MathWorks Math Modeling Challenge 2020

Pine View School

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M3 Challenge CHAMPION—$20,000 Team Prize

JUDGE COMMENTS

This was a well-received paper, and the judges responded positively to its excellent writing and strong modeling. The paper did have some relative weaknesses. First, one important improvement would include an analysis of the method. For example, an examination of how the results would differ under small changes of the transition probability in section 1 would provide the reader with more insights into how the model behaves under different circumstances. Additionally, the inclusion of a modest statistical analysis of the results from the Monte Carlo simulation would have been helpful to better understand how much trust can be placed in the results.

While a deeper analysis of the model would have been helpful, the team produced excellent models for all three questions. In particular, the use of a Markov chain to model how the distribution of trucks changes in time demonstrated that the team recognized the overall balance between the different types of vehicles. More importantly, the team demonstrated an outstanding insight into question two by first recognizing the relationship between charge time and number of stops is a nontrivial relationship. Finally, this was one of the very few teams that recognized the statistical nature of simulations and presented their results in an appropriate manner consistent with the statistical nature of the results.

The judges had a number of questions regarding this entry:

1. Question 1, assumption 1-2: You assume the demand is at a constant level of 210,466. In view of the previous 10 years of data, please comment on this assumption.
2. Page 6: Can you provide more details how you computed the probabilities for the transition matrices?
3. Question one: The team set the values of P as 0.2, .4, and .6 and justified somewhat the relation between them from the total cost consideration. If these assumptions or calculations are off by a small amount how will it impact your conclusions?
4. Question one: Can your model be adapted if some of the retired long haul trucks are moved to the pool of reginal trucks. Also, what additional changes can then be made if some fraction of the regional trucks are moved into the pool of local trucks. How will such consideration change given different values of P?
5. Question 2, Assumption 2-1 (page 10): Discuss the "exponential" characteristic of charging the batteries and the equation for I (on page 11).
6. In the simulation C0 was assumed to be normally distributed with mu =.6 and std dev = .125. Since C0 is the initial state of charge and listed as 20% in the table on page 10, how does this go with mu = .60
7. Question 3: In the Importance score, X, (page 15) you add the 3 normalized values. Discuss what you are adding and explain why S, the cost associated with chargers is added (that is why is the higher cost a positive characteristic).

Keep on Trucking

Executive Summary

In the past century, as energy usage rapidly increased and fossil fuel consumption and carbon emissions have increased along with it, transportation has accounted for a large share of this. With e-commerce and delivery increasing in popularity and trucks accounting for around a third of transport-related carbon emissions and 20% of the global demand for oil [1], it is important to evaluate more energy-efficient and sustainable alternatives. One example of such is using electricity powered semi-trucks instead of semi-trucks fueled by diesel. Multiple companies are already in the process of producing electric semi-trucks, including Freightliner and Tesla, whose electric semis are supposed to enter production this year. Transitioning to electric semi-trucks could help with both reducing the environmental impact of trucks and reducing the total operating cost in the long run.

We predicted the percentage of semis that would be electric in the next twenty years by using Markov chains. Semi-trucks were split into short haul, regional haul, and long haul, and a model was created for each type of truck. Operating costs were calculated using values found in the "Truck Usage Data" and the cost of operating an electric and diesel truck per mile ($1.26 vs $1.51). Purchasing costs were based on the prices of current day cab and sleeper semi-trucks along with base prices for Tesla electric semis. The difference in costs was used to estimate the probability values of replacing diesel trucks with electric trucks. These probability values were placed into three separate transition matrices for each type of semi and were then used in calculating the number of electric cars in the next 5 and 10 years in tandem with the number of inoperable diesel semi-trucks each year. We predicted the population of inoperable diesel semi-trucks in the next 8 years with the transition matrices to calculate the number of electric cars in 20 years. Our model predicts that in 5 years, 10 years, and 20 years, electric semi-trucks will make up 27.39%, 69.49%, and 97.77% of the number of semis, respectively.

In view of the drastic change suggested in Part 1, a model was also created to determine the amount of infrastructure necessary to make a full shift to electric semi-trucks. We first took into account the variety of ranges and charging times of electric vehicles, along with the quirks of exponential approach charging, to find an optimal pit stop schedule for long-haul single driver trips. We then used this strategy, along with a Monte Carlo simulation, to simulate the resource needs of a large population of trucks on five shipping corridors. Interestingly, all five revealed an optimal stopping interval of 90 minutes. Finally, another Monte Carlo simulation revealed the optimal number of charging stations per truck stop.

In order to model which of the corridors should be developed for electrification we first created an importance score based on three different factors: economic growth, environmental consideration, and total cost for installation. Economic growth was found based on money saved by the decreased idling times of DCFC chargers and total average traffic. Environmental consideration was based on the average number of electric vehicle policy/actions in the state. Total cost was calculated using values found from the previous part on number of

charging stations and chargers needed per trucking corridor. These values were then normalized and used to rank the five corridors in Part 2. The results showed that the Minneapolis to Chicago corridor should be targeted first, followed by Los Angeles to San Francisco, then San Antonio to New Orleans, then Jacksonville to D.C., and then Boston to Harrisburg.

