Achieving Operational Excellence by Ensuring Optimization of Electric Vehicles (EV) vs. Internal Combustion Engines (ICE) in Fleet Vehicles

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ABSTRACT

Recognition of the need to reduce greenhouse gases and carbon footprints has led us to investigate what actions are available to companies that rely on fleets for business purposes. A strong alignment of the collective contributions of all actors, i.e. nations, firms, and individuals, is needed to limit the annual global warming to below 2 degrees Celsius. Our sponsor Company, a global corporation with a global fleet of over 25,000 vehicles primarily comprised of Internal Combustion Engine (ICE) vehicles, is committed to significantly decarbonizing its fleet by 2030 to mitigate its CO_2 emissions footprint and contribute to global warming reduction. This goal is to be achieved while maintaining operational excellence and within the Company's economic and operational constraints. To this end, our study first identified optimal locations for transitioning fleets from ICEs to Electric Vehicles (EVs), considering the geographical scope of the 50 US states plus the District of Columbia. Using Machine Learning Clustering techniques, we included endogenous factors (age of fleet, number of vehicles) and exogenous factors (laws and incentives, temperature, gas price, and electricity price) to identify how to rank states according to their impact. Then we used a logistic growth function with a growth rate factor derived from 5 metrics to model the timing and strategy of EV implementation: Total Cost of Ownership (TCO), driving range, refueling, CO_2 emissions, and value-perception. We found that the adoption of EVs in a global corporation with a significantly large fleet is equally dependent on both endogenous and exogenous factors. Furthermore, to reap optimal benefits, the number of EVs in the Company's fleet mix should be gradually increased over the target period. Combining these two approaches allows the Company to maintain control over operational performance objectives and predict future TCO and decarbonization implications. The model's applicability extends beyond the studied region to other geographical, political, and economic contexts, such as Europe or East Asia.

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To India, my home, the source of inspiration and answers for many.

And to UAE, I am immensely grateful:
عملي في دولة الإمارات العربية المتحدة ألهمني لأحظى بهذه الفرصة الاستثنائية لأحقق احد طموحاتي المستقبلية
... شكرا دبي ... أنا ممتن للغاية
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I would like to express my deepest gratitude to my late father, Celestin Kalumire Kabuha, who instilled in us, his children, the seeds of determination from our early years, teaching us that willpower can conquer even the highest mountains. I also extend my heartfelt appreciation to my children: Ruben, Nathan, and Benjamin R., for their unwavering love, support, and understanding throughout the completion of this work. Your patience, encouragement, and understanding have been a constant source of strength for me during this challenging journey. Your smiles and laughter have illuminated even the darkest days. I am profoundly grateful for your role as my motivation and joy. This achievement is as much yours as it is mine.

Jospin K. Mubaki

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1 INTRODUCTION

1.1 Motivation

One of the key takeaways of the latest United Nations 27th Conference of the Parties (COP27, 2022), which took place in Egypt in November 2022, was the statement made by the Intergovernmental Panel on Climate Change (IPCC): "To keep warming to approximately 1.5°C, Global Greenhouse Gas (GHG) emissions must reach their highest point no later than 2025 and then decrease by 43% by 2030 (Five Key Takeaways from COP27, 2022). Similarly, participating nations in the previous year's Conference of the Parties (COP26) held in Scotland in November 2021 adopted a climate pact that included commitments from countries to limit global warming to well below 2 degrees Celsius and strive for 1.5 degrees Celsius (Key Outcomes from COP26, 2021).

The sixth Assessment Report (AR6) of the IPCC, published in March 2023, states that the global net anthropogenic GHG emissions have been estimated to be 59 ± 6.6 $GtCO_2$-eq9 in 2019, about 12% (6.5 $GtCO_2$-eq) higher than in 2010 and 54% (21 $GtCO_2$-eq) higher than in 1990, with the largest share and growth in gross GHG emissions occurring in CO_2 from fossil fuels combustion and industrial processes (CO_2-FFI). It further reveals that the average annual GHG emissions during 2010–2019 were higher than in any previous decade on record, while the rate of growth between 2010 and 2019 (1.3% yr-1) was lower than that between 2000 and 2009 (2.1% yr-1) (Synthesis Report, IPCC 2023).

To achieve the IPCC 43% GHG reduction goal by 2030, many countries are implementing stricter emission regulations, putting pressure and restrictions on the use of fossil fuel-powered vehicles. Moreover, many countries and cities are now providing policy incentives, grants, or tax credits, and feebates to boost and accelerate the switch from fuel-powered vehicles to electric vehicles (Brand, et al. 2013).

Conscious of the global warming impact on our planet and United States (US) Government's environmental programs like the Inflation Reduction Act (IRA), our partner Company (hereinafter referred to as 'Company') has developed an Environmental, Social, and Governance (ESG) strategy aiming at promoting responsible business practices through a culture of integrity and accountable leadership. One of the areas the company focuses its ESG Strategy is the promotion of environmental best practices and sustainability, essentially nurturing the view that healthy people and communities require a healthy environment to live in (ESG Strategy, 2023). To implement their strategy, the Company has set up two goals: (1), To achieve carbon neutrality for its operations by 2030, going beyond their science-based target to reduce absolute Scope 1 and 2 emissions by 60% from their 2016 levels, (2) By 2030, to reduce their absolute scope 3 upstream value chain emissions 20% from 2016 levels (ESG Strategy, 2023).

Studies have demonstrated that the transportation sector is one of the major contributors to global GHG emissions (OECD/ITF, 2010). For instance, the World Resources Institute's (WRI) Climate Watch attributes 16.2% of the global GHG emissions to the transport sector alone, through the combustion of fossil fuel emissions by automotive, ships, and aircraft engines.

Hence, the Company is committed to mitigating climate change by decarbonizing its fleet operations, and specifically by seeking ways to adapt its business to reduce its fleet's carbon footprint and leverage emerging technologies. Currently, the Company's global fleet size consists of over 25,000 units operating in 60 countries, with a mix of approximately 87% of fuel-powered vehicles and 13% of electrical battery-powered vehicles. It should also be noted that the Company owns 80% of its fleet and leases the balance 20%, (Company fleet reimagination Laboratory Output, June 2023). The entire US fleet is fuel powered. Thus, the Company has decided to transform and progressively transition to a more sustainable fleet, within the study region of the US.

The Company has formed a focus group that carried out a preliminary assessment through meetings, interviews of managers and staff, and through analysis of Company data, of the fleet transition potential. The focus group further assessed a few exogenous factors such as tax incentives and recent labor policies and laws; it also considered the development of new renewable energy technologies. Based on the findings of these preliminary assessments, the Company noted potential opportunities to undertake progressive electrification of its fleet and other major efforts such as the adoption of mobility as a service (MaaS) in its operations, with the aim to reduce GHG emissions by 30% by the year 2030.

1.2 Problem Statement and Research Questions

As part of their focus on fleet electrification, the Company intends to transition to Electric Vehicles (EV) from Internal Combustion Engine (ICE) vehicles in phases. The Company also intends to leverage emerging technologies and obtain preliminary information on various such technologies and their nuances. Taking an industry perspective, the Company desires to understand the trade-offs between the Total Cost of Ownership (TCO) of various fleet options, including aspects like capital and operational costs, environmental impacts, and customer service levels. It also seeks to define all explanatory factors (dependent and independent variables) to identify the factors that have an impact on costs, carbon emissions footprint, and operational performance. This problem is inherently complex given that EVs do not have a long precedence of operation and their viability hinges on many exogenous factors such as climate, topography, infrastructure, policies and legislations, environmental and sustainability laws and tax incentives, customer requirements and expectancies.

