

MathWorks Math Modeling Challenge 2020

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M3 Challenge FINALIST—\$5,000 Team Prize

JUDGE COMMENTS

Team 13702's paper took three good approaches to solving the problems posed in this challenge. First, when estimating the percentage of total trucks that will be electric by 2040, they used a two-state Markov Chain. Their novel use of cost differential and payback time to estimate the adoption rate for electric trucks really distinguishes their model from other teams, although their model produces one of the more conservative values for electric truck adoption by 2040 (38.74%).

They take a pretty straightforward approach to the second problem, finding the required number of charging stations between two locations by taking the ratio of the energy necessary to drive between the two cities divided by the number of kilowatt hours to do so. They use an estimate for the amount of time a truck needs to charge and the number of trucks that require charging during peak hours to derive estimated number of charging stations required per location.

The authors finish by ranking five trucking corridors for development of electric trunk adoption. They use the preferences for each city, along with things like the population of each city, population of each corridor, to find that the corridor from Los Angeles to San Francisco, followed by that from Minneapolis to Chicago, are the most primed for development. Sensitivity analyses were done on all three parts of the problem.

As a whole, this paper provided good models for all three parts and appropriately addressed all of the prompts. The authors clearly had a good understanding of how their models were built and how they could be interpreted to reflect reality.

1. Walk us through the 2.5% figure you use in 1) in your Markov matrix. You show that 29% of trucks drive the requisite number of miles to make the cost worth it, and the average truck travels for 12 years, but the current age of the trucks is variable. Are you suggesting that owners will purchase new electric trucks regardless of the age of their current truck? How could you modify your model to take into account the current age distribution of trucks?
2. a) In your second calculation for 2), you use the 20% figure for the amount of time a truck is charging. Does any allowance for the staggering of trucks entering the stations need to be made?
b) How did you calculate the mean and standard deviations in your figure 9? It looks like you're assuming that all stations along a corridor need to be able to handle the same peak traffic volume, even though relatively few regions along each corridor have recorded traffic volumes that high. How could you incorporate traffic heterogeneity into your model?
c) Charging stations and diesel pumps can take up a lot of space. Typical truck fueling stations have 10-12 diesel pumps and sit on 20 acres of land. Some of your stops would require almost 10 times as much space. What can you do to address this concern?
3. What do you think would be good weighting variables "supporters", "income", "smog" and "populations" if you were forced not to make them equal?

KEEP ON TRUCKING: U.S. BIG RIGS TURNOVER FROM DIESEL TO ELECTRIC

Team #13702

Executive Summary

Truckers and their vehicles play a vital role in the American economy by transporting goods and materials across the United States, and in recent years there has been buzz about a revolutionary change in the industry. The need to fuel inefficient semi-trucks with diesel has become a problem of contention: diesel semi-trucks have been historically inefficient and their use pollutes the environment. Because of this, electric trucking has seen a recent spike in interest [1].

Our team was asked to predict the growth of electric trucks over the next 20 years under the assumption that all necessary infrastructure is in place. First, we assume the daily miles driven by a truck follow a distribution we obtained from a sample government dataset. Additionally, we assume that a uniform proportion of trucks would go out of commission annually. Our model uses a Markov chain to predict the changing proportions of trucks that are electric. We predict that in 2025, 11.53% of trucks will be electric; in 2030, 21.73% will be electric; and in 2040, 38.74% will be electric. Our trend showed electric trucks initially increase very quickly, but eventually slow down. These trends and results are similar to those found in literature.

We were also asked to create a model to predict the number of electric truck charging stations and chargers along five given corridors: Minneapolis-Chicago, Los Angeles-San Francisco, San Antonio-New Orleans, Jacksonville-Washington DC, and Boston-Harrisburg. We assumed that travel inefficiency due to traffic does not affect battery efficiency of electric trucks. We then created a model that considered battery capacity, battery usage, distance traveled by trucks, and the effects of altitude differences on electric truck battery usage. We found that the Jacksonville-Washington DC corridor would require the most charging stations along its length. We were also tasked with determining the number of chargers needed to sufficiently service these charging stations. Using average daily truck traffic data along the corridors, we predicted the amount of trucks that each charging station would have to accommodate. Operating under the framework that at least 99.7% of trucks in need of charging should be accommodated at a time, we calculated that Minneapolis-Chicago charging stations should have the most chargers per station with 112 chargers.

Finally, our team was tasked with ranking the aforementioned five trucking corridors in terms of suitability and benefit from electric truck infrastructure development. We chose to implement an index score that accounts for the preferences of locals for electric trucking. Our model assumed that people only voted Democrat or Republican and that the preferences of a corridor can be represented by three key cities along the corridor. We normalized the voting preferences, income, and air pollution of the corridor area; in addition, we incorporated the number of chargers derived previously to represent truck usage and economic benefit for the corridor. Then, we summed the various scores and determined that the Los Angeles-San Francisco corridor is the best choice for electric truck infrastructure development.

Electric trucking has the potential to drastically change the landscape of American freight shipping. The associated drops in costs to truckers, as well as the immense benefit to the environment, make electric trucking a tantalizing choice for the future.

Background

Trucking is a major American industry, facilitating the transportation of essential goods across the nation. Trucking accounts for \$288.2 billion of the economy and over 1% of the annual American GDP [2]. The industry also has far-reaching influence—disruptions in trucking networks can interfere with the operation of a plethora of other industries that rely on freight shipping.

With the development of electric trucks, many firms have begun considering transitioning their diesel fleets to more efficient electric vehicles. The car company Tesla recently released an all-electric truck tractor. Electric trucks rid firms of high diesel prices and are exceptionally beneficial for the environment. However, they come with the downside of being able to haul less cargo; the lack of infrastructure in place to support electric trucks is also a hampering condition.

Electric trucks require a significant amount of infrastructure, such as charging stations, to be properly implemented. Chargers come in several different levels, each with a different amount of power and charging speed. Unfortunately, the cost of these chargers is currently very high, with charger prices ranging into the tens of thousands of dollars; this is another barrier to the large-scale implementation of electric trucks [19].

