MathWorks Math Modeling Challenge 2020

Montgomery Blair High School

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M3 Challenge Technical Computing Award
WINNER—$3,000 Team Prize

JUDGE COMMENTS

Specifically for Team # 13662:

This paper used technical computing to implement a simple but effective simulation for Part 1. In Part 2 it very effectively used AADTT to model a "need" function for chargers along a corridor, which informed charging station placement. This paper had outstanding explanations of its algorithms. Each has a clear breakdown, including why the team made certain choices. Over all, the paper's algorithms were simple, but well executed with good visualizations. The students' code was also very flexible. For example, the team realized how general their "need" function for modeling fuel depletion was, and repurposed it to model diesel trucks in Part 3. They also performed sensitivity analyses by easily modifying parameters in their code.

Overall Judging Perspective for Technical Computing Submissions:

The use of technical computing in the final papers was judged on its effectiveness in advancing a papers' modeling, its creativity, and how it was communicated. We rewarded papers where technical computing was used in an essential way, and did not simply replace functionality which could have been implemented in a spreadsheet or on a calculator. We also rewarded clear explanations, even if the underlying algorithm was relatively simple. This year we noticed that technical computing was used in many papers to enhance presentation: some beautiful plots were used to effectively communicate student ideas and final solutions. Such uses of technical computing were also rewarded. Finally, one of the benefits of implementing a model in code is that it is very easy to change modeling choices or parameters to see how these choices effect the final problem solution. Teams which took advantage of this (through sensitivity analysis, testing multiple models, etc.) were rewarded.

MathWorks Math Modeling Challenge

Fully Charged: An Analysis of Electric Freight Trucks

Team #13662

March 2, 2020

Executive Summary

The United States is heavily dependent on semi-trucks to transport products and resources throughout the country. The semi-trucks come in three types: long haul (500 miles a day and far from home terminal), regional haul (within 300 miles of home terminal), and short haul (within 50 miles of home terminal). Nearly all of these semi-trucks are powered by diesel fuel, and semi-trucks account for more than 12% of the fuel purchased in the U.S. Due to a combination of factors such as diesel trucks' harmful environmental effect, low fuel efficiency, and high maintenance costs, we find an enticing alternative in electric semi-trucks. The advantages of electric semi-trucks present themselves in environmental factors (use of rechargeable batteries rather than fossil fuels, preservation of safe air quality) as well as economic factors (with fewer parts, the electric semis cost less to maintain).

Beginning in 2020, vehicle manufacturers such as Tesla are rolling out a line of electric semis to many companies, including PepsiCo, Walmart, and UPS. As companies' current fleets of diesel trucks age and go out of use, electric semis have become an increasingly attractive option. In this paper, we model the integration of electric semi-trucks into the current fleets as well as the construction of charging infrastructure that such an integration requires.

We were first tasked with predicting the percentage of semi-trucks in a fleet that will be electric in 5, 10, and 20 years. We determined a maximum cap for a truck's mileage before it will break down and become unusable. Our model presents a pipeline for semi-trucks as they age: electric trucks replace broken or aging long haul trucks, older long haul trucks replace defunct regional haul trucks, and regional haul trucks replace defunct short haul trucks. We simulated the evolution of a fleet of 1.7 million semi-trucks based on randomly assigned initial mileages. Our findings show that 58.41% of a fleet of semi-trucks will be electric by 2025, 91.95% by 2030, and 99.86% by 2040.

Afterwards, we looked at five different trucking corridors across the United States to determine how many charging stations must be constructed in order to support their current level of single-driver, long haul traffic. We created a "need" function that represents the number of semi-trucks that will need to recharge at every mile along the route. This function models the ideal scenario for truckers, where they are able to recharge until the very last minute, and uses this ideal model to inform us of how many trucks will end up charging at each station. We assume that the trucks entering the highway have initial mileages assigned by a uniform probability distribution. Our model found that the charging stations should be evenly distributed every 50 miles and typically have a number of chargers around 600 but ranging up to 1300.

Finally, we ranked the five corridors in order of when they should be developed into routes sustainable for electric semi-trucks. Our model looks at the economic and environmental effects, such as diesel/electricity prices and air quality, of switching to electric semi-trucks along the five routes. We conclude that the routes should be developed in the following order: New Orleans to San Antonio, Jacksonville to DC, Minneapolis to Chicago, San Francisco to Los Angeles, and Boston to Harrisburg.

Contents

1 Introduction

This section outlines the modeling problems we are asked to solve, and their objectives. We also list global assumptions that will be applied throughout the whole modeling process.

1.1 Background

Transportation of cargo shipments in the United States is mostly done by semi-trucks, which are also known as tractor trailers. These semis are powered by diesel fuel, which is both harmful to the environment and inefficient for the vast number of miles traveled. A modern alternative to diesel semi-trucks presents itself in the form of electric semis, which are becoming more and more attractive to companies due to their environmentally friendly, cost-efficient nature.

In 2020, the production of electric semi-trucks remains in a primitive state. However, companies such as Tesla plan to roll out production of 100,000 electric semi-trucks by 2024. To prepare for the overhaul of diesel semis with electric semis, we must consider how to sustain large-scale electric trucking and the charging infrastructure it necessitates.

In this paper, we model the percentage of electric semi-trucks in a fleet of operational semi-trucks at different time intervals into the future. We also look at five specific trucking corridors across the United States and model the charging infrastructure that must be constructed along those routes in order to sustain electric semi-trucks. Finally, we rank these routes based on how pressing their development is.

1.2 Restatement of the Problem

The problem asks us to do the following:

1. Predict what percentage of companies' semi-trucks will be electric in 2025, 2030, and 2040

2. Build a mathematical model to determine how many charging stations are necessary along the following routes, as well as how many chargers should be constructed at each station:

   - San Antonio, Texas to/from New Orleans, Louisiana

   - Minneapolis, Minnesota to/from Chicago, Illinois

   - Boston, Massachusetts to/from Harrisburg, Pennsylvania

   - Jacksonville, Florida to/from Washington, DC

   - Los Angeles, California to/from San Francisco, California

3. Rank each of 5 the trucking corridors to determine which one should be developed for electric trucking first

2 Part 1: Shape Up or Ship Out

2.1 Restatement of the Problem

The problem asks us to model the percentage of semi-trucks in a fleet that are electric as companies attempt to transition from diesel fleets to all-electric fleets in the upcoming years. We take into account the lifespan of long haul, regional haul, and short haul semis and their probability of breaking down in order to predict the proportion of electric semis in 2025, 2030, and 2040.

2.2 Assumptions

Assumption 2.1. The only two types of truck power sources to be considered are diesel and electric.

Justification. Semi-trucks powered by all other sources of energy make up a negligible part of the fleet. A mere 4% of semi-trucks use natural gas as fuel [13], and the National Renewable Energy Laboratory does not even list other viable forms of alternative fuel [2].

Assumption 2.2. An electric truck is more cost effective than a diesel truck.

Justification. In an article published on UPS's website [14], it states that "electric trucks are expected to cost UPS no more than regular diesel vehicles." Thus, we assume that the upfront costs of electric and diesel trucks are equal. At the same time, electric trucks cost $1.26 to operate, compared to $1.51 for diesel trucks, due to fewer moving parts [17]. Thus, the aggregate cost for electric trucks is less than that for diesel trucks, and electric trucks have been claimed to save its owner $200 000 compared to a diesel truck over the same lifetime [18].

Assumption 2.3. Charging stations, additional electrical grid equipment, and electric vehicle factories have been sufficiently implemented so that they do not hinder the production or usage of electric semi-trucks.