Contents

Global Assumptions

G-1. **There are currently 1.7 million semi-trucks in operation in the United States. [2]**

- **Justification:** It is reasonable to assume that this provided data is about the United States because there are around 2 million semi-trucks on the road in the United States [9].

1 Shape Up or Ship Out

1.1 Defining the Problem

Develop a model to predict the percentage of semi-trucks that will be electric 5, 10, and 20 years from 2020.

1.2 Assumptions

1-1. **There are no electric semi-trucks currently in operation.**

- **Justification:** Production has started for electric semi-trucks, but they will hit the roads in 2020 [10].

1-2. **The market for semi-trucks demands the production of 210,466 semi-trucks per year.**

- **Justification:** Since the production of Class 8 trucks in 2019 was 210,466 according to Truck Production Data, 2020 MathWorks Math Modeling Challenge [16], the market is assumed to be constant.

1-3. **Electric semi-trucks have the same life expectancy as diesel semi-trucks (12 years).**

- **Justification:** Since electric semi-trucks are a new invention, the average life expectancy of an electric semi-truck cannot be observationally determined yet. The life expectancy will most likely depend on the owner's willingness to replace its battery.

1-4. **The total difference in cost between electric and diesel semi-trucks is proportional to the probability that a diesel semi-truck will be replaced with an electric semi-truck.**

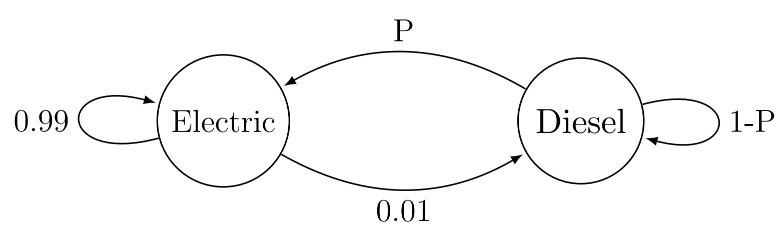
- **Justification:** Since there is no data on the consumers purchasing electric cars, we assumed that a greater difference in cost will make consumers replace more diesel semi-trucks with electric semi-trucks.

1.3 Variables Used

Symbol	Definition	Units	Value
Q_e	Quantity of Electric Semis Replaced from Inoperable	trucks	...
Q_d	Quantity of Diesel Semis Converted from Inoperable	trucks	...
P_e	Proportion of Electric Semi-Trucks	...	...
P_S	Replacement Probability (Short Haul)	...	...
P_R	Replacement Probability (Regional Haul)	...	...
P_L	Replacement Probability (Long Haul)	...	...
S_p	Sum of Predicted Production - Diesel Semi-Trucks (2020-2027)	...	124,348
P_0	Amount of Semi Trucks in 2019	trucks	1,734,721

1.4 Developing the Model

To predict the future percentages of electric and diesel semi-trucks in the next 5, 10, and 20 years, we divided semi-trucks into three types and created model for each: short haul, regional haul, and long haul. We created three transition matrices (one for each type of semi-truck) to input into the following Markov chain to do this:



The model assumed that 0.01 of the electric cars would revert back to diesel, possibly after seeing some of the disadvantages of electric semi-trucks, including its high charge time or lower on-the-road time per refuel.

We looked into the costs of diesel and electric trucks. There were two types of diesel trucks found when researching purchase costs: day cabs, which are ideal for shorter routes and would likely be used for short and regional hauls, and sleeper trucks, which are ideal for longer routes and would likely be used for long hauls [3]. The average prices for these were found along with prices for electric semi-trucks, which were based on the base prices for the Tesla semi-trucks set to start production in 2020: \$150,000 for a 300-mile range truck (likely to be used for short hauls) and \$180,000 for a 500-mile range truck (likely to be used for long hauls). Operating costs were then calculated and found to be \$1.51 per mile for diesel semi-trucks and \$1.26 per mile for electric semi-trucks [11].

Using those values and annual travel mileage found in “Truck Usage Data” from the 2020 MathWorks Math Modeling Challenge, which was 42,640 miles for short haul, 70,000 miles for regional, and 118,820 miles for long haul [16], the total cost over the course of 12 years (the average lifetime of a truck) and annual operating cost were calculated as shown in the table below:

	Type	Purchase Cost	Annual Operating Cost	Total Operating Cost	Total Cost
Diesel	Short Haul	\$80,000	\$64386.40	\$772,636.80	\$852,636.80
	Regional	\$80,000	\$105,700	\$1,268,400	\$1,348,400
	Long Haul	\$125,000 [14]	\$179,418.20	\$2,153,018.40	\$2,278,018.40
Electric	Short Haul	\$150,000 [15]	\$53,726.40	\$644,716.80	\$794,716.80
	Regional	\$150,000	\$88,200	\$1,050,000	\$1,208,400
	Long Haul	\$180,000 [15]	\$149,713.20	\$1,782,300	\$1,976,558.40

Table 1: Semi-truck Operation and Purchase Costs

With the values found in the table above, we then calculated the difference between electric semi-truck and diesel costs for purchase, operation, and total difference:

Type	Difference in Purchasing	Difference in Operating	Total Difference
Short Haul	-\$70,000	\$127,920	\$57,920
Regional	-\$70,000	\$210,000	\$140,000
Long Haul	-\$55,000	\$356,460	\$301,460

