileage of this category is 3,244 miles/year.

Table 3.1 Average annual mileage per vehicle for heavy-duty trucks categorized based on AMAD

Average Mileage Range (miles/active day)	Number of Trucks	Average annual mileage (miles/year)
1-50	289	3,244
51-100	221	7,758
101-150	39	12,936
151-200	2	17,428

For the second approach, monthly mileage was divided by the active days within a month to yield the MMAD, as follows:

$$\text{MMAD} = \frac{\Sigma\ \text{Vehicle Mileage Traveled in a month}}{\Sigma\ \text{Active days within a month}}$$

MMAD is calculated for each vehicle per month, from October 2018 to September 2019. Vehicles are assigned to appropriate categories based on their highest MMAD. For example, when a truck had 130 and 30 miles/active day in November and in December, respectively, the truck will be assigned to the third category, 101-150 mile/active day. Figure 3.3 represents the number and percentage of categorized heavy-duty trucks based on their highest month-wise mile/active day. Table 3.2 includes the average annual mileage per vehicle for each category when the trucks are categorized based on the highest MMAD. The MMAD approach shows that the largest number of trucks is in the second category, 101-150 mile/active day, which is different than the AAMD approach. The average annual mileage of this category is 5,057 miles/year.

3.1.2 Pickups in UDOT's Fleet

In the UDOT fleet system, 51 medium-duty trucks were identified with their full profile information. The data were collected based on vehicle activity between October 2018 and September 2019. Forty-five pickups were driven for at least one mile during the data collection period (October 2018 to September 2019). The remaining six pickups were not driven during this period. Approximately 90% of total pickups are within an age range

of ten years. The remaining trucks are between 11 and 13 years old. Figure 3.4 shows a frequency plot of the pickups' age.

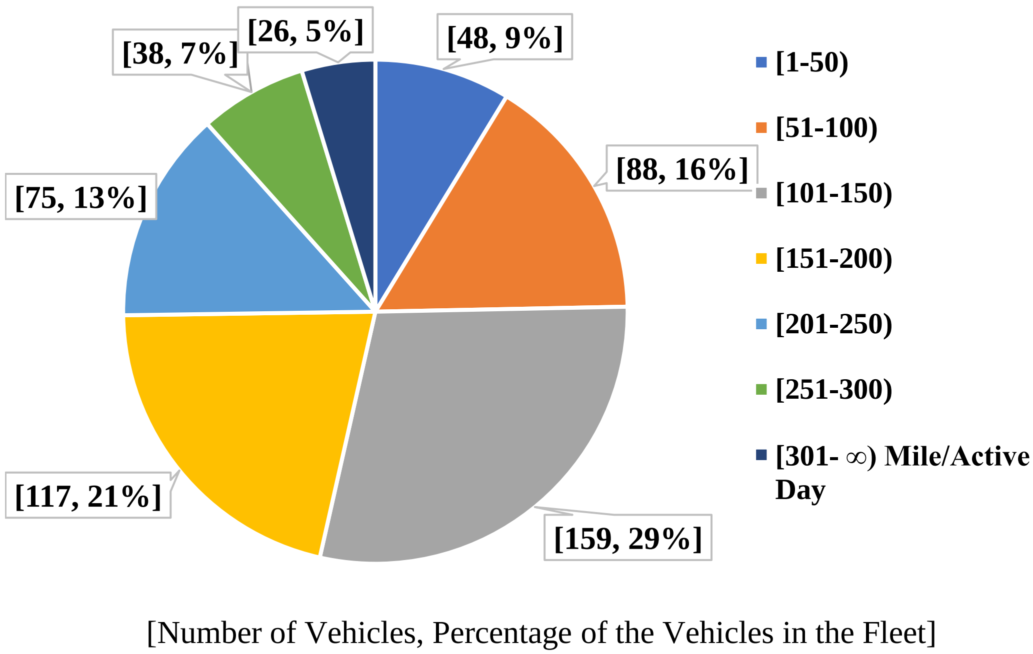


Figure 3.3 Representation of trucks in UDOT's fleet based on highest MMAD

Pickups were categorized based on the same two approaches used for trucks. In the first approach, pickups were categorized based on AMAD. The majority of pickups were found to be in the second and fourth categories, 51-100 and 151-200 mile/active day, respectively. Figure 3.5 represents the number and percentage of pickups based on their AMAD. Table 3.3 shows the average annual mileage for each range category. The average annual mileage for the second and fourth categories are 803 and 1,874 miles/year, respectively. Average annual mileage data show that pickups are not utilized all that much per year.

Table 3.2 Average annual mileage per vehicle for heavy-duty trucks categorized based on highest MMAD

Mileage Range (miles/active day)	Number of Trucks	Average Annual Mileage (miles/year)
1-50	48	570
51-100	88	2,490
101-150	159	5,057
151-200	117	7,242
201-250	75	8,412
251-300	38	9,219
301-∞	26	10,673

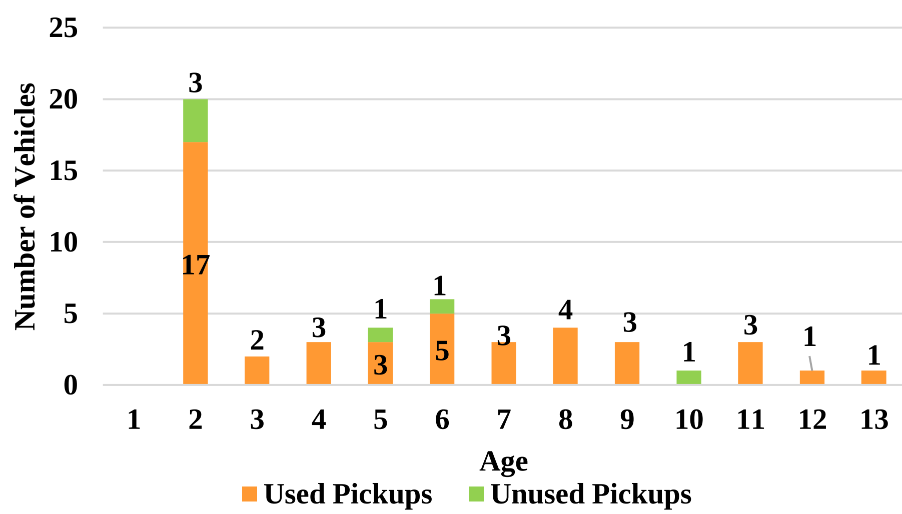


Figure 3.4 Histogram of pickups in UDOT’s fleet

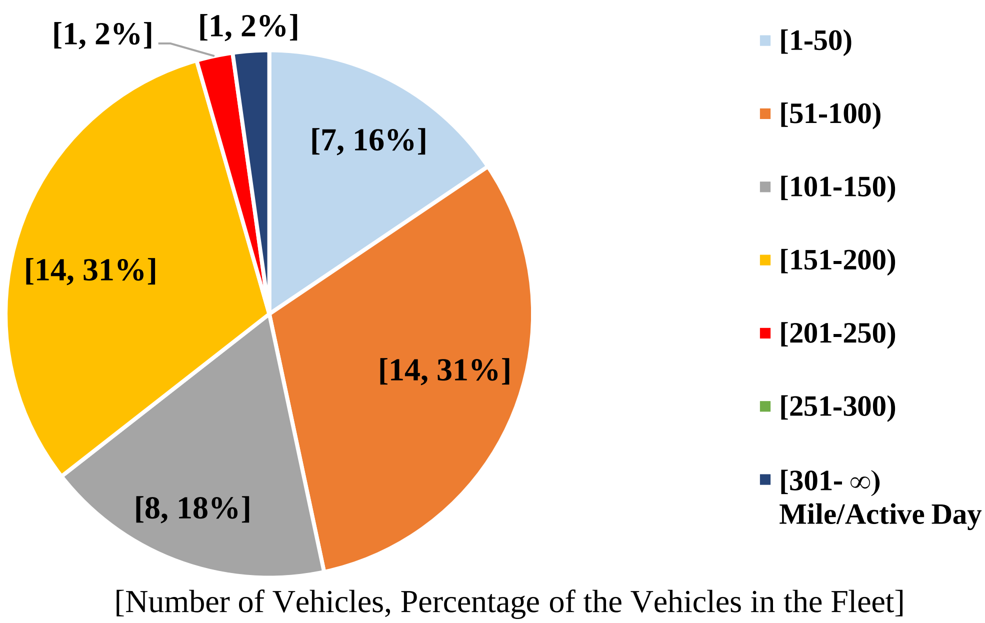


Figure 3.5 Representation of pickups based on AMAD

Table 3.3 Average annual mileage per vehicle for pickups categorized based on AMAD

Mileage Range (miles/active day)	Number of Pickups	Average Annual Mileage (miles/year)
1-50	7	385
51-100	14	803
101-150	8	1,181
151-200	14	1,874
201-250	1	2,545
251-300	-	-
301-∞	1	3,227

Figure 3.6 and Table 3.4 represent the number of pickups, the percentage of pickups in each category, and the annual mileage per pickup vehicle when they are categorized

based on their highest MMAD. The fifth category 201-250 miles/active day contains the largest number of pickups, which is different from the AMAD approach. The average annual mileage for this category is 1,341 miles/year.

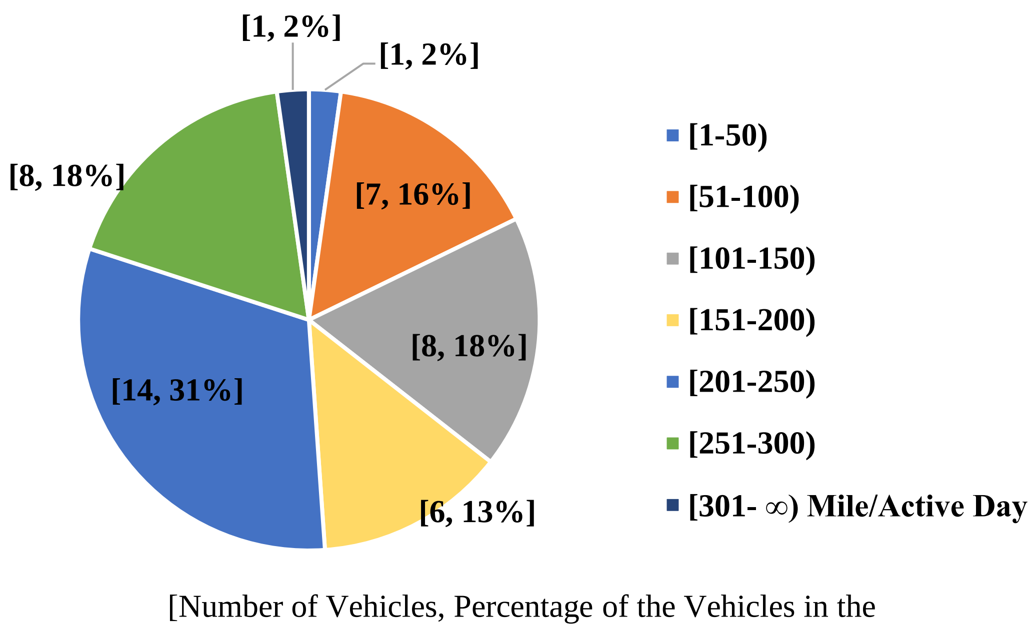


Figure 3.6 Representation of pickups in UDOT's fleet based on highest MMAD

Table 3.4 Average annual mileage per vehicle for pickups categorized based on highest MMAD

Mileage Range (miles/active day)	Number of Pickups	Average Annual Mileage (miles/year)
1-50	1	25
51-100	7	578
101-150	8	689
151-200	6	930
201-250	14	1,341
251-300	8	2,174
300-∞	1	3,227

3.2 Description of Used Data

To decide on an action needed to be taken regarding a possible option (e.g., to be bought, sold, or kept), the options and their related costs should be known. This subsection is dedicated to recognizing the options and their costs.

3.2.1 AFVs' Options

A few AFV options were discussed in Section 2.2.4. In addition to EVs, a few other AFV options, such as diesel hybrid electric vehicle (HEV), diesel-hydraulic hybrid (HHV), biodiesel (B-20), ethanol (E85), compressed natural gas (CNG), liquefied natural gas (LNG), propane/ liquefied petroleum gas (LPG), and LNG/diesel pilot ignition are considered in this study.

In 2019, the use of natural gas for new heavy-duty trucks increased as compared to the previous years (HDT stuff of Truckinginfo, 2019). The U.S. Department of Energy (DOE) provides funding for the adoption of AFVs. DOE has awarded approximately $460 million for projects related to AFV technologies (U.S. Department of Energy). Biodiesel is one of the most popular AFV fuel options. Biodiesel is developed from renewable energy sources like vegetable oils and animal fats and can be used as a replacement for diesel. Biodiesel is generally blended with diesel. For example, B-20 is composed of 20% biodiesel and 80% diesel and B-20 meets the Federal Energy Policy Act (EPAct) requirements to be used as AFV fuel (Commonwealth of Massachusetts). LNG and CNG are suited to heavy-duty trucks, since trucks using these fuels would have horsepower and torque characteristics similar to diesel trucks (Jackson, 2013).

A few companies have already announced plans for their future production of electric and hybrid vehicles. eCascadia & eM2 from Daimler, Semi from Tesla, and 8TT from BYD, are the options for electric trucks (Lambert, 2019; O'Dell, 2017; Freightliner,2020). Ford, Bollinger, Rivian, and a few other companies have announced plans for hybrid-electric pickups (Brzozowski, 2019).