In this context, this capstone project addresses the following questions:

1. In line with the Company's ESG objective, we address three questions:

- *Where* in the US should EVs be implemented?
- *When* should EVs be implemented?
- *How Many* of the fleet should be moved to EVs?

The final plan will constitute US state-wise implementation, across the next 6 years (2024-2030), to achieve maximum reduction of GHG emissions.

2. What are the emerging technologies in the sustainable fleet domain along with their limitations and relative merits, and how can a Company prepare for these technologies from early on?

1.3 Project Goals and Expected Outcomes

The project goal was to provide fundamental 'Where' and 'When' answers to the EV transition for the Company. For 'Where', all 50 US states were divided into 3 categories based on their conduciveness to EV adoption, considering endogenous features like current driving mileage, current number of drivers, current fleet age and exogenous factors like state average temperature, gradient, fuel price, electricity price, environmental incentives, and infrastructure availability. For 'When,' the focus was on the growth factor analysis, giving a 6-year phased plan starting from 2024 till 2030 of a well-defined portion of the fleet transitioning to EVs by states, thus achieving an optimal fleet mix. The geographical spread and the timeline were arrived at by using an unsupervised Machine Learning (ML) model, using clustering techniques. The base year is 2024 and horizon year is 2030, according to the information given by the Company. The model will be scalable for the Company to incorporate updated data or add/remove model features to apply to the US or other regions and scenarios. The answer to the final question of *How Many* fleet vehicles to move to EVs was derived from the logistic growth equation and TCO analysis, based on parameters like capital cost, operational cost, CO_2 emissions, and vehicle useful life.

1.4 Approach

The work was conducted across the fall and spring semesters of the graduate program of 2024, including weekly Company meetings, data gathering, literature review, and internal interactions and resource gathering, to arrive at the appropriate approach and functioning. The model features and analysis were also rigorously reviewed prior to implementation, and along the way, to ensure relevance and applicability with the Company's on-the-ground conditions. At critical milestones, a buy-in was taken from the Company, to confirm the approach and outcome.

2 STATE OF THE PRACTICE

In this section, we review the current state of knowledge through scholarly works and ongoing research available about EVs. These materials have helped the authors to channel their project methodology and can also help the Company to further this work after the duration of the project. We are particularly looking at the macro environment of EV adoption in the US, relevant case studies in EV transition, assessment of ML model features, growth factor, and assessment of TCO components.

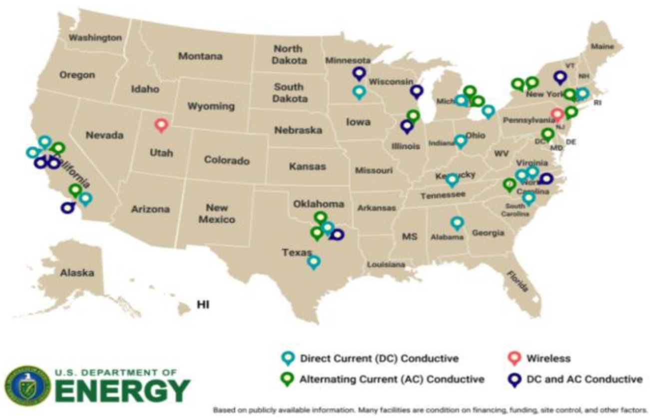
2.1 Macro Environment: Regulations, Supply and Demand

In the United States, the federal legislations, such as the recent Inflation Reduction Act (IRA) of 2022 and the Bipartisan Infrastructure Law (BIL) of 2021, are notable developments to promote manufacturing and purchase of EV vehicles and thereby promote green energy transition. The IRA has proposed several tax credits available through December 31, 2032, and an estimated investment of over $370 Billion. BIL provisions increase investment in alternative fuel infrastructure, batteries and mass transit investing over $190 Billion. These and other initiatives are expected to reduce CO_2 emissions by 40% in 2030 versus 2005 (World Energy Outlook 2023, page 206). State level legislation is also facilitating the EV transition.

According to the US Department of Energy's Vehicles Technologies Office (www.energy.gov, Oct 30, 2023), since 2021, manufacturers have announced more than $500 million of investment in over 40 American made EV charger plants. Furthermore, in June 2023, Society of Automotive Engineers (SAE) announced that it will 'standardize' the Tesla developed North American Charging Standard (NACS) charging connectors for all vehicles (Kane, 2023). The standardization of chargers will further boost EV vehicle proliferation and ease of use across the US.

Figure 1

EV Charger Manufacturers' Investment in US



Note: From US Department of Energy (energy.gov).

Many Original Equipment Manufacturers (OEM) have also volunteered and provided targets on their EV production, CAPEX and Research and Development (R&D), as shown in Figure 1. For example, per the International Energy Agency (2023) report, General Motors has a target of 1 million EV production capacity by 2025 in North America, and Volkswagen had one of the highest EV spent on CAPEX and R&D technologies of over $15 Billion. The report noted that "Major carmakers are committing up to 50-70% of CAPEX and R&D budgets to electric vehicles and digital technologies."

Brown et al. (2023) notes that Electrical Vehicle Supply Equipment (EVSE) infrastructure has grown to 168,040 ports in Q2 2023 vs 87,352 ports in Q4 2019. The public infrastructure accounts for over 75% of the total. The report quotes the Executive Order 14037: Strengthening American Leadership in Clean Cars and Trucks, which mandates 50% of all new passenger vehicles and light trucks sold in the United States be zero-emission vehicles (ZEVs), including EVs and fuel cell electric vehicles by 2030. Commensurate with this sale, Brown et al. (2023) estimates the charging station requirements of 28 million EVSE ports by 2030, reflecting a steep infrastructure deployment need. From the demand side, as per IEA (2023), in 2020, one in 25 cars sold was electric, whereas in 2023, it is 1 in 5 cars.

While both the supply and demand sides witness growth, consumer confidence in adopting the new technology is taking time, owing to varying regulatory messages, political agenda, infrastructure, pricing and occasional safety concerns. However, per Campbell (2023), lack of consumer confidence is an "early blip on what is a long journey" (page number). As EV is a new technology, one should also wait and see the developments across the value chain of EVs. Certain developments like the solid-state battery technology from Toyota will prove to be a game changer, versus the current lithium-ion battery. What is imperative to note here for the Company is that the sector is evolving rapidly; our model thus adopts both endogenous and exogenous features in the variable to enable the Company to make an informed decision.

2.2 Case Studies

We looked at two case studies to understand the adoption of EVs in corporate fleets in the US, focusing on passenger vehicles. The first case study is taken from the public sector – US Federal Government initiative; the second is from private sector – Consumer Energy in Michigan. The two cases reflect different scales of EV adoption and lessons learnt for our Company's adoption plan.

2.2.1 US Federal Government Fleet

Noblet (2023) reports that The White House has set a goal to electrify its fleet in an Executive Order 14057, requiring 100% EV acquisitions by 2035. For over 650,000 US Federal fleet, this is an ambitious target. Electrifying the entire fleet to EVs will save the Federal Government $6 Billion in over 15 years and a saving of 1.7 million metric tons of GHG emissions (Walsh & Coletti, 2023). Some of the key learnings from this case study:

- A phased approach to this transition was found to be a viable option, not just from the manageability aspect but also the cost savings.
- The concept of TCO reflected EV investment breaking even after 4 years of the transition, after which they were more cost effective to operate.

