M3 2020

Team 14059

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1 Executive Summary

Containerized cargo shipments account for a large segment of the United States transport infrastructure; an estimated 1.7 million semi-trucks (also known as tractor trailers and big rigs) carry nearly everything we buy or build. Diesel fuel powers these semis as they travel an estimated 150 billion miles annually, accounting for more than 12 % of the fuel purchased in the U.S. Yet, a new era of electrically-fueled semi trucks may be approaching. With the Tesla announcement to release their own new line of electric driven semis to companies including PepsiCo and UPS.

To project the growth of electric semis in the future, we composed a recursive mathematical model based on data of previous growth of the semi industry. Using this data, we then formulated the proportion of the total semi population replaced by new semis, inputting the given lifespan of diesel semis as 12 years. By initiating a variable $P_e(t)$ for the probability the company will buy an electric car, we use a recursive equation to find the percent of cars that are electric based on previous number of electric cars added to $P_e(t)$ multiplied by the number of cars needed to be replaced.

In order to arrive at $P_e(t)$, we consider multiple factors to find the likelihood that the company chooses an electric semi over a diesel semi. These factors included the starting price of each model and the price of oil and electricity, modeled using a projection of prices into 2050. We also considered when a company would decide to change to electric semis versus diesel semis.

Additionally, we developed a two-part model to calculate the minimum number of stations and chargers necessary to support our current trucking infrastructure of all diesel trucks were to be replaced with electric trucks.

For part 3, we determined the ranking of each corridor in part 2 to be developed first. We used three factors, pollution, revenue, and costs. This is because areas with higher pollution will want to switch to electric vehicles first and stations with high revenue and low costs will be developed first.

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2 Problem 1: Shape up or ship out

2.1 Defining the Problem

The problem asks us to model the change in the global prevalence of electric semi trucks (semis) within the next twenty years. The problem tells us that it is given that all infrastructure needed to produce and charge all electric semi trucks already exists. We interpret this to mean that all charging stations and factories producing electric semis are already fully equipped to allow for the integration of electric semis.

2.2 Assumptions and Justifications

- **Assumption:** The diesel semi lifespan will always be 12 years. [5]
  - **Justification:** Within 20 years, there will not be enough significant technological development to improve the lifespan of semis.
- **Assumption:** All electric semis will continue to be used within the next 20 years.
  - **Justification:** Tesla's electric "pickup truck" model, Cybertruck, has been estimated to be able to last close to a million miles in its lifetime [8]. Since Cybertruck is an electric vehicle also made by the Tesla company and it is a vehicle recently put on the market, we will assume that Tesla's upcoming electric semi will have approximately the same lifespan. Since the average semi truck will travel 45000 miles per year, the electric semi lifespan will be approximately 22 years, which is greater than 20. [9].
- **Assumption:** The Tesla Semi with a 500 mile range is representative of all semis produced in total costs, speed, mileage, charging capacity, etc.
  - **Justification:** Tesla is the major company producing electric cars, and is the leading producer of electric cars.
- **Assumption:** All semis are either electric semis or diesel semis.
  - **Justification:** Currently, 97% of Class 8 trucks are on diesel, which includes semis [4]. When electric semis are introduced, electric or diesel semis will be the major types of semis in the industry.
- **Assumption:** If the total costs of an electric semi is less than the total costs of a diesel semi, then the percentage of electric semis in the industry will increase because companies will choose to reduce their production costs immediately by switching to the electric semi.
  - **Justification:** Logically, if it is cheaper to switch to electric cars, a company will switch because companies want to make more money.
- **Assumption:** The amount of semis will increase linearly.
  - **Justification:** Graphing the data for the number of semis from 2010 to 2019 yields a fluctuating graph that is approximately linear. Even though there are fluctuations in the graph that look similar to those of a sine or a cosine graph, we assume that these reflect the fluctuations in the economic business cycle and that the generally up-sloping trend is more accurate because it reflects the impacts of economic growth.
- **Assumption:** There is a 50% chance a new car will be electric if the operating and starting costs between electric and diesel semis are equal.

  - **Justification:** If we find the cost equations for the electric and diesel semis, then at their intersection, their total costs should be equal. At this time, because it does not harm companies which option they choose, we assume that 1/2 of companies will choose electric cars to use, while 1/2 of companies will choose diesel cars to use.

