With the unveiling and introduction of electric trucks by various technology companies into the market as well as the positive response from large shipping companies, there has been a strong interest created in the effects this technology will have on the companies and communities. Diesel trucks, specifically semi trucks, are of particular interest due to their ability to be improved upon in terms of their efficiency and effects on the environment making them a suitable industry for change.

First, in order to understand how the proportion of electric semi trucks in the truck industry will change over time we ran logarithmic regressions to create a measurement of operational costs for diesel vehicles and initial costs for electric vehicles using future parity predictions to see where electric vehicles become more cost efficient. Along with the derivation of other important factors in the growth of electric trucks such as fuel efficiency and initial truck type distribution, we implemented an agents-based NetLogo model which illustrates the change in electric vehicle proportion over time. The fraction of each type of truck purchase was modeled after an inverse relationship regarding a normalized price proportion of the certain type of truck of interest. This lead us to see that after 5, 10, and 20 years the percentage of the truck fleet that was electric was 28.22%, 53.98%, and 87.99% respectively.

Secondly, to determine the number of charging stations, their location, and the number of chargers located along a certain truck corridor/path, we developed a stochastic agents-based NetLogo model. In this model, cars are initially distributed along the path based upon extrapolated data, and are assigned an initial battery percentage as well as a remaining amount of time in a truck driver's shift based upon information from reputable sources. Both of these values decrease over time as the cars dynamically move with varying speeds with a resulting value of 0 for either initiating a "stop." Where a stop occurs for each car was taken into account allowing for the creation of a density distribution graph allowing us to understand the strategic location of charging stations as well as their number and number of chargers. This scalable model is able to be used for a varying number of cars as well as length of corridor allowing for accurate modeling of the various corridors in which we found 7 stations to be necessary for the San Antonio to New Orleans and Jacksonville to Washington corridors while 2 stations was appropriate for the other three corridors. Additionally, through an amplitude analysis of our density distribution graphs, we found an approximate value of 18 chargers per station to be valid.

Lastly, to analyze the motivations of communities for transitioning to electric vehicles, we developed an analytical function model that took into account the environmental and economic impacts that a change to electric vehicles would induce upon a corridor. The environmental impact was based upon carbon dioxide emissions that could be reduced by changing the number of diesel trucks that travel along a corridor to electric utilizing diesel truck mileage as well as carbon dioxide emissions. The economic model relies upon the fact that electric vehicles generate revenue but also maintenance costs due to the construction of charging stations at rest stops. Taking into account both of these and their relative weights, we can consider a coefficient of transition motivation for a community and rank which corridors should be considered first (and then in descending order) for the adoption of electric trucks due to this coefficient: San Antonio-New Orleans, Jacksonville-Washington, Minneapolis-Chicago, Boston-Harrisburg, Los-Angeles- San Francisco.

We created effective and robust model to predict the patterns of electric vehicle market penetration over time. Additionally, our thorough analysis of parameter variation and stochastic modeling allowed for a detailed exploration into strategic charger locations for various paths. Lastly, our accounting of impacts of the oncoming transition of electric trucks allows for a realistic understanding of the desire of communities to adopt electric trucks.

Contents

1 Introduction

1.1 Restatement of the Problem

Our problem involves the modeling of the electrification of the semi-truck industry, and of the transitions in infrastructure and trucking corridor communities which are necessary for this to occur. This problem is divided into three parts:

Part 1. **Shape up or ship out.** Assuming that the necessary EV infrastructure is already in place, create a model of the replacement of traditional diesel semi-trucks with electric semi-trucks. Use this model to predict the percentage of the US semi fleet which will be electric in 5, 10, and 20 years from 2020.

Part 2. **In it for the long haul.** Develop a general model which determines the necessary distribution of electric charging stations and the number of chargers at each station in a major trucking route. Use the following corridors as examples:

- 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

Part 3. **I like to move it, move it.** Build a model that ranks trucking corridor communities by which should be targeted first for EV development, considering the environmental and economic incentives for and drawbacks involved in such transitions. Use the previous five corridors named in part 2 as example cases.

1.2 Global Definitions

Electric Vehicle Charger (EVC): A device which is responsible for charging the battery of an electric vehicle

Electric Vehicle / Electric Trucks: A vehicle which is electrically powered, as opposed to traditionally diesel-powered vehicles.

Electric Vehicle Stations (EVS): As gas stations are to gas-powered vehicles, electric vehicle stations are to EV's. Each EVS has a number of EVC's, instead of the usual gas pumps.

Trucks, Semi-Trucks, semis: All three terms are interchangeable and refer to class 8 vehicles according to the US GVWR classifcations.

1.3 Global Assumptions

Assumption: All electric semi-truck infrastructure is in place and fully functional.
Justification: As stated in the m3 problem challenge, electric car infrastructure is in place and does not require additional maintenance or production.

Assumption: Truck drivers drive anytime during the day, including during the night.

Justification: Due to factors such as the availability of parking or traffic congestion, truck drivers often have a flexible schedule so that they can arrive to their final destination most efficiently.[2] Consequently, any time during the day, a trucker will often be driving.

Assumption: Electric semi-trucks and standard diesel semi-trucks are substitute goods.

Justification: Both electric and diesel trucks equally meet the trucking industry's demand and can replace each other in the market. Although they are significantly different in construction and capabilities, both types of trucks essentially serve the same purpose

Assumption: All electric semis operate with the same capabilities as the 500 mile range Tesla semi.

Justification: Because there are not yet any commercially available electric semis, little is confirmed about the capabilities of electric semis. Given that the Tesla semi is beginning production later this year, it is likely that future semis will at least have the capabilities which Tesla has already promised.[7]

Assumption: All semi-trucks are long haul and regional trucks

Justification: As explained in m3 challenge info sheet, a nearly negligible 5% of all trucks are smaller, short haul semis.

2 Part I: Shape up or Ship Out

With the benefits of increased efficiency, reduced maintenance cost, and other factors, the current trucking industry has began to transition from diesel based truck fleet to an electric truck fleet.[5] Assuming that all necessary electric semi infrastructure (i.e. electric vehicle charging stations) are in place, we outline a mathematical model predicting the percentage of semi that will be electric over the next twenty years. Our objective is to create a model of the transition of semi-trucks from diesel to electric over the next, five, ten, and twenty years.

2.1 Model Assumptions

Assumption: Semi-trucks are replaced when decommissioned.

Justification: To meet the demand of its suppliers, the trucking industry must constantly maintain a minimum number of semi-trucks.

Assumption: The ratio of trucks to truck drivers is constant.

Justification: Standard practices and regulations ensure that trucking logistics are fully optimized for efficiency and safety. These practices are unlikely to change as the number of trucks change.

Assumption: The cost of diesel trucks will remain relatively constant over the course of 20 years.

Justification: Diesel trucks have been an industry standard for decades. Therefore all infrastructure and production processes have been fully optimized and cost has nearly plateaued.

Assumption: The operating costs of electric trucks is constant.

Justification: Infrastructure for electric charging (charging stations and the electric power grid) have been well established. Electricity prices have remained relatively constant resulting in a near constant operating cost for electric trucks.

Assumption: The only types of trucks available are electric trucks and diesel trucks

Justification: Class 8 diesel trucks currently account for 97% of the all commercial trucks in the United States. There are currently no relevant alternatives other than electric trucks in the near future.

Assumption: The total number of trucks in the future will not be affected by the proportion of electric and diesel trucks.

Justification: While electric trucks may be more efficient than diesel trucks in the future, they both accomplish the same task and meet the demand of the market. This consistent market demand will not be affected by the type of truck a company uses.

Assumption: Any electric truck will be replaced by another electric truck.

Justification: Because companies are transitioning into using electric trucks, and the NACFE executive summary states that the electric trucks are set to be the same cost or cheaper than diesel trucks in 2025 and beyond [4], it doesn't make sense to replace an electric truck with the diesel truck, which will most likely become obsolete.