Global Assumptions

G.1 *We assume that the government does not directly intervene in the trucking industry; that is, the government does not subsidize the purchase of electric trucks or implement carbon taxes on diesel trucks.* It is difficult to predict the actions of the federal government; thus, for simplicity reasons, we choose to exclude government intervention from our models.

Part I: Shape Up or Ship Out

1.1 Restatement of Problem

We are tasked with creating a mathematical model to predict the percentage of semi-trucks that will be electric in 2025, 2030, and 2040.

1.2 Local Assumptions

1. *The base cost of electric trucks will not change over the next twenty years.* Since electric trucks are a developing technology, it is unlikely that the base cost of electric trucks will increase or decrease drastically--firms have no incentive to lower the price since they must reinvest their profits into research and development. Furthermore, given the high barriers to entry to the electric truck market, competition will remain low, causing prices to remain mostly constant.
2. *The revenue for diesel-powered trucks is equal to the revenue for electric-powered trucks.* The revenue that a truck produces is directly related to the number of shipments that truck makes. Both diesel-powered and electric-powered trucks are capable of shipping the maximum legal cargo weight, 80,000 pounds gross weight, and the speed of both trucks is limited by legal speed limits.
3. *The tare weights of both electric and diesel trucks will remain the same over the next twenty years.* It is difficult to predict technological innovations in trucks that can reduce tare weight, so we exclude these potential changes from our analysis.
4. *The per-mile operational costs for diesel and electric trucks will remain the same for the next twenty years.* The problem tells us that the infrastructure necessary to support

electric trucks is fully available, so operational costs should not change due to increased access to chargers.

5. *Truck owners will only purchase an electric truck if they can recover their losses from purchasing an electric truck within a year.* The cost of an electric truck is prohibitive for many trucking companies; unless the firm can quickly recoup its investment in expensive electric vehicles, it is unlikely that they would do so. Additionally, investors want to see profits from new investments as soon as possible. The validity of this assumption is further addressed in our validation.
6. *Trucking companies will immediately seek to purchase new trucks when old trucks outlive their lifetimes.* To stay in business, it is reasonable to expect that companies will purchase replacements for worn-out equipment.
7. *1/12 of all diesel trucks need to be replaced annually.* The average lifetime of a diesel truck is 12 years, so we assume that a uniform proportion of trucks wear out their lifetimes every year [3].
8. *Electric truck owners do not revert to using diesel trucks.* Electric truck owners that were willing and able to pay the initial price and maintenance costs of an electric truck will not revert back to purchasing a diesel truck, as diesel trucks will no longer provide more profit and are generally not seen as an advancement in business.

1.3 Variables

Symbol	Definition	Units
m	Miles driven	Miles
p	The probability that a truck will transition from diesel to electric	Unitless
\vec{v}_t	The vector describing the truck demographics at given time t	Unitless

Figure 1: Variable definitions for problem 1.

1.4 Solution & Results

We want to determine the proportion of trucks that will be electric trucks at a given time in the future. To do so, we model the growth of electric cars using Markov chains. We define two classes of trucks: diesel, D, and electric, E. We then write the general transition matrix A as

$$A = \begin{matrix} & \begin{matrix} E & D \end{matrix} \\ \begin{matrix} E \\ D \end{matrix} & \begin{bmatrix} 1 & p \\ 0 & 1-p \end{bmatrix} \end{matrix}$$

where p is the probability of a diesel truck owner getting rid of the diesel truck and instead choosing to purchase an electric one.

To calculate p , we first write a linear equation that describes the savings of using an electric truck in terms of distance. The average operational cost savings of switching to electric trucks is \$0.279 per mile, but the initial cost of switching is \$30,000 more than diesel [4].

Therefore, the more a truck drives, the greater the company’s savings. We can thus write the linear equation as

$$\text{cost difference}_{(diesel-electric)} = .279m - 30,000$$

A truck company would begin to save money on electric trucks if the cost difference exceeds 0. Thus, an electric truck will pay for its initial costs in a year if the truck drives 107,527 miles. Assuming the truck is in use 260 days per year (only on weekdays), the truck must drive 413 miles each day that year [4].

Using a set of trucking data from the Department of Energy [18], we construct a distribution of distances that truckers would drive if they chose to drive for 11 hours, the maximum legal driving duration for truckers.

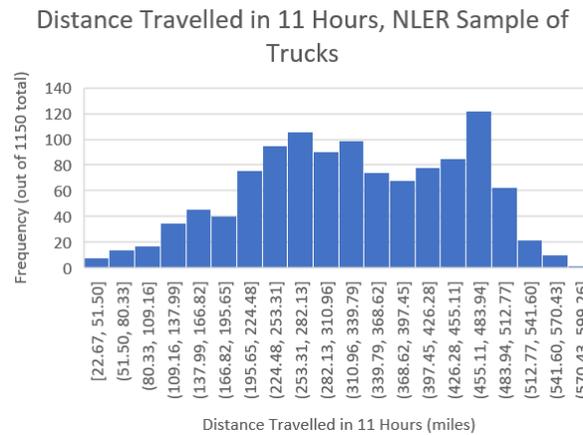


Figure 2: The distribution of distances that trucks drive each day [18].

Approximately 29% of the trucks in the sample data drive more than 413 miles per day, our previously derived breakeven point for purchasing an electric truck. Since diesel trucks lasts approximately 12 years on average [5], we divide the percentage of trucks that “should” transition by 12 to account for the rate at which diesel trucks become unusable. We therefore derive the probability of a diesel truck being replaced by an electric truck to be 2.5% each year.

Using this information, we construct our transition matrix A as

$$\begin{bmatrix} 1 & .025 \\ 0 & .975 \end{bmatrix}$$

and construct the Markov chain

$$\vec{v}_t = \begin{bmatrix} 1 & .025 \\ 0 & .975 \end{bmatrix}^t \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

where A is the transition matrix and t is the number of years. We define the seed of the Markov chain v , the vector with the current distribution of trucks, as $\langle 0, 1 \rangle$, as the proportion of electric trucks currently in use is negligible. Our Markov chain model is thus

$$\vec{v}_{t+1} = A * \vec{v}_t$$

The other values in the matrix can be calculated from this percentage. Because each column in a transition matrix adds up to one, the probability of a diesel truck remaining diesel is

equal to 1 minus p . For the other column, because of logistics and costs, the probability of a truck transitioning from electric trucks back to diesel is assumed to be zero (Assumption 9). Thus, the probability of an electric truck staying electric is 100%.

