PREVIEW PAPER: EXCELLENT

This was one of the higher ranked papers that was examined during pre-triage. It likely will not compare well with the best papers, though, and you may see one or two papers that will have a higher score. The paper received mixed reviews. There were some deficiencies, and some parts of the paper that are good had some problematic aspects. On the whole, though, the overall paper is good, and the team earned some points in every category.

With respect to question 1, the variables that were used are briefly described but no written description is given afterwards that provide motivation or reasons for their use. The coefficients appear with little discussion and are based on a simulation that was also not well described. The presentation and organization of the first section is confusing. Overall, the presentation of their results in multiple formats was well received and made it easier to understand some of their results. Unfortunately, it was not consistent. For example, question 1 was difficult to follow in places, but question 3 was easier to follow.

The team produced a very good summary. The summary includes an overview of the problem as well as how the team approached the problem. On the downside, the final results were not adequately stated.

The overall quality of writing is not consistent. For example, section two is better written and easier to follow than the first section. The team did a good job of conveying a general sense of the direction of their results. A good description of the initial model is given, the team realized the potential problems, and then they made changes/updates. In doing so the team demonstrated a good sense of the process to evaluate and improve a model.

The way that the team incorporated multiple types and multiple power charging stations was well received. It was not clear, though, how the team determined the resulting distributions. On the plus side, though, they recognized that this is an important aspect of the problem.

The team included a good sensitivity analysis. Unfortunately, they looked at very large changes in their model rather than small changes, and it was not clear which parameters were changed.

One interesting part of their modeling was the use of an advanced model employing Shannon entropy. Unfortunately, they did not provide any citations nor any references. It was not clear where they got the idea from, but they did have a good discussion as to why this is an appropriate approach. They provided a good description of the approach. The pre-triage team struggled with how to reward the team, and they would have received higher marks with a few simple additions to their presentation.

Finally, one strength is that unlike many others, the teams did not use arbitrary weights in question 3. They went further than other teams that simply recognized that this was a problem. This team had the insight and ability to take steps to develop and then adjust their model.

Big Rigs Turnover from Diesel to Electric

Executive Summary

Environmental sustainability is one of the largest concerns in the 21st century. As consumerism continues to rise, humans must be mindful of their impact on the environment. Recent technological developments have improved the attractiveness of electric semi-trucks, and several leading companies have already pledged to improve their freight efficiency and reduce their environmental footprint by beginning to replace old and nonoperational diesel trucks with electric semi-trucks. We were tasked with creating mathematical models to predict the percentage of electrical semis 5, 10, and 20 years from 2020, to determine the number of charging stations and chargers to install along major trucking routes, and to identify a trucking corridor to develop depending on both social and technical factors.

We compared electrical trucks to diesel trucks to determine factors that would affect the replacement rate of nonoperational diesel with EV trucks, focusing on electricity costs, diesel prices, electric vehicle sales, carbon emissions, and vehicle prices to determine affordability and long-term economic and environmental benefits of purchasing an electric semi. By regressing data from the past two decades, we found predicted values for a multivariable linear regression program that allowed us to calculate the percentage of electric trucks in the next 5, 10, and 20 years from 2020 using registered electric vehicles as our dependent value with a python program.

In order to fully convert the trucking industry to electric trucks, it is essential that the necessary amount of infrastructure will be provided, especially in terms of electric charging stations. We created a model that will efficiently determine the amount of electric charging stations given any route with a given starting and ending destination. Our model takes into account a realistic prediction of the maximum number of miles an electric long haul truck would be able to drive in between charging stations derived from current data on electric cars. As well as the total number of stations, we created a model to specify how many Level 1, Level 2, and DC charging stations are necessary to support the current long haul trucking traffic. This gives accurate and detailed insight into a proposed plan on where to place electric charging stations, as well as how many of each type of chargers are necessary.

For part 3, we created a ranking system in order to decide which highway to develop first. In order to comprehensively evaluate each highway, we analyze three factors: viability, economic, adn environmental aspects associated with developing the highway. Moreover, we further divide the economic criteria into GDP, scale of the shipping industry, and the number of chargers needed along the road. In order to objectively assign weights to these various factors, we use the Entropy Weight Method, which uses the degree of differences between data to decide which metric is more important. As a result, we get that the highway from Boston to Harrisburg should be prioritized first.

Overall, using electric trucks are a future trend that has both drawbacks and opportunities.

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1 Introduction and Interpretation

Electric vehicles are on the rise daily. In fact, Tesla is about to release the first line of electric truck this year. There are many benefits and harms associated with this progress.

