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Leveraging Alternative Fuel Vehicles in Operation and Asset Management Strategies to Reduce Fleet Economic and Societal Impacts

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Abstract

Managing and owning a diverse fleet of vehicles encompass several essential factors including vehicle selection (make, model, fuel type, etc.), maintenance, refueling, capital cost, and sustainability. However, many organizations lack a systematic approach to evaluate and transition to a cost-efficient and low-emission fleet composition under varying operational conditions. As one of the major contributors to emissions, the transportation sector aims to reduce tailpipe emissions through various strategies. A comprehensive plan for procuring, salvaging, storing, and strategically managing the fleet can result in a sustainable and cost-efficient fleet. Because of their lower maintenance, fuel, emissions, and operations costs, alternative fuel vehicles (AFVs) could pave the way toward a sustainable fleet. This study aims to develop an optimization framework that identifies the most cost- and emission-efficient fleet composition strategy under real-world operational and environmental conditions. In this study, the emissions of the vehicles, estimated by the EPA's MOVES simulation tools, and the real-world dataset from the Michigan State University (MSU) fleet are employed to calibrate emission regression models embedded within the proposed optimization framework. The proposed integer linear mathematical optimization model suggests the optimal fleet composition and operations plan while the total fleet cost (including the monetary and societal cost of emissions) is minimized. Various operational and environmental conditions, such as the vehicles' seasonal VMT, speed, idle time, age, and temperature are considered in the framework. The results of deploying the proposed optimization framework express a rapid transition toward AFVs, besides a reduction of 38% to 74% in emissions, 40% to 78% in fossil fuels consumption, and up to 15% in total fleet cost depending on the emission and fuel types and the fleet operating scenario.

Keywords

Fleet Management, Alternative Fuel Vehicle, Electric Vehicle, Societal Emissions Cost, Integer Linear Programming

1. Introduction

In recent years, the transportation sector has faced increasing pressure to address the economic and societal impacts of conventional fuel vehicles [1]. Rising fuel prices, depletion of fossil fuel resources, increasing emissions, especially greenhouse gas emissions (GHGs), and the considerable tear and wear costs of traditional vehicles have prompted a shift towards alternative fuel vehicles (AFVs) in fleet management [1] [2]. This paper investigates the optimal integration of AFVs into operation and asset management strategies of fleet vehicles to mitigate environmental impacts, reduce monetary costs, and improve overall fleet efficiency. This study seeks to provide insights into how organizations can effectively leverage AFVs to achieve sustainable transportation solutions.

The increasing emissions, air pollution, and the associated consequences (e.g., adverse health effects) have been a worldwide concern in recent decades [3] [4]. Transportation is responsible for nearly 28% of US GHG emissions in 2022, making this sector the most significant contributor to US GHG emissions [3]. Among all transportation modes, light, medium, and heavy-duty vehicles contribute to 80% of the tailpipe emitted GHGs [3] [5]. The 2007 Energy Independence and Security Act mandates federal agencies to acquire low greenhouse gas-emitting vehicles [6]. Thus, actions are required to control transportation-related emissions, primarily by the entities operating large fleets [7].

Organizations are encouraged to prioritize sustainable, clean, and carbon-friendly transportation equipment as a central element of their operational strategies besides their cost priorities. Adopting an efficient strategy in asset management saves fuel, cuts emissions, reduces maintenance costs, promotes a cleaner environment, and boosts economic sustainability [8]. AFVs could help fleet owners cut their entities' environmental side effects (which benefit the entity and society) and reduce some other fleet management costs [9]. They have a dual advantage: not only do they contribute significantly to emissions reduction, but they also enhance the cost-effectiveness of managing a fleet of vehicles. The most prominent costs discussed extensively in the literature that significantly affect fleet management are the vehicles' operations and management (O&M), fuel, storage, purchase, and societal emissions costs. The O&M cost includes any cost related to vehicles' maintenance as well as personnel operations [10]. Due to the significant cost of the fuel provision compared to O&M costs, the fuel is considered a separate cost term in this study. Operating AFVs requires potential marginal expenditures, such as constructing the refueling infrastructure [11] [12]. Considering the greater cost components of AFVs (such as purchasing vehicles and building refueling stations) and gasoline/diesel vehicles (G/DVs), (such as O&M, fuel, and societal emissions costs), fleet managers must exercise caution in order to achieve the optimal fleet composition [2].

Thus, the primary goal of this study is to thoroughly analyze an extensive list of factors impacting fleet acquisition and operation, and develop a fleet replacement model that describes a sustainable and efficient approach toward promoting eco-friendly practices. First, a set of regression models is calibrated to estimate tailpipe emissions in different operation statuses (e.g., moving, idle, and start). For this purpose, the outputs of MOVES (Motor Vehicle Emission Simulator), a state-of-the-science emission estimation tool developed by the US Environmental Protection Agency (EPA), are employed along with the Michigan State University (MSU) dataset to estimate the emission production of the fleet under various weather conditions. Then, the calibrated models are embedded in a proposed mixed integer linear mathematical optimization model (MILP) to minimize the fleet operation, asset, and environmental costs, considering budgetary limitations and operational requirements. The integration of the calibrated emission models and the optimization model assists with accurate emission estimation while optimizing operation strategies through various years of study. Additionally, the proposed framework effectively accounts for the effects of weather and fluctuations in operational demand on seasonal fleet composition and operation.

The review of the relevant studies is explained in the next section, followed by the problem of interest. Then the next section describes the methodology, followed by data collection. Finally, the results and conclusion are presented.

2. Literature Review

This section reviews the literature and background of the topic in three scopes. First, the previous studies regarding fleet replacement strategies and methodologies are introduced. Then, it brings some approaches utilized to simulate the fleet's emission in different conditions. Finally, the application of AFVs and more specifically electric vehicles (EVs) in optimal fleet management will be discussed.

2.1. Fleet Replacement Strategies

Introduced in 1955, one of the first models for equipment replacement was proposed to swap out old, low-output equipment for newer models [13]. When determining if replacement of the equipment is necessary, this model considers various aspects, including the equipment's age, output, and purchase price. This idea has been further developed in other research, which has considered variables including the variety of vehicle types and ages [14], stochastic demand patterns, and environmental considerations in vehicle replacement modeling [15]. Apart from the procurement and disposal of vehicles, a fleet management plan that involves the storage of vehicles that are not in use for predetermined periods and their subsequent reuse can greatly improve efficiency [16].

To find the ideal fleet composition based on replacement policies, requirements, and constraints (such as the annual budget and the maximum age of cars), optimization models—in particular, integer and mixed-integer programming, or IP and MIP—are frequently used [17]. To solve the optimization problems in this area, various approaches such as simplex and branch & bound for linear and integer problems and genetic algorithm for non-linear problems have been used in the literature [18]. The genetic algorithm has been used to find an efficient fleet renewal strategy under uncertainty for a naval vessel fleet with a fleet size of six old vessels by maximizing vessel availability [18]. A mathematical optimization approach has been employed to determine the best mix of vehicles for urban freight transport by minimizing the total cost including energy, operation, maintenance, purchase, and emissions, over a pre-specified period. To evaluate the sensitivity of the model, the study examines two scenarios: one with 28 existing diesel vehicles and another requiring the purchase of new vehicles. In this study, the old vehicles' count is decreased annually from the 8th year until the 21st year, when no diesel vehicles will remain in the fleet [19].

Previous studies have also investigated replacement problems by considering fleets of electric, hybrid, diesel, and natural gas vehicles [1] [20], fluctuations in fuel and energy prices [2] [21], and the route choices influenced by travel demand [22] [23]. A French bus operator running a fleet of 100 diesel buses has utilized an integer linear program to plan the bus replacement strategy to meet the fleet electrification target. Among new diesel, hybrid, CNG, and electric buses, the optimum strategy recommends the gradual transition from all current diesel buses to 74 electric and 26 CNG buses [24].

A mathematical fleet optimization model usually finds the optimal or near-optimal fleet composition over a certain time span considering various types of costs [16]. Pollutions and GHG emissions might be included as one of the model's charges in order to account for the fleet's environmental impact. Predictive models that calculate the external carbon cost or fixed coefficients can be used to monetize these emissions [16]. Some studies have included factors such as vehicle utilization and technology, storage costs, the purchase of new vehicles, O&M costs, and the revenue from salvaging unprofitable equipment in their objective functions [12] [15]. Among costs and revenues included in the model, some of them, such as GHG taxes, gasoline/diesel (G/D) prices, and incentives for acquiring new clean vehicles, are often beyond the control of fleet managers and are determined by policy-makers [15].

2.2. Emissions Simulation

Fossil fuels generate two types of pollutants when they burn: criterion and non-criteria. To ensure sustainable transportation, the US EPA sets rules especially for criterion pollutants such as Nitrogen oxides (NO_x), carbon monoxide (CO), and particulate matter (PM), and non-criteria such as GHGs, hydrocarbons (HC), and volatile organic compounds (VOC) [25] [26]. A robust fleet strategy can significantly cut carbon emissions, promoting a greener business [27]. Some classic strategies implemented extensively to follow the emissions regulation by reducing tailpipe emissions are replacing, storing, and salvaging vehicles with higher emission rates [12]. As an example of fleet replacement benefits, recent analyses show that upgrading from 2016 to 2021 model year truck cuts carbon dioxide (CO_2) by 21 metric tons per year and NO_x by 15%, saving $16,856 per truck per year in the associated fleet [8].

Several methods have been utilized to assess the fleet's emissions. AVL CRUISE is a software that is used to simulate the CO_2 emissions of a taxi fleet of electric and G/DVs in Sete Lagoas, MG, Brazil. The results suggest EVs produce 10 to 26 times lower CO_2 compared to G/D ones [28]. By employing the COPERT emissions tool to model the emissions of a fleet of 10,050 vehicles of different types, a 77% reduction in CO_2 emission is seen by fully electrifying the fleet of taxis [29]. Another tool commonly used in the literature to estimate average and instantaneous emission rates per unit of time and distance is the MOVES. This tool considers various elements, including but not limited to emission sources, ambient conditions, vehicle status (driving, idling, starting), speed, and acceleration [30]-[32]. Based on the vehicle's age, class (such as truck or passenger car), speed, and acceleration, MOVES calculates unique emission rates. For example, real-world traffic data has been used in MOVES to predict CO, HC, and NO_x emissions depending on driving circumstances [33]. MOVES emission estimator framework has also been employed to estimate transport-related pollution emissions for a university campus [34]. In conjunction with a traffic microsimulation tool, MOVES has also been utilized to simulate the emissions resulting from the transportation demand [35].

2.3. AFVs and Fleet Electrification

Due to their significant role in emission, fuel, and maintenance cost reduction, AFVs, especially EVs, are among the most common and effective solutions for achieving an efficient-clean fleet [2] [7] [36]. In a fleet of 619 vehicles in a Polish company, despite the power system relying on fossil fuels, fleet electrification reduced carbon emissions by 24% and cut operational costs by EUR 370,000 per year [37]. Additionally, across all vehicle sizes, the O&M expenses of EVs are lower than those of G/DV [38]. Research reveals that EVs can cut GHG emissions by 38% - 41% compared to G/DVs and–12% compared to traditional hybrids [39]. A recent study simulates the emissions reduction after replacing 6% of the passenger G/DVs with EVs for state-wide intercity trips in Michigan. The results express 0.68 - 0.96 million tons of CO_2 annual reduction, which is 5.9% - 8.3%. The total annual savings societal emission cost reductions are 105.66 million-dollar for CO_2, and 13.52 million-dollar for NO_x, CO, and HC, altogether [40].

Implementing the replacement and electrification in the scope of the university necessitates the knowledge of the fleet's vehicle miles traveled (VMT), which represents the demand for vehicles. This demand can be found through surveys [35], simulating tools [34], statistical analysis [41], or probe data collection, as in this study. The campus travel studies primarily emphasize commuting to and from the campus or the commuter's trips within the campus rather than the operational aspects of fleet management within the campus. The University of Dayton's fleet of 145 G/DVs is studied to assess fuel consumption reduction by fully electrifying its fleet by 2025 [42]. By employing RETScreen Expert, which models different transition scenarios, the University of Saskatchewan's campus fleet is also examined to evaluate the economic viability of transitioning toward EVs [43]. Additionally, there are cases of fleet conversion to AFVs, encompassing fleets of entities rather than campuses [44]. Through fleet electrification, Amazon aims to achieve net-zero carbon emissions across its delivery fleet operations by 2040 [45]. FedEx wants to purchase 50% of electric pick-up vehicles and all delivery vehicles by 2025 and 2030, respectively [46].

Overall, the reviewed literature highlights substantial progress in fleet replacement modeling, emissions estimation, and the integration of AFVs. Moreover, insights from prior research emphasize the importance of incorporating real-world data into fleet optimization models. However, to the best of the authors' knowledge, few studies have proposed a comprehensive approach that considers all the essential factors mentioned above (including but not limited to the impact of vehicles' age, type, and driving mode on various emission types, and O&M costs) in an integrated optimization model. Additional impactful factors, such as the societal cost of emissions, the cost of building refueling stations, and temperature variations should also be incorporated into a comprehensive modeling framework. Among various tools examined in the literature, MOVES emerges as a widely validated and flexible emissions simulation platform that accounts for detailed vehicle attributes, driving behavior, ambient conditions, and operating modes, and is used in this study to simulate fleet emissions.

3. Problem Statement

Managing a fleet of vehicles efficiently is a complex challenge due to a variety of interrelated factors. Key variables such as the age of the vehicle, its type, purchase expenses, O&M and fuel costs, and emission profiles of the vehicles all play significant roles in fleet management decisions. Additionally, external factors including temperature and surrounding traffic conditions, further complicate the process of determining the optimal fleet composition for a given period. Due to this complex network of factors, determining the optimal fleet composition requires a sophisticated procedure to balance economic feasibility and environmental sustainability.