2.2.2 Consumers Energy, Michigan

Consumers Energy (n.d.) describes a program to electrify its existing truck fleet from 2022 to 2029. The TCO period was till 2035. Electrifying 20 out of 249 vehicles in the Company's fleet gives a saving of $541,930 over the next 14 years and over 3500 metric tons of CO_2 reduction. It is worth noting that only 20 vehicles were found feasible for EV adoption, while conducting the TCO comparison in their study. The key learnings from this case:

- Not all vehicles in the existing fleet were feasible for the transition. The key reason for TCO tilting towards EVs was the IRA credits and rebates.
- The vehicle replacement period and the TCO period of assessment were separate.

- The cost breakeven period is approximately 3 years.

A common theme that emerges from these case studies is that subsidies for capital cost of the vehicle is critical for making the transition feasible and that a phased approach is ideal, given the Company specific aspects like fleet structure, vehicle replacement policy and so on.

2.3 Assessment of Model Features

There are very few examples of modeling EV transition behavior in the literature review as the concept of EV and its overall environmental and economic impact is fairly new. However, there are examples of similar transition, wherein, certain types of features were studied independently or in combination, depending on particular cases of EVs or regions. Some of the features we think are relevant to our project are discussed in the following sections.

2.3.1 Environmental

Environmental laws and incentives are a significant indicator of how feasible the transition will be. US has federal laws and individual state laws that are promoting EV transition. It is also important to note that over and above laws, there are individual grants and programs that are promoting the EV and other alternate fuel transitions. As per the Department of Energy database, there are federal laws and incentives, and state laws and incentives or rebates to promote energy transition and use of EVs. Our assumption in this feature is that the higher the number of laws, incentives, and programs, the higher is the interest of the state to adopt EVs. This is reflective of the state being more prepared to adopt the transition and therefore more lucrative for the Company.

2.3.2 Temperature

Geotab is a telematic hardware and software Company headquartered in Canada. Geotab (n.d.) looked at "anonymized data from 5.2 million trips taken by 4,200 EVs representing 102 different make/model/year combinations and analyzed average vehicle trip efficiency by temperature." Their 3 key findings were: Most EVs follow a similar temperature range curve, regardless of make or model; both cold and hot temperatures impact range, colder climates have a larger impact; and 70F (21.5C) is the vehicle trip efficiency sweet spot.

We therefore took temperature as one of the flags, which will impact the EV performance and be one of the decision variables in deciding upon the states that are conducive with temperature to adopt EVs. As per Geotab (n.d.), at 5F (-15 degrees C), EVs drop to 54% of their rated range, i.e. a car that has 250 miles (402 km) will only get on average 135 miles (217 km) of range. Heat is equally diminishing the EV performance (the slope steeps faster in higher temperatures). At optimum temperature of 70F or 21.5C, EVs are performing better than their rated range, peaking at 115%. We have therefore created 3 flags of temperature: below 50F, 51F-86F and above 87F in our cluster modeling, reflecting peak performance between 50F and 86F, and the other two ranges show lower and higher temperatures.

2.3.3 Fuel and Electricity Price

As per the recommendation of the Company, an interesting feature we consider relevant to the modeling is the fuel and electricity price. The higher the price of fuel, the more relevant the state becomes in EV transition, as there is an incentive for the user to adopt EVs. Similarly, the lower the price of electricity (both at home charging locations and public charging stations) has an impact on EV adoption, given that the lower the electricity price, higher is the propensity to adopt EV.

2.3.4 Review of EVs and AFVs Adoption and Diffusion Models

In the past few decades, researchers have produced studies and models helping to compute the optimal fleet size and fleet composition (Golden et al., 1984; Osman & Salhi, 1996; Redmer et al., 2012; Alazzawi et al., 2021). Generally, the focus has been on some of the typical transportation issues such as vehicle routing problems (VRP) (Cordeau et al., 2007; Golden et al., 2008; Kim., 2015), Travelling Salesman Problems (TSP) (Gavish & Graves, 1978; Laporte & Martello, 1990), last-mile delivery efficiency (Mangiaracina et al., 2019), truck loads and freight shipment (Powell, 1996; Spivey & Powell, 2004), urban and public transportation (Motta et al., 2013; Preston, 2012; Schade et al., 2014).

Most of these problems are external-oriented, either supplying raw materials or work-in-progress inventories from the vendors to the factory or delivering finished goods and products to distribution centers, customers, or end consumers. Only a few studies have thus far focused on the modeling of a fleet mix of ICEs, EVs, AFVs, and other Alternative Mobility Solutions (AMS) aiming to achieve simultaneously, efficiency, effectiveness, and CO_2 emission reduction. Similarly, very few to no studies have focused on quantitative modeling of optimal fleet mix and optimal fleet size to support the intra-company mobility requirements.

In contrast, this case relates to an internal-oriented problem that is not concerned either with the inbound transportation of materials or with the outbound delivery of products to distribution centers or to fulfill consumer orders. In other words, the purpose is to holistically assess and accurately identify operational mobility needs first and secondly find optimal solutions to fulfill them. Contrary to the

Company’s internal-oriented transportation problems, the external-oriented problems have been the subject of many studies and have benefitted from a wide array of supply chain optimization and simulation models, such as the Supply Chain Network Design (SCND) (Amiri, 2006; Babazadeh et al., 2013; Amin & Baki, 2017), the TSP (Gavish & Graves, 1978; Laporte & Martello, 1990), the VRP (Cordeau et al., 2007; Golden et al., 2008; Kim, 2015), optimal load assignment (Powell, 1996; Spivey& Powell, 2004).

Upon closer examination, the Company aims to provide its workforce, especially its sales team, with light passenger vehicles or AMS vehicles to be utilized as a trade tool to primarily support their work-related mobility needs while maintaining an optimal fleet mix and size and undertaking gradual electrification to achieve decarbonization objectives.

When reviewing the literature, we noticed that the approach taken by many researchers to solve similar problems includes system dynamics simulations. In their paper “Transition challenges for alternative fuel vehicle and transportation systems”, published in 2008, Struben J. and Sterman J.D., argue that the diffusion and the adoption of AFVs are dictated by several strong and reinforcing feedback (Struben & Sterman, 2008). Specifically, Keith et al. (2020); provide a generalized system dynamics model that describes how stocks and loops are interrelated through causal links, producing reinforcing feedback. The authors list the following stocks: (1) installed base of different types of the fuel-powered automotive industry, (2) numbers of consumers willing to consider a particular vehicle type, (3) particular automotive capabilities, and (4) number of available refueling infrastructure. The model has three reinforcing loops, they are: (1) social exposure; (2) learning-by-doing/R&D/Marketing; (3) refueling infrastructure/chicken-and-egg. Keith et al. (2020) model demonstrates that the system is interrelated through many causal links, such as vehicle sales, vehicle retirement, vehicle utility, fuel demand, market share, reinforce the rate of adoption of vehicles powered by emerging technologies other than the Fossil fuel-powered/ICEs.

2.4 Assessment of TCO Components

A Company’s fleet has significant potential to influence, positively or negatively, its financial performance. In the Company’s financial statements report, the fleet’s acquisition costs are recorded as capital expenditures (CAPEX) on the balance sheet as assets, under the PP&Es line. In contrast, the expenses related to leasing a vehicle generally appear as a current liability on the balance sheet. Similarly, these expenses are also present on its Income statement as asset depreciation (noncash expense) or as an operating/SG&A expense when the fleet is leased. In one way or the other, the Company's fleet directly affects its profit margins and, thus its financial performance (Financial Accounting, MOOC Edx-MITx/Course 15.516x, attended in April 2022).

