THESIS

PREDICTING HYBRID VEHICLE FUEL ECONOMY AND EMISSIONS WITH NEURAL NETWORK MODELS TRAINED WITH REAL WORLD DATA

Submitted by

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ABSTRACT

PREDICTING HYBRID VEHICLE FUEL ECONOMY AND EMISSIONS WITH NEURAL NETWORK MODELS TRAINED WITH REAL WORLD, ON-ROAD DATA

Physics-based hybrid vehicle simulation models for fuel economy (FE) exist but are computationally and financially expensive. These models simulate aspects of real-world drive cycles that include the driving environment, thermal management, driver input, and powertrain component behavior. In this study, an alternative method of hybrid vehicle FE simulation is developed by training and testing a time series neural network (NN) model using real world, on-road data. This enables NN models to model many aspects of on-road vehicle dynamics, like regular traffic stops, turning, and irregular accelerations and stops. Unlike the physics-based models, NNs have the advantage of lower computational costs, which could be utilized in near-real-time vehicle system control to determine optimal velocity planning and powertrain control. Models trained in this study used velocity-time traces as an input to predict instantaneous FE. The NN model predicted fuel economy within a mean absolute error of 0-5% for on-road measurements over a 40 minute, real world, city and highway drive cycle. NN models trained with varying lengths of datasets did not improve with training data longer than 35 minutes. When trained with this method, NN models were accurate when tested with data from multiple days of tests and various drive cycles. Multiple NN models were also trained with hybrid vehicles with varying control system settings. NNs can only successfully model a vehicle whose control system settings reflect the training of the model. These results are expected to improve with more comprehensive drive cycle data that includes data from different elevations and various climatic conditions. The predictions from the FE NN model were compared against predictions from the physics-based Autonomie model and a custom HEV simulation model developed at Colorado State University. NNs outperform these models when tested with on-road data to predict FE of a known vehicle. Using a portable emissions monitoring system (PEMS), NN models were also able to predict nitrous oxides and particulate matter emissions with <5% mean absolute error. The NN model method could be used to improve emissions estimates by capturing differences between real world and laboratory tested emissions. Recording and including more data from the vehicle and devices like the PEMS could further improve these NN models.

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I want to thank Dr. Tom Bradley for initially initiating this project in conjuncture with Lightning Hybrids. I want to thank the engineers at Lightning Hybrids for collecting data and letting me use their equipment. I hope that this project benefits Lightning Hybrid's endeavors to improve the efficiency of their vehicles. I would like to thank all my colleagues at CSU that helped with data collection and reviewing my papers.

Lastly, I would like to thank my parents, siblings, and friends for their words of encouragement and their uncanny ability to keep me sane during my years in graduate school.

1. INTRODUCTION

Project Introduction

The transportation sector accounts for 28% of all energy use in the US and 5% globally [1, 2]. Most of this energy is generated from the combustion of fossil fuels, which produces greenhouse gases (GHG) such as CO_2 and CH_4, and harmful pollutants such as CO, NO_X, hydrocarbons (HC), and particulate matter less than 2.5 μm in diameter ($PM_{2.5}$), that affect air quality, climate and human health [3, 4, 5, 6, 7, 8, 9]. There is an urgent need to improve vehicle fuel economy (FE) that will reduce dependence on fossil fuels and reduce environmental impacts. The Corporate Average Fuel Economy (CAFE) standards were enacted by the US Congress in 1975 to reduce dependence on oil and reduce energy consumption [10]. CAFE standards are fleet-wide averages to be achieved by individual automakers for its car and truck fleet. Recently, in 2012, CAFÉ standards were updated to project a fleet wide average FE of 40.3-41.0 mpg by model year 2021. This goal operates in tandem with the Environmental Protection Agency's (EPA) goal to limit CO_2 emissions to 163 grams/mile by model year 2025. In addition to the CAFÉ standards, the California Air Resource Board (CARB) standards which regulate other emissions such as CO, NO_x, and HC.