Justification. The problem statement tells us to assume that all necessary electric semi infrastructure is in place in order to make a transition to all-electric fleets *today*. Thus, we can assume that the gradual construction of charging stations, the development of the electric grid, and electric truck factories and production methods that normally would have taken place over an extended period of time have been instantaneously achieved.

Assumption 2.4. The goal of a company is to maximize revenue.

Justification. If a company does not make money, it is not sustainable. In order to prevent itself from failing, companies must maximize their revenue in order to have the most profit buffer in the case of negative economic shock. Revenue is profit − cost, so this assumption implies that companies want to maximize profit while minimizing cost.

Assumption 2.5. The total number of semi-trucks on the road does not change.

Justification. A truck costs money to maintain, so as a result of Assumption 1.5, they are incentivized to have as few as possible. In fact, truck routes are optimized to minimize the number of trucks needed [14]. Therefore, a company will only replace a truck when it has reached its lifespan. This can either be done by purchasing a new semi-truck, or repurposing an aging semi-truck while purchasing a new-truck to replace that aging truck's route.

Assumption 2.6. Companies will begin to transition their diesel fleets into all-electric ones by replacing their aging long haul semi-trucks.

Justification. After a long period of use, most long haul fleets sell their trucks to smaller fleets, such as for short and regional haul [15]. We assume that companies will not want to waste the diesel semis that they already own; thus, long haul trucks will be used to replace short and regional haul semis that have broken down or become unsafe to use. At the same time, due to Assumptions 1.1, 1.2, 1.3, and 1.4, companies will replace vacant truck routes with purely electric trucks. Using electric semi-trucks costs less in terms of both upfront and maintenance costs, and there are no production constraints to prevent the purchase of electric trucks.

2.3   Model Development

In order to determine the percentage of electric semi-trucks in a fleet over time, we model the entrance of electric semi-trucks into the fleet. By Assumption 1.5,

$$\frac{\mathrm{d}T}{\mathrm{d}t} = 0$$

where T is the total number of semi-trucks on the road. By Assumption 1.1,

$$\frac{\mathrm{d}T}{\mathrm{d}t} = \frac{\mathrm{d}D}{\mathrm{d}t} + \frac{\mathrm{d}E}{\mathrm{d}t} = 0$$

where D is the total number of diesel vehicles, and E is the total number of electric vehicles. According to Assumption 1.6, $\frac{\mathrm{d}D}{\mathrm{d}t}$ only occurs when trucks break down or aging long haul diesel trucks transition into regional haul trucks following five years of usage [15], and $\frac{\mathrm{d}E}{\mathrm{d}t}$ only matters in regards to replacing trucks that have transitioned or been retired.

Trucks go out of commission when they reach the end of their lifespan, which our model defines in terms of mileage. We use mileage by analogizing the effects of truck mileage to car mileage [12], and reasoning based on the fact that long haul trucks are reassigned to regional haul routes after 5 years to decrease the distance it travels per year [15].

We calculate a lifespan, in miles, that a diesel and electric semi-truck can respectively travel. According to the Truck Usage Data [21], short haul trucks travel 42,640 miles annually, regional haul trucks travel 70,000 miles annually, and long haul trucks travel 118,820 miles annually. The lifespan, in years, for a short haul truck can be expressed as

$$\frac{M\,\text{miles}}{42\,640\,\text{miles/year}}$$

where M is the number of miles a truck can be expected to drive before becoming unsafe. We can similarly express the lifespan of the regional haul truck. Long haul trucks are reassigned as medium haul trucks after 5 years, so that has to be taken into account in the calculation of its lifespan, yielding

$$\frac{M\,\text{miles} - 5 * 118\,820\,\text{miles}}{70\,000\,\text{miles/year}} + 5\,\text{years}$$

The average lifespan of a semi-truck would be the average of the lifespans of each kind of truck, accounting for their relative frequencies in the population of semi-trucks.

We hold the proportion of short, regional, and long haul trucks to be constant. Short haul trucks make up 5% of all semis, regional haul trucks make up 45% of all semis, and long haul trucks make up 50% of all semis [15]. This means that we can now write our expression for the average lifespan as

$$(0.05)\left(\frac{M}{42640}\right) + (0.45)\left(\frac{M}{70000}\right) + (0.5)\left(\frac{M - (5)(118820)}{70000} + 5\right)$$

Since we know that the average lifespan of a diesel truck is 12 years [15], we can solve for M to obtain a value for the average lifespan in terms of mileage: $M = 932\,144\,\text{miles}$.

There has been little published work on the mileage lifespan of electric semi-trucks. However, new research by Tesla has shown the potential for their lithium-ion battery technology to be deployed in their electric semi-truck could last more than 1 million miles [1] [16]. We can assume that all necessary electric infrastucture is in place to make a transition today, so we can assume that the development of electric batteries has stabilized and these experimental results have been properly implemented. Therefore, 1 million miles becomes a lower bound on the mileage lifespan of an electric semi-truck, so we use it for the average lifespan of an electric truck in terms of mileage.

We also model the probability of a semi-truck breaking down as its mileage approaches its lifespan. We introduce a small probability of a truck spontaneously breaking down, which varies directly with the proportion of its current mileage over its mileage cap. In a given year, a truck t can break down with some probability:

$$P(t) = \frac{t\text{'s current mileage}}{t\text{'s lifespan mileage}}$$

This probability function is motivated by the reasoning that as a truck logs more miles, the parts inside become more used and worn out, which leads to a higher chance of damage or breaking down.

Finally, we abide by the rule that after 5 years, long haul diesel trucks are transitioned to regional or short haul trucks [15]. Given that a long haul truck travels 118 820 miles/year, we transition a diesel truck from long haul to regional haul when it has surpassed $5 * 118820 = 594\,100\,\text{miles}$.

We ran our simulation given a lifespan mileage, this probability of a truck breaking down prior to reaching the maximum cap, and the associated rearrangement of the fleet. The following flowchart is a summary of the possible states of a truck as it transitions throughout its lifestyle.
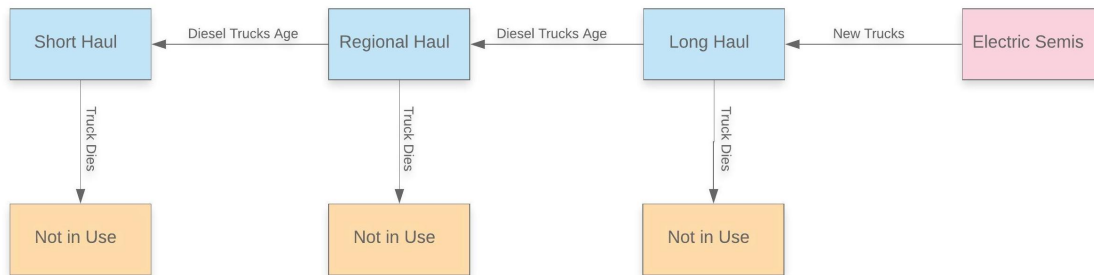
Figure 1   Diagram of the Cycle of Electric and Diesel Semi-Trucks

2.4   Model Application

We build a simulation for a fleet of trucks, where each truck is assigned to start at a random mileage ranging from 0 miles (brand new) to 932144 miles (its mileage cap). After running the simulation for a year, we assume each type of truck (long haul, regional haul, and short haul) travels a certain mileage value (118820, 70000, and 42640 respectively).