1.1 Restatement of the Problem

The problem we were tasked with asked us to do the following:

1. Create a mathematical model to predict what percentage of semi trucks will be electric 5, 10, and 20 years from 2020.
2. Create a mathematical model that determines how many stations are needed along a given route and how many chargers are sufficient at each station to ensure the current level of single-driver, long haul traffic would be supported if all trucks were electric.
3. Develop a mathematical model to rank trucking corridors to determine which should be targeted for development first.

2 Part I: Replacing Diesel with Electric Semitrucks

2.1 Assumptions

- Assumption: The number of EV trucks produced perfectly replace nonoperational diesel trucks every twelve years. This is given by the number of trucks produced.

  Justification: Every twelve years, long haul fleets sell their diesel trucks and replace them with new trucks.

- Assumption: It won't be possible to change a diesel fuel truck into an EV truck within the next 20 years.

  Justification: Currently, there is not enough research to develop the technology necessary to convert a diesel fuel truck into an electric truck. All EV trucks are new.

- Assumption: Only diesel and electric trucks will be used in our data.

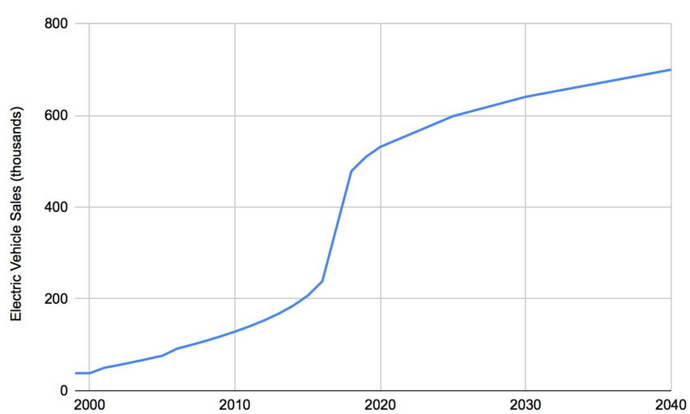
  Justification: There are not many options for truck energy sources, and these were the only types of trucks mentioned in the problem, so it was implied that we should focus on these two types.

2.2 Variables

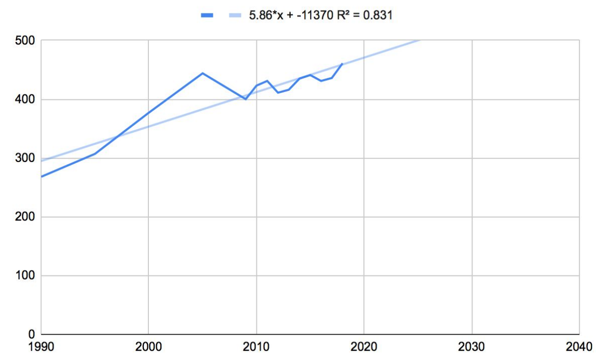
E	US electricity costs in cents per kilowatt hour	M	CO2 Emissions of Diesel in million metric tons
D	Diesel Cost in cents per gallon	S	Electric Vehicle Sales in thousands
C	Average Cost of one Class 8 Truck (dollars)	N	% of registered vehicles that are electric vehicles
P	Number of Class 8 Vehicles Produced	P_E	Number of Electric Class 8 Vehicles Produced

2.3 Model Description

Benefits of choosing an electric truck in comparison to a diesel truck were weighed. We considered five factors important when considering if an electrical vehicle would replace a diesel vehicle: electricity costs, the cost of diesel, electric vehicle sales, carbon emissions, class 8 truck prices. These factors summarized three important questions a consumer would consider before buying an electrical vehicle and included the growing rate of electrical trucks being purchased in the market. In comparison to a diesel truck, will an electrical one eventually be cheaper to buy? What about fuel price? Is the fuel price for an electrical semi-truck going to be cheaper than a diesel one? The last question was the least economically important yet the most environmentally significant. As the amount of carbon emission grows, what kind of impact do I make towards the environment?



Electric vehicle sales



Carbon emissions

In choosing our modeling decisions, we decided that there were far too many factors to consider when creating this model, therefore a few important factors were singled out. For example, we realized that when a consumer would try to examine the difference in the value of an electrical truck versus a diesel truck, they would have to consider variables such as age, mileage, fuel efficiency, weight capacity, fuel costs, and initial cost. We decided that fuel costs and initial costs outweighed the other factors with the reasoning that the the total cost of maintaining a truck was more significant to the factors that are used to calculate maximum income.

Age, mileage, and weight capacity determine how much products or objects a truck can carry as well as how much fuel it can save. Profit is represented as income - costs and therefore we reasoned that in order to maximize benefits, a consumer would first have to act to minimize the costs before preserving the benefit.