Hybrid vehicles, in particular hybrid electric vehicles (HEV), are showing increased consumer demand and are considered a crucial vehicle architecture to improve FE. Annual US sales of HEVs have increased from 9,350 in 2000 to over 500,000 in 2014 [11]. Vehicle FE is commonly characterized on a chassis dynamometer, a device that measures and imposes torque and power on an engine or vehicle. Numerical models, such as Autonomie and Modelica, simulate the physical processes in the vehicle and predict FE. Using these measurements and predictions, vehicles can be optimized to improve FE through modification of the powertrain and energy system control [12, 13, 14]. By improving HEV energy management techniques, FE can be increased by approximately 20% depending on the cycle driven [15]. This can be achieved in part by improving the model representation of the powertrain and energy control system (Figure 1).

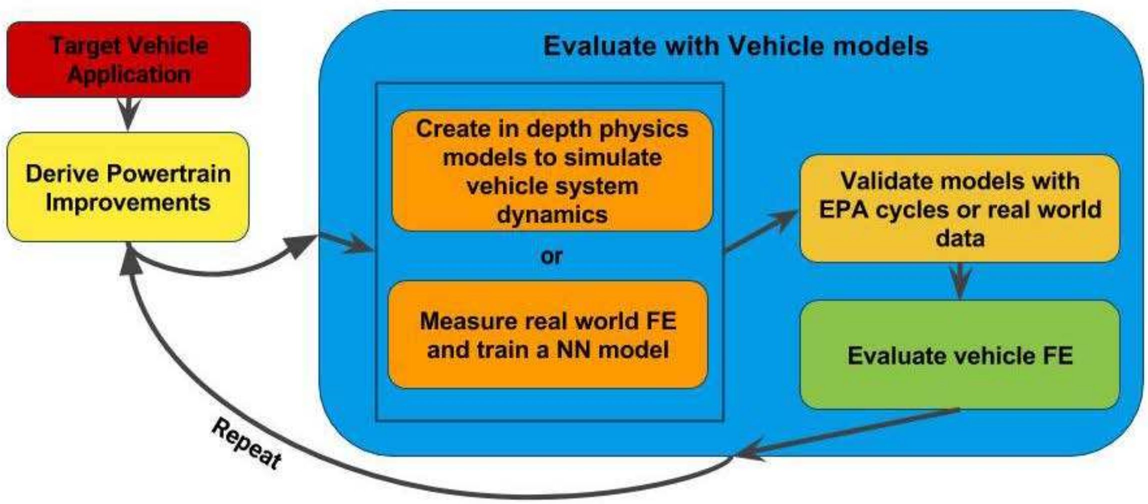


Figure 1: Optimization of HEVs is a multi-step, iterative process that requires evaluation to model vehicle FE on a given route. There are a growing number of methods to improve powertrain control including dynamic programming (DP), Pontryagin's Minimum Principle (PMP), and NNs [12]. This study is aimed at improving the FE model evaluation portion of optimizing powertrain control. Physics-based models provide more detailed information for specific vehicle parameters studies but for FE studies, as shown in this work, comprehensive information is not needed.

Hybrid vehicle FE modeling is difficult due to complicated engine and energy management strategies resulting from a combination of multiple drivetrain energy sources [16]. Models allow researchers to optimize control strategies that can reduce fuel consumption of HEVs without the need for on-road tests. Current models can accurately predict FE in conventional vehicles (CV) and HEVs but these are computationally and financially costly [17].

Consequently, improving FE also reduces total emissions produced due to less fuel consumed. However, emissions composition changes with vehicle specific power (VSP) and steady state engine operation [18, 19]. The EPA has developed the MOtor Vehicle Emission Simulator (MOVES) [20, 21, 22, 23, 24] to model emissions from on-road mobile sources. This method works well for internal combustion engines in CVs but it has been shown that the model does not perform as well with HEVs [25]. Emissions tests on dynamometers, using certification cycles, have underestimated some pollutants by 10-20% when compared to real world, on-road test conditions [26]. Tests completed on a chassis dynamometer cannot fully mimic turns and potholes, unexpected and inopportune traffic incidents, and aggressive or uncommon driving habits. These are characterized primarily in real world, on-road collected data. A model built to anticipate on road driving occurrences could improve FE and emissions predictions.