Table 2: Difference in Costs for Diesel and Electric Semi-Trucks

These values were then used to calculate P, the probability of a diesel semi-truck being replaced by an electric semi-truck in the first year, for each of the transition matrices. Short haul, regional haul, and long haul received P values of 0.2, 0.4, and 0.6, respectively, due to an increase by a factor of around 2 between short haul and regional haul and regional haul and long haul total cost differences. These P values are then inserted into the following transition matrices to run a Markov chain model:

$$\mathbf{P_S} = \begin{array}{c||cc} & D & E \\ D & 0.8 & 0.2 \\ E & 0.01 & 0.99 \end{array}$$

$$\mathbf{P_R} = \begin{array}{c||cc} & D & E \\ D & 0.6 & 0.4 \\ E & 0.01 & 0.99 \end{array}$$

$$\mathbf{P_L} = \begin{array}{c||cc} & D & E \\ D & 0.4 & 0.6 \\ E & 0.01 & 0.99 \end{array}$$

These transition matrices are used to calculate the proportion of diesel and electric cars in Matlab.

From the Truck Production Data sheet [16], we calculated the total number of trucks produced for short haul, regional haul, and long haul based on values given for total number of tractors produced and total number of long haul tractors produced. Number of short and regional haul trucks were found by subtracting the number of long hauls produced from the total. Short haul was then found by multiplying that value by 10% as short haul trucks are 5% of all semi-trucks, while regional haul trucks are 45% [2], meaning that short haul trucks would account for 10% of the total of short haul and regional trucks combined.

Year	Class 8 Tractor Short Haul	Class 8 Tractor Regional Haul	Class 8 Tractor Long Haul
1999	3691	33219	180,205
2000	3521.1	31689.9	105,632
2001	2512.4	22611.6	48,771
2002	3979.4	35814.6	62,241
2003	4565.2	41086.8	60,516
2004	7703.5	69331.5	77,035
2005	7789.3	70103.7	112,091
2006	9000.8	81007.2	114,555
2007	3687.8	33190.2	48,884
2008	3550.5	31954.5	57,930
2009	2300.9	20708.1	46,715
2010	3779.8	34018.2	44,372
2011	7423.7	66813.3	71,325
2012	7436.1	66924.9	80,558
2013	7066.7	63600.3	67,896
2014	10329.5	92965.5	74,799
2015	10799.5	97195.5	95,769
2016	6835.5	61519.5	55,927
2017	6808.6	61277.4	70,866
2018	10323.9	92915.1	91,551
2019	10944.2	98497.8	101,024

Figure 1: Production of short haul, regional haul, and long haul trucks

These values were used to find the number of inoperable diesel semi-trucks in the next 5 years and the next 10 years. Since the lifetime of a semi-truck is about 12 years, the semi-trucks that were produced from 2008-2012 will be inoperable in the next 5 years, the sum of these would be the number of inoperable trucks by the next 5 years that could be potentially replaced by electric trucks.

To find the number of electric and diesel cars in the next 20 years we predicted the amount of inoperable diesel semi-trucks from 2020-2027 that were calculated from the transition matrices to use for the basis of inoperable vehicle conversions from diesel to electric. We added these predicted values to the amount of operable semi-trucks to get the total population for the proportion calculation in the execution of the model.

1.5 Executing the Model

Using the Markov chain and the three different transformation matrices (for short, regional, and long haul) above, we were able to forecast the number of electric semi-trucks and the number of diesel semi-trucks in use in 5, 10, and 20 years from 2020 by using Matlab. We did this by simulating Markov chains with an initial condition of all diesel semi-trucks. We can calculate the amount of electric and diesel semi-trucks in a given year by multiplying the probability of a semi-truck being electric or diesel by the amount of inoperable trucks in that year. This is calculated by using semi-truck production data from 12 years (the life expectancy of a semi-truck) prior to the forecasted year.

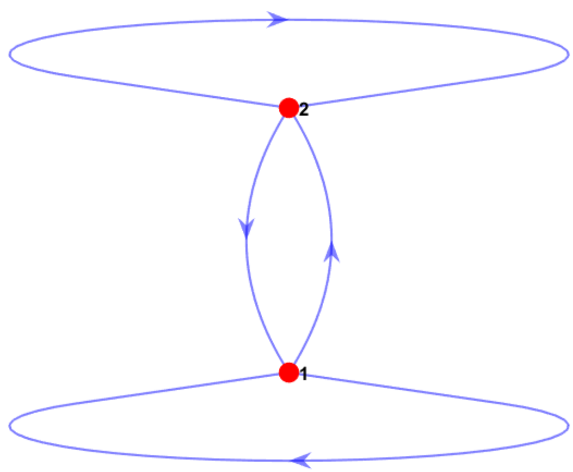


Figure 2: Markov chain produced in Matlab

	Short Haul	**Regional Haul**	**Long Haul**	**Total**
5 years	16,147	199,668	293,295	509,110
10 years	57,190	579,439	655,183	1,291,812
20 years	99,990	830,252	887309	1,817,551

Table 3: Quantity of Electric Semi-Trucks Replaced from Inoperable Semi-Trucks, Q_e (rounded down to the nearest whole truck)