For each variable, in order to actually regress the charts and predict outcomes, we had to consider the real world rates of each variable. Would vehicle prices really increase exponentially? Would diesel prices increase at a near non-stop rate? These were important questions to ask ourselves when regressing the data points. Often the regression would create graphs that were unrealistic, and therefore we had to find a better function that would both satisfy the consistency of our points as well as the real world rate of increase.

Using data varying from at least 1990 to most 2020 in order to answer these questions, regression was applied to get functions and lines of best fit. These lines were used to predict future values in multivariable linear regression program, using the percentage of registered vehicles that are electric vehicles as our dependent value. Using python, we were given coefficients of:

[-0.10390077, 0.00041555, 0.00676561, -0.00172964, 0.00558544] which corresponded with:

[E, D, C, M, S]

and gave us a y-intercept of:

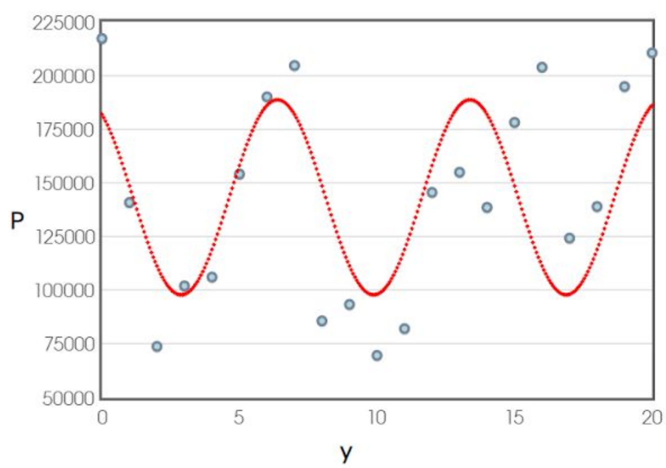
0.4658986249701645

resulting in the function:

$$N = -0.10390077E + 0.00041555D + 0.00676561C - 0.00172964M + 0.00558544S$$

Using this function, we were able to estimate N for 2025, 2030, and 2040.

Next, using the data provided on the number of Class 8 Vehicles produced from 1999-2019 and predicted future P values using the sinusoidal regression, where y was the number of years since 1999.



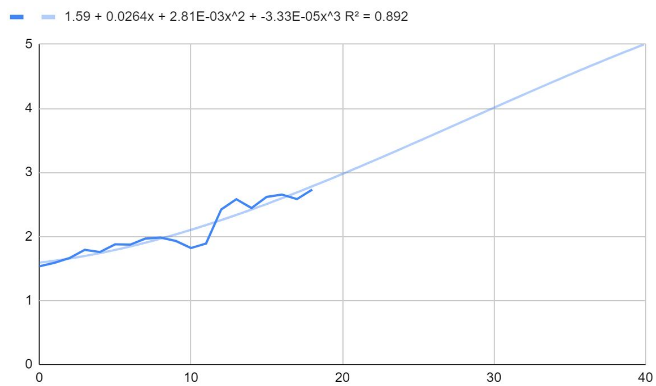
Regression Equation: $P = 45378.6849 \cdot \sin(0.8976Y + 2.1271) + 143293.1429$

R-squared: $r^2 = 0.4608$

Because electric vehicles that were bought less than 12 years ago (or after 2020) would be kept in use, we also determined the total number of electric trucks on the road each year, assuming that 2020 started with no electric trucks. Here, we used the integral

$$\int_{y-12\ (\textit{or } y-5 \textit{ in the case of } 2025 \textit{ and } y-10 \textit{ in the case of } 2030)}^{y} P\,dy$$

to determine P_T. To determine, $P_{E,}$ what percentage of Class 8 produced would be electric, we then used the formula, $P_T * N$. *F*ollowing this, we used a polynomial regression to determine the total number of trucks that would be on the road each year. Since this data gave us how many trucks, including trucks other than Class 8 trucks, were registered, we divided 1.7 million, which was the number of Class 8 trucks provided by the original data, and multiplied this number by the total number of trucks for each year, giving us T, the number of Class 8 Trucks.



Finally, to determine the percent of Class 8 Vehicles that were electric, we used the equation

$$P_E / T$$

Our final results are listed in the table below:

Year	N	p_T	P_E	T	A
2025	2.63175758	641972	16895	2051403	**0.824%**
2030	2.76319717	1400805	38707	2351965	**1.646%**
2040	3.74259956	1652389	61842	2914236	**2.212%**

2.4 Results and Interpretations

0.824% of semis will be electric 5 years from 2020, 1.646% will be electric 10 years from 2020, and 2.212% of semis will be electric 20 years from 2020.