The following steps occur within the simulation every year:

1. If a truck reaches its mileage cap in a given year, it is retired from the fleet. Trucks are also retired if they have "broken down" according to our probability function.

2. After retiring trucks, the fleet assignments are rearranged to restore the relative proportion of each type of truck, which we recall are 50% (long haul), 45% (regional haul), and 5% (short haul). They are rearranged in the following way: any deficiency in the number of short haul trucks is resolved by repurposing regional haul trucks into short haul trucks. Then, a deficit in regional haul trucks is filled by repurposing long haul trucks. The resulting deficit in long haul trucks is resolved by purchasing new electric trucks, by Assumption 1.6.

3. Finally, any long haul diesel trucks above 594 100 miles are transitioned to regional haul. To maintain the relative proportions, this pushes regional haul truck(s) to short haul, and leads to the forced retirement of short haul trucks.

The trucks that will be repurposed or retired will be the ones with the most mileage, as they have the largest chance of spontaneously breaking down according to our probability function. Repurposing those trucks in particular will slow the growth of their already high chance of breaking down while preserving younger trucks with lower chances of breaking down, minimizing the cost that must be spent on replacing trucks expected to be retired, which is an objective of Assumption 1.5.

According to the Information Sheet [15], there are around 1.7 million semi-trucks transporting cargo around the United States today. Therefore, our simulation was run with a fleet size of 1.7 million. The mileage cap for diesel trucks was taken to be 932 144, while the cap for electric was taken to be 1 000 000. The simulation was run for 20 years.
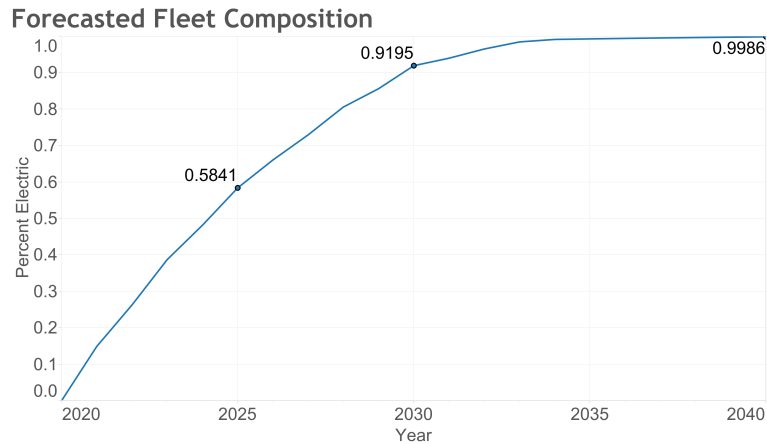
Figure 2　The composition of the fleet based on the results of our simluation, averaged across 10 trials

Our simulation shows that 58.41% of a fleet of semi-trucks will be electric by 2025, 91.95% by 2030, and 99.86% by 2040.

2.5 Model Analysis

2.5.1 Sensitivity Analysis

We conducted sensitivity analysis on our model by changing our input variables and analyzing the changes' impact on our outputs. We present our model's results when it used altered values for the cap on diesel mileage, cap on electric mileage, and the number of trials used.

Variable Change	2025	2030	2040
Original (Electric cap: 932 144)	0.584	0.920	0.999
Diesel Cap: 697 500	0.700	0.989	1.000
Diesel Cap: 750 000	0.667	0.970	1.000
Diesel Cap: 1 000 000	0.558	0.882	0.998

Figure 3　The effect of changing the diesel lifespan mileage on the fleet composition after 5, 10, and 20 years

Our simulation predicts a higher percentage of electric semi-trucks in a fleet if the cap for diesel mileage decreases by around 200,000. This behavior aligns with our expectations—a lower mileage cap means the diesel semis will break down faster, thus requiring a higher proportion of electric semis in order to replace the losses.

In our simulation, decreasing the electric cap by more than 20% from 1 million to 796496 does not affect the results. This makes sense because most of the electric vehicles would not have been in the fleet for long enough to reach the cap at all. The simulation also performs consistently through the trials, mostly due to the large fleet size of 1.7 million.

Variable Change	2025	2030	2040
Original (Electric cap: 1 000 000)	0.584	0.920	0.999
Electric Cap: 796 496	0.584	0.920	0.999

Figure 4 The effect of electric lifespan mileage on the fleet composition after 5, 10, and 20 years

Variable Change	2025	2030	2040
Original (10 trials)	0.584	0.920	0.999
5 trials	0.584	0.920	0.999
1 trial	0.584	0.920	0.999

Figure 5 The effect of trials on the fleet composition after 5, 10, and 20 years

In our simulation, changing the number of trials has little effect on the fleet composition after 5, 10, and 20 years. This is due to the robustness of simulating across 1.7 million trials.

2.5.2 Strengths and Weaknesses

Our model's strength lies in the fact that it is resilient to small changes in inputs. In addition, our sensitivity testing shows that its results are consistent regardless of the number of trials and also make sense intuitively.

A weakness of our model is that it heavily relies on our pipeline of electric semi-trucks only entering the fleet of semi-trucks when they replace aging long haul trucks. Companies may choose to use electric trucks to replace short haul trucks instead: because the electric semis are a new product, they may want to minimize risk by testing the electric vehicles on short distances first. This would greatly complicate our model, as we have no quantifiable way to determine when a company would become trusting enough of electric semis to use them on longer routes.

3 Part 2: In It for the Long Haul

3.1 Restatement of the Problem

The problem asks us to determine how many charging stations are *necessary* and how many chargers are *sufficient* at each station along the five traffic corridors. Our interpretation of this problem is that we want to minimize the number of constructed chargers and stations while still supporting the current level of long haul traffic from diesel trucks.

3.2 Definition of Terms and Variables

- $T(x)$: the number of trucks per day that are on the corridor x miles from the start of the corridor.

- $T'(x)$: the rate of change of T per mile, at a distance x miles from the start of the corridor.

- α: truck drivers will wait until their battery has fewer than α miles left before they stop to recharge.

- β: the number of miles a truck can drive after filling up the battery.

- τ: the time it takes, in hours, for a truck to recharge to full battery.

- κ: the ratio of total number of chargers in a station to the average number of trucks that are using the station at any given time.

- **mileage**: the number of miles that a given truck can continue to travel before it runs out of electricity. As a truck travels along its route, its mileage decreases. The mileage resets to β once it recharges. *This is not to be confused with the standard use of the word* mileage, *which is a measure of efficiency.*

   The following functions will be further explained in the Model Development section.

- $D(x, m)$: The number of trucks (per day) on mile x of the corridor and have mileage m.

- $N(x)$: The number of trucks (per day) that naturally reach a mileage of 0 at mile x of the corridor.

3.3   Assumptions

Assumption 3.1. For all trucks, let $\alpha = 50$, $\beta = 400$, and $\tau = 9$.

Justification. Assuming that all trucks are identical makes our model simpler. [7] reports that electric trucks have a maximum mileage (range) of 400 to 500 miles, so we choose $\beta = 400$. According to [9], it takes about 8 hours to charge an electric car. We assume that trucks take a bit longer to charge than cars, so $\tau = 9$. Finally, we let $\beta = 50$ because recharging at one-eighth of the maximum charge is a reasonable estimate. Note that the exact values of these constants do not affect the structure of our model.

Assumption 3.2. On any part of the corridor, trucks are either entering or exiting, not both. That is, if $T'(x) > 0$, no truck leaves the corridor at mile x. If $T'(0) < 0$, no truck enters the corridor at mile x.

