**Estimating the Energy and Emissions Impacts of a Commuter Rail System in North Carolina**

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# 1. Introduction

## 1.1 Background

The United States stands as a significant contributor to global greenhouse gas (GHG) emissions, accounting for 11.2% of the global total in 2022, following China (European Commission, 2023). It is worth noting that the transportation sector has been one of the largest GHG emitters (~29% of total emissions) in the United States, with more than 80% coming from passenger vehicles and trucks on the road. Projected demographic trends exacerbate the situation; as per forecasts by GoTriangle, a regional transit authority in North Carolina, the Triangle region is anticipated to welcome over one million new inhabitants by 2050, potentially leading to a substantial increase in vehicular presence on the roads (Duncan, 2023). In light of the escalating challenges posed by climate change, it becomes imperative to prioritize the mitigation of emissions originating from the transportation sector in the United States.

Advocating the utilization of public transit systems emerges as a compelling strategy to reduce GHG emissions, primarily due to the typically lower per-passenger emissions compared to private vehicles. Additionally, this approach offers dual benefits: enhancing energy efficiency and alleviating traffic congestion. Nevertheless, private automobiles are still a very common mode of transportation in North Carolina. According to statistics, 85.9% of people commute by private car (Gomes, 2022). The remaining residents rely mainly on public transportation. The Triangle's transportation infrastructure does offer alternatives to private vehicle commuting, with services provided by various agencies like GoTriangle, which is responsible for regional bus services, and plans for future transit expansions. Specific to each city, each location is gradually expanding their respective public transportation service. For example, according to GoTriangle fiscal year 2023 Annual Report, four Bus Rapid Transit corridors are being developed by Wake County's Transit Plan. This can help Wake County better streamline traffic and shorten people's time on the road. In addition, GoTriangle and GoDurham will continue to use funds from the Durham County Transportation Plan to provide people with faster and more convenient buses through 2023, especially projects like transit emphasis corridors, bus speed and reliability projects and more (GoTriangle, 2023). However, the challenges posed by growing population are ongoing. Together, Wake, Durham, Orange, and Johnston counties will experience an annual increase of over 32,000 residents, leading to congested roads and continuously extending commuting times (GoForward, 2023). In order to manage the rapid population growth and urban expansion in the Triangle region of North Carolina, the entire region still needs a robust regional transportation network to meet the challenges of high-speed growth to provide transportation options and ensure regional mobility (GoTriangle et al., 2022).

In North Carolina, the intercity passenger rail has gained prominence as a key mode of public transportation, driven by factors such as urban expansion and population growth. Passenger rail service is available in 16 cities across North Carolina currently. Several major lines include Piedmont, Carolinian, etc. They run through major North Carolina cities, including Raleigh, Cary, Durham, Burlington, Greensboro, High Point, Salisbury, Kannapolis, Charlotte, and so on (Mooneyham, 2023). Notably, the NC By Train service witnessed over 522,000 rail passengers in 2022, operating four daily round trips between Raleigh and Charlotte and extending services to the Northeast (NCDOT, 2023). This figure not only sets a new annual ridership record in the service's 32-year history but also underscores the escalating demand and the parallel need for increased investment in passenger rail infrastructure in North Carolina (NCDOT, 2023).

Besides the intercity passenger rail services, the proposed commuter rail services in the Greater Triangle region during past decades can provide a quick and reliable commuting option. Commuter Rail offers residents greater opportunities to access nearby urban areas due to its numerous stops and higher operating frequency. As a result, compared to intercity passenger rail, it is more effective in reducing the pressures associated with population growth and peak-hour commuting. It can help NC residents stay away from the frustration of gridlock traffic and ensure a smoother way to work. Also, the commuter rail increases accessibility and opportunities by enhancing connectivity. It facilitates residents' travel and improves their quality of life. In the end, the proposed commuter rail can serve as an economic development driver that improves investments in communities and attracts new businesses in the future. According to a survey conducted by GoTriangle in early 2023, business leaders and residents in the Triangle area have shown strong support for a proposed commuter rail project in the region (GoForward, 2023). With strategic planning, sufficient funding, and community support, the expansion of public transit systems can serve as a cornerstone in the transition towards a more sustainable and equitable transportation future, offering a practical solution to some of the most pressing environmental and urban challenges of our time.

## 1.2 Motivation

While the adoption of rail transport is often touted for its potential to lower transportation emissions on a per-passenger basis, this advantage is not inherently guaranteed. This complex interplay is underscored by a paper of Accelerating Decarbonization of the U.S. Energy System (Energy & Systems, 2021), which emphasizes that rail systems to net a positive impact on emission reductions, they must operate at ridership levels that effectively offset the energy and emissions associated with their infrastructure and operations. Furthermore, the extensive investments required for the development and expansion of rail infrastructure, along with its consequential impact on land use, present significant considerations in the pursuit of maximizing public good through transportation projects. Therefore, a multifaceted approach is essential to navigate these challenges, and the integration of rail systems into broader urban planning and development strategies is crucial for leveraging these investments to facilitate not only improved mobility but also economic development, environmental conservation, and social equity.

## 1.3 Area of Interest

To support NC government officials, transportation agencies, and environmental regulatory bodies in strategic planning about commuter rail projects, we aimed to assess how varying operation and technology scenarios – such as different train schedule, ridership, and fuel types – can affect the energy and emission impact of this commuter rail project. Our analysis focuses on the recently proposed **Greater Triangle Commuter Rail (GTCR)** project. GTCR is a commuter rail route in the current transit blueprints of Wake County and Durham County which plans to utilize “H-Line” owned and managed by North Carolina Railroad Company (NCRR), sharing the corridor with the existing freight and intercity passenger rail service (i.e., two Amtrak trains, Piedmont and Carolinian) (RSG, 2022).

Starting 2019, a series of GTCR studies (e.g., stations, schedules, ridership, infrastructure) have been led by GoTriangle in partnership with CAMPO[[1]](#footnote-2), DCHC[[2]](#footnote-3), NCDOT[[3]](#footnote-4), NCRR, and Durham, Wake, and Johnston County (GoTriangle et al., 2022). To decide the implementation stages, in early 2023, GoTriangle has initiated a “public feedback campaign” featuring online surveys, community gatherings, and public forums in Durham, Cary, Raleigh, and Clayton – communities traversed by the proposed GTCR. The entire project would take 10 to 12.5 years to complete (i.e., starting in service during 2033 - 2035) (GoTriangle et al., 2022).

According to the latest Phase II feasibility study report published in December 2022, this 37-mile corridor (**Figure 1**) has 14 possible stations linking West Durham and Auburn, with potential expansion towards Clayton to the east, providing 12,000 to 18,000 daily trips (GoForward, 2023). The stations (from west to east) we considered in this study include West Durham, Downtown Durham, East Durham, Ellis Road, Research Triangle Park, Morrisville, Downtown Cary, Corporate Center Drive, Blue Ridge Road, North Carolina State University, Downtown Raleigh, Hammond Road, Garner, and Auburn. Clayton was excluded from the analysis because the GTCR station in the region is still under consideration and thus limited information was available at the time.