Conventional fuel vehicles have also been considered for adoption. Generally, gasoline and propane trucks are not used in fleets due to their characteristics. These two fuels are popular options for light-and medium-duty vehicles (Jackson, 2013). The Alternative Fuel Life-Cycle Environmental and Economic Transportation (AFLEET) Model 2018 that was developed by Argonne National Lab (ANL) did not include gasoline and propane as viable options for heavy-duty trucks (Argonne National Library, 2018). Thus, gasoline and propane heavy-duty trucks were excluded from the model as potential options, while gasoline and propane pickups were considered in this model.

3.2.2 Battery Price and Charging Stations for EV

Battery price is an important factor in the selection of an electric truck/pickup as a replacement since the purchasing price of electric trucks/pickups depends on it. In the past few years, the battery pack price has been decreasing at a steep rate. Figure 3.7, published by Bloomberg NEF, shows the rapid reduction of battery pack price over the last nine years (Scot, 2019). In 2019, the battery pack price went down to \$156/kwh. From 2018 to 2019, the price decreased by 13%.

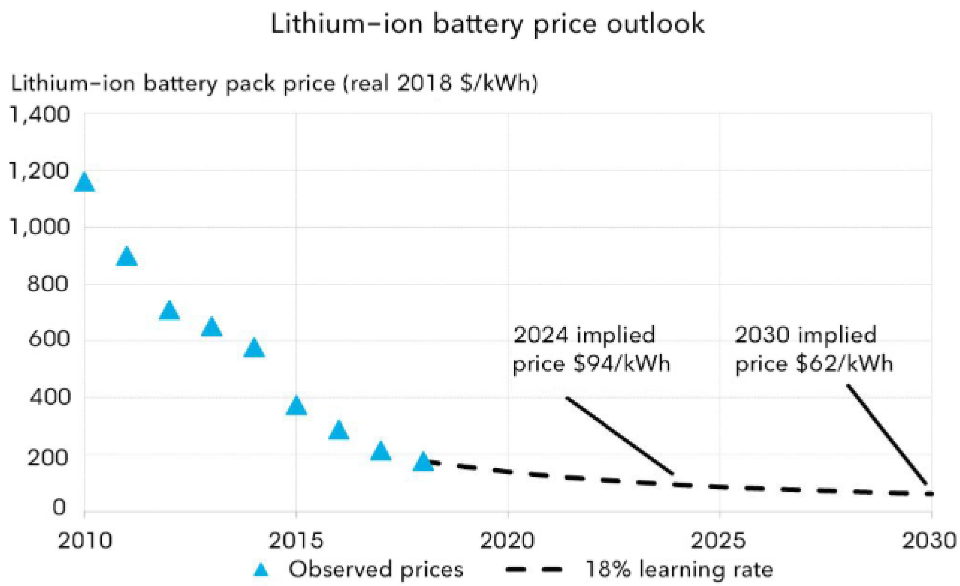


Figure 3.7 Reduction and forecast of battery pack price (Scot, 2019)

Studies on predicting future battery price have been conducted, resulting in various different forecasts. Figure 3.8 shows the trends and predictions based on different sources and publications (Nykvist and Nilson, 2015). In this study, the prediction made by BloombergNEF is used in which the battery price will be reduced to $100/kWh by 2024 and below $62/kWh by 2030 (Figure 3.7) (Scot, 2019).

There are three types of charging systems available for EVs, known as Level 1, Level 2, and Level 3. A Level 1 charging facility requires a 120V outlet, which allows vehicles to be charged for 100 miles within 17-25 hours. A Level 2 charging facility requires a 240V outlet, which allows vehicles to be charged for 100 miles within 4-5 hours. A Level 3 charger is a fast charger that costs substantially more than Level 1 and Level 2 chargers. In this project, only Level 2 chargers are considered for installation if the benefits

of electric trucks/pickups outweigh their costs. The cost of installing a Level 2 charger is assumed to be $1,200 in this study (Levinson and West, 2018).

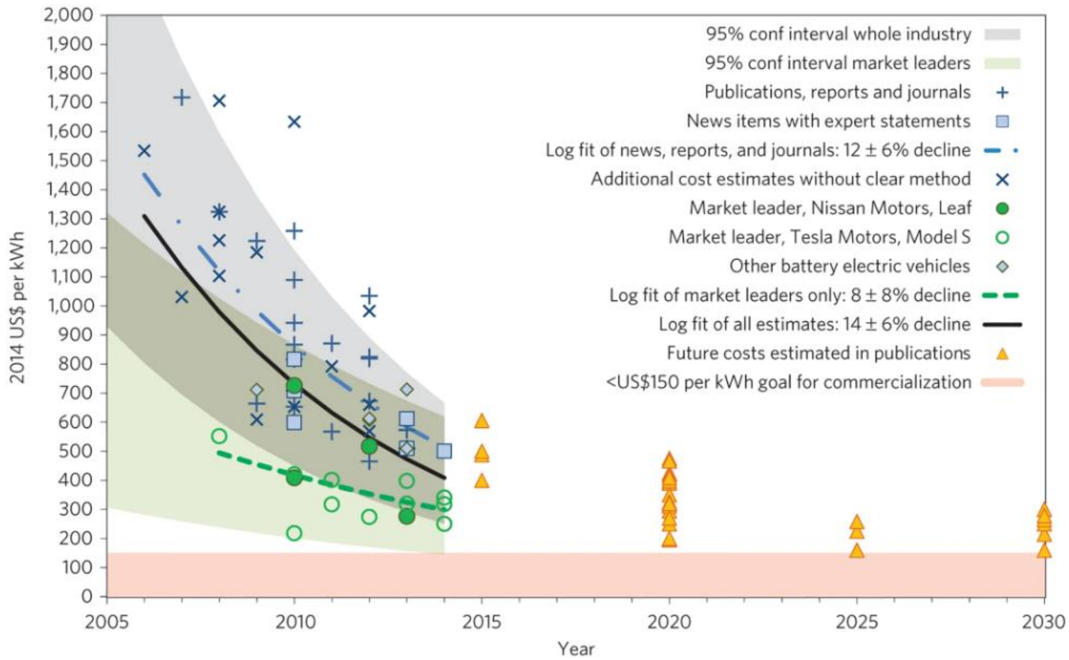


Figure 3.8 Trend and forecast of battery pack price according to publications (Levinson and West, 2018)

3.2.3 Purchasing Price of AFVs

The purchasing price of each type of AFV, except EVs, was collected from the data used in the AFLEET Model 2018 (Argonne National Library, 2018). The AFLEET Model calculates total ownership cost and the emissions of GHG for different AFVs. Table 3.5 and Table 3.6 include the purchasing prices of alternative fuel trucks and pickups, respectively. The Department of Energy (DOE), ANL, and other research organizations

(Open EI, 2019) conducted research into future changes of purchasing prices. It was found that there will not be a significant change in the purchasing prices of AFVs, except for EVs.

The price of an EV is divided into two parts: a fixed proportion and a variable proportion (Lajevardi et al., 2019). The variable proportion depends on the price of the battery pack, which varies based on the capacity of the battery pack. In this study, it was assumed that vehicles have battery packs that are dependent on the traveled miles/day. Furthermore, we assumed that any electric vehicle would be operated following the hub-and-spoke operation system. In a hub-and-spoke operation system, trucks leave the hub (storage station of trucks) after refueling each day and return to the same hub at night for refueling. In this arrangement, electric trucks can charge only once a day. Thus, the capacity of the battery pack should satisfy the demand of the vehicle for the entire day.

Table 3.5 Purchasing price of heavy-duty trucks

Truck Fuel Type	**Diesel**	**EV**	**HEV**	**B-20**	**CNG**	**LNG**	**LNG /Diesel Pilot Ignitio n**
Purchasing Price (1000$/ Vehicle)	$100	$120*	$140	$100	$165	$150	$190

* This value does not include the battery pack price, which can be calculated as: Battery Price ($/kWh)* Battery Pack Capacity (kWh)

3.2.1 Fuel Price

The fuel price data set was collected from the “Alternative Fuels Data Center” hosted by the DOE, which provides national average fuel prices between October 1 and October 31, 2019 (Alternative Fuel Data Center, 2019). Fuel prices fluctuate based on several factors, including seasonal changes and the worldwide economy. The annual growth rate of fuel price was collected from Annual Energy Outlook 2019 (U.S. Energy Information Administration, 2019). It was assumed that fuel prices would change at an exponential rate.

Table 3.6 Purchasing price of pickups

Pickup Fuel Type	**Diesel**	**Gasoline**	**EV**	**B-20**	**E85**	**CNG**	**LPG**
Purchasing Price (1000$/Vehicle)	$46.5	$36	$30*	$46.5	$36	$44	$44

* This value does not include the battery pack price, which can be calculated as: Battery Price ($/kWh)* Battery Pack Capacity (kWh)

Table 3.7 Fuel price

Fuel Type	**Fuel price ($/unit)**	**Fuel Price Annual Change Rate (%)**
Gasoline	2.68/GGE	0.7
Diesel	3.08/gallon	0.7
Electricity	0.13/kWh	0.3
Biodiesel (B20)	2.87/gallon	0.7
Ethanol (E85)	2.28/gallon	0.5
Liquefied Natural Gas (LNG)	2.69/gallon	-0.3
Compressed Natural Gas (CNG)	2.20/GGE	-0.3
Propane (LPG)	2.76/gallon	-0.3

3.2.2 Operating Cost

The operating cost of a vehicle is calculated based on per mile maintenance and energy costs, fuel type, annual per vehicle mileage, fuel economy, and age of the vehicle. Table 3.8 and Table 3.9 tabulate the data used for our case study, which were collected from AFLEET Model 2018 (Argonne National Library, 2018). Based on the literature, maintenance costs increase with increases in vehicle age (Gransberg, 2016; Powell, 2014). Maintenance costs change with the age of a vehicle with different trends. Maintenance costs are considered to increase exponentially at a rate of 12.7% with each one-year increase in the vehicle's age. The rate of increase was found from the UDOT research report for class 8 type vehicles (snowplow truck) (Utah Department of Transportation, 2015). Fuel economy does not significantly change with age (Feng and Figliozzi, 2012). Hence, it was assumed to be constant throughout the vehicle life-cycle in this model.

Table 3.8 Maintenance cost and fuel economy data for heavy-duty trucks

Truck Fuel Type	**Diesel**	**EV**	**HEV**	**B-20**	**CNG**	**LNG**	**LNG/Diesel Pilot Ignition**
Maintenance Cost ($/mile)	0.2	0.14	0.16	0.2	0.22	0.22	0.22
Fuel Economy (mile/gallon)	7.3	2*	7.8	7.9	7.6	11.4	11.9

*Fuel economy of EV is in kWh/mile unit

Table 3.9 Maintenance cost and fuel economy data for pickups

Pickup Fuel Type	**Diesel**	**EV**	**Gasoline**	**B-20**	**E85**	**CNG**	**LPG**
Maintenance cost ($/mile)	0.29	0.17	0.18	0.29	0.18	0.18	0.18
Fuel economy (mile/gallon)	18	0.45*	13	16.6	9.5	12.4	9.9

*Fuel economy of EV is in kWh/mile unit

3.2.3 Infrastructure Cost

Infrastructure cost is associated with the development of new infrastructure that is used to facilitate the fueling of AFVs, if demand for them increases. To select an appropriate AFV, adequate refueling stations should also be deployed by proper authorities (here, the UDOT). Thus, the adoption of any AFV is dependent on the infrastructure cost. However, this cost is considerably complex to be incorporated into the decision-making process. Cost variations are dependent on many factors, such as fuel type, location of the station, storage capacity, labor cost, transfer cost of fuel, and land costs. For small CNG stations, the cost has been roughly estimated to be between $400,000- $600,000 (U.S. Department of Energy, 2014). The cost of a CNG refueling station can range up to 1.8 million (U.S. Department of Energy, 2014). LNG fueling station costs can vary widely, with an average of $2.5 million (Alternative Fuel Data Center, 2019). According to the DOE, the cost of equipping an E85 refueling station is between $50,000 to $70,000, if the station installs a new underground tank. The cost is $5000–$30,000 if the station converts an existing tank (Seki et al., 2018).

Considering these infrastructure costs, introducing AFVs is an expensive decision when there is a need for the construction of fuel stations. The upfront cost will be very high, which will impose more challenges for the introduction of AFVs. In this report, we assumed that CNG, LNG, E85, and other types of fueling facilities are available for refueling UDOT's fleet vehicles, except for EVs. Hence, the cost of Level-2 charging facilities for EVs has been included in the model.

3.2.4 Salvage price

The salvage price depends on vehicle type, brand, usage level, current condition, and age (Hagman et al., 2016). The depreciation rate remains high during the first 5-years of any vehicle, and then it declines. As the depreciation rate depends on many factors, researchers avoid the complexity of the salvage function by using a fixed salvage price for all vehicles (Feng and Figliozzi, 2012 and 2014). In this study, the following formula was adopted, which is a modified version of Ahani et al. (2016) and Feng & Figliozzi Figliozzi et al. (2011),

$$s_{jkc} = v_{(j-i)kc}\,(1-\theta)^{i}$$

where s_{jkc} is the salvage price of a vehicle of type k in category c in the year j, $v_{(j-i)kc}$ is the purchasing price of that particular vehicle in the year $(j-i)$, and $\boldsymbol{\theta}$ is the depreciation rate with age i. In this model, θ is assumed to be 10%.

3.3 Chapter Summary

This chapter introduced the data that were used to accommodate the deployment cost of AFVs and other required parameters. Briefly, the data was acquired from the UDOT

Fleet Tracking Website (verizonconnect.com), which were collected from October 2018 to September 2019. Brief descriptions of the parameters to calculate life-cycle cost were also provided.

CHAPTER 4

REPLACEMENT MODEL

4.1 Model Formulation

As mentioned in the previous section, six types of costs are considered in this FRM: purchasing cost (PC), maintenance cost (MC), energy cost (EC), emission cost (EMC), infrastructure cost (IC), and salvage cost (SC) (negative cost). The objective of this study is to minimize the total cost of fleets over the planning horizon. Several decision variables are critical, such as the number of vehicles to be bought or sold in a given year.

