MathWorks Math Modeling Challenge 2020: U.S. Big Rigs Turnover from Diesel to Electric

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Executive Summary

The trucking industry lies at the heart of the U.S. economy, moving 71% of freight annually and contributing over $700 billion to GDP [1]. However, in recent years, as the need for transportation has dramatically increased, the fuel consumption of diesel trucks has ballooned to 12% of total U.S. fuel usage. As more and more electric trucks will replace the diesel ones, an infrastructure for the electric truck system is needed. In this paper, we explore and develop mathematical models to help aid in building the basic infrastructure and utilities needed for a successful electric truck system in the U.S.

We started by creating two differential equations to model the annual change in number of electric and diesel trucks. We used Python code to graph the predicted number of electrical and diesel trucks in the next 20 years. We discovered an influx of adoption in the first 5 years, which tapered off toward the 10-20 year marks. This allowed us to analyze the spread of electric trucks in the next 5, 10, and 20 years assuming a pre-existing electric semi infrastructure network.

In our second part, we sought to calculate the number of charging stations and charging units needed at each of 5 key U.S. transportation corridors. To do so, we developed and trained a mathematical model that took into account the average annual regional temperature of the corridor, the distance of the corridor, charge of truck, charging speed, and miles per energy spent. With this model, we discovered that combination of high charge times with low ranges for electric trucks required a large number of chargers per station, which may be difficult to implement in the real world without a future advancement in electric truck technology.

We then looked at the economic and environmental benefits of electric trucks. Assuming that replacing diesel with electric trucks contribute to the economy and improve the environment, we used an index called the Eco-Friendly Behaviors Rank to link the receptiveness of each state to the more environmentally-friendly electric trucks. As with the previous portion, this allowed us to take into account regional differences among community values, as some communities may value economic growth over environmental friendliness, while others cherish the opposite. Using these two main factors, we developed our own Community Motivation for Development. It was found that the communities with the greatest motivation to develop electric truck charging stations were (in order from greatest to least) Los Angeles-San Francisco, Minneapolis-Chicago, San Antonio-New Orleans, Jacksonville-Washington D.C., and Boston-Harrisburg.

The potential for the growth of electric trucking in the United States is challenging, yet exciting. Before a large fleet of electric trucks spanning the entire country can become a reality, it is imperative that strong infrastructure is developed. Our models help identify key factors to adoption such as life cycle costs, as well as help determine which communities would be ideal to host such large electric truck charging stations. Ultimately, we hope that these methods can help spread the adoption and advancement of electric trucks.

0.1 Global Assumptions

- *No energy shocks that would drive the price of gas or electricity up/down.* This assumption is imperative because attempting to account for volatile factors such as future energy shocks would make model development nearly impossible [2].
- *We look only at the U.S. trucking industry.* By looking only at United States trucking data, we can ensure standardized metrics. In addition, the transport corridors referred to in parts 2 and 3 are all in the U.S.
- *Predictions of future electric truck statistics are accurate.* It is difficult to predict the market even 5 years from now, but all cited statistics are from credible sources and predictions should be taken as reasonably accurate. Sensitivity analysis is provided to account for possible deviations in predictions.

1 Problem-Solving Process

1.1 Shape Up or Ship Out

Diesel trucks, which account for 12% of the total fuel purchase in the US, have been responsible for global air pollution. Therefore, a replacement, electric semi trucks, has been invented to alleviate the problem. This part predict the rate of electric semi-truck usage over the next 5, 10, and 20 years.

1.1.1 Local Assumptions

- *More people will buy electric semi-trucks if they are cheaper to operate and offer more convenience than diesel trucks.* We assume that there are no illogical biases against electric trucks or diesel trucks.
- *Diesel truck life is 12 years.* [3]
- *We ignore government subsidies and others who pay no attention on electric trucks.*
- *Electric trucks and diesel trucks are substitutes.*
- *Number of first-time consumers per year of semi-trucks remains constant.*
- *A constant fraction of the current number of trucks break down each year according to the lifespan of an electric and diesel car, respectively.*
- *A constant fraction of semi-truck consumers will buy electrical trucks.*
- *When referring to semi-trucks, the term "truck" will be used, which does not refer to non-semi-trucks.*

1.1.2 Model Development

t is the time in years from 2020. Let T_e and T_d be the number of electrical and diesel semi-trucks, respectively, being used in the U.S. Let c_e and c_d be the proportion of consumers looking for semi-trucks that buy electrical and diesel semi-trucks, respectively, such that $c_1 + c_2 = 1$. Let D be the total first-time buyer demand for semi-trucks in the U.S., quantified by the number of consumers per year. k_e and k_d represent the proportion of electrical and diesel semi-trucks, respectively, that will break down.