	Short Haul	**Regional Haul**	**Long Haul**	**Total**
5 years	8,343	20,750	7,603	36,696
10 years	9,139	17,537	10,973	37,649
20 years	5,043	19,372	14,190	38,605

Table 4: Quantity of Diesel Semi-Trucks Replaced from Inoperable Semi-Trucks, Q_d (rounded down to the nearest whole truck)

To determine the proportion of semi-trucks that will be electric 5, 10, and 20 years from 2020, we then take the quotient of the quantity of electric semi-trucks and the total number of semi-trucks, which is found by analyzing the production data of diesel trucks of the past 12 years, assuming that a semi-truck is used immediately after its production:

$$P_e = \frac{Q_e}{S_p + P_0}.$$

The resulting proportions of electric semi-trucks for each type of haul in 5, 10, and 20 years from 2020 are shown in Table 5:

	Proportion
5 years	0.2739
10 years	0.6949
20 years	0.9777

Table 5: Proportion of Electric Semi-Trucks, P_e (rounded)

1.6 Results and Discussion

Seeing as the total cost difference of long haul semi-trucks was the greatest, the results showed that it had the largest proportion of the electric semi-trucks. Short haul electric semi-trucks had the smallest total difference in cost between diesel short haul semi-trucks, but the growth was still substantive. The growth of the diesel semi-trucks was fairly irregular and the short haul and regional haul diesel semi-truck data seemed to depend more heavily on the previous irregular productions that had no pattern. The long haul diesel data depended more on the predicted patterns of the production of inoperable diesel trucks and, therefore, had a more linear growth.

1.6.1 Strengths and Weaknesses

The Markov chain model allows for multiple factors to be accounted for in determining the amount of electric cars at a given year after 2019. The model accounts for all of the factors given to us and includes an extra factor in the type of semi-truck. The model accounts for the annual new production rates and life expectancy by using the values 12 years prior to the predicted year in calculating how many inoperable diesel cars are expected to be replaced by electric cars. It accounts for the cost difference between electric and diesel semi-trucks by comparing the total difference between the three types of semi-trucks when determining the probability of converting an inoperable diesel semi-truck to an electric semi-truck. The model implicitly accounts for the current fleet of operational semi-trucks.

The Markov chain model does have a weakness in its determination of probability values for different types of semi-trucks. Once the trucks are released to the market, the values for these can be determined on the basis empirical data. It is also weak in its inability to determine the amount of electric semi-trucks that will replace operable diesel semi-trucks. This can be factored into the model once 2020 data is released for this purpose. The model fails to take hybrid cars into account, but the Markov chain can be modified to include a third state of hybrid vehicles.

2 In It for the Long Haul

2.1 Defining the Problem

Even if all shipping companies switched over to electric semis tomorrow, the infrastructure necessary for making electric semis feasible still requires significant capital investment. The purpose of this model is to determine the most effective distribution of Electric Vehicle Supply Equipment (EVSE) along common shipping corridors in terms of money and time saved.
In order to answer this, we will also find the best charging schedule for drivers.

2.2 Assumptions

2-1. **The state of charge of a $LiFePO_4$ rechargeable battery exponentially approaches 100%.**

- **Justification:** The rechargeable batteries are controlled by a battery management system [12], [13].

2-2. **The range of a semi truck is directly proportional to its state of charge.**

- **Justification:** Batteries emit a constant voltage.

2-3. **All EVSEs use Direct Current Fast Charging hardware, which greatly decreases charge time.**

- **Justification:** We will prove this is optimal in Part 3.

2-4. **Semi-trucks will stop to recharge upon reaching a state of 20% or less.**

- **Justification:** This reduces both risk of running empty and drivers' range anxiety [4].

2.3 Variables Used

Symbol	**Definition**	**Units**	**Value**
I	Idle Time at Charging Station	Minutes	...
C_0	Initial State of Charge [0, 1]	N/A	20%
C_f	Final State of Charge [0, 1]	N/A	...
R	Range	Miles	...
D	Distance	Miles	...
t_{80}	Charge Time to 80%	Minutes	...
I_{min}	Minimum Time at Charging Station	Minutes	10
T_{tot}	Annual Average Daily Truck Traffic	Trucks/Day	...

2.4 Developing the Model

Ultimately, the number of stations along a given route will depend on how often the truck needs to stop to recharge. The time taken to charge, however, must be carefully considered. Because of Assumption 2-1, it would be a waste of time to charge to 100% every time; simple algebra shows that with exponential approach, it would take the same amount of time to charge the first 70% that it would to charge the final 30%.

In order to quantify this, we created a model to find the optimal charging value, C_f, that minimizes the total charging time, I, on a trip given the range of the truck R, the trip distance D, and the 80% recharging time t_{80}:

$$I\left(C_f, R, D, t_{80}\right) = \left\lceil \frac{D}{\left(C_f - C_0\right) R} \right\rceil \left(t_{80} \cdot \frac{\ln\left(1 - C_f\right)}{\ln 0.2} + I_{min} \right)$$

Explanation: The equation is essentially $number\ of\ stops \cdot idle\ time\ per\ stop$.