- **Assumption:** The number of semis and years can be quantified in terms of one year intervals.
  - **Justification:** The data provided only had semi numbers per year. Since we are considering the number of semis over many years, each individual year is a small enough increment for the model. Thus, the number of semis can be calculated using discrete intervals of one year instead of continuous intervals throughout each year.

2.3 Defining the Variables

Symbol	Definition	Units
t	Years since 2020	Years
$E(t)$	Prevalence of Electric Semis	%
$S_d(t)$	Number of Diesel Semis	Semis
$S_e(t)$	Number of Electric Semis	Semis
$S(t)$	Number of Total Semis	Semis
$P_e(t)$	Average probability that a newly bought semi is electric	None
$C_d(t)$	Total cost of a diesel semi	$/year/vehicle
$C_e(t)$	Total cost of an electric semi	$/year/vehicle
$C(t)$	Cost differential: $C_e(t) - C_d(t)$	$/year/vehicle

2.4 Developing and Applying the Model

We will develop an economic model that examines the cost of switching to electric semis and choice for companies of whether or not to switch to electric semis once their old diesel semis break down. The percent of semis that will be electric can be modeled by

$$f(t) = \frac{S_e(t)}{S(t)},$$

where $S_e(t)$ and $S(t)$ are the number of electric semis and semis as a function of time respectively.

We can model $S_e(t)$ using a recursive function. The number of electric semis one year is simply the number of electric semis the year before plus the new semis created. We will define $N(t)$ as the number of electric semis produced in any given year t after 2020. Thus, we have

$$S_e(t) = S_e(t-1) + N(t).$$

We are given the total class 8 semis built from 1999 to 2019 [13]. Since the average diesel truck has a life span of 12 years [5], the number of current trucks if given by

$$S(t) = \sum_{n=t-11}^{t} S(n).$$

Running this formula with the data provided by the Keep on Trucking Information Sheet through a computer program and letting negative t values represent years before 2020 yields the following values of $S(t)$:

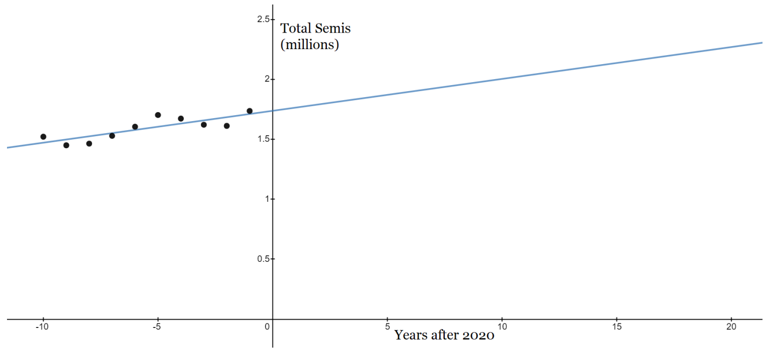
Years since 2020, t	-10	-9	-8	-7	-6
Number of Semis, $S(t)$	$1,519,764$	$1,448,211$	$1,462,287$	$1,526,955$	$1,603,014$

Years since 2020, t	-5	-4	-3	-2	-1
Number of Semis, $S(t)$	$1,700,610$	$1,670,822$	$1,619,790$	$1,610,017$	$1,734,721$

We used a linear regression for the data, which yields

$$S(t) = 1735751.333 + 26569.49697t,$$

with $R^2 = 0.6734$. This correlation is decent and enough for the model, especially because the growth of the total number of semis only slightly affects the percentage of those semis that are electric.



Number of Semis Extrapolation

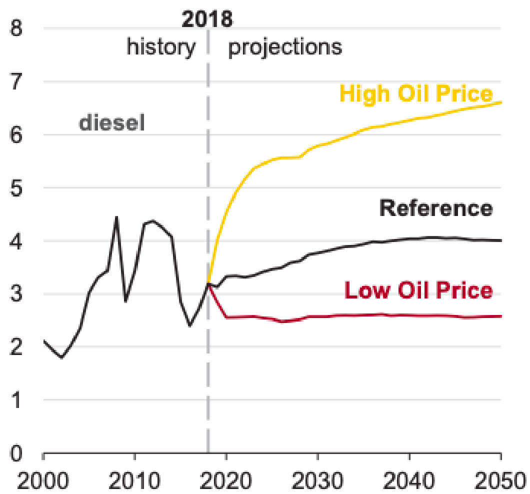
Approximately a twelfth of the current number of diesel semi trucks will be out of use because their average life span is 12 years. $\frac{d}{dt}S(t) = 26569.49697$ would be the additional number of semis each year. Thus, $\frac{S_d(t)}{12} + \frac{d}{dt}S_d(t)$ is the total number of semis that need to be created each year. Multiplying this by $P_e(t)$, the average probability that a company will switch to electric semis yields