Every year, out of the total D first-time buyers, c_eD of them will buy electric trucks and c_dD will buy diesel trucks. Also, out of the current T_e electric trucks, k_eT_e of them will break down, decreasing the number of electric trucks by this amount. Similarly, k_dT_d of the current T_d diesel trucks will break down each year.

Therefore, we get the following differential equations:

$$\frac{dT_e}{dt} = c_eD - k_eT_e \tag{1}$$

$$\frac{dT_d}{dt} = c_dD - k_dT_d \tag{2}$$

Solving by separating variables, we get

$$T_e = -\frac{m_e e^{-k_e t}}{k_e} + \frac{c_eD}{k_e} \tag{3}$$

$$T_d = -\frac{m_d e^{-k_d t}}{k_d} + \frac{c_dD}{k_d} \tag{4}$$

where m_e and m_d are constants.

Now, we will find values for each of the constants $D, c_e, c_d, k_e, k_d, m_e, m_d$.

D represents the number of first-time consumers of all trucks. This will be based on truck statistics of the time period 2001-2018 from Statista [4]. From this data, an algorithm was used to determine various statistics. The mean of the class 8 semi-truck sales was 183888 trucks, with a standard deviation of 51775 trucks. A linear regression using Wolfram Alpha [5] yields a line of best fit of

$$T = 3201.24t + 153477, R = 0.321 \tag{5}$$

where T is the total number of truck sales after t years since year 2000. Given the low slope of the line (less than 2 percent of the average truck sale) and the relatively low correlation coefficient, no meaningful linear relationship exists between t and T. Therefore, we can safely assume that class 8 semi-truck sales will remain relatively constant over the next 20 years. We will set D as the average annual semi-truck sales over the last 18 years, or 183888.

k_e and k_d represent the proportion of electrical and diesel semi-trucks that will break down every year. The projected electrical and diesel semi-truck lifespans over the next years are 10 and 12 years, respectively 6. Therefore, every year, approximately $\frac{1}{10} = 0.1$ and $\frac{1}{12} = 0.0867$ of electrical and diesel semi-trucks, respectively, will break down. This yields the values $k_e = 0.1, k_d = 0.0867$.

c_e and c_d represent the proportion of consumers looking for semi-trucks that will buy electrical and diesel semi-trucks, respectively. To find these two coefficients, we will use a combination of the cost difference between electrical and diesel truck operational costs and the demand sensitivity due to price. According to the 2019 Electric Vehicle Outlook Report by BloombergNEF [6], approximately 57% of all passenger vehicle sales will be electric by 2040. Assuming that all necessary electric semi infrastructure is already in place now (given in the problem statement), we can assume that at least 57% of all semi-truck sales will be electric over the time period from 2020 to 2040. This implies that $c_e = 0.57$ and $c_d = 0.43$.

Plugging in the values for the coefficients, we have

$$T_e = -\frac{m_e e^{-0.1t}}{0.1} + \frac{0.57 * 183888}{0.1} \tag{6}$$

$$T_d = -\frac{m_d e^{-0.0867t}}{0.0867} + \frac{0.43 * 183888}{0.0867} \tag{7}$$

In the problem statement, we are given that a few hundred electrical trucks will "roll off Tesla's line," so we approximate $T_e(0) = 500$. We know that $T_d(0) = 1800000$. From this, we get $m_e = c_e * D - 500 * k_e$ and $m_d = c_d * D - 1800000k_d$. From these numbers, Figure 1 was created, graphing electrical, diesel, and total semi trucks over time for the next 25 years. Figure 2 shows the projected percentage of all semi trucks that will be electrical over time.