Despite the fact that many organizations have started fleet electrification programs, there is still a dearth of comprehensive expertise on the size of a university campus because of the fleet's varied vehicle makeup. A variety of vehicles are essential to support the diverse operations and activities across university campuses. Buses and sedans are used for transporting students and staff, while vans manage tasks such as maintenance and transporting equipment. Trucks are mainly employed for infrastructure projects and maintenance duties, ensuring the smooth functioning of campus facilities. Thus, a method that combines the campus's varied fleet into a unified framework is required. The framework should be capable of considering operations costs as well as societal costs and benefits. This study aims to propose a comprehensive model and a sustainable management strategy for fleet vehicles. The problem of interest is to find the number and type of in-service, stored, purchased, and salvaged vehicles as well the refueling stations in a unit of time while the total system cost, including O&M, fuel, and societal emissions cost, is minimized. Emission production, which is influenced by various factors such as vehicle type, age, operation, and environment temperature, is an essential contributing factor in fleet management. Consequently, incorporating dynamic emission estimations becomes imperative while optimizing operational strategies.

The main constraints include budget limits and travel demand requirements. The emission models developed and calibrated using MOVES data are embedded in the proposed optimization framework. Thus, the primary contribution of this study is to bridge the gap in the existing literature by integrating O&M, fuel, and emission costs focusing on AFVs while accounting for the influence of adverse weather along with numerous other factors within a unified modeling framework. The proposed optimization model is developed and calibrated using a variety of novel measures as follows:

- A 1-year real-time comprehensive probe data collection from campus vehicles including daily vehicles' status, such as VMT, number of stops and starts, idle time, speed, and other characteristics, e.g., vehicles' type, age, fuel economy, and salvage value.
- Simulating important pollutants emitted by different vehicle types in various engine statuses (e.g., running, idle, and start) and peripheral conditions (e.g., temperature) in MOVES.
- Developing an extensive set of emission regression models embedded within the optimization model to estimate the vehicles' emissions and salvage value based on vehicle type and age, temperature, and other contributing factors.

4. Methodology

This section details the research approach for this study. First, regression emission estimation models are calibrated to assess the emission rates of the campus's vehicles in various conditions within the optimization framework. These models are developed using the emission rates obtained from simulating the properties of the case study with MOVES as the dataset. Then, the mathematical modeling framework is introduced, which formulates the problem as a linear integer optimization model.

4.1. Emission Models

The optimization model is built upon vehicles' emissions as one of the primary inputs. This research develops emission models to be included in the optimization model to address this variability instead of depending on constant emission rates. Emissions are subject to variation based on operational characteristics and peripheral conditions, as well as the specific characteristics of the vehicle. These variables include but are not limited to speed, make, and model. The calibrated models estimate the emission rates of vehicles in various operating stages, such as running, idling, and cold/warm start.

An initial dataset of emission rates is created for this investigation using the MOVES to calibrate the emission regression models. In all, 72 regression models incorporating four vehicle types, six pollutants, three types of emission rates, and two fuel types were created. The emission rate is the dependent variable, with the vehicle's age, average speed, fuel type, and average ambient temperature as the independent variables. It is important to highlight that EVs, due to their zero tailpipe emissions, are not included in emission models. For flex-fuel vehicles, their emission rates are derived from those of equivalent gasoline vehicles using a conversion factor. Based on campus data, this factor is set at 0.7 across all vehicle types. Additionally, for all vehicles (except EVs), warm start emission rates are estimated from cold start emission rates using specific conversion factors obtained from MOVES simulation results. These emission-specific factors are detailed in the appendix. Additionally, certain vehicle-fuel combinations, such as gasoline buses and diesel sedans, were excluded from the analysis as they are not present in the fleet. Equations (1)-(3) exemplify some developed regression models along with the R-squared for CO emissions from sedans, estimating the running (gr/mile), idle (gr/hr), and cold start (gr/start) emission rates. All other developed models are presented in the Appendix.

$$\begin{gathered}\text{Running}: \; e_{i,sedan,f,t',CO} = 2.011 + 0.357I - 0.223V + 0.011T + 0.27F \\ R^2 = 0.400\end{gathered} \tag{1}$$

$$\begin{gathered}\text{Idle}: \; r_{i,sedan,f,t',CO} = 0.287 + 0.182I + 0.001T - 0.009F \\ R^2 = 0.412\end{gathered} \tag{2}$$

$$\begin{gathered}\text{Cold start}: \; c_{i,sedan,f,t',CO} = 6.352 + 0.808I - 0.102T + 2.353F \\ R^2 = 0.690\end{gathered} \tag{3}$$

i, f and t' are indices of age, fuel, and season, and the dependent variables of I, V, F and T stand for the vehicle's age (year), average speed (mph), and fuel type (=0 if fuel is diesel, and =1 if gasoline), and environment temperature (˚F), respectively. In this study, Michigan's average Spring, Summer, Fall, and Winter temperatures are calculated as 50, 73, 54, and 28 ˚F, respectively [47]. These emission rates would be embedded into the objective function and converted to the monetary cost using the external societal cost coefficient, E_q.

4.2. Fleet Management Optimization Model

The optimization model aims to minimize the overall cost of the fleet, which comprises the expenses related to purchasing, maintaining, operating, and fueling the vehicles, the costs of developing refueling infrastructure, and the societal costs of emissions. The costs of developing refueling infrastructure include the infrastructure and installation costs. The societal emissions cost is utilized to quantify the vehicles' tailpipe emissions into monetary values for integration into the mathematical program. This study evaluates six primary pollutants emitted by the fleet: HC, CO, NO_x, VOC, CO_2, and PM_{10}. The decision variables of the model include the quantities of in-service, salvaged, stored, and purchased vehicles for each season, as well as the number of new refueling stations constructed annually. In-service vehicles are those actively operating and providing service during each season of the predetermined horizon. Conversely, stored vehicles are deactivated for an entire season. In other words, in-service vehicles may be either in operation or turned off during a given day of a season, whereas stored vehicles must remain parked and stored at designated parking lots for the entire season. It's important to clarify that according to university policy, vehicles are purchased and salvaged at the beginning and end of each year, thus, no transactions occur mid-year. Additionally, all purchased vehicles are brand-new. The model's main constraints include the budgetary limitations defined based on the annual budget, the maximum allowable vehicle age, the availability of charging stations, and the seasonal service requirements of each vehicle type defined based on VMT for each vehicle type. Note that the unused budget carries over to the next year. The model's sets, parameters, and variables are detailed in Table 1. Then, Equation (4) defines the objective function of the problem followed by its constraints.

Table 1. Sets, variables, and parameters of the mathematical model.

Term	Description	Unit
Sets		
k	vehicle type (*i.e.*, sedan/SUV, van, passenger truck, and bus); $k \in K$	
i	age of the vehicle; $i \in A = \{0,1,2,\cdots,A_k\}$; (A_k = maximum age of the vehicle type k)	
t	year of the study; $t \in T = \{1,2,\cdots,\tau\}$; (τ = The study's horizon in years)	
t'	season; $t' \in T' = \{1,2,3,4\}$; 1: Spring, 2: Summer 3: Fall, 4: Winter	
q	pollutant type; $q \in Q = \{CO_2, CO, NO_x, HC, VOC, PM_{10}\}$	
f	fuel type (*i.e.*, gasoline, diesel, flex-fuel, and electric)	
Parameters		
α	annual inflation rate	*%*
v_{kf}	purchase price of a type- k , fuel- f vehicle	*US$/vehicle*
s_{ikf}	salvage revenue of an age- i , type- k , fuel- f vehicle	*US$/vehicle*
η_k	inventory cost of a type- k vehicle per season	*US$/season*
m_{ikf}	O&M cost of an age- i , type- k , fuel- f vehicle	*US$/mile*
E_q	unit societal cost of pollutant q	*US$/gr*
$e_{ikft'q}$	running emission rate of an age- i , type- k , fuel- f vehicle, in season t' , for pollutant q	*gr/mile*
$u_{kt'}$	vehicle miles traveled (VMT) by a type- k vehicle in season t' of each year (status quo)	*mile/(season.veh)*

Continued

$r_{ikft'q}$	idle emission rate of age- i , type- k , fuel- f vehicle, in season t' , for pollutant q	*gr/hr*
$\rho_{kt'}$	idle time passed by a type- k vehicle in season t' in each year (status quo)	*hr*
$c_{ikft'q}$	cold start emission rate of age- i , type- k , fuel- f vehicle, in season t' , for pollutant q	*gr/start*
$n_{kt'}$	number of cold starts by a type- k vehicle in season t' in each year (status quo)	*start/season*
$w_{ikft'q}$	warm start emission rate of age- i , type- k , fuel- f vehicle, in season t' , for pollutant q	*gr/start*
$n'_{kt'}$	number of warm starts by a type- k vehicle in season t' in each year (status quo)	*start/season*
$Fe_{ikft'}$	running fuel consumption of age- i , type- k , fuel- f vehicle in season t'	*Gal(kWh)/mile*
$Fr_{ikft'}$	idle fuel consumption of age- i , type- k , fuel- f vehicle in season t'	*Gal(kWh)/hr*
$Fc_{ikft'}$	cold start fuel consumption of age- i , type- k , fuel- f vehicle in season t'	*Gal(kWh)/start*
$Fw_{ikft'}$	warm start fuel consumption of age- i , type- k , fuel- f vehicle in season t'	*Gal(kWh)/start*
Fp_f	fuel price for fuel f	*US$/Gal(kWh)*
h_{ikf}	number of age- i , type- k , fuel- f vehicles at the beginning of the first year	
b_t	Available money at the beginning of year t	*US$*
b_c	Fixed allocated annual budget at the beginning of year t	*US$/year*
Rd_t	Residual (extra) money at the end of year t	*US$*
$obj(t)$	Total cost (objective function) of year t	*US$*
$d_{kt't}$	minimum demanding travel distance needed by vehicle type- k in season t' of year t	*mile/(season.veh)*
R_f	power of refueling station of fuel- f	*kW/hr or Gal/hr*
β_f	Refueling station's efficiency of fuel- f (=100% for non-electric stations)	*%*
Φ_f	cost of each new refueling station of fuel- f	*US$/station*
Υ	the average life of a refueling station	*year*
Γ	daily availability of charging stations	*hr/day*

Variables

$X_{ikftt'}$	number of age- i , type- k , fuel- f **in-service** vehicles in season t' of year t
Y_{ikft}	number of age- i , type- k , fuel- f vehicles **salvaged** at the end of year t
P_{kft}	number of brand-new type- k , fuel- f vehicles **purchased** at the beginning of the year t
$Z_{ikftt'}$	number of age- i , type- k , fuel- f vehicles **stored** in the season t' of year t
N_{ft}	number of refueling stations of fuel- f in year t
N'_{ft}	number of newly added refueling stations of fuel- f in year t

$$
\begin{aligned}
\text{Minimize}: & \sum_{t=1}^{\tau}\sum_{f=1}^{F}\sum_{k=1}^{K} v_{kf} P_{kft}(1+\alpha)^t - \sum_{t=1}^{\tau}\sum_{f=1}^{F}\sum_{k=1}^{K}\sum_{i=1}^{A_k} s_{ikf} Y_{ikft}(1+\alpha)^t \\
& + \sum_{t'=1}^{4}\sum_{t=1}^{\tau}\sum_{f=1}^{F}\sum_{k=1}^{K}\sum_{i=1}^{A_k} \eta_k Z_{ikftt'}(1+\alpha)^t + \sum_{t=1}^{\tau}\sum_{f=1}^{F} N'_{ft}\Phi_f(1+\alpha)^t \\
& + \sum_{q=1}^{Q}\sum_{t'=1}^{4}\sum_{t=1}^{\tau}\sum_{f=1}^{F}\sum_{k=1}^{K}\sum_{i=1}^{A_k} X_{ikftt'}(1+\alpha)^t \Big\{ u_{kt'}\left[m_{ikf} + Fp_f \cdot Fe_{ikft'} + E_q \cdot e_{ikft'q} \right] \\
& + E_q\left[r_{ikft'q}\cdot\rho_{kt'} + c_{ikft'q}\cdot n_{kt'} + w_{ikft'q}\cdot n'_{kt'} \right] \\
& + Fp_f\left[Fr_{ikft'}\cdot\rho_{kt'} + Fc_{ikft'}\cdot n_{kt'} + Fw_{ikft'}\cdot n'_{kt'} \right]\Big\}
\end{aligned}
$$