Prediction of vehicle parameters using a neural network (NN) model has been previously studied [27, 28, 29, 30, 31, 32, 33]. NNs build associations from known data to create simulation models. These studies have focused on predicting emissions and engine and fuel performance for an engine on a dynamometer only and not an on-road driven vehicle. Researchers at the National Renewable Energy Laboratory (NREL) have utilized NNs to determine optimal engine control for HEVs using an input drive cycle [33, 34, 35]. While these studies utilize NNs, predicting vehicle FE using real-world data is less explored. However, these studies and physics-based model approaches all forgo the use of real world, on-road testing for controlled laboratory data. NNs in HEVs and CVs will allow investigation of alternate control strategies to improve FE based on on-road driving data. A NN trained on on-road data could predict the FE of future routes, which would progressively improve with more data from the given route and from multiple drivers. If the route is known, the vehicle's energy management system can be modified to optimize efficiency. This benefits the manufacturer by enhancing their product and the consumer by saving on long term fuel cost (Figure 1). On-road driving data has an advantage over characteristic drive cycles in the fact that the models can be trained to anticipate real world instances, driving habits, and multiple drivers. NNs can also be trained in a time series configuration, which accounts for short term, nonlinear engine dynamics and hysteresis.

Research Objective and Overview

In this study, we developed and applied neural network models to simulate fuel economy and emissions from hybrid vehicles operating in the real world. The neural network models were trained, tested, and evaluated on real-world, on-road measurements made on a combination of hydraulic and electric hybrid vehicles. The neural network models were also tested against physics-based models. Our work was used to answer the following research questions: (i) Are NN models built to predict FE and emissions from real world data viable as a modeling technique?, (ii) Under what conditions (e.g. drive cycle and data length, model training parameters) do NN models for FE and emissions predict with less error?, and (iii) Is there a methodology to consistently train FE and emissions NN models?

Materials and Methods

Neural Network Models

A NN is a computing tool originally designed to loosely model the pathways found in the brain and nervous system. NNs establish interconnected links called neurons which accept inputs and pass them through transfer functions, in hidden layers within the model, to compute an output. The network trains weights within these transfer functions with the objective of minimizing the error between the measured and predicted output. NNs are ideal for creating predictive models when large datasets exist and there are complex, nonlinear relationships between the inputs and outputs. They have been widely utilized in weather, energy systems, economic trends, and can be applied to any scenario where non-linear relationships occur [36, 37, 38, 39, 40].

NNs are trained iteratively to change the weights and biases in a neuron with the transfer function:

$$\boldsymbol{n} = \sum_{\boldsymbol{i=1}}^{\boldsymbol{p}} \boldsymbol{x_i}\,\boldsymbol{w_i} + \boldsymbol{b} \tag{1}$$

Where n is the neuron output, P is the number of input elements, x_i is the input value, w_i is the weight of the input value, and b is the bias. Weights and biases are altered with each iteration, influencing the output relative to the importance of the input [41]. The summation of the weighted inputs and the network biases yield an output, *n,* in the hidden layer [42]. Figure 2 shows the architecture of a Nonlinear AutoRegressive network with eXogenous (NARX) inputs which is the form of all NNs in this study. A sigmoid transfer function is used in the hidden layer neurons producing an output from 0 to 1. Using a sigmoid function in the hidden layer allows the weights and biases to generalize an output unlike a step function. Neurons in the hidden layer pass predictions to a single neuron in the output layer. The output layer uses a linear transfer function to scale the overall output for the target units and scale. Time series datasets utilize more inputs dependent on a time delay *d*:

$$\boldsymbol{y(t) = f(y(t-1), y(t-2), \ldots, y(t-d),}$$
$$\boldsymbol{x(t-1), x(t-2), \ldots, x(t-d))} \qquad (2)$$

Where *y(t)* is the network output, *x* is the training input, and *t* is the time step. The time delay determines the amount of time each data point is included in the transfer functions.