1.1.3 Results

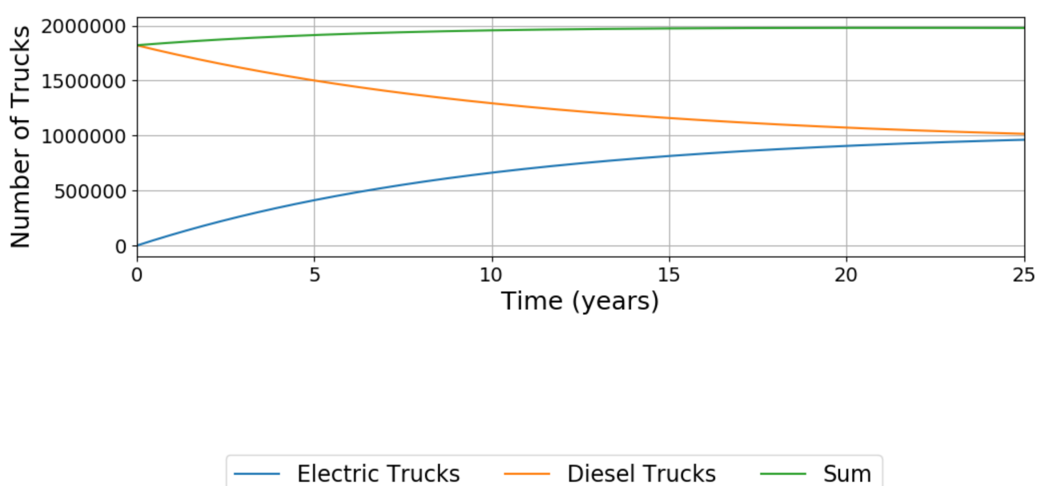

Figure 1: Projected numbers of trucks over time

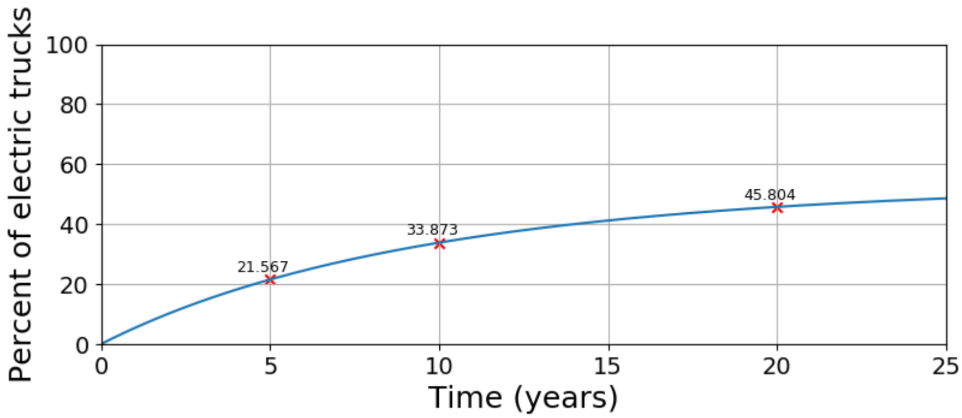

Figure 2: Projected percentage of electric trucks over time

Since the introduction of electric trucks brings tangible economic and environmental benefits, there will be a huge demand for electric trucks. Therefore, we expect a dramatic shift from diesel trucks to electric trucks and increase in the purchase of electric trucks in the first five years. However, as time proceeds, we don't expect this growth to sustain in the following 10 years because we assume that the number of purchase of both types of trucks remain constant.

1.1.4 Sensitivity Analysis

Each of the constants were increased and decreased by 10% and the resulting changes in the proportion of electric trucks in 5, 10, and 25 years were measured and placed in the following table. Based on the variables D, the first-time buyer demand, c_e, proportion of consumers that will buy electric trucks, c_d, the proportion of consumers that will buy diesel trucks, k_e, proportion of breakdown of electrical cars, k_d, proportion of diesel trucks that will breakdown, and m_e and m_d, which are arbitrary constants derived from the differential equations. When either truck's proportion of breakdown increases, the consumption of that type of truck tends to increase because people need to get new trucks for further operations. In contrast, when either truck's proportion of breakdown decreases, the consumption of that type of truck tends to decrease because people are less likely to get new trucks for further operations. When either truck's consumption goes up, the proportion of that type of truck will increase because of consumer spending.

Table 2.1.3 Sensitivity analysis for Part I

Constant	% Change of Constant	% Change in proportion of electric trucks in 5 years	% Change in proportion of electric trucks in 10 years	% Change in proportion of electric trucks in 20 years
D	10	13.74	4.54	1.21
D	-10	-16.89	-5.57	-1.49
K_e	10	-1.79	-2.98	-4.27
K_e	-10	1.82	3.08	4.53
K_d	10	9.07	7.77	5.58
K_d	-10	-9.29	-8.26	-6.31
C_e	10	18.88	8.92	5.19
C_e	-10	-21.08	-9.99	-5.83
C_d	10	-4.55	-4.68	-4.84
C_d	-10	5	5.15	5.35
m_e	10	-12.5	-4.69	-1.09
m_e	-10	11.68	4.48	1.061
m_d	10	-2.99	-2.07	-0.94
m_d	-10	3.17	2.15	0.97

1.1.5 Strengths and weaknesses

Since the model used in this projection was analytically solvable, no approximations were necessary in order to perform calculations, improving the quality of the predictions made by the model. The 48% of increase in the use of electric trucks is reasonable because there will be an increase of demand due to the benefits of the electric semis, leading to an increase in the proportion of the electric trucks. Our sensitivity analysis, by increasing and decreasing by 10%, it shows how the final results would fluctuate as the variables change in values.

However, the simplicity of the model comes at a price. It assumes that the every year, the number of electric and diesel semis bought remains constant. This assumption was chosen based on the stipulation that the necessary semi infrastructure is already established, but it may neglect other factors such as improving technology or changes of tastes.

