

MathWorks Math Modeling Challenge 2020

Pine View School

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M3 Challenge FINALIST—\$5,000 Team Prize

JUDGE COMMENTS

In this paper, the team consider 50% were long haul truck and 45% were regional haul. Therefore, they simulated 850,000 long haul and 765,000 regional haul trucks with normally distributed lifespans. They also included cost analysis information and entered all into their MATLAB simulation. They ran this 20 times and obtained 20 estimates for the proportion of electric trucks in the years 2025, 2030, and 2040. In addition, the computed means, standard deviations, and confidence intervals for this proportion in years 2025 and 2030. For year 2040, all runs produced 100%.

For question 2, they stated they were placing stations 150 miles apart because of them using 60% of battery life between charges. (We have had some discussion about this). It seemed they rounded this number down to make stations equidistant apart. They say they obtained traffic densities at various miles for each route, considering city closest to the corresponding station. They did provide a nice graphic of the routes with the size dot relative in size to the number of chargers. Another plus for this part is that they also considered another type of battery (Chanje V8100) that charges in less time. This would result in more stations but fewer chargers per station.

They considered environment, carbon emissions, budget, cost of electricity, and operating costs for question 3. After obtaining information, they normalized each factor so they could be added or subtracted if negative. They should explain more clearly why higher is better. This is seen in several papers.

Questions:

1. Please tell us more about your MATLAB code and why you used the variables or factors that you used.
2. Would you discuss in more detail why you used the factors that you used for question 3 and why higher values are ones would indicate higher need?
3. Could you please tell more about your sources? Namely what did you use to start with 3 hours charging time for a standard electric truck battery to charge from 20% to 60%?
4. It is impressive that you tried to optimize number of chargers per station after you came up with large numbers (above 1000 for most stations). Also, what makes you to believe that Chanje batteries will charge in 35 minutes from 20% to 80% compared to your initial assumption of 3 hours?

Overall: Impressive work with modeling using Matlab and factors you used. Very clear graphs and adequate explanations accompanying graphs.

Executive Summary

Trucking is one of America's most vital industries: anyone who has ever bought groceries, ordered a package online, or picked up medicine from a pharmacy is dependent on truckers and the goods they transport. Yet the industry, which brings in nearly \$800 billion annually in the U.S. [1], is on the precipice of a dramatic change. Heavily polluting diesel vehicles are becoming outdated, and, in their place, companies across the nation are investing in a groundbreaking new technology: electric semi-trucks.

To predict the percentage of semis that will be electric in the near future, we developed a Monte Carlo simulation for the purchasing choice of a shipping firm. Our model simulates that when a truck becomes too old, the owner will be a financially rational consumer and will buy the electric or diesel semi that will come at the cheapest annual cost. Our model accounts for variance in cost and lifespans and the annual change in typical prices, from inflation and technology improvements. It predicts that 43%, 83%, and 100% of semis on the road will be electric, in 2025, 2030, and 2040, respectively.

Our second model determines the minimum number of charging stations along a corridor to ensure that, if all trucks on the corridor were electric, no truck would run out of charge. The longest route we tested, San Antonio to and from New Orleans, would require 7 charging stations. Our model then considers the number of chargers that would be needed to accommodate the average truck traffic that passes a given station. Along the tested routes, between 330 and 1843 chargers would be needed per station, which is likely unfeasible. If the typical battery charging time was only 11 minutes, however, each station would have, at most, a more reasonable 120 chargers.

Our third model uses normalized metrics to determine the relative benefit of switching to electric trucks along each of the five corridors considered. The factors addressed include the environmental friendliness of the regions near the route, the environmental benefit of switching, the budget available, and the costs of the chargers and station needed. We determined that it is most beneficial to develop the corridor from Minneapolis and Chicago and least beneficial to do so on the route to and from San Antonio and New Orleans. Our models provide valuable insights into the potential growth of electric semi-trucks, the infrastructure that will be needed to be developed to match the growth, and the corridors along which developing said infrastructure should be prioritized. We are excited to see this technological development revolutionize the trucking industry.

Global Assumption

1 Electronic vehicles will be the only disruptive technology to impact the trucking industry in the next twenty years.

1 Shape up or ship out

1.1 Restatement of the Problem

Predict the percentage of semi-trucks that will be electric within 5, 10, and 20 years, assuming a readily available supply.

1.2 Local Assumptions

1. *The semi-truck market size will stay constant.* The production of semi-trucks has had no clear trend in recent history. A linear regression of the percentage of trucks produced for regional hauling [4] has a statistically insignificant R^2 of 0.03. Likewise, a linear regression of the overall market size (number of trucks produced annually) has a statistically insignificant R^2 of 0.07.
2. *Consumers act financially rational.* Since semis are almost exclusively used for commercial transportation, we assume that they are acting to maximize profits and will not altruistically make purchases for the sake of the environment.
3. *All short haulers will be supplied from old long and regional haulers.* When long haul trucks are retired, they are frequently used as short haulers [2], as reflected in the zero total production of short haul trucks [4].
4. *Semis are retired only due to typical wear and tear that accumulates over time.* Though some semis may be put out of service due to accidents, etc., these trucks will typically be replaced with a similar truck by insurance. Therefore, the only reason for a new truck to be purchased is if another truck is no longer usable due to age.
5. *All decisions by electric car companies are made solely for economic gain.* In America's current economic climate, the principal goal of most

firms is to make profit. Thus, we assume that altruistic considerations and environmental concern are negligible in firms' decision-making processes.

6. *No government regulation requiring firms to transition to electric vehicles is implemented.* Diesel trucks will only transition to electric trucks if it is economically advantageous under free-market conditions.