A map of a city

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**Figure 1. Route map of the proposed Greater Triangle Commuter Rail.**

*The proposed stations from west to east are West Durham, Downtown Durham, East Durham, Ellis Road, Research Triangle Park, Morrisville, Downtown Cary, Corporate Center Drive, Blue Ridge Road, North Carolina State University, Downtown Raleigh, Hammond Road, Garner, Auburn, and East Clayton (Go Forward, 2023).*

To provide the aforementioned stakeholders with precise and actionable insights, we have developed a detailed **spreadsheet model** to quantify the **energy consumption** and **GHG emissions** (carbon dioxide equivalent/CO2-eq) **of the GTCR service**. This tool is designed to offer quick and accurate estimates of the environmental impacts associated with various operational configurations of the GTCR. It enables local government officials, state transportation authorities, and environmental regulatory agencies tasked with urban planning, transportation development, and emission control to make informed decisions. Although the current model only includes one commuter rail service, its framework and database are designed to be easily adaptable to other routes or transportation projects. This scalability and adaptability aids in the formulation of policies and strategies that balance the need for efficient transportation with environmental preservation objectives.

# 2. Methods

## 2.1 Literature Review

To identify and analyze critical technologies, services, and modeling approaches for estimating rail emissions, we examined the official reports from governmental and business sources, reputable news outlets, and academic literature focusing on locomotive technologies, fuel types, route service strategies, and existing rail models. We also explored various methodologies for quantifying energy consumption and GHGs, alongside criteria air pollutants emissions, originating from rail operations.

One of the foundational elements of our review was an analysis of existing emission estimation models tailored to rail transportation. The summary table of existing models we examined is in Appendix 1. These models varied significantly across several dimensions, including their geographical focus, rail type coverage (e.g., high-speed, intercity, commuter), fuel types considered, the life cycle of fuel (well-to-tank/WTT, and tank-to-wheels/TTW), the flexibility for user-defined inputs versus reliance on default values, and the types of emission quantified (e.g., CO2, CH4, N2O, CO, NOX, PM). This comparative analysis of existing models allowed us to understand the diverse parameters and assumptions underpinning energy and emission estimations in rail systems, providing insights about how our model can fit into the larger ecosystem of rail modeling. In addition, we closely examined a review paper by Arne Heinold (2020), “Comparing emission estimation models for rail freight transportation,” and identified the model framework to adopt in our model, i.e., the microscopic model – Assessment and Reliability of Transport Emission Models and Inventory Systems (ARTEMIS), one of the early seminal model for transportation emission estimation.

## 2.2 Overview of the Microscopic Model for the Emission Estimation

Table . Notation of Trip and Train Parameters

|  |  |  |
| --- | --- | --- |
| **Parameter** | **Description** | **Unit** |
|  | Fuel weight | kg |
| u | Energy density | MMBtu/kg |
|  | Emission coefficient | kg·CO2e/MMBtu |
|  | The anticipated energy necessary for propelling the vehicle along a given distance | J |
|  | The heating value of the fuel | MJ/kg |
|  | The force needed to propel the train. The underscore represents the type of resistances. | Newton |
|  | Distance | m or km |
|  | Altitude difference | m |
|  | Locomotive weight | kg or ton |
|  | Car weight | kg or ton |
|  | Total weight | kg or ton |
|  | Speed | m/s or km/h |
|  | Train specific aerodynamic coefficient | - |
|  | Train specific rolling coefficient | - |
|  | Air density (assumed 1.25 kg/m3) | kg/m3 |
|  | Locomotive frontal area | m2 |
|  | Gravitational acceleration (assumed 9.8 m/s2) | m/s2 |
|  | Locomotive specific air resistance coefficient |  |
|  | Car specific air resistance coefficient | - |
|  | Locomotive specific rolling resistance coefficient | - |
|  | Car specific rolling resistance coefficient | - |
|  | Number of cars | - |
|  | Locomotive efficiency rate | - |
|  | Rate of fuel flow | kg/s |
|  | The lower heating value of the diesel (assumed 42700 kJ/kg) | kJ/kg |

To initiate the development of our microscopic models, we adopt a foundational consumption-based approach. We denote the amount of fossil fuel consumed by a vehicle during a transportation process as . The emissions of GHG associated with this consumption are determined by multiplying by the corresponding energy density and emission coefficient . This coefficient represents the amount of CO2 equivalent emitted from burning one unit of fuel. To unify the unit of measuring diesel and hydrogen, we use kilogram as the measurement unit. GHG emissions are subsequently calculated by:

|  |  |
| --- | --- |
|  | (1) |

The fuel consumed is unknown since we do not possess the empirical data. Thus, we estimate the fuel consumption by estimating the energy consumption:

|  |  |
| --- | --- |
|  | (2) |

Here, represents the anticipated total energy necessary for propelling the vehicle along its designated route. To account for the energy loss in the process of converting fuel’s chemical energy to vehicle’s kinetic energy, we use coefficient as the efficiency of both the combustion engine () and the powertrain (). As demonstrated later in this section, the estimation of can be derived from the vehicle's physical attributes, route characteristics, and anticipated driving speed. Combining Equation (1) and (2), the GHG emissions can be calculated by

|  |  |
| --- | --- |
|  | (3) |

Given that , , and are essentially parameters, whether physical or manufacture constants, the primary challenge associated with applying the Equation (3) revolves around determining . This kinetic energy component can be computed using the fundamental physics principles. Specifically, is derived by evaluating the power necessary to move the train, counteracting the four primary forces encountered during motion: (i) rolling resistance, (ii) air drag, (iii) grade, and (iv) inertia. In our calculations of these energy demands, we largely adhere to the methodologies outlined by Lindgreen and Sorenson (2005).

|  |  |
| --- | --- |
|  | (4) |

To overcome air resistance, the required power is calculated by

|  |  |
| --- | --- |
|  | (5) |

where is the drag coefficient, is the air density (typically ) and is the area of the vehicle’s front surface. The power that is required to overcome rolling resistance is calculated by

|  |  |
| --- | --- |
|  | (6) |

where denotes the rolling resistance coefficient, is the gravitational acceleration (i.e. ), is the vehicle’s total weight, and is the speed. To overcome the grade, power is computed by

|  |  |
| --- | --- |
|  | (7) |

where is the elevation difference between the given horizontal distance, , making the last term the slope of the segment. Applying Newton’s 2nd law, the last resistance, is the acceleration force that is required for increasing the train speed in a given time, which is computed by

|  |  |
| --- | --- |
|  | (8) |

Regarding the coefficient in the air and rolling resistance, the air resistance of trains depends not only on the front surface of the locomotive but also on the number and the surface of the attached railcars. In general, air resistance increases with increasing train length (Lindgreen & Sorenson, 2005). Thus, the for a train is:

|  |  |
| --- | --- |
|  | (9) |

where is the number of railcars attached to the train. The rolling resistance encountered by trains also escalates with the quantity of wheels present on a train. Lindgreen and Sorenson (2005) offer the subsequent formula for determining it.

|  |  |
| --- | --- |
|  | (10) |

After we obtain all the resistances above, we can simulate the energy required for every single segment with

|  |  |
| --- | --- |
|  | (11) |

This is feasible because we have detailed route characteristics that can be measured with a granularity of 50 feet (15.24 meters). The energy estimated by the Equation (11) for moving the train is then aggregated as Equation (4).

