High-Dimensional Data-Driven Energy Optimization for Multi-Modal Transit Agencies

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Executive Summary

Public bus transit services in the U.S. are responsible for at least 19.7 million metric tons of CO_2 emission annually. Electric vehicles (EVs) can have a much lower environmental impact than comparable internal combustion engine vehicles (ICEVs), especially in urban areas. Unfortunately, EVs are also much more expensive than ICEVs. As a result, many public transit agencies can afford only mixed fleets of transit vehicles, consisting of EVs, hybrids (HEVs), and ICEVs. Transit agencies that operate such mixed fleets of vehicles face a challenging optimization problem: these agencies need to decide *which vehicles are assigned to serving which transit trips*. Since the advantage of EVs over ICEVs varies depending on the route and time of day (e.g., the benefit of EVs is higher in slower traffic with frequent stops and lower on highways), the assignment can have a significant effect on energy use and, hence, environmental impact.

Through this project, we have developed reference data about energy collections and constructed a set of machine learning models that can accurately predict the energy consumption for the whole fleet at the level of each trip. We have used these models to develop a scheduling and assignment strategy that can rotate the different vehicle types across the transit agencies' routes. The optimization algorithm ensures that the vehicles are matched to trips considering weather patterns, expected congestion, and road gradients to minimize the overall energy usage. We list the key observations from our project for other practitioners below. Details are available in the report, and the list of source code and our publications are included in the appendix.

1. We have demonstrated the feasibility of collecting, merging and analyzing large volumes of high-resolution real-world telemetry data from a mixed vehicle fleet. To mitigate the inherent noise of the recorded GPS points, the team developed an algorithm that filters data and maps the points onto a street. The algorithm considers previous and subsequent location measurements and different characteristics of nearby streets to determine how likely the vehicle travels on them. Then, the team segmented the time series into disjoint contiguous samples based on adjacent road segments and repeated the outlier detection and removal. For each data point, the team added features corresponding to elevation changes within the samples, weather features, such as temperature, and traffic data, such as speed ratio between actual speed and free-flow speed.
2. We have developed two forms of machine learning models that be used to understand and analyze the energy operations of a mixed vehicle transit fleet. The micro prediction model provides estimates of instantaneous energy prediction for all types of buses (diesel, hybrid, and electric). Such a model is important in evaluating the energy impacts of real-time bus operation strategies, but it is challenging due to diversified driving cycles of transit buses. The model can help the drivers understand the impact of their driving behaviors and short-term congestions. The macro prediction models estimate average energy consumption across the whole trip considering the features: distance traveled, various road-type features, elevation change, day of the week, time of day, various weather features (temperature, humidity, etc.), and traffic features (speed ratio and jam factor)
3. We have demonstrated that it is possible to transfer the machine learning models we have developed in this project to other teams and cities by using inductive transfer learning. We also showed that the performance of the macro energy prediction models can be improved using a multi-task learning approach where the learning parameters are shared between the models being developed for different vehicle types. The advantage of this approach is improved

learning performance as the models can exploit common spatio-temporal and environmental characteristics.

4. Finally, we have developed trip and vehicle assignment and scheduling algorithms that use the energy prediction models and develop a trip to vehicle type (diesel, electric, hybrid) assignment for the whole operation to reduce overall emissions and cost. We have shown through simulations that the proposed algorithms can save \$48,910 in energy costs and 175 metric tons of CO2 emission annually for CARTA.

1 Project Overview

Transportation accounts for 28% of the total energy use in the U.S. [1]. It is responsible for immense environmental impact, including urban air pollution and greenhouse gas emissions, and may pose a severe threat to energy security. Switching from personal vehicles to public transit systems can significantly reduce energy use and environmental impact. However, even public transit systems require substantial amounts of energy; for example, public bus transit services in the U.S. are responsible for at least 19.7 million metric tons of CO_2 emission annually [2]. Electric vehicles (EVs) can have a much lower environmental impact than comparable internal combustion engine vehicles (ICEVs), especially in urban areas. Unfortunately, EVs are also much more expensive than ICEVs (typically, diesel transit buses cost less than \$500K, while electric ones cost more than \$700K, or close to around \$1M with charging infrastructure [3]). As a result, many public transit agencies can afford only mixed fleets of transit vehicles, consisting of EVs, hybrids (HEVs), and ICEVs. Transit agencies that operate such mixed fleets of vehicles face a challenging optimization problem: these agencies need to decide *which vehicles are assigned to serving which transit trips*. Since the advantage of EVs over ICEVs varies depending on the route and time of day (e.g., the benefit of EVs is higher in slower traffic with frequent stops and lower on highways), the assignment can have a significant effect on energy use and, hence, environmental impact.

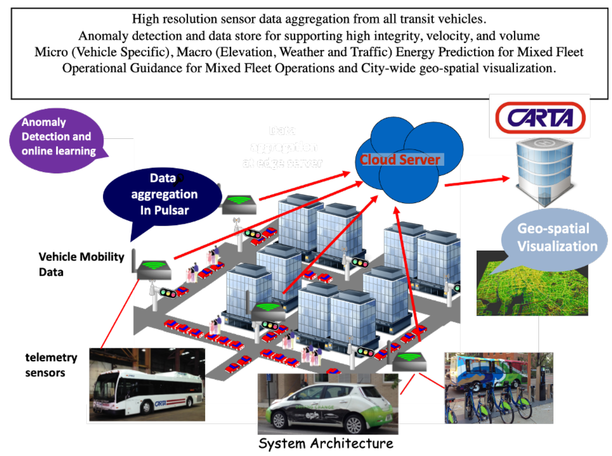


Figure 1: This project builds a high-resolution system-level data capture and analysis framework for transit operations that enables CARTA to identify energy bottlenecks and accurately predict energy costs of all operations. The captured datasets contain real-time transit information about engine idling status, engine temperature, engine speed, throttle, vehicle speed, fuel level, and road gradient.