$$N(t) = (\frac{S_d(t)}{12} + \frac{d}{dt}S_d(t))P_e(t),$$

which means we now have

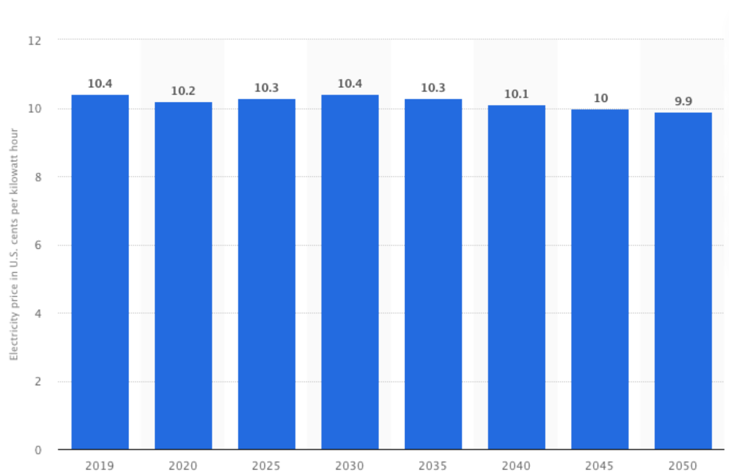
$$S_e(t) = S_e(t-1) + \left(\frac{S_d(t)}{12} + \frac{d}{dt}S_d(t)\right)P_e(t).$$

We will base $P_e(t)$ on the cost difference between electric semis and diesel semis. To evaluate this, we must consider the cost of operating the vehicle over time. For diesel semis, we obtain a projection of the price of diesel for the future 30 years.



Price of Diesel (Dollars Per Gallon) Projected to 2050 (U.S. Energy Information Administration)

Using a linear regression, we find that the pattern of the price of oil projected into 2050 can be approximated as $D(t)$, where $D(t)$ refers to the price of diesel per gallon as a function of t, time. $D(t)$ can be approximated using linear regression to be $0.036t + 3.3$.



Price of Electricity (Dollars per Kilowatt-Hour) Projected to 2050

Similarly, a linear regression was used to calculate the costs of using electricity as a fuel for electric semi trucks. This information was obtained through a projection of electricity price [11]. We calculated that the price of electricity was a function of time $E(t)$, simplified as $12.857x + 190364.286$.

Finally, with these linear regression equations, we can find a cost equation for diesel cars compared against an equation for electricity ran cars. We multiply each equation by the number of miles driven for each model per year, and then add the final cost of each model, adding $150,000$ to the cost equation $C_d(t)$, representing total price and operational costs of diesel semis. We then add $180,000$ to the cost equation $C_e(t)$, as it is the cost of the Tesla 500 mile electric semi model, which we assume to represent all electric semis. Using this yields

$$C_d(t) = 515.3095x + 187666.1323.$$

We also find the total costs of the electric vehicle as

$$C_e(t) = -12.857x + 190364.286.$$

Calculating the difference, we obtain the cost difference as a function

$$C(t) = C_e(t) - C_d(t) = 502.4525x + 378030.4183.$$

Finding when function C(t) equals 0, we find that the difference between the costs of a diesel semi and an electric semi are equal when $t = 5.108528655$, signifying that the costs are equal at approximately 5 years.

We now apply a logistic model to model when a company would decide to switch to electric semis versus diesel semis. Since the costs of a diesel semi and an electric semi are equal at $t = 5.108528655$, we can assume that half of all companies will switch, while half will not.