Subject to:

$$\begin{gathered} b_t = b_c + Rd_{t-1} \\ \forall t \in \{1, \cdots, \tau\} \end{gathered} \tag{5}$$

$$\begin{gathered} Rd_t = b_t - obj(t) \\ \forall t \in \{1, \cdots, \tau\} \end{gathered} \tag{6}$$

$$\begin{gathered} Rd_t = 0 \\ \forall t = 0 \end{gathered} \tag{7}$$

$$\begin{gathered} Rd_t \geq 0 \\ \forall t \in \{1, \cdots, \tau\} \end{gathered} \tag{8}$$

$$\begin{gathered} \sum_{f=1}^{F} \sum_{i=1}^{A_k} X_{ikftt'} u_{kt'} \geq d_{kt't} \\ \forall t \in \{1, \cdots, \tau\}, \forall t' \in \{1, 2, 3, 4\}, \forall k \in \{1, \cdots, K\} \end{gathered} \tag{9}$$

$$\begin{gathered} X_{ikftt'} + Z_{ikftt'} + Y_{ikft} = h_{ikf} \\ \forall i \in \{2, \cdots, A_k\}, t = 1, t' = 1, \forall f \in \{1, \cdots, F\}, \forall k \in \{1, \cdots, K\} \end{gathered} \tag{10}$$

$$\begin{gathered} X_{ikftt'} + Z_{ikftt'} = h_{ikf} + P_{kft} \\ \forall i = 1, t = 1, t' = 1, \forall f \in \{1, \cdots, F\}, \forall k \in \{1, \cdots, K\} \end{gathered} \tag{11}$$

$$\begin{gathered} X_{ikftt'} + Z_{ikftt'} = P_{kft} \\ i = 1, \forall t \in \{2, \cdots, \tau\}, t' = 1, \forall f \in \{1, \cdots, F\}, \forall k \in \{1, \cdots, K\} \end{gathered} \tag{12}$$

$$\begin{gathered} X_{(i-1)kf(t-1)(t'+3)} + Z_{(i-1)kf(t-1)(t'+3)} = X_{ikftt'} + Z_{ikftt'} + Y_{ikft} \\ \forall i \in \{2, \cdots, A_k\}, \forall t \in \{2, \cdots, \tau\}, t' = 1, \forall f \in \{1, \cdots, F\}, \forall k \in \{1, \cdots, K\} \end{gathered} \tag{13}$$

$$\begin{gathered} X_{ikft(t'-1)} + Z_{ikft(t'-1)} = X_{ikftt'} + Z_{ikftt'} \\ \forall i \in \{1, \cdots, A_k\}, \forall t \in \{1, \cdots, \tau\}, t' \in \{2, 3, 4\}, \forall f \in \{1, \cdots, F\}, \forall k \in \{1, \cdots, K\} \end{gathered} \tag{14}$$

$$\begin{gathered} \sum_{t'=1}^{4} \sum_{t=1}^{\tau} \sum_{f=1}^{F} \sum_{k=1}^{K} X_{ikftt'} + Z_{ikftt'} = 0 \\ i = A_k \end{gathered} \tag{15}$$

$$\begin{gathered} Y_{ikft} = 0 \\ i = 1, \forall t \in \{1, \cdots, \tau\}, \forall f \in \{1, \cdots, F\}, \forall k \in \{1, \cdots, K\} \end{gathered} \tag{16}$$

$$\begin{gathered} \sum_{k=1}^{K} \sum_{i=1}^{A_k} \left(Fe_{ikft'} \cdot u_{kt'} + Fr_{ikft'} \cdot \rho_{kt'} + Fc_{ikft'} \cdot n_{kt'} + Fw_{ikft'} \cdot n'_{kt'} \right) \\ \cdot X_{ikftt'} \big/ \left(R_f \times \beta_f \times 30 \times 3 \right) \leq N_{ft} \Gamma \\ \forall t \in \{1, \cdots, \tau\}, \forall t' \in \{1, 2, 3, 4\}, \forall f \in \{1, \cdots, F\} \end{gathered} \tag{17}$$

$$\begin{gathered} N_{f(t+1)} = N_{ft} + N'_{f(t+1)} \\ \forall t \in \{1, 2, \cdots, \Upsilon - 1\}, \forall f \in \{1, \cdots, F\} \end{gathered} \tag{18}$$

$$\begin{gathered} N_{f(t+1)} = N_{ft} + N'_{f(t+1)} - N'_{f(t-\Upsilon+1)} \\ \forall t \in \{\Upsilon, \cdots, \tau - 1\}, \forall f \in \{1, \cdots, F\} \end{gathered} \tag{19}$$

$$\begin{gathered} N_{ft} = N'_{ft} \\ t = 1, \forall f \in \{1, \cdots, F\} \end{gathered} \tag{20}$$

$$\begin{gathered} X_{ikftt'}, Y_{ikft}, Z_{ikftt'}, P_{kft}, N_{ft}, N'_{ft} \geq 0 \\ \forall t \in \{1, \cdots, \tau\}, \forall t' \in \{1, 2, 3, 4\}, \forall f \in \{1, \cdots, F\}, \\ \forall k \in \{1, \cdots, K\}, \forall i \in \{1, 2, \cdots, A_k\} \end{gathered} \tag{21}$$

Equation (4) minimizes the total fleet's cost including the costs of purchasing and storing vehicles, refueling infrastructure provision, emissions, O&M, and fuel, as well as the revenue of vehicle salvaging. Equation (5) ensures that the available money at the beginning of each year, b_t, is equal to the remaining money from the previous year, Rd_{t-1}, plus the fixed annual budget, b_c. Equation (6) calculates the residual funds at the end of year *t*, which is the difference between the total cost for year *t* (denoted as $obj(t)$) and the available funds at the beginning of the year, b_t. Equations (7) and (8) respectively specify that there should be no residual funds at the beginning of the first year and that residual funds should be non-negative in all years. Equation (9) stipulates that the total miles traveled by each vehicle type must meet or exceed the minimum VMT required to fulfill the fleet's assigned tasks. Equation (10) specifies that in the initial year of the study period, the count of active, salvaged, and stored vehicles of age *i* equals the total number of *i*-years-old vehicles. Equation (11) ensures that the sum of brand-new in-service and stored vehicles in the first year equals the total of existing brand-new vehicles (*h)* plus the number of vehicles purchased at the start of the first year. Equation (12) guarantees that all purchased vehicles are brand-new. Equation (13) delineates the evolution of in-service, stored, and salvaged vehicles over the study's duration. Equation (14) implies that purchases and salvages occur exclusively at the year's start and end, respectively. Equation (15) ensures that no in-service or stored vehicles are beyond the maximum allowable age. Based on Equation (16) no brand-new vehicles are salvaged in the year they were bought. Equation (17) introduces the number of refueling stations required for each fuel type *f* based on the energy efficiency, VMT, and operation of the associated vehicles with fuel type *f*. The model assumes that the fleet's EVs use only campus stations; however, other vehicles use off-campus ones. Equations (18)-(20) calculate the number of required refueling stations considering their average life, Υ. Finally, Equation (21) shows the feasibility constraint.

5. Case Study and Data Collection

To validate the proposed optimization model and calibrate the input parameters, MSU campus fleet data is collected and used as the case study. Five main departments—Motor Pool, Infrastructure Planning and Facilities (IPF), Landscaping, Surplus and Recycling, and the Police Department—agreed to share their fleet data for the project. **Figure 1** shows a comprehensive flow plan for collecting data.

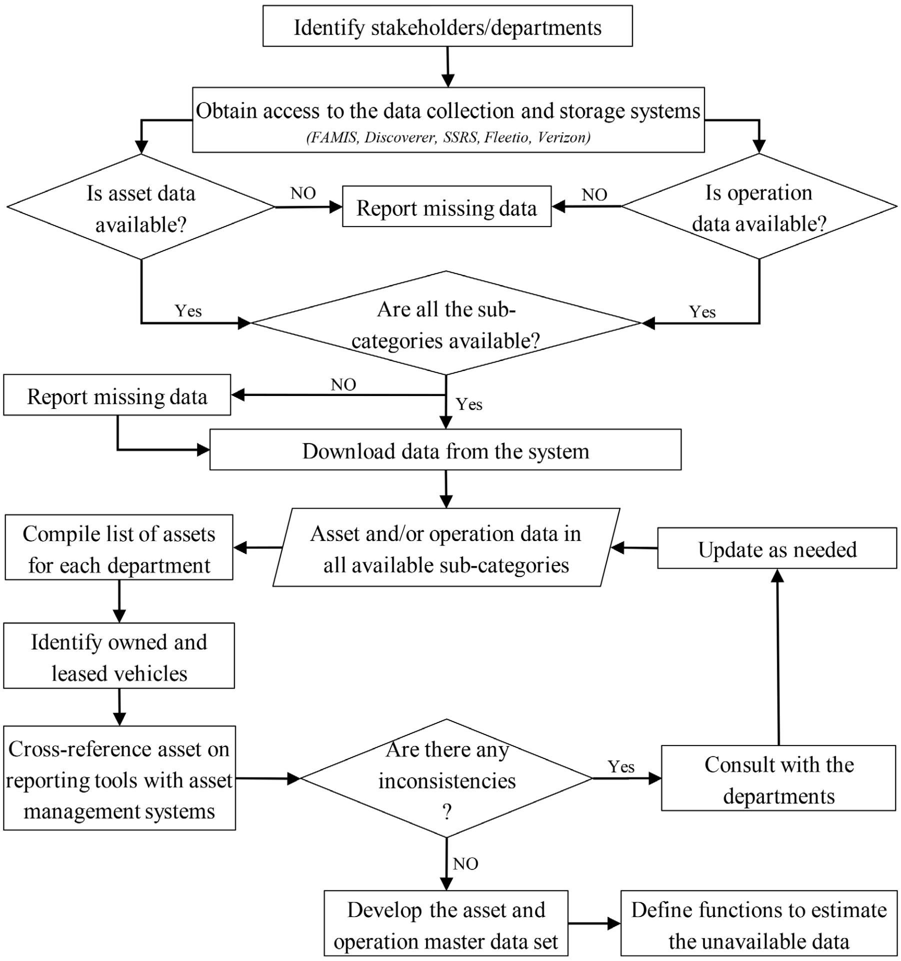
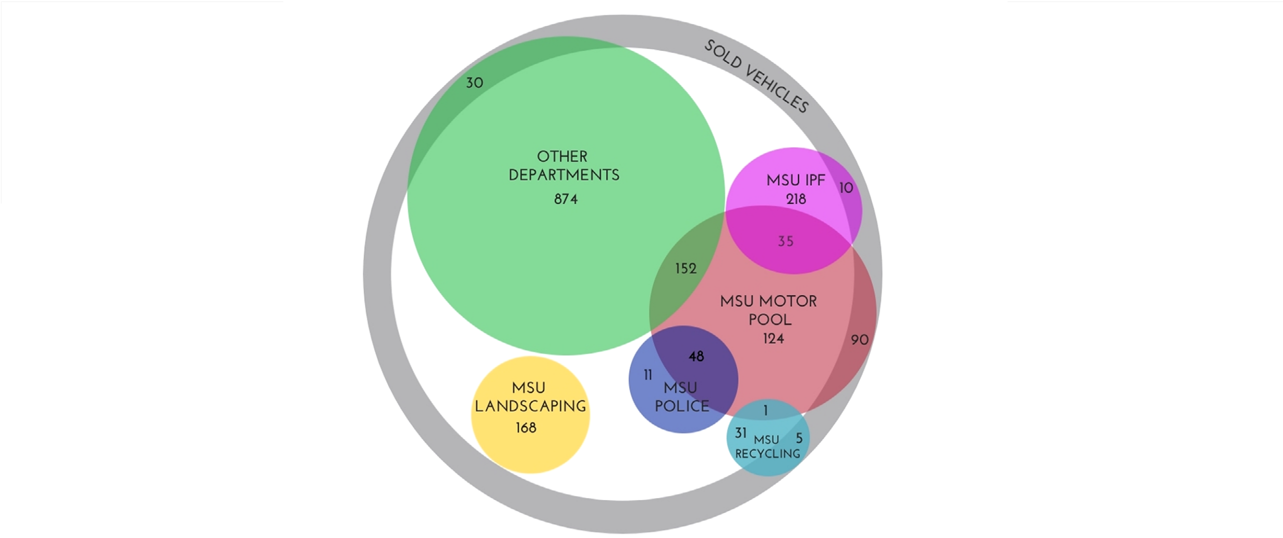


Figure 1. Data collection flow chart.

Numerous methods are used to gather data, including surveys, reports, and real-time data gathered via sensors and equipment installed on vehicles. FAMIS, Discoverer, SSRS, Fleetio, and Verizon are the five data management systems employed in this study. Asset and operational data are the two types of data that were sought. As of March 2020, the MSU campus housed 1662 vehicles across five departments. Figure 2 displays a breakdown of the fleet by department. The number of cars operated by each department is shown in Figure 2(a). The vehicles that are owned by one department and leased to another are shown by the overlap among the departments. Figure 2(b) to Figure 2(f) provide an additional illustration of the fleet breakdown by vehicle type for each of the five departments.

This study captures several categories of data, including specific asset attributes (such as body type, fuel type, and fuel efficiency), general operational information (such as average VMT, engine idle hours, fuel consumption, maintenance cost, and location of operation), and the variation of vehicle usage in different seasons. Due to inevitable gaps in the collected dataset, some attributes (such as fuel consumption, O&M cost, and the purchase price of vehicles that are missing in the dataset) are estimated using information from literature and technical reports.