The FRM also includes two types of parameters: (1) economic factors (e.g., planned time horizon, the demand of vehicles, annual miles to be traveled, future fuel costs, and discount rate) and (2) vehicle factors (e.g., types of vehicles, vehicle life, purchasing cost, and salvage price). The optimization model is a deterministic homogeneous replacement model, which minimizes total cost. Before introducing the model, which is an extension of a model proposed by Feng and Figliozzi (2012 and 2014), notations and terms are introduced, as follows:

Sets	
$\boldsymbol{K}$	Set of all vehicle types
$\boldsymbol{A}$	Set of vehicle age in year
$\boldsymbol{T}$	Set of planning horizon
$\boldsymbol{C}$	Set of mileage range-based categories
Indices	
k	Vehicle type
i	Age of any vehicle (year)

j	Time (year)
c	Mileage range-based category
Decision variables	
X_{ijkc}	The number of *i*-year old, type *k* vehicles of mileage range *c* in use from the end of year *j* to the end of year *j+1*
P_{jkc}	The number of *i*-year old, type *k* vehicles of mileage range *c* purchased at the end of year *j*
Y_{ijkc}	The number of *i*-year old, type *k* vehicles of mileage range *c* salvaged at the end of year *j*
CC_j	The number of chargers in operation in year *j*
QC_j	The number of new chargers needed to be installed in year *j*
Parameters	
A	Maximum age of vehicles
$AVAIL_{jkc}$	A binary number that indicates if, in any year j, type *k* vehicle of range c is available for purchase
h_{ikc}	Number of *i*-year old, type *k* vehicles of mileage range *c* available at time zero (beginning year)
u_{kjc}	Annual miles traveled by type *k* vehicle with mileage range *c* in year *j*
b_j	Budget for purchasing new vehicles in year *j*
v_{kjc}	Purchase cost of type *k* vehicle with mileage range *c* in year *j*
f_{jk}	Fuel cost per year for type *k* of vehicle in year *j*
m_{kc}	Maintenance cost per year for type *k* vehicle with mileage range *c*
s_{jkc}	Salvage cost of type *k* vehicle in year *j*
dr	Discount rate
cp	Charger price
ic	The number of chargers in year zero
p_j	Vehicle purchasing price change rate in year *j*
e_j	Fuel price change rate in year *j*
ec	Emission cost per ton GHG
em_{ik}	Emission of GHG in tons per mile for an *i*-year old and type *k* vehicle
b_i	Maintenance cost increase rate with age *i* years

The replacement model can be expressed as follows:

FRM:

$$\min Z = \sum_{j=0}^{T-1}\sum_{k=1}^{K} v_{kjc}\, P_{ijkc}\ \ .AVAIL_{jkc}\ \ .(1 \pm p_j\ \ )^j (1+dr)^{-j}$$

$$+ \sum_{j=0}^{T-1}\sum_{k=1}^{K}\sum_{i=0}^{A-1} f_{jk}\ \ u_{kjc}\ X_{ijkc}\ \ (1 \pm e_j\ \ )^j (1+dr)^{-j}$$

$$+ \sum_{j=0}^{T-1}\sum_{k=1}^{K}\sum_{i=0}^{A-1} m_{kc}\ .\ X_{ijkc}\ \ (1+b_i\ \ )^i (1+dr)^{-j} + \sum_{j=1}^{T-1} cp\,.\,QC_j$$

$$+ \sum_{j=0}^{T-1}\sum_{k=1}^{K}\sum_{i=0}^{A-1} u_{kjc}\ .X_{ijkc}\ \ .ec\ \ .em_{ik}\,.\,(1+dr)^{-j}$$

$$- \sum_{j=0}^{T}\sum_{k=1}^{K}\sum_{i=0}^{A} s_{jkc}\ .\ Y_{ijkc}\ \ (1+dr)^{-j} \qquad (1)$$

s.t.

$$\sum_{k=1}^{K}\sum_{c=1}^{C} v_{kjc}\,.\,P_{ijkc} \le b_j\ , \forall j \in \{0,1,2,3,\ldots..T-1\} \qquad (2)$$

$$\sum_{k=1}^{K}\sum_{i=0}^{A-1} X_{ijkc} = h_{ikc}\ , \forall j \in \{0,1,2,3,\ldots..T-1\} \qquad (3)$$

$$P_{jkc}.AVAIL_{jkc} = X_{0jkc}, \forall j \in \{1,2,3,\ldots..T-1\}\ , \forall k \in K\ , \forall c \in C \qquad (4)$$

$$P_{0kc}AVAIL_{jkc} + h_{0kc} = X_{00kc}\ , \forall k \in K\ \ \forall j \in \{0,1,2,3,\ldots..T-1\} \qquad (5)$$

$$X_{i0kc} + Y_{i0kc} = h_{ikc}, \forall i \in \{1,2,3,\ldots..A\}\ , \forall k \in K\ \ \forall c \in C \qquad (6)$$

$$X_{ijkc} + Y_{ijkc} = X_{(i-1)(j-1)kc}, \forall i \in \{1,2,\ldots..A\}, \forall j \in \{1,2..T\}, \forall k \in K\ \forall c \in C \qquad (7)$$

$$X_{iTkc} = 0, \forall i \in \{0,1,2,3,\ldots.A-1\}\ , \forall k \in K\ \forall c \in C \qquad (8)$$

$$Y_{0jkc} = 0, \forall j \in \{0,1,2,3,\ldots.T\}\ , \forall k \in K\ \ \forall c \in C \qquad (9)$$

$$Y_{i0kc} = 0, \forall i \in \{0,1,2,3,\ldots.T\}\ , \forall k \in K\ \ \forall c \in C \qquad (10)$$

$$\sum_{i=0}^{A}\sum_{c=1}^{C} X_{ijEVc} = CC_j\ , \forall j \in \{0,1,2,3,\ldots..T-1\} \qquad (11)$$

$CC_{j-1} + QC_j = CC_j, \forall j \in \{1, 2, 3, \dots . . T\}$ (12)

$X_{ijkc}, P_{jkc}, Y_{ijkc} \quad \in \{0, 1, 2, 3, \dots .\}$ (13)

In the above formulation, equation (1), the objective function, minimizes the sum of purchasing cost, energy cost, maintenance cost, and salvage cost for the planning horizon. The first term of the objective function is the purchasing cost (PC), where v_{kjc} is the purchasing cost of a type *k* vehicle with mileage range *c* in year *j*. P_{ijkc} is the number of *i*-year old, type *k* vehicles of mileage range *c* purchased at the end of year *j*. $AVAIL_{jkc}$ is a binary number that indicates whether type *k* vehicles of mileage range *c* are available for purchase in year-*j*. Each year the cost of newly purchased vehicles will be totaled by the following equation:

$$PC = \sum_{j=0}^{T-1} \sum_{k=1}^{K} v_{kjc} \,.\, P_{ijkc} \;.\, AVAIL_{jkc} \;.\, (1 \pm p_j)^j . (1 + dr)^{-j}$$

where p_j and *dr* are the rate of purchasing price increase with time and the discount rate, respectively. Note that PC is the net present value of the sum of all purchasing costs during the planning horizon.

The second term of the objective function is the energy cost (EC) that is calculated from annual usage, u_{jkc}, and fuel cost, f_{jk}, for a type *k* vehicle in year *j*. X_{ijkc} is the number of *i*-year old, type *k* vehicles of mileage range *c* that are in use from the end of year *j* to the end of year *j+1*. The change in fuel price in year *j* is captured by the parameter e_j. EC sums the energy costs for all the used vehicles in the fleet and presents the cost as the net present value.

$$EC = \sum_{j=0}^{T-1} \sum_{k=1}^{K} \sum_{i=0}^{A-1} f_{jk} \,.\, u_{kjc} \,.\, X_{ijkc} \,.\, (1 \pm e_j)^j . (1 + dr)^{-j}$$

The third term is the maintenance cost (MC), which is calculated using m_{kc} to yield maintenance cost per year for type *k* vehicles with mileage range *c*. It also considers the change of maintenance cost with age *i* using parameter b_i.

$$MC = \sum_{j=0}^{T-1} \sum_{k=1}^{K} \sum_{i=0}^{A-1} m_{kc} \,.\, X_{ijkc} \,.\, (1 + b_i)^i . (1 + dr)^{-j}$$

The fourth term in the objective function is infrastructure cost (IC). The IC includes only the cost of chargers for EVs. Here, *cp* is the price of a charger and QC_j is the number of new chargers that need to be installed in year *j*.

$$IC = \sum_{j=1}^{T-1} cp \,.\, QC_j$$

The emission cost (EMC) is the monetary value of emissions. EMC is calculated using utilization (u_{kjc}) of type *k* vehicles of mileage range *c* in year *j*. *ec* is the emission cost per ton of GHG and em_{ik} denotes the emission of GHG in tons per mile for *i*-year old and type *k* vehicles.

$$EMC = \sum_{j=0}^{T-1} \sum_{k=1}^{K} \sum_{i=0}^{A-1} u_{kjc} \,.\, X_{ijkc} \,.\, ec \,.\, em_{ik} \,.\, (1 + dr)^{-j}$$

The last term is salvage cost (SC) that is calculated by multiplying the salvage price s_{jkc} of type *k* vehicles in year *j* with mileage range *c* and Y_{ijkc}. Here, Y_{ijkc} is the number of *i*-year old, type *k* vehicles of mileage range *c* salvaged at the end of year *j*.

$$SC = \sum_{j=0}^{T} \sum_{k=1}^{K} \sum_{i=0}^{A} s_{jkc} \;.\; Y_{ijkc} \;.\; (1 + dr)^{-j}$$

All costs are converted into net present value.

Equation (2) guarantees that the total purchasing cost in a year should not exceed the budget of that year. Equation (3) states that at any year j, the number of type *k* vehicles with range c should be the same as the number of total vehicles of mileage range c at time zero. For the FRM, it is assumed that only new vehicles will be purchased for the fleet. Equation (4) relates the purchased vehicles to the new vehicles. $AVAIL_{jkc}$ ensures that the purchased vehicle is available in the market. Equation (5) guarantees that the number of new vehicles utilized during year 0 must equal the sum of the existing new vehicles plus purchased vehicles. Equation (6) imposes the conservation of vehicles (i.e., the initial vehicles (not of age 0) should be either used or sold). Equation (7) ensures that the age of any vehicle in use will increase by one year after each year. Equation (8) ensures that all vehicles will be sold at the end of the planning horizon. In actual practice, all the vehicles will not be salvaged at the end of the planning horizon; instead, they will continue to be operated. However, this assumption is made here to provide a fair estimation of the costs for the entire planning horizon and to facilitate comparisons of different scenarios. Equation (9) ensures that a newly purchased vehicle should not be sold before use. Equation (10) states that no vehicle can be sold before the first year of the planning horizon. Equation (10) states that the total number of chargers in operation in any year should be equal to the total number of EVs present in the UDOT fleet. The ratio of EVs to chargers is assumed to be 1:1 for the FRM, as the charging time of the vehicles has not been

considered. Hence, one charger for each vehicle will allow each vehicle to be fully charged through the night. Equation (12) states that the number of chargers to be installed in a year plus the number of chargers already in operation from the previous year will be equal to the number of chargers in operation in the year. Finally, equation (13) states that the decision variables associated with purchasing, utilization, and salvaging decisions must be integer numbers.

4.2 Baseline Scenario

The baseline scenario is our first scenario, in which the values of the parameters determined at the beginning of the planning horizon are used to determine the best composition of the yearly fleet for the planning horizon. In other words, once the parameters are inputted into the model, the model will output the replacement plan for the entire planning horizon. The baseline scenario uses a single-run optimization model.

The rates of fuel price increases over the planning horizon are extracted from Table 3.7. The discount rate is considered to be 6.5% per year, and the depreciation rate is assumed to be 10% per year for all types of vehicles. Emission cost calculations were done using AFLEET Tool 2018.

4.3 Rolling Horizon Methodology

Planning models are exposed to a great deal of uncertainty while determining parameter values, especially when the planning horizon is long. RH is a widely-used approach used to handle parameter uncertainties in the field of transportation (Sama et al., 2013; Gkiotsalitis, and Berkum, 2020; Zhan et al., 2016), such as supply, demand, and

scheduling sectors (Sama et al., 2013; Gkiotsalitis, and Berkum, 2020). This approach is used to capture the variability of the parameters and data by frequently updating the parameters and data within the planning horizon.

In this approach, a fixed period called Prediction Horizon (PH) is set, which can be equal to or less than the planning horizon. At the beginning of each PH, the variables and data are updated; then, based on the updated values, the optimization model generates results that are implemented for smaller time intervals called Implementation Horizon (IH). For the next iteration, PH will start from the end of the previous IH. The process iteratively continues until it covers the entire PH. Figure 4.1 depicts the entire process. We refer to the entire process as the rolling horizon algorithm (RHA).

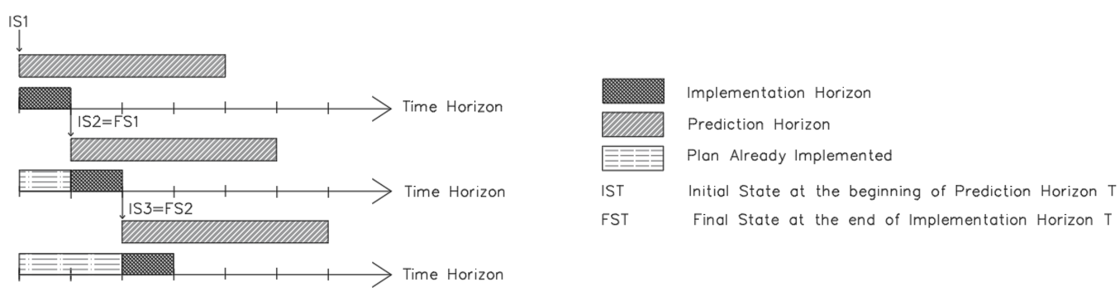


Figure 4.1 Rolling Horizon Framework

The RHA can be summarized as follows:

❖ **Step 0**: Initializing the length of the planning horizon, PH, and IH.