Since the probability of choosing an electric vehicle is at most 1, the numerator is 1. Applying the logistic model then yields

$$P_e(t) = \frac{1}{1 + e^{0.5281665*(5.108528655-t)}},$$

so our final model is

$$S_e(t) = S_e(t-1) + \left(\frac{S_d(t)}{12} + \frac{d}{dt}S_d(t)\right)\left(\frac{1}{1 + e^{0.5281665*(5.108528655-t)}}\right).$$

Using the Python program in Appendix A yields the percentage of semis that are electric in 5, 10, and 20 years as $\boxed{12.3\%}$, $\boxed{40.9\%}$, and $\boxed{77.9\%}$ respectively.

2.5 Evaluating the Model

2.5.1 Strengths and Weaknesses

Strengths:

- The model builds on past data of total number of diesel semis, which increases the model's credibility.
- The model incorporates the fact that diesel semis go out of use in 12 years.

Weaknesses:

- Since the time span we were interested in was less than the lifespan of the new electric semis, we assumed that all manufactured electric semis would still be in use by 2040. If we were to expand our model past 2042, we would need to account for this replacement of electric semis as well.
- We could have incorporated more costs for both electric and diesel semis.

2.5.2 Extensions of the Model

- If we had more data points then $S(t)$ would be more accurate. Data from years before 1999 would allow us to better extrapolate the total number of semis.
- We assumed that the addition of electric semis would not affect the total number of semis; however, this may not be exactly true. Since electric semis have a greater life span than diesel semis, after 12 years in 2032, the model may not be accurate.
- The introduction of electric semis could change the supply and demand of diesel semis, which may affect the costs of both electric and diesel semis. We could research more into this and account for this in the costs.

3 Problem 2: In it for the long haul

3.1 Defining the Problem

We are asked to develop a model that would support electric trucking infrastructure using current levels of single-driver, long haul traffic. We are asked to assume that all trucks in single-driver, long haul traffic are electric. Hence, we are asked to find:

- Number of charging stations required along a given route
- Number of chargers required at each station

3.2 Assumptions and Justifications

- **Assumption:** All long-haul electric trucks are Tesla Semi models with a 500 mile range. [12]
  - **Justification:** Although Tesla Semi models are to be made with both 300 mile and 500 mile ranges, the 500 mile range model is most suited for long haul drivers, which operate about 500 miles per day.[5] Tesla Semis, which are projected to be the most efficient electric trucks, also offer the most incentive for replacement of diesel trucks, as evidenced by UPS, Walmart, and PepsiCo pre-ordering Tesla Semis.[14] The use of Tesla Semis by other companies as well is thus a reasonable assumption. Since Tesla has developed technology of high efficiency and standard, it is also reasonable to assume that other electric car companies will improve their models in a similar fashion.
- **Assumption:** 500 miles is the lower bound for the distance that each Tesla Semi can travel with one full charge.
  - **Justification:** Tesla claims that their Semi travels 500 miles at maximum weight at highway speeds[1], which range from 60 mph to 85 mph in the US. [10]. Because Tesla's Model X100 electric car loses efficiency as their mileage per hour increases beyond 40 mph[7], it is reasonable to assume that the Tesla Semi, another electric vehicle manufactured by the same company, follows a similar maximum range to mph trend.

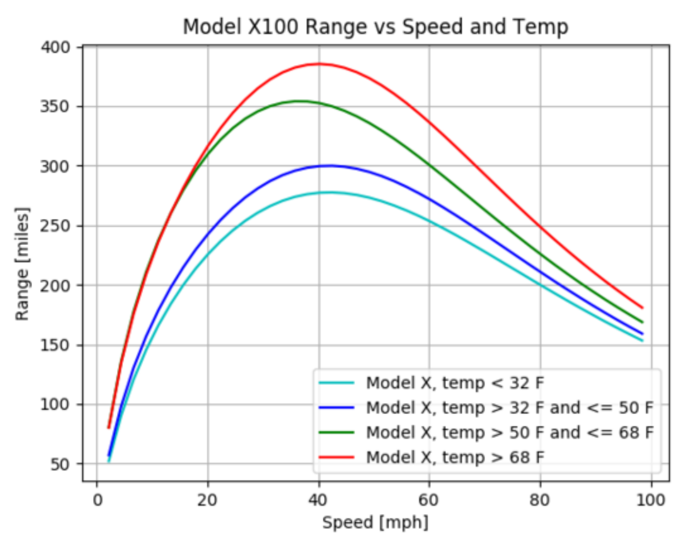


Figure [7]