A vehicle's TCO encompasses all costs from the acquisition (purchasing, delivery, registration), through the costs incurred by its usage (fuel or energy, maintenance and repairs, insurance), to its disposal. Szumska et al. (2022) suggest that a vehicle's total cost of ownership should consist of: one-time costs, e.g. purchase cost, registration cost; and recurring costs, e.g. fuel, repair, insurance costs. In the specific case of battery-powered vehicles, scholars have proposed different frameworks to analyse the total cost of ownership, for example, Van Velzen et al. (2019) propose a more comprehensive framework consisting of 34 factors to include in the TCO analysis of EVs. Conversely, according to the authors of "*How Expensive are Electric Vehicles? A Total Cost of Ownership Analysis, 2019*" (Lebeau et al., 2013), the TCO analysis can be approached in two ways: either as a consumer-oriented study or as a society-oriented study. They argue that, in the first approach, only the costs perceived by the consumers (users) are considered, while the second approach considers a broader scope by adding externalities such as gas emissions, noise, etc., in addition to the consumer costs. In line with the Company's environmental and sustainability objectives, we strive to consider the society-oriented costs of its fleet and incorporate them into the final analysis.

2.5 New Technologies

As per the Alternative Fuels Data Center (AFDC, n.d), more than a dozen fuels are under research and development and some under production, for potential use as alternate fuels. All these fuels are under consideration to fundamentally address the climate agenda, reduce emissions, cut costs and perhaps to improve the efficiency. As shown in Table 1, we will look at 3 types of fuels that are gaining traction in their potential to address the aspect of sustainability and the extent of emergence of these new technologies.

Table 1

New Technologies beyond EVs

Technology	Description	Pros and Cons
Hydrogen Fuel Cell Electric Vehicles (FCEVs)	These vehicles are powered by hydrogen, and they emit water vapor and warm air. As per AFDC (n.d), FCEVs are fuelled with pure hydrogen gas stored in a tank on the vehicle. Similar to conventional internal combustion engine vehicles, they can fuel in about 5 minutes and have a driving range of more than 300 miles.	US Dept of Energy is leading efforts to make this as a mainstream fuel. Hydrogen is taken as an alternative fuel under the Energy Policy Act of 1992 and qualifies for alternative fuel vehicle tax credits. One of the major disadvantages is the higher production cost due to rare raw materials and complex production process.
Biodiesel	Biodiesel is a renewable fuel that can be manufactured from vegetable oils, animal fats, or recycled restaurant grease for use in diesel vehicles or an equipment that operates on diesel fuel.	Biodiesel improves fuel lubricity and raises the cetane number of the fuel. One of the major limitations of this fuel is that it does not function in colder climates.
Renewable Natural Gas (RNG)	RNG, also known as biomethane, is a pipeline-quality vehicle fuel. It is produced by purifying biogas, which is generated through anaerobic digestion of organic materials, such as waste from landfills or through thermochemical processes, such as gasification. RNG qualifies as an advanced biofuel under the Renewable Fuel Standard.	The vehicles are similar to gasoline or diesel vehicles with regard to power, acceleration, and cruising speed. RNG is chemically identical to CNG and it has a high potential for greenhouse gas emissions.

Note: The Department of Energy has extensive information on alternate fuels that are under development within the United States.

3 DATA AND METHODOLOGY

The first section discusses the 'Where' aspect—how the Company's data is used to determine the location preferences for EV rollout within the US; the second section discusses the "When" and "How Many" aspects—how the transition will happen and whether it is economically feasible—by comparing the total cost of procuring EVs.

3.1 Assessment of 'Where' through K-means clustering

The Company has shared information about their state wise characteristics of the passenger fleet as of 2024: driving range, age of fleet, number of drivers, number of vehicles and so on. We have considered the data provided by the Company as endogenous features, over which the Company has some control. The exogenous features considered for the study are temperature, environmental laws and incentives, price of gas and price of electricity, which are commonly affecting the EV performance and wherein the Company has no control.

We have used a Machine Learning technique called K-means, as this is an unsupervised learning scenario. After much deliberation and literature review, a method of clustering within clustering was evolved, whereby, the data was evaluated first on endogenous features, called main clusters, and then sub clusters were created for each of the master cluster using exogeneous factors that are out of the Company's control. These sub clusters were then ranked by importance, to enable the Company to implement the EVs in a phased manner.

The data sources for exogeneous variables are as below:

- Temperature: State wise temperature from National Center of Environment and, NCEI
- Environmental Laws and Incentives: Department of Energy, United States Government
- Price of Gas: gas prices from American Automobile Association (AAA)
- Price of electricity: Prices by state from electricitychoice.com

3.2 Assessment of 'When' and 'How Many' through growth factor and TCO analysis

From the problem statement and research question, it is clear that the adoption of EVs, or to put it differently, the decarbonization of the fleet, is seen by the Company executives as a strategic direction through which the Company will position itself as one of the leading pioneers in this field. While this project holds promise for the Company, it necessitates cautious navigation from inception through deployment to completion, making sure that the operational excellence is guaranteed, and that any unpredicted outcome is timely detected and adjusted. It is imperative to recognize that the Company's fleet serves as the primary "mobility tool," particularly enabling the salesforce to connect with various customers but also allowing all employees in general to fulfill other mobility requirements. Rushing or oversimplifying fleet decarbonization could lead to subpar operational performance or inflated costs.

To uphold operational excellence and cost control consistently, we devised a model envisioning a gradual, optimized fleet mix of ICEs and EVs over each unit period (a quarter, a semester, or a year). This model was devised to account for all quantitative and qualitative variables influencing fleet acquisition, deployment, utilization, and disposal.

The central questions we addressed were: “When” should we incrementally adjust the Optimal fleet mix, and “How many” EVs should be introduced? In essence, what growth rate is optimal? An in-depth review of academic literature oriented us to select and adapt logistic growth simulation modeling (Banks, 1993; Tsoularis & Wallace, 2002). This kind of model is generally used to study and predict a specific population growth under certain given constraints and limits. In the subsequent sections will elaborate on the formulation of this model, starting with the growth factor.

3.2.1 Growth Factor

The exponential or growth factor is usually denoted by “k” in the academic literature; it is the parameter that represents the maximum growth rate of the population when the population is small relative to the carrying capacity of the environment (Wei & Zhang, 2019). The higher the “k”, the faster the population grows over time. In our specific case, this factor is interpreted as the maximum or optimal growth rate of the EVs in the Company’s fleet by quarter, semester, or a year until the target year of 2030 without exceeding the total target percentage of ICEs set to be replaced. To appropriately estimate the growth factor to be used in our logistic growth equation, we needed to have a good understanding of the current status of EV technology and the trends in the Alternative Fuel Vehicles industry. Through a thorough literature review, we concluded that five ratios will significantly influence the adoption and diffusion of EVs in the Company and therefore must be used to estimate the suitable growth rate:

- Ratio 1:

  The ratio of the TCO of the existing ICEs versus the TCO of the EVs to be eventually acquired, which at first sight tends to be in favor of the ICEs, given the 5-year vehicle replacement policy of the Company and given the current purchase price. However, considering tax incentive policies in the US and other trends such as advancements in battery technology, this advantage is fast shifting in favor of EVs.