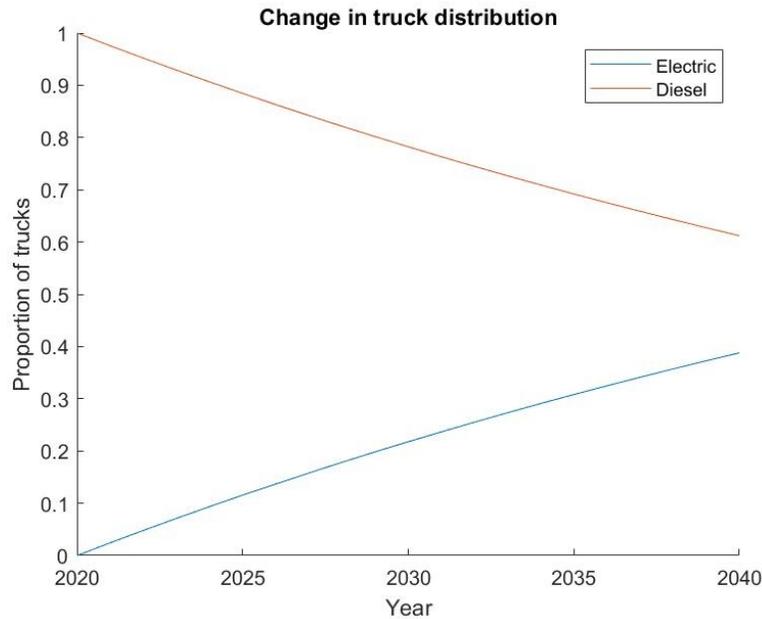


Figure 3: Projected changes in the proportion of trucks that are electric.

We iterate our Markov chain model for $t= 5, 10,$ and 20 to find the proportion of trucks that are electric in the years 2025, 2030, and 2040, respectively. The results are as follows:

Year	Vector
2025	(.1153, .8847)
2030	(.2173, .7927)
2040	(.3874, .6126)

Figure 4: The projected state vectors of our Markov chain. The first value is the proportion of trucks that are electric, and the second value is the proportion of trucks that are diesel-powered.

Using our model, we thus predict that in 2025, 11.53% of trucks will be electric; in 2030, 21.73% will be electric; and in 2040, 38.74% will be electric.

1.5 Validation

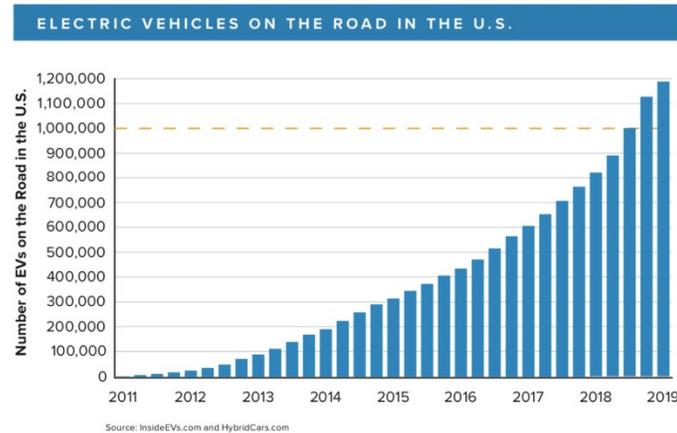


Figure 5: Amount of electric vehicles (no trucks) on the road since 2011 [5].

When electric trucking develops, we should expect the industry to grow faster than the electric car industry since it has access to infrastructure used by electric cars, like charging stations, which was not available for electric cars at their introduction. Our model displays this as we predict 9% of trucks to be electric by 2024, four years after 2020, which is when we claim the electric trucking industry began; however, four years after the electric car industry emerged in America in 2011 [5], only 1% of cars were electric [6], which matches our prediction that the electric trucking industry will grow faster than the electric car industry in its first years. After a period of time, the electric trucking industry should lose its comparative advantage in development since further growth occurs due to the expansion of access of the infrastructure, so the industries should be similar after a long period of time. Our model predicts that, in 2034, 29% of trucks will be electric, and projections show that 31% of cars will be electric in 2025 [6], which show that the strength of the two industries will become similar in the long run.

Moreover, the growth of the electric car industry is monotonic and increasing [5], which matches our projections that also show that the electric trucking industry will only increase.

1.6 Sensitivity Analysis

As noted in assumption 6, we assume that truck owners will want to switch from diesel trucks to electric trucks if the savings accrued by the lower operational costs the electric trucks pays for higher sticker price in one year. We perform an analysis to determine the reasonability of this one-year payback period.

We repeat the process outlined in section 1.5 to determine the proportion of trucks that will be electric in the year 2040, except we vary the payback period from 0 years to 1.5 years in 0.01-year increments. We find that as the payback period increases, the proportion of electric trucks also increases, which makes sense because electric trucks tend to make higher profits the longer they are in use.