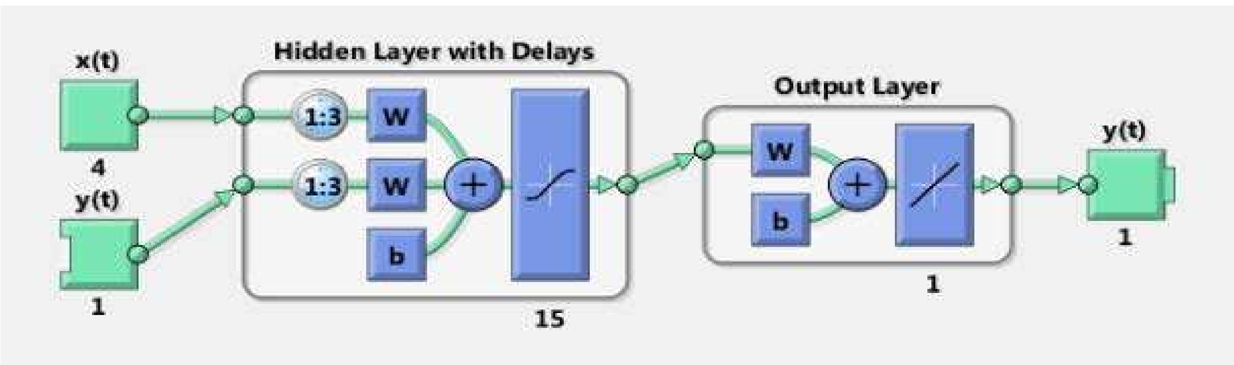


Figure 2: Schematic for a NARX NN trained to predict FE and emissions predictions. In this case, 4 inputs (x(t)) and 1 feed-forward output (y(t)) enter the network. The output of the network is used as an input from pervious time steps. The time delay for this network is 3 seconds (1:3) and there are 15 neurons in the Hidden Layer [42].

The performance of NNs are evaluated by calculating the correlation coefficient (*R*) and the mean square error (*MSE*) in each training iteration:

$$\boldsymbol{R(a,p) = \frac{E[(a-u_a)(p-u_p)]}{E\sqrt{(a-u_a)^2(p-u_p)^2}}} \qquad (3)$$

$$\boldsymbol{MSE = \frac{1}{n}\sum_{i=1}^{n}(p_i - a_i)^2} \qquad (4)$$

Where *E* is the expected value, *a* and *p* are measured and predicted output sets respectively, u_a and u_p are the mean values of the *a* and *p* sets respectively, and *n* is the length of the *a* and *p* sets. The R-value, *R(a,p)*, is a measure of how well the predictions correlate linearly to the measurements. The *MSE* measures average squared error in the prediction. The training process attempts to maximize the *R* value and minimize the *MSE*. The weights and biases are improved using backpropagation algorithms in an iterative process [41]. Each iteration builds on the previous network, changing weights and biases, to optimize *MSE* and *R*.

In this work, the performance of the trained networks was judged by calculating the percent error in the measured and predicted FE over an entire cycle:

$$\%\,\boldsymbol{Error} = \frac{\sum_{i=1}^{n} \boldsymbol{measured}_i - \sum_{i=1}^{n} \boldsymbol{predicted}_i}{\sum_{i=1}^{n} \boldsymbol{measured}_i} * \mathbf{100} \tag{5}$$

Where *n* is the number of predicted and measured values, $measured_i$ is the measured value, and $predicted_i$ is the model predicted value. The sign of percent error calculated depicts whether a model under or over estimates a prediction.

Training networks from comprehensive driving data can create networks that can predict the FE or emissions for any drive cycle. This study explores NNs as a method to train models from on-road data to predict FE and emissions from hybrid vehicles.