The number of stops is given by $\left\lceil \frac{D}{\left(C_f - C_0\right) R} \right\rceil$, or the total distance divided by the range possible with the current charge. It is rounded up to avoid a noninteger number of stops. The total time per stop is given by $t_{80} \cdot \frac{\ln\left(1-C_f\right)}{\ln 0.2} + I_{min}$, where I_{min} is the baseline time lost by making a stop [4]. $t_{80} \cdot \frac{\ln\left(1-C_f\right)}{\ln 0.2}$ is derived from the general exponential approach equation $C_f = 1 - e^{-kt}$ given the point $(t_{80}, 0.8)$.

From all this, it is confirmed that waiting for 100% charge is highly disadvantageous, and in order to minimize wait time, trucks should be charged to a mid-range state.
The following graph shows an example of this minimum value:

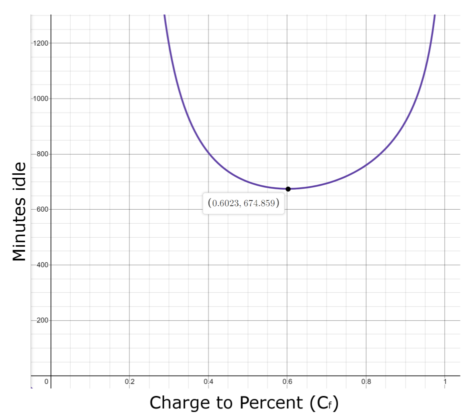


Figure 3: Freightliner eCascadia, $R = 250$ mi, $D = 600$ mi, $t_{80} = 180$ min

2.5 Executing the Model

2.5.1 Optimal Stations per Shipping Corridor

To address the first problem stated in Part 2, in order to determine the number of stops needed along a given shipping corridor of distance D, we will use a Monte Carlo simulation with our formula for number of stops:

$$\left\lceil \frac{D}{(C_f - C_0)\, R} \right\rceil .$$

We will hold C_0 constant at 0.2 (Assumption 2-4) and randomly vary R and C_f to test how frequently different trucks will need to stop.

- R values will be normally distributed with $\mu = 300$ and $\sigma = 100$ conferring with the projected ranges of commercial electric semis [4].
- C_f values will be normally distributed with $\mu = 0.6$ (the calculated optimal charge) and $\sigma = 0.125$.

The Monte Carlo simulation was run for 1000 unique trucks, calculated for each of the given shipping corridors.

2.5.2 Optimal Charging Stations per Truck Stop

To address the second problem, another Monte Carlo simulation was used to determine the average number of trucks at a given station at any time and, thus, the optimal number of chargers for the station. The formula is as follows:

$$\text{Avg. Trucks Present} = \sum_i \frac{I_i}{1440min},$$

$$I_i = \frac{t_{80_i}}{\ln 0.2} \ln(1 - C_f) - \ln(1 - C_0),$$

where I_i is the time spent at the station by an individual truck derived from the exponential approach equation. Dividing by the number of minutes in a day provides the probability of encountering the truck at the station at any time.
To find this value, we ran the formula with 1000 different trucks with different idle times due to initial charge and charging speeds. So the Monte Carlo simulation was run varying the C_0, C_f, and t_{80} values.

- C_0 values will be normally distributed with $\mu = 0.6$ and $\sigma = 0.125$, as before.
- C_f values will be uniformly distributed between C_0 and 1, to simulate differing charging schedules used by drivers.
- t_{80} values will be uniformly distributed between 30 and 300 to account for the projected charging times of commercial electric semis [4].

2.6 Results and Discussion

Shown below are the results from the first Monte Carlo simulation, which found the optimal number of charging stops for each shipping corridor. It is worth noting that for all of them, it is almost exactly one stop every 90 minutes. This is unreasonable for diesel engines, but it makes sense, given the nature of the electric batteries.