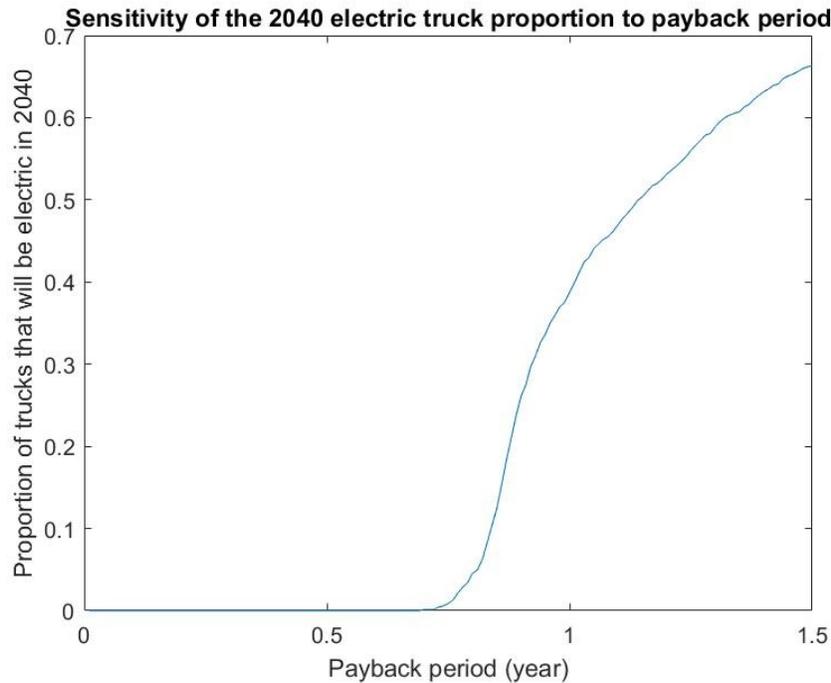


Figure 6: Sensitivity of the proportion of trucks that are electric by 2040 to the desired payback period.

Our assumption of a one-year payback period is not the strongest. The above curve has a relatively high slope at the one-year payback period, suggesting that the proportion of electric trucks is extremely sensitive to the payback period. However, our assumption is not unreasonable because the results were validated in section 1.5. The high sensitivity could possibly be because of the relative lack of information regarding electric trucks; since they are a relatively new innovation, there is quite a bit of uncertainty about the future of such vehicles.

1.7 Strengths & Weaknesses

Strengths

- Our model accounts for a number of factors, including the operational cost differences between diesel and electric trucks, initial purchase prices, and truck lifetime. These factors ensure that our model provides a fairly detailed assessment of the future growth of electric trucks.
- Our use of Markov chains allowed us to create a dynamic computational model that can account for the rate of new truck production.
- Our model focuses on changes in electric truck usage due to profit rather than taste preferences for going “green” or other subjective standards. This is a better reflection of real-world business models.

Weaknesses

- We do not account for the relationship between increasing travel distances and increasing repair costs associated with those distances.
- Our Markov chain model is discrete. In reality, truck purchases are not discrete but continuous: people can purchase trucks at almost any time they choose. Our model assumed that truck purchases all occur at the beginning of a given year.

- The proportion of trucks that will be electric in 2040 is extremely sensitive to the payback period, the period of time after which the truck owners expect an investment return.

Part II: In It for the Long Haul

2.1 Restatement of Problem

We are asked to create a mathematical model to determine how many charging stations should be installed along a route a trucker travels on, as well as how many chargers would be sufficient at each station. We define sufficient chargers to mean that a charging station is able to accommodate, on average, at least 99.7% of potential customers.

2.2 Local Assumptions

1. *Cars cannot use charging stations designated for electric trucks.* The level 3 chargers usually used by trucks are incompatible with electric personal vehicles.
2. *Truckers do not take detours or side-paths but instead follow the suggested routes on Google Maps.* It is very difficult to account for the smaller, local roads that truckers occasionally take, so we choose to assume that truckers do not deviate from large highways.
3. *High amounts of traffic and slowdown do not substantially impact the battery efficiency of electric trucks.* Electric vehicles do not face the same efficiency problems that petroleum-based vehicles do in traffic jam situations. For example, an electric car that has come to a full stop in traffic spends nearly none of its battery [7].

2.3 Variables

Symbol	Definition	Units
d	Distance from end city to end city of a trucking corridor	Miles
h	Elevation difference between two cities	Feet
S	The number of stations required between two locations	Stations
FuelUse	Percentage of semi-truck battery to be used We assume this to be 80% - 25% as more than 80% charge damages the battery and truckers prefer keeping their fuel above 25% [20]	Unitless
FuelCapacity	Energy capacity of a fully charged semi-truck battery [19]	Kilowatt Hours
mileage	Energy required per mile for an electric semi-truck [19]	Kilowatt Hours/Mile

Figure 7: Variable definitions for Problem 2.

2.4.1 Charging Stations Solution & Results

To find the number of stations required between two locations, we use the distance between the cities, the altitude difference, and the mileage capabilities of electric trucks. We derive the following equation:

$$S = \frac{\left(\frac{d}{\text{mileage}}\right) + mgh}{\text{FuelUse} * \text{FuelCapacity}}$$

For the numerator, we find the amount of energy required in driving between two locations. First, altitude differences between cities can have a substantial impact on the efficiency of electric trucks, so we account for these. We use the equation $PE = mgh$ to calculate energy required of the truck for driving between cities with elevation differences, with m , mass, the gravitational constant 9.801 m/s^2 , and h , the altitude differences. We then add this value, converted to kilowatt hours, to the distance driven between the two locations divided by the mileage. Thus, the units are consistent, and the sum is equal to the energy required to drive from the first location to the second.

In the denominator, we find the product of the percentage of battery charge used before recharging and the total fuel capacity of a heavy electric truck. This will give the kilowatt hours used per trip of an electric truck.

We divide the numerator by the denominator to find S and round it up to the next largest integer to give a conservative estimate for how many charging stations are needed between two locations. We obtain the following:

Corridor	Number of Charging Stations
San Antonio-New Orleans	5
Boston-Harrisburg	3
Los Angeles-San Francisco	3
Minneapolis-Chicago	3
Jacksonville-Washington, DC	6

Figure 8: Recommended number of charging stations for each corridor.

2.4.2 Chargers per Station Solutions & Results

In the problem statement, we define “sufficient charger” availability to be: each charging station must have enough chargers to serve all trucks during peak traffic hours 97.7% of days. The number of trucks is equal to

$$\# \text{ Trucks} = \# \text{ vehicles} * \text{proportion of vehicles that are trucks}$$

We can calculate that trucks travel 137.5 miles between charges by multiplying the estimated 55% battery usage with the 250 miles a long-haul car can travel with 100% battery usage [8]. Considering that trucks travel around speed limits of 70 mph, and trucks last about 2 hours between charges. Charging a truck from 25% to 80% battery level requires 30 minutes [9]. A truck therefore spends approximately 20% of its trip charging at a station.