1.2 In It For the Long Haul

In order to provide sufficient electric support for drivers, we are considering the following in this section:

- Number of stations with different types of EVSE
- Number of chargers per station

In general, the time required to charge an electric truck is linearly proportional to the power of the charger. The charger power denotes the efficiency of the charger (e.g. 80kw requires the truck driver 10 hours of charging, which 800kw, meaning a higher efficiency, requires the driver 1 hour of charging. However, the higher the efficiency, the higher the expense of the charger).

1.2.1 Restatement of Problem

1. To run long routes, we need to create a mathematical model that determines how many stations and charges are needed on the premise that all trucks were electric. We need to test the model with the following routes:
   - 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

1.2.2 Local Assumptions

1. All trucks are long-haul and travel at an average speed of 55mph.
2. The lengths of the five routes, traveled by car, are the following:
   - 541 miles from San Antonio, TX, to New Orleans, LA
   - 408 miles from Minneapolis, MN, to Chicago, IL
   - 390 miles from Boston, MA, to Harrisburg, PA
   - 702 miles from Jacksonville, FL, to Washington D. C.
   - 382 miles from Los Angeles, LA, to San Francisco, LA
3. *The types of EVSEs at the charging stations are all DC Fast Charge.* According to the Battery Data document, the Level 1 and Level 2 EVSEs would require a charging time of greater than 10 hours, which is not feasible for electric trucks, which are primarily designed to be daytime trucks (Battery Data, MathWorks Math Modeling Challenge 2020, url). We will use 1MW for the power of a charger.
4. *We consider only the Chanje V8100.* The Chanje V8100 has been in service longer than the Cascadia and the Tesla Semi. In addition, it has a shorter range, meaning that stations designed around its range will automatically cover other electric trucks, which will have larger ranges.
5. *T*rucks will always charge to 100% capacity.
6. *T*he total number of trucks on a route at any given point in time is equal to the Average Annual Daily Truck Traffic (AADTT) average value across a route. [7]

1.2.3 Model Development

Our model will take into account the average speed of a truck, the total charge of a truck, charging speed, miles per energy spent, distance of the entire road, and temperature (when calculating battery efficiency).

Given that the proposed radius of the Tesla truck is 600 miles, the impact of temperature on battery life is also taken into account. Typically, an EV will cover around 20 percent fewer miles in cold weather versus beach weather. [8]

Numerous reports have indicated that colder weather results in lower ranges for electric vehicles such as Teslas. According to a study by the AAA, this loss could be as high as 41 percent if the heater or AC is used. [12]

Using a model created from data from the AAA report, we calculated the range efficiency of electric vehicles in relationship to temperature. Let R_a and R_l be the actual and listed range of a truck, in miles. We have

$$R_{actual} = R_{listed}(0.1218 + 0.02766T - 0.0002127T^2) \tag{8}$$

where T represents the average temperature of the corridor in degrees Fahrenheit, as determined by the average of the average year round daily temperatures of the start and end points, and $0.1218 + 0.02766T - 0.0002127T^2$ represents the coefficient of range reduction due to temperature. If the temperature is too high or too low, the range of a truck will be much lower.

We recommend that trucks charge at 25 percent of capacity, so we are spacing our stations accordingly. [10]

The actual distance a truck can travel before needing to charge is denoted by R_{actual}. After using up 0.75 of its charge, a truck must encounter another charging station, so the distance between charging station must equal $0.75R_{actual}$. We also know that the total distance between the two endpoints of a route must equal the number of stations multiplied by the distance between stations, or

$$d_{endpoints} = st * 0.75R_{actual} \tag{9}$$

where st is the number of stations we will place across the route. Therefore, we have

$$st = \frac{d_{endpoints}}{0.75R_{listed} * (0.1218 + 0.02766T - 0.0002127T^2)} \tag{10}$$

Given that we are modeling long haul transportation, it is safe to assume that the electric Chanjes travel at an average range of 150, so we have $R_{listed} = 150$. Plugging this in, we have

$$st = \frac{d_{endpoints}}{112.5 * (0.1218 + 0.02766T - 0.0002127T^2)} \tag{11}$$

This completes the first part of our model. Now, we know that the time a truck can travel before charging (TPC, in hours per charge) is equal to the total distance traveled per charge (R_{actual}) divided by the speed of the truck (v, mph), so we have

$$TPC = \frac{R_{actual}}{v} = \frac{R_{listed} * (0.1218 + 0.02766T - 0.0002127T^2)}{v}. \tag{12}$$

Next, we know that the number of trucks on the road (TRU, in trucks, collected with the AADTT data) at a given point in time divided by the amount of time a truck can last without charging is equal to the total number of charges on this route needed per hour. In order to keep all trucks charged at all points in time, all charging stations must make charges at the same rate. Therefore, the total number of chargers (C) divided by the charge time per truck per charger (CTC)must have the same charge per hour quantity.