Assumption: The primary factors determining the percentage of electric trucks purchased in the short-term are the cost and the limited lifetime of the current operational semi-truck fleets.

Justification: The problem statement assumes that all electrical infrastructure exists for companies to seamlessly transition to an electronic fleet. With the electric truck being more environmentally sustainable than current diesel trucks, and the government providing taxes and subsidies to encourage electric vehicles, the main reasons a company would hesitate to purchase an electric truck are the current cost and the lack of need to while its current fleet is still operational.

2.2 Model Development

Since market penetration is highly dependent on multiple variables including total number of trucks in the market, cost of individual trucks, and operating costs of each truck, we decided to use a NetLogo simulation to visualize and account for each variable. To do so, our first step was to calculate and research the values mentioned above.

2.2.1 Determining Netlogo Variables

The first step towards calculating the percentage of electric trucks in the market is to calculate the total number of semi-trucks. According to Truckinginfo, there are approximately 2 million semi-trucks with 3.5 million truck drivers in the United States.[9] Unfortunately, due to a lack of data, we were unable to find exact numbers for future estimates of trucks in the United States; however, assuming that the ratio of truck drivers and trucks to be constant allowed us to estimate the growth in total trucks in the United States. Using data from the US Census Bureau on the number of truck drivers between 2005 and 2017, we were able to estimate the change in truck drivers. With the ratio of 0.57 trucks per truck driver calculated from 2 million trucks and 3.5 million truck drivers, we were able to calculate the number of trucks as a function of the year. A natural logarithm was determined to be the most accurate model with a high R-squared value and reduced rate of change characteristic of growth in the real world.

$$\text{Truck (in millions)} = 37.8 \cdot \log(0.0005203 \cdot \text{Year}) \tag{1}$$

The next step was to calculate the relative costs of each truck type as a function of time. Based on data from Fortune, the average price of diesel semi-trucks is approximately 120,000 dollars.[6] Additionally, each year 20,600 is spent on repairs and general upkeep. Furthermore, approximately 47,000 dollars are spent annually on gasoline. However, as research continues in diesel truck fuel efficiency, it will continually increase, reducing the cost associated with gasoline. Using the data set provided in M3, we calculated the fuel efficiency as a function of time:

$$\text{miles per gallon} = 133.3 \cdot \log(0.0005313 \cdot \text{Year}) \tag{2}$$

Similar to the number of trucks function, a natural logarithm was determined to be the best model because of its high R-squared value and curve characteristic of development and growth in the real world.

We also found that trucks on average travel 130,000 miles each year.

$$\text{Average gallons used per year} = \frac{130000}{133.3 \cdot \log(0.0005313 \cdot \text{Year})} \tag{3}$$

With an average price per gallon of gasoline of \$2.7, the average price spent on gasoline per semi-truck as a function of the year can be calculated by:

$$\text{Average price spent on gasoline} = \frac{2.7 * 130000}{133.3 \cdot \log(0.0005313 \cdot \text{Year})} \tag{4}$$

Once the average gasoline price per year was calculated, we estimated the value of diesel vehicles in the 20 years following 2020 by summing the values for the constant car and decreasing operation cost.

$$\text{Diesel Truck Value} = \text{Initial Price} + \text{Operation Cost} \tag{5}$$

$$\text{Diesel Truck Value} = 120000 + \left(\frac{2.7 * 130000}{133.3 \cdot \log(0.0005313 \cdot \text{Year})} + 20,600\right) \tag{6}$$

Unfortunately, like the number of trucks, there existed sparse and limited data regarding electric vehicles in the near future. As such, we had to estimate the change in price of electric vehicles overtime using alternate methods. Using data on Fortune, we calculated the cost of operating an electric truck to be approximately \$0.26 per mile travelled and an operating cost of 33,000 dollars per year.

To do so, we used the fact that parity, the time of equal price, between electric semi-trucks and diesel semi-trucks is predicted to occur in 2025. Since the cost of diesel semi-trucks and operation costs was predicted to be 184,600 dollars in 2025, the cost of electric vehicles and operation must be 184,600 in 2025.

$$\text{Price of Diesel Semi-trucks}_{2025} = \text{Price of Electric Semi-trucks}_{2025} \tag{7}$$

$$\text{Price of Electric Trucks}_{2025} + 33,000 = 184600 \tag{8}$$

$$\text{Initial Price of Electric Semi-trucks}_{2025} = 184600 - 33000 = 152,000 \tag{9}$$

With the newly calculated data points and a logarithmic model, we found a regression line for the cost of electric semi-trucks overtime. We used a logarithmic model since this model is analogous to the function of operating costs for diesel functions which was found to closely follow a logarithmic curve. Given the constraints of a lack of a data set and limited data points, this regression model was the best estimate we could make for the price of electric semi-trucks over a twenty year period.

Finally, to make our model closely resemble the real world we must include the replacement rate of semi-trucks in the industry. According to "Keep on Trucking Information Sheet, MathWorks Math Modeling Challenge 2020", semi-trucks are used for about 5 years to 15 years. The NACFE executive summary states that electric trucks achieve a 10-year lifetime or better; we assume a 10-15 year lifetime for electric trucks in this scenario, and a 5-10 year lifetime for diesel trucks. Most diesel trucks are sold after 5 years for small haul purposes, which were not considered in this paper.

2.2.2 Netlogo Implementation

We implement our model off the following approximation: let f_e be the fraction of electric trucks in use in a given year, and f_d be the fraction of diesel trucks in use in a given year. Let p_e and p_d be the respective prices of the average electric truck and diesel truck in that year. Then $\frac{f_e}{f_d} \sim \frac{p_d}{p_e}$. This is based off the observation that as the ratio of electric truck prices to diesel trucks decreases, the fraction of electric trucks purchased will increase because companies will find their prices cheaper. It follows that $f_e : f_d$ represents how many more times companies as a whole prefer electric trucks than diesel trucks. We can determine the change in number of trucks every year from the data obtained above, and thus determine the change in both the electric and diesel trucks. Let $\bar{t}$ be the number of new trucks in use over the course of year X, t_e be the total number of electric trucks in use from 2020 to year X and t_d be the total number of diesel trucks from 2020 to year X, where $2020 \leq X \leq 2040$. Knowing that $\frac{f_e}{f_d} \sim \frac{p_d}{p_e}$ is also an approximation, we assign a variance v to f_e. Then we can update t_e and t_d as

$$t_e := t_e + (1-v)\bar{t} \cdot \frac{f_e}{f_e + f_d} = t_e + (1-v)\bar{} \cdot (1-v)\frac{p_d}{p_e + p_d}$$

and

$$t_d := t_d + (1-v)\bar{t} \cdot \frac{f_d}{f_e + f_d} = t_d + (1-v)\bar{t} \cdot \frac{p_e}{p_e + p_d},$$

where v ranges from $[-0.1, 0.1]$ and can be adjusted accordingly. Storing the values of $\bar{t}, p_e, p_d$ for each year in an array, allows us to update these values year-by-year until 2040. We also assign a random lifespan to each truck in the interval corresponding to its type, and replace each truck once it reaches the end of a lifespan. An electric truck is replaced with an electric truck per our assumption, and a diesel truck is replaced with an electric truck with probability $\frac{f_e}{f_e+f_d}$, and a diesel truck with probability $\frac{f_d}{f_e+f_d}$ according to its preferences. We also assign a random lifespan to each truck in the interval corresponding to its type, and replace each truck once it reaches the end of a lifespan. An electric truck is replaced with an electric truck per our assumption. A diesel truck is replaced with an electric truck with probability $\frac{f_e}{f_e+f_d}$ for the, and a diesel truck with probability $\frac{f_d}{f_e+f_d}$. From here, we plot $\frac{t_e}{t_e+t_d} \cdot 100\%$ vs. year to determine the percentage of electric trucks in use in 5 years, 10 years, and 20 years.