Let N be the number of charging stations on a corridor. Therefore, a truck spends $(\frac{20\%}{N})$ percentage of its trip charging at each station. During peak hours--approximately noon to 1pm--the number of trucks that require charging represents 6.8% of all trucks that use the corridor that day. This means, during peak hours, $20\% * (\frac{6.8\%}{N}) = (\frac{1.36\%}{N})$ of all trucks that use the corridor will be charging at a single given station.

We use the given corridor data on Annual Average Daily Truck Traffic to find the daily truck traffic [10]. In some states, Annual Average Daily Truck Traffic is unavailable. We instead calculate our own Annual Average Daily Truck Traffic by multiplying the list of Annual Average Daily Traffic (all vehicles) by the average percentage of vehicles that are trucks. We use this process to find the Annual Average Daily Truck Traffic values for each of the five corridors. The mean and standard deviation of these lists are below.

Corridor	Daily Truck Traffic Mean	Daily Truck Traffic Standard Deviation
San Antonio-New Orleans	3318	1541
Boston-Harrisburg	4580	1822
Los Angeles-San Francisco	7950	5961
Minneapolis-Chicago	9596	7415
Jacksonville-Washington, DC	6522	4392

Figure 9: Daily truck traffic statistics for each of the five corridors.

We know that $\frac{1.36\%}{N}$ of trucks are charging at a given station during peak hours, from the above means and standard deviations, we can determine the number of trucks that require service during peak hours. For all trucks to be able to be simultaneously charged during peak hours 97.7% of days, we need to supply one charger for each of *Mean daily # of trucks that require charging during peak hours + 2 Standard deviations* (97.9% of values fall to the left of 2 positive standard deviations).

Corridor	Number stations	Daily number of trucks that require charging during peak hours		Chargers per Station
		Mean	Standard Deviation	
San Antonio-New Orleans	5	9.2	4.2	18

Boston-Harrisburg	3	21.2	8.4	38
Los Angeles-San Francisco	3	36.6	27.4	92
Minneapolis-Chicago	3	44.1	33.7	112
Jacksonville-Washington, DC	6	15.0	10.1	36

Figure 10: Projected number of trucks that require charging and recommended chargers per station along the given corridors.

2.5.1 Charging Stations Sensitivity Analysis

Fuel Use (% of tank)	SA ⇌ NO	MPS ⇌ CHI	BSTN ⇌ HBG	JX ⇌ DC	SF ⇌ LA
45	5	4	4	7	4
50	5	4	4	6	4
55	5	3	3	6	3
60	4	3	3	5	3
65	4	3	3	5	3

Figure 11: Number of stations needed for each corridor based on varying percentages of fuel use/battery charge.

Some truckers want to charge when their fuel capacity is lower than 25%. Assuming that they still charge their tank up to 80% of its total capacity, we consider how many stations are needed given that they want to charge their trucks at 15% to 35% capacity instead, which corresponds to 65% and 45% fuel use, respectively. Though the number of stations varies by up to two stations, a general trend emerges, with longer roads requiring more stations, regardless of the percent of their tank a trucker may run down.

2.5.2 Chargers per Station Sensitivity Analysis

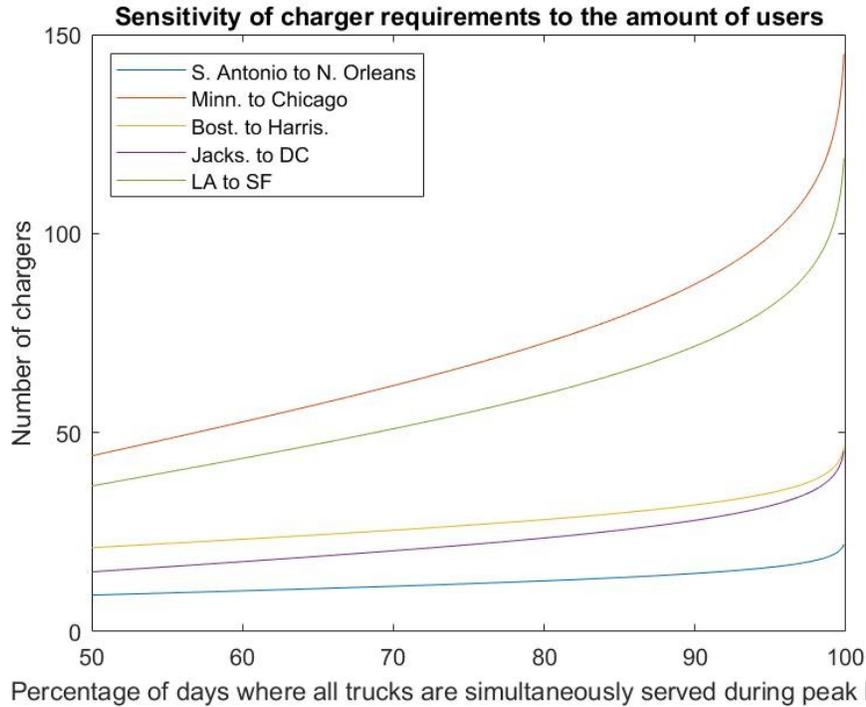


Figure 12: The number of chargers per station needed along each corridor as days where all trucks are charged changes.

As expected, as the demand for chargers increases, the number of chargers required also increases. Near the 97.7% value, the number of required chargers is moderately sensitive because the slope of the sensitivity analysis graph is large; however, even as the demand for chargers changes, the number of chargers per station remains qualitatively similar.

2.7 Validation

Corridor	Predicted Number of Charging Stations	Number of PlugShare Supercharging Stations [11]
San Antonio-New Orleans	5	7
Boston-Harrisburg	3	6
Los Angeles-San Francisco	3	6
Minneapolis-Chicago	3	5
Jacksonville-Washington, DC	6	9

Figure 13: Comparison between predicted number of truck charging stations and the number of electric car charging stations along each corridor.

Although the range of electric cars is similar to the range of electric trucks, it is reasonable that the number of car charging stations is higher than the number of truck charging stations, as the PlugShare company must produce enough stations to provide charging security for electric car drivers. The general trend of the number of truck charging stations is relatively similar to the trend of Supercharging stations data; for example, the San Antonio-New Orleans and Jacksonville-Washington DC have more stations than the other three corridors.