1.3 Model Development

Our simulation begins by creating a representation of the current semi-truck fleet. There are 1.7 million semi-trucks in the US, but only 50% of those are long haul and 45% are regional haul [2]. Since we are not considering short haul trucks, we only created data points for the 850,000 long haul trucks and the 765,000 regional trucks. We used the annual truck production numbers to determine the age of each truck [4]. For example, the 850,000 most recently produced long haul trucks are considered to be the long haul trucks currently on the road.

Another important aspect of a semi-truck is its lifespan. We used a normally distributed range to generate truck lifespans by dividing estimates for diesel trucks' mileage capacities [5, 6] by the typical yearly miles traveled by each type of truck [7]. The electrical semis' lifespans were also normally distributed, per predictions based on current electric vehicle lifespans [8]. The lifespan of each of the 1.61 million long haul and regional trucks currently in operation was generated randomly from these distributions. The values for these characteristics are as follows:

Symbol	Value	Units
Total Long Haul	850,000	Trucks
Total Regional Haul	765,000	Trucks
Long Haul Age Range	0-11	Years
Regional Haul Age Range	0-8	Years
Long Diesel Haul Lifespan	$\mu = 7.46, \sigma = 1.14$	Years
Regional Diesel Haul Lifespan	$\mu = 12.5, \sigma = 1.79$	Years
All Electric Lifespans	$\mu = 8.5, \sigma = 1.5$	Years

The simulation also includes a cost analysis to determine the optimal financial purchase for a consumer in need of a new semi. The function cal-

culates the annualized cost of the purchase of a new semi as follows:

$$AnnualCost = \frac{PurchaseCost}{AverageLifetime} + YearlyOperationalCost$$

The purchase cost was calculated as a normally distributed random variable from current estimates [10, 11] that changes each year at future market price estimates [9], factoring in inflation and improving technology. This is modeled using the following exponential increase equation:

$$PurchaseCost = InitialCost \cdot IncreaseRate^{years}$$

The function uses the average of the lifespan distributions used above, seeing as the consumer will be unsure of what the actual lifespan will be.

The annual operational cost was calculated as

$$OperationalCost = \frac{MilesDriven}{Year} \cdot \frac{Cost}{Mile}$$

where the miles driven per year is based on the average for regional and long hauls [7] and the cost per mile is from cost estimates [12, 13].

The values for these variables are as follows:

Symbol	Value	Units
Years	Current year – 2020	Years
Initial Cost Electric	$\mu = 165,000, \sigma = 15,000$	Dollars
Initial Cost Diesel	$\mu = 102,500, \sigma = 22,500$	Dollars
Increase Rate Electric	1.00263	
Increase Rate Diesel	1.0057	
Driving Per Year, Long Haul	118,820	Miles
Driving Per Year, Regional Haul	70,000	Miles
Per Mile Cost, Electric	1.26	Dollars
Per Mile Diesel, Diesel	1.593	Dollars

As expected, the initial cost for an electric semi will typically be more expensive, but the operational cost will be cheaper.

The above characteristics were implemented in a MATLAB program. The initial truck fleet is described by a 4 by 1.615 million matrix in which each column represents a single truck. Each truck's type (electric or diesel), mode

(long haul or regional haul), current age, and lifespan are stored in the first, second, third, and fourth rows, respectively. At the the start of each year, the age of every truck is increased by one. For the trucks that have reached the end of their individual lifespan, the code evaluates the cost function to replace that vehicle with a diesel versus electric truck. If the electric option has a lower cost function, then the old truck will be replaced with an electric truck. If not, it will be replaced with a new diesel truck. The new truck will have its age set to 0 and a new lifespan created. This procedure is repeated for a specific number of years, t . For this paper, t is set to 5, 10, and 20 years.

1.4 Results and Sensitivity Analysis

In order to gain a detailed understanding of the variation and uncertainty of our model, we ran our code 20 times for each value of t (5, 10, and 20 years), resulting in 20 estimates for the proportion of trucks that are electric. These results are shown in the following histograms.

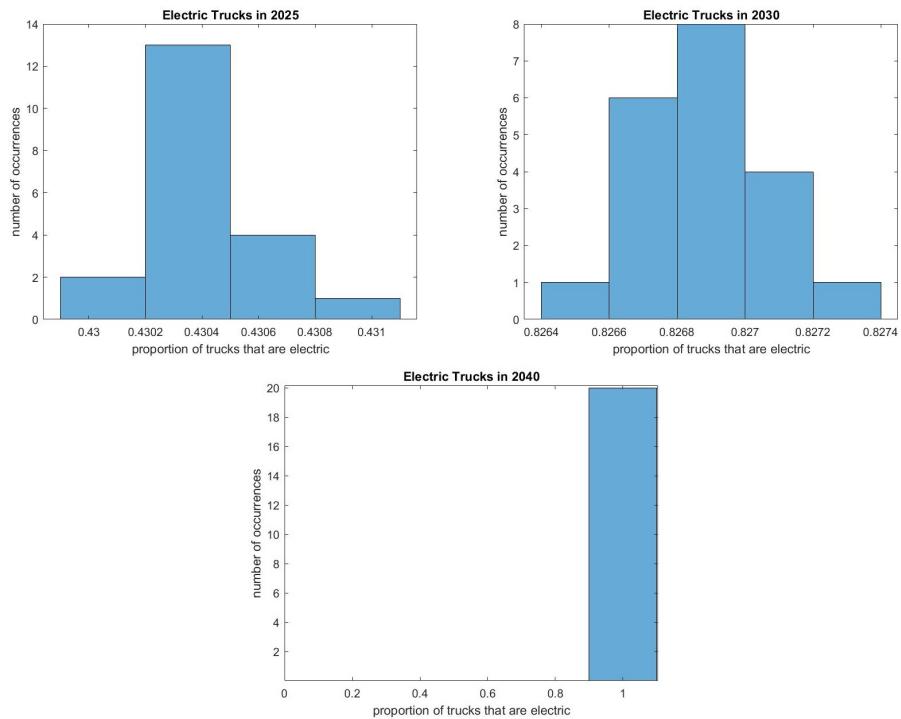


Figure 1: Proportion of trucks that are electric versus number of occurrences for 2025, 2030, and 2040. Note that for 2040, all trucks were predicted to be electric in all twenty simulations, resulting in a histogram with no spread.