NOTES
- The diagram is not to scale
- 'Other Departments' are inclusive of all department that owns their own asset database
- 'Sold Vehicles' are from 12/31/2018 - 12/31/2019
- As of data availability: May 5th,2020, Fleet Size: 1,662 vehicles

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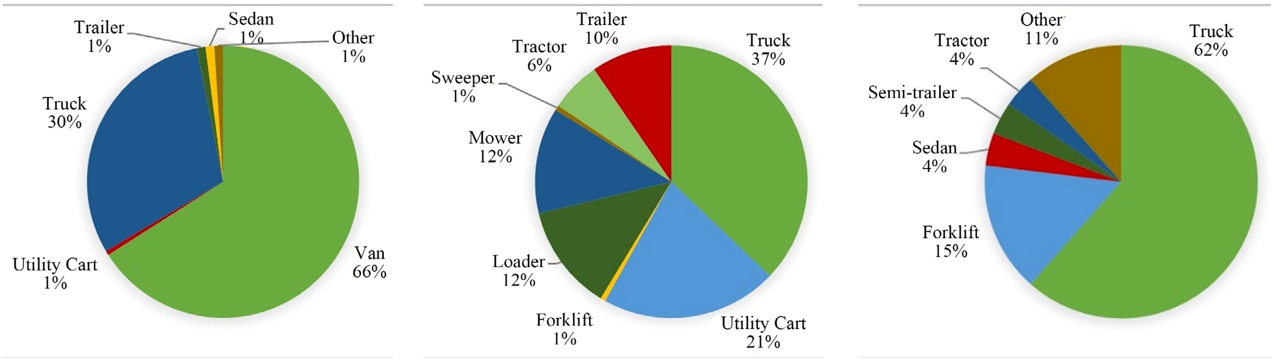
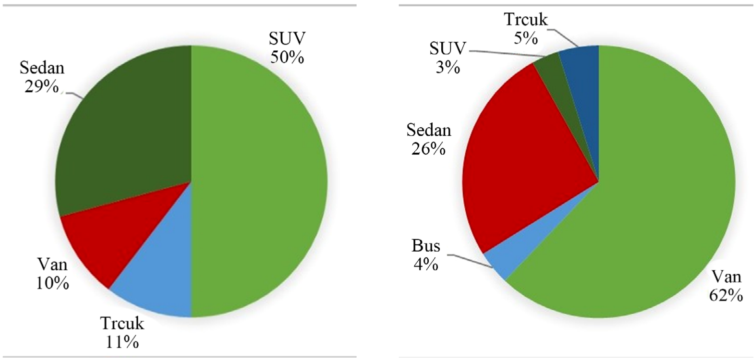
(a) Overall MSU fleet composition



(b) IPF fleet (c) Landscaping fleet (d) Surplus and Recycling fleet



(e) Police fleet (f) Motor Pool fleet

Figure 2. The breakdown of the MSU fleet by department.

After further analyses, it became evident that the IPF department is the only one with a comprehensive operational dataset. Thus, IPF has been selected for the rest of the analyses. IPF primarily utilizes the Verizon data management system. Out of the 218 vehicles operated by IPF, two sedans, 59 passenger trucks, and 128 vans are equipped with Verizon. Additionally, the five buses with adequate data were selected from the Motor Pool department to include this vehicle type in the analysis, bringing the total number of vehicles to 194. The following subsection investigates the estimation of the mathematical model's parameters using the case study dataset and other externally collected data.

Parameter Estimation

The assessments consider four vehicle types (sedan/SUV, truck, van, and bus) and four fuel types (gasoline, diesel, flex-fuel, and electricity). Due to their rarity in the market, some vehicle-fuel combinations—*i.e.*, gasoline/flex fuel buses and diesel sedans and vans—are not viewed as possible fleet expansions. Thus, the analysis will employ a total of 12 fuel-vehicle combinations. For these 12 fuel-vehicle combinations, which range in age and operate in a variety of environments (different years, seasons, and speeds), the model parameters are estimated separately. The average purchase prices of these 12 fuel-vehicle combinations are expressed in **Table 2**. The prices are approximated using the available campus dataset and the current market rates.

Table 2. Estimated purchase price of the vehicles in US$/vehicle.

Vehicle\Fuel	Gasoline	Diesel	Flex-fuel	Electricity
Sedan/SUV	40,000 [48]	-	40,000	59,000 [48]
Truck	42,000 [48]	102,000 [49] [50]	42,000	62,000 [51]
Van	47,000 [48]	-	47,000	55,000 [52] [53]
Bus	-	206,000 [49] [50]	-	280,000 [49] [50]

Salvage value (s_{ikf}) is the revenue from selling the fleet vehicles. The collected MSU asset dataset provides the resale values of 1393 G/DVs in different ages and conditions sold in the past years. Each vehicle is specified by type, age, purchase price, and odometer reading. Using these parameters as the independent variables, three regression models (Equations (22)-(24) for the sedans/SUVs, trucks, and vans) are developed to estimate s_{ikf}. Since there was no previous data on buses' resale values, this study uses the regression model of the van for buses as it has the best R^2.

Based on campus asset management strategies and the average life of vehicles, this study assumes a maximum allowable age of ten years for vehicles. Thereafter, it will be salvaged. Here, the dependent variable s_{ikf} is the salvage value of vehicle type k and fuel f at age i-years, while independent variables M, i, and p_{kf} represent the vehicle's mileage at the time of salvaging, the age of the vehicle in months, and the purchase price of a brand-new vehicle of type k and fuel f, respectively.

$$\begin{gathered} s_{ikf} = 8954 - 0.10M + 0.43p_{kf} - 55.63i \\ \forall i \in \{2,\cdots,10\}, f \in \{1,\cdots,F\}, k \in \{\text{sedan}\} \\ R^2 = 0.591 \end{gathered} \tag{22}$$

$$\begin{aligned}&s_{ikf}=5379-0.00M+0.37p_{kf}-40.62i\\&\forall i\in\{2,\cdots,10\},\ f\in\{1,\cdots,F\},k\in\{\text{truck}\}\\&R^2=0.275\end{aligned}\tag{23}$$

$$\begin{aligned}&s_{ikf}=3457-0.01M+0.41p_{kf}-35.80i\\&\forall i\in\{2,\cdots,10\},\ f\in\{1,\cdots,F\},k\in\{\text{van},\text{bus}\}\\&R^2=0.690\end{aligned}\tag{24}$$

A vehicle's O&M cost (m_{ikf}) encompasses expenses such as oil changes (for non-EVs), battery and tire replacement, periodic servicing, personnel stipend, and other possible repairs. Using the available dataset from the IPF's fleet, five distinct regression models are developed to estimate the annual O&M cost for each non-EV. Table 3 presents the coefficients and R-squared of all five trained models categorized by vehicle-fuel combinations.

Table 3. Coefficients of the regression models to estimate the O&M cost.

Vehicle type	Fuel type	Coefficients			R-squared
		Constant	Annual VMT	Age in years	
Sedan/SUV	Gas/Flex	247.10	0.4871	-	0.335
Truck	Gas/Flex	165.71	0.4653	41.649	0.176
Truck	Diesel	2497.09	-	275.84	0.473
Van	Gas/Flex	615.44	0.66	1.04	0.088
Bus	Diesel	3737.49	-	1713.84	0.91

Statistical analysis of the IPF's dataset highlights the significance of the vehicle's age and annual VMT as independent variables in the models. However, due to the limited number of EVs and their recent introduction into the campus fleet, there is insufficient data for comprehensive model training. Thus, an adjustment coefficient is calculated by dividing the O&M expenses of EVs by the costs of gasoline,

Table 4. Fuel consumption parameters of brand-new vehicles in summer.

Vehicle type	Fuel type	Running fuel consumption (Gal(kWh)/mile)	Idle fuel consumption (Gal(kWh)/hour)	Cold start fuel consumption (Gal/start)	Warm start fuel consumption (Gal/start)
Sedan	Gas	0.0347	0.2692	0.0074	0.0064
	Electricity	0.330	2.500	-	-
Truck	Gas	0.0464	0.3090	0.0097	0.0083
	Diesel	0.0544	0.3936	0.0072	0.0062
	Electricity	0.480	3.620	-	-
Van	Gas	0.0385	0.3090	0.0095	0.0082
	Electricity	0.400	3.020	-	-
Bus	Diesel	0.1394	0.7352	0.0081	0.0070
	Electricity	2.360	17.870	-	-

diesel, and flex-fuel vehicles [54]. The coefficient is calculated as 0.42. Fuel consumption rates for vehicles in various states (*i.e.*, running, $Fe_{ikft'}$, idle, $Fr_{ikft'}$, cold start, $Fc_{ikft'}$, and warm start, $Fw_{ikft'}$) are another set of parameters estimated to calculate fuel costs. **Table 4** presents the fuel/energy consumption rates for brand-new vehicles at a temperature of 73 ˚F, the average temperature in Michigan during summer. It should be noted that EVs have zero energy consumption during startup, meaning there is no specific energy required to turn the vehicle on.

The values in **Table 4** represent the average fuel (energy) consumption rates for all vehicles available on campus. Based on the collected data, flex-fuel vehicles consume approximately 70% of the fuel consumed by gasoline vehicles. Fuel consumption in seasons other than summer is calculated based on fluctuations in CO_2 production, estimated by the developed emission models. For EV energy consumption, this study uses the most recent values provided by automakers. Additionally, the analysis accounts for a significant increase in EV energy consumption, with a 30% rise estimated during the winter and fall seasons when average temperatures are significantly lower (54 ˚F and 28 ˚F in fall and winter, respectively) [55] [56].

The optimization model also requires input on the fleet's average operation over seasons, including the seasonal miles driven by each vehicle type, $u_{kt'}$, the hours spent in idle status, $\rho_{kt'}$, and the number of cold and warm starts, $n_{kt'}$ and $n'_{kt'}$. A seasonal average is estimated for every type of vehicle using real-time data obtained from the Verizon data system. Additionally, by analyzing the Verizon data, the minimum necessary seasonal VMT for every type of vehicle, $d_{kt't}$, is established. **Table 5** provides a summary of all other parameters utilized in the optimization model.

The budget is assumed to rise over time in accordance with the rate of inflation. Any leftover amount of the annual budget can be carried over to subsequent years, along with the cash from salvaging outdated vehicles. Every year, the increase in the MSU staff count serves as a signal for modifying the minimum needed seasonal VMT ($d_{kt't}$), which rises by 2.34% annually. The ratio of energy supplied to the car's battery to energy extracted from the chargers is known as the efficiency of the EV chargers. Level 2 (L2) chargers (the most commonly utilized type on campus) have an efficiency of 85% [55]-[57]. The fuel prices are approximated based on the average fuel price in Michigan in 2020, which seems like a standard price for the subsequent years after 2020.

6. Results

The numerical results presented in this section are intended to establish the optimal and sustainable procurement and operational plan for the campus fleet vehicles. Furthermore, the outcomes evaluate the effects of price and policy fluctuations on fleet management strategies. To assess these impacts, several scenarios are formulated and examined in the subsequent subsections.

The optimization model is implemented using AMPL and solved with the CPLEX solver on a standard PC equipped with an Intel Core i-5 CPU and 16 GB RAM. It took 50 seconds for the solver to find the optimum solution for the benchmark scenario, involving 878,955 MIP simplex iterations and 40,520 branch-and-bound nodes. This linear integer optimization problem yielded the seasonal quantities of in-service, stored, salvaged, and purchased vehicles over a 10-year timeframe, as well as the number of required charging stations. Additionally, the annual cost breakdown will be discussed and compared among operating scenarios.

Table 5. The value of the other objective function's parameters.

Parameter		Value	Unit	Description
Average annual interest rate (α)		2.4	%	Over the years 2010-2019, from the Federal Reserve Bank of St. Louis, USA [58]
Vehicle's storage cost (η_k)		0	$/season/veh	IPF department is not charged for storing vehicles in MSU parking lots.
Fixed annual budget (b_c)		1.1	million $/year	
Annual rise in employee numbers		2.34	%	The trend over the years 2009-2019 [59]
Electric Charger's efficiency (β_4)		85	%	$\beta_1, \beta_2, \beta_3 = 100\%$ [57] [60] [61]
power of L2 EV chargers (R_{kf})		11	kW	Average power of level 2 (L2) chargers at MSU and Michigan's public stations
Cost of building L2 EV charger (Φ_{kf})		9990	$/charger	Inquiry form energy authorities of Michigan
Average life of L2 EV chargers (Υ)		10	year	[62] [63]
Daily availability of charging (Γ)		24	hour	
Fuel Price (Fp_f)	Gasoline	3.0	$/Gal	Average fuel price in Michigan in 2020 [64]
	Diesel	3.3	$/Gal	
	Flex-fuel	3.3	$/Gal	
	Electricity	0.0923	$/kWh	University policy for the campus fleet
Societal emission cost (E_q)	HC	1.87	$/kg	Literature [65] [66]
	CO	0.068		
	NO_x	23.40		
	VOC	1.32		
	CO_2	0.11		
	PM_{10}	277		

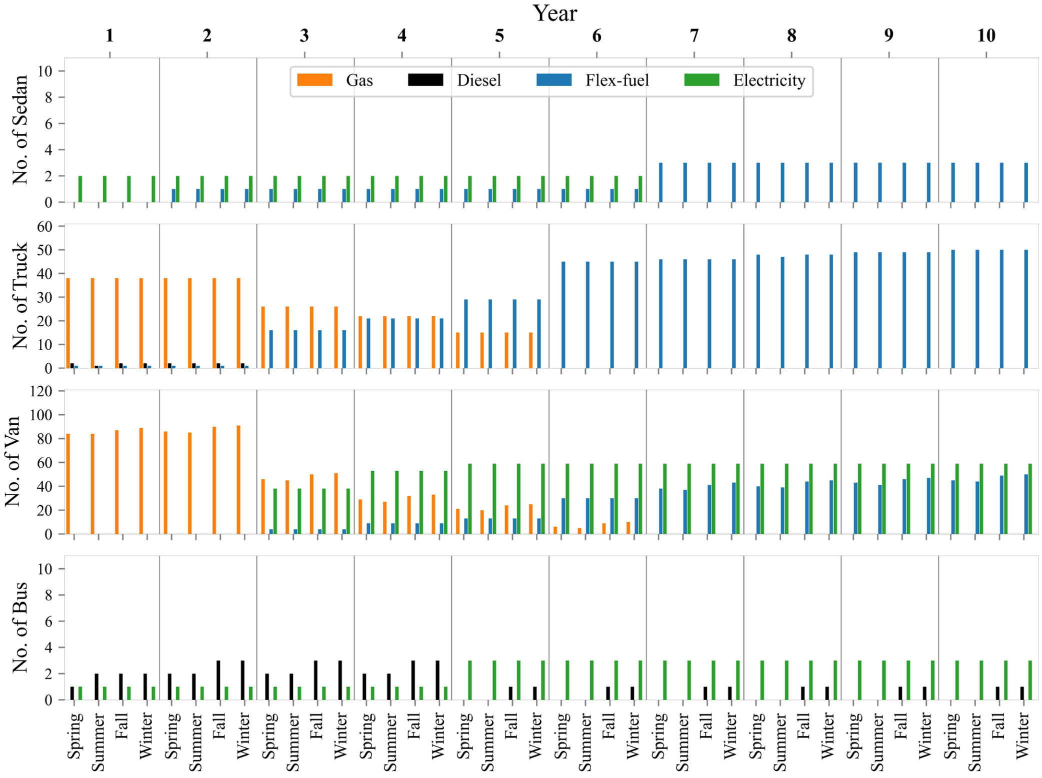
6.1. Analysis of Scenarios

This study categorizes operating scenarios into three categories: i) the benchmark scenario, representing the current fleet status based on collected or estimated data; ii) "decision-based" scenarios under the control of the fleet manager, such as determining available vehicle-fuel type combinations and the vehicle's storage cost; and iii) "policy-based" scenarios beyond the fleet manager's control, including factors like vehicle purchase price, societal emissions costs, and fuel prices fluctuations. This subsection explores how such variability may impact the results by going over five scenarios in addition to the benchmark case. To determine how sensitive the model is to the changes, one or more benchmark elements might be changed in each of the five situations. The decision variables and the objective function value under various scenarios—the model's outputs—will be thoroughly examined, presented, and compared to the benchmark at the end.