We simulate this visually using NetLogo. We define 'Diesels' and 'Electrics' to be the two breeds of turtles, and assign the Diesels to be light red and Electrics to be light blue. We also set the electric truck fraction f_e to be 0 at the start of the simulation; this aligns with the fact that the amount of electric trucks are currently negligible compared to diesel trucks. Each tick, or timestep, of the simulation, represents a month, so we update all of our calculations by assuming the changes between consecutive years are evenly spaced between the months. An initial configuration is seen below for 6000 initial trucks, or turtles. We scaled down from the $\sim$ 2 million commercial trucks in use for 2020 in order to save computational time:

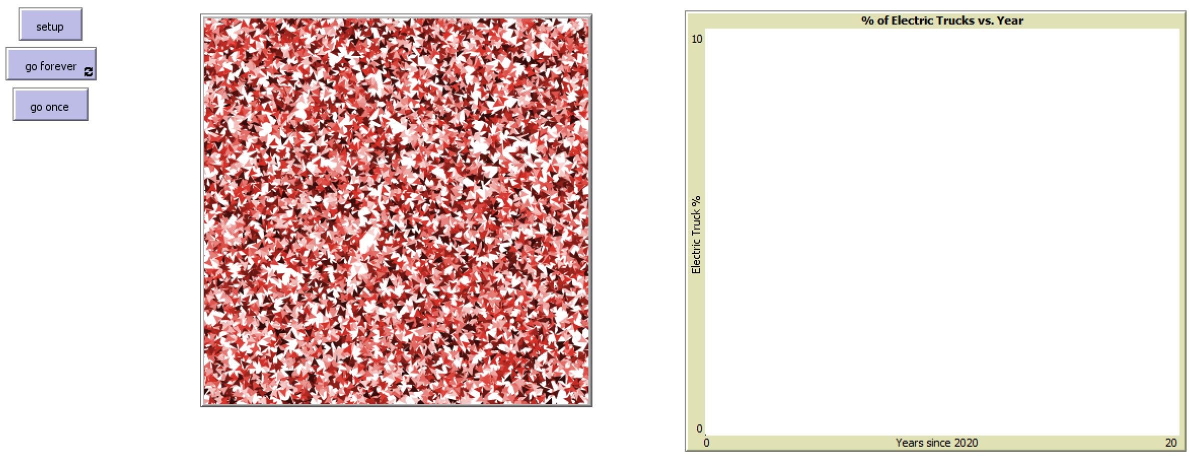


Figure 1: Initial setup of diesel trucks

The simulation is set up so that as a turtle ages, its color becomes darker, and it becomes replaced according to the conditions described above. An example of the first 24 months, or two years is seen below:

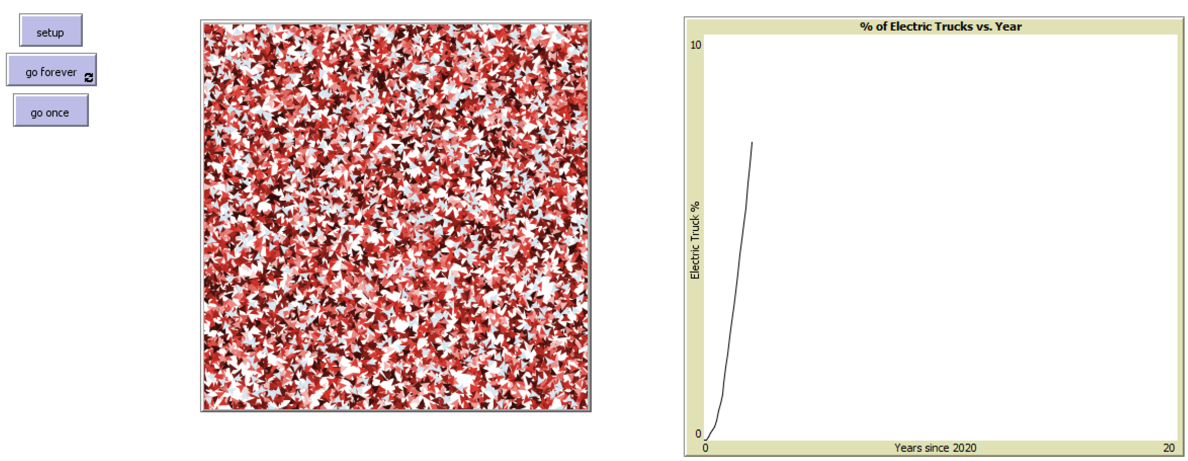


Figure 2: First 2 years of simulation. The electric trucks now make up around 7.35% of the turtles.

% change (diesel, electric cost)	electric trucks % in 5	electric trucks % in 10	electric trucks % in 20
(0, 0)	28.22	53.98	87.99
(0, 10)	27.29	54.21	87.42
(0, -10)	26.12	51.23	86.43
(10, 0)	31.43	48.41	88.32
(10, 10)	29.31	53.57	90.12
(10, -10)	34.41	56.21	92.12
(-10, 0)	29.76	55.21	89.16
(-10, 10)	32.48	54.98	91.21
(-10, -10)	26.65	52.38	86.27

Noticeably, as diesel trucks in the current fleet start reaching the end of their lifespan, companies choose to replace them with electric trucks. This starts a large spike in the percentage of electric trucks that continues until the end of 240 months or 20 years. Results are seen below.

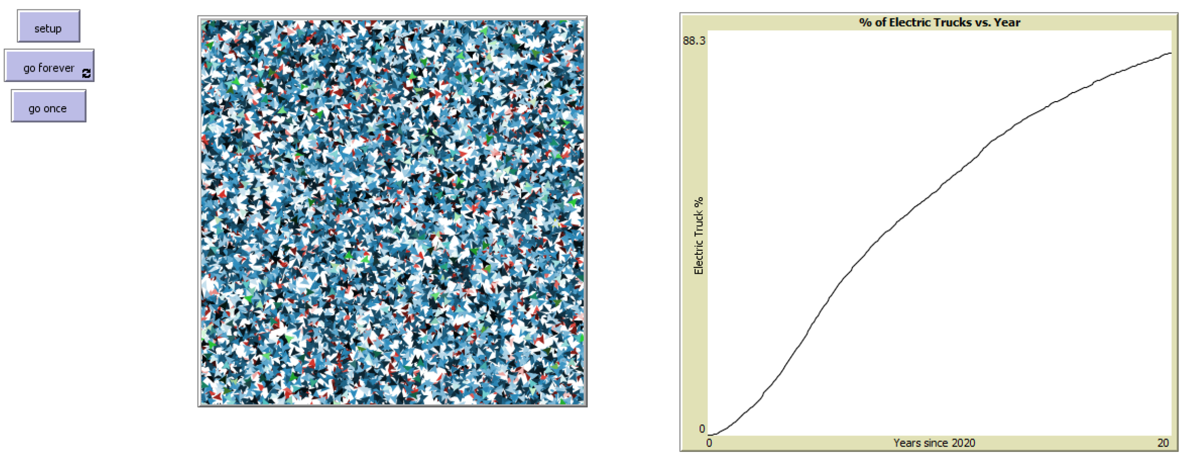


Figure 3: Final snapshot of simulation. The electric trucks now make up 87.99% of the turtles.

The values for 5 years, 10 years, and 20 years are 28.22%, 53.98% and 87.99%.

2.3 Sensitivity Analysis

Given that our projections for the cost of the average diesel and electrical trucks hinged on secondary data sources with a possibility for uncertainty, we test the sensitivity of our model against different values of average diesel and electrical truck costs. Below is a table for the electrical truck percentage after 5, 10, and 20 years, assuming ±10% or no variances in the cost projections. We adjust every value in a single list when performing the simulations.

Our model holds up to a sensitivity analysis, and we expect the percentage of electric cars to be about 30% after 5 years, about 50% after 10 years, and about 90% after 20 years.