Physics-Based Models

Autonomie is a simulation tool developed by the Vehicle Testing Group at Argonne National Labs (ANL) [43]. ANL has developed models that simulate real world Chevrolet Volt PHEV operation [44] and Toyota Prius HEV operation [45] using Autonomie. However, in practice, ANL does not provide these individual vehicle models to researchers. Customers are required to learn the simulation architecture and details as well as input vehicle parameters manually such as control logic, engine operation maps, and component efficiency maps. Without modification, Autonomie essentially acts as a “black-box” in practice, making rigorous investigation of new control strategies difficult. Because of these drawbacks, some researchers elect to build their own custom models.

Custom models to evaluate the effect on FE of various methods of energy management are well developed in the literature [45]. Development of FE simulation models has been accomplished by several researchers, including our group, which developed a FE simulation model in the Modelica language [46]. Modelica is a free tool that uses forward dynamics to simulate real-world stimulus responses as well as a differential algebraic equation solver [47, 48]. This custom simulation tool is useful because modifications for various energy management scenarios are clear and transparent in comparison with Autonomie. The drawback of this simulation technique is the large amount of required development time, program compatibility issues, and common open source program drawbacks like lack of resources, frequent program crashes and arduous troubleshooting. This study uses these alternate fuel economy models to check the viability of a NN approach to vehicle FE modeling.

Portable Emissions Monitoring System

Portable Emissions Monitoring System (PEMS) devices have been used to measure on-road emissions in real world traffic [25, 49, 50, 51, 52, 53, 54]. The emissions data in this study was collected using an AxionS+ PEMS manufactured by Global MRV. Similar PEMS devices from the same manufacturer have performed well and have been used on many different vehicles including light duty vehicles, refuse trucks, and conventional and hybrid transit buses [25, 50, 51].

The PEMS device collected mass emission rates of CO_2, CO, HC, O_2, NO_X, and particulate matter less than 10μm (PM_{10}) measurements at 1Hz. The CO_2, CO, and HC measurements are made using a nondispersive infrared (NDIR) sensor, the O_2 and NO_X are measured with electrochemical sensors, and PM_{10} measurements made with a laser scattering detector. GPS coordinates and engine parameters from Controller Area Network (CAN) signals available through a vehicle's OBD-II port can also be recorded. The emissions were captured with an exhaust tailpipe probe, connected to the main device with ruggedized tubing. A 12 second delay correction was made in the PEMS to compile and synchronize all emission data to account for delays from plumbing and sensors.

Background

Conventional Characterization of Vehicle FE and Emissions

Fuel consumption in vehicles is typically measured during chassis dynamometer testing, which requires expensive equipment and a specialized laboratory. However, real world driving conditions may not be captured well on a chassis dynamometer and fail to represent driving occurrences such as traffic stops or abrupt changes in vehicle acceleration.

Characteristic drive cycles are velocity-time cycles formulated to represent real world driving profiles of various driving applications. These drive cycles (e.g. UDDS, HWFET, and US06) are used for regulatory purposes to calculate FE and to determine compliance with emissions standards. These and other cycles are composed of many driving instances to represent driving routes utilized in, but not limited to commuting, delivery vehicles, and public transit. Physics-based models are built to match drive cycle test results from these laboratory tests but are not typically tested with real world data. A model that is built from real world data should perform as well as these laboratory derived models and compare well to laboratory collected data.

2. LIGHTNING HYBRIDS MODELS

Lightning Hybrids (LH) in Loveland, CO retrofits trucks, buses and other large transit and delivery vehicles with hydraulic drivetrain-integrated systems. LH converts CVs to hydraulic hybrid vehicles (HHV) that have similarly complex energy management and powertrain control systems compared to HEVs. LH encountered problems when attempting to drive characteristic drive cycles generated to represent their customers' driving applications. These drive cycles were not always drivable due to driver response and the operation of the hybrid vehicle. CSU was commissioned to research a method to create more realistic drive cycles or to model FE in their vehicles. A preliminary NN approach was explored with real world, test track data provided by LH.

NN Test and Training Procedures

The MATLAB Neural Time Series tool was used to train all NNs with a 3 second time delay. The time delay was included to account for short term operating history of the vehicles such as the vehicle's acceleration and momentum. Preliminary tests showed a 3 second delay yielded more consistent NNs over a 2 second delay but showed no discernable improvements for 4 to 5 second delays. Vehicle parameters and fuel consumption data was collected using the LH system controller at 1Hz and emissions data collected at 1Hz using the PEMS.