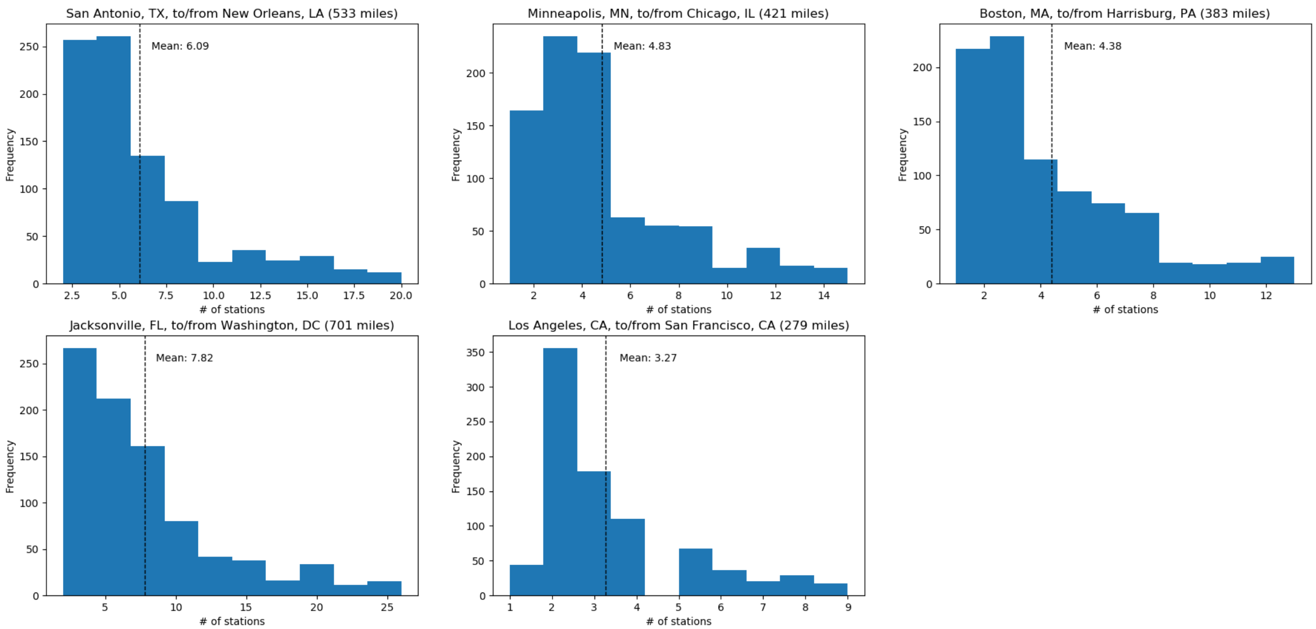


Figure 4: Monte Carlo simulation results, showing mean number of stops taken

The following table shows the results from the second Monte Carlo simulation, which found the optimal number of charging stations at any given truck stop using its Annual Average Daily Truck Traffic:

Corridor	**Number of Chargers per Station**
San Antonio to New Orleans	17
Minneapolis to Chicago	29
Boston to Harrisburg	14
Jacksonville to Washington D.C.	28
Los Angeles to San Francisco	28

It is worth comparing these numbers to a similar metric, the average number of Teslas at a supercharger, recently measured to be about 9 [5]. Since in this scenario, all semi-trucks are electric, the slightly increased numbers still make sense but are not unreasonable for a truck stop.

2.6.1 Strengths and Weaknesses

Due to the nature of the Monte Carlo simulations used, these models are fairly robust in that they account for a wide range of possibilities. The numbers, both constants and variables, were based on widely agreed-upon statistics.

However, the outputs—particularly for the first simulation—showed a larger-than-optimal standard deviation. There were a few significant outliers which required far more stops than the other trucks. We expect that this is an unrealistic product of our model, which could create an individual that would choose to refuel for a very small amount of time multiple times in a row.

3 I Like to Move It, Move It

3.1 Defining the Problem

Create a model that ranks which trucking corridors should begin development of charging stations first and use this model to rank the five trucking corridors from the previous part.

3.2 Assumptions

3-1. The cost per mile of Semi Shipping is $2.75.

- **Justification:** This is the current middle-of-the-market average value [7].

3-2 The cost is $22,626 to install one DCFC station.

- **Justification:** The mean cost of installing a DCFC Station was $22,626, based on data published by the U.S. Department of Energy [6].

3-3. 50% trucks using the corridors are long haul shipments.

- This statistic is provided on the Information Sheet [2].

3.3 Variables Used

Symbol	Definition	Units	Value
F	Cost per Mile of Semi Shipping	$/Mile	2.75
V	Net value per minute of Semi Shipping	$/Mile	...
T_{avg}	Average Daily Truck Traffic of the route	Trucks/Day	...
S	Total Cost of Charging Station Installations	$	...
X	Importance Score for each corridor	-	...
E	Community Environmental Measures (Dummy Variable)	-	...
G	Increase in GDP from Trucking Time	$/Year	...

3.4 Developing the Model

In order to rank which trucking corridors to develop first, we will consider four metrics:

1. Economic Growth, i.e., GDP increase,
2. Environmental considerations, and
3. Cost to implement the necessary infrastructure.

All metrics for each of the five corridors will be normalized, equally weighted, and combined into a final importance score for each corridor, X, as follows:

$$X = E_{norm} + G_{norm} + S_{norm}.$$

For the first metric, economic growth, G, was calculated by the money saved by decreased idle charging times of DCFC chargers. V, the dollar value of an on-route semi's time, was calculated using the average cost of semi shipping, $F = 2.75/\text{mi}$ (Assumption 3-1), and the average number of trucks using the corridor, T_{avg}. T_{avg} was found by taking 50% of the average value of the Annual Average Daily Truck Traffic (AADTT) for each corridor (Assumption 3-3).
For each corridor, V was found by the following formula:

$$V = \frac{FD}{D \cdot \frac{1min}{1mi} + I},$$

where D is the length of the corridor and I is the total idle time while charging, calculated using recharge and rage values from the Freightliner eCascadia.
The results are shown below:

Corridor	T_{avg}
San Antonio to New Orleans	7,144.05
Minneapolis to Chicago	8,010.75
Boston to Harrisburg	4,646.43
Jacksonville to Washington D.C.	4757.54
Los Angeles to San Francisco	6987.43

Thus, the total economic value generated, G, is given by

$$V \cdot T_{avg}.$$

For the second metric, environmental considerations were based on number of state actions on electric vehicles found in a report conducted by the NC Clean Energy Technology Center [8]. Actions consisted of setting targets for zero-emission vehicle, plans for transportation electrification plans, and exemptions of charging stations from public utility regulation. Number of actions was categorized into four levels:

Level	# of Actions
0	none
1	1 to 2
2	3 to 5
3	6 to 9
4	10 or more

Table 6: Environmental Consideration Levels

Environmental considerations was considered as communities who were more environmentally conscious and had more incentives and actions regarding electric vehicles would likely be more motivated to support development of charging stations. The environmental consideration score per trucking corridor was calculated by the averaging level of all the states as listed below:

For the third metric, the cost of charging station installations, S, is based on the cost to install one DCFC station and the solution to Part 2, as follows:

$$\text{Avg. Trucks Present} = \text{chargers/station}$$

$$S = \$22,626 \cdot \text{chargers/station} \cdot \text{stations}$$

These metrics are then normalized through the use of min-max normalization to weight the values the same and be able to add them together in determining the Importance Score. The formula is as follows:

$$NormalizedValue = \frac{x_i - x_(min)}{x_(max) - x_(min)}.$$

3.5 Executing the Model

Trucking Corridors	E	S	G
San Antonio to New Orleans	3	\$2,692,494	\$9,644.47
Minneapolis to Chicago	3.67	\$3,280,770	\$10,813.5
Boston to Harrisburg	3.8	\$1,583,820	\$6,272
Jacksonville to Washington D.C.	2.5	\$5,068,224	\$6,421
Los Angeles to San Francisco	4	\$2,534,112	\$9,432

Table 7: Importance Score for Trucking Corridors

Trucking Corridors	E	S	G	X
San Antonio to New Orleans	0.33	0.32	0.74	1.39
Minneapolis to Chicago	0.78	0.49	1	2.27
Boston to Harrisburg	0.87	0	0	0.87
Jacksonville to Washington D.C.	0	1	0.03	1.03
Los Angeles to San Francisco	1	0.27	0.70	1.97

Table 8: Normalized Importance Score for Trucking Corridors

3.6 Results and Discussion

The results showed that the Minneapolis to Chicago corridor should be targeted first, followed by Los Angeles to San Francisco, then San Antonio to New Orleans, then Jacksonville to D.C., and then Boston to Harrisburg.

3.6.1 Strengths and Weaknesses

The strength of our model is that we consider three different variables.
A weakness of the model is that there are other variables that could be considered in the making of the model. A second weakness is that the cost has a high standard deviation, which could greatly affect the results of the model.

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Code Used

Part 1

```
format longG
years = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 20]; % number of ...
   years after 2019
len = length(years);
% 2008-2015 production of diesel semitrucks
production = ...
   [3550.5,31954.5,57930;2300.9,20708.1,46715;3779.8,34018.2,44372;...
7423.7,66813.3,71325;7436.1,66924.9,80558;7066.7,63600.3,67896;...
10329.5,92965.5,74799;10799.5,97195.5,95769];
% 2008-2027 number of inoperable semitrucks
inoperable = ...
   [24491,66330.8,87598.9;220419,596977,788390.1;300899,666157,858732]';
% 2019 production of diesel semitrucks
production_short = 10944.2;
production_regional = 98497.8;
production_long = 101024;
% TRANSITION MATRICES
T = [1, 0];
% Transition matrix for Markov chain describing the switch ...
   to electric
P1 = [0.8, 0.2; 0.01, 0.99]; % short haul
P2 = [0.6, 0.4; 0.01, 0.99]; % regional haul
P3 = [0.4, 0.6; 0.01, 0.99]; % long haul

% Calculate the proportion of semitrucks that switch to ...
   electric
P = {{}, {}, {}};
for i = 1:(len - 1)
    P{1}{i} = T * P1 ^ i; % short haul
    P{2}{i} = T * P2 ^ i; % regional haul
    P{3}{i} = T * P3 ^ i; % long haul
end
P{1}{11} = T * P1 ^ 20;
P{2}{11} = T * P2 ^ 20;
P{3}{11} = T * P3 ^ 20;

% Predict the production of electric semitrucks in the next ...
   8 years:
% Pred = Prop_N(1, 1) * Prod(N)
predictions = zeros(8, 3); % three types of semitruck
```

```
for i = 1:8
    for j = 1:3
        % number of electric semitrucks N years after 2019
        predictions(i, j) = P{j}{i}(1, 1) * production(i, j);
    end
end
% Ensures that production is not below zero.
predictions(predictions ¡ 0) = 0;

% Calculate the number of
% short haul semitrucks after 5 years - I(1, 1) * Prop_5
short_5 = inoperable(1, 1) * P{1}{5}
% short haul semitrucks after 10 years - I(1, 2) * Prop_10
short_10 = inoperable(1, 2) * P{1}{10}
% short haul semitrucks after 20 years - I(1, 3) * Prop_20
short_20 = (inoperable(1, 3) + sum(predictions(:,1))) * ...
   P{1}{11}
% regional haul semitrucks after 5 years - I(2, 1) * Prop_5
regional_5 = inoperable(2, 1) * P{2}{5}
% regional haul semitrucks after 10 years - I(2, 2) * Prop_10
regional_10 = inoperable(2, 2) * P{2}{10}
% regional haul semitrucks after 20 years - I(2, 3) * Prop_20
regional_20 = (inoperable(2, 3) + sum(predictions(:,2))) * ...
   P{2}{11}
% long haul semitrucks after 5 years - I(3, 1) * Prop_5
long_5 = inoperable(3, 1) * P{3}{5}
% long haul semitrucks after 10 years - I(3, 2) * Prop_10
long_10 = inoperable(3, 2) * P{3}{10}
% long haul semitrucks after 20 years - I(3, 3) * Prop_20
long_20 = (inoperable(3, 3) + sum(predictions(:,3))) * ...
   P{3}{11}

% Diagram of the Markov chain
P = [0.8, 0.2;
     0.01, 0.99];
%mc = dtmc(P);
figure;
%graphplot(mc);
```