- Ratio 2:

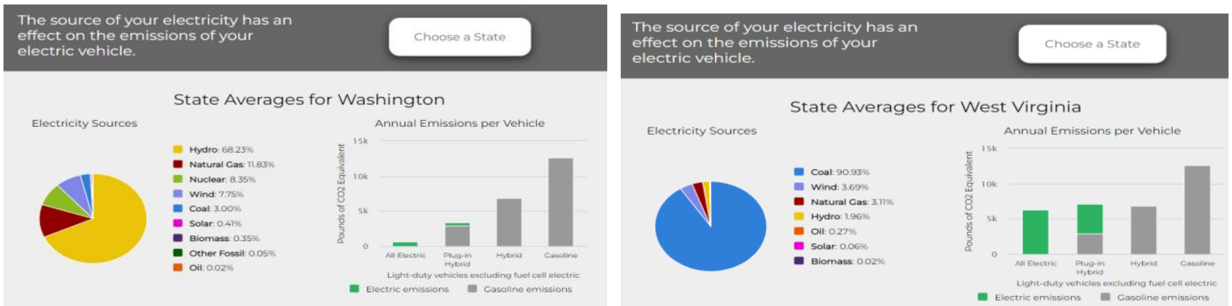
  The ratio of the driving range of the EV to be eventually acquired versus the driving range of the existing ICEs. This ratio is largely to the advantage of the ICEs; this situation is directly dependent on the advancement of battery technologies. Also, the analysis of the Company data revealed that none of the 50 states plus DC has a record of driving more than 120 miles on average per day. Even though these daily driving distances will not be affected by the current short driving ranges of most EV makes and models, this ratio is a critical differentiator between ICE and EV technologies, hence it is still included in the computation of the growth factor.

- Ratio 3:

  This ratio is obtained by dividing the CO_2 emitted by the EVs to be eventually acquired over the CO_2 emitted by the portion of ICEs remaining in the fleet. A study by the US Department of Energy (Alternative Fuels Data Center, 2022) states that an ICE vehicle produces on average 12,594 pounds of CO_2 equivalent per year, while an EV produces on average 2,797, meaning that ICEs emit on average 78% more emissions than EVs. For this capstone, using the national average CO_2 emissions of EVs would have been a misleading input because of the substantial difference in specific CO_2 emissions of EVs per US State as calculated by the Department of Energy's Alternative Fuels Data Center (2022) based on the energy generation source in various US States. The two images in Figure 2 reflect the significant variation between the cleanest energy generation source US State, i.e., Washington State, and the most polluting energy generation source US State, i.e., West Virginia. By using these specific CO_2 emissions for each state, we were able to come up with varying ratios.

Figure 2

Energy Generation Sources in Washington and West Virginia States



Note: The State of Washington generates the cleanest energy in the US, while West Virginia generates the most polluting energy.

- Ratio 4:

For this ratio, the availability of Levels 2 & 3 charging ports is compared to the availability of gasoline refueling pumps in a given state. The numbers of the charging ports across the US for each state were easily obtained on the Department of Energy's website (AFDC, Alternative Fueling Station Counts by State, 2022). In contrast, an accurate list of gas stations in the US per State could not be found online. An article published by the National Association of Convenience Stores (NACS) estimates a total of 145,000 gas stations countrywide; of these, 127,588 are operating as convenience stores (Convenience Stores Sell the Most Gas, March 2024). Another webpage published an annual list of gas stations in the US by state from the year 1996 to the year 2012 (AFDC, 2014). Thus, from this 16-year historical data, we applied the ARIMA statistical forecasting model to predict the expected counts of gas stations per US State for the year 2024. By summing up the output of our model we obtained a total number of 155,788 Gas Stations. To validate our model, we compared its output with the number (145,000) published by the NACS, presenting a variation of 7%, which we appraised to be acceptable for our model. It is worth highlighting that this ratio is expected to increase as more investments are being deployed in the installation of public and private charging infrastructures across the US.

- Ratio 5:

The fifth ratio influencing the growth rate at the Company is the ratio of the level of the Value-Perception associated with the EVs versus the one associated with the ICEs, by the users. In this factor, non-quantifiable aspects, such as the costs and benefits of shifting from an ICE to an EV, are included. This factor involves such elements as noise reduction of EVs, charging time of EVs, socio-economic considerations, and environmental awareness. To gauge the value perception of ICEs versus EVs among the Company employees, we propose utilizing a survey instrument. Each vehicle user would assign a numerical value, ranging from 0 to 5, to both ICEs and EVs, indicating their perceived value on this scale, with 0 indicating the lowest value and 5 indicating the highest value. By averaging the EV value-perception scores over those of ICEs, a ratio can be derived.

As the result of the above steps, the growth factor was computed using the below equation:

$$\boldsymbol{Growth\ Factor(k) = Ratio1 + Ratio2 - Ratio3 + Ratio4 + Ratio5}$$

By running multiple sensitivity analyses, we obtained multiple growth rate values ranging from 1.5 to 2.9. Then, plugging in these different growth rates into the below logistic growth equation, the optimal number of EVs in the fleet for each year till 2030 was obtained.

$$\boldsymbol{EV_{growth} = \frac{Max\ No\ of\ ICE\ Replacement}{(1 + C * e^{-k*t})}}$$

where:

Max ICE Replacement: is the percentage of ICE Vehicles that have reached the end of their 5 years useful lifetime and are due for replacement and write-off.

C: A constant number adjusting the EV growth rate, it is obtained by:

$$\boldsymbol{C = \frac{(Max\ No\ of\ ICE\ Replacement - Initial\ No\ of\ EVs)}{Initial\ No\ of\ EVs}}$$

e = Euler number.

(t) = the particular year associated with the growth.

3.2.2 TCO Analysis

As described above, Ratio 1 was obtained by dividing the average TCO of an EV versus the TCO of the ICE. In financial terms, this first ratio is meant to control all costs and implications associated with replacing an ICE with an EV. In compliance with the existing policy within the Company, the average TCO was computed for a 5-year period, which is the established useful age of an ICE before its disposal. The components included in the calculations are:

- Purchase cost: for the ICEs, this information was retrieved from the data provided by the sponsor Company. In the case of EV's TCO, we referenced the Manufacturer's Suggested Retail Price (MSRP) of the nearest comparable EV, the Nissan Ariya, in relation to the Company's most used ICE vehicle, the Ford Equinox. This information was accessed online through the website EVadoption.com, BEV Models Currently Available in the US (2023).
- Maintenance cost: as an alternative to the lack of actual maintenance data, we applied the US national average cost of maintaining both an ICE and an EV light passenger vehicle (Gorzelany, 2022)
- Annual insurance cost: this information was available in the dataset provided by the Company as a flat lump sum across the nation and per ICE vehicle. Conversely, the annual insurance cost for an EV was estimated given that the EVs are not part of our sponsor Company's fleet in the US. After reviewing different online resources (Consumer Reports, Benjamin Preston, March 2023), we opted to estimate EVs annual insurance cost of a light passenger EV at 20% higher than that of the ICEs (actual cost). This estimation was deemed to be both conservative and sufficiently reasonable.
- Refueling cost: this element was computed separately by state using respective average prices of a gallon of fuel, this data is published online and daily updated (AAA, n.d).
- EV charging cost: the average cost of a kWh of electricity per state, the battery capacity, and the driving range drove the calculation for the expected charging cost of EVs in each US State.
- Tax rebates and incentives: we referred to the US Internal Revenue Service online resources to infer the applicable rebates and incentives (Internal Revenue Service, 2024).