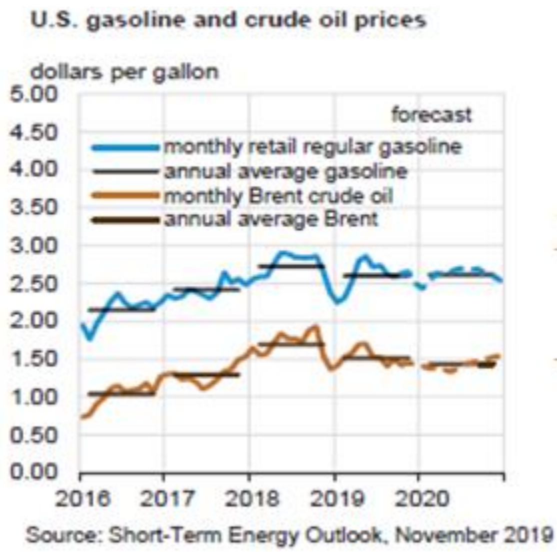
❖ **Step 1**: For the determined planning horizon and IH, calculate the number of iterations, L. The number of iterations can be found by dividing the planning horizon by the length of IH.

- ❖ **Step 2**: Update variables and data at the beginning of PH, then run FRM. The results/decisions obtained by running FRM will be implemented for IH.
- ❖ **Step 3**: Update the initial state of the next new PH, which will be the same as the final state of the previous IH.
- ❖ **Step 4**: If the current iteration number is less than the total iteration number calculated in the second step, go to Step 2; otherwise, stop.

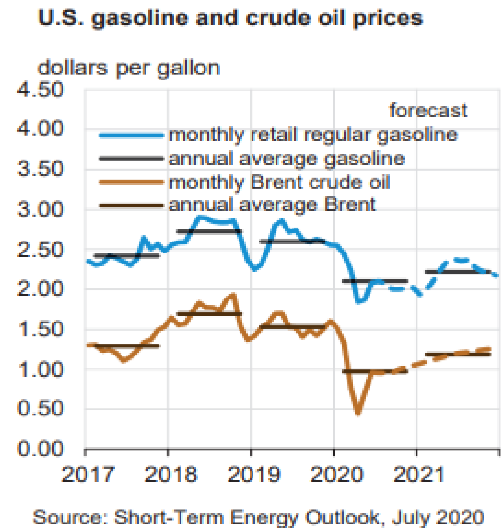
In general, the RHA approach uses a multi-run optimization mechanism. For this study, the planning horizon and PH are assumed to be 30 years and IH is assumed to be five years.

4.4 Scenarios for Sensitivity Analysis

Fuel price is one of the most uncertain factors among all the model's parameters. The US EIA publishes a forecast for fuel production and price every year. Based on the forecast report for the past few years, this forecast may not be very close to the actual price. Fuel prices change based on global and national politics, the economy, and social issues (e.g., holidays, riots, and social movements). For example, the ongoing Covid-19 pandemic reshaped the entire fuel market. Figures 4.2 and 4.3 represent a comparison between fuel price predictions made by US EIA in November 2019 and the actual scenario in July 2020 for gasoline and diesel, respectively (U.S. Energy Information Administration, 2019 and 2020). The predictions of gasoline, oil and diesel price for 2020 made in 2019 (Figure 4.2(a) and Figure 4.3(a)) are not close to the actual fuel prices in 2020 (Figure 4.2(b) and Figure 4.3(b)) due to the Covid-19 pandemic.



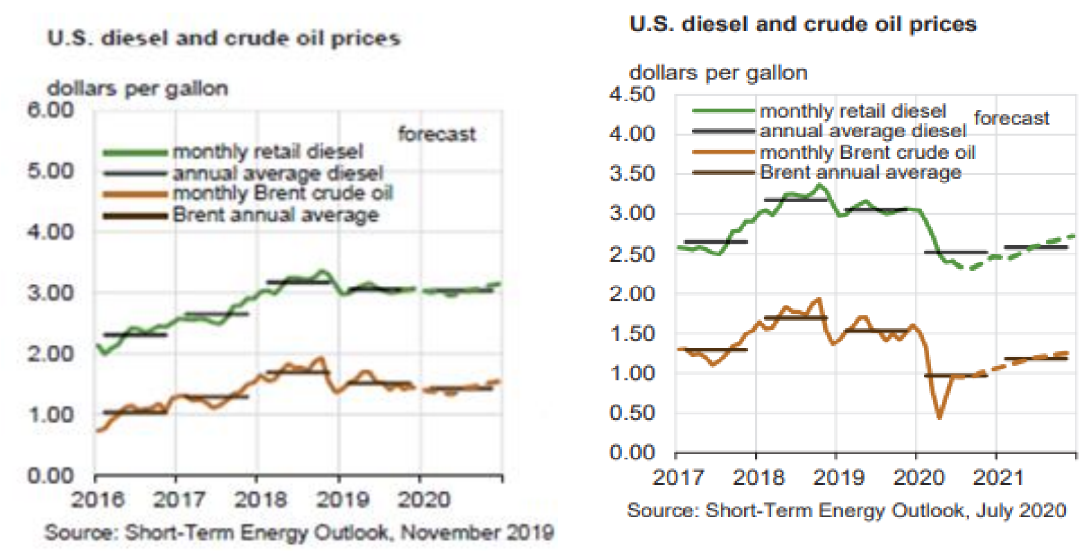
(a)



(b)

Figure 4.2 Oil price historical and predicted data for gasoline published by the US EIA in 2019(a) and 2020(b)

Although situations like this may not happen frequently, differences between the predicted prices and actual prices always exist. To address the fuel price oscillation, a few fuel price scenarios were considered as sensitivity analyses. Four scenarios were selected where the prices of gasoline, diesel, and biodiesel change by the rate of -10%, -5%, 5%, and 10% per year, while other parameters remain unchanged. RHA uses these price scenarios and provides replacement decisions. Note that the biodiesel (B-20) price is also assumed to change because 80% of its ingredients is petroleum diesel. The change rate will be applied to the base price of fuels, which are mentioned in Section 3.3.4. For other types of fuel, the prices are mentioned in Section 3.3.4.



(a) (b)

Figure 4.3 Oil price historical and predicted data for diesel published by the US EIA in 2019(a) and 2020(b)

4.5 Chapter Summary

This chapter included the formulation of FRM model, which yields the feasibility decisions of introducing AFVs into fleet by minimizing total cost considering purchasing cost, energy cost, maintenance cost, infrastructure cost, emission cost, and salvage cost. The model provides the decision of buying a new vehicle when there is demand prevailing in the fleet. Then rolling horizon (RH) approach was discussed. The RH approach handles the fluctuating parameters and adjusts the model decisions. Finally, the scenarios for sensitivity analysis were discussed in this chapter.

CHAPTER 5

RESULTS

4.6 AMAD Categorization of Trucks

In this subsection, the baseline is compared with scenarios 1,2, 3, and 4 when trucks are categorized based on AMAD. Categorization based on AMAD is associated with a higher annual average mileage in each category as compared to the MMAD approach. This allows the FRM to present feasibility decisions for trucks that have high annual mileage. Fleet composition for the baseline scenario was found by using the single-run optimization model, whereas fleet compositions for scenarios 1-4 were found by applying the RHA to the FRM.

Table 5.1 presents the new truck compositions for the baseline scenario, scenario 1, scenario 2, scenario 3, and scenario 4. The results obtained by solving the model for the baseline scenario, scenarios 1, and scenario 2 show a similar type of truck composition that consists of diesel and B-20 fueled trucks. At the end of the planning horizon, all the trucks are converted from diesel to B-20. The reason behind this choice is the low purchasing price as compared to other options and the decrease in fuel price, which provides a low energy cost for B-20 and thus a better cost-saving plan than other possible plans that proposed compositions consisting of options such as EV and LNG for the given fuel price forecasts presented in the baseline scenario and scenarios 1-2.

When fuel prices (gasoline, diesel, biodiesel) increase, the model selects LNG and EV along with B-20 (Table 5.1). The inclusion of LNG and EV is higher in scenario 4 than scenario 3 because the price of B-20 is higher in scenario 4. Hence, in scenario 4, B-20 is opted out by LNG and EV at the end of 30 years. It was also found that EV is not included in the high mileage range category (i.e., 151-200 mile/active day category). The reason behind this is that, for long distances, EVs require high capacity batteries, which results in high purchasing costs. In this case, the high purchasing price of EV does not outweigh its low operating cost. Hence, LNG is suggested by the model for the long-distance category.

Figure 5.1 demonstrates that, at the beginning of the time horizon, the number of B-20 trucks to be included in the fleet is greater than any other type of vehicle. Only LNG trucks are included after five years in scenario 4 (10% increase). EV is also introduced in the early years of scenarios 3 and 4. At the end of the planning horizon, scenario 1 (10% decrease), scenario 2 (5% decrease), and the baseline scenario adopt only B-20 trucks, whereas scenario 3 (5% increase) and scenario 4 (10% increase) include LNG and EV as well. Figure 5.2 presents a visual comparison of AFV and conventional vehicles within the fleet, which shows that, depending on the growth of the petroleum fuel price (scenarios 3 and 4), AFVs would replace conventional vehicles within 20 to 25 years.

Figure 5.3 displays the advantages of the RH approach by comparing total costs between the baseline scenario and other scenarios for trucks. For a fair comparison, the total cost for the baseline scenario was calculated by obtaining the fleet composition from the baseline scenario (by solving the FRM) and obtaining the fuel prices from the corresponding scenarios. Given the fleet composition and fuel prices, the FRM's objective function was recalculated in order to provide the cost of implementing the baseline scenario

in a situation where the actual fuel prices follow the corresponding scenarios. Cost-wise, Figure 5.3 shows that the RHA provides better results than the FRM by lowering the total cost. Figure 5.4 depicts the amount of cost savings realized by applying the RH algorithm. The highest amount of savings corresponds to scenario 4.

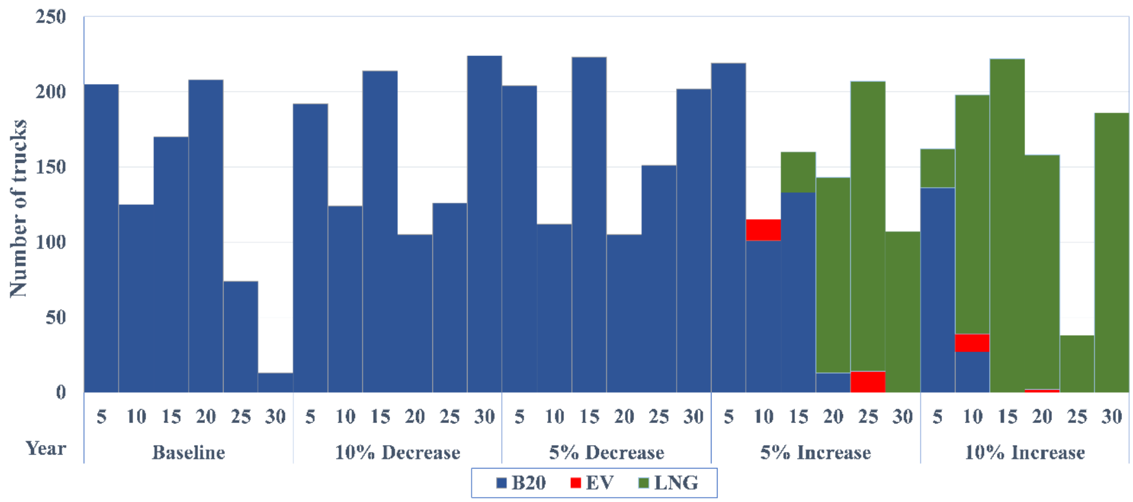


Figure 0.1 New truck purchases for each 5 years over time

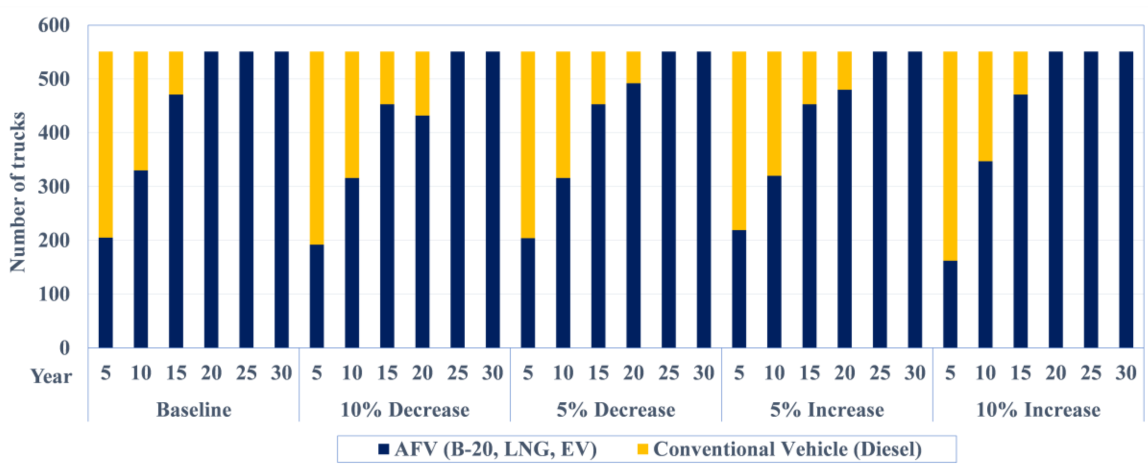


Figure 0.2 Fleet composition of trucks in different years for different scenarios