Part 2

```python
#pylint: disable=bad-continuation,invalid-name,multiple-imports,redefined-outer-name
"""
Created by Team #13343 1 March 2020

This is the Monte Carlo method for Part 2.
"""
import math, random
import numpy as np
import matplotlib.pyplot as plt
import matplotlib
matplotlib.rcParams["figure.figsize"] = [22, 10]
initial = 0.2 # initial state of charge
epsilon = 10e-6 # avoid division by zero
k = 1.5 # Tukey's fence "outlier" constant
nos = [] # number of stations array
def tukeys_fences(arr, q_1, q_3):
    """Tukey's fences for defining outliers."""
    iqr = q_3 - q_1 # interquartile range
    arr_t = arr # temporary array to avoid iteration problems
    for i in arr: # iterate over array
        if i < (q_1 - k * iqr) or i > (q_3 + k * iqr): # Tukey's fences
            arr_t = np.delete(arr_t, np.argwhere(arr_t == i)) # exclude outliers
    return arr_t # array without outliers
def number_of_stations(final, erange, distance):
    """The number of stations needed along a given route."""
    return math.ceil(distance / ((final - initial) * erange + epsilon)) # see 2.4
def truck_time_at_station(initial, final, t80):
    """A truck's time at a station."""
    return (t80 / math.log(0.2)) * (math.log(1 - final) - math.log(1 - initial)) # see 2.5
# Substitute proper distances for corridors
distances = [533, # SanTX_NewLA
    421, # MinMN_ChiIL
    383, # BosMA_HarPA
    701, # JacFL_WasDC
    279] # LosCA_SanCA
corridors = ["San Antonio, TX, to/from New Orleans, LA",
    "Minneapolis, MN, to/from Chicago, IL",
    "Boston, MA, to/from Harrisburg, PA",
    "Jacksonville, FL, to/from Washington, DC",
    "Los Angeles, CA, to/from San Francisco, CA"]
corridors = [corridors[i] + " (" + str(x) + " miles)" for i, x in enumerate(distances)]
AADT_max = [168267, # SanTX_NewLA
    305100, # MinMN_ChiIL
    144200, # BosMA_HarPA
    264000, # JacFL_WasDC
    304000] # LosCA_SanCA
# Initialize random convoy of 1,000 all-electric trucks
# Discrete uniform distribution
final_mc1 = np.random.uniform(0.2 + epsilon, 1.0, 1000)
# Discrete normal distribution
erange_mc = np.random.normal(300, 100, 1000)
# Exclude values outside the domain
erange_mc[erange_mc < 0] = 0
# Vectorize functions to parallelize them
vnos = np.vectorize(number_of_stations)
vttas = np.vectorize(truck_time_at_station)
# Evaluate vectorized functions for random samples
for d in distances: # iterate over array of distances for corridors
    array_vnos = vnos(final_mc1, erange_mc, d)
    Q1 = np.percentile(array_vnos, 25, interpolation="midpoint") # first quartile
    Q3 = np.percentile(array_vnos, 75, interpolation="midpoint") # third quartile
    nos.append(tukeys_fences(array_vnos, Q1, Q3)) # exclude outliers and append results to nos
for AADT in AADT_max: # iterate over array of Annual Average Daily Traffic data
    t80_mc = np.random.uniform(30, 300, AADT)
    initial_mc = np.random.normal(0.6, 0.125, AADT)
    initial_mc[np.logical_or(initial_mc < 0, initial_mc >= 1)] = 0
    final_mc2 = [random.uniform(x, 1.0) for x in initial_mc.tolist()]
    array_ttas = vttas(initial_mc, final_mc2, t80_mc)[np.argwhere(initial_mc <= 0.2)]
    number_of_chargers_station = math.ceil(sum(array_ttas)[0] / 1440)
means = [nos[i].mean() for i in range(len(nos))] # evaluate mean for all corridors
fig, axs = plt.subplots(2, 3)
for i, ax in np.ndenumerate(np.delete(axs, -1)):
    ax.hist(nos[i[0]])
    ax.axvline(means[i[0]], color="k", linestyle="dashed", linewidth=1)
    ax.text(means[i[0]] * 1.1, ax.get_ylim()[1] * 0.9, "Mean: {:.2f}".format(means[i[0]]))
    ax.set_title(corridors[i[0]])
    ax.set_xlabel("# of stations")
    ax.set_ylabel("Frequency")
axs[1, 2].axis("off")
```