Assumption: the disposal cost and the salvage (residual) value for both the ICEs and the EVs were presumed to balance each other out, and thus considered negligible and hence not factored into the 5-year Total Cost of Ownership (TCO) calculations.

4 RESULTS

The results from both K-means clustering, and logistics growth equation and TCO analysis are discussed in following sections.

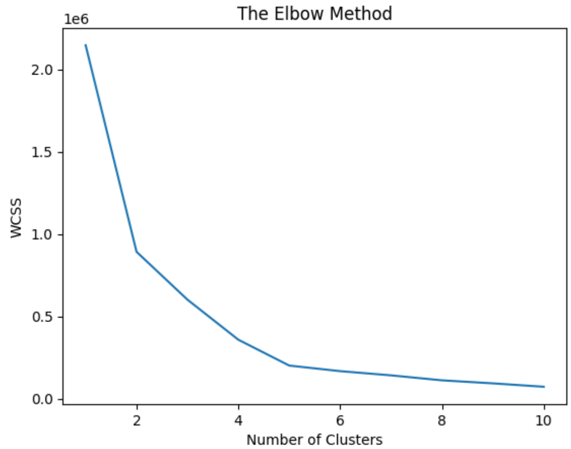
4.1 Clustering

We describe here the results of the main clustering and sub-clustering, followed by the ranking of states in order of preference for the Company to implement a phased rollout.

Upon conducting a Python programming code for endogenous features, the elbow curve showed the most optimum clusters at 5, below which the reduction of error was minimal.

Figure 3

Elbow curve for main clustering.

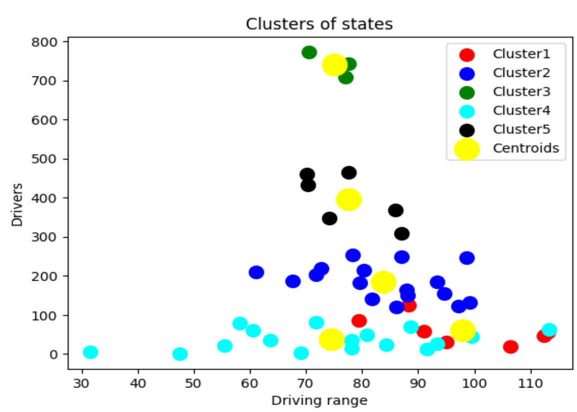


Note: Author's independent analysis on K-Means clustering

The 5 clusters formed show a clear distinct pattern. Figure X is the plot showing the clusters between two prominent features – driving range and drivers. The clusters can be broadly segmented into 1. cluster 3: mid-range, high # of drivers, 2. cluster 5: mid-range, mid # drivers, 3. cluster 2: mid to high range, lower # of drivers, 4. Cluster 4: low range, low # drivers, 5. cluster 1: high range, low # drivers

Figure 4

Main clusters



Note: A representation between driving range and drivers,
Two prominent features evolving from the clustering technique.

We have given names to the clusters in order of prominence.

Cluster 3 (green) – Champions (Leaders in green technology implementation)

Cluster 5 (black) – Aspirants (Significant progress made in green technology)

Cluster 2 (blue) – Challengers (At the cusp of a visible progress)

Cluster 4 (cyan) – Switchers (Considering the green transition change)

Cluster 1 (red) – Laggers (Yet to evolve and implement green transition technology)

The states that fall into these respective clusters are shown in Table 2.

Table 2

Main clusters and states

Champions	**Aspirants**	**Challengers**	**Switchers**	**Laggers**
CA, TX, FL	NY, NJ, IL, NC, PA, OH	WA, CO, MA, VA, MD, MN, CT, IN, MI, AZ, WI, SC, TN, GA, MO, LA, KY	OR, VT, UT, RI, NH, NM, NV, DC, ND, DE, MS, NE, MT, AR, WY, ID, AK	OK, ME, IA, KS, AL, WV, SD

Clusters Switchers and Laggers overlapped in some areas, but they were handled in the sub-clustering exercise.

The sub-clustering was then performed on the main clusters using exogenous variables to study the aspects that are out of the Company's control and that will help them further segment the large main clusters or overlapping clusters. The nomenclature for sub-clusters is A and B for each main cluster category.

Table 3

Sub-clusters to main clusters

Clusters	Champions		Aspirants		Challengers		Switchers		Laggers	
Sub Clusters	A	B	A	B	A	B	A	B	A	B
States	CA	TX	PA	NY	WA	IN	OR	NV	KS	OK
		FL	OH	NJ	CO	MI	VT	DC	AL	ME
				IL	MA	AZ	UT	ND	WV	IA
				NC	VA	WI	RI	DE	SD	
					MD	SC	NH	MS		
					MN	TN	NM	NE		
					CT	GA		MT		
						MO		AR		
						LA		WY		
						KY		ID		
								AK		

Note: Author's independent analysis conducting sub-clustering to main clusters

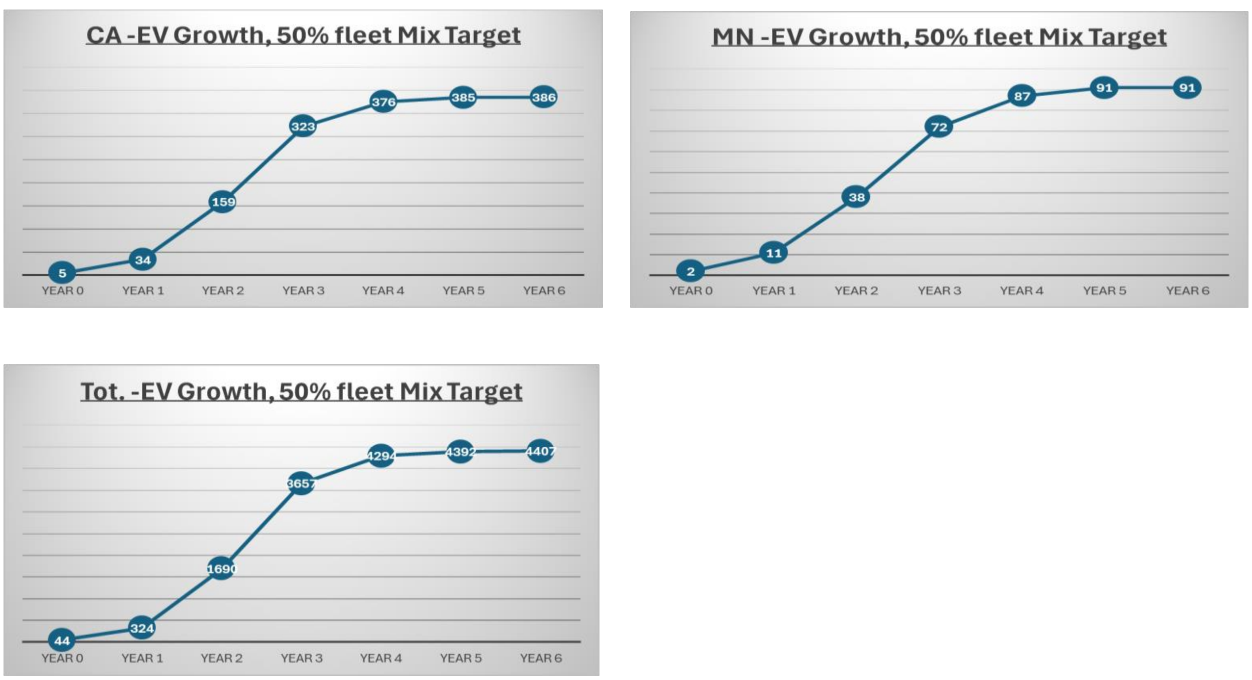
Given the above classification, we then devised a methodology to rank these states in the order of preference for rollout.