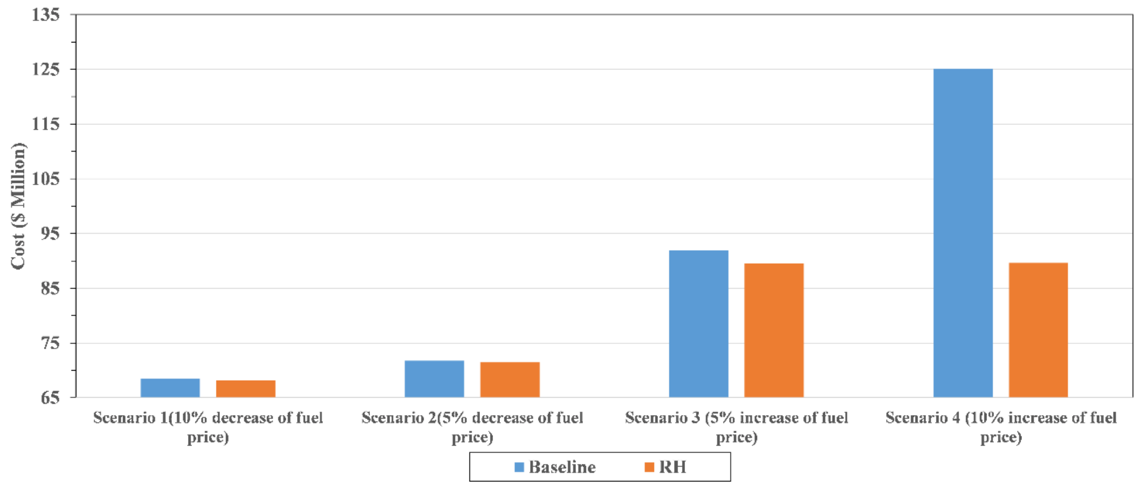


Figure 0.3 Cost comparison between baseline and the RH approach for trucks

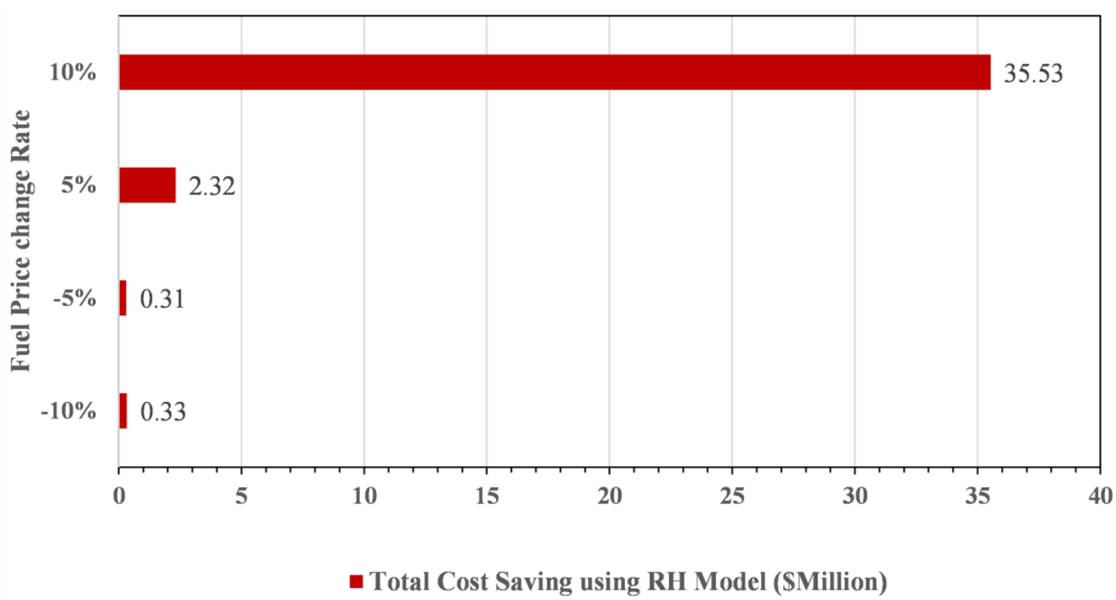


Figure 0.4 Total cost savings using the RH approach for trucks

Table 0.1 Results of all scenarios for trucks categorized based on AMAD

Year	Mileage Range Category													
	1-50				51-100			101-150				151-200		
	Vehicles													
	Diesel	B20	EV	LNG	Diesel	B20	LNG	Diesel	B20	EV	LNG	B20	EV	LNG
	Baseline Scenario													
5	227	62			111	110		8	31			2		
10	138	151			83	138			39			2		
15	80	209				221			39			2		
20		289				221			39			2		
25		289				221			39			2		
30		289				221			39			2		
	Scenario 1 (10% decrease)													
5	227	62			115	106		17	22			2		
10	151	138			84	137			39			2		
15	98	191				221			39			2		
20	59	230				221			39			2		
25		289				221			39			2		
30		289				221			39			2		
	Scenario 2 (5% decrease)													
5	227	62			115	106		5	34			2		
10	151	138			84	137			39			2		
15	98	191				221			39			2		
20	59	230				221			39			2		
25		289				221			39			2		
30		289				221			39			2		
	Scenario 3 (5% increase)													
5	227	62			105	116			39			2		
10	151	138			80	141			27	12			2	
15	98	191				221				12	27		2	
20	71	204		14		105	116			12	27		2	
25		187	14	88			221				39			2
30		80	14	195			221				39			2
	Scenario 4 (10% increase)													
5	266	23			123	98			13	2	24			2
10	165	50	12	62	39	98	84			2	37			2
15	80	50	12	147			221			2	37			2
20			13	276			221			1	38			2
25			13	276			221			1	38			2
30			13	276			221			1	38			2

4.7 MMAD Categorization of Trucks

When trucks are categorized based on the MMAD, the optimum truck composition for different scenarios varies. MMAD categorization allows seasonal demand to be captured. For example, if a vehicle is driven 1,000 miles/month during the summer, but remains unutilized for the rest of the year, then this MMAD approach is capable of capturing the demand for that vehicle during the summer. Moreover, the MMAD categorization approach keeps some vehicles with high mileage range categories, such as 201-250, 251-300, and 301-∞ miles/active day. This allows the agency to retain some vehicles in the fleet that will be utilized for long trips. The reason behind this is the changes in the annual mileage of each category, which depends on how trucks are categorized.

Based on Tables 5.2 and 5.3, when petroleum fuel prices decline (in the baseline scenario and scenarios 1 and 2), the truck composition shifts from diesel trucks to B-20 trucks for all mileage categories within the planning horizon (except for 1-50 mile/active day category). For diesel trucks in the category 1-50 miles/active day category, it is not feasible to replace all of them with B-20 trucks. To illustrate this, since this category has low annual mileage, the operating cost does not outweigh the purchasing cost. When AMAD is used, all the diesel trucks of the 1-50 miles/active day category are replaced by B-20 trucks at the end of the planning horizon in the baseline scenario, scenario 1, and scenario 2. This is because trucks of the 1-50 miles/active day category would be driven more in a year when AMAD categorization is applied as compared to when MMAD categorization is applied. For scenarios 3 and 4, diesel trucks are replaced by B-20 trucks at the beginning of the planning horizon and later by LNG trucks and electric trucks when

approaching the end of the planning horizon. Figure 5.5 shows that the inclusion of B-20 trucks is higher than any other type of vehicle at the beginning of the planning horizon. At the end of the planning horizon, scenario 1 (10% decrease), scenario 2 (5% decrease), and the baseline scenario adopt only B-20 trucks, whereas scenario 3 (5% increase) and scenario 4 (10% increase) adopt LNG and EV as well. Figure 5.6 shows that the number of conventional trucks gradually decreases over time for any of these scenarios. Figure 5.6 also demonstrates that it is not beneficial to replace all diesel trucks with AFVs because, for underutilized vehicles with low annual mileage, the benefits of low operational costs do not outweigh the high upfront costs. Figure 5.6 presents a comparison between AFV and conventional vehicles within the fleet, which shows that the number of conventional trucks is reduced over time for all scenarios.

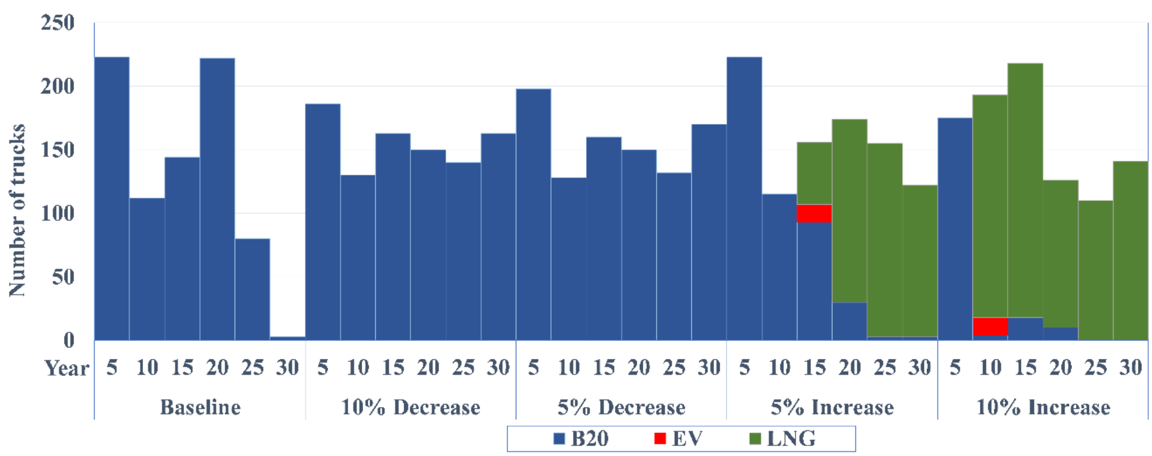


Figure 0.5 New truck purchases for each 5 years over time

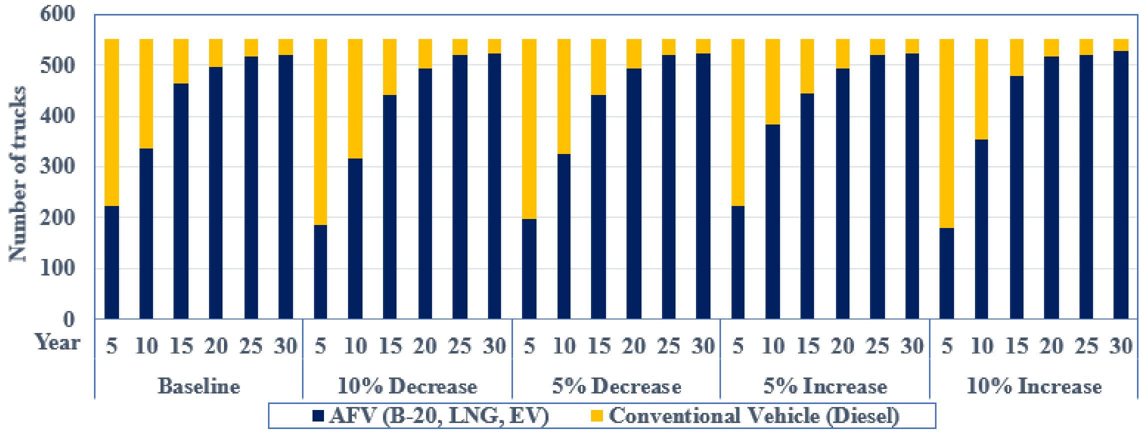


Figure 0.6 Fleet composition for trucks in different years for different scenarios

Figure 5.7 compares the cost of the FRM and RH approach for all scenarios. It can be seen that when the price increase rates of gasoline, diesel, and biodiesel escalate, savings also escalates. Figure 5.8 presents the cost-saving that results after applying the RHA to solve the FRM. The highest value occurs in scenario 4, where the fuel price increase rate is the highest.