Therefore, we have

$$\frac{TRU}{TPC} = \frac{C}{CTC}. \tag{13}$$

Solving for C, we have

$$C = \frac{TRU * CTC}{TPC},$$

so by substituting in our value for TPC, we have

$$C = \frac{TRU * CTCv}{R_{listed} * (0.1218 + 0.02766T - 0.0002127T^2)} \tag{14}$$

We are assuming that we are using only using DC Fast Charge on Chanjes, which can charge in 1.5 hours and has a listed range of 150 miles. We are also assuming that all trucks travel at 55mph, so by plugging in these values, we have that the total number of chargers needed is equal to

$$C = \frac{0.55TRU}{0.1218 + 0.02766T - 0.0002127T^2} \tag{15}$$

1.2.4 Results

We will now test our model on each of the 5 corridors. We will find the number of stations (st) and chargers (C) needed for each of the 5 corridors.

Calculated st and C Values						
Route	TRU (AADT)	T	$d_{endpoints}$	st	C	C/st
TX-LA	14288	65.6	541	4.71	8288.76	1760
MN-IL	16735	46.5	408	3.83	9708.31	2535
MA-PA	9843	48.4	390	3.6	5625.85	1563
FL-DC	9429	62.9	702	6.12	5083.84	830
CA-CA	13975	59.4	382	3.35	7577.72	2262

AADT accessed through corridor data MathWorks Math Modeling Challenge 2020 and NOAA temperature

If we place stations so that drivers will charge when one-fourth of their battery's charge is left, then we will need very few stations to place chargers (3 in CA up to 6 in Florida). However, due to the high charge time for electric trucks and the low distance ranges, a very large number of chargers are needed. Thus, electric trucks with their current capabilities in charging speed and range are not feasible for long haul driving.

1.2.5 Strengths and weaknesses

One strength of this approach is that it takes into account regional weather and how that affects the range of electric trucks. This seemingly small factor actually has big impact on battery performance, as demonstrated by our sources. This detail allows our model to tailor a region-specific suggestion for each corridor, thereby increasing the accuracy. Another strength of this model is that it has a built-in margin of error taking into account 3 factors– the 25% charging rate, the lowest range (the Chanje), and the negative impact of temperature on range.

One unique aspect to our model is that it places greater preference on fewer stations with larger number of chargers per station. Though this will result in mega-stations, with the largest (MA-PA) having 2535 chargers in each station, the large size is also a strength, as it allows for more centralized repairs.

This model has several weaknesses. One is the assumption that the AADT of the sections without listed AADT data was equal to the average . This assumption, due to the missing data on the annual average daily truck traffic, was a necessary one, as it would not have been possible to develop our model without continuous data on the AADT Originally, we considered using population density to predict AADT by county, but given our time constraints, it proved to take too long. Another weakness was the assumption that there are a constant number of chargers at each station. In reality, stations with greater traffic should have greater number of chargers, but this assumption was important for developing the model in a timely manner.

1.3 I Like to Move It, Move It

As we have previously discussed, the use of electric trucks has possible benefits on both the environment and economy. In this section, we evaluate the benefits on both parts and figure out whether economic or environmental development should be targeted first by computing two composite scores.

1.3.1 Restatement of Problem

1. Electric trucking can bring enormous benefits to our environment and economy. In this scenario, we need to design a mathematical model to evaluate which communities value these two facets of electric trucking charging stations.

1.3.2 Local Assumptions

1. On average, two people will operate a single electrical truck charger, resulting in two jobs created per charger
2. Each charging station contributes a constant amount of revenue to the state, adding to its GDP.
3. Total amount of CO2 emissions due to trucks is proportional to the average Average Annual Daily Truck Traffic (AADTT) across that route.
4. More Eco-Friendly Behavior implies that more people value the environment over the economy.
5. Carbon Dioxide emissions due to trucks are directly proportional to the average AADTT across a route.
6. Higher air pollution and carbon dioxide emissions imply that a state is more likely to benefit from transitioning to electric trucks.
7. All surveys are accurate.

1.3.3 Model Development

Our model uses a weighted average of Economic and Environmental impacts to determine community motivation for electrical trucking development. Data is gathered from each of the 5 corridors indicated in the problem statement.

Total community motivation for the change will be denoted by M, a real number between 0 and 1. Economic and Environmental factors will be quantified by numbers between 0 and 1. The weights of each of the factors will be denoted by w_E, w_N respectively, with $w_E + w_N = 1$. Each of the weights will be based off of survey data.