4.2 Logistic Growth Equation and TCO Analysis

The benefits of applying a sustained logistic growth equation to fleet electrification have been largely discussed throughout this paper. Obviously, by controlling the "When" and the "How", the pace and the scope of bringing change into the mobility practices in the Company are simultaneously controlled as well. We can argue that the most important benefit of this model is the modelized capability to control the rate of fleet decarbonization. The controlled growth rate allows time for all stakeholders in the Company to adjust and secondly allows managers to monitor technological evolvement changes in the exogenous factors and adapt accordingly. In the next sections, we will analyze further the application and expected outcome of the model on the Company fleet. EVs Growth Curve in various US States displays different characteristics in terms of TCOs, fleet sizes, and average driving mileage per day. In addition, exogenous factors described earlier impact differently our variables. Not surprising that these peculiarities have resulted in a unique growth curve for each US State. For instance, the output of the model when applied to California state which has the largest fleet number, recommends a completely different growth curve compared to the model's output when applied to Wyoming state which has the smallest number of fleets. The below graphs depict the growth curve obtained for the largest state, i.e. California, for the medium-sized fleet state, i.e. Minnesota, and the whole Company's EV growth curve. It is worth noting that the 50% target mix of ICEs and EVs in the fleet composition is applied here for demonstrative purposes. This target should be reviewed and adjusted by the Company before implementation.

Figure 5

Growth Curve for Various Fleet Sizes



4.2.1 Growth Factor and TCO Analysis

We have already mentioned that the Company considers 5 years useful lifespan for its ICEs, thus all vehicles aged 5 years old are technically earmarked and due for replacement and write-off. Therefore, we calculated the average TCO for all existing ICEs in a specific state. The calculation includes the purchase landed cost, 5 years cost of insurance (undiscounted), and the expected 5 years cost of fuel and maintenance costs (Department of Energy). As an illustration, table 4 depicts the amounts obtained for the top 6 states in terms of the vehicle count in use in the states.

Table 4

5-Year ICEs Average TCO Amounts for the Top 6 US States

State/ Province	Avge Mile	Purchase price	Mainten Cost_5 Years	Insurance Cost 5-Yea	Fuel Cost 5-Years	5-Year TCO
CA	58	$ 25,975.00	$ 10,585.00	$ 6,000.00	$ 20,372	$ 62,932.34
TX	82	$ 25,975.00	$ 14,965.00	$ 6,000.00	$ 19,075	$ 66,015.03
FL	79	$ 25,975.00	$ 14,417.50	$ 6,000.00	$ 20,226	$ 66,618.19
PA	59	$ 25,975.00	$ 10,767.50	$ 6,000.00	$ 15,409	$ 58,151.56
NY	56	$ 25,975.00	$ 10,220.00	$ 6,000.00	$ 14,414	$ 56,608.85
NJ	71	$ 25,975.00	$ 12,957.50	$ 6,000.00	$ 17,548	$ 62,480.66

Conversely, to obtain the estimates of the 5-year TCOs for the nearest comparable Electric Vehicle (EV) to be most likely purchased as a replacement of a phased-out ICE, we surveyed the current EV market, then consulted with the Company representative and set the estimated purchased price of $44,485.00. Thereafter, we added the expected 5-year cost of insurance at twenty percent higher than ICE's (undiscounted), the expected 5-year fuel and maintenance costs (Department of Energy). As an illustration, Table 5 depicts the amounts obtained for the 5 states.

Table 5

5-Year EVs Average TCO Amounts for the Top 6 US States

State/ Province	Avge Mile	Expected Purchase price	Expected Rebate	Estimates of Tax incentives	Mainten Cost 5-Years	Insurance Cost 5-Years	Fuel Cost per year	5 Year TCO
CA	58	$ 44,485.00	$ 5,500.00	$ 500.00	$ 6,351.00	$ 7,200.00	$ 1,437	$ 53,472.94
TX	82	$ 44,485.00	$ 5,500.00	$ 500.00	$ 8,979.00	$ 7,200.00	$ 931	$ 55,595.16
FL	79	$ 44,485.00	$ 5,500.00	$ 500.00	$ 8,650.50	$ 7,200.00	$ 1,106	$ 55,441.38
PA	59	$ 44,485.00	$ 5,500.00	$ 500.00	$ 6,460.50	$ 7,200.00	$ 786	$ 52,931.82
NY	56	$ 44,485.00	$ 5,500.00	$ 500.00	$ 6,132.00	$ 7,200.00	$ 1,156	$ 52,972.71
NJ	71	$ 44,485.00	$ 5,500.00	$ 500.00	$ 7,774.50	$ 7,200.00	$ 1,174	$ 54,633.14

Due to the numerous criteria necessary for a commercial vehicle to qualify for the federal rebate, and taking a cautious approach, we opted not to utilize the ceiling credit rebate amount of $7,500.00 as stated on the IRS website. Instead, we employed a figure of $5,500.00. This rationale also extends to the estimated amounts of other tax incentives detailed in the table.

A comparison of the 5-year Total Cost of Ownership (TCO) for the fleet composed of only ICEs versus the 5th year's TCO of a fleet comprised of 50% mix of EVs across the top 6 states in terms of vehicle count reveals a reduction of 3 to 8% (see Table 6).

Table 6

Expected Average TCO Change per State (%) for 6 States, Last Column.

State/Province	Vehicle Count	TCO 5th Yr-ICEs Only	TCO 5th Yr-Mix	5th Year TCO Change
CA	772	$ 48,583,770.06	$ 47,154,786.88	-2.9%
TX	744	$ 49,115,182.59	$ 46,671,423.51	-5.0%
FL	708	$ 47,165,680.54	$ 44,808,781.34	-5.0%
PA	464	$ 26,982,324.59	$ 26,507,272.88	-1.8%
NY	461	$ 26,096,679.85	$ 26,321,647.45	0.9%
NJ	432	$ 26,991,643.89	$ 26,320,064.01	-2.5%

4.2.2 CO_2 Emissions Analysis and Results

Using the same comparison as for the TCOs, we computed CO_2 emissions based on the fleet consisting solely of ICEs. We then projected CO_2 emissions for the fleet in 2030, assuming a mix composition of 50% EVs and 50% ICEs. The outcome reveals a substantial reduction of nearly 38 - 45% in CO_2 footprint. Table 7 illustrates the CO_2 reduction for the top 6 states in terms of vehicle count.

Table 7

2030 Expected CO_2 Emissions Reductions at 6 US States

State/Province	Vehicle Count	CO2 emission 5th Year ICEs Only	CO2 emission 5th Yearr Fleet Mix	CO2 Reductio
CA	772	9,722,568	5,407,103	-44.4%
TX	744	9,369,936	5,819,216	-37.9%
FL	708	8,916,552	5,445,049	-38.9%
PA	464	5,843,616	3,484,229	-40.4%
NY	461	5,805,834	3,321,318	-42.8%
NJ	432	5,440,608	3,109,749	-42.8%

The evaluation of the TCOs and CO_2 emissions results from the optimized fleet mix comprising 50% ICEs and 50% EVs achieved over a 6-year period demonstrates significant dual benefits in terms of cost efficiency and environmental impact. The analysis reveals slight cost advantages, driven primarily by the US federal government rebates, tax incentives, and the lower maintenance costs associated with EVs. As long as these rebates remain available at either the federal or state level in the US, the 5-year TCO of a standard light passenger EV is expected to outperform that of a light passenger ICE. The anticipated reductions in CO_2 emissions may vary slightly across states, influenced by factors such as the predominant energy generation sources in each state and the distribution of vehicle numbers.