This allowed us to calculate 1) a mean value for the desired proportion and 2) a 95% confidence interval for the proportion using a bootstrapping routine in which 1000 re-samples were taken from the original sample of 20.

Year	Mean Proportion of Trucks Electric	95% Confidence Interval
2025	0.43045	(0.4303, 0.4306)
2030	0.8269	(0.8268, 0.8270)
2040	1.00	(1.00, 1.00)

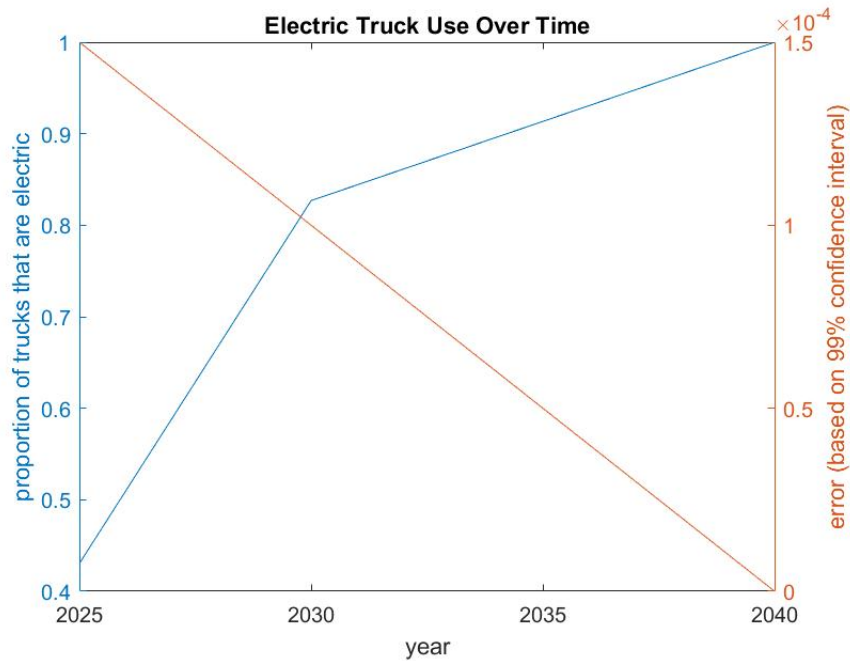


Figure 2: On the left vertical axis is the proportion of trucks that are electric for each year simulated: 2025, 2030, and 2040. On the right vertical axis is the margin of error for this proportion, calculated based on a 99% confidence interval. In other words, we are 99% certain that the population mean

proportion deviates from the sample mean proportion less than the margin of error shown above. As stated above, this margin of error was calculated in MATLAB using a bootstrapping procedure that took 1,000 re-samples of the original sample of 20.

Based on these results, we predict the rapid and total adoption of electric trucks within the next 20 years, with the majority of trucks on the road becoming electric between 2025 and 2030. Our error decreases as the number of years we simulate increases, due to the fact that abnormal behavior of the simulation in a given year is likely to cancel out in subsequent years.

1.5 Strengths and Weaknesses

The greatest strength of our model is that it simulates every truck in the United States individually. Our code evaluates the relative cost of replacing an old truck with a diesel versus electric vehicle for each truck that reaches its maximum age. This allows us to incorporate the natural variability of truck lifespan and cost into the model by using random variables rather than relying on a macro-scale architecture based on point estimates for these quantities. As evidenced in section 1.4, this approach results in an extremely low error due to the fact the random variables that characterize each truck are computed more than one million times.

The primary weakness of this model is that it does not account for companies who may switch to electric cars before it is economically advantageous in order to differentiate themselves, improve the environment, or generate positive publicity with an increasingly environmentally conscious public. Moreover, our model does not account for economies of scale. In reality, the cost of each additional truck of a certain type in a given year would be less expensive than the last.

2 In it for the long haul

2.1 Restatement of the Problem

Determine, for any given trucking route, the number of charging stations and the number of chargers at each station that would be necessary to make current levels of long haul trucking possible if every truck was electric.

2.2 Local Assumptions

1. *Configurations with a lower number of charging stations are preferable to those with a higher number of charging stations if they both allow drivers to recharge when needed.* We assume that the cost to add additional chargers to a charging station is far less than the cost to build a new charging station. Thus, we seek to minimize the number of charging stations.
2. *Charging stations along any given route should be equidistant from each other and from the cities at either end of the route.* While this may not be true of the optimal configuration, it will certainly yield the same number of charging stations, as is now mathematically proved. **Proof:** Let the minimum number of equidistant charging stations required to supply drivers with the opportunity to recharge when necessary be n . Let the distance d between charging stations be the maximum distance a truck can drive beginning with 80% charge (the level to which a truck is typically charged at the station)[3] and ending with 20% charge (considered to be the point at which recharging is mandatory). It follows that the total length of the corridor is $d \cdot (n + 1)$. Since we seek to determine only the number of charging stations necessary, not their spatial distribution, this assumption would only result in an inaccurate result if there existed a nonequidistant configuration that a) supplied drivers with the opportunity to recharge when necessary and b) had fewer than n charging stations. With fewer than n charging stations, there is necessarily a pair of stations separated by more than d . Since this would make it impossible for a truck to travel between these stations without going below 20% charge, n must be the minimum number of charging stations, and this assumption can be made without affecting the resulting number of charging stations.
3. *All trucks entering a route have at least 80% battery.* Trucks entering the route are just beginning their trip and will have had time to fully charge overnight prior to entering the route.
4. *All trucks traveling on any given route are tractor-trailers and have the same type of battery as the Freightlander eCascadia model.* In this idealistic scenario, we assume that all of the trucks will be of the same model, which can travel 250 miles on a full charge and take 3 hours to

recharge from 20% to 80% [3].