Then, we can plug the energy value in the Equation (2) together with the total efficiency rate, , of the locomotive to estimate the CO2 equivalent emissions of a trip. The efficiency rate is differed by locomotives, considering various compositions such as the transmission, the engine, and the gearing, respectively. In this study, we use the value simulated by Lindgreen and Sorenson (2005), who has validated their result with existing empirical diesel train data in Denmark, as a constant input. The rate for each component of the locomotive could be calculated with

|  |  |
| --- | --- |
|  | (12) |
|  |  |

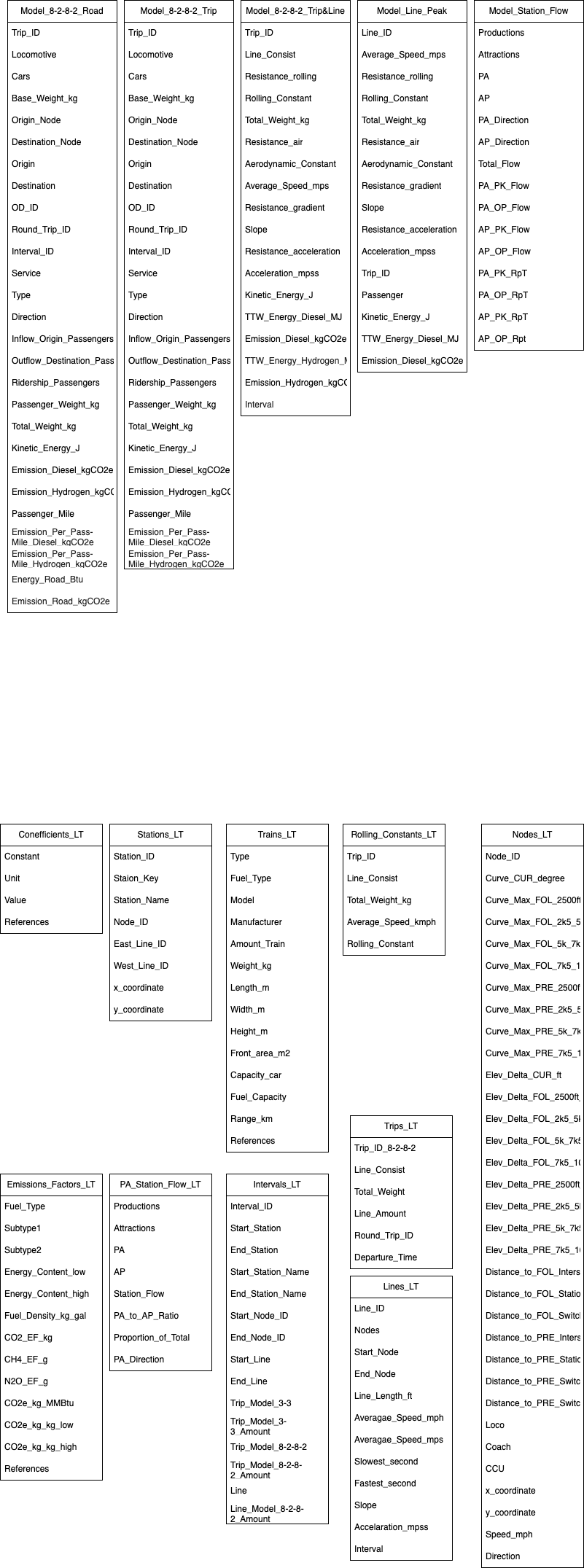
, where is the rate of fuel flow and LHV is the lower heating value of the diesel (assumed 42700 kJ/kg). Combine the value we get from Equation (10) and (11), we get the tank-to-wheel energy needed for the whole trip with

|  |  |
| --- | --- |
|  | (13) |

Since diesel energy is typically measured in megajoules, we multiply the energy by the conversion factor 10-6 MJ per J. With the , we can calculate the GHG emissions with the Equation (1) and (2) eventually.

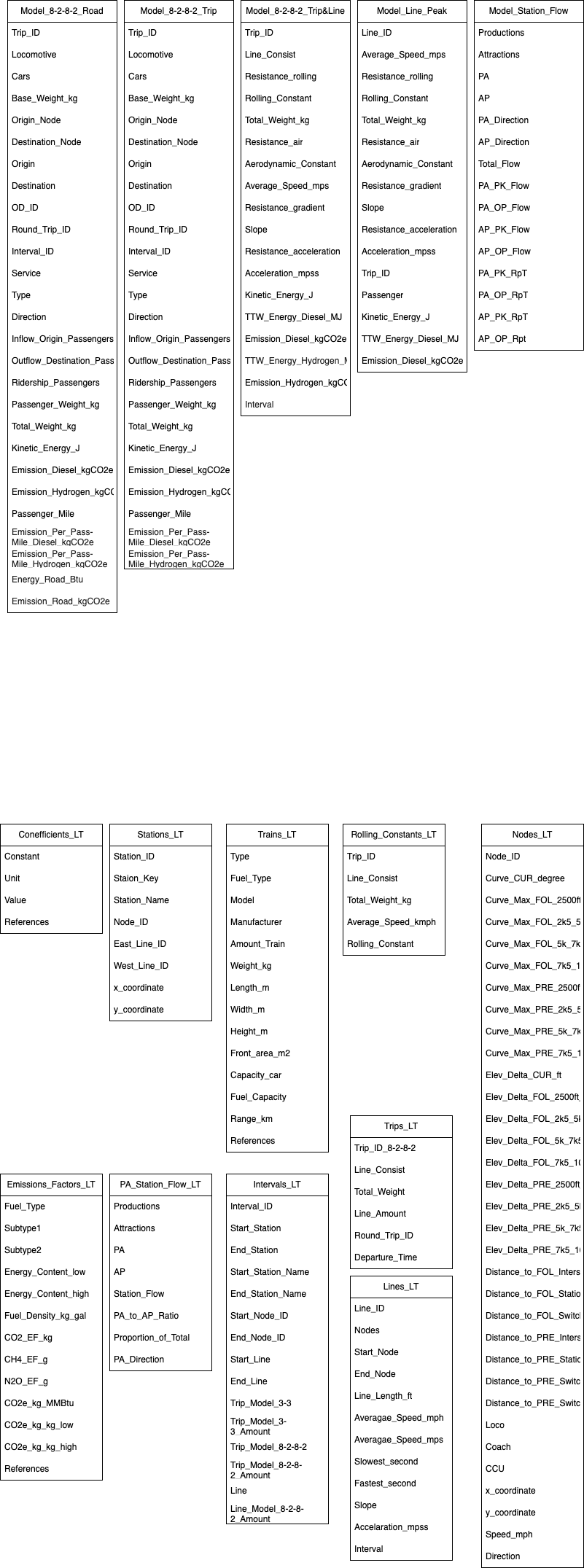
## 2.3 Data Collection and Compilation

To build the microscopic model, we further break down the route to **line segments** separated by fixed distance, 50 feet. The speed and elevation change will be given to each node and line at this granularity. The weight of the train, on the other hand, is the function of ridership and fuel. Thus, we create another dataset recording the ridership estimation for every single **trip** between the adjacent stations. After we have the sheets for the geographic and the societal feature of the service, we model the emission from a line, a trip, then a day. The whole picture of the model sheets and variables are shown in **Figure 2** and **Figure 3**.