5 RECOMMENDATIONS AND DISCUSSIONS

5.1 Clustering

The K-Means clustering proved very useful in the current context of EV rollout for the Company. The unique approach of clustering within clustering has helped us to narrow down the states that are important, followed by the ones that are lagging behind in the EV adoption. The idea that this sector is prone to various externalities is proven through the work. However, the approach serves as a possible method to put structure and science to the adoption of the new EV technology. The clustering approach adopted here is scalable and transferable. The features can change based on the geography and it can be utilized for another type of fuel. The clustering concept will prove useful in implementation. We hope that the Company leverages this study, and perhaps it will also serve as a reference point for similar firms intending to transition their fleet to sustainable fuels.

Further, it is recommended that the Company and the wider researcher community study the upstream source of power and its sustainability. The source from renewable energy for the electricity at charging locations will reflect a true measure of the efforts to reduce GHG emissions. Various approaches and studies can enable this particular research, including commercial benefits to the firms such as carbon credits.

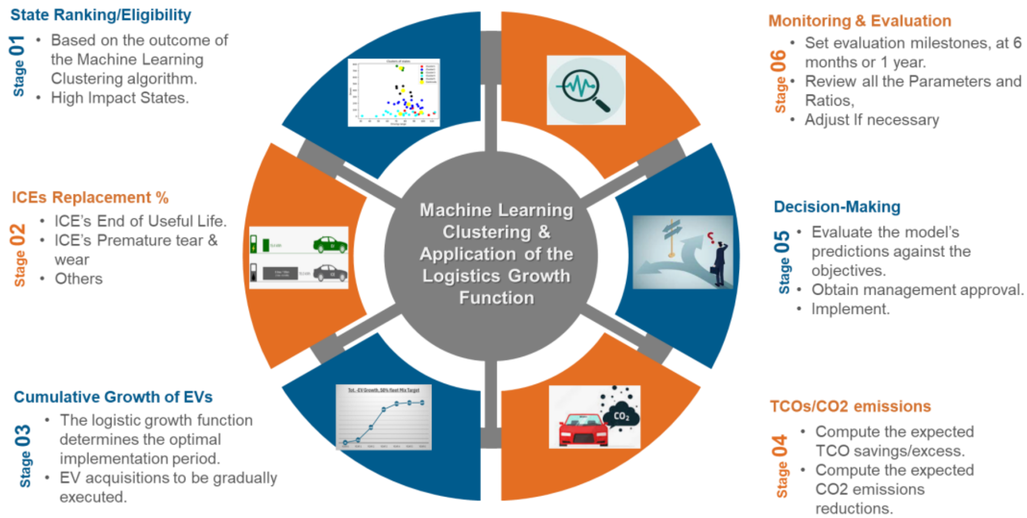
5.2 Growth Factor and TCO Analysis

The successful adoption and integration of EVs into the fleet mix heavily relies on the collaborative efforts of the Company's management, the fleet management team, and the vehicle users. The overarching objective is to revolutionize the concept of mobility within the Company. To foster collaboration, streamline communication, and ensure the sustainable implementation of this model, we propose that the Company operate within a circular framework comprising six stages. This framework entails the development of a roadmap with specific milestones, enabling regular review and recalibration of the model in a cyclical manner. Essentially, the framework translates our mathematically conceptualized model into practical operational activities that can be easily monitored, evaluated, and adjusted. Below is a detailed breakdown of each stage:

- Stage 1: States Ranking and Eligibility.
  As indicated earlier, the output of our Machine learning clustering model informs the Company management on the ranking of US States, on their current readiness level to embrace fleet electrification. This information will then be used to decide on the eligibility of a given state to qualify for the model deployment.
- Stage 2: ICEs Replacement Percentage.
  This stage involves determining the number of ICEs in selected states (from Stage 1) that will be replaced by EVs. Criteria for replacement include factors like the useful lifespan, premature wear and tear, breakdown frequency, and repair downtimes. Other exogenous factors can also be taken into account such as attractive rebates and interesting tax incentives.
- Stage 3: Compute the Optimal Cumulative Growth of EVs in each State fleet.
  By plugging in the growth rate factor and state-specific parameters into the logistics growth equation, the optimal cumulative growth of EVs in each state's fleet will be calculated, leading to the determination of the annual EV acquisition targets.
- Stage 4: Compute the TCOs variations and CO_2 Emissions Reductions
  Following the outlined methodology and plugging in relevant parameters, projections for Total Cost of Ownership (TCO) and CO_2 emissions reduction for each state can be computed, providing crucial insights for decision-making.
- Stage 5: Decision-making.
  Decisions regarding EV acquisition and ICE replacement will be based on the outcomes of Stages 3 and 4. Flexibility to accommodate local dynamics is essential before implementation commences.
- Stage 6: Monitoring & Evaluation.
  Establish a review schedule (quarterly, biannually, or annually) to assess progress, expected outcomes, and performance. Evaluate changes in internal and external factors, automotive market dynamics, technological advancement, and environmental regulations. Periodic reviews will facilitate parameter maintenance or adjustments as needed. See the visual representation of the 6-stage circular framework in Figure 6.

Figure 6

Six-Stage Circular Framework



Note: 6-stage circular framework highlighting major steps and activities to be carried out at each milestone. Image Source: Downloaded and adapted from https://www.slidegeeks.com/circular-free-owerpoint-slide (Slide Geeks).

6 CONCLUSIONS

This capstone project addressed the question of how to achieve operational excellence by optimizing Electric Vehicles (EVs) over Internal Combustion Engines (ICEs) in a fleet exceeding 25,000 vehicles owned by a multinational corporation. The primary objective was to reduce the fleet's carbon footprint by 2030 while maintaining operational efficiency within financial and operational boundaries.

Leveraging Machine Learning clustering techniques, the study identified prime locations for transitioning from ICEs to EVs across the 50 US states. Factors such as fleet age, vehicle quantity, regulatory environmental incentives and laws, climate conditions, fuel costs, and electricity expenses were carefully assessed to cluster states based on their potential impact.

Furthermore, a logistic growth model was utilized to ascertain the optimal timing and strategy for integrating EVs, taking into consideration variables like Total Cost of Ownership (TCO), driving range, charging infrastructure, carbon emissions, and public perception. The study emphasized that the transition to EVs in a large fleet is influenced by a mix of endogenous and exogenous factors. It suggested a gradual increase in the EV proportion within the fleet mix over the designated timeline to uphold operational objectives and predict forthcoming TCO and environmental implications.

The insights from this research provide a strategic roadmap for the Company's shift to electric vehicles, presenting a structured approach to embracing sustainable transportation while addressing economic and environmental considerations. The proposed framework and recommendations can serve as a roadmap for the Company's future fleet management decisions and contribute to the global efforts to reduce greenhouse gas emissions and combat climate change.

Finally, we recommend that the Company and the wider researcher community study the upstream source of power and its sustainability. The source from renewable energy for the electricity at charging locations will reflect a true measure of the efforts to reduce GHG emissions and that additional research be carried out to assess ways and possibilities of translating our model into simulation software. This additional work would aim at producing a generalizable descriptive simulation model that would enhance managers' decision-making process in the adoption and implementation of fleet decarbonization.

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