2.8 Strengths & Weaknesses

Strengths

- Our model is simplistic and intuitive to understand and thus has easily interpretable results. It can also be applied to a wide variety of cities with minimal data.
- Our model uses statistically significant results to justify the minimum number of chargers needed per station.

Weaknesses

- Our model does not take into account a number of factors, such as the availability of rest stops. It only considers data regarding the corridors and the cities themselves; less attention is given to the route between the cities.
- We assume that the charging stations are optimally distributed across the corridor while in reality, charging stations are usually clustered around major cities.
- Our model only finds the minimum number of charging stations needed between the corridors. Some corridors are more popular and require more stations as more trucks need to stop on them. This explains why our number of chargers per station to popular cities like Chicago and Los Angeles are so high, near a hundred.

Part III: I Like to Move It, Move It

3.1 Restatement of Problem

We are asked to rank the five trucking corridors addressed in Part II to determine which of the five should be targeted for the development of electric truck infrastructure first.

3.2 Local Assumptions

1. *The preferences of the population of towns and cities along the corridor can be represented by the preferences of three cities: the two endpoints and the largest city in between.* The given corridors are not especially long; in most cases, the corridors only traverse one other major city, excluding the endpoints. Furthermore, in most corridors, the three key cities that we examine account for a plurality of the population.
2. *Everyone votes for either Republican or Democratic candidates; that is, there are no independents.* It is difficult to account for independents, since there is no way of determining how self-proclaimed independents choose to vote. We thus exclude them from our model and assume that voting patterns align with the traditional dichotomy of Republican and Democrat.
3. *People do not like smog and will prefer cleaner air to polluted air.* Air pollution can lead to serious health problems, including lung disease. It is widely acknowledged that clean air is preferable to polluted air.

3.3 Variables

Symbol	Definition	Units
$m_{x,y,z}$	The value of metric x for city y , which lies on corridor z	Variable depending on the metric
$wm_{x,y,z}$	The value of the population-weighted metric for city y , which lies on corridor z	Variable depending on the metric
$cm_{x,z}$	The metric x across the entire corridor z , found by summing the weighted $wm_{x,y,z}$ of each city	Variable depending on the metric
$rcm_{x,z}$	The value of the metric x across the corridor z , but relative to the total values of metric x across all five corridors	Unitless (a proportion)
FR_z	The final ranking value of corridor z , found by summing all the $rcm_{x,z}$ values for the corridor z	Unitless (a proportion)

Figure 14: Variable definitions for problem 3.

3.4 Solution and Results

For each corridor, we choose to examine the two endpoint cities and the largest intermediate city along the corridor; these three cities represent the demographics along the corridor. We compiled data on the various cities' political leanings, median household income, air quality, and population.

Corridor	Endpoint City 1	Endpoint City 2	Major Midpoint City
S. Antonio to Houston	San Antonio	New Orleans	Houston
Jacksonville to D.C.	Jacksonville	Washington D.C.	Richmond
Boston to Harrisburg	Boston	Harrisburg	Hartford
Minneapolis to Chicago	Minneapolis	Chicago	Richmond
S. Francisco to LA	San Francisco	Los Angeles	San Jose

For each city, we found the number of Democrats and Republicans [12], from which we could calculate the total number of people who politically support green energy measures, such as electric trucks; 90% of Democrats and 52% of Republicans support increased use of electric transportation [13]. The greater the number of supporters, the more a city desires electric trucking implementation.

Higher income has been found to be correlated to a higher preference for electric transportation adoption [14]. A higher smog/air pollution index indicates that a corridor more desperately needs electric vehicles to reduce air pollution [15]. Higher population along a trucking corridor means that a greater number of individuals would enjoy the plethora of environmental and economic benefits that electric trucking stations bring [16].

Using our predictions from Part II, we were also able to consider the total number of electric truck chargers stations along the corridors, which is equal to the number of charging stations multiplied by the number of chargers per station. The total number of chargers along each corridor is an important metric:

1. Truckers' usage of a corridor is proportional to the total number of chargers. This is because in Part II, we used daily truck traffic to calculate the number of chargers per corridor.
2. The initial economic benefit conferred by hiring builders to construct chargers and stations is proportional to the number of chargers that need to be built.
3. The long-term economic benefit conferred by hiring employees to maintain the chargers is proportional to the number of chargers in use.

Then, within each corridor, we scale each of the three cities’ metrics according “influence” on the corridor. To do so, we multiplied each metric by that city’s population, which we then divided by the population of each corridor. Summing the results of the three cities in a corridor creates a weighted average for each metric.

$$wm_{x,y,z} = m_{x,y,z} * \left(\frac{Population_{city y}}{Population_{corridor z}} \right)$$

To find the total population of the corridor, we simply summed populations of the three cities. Then, for each corridor, the modified metrics of the three cities were summed together to produce the corridor metrics.

$$cm_{x,z} = wm_{x,city 1,z} + wm_{x,city 2,z} + wm_{x,city 3,z}$$

	San Antonio to New Orleans	Jacksonville to Richmond	Boston to Harrisburg	Minneapolis to Chicago	San Francisco to Los Angeles
Supporters	3211929.256	3716183.29	674564.5037	2865916.811	4871122.647
Income	3.00151033	7.460849709	17.60022685	14.06471036	12.23343926
Smog	221	148	128	262	307
Populations	4,248,741	5,210,421	874,576	3,684,418	6,027,675
Charger number	90	216	114	336	276

Figure 15: Corridor metrics cm for each of the five metrics for each of the five corridors. The corridor metrics represent the total electric-truck desirability contributed by each of the five demographic factors. The metrics were found by summing the desirability contributed by each of the three cities within that corridor.