**Figure 2. The necessary modeling components for the microscopic emission model.**

Plotted by the authors.



**Figure 3. The necessary lookup tables for the microscopic emission model.**

Plotted by the authors.

### 2.3.1 Train data

The analysis of commuter rail infrastructure is primarily informed by data from the "Greater Triangle Commuter Rail Feasibility Study: Phase II Summary Report" (GoTriangle et al., 2022). This study reveals that the proposed service has nine trainsets, each equipped with four coach cars, totaling thirty-six coaches across the system. For now, both diesel locomotives and Diesel Multiple Units (DMU) have been considered. Different from diesel locomotives, DMUs do not require a separate locomotive. A Diesel Multiple Unit (DMU) is a train set with two to four cars, powered by diesel engines located in the first or last cars, with the middle cars unpowered (*Diesel Multiple Unit*, 2024). Back to the "Greater Triangle Commuter Rail Feasibility Study: Phase II Summary Report", each transit is designed to offer a seating capacity of 600, and each transit includes one locomotive and four coach cars. Cumulatively, this configuration results in a system-wide seating capacity of 5400 (GoTriangle et al., 2022).

Additional data relevant to our study were sourced from external research and comparative analysis. According to the “Simulation of Energy Consumption and Emissions from Rail Traffic”, the efficiency rate for diesel locomotives and electrical locomotives are 0.35 and 0.65 respectively (Lindgreen & Sorenson, 2005). To address gaps in our dataset for the GTCR, we drew parallels with the Coaster commuter rail service in San Diego County, California. Based on what we found so far, missing data includes weight of the coach and maximum capacity of the railcar. The Coaster's route has a very similar length to the GTCR, with both services covering shorter commuter distances. BiLevel Commuter Rail Cars are currently used on this line, recognized as the lightest and most economically beneficial option in North America (Sklar, 2020). At the same time, this rail car is also being updated in a timely manner and has great potential to become a suitable and efficient model. Therefore, we assume that the proposed service will also use this car type.

Following consultations with GoTriangle, the organization has indicated its interest in acquiring the new Siemens Chargers, specifically the ALC 42 Charger model. Consequently, for the purposes of this analysis, it is presumed that the locomotive under consideration is the Siemens ALC 42 Charger. This model has a mass of 127.006 metric tons, with dimensions measuring 21.79 meters (71.5 feet) in length, 3.05 meters (10 feet) in width, and 4.5 meters (14.7 feet) in height (Siemens Mobility, Inc., 2023). This detailed comparison can help in understanding the GTCR's operational parameters.

Drawing a parallel with the Coaster commuter rail service in San Diego, CA provides a foundation for extending our analysis to additional dimensions. Both the GTCR and the Coaster service utilize configurations consisting of four cars. In order to supplement other data currently missing for GTCR, we extrapolated based on the known specifications of the Coaster commuter rail. Specifically, the weight of a BiLevel coach is noted to be 50 metric tons. With a total of four railcars, the cumulative weight amounts to 200 metric tons. On average, each railcar can seat 136 to 162 passengers, with a mean capacity of 149 seated passengers. Additionally, the number of people standing is 276, bringing the maximum capacity to 438 individuals per railcar. In this way, the maximum total capacity of this four-car unit is 1752 (Garcia et al., 2016).

### 2.3.2 Ridership data

The raw data of GTCR’s weekday ridership by station (i.e., production-attraction station flows) was retrieved from GTCR Appendix H: Phase 2 Ridership Analysis Technical Memorandum (Table 80) released in July 2022 (RSG, 2022). This production-attraction (PA) matrix was transformed to the table in “PA\_Station\_Flow\_LT” sheet in the model. Assuming that there will be 20 (8-2-8-2[[4]](#footnote-5)) daily round trips between West Durham and Auburn, and commuter rail fare is equal to regional bus fare, this weekday total flow of 12,183 in 2040 was obtained using the Federal Transit Administration’s (FTA) Simplified Trips-on-Project Software (STOPS) with the 2018 ridership as the baseline (RSG, 2022). The 2018 data came from two sources: (1) three relatively recent transit rider surveys cover most of the corridor to be served by the GTCR project, and (2) Census Transportation Planning Products (CTPP) Journey-to-Work (JTW) flow data from the 2006-2010 Census American Community Survey (ACS) (**Figure 4**).

A map of a city

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**Figure 4.** **Modeling area with trip information from on-board transit surveys and CTPP JTW data.**

Source: (RSG, 2022)

To capture the station flow pattern, we first calculated the proportion of each station flow from the default daily total flow along the entire route, then the daily total station flow can be obtained by multiplying the proportion with the user input flow value. Then, the daily station flow of morning (PA) and evening (AP) trips during peak (PK) and off-peak (OP) periods were calculated from the daily total station flow. Specifically, we split the total station flow into four components: (1) all morning trips during peak period (i.e., **morning peak trips**), (2) all morning trips during off-peak period (i.e., **midday trips**), (3) all **evening peak trips,** and (4) all **evening trips**. Assuming all the passengers who travel from station A to station B in the morning would travel back to A from B in the evening, the Column H to K were calculated by the equation:

*Total\_Flow \* Peak/Off-peak Proportion \* 0.5*

The “Peak/Off-peak Proportion” is the proportion of ridership during peak periods and off-peak periods during a day which can be adjusted by users in the model dashboard (“Peak / Off-Peak Ratio”). The **daily station flows per train** were then obtained by dividing the total station flow during each period by **the number of trips** during each period.

Next, we derived the **inflow passengers at origin stations** and the **outflow passengers at destination stations** for every two adjacent stations (both directions, east and west bound) from the daily station flow per train. To obtain the inflow passengers for east (west) bound trips, we summed morning (PA)/evening (AP) flow for all stations east (west) of current origin station using peak (PK)/off-peak (OP) column. While for the outflow passengers for east (west) bound trips, we summed PA/AP flow for all stations west (east) of current destination station using PK/OP column.

Finally, the **ridership** of GTCR between every two adjacent stations was calculated by summing the ridership of previous trip and the inflow passengers at current origin station, and then subtract the outflow passengers at current destination station (Figure 5). To estimate the total passenger weight, we assumed the **average passenger weight** to be 79 kg (175 pounds), which aligns with the assumption adopted by most transit agencies and track component suppliers (Lin et al., 2016). Finally, the **ridership** of GTCR between every two adjacent stations was calculated by summing the ridership of previous trip and the inflow passengers at current origin station, and then subtract the outflow passengers at current destination station (Figure 4). To estimate the total passenger weight, we assumed the **average passenger weight** to be 79 kg (175 pounds), which aligns with the assumption adopted by most transit agencies and track component suppliers (Lin et al., 2016).

A graph of a passenger

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**A**.

A graph of a passenger

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**B**.