This project aimed to enable transit agencies like the Chattanooga Area Regional Transportation Authority (CARTA) to perform this optimization strategically and systemically. We have developed novel data architectures to collect, process, and analyze high frequency sensor telemetry data, containing information about engine idling status, engine temperature, engine speed, throttle, vehicle speed, GPS position, fuel usage (diesel vehicles), and state of charge (electrical vehicles) from all vehicles in the fleet of the transit agency. We combine these datasets with road gradient, traffic congestion, current events in the city, and braking and acceleration patterns. These high-

Table 1: Overview of Datasets

Data	Source	Frequency	Scope	Features
Diesel Vehicles (2014 Gillig Phantom diesel buses)	ViriCiti & CARTA	1 Hz	3 vehicles for 244 days (veh. IDs: 147, 149, 150; 2019-8-1 to 2020-10-31)	GPS location, fuel-level, fuel rate, odometer
Electric Vehicles (2016 BYD K9S 35-foot battery-electric buses)	ViriCiti & CARTA	1 Hz	3 vehicles for 244 days (veh. IDs: 751, 752, 753; 2019-8-1 to 2020-10-31)	GPS location, charging status, battery current, battery voltage, battery state of charge, odometer
Traffic	HERE [4]	1 Hz	TMC segments for major roads in Chattanooga	TMC ID, confidence of reading, unconstrained speed, free-flow speed, jam factor
Weather	DarkSky [5]	0.1 Hz	Chattanooga region	location, temperature, wind speed, precipitation, humidity, visibility, apparent temperature
Elevation	TN GIC [6]	static	Chattanooga region	location, elevation

dimensional datasets enable us to train accurate data-driven predictors of energy consumption for various routes and schedules using deep neural networks. After that, we developed optimization procedures to generate trip rosters that reduce the overall energy consumption. An essential aspect of the project is the focus on the explainability of results. For that purpose, we build publicly accessible data dashboards and simulation engines to show the approach's effectiveness. Our future work includes the design of experiments to showcase the approach's effectiveness in practice on the CARTA fleet. Our overall process is summarized in Fig. 1. We describe the specific activities of the project in the following sections.

2 Data

We first describe the data we have collected and the framework that we have designed as part of the project to ensure that other transit agencies can replicate our effort. Table 1 provides an overview of our data sources.

To collect data from CARTA's fleet of vehicles, we partnered with ViriCiti, a company that offers sensor devices and an online platform to support transit operators with real-time insight into their fleets. ViriCiti has installed sensors on CARTA's mixed fleet of three electric, forty-one diesel, and six hybrid buses, and it has been collecting data continuously at 1-second (or shorter) intervals since installation. For each vehicle, we obtain time-series data from ViriCiti, which includes a series of timestamps and vehicle locations based on GPS. For electric buses, we also have features such as battery current in ampere (A), battery voltage (V), battery state of charge, and charging cable status. We include fuel level and the total amount of fuel used over time in gallons for diesel buses. In total, we have already obtained around 32.3 million data points for electric buses and 29.8 million data points for diesel buses (Table 1). Fuel data is recorded less frequently; hence, there are fewer data points for diesel buses.

In addition, we collect static GIS elevation data from the Tennessee Geographic Information Council [6]. From this source, we download high-resolution digital elevation models (DEMs), derived from LIDAR elevation imaging, with a vertical accuracy of approximately 10 cm [7]. We join the DEMs for Chattanooga into a single DEM file, which we then use to determine the elevation of any location within the geographical region of our project

We also collect weather data from multiple weather stations in Chattanooga at 5-minute intervals using the DarkSky API [5]. This data includes real-time temperature, humidity, air pressure, wind speed, direction, and precipitation. In addition, we collect traffic data at 1-minute intervals using the HERE API [4], which provides speed recordings for segments of major roads, which provides data in timestamped speed recordings from selected streets. Every road segment is identified by a unique Traffic Message Channel identifier (TMC ID) [8]. Each TMC ID is also associated with a list of latitude and longitude coordinates, which describe the geometry of the road segment.

Given the volume and the rate of the data being collected, we had to design a new data architecture for the project. The purpose of this architecture is to store the data streams in a way that provides easy access for offline model training and updates and real-time access for system monitoring prediction. This architecture consists of a publish-subscribe cluster implemented with Apache Pulsar [9], which stores topic-labeled sensor streams, and a MongoDB database back-end. An overview of the data architecture is provided in Fig. 2.

This architecture solves two challenges. The first challenge is the persistent storage of the high-velocity, high-volume data streams. In this study, the real-time data sources—ViriCiti, HERE, and DarkSky—produce around 100 GiB of data per month. Therefore, we choose a cloud-based design to allow for fast horizontal scalability of the system. The second concern is that the data itself is highly unstructured and irregular as the sources produce data at different rates. Therefore, we stream each data source to a topic-based publish-subscribe (pub-sub) layer that persistently stores each data stream as a separate topic. The pub-sub system consists of a single Apache Pulsar [9] cluster running on VMware [10] virtual machines hosted at Vanderbilt University.

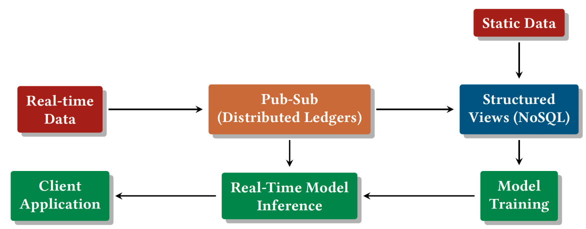
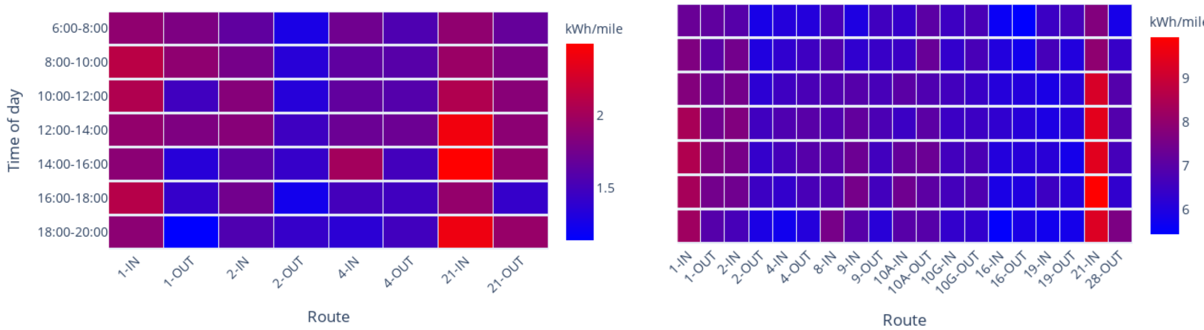


Figure 2: HD-EMMA data architecture overview.

We used a three-tiered naming convention for topic labeling. The first tier represents the name of the data tenant, and all authentication and access is managed at this level. The second tier is the data category, i.e., vehicle telemetry, traffic, weather, etc. The third tier is the topic name, representing the data source or provider, such as ViriCiti, HERE, or DarkSky. For ViriCiti vehicle-telemetry data, the fleet name is appended to the topic name to separate electric, diesel, and hybrid vehicles. The tenant, category, and topic names together form a topic, which downstream applications can use to access the data streams. We persistently store all messages on each topic in an append-only ledger. Therefore, the topic can be used to read data in near real-time or to playback previous data streams to synchronize new downstream applications. All replication is handled at the ledger level, allowing downstream storage and applications to adapt and expand without concern for data resiliency.