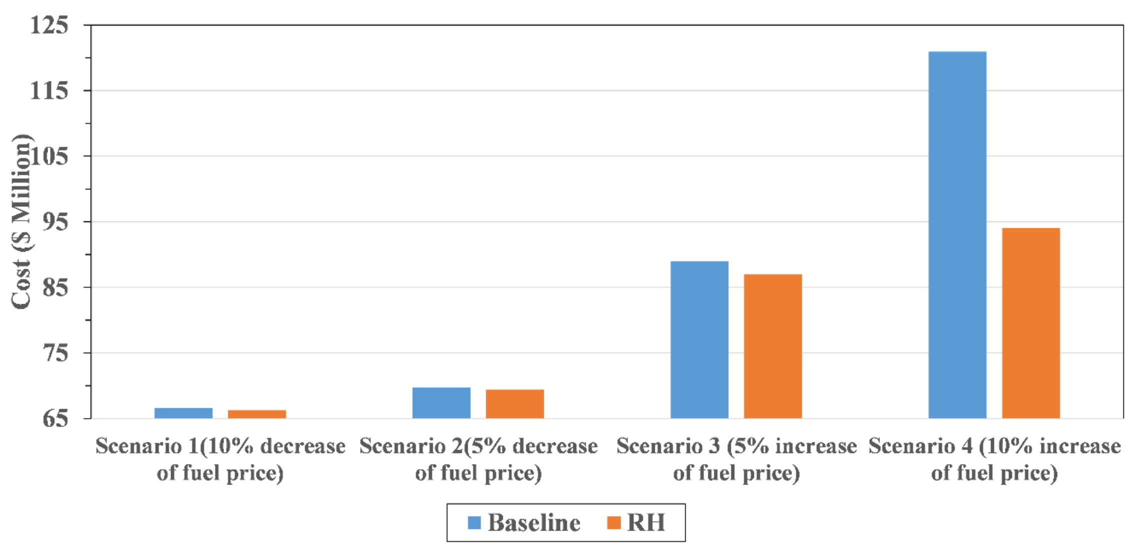


Figure 0.7 Cost comparison between baseline and the RH approach for trucks

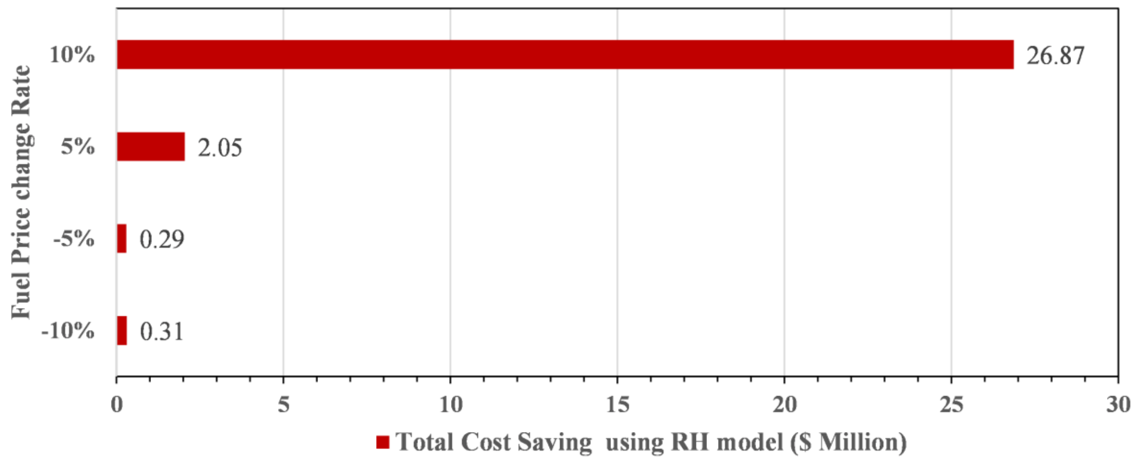


Figure 0.8 Total cost saving using the RH approach for trucks

Table 0.2 Results of all scenarios for trucks of 1-50, 51-100, and 101-150 categories based on MMAD categorization approach

Year	Mileage Range Category										
	1-50			51-100				101-150			
	Vehicles										
	Diesel	B20	LNG	Diesel	B20	EV	LNG	Diesel	B20	EV	LNG
	Baseline Scenario										
5	48			82	6			81	78		
10	48			45	43			53	106		
15	38	10		29	59			19	140		
20	34	14		20	68				159		
25	34	14			88				159		
30	32	16			88				159		
	Scenario 1 (10% decrease)										
5	48			82	6			105	54		
10	48			48	40			55	104		
15	38	10		34	54			37	122		
20	34	14		23	65				159		
25	31	17			88				159		
30	28	20			88				159		
	Scenario 2 (5% decrease)										
5	48			82	6			105	54		
10	48			48	40			55	104		
15	38	10		34	54			37	122		
20	34	14		23	65				159		
25	31	17			88				159		
30	28	20			88				159		
	Scenario 3 (5% increase)										
5	48			82	6			105	54		
10	48			48	40			55	104		
15	38	10		34	54			34	118	7	
20	34	14		23	65				133	7	19
25	31	17			65		23		79	7	73
30	28	20			59		29		15	7	137
	Scenario 4 (10% increase)										
5	48			85	3			105	54		
10	48			54	3	3	28	55	72	11	21
15	38	10		31	3	3	51	4	72	11	72
20	34	10	4		3	3	82			11	148
25	31	10	7			3	85			11	148
30	23	10	15			3	85			11	148

Table 0.3 Results of all scenarios for trucks of 151-200, 201-250, 251-300, and 301-∞ categories based on MMAD categorization approach

Year	Mileage Range Category												
	151-200				201-250			251-300			301-∞		
	Vehicles												
	Diesel	B20	EV	LNG	Diesel	B20	LNG	Diesel	B20	LNG	Diesel	B20	LNG
	Baseline Scenario												
5	61	56			34	41		14	24		8	18	
10	45	72			25	50			38			26	
15		117				75			38			26	
20		117				75			38			26	
25		117				75			38			26	
30		117				75			38			26	
	Scenario 1 (10% decrease)												
5	59	58			36	39		22	16		13	13	
10	41	76			27	48		11	27		5	21	
15		117				75			38			26	
20		117				75			38			26	
25		117				75			38			26	
30		117				75			38			26	
	Scenario 2 (5% decrease)												
5	59	58			34	41		19	19		6	20	
10	41	76			22	53		11	27			26	
15		117				75			38			26	
20		117				75			38			26	
25		117				75			38			26	
30		117				75			38			26	
	Scenario 3 (5% increase)												
5	53	64			31	44		9	29			26	
10	40	77			22	53			38			26	
15		110	7			75			15	23			26
20		50	7	60		25	50			38			26
25			7	110			75			38			26
30			7	110			75			38			26
	Scenario 4 (10% increase)												
5	66	51			40	35		22	16		6	16	4
10	40	51		26		35	40			38			26
15				117			75			38			26
20				117			75			38			26
25				117			75			38			26
30				117			75			38			26

4.8 AMAD Categorization of Pickups

Results of the model for pickups show that the optimal fleet composition consists of gasoline and E85 fueled pickups (Table 5.4). In the baseline scenario, gasoline and E85 pickups were preferred over diesel trucks. When the fuel price of gasoline, diesel, and B-20 declines more significantly than the baseline scenario (scenarios 1 and 2), the fleet composition consists only of gasoline pickups. This raises the question that if gasoline pickups seem profitable in terms of total life-cycle cost, then why are diesel pickups more popular than gasoline pickups? By exploring relevant studies, it can be found that gasoline pickups have a lower MPG than other types of pickups, such as diesel pickups, which lowers the fuel cost for diesel pickups (Belzowski and Green, 2013). It can also be found that diesel engines have a longer lifespan as compared to other engines (Belzowski and Green, 2013). The depreciation rate of diesel vehicles is also lower than that for gasoline vehicles (Belzowski and Green, 2013), although we have used the same depreciation rate for all types of pickups in this study. On the other hand, the purchasing price and resale price of diesel pickups are higher than for gasoline pickups. The decision to introduce diesel or gasoline pickups into a fleet will depend entirely on the answer as to whether diesel pickups will be driven enough to save on fuel costs and balance the high initial investment over their life-cycle. For this study, the annual mileage of pickups is not very high. Hence, despite offering low operating costs, diesel pickups are not a preferred choice for a fleet.

Figure 5.9 presents the results when pickups are included in different scenarios. It was found that only E85 and gasoline pickups are part of the fleet composition during the

entire planning horizon. The reason behind this adoption choice is the low annual mileage and the low purchasing price of pickups. Because of the low annual mileage, the annual operating cost is also low, which does not impact vehicle adoption choice significantly. Hence, the high purchasing costs of other AFVs (i.e., EVs) become the main hindrance of adopting these AFV options. Regarding E85 pickups, the purchasing price is assumed to be the same as the purchasing price of gasoline pickups. Hence, E85 pickups are more favorable in scenarios 4 and 5 in which the petroleum fuel prices go up. In other scenarios, gasoline pickups are preferred in the fleet composition because of the low fuel price and their low initial costs.

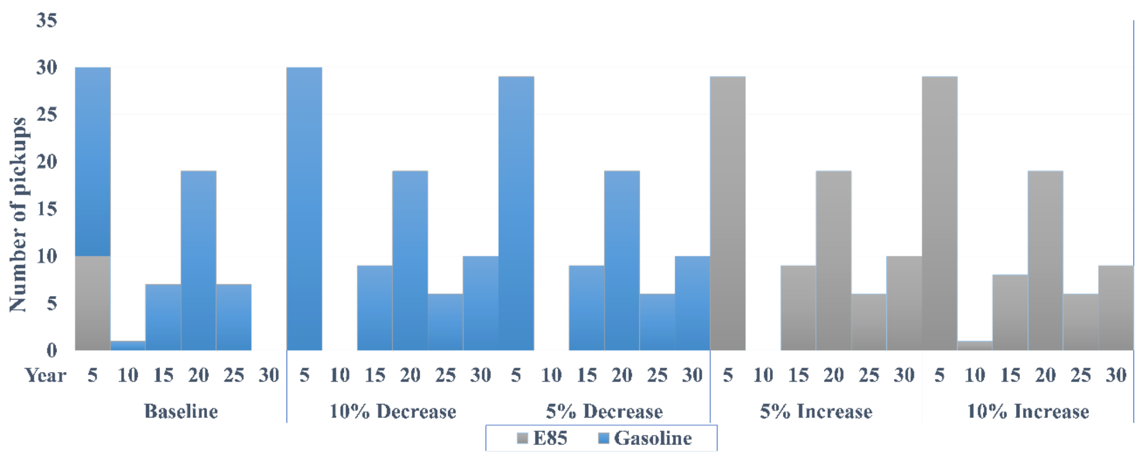


Figure 0.9 New pickup purchases for each 5 years over time

Figure 5.10 shows a visual comparison of the number of AFV and conventional pickups in different years of the planning horizon. As can be seen, the low prices of gasoline and diesel allow the fleet to maintain the operations of conventional pickups during the entire planning horizon (see scenarios 1 and 2); whereas the increase in fuel

prices leads to the adoption of alternative fuel pickups, starting at the beginning of the planning horizon and moving toward their total domination at the end of the planning horizon (see scenarios 3 and 4).

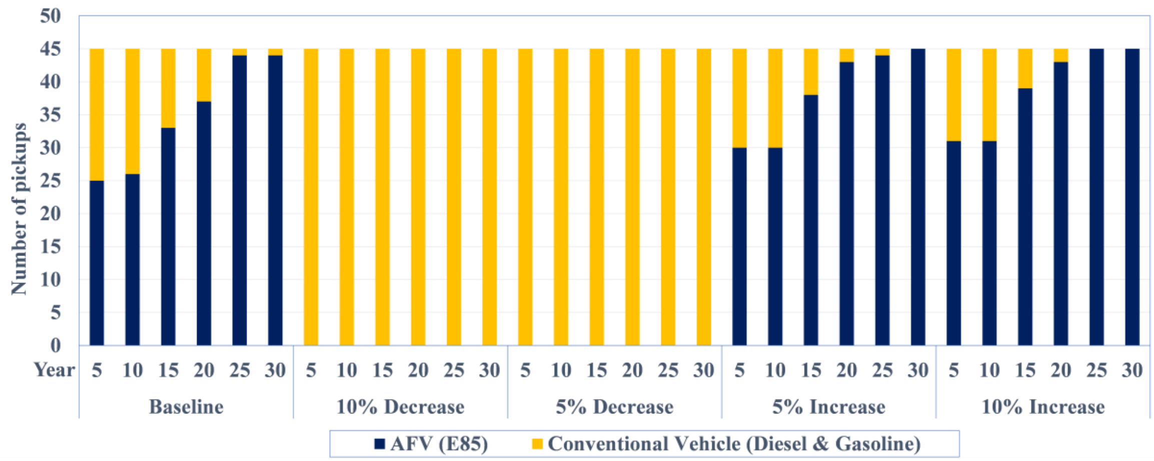


Figure 0.10 Fleet composition for pickups in different years for different scenarios

Figure 5.11 presents the advantages of the RH approach. As can be seen, the RHA provides the fleet composition that results in a lower cost than the cost of the fleet composition that results from the baseline scenario. The amount of cost-savings using the RHA is estimated in Figure 5.12. In scenarios 1 to 3, savings are $40-50k using the RH algorithm over the planning horizon while in scenario 4, savings are greater than $110k.