For a given corridor metric $cm_{x,z}$ divide the value $cm_{x,z}$ by the sum of each corridor’s value for that metric. This gives us a corridor metric value $rcm_{x,z}$ relative to the sum of all five corridor metrics. This will also make the metric unitless. Like before, as $rcm_{x,z}$ increases, the corridor z increases in desirability.

$$rcm_{x,z} = \frac{cm_{x,z}}{cm_{x,corridor 1} + cm_{x,corridor 2} + cm_{x,corridor 3} + cm_{x,corridor 4} + cm_{x,corridor 5}}$$

The results are as follows:

	Weight	SA ⇌ NO	MPS ⇌ CHI	BSTN ⇌ HBG	JX ⇌ DC	SF ⇌ LA
Supporters	1	0.20938	0.18682	0.04397	0.24225	0.31754
Income	1	0.05521	0.25872	0.32376	0.13724	0.22504
Smog	1	0.20731	0.24577	0.12007	0.13883	0.28799
Populations	1	0.21195	0.18379	0.04362	0.25992	0.30069
Charger number	3	0.26162	0.97674	0.33139	0.62790	0.80232

Sum	----	0.94549	1.85188	0.86284	1.40617	1.93360
-----	------	---------	---------	---------	---------	---------

Figure 16: Corridor ranking metrics and sum of metrics for each corridor.

Finally, we sum the metrics within each column to obtain each corridor’s final ranking value. We weight the $rcm_{charger\ count,z}$ count three times higher because chargers have critical economic functions, as detailed above. The importance of charger count justifies this higher weight.

$$FR_z = rcm_{political\ support,z} + rcm_{income,z} + rcm_{pollution,z} + rcm_{population,z} + rcm_{charger\ count,z}$$

The weights and final sums for each of the five corridors are shown in the above table.

Using our model, we conclude that the San Francisco-Los Angeles corridor is the best choice for electric truck infrastructure development, while of the five corridors, the San Antonio-New Orleans corridor is the worst.

3.5 Sensitivity Analysis

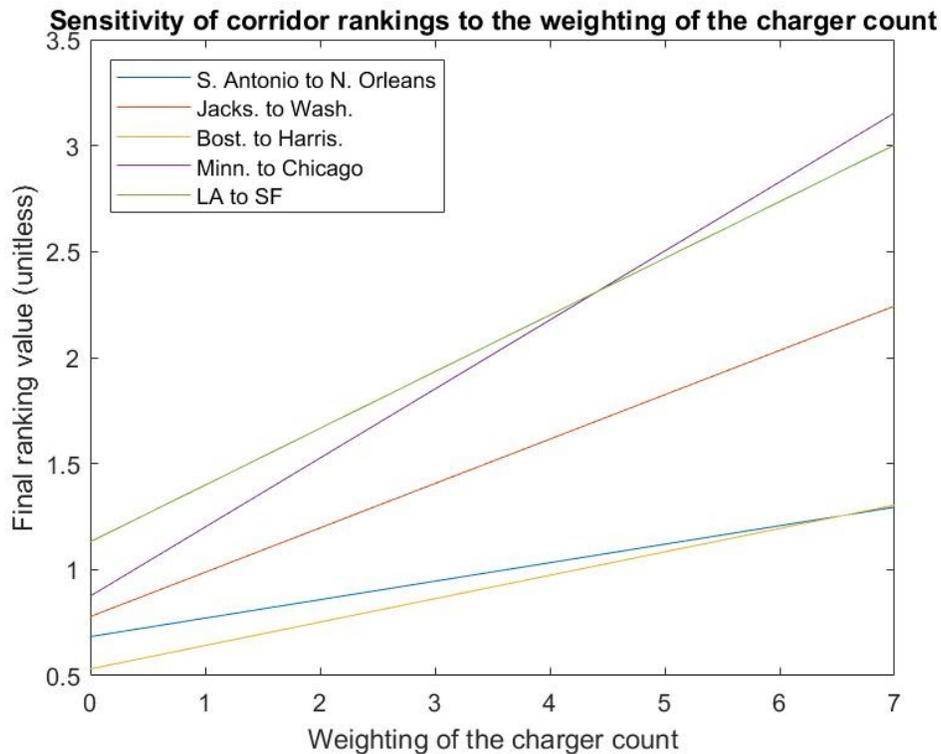


Figure 17: Relationship between final ranking values of each corridor with varying weight on charger count.

It appears that the best corridor depends substantially on the charger count; the San Francisco-Los Angeles corridor is the best choice in our model only because of the lower weight on charger count. When charger count weight is increased, Minneapolis-Chicago becomes the best choice. Thus, the actor can assign their own importance to the number of chargers.

3.6 Validation

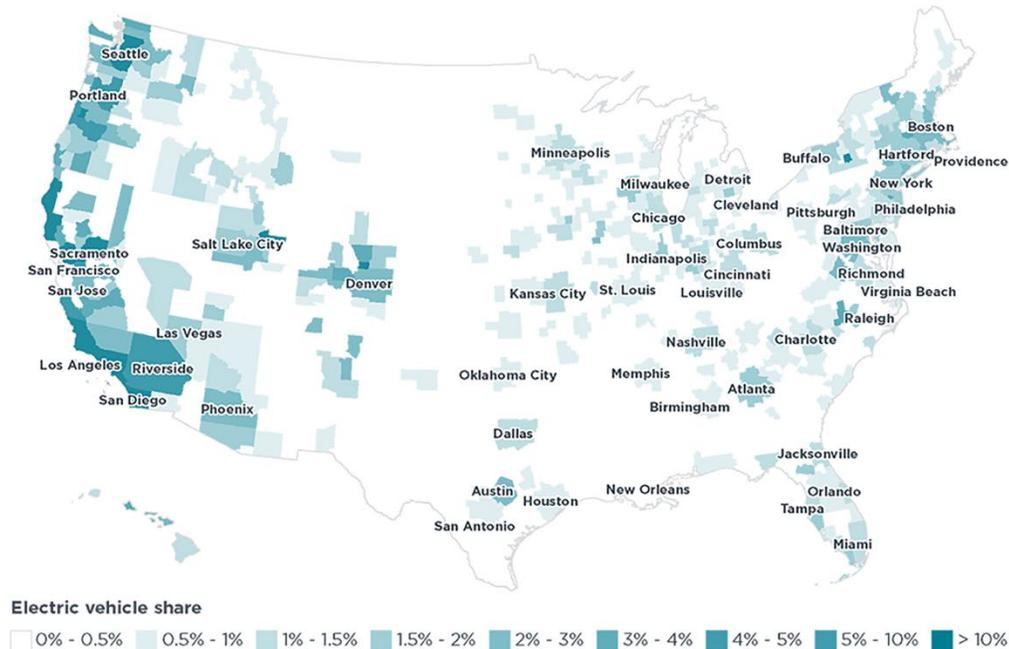


Figure 18: Map of electric car ownership in the US [17].