- **Assumption:** Each truck driver will take their truck to the nearest charging station when their truck's battery is at 20% or less. Each truck driver will also start driving every day with at least 20% of their truck's battery.
  - **Justification:** Battery life for electric trucks is better when charge is kept between 20% and 80% of capacity.[5] This offers an incentive for truck drivers to charge their truck batteries when charge is at 20% or less. We will also explore this 20% upper bound in a sensitivity test later on in our model.
- **Assumption:** Electric trucks are charged to a minimum of 80% every time they stop at a charging station.
  - **Justification:** Battery life for electric trucks is optimized when charge is kept between 20% and 80%.[5] Charging up to a minimum of 80% is the most efficient choice for drivers who need to both balance maintaining battery life and minimize stopping time when driving. We assume that drivers would not charge up to less than 80% for optimizing time spent on the road, but that they may charge to more than 80% for longer distances needed to be traveled.
- **Assumption:** Each truck driver will spend a maximum of 40 minutes at each charging session.
  - **Justification:** Tesla's new megacharger for their Semi allows for the truck to be charged from 0% to 80% in 30 minutes.[1] Assuming a linear charging rate, we extrapolated that the Tesla Semi could feasibly be charged from 0% to 100% in 37.5 minutes, which we rounded to 40 minutes or hours for a maximum time that an electric truck would spend at a charging station given that a charger was vacant.
- **Assumption:** Charging stations are distributed evenly along the given route, with only one charging station per distance interval.
  - **Justification:** Evenly distributed charging stations allow for our model to calculate the minimum number of charging stations needed to support electric trucking infrastructure. Assuming only one charging station exists per a calculated distance interval (rather than multiple stations) models a traffic situation where the greatest possible number of trucks enters a charging station. This ensures that our model accounts for more realistic electric trucking infrastructure goals, where there would likely be multiple charging stations in a given distance interval.

3.3 Defining the Variables

Variable	Definition	Units
d	Distance of a given route between two cities	miles
p	Maximum percentage of charged battery remaining at which drivers will seek out stations to recharge trucks	%
c	Maximum distance a given electric truck can travel on a fully charged battery	miles
x	Minimum distance between evenly distributed charging stations	miles
n	Minimum number of charging stations along a given route	none
q	Mininum percentage of charged battery remaining at which drivers will stop charging trucks during one station visit	%
r_n	Maximum Annual Average Daily Truck Traffic (business and commerical vehicles Class 4 and above)[3] in an x mile long distance interval	trucks passing through per day
t	Maximum amount of time a Tesla Semi spends at a charging station	hours
c_n	Maximum number of chargers needed in a station	none

3.4 Developing the Model

3.4.1 Finding Minimum Number of Charging Stations Required Along a Given Route

To develop the first part of our model, we considered several factors which would affect the minimum amount of stations that would be needed to sustain the current level of trucking infrastructure, including the distance of a given route between two cities, the maximum distance a specific electric truck (The Tesla Semi with 500 mile range) could travel while fully charged, and the highest percentage of charged battery that would cause drivers to take their truck to the nearest station to recharge their vehicle.

Hence, the first part of our model takes three parameters (d, c, and p). Because we chose to use a Tesla Semi with a 500 mile range as our representative electric truck, we assigned a maximum of 500 miles to c. Additionally, for our first implementation of this model we assigned 0.20 to p to indicate the highest percentage of charged battery at which drivers would recharge their vehicle. In our sensitivity test we explore how using different values of p affected our calculated minimum number of stations. However, because electric trucks batteries have the longest retention rate when kept between 20% and 80%, assigning 0.20 to p is a reasonable action as we can assume drivers would wish to optimize their use of electric truck batteries.