Justification. This is clearly an oversimplification of the way trucking routes work. However, we could not find separate data on the number of trucks entering and the number of trucks exiting the corridor at each mile. Only the net change in trucks ($T'(x)$) was available to us. Without more detailed information, we were forced to make this assumption.

Assumption 3.3. Let m be the mileage of a truck entering the corridor (either at the start of the corridor or somewhere in the middle). We assume m comes from a uniform probability distribution ranging from α to β.

Justification. The mileage of a truck decreases linearly with miles traveled, and always stays below its maximum, β. A truck driver would not want to enter a highway with a low battery, so we can assume $m > \alpha$. Thus, at a random time, the probability of a truck having mileage m should be uniformly distributed over this interval $[\alpha, \beta]$.

Assumption 3.4. Recharging stations should occur at evenly spaced locations along the corridor. They are located every α miles, starting at mile 0 (at the starting city).

Justification. First, it is important to realize that the distance between consecutive stations should never be greater than α. This is because a truck may enter the corridor right after a refueling station and have mileage of α (due to Assumption 3.3). If the distance to the next recharging station is greater than α, the truck will run out of energy on the highway. This is clearly an issue, so we should make sure no pair of refueling stations are over α miles apart.

The goal of the problem is to minimize the number of recharging stations. With the previous restriction in mind, the farthest apart we can have consecutive stations is α miles. Thus, we choose to uniformly space the stations with exactly α miles between them.

Assumption 3.5. The trucks that leave the corridor at mile x are a perfectly representative sample of all of the trucks that are on the highway at mile x.

Justification. This is a simplifying assumption. We could not find data on the breakdown of mileages of trucks that leave the corridor, so it is necessary to assume that the trucks that leave come uniformly at random from all trucks on the highway at that mile.

Assumption 3.6. The value of κ, the ratio of chargers in a station to number of trucks using the station, is 1.5.

Justification. The number of trucks in a station can fluctuate. Because of this, we want to make sure that the station has more chargers than it usually needs (so $\kappa > 1$). However, we do not want to have too many extra unused chargers. $\kappa = 1.5$ is a good middle ground.

3.4   Model Development

In our model, we attempt to simulate a highway system where we are able to keep track of the number of trucks that have each possible mileage $m \in [\alpha, \beta]$ at each mile x.

The purpose of our simulation is to develop a "need" function, $N(x)$. This function represents the number of trucks that naturally run out of mileage at mile x (technically, along the interval $[x, x+1)$). To calculate this need function, we ignore the planned locations of charging stations and instead assume that trucks are able to recharge wherever they want. Trucks in our simulation keep driving until they hit a mileage of 0. When this happens, we take note of it by increasing $N(x)$ by 1. We then refill the truck's mileage to β (full).

The motivation for creating $N(x)$ is that it models an *ideal* scenario for truckers, allowing them to recharge at the very last minute. Once we know where truckers are recharging in this ideal scenario, we can impose our equally spaced charging stations as described in Assumption 3.4 to see how many trucks will end up charging at each station. Note that the units of $N(x)$ is in trucks per day per mile.

The Corridor Data dataset [5] gives us observations of T, the number of trucks per day for certain values of x along the corridors of interest. We use first order linear approximations to interpolate the values of T between consecutive observations by connecting the given points with line segments. This lets us generate the continuous function, $T(x)$, by connecting consecutive points.

Once we have T at all miles x, we can take a derivative, $T'(x) = T(x + 1) - T(x)$. Note that this is not a true derivative, because we are not taking a limit. For this algorithm, all of our functions take in integer inputs (as opposed to inputs that are all real numbers) for simplicity.

We start at the beginning of the corridor ($x = 0$). We set $D(0, m)$, which is the number of trucks per day on mile 0 of the corridor and with mileage m, to be a uniform distribution from α to β, scaled so that the total number of trucks is $T(0)$. This is consistent with Assumption 3.3. We use a step size of 1 mile to carry out the simulation. For each new step, we do the following to calculate $D(x + 1, m)$ from $D(x, m)$ for all values of m:

1. Count the number of trucks which have mileage of 0. This is $D(x, 0)$. These trucks have run out of electricity, so now we will let them recharge. As described before, we set $N(x) = D(x, 0)$ to keep track of the "need function." Now, set $D(x + 1, \beta) = D(x, 0)$ because these trucks now have full battery.

2. Account for the inflow or outflow of trucks. Note that we apply Assumption 3.2 here.

   a) If $T' > 0$: this means that in the interval in question, there is a net gain in the number of trucks. From Assumption 3.3, the trucks entering the highway have mileages evenly distributed in $[\alpha, \beta]$. Let $P(m)$ be a probability density function that represents this even distribution. Then, we simply add $P(m) \cdot T'(m)$ to $D(x + 1, m)$ for each $m \in [\alpha, \beta]$.

   b) If $T' < 0$: this means that in the interval in question, there is a net loss in the number of trucks. From Assumption 3.5, we can simply scale down $D(x, m)$ at all values of m by a certain factor that results in a decrease of $T'(x)$ total trucks. This factor is $1 + \frac{T'}{T}$, because when multiplied by T, it results in $T + T'$ total trucks. Thus, we simply set $D(x + 1, m) = D(x, m) \cdot (1 + \frac{T'}{T})$ for all $m \in [0, \beta]$

3. We now have $D(x + 1, m)$ for all values of m. However, the trucks must now drive another mile to reach the next step of the simulation. Thus, we simply shift all values of mileage down by 1 by setting $D(x + 1, m) = D(x + 1, m + 1)$.

Once we simulate this process over every mile of the corridor, we have our need function, $N(x)$. Now, we can calculate the number of trucks that stop at each station per day. From Assumption 3.4, the stations occur at locations $0, \alpha, 2\alpha, \ldots, n\alpha$. In the ideal scenario that $N(x)$ models, if a trucker reaches mileage 0 at mile $x \in [c\alpha, (c + 1)\alpha)$, they really should have recharged at the station located at mile $c\alpha$. Thus, we can say that the number of trucks (per day) that use a station located at mile $c\alpha$ is

$$\int_{c\alpha}^{(c+1)\alpha-1} N(x)dx$$

This gives us the number of trucks per day which use any given station. Call this value n for a station S. To get the number of chargers S should have, we note that if a truck uses station S, it requires $\frac{\tau}{24}$ charger-days at the station. Thus, S must be able to provide an average $n\frac{\tau}{24}$ charger-days of energy per day. Applying our definition of κ, the station should have $\kappa n\frac{\tau}{24}$ chargers. Our final formula for the number of chargers a station should have is

$$\frac{\kappa\tau}{24}\int_{c\alpha}^{(c+1)\alpha-1} N(x)dx$$

3.4.1 Dealing with Incomplete Data

Many of the observations in the corridor traffic data provided in [5] were missing. To resolve this, we used linear interpolation on the AADTT% to calculate the AADTT of the missing observations (AADTT stands for Annual Average Daily Truck Traffic).