3 Machine Learning Models

The data that we collect helps us to analyze the energy consumption of the fleet and to understand how environmental factors, traffic congestion, and road elevation affect energy consumption (Fig. 3b and Fig. 3a). This analysis is then used to train machine learning models that can predict the energy consumption for any day in the future. Finally, these predictions are used to configure the optimization routines.



(a) Energy use of electric fixed-route vehicles

(b) Energy use of diesel fixed-route vehicles

Figure 3: Average energy used in kWh/mile by trip and by the time of day for (a) electric and (b) diesel fixed-route transit vehicles. Scale for diesel is between 5-10 KWh/mile; scale for electric is between 0.7-3 KWh/mile. The variance shows that there are specific trips that are more energy efficient with electric vehicles than others. Further, there are specific routes like 21-inbound where using an EV will have a higher impact than other routes. All of these differences factor into the optimization problem.

3.1 Macro Energy Predictors

The first machine learning model that we built from the collected data is the macro energy consumption estimator, which can analyze and predict energy consumption for each route. To construct the macro-level energy predictor, the team used vehicle telemetry data from the ViriCiti DataHub. For EVs, the team collected the following features: timestamp, GPS-based position, battery current (A), battery voltage (V), battery state of charge (%), and charging cable status (0 or 1). For diesel and hybrid vehicles, instead of battery data, the team collected fuel usage in gallons.

Our team had to perform several steps to process the time-series data recorded from the vehicles by cleaning them, generating samples with a fixed-dimension feature space, and incorporating data from other sources, including traffic and weather data. First, the team removed all data points recorded when the vehicle was in the garage or was charging (for EVs). Next, the team calculated energy consumption by integrating the product of the measured current and voltage values and verified that these consumption values coincided with changes in the state of charge. For diesel and hybrid vehicles, the team performed similar steps with the fuel used.

To mitigate the inherent noise of the recorded GPS points, the team developed an algorithm that filters data and maps the points onto a street. The algorithm considers previous and subsequent location measurements and different characteristics of nearby streets to determine how likely the vehicle travels on them. Then, the team segmented the time series into disjoint contiguous samples based on adjacent road segments and repeated the outlier detection and removal. For each data point, the team added features corresponding to elevation changes within the samples, weather features, such as temperature, and traffic data, such as speed ratio between actual speed and free-flow speed. For each type of vehicle, the team created training and test sets by dividing samples randomly.

The team applied three different machine-learning models for predicting energy consumption: artificial neural network, linear regression, and decision tree regression. These models used the following features: distance traveled, various road-type features, elevation change, day of the week, time of day, various weather features (temperature, humidity, etc.), and traffic features (speed ratio and jam factor). The performance of these approaches was compared based on their mean prediction errors for the test datasets. We ultimately chose neural networks because of their superior

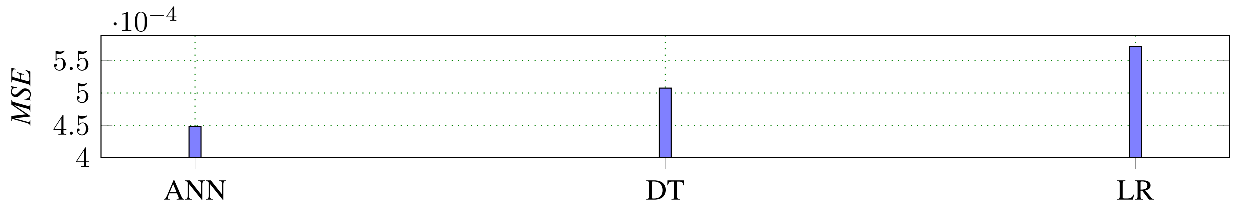


Figure 4: Mean squared error (MSE) of macro prediction models for diesel vehicles. We compare artificial neural networks (ANN), decision tree regression (DT), and linear regression (LR). Lower values are better.

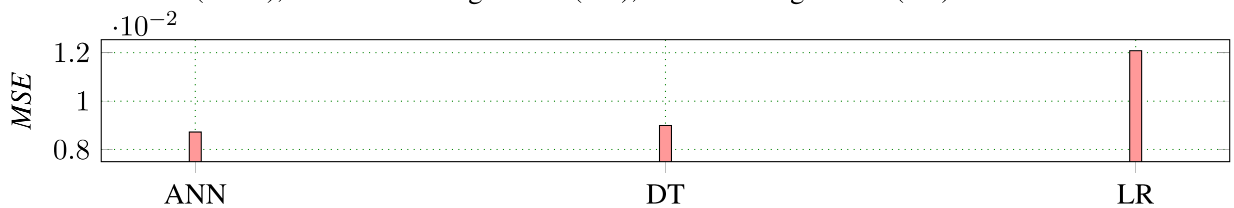
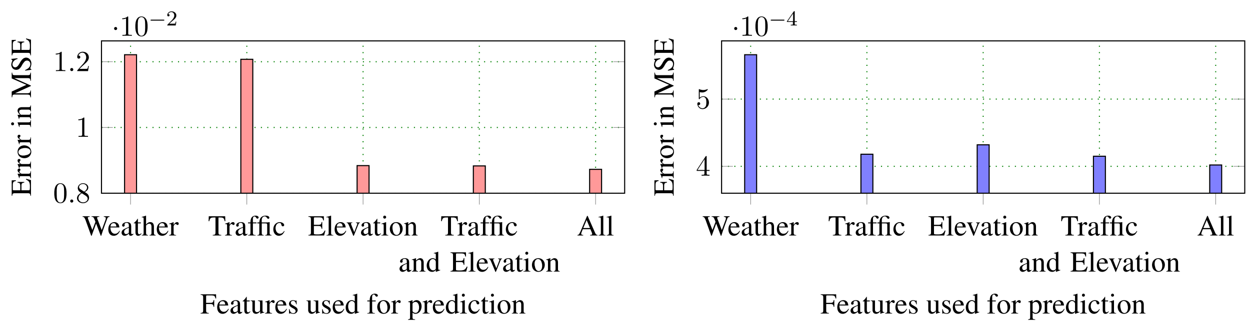


Figure 5: Mean squared error (MSE) of macro prediction models (ANN, DT, and LR) for electric vehicles.