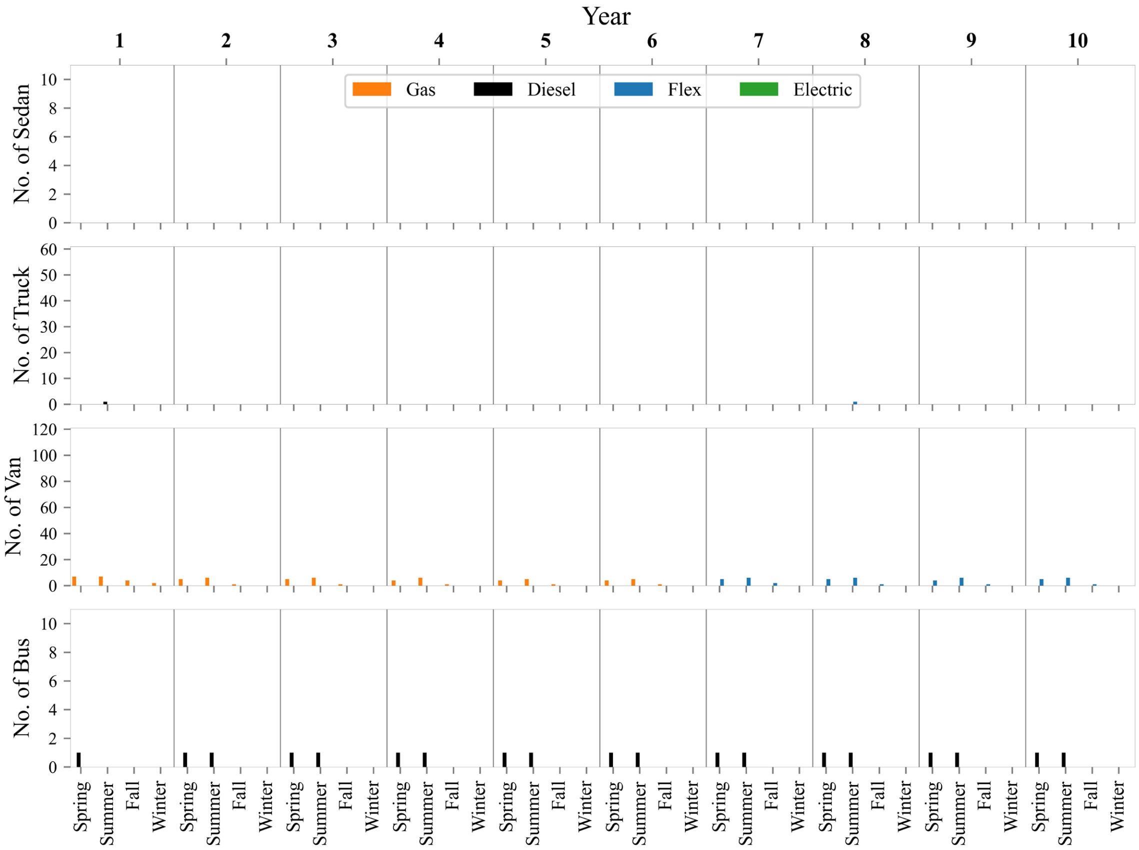
6.1.1. Benchmark Scenario (Scenario 1)

In the benchmark scenario (Scenario 1), all parameters are derived or estimated from the data collected on campus, maintaining the initial fleet status (status quo). Subsequent scenarios will be evaluated against this baseline for comparison.

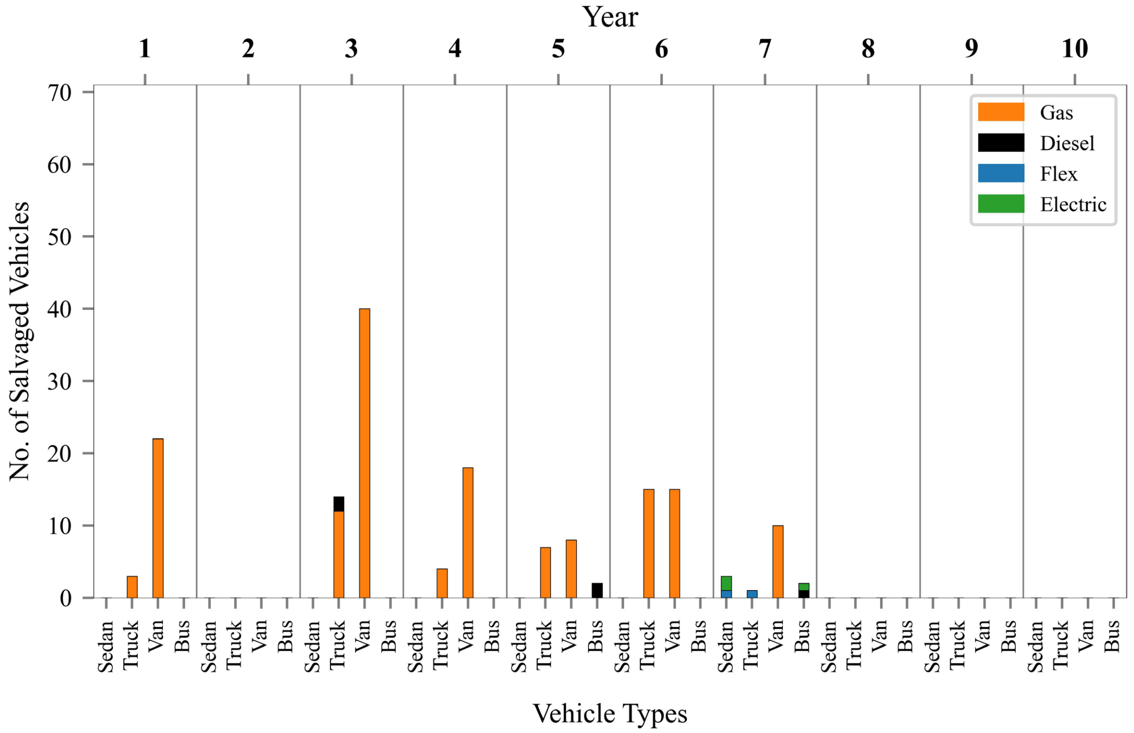
Figure 3(a) and Figure 3(b) present the optimum number and composition of in-service and stored vehicles, respectively, over the 10-year study horizon. Each subplot on each figure corresponds to a specific vehicle type with the color of bars expressing the fuel type. The top x-axis of the figures shows the years, and the lower x-axis displays the seasons. As shown in the figures, the overall fleet is moving toward AFVs over the years by salvaging the present G/DVs. This transition is more vivid when looking at Figure 3(c) and Figure 3(d) which illustrate the planned number of vehicles to be salvaged and purchased over the next decade, categorized by vehicle type on the x-axis and color-coded by fuel type. The purchasing and salvaging occur once a year, so these figures represent the annual totals rather than seasonal variations. These results not only demonstrate the seasonal optimal fleet composition but also outline the fleet management strategy (storage, salvage, or purchase) for the next ten years, classified by vehicle-fuel type.



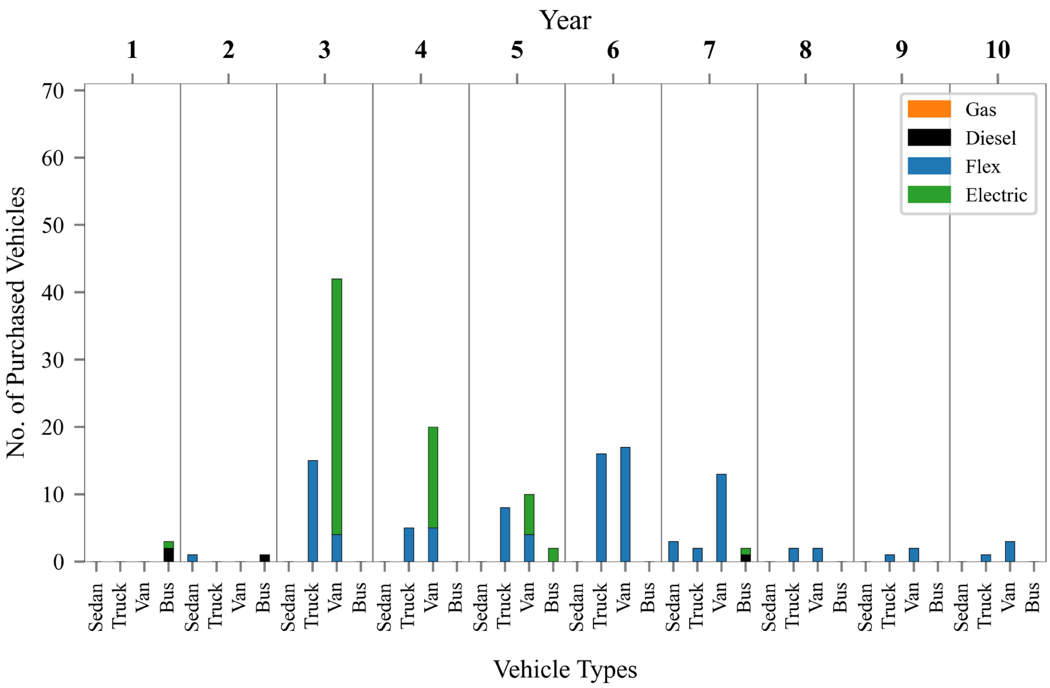
(a)


Year
1
2
3
4
5
6
7
8
9
10
Gas
Diesel
Flex
Electric
No. of Sedan
No. of Truck
No. of Van
No. of Bus
Spring
Summer
Fall
Winter

(b)


Year
1
2
3
4
5
6
7
8
9
10
Gas
Diesel
Flex
Electric
No. of Salvaged Vehicles
0
10
20
30
40
50
60
70
Sedan
Truck
Van
Bus
Vehicle Types

(c)



(d)

Figure 3. Annual and seasonal number of (a) in-service, (b) stored, (c) salvaged, and (d) purchased vehicles over the next decade in the benchmark scenario (scenario 1).

According to **Figure 3**, the optimal solution indicates an abundance of redundant vans and the lack of buses in the current fleet status. Thus, it is advisable to salvage some gasoline vans (G-vans) in the initial year to prevent additional costs in subsequent years. Also, some buses are added to the fleet in the first and second years to respond to the fleet's demand. Then during the third year, new flex-fuel trucks and electric vans are purchased to replace the outdated gasoline counterparts, using the money recovered from salvage.

For the cases of vans and trucks, there has been a discernible tendency over time toward their flex-fuel alternatives: most purchased vans and trucks tend to be flex-fuel by getting closer to the end of the study period. This tendency can be explained by the fact that flex-fuel cars have lower emissions and O&M costs than gasoline vans at a more affordable purchase price than electric ones. Although electric cars have fewer marginal costs, such as emissions, fuel, and O&M costs, the budget limitation does not allow gasoline trucks to be replaced by electric ones as fast as vans due to the greater purchase price of electric trucks compared to electric vans (**Table 2**). Also, since trucks do fewer tasks than vans, it is more advantageous to pay the limited money for the electric vans rather than trucks and go for the cheaper flex-fuel trucks, which are still more beneficial than gasoline ones.

Regarding the sedans, due to the type of work that IPF does, it requires a much smaller number of sedans than vans and trucks. The best course of action is for the addition of one electric sedan to the current fleet in the second year, and the continued use of the currently in-service electric sedans until year six (the maximum allowable age of previously presented sedans), when they will be replaced by brand-new flex-fuel sedans thereafter, which are a more economical alternative than the expensive E-sedans considering the budget limitation. The newly added flex-fuel ones would be in-service till the end of the horizon.

For buses, things are different, though. Over time, a mix of diesel and electric buses will be utilized over the horizon with a slight movement toward electric buses. Due to financial restrictions, diesel buses will continue to operate alongside electric ones. Compared to other vehicle types, electric buses are significantly more expensive. Therefore, rather than concentrating on the few electric buses with lower activity levels, it is more economical to spend the budget to replace other vehicle types with higher activity levels, which will result in fewer overall O&M, emissions, and fuel expenses. In conclusion, given the restricted budget, the fleet would gain more from replacing vans and trucks with their alternative AFVs than from replacing all diesel buses.