2.4 Strength and Weaknesses

Our model is robust with all inputs based on real-world data from trusted websites and governmental agencies such as the U.S. Energy Information Administration and the United States Census Bureau. Moreover, our model was designed using information that is specific to the M3 Challenge and further augmented by external resources. With a strong statistical and research background, our calculations and predictions are strong indicators of future changes. Furthermore, our Netlogo agents-based model allowed us to incorporate a wide range of variables over extended periods of time including truck population and diesel fuel efficiency.

However, one weakness associated with the model lies with our assumption that the ratio of the prices of diesel vehicles to electric vehicles is indirectly correlated and equal to the ratio of the number of electric vehicles to diesel vehicles. While we tried our best to incorporate the differences and changing of costs of electric and diesel vehicles, there is no found exact coefficient of correlation with the demand. Nevertheless, from the economic principles of demand and supply, we know that a decrease in price will result in an increase in demand by the consumer leading our model to model the correct trend and relationship. Furthermore, some of the data used in our model was calculated through secondary data sets since there is insufficient data regarding electric and diesel semi-trucks. This usage of secondary data sets allows for more possibility of error; however, given the constraints of our data and the problem, they provide the most accurate information for our model.

3 Part II: In it for a long haul

With the rise of electric trucks on the road is expected to increase substantially over the next couple of decades, electric semi infrastructure is desperately needed to keep up with the demand. In particular, electric vehicle stations with electric chargers are needed along frequently used trucking highways in order for electric semis to be viable and appealing for long haul fleets. Using truck density and various traveling factors, we outlined a mathematical model to determine the number of stations and chargers at each station needed along the five different corridors, as mentioned in Section 1.1.

3.1 Model Definitions

Initial Charging Percentage: The charging percentage which value is randomly distributed from 0.9% to the full charge that the electric vehicle enters the simulation with.

Initial Driver Shift: The number of hours into their shift which value is randomly distributed from 0 hours to 8 hours that the driver of the electric vehicle enters the simulation with.

Total Time of Driver Shift: According to the given trucking information sheet, a truck driver is restricted to fourteen hours of working with ten hours of off-time during a day.[3] Additionally, within those fourteen hours, only eleven hours can the driver be driving, limiting the total amount of driver shift to eleven hours.

3.2 Model Assumptions

Assumption: All semis currently in use are electric.

Justification: Problem statement.

Assumption: Drivers enter the corridor with a random initial driver shift of some number of hours between 0 to 8.

Justification: The amount of time which a driver has already driven prior to entering the corridor is unknown, but most drivers will not enter a long-term corridor with little to no remaining driving hours left.

Assumption: Drivers enter the route with a charge between .9 to 1.

Justification: Similarly to our previous assumption, drivers will tend to charge immediately before entering a long corridor.

Assumption: Truckers will charge once their shift ends.

Justification: Truckers will typically fully charge once their shift ends, supposing that a charging station is available, since it prevents them from having to delay their departure the next day in waiting for their truck to finish charging.

Assumption: Drivers will charge from 20% to 100%

Justification: Both the driver and the semi will enter a risky and undesirable situation when the semi's battery dips below 20%. Thus, drivers will tend to plan out their trips to reach stations when or before their battery reaches 20% left. For very long trips such as those along the corridor, we also expect truckers to prefer longer, sparser charging sessions rather than shorter, more frequent ones. Thus, it is reasonable to assume that drivers will charge to 100% whenever they stop, whether only to charge or for a break.

Assumption: Trucks always travel at 55 mph, and there are no obstacles along the corridor which disrupt travel speeds.

Justification: Because trucks will be spending the vast majority of their traveling time on the highway, their speed there is effectively their average speed. According to the provided semi usage data set, "heavy duty long haul tractors" operate on average at 55 mph. It has been confirmed that the Tesla semi can drive at least this speed in normal conditions, since it has a larger top speed of 60 mph at a 5% uphill incline.[7]

Assumption: The daily truck traffic in a particular location along a corridor travels along the entire corridor.

Justification: The traffic in a particular location is representative of the density of trucks there, and corridors are major, well-traveled routes (at least for truckers). Thus, trucks which enter the corridor are typically traveling significant distances, which we approximate as the entire path length.

Assumption: Missing points in the daily traffic of a corridor can be reasonably approximated by the average of the entire data set.

Justification: As we see in the complete data sets for the non-truck traffic, the most erratic sections of the traffic data tend to be in the beginning and end of a corridor, since trucks and other vehicles tend to enter and exit at these locations. As a result, the mid-section of the traffic of a corridor tends to be flatter and more consistent than the ends are. We use the average of the data set to approximate this flat traffic flow since the average will not have a strong impact on the maximum and minimums of the data set, and will thus not interfere with our modeling of the locations in most need of charging.

3.3 Model Development

We model each corridor as a linear path with an initial truck density distribution determined by the traffic data given in the provided corridor data.[1] As per our assumptions, we used the “Annual Average Daily Truck Traffic” to determine the initial distribution of trucks throughout the route. There are, however, several states in which daily truck traffic data is restricted or otherwise unknown. As a result, our picture of the overall density distribution is at least partially incomplete for all of the five corridors except the Los Angeles-to-San Francisco route. To fill in these data gaps, we, according to our assumption, substituted the average daily traffic into all of the missing data points.

In order to determine the most common locations at which truckers required fueling along the corridor, we used NetLogo to create a computational model of the drivers’ resting and charging tendencies. Because of the limitations of NetLogo, we used a downscaled number of turtles (i.e. trucks) to represent the population of trucks by placing 500 trucks in the general form of the truck density distribution. Since this caused significant locations along the corridor to be left empty due to the size of the plot and limited number of turtles, we also included 100 additional trucks in a random distribution to make the distribution more continuous. We used 500 patches to match the length of the corridor, regardless of the actual length of the route—for each corridor, each patch represented a different length $L/500$mi, where L is the actual distance and 500 is the number of patches. The specific number of trucks that an agent truck represents and the number of miles a patch spans for each corridor is shown in the table below 4.

Corridor	Truck Number	Trucks/Turtle	Length (miles)	Miles/patch
San Antonio, TX - New Orleans, LA	1071601	1786	1108	2.216
Minneapolis, MN - Chicago, IL	640860	1068	419	0.838
Boston, MA - Harrisburg, PA	594738	991	383	0.766
Jacksonville, FL - Washington, DC	1665138	2775	694	1.388
Los Angeles, CA - Francisco, CA	531045	885	302	0.604

Table 1: Length and truck number for each corridor.

We then performed a simulation of the traffic through the corridor by assigning a constant speed of 55 mph to each of the 600 trucks, and let the trucks run for 30 days, with each tick equivalent to a single minute. When a driver either reached 11 hours in his shift, or hit 20% on his charge, a charge would be recorded at the driver’s current patch. The color of the patch would also be reduced by one in order to differentiate locations at which truckers charged often from those where they did not. Both the end of shifts and charging-only sessions are considered identically since we assume that the driver recharges in either scenario. Because the model is time independent, as it is only concerned with the relative number of charges at each location, we allow a truck to instantaneously continue after stopping to charge. After the runtime of the simulation, we use the charge number at each x-position to determine the frequency with which truckers needed to charge at the location, and thus identify the priority locations for charging stations and the actual number of chargers desired at each location.

We space out the charging stations relatively evenly at the local maxima of the charging distribution, but we limit the minimum spacing between adjacent charging stations to at least 100 mi, since these distances are well within a single electric charge and would approach redundancy. To find the number of chargers required per station, we count the total number of charges per day at a corridor, and determine the number of charges per station per charging period, where the charging period is how long it takes to charge a truck—about half an hour—using the following formula:[7]

$$\text{Charges per station per hour} = \frac{\text{Total \# of charges}}{\text{\# of Stations} \cdot \text{\# of hours}}. \tag{10}$$

3.3.1 Netlogo Model Setup

Following the setup described above, we developed a netlogo model with the interface shown in Figure 4. Within this model, we developed inputs/buttons that will allow us to track the movement of truck and the resulting needed stops for varying lengths of time. As the trucks moved along the corridor, they may need to take a rest break to use a charging station or at the end of their shift. For each location, its corresponding color of its patch can be seen.