5. *All charging stations exclusively use Direct Current Fast Charging (DCFC) chargers.* DCFC chargers have already seen widespread use across the United States and are much more efficient than any other electric vehicle charger [3]; in order to develop electric car charging infrastructure on this large of a scale, it is necessary to use DCFC chargers.

2.3 Variables

Symbol	Definition	Units
S	Number of charging stations along a given route	
M	Mile along route closest to a given charging station	
D	Total length of a route	Miles
n	Position of a given charging station	
C	Number of chargers at a given charging station	
T	Number of trucks that pass a given highway mile per day	

2.4 Model Development

Per our assumptions, the optimal system along a route consists of charging stations that are equidistant from each other and from the ends of the route. Additionally, drivers recharge to 80% and will keep driving until they are down to 20% of their truck battery, then visit a charging station to recharge. Thus, the number of charging stations on the route can be found by dividing the total length of the route by the distance an electric truck can drive using 60% of its battery (in our model, a truck can drive 250 miles on a full charge, so using sixty percent of its battery, it will drive 150 miles) and then taking the floor of that value:

$$S = \left\lfloor \frac{D}{150} \right\rfloor$$

After determining the number of charging stations on each route, we sought to find the number of chargers that would be necessary at each charging station in order to accommodate current levels of truck traffic. There must be enough chargers at each station to accommodate every truck driver who

must use them in a day.

Because our model places charging stations equidistant from each other and relatively far apart, trucks that receive charging at a given station will need to be charged again by the time they reach the next station on their route. Thus, we determined that the amount of trucks that would need to be charged at a charging station would be directly proportional to the amount of truck traffic it receives.

To find the number of chargers required at a given charging station, we first found the highway mile that the charging station is closest to. This was accomplished by calculating the distance between stations ($\frac{D}{S}$), then multiplying it by the position of the charging station in question (the charging station closest to the first city listed would have a position of 0, the charging station second-closest to the first city would have a position of 1, and so on):

$$M = \frac{D}{S}n$$

Using the mile on the route that is closest to the charging station, we used national traffic data [14] to determine the average number of trucks that pass the charging station daily.

We divided that figure by 24 to determine the average number of trucks that would pass the charging station per hour, then multiplied by amount of time each truck would need to spend at a charger in order to return to 80% of a full charge and taking the roof of that number; the result is the minimum number of operational chargers that the charging station would need in order to accommodate all of the trucks that planned to use it:

$$C = \left\lceil \frac{3T}{24} \right\rceil$$

2.5 Results

We tested our model by using it to analyze five heavily used American trucking corridors:

- San Antonio, Texas to/from New Orleans, Louisiana,
- Minneapolis, Minnesota to/from Chicago, Illinois,
- Boston, Massachusetts to/from Chicago, Illinois,

- Jacksonville, Florida to/from Washington, DC, and
- Los Angeles, California to/from San Francisco, California.

The number of charging stations required for each corridor was dependent on the total length of each route. The longest route, San Antonio to/from New Orleans, had seven charging stations, while the others, which were all hundreds of miles shorter in length, had significantly fewer. The amount of charging stations necessary for each route is as follows:

Route	Charging Stations Required
San Antonio, TX to/from New Orleans, LA	7
Minneapolis, MN to/from Chicago, IL	2
Boston, MA to/from Harrisburg, PA	2
Jacksonville, FL to/from Washington, DC	4
Los Angeles, CA to/from San Francisco, CA	2

Though the stations were equally spaced, some stations had many more chargers than other stations on the same route, due to differences in traffic density at various miles on each route. The number of chargers at each station on each route is listed in the tables and graphic below.

Distance of Charging Station From San Antonio, TX (miles)	Number of Chargers Required
138	1750
276	1504
414	1843
552	1843
690	1367
828	1367
966	959

Distance of Charging Station From Minneapolis, MN (miles)	Number of Chargers Required
140	330
280	1403

Distance of Charging Station From Boston, MA (miles)	Number of Chargers Required
128	839
256	842

Distance of Charging Station From Jacksonville, FL (miles)	Number of Chargers Required
139	1241
278	748
417	724
556	670

Distance of Charging Station From San Francisco, CA (miles)	Number of Chargers Required
101	659
202	1270