(a) Electric

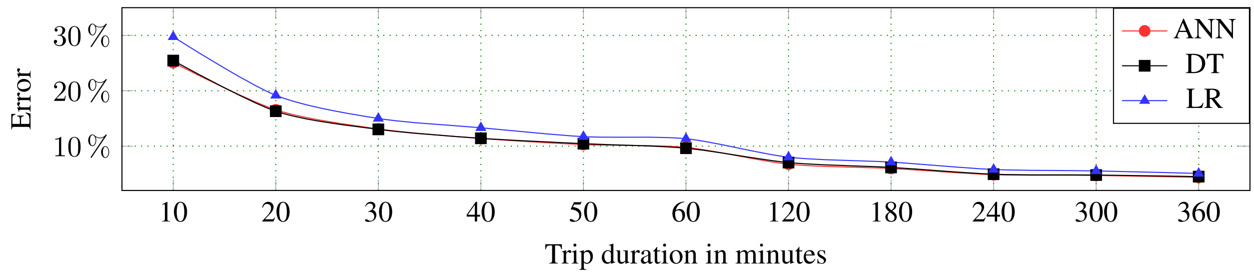
(b) Diesel

Figure 6: Mean squared error for energy prediction with various sets of features. Note that electric and diesel energy are measured in different units. The predictions are based on artificial neural networks.

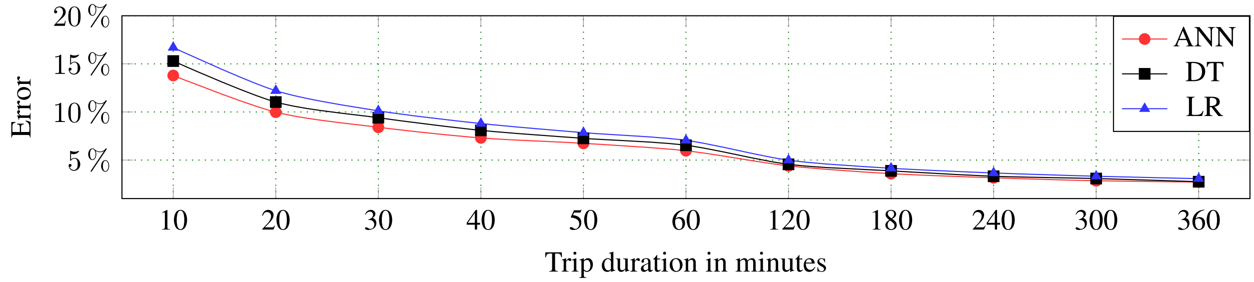
prediction performance.

Figures 4 and 5 compare the performance of different models based on mean squared error (MSE) for diesel and electric vehicles, respectively. Based on these results, neural networks are the best predictors for both types of vehicles. However, we found that different network structures work best for diesel and electric vehicles. For electric vehicles, the best model has one input, two hidden, and one output layer. The input layer has one neuron for each predictor variable. The two hidden layers have 100 neurons and 80 neurons, respectively. For diesel, the best model has one input, five hidden, and one output layer. The five hidden layers have 400, 200, 100, 50, and 25 neurons, respectively. We use sigmoid activation in all hidden layers and linear activation in the output layer. We train the models using the *Adam* optimizer [11] with learning rate 0.001. To implement the ANN models, we use Keras, which is a high-level API of TensorFlow for building and training deep learning models [12]. Figure 6 show the influence of various features on the models.

We also study how prediction accuracy varies with the length of transit trips. We divide our time series into longer trips, varying the length of the trips between 10 minutes and 6 hours. For each trip, we generate a set of samples, use our models to predict energy usage for each sample, and then compare the sum of these predictions to the actual energy usage of the trip.



(a) Electric



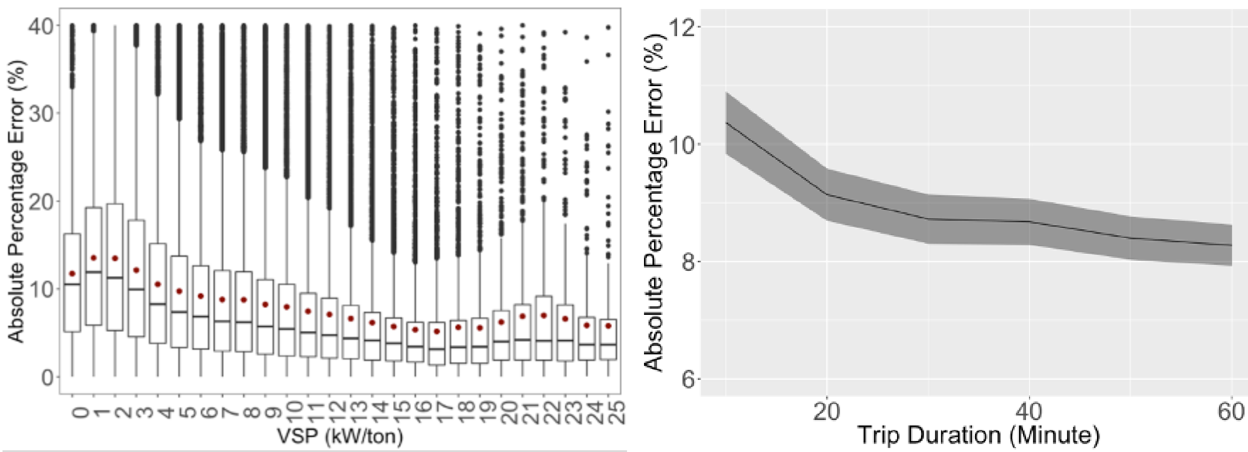
(b) Diesel

Figure 7: Energy prediction error for longer trips, consisting of many samples, with neural network (ANN), decision tree (DT), and linear regression (LR).

Figure 7 shows the relative prediction error for trips of various lengths. For each length, we plot an average error value computed over many trips. We see that relative prediction error is generally lower for longer trips; this is expected as the individual errors of large numbers of samples cancel each other out with an unbiased prediction model. For diesel vehicles, we find that the ANN outperforms the other models significantly for all trip lengths. On the other hand, for electric vehicles, ANN and DT perform equally well for most trip lengths.

4 Micro Energy Predictors

In addition to the macro energy models applicable for route-specific analysis, we have also developed micro models that are finely tuned to individual vehicles. Such instantaneous energy prediction are important in evaluating the energy impacts of real-time bus operation strategies. However, they are challenge to build due to diversified driving cycles of transit buses. In this project, we developed machine learning-based models to estimate the instantaneous power and cumulative energy consumption of buses under real-world driving conditions. The training, validation, and testing were done based on bus driving, road grade, and environment data in a long-term bus operation monitoring experiment in Chattanooga, Tennessee. The most relevant predicting variables are instantaneous speed, acceleration, VSP, weather, and road grade and functional class of road links. We develop one model for each type of bus, i.e. diesel, hybrid, and electric buses. We explore various machine learning models, including Long-Short-Term-Memory, neural network with different structural, etc. A K-fold cross-validation-based model selection process was conducted to identify the optimal model structure and input variables in terms of prediction accuracy. The estimation results show that the predicted mean absolute percentage error rates of the best prediction models were within 10% for different types of buses. We compared the proposed models with existing models in the literature based on the same testing data to demonstrate the predictability of our models. There are two possible applications of the proposed model. One application is to



(a) (b)

Figure 8: (a) Boxplot of absolute percentage error (%) for the microscopic energy consumption as a function of vehicle specific power. (b) Mean and 95% confidence interval of absolute percentage errors of microscopic energy prediction at different trip duration

retrospectively estimate energy savings of microscopic operation controls of electric buses, e.g. transit bus intelligent transportation system applications. Another application is to predict energy consumptions of future bus operations by integrating with a traffic simulator that can generate bus trajectories under different route assignments as well as various background traffic conditions. We discuss the specific models for electric buses and hybrid-diesel vehicles below.