3.5 Model Application

We ran our model on the data provided in Corridor Data [5] on the five required corridors. Below are the model's results for the Boston, MA to Harrisburg, PA corridor. Figures for the four other corridors can be found in the appendix.
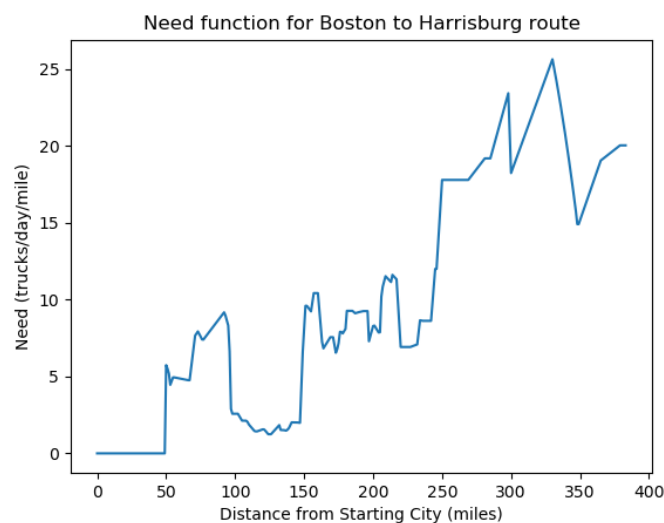
Figure 6 The number of trucks that have used up all of their electricity on a given mile from Boston to Harrisburg

The results above allow us calculate the number of chargers needed at each station on the corridor. If we space out the stations every α miles along the corridor and overlay it onto the map of the corridor, we get the following figure.
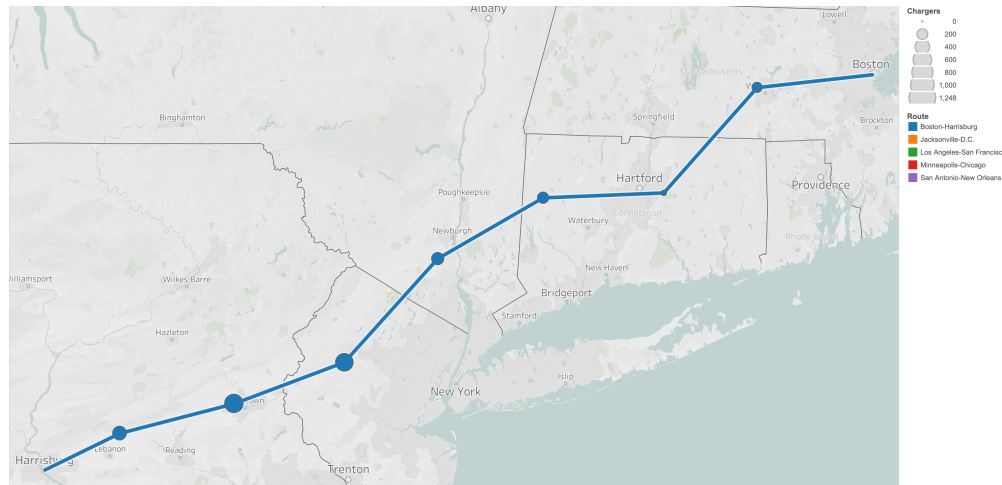
Figure 7   Number of chargers needed at each station from Boston to Harrisburg

The largest stations in our model have up to 1300 chargers, but the typical station has 600 chargers. While this may seem too large to be true, we believe that these are actually reasonably sized results. The important thing to keep in mind is that it takes $\tau = 9$ hours for a truck to charge. Unlike a gas station, where diesel trucks only need to visit for 15 minutes to refuel, the 9 hours of waiting time means that many more chargers are necessary. We can do a quick sanity check to confirm this—gas stations refuel about 36 times faster than charging stations; the typical gas station could have around 20 pumps: $20 \cdot 36 = 720$, which is around 600.

3.6   Strengths and Weaknesses

One of the strengths of our model is its ability to produce a need function, which provides us with a general idea of where chargers are needed. In our model, we used the assumption that a charging station will be placed every 50 miles; however, our need function allows for a general consideration of the placement of charging stations and the number of chargers needed at a station. For example, if charging stations are placed at locations x_0 and x_1 along a highway, the number of trucks that visit the mile x_0 station per day is simply $\int_{x_0}^{x_1} N(x)dx$. This demonstrates the *flexibility* of our model: adapting the use of our need function is very convenient.

The major weaknesses of our the model come from unrealistic assumptions. The most obvious flaw is Assumptions 3.2: trucks often enter and leave on the same part of the highway. Assumption 3.1 is also unrealistic because electric trucks may come in different models and have different specifications. The arbitrary choice of κ in Assumption 3.6 is not based on any data; however, this only scales our results by a constant factor and does not affect the underlying reasoning and mathematics that our model is based on.

4 Part 3: I Like to Move It, Move It

4.1 Restatement of the Problem

We are asked to rank the five trucking corridors in order of how soon they should be developed for electric trucking. We consider both the economic and environmental impacts of electric trucking for each of the five corridors.

4.2 Assumptions

As we continue to use need functions as in Part 2 for both electric and diesel trucks, the assumptions in Part 2 are also applicable for this part.

4.3 Definition of Variables

- x: distance from starting point along a corridor
- $g(x)$: average price per gallon of diesel gasoline in the state which contains point x
- $e(x)$: average price of electricity per kWh in the state which contains point x
- c_e: average electric battery capacity per truck, in kWh
- c_g: average gas tank capacity per truck, in gallons

4.4 Model Development

4.4.1 Economic Component

Take the need function for electric trucks. Now consider how often diesel trucks need to refuel. This distribution necessarily looks very different, since diesel trucks need to refuel much less often. We will calculate the difference in spending after a switch to electric truck as follows:

$$\Delta F = \int g(x)c_g N_g(x) - e(x)c_e N_e(x)dx$$

where ΔF is the change in fuel related spending per day. The need function $N(x)$ outputs the number of trucks per day per mile that need to be refueled. Thus the need function multiplied by the fuel capacity of a truck represents the volume of fuel per day per mile. Integrating gives the amount spent on fuel day in the entire corridor.

The need functions $N_e(x)$ were generated in part 2 (section 3). To generate the need functions $N_g(x)$, we simply run the same simulation as in part 2, simply changing the number of miles needed to recharge from the value of 400 for electric trucks to 2000 for diesel trucks [22].

4.4.2   Environmental Component

We split this component into the financial and nonfinancial components. For the financial component, we consider the cost due to carbon emissions as detailed in [19]. We can place a cost on each corridor based on the volume of CO2 that would have been emitted if diesel trucks were used instead of electric.

We want to estimate the carbon cost ΔC. We will calculate this as a function of truck traffic volume. We can calculate the amount of CO2 emitted using the conversion detailed in [11], which expresses the tonnage of CO2 emitted as a function of the load carried and the mileage traveled. Since we will be integrating for a total value over all trucks eventually, we will assume a uniform payload weight, equal to the average over all trucks.

$$\Delta C = cmW \int T(x)\,dx$$

where $T(x)$ represents the number of trucks at any given point x along the route, c is the carbon cost in dollars per ton, m is a constant representing CO2 emissions per mile per ton of payload, and W is the payload weight in tons.

We can also consider the non-financial impact of corridor conversion on the air quality of the surrounding region [23]. First, we need to calculate the average value of the air quality index (AQI) along the corridor to get a baseline vale. We will compute this by considering the path integral:

$$\frac{1}{s} \int_C A(x, y)\,d\vec{r}$$

where s is the total arc length of the corridor, and $A(x, y)$ is the AQI at any coordinate. From [3], we can calculate how much carbon monoxide O trucks produce in a day:

$$O = o \int T(x)\,dx$$

where o is a constant representing how much carbon monoxide trucks produce per mile (2.311 grams/mile [3]).

This O gives a tonnage of carbon monoxide produced per day. For a better sense of magnitude, let us consider the effect after 1 month (30 days). Based on the prior AQI, we can find what the concentration of carbon monoxide was, and the equivalent volume. We then subtract the monthly contribution volume that was produced by the diesel trucks, since this would not be a source of pollutants after a switch to electric trucks. This new concentration of carbon monoxide can be converted back to an AQI, which will be purer than the previous.