**Figure 5. Weekday passenger flow and ridership within the 8-2-8-2 schedule.**

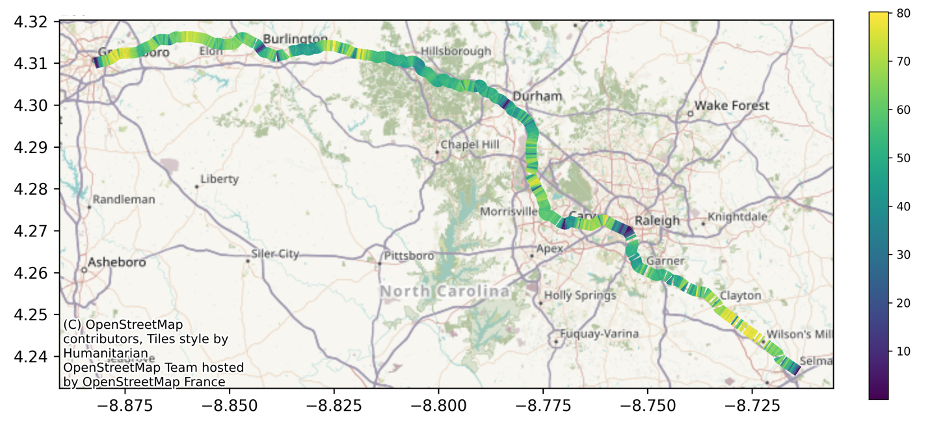
(A) Eastbound trips during morning peak hours. (B) Westbound trips during evening peak hours. Plotted by the authors.

### 2.3.3 Speed data

#### 2.3.3.1 Data Preparation

To forecast the rail-running speed for the forthcoming commuter rail service between Auburn and Durham, we developed a machine-learning model using empirical data from the intercity rail service operating on the same corridor. Through interviews with the client and GoTriangle staff, we identified the primary factors influencing speed-change decisions. These factors were narrowed down to five types: continuous characteristics such as curvature and gradient, as well as discrete features such as stations, crossings, and switches.

We utilized a broader dataset, the H-line, covering the GTCR area to train the model. In terms of passenger rail, this encompasses the Piedmont/Carolinian and the Crescent routes operated by both NCDOT's Rail Division and Amtrak. For the dependent variable, speed, we scraped empirical intercity rail running data from an unofficial site that utilizes Amtrak's Track-A-Train service (Amtrak, n.d.) from January 24th to February 7th and from March 3rd to 9th. This data is provided in GTFS-RT[[5]](#footnote-6) format and updates every 45 seconds on average, with a maximum gap of 3 minutes between updates. We validated the data by matching the real-time data feeds against station locations and speed limit recorded in the NCDOT’s schematic of the rail roads[[6]](#footnote-7)(2017), ensuring high reliability.

****

**Figure 6. Average speed calculated from empirical data for each 0.1 mile on the intercity Amtrak service using the H-line.**

Plotted by the authors. The dark segments are consecutively Greensboro, Burlington, Durham, Cary, Raleigh, and Selma-Smithfield, corresponding to the existing Amtrak station.

To characterize the location on the route, we defined the variables by every 50 feet along the track. For each node's curve and slope features, we estimated the arc angle and elevation change between its preceding and succeeding nodes. To ensure a smooth profile and accommodate any sudden changes in the route, such as when crossing a river, we conducted a zonal analysis by averaging the elevations of the adjacent six points for each node. Additionally, to consider the timing of the operator's braking decision, we created variables that identify the maximum angles and slopes ahead within a specified range differing by two thousand five hundred feet, approximately half a mile, extending up to ten thousand feet (see the list of the variables in the Table 4 Variables for the H-Line Speed Model listed in Appendix 2).

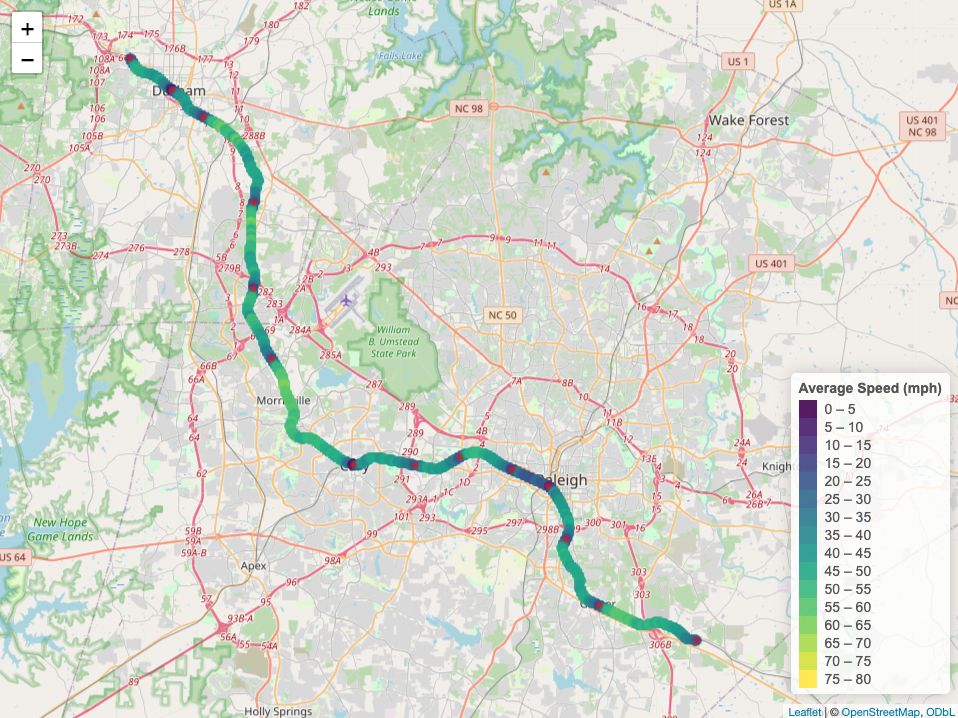
For the crossings, we utilized the crossing inventory provided by the Office of Railroad Safety under the Federal Railroad Administration (2024) and the station list offered by the Bureau of Transportation Statistics (2023). On the other hand, we found the switches by identifying the milepost where there are two tracks on the H-Line existing track schematic provided by NCDOT (2017). After adding the categorical feature to each node, we calculated the distances to the following crossing, station, and switches that will maximize when passing a key node and incrementally decrease as the index goes on. To capture the impact of consecutive key nodes occurrence in a short distance, we also define a variable that indicate the distance to the previous key node for each type of key nodes.

#### 2.3.3.2 Random Forest Model Setting and Result

We use random forest instead of linear regression because the relationship between the explanatory variables and the speed are highly possible non-linear. Random Forest reduces overfitting and handles complex relationships in data better than traditional regression models, which can be limited by assumptions like linearity (Breiman, 2001). Additionally, Random Forest provides more robust predictions, especially in the presence of noisy data or outliers, making it a preferred choice for many predictive modeling tasks where accuracy and generalization are crucial (Liaw & Wiener, 2002). Moreover, it is highly user-friendly as it requires only two parameters: the number of variables in the random subset at each node and the number of trees in the forest, making it easy to employ.