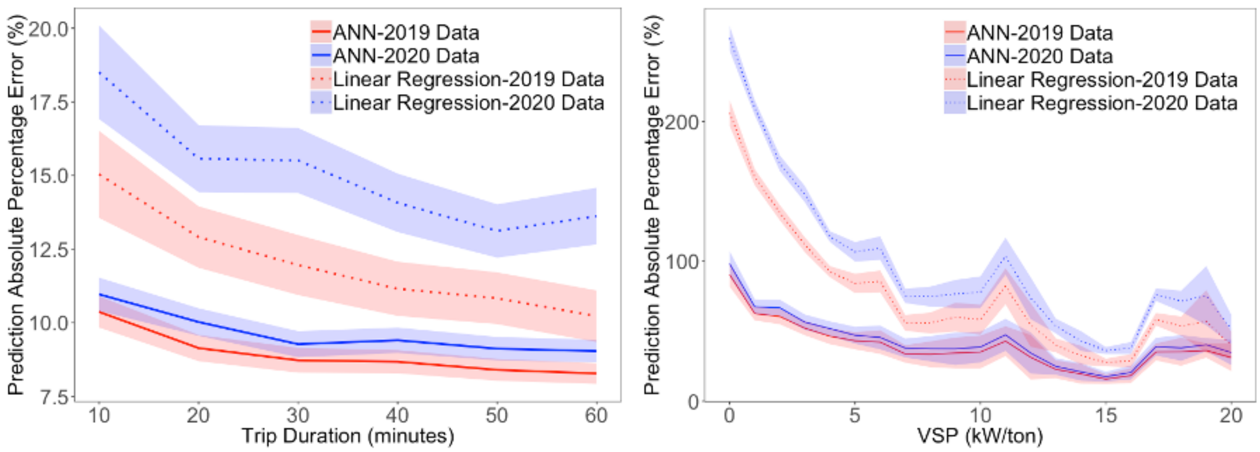
4.1 Electric Buses

Energy prediction for electric buses is challenging because of the diversified driving cycles of transit services. Literature review shows limited studies on the energy consumption of electric buses. To solve the challenge, the team developed an ensemble of neural network-based EV bus prediction models that achieves better accuracy performance compared with regular regression models and accuracy performance comparable to physics-based models. The models cover three different driving situations: regenerative braking ($acceleration < -2ft/s^2$); aggressive acceleration ($acceleration > 2ft/s^2$); and cruising ($acceleration \in [-2, 2]ft/s^2$). The accuracy of the three models outperforms the single model for predicting all driving conditions. This is primarily because these three different scenarios are effectively three different modes, and energy consumption dynamics vary significantly.

The model was tested with data collected in 2019 and 2020. Figure 8 shows the performance of the model. We also trained a non-neural network model and compared its performance with our neural network-based model. We use the 2019 data as a training set and the 2020 data as the validation dataset. The results (Fig. 9) show that the mean absolute percentage errors and confidence intervals of the artificial neural network model are consistently lower than those of the linear regress model using either the original training data collected in 2019 or validation data collected in 2020. Though, the differences seem to diminish as trip duration increase in all cases.

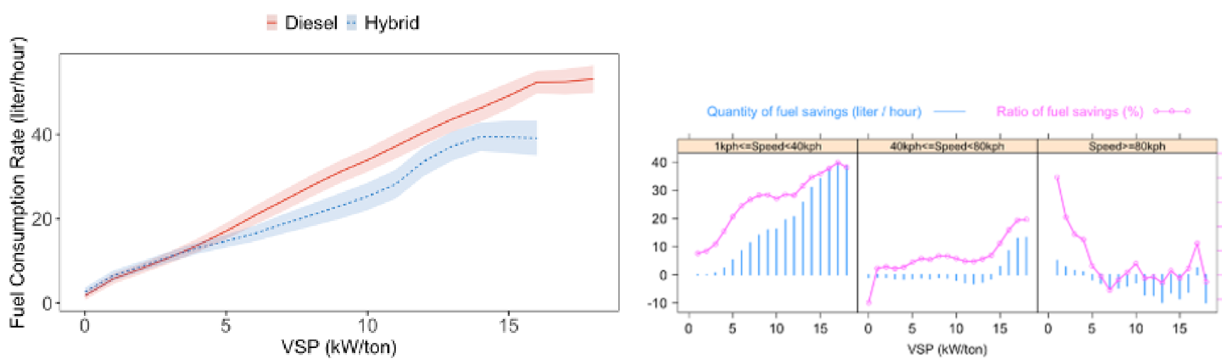
4.2 Hybrid Diesel Buses

As part of this project, we also designed a micro-prediction model for diesel and hybrid vehicles. For this purpose, we developed an artificial neural network (ANN) based fuel consumption estimation model that utilized $1Hz$ granularity real-world operation data. Figure 10 shows the



(a) (b)

Figure 9: (a) Mean and 95% confidence interval of absolute percentage errors of microscopic energy prediction with trip duration for different models. (b) Mean and 95% confidence interval of absolute percentage errors of microscopic energy prediction at with respect to the vehicle specific power.



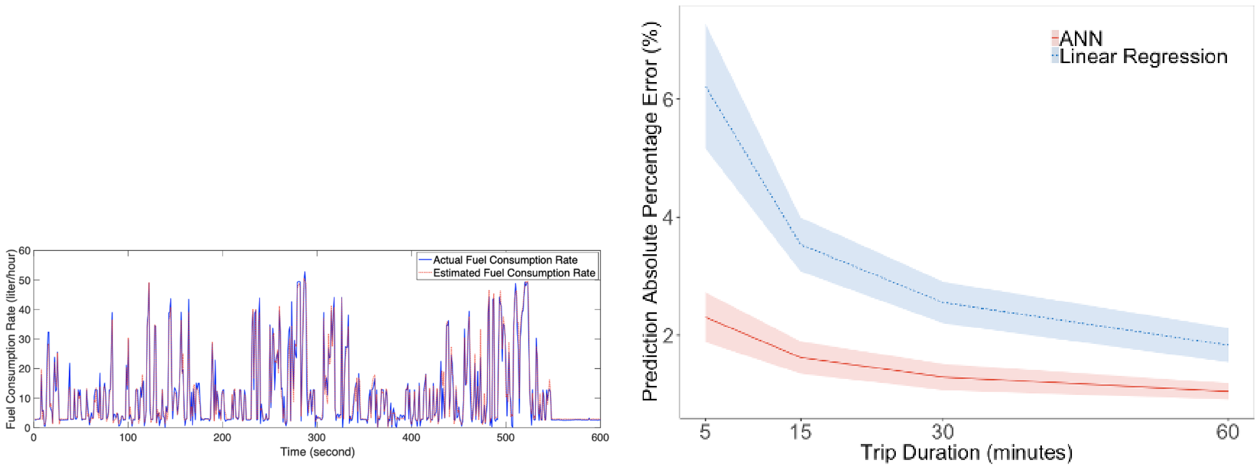
(a) (b)