2.5 Strength and Weaknesses

- Our model worked under the assumption that the factors we used for multivariable regression would change in the next 20 years, allowing the our predictions made with the model to be more accurate.
- In addition, if new or more accurate data is made available, our model is very flexible and can easily be changed to both accommodate changes made to data and to include additional factors.

- Our model did not truly model the complexity of decisions that a real world consumer would have to consider before buying. Some of the factors that we had ignored were important enough to have been included in a more advanced study with greater time. In addition to this issue, we did not always have ample data to work with. Some data did not include all years 1999 to 2020 as needed in order to increase the accuracy of our models.
- It would have been more accurate if we had searched online much more for greater statistics.

3 Part II: Infrastructure Along Major Trucking Routines

3.1 Assumptions

- Assumption: Electric charging stations operate 24 hours a day.
  Justification: Gas stations usually work 24 hours a day. Since electric vehicle charging stations have the same functions as gas stations, they should work all day as well.

- Assumption: The electric vehicles charge fully when stopping at a charge station.
  Justification: In order for a driver to minimize the amount of stops needed, and therefore time wasted on long trips, it makes sense that the truck would be fully, or almost fully charged at each charging station.

- Assumption: Every EV charging station has the same prices of charging.
  Justification: Currently the average cost of charging electric cars is very low ($0.1249 per kilowatt-hour)[8], so we can assume that the price difference between different electric charging stations would not be an important factor in a driver's decision to stop at a specific charging station. A driver has the same likelihood to stop at any EV charging station solely based on pricing.

- Assumption: Every truck driver would like to reach a charging station within 30 minutes.
  Justification: Even though a truck could travel 150-250 miles after one charge [7], one cannot expect a truck driver to only recharge once its fuel is completely depleted. If a driver misses one charging station along their route, they would still be able to recharge at the next station without the inconvenience of turning around.

3.2 Models and Results

Constants	**Meaning**	**Value**
R_{μ}	Average range of a vehicle (per charge)	200 miles
P_i	Power supplied by type of charger in the i^{th} row (in Watts)	[L1, L2, DC] = [13.2, 1.9,

		76]
d	Minimum distance between each charging station	30 miles
B	Battery capacity / How much charged before departure	325 kWh
Pref, L1	Preference for Level 1 Charging Stations	0.1
Pref, L2	Preference for Level 2 Charging Stations	0.3
Pref, L3	Preference for DC Charging Stations	0.6
T_i	Working duration of the charger in the i^{th} row (hours)	24 hours

All the data listed above is offered in the contest dataset, corridor data, or is explained below. We used two models to solve Part II, one to predict the number of charging stations and another to predict the number of chargers at each station.

3.2.1 Number of Charging Stations

Model Description

According to our assumptions, each truck driver would like to be within a 30 minutes radius with the nearest charging stations. We also know that the average speed (Spd) on an international highway is 60 mph, as we take the average of the maximum (65) and minimum (55) speed limit.[1] Therefore, the the distance between every charging stations is:

$$0.5\ hours \times \frac{60\ \ miles}{hour} = 30\ miles$$

Then, we use the formula:

$$N_c = \frac{Dj\ \ (miles)}{30\ \ (miles)}$$

to figure out how many charging stations are required for each highway.

[1] https://safety.fhwa.dot.gov/speedmgt/ref_mats/fhwasa16076/fhwasa16076.pdf

N_c is the number of charging stations for each of the 5 highways, represented as a vector;

D_j is the distances of the 5 different fiveways, represented as a vector. The distance vector D_j is included in the dataset given in the contest. [15]

Results and Interpretations

The final result for number of charging stations is

$$[San\ Antonia,\ Minneapolis,\ Boston,\ Jacksonville,\ Los\ Angeles] = [18, 14,\ 13,\ 24,\ 13]$$

This shows that highways with longer distances require more charging stations.

3.2.2 Number of Chargers per Station

The purpose of the second model is to determine how many chargers per station in order to ensure that all incoming traffic can be charged in a timely fashion. Based on a pre-existing model for predicting public electric vehicle charging stations [3] we found in our research, we modified the model to work specifically for efficient highway distribution of electric charging stations for each of the three types of electric charger types.

Using dimensional analysis, we derive the following formula to convert the AADTT [10] (truck traffic flow) into the number of cars that passes through each 30-miles interval. In other words, on the highway, C cars pass between two charging stations that are spaced 30 miles apart from each other. This is a vector.

$$C = \frac{AADTT \times 30}{24 \times Spd} = \frac{\frac{cars}{days} \times miles}{\frac{hours}{days} \times \frac{miles}{hours}}$$

C is calculated to be

$$\left[San\ Antonia,\ Minnepolis,\ Boston,\ Jacksonvillle,\ Los\ Angeles\right] = \left[\ 2495,\ 1401,\ 1631,\ 1269,\ 1940\ \right]$$

for each highway.