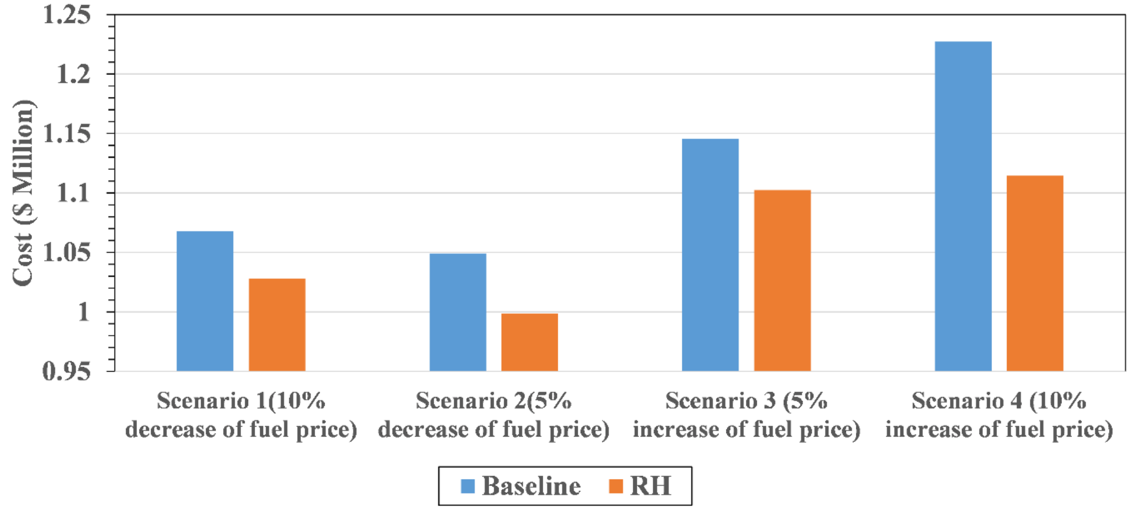


Figure 0.11 Cost comparison between baseline and the RH approach for pickups

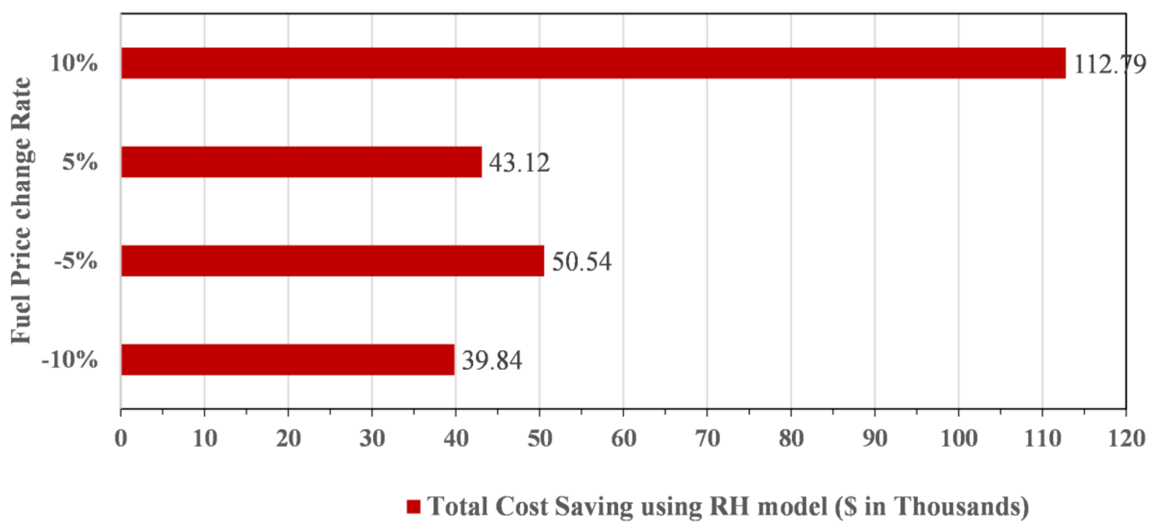


Figure 0.12 Total cost savings using the RH approach for pickups

Table 0.4 Results of all scenarios for pickups categorized based on AMAD

Year	Mileage Range Category																
	1-50			51-100			101-150			151-200			201-250			301-∞	
	Vehicles																
	Diesel	Gasoline	E85	Diesel	Gasoline	E85	Diesel	Gasoline	E85	Diesel	Gasoline	E85	Diesel	Gasoline	E85	Gasoline	E85
	Baseline Scenario																
5	5	1	2	3	4	7	1	6	1			13			1		1
10	5	1	2	3	4	7		6	2			13			1		1
15	2	1	5		4	10		5	3			13			1		1
20	1	1	6		1	13		5	3			13			1		1
25		1	7			14			8			13			1		1
30		1	7			14			8			13			1		1
	Scenario 1 (10% decrease)																
5	5	3		3	11		1	7			13			1		1	
10	5	3		3	11		1	7			13			1		1	
15	2	6			14			8			13			1		1	
20		8			14			8			13			1		1	
25		8			14			8			13			1		1	
30		8			14			8			13			1		1	
	Scenario 2 (5% decrease)																
5	5	3		3	11		1	7			13			1		1	
10	5	3		3	11		1	7			13			1		1	
15	2	6			14			8			13			1		1	
20		8			14			8			13			1		1	
25		8			14			8			13			1		1	
30		8			14			8			13			1		1	
	Scenario 3 (5% increase)																
5	5	1	2	3	4	7	1	1	6			13			1		1
10	5	1	2	3	4	7	1	1	6			13			1		1
15	2	1	5		4	10			8			13			1		1
20		1	7		1	13			8			13			1		1
25		1	7			14			8			13			1		1
30			8			14			8			13			1		1
	Scenario 4 (10% increase)																
5	4	1	3	3	4	7	1	1	6			13			1		1
10	4	1	3	3	4	7	1	1	6			13			1		1
15	1	1	6		4	10			8			13			1		1
20		1	7		1	13			8			13			1		1
25			8			14			8			13			1		1
30			8			14			8			13			1		1

4.9 MMAD Categorization of Pickups

When pickups are categorized based on the MMAD, the fleet composition at the end of the planning horizon is similar to the fleet composition found in Table 5.5. For scenarios 1 and 2, gasoline pickups are the main choice for fleet composition, since the fuel cost and the purchasing cost are low. For scenarios 3 and 4, E85 pickups are prioritized in the fleet composition because of high gasoline and diesel prices and the low purchasing price of E85 pickups.

Figure 5.13 shows the inclusion of new AFV pickups in the fleet. Scenario 1 (10% decrease) and scenario 2 (5% decrease) result in pickup compositions that contain only gasoline and diesel pickups during the entire planning horizon. In contrast, the baseline scenario, scenario 3 (5% increase), and scenario 4 (10% increase) lead to pickup compositions that adopt both gasoline, diesel, and E85 pickups at the beginning of the planning horizon. However, at the end of the planning horizon, compositions consist only of E85 pickups. For scenarios 1 and 2, gasoline and diesel pickups are selected because they have low fuel costs and low purchasing costs. For scenarios 3 and 4, E85 pickups are prioritized in the fleet composition because of high gasoline and diesel prices and their relatively low purchasing price.

Figure 5.14 shows the changes in fleet composition. As can be seen, low prices of gasoline and diesel allow the fleet to maintain the operation of conventional pickups during the entire planning horizon (see scenarios 1 and 2); whereas the increase in fuel prices leads to the adoption of alternative fuel pickups, starting at the beginning of the planning horizon

and moving toward their total domination at the end of the planning horizon (see scenarios 3 and 4).

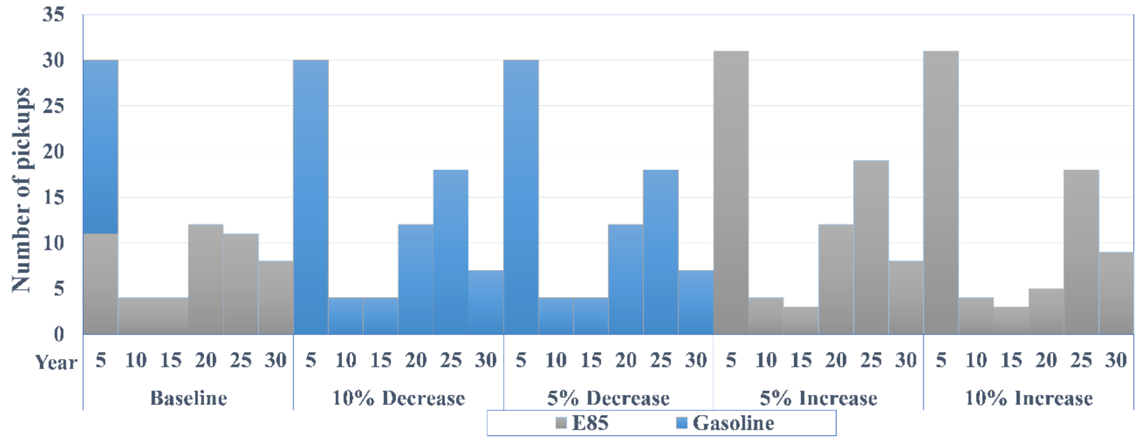


Figure 0.13 New pickup purchases for each 5 years over time

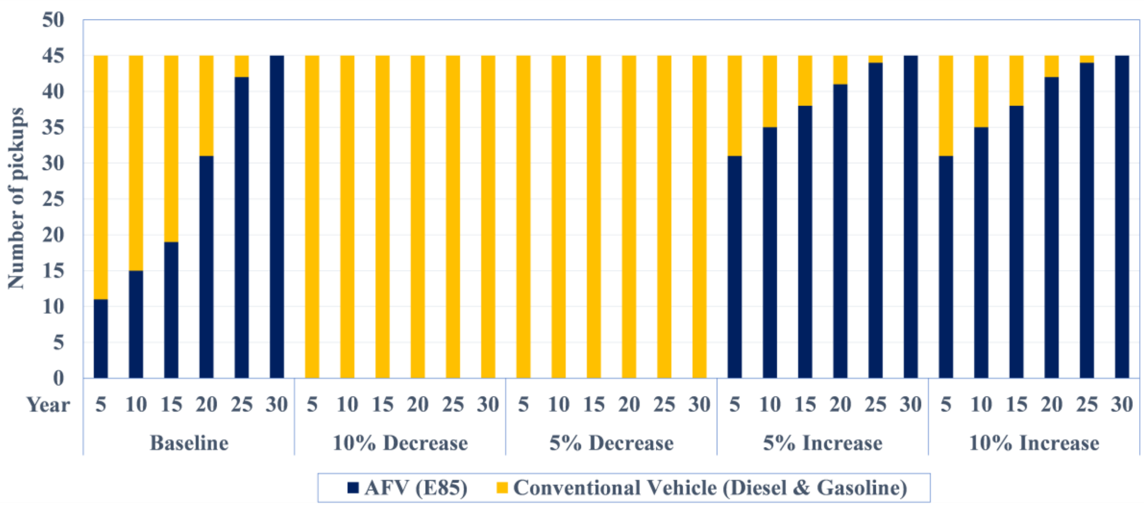


Figure 0.14 Fleet composition for pickups in different years for different scenarios

Figures 5.15 and 5.16 present the cost-savings that are realized by applying RHA to the FRM model. The RH approach clearly provided better results in terms of total costs and cost savings.

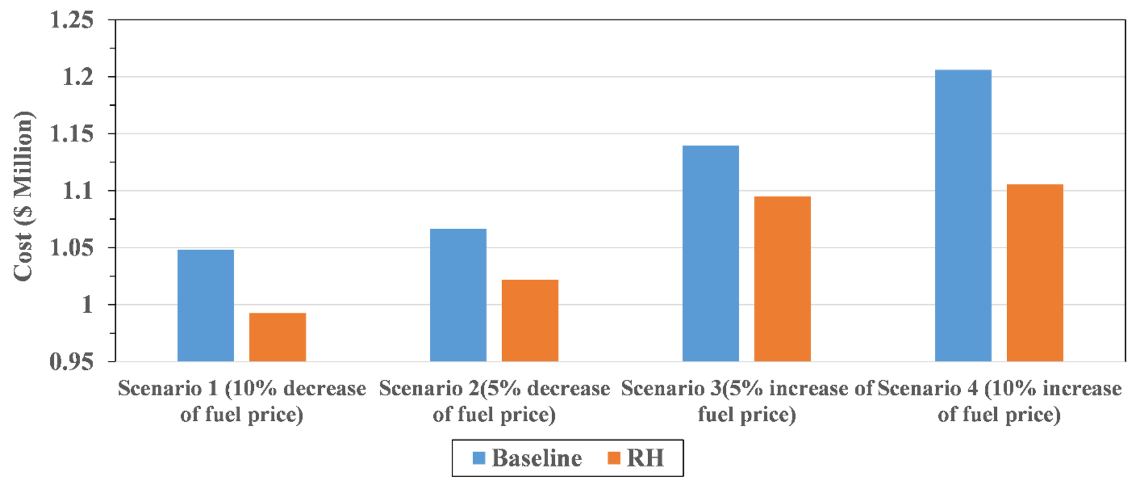


Figure 0.15 Cost comparison between baseline and the RH approach for pickups

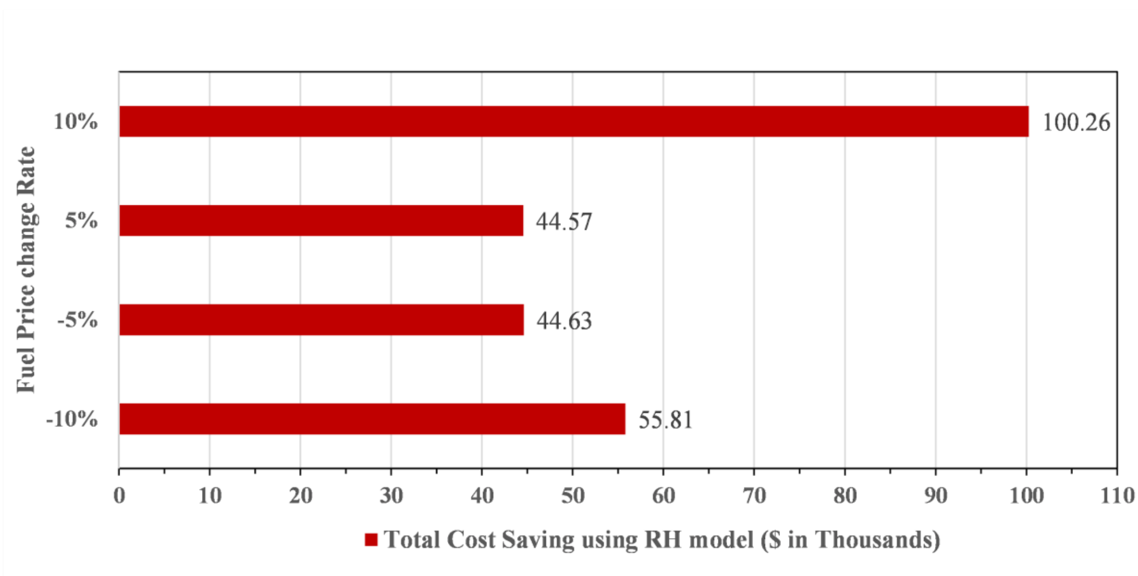


Figure 0.16 Total cost savings using the RH approach for pickups

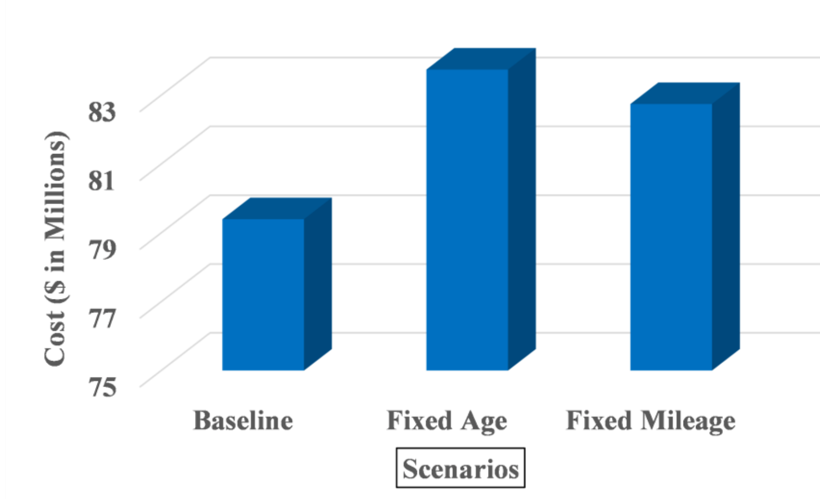
Table 0.5 Results of all scenarios for pickups categorized based on MMAD