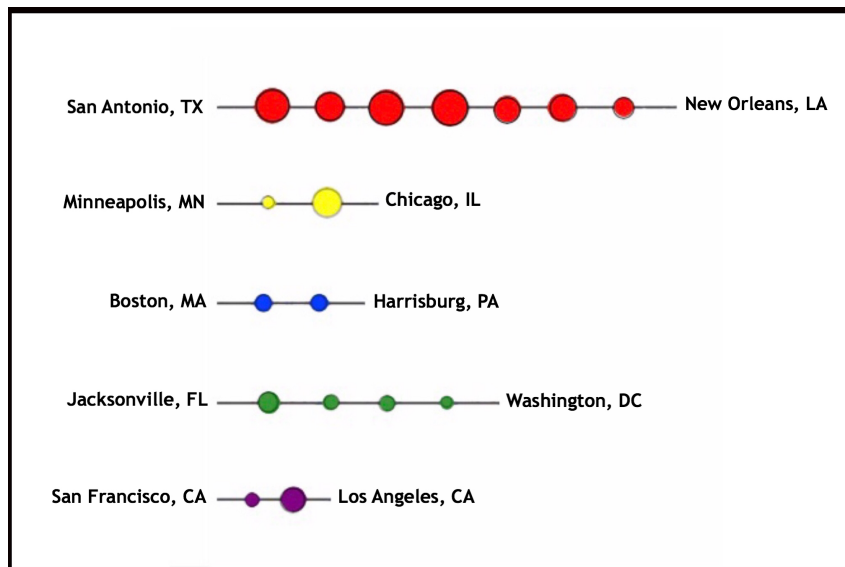


Figure 3: A visual representation of each trucking corridor. Each line represents a trucking corridor, and each dot represents a the location of a charging station. The length of each line is proportional to the length of the corridor, and the area of each dot is proportional to the number of chargers at the charging station located there.

It is important to note that the amount of chargers at some stations listed is too large to feasibly implement with current battery technologies and rates of electric vehicle adoption. This shows that, realistically, the entire trucking industry could not suddenly switch to electric vehicles. To do so, we would need to implement a more gradual solution than that described in the problem; furthermore, we would need much more reliable technology than that which is currently available.

2.6 Further Analysis and Validation

We used two different methods of analysis to better understand our results. Since our model determined that with current battery technology it would be not feasible to create a low number of charging stations that handle the demand of traffic, we wanted to figure out how much more efficient charging times would have to be for these stations to be of a feasible size. To have charging stations with a max of 120 chargers, the number of pumps in a very large gas station [15], we rearranged the formula used to calculate the number of pumps needed in a given station. We set the number of pumps in each station equal to 120 and solved for the charging time, which was previously 3 hours.

For all 17 of the charging stations to have at most 120 pumps, the recharging to 80% battery would have to take at most 11.7 minutes. This seems like an incredible advance in battery technology, cutting the charging time to almost $\frac{1}{18}$ of what it currently is, but other batteries, such as the Chanje V8100 battery [3], can already charge in less than an hour, so in the near future this technology could be readily available. Additionally, current diesel refueling stops average 10-15 minutes [16], so it seems extremely plausible that with better charging and battery technology, refueling times can reach 11.7 minutes and our suggested refueling stations can be developed to handle the entire fleet of semi-trucks being electric.

To further test our model, we implemented it using the Chanje V8100 batteries as the battery of every truck. These batteries would be able to travel

only 90 miles on each charge but would only require 35 minutes on average to recharge [3]. As expected, the number of charging stations required on each route would increase to the amounts as follows:

Route	Number of Charging Stations Required
San Antonio, TX to/from New Orleans, LA	12
Minneapolis, MN to/from Chicago, IL	4
Boston, MA to/from Harrisburg, PA	4
Jacksonville, FL to/from Washington, DC	7
Los Angeles, CA to/from San Francisco, CA	3

The number of chargers required at each station would significantly decrease, with the most chargers being 666, as compared to 1,843 originally. The overall number of chargers would decrease, albeit less significantly, to 8,118 (from 19,359 total chargers originally).

These results all make logical sense considering the faster charging, shorter ranged engines, and shows that are model is working as expected.

2.7 Strengths and Weaknesses

The most important strength of this model is its simplicity. It is very easy to understand our results. The model is very malleable and can be changed for new battery types, as seen in the Sensitivity Analysis. Additionally, the derivation of the model is logical, which leads to a setup that would theoretically work. Additionally our model does account for different traffic densities in different regions. Charging stations will have a number of chargers that meet the demand of that specific station. This ensures no waste due to locally modified results.

Our model is weakened in that it assumes that the optimal approach will be in a minimal number of equidistant charging stations. This ignores the costs associated with creating a large number of chargers in a single station, namely the vast land that would be needed to do so. Additionally, with various areas of traffic density, equidistant charging stations might not be the option that leads to the minimum number of chargers. Our model also oversimplifies wait times. The wait times considered assume that a trucker is an ideal driver who immediately begins charging upon arrival and leaves

right after which is impossible in real life. Also, by just using the average traffic throughout a day, our system ensures no traffic backups, but there will be heavy delays during peak traffic times that will cause backups that will take most of the rest of the day to pass, and it doesn't account for seasonal traffic trends.

Although our system may lead to unnecessary traffic and wasted driver time, the traffic will dissipate at slower traffic times, so the buildup would not increase infinitely and our model does accurately provide the theoretical minimum number of charging stations for each corridor.

3 I like to move it, move it

3.1 Restatement of the Problem

Create a model that will determine how beneficial it would be to develop electric vehicle infrastructure on a given trucking corridor. Use this model to rank each of the five trucking corridors discussed in Part 2 and decide which of them should be developed first.

3.2 Local Assumptions

1. *The regional preferences of a given trucking corridor will be based on the states the corridor passes through.* The development and maintenance of an interstate highway are funded by the states that it runs through [17].
2. *Public opinion on regulating CO₂ emissions is directly related to public support for transitioning to electric vehicles.* Greenhouse gases are emitted by diesel engines through the burning of fossil fuels. Therefore, the adoption of electric vehicles would decrease CO₂ emissions [18].

3.3 Model Development

We identified five primary factors that have a clear impact on whether it would be beneficial to develop electric vehicle infrastructure on a route:

- the environmental friendliness of regions surrounding the route,

- the decrease in carbon emissions that would result if drivers on the route switched to electric vehicles,
- the percentage of budget in surrounding regions that is dedicated to highway maintenance and development,
- the initial cost of electric vehicle infrastructure,
- and the operational cost of charging.