4.5   Model Application

4.5.1   Economic Component

In the table below, we have listed energy prices by region from [8] and [6]:

Corridor	Electricity Prices (cents/kWh)	Diesel Prices (dollars/gallon)
New Orleans to San Antonio	7.81	2.654
Minneapolis to Chicago	9.61	2.756
Boston to Harrisburg	9.16	3.17
Jacksonville to DC	7.57	2.779
San Francisco to Los Angeles	9.07	3.778

Figure 8   Energy Prices by Region

We use that c_e = 325 kWh by the Battery Data [4] provided and c_g = 225 gallons of gasoline [10]. We applied the need functions to both electric and diesel trucks, and the results are shown in the table below.

Corridor	Need (electric)	Need (gasoline)
New Orleans to San Antonio	30086	5881
Minneapolis to Chicago	6686	1204
Boston to Harrisburg	3960	713
Jacksonville to DC	10582	1930
San Francisco to Los Angeles	5318	957

Figure 9   Total Need (trucks/day)

After generating the new need functions N_g, we can calculate the following table of values ΔF:

Corridor	ΔF
New Orleans to San Antonio	2 748 181
Minneapolis to Chicago	537 779
Boston to Harrisburg	390 658
Jacksonville to DC	946 437
San Francisco to Los Angeles	656 736

Figure 10   Reduction in Spending for Electric Trucks versus Diesel Trucks

4.5.2   Environmental Component

We can assume an average load of 20.665 tons [20]. Multiplying this factor by integral representing the daily traffic through the corridor, we get the carbon cost ΔC that is eliminated due to the transition to electric trucks:

$$\Delta C = (50) \left(1.783 \times 10^{-4}\right) (20.665) \int T(x)\,dx$$

Corridor	ΔC
New Orleans to San Antonio	2 459 969
Minneapolis to Chicago	910 970
Boston to Harrisburg	730 508
Jacksonville to DC	1 149 699
San Francisco to Los Angeles	676 381

Figure 11 Change in carbon cost, in dollars per day

We approximated the path integral with a Riemann sum along segments of the corridor.

Corridor	Average AQI
New Orleans to San Antonio	39.29
Minneapolis to Chicago	46
Boston to Harrisburg	33.14
Jacksonville to DC	35.3
San Francisco to Los Angeles	29

Figure 12 The average Air Quality Index along each corridor, as sampled by measurements provided by [23]

The following table explains the estimated new AQI after diesel trucks are converted to electric trucks.

Corridor	New AQI	Percent Decrease
New Orleans to San Antonio	36.5	7.1%
Minneapolis to Chicago	44	4.34%
Boston to Harrisburg	32	3.44%
Jacksonville to DC	32	9.35%
San Francisco to Los Angeles	28	3.45%

Figure 13 The predicted Air Quality Index along each corridor after 1 month of electric trucks

4.6 Summary

We standardize each variable to 1 by dividing each variable by the maximum value in the category.

Corridor	ΔF	ΔC	AQI	Σ	Rank
New Orleans to San Antonio	1	1	0.759	2.759	1
Jacksonville to DC	0.344	0.467	1	1.811	2
Minneapolis to Chicago	0.196	0.370	0.464	1.03	3
San Francisco to Los Angeles	0.239	0.275	0.369	0.883	4
Boston to Harrisburg	0.142	0.297	0.367	0.806	5

Figure 14 Overall rankings

We summed the values across each variable for all five corridors. Since the New Orleans-San Antonio corridor has the highest value, clearly, the first corridor to be targeted for development should be the New Orleans to San Antonio corridor.

4.7   Strengths and Weaknesses

One of the strengths of our model was that we were able to consider multiple aspects of the effects. By separating the model into various aspects of cost, carbon emissions, and AQI, we can see in greater detail the effects of switching to electric trucks. Also, the relative impacts of each variable contributing to the final ranking can be distinguished due to the standardization of values. However, one of our model's weaknesses was a failure to consider additional qualitative factors such as community support and public opinion to the changes in trucking.

5   Conclusion

Diesel semi-trucks present a serious issue in today's world because of their inefficiency and massive consumption of fossil fuels. Fortunately, we have found an outstanding alternative in electric semi-trucks, which are simultaneously better for the environment and more cost-effective than diesel semi-trucks. Our models suggest that within 5 years, more than 50% of the current operational semi-truck fleets will be electric, and by 2040, nearly 100% of the fleets will be electric. Our models further analyze the implementation of charging infrastructure that will be necessary to sustain the transition to electric semi-trucks. Our model finds that the number of charging stations should be evenly placed every 50 miles along the 5 trucking corridors that were provided for evaluation. At each station along the 5 corridors, our results show that there should typically be 600 chargers, but this number may range up to 1300 chargers. Finally, we evaluated the 5 corridors based on the economic and environmental consequences of switching from diesel trucks to electric trucks on each of the 5 corridors, and found that the first corridor that should be targeted is the San Antonio-New Orleans corridor.

A Additional Figures
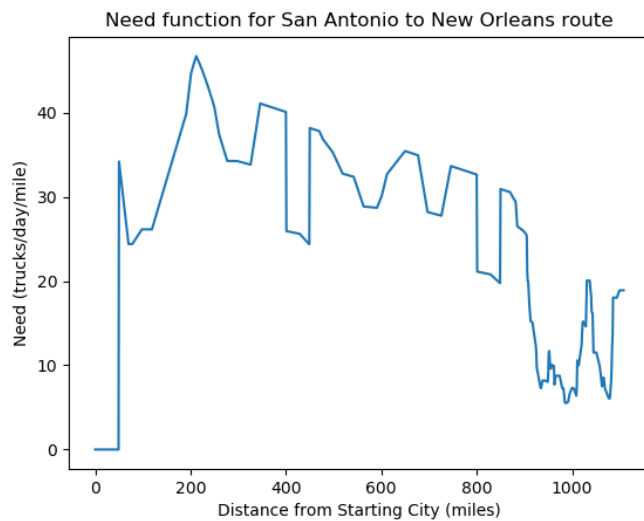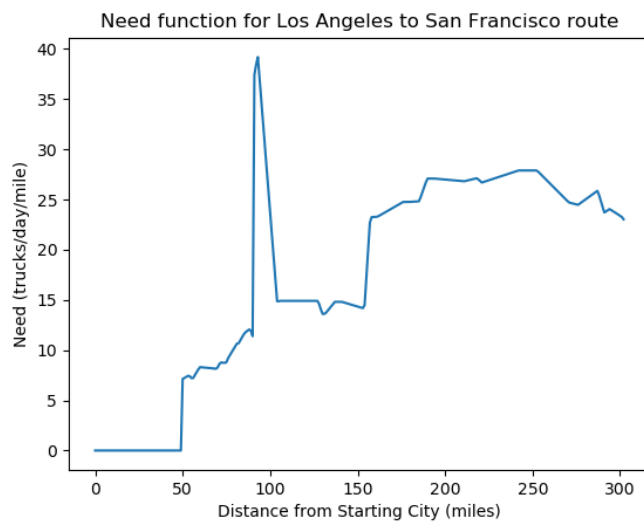
A.1 Problem 2 Additional Figures
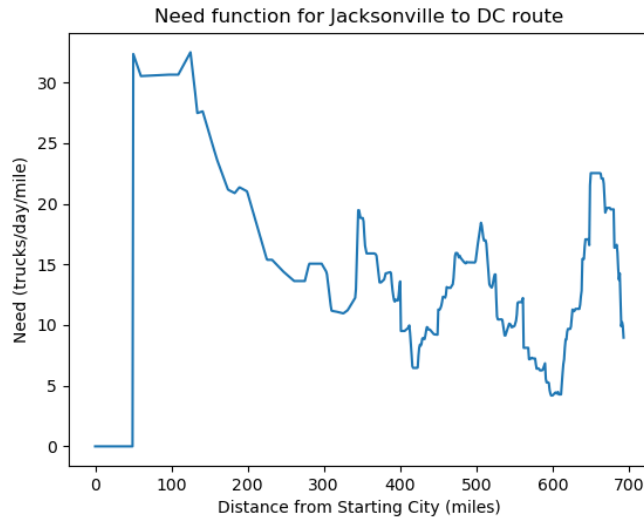
Figure 15 The number of trucks that have used up all of their electricity on a given mile from Jacksonville to DC
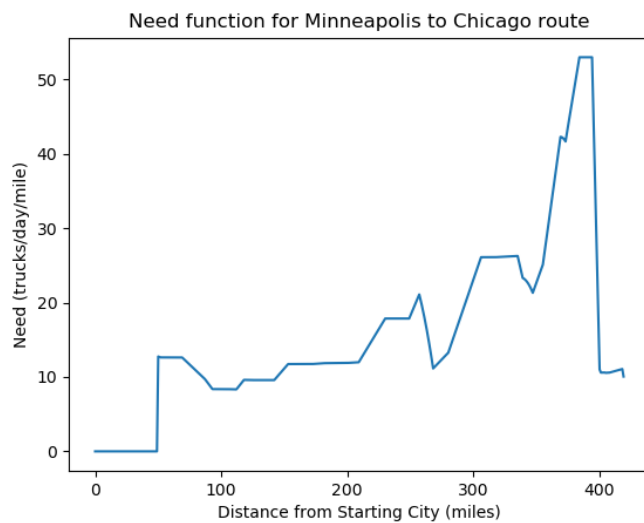
Figure 16 The number of trucks that have used up all of their electricity on a given mile from Minneapolis to Chicago