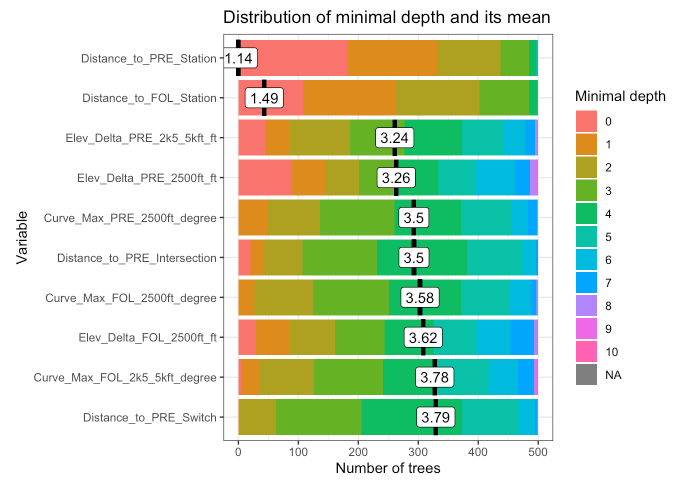
We trained the model using a range of five hundred to four thousand trees and utilized nine variables in the subset at each node. The results indicate that the model can explain 68.72% of the variance in the test dataset, with a mean square residual of 142.47. The most impactful variable is the distance to the station, which is expected as it affects train stopping. However, the remaining attributes exhibit mixed signals (**Figure 8**). Despite this, we chose the random forest model for its robustness rather than its ability to establish causal relationships. Therefore, we assert that the explanatory power is sufficient for estimating speeds for the commuter rail session of interest.

After we have the trained model, we create a pseudo dataset based on the station locations proposed in the GTCR project and feed it into the model. The simulation result is shown in **Figure 7**.



**Figure 7. The estimated operating speed along the GTCR.**

Plotted by the authors. The red dots are where the proposed stations are.



**Figure 8. Distribution of minimal depth and its mean of each variable in the Random Forest model for the speed** **estimation.**

### 2.3.4 Emission factors

The model allows users to choose from two locomotive types: **hybrid diesel** and **hydrogen (H2) fuel cell** locomotives. The model can return GHG emissions of the selected trip in the form of **CO2-eq** which is calculated from the emission factors of three dominant GHGs – CO2, CH4 (methane), and N2O (nitrous oxide) and their global warming potential in IPCC Fifth Assessment Report (AR5) (Greenhouse Gas Protocol, 2014). The emission factors for diesel fuels and H2 were retrieved from the latest (2023) **GREET 1 model** (Argonne National Laboratory, 2023), and the fuel life cycle considered was well-to-wheel (WTW), i.e., the emissions associated with fuel extraction, distribution, and combustion. Detailed information related to fuels can be found in the “Emissions\_Factors\_LT” sheet.

Diesel locomotives, which have historically dominated the rail system, rely on internal combustion engines. The primary emissions from diesel locomotives include CO2, NOx, particulate matter (PM), and sulfur dioxide (SO2). The emission factor for diesel locomotives varies based on the engine type, age, operational practices, and maintenance but is generally high due to the combustion of fossil fuels (EPA, 2009). Current passenger train services in North Carolina adopt **diesel-electric (or hybrid diesel) locomotives** which use a diesel engine to generate electricity that powers traction motors (NCDOT, 2020). While they share similar profiles with traditional diesel engines, improvements in engine efficiency and emissions control technologies have led to reduced GHG emissions. However, they still emit significant amounts of NOx and PM at this point.

On the other hand, **H2 fuel cell** technology offers a promising alternative for commuter trains due to its zero-tailpipe-emission feature, making it an attractive option for reducing the environmental impact of transportation. However, the deployment of hydrogen-powered trains entails the creation of an entirely new infrastructure, from production and distribution to refueling stations (El-Shafie et al., 2019). More importantly, the environmental benefits of hydrogen fuel depend significantly on its production methods (Pahwa & Pahwa, 2014). Currently, the majority of hydrogen is generated through steam reforming of methane with (blue H2) or without (grey H2) carbon capture and storage (CCS), a process that, while effective, produces significant carbon emissions (Hydrogen Council, 2021). Another type of H2 produced from water electrolysis that powered by mix energy sources is yellow H2. The emission factor of yellow H2depends on the emission intensity of the grid which is relatively high at the current stage but will see a significant decrease over the next decades (Enerdata, 2023). By contrast, electrolysis can achieve much lower emissions when powered by renewable energy sources (green H2) or nuclear energy (pink H2) (Hydrogen Council, 2021). Therefore, the transition to hydrogen fuel cell technology in the rail sector not only necessitates an overhaul of the existing fuel infrastructure but also hinges on the adoption of sustainable hydrogen production methods (EFI Foundation, 2023).

## 2.4 Scenario Modeling Development

### 2.4.1 Train Parameters

Users have the option to select between two types of locomotives: hybrid diesel and hydrogen fuel cells. The hybrid diesel locomotive can be fueled with either low-sulfur diesel[[7]](#footnote-8) and biodiesel (B20)[[8]](#footnote-9). In the case of the hydrogen fuel cell locomotive, users can evaluate the emission effects of four hydrogen types as detailed in section 2.3.4: grey, yellow, pink, and green hydrogen. Additionally, users can modify the number of locomotives and railcars to assess how train weight influences energy consumption and emissions.

### 2.4.2 Trip Parameters

#### 2.4.2.1 Weekday Total Flow

In the model, the default total weekday GTCR flow from West Durham to Auburn is set at 12,183 as explained in section 2.3.2. However, projected ridership is expected to vary between 10,000 and 18,000 depending on the fare scenario (RSG, 2022). Consequently, we have made this a user-configurable variable, labeled "Weekday Total," on the model dashboard.

#### 2.4.2.2 Service Schedule and Peak/Off-peak Ratio

Users can choose one of the two service scenarios: 8P-2O-8P-2O and 3P-3P. The 8P-2O-8P-2O (8-2-8-2) scenario consists of 8 trips during the morning peak, 2 trips during midday, followed by 8 trips during the evening peak and 2 additional trips in the evening. The 3P-3P (3-3) scenario comprises three peak trips in both the morning and evening. In addition, the ratio of ridership during peak hours and off-peak hours is adjustable, while the ratios of some existing commuter rail services in the U.S. range from 0.66:0.34 to 0.81:0.19 (Division of Strategic Planning & Performance, 2022; Humphrey, 2012). If the 3P-3P scenario is chosen, the peak and off-peak ratio should be adjusted to 1, as this scenario does not include any off-peak trips.

### 2.4.3 Station

Besides returning the energy consumption and GHG emissions of an entire GTCR roundtrip between West Durham and Auburn (14 stations), the model also allows users to specify the origin and destination station.

# 3. Results and Discussions

We have developed an analytical framework that integrates the data collected above, drawing connections between the dependent variables (i.e., energy consumption and emissions), the intermediate variables (e.g., ridership and system efficiency), and the input parameter that users specify.

With the framework, our spreadsheet model allows users to build their own scenarios by adjusting parameters related to fuel technologies and rail service strategies. With different combinations of parameters, users will be able to assess the sensitivity of energy consumption and emissions to changes in factors such as fuel type (diesel hybrid and hydrogen fuel cell), train frequency, route coverage, and operational hours. For the road emission comparison, we also allow the users to specify the fuel economy of light-duty-vehicle (LDV) in North Carolina in 2040 and the distance adjustment factor.

## 3.1 Compositions of Driving Resistance

The energy consumption is unchangeable with a given route and operation schedule is we apply the physical approach to estimate it. The proportion of each resistance are shown in **Figure 9**. When analyzing the resistances encountered during eastbound trips, it is observed that both air and rolling resistance are relatively minor contributors. The predominant factors affecting the train's performance is acceleration resistance. For westbound trips, though the acceleration resistance is still the primary contributor to the overall resistance, the gradient resistance plays a more dominant role compared to eastbound trips since the westbound trips consistently involve an uphill journey. This suggests that the train consume more energy overcoming the incline and acceleration compared to other resistances.