We first noted that the environmental preferences of the areas near the corridor will directly affect the degree to which locals care about the environmental benefits of switching to electric semis. Thus, we determined a value for each corridor by using survey data regarding the percentage of people who believe that CO₂ emissions should be regulated [19]. This value should be similar to the percent of people who would support environmentally friendly measures, including switching to electric semis [18]. For corridors that span multiple states, we averaged the polling data for each state it passes through. To determine the impact of such a change, we calculated the approximate number of miles traveled daily by trucks on the route. The number of miles is found by first averaging the number of trucks on each recorded section of road, then multiplying that value by the length of the route [14]:

$$MilesTraveled = Trucks * Distance$$

This value is proportional to the environmental benefit of switching to electric trucks, as each mile driven by each electric truck will result in a reduction of carbon emissions.

Another positive factor is the percentage of the budget in regions surrounding a corridor that is dedicated to highways. We use this to extrapolate the amount of upkeep dedicated to the corridor and, in turn, the likelihood of a dramatic infrastructure project—creating charging stations—being approved. This was found by averaging the percent of the state budget dedicated to highways [20] for each state bordering a corridor.

A negative factor is the initial cost of building the infrastructure necessary for a route to switch to electric semis. This contained parts of the results of Part 2—specifically, the number of charging stations and the total number of individual chargers.

A final negative factor is the cost of operating an electric vehicle. This was found by using the average cost of electricity for transportation, as of

December 2019 [21]. Similar to how people are less likely to drive when gasoline prices are high [22], people will be less likely to use electric vehicles when electricity is expensive. Electric truck infrastructure created in areas where the cost of electricity is high will thus be used less and be less beneficial. The operational cost of an electric vehicle was tabulated by averaging the electricity costs for all states that a corridor passes through.

Each of the factors listed above was normalized using featured scaling, which fits each of the values to a relative score between 0 and 1:

$$\frac{X - X_{min}}{X_{max} - X_{min}}$$

The two components of the cost of building infrastructure were separately normalized and then averaged. The normalization makes it possible to add the individual scores (and subtract the negative factors) and get a total score that represents how beneficial it would be to add electric vehicle infrastructure to a given route.

This model can be generalized to rank any corridor by adding in data for additional corridors.

3.4 Results

The following tables show the results of the normalization and the total “Benefit Score” for each corridor:

Variable	Definition
C1	Minneapolis, MN, to/from Chicago, IL
C2	Jacksonville, FL, to/from Washington, DC
C3	Los Angeles, CA, to/from San Francisco, CA
C4	Boston, MA, to/from Harrisburg, PA
C5	San Antonio, TX, to/from New Orleans, LA
Score	Local Opinion + Miles + Budget - Operational - Initial

	Environmental	Miles	Budget	Operational (-)	Initial (-)	Score
C1	0.640	0.26	1.000	1.000	0.003	0.897
C2	0.390	0.25	0.330	0.000	0.300	0.670
C3	0.740	0.0	0.330	0.530	0.010	0.580
C4	1.000	0.000	0.380	0.920	0.000	0.460
C5	0.000	1.000	0.420	0.060	1.000	0.360

Our model determined that the corridor that runs from Minneapolis, Minnesota to Chicago, Illinois would benefit most from transitioning to accommodate more electric trucks. The states which own and maintain this corridor—Minnesota, Wisconsin, and Illinois—have the greatest budget to make such changes and nearly the lowest expected initial costs to build charging stations.

The corridor that runs from San Antonio, Texas, to New Orleans, Louisiana, benefits the least from such a transition despite the high amount of traffic that travels along it and the states' high budgets. This can be attributed to the extremely high cost of building enough charging stations and chargers to accommodate the high level of traffic and the length of the route. Locals of Texas and Louisiana will also be less receptive to the investment of taxpayer money into the development of electric truck infrastructure.

3.5 Sensitivity Analysis

Our normalized values for local opinion, miles, budget, and operational costs are all based on averages of large, well established data sets. However, we did not find information that established the relative cost of building new chargers and new stations. Thus, we simply normalized the cost to build chargers and stations separately on each route and then averaged those two values. In this sensitivity analysis, we justify this simplification by showing that our model is robust to variation in the relative costs of stations and chargers by considering alternative weightings. In particular, we will now evaluate the initial cost of building infrastructure for a given corridor as follows:

$$I = a \left(\frac{c - c_{min}}{c_{max} - c_{min}} \right) + b \left(\frac{s - s_{min}}{s_{max} - s_{min}} \right)$$

where c is total number of chargers on the corridor being considered, c_{min} is the number of chargers on the corridor with the least number of chargers,

c_{max} is the number of chargers on the corridor with the greatest number of chargers, s is the number of charging stations on the corridor being considered, s_{min} is the number of charging stations on the corridor with the least number of stations, s_{max} is the number of charging stations on the corridor with the greatest number of charging stations, and a and b are constants that sum to 1 and represent the relative weighting of the cost to build chargers and stations. The effects of the changes in a and b are shown in the table below.

	a = 0.25, Initial (-)	b = 0.75 Score	a = 0.75, Initial (-)	b = 0.25 Score
C1	0.001	0.899	0.004	0.896
C2	0.348	0.622	0.245	0.727
C3	0.007	0.583	0.021	0.569
C4	0.000	0.460	0.000	0.460
C5	1.000	0.360	1.000	0.360

When shown as a bar graph, the robustness of our model to variation in a and b becomes more apparent.