The fervor for the electric trucking industry should mirror that of electric cars. Currently, San Jose, followed by other major California cities like Los Angeles and San Francisco, have the highest market shares for electric vehicles, with San Jose itself accounting for 21% of market shares [17]. Our model claims that electric trucking efforts should be focused on the San Francisco to Los Angeles, which the electric car industry focused its efforts on. The electric vehicle industry is the smallest along the San Antonio to New Orleans corridor compared to the other four, with less than 2% of the industry concentrated there [17]. Our model also claims that development of the electric trucking industry should focus on that corridor last, corroborating the fact that the electric vehicle development is smallest there.

3.7 Strengths & Weaknesses

Strengths

- Our model is relatively simple, so we can choose to account for many different factors, and also how important that factor is to whether a person or city would desire electric trucks over diesel ones.
- Our model incorporates just a few key indicators, making it easily adaptable to any other corridors for future analysis.

Weaknesses

- Our model uses only one factor in assigning scores for certain categories; for example, the political support that electric trucks have in a city is determined solely by the voting patterns in the last election. This means that some of the more subtle dynamics of some cities--historical voting patterns, preference for traditional transportation methods, etc.--are overlooked by our model.

Part IV: Conclusion

In our first model, we were asked to project the growth of electric trucks in the trucking industry over the next twenty years. By creating a transition matrix, we were able to use Markov chains to predict the number of trucks that companies would transition towards electric rather than diesel. We found that in 5, 10, and 20 years, 11.53%, 21.73%, and 38.74% of all heavy trucking would be composed of electric models. Our validation found that our model closely corresponded to predictions for electric truck use published in literature.

Next, we created a model that could determine the number of electric truck charging stations along any trucking corridor by examining electric truck mileage. We then used traffic data to calculate the number of chargers required at each station so that all trucks could be served at peak hours 97.7% of all days. We applied this model to five corridors: San Antonio to New Orleans, Minneapolis to Chicago, Boston to Harrisburg, Jacksonville to Washington, and Los Angeles to San Francisco.

Finally, we used the predicted number of chargers along the five given corridors to model truck usage of the corridors. In addition, we compiled and weighted factors including income, political leaning, and air pollution in key cities along the corridor to determine where electric trucks would be the most welcome. Using this framework, we were able to assemble and index to rank each of the five corridors based on suitability for electric truck infrastructure development.

Electric trucks are an exciting alternative to fuel-inefficient diesel trucks. They provide a key step in the reduction of carbon emissions and thus the preservation of the environment, and are a notable landmark in the nation's technological advancement.

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Appendix:

The following three MATLAB functions were used to solve Problem 1.

%% MarkovTrucks function

```
%Performs a Markov chain analysis to project transitions from
diesel to
%electric trucks. 20 time steps are performed.
%Assumes electric trucks do not convert back to diesel.
%INPUT: The input p represents the proportion of diesel trucks
that
%transition to electric each year.
function newvals=MarkovTrucks(p)
initialvals=[0;1]; %seed vector
newvals=zeros(2,21); %stores results across the years
newvals(:,1)=initialvals; %set the initial seed vector
for year=2:21
    A=[1 p;0 1-p]; %transition matrix
    newvals(:,year)=A*newvals(:,year-1); %project the next time
step's vector
end
```

%% MarkovOutcomes function

```
% Performs MarkovTrucks to find the proportion of trucks that
will be
% electric.
function data=MarkovOutcomes(d,truckdist)
%% Find daily miles driven necessary to make a profit in d years
[truckcount,~]=size(truckdist); %number of trucks in our dataset
replacement=1/12; %the rate at which diesel trucks must be
replaced each year
daysperyear=260; %number of days each year that trucks are in
use
profitdistance=30000/0.279; %the minimum lifetime distance that
must be driven for electric cars to be more profitable than
diesel cars
profitdistanceperyear=profitdistance/d; %the minimum yearly
distance that must be driven for electric vehicles to be
profitable
profitdistanceperday=profitdistanceperyear/daysperyear; %the
minimum daily yearly distance
[drivetruck,~]=size(find(truckdist>profitdistanceperday)); %numb
er of trucks that drive the profitdistanceperday distance per
day
proptruck=drivetruck/truckcount; %proportion of trucks that
drive the profitdistanceperday
transitionprop=proptruck*replacement; %finds the p value used in
the transition matrix
%% Markov chain
```

```
years=2020:2040;
newvals=MarkovTrucks(transitionprop); %Perform Markov chains
using Markov Trucks
data=[years' newvals']; %concatenate data and years into the
same matrix
if d==1 %if this function is NOT being used for sensitivity
analysis, plot the results
    figure('Name','Change in truck distribution')
    hold on
    plot(data(:,1),data(:,2))
    plot(data(:,1),data(:,3))
    hold off
    title('Change in truck
distribution'),xlabel('Year'),ylabel('Proportion of trucks')
    legend('Electric','Diesel')
end
end

%% TruckSensitivity function
%Performs sensitivity analysis on Markov Outcomes to determine
if projected
%truck proportions are sensitive to the desired payback period
(d in years)
clc
sensdata=[]; %create matrix to store data
for d=0.01:0.01:1.5 %vary the payback period from 0 to 1.5 years
data=MarkovOutcomes(d,truckdist); %perform Markov chain using
the payback period
sensdata=[sensdata; [d,data(21,2)]]; %store Markov chain results
end
sensdata %print out data
figure('Name','Sensitivity of the 2040 electric truck proportion
to payback period')
plot(sensdata(:,1),sensdata(:,2)) %plot the sensitivity analysis
graph
xlabel('Payback period (year)'),ylabel('Proportion of trucks
that will be electric in 2040'),title('Sensitivity of the 2040
electric truck proportion to payback period')
```