A graph of different colored bars

Description automatically generated

**A**.

A graph of different colored bars

Description automatically generated

**B**.

**Figure 9. The composition of driving resistance for every two adjacent stations.**

(A) Eastbound trips from West Durham to Auburn. (B) Westbound trips from Auburn to West Durham. Plotted by the authors.

In the following results, we are implementing an 8-2-8-2 schedule, with the trainset consisting of 1 locomotive and 4 railcars. The peak and off-peak passenger ratio is 0.85:0.15, prioritizing more passengers during peak times. The model enables users to determine: 1) the amount of emission reduction achieved by using a hydrogen locomotive compared to a diesel locomotive, and 2) the number of passengers required to guarantee emission reduction via commuter rail compared to single-occupancy vehicles with the same number of commuters. In essence, the model is designed to facilitate rapid reparameterization for users to compare emissions across different fuel types and transportation modes.

## 3.2 Emissions from Different Fuel Types

**Figure 10** illustrates the daily GHG emissions for the GTCR service utilizing various fuels within the 8-2-8-2 schedule (20 roundtrips). Panel (A) demonstrates the emission contrast between low-sulfur diesel and yellow H2, whereas panel (B) depicts the comparison between biodiesel (B20) and grey H2. Our analysis indicates that the least environmentally friendly hydrogen option offers a 3% reduction in emissions compared to the most eco-conscious diesel option. This is attributed to the fact that, despite grey H2 having a higher emission factor, H2-powered locomotives achieve double the efficiency of their diesel counterparts. Notably, when contrasting more eco-friendly H2 against more pollutant diesel, emissions are cut by 54%.

A screenshot of a graph

Description automatically generated

**A**.

A graph with numbers and a few lines

Description automatically generated with medium confidence

**B**.

**Figure 10. The daily GHG emissions of GTCR service utilizing several fuel types within the 8-2-8-2 schedule.**

(A) The comparison between the biodiesel (B20) and the grey hydrogen. (B) The comparison between the low-sulfur diesel and the yellow hydrogen. Plotted by the authors.

In short, the transition from diesel to hydrogen fuel cell locomotive can result in a significant reduction in GHG emissions. While there are technical and economic challenges to overcome, the long-term environmental benefits make hydrogen fuel cell a viable and attractive option for rail service. Strategic investments in hydrogen infrastructure and technology development, supported by policy incentives, will be critical to realizing the potential of hydrogen fuel cell locomotives.

## 3.3 Emissions Comparison with Road Transportation

To assess the environmental benefits of commuter rail relative to single-occupancy vehicles, we must consider passenger numbers as a variable factor. Utilizing the average fuel economy statistic for vehicles in North Carolina, which stands at 25.6 miles per gallon[[9]](#footnote-10) (Bureau of Transportation Statistics, 2019; U.S. Energy Information Administration, 2024), we analyzed the emissions per passenger. The inherent energy consumption of operating a train means that a higher passenger count is required to distribute the emissions more efficiently on a per capita basis. In contrast, emissions per passenger for a single-occupancy vehicle remain consistent, as they do not benefit from shared energy consumption.

**Figure 11** (A) indicates that commuter rail emissions per passenger decrease as ridership increases, reaching a point of environmental advantage over single-occupancy passenger vehicle at a ridership level of approximately 16,500 passengers if the locomotive is powered by grey H2. The minimum ridership level should reach around 26,000 if utilizing low-sulfur diesel fuel. Figure 11 (B) reinforces this narrative, suggesting that without sufficient ridership, commuter rails may not always present a lower-emission alternative to road transportation by single-occupancy vehicles.

A graph of a train

Description automatically generated

**A**.

A graph of a graph of a train

Description automatically generated with medium confidence

**B**.

**Figure 11. The comparison of GHG emissions from GTCR service and road transportation (single-occupancy passenger vehicle) by passenger number.**

(A) Emission per passenger. (B) Total emission per day. Plotted by the authors.

# 4. Limitation & Future Work

The granularity of data significantly influences the accuracy of speed calculations. Fine-grained data allow for a nuanced understanding of speed dynamics, capturing minute variations that coarse-grained data overlook. One significant limitation of this research is its reliance on available empirical data from commuter rails, which may not capture all potential variables influencing speed. Furthermore, our route’s geographical scope may limit the generalizability of its finding to other regions with different commuter rail systems. On this report, we have elaborated on the multifaceted nature of speed calculations in commuter rail systems and the importance of data granularity, overlooked attributes, and external factors. However, there exists a gap in load factors regarding the comprehensive analysis of omitted attributes and external factors that could influence speed calculations, such as stations, flexibility scheduling, and urban planning. The absence of a detailed examination of these factors underscores the need for a more holistic approach to modeling speed within commuter rail systems, one that incorporates a wider array of both internal and operational variables and external environmental influences.

In the future, there are still some aspects worth improving in order to obtain better accuracy and use a wider range of models. A critical enhancement would be the inclusion of fuel weight as a variable within the model, which is crucial to get more precise results. Since the commuter rail continuously consumes fuel during travel, changes in weight will affect energy efficiency. Therefore, it is proposed that future models integrate this variable to simulate the dynamic relationship between fuel consumption rates and total weight more accurately. In addition, our current model is based on just one line, therefore, we are also considering incorporating route-specific requirements or accommodating the unique demands of different routes in the future. This includes models that can adapt to different routes and different situations, such as distances from different stops and differences in ridership. In this way, our model can adapt to more complex situations and become a powerful tool that can be widely applied to different needs. In addition, enhancing flexibility in service schedule is also a top priority. Different peak and off-peak periods will significantly affect the passenger ratio, etc. In the future, more possibilities can be added to the schedule to facilitate key stakeholders when making decisions. The last point for future enhancement involves evaluating emission mitigation strategies across various scenarios. At present, our study primarily focuses on the calculation of emissions and energy consumption, but specific emission reduction policies and simulations are content that can be further strengthened in the future. By integrating additional parameters into our existing model, people can investigate specific emission reduction technologies and strategies. Overall, these enhancements can further meet North Carolina's commuter rail transportation requirements and support sustainable environmental development, making this model a valuable tool for broader application in rail transportation planning and environmental management.

# Acknowledgement

We extend our deepest gratitude to a wide array of individuals and organizations whose invaluable contributions have been instrumental in the development and success of this project. Our acknowledgment begins with recognizing the United States for its ongoing efforts to address and mitigate greenhouse gas (GHG) emissions within the transportation sector, an area identified as a significant contributor to the nation’s environmental footprint.

We are particularly thankful to GoTriangle and other regional transit authorities in North Carolina for their foresight and commitment to sustainable transportation solutions. The demographics projections and support from GoTriangle have underscored the critical need for innovative transit strategies to accommodate the Triangle region’s anticipated growth. We appreciate the strong support from business leaders and residents in the Triangle area, as evidenced by the report conducted by GoTriangle (Go Forward), which reflects the community’s commitment to sustainable and efficient transportation.