Figure 10: (a) Mean fuel rate (liter per hour) and 95% confidence interval (shaded area) for diesel and hybrid bus as a function of instantaneous vehicle specific power bins from 0 to 18 kW/ton with 1 kW/ton interval. (b) Fuel savings of hybrid buses as compared with diesel buses by driving speed and instantaneous vehicle specific power bins.

difference between diesel and hybrid vehicles in terms of fuel consumption. Figure 11 describes the performance of the prediction model. The error decreases as the trip duration increases. This is in line with the observations from the macro prediction models.

5 Transferring the Models to Other Communities

There are several challenges that another community trying to implement this approach of developing the prediction models may face. However, one of the foremost challenges is that they will need to collect enough data to build a generalizable model. In agencies with smaller fleets of a particular type of vehicle, this becomes difficult. The problem in particular stems from the fact that separately training models for each type of vehicle ignore generalizable information not explicitly modeled in the feature space. For example, our previous work modeled EVs and ICEVs without sharing model parameters between classes [13]. Second, the number of vehicles in each



(a) (b)

Figure 11: (a) Second-by-second actual fuel consumption rate (liter per hour) versus estimated fuel consumption rate for one trip. (b) Mean absolute percentage error and 95 percentage confidence intervals for predictions of artificial neural network (ANN) model and linear regression model with the same independent variables as a function of trip duration.

class varies greatly, which leads to an uneven distribution of data available for training the energy or emission prediction models. Third, and similar to the second problem in principle, when a new vehicle class is added to an existing fleet, the agency must deploy vehicles, obtain data, and then learn a new predictive model from scratch.

We addressed these challenges as multi-task learning (MTL) and inductive transfer learning (ITL) problems [14]. Although different vehicle classes' energy consumption depends on a varied set of covariates through other non-linear functions, we hypothesize that broader generalizable patterns govern the consumption of energy and vehicle emission. Thus, we formulated the emission (and energy) forecasting as an MTL problem. Our work found that this approach improves the predictive accuracy for all vehicle classes compared to the macro prediction model described earlier, where separate networks are trained to predict emissions (and energy) for each category (hybrid, EV, and ICEV).

In a situation with imbalanced data or when an agency introduces a new model or class, we were able to show that it is possible to learn a model for bus types with sufficient data, and subsequently, *transfer* the learned abstraction to improve the predictive accuracy for the category with insufficient data. The benefit of ITL is the ability to deploy the model earlier than the time required to collect enough samples to train a separate model for the new class. We evaluated our MTL and ITL models using real-world data from our CARTA's mixed-fleet of EVs, HVs, and ICEVs. We found that in both the MTL and ITL settings, our approach outperforms state-of-the-art methods. The most significant improvements over baselines were in the ITL setting when the target vehicle class suffers from a lack of data. However, we also find that ITL does not work well in some cases, such as when transferring learned abstractions from EV to ICEV. The architecture of our approach is shown in figure 12.

Figure 13 presents the key results. We find that for all vehicle classes, the MTL model outperforms the vehicle-specific baseline models. The mean percent improvement in MSE is 8.6%, 17.0%, and 7.0% for ICEVs, HVs, and EVs, respectively. The mean percent improvement in MAE

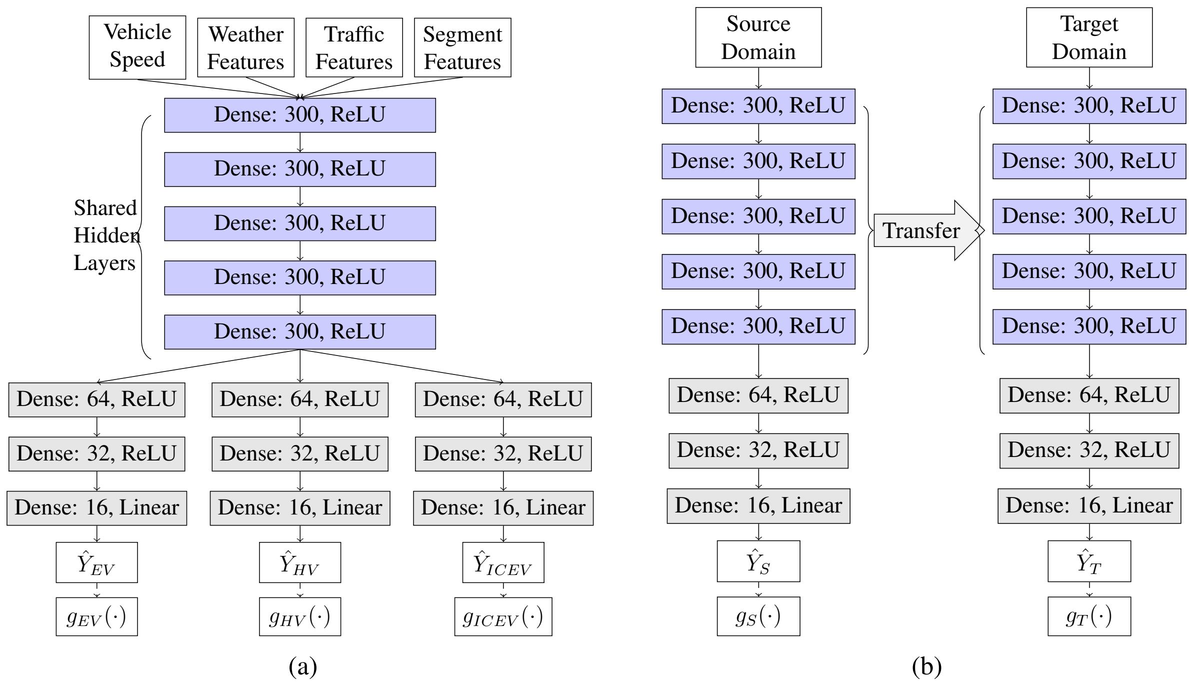


Figure 12: (a) MTL Model: DNN with hard parameter sharing for predicting emissions (kg CO_2) of EVs ($\hat{Y}_{EV}$), HVs ($\hat{Y}_{HV}$) and ICEVs ($\hat{Y}_{ICEV}$). (b) ITL Model: shared-hidden layer parameters are frozen and transfered to the target model. Energy consumed (kWh) is a linear function $g_i(\cdot)$ for vehicle class i.

is 6.4%, 9.0%, and 4.0% for ICEVs, HVs, and EVs, respectively.