Therefore, we have

$$M = w_E E + w_N N \tag{16}$$

Weights

We define w_E and w_N to be how important Economic and Environmental factors matter to the people of the communities around each route. For each route, we will take the average of the Eco-Friendly Behaviors Rank ([9]) of each state across the route and divide by 50 to get w_E. A lower position in the rankings indicates that the citizens in the state value their environment and economy more, which would imply a higher w_E value. To obtain w_N, we calculate $1 - w_E$.

Calculated Weights			
Route	Eco Friendly Rank	w_E	w_N
TX-LA	39	0.78	0.22
MN-IL	13.67	0.27	0.73
MA-PA	11.4	0.23	0.77
FL-DC	35.5	0.71	0.29
CA-CA	2	0.04	0.96

Economic Factor

We will denote the quantified Economic factor by E. This will be based off of the total revenue from the charging station and the total number of jobs created. Revenue will be quantified by a unitless quantity Rev between 0 and 1, normalized by the maximum expected revenue of the 5 corridors. We have assumed that revenue is proportional to number of stations. Similarly, number of jobs will be quantified by a unitless quantity Job between 0 and 1. We have assumed that the number of jobs created is proportional to the total number of chargers in the corridor. These two values are chosen because total revenue and jobs gained by the state both contribute to the economic development of the region, which is desirable for many communities. To calculate the aggregate Economic factor, we will take the average of Rev and Job :

$$E = \frac{Rev + Job}{2} \tag{17}$$

Environmental Factor

We will denote the quantified Environmental factor by N. This will be calculated based on the current total amount of carbon dioxide emissions and the current air pollution levels in the area. Total carbon dioxide emissions will be calculated based on the Average Annual Daily Truck Traffic (AADTT) values of the routes. Air pollution levels will be measured by the average exposure of the general public to particulate matter of 2.5 microns or less ([11]), normalized to a score between 0 and 1. Again, each of the two values will be calculated by the average of the values for each of the states along the path of the corridor. Carbon dioxide emission levels are used because transitioning towards electrical vehicles will decrease the total amount of carbon dioxide emission levels. Current air pollution levels are used because a state with more air pollution would benefit more from transitioning to electrical trucks. To calculate the aggregate Environmental factor, we will take the average of Tru and Air:

$$N = \frac{Tru + Air}{2} \tag{18}$$

We will now find the Economic values for each of the 5 corridors and present them in a table.

Calculated Economic Factor E					
Route	Total Stations	Total Chargers	Rev	Job	E
TX-LA	4.71	8288.76	0.77	0.85	0.81
MN-IL	3.83	9708.31	0.63	1.00	0.82
MA-PA	3.6	5625.85	0.59	0.58	0.59
FL-DC	6.12	5083.84	1.00	0.52	0.76
CA-CA	3.35	7577.72	0.55	0.78	0.67

The Tru values will be calculated using the average AADTT values along each route and dividing by the maximum average.

Calculated *Tru* Values		
Route	Average AADTT	*Tru* Value
TX-LA	14288	0.85
MN-IL	16735	1.00
MA-PA	9843	0.59
FL-DC	9429	0.56
CA-CA	13975	0.84

Each AADTT value was divided by 16735, the maximum average AADTT, to obtain the *Tru* Factor. Now, we calculate the *Air* Factor for each relevant state and present them in a table.

Calculated *Air* Values		
State	Air Pollution Level	*Air* Value
Texas	8.4	0.66
Louisiana	7.9	0.62
Minnesota	6.6	0.52
Wisconsin	6.8	0.53
Illinois	9.3	0.73
Pennsylvania	9.2	0.72
New Jersey	8.1	0.63
New York	6.6	0.52
Connecticut	7.2	0.56
Massachusetts	6.3	0.49
Florida	7.4	0.58
Georgia	8.3	0.65
South Carolina	7.4	0.58
Virginia	6.9	0.54
California	12.8	1.00

Air normalized values are calculated by dividing the Air Pollution Level by 12.8, the maximum in the U.S. By taking averages for each of the routes, the *Air* values for TX-LA, MN-IL, MA-PA, FL-DC, and CA-CA are 0.64, 0.59, 0.61, 0.59, and 1.00, respectively. By averaging the *Tru* and *Air* values, we can calculate the total Environmental factor N.

Now, we present our final w_E, w_N, E, N values and use the aforementioned formulas to calculate total community motivation M in the following table:

w_E, w_N, E, N, M values					
Route	w_E	w_N	E	N	M
TX-LA	0.78	0.22	0.81	0.75	0.80
MN-IL	0.27	0.73	0.82	0.80	0.81
MA-PA	0.23	0.77	0.59	0.60	0.60
FL-DC	0.71	0.29	0.76	0.58	0.71
CA-CA	0.04	0.96	0.67	0.92	0.91

1.3.4 Sensitivity

Table 2.1.3 Sensitivity analysis for Part I				
Constant	% Change of Constant	% TX-LA % MN-IL % MA-PA % FL-DC % CA-CA		
w_e	10			
w_d	-10	1.000152560801425	0.9980908595187932	-5.57
-1.49				

1.3.5 Results

Our model used a robust combination of both Economic and Environmental factors, taking into account revenue, jobs, CO2 emissions, and air pollution. Then, the weights of each type of factor was calculated based on how much a state valued the economy over the environment. Finally, a weighted average was taken to determine a community's overall motivation to begin truck development.