Figure 17   The number of trucks that have used up all of their electricity on a given mile from San Antonio to New Orleans

Figure 18   The number of trucks that have used up all of their electricity on a given mile from LA to San Francisco
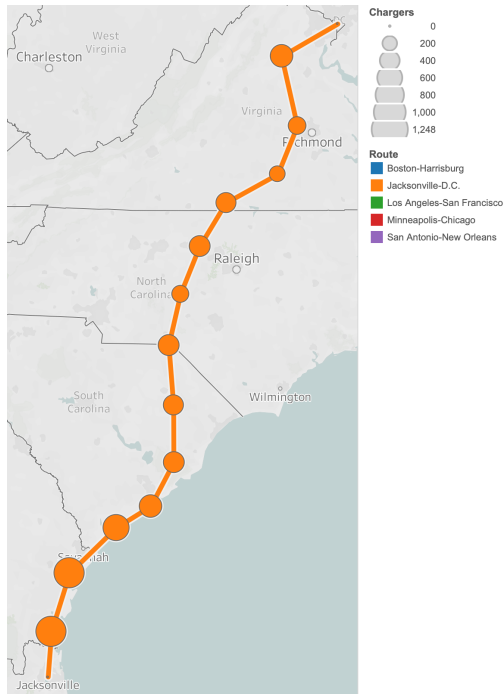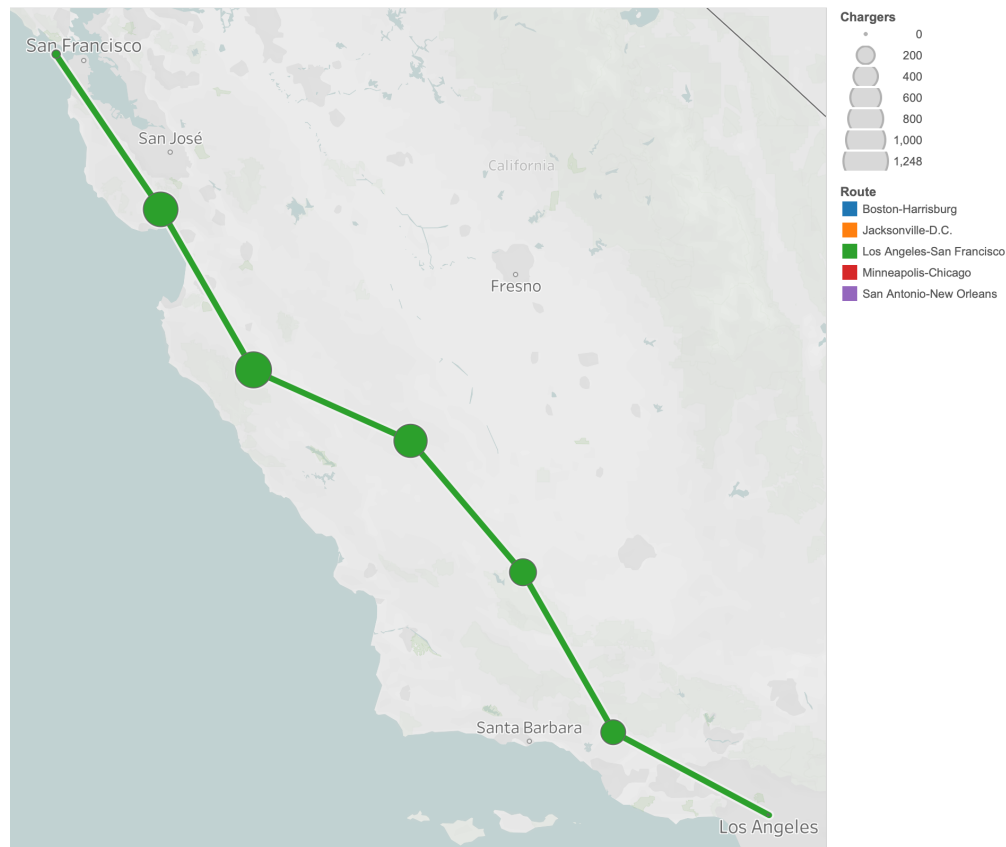
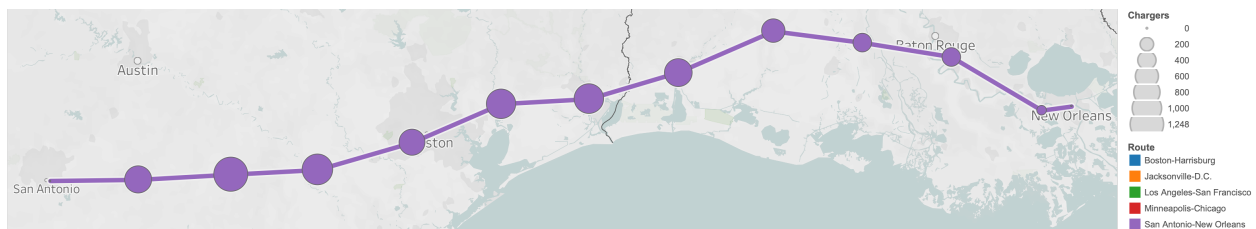**Figure 19**   Stations on Jacksonville to DC