Next, we evaluated the performance of the ITL model. To train the ITL models, we use data from all of the three-vehicle classes. We first prepare the source model for each source and target task pair, freeze the shared hidden layers and transfer to the target model. Then, we optimize the target model's vehicle-specific layers. For each model, the available sample size to train the target model is varied from 2%, 5%, 10%, and 15% of the total number of available samples to investigate the influence of sample size in training the target models. This is consistent with what transit agencies might face in practice; as a new vehicle is introduced, agencies gradually collect more data from it. We test our approach for all pairs of vehicle classes. To compare the performance of the models, we train baseline models that only use the training data from the target domain. For example, while evaluating inductive transfer from EV to ICEV with 2% of the target data available, the baseline model is trained exclusively on the same amount of data from ICEV class. To consider the randomness in the training process, when evaluating the target and baseline models, we trained each model 10 times on ten random samples from the target domain's dataset and ten different initial values for the parameters using Kaiming initialization.

We provide the results of the proposed ITL approach in Figure 14. We observe that the proposed approach generally results in improved forecasting accuracy across the tested scenarios (except when EV is used as source and ICEV is used as the target). We also observe that as the amount of data from the target domain increases, both the ITL and the baseline (previously developed macro prediction models) method show improved forecasting accuracy; however, the baseline methods shows relatively higher improvement, to the extent of outperforming the ITL framework in some cases (15% data from target domain in Figure 14 b, c, e and f). We therefore concluded that when large enough data is available, the ITL approach should lead the way to either multi-task learning

(a) MSE (b) MAE

Figure 13: (a) MSE and (b) MAE of MTL model compared to vehicle-specific neural network models (baseline) on testing set. Prediction target: emissions (kg CO_2).

or baseline approach (models described in earlier sections). However, agencies, where not a lot of data is available, they can start from models trained for other classes or other agencies and slowly update the models as new data becomes available. The advantage is the speed with which the predictive models become available to the transit agency.

6 Optimization of Mixed Transit Fleet

Based on the energy prediction models, the team set up an optimization problem that minimizes fuel and electricity use by assigning vehicles to transit trips and scheduling them for charging while serving the existing fixed-route transit schedule in Chattanooga. The problem formulation is general and applies to any transit agency that has to provide fixed-route transit service using a mixed fleet. The team introduced an integer program, a greedy algorithm, and simulated annealing algorithms to solve the problem.

The greedy algorithm follows an iterative process, wherein each iteration computes the energy cost for serving each unassigned trip using each of the available buses, chooses a pair of a trip and a bus with minimum energy cost, and assigns the bus to the trip. In this process, the algorithm computes the energy cost for serving a trip using a bus by factoring in the waiting times between assignments to maximize utilization. The algorithm terminates once all the trips are assigned to a bus or no more feasible assignments exist.

The simulated annealing algorithm generates an initial solution using the greedy algorithm. Then in each cycle of simulated annealing, the algorithm generates a new solution, which is chosen at random from the neighborhood of the current solution, and then either adopts or rejects the new solution with some probability based on the difference in the quality of the existing and new solutions. The random neighbor generation chooses two buses at random and groups the assignments of the selected two buses into two groups based on the start time of the trips, then picks one group and swaps the bus assignments in the selected group. The algorithm repeats this process until a required number of swaps have been performed.

The team evaluated the algorithms on CARTA's transit routes using the macro-level energy predictors to assess the objective. Fig. 15(a) compares the solution quality of simulated annealing and greedy algorithms to the integer program (IP), which is optimal but does not scale computationally. The figure shows that simulated annealing performs slightly better than greedy, but neither is optimal. On the bright side, the cost ratio between IP and our heuristics improves for more significant instances. Fig. 15(b) shows energy costs for the complete daily schedule of CARTA using three

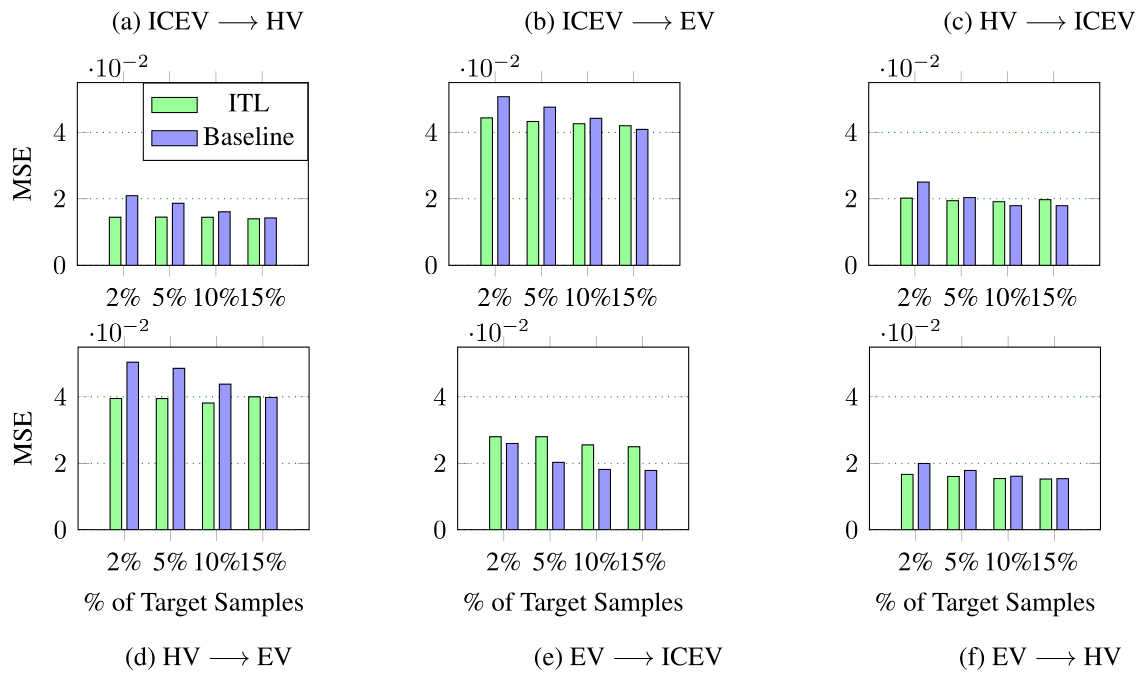


Figure 14: ITL models compared to corresponding baselines. ITL model is trained on full dataset in the source vehicle class and is evaluated on the target vehicle class (source ⟶ target). Average MSE compared to fraction of data samples used for training in the target vehicle class. Prediction target: emissions (kg CO_2).