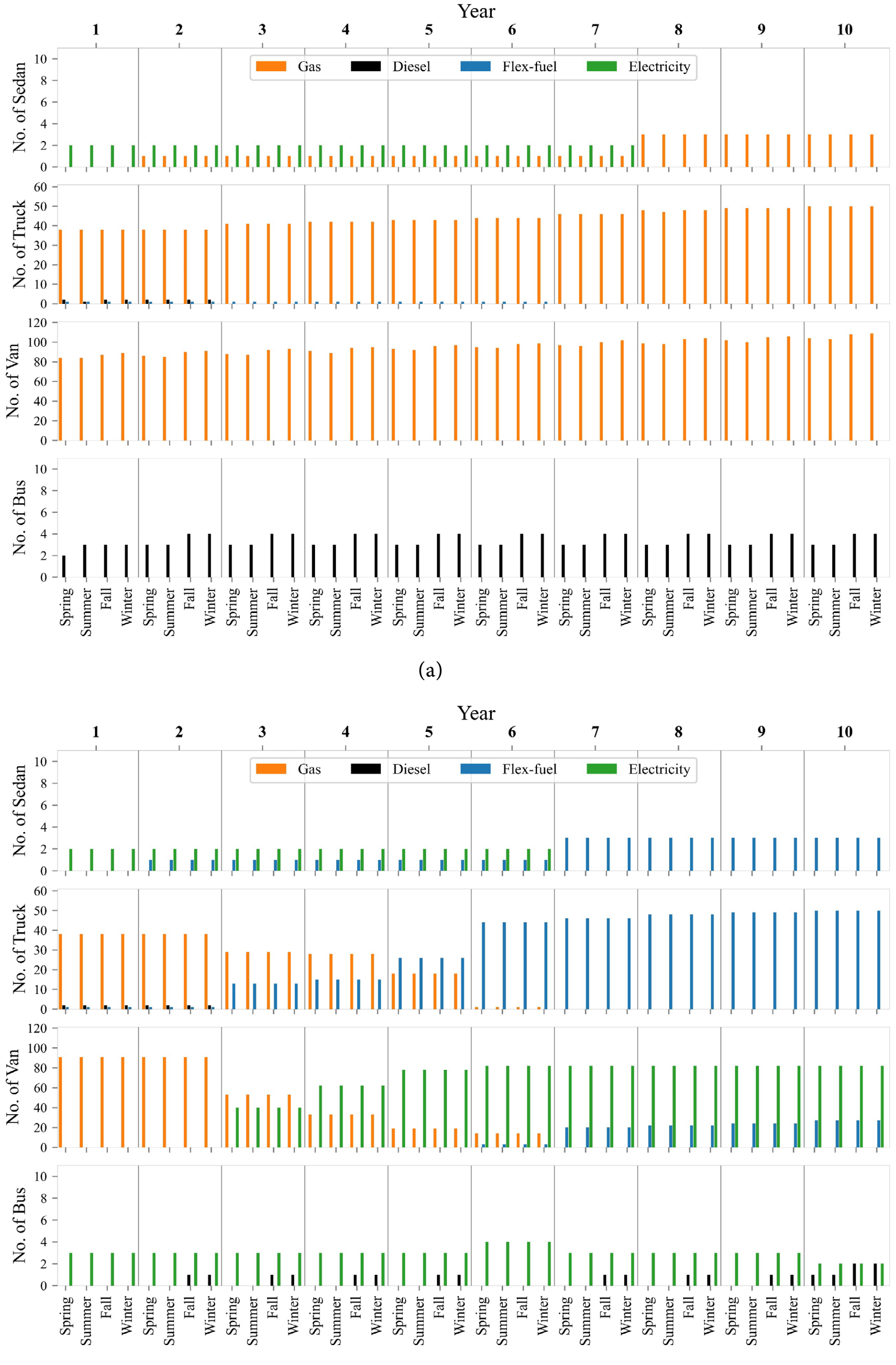
As depicted in **Figure 3(b)**, there are few stored vehicles in the fleet. The optimal solution recommends this to avoid additional costs associated with storing vehicles. While storage is free of charge in the benchmark scenario, keeping vehicles in storage incurs O&M costs (assumed to be 20% of the O&M cost of in-service vehicles in this study) plus depreciation even when they are not in use. Therefore, it is more advantageous to salvage unused vehicles instead of storing them and to reinvest the proceeds into renewing the fleet.

Finally, the growing annual number of in-service vehicles, primarily vans, and trucks, as indicated in **Figure 3(a)**, is a result of the annual campus's growing minimum required VMT. This study estimates an annual growth rate of 2.34% based on the rising trend in the number of employees at MSU between 2010 and 2019 [59]. The subsequent subsections will delve into the detailed discussion and comparison of the results obtained from running various scenarios with the benchmark scenario.

6.1.2. Decision-Based Scenarios (Scenarios 2 and 3)

This study introduces two scenarios within this category: the "no-AFV" scenario (scenario 2) and the "storage cost" scenario (scenario 3). In scenario 2, all parameters are identical to the benchmark scenario except for the absence of AFVs; no new AFVs are added to the fleet. In scenario 3, the cost of storing vehicles is considered an extra expense to the fleet, which was not the case in the benchmark scenario. Vehicles in storage remain there for the entire season and incur costs of $4000 per season per bus and $1000 per season per vehicle for all other vehicle types. **Figure 4** depicts the optimal number of in-service fleets resulting from the execution of scenarios 2 and 3.

According to **Figure 4(a)**, it is evident that the majority of in-service vehicles in scenario 2 run on fossil fuels, with the exception of a few electric sedans and flex-fuel trucks in the initial years that are the fleet's existing vehicles from the outset. Also, comparing **Figure 3(a)** and **Figure 4(a)**, the AFVs are the superior vehicles in the best-case scenario, highlighting their advantages and significance for the fleet. Later in the cost analysis segment, a thorough cost comparison between the scenarios is presented.



(a)

(b)

Figure 4. Seasonal number of in-service vehicles over the next decade under (a) no-AFV scenario (scenario 2), and (b) storage cost scenario (scenario 3).

The "storage cost" scenario (scenario 3) considers a charge for vehicle storage. The optimal solution identified in scenario 3 recommends reducing the number of vehicles purchased and salvaged while extending the use of older vehicles. By maintaining older vehicles, the solution balances operational needs with financial constraints, optimizing resource allocation and minimizing unnecessary expenditures on storage. Nonetheless, there is little discernible difference between the optimal outcomes of scenarios 1 and 3, suggesting that storage costs have little effect on asset management. **Figure 3(b)** shows a few numbers of stored vehicles expressing the insignificant role of storage cost in the total fleet costs. The seasonal number of in-service vehicles in scenario 3 is also shown in **Figure 4(b)**.

In the benchmark scenario, the optimum solution suggests buying cheaper D-buses and storing them in the free-charge storages throughout the spring and summer months when there is less demand for buses. Even though D-buses are more expensive to operate, emit, and fuel than their electric counterpart, it is still more economical to store them during off-seasons rather than buying pricey E-buses. The optimum solution of scenario 3, however, suggests buying the costlier electric buses and keeping them in operation for the entire year in order to minimize the significant storage expenses when the cost of storage is high. In this case, the required demand for buses will be shared over more in-service buses, *i.e.*, the buses will have more idle/off time. The same logic leads to having more electric vans in service in the last four years when operating scenario 3.

6.1.3. Policy-Based Scenarios (Scenarios 4-6)

There are three different scenarios in this category: the "affordable EVs" scenario (scenario 4), the "magnified societal cost of emission" (scenario 5), and the "fossil fuels price surge" (scenario 6). In scenario 4, the purchase prices of new EVs are assumed to decrease by 15%. This policy accounts for subsidizing EVs or economies of scale that encourage EV adoption. In scenario 5, the societal emission cost is increased fivefold to emphasize the adverse impacts of emissions. This situation could be the case when air quality is among the main concerns, making policymakers prioritize emission reduction regardless of other associated costs. In scenario 6, the fossil fuel prices are presumed to increase by 100% which is expected to enhance the desirability of EVs. **Figure 5** illustrates the optimal composition of in-service and purchased vehicles resulting from the execution of scenario 4, which assumes subsidized EVs.

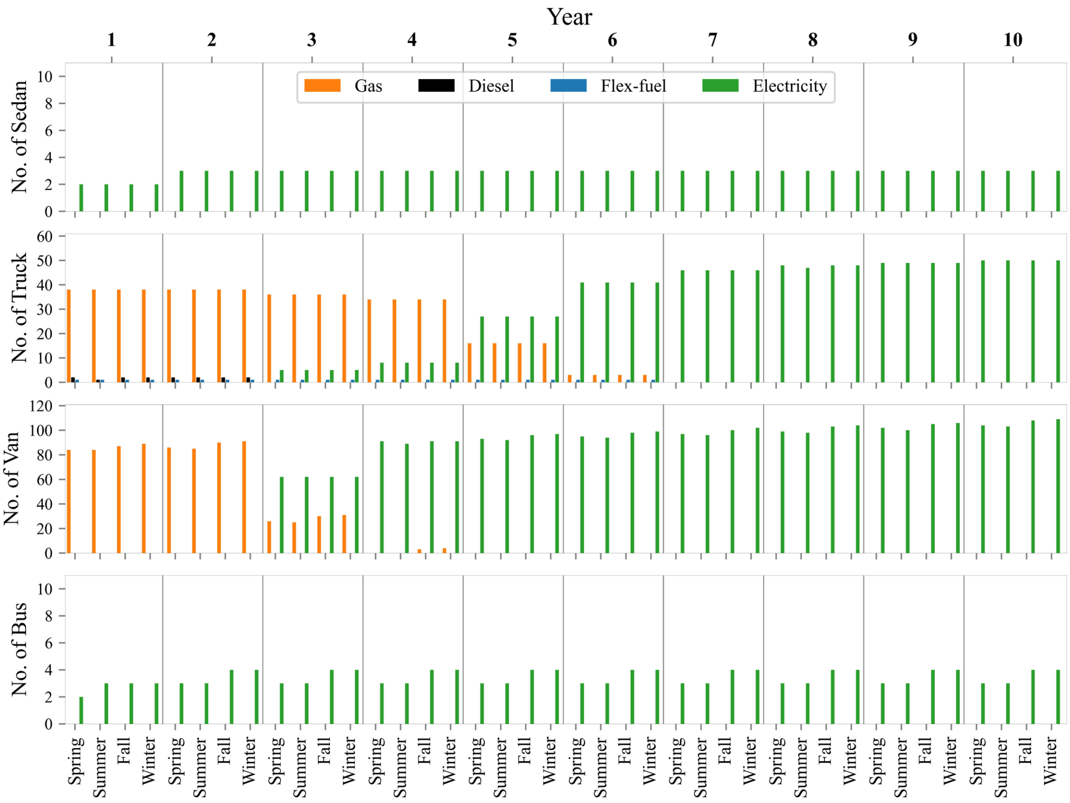
In this scenario, nearly all newly added vehicles would be EVs (**Figure 5(b)**). When comparing **Figure 3(d)** and **Figure 5(b)**, it is evident that EVs outperform flex-fuel vehicles in terms of new vehicle purchases in scenario 4. This increase in the number of purchased EVs suggests their operational advantages over the other vehicle types even flex-fuel; the main significant factor causing non-EVs in the fleet is EV's higher prices which could be alleviated over time.

The magnified societal cost of emission scenario (scenario 5) involves assuming a fivefold increase in monetary emission costs compared to the benchmark scenario. **Figure 6(a)** shows the composition of in-service vehicles resulting from the implementation of scenario 5. It illustrates the considerable effect of emissions on the overall system cost, in addition to the noteworthy contribution of EVs towards emissions reduction.

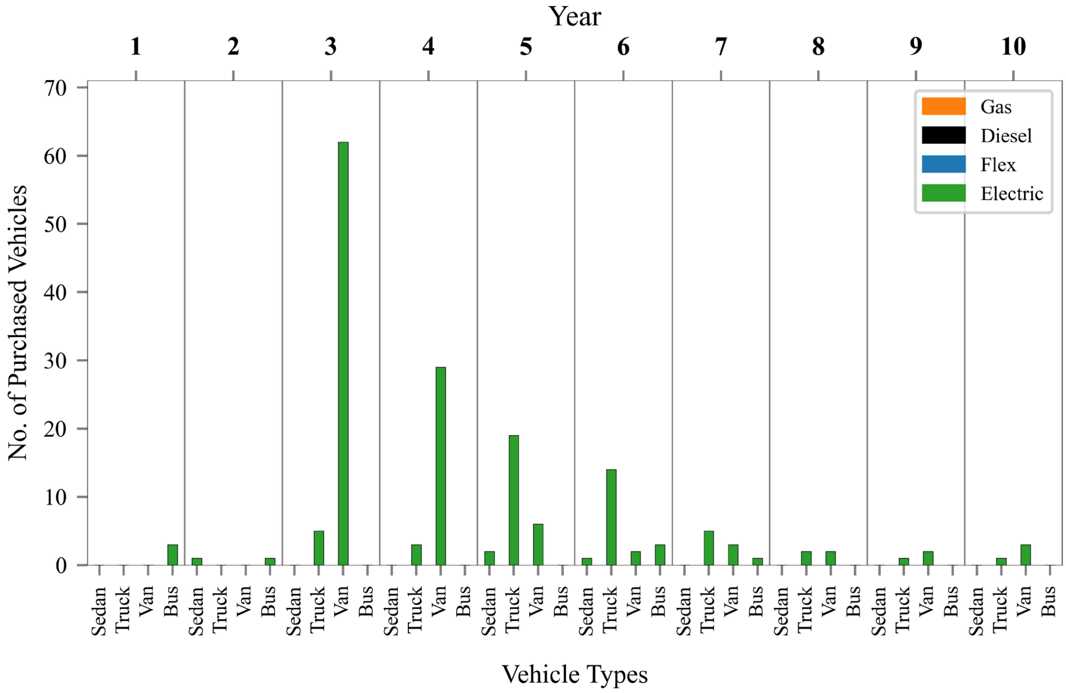
A comparison between **Figure 5(a)** and **Figure 6(a)** reveals the fact that the number of in-service EVs in scenario 5 exceeds even that of scenario 4, which assumes affordable EV prices. Therefore, the fleet manager's decision is heavily influenced by the emission costs or taxes imposed by policymakers. It can be inferred that moving towards EVs would be amongst the most effective approaches to minimize emissions if budget constraint allows.