For each of the button we programmed, it had the following specific function:

1. **number-of-cars**: The number of trucks we placed according to the truck density distribution for each corridor. Note that the number was restrained by the limitations of Netlogo.
2. **setup**: Places the truck according to their distribution as well as set up the "world" of Netlogo.
3. **go**: Moves each of the truck one tick, or one minute forward.
4. **go with infinite sign**: Moves each of the truck an infinite number of times forward until the user stops it.
5. **make-scatterplot**: At the end of the iteration that the button is pressed, the number of needed stops at a specific path is plotted against the distance of patches from the original starting point.
6. **one-monthperiod**: Used during our Behavior Space simulations (elaborated in Section 3.4.1), this button iterates the movement of the truck over a month long time period, otherwise numerated as 43200 ticks.

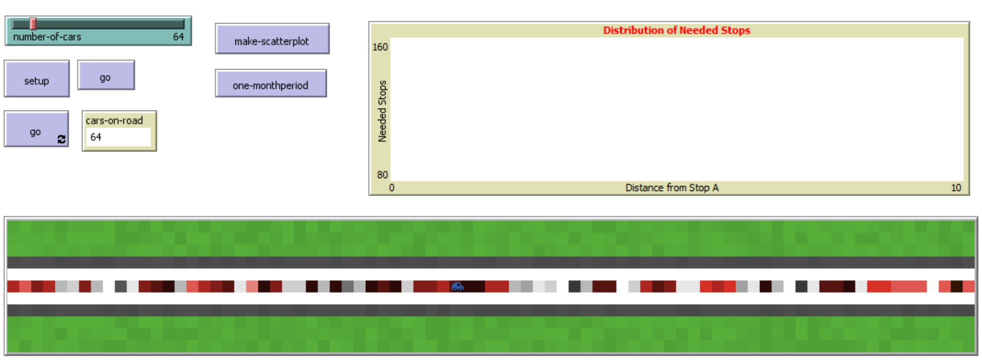
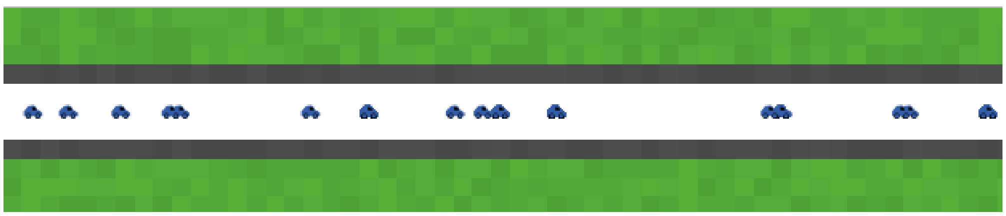


Figure 4: The Netlogo Setup Interface for Part II

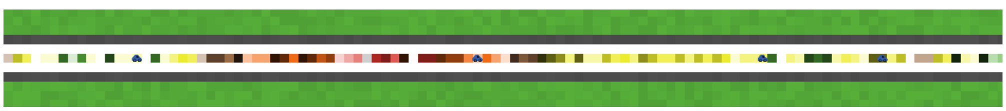
3.4 Results

3.4.1 Corridor Charge Density Trends

For each of the five corridors, we specified the specific truck density throughout the corridor based off the given data set, and used BehaviorSpace in NetLogo to run 20 30-day trials, taking the average of all of the trials as our result.[1] An scenario of the starting truck density in the corridor of Minneapolis, MN to/from Chicago, IL and the resulting needed charging spots is shown in Figure 5. With the resulting charge distributions, we were able to predict the number of stations as well as the number of chargers that should be implemented throughout the corridor.



(a)



(b)

Figure 5: The before and after simulation of a particular stretch of road. Each blue car represents a number of cars, dependent on each corridor.

From our plots of distance from the original departure spots versus the number of needed spots, we observed a couple of different trends that results from the differing initial distributions of trucks as well as the different lengths of corridors. As seen throughout all five different corridors, the density of needed charging spots follows a cyclic pattern, albeit each cycle has a different length, number of peaks, and amplitude. This cyclic pattern can be attributed to the fact that the decrease of charging capacity as well as the total charging capacity an electric truck can hold were the same across corridors, since we assumed that each electric truck would be Tesla's new model. Combined with the constant maximum driver shift time of eleven hours, the cyclic function is very apparent across the graphs. The noise across each of the graph result from the slight random variations of the initial driver shift and initial battery charge.

Note that the number of needed spots throughout the graph as seen on the graph is a product of the constraint of six hundred turtles we placed initially on the corridor. In other words, the seemingly maximum peaks of around 160 for each graph is based off that total constraint. The true number of the needed spots for electric vehicles is based on the varying number of trucks that each turtle represents in each corridor.

Additionally, we continue to observe similarities across the different corridors. In the corridor from San Antonio Texas, to/from New Orleans, LA, and the corridor from Los Angeles, CA, to/from San Francisco, CA, the graphs follow a similar pattern with a minor peak followed by a major peak and repeats. This is due to the similar initial distribution with a more constant number of traffic density in the later half of the corridor that will cycle throughout the entire corridor. On the other hand, Minneapolis, MN, to/from Chicago, IL corridor and Boston, MA, to/from Harrisburg, PA, follow a similar pattern. Both corridors have a less substantial major peak before followed by a minor peak. Completely different from the rest is the pattern of the corridor from Jacksonville, FL, to/from Washington, DC, with two major peaks side by side each other in each cycle. From the initial distribution of corridors, we can see consecutive high areas of truck density before dropping off in regions.

By analyzing the charge distribution, we were able to develop the number of charging stations along with the number of chargers per station.

3.4.2 Corridor Recommended Number of Charging Stations and Chargers

Table 2 shows the number of charging stations and the number of chargers per station which we determined each station required. We placed a charging station at the beginning and end of each route, and for every significant peak we added a station, with the constraint that the stations had to be at least 100 mi apart. We found that the San Antonio and Jacksonville corridors have the most number of stations, which is expected since these routes were the longest of the corridors, at 1100 miles and 700 miles, respectively. Our chargers per station results vary significantly between the routes, from as low as 4 to as high as 18. These numbers are roughly in the same range as the approximately 10 chargers that Tesla employs on average at their supercharger stations.[8] Interestingly, although the Jacksonville route was significantly shorter than that of the San Antonio, the Jacksonville route demanded more than twice as many chargers per station—18 compared to 8—for the same 7 stations. This was because of the significantly greater truck density in Jacksonville compared to San Antonio; the Jacksonville corridor had more than 50% total daily truck traffic.