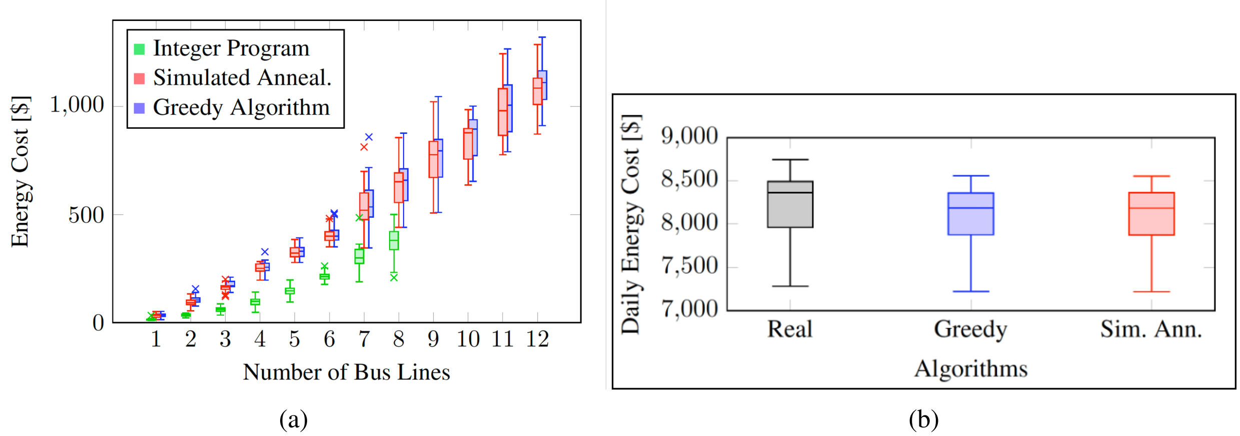


Figure 15: (a) Energy costs for assignments using the integer program, simulated annealing, and greedy algorithm for various number of bus lines. (b) Energy costs for assignments using the greedy algorithm and simulated annealing for complete daily schedules, compared to existing real-world assignments.

electric and 50 diesel buses using greedy and simulated annealing algorithms. The results show that the proposed algorithms are scalable and can reduce energy usage, environmental impact, and operational costs. The proposed algorithms could save $48,910 in energy costs and 175 metric tons of CO2 emission annually for CARTA.

7 Data Dashboards and Simulator

To ensure the outreach of our results, we have also developed a simulator and a set of web applications (Fig. 16). They enable the research community to simulate different trip rosters and check their overall energy efficiency. The simulator provides the ability to program specific scenarios—time of day, weather, traffic patterns, route schedules, and trip assignments (vehicles to routes)—and simulate energy consumption for the day. The simulator uses the energy prediction models and the travel demand and occupancy data collected from the CARTA vehicles during the project.

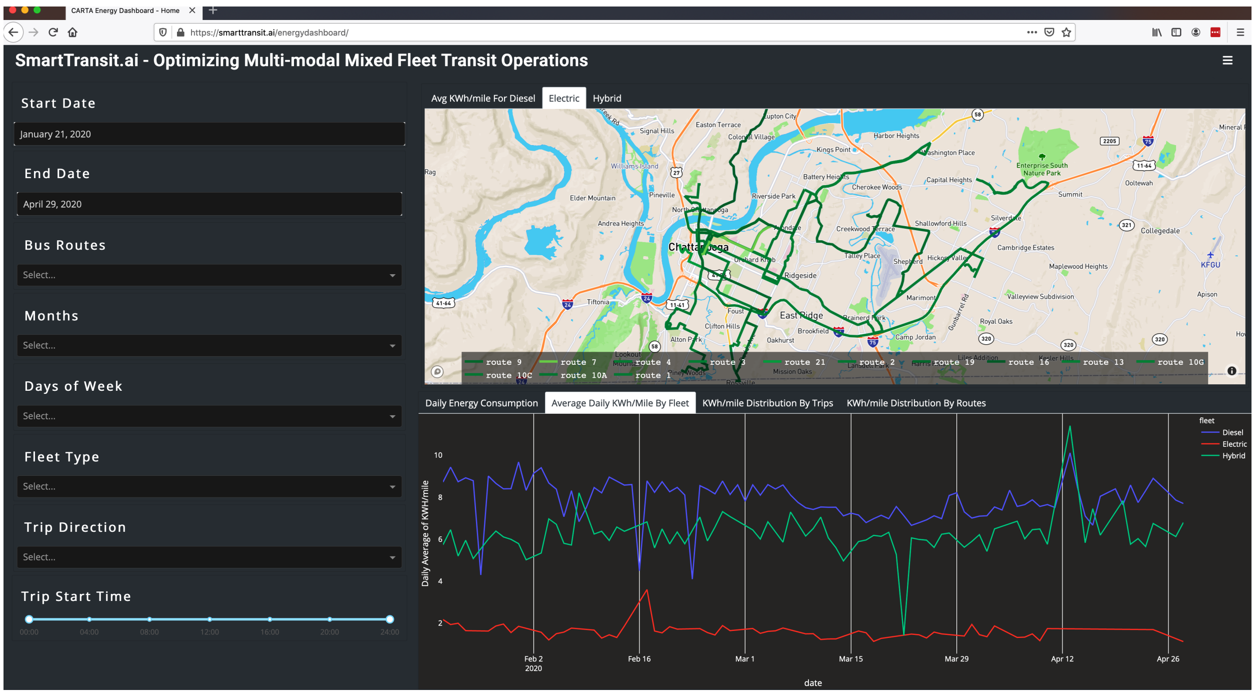


Figure 16: The energy dashboard is available at https://smarttransit.ai/energydashboard/ and provides statistics and analysis from the data collected in the project.

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A Source Code

The project toolchain is available at the following repositories

- https://github.com/smarttransit-ai/macro-energy-prediction - This repository contains the code for estimating the energy consumption for all trips on a given day in the future in the CARTA fleet using the machine learning models built during the project. The repository provides instructions to build a docker image and provides instructions on using the models. The archive folder withing the repository describes the source code for replicating the data collection and prediction scripts at a different transit performer location.
- https://github.com/smarttransit-ai/micro-energy-prediction describes the micro prediction models and how to train them and use them.
- https://github.com/smarttransit-ai/ECML-energy-prediction-public describes the improvements to the prediction models using multi-task learning and inductive transfer learning.
- https://github.com/smarttransit-ai/EnergyOptCode-AAAI describes the optimization routines.

Further information about the project is available from https://smarttransit.ai/.

B List of Publications Of This Project

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