Using c and p, we find x, the distance an electric truck will travel on 20% of charged battery, or the maximum distance an electric truck on any percentage of charged battery greater than or equal to 20% will have to travel to encounter a charging station. Hence, x represents the minimum distance between two charging stations (assuming that all charging stations are spread out evenly over the entire route traveled) that is necessary to have enough charging stations to sustain the charging needs of electric trucks, so long as all electric trucks only seek out charging stations when their battery percentage (p) is at 20% or less.

$$x = cp \tag{1}$$

We then use x to calculate the minimum number of charging stations in a given route between two cities:

$$n = \lceil d/x \rceil \tag{2}$$

3.4.2 Finding Minimum Number of Chargers Required at Each Station

For the second part of our model, we first used our x value to divide all possible r values (Maximum Annual Average Daily Truck Traffic (business and commercial vehicles Class 4 and above)) into n segments each of maximum x length. We then parsed through the r values in each segment for the maximum value, which we then assigned to r_n for each of the n segments. These r_n values represent the trucks passing through a segment of x length per day, which we then use to indicate the maximum possible number of electric trucks that may enter the single charging station located in each segment of x length per day. However, because r_n is measured in trucks passing through a segment per day, and our designated electric truck takes a maximum of $t = 2/3$ hours to charge up from any given battery percentage to 100%, we calculate $r_n/24$ to get trucks entering a charging station per hour, and $(r_n/24) * t$ for maximum amount of trucks that could possibly enter a charging station at any given time.

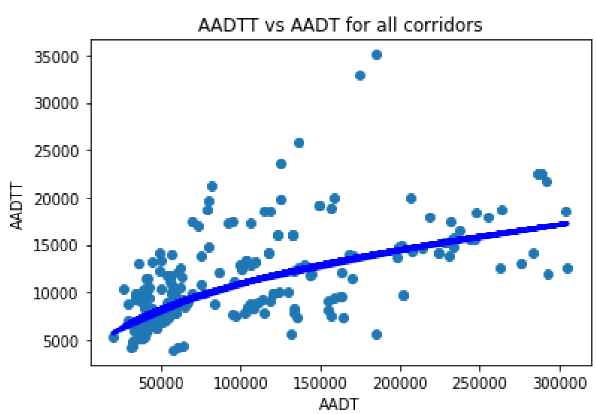
Moreover, because we assigned the minimum charged battery percentage as q, or 80%, and we assumed that the maximum battery charge would be p, or 20%, we divide p/q to find the true proportion of electric cars that would enter the station to charge. We then multiply p/q to $(r_n/24) * t$.

Following this step, we must also multiply the total expression by a constant of 0.104, because only 10.4% of class 4 vehicles or above are considered semi trucks.[3].

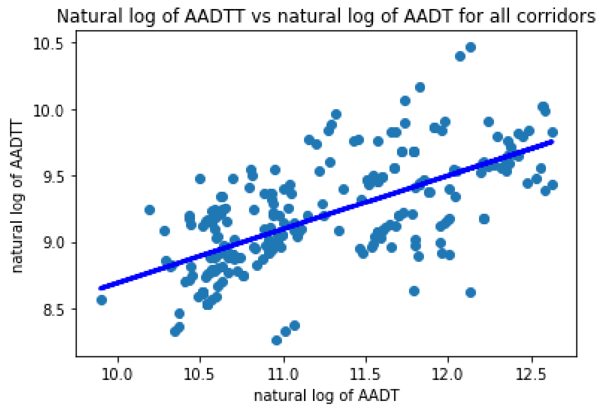
Finally, for every station $1 - n$, we sum up our calculated expression to return the maximum amount of electric cars that will occupy all the stations at any given time– This represents the maximum number of chargers we need to support an electric trucking traffic situation with the most stress.

$$\sum_{n=1}^{n} (r_n/24) * t * (p/q) * 0.104 = c_n$$

To find r_n values that were missing from our corridor data, we first took existing r_n values and plotted them in relation to the max number of cars passing per day through our designated x mile long segments. From these plots, we then created a least-squared linear regression fit that extrapolated our missing r_n values.



Original Scatter-plot fitted with a Natural Log Curve



Scatter-plot with Natural Log mapped to both axes, Fitted with a Least-Squared Linear Regression