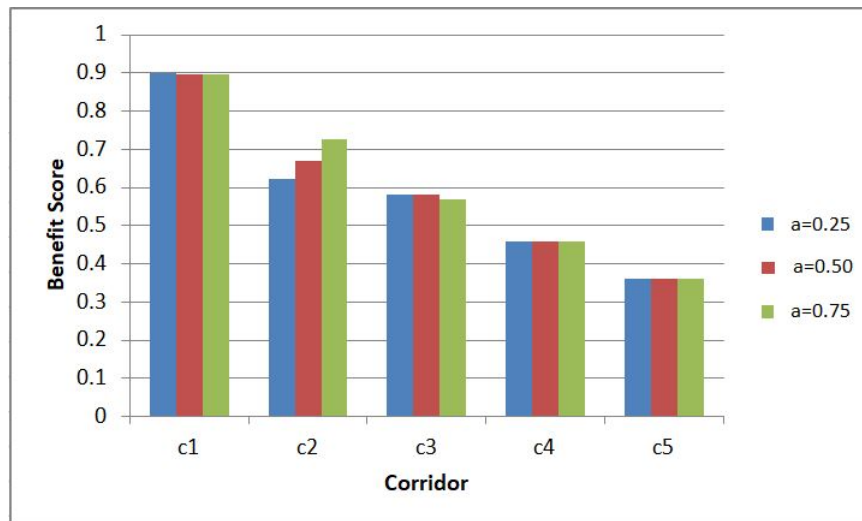


Figure 4: Benefit scores for each corridor and three different values of a . The score is largely invariant with respect to a .

Since our rankings remain the same despite significantly varying the values of a and b , we can be more confident in our simplifying decision to average them in our main model. The only corridor that shows appreciable sensitivity to a and b is from Jacksonville to Washington, DC. This is because this stretch is very long and has comparatively low traffic.

3.6 Strengths and Weaknesses

Our model's main strength is that it considers many different factors through the normalization process. It is a multifaceted approach that counts for environmental effects as well budgeting and expenses. Additionally, using normalized factors allows for easy adding of additional factors and manipulation of current ones, as data becomes available.

The model is weak because it is dependent on arbitrary factors. We considered several factors and left out several more that could be argued to be included, such as legislative policies and infrastructure readiness. We decided that determining weightings for each factor would be arbitrary, but not weighting any is arbitrary in its own nature.

One benefit of including the separate factors' scores is that one can combine them as will depending on what aspect of the model they find important. For example, if a politician just wanted to complete the infrastructure along one corridor, they could simply chose the one with the least total cost: Boston to and from Harrisburg.

4 Conclusion

Our analysis highlights the many ways in which electric vehicles could revolutionize the American trucking industry: they are cost-efficient, environmentally friendly, and potentially market disruptive within the next decade (Part 1). This will only be feasible, though, with substantial infrastructure development and improved battery technology (Part 2). Still, it is worth the investment: electric semi-trucks can greatly improve sustainability efforts and economic efficiency as they are rolled out onto trucking corridors such as that between Minneapolis and Chicago (Part 3). We encourage Americans to listen to the buzz about electric trucks and help make our country a more innovative place.

References

- [1] <https://www.statista.com/topics/4912/trucking-industry-in-the-us/>
- [2] Keep on Trucking Information Sheet, MathWorks Math Modeling Challenge 2020, <https://m3challenge.siam.org/node/478>
- [3] Battery Data, 2020 MathWorks Math Modeling Challenge, <https://m3challenge.siam.org/node/478>
- [4] Truck Production Data, 2020 MathWorks Math Modeling Challenge, <https://m3challenge.siam.org/node/478>
- [5] <https://www.auto.edu/blog/13-solid-stats-about-driving-a-semi-truck-for-a-living/>
- [6] <https://www.commerceexpressinc.com/2020/01/09/5-quick-facts-about-semi-trucks/>
- [7] Truck Usage Data, 2020 MathWorks Math Modeling Challenge, <https://m3challenge.siam.org/node/478>
- [8] https://nacfe.org/wp-content/uploads/2018/04/Electric_Trucks_Guidance_Report_Executive_Summary.pdf
- [9] <https://ww2.energy.ca.gov/2018publications/CEC-200-2018-005/CEC-200-2018-005.pdf>
- [10] <https://cleantechnica.com/2017/12/16/electric-semi-trucks-heavy-duty-trucks-available-models-planned-models/>
- [11] <https://www.bizjournals.com/sanjose/news/2017/11/27/tesla-semi-truck-price-cost-fuel-tsla.html>
- [12] <https://gtgtechnologygroup.com/how-the-total-cost-of-ownership-of-electric-trucks-influences-fleet-decisions/>
- [13] <https://truckingresearch.org/wp-content/uploads/2016/10/ATRI-Operational-Costs-of-Trucking-2016-09-2016.pdf>
- [14] Corridor Data, MathWorks Math Modeling Challenge 2020, <https://m3challenge.siam.org/node/478>

- [15] <https://www.thebalancesmb.com/world-s-largest-retail-convenience-store-2892134>
- [16] <http://www.aboutrving.com/rv-topics/fueling-up-at-truck-pumps/>
- [17] <https://www.fhwa.dot.gov/interstate/faq.cfm#question5>
- [18] <https://www.carbonbrief.org/factcheck-how-electric-vehicles-help-to-tackle-climate-change>
- [19] <https://climatecommunication.yale.edu/visualizations-data/ycom-us-2018/?est=regulate&type=value&geo=state>
- [20] <https://www.taxpolicycenter.org/statistics/state-and-local-general-expenditures-capita>
- [21] https://www.eia.gov/electricity/monthly/epm_table_grapher.php?t=epmt_5_06_b
- [22] <https://blogs.wsj.com/dailyshot/2018/07/26/the-daily-shot-americans-are-driving-less-as-higher-gas-prices-sting/>