Overall, our models predicts that the Los Angeles to San Francisco (CA-CA) route should be targeted for electric truck charging station development first, as it has the highest M value (Community Motivation for Development). This was a result of the high community value of the Environment over the Economy and the high air pollution values in California. The next two optimal routes for development were the Minneapolis to Chicago (MN-IL) route and the San Antonio to New Orleans (TX-LA) route. Both of these corridors would benefit greatly due to both economic and environmental factors, but the states along the two routes valued the Environment and the Economy more, respectively. The Jacksonville to Washington D.C. (FL-DC) route had the second least community motivation for development, as it already had relatively low air pollution and CO2 emission levels, yielding a low N value. Finally, Boston to Harrisburg (MA-PA) had the lowest predicted motivation for development, with low E and N values, meaning that they would not benefit greatly economically or environmentally.

1.3.6 Strengths and weaknesses

Our model took into account both economic and environmental factors, both of which are the two primary motivations for constructing electrical truck charging stations. In addition, it was able to take into account the community's attitude towards the economy and environment. Our model also produced a strong and significant result: the California corridor would improve greatly as the citizens place a large emphasis on the environment, and the current CO2 and air pollution levels are the highest in the U.S.

However, our model did not take into account the high starting cost for building chargers. In Part 2, we found that a very large amount of charging stations would need to be built to support the current amount of trucks, which would require a great deal of starting capital. In addition, political factors and government subsidies were not taken into account, both of which play a large role in the total community motivation towards electric truck development. For example, a more economically conservative community might view any government expenditure negatively.

2 Conclusion

2.1 Future Studies and Research

This modeling project raised many questions and insights for further exploration. In the first question, we assume that all the infrastructure was pre-built, which in the real world, is difficult, if not impossible to do. To improve our model, we could find a coefficient for adoption based on the number of existing charging stations (i.e. the more charging stations the more receptive companies are to purchasing electric trucks). In addition, the third model could be improved by considering another factor that causes communities to adopt new truck charging stations– the name recognition. Having the positive image of a clean energy charging station associated with a town, though harder to quantify, could be a strong pull factor toward motivating communities to house large charging centers. Finally, our first and third models could both be strengthened by taking into account government subsidies. Since this varies at the state level, this approach would be tedious, but could yield important insights into the willingness people and their communities are willing to adopt and support the growing electric truck movement.

2.2 Summary

In this research, our first model used differential equations to model future demand for electric vehicles. Taking into account the number of first time buyers of trucks, the breakdown rate of both diesel and electric trucks, this model assumes a fixed number of buyers per year of trucks, and reveals that the level of . This can be improved by modeling the growth of trucks as non-constant growth, further improving the accuracy of our model.

In the second part, we sought to find how many charging stations and charging units would be needed along 5 major trucking corridors. Our model took into account the impact weather can have on battery efficiency (and thus the range), the range, and the charging time for a full charge. Our model, however, lacks consistent data, as the given sources vary by state. In the future, we could strengthen the data and thus the model by seeking alternative methods to derive the AADT.

In the third part, we sought to model how receptive the communities around the 5 given major corridors are to trucking charging stations based on their regional Eco-Friendly Behaviors index and their economic receptivity. We found that the communities with the greatest motivation to develop electric truck charging stations were (in order from greatest to least) Los Angeles-San Francisco, Minneapolis-Chicago, San Antonio-New Orleans, Jacksonville-Washington D.C., and Boston-Harrisburg.

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3 Appendix

Modeling for Part 1:

```
import numpy as np
from scipy.integrate import odeint
import matplotlib.pyplot as plt
from matplotlib import pylab
from pylab import *

N = 100000
t = linspace(0,100,N)

#### - Constants
D = 183888
ke  = 0.1
kd = 0.0867
ce = 0.57
cd = 0.43
me = ce*D-500*ke
md = cd*D-1820483*kd

def getTe(t):
    return -me*exp(-ke*t)/ke+ce*D/ke

def getTd(t):
    return -md*exp(-kd*t)/kd+cd*D/kd

def getPercentA(a,b):
    return a/(a+b)*100

p = 0.1
values = [5,10,20]
outputs = [[0,0,0],[0,0,0]]
for i in range(len(values)):
    va = getPercentA(getTe(values[i]),getTd(values[i]))
    md *= (1-p)
    vb = getPercentA(getTe(values[i]),getTd(values[i]))
    outputs[0][i] = (vb-va)/va-mod((vb-va)/va,0.0001)
    md *= (1+p)/(1-p)
    vc = getPercentA(getTe(values[i]),getTd(values[i]))
    outputs[1][i] = (vc-va)/va-mod((vc-va)/va,0.0001)

print("md")
print(outputs)

rcParams["axes.grid"] = True
rcParams['font.size'] = 14
rcParams['axes.labelsize'] = 18

figure()
subplot(211)

plot(t,getPercentA(getTe(t),getTd(t)))