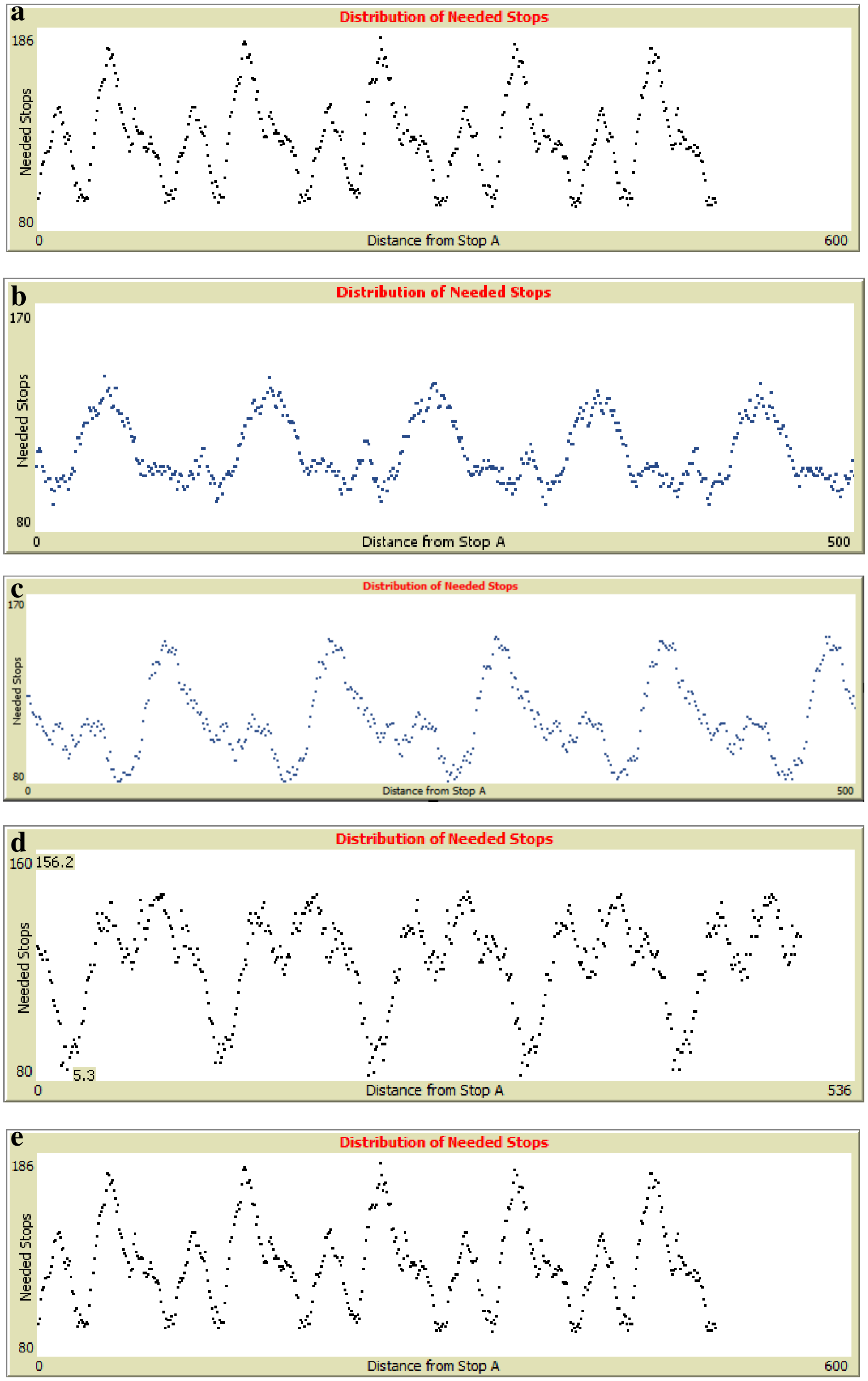


Figure 6: Results for distribution of required stops for each of the five corridors. (a) San Antonio, TX, to/from New Orleans, LA; (b) Minneapolis, MN, to/from Chicago, IL; (c) Boston, MA, to/from Harrisburg, PA; (d) Jacksonville, FL, to/from Washington, DC; (e) Los Angeles, CA, to/from San Francisco, CA.

Corridor	Total Charges (30 day)	Number of stations	Chargers per station
San Antonio, TX - New Orleans, LA	38920	7	8
Minneapolis, MN - Chicago, IL	23277	3	6
Boston, MA - Harrisburg, PA	21601	3	6
Jacksonville, FL - Washington, DC	60480	7	18
Los Angeles, CA - Francisco, CA	19289	3	4

Table 2: Number of stations and chargers per station at each of the five corridors.

3.5 Strengths and Weakness

Our agent-based model for the movement of trucks and the current needed spots allows for an accurate representation of the inherent randomness present within any system and its variables. The model is able to run a large sample size, of up to hundreds of trucks, of random distributions of the differing speeds, initial shift times of drivers, initial amount of charge an electric vehicle would have, giving an accurate estimation of the car density, and the consequent number of stations needed along the route.

Nevertheless, our model is not without some weaknesses. While our model is fairly accurate in approximating car density throughout the corridor, it does not take into account congestion and consequent speed changes from other vehicles, such as passenger cars, entering the corridor. The resulting traffic jams may cause the trucks to spend more electric charge and drivers to spend more of their shift waiting, without any real movement. Consequently, trucks may be forced to leave the corridor earlier than expected. However, this weakness is offset by the fact that trucks, especially commercial trucks, often travel at night to avoid these congestion issues so they won't have as much as an impact as originally expected.

Additionally, as addressed earlier, one of our weaknesses stems from our assumption that all electric trucks will be Telsas' new model, thus creating constant charging capacities and charging declines. This is one of the main reasons why the cyclic pattern was observed throughout the corridor. However, while all electric trucks may not be Telsas, we can assume a large portion of them will be do to the large command Telsa has over the market of electric trucks.

4 Part III: I like to move it, move it

As electric trucking begins making it way across America, communities surrounding the trucking corridor are reacting to the news with various enthusiasm. With the five corridors originally given, as mentioned in Section 1.1, we developed a mathematical model on which corridors to develop first based off the environmental impact and economic factors.

4.1 Model Assumptions

Assumption: Charging Station infrastructure already exists.

Justification: In accordance with part 1 of this problem, we are assuming that charging infrastructure already exists and that the cost and environmental impact of charging stations are negligible.

Assumption: Charging stations are analogous to current rest stops

Justification: Charging stations are areas for truck drivers to charge their trucks and rest according to trucking regulations. Therefore, they serve the same purpose as rest stops in our model.

Assumption: Charging stations are commercialized

Justification: In recent years, rest stops have become increasingly commercialized to counteract the maintenance costs associated with running rest stops and to help improve the community economy[**spartner**]. As stated in a previous assumption, charging stations are analogous to rest stops, so in our model, charging stations are commercialized locations with restaurants and other corporate partnerships.

4.2 Model Development

We believed that a community's desire to transition to using electric trucks in replacement of diesel-fueled trucks stems from the environmental impact and economic impact.

$$T_e = Ev_i + En_i \tag{11}$$

Here, T_e represents the transition motivation value for switching to electric trucks and Ev_i and En_i represent the environmental and economic impacts respectively.

$$Ev_i = \frac{l * d}{m} * c \tag{12}$$

This equation yields the pounds of CO_2 that are produced along a certain corridor with length l and number of cars c. In order to calculate this the extrapolated mileage (m) in 2020 of a diesel truck of 7.49 mpg was used along with a carbon dioxide emissions per gallon of diesel fuel consumed value (d) of 22.38 lbs per gallon.

Since electric charging stations for electric trucks do not currently exist, we assumed that charging stations are analogous to rest stops. Assuming that the only difference between charging stations and rest stops is the existence of the charging ports themselves, we can model the economic impact of charging stations by analyzing the impact of rest stops on local economies.

Corridor	**Possible CO_2 Reduction (millions of tons)**
San Antonio - New Orleans	1.773867
Minneapolis - Chicago	0.401167
Boston - Harrisburg	0.340314
Jacksonville - Washington DC	1.726465
Los Angeles - San Francisco	0.239600

Table 3: Annual millions of tons of CO_2 produced by each truck corridor route

$$En_i = (R - m) * n \tag{13}$$

The economic impact of changing to electric vehicles for a truck corridor was seen to be related based upon the number of rest stations that would be caused due to the need of electric charging

(n). The net revenue was calculated based upon the fact that each charging station would yield a certain revenue (R) but also require a maintenance cost (m).

According to spartnerships**[spartner]**, rest stops tend to generate approximately 4.23 million dollars a year but at the cost of 300,000 dollars per year. Therefore, the net revenue of a charging station is approximately 3.93 million dollars per year.

For each corridor, we calculated the net revenue per year by multiplying the number of charging stations by the revenue per charging station.