3.5 Applying the Model

Route	n **(Min number of charging stations)**	r_n **(Max trucks passing per day through** n x **mile long intervals)[3]**	c_n **(Max number of chargers in a station)**	$Sum(c_n)$ **(Total chargers)**
San Antonio, TX, to and from New Orleans, LA	12	17,259, 19,818, n-a, n-a, n-a, n-a, n-a, n-a, 8938.0*, 11010.0*, 13525.3*, 13446.2*	13, 13, 15, 12**, 12**, 12**, 12**, 12**, 12**, 8*, 8*, 10*	139
Minneapolis, MN, to and from Chicago, IL	5	18,840*, 7229.3*, 35,100, 13,100	14*, 5*, 7*, 10*, 26*	62
Boston, MA, to and from Harrisburg, PA	4	12,446, 12706.2*, 13821, 21214	13*, 10*, 10, 16	49
Jacksonville, FL, to and from Washington, DC	7	12,082, 11,726, 8733.0*, 10,070, 9,290, 11,890, 19,221	9, 9*, 7*, 8*, 7, 8, 14	62
Los Angeles, CA, to and from San Francisco, CA	4	22455, 10270, 11397, 10490	17, 14, 9, 9	49

* denotes a value extrapolated from our least-squared linear regression, ** denotes a value calculated from the mean of the other values due to missing data values

3.6 Evaluating the Model

3.6.1 Sensitivity Analysis

For our sensitivity analysis, we varied our p values for one corridor: Los Angeles, CA, to and from San Francisco, CA.

p **value**	x **Max distance between stations**	n **(Min number of charging stations)**	c_n **(Max number of chargers in a station)**	$Sum(c_n)$ **(Total chargers)**
0.10	50	7	9, 9, 7, 4, 4, 5, 5	43
0.15	75	5	13, 11, 6, 6, 7	43
0.20	100	4	17, 14, 9, 9	49
0.25	125	3	21, 10, 11	42
0.30	150	3	25, 12, 13	50
0.35	175	2	29, 15	44

- As the maximum percentage at which people start looking for charging station (p) increases, number of stations (n) decrease, and number of chargers (c_n) per station increase.
- Total amount of chargers ($Sum(c_n)$) stay around the same amount.
  - In context of our model, these results are reasonable since total input energy stays the same, as drivers are still travelling around the same amount. Essentially, we calculated these results while keeping our r_n values constant.
  - Variations in number of total chargers are caused by rounding of each of the length of the original n distance segments in the raw data[3].

3.6.2 Strengths, Weaknesses, and Extensions

- **Strengths:** Our model takes the extreme bounds of various variables– it offers generous bounds on upper and lower ends for various parameters (i.e. t, c_n). In doing so, our model often also takes into consideration the most stressful and congested traffic situation possible (ex. taking max r_n values), which ensures that our model of the current level of single-driver long haul traffic with all electric cars would be supported for a variety of traffic situations. Thus, the flexibility of our model ensures that the electric trucking infrastructure with similar levels to our current trucking infrastructure would be supported.
- Weaknesses and Extensions: Our model is limited by the various assumptions we made that standardized the charging rate, efficiency, and type of electric truck that would be traveling on the roads. Although Tesla Semi models with 500 mile ranges are certainly projected to be an integral part of the growing electric car population in the future, testing a variety of electric car builds– each with would allow our model to be a more robust and inclusive calculator of the necessary stations and chargers to support electric trucking infrastructure. Although we were unable to develop our model in this way due to time constraints, a future extension to make our model more robust would be to use a uniform distribution of an electric truck with much a much lower mile range and longer charging time than the Tesla Semi.

4 Problem 3: I like to move it, move it

4.1 Defining the Problem

4.2 Assumptions and Justifications

In our model, we identified three factors that would affect the rankings of the corridors to be developed:

- **Assumption:** The environmental conditions of the cities surrounding the corridors
  - **Justification:** The people living in the areas with the worst environmental conditions will want to switch to electric vehicles first, since electric vehicles decrease pollution.
- **Assumption:** The average number of chargers per station
  - **Justification:** The average number of charger per station affects the revenue earned, since more chargers would mean more revenue. People would be more likely to develop stations that will earn high revenue.
- **Assumption:** The cost of each station
  - **Justification:** Costs of each station vary across the US. It would be more reasonable to start development in an area with lower costs.

4.3 Defining the Variables

Symbol	**Definition**	**Units**
S	Ranking Score Of the Corridor	None
P	Pollution Factor	None
R	Revenue Factor	None
C	Cost Factor	None

4.4 Developing the Model

In our model, we identified three factors that would affect the rankings of the corridors to be developed: the environmental conditions of the cities surrounding the corridors, the revenue for each station, and the cost of each station. We first found data for every corridors, then we standardized the data using z-scores per each category.