After that, we found the Demand matrix, which is the number of chargers for each of the three types for each highway.

$$D_{ij} = \frac{PW \times \ C_j \times Pref_{\ i}}{P_i \times T_i}.$$

D_{ij} is the demand matrix, with rows being the 3 types of chargers and columns being the 5 different highways.

PW is the consuming power of an individual truck driver between each charge.

$$PW = \frac{B}{R_{\mu}} \times 30\ miles$$

Using the values of B = 325 kwh and R_{μ} is 200 miles from the constant table above, we calculated that PW = 29 kWh. This PW value is constant for all highways and charging types, because we assume that every car will charge at every station. Therefore, the power consumed between charges is $\frac{B}{R_{\mu}}$ multiplied by the distance 30 miles.

C is the total number of drivers that are driving between 2 charging stations at any time.

$Pref_i$ is percentage that Electric Vehicle driver prefers to charge on the i^{th} type of charger.

P is the output power (watts) of the i^{th} type charger, and T is the duration of i^{th} type of charger.

In order to find Pref, L2 and Pref, L3 we determined the efficiency of each type of charging and time spent for charging that would influence a driver's preference of charging station. DC charging stations are the most efficient at charging based on data for normal cars, charging at 72kW--1MW, followed by Level 2 charging 7.2--19.2kW and lastly Level 1 chargers at 1.9kW. This data is given by the battery data in the challenge. [14]

From this information we know that DC charges are the most time-efficient and preferred for short stops between long distances, like single-driver, long haul trips. Though DC charges are the most efficient, they can be much more expensive. During the last 20% of charging the rate of charge power between DC and Level 2 are similar, making Level 2 the most cost-efficient for the last portion of charging. [4] From this reasoning we assigned each station a percentage-- 0.6 to Pref, L3. 0.3 to Level 2, and Level 1 at 0.1-- that adds up to equal the total of 1.

Results and Interpretations

Below is our demand matrix, D_{ij}

Route	**Level 1 Chargers per**	**Level 2 Chargers per**	**DC Chargers per Station**	**Total Charging**

	Station	Station		Stations
San Antonio, TX, to/from New Orleans, LA	22	9	3	34
Minneapolis, MN, to/from Chicago, IL	13	6	2	21
Boston, MA, to/from Harrisburg, PA	16	7	2	25
Jacksonville, FL, to/from Washington, DC	12	5	2	19
Los Angeles, CA, to/from San Francisco, CA	19	8	3	30

The results of our established model describe how many charging stations are needed along the entire route with the main assumption that there should be 30 miles in between each station. We used a formula to model the total number of chargers needed along an entire route as well as another formula based off the results we got combined with the appropriate constants for each factor into how many of each type of charger we would need at each station. The resulting table gives us the direct amount of Level 1, Level 2, and DC (Level 3) chargers needed to support the current amount of trucks if they all were electric.

3.4 Sensitivity Analysis

This table shows the sensitivity analysis based on a percent change to an independent variable, the distance between charging stations.

Constant	% Change in Constant	Route	$\Delta L1$ (%)	$\Delta L2$ (%)	ΔDC (%)	$\Delta total$ (%)
Distance between stations	-50%	San Antonio	-50%	-50%	-55.56%	-60.79%
		Minneapolis	-50%	-53.85%	-50%	-49.50%

		Boston	-50%	-50%	-42.86%	-42.74%
		Jacksonville	-48.93%	-50%	-60%	-54.70%
		Los Angeles	-47.39%	-47.37%	-50%	-35.84%

A decrease in distance by half resulted in 50% of the total number of charging stations needed along the entire route, as well as at each station because the number of vehicles passing through half the total distance would also be 50%. Therefore, we can see that a change in the constant of charging stations significantly impacts the change in the number of charging stations.

3.5 Strength and Weaknesses

Our model is strong in that it returns a detailed output with projections for each type of charger. The model takes into account the minimum number of miles most electric long haul trucks would be able to drive off of one charge, so the range difference between electric trucks would not create issues for trucks with lower ranges. Also, since the number of miles between each charging station is an essential value of our model, it is easy to modify the chart based on future research that would yield more accurate data than the estimations we have on hand. The sensitivity analysis conveys how a change in percentage of independent variables will change the results based on predictable trends.

The weaknesses of this model includes the fact that the results depend heavily on factors with little research available or that vary heavily, such as the projected average amount of hours an electric long haul truck would be able to run, and the total amount of trucks on a specified route. Also, unpredictable events such as major traffic jams could not be predicted by our model. Furthermore, our data also does not account for population density in specific areas which could lead to an increased demand for more electric charging stations on a specific part of a route.