Two distinct NN models were created for fuel consumption and emissions modeling. When PEMS data were available, fuel consumption measured by the PEMS was used instead of the LH controller measurement. The two NN models were trained with a varying set of input variables as shown in Table 1 and Table 2. In theory, a NN model trained on more variables related to the output should produce a more robust model.

NNs were trained using the Levenberg-Marquardt backpropagation algorithm. Ten NNs were trained for each input scenario and the NN with the most optimized R-value and MSE was chosen.

All drive cycle data was collected and provided by LH using vehicles with LH's HHV system. Every NN model generated was tested and evaluated to determine the absolute percent error for the FE and emissions for the entire length of the tested drive cycle. Every model was tested on data independent from training data. The following paragraphs include descriptions of how the models were trained and tested with a varying number of neurons and inputs and varying lengths of data during training, different drive cycles, and LH control system settings. The limited testing of the emissions models from LH data is also included.

Table 1: Fuel Consumption training input scenarios, Bare, Vehicle Specific, and All In

FC Training Inputs		Bare	Vehicle Specific (VS)	All In
System State [Hybrid On/Off]		x	x	x
Velocity [mi/hr]		x	x	x
Acceleration (time series derived) [mi/hr/s]		x	x	x
Engine Speed [rev/min]			x	x
Arbitrary Units	LH System High Pressure			x
	LH System Low Pressure			x
	Throttle Position In			x
	Brake Position			x

Table 2: Emissions training input scenarios, Bare, Vehicle Specific, and All In

Emissions Training Inputs	Bare	Vehicle Specific	All In
Velocity [mi/hr]	x	x	x
Acceleration (time series derived) [mi/hr/s]	x	x	x
Engine Speed (rev/min)		x	x
ΔElevation (m)			x

Number of Neurons

Four different amounts of 1, 3, 12, and 48 neurons in the hidden layer were used in training of a NN model. The Keisling cycle was utilized for this exercise due to it having the longest drive cycle. For all other NNs trained, Eqn. 6 was used; this method is evident in the gray literature [55].

$$n = \frac{N_{in}+N_{out}}{2} \tag{6}$$

Where n is the number of neurons, N_{in} is the number of unique inputs, and N_{out} is the number of unique outputs.

Number of Inputs

The fuel consumption NNs were each tested for performance among three training input scenarios as seen in Table 1. The NN models were trained on the Keisling cycle again due to its length.

Length of Training Data

Previous work has not explored the influence of the length of real world training data to create fuel consumption NN fits. The fuel consumption NN models were trained with 5 datasets of varying length to show how training length affects NN performance.

Different Drive Cycles

LH provided data for Orange County bus (OCBUS) and Keisling cycles for the fuel consumption models and the UPSUK cycle for emissions models. The OCBUS cycle is dominated by lower cruising speeds (~20 mi/hr) and time spent at idle. The Keisling cycle has periods of time spent at a stop with trends at intermediate to high speeds (30 to 70 mi/hr). Both of these cycles are explained in depth later in Chapter 2. The UPSUK cycle depicts a delivery route and trends around intermediate speeds (25 to 40 mi/hr). The OCBUS cycle is approximately 35 minutes, the Keisling cycle up to 9 hours, and the UPSUK cycle is approximately 8 minutes long.

Control System Settings

LH HHVs can change the state of their hybrid vehicles (System on/off) during testing. This enabled a strong comparison in models depicting either a conventional or hybrid vehicle. Drive data included system on and off control setting and some included 2 different system-on settings: Torque Addition (TA) and Torque Replacement (TR).TA adds torque from the hybrid system to the conventional drivetrain system. This reduces the driver's need to increase the throttle during operation. TR anticipates the throttle operation from the driver and the hybrid system replaces some of the torque in conventional drivetrain operation. This creates a more conventional driving experience for the driver since the input on the throttle should not differ between hybrid system on and off.