Environmental Condition: We got our data from the American Lung Association [2]. We used their weighted average score for ozone pollution and particle pollution for each city at the ends of the corridors, and we summed the scores up per corridor. We assume that these cities are representative of all the cities around the corridor. Then, we calculated the mean and standard deviation, which are 34.58 and 56.1 respectively.

	Ozone	Particle
San Antonio	8.7	0.3
New Orleans	1	0
Total	10	

	Ozone	Particle
Minneapolis	0	0.7
Chicago	14.0	1.2
Total	15.9	

	Ozone	Particle
Boston	1.3	0
Harrisburg	2.7	2.3
Total	6.3	

	Ozone	Particle
Minneapolis	0	0.7
Chicago	2.7	2.3
Total	6.3	

	Ozone	Particle
Jacksonville	0.3	0.3
Washington DC	4.7	0.7
Total	6	

	Ozone	Particle
Los Angeles	119.2	13.2
San Francisco	0	2.3
Total	134.7	

Revenue condition: The amount of revenue that can be earned depends on the number of chargers per charging station, which can be calculated based on the data in part 2. This is because if there are more chargers per charging station, more revenue can be earned, and we want to maximize revenue. The mean and standard deviation are 11.468 and 1.492.

Cost condition: The ranking of the corridors also depends on the cost of buying the land for each station, since it varies based on location. We assumed that one station covers 1 acre of land. Then, we found cost per acre for each state at the ends of each corridor. We averaged the costs per corridor [6]. We calculated the mean as 36884.5 and the standard deviation as 23999.6.

Combining the conditions: We standardized each condition by calculating the z-scores for each corridor. We made sure that higher z-scores correspond to a higher rank (highest is first). This means that we flipped the sign for the cost, since we want to minimize the cost. We can also write our model as the following equation:

$$S = P + R + C \tag{3}$$

4.5 Applying the Model

Corridor	Pollution Factor (P)	Revenue Factor (R)	Cost Factor (C)	Ranking Score (R)	Rank
San Antonio, TX, to and from New Orleans, LA	0.075	-0.438	1.111	0.748	3
Minneapolis, MN, to and from Chicago, IL	-0.333	0.980	0.877	1.524	2
Boston, MA, to and from Harrisburg, PA	-0.504	0.524	-1.258	-1.238	4
Jacksonville, FL, to and from Washington, DC	-0.509	-1.748	-0.638	-2.895	5
Los Angeles, CA, to and from San Francisco	1.785	0.524	-0.092	2.217	1

4.6 Evaluating the Model

Out of the five different prospective corridors, the model found that the corridor from Los Angeles to San Francisco is the place where charging stations should first be developed.

4.6.1 Strengths and Weaknesses

A strength of this model is that it accounts for multiple factors. However, some weaknesses are that the model weighed each factor evenly and it only considered the cities/states at the ends of each corridor. These are weaknesses because people may prioritize these factors differently. However, this was in part due to the fact that we were constrained by the amount of limited data on the price of developed land across the corridors. Also, the characteristics of the areas in the middle of each corridor may differ from those of the ends. In addition, for the cost data, we used average data for each state. However, developed land would cost more than undeveloped land, so costs may be higher.

4.6.2 Extensions of the Model

To improve the accuracy of the model, we should decide to add more factors to our model that could influence the value of S. For example, we could take into account community motivation toward the transition. Additionally, we could choose to weight our different factors unevenly based on other research.

5 Appendixes

5.1 Appendix A: Code For Problem 1

The following Python code applies the model and returns the predicted percent of semis that are electric in 5, 10, and 15 years respectively.

```
from math import e

def totalSemis(x):
    return 1735751.333 + 26569.49697 * x

def logistic(x):
    return 1 / (1 + e**(0.5281665 * (5.108528655 - x)))

values = [0]
for i in range(1, 21):
    values.append(values[i - 1] + (((totalSemis(i - 1) - values[i - 1]) / 12 + 26569.49697))
        * logistic(i))

for i in range(21):
    values[i] = values[i] / totalSemis(i)

print("Percent of electric semis in 5 years: " + str(round(values[5] * 100, 1)) + "%")
print("Percent of electric semis in 10 years: " + str(round(values[10] * 100, 1)) + "%")
print("Percent of electric semis in 20 years: " + str(round(values[20] * 100, 1)) + "%")
```

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