4 Part III : Development of Trucking Corridors

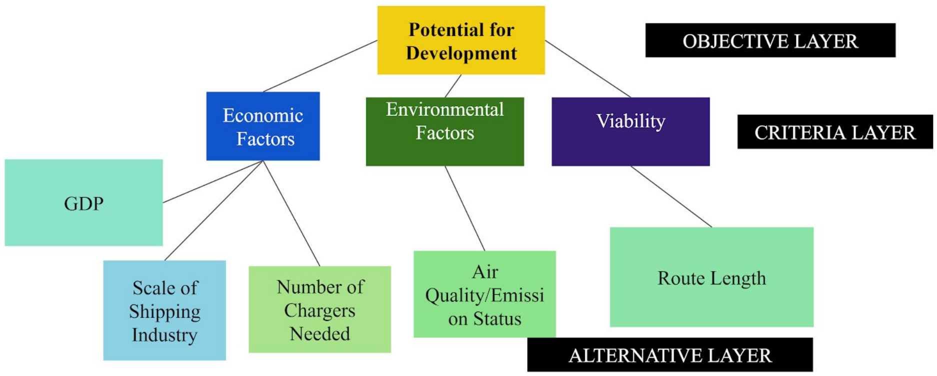
4.1 Assumptions

Assumption: Economic and environmental factors associated with a highway that spans over several states can be determined by averaging the values of the factors across the states.

Justification: Since the main users of a highway comes from residents in the states covered by the highway, the development of highways would impact the states' residents the most. Therefore, we can use data about the states' population in our model.

4.2 Model Description

We are asked to create a ranking system to decide which highway we should first start developing charging stations for electric trucks. Making this impactful decision requires a comprehensive approach. We need to consider the economic factors, environmental factors, as well as the viability associated with making developments.



Moreover, we further divide economy, environment, and viability into smaller factors. Under the economic criteria, we consider the GDP of the states. Since switching from normal to electric vehicles takes operational costs and electric vehicles are more expensive than normal ones, states with higher GDP are more likely to afford such change. Therefore, if a state has higher GDP, we should focus on their development more. Another factor under economics is the scale of the shipping industry. A state with a massive shipping industry should be prioritized for development because it will impact more vehicles.

GDP and industry data is obtained through statista.com. Under the environmental factors, we consider the air quality situation of individual states. A state with poorer air quality, data for which was obtained from AirNow.gov, should be prioritized for improvements because they desperately need environmental changes. Last, but not least, we used route length to quantify the viability of the developments, data for which was obtained from Google Maps. A corridor that is shorter in length is easier to be developed and should therefore be prioritized.

After collecting data for each of the metric, we need to assign weightings to each factor. We decided to use the Entropy Weight Method, which weights factors objectively. Shannon defined the entropy of distribution as:

$$E\left(p_1, p_2, p_3, \ldots p_n\right) = -h\sum_{i=1}^{n} \ln\left(p_i\right) \times p_i$$

According to this formula, when $p_i = \frac{1}{n}$, $\ln(p_i)$ is the largest, and E will take its maximum value. This shows that as the probability distribution becomes uniform, the outcome of the variable is random, and thereby, the Entropy value becomes the largest. Entropy is very useful when deciding the weights of multiple factors that contribute to an objective. Based on the degree of randomness, a weight is assigned for each factor with the following set of steps: First, with m targets and n factors to weight, a decision matrix is created, in which a_{ij} represents the performance of the i^{th} target in the j^{th} criteria:

$$D = a_{ij}(m \times n) = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix}$$

Then, a probability distribution, p_{ij} is calculated, and a p_{ij} probability distribution matrix is constructed. p_{ij} is calculated through dividing the element in the above matrix by the sum of all the elements in the same column, as illustrated below:

$$P = \begin{bmatrix} p_{11} & \cdots & p_{1n} \\ \vdots & \ddots & \vdots \\ p_{m1} & \cdots & p_{mn} \end{bmatrix} where\ p_{ij} = \frac{a_{ij}}{\sum_{i=1}^{m} p_{ij}},\ \forall\, i,\, j$$