Corridor	Number of Stations	Annual Revenue in Millions of Dollars
San Antonio, TX - New Orleans, LA	7	27.51
Minneapolis, MN - Chicago, IL	3	11.79
Boston, MA - Harrisburg, PA	3	11.79
Jacksonville, FL - Washington, DC	7	27.51
Los Angeles, CA - San Francisco, CA	3	11.79

Table 4: Annual Revenue for each corridor

4.3 Results and Analysis

In terms of the impacts that the switch to electric vehicles would have a community, the list supersedes that of purely carbon dioxide emissions and the bolstering of economic activity at rest stops. The summation of these two values yields a reasonable metric that incorporates both values aptly. Furthermore, due the nature of the calculations, the transition motivation is weighted in favor of economic impact. This aligns with the current American emphasis on economic gain over environmental sustainability.

Corridor	Transition Motivation Value (millions)
San Antonio - New Orleans	29.28
Jacksonville-Washington DC	29.24
Minneapolis-Chicago	12.19
Boston - Harrisburg	12.13
Los-Angeles - San Francisco	12.03

Table 5: Corridors ordered in descending order of transition motivation value

We found that the San Antonio-New Orleans corridor would be most receptive to the integration of electric trucks into trucking fleets with a transition motivation value of 29.28 million. They were closely followed by the Jacksonville-Washington DC corridor which was only 0.04 million behind. These large transition motivation values were attributed to the financial benefits provided by additional charging stations. These corridors were also the corridors that had the greatest number of stations, so from our results and model it is apparent that the number of stations is strongly correlated with community reception for both economic and environmental reasons. This is because charging stations increase economic output of an area providing another area for commerce as well as increasing the number electric trucks. Electric trucks provide multiple benefits including reducing the total CO2 emissions as well as reducing the noise pollution. Diesel trucks, on the other hand, produce noise levels up to 90 decibels where as electric trucks produce much less. According to futurism.com, prolonged exposure to noise levels greater than 85 decibels can cause long term hearing damage. Therefore, electric truck integration provides three pronged benefits in terms of economic, health and environmental avenues.

4.4 Strengths and Weaknesses

Our model takes into account economic and environmental impacts, two incredibly prominent and influential factors affecting our society today. In doing so, our model is able to account for the main factors influencing a community's reaction towards the integration of electric trucks into the trucking industry and the subsequent creation of charging areas. Our data was collected from and verified by various sources giving us a robust and complete picture of the associated costs and impacts of electric truck adaptation. However, despite these strengths, our model generalizes the economic and environmental impacts of electric truck integration. By doing so, our model loses some of the nuance associated with each individual location and their respective impacts on the the reaction to new charging areas.

5 Conclusion

As electric semi trucks are already making an infiltration into the market acting as a replacement to diesel-fueled trucks. With this oncoming penetration, we were tasked with predicting the proportion of semi trucks that will be electric after 5, 10, and 20 years from 2020, assessing the number of charging stations and chargers along designated truck routes with long haul traffic, and finally detailing a community's motivation to transition to electric vehicles.

To accomplish our first objective, we first developed a deterministic model to predict the proportion of electric semi trucks in the coming years based upon a time-based consideration of the difference in prices of electric trucks and diesel trucks. We also took into account many variables including the initial amount of trucks, changing prices of electric trucks, total cost of diesel trucks, and others. Additionally, we ran a sensitivity analysis based off a plus or minus 10% variances to test the robustness of our model. From our Netlogo model that took into statistic variance for specific variables, we predicted that the percentage of trucks that will become electric is 28.22%, 53.98%, and 87.99% within the next five, ten, and twenty years.

For our second objective in determining the number of charging stations and chargers needed for a particular truck corridor, we developed a stochastic model in order to simulate the movement of vehicles along the corridor. Based off battery drainage patterns and the requirement of truck drivers to take rest, we created density distributions to find where large concentrations of trucks would need to stop. This allowed us to find the locations of where to install charging station along a specific corridor. From our model, we found a similar cyclic pattern of charge distribution needed for each corridor; however, each corridor had a differing amplitude, period of a cycle, and frequency. From our result, we found that it is recommended to have seven stations with eight chargers per station, three with six chargers per station, three with six chargers per station, seven with eighteen chargers per station, and three with four chargers per station, for San Antonio TX - New Orleans LA, Minneapolis MN - Chicago, IL, Boston MA - Harrisburg, PA, Jacksonville, FL - Washington, DC, and Los Angeles, CA - San Francisco, CA, respectively.

With the thought of an electric truck fleet becoming more and more realistic, it is especially important now, more than ever, to model the future impacts of this transitioning time on the communities that it will most impact. In order to do so, we determined the sum impact of the environmental impact and the economic impact from the rise of electric vehicles. To put it in accessible and simplistic terms, we valued the impact as a transition motivational value in millions. From our modeling, we found that San Antonio - New Orleans is the most motivated with Jacksonville - Washington DC followed closely behind and Los Angelos - San Francisco the least motivated.

In conclusion, we created a robust and flexible agent-based model to model the integration of electric semi-trucks into the trucking industry based on vehicle pricing. To understand the domestic impact of this integration, we modeled the locations of charging stations placed along five key trucking corridors in the United States. We then modelled the societal impact of the integration of electric trucks by looking into the environmental and economic impacts of the resulting changes. We found that this integration would almost fully complete after 2040 with positive economic and environmental impacts across the board.

References

[1] 2020 MathWorks Math Modeling Challenge. *Corridor Data*. URL: https://m3challenge.siam.org/sites/default/files/uploads/corridor_data.xlsx (visited on 03/02/2019).

[2] Aquila, Brett. *Trucking At Night Versus During The Day - What Should Your Strategy Be?* URL: https://www.truckingtruth.com/trucking_blogs/Article-3837/trucking-at-night-or-during-the-day (visited on 03/02/2019).

[3] Challenge, 2020 MathWorks Math Modeling. *Keep on Trucking information Sheet*. URL: https://m3challenge.siam.org/sites/default/files/uploads/M3%20Challenge%202020_PROBLEM%20INFO%20SHEET.pdf (visited on 03/02/2019).

[4] *Electric Trucks: Where They Make Sense*. URL: https://nacfe.org/future-technology/electric-trucks/.

[5] Midwest Evolve. *How Commercial Fleets can Benefit from Electric Vehicles*. 2020. URL: https://www.midwestevolve.org/advantages-of-evs/fleet-advantages/ (visited on 03/02/2019).

[6] Morris, David Z. *At $180,000, Tesla's Semi Could Be a Game-Changer for Trucking*. Nov. 2017. URL: https://fortune.com/2017/11/25/tesla-semi-price-180000/ (visited on 03/02/2019).

[7] O'Dell, John. *Here's Everything We Know About the Tesla Semi*. Sept. 2019. URL: https://www.trucks.com/2019/09/05/everything-we-know-about-the-tesla-semi-truck/ (visited on 03/02/2019).

[8] Tesla. *Tesla Supercharger*. URL: https://www.tesla.com/supercharger (visited on 03/02/2019).

[9] TruckInfo. *Trucking Statistics*. URL: https://www.truckinfo.net/trucking/stats.htm (visited on 03/02/2019).