The final operational scenario explored in this study is the fossil fuel cost surge scenario (scenario 6) where the prices of gasoline, diesel, and flex-fuel are assumed to be doubled. Such a scenario could occur (and has occurred before) due to an unexpected rise in oil prices, which is beyond the control of fleet managers. **Figure 6(b)** depicts the number of in-service vehicles by implementing scenario 6.

The optimum solution in this scenario is relatively similar to the benchmark scenario but with a more widespread utilization of EVs. The most considerable change toward EVs is seen in the buses because of the significant portion of fuel cost in buses compared to other vehicle types. It is worth investing in more expensive E-buses to avoid the huge two-fold cost of diesel. Therefore, the presence of more in-service EVs compared to the benchmark scenario emphasizes the EVs' superiority in the cases where the fleet experiences an increase in operational cost.

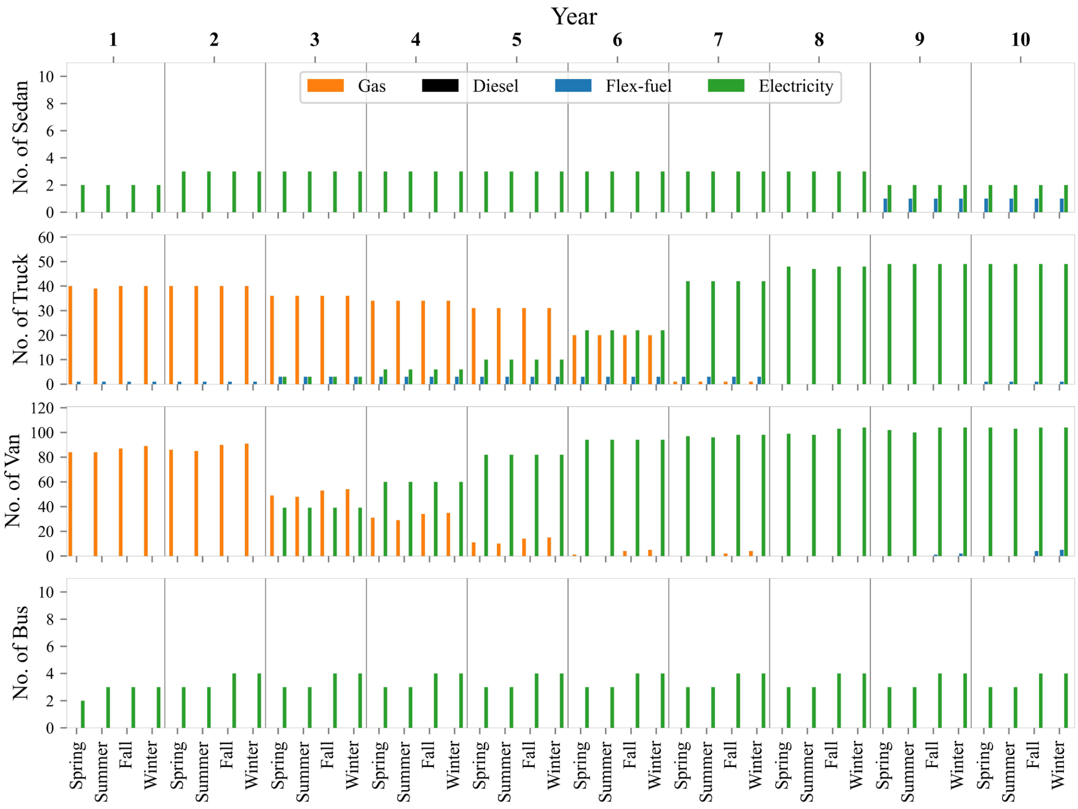


(a)

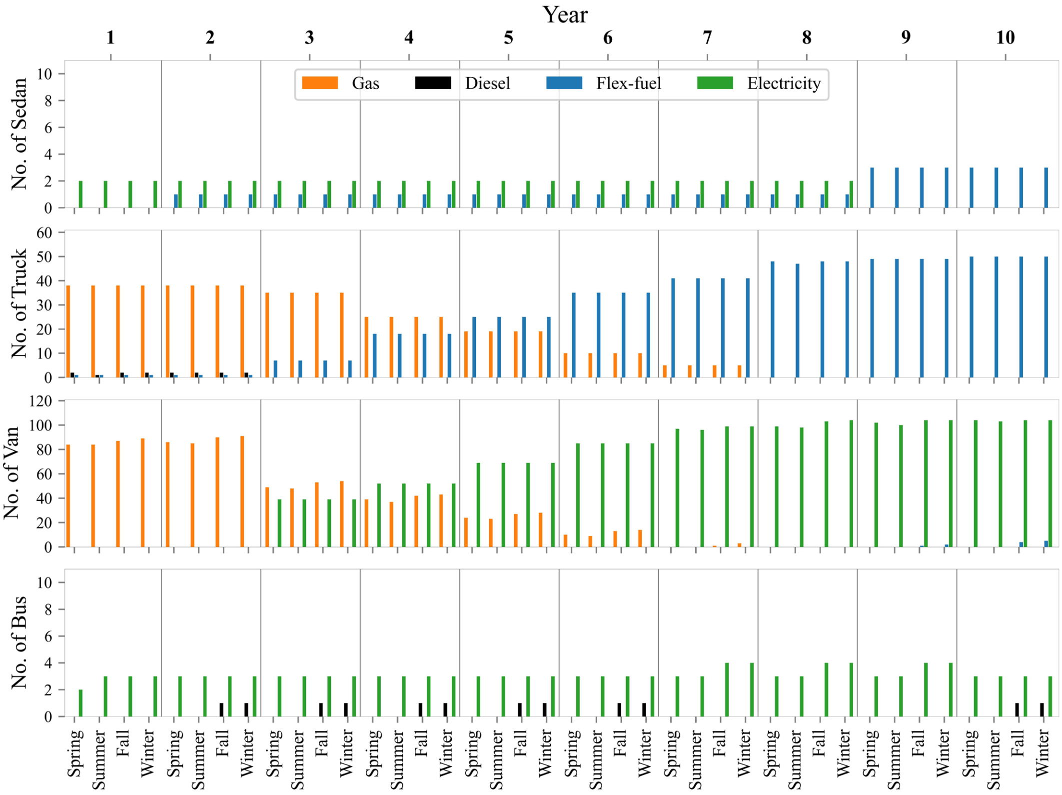


(b)

Figure 5. Annual and seasonal number of (a) in-service, and (b) purchased vehicles in the next decade in affordable EVs scenario (scenario 4).



(a)



(b)

Figure 6. Seasonal number of in-service vehicles in (a) magnified societal cost of emission scenario (scenario 5), and (b) fossil fuel cost surge (scenario 6).

6.2. Costs-Benefit Analysis

This section discusses a cost-benefit analysis of the scenarios. The previous section detailed changes in fleet under different circumstances. This section evaluates the costs of all scenarios and the advantages of including AFVs. Figure 7 illustrates the annual cost breakdown for all six scenarios.

Among scenarios, scenario 4, which features affordable EVs, has the lowest total cost. If EV purchase prices were to decrease by 15% in the future, the annual total cost, emission cost, and fuel cost could be reduced by 14%, 67%, and 33%, respectively. This shows that a 15% drop in EV purchase price significantly reduces the total fleet cost. On the other hand, an increase in the storage costs (scenario 3) causes a minimal change in the total costs. In scenarios 5 and 6, increased emissions and fuel costs lead to a higher total cost. However, these increases are insignificant, as the optimal solution recommends the optimal composition to minimize the costs in response to policy changes. Thus, to see the effects of AFVs on fleet cost reduction, the following analysis examines the optimal solution for each scenario, both with and without the presence of AFVs.

Based on Figure 7, the comparison of scenario 2 (No-AFVs) with other scenarios reveals that all scenarios, except scenario 4, experience reductions in emissions, fuel, and total costs when AFVs are integrated into the fleet (Scenario 4 is excluded from this comparison since it is designed based off of the decrease in EV purchase price, *i.e.*, the existence of EVs is necessary to interpret this scenario.). The most significant savings from employing AFVs are observed in scenarios 5 and 6. Although vehicle purchase costs in scenarios 5 and 6 increase by 18% and 8%, respectively, annual total costs, emission costs, and fuel costs decrease by 27%, 80%, and 50% in scenario 5, and by 13%, 60%, and 47% in scenario 6. The rise in vehicle purchase costs and salvage revenue in these two scenarios is because of the purchasing and salvaging of more expensive AFVs to mitigate higher emissions and fuel costs. Incorporating AFVs into the optimal solutions for scenarios 1 and 3 also results in reductions in total costs, emissions, and fuel consumption, although these reductions are not as substantial as those in scenarios 5 and 6. Therefore, while integrating AFVs into the optimal solution consistently yields a cleaner, more cost-effective, and sustainable fleet, their inclusion is particularly advantageous when fuel prices or societal cost of emissions are elevated.

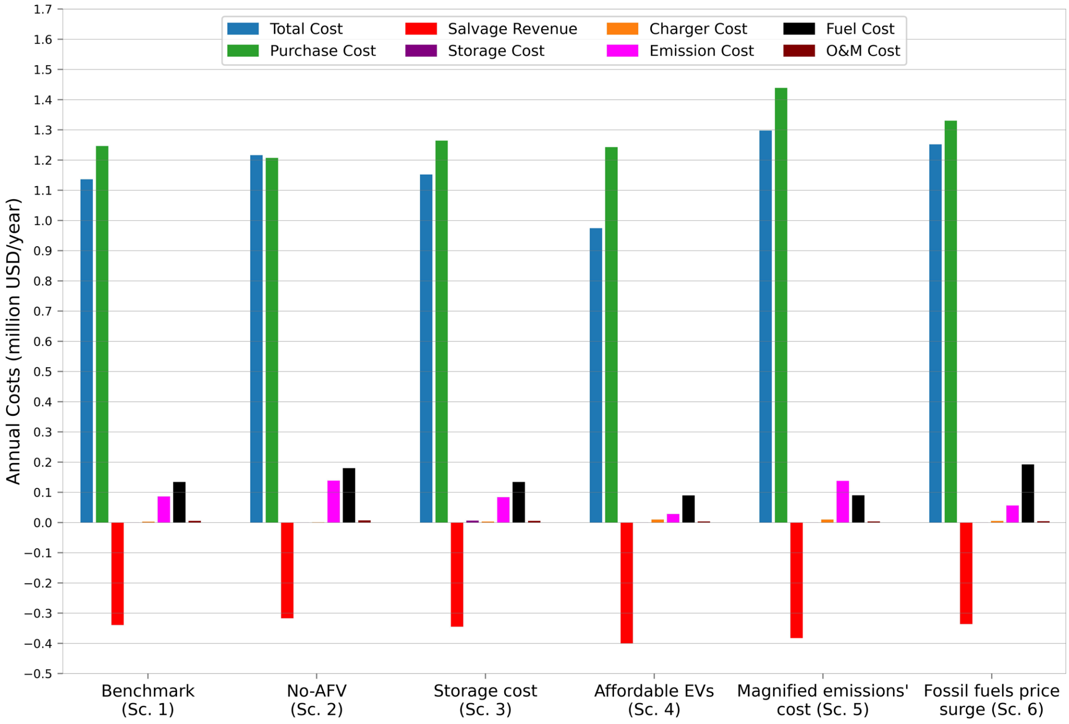
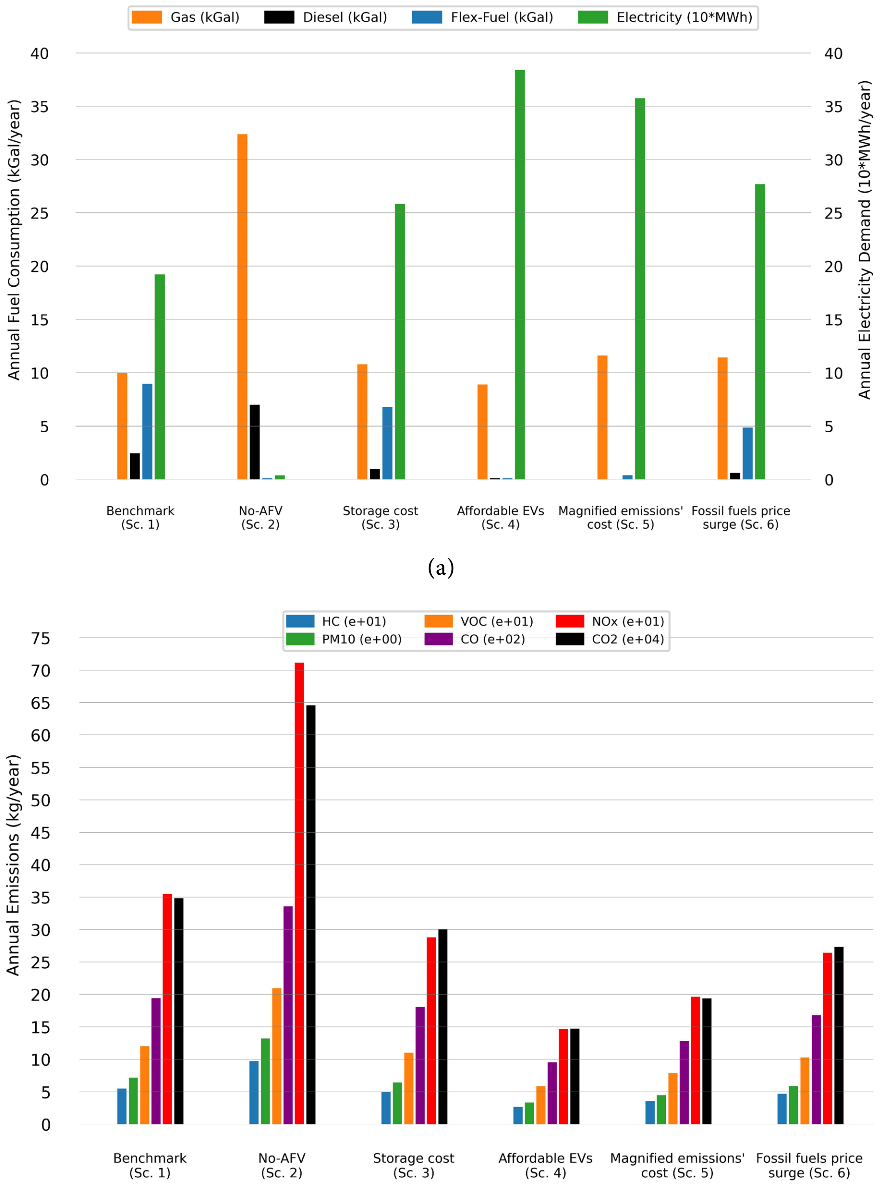