Figure 20   Stations on Minneapolis to Chicago

Figure 21 Stations on Los Angeles to San Francisco

Figure 22 Stations on San Antonio to New Orleans

B Code

B.1 Problem 1 Simulation Code

```python
import random
import csv

fleetSize=1700000
# Long Haul avg. miles driven per year, regional, etc.
multipliers={"L":118820,"R":70000,"S":42640}
```

```python
class Truck:
    def __init__(self, t,m=0,f="Diesel"):
        self.mileage=m
        self.type=t
        self.fuel=f
        # Average mileage until retirement based on truck type
        if self.fuel=="Diesel":
            self.cap=932144
        else:
            self.cap=1000000


    def birthday(self):
        self.mileage += multipliers[self.type]
        return self.mileage


def stillYoung(truck):
    if truck.mileage>truck.cap:
        return False
    else:
        # Small probability of truck failing before EOL
        if random.random()<truck.mileage/truck.cap*0.1:
            return False
    return True


# Run multiple times, then average for sensitivity
for run in range(10):
    fleet = []
    electric=[]
    total=[]
    # Construct a fleet of all diesel trucks with uniformly distributed odometers
    for count in range(fleetSize):
        fleet.append(Truck(random.choices(population=
        ["L","R","S"],weights=[0.5,0.45,0.05],k=1)[0]))
        fleet[-1].mileage=random.randint(0,fleet[-1].cap)

    for year in range(2020,2041):
        total.append(len(fleet))
        eCount=0
        avgAge=0
        for truck in fleet:
            if truck.fuel!="Diesel":
                eCount+=1
            avgAge+=truck.mileage
            truck.birthday()

        electric.append(eCount)
        fleet = list(filter(stillYoung, fleet))
```

```python
        short=list(filter(lambda truck: truck.type=="S",fleet))

        regional = list(filter(lambda truck: truck.type == "R", fleet))
        regional.sort(key=lambda truck: truck.mileage, reverse=True)

        long = list(filter(lambda truck: truck.type == "L", fleet))
        long.sort(key=lambda truck: truck.mileage, reverse=True)

        # Shift trucks down the hierarchy of less taxing positions
        transfer1=0.05*fleetSize-len(short)
        for count in range(int(transfer1)):
            regional[count].type="S"

        transfer2=0.45*fleetSize-( len(regional)-transfer1 )
        for count in range(int(transfer2)):
            long[count].type="R"

        for count in range(fleetSize-len(fleet)):
            fleet.append(Truck("L",0,"Electric"))

    prop=[]
    for count in range(21):
        prop.append(electric[count]/total[count])

    # Produce data for graphs
    with open('percents'+str(run)+'.csv', 'w', newline='') as csvfile:
        writer = csv.writer(csvfile, delimiter=',')
        writer.writerow(["Year","Percent Electric"])
        for count in range(21):
            writer.writerow([2020+count,prop[count]])
```

B.2   Problem 2 Simulating Code

```python
import matplotlib.pyplot as mp
import csv

#Constants
MAX_MILES = 400 #Maximum miles of electricity a truck battery can hold.
CHARGER_SPACING = 50 #How far apart are charging stations along the highway?
RECHARGING_HOURS = 9 #How long does it take for a truck to recharge to full
    battery?
CAPACITY_OVER_AVERAGE = 1.5 #How many chargers do we want in a station (in terms
    of the number of average trucks it has)
```

```python
#P function
def P(m):
    """
    Input: m, a number of miles of charge
    Output: the probability that a new truck has m miles left on their battery
    """
    #Assumption: p is a uniform distribution from CHARGER_SPACING to MAX_MILES
    if int(m) < CHARGER_SPACING or int(m) > MAX_MILES:
        return 0
    else:
        return 1/(MAX_MILES - CHARGER_SPACING + 1) #So that the integral from 0 to
            MAX_MILES of P is 1.

def get_T(obs):
    """
    Input: obs, a list of ordered pairs (number of miles, AADTT) observations
    Output: A list of T at each mile
    """

    #Assumption: The value T between observations are approximated linearly
    T = []
    mile = 0
    obs_num = 0
    while obs_num < len(obs)-1:
        slope = (obs[obs_num + 1][1] - obs[obs_num][1])/(obs[obs_num + 1][0] -
            obs[obs_num][0]) #Slope of the line segment
        T.append(obs[obs_num][1] + slope*(mile-obs[obs_num][0])) #First order
            approximation (linear) of T

        #Move on to next mile. Use next line segment if necessary.
        mile += 1
        while obs_num<len(obs)-1 and mile > obs[obs_num + 1][0]:
            obs_num += 1

    return T

def ddx(y):
    """
    Input: y, a sequence (function) of x
    Output: dy/dx (discrete derivative)
    """
    dydx = []
    for i in range(len(y)-1):
        dydx.append(y[i+1]-y[i])

    dydx.append(0) #Add 0 to the end to pad it to be the same length as y
```

```
    return dydx

def get_need(obs):
    """
    Input: obs, a list of ordered pairs (number of miles, AADTT) observations
           num_miles, the total number of miles in the route
    Output: The need funcion (how many trucks run out of battery on any given mile)
    """
    T = get_T(obs)
    dTdx = ddx(T)

    num_miles = len(T) #Length of the route (in miles)

    #The distribution of trucks. dist[m] is the number of trucks with m miles of
        battery left.
    dist = [P(m)*T[0] for m in range(0,MAX_MILES + 1)] #Start out as the
        distribution of P.

    #need[m] represents how many trucks would end up recharging at mile m, if
        recharging stations were everywhere
    need = [0 for m in range(0,num_miles)]

    #Actual simulation
    for mile in range(num_miles):

        #All trucks with no battery must recharge at this mile.
        need[mile] += dist[0]
        dist[MAX_MILES] += dist[0]
        dist[0] = 0

        #Assumption: trucks are either leaving or entering. There is no part of
            the highway in which some trucks enter and others leave.
        if dTdx[mile] > 0: #Trucks are entering

            #Assumption: they enter with battery distribution P
            for m in range(MAX_MILES + 1):
                dist[m] += dTdx[mile] * P(m)

        else: #Trucks are leaving

            #Assumption: leaving trucks are a perfectly representative sample of
                all trucks on the highway
            leaving_proportion = -dTdx[mile]/T[mile]
            for m in range(MAX_MILES + 1):
                dist[m] *= (1 - leaving_proportion)
```

```python
        #Decrease every truck's battery by 1 mile for the next pass through the
            loop
        for m in range(MAX_MILES):
            dist[m] = dist[m+1]
        dist[MAX_MILES] = 0

    return need, num_miles

def get_stations(obs):
    """
    Input: obs, a list of ordered pairs (number of miles, AADTT) observations
    Output: the stations as ordered pairs (mile marker, number of chargers)
    """
    need, num_miles = get_need(obs)

    #The locations of charger stations
    locs = [m for m in range(0,num_miles,CHARGER_SPACING)]

    #The locations (mile marker) and size (number of chargers) of the stations
    #Stored as ordered pairs
    stations = []
    for loc in locs:
        usage = 0 #Number of trucks that use it per day

        #Integrate need from loc to loc+CHARGER_SPACING
        for m in range(loc, min(loc+CHARGER_SPACING, num_miles)):
            usage += need[m]

        size = (usage * (RECHARGING_HOURS / 24) ) * CAPACITY_OVER_AVERAGE
        stations.append([loc, size])

    return stations

def get_obs(route_name):
    miles = [float(x.strip().replace(",","")) for x in
        open(route_name+"_miles.txt", "r").readlines()]
    AADTTs = [float(x.strip().replace(",","")) for x in
        open(route_name+"_AADTT.txt", "r").readlines()]

    obs = list(zip(miles,AADTTs))
    return obs
```

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