Using the definition of entropy as mentioned above, E_j can be calculated for all n decision criteria, where E_j represents the objective weight of the j^{th} criteria

$$E_j = -h \sum_{i=1}^{m} \ln\left(p_i\right) \times p_i,\ \forall j$$

h is a constant, defined as:

$$h = \frac{1}{\ln(m)}$$

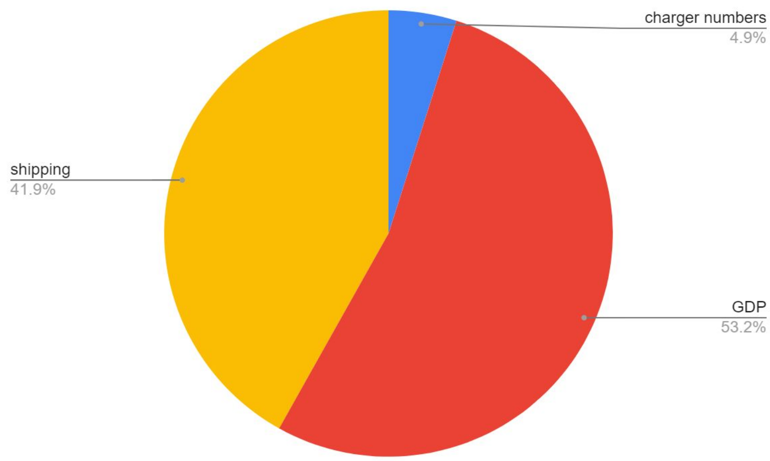
With E_j, we can calculate the degree of diversification, d_j for each criteria. This measure the randomness of information within the j^{th} criteria, as defined below:

$$d_j = 1 - E_j,\ \forall j$$

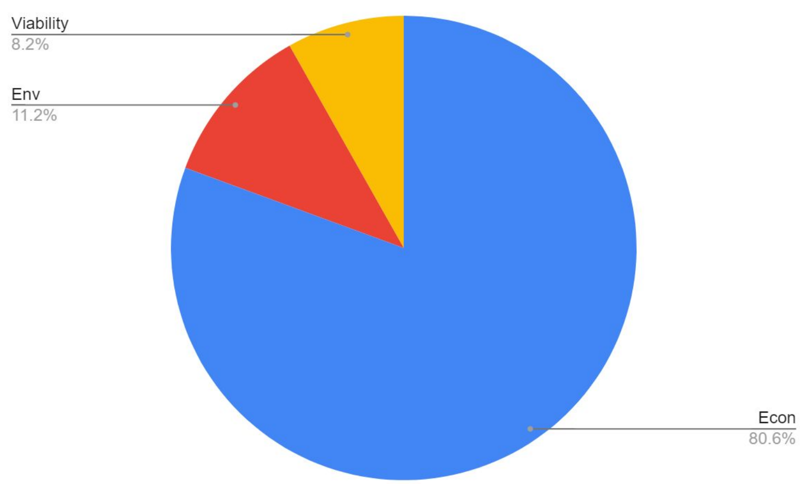
A target that has similar values with little spontaneity has a low degree of diversification and has a less weight, according to the principle of entropy weight method. Finally, the weight, w_j of a criteria is calculated as below:

$$w_j = \frac{d_{ij}}{\sum_{i=1}^{n} d_{ij}},\ \forall j$$

The entropy weight method is applicable to our model, because if a certain factor has a large degree of randomness, it contributes more to our evaluation of the potential for development. Through entropy weight method, as described above, we are able to calculate the weights of the three sub-factors within the economic category:

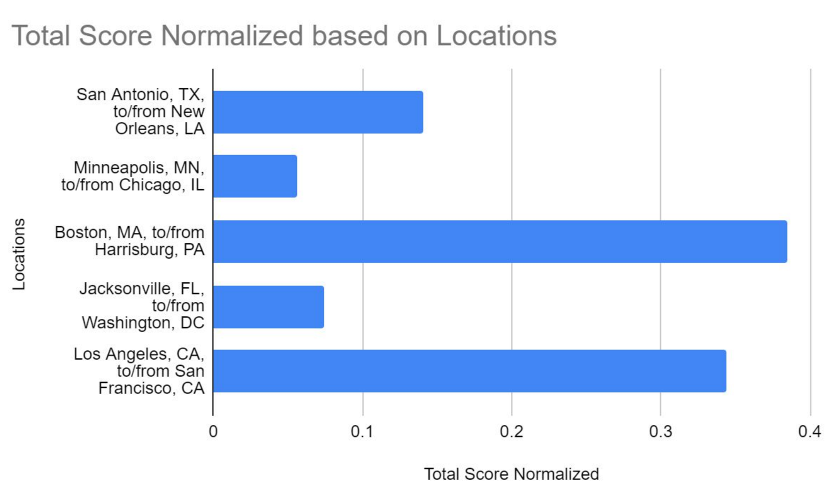


With the same approach, we were able to calculate the weightings of the factors on the criteria layer:



4.3 Results and Interpretations

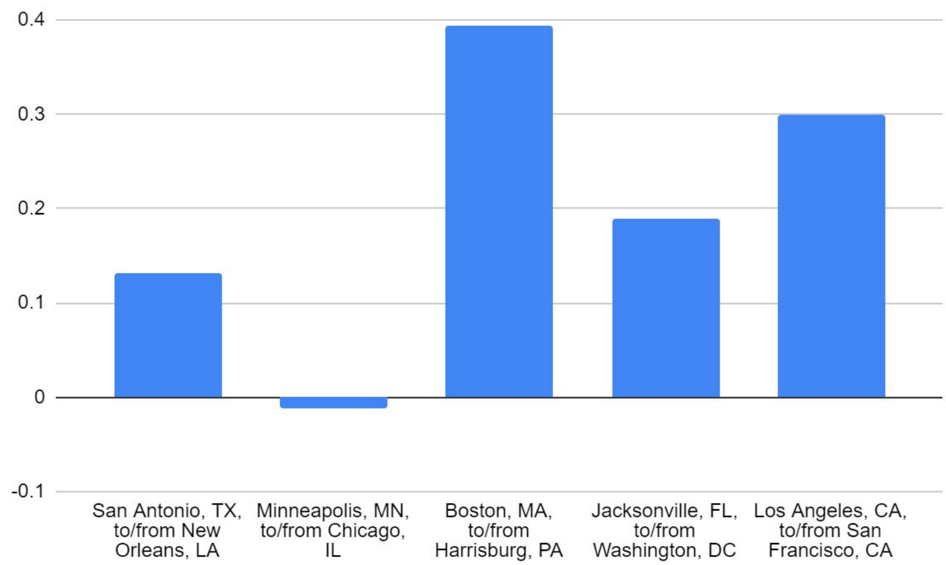
With the weightings calculated above, we multiply the weightings by the data for each criteria to generate a final score for each highway. If the final score is higher, then the highway should be prioritized for development. The scores for the five highways are shown below:



Therefore, we can conclude that Boston to Harrisburg should be prioritized for development, because it has a large shipping industry, which means developing this highway will result in many normal trucks being replaced by diesel ones. This highway also has a route length of only 390 miles, the shortest of all five highways, which means the development would be relatively easily implemented.

4.4 Sensitivity Analysis

The results of our ranking would change if we alter the weights of the different factors. For example, if we decided that economic, environment, and viability are deemed equally important by the decision maker, meaning that the weight vector is [economic, environment, viability] = [0.33, 0.33, 0.33], we would have a different result. The final score in this scenario is as follows:



When comparing with the actual weightings from entropy model, we see that Jacksonville and San Antonio highways switch places. Since the decision maker can either use subjective or objective ways to change the weightings of each factor, the ranking results would vary.

4.5 Strength and weaknesses

The advantage of the model is that it is a comprehensive model that takes into account both economic, environmental, and viability factors. Because developing a high way to be suitable for electric truck is a significant decision that impacts many aspects of society, such a well-rounded model represents the complex nature of the policy. Moreover, the usage of entropy weight method is valid because it is not based on subjective senses but rather based on objective data.

The weakness of our model is that there are even more factors that can be incorporated into our ranking system. For example, we can think about the population in the states of the highway or the cost of diesel in each state under the economic criteria. Including more diverse factors and even adding more layers to the ranking system would improve its accuracy.

5 Conclusion

Our first model used a multivariable linear regression program using python to predict the percentage of electric trucks in future years by regressing data related to carbon emissions, vehicle sales, vehicle and diesel prices, and electricity costs from the past two decades. According to our model, the percentage of electric semis will be 0.824% in 2025, 1.646% in 2030, and 2.212% in 2040.

For our second model, we first decided how many charging stations we needed, assuming that drivers need a station every 30 minutes, then used an established research model in order to find the number of chargers for each type at each station.

In our third and final model, we used the entropy weight method to quantify the different factors associated with the development of the highway. After looking at the economic, environment, and viability of the development process, we obtained a final score for each highway. The highway from Boston has the highest score and the one from Minneapolis has the lowest score.

Overall, we can not deny that replacing diesel trucks with electric cars is a positive step for humans. Even though this decision will require the installation of new charging stations and large operations cost, we can still look forward to a more environmentally-friendly future.

6 References

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7 Appendix

```
import pandas as pd
import numpy as np

def entropy(data):
        table = data.copy()
        for col in table.columns:
        table[col] = table[col]/sum(table[col])
        for col in table.columns:
        table[col] = table[col]*np.log(table[col])
        sums = []
        for cols in table.columns:
        sums.append(sum(table[cols]))
        sums = [sums]
        weights = pd.DataFrame(sums, columns=table.columns, index=['Weights'])
        h = 1/np.log(len(table.index))
        for col in weights.columns:
        weights[col] = weights[col] * -1 * h
        s = 0
        for col in weights.columns:
        for val in weights[col]:
        s += 1 - val
        for col in weights.columns:
        weights[col] = (1 - weights[col])/s
        return weights
```