Appendices

A Netlogo Code for Part I

```
breed [diesels diesel]
breed [electrics electric]

diesels-own [curr-age dying-rate]
electrics-own [dying-rate]
globals [
  tot-production-list ;projection of number of trucks produced
  for the years 2020-2040
  diesel-cost-list ;projection of the average cost of a diesel truck +
  yearly operating cost for the years 2020-2040
  electric-cost-list ;projection of the average cost of an electric truck +
  yearly operating cost for the years 2020-2040
  adjust-diesel-list0 ;adjusted diesel cost for sensitivity analysis
  adjust-diesel-list1 ;adjusted diesel cost for sensitivity analysis
  adjust-diesel-list2 ;adjusted diesel cost for sensitivity analysis
  adjust-electric-list0 ;adjusted electric cost for sensitivity analysis
  adjust-electric-list1 ;adjusted electric cost for sensitivity analysis
  adjust-electric-list2 ;adjusted electric cost for sensitivity analysis
  variances-list ;variances for senstivity analysis
  want-electric-fraction ;percentage of electric trucks purchased
  electric-variance ;variance in fraction of electric trucks purchased
  num-trucks ;number of trucks/turtles in the simulation, scaled down from tot-
     production-list
  temp-fraction ;percentage of electric trucks purchased
  at the end of the calendar year
  ]

to setup
  clear-all
  ask patches [set pcolor white]
  set num-trucks 6000
  create-diesels num-trucks [setxy random-xcor random-ycor set color

  11 + random-float(19 - 11) set dying-rate .9909 + random-float (.9955 - .9909)]
  ;set the dying rate to be .9909 <= r <= .9955 so r to the

  power of (12*death time) ~ 11/19, with death time ranging from 5-10 years. The
     reason for 11/19 is that
  ;the color for

  11 is dark red, while the color for 19 is light red. When the truck is dark red
     it reaches the end of its lifespan
```

```
  set electric-variance 0.1
  set want-electric-fraction 0.0
  set tot-production-list [2.0766 2.0953 2.1140 2.1327 2.1514 2.1700 2.1887
                         2.2074 2.2260 2.2446 2.2633 2.2819 2.3005 2.3191
                         2.3377 2.3563 2.3749 2.3934 2.4120 2.4305 2.4491]
  set diesel-cost-list [187450 186850 186260 185680 185120 184570 184040
                      183520 183010 182520 182030 181560 181100 180650
                      180210 179780 179360 178940 178540 178140 177760]

                      ;years 2020-2040
  set electric-cost-list [213180 207450 201730 196010 190290 184570 178860
                        173150 167450 161740 156040 150340 144650 138960
                        133270 127580 121890 116210 110530 104860 99190
                        93520]

                        ;years 2020-2040
  set variances [0.90, 1.0, 1.10]


  reset-ticks
end

to change-age
  ask diesels [set color ( (color) * dying-rate ) ] ;age the diesel trucks, assume
      electric trucks don't age
  ask electrics [ set color ( (color) * dying-rate ) ] ;replace old electric
     trucks with new ones
  ask diesels with [color <= 11] [ ;
    let p random-float 1 ;assign type based on probability
    ifelse p < want-electric-fraction
    [set breed electrics setxy random-xcor random-ycor set color 99 set dying-rate
        .9995 + random-float

    (.9995 - .9993)] ;the fraction of companies that want an electric

    truck will replace diesel with an electric truck
    [setxy random-xcor random-ycor set color 19
     set dying-rate .9909 + random-float (.9955 - .9909)] ;replace diesel with a
        diesel truck
  ]


end

to go
  if ticks > 240 [ stop ]
```

```
  change-age

  let years-since floor ticks / 12

  if ticks mod 12 = 0 [set temp-fraction ( item (years-since) diesel-cost-list )
       / ( item (years-since) electric-cost-list
       + ( item (years-since) diesel-cost-list) ) ] ;set fraction of companies
           wanting an electric truck based on price ratios of semis and electrics

  set want-electric-fraction want-electric-fraction + ( temp-fraction - want-
     electric-fraction ) / 12 ;space out the increase in fraction of companies
  ;wanting an electric truck over 12 months

  let tot-coming-in floor ((num-trucks * ( item (years-since + 1) tot-production-
     list)
                     / (item (years-since) tot-production-list) - num-trucks) /
                         12) ;number of trucks coming in for the
                     month, scaled to the number of turtles

  let lower-electric-bound (1 - electric-variance) * tot-coming-in * want-electric
     -fraction
  let upper-electric-bound (1 + electric-variance) * tot-coming-in * want-electric
     -fraction

  let electric-coming-in floor (lower-electric-bound
     + random-float (upper-electric-bound - lower-electric-bound))

  create-electrics electric-coming-in [setxy random-xcor random-ycor

  set color 99 set dying-rate .9993 + random-float (.9964 - .9993)] ;new electric
     trucks set to light blue

  create-diesels (tot-coming-in - electric-coming-in)

  [setxy random-xcor random-ycor set color 19 set dying-rate .9909 + random-float
     (.9955 - .9909)] ;new diesel trucks
  set num-trucks num-trucks + tot-coming-in
  tick
end
```

B Netlogo Code for Part II

```
; 1 tick = 1 minute

; global variables used throughout the program
globals [
  cars-on-road ; tracking the number of trucks on the road

  init-distribution; initial distribution of truck density along the corridor
  ; distribution for each corridor
  init-TXLA
  init-MNCHC
  init-MAPA
  init-FLDC
  init-CACA

  driver-shiftup
  driver-shiftlow
]

; variables specific to each turtle
turtles-own [
  speed ; speed the truck is traveling at
  driver-shift ; the number of hours a truck driver is into his shift
  init-charge ; the initial charge of a truck
]

; variables specific to each patch
patches-own[
  car-deaths ; the number of vehicles that need a charging spot at its location
]

to setup
  clear-all

  setup-world
  ask patches [setup-road]
  ask turtles [set speed 1.2]
  set driver-shiftup 60 * 8
  set driver-shiftlow 0
  ask patches [set car-deaths 0]
  setup-cars

  reset-ticks
end

to setup-world ; set up the road and the grassy areas
```

```
  resize-world 0 80 -5 5

  ask patches[
     set pcolor green - random-float 0.5
  ]

  ask patches with [ abs pycor <= 2 ] [
    set pcolor grey - 2.5 + random-float 0.25
  ]

  set cars-on-road number-of-cars
end

to setup-road ; set up the aesthetic of a road (green surrounding, white inside)
  if pycor > 2 and pycor < -2 [set pcolor green]
  if pycor < 2 and pycor > -2 [ set pcolor white]
end

to setup-cars ; setting up the cars on the road
  if number-of-cars > world-width [
    user-message (word
      "There are too many cars for the amount of road. "
      "Please decrease the NUMBER-OF-CARS slider to below "
      (world-width + 1) " and press the SETUP button again. "
      "The setup has stopped.")
    stop
  ]
  set-default-shape turtles "car"

  let init-dist init-MNCHC ; for each corridor, we change to the specific
      distribution
  create-turtles number-of-cars [ ; placement of the trucks onto the road
    set color blue
    set heading 90
    set driver-shift driver-shiftlow + random-float 480
    set init-charge 0.9 + random-float 0.1
  ]
end

to go
  ask turtles[move-forward] ; each truck move forward a certain amount for each
      tick

  ask turtles [set driver-shift driver-shift + 0.01666] ; the amount a driver
      shift increases per minute
  ask turtles [set init-charge init-charge - 0.002] ;; how much charge is lost per
       minute
```

```
  ask turtles with [driver-shift >= 11 * 60] [ ; check when the driver shift is
      over and a rest spot/charging station is needed
    ask patch-here [set pcolor pcolor - 1]
    ask patch-here [set car-deaths car-deaths + 1]
    set driver-shift 0
  ]

  ask turtles with [init-charge <= 0.2] [ ; check when the charge has reached
      below the threshold and charging station is needed
    ask patch-here [set pcolor pcolor - 1]
    ask patch-here [set car-deaths car-deaths + 1]
    set init-charge 1
  ]

  set cars-on-road count turtles

  tick
end

to move-forward ; movement of the truck
  forward 0.25 ; value changes for each corridor since the miles of a patch
      changes
end

to make-scatterplot ; plotting charging spots needed against place on track
  ask patches [
    if pycor = 0 [
      plotxy pxcor car-deaths
    ]
  ]
end

to until-day ; run it for a thirty day period
  while [ticks < 60 * 30 * 25] [
    go
  ]
end
```