Year	Mileage Range Category																		
	1-50			51-100			101-150			151-200			201-250			251-300		301-∞	
	Vehicles																		
	Diesel	Gasoline	E85	Diesel	Gasoline	E85	Diesel	Gasoline	E85	Diesel	Gasoline	E85	Diesel	Gasoline	E85	Gasoline	E85	Gasoline	E85
	Baseline Scenario																		
5	1			2	3	2	2	4	3	1		5	2	10	1	8		1	
10	1			1	3	3	2	3	4	1		5		10	3	8		1	
15	1				3	4		3	6			6		10	3	8		1	
20	1				2	5		1	8			6		10	3		8		1
25	1				1	6		1	8			6			13		8		1
30			1			7			9			6			13		8		1
	Scenario 1 (10% decrease)																		
5	1			2	5		2	7		1	5		2	11		8		1	
10	1			1	6		2	7		1	5			13		8		1	
15	1				7			9			6			13		8		1	
20	1				7			9			6			13		8		1	
25	1				7			9			6			13		8		1	
30		1			7			9			6			13		8		1	
	Scenario 2 (5% decrease)																		
5	1			2	5		2	7		1	5		2	11		8		1	
10	1			1	6		2	7		1	5			13		8		1	
15	1				7			9			6			13		8		1	
20	1				7			9			6			13		8		1	
25	1				7			9			6			13		8		1	
30		1			7			9			6			13		8		1	
	Scenario 3 (5% increase)																		
5	1			2	3	2	2	4	3			6	2		11		8		1
10	1			1	3	3	2	3	4			6			13		8		1
15	1				3	4		3	6			6			13		8		1
20	1				2	5		1	8			6			13		8		1
25	1					7			9			6			13		8		1
30			1			7			9			6			13		8		1
	Scenario 4 (10% increase)																		
5	1			2	3	2	2	4	3			6	2		11		8		1
10	1			1	3	3	2	3	4			6			13		8		1
15	1				3	4		3	6			6			13		8		1
20	1				1	6		1	8			6			13		8		1
25	1					7			9			6			13		8		1
30			1			7			9			6			13		8		1

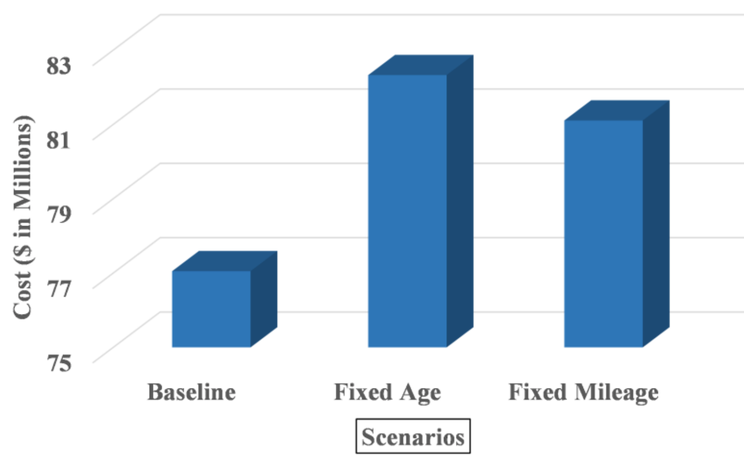
4.10 Comparison of the FRM and current practices

This study adopted an optimization model that was used to provide optimum fleet compositions for different fuel price scenarios over the planning horizon. As discussed, DOTs follow various practices for replacing their fleet. The most common practice is to use thresholds to replace vehicles, based on vehicle age, odometer, and maintenance costs. This section demonstrates how the proposed optimization model can outperform current practices. For cost comparison, two scenarios of “fixed age” and “fixed mileage” are considered. In the fixed age scenario, trucks and pickups are sold when they are 15 and 5 years old, respectively. In the fixed mileage scenario, trucks and pickups are sold when they have been driven for 60,000 and 50,000 miles, respectively. For the optimization model, the baseline scenario is used and is compared with the two scenarios.

Figure 5.17 (a) and (b) presents cost comparisons of the three scenarios (baseline, “fixed age”, “fixed mileage” scenario) of trucks when they are categorized based on AMAD and MMAD, respectively. The baseline scenario (FRM) provides the best cost-saving fleet compositions over the planning horizon. This is because the FRM considers various types of costs in the optimization model and provides a fleet composition that ensures the lowest cost. In contrast, current practices of using fixed thresholds ignore various costs that are considered in the FRM model. As a result, current practices cannot provide optimal fleet compositions. Furthermore, applying the RHA to the FRM could further improve the results, as shown in the previous subsections.



(a)

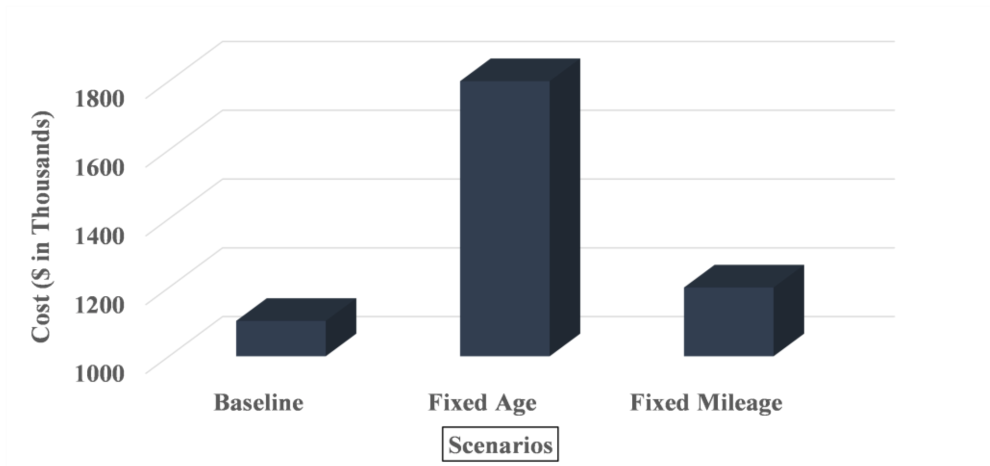


(b)

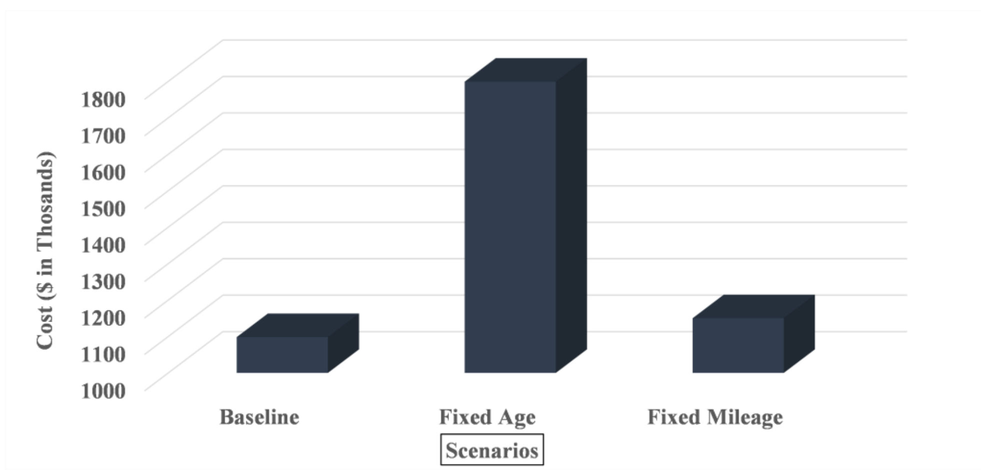
Figure 0.17 Cost comparison between the baseline, fixed age, and fixed mileage scenarios for trucks categorized based on (a) AMAD, and (b) MMAD

Figure 5.18 (a) and (b) compare the cost of the three scenarios for pickups when they are categorized based on AMAD and MMAD, respectively. As can be seen, the baseline scenario (FRM) provides the fleet composition with the best cost-savings.

Applying the RHA to the FRM can further improve the results, as shown in the previous subsections.



(a)



(b)

Figure 0.18 Cost comparison between baseline, fixed age, and fixed mileage scenarios for pickups categorized based on (a) AMAD, and (b) MMAD

4.11 Chapter Summary

This chapter evaluated the FRM by investigating the outputs of the model for the previously mentioned scenarios. For trucks, B-20, LNG, and electric trucks were adopted on different scenarios during the planning horizon. In the case of pickups, E85 and gasoline pickups had received priority. Cost comparisons were made using the FRM and RHA for different scenarios. For all the scenarios, RH model provided higher cost saving fleet composition decisions. This chapter also compared the performance of the FRM and that of other practical methods by comparing total costs. The comparison presented that the FRM is able to provide better fleet composition decision in respect of the total cost.

The results of fleet compositions for both AMAD and MMAD categorization approaches were very similar, as annual mileage of each range category for both AMAD and MMAD categorization methods was very similar for our dataset. The similar results were expected, as the results were generated from the same FRM. If there was a considerable difference in annual mileage for any mileage range category of both AMAD and MMAD categorization approach, the results would be different. The fleet agencies should evaluate the utilization data of the vehicles at first to check if the vehicles are utilized similarly throughout the year or seasonally. Based on the utilization pattern, any approach of classification should be selected.

CHAPTER 6

CONCLUSIONS

4.12 Summary of Major Findings

This study presented an optimization model that provides the optimum fleet composition that ensures the lowest possible cost for maintaining the fleet. In this study, multiple sources were used to form our input data. A certain proportion of the data was gathered from the literature that was used to fill the gaps in the data collected from the UDOT Fleet Tracking Website (verizonconnect.com). As the fleet composition decision is affected by fluctuations in fuel costs, several different scenarios were investigated in this study to provide insight into what the fleet composition will be at the end and during the 30-year planning horizon. Through a complementary study on forecasting the costs of the planning horizon, the model and the algorithm proposed in this study can be applied to plan for AFV adaptation for UDOT. The detailed recommendations of this study are as follows:

i. This thesis demonstrated a systemic approach can be used to handle the fleet replacement problem. Currently, different types of practices for fleet replacement are in use. However, most of these do not use optimization models that can generate better cost-saving decisions as compared to other approaches with fixed criteria (fixed age/fixed mileage).

ii. This study analyzed the fleet replacement problem applying the FRM. Two vehicle classification approaches- AMAD and MMAD were used for

categorizing vehicle data. AMAD and MMAD showed similar patterns of fleet composition based on the used dataset. AMAD is recommended to be used when vehicles are utilized at the same rate throughout the year. On the other hand, MMAD is suggested to be used when vehicles are seasonally utilized (like snowplows).

iii. This study investigated the cost efficiency of applying the RH method to the optimization model, showing that the RH algorithm can utilize the most recent updated parameters to update the fleet composition decisions to further minimize costs. RHA is also capable of addressing the uncertainty of future cost data, through which organizations can have a better view of fleet replacement decisions.

iv. A relationship between fuel prices and the inclusion of AFVs was established. When gasoline, diesel, and biodiesel prices decrease over time, the inclusion of AFV is slower as compared to when fuel prices increase. For pickups, AFVs were included in the fleet composition when the fuel price has a descending trend. In contrast, when the fuel price has an ascending trend, the inclusion of AFV in the fleet is dominating.

v. The purchasing price of AFV and annual usage of the vehicle were found to be significant factors for the introduction of AFVs into the fleet. The type of AFV that is introduced into the model is determined by the purchase price along with their operating costs. AFVs offer low energy costs and low maintenance costs that would be beneficial when the annual usage is high. However, in the case of low annual usage, a high purchase cost cannot be justified by the low

operating costs within the planning horizon. For example, if replacing trucks that are used 300 miles/day or more with electric trucks, they require batteries with high capacities that would increase the purchase price of electric trucks. Hence, despite being a promising option, EVs are not included in the fleet composition in some scenarios and categories. These problems can be solved through the national-wide deployment of charging stations and wireless charging lanes, which make long-haul travel of electric trucks possible.

4.13 Scope of Future Works

The uncertain future of fuel and AFV markets poses challenges to the application of the model, which was addressed by investigating different scenarios. An appropriate market prediction study can improve the results of the model proposed here, which remains for future studies. Moreover, calculating the salvage cost is very complex, as it changes based on several factors, such as total mileage, age, vehicle condition, fuel type, vehicle type, and demographic location. In this study, salvage cost was calculated straightforwardly. A more precise approach based on the historical data of UDOT's fleet salvage costs can be used to improve the results of the proposed model.

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