```

```
ylabel("Percent of electric trucks")

xlabel("Time (years)")
axes = plt.gca()
axes.set_xlim([0,25])
axes.set_ylim([0,100])

a = getPercentA(getTe(5),getTd(5))
b = getPercentA(getTe(10),getTd(10))
c = getPercentA(getTe(20),getTd(20))
types = [a-mod(a,0.001),b-mod(b,0.001),c-mod(c,0.001)]
x_coords = [5, 10, 20]
y_coords = [getPercentA(getTe(5),getTd(5)),getPercentA(getTe(10),getTd(10)),getPercentA(getTe(20),getTd(20))]

for i,type in enumerate(types):
    x = x_coords[i]
    y = y_coords[i]
    plt.scatter(x, y, marker='x', color='red')
    plt.text(x-1, y+2.5, type, fontsize=9)

figure()
subplot(211)

axes = plt.gca()
axes.set_xlim([0,25])

plot(t,getTe(t), label="Electric Trucks")
plot(t,getTd(t), label="Diesel Trucks")
plot(t, getTe(t) + getTd(t), label = "Sum")

xlabel("Time (years)")
ylabel("Number of Trucks")

rcParams['legend.fontsize'] = 16.0
legend(loc=(0.1,-1),ncol=3)

#show()

tight_layout()
```

Sensitivity Analysis for Part 3:

```
import numpy as np
from scipy.integrate import odeint
import matplotlib.pyplot as plt
from matplotlib import pylab
from pylab import *

N = 100000
t = linspace(0,100,N)

#### - Constants
D = 183888
ke  = 0.1
```

```
kd = 0.0867
ce = 0.57
cd = 0.43
me = ce*D-500*ke
md = cd*D-1820483*kd

#M =
Stations = [4.71,3.83,3.6,6.12,3.35]
Chargers = [8288.76,9708.31,5265.85,5083.84,7577.72]
AADTT = [14288,12735,9843,9429,13975]
Air = [[8.4,7.9],[6.6,6.8,9.3],[9.2,8.1,6.6,7.2,6.3],[7.4,8.3,7.4,6.9],[12.8]]
weights = [0.78,0.27,0.23,0.71,0.04]

def getE(S,C):
    Econ = [0,0,0,0,0]
    cs = max(S)
    cc = max(C)
    for i in range(len(Econ)):
        Econ[i] = (S[i]/cs + C[i]/cc)/2
    return Econ

def getN(T,A):
    Enviro = [0,0,0,0,0]
    X = [0,0,0,0,0]
    for i in range(len(A)):
        for j in range(len(A[i])):
            X[i] += A[i][j]/len(A[i])
    ct = max(T)
    ca = max(X)
    for i in range(len(Enviro)):
        avg = 0
        Enviro[i] = (T[i]/ct+X[i]/ca)/2
    return Enviro

def getScore3(S,C,T,A,we,r,n):
    ret = [0,0,0,0,0]
    wn = [0,0,0,0,0]
    for i in range(5):
        wn[i] = 1 - we[i]
    if(n==3):
        for i in range(5):
            ret[i] = we[i]*r/(we[i]*r+wn[i])*getE(S,C)[i]+wn[i]/(we[i]*r+wn[i])*getN(T,A)[i]
    if(n==4):
        for i in range(5):
            ret[i] = we[i]/(we[i]+wn[i]*r)*getE(S,C)[i]+wn[i]*r/(we[i]+wn[i]*r)*getN(T,A)[i]
    if(n==0):
        for i in range(5):
            ret[i] = we[i]*getE(S,C)[i]+wn[i]*getN(T,A)[i]
    return ret

p = 0.1
percentages = [[0,0,0,0,0],[0,0,0,0,0]]
for i in range(5):
    percentages[0][i] = getScore3(Stations,Chargers,AADTT,Air,weights,1-p,4)[i]/getScore3(
```

```
        Stations,Chargers,AADTT,Air,weights,1,0)[i]
    percentages[1][i] = getScore3(Stations,Chargers,AADTT,Air,weights,1+p,4)[i]/getScore3(Stations,Chargers,AADTT,Air,weights,1,0)[i]

print("wd")
print(percentages)
```