A Code

MATLAB Code for Part 1 Monte Carlo Simulation:

```
n1 = 20;
n2 = 1000;

d = zeros(n1,1);

for i = 1:n1
    d(i,1) = Proportion_electric();
end

arithmetic_mean = mean(d)

standard_deviation = std(d)

confidence_interval = bootci(n2, {@(x) mean(x), d}, 'alpha', 0.01)
```

```
histogram(d)
```

```
function p = Proportion_electric()
%output is the proportion of trucks that are ELECTRIC
%each column represents one truck
%truck type: stored in first row;
%0 = deisel, 1 = electric
%truck usage mode: stored in second row; 0 = long haul, 1 = regional haul
%current age: stored in thrid row
%lifespan: stored in fourth row

t = 5; %time span being modeled in years
n = 1.615*10^6; % number of operating electric trucks
r_t = 765000; %number of regional haul trucks initially
ar_0 = 107401; %number of regional trucks that
%are at most 0 years old
ar_1 = 208715; %number of regional trucks that
%are at most 1 years old
ar_2 = 275532; %number of regional trucks that
%are at most 2 years old
ar_3 = 342613; %same pattern as above
ar_4 = 448594;
ar_5 = 549963;
ar_6 = 619312;
ar_7 = 692287;
ar_8 = 765000;
al_0 = 99997; %number of long haul trucks that
%are at most 0 years old
al_1 = 190617; %number of long haul trucks that
%are at most 1 years old
al_2 = 260762; %number of long haul trucks that
%are at most 2 years old
al_3 = 316120; %same pattern as above
al_4 = 410915;
al_5 = 484953;
al_6 = 552159;
al_7 = 631898;
```



```
al_8 = 702498;
al_9 = 746419;
al_10 = 792659;
al_11 = 850000;

x = zeros(4, n); %setup initial fleet
x(2,1:r_t) = 1;

x(3,1:ar_0) = 0;
x(3,ar_0 + 1:ar_1) = 1;
x(3,ar_1 + 1:ar_2) = 2;
x(3,ar_2 + 1:ar_3) = 3;
x(3,ar_3 + 1:ar_4) = 4;
x(3,ar_4 + 1:ar_5) = 5;
x(3,ar_5 + 1:ar_6) = 6;
x(3,ar_6 + 1:ar_7) = 7;
x(3,ar_7 + 1:ar_8) = 8;
x(3,ar_8 + 1:al_0) = 0;
x(3,ar_8 + al_0 + 1:ar_8 + al_1) = 1;
x(3,ar_8 + al_1 + 1:ar_8 + al_2) = 2;
x(3,ar_8 + al_2 + 1:ar_8 + al_3) = 3;
x(3,ar_8 + al_3 + 1:ar_8 + al_4) = 4;
x(3,ar_8 + al_4 + 1:ar_8 + al_5) = 5;
x(3,ar_8 + al_5 + 1:ar_8 + al_6) = 6;
x(3,ar_8 + al_6 + 1:ar_8 + al_7) = 7;
x(3,ar_8 + al_7 + 1:ar_8 + al_8) = 8;
x(3,ar_8 + al_8 + 1:ar_8 + al_9) = 9;
x(3,ar_8 + al_9 + 1:ar_8 + al_10) = 10;
x(3,ar_8 + al_10 + 1:ar_8 + al_11) = 11;

for k = 1:n
    x(4,k) = Lifespan(x(1,k), x(2,k));
end

for i = 1:t %t is the numebr of years since 2020
    x(3,:)=x(3,:) + 1;
    for j = 1:n
        if x(3,j) > x(4,j)
```

```
%has the truck surpassed its lifespan?
    x(1,j) = type_of_truck(x(2,j), t);
    x(3,j) = 0;
    x(4,j) = Lifespan(x(1,j), x(2,j));
else
end
end
end

a = x(1,:);
b = a > 0;
c = a(b);

p = length(c)./n;

end

function type = type_of_truck(mode, t)

p_e = 165000; %base price of a electric car in 2020
r_e = 1.00263; %rate at which electric base price
%increased per year
s_e = 15000; %standard deviation in electric base
%price in 2020

b_e = random('Normal', p_e.*(r_e.^t), s_e.*(r_e.^t));
%base price of an electric car in year 2020 + t

l_e = 8.5; %expected lifetime of an electric truck

if mode == 0
    o_e = 149713.2; %cost per year for a long haul
%electric truck
else
    o_e = 88200; %cost per year for a regional haul
%electric truck
end
```

```
cost_electric = (b_e./l_e) + o_e;

p_d = 102500; %base price of a diesel car in 2020
r_d = 1.005706; %rate at which diesel base price
%increases per year
s_d = 22500; %standard deviation in diesel
%base price in 2020

b_d = random('Normal', p_d.*(r_d.^t), s_d.*(r_d.^t));
%base price of an
%diesel car in year 2020 + t

if mode == 0
    l_d = 7.457; %lifetime of a long haul diesel truck
else
    l_d = 12.5; %lifetime of a regional haul diesel truck
end

if mode == 0
    o_d = 189280.26;
%cost per year for a long haul diesel truck
else
    o_d = 111510;
%cost per year for a regional haul diesel truck
end

cost_diesel = (b_d./l_d) + o_d;

if cost_diesel < cost_electric
    type = 0;
else
    type = 1;
end

end

function l = Lifespan(type, mode)
```

```
if type == 0
    if mode == 0
        l = random('Normal', 7.457, 1.14);
%longhaul diesel
    else
        l = random('Normal', 12.5, 1.785871);
%regional haul diesel
    end
else
    l = random('Normal', 8.5, 1.5); %electric
end

end
```