Figure 7. Annual cost breakdown across all implementing scenarios.

Since the optimization framework monetizes emissions and fuel consumption to minimize total costs, the variations in them across scenarios cannot be directly observed in Figure 7. Therefore, Figure 8(a) and Figure 8(b) illustrate fuel consumption and emissions levels, respectively, for all six scenarios. In Figure 8(a), gasoline, diesel, and flex-fuel consumptions are measured in kilogallons per year (left y-axis), while electricity demand is shown in units of 10× megawatt-hours per year (right y-axis). All emissions are scaled in Figure 8(b) to ensure they are visible within a chart.



(a)

(b)

Figure 8. Annual amount of (a) fuels consumption, and (b) emission across all scenarios.

A comparison of **Figure 8(a)** and **Figure 8(b)** reveals that higher electricity usage in the fleet corresponds to lower emissions across the scenarios. In Scenario 2 (No-AFV), where gasoline and diesel are the primary fuels, emissions are significantly higher. In contrast, under Scenarios 4 and 5, which include subsidized EV prices and increased emissions penalties, the optimization model recommends a shift toward predominantly EVs. This results in the lowest fossil fuel consumption and emissions among all scenarios. Thus, in response to changes in policy or decision-making, the optimization model not only minimizes total fleet costs but also promotes the most sustainable fleet operations by reducing fuel consumption and emissions. Magnified Emissions' Cost (Scenario 5) shows the importance of policies targeting emissions reductions, effectively minimizing pollutants while balancing costs.

7. Conclusions

This study introduces a mathematical framework to identify a sustainable and cost-effective strategy for fleet management by minimizing both expenses and tailpipe emissions. Due to the various fleet configurations—such as vehicle count, type, age, as well as travel demand, and environmental factors—determining an optimal management strategy can be complicated. To address this variability and ensure practical application, the study incorporates data collected from the MSU fleet along with vehicle emission rates simulated by the EPA's MOVES model, including idle, start, and running emissions. Using this data, multiple linear regression models (which estimate fleet emissions under various conditions) are integrated into the framework's MILP optimization module. These emission estimates serve as inputs for the optimization process.

The proposed framework aims to minimize two main costs: monetary and societal costs. In this study, monetary costs include the costs of vehicle purchase and storage, fuel, O&M, and refueling station construction, as well as the revenue from salvage vehicles. Tailpipe emissions are monetized using societal cost conversion ratios. The model's output determines the optimal seasonal allocation of in-service, stored, purchased, and salvaged vehicles, along with the necessary refueling infrastructure over a specified timeframe. To assess the performance of the proposed framework, various scenarios are analyzed, where fleet managers or policymakers modify the problem's parameters. The results of these scenarios yield key insights, which are summarized as follows:

- The proposed approach highlights inefficiencies in fleet composition, such as redundant and underutilized vehicles (primarily vans), suggesting opportunities to streamline operations and optimize resource allocation. This insight provides a clear path for improving fleet utilization and reducing unnecessary expenditures.
- Across all scenarios, AFVs emerge as the dominant choice due to their higher efficiency and lower costs. The preference for flex-fuel vehicles in budget-constrained scenarios highlights their affordability advantage over EVs. This finding underscores the importance of aligning fleet strategies with financial realities, particularly for organizations with limited budgets.
- Integrating AFVs, especially EVs, into the fleet reduces overall costs and improves metrics such as emissions and fuel consumption, particularly in scenarios with higher emissions or fossil fuel costs. In other scenarios, while the total cost reduction may be less significant, emissions and fuel costs still decline considerably.
- The study finds that due to the higher price of electric trucks, fleets benefit more from incorporating flex-fuel trucks and using the cost savings to invest in more efficient, low-emission vehicles like E-vans and E-buses. This strategic

allocation maximizes fleet efficiency and reduces emissions while managing budget constraints.

- The Affordable EV scenario achieves the lowest fossil fuel consumption and emissions compared to other scenarios, such as the fossil fuel price surge and magnified emissions cost scenarios. This underscores the transformative potential of reducing EV purchase prices and highlights the critical role of EVs in cost and emissions reduction strategies.
- High EV purchase prices and limited annual budgets are identified as key barriers to transitioning to EVs. By addressing these constraints, such as through subsidies or innovative financing mechanisms, the transition can be accelerated, enabling fleets to reap the benefits of electrification sooner.
- In the studied fleet, factors like annual budgets, EV purchase prices, and the societal cost of emissions are shown to have a significant influence on fleet composition and operations. By contrast, storage, fuel, and O&M costs have a more modest impact, suggesting that policymakers and planners should focus their efforts on addressing the more critical factors.

The study equips fleet managers with actionable strategies to improve efficiency, reduce costs, and meet emissions reduction targets without compromising operations. These findings can guide the development of cost-efficient and sustainable fleet management plans tailored to varying financial and operational constraints, and provide a compelling case for incentives to reduce EV purchase prices and address emissions costs, facilitating a smoother transition to cleaner transportation systems. Overall, this study serves as a roadmap for decision-makers seeking to achieve a balanced, efficient, and sustainable fleet configuration. Its findings provide a strong foundation for advancing transportation electrification while addressing the economic and environmental challenges of fleet operations. The insights highlight areas for further research, such as optimizing vehicle type allocation and evaluating the long-term impacts of transitioning to EVs on cost and emissions.

Due to the limited available data, this study only considers on-road vehicles; however, the proposed mathematical model has the capability to consider unconventional and non-road equipment, e.g., tractors, mowers, and snowplows. Other types of AFVs, such as hydrogen fuel cell technologies, could be considered in the alternative vehicles in the case of data availability. Also, the current paper considered only the tail-pipe exhausted emissions; future research may extend the scope of this study by including life cycle emissions. Also, as different societies would have different external societal emissions costs, more research may be needed to establish a robust tool to determine each society's external emissions costs.

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Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work, the authors used AI-assisted tools to refine editorial flow. The authors subsequently reviewed and edited the content as needed and took full responsibility for the content of the publication. Study design and results are purely independent and novel works without AI assistances.

CRediT Authorship Contribution Statement

All authors contributed to all aspects of the study, from conception and design to analysis and interpretation of results and manuscript preparation. All authors reviewed the results and approved the final version of the manuscript. The authors do not have any conflicts of interest to declare.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Regression models to estimate the emission rates of the vehicles.

Running Emission Model's Coefficients

Emission Type	Vehicle Type	Constant Value	Age (year)	Speed (mph)	Temperature (F)	Fuel coefficient (=0 if diesel)
HC	Sedan	0.045	0.003	−0.003	6.45E−05	−0.010
	Truck	0.278	0.023	−0.033	0	0.261
	Van	0.092	0.008	−0.008	8.30E−05	−0.041
	Bus	0.200	0.031	−0.030	5.00E−04	0
CO	Sedan	2.011	0.357	−0.223	1.10E−02	0.027
	Truck	2.601	−0.144	0.054	1.00E−03	19.308
	Van	1.496	0.212	−0.190	9.00E−03	1.350
	Bus	−10.100	1.008	0.854	2.50E−03	0
NO_x	Sedan	0.031	0.005	0	−3.72E−05	−0.015
	Truck	8.772	0.375	−0.640	−9.50E−03	−5.063
	Van	1.509	0.131	−0.120	2.00E−03	−1.187
	Bus	7.059	0.240	−0.412	−6.50E−03	0
VOC	Sedan	0.042	0.002	−0.003	4.55E−05	−0.016
	Truck	0.191	0.014	−0.023	0	0.271
	Van	0.060	0.005	−0.005	5.38E−05	−0.025
	Bus	0.127	0.023	−0.022	0	0
CO_2	Sedan	783	20.096	−52.919	4.40E−01	−14.720
	Truck	3130	13.831	−168.190	1.00E−03	33.020
	Van	1102	31.280	−67.878	6.01E−01	−161.228
	Bus	3252	7.568	−167.654	2.00E−03	0
$PM_{2.5}$	Sedan	2.00E−03	3.78E−05	0	1.01E−06	0
	Truck	2.10E−02	3.00E−03	−2.50E−03	7.46E−06	−8.00E−03
	Van	5.00E−03	1.00E−03	0	1.35E−06	−4.00E−03
	Bus	3.15E−02	4.00E−03	−3.50E−03	1.47E−05	0

Idle Emission Model's Coefficients

Emission Type	Vehicle Type	Constant Value	Age (year)	Temperature (F)	Fuel Coefficient (=0 if diesel)
HC	Sedan	0.088	0.014	7.93E−05	−0.057
	Truck	0.456	0.106	0	−0.058
	Van	0.369	0.079	0	−0.663
	Bus	0.310	0.122	0	0
CO	Sedan	0.287	0.182	1.00E−03	0.009
	Truck	10.627	0.644	0	4.124
	Van	6.054	0.623	5.00E−03	−7.917
	Bus	10.722	0.355	0	0

Continued

NO_x	Sedan	−0.027	0.010	0.001	−0.032
	Truck	30.077	0.946	−0.097	−10.767
	Van	1.268	1.582	0.157	−17.750
	Bus	29.171	1.325	−0.119	0
VOC	Sedan	0.095	0.009	6.21E−05	−0.078
	Truck	0.264	0.062	0	0.081
	Van	0.238	0.045	0	−0.393
	Bus	0.210	0.065	0	0
CO_2	Sedan	1949	108.026	7.717	31.466
	Truck	6569	63.090	0	997.226
	Van	2965	182.408	10.325	−799.581
	Bus	6951	115.985	0	0
$PM_{2.5}$	Sedan	8.00E−03	0	0	1.00E−03
	Truck	−6.50E−03	1.75E−02	0	−1.90E−02
	Van	−9.09E−05	1.00E−02	0	−3.90E−02
	Bus	−2.90E−02	2.85E−02	0	0

Cold Start Emission Model's Coefficients*

Emission Type	Vehicle Type	Constant Value	Age (year)	Temperature (F)	Fuel Coefficient (=0 if diesel)
HC	Sedan	1.838	0.083	−0.022	−0.325
	Truck	1.642	0	−0.021	0
	Van	1.578	0.053	−0.021	−0.055
	Bus	1.610	0	−0.021	0
CO	Sedan	6.352	0.808	−0.102	2.353
	Truck	6.204	0.019	−0.022	0
	Van	4.060	0.558	−0.088	4.809
	Bus	8.529	4.17E−06	−0.028	0
NO_x	Sedan	0.177	0.037	−0.002	0.122
	Truck	0.847	−0.004	−0.002	0
	Van	0.933	0.026	−0.002	−0.557
	Bus	0.026	0	−3.24E−05	0
VOC	Sedan	1.115	0.063	−0.016	0.135
	Truck	0.891	0	−0.012	0
	Van	0.956	0.045	−0.015	0.248
	Bus	0.874	0	−0.011	0
CO_2	Sedan	224	3.438	−2.410	22.079
	Truck	249	1.207	−2.375	0
	Van	273	2.488	−2.764	19.377
	Bus	248	1.165	−2.332	0

Continued

$PM_{2.5}$	Sedan	1.10E−02	1.00E−03	0	8.00E−03
	Truck	2.50E−03	0	−1.64E−05	0
	Van	1.40E−02	1.00E−03	0	1.40E−02
	Bus	2.00E−03	0	−1.50E−05	0

*Warm start conversion coefficients for HC, CO, NO_x, VOC, CO_2, and $PM_{2.5}$ are 0.21, 0.77, 1.83, 1.00, 0.86, and 1.00, respectively. These coefficients convert cold start to warm start emission rate.