Our efforts were significantly bolstered by the Applied Data Research Institute (ADRI), whose expertise in data analytics and systems modeling has been pivotal in navigating the complexities of this project. ADRI’s proactive engagement with key transportation authorities and their guidance on Geographic Information Systems (GIS) work have been invaluable in ensuring the accuracy and completeness of our analyses. Special recognition is extended to Alexander Yoshizumi for this exceptional contribution in modeling guidelines that have been crucial in refining our analytical processes. His expertise and meticulous approach have significantly enhanced the quality and reliability of our model outputs.

We are also profoundly thankful to advisor Dr. Timothy Johnson for his guidance and wisdom throughout the project. His expertise in the field and his role as a steadfast advisor have been indispensable in navigating the project’s challenges and achieving our goals.

Lastly, we acknowledge that collaborative spirit and shared vision of all stakeholders and policymakers involved in this initiative. By focusing on different scenarios pertinent to the region’s needs and employing evidence-based assumptions, we aim to catalyze meaningful change towards rail system an analytical endeavor and environmental sustainability in North Carolina. It highlights the critical role that infrastructure projects, particularly those focused on sustainable transportation, can play in achieving broader environmental and social goals. Through continued collaboration, innovation, and commitment to evidence-based practices, we can realize the vision of a more sustainable and prosperous North Carolina for current and future generations.

# Appendices

## Appendix 1: Existing Emission Estimation Models

The table compares six models for transportation emission estimation by parameters such as fuel type, environmental impacts, user-defined inputs, and default values/optional user inputs. The table can be retrieved from the link below:

<https://docs.google.com/spreadsheets/d/1f2ZErjOSDy0MYBGI8J3e9XF8vMXWrxRe/edit?usp=sharing&ouid=110389393509154763265&rtpof=true&sd=true>

## Appendix 2: Variables for the H-Line Speed Model

|  |  |
| --- | --- |
| **Variable** | **Description** |
| Speed\_mph | Instantaneous speed from the real time data from Amtrak, but removing zeroes that are not att a station to avoid capturing unusual stops. |
| Curve\_CUR\_degree | Current curve's angle with regard to the next and the previous point |
| Curve\_Max\_FOL\_2500ft\_degree | The maximum angle in the ten following observations, measured in angular degrees. |
| Curve\_Max\_FOL\_2k5\_5kft\_degree | The maximum angle between the eleventh to the twentieth following observations, measured in angular degrees. |
| Curve\_Max\_FOL\_5k\_7k5ft\_degree | The maximum angle between the twenty first to the thirtieth following observations, measured in angular degrees. |
| Curve\_Max\_FOL\_7k5\_10kft\_degree | The maximum angle between the thrity first to the fortieth following observations, measured in angular degrees. |
| Curve\_Max\_PRE\_2500ft\_degree | The maximum angle in the ten preceding observations, measured in angular degrees. |
| Curve\_Max\_PRE\_2k5\_5kft\_degree | The maximum angle between the eleventh to the twentieth preceding observations, measured in angular degrees. |
| Curve\_Max\_PRE\_5k\_7k5ft\_degree | The maximum angle between the twenty first to thirtieth preceding observations, measured in angular degrees. |
| Curve\_Max\_PRE\_7k5\_10kft\_degree | The maximum angle between the thrity first to the fortieth preceding observations, measured in angular degrees. |
| Elev\_Delta\_CUR\_ft | The change in elevation from the preceding observation to the following observation. Using observations spaced 50 feet apart, this corresponds to the change in elevation over a 100-feet run. |
| Elev\_Delta\_FOL\_2500ft\_ft | The maximum change in elevation (Elev\_Delta\_CUR\_ft) from the ten following observations. |
| Elev\_Delta\_FOL\_2k5\_5kft\_ft | The maximum change in elevation (Elev\_Delta\_CUR\_ft) between the eleventh and the twentieth following observations. |
| Elev\_Delta\_FOL\_5k\_7k5ft\_ft | The maximum change in elevation (Elev\_Delta\_CUR\_ft) between the twenty first and the thirtieth following observations. |
| Elev\_Delta\_FOL\_7k5\_10kft\_ft | The maximum change in elevation (Elev\_Delta\_CUR\_ft) between the thirty first and the fortieth following observations. |
| Elev\_Delta\_PRE\_2500ft\_ft | The maximum change in elevation (Elev\_Delta\_CUR\_ft) from the ten preceding observations. |
| Elev\_Delta\_PRE\_2k5\_5kft\_ft | The maximum change in elevation (Elev\_Delta\_CUR\_ft) between the eleventh and the twentieth preceding observations. |
| Elev\_Delta\_PRE\_5k\_7k5ft\_ft | The maximum change in elevation (Elev\_Delta\_CUR\_ft) between the twenty first and the thirtieth preceding observations. |
| Elev\_Delta\_PRE\_7k5\_10kft\_ft | The maximum change in elevation (Elev\_Delta\_CUR\_ft) between the thirty first and the fortieth preceding observations. |
| Distance\_to\_FOL\_Intersection | Given the direction of the train, distance along route to the intersection |
| Distance\_to\_FOL\_Station | Given the direction of the train, distance along route to the station |
| Distance\_to\_FOL\_Switch | Given the direction of the train, distance along route to the next switch |
| Distance\_to\_PRE\_Intersection | Given the direction of the train, distance along route to the previous intersection |
| Distance\_to\_PRE\_Station | Given the direction of the train, distance along route to the preivous station |
| Distance\_to\_PRE\_Switch | Given the direction of the train, distance along route to the previous switch |
| Carolinian | A binary variable indicating whether the data is from a Carolinian service. |
| Piedmont | A binary variable indicating whether the data is from a Piedmont service. |
| Crescent | A binary variable indicating whether the data is from a Crescent service. |

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1. NC Capital Area Metropolitan Planning Organization [↑](#footnote-ref-2)
2. Durham - Chapel Hill - Carrboro Metropolitan Planning Organization [↑](#footnote-ref-3)
3. North Carolina Department of Transportation [↑](#footnote-ref-4)
4. 8-2-8-2 sequence entails 8 round trips during the morning peak period, 2 round trips in the midday period, 8 round trips during the evening peak period, and 2 round trips in the evening period. [↑](#footnote-ref-5)
5. GTFS-RT (General Transit Feed Service – Real Time) is a widely-used format that allows public transportation agencies to provide real-time updates about their fleet to application developers. [↑](#footnote-ref-6)
6. This schematic provides information on speed limits, curvature, superelevation, and crossing details along the entire rail line, indexed by milepost. [↑](#footnote-ref-7)
7. Diesel fuel currently available for off-highway (or non-road) use in the United States is ultra-low sulfur diesel (ULSD), containing 15 parts per million or less of sulfur (EIA, 2023). [↑](#footnote-ref-8)
8. Biodiesel can be blended and utilized in various proportions, such as B100 (pure biodiesel), B20 (20% biodiesel, 80% petroleum diesel) and B5, and B2 with B20 being the most common blend in the United States (DOE Vehicle Technologies Program, 2011). [↑](#footnote-ref-9)
9. We extrapolate the average mpg number by applying the estimated growth in fuel economy in National scale (U.S. Energy Information Administration, 2024) to the average mpg in North Carolina in 2018 (Vehicle Technologies Office, 2021). [↑](#footnote-ref-10)