Emissions Models

The UPSUK cycle was the only cycle tested for the PEMS and was not explored extensively due to a limited amount of data. The training input scenarios were explored and are described in Table 2.

Results

Number of Neurons

The number of neurons used to train the NN did not seem to affect the NN fit and produced small errors in the predictions for fuel consumption. However, we did observe small differences in the errors as the number of neurons used to train the NN model were changed. NNs trained with too few or too many neurons performed poorly. The NNs trained with 1 and 48 neurons generated more error compared to the 3 neuron NN which adhered to Eqn. 6 (Table 3). Figure 3 shows the 1 neuron NN under predicting fuel consumption at 30.5 min and 33 min and the 48 neuron NN under predicting at 31.6 min. While the 3 and 12 neuron NNs under or over predict in some instances, the 1 and 48 neuron NNs under or over predict more often resulting in a larger percent error over the length of the cycle.

Table 3: Percent error from testing Keisling trained NNs and the approximate times to train each NN. 4 NNs were trained with varying number of neurons in the hidden layer and tested with the same Keisling cycle

Number of Neurons in Hidden Layer	Fuel Conumption % Error for 9 hour Drive Cycle	Approximate Time to Train (s)
1	0.23 %	<5
3	0.12 %	5
12	0.01 %	15
48	0.22 %	30

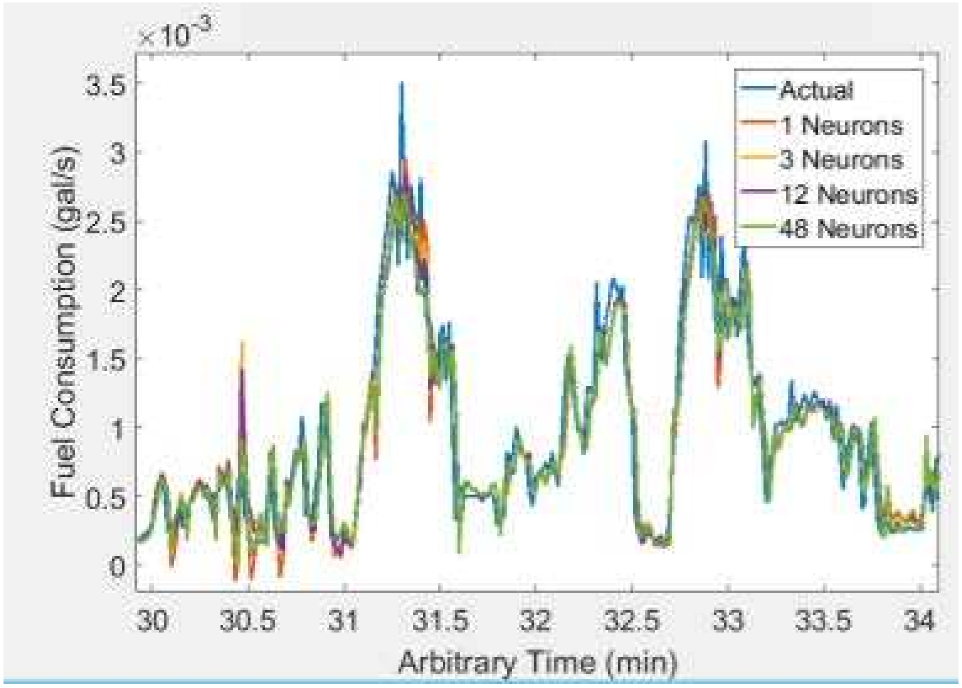


Figure 3: Comparisons of predicted fuel consumption values from NNs trained with varying amount of neurons in the hidden layer.

Number of Inputs

NNs trained to predict fuel consumption all performed well with absolute errors smaller than 1% for all training scenarios. Models with more inputs beyond velocity, time, and consequently acceleration, did not drastically improve performance among these scenarios (Figure 4). Bare, VS, and All In training scenarios yield 0.461%, 0.124%, and 0.974% errors respectively. All subsequent fuel consumption NNs reported will be of the VS variety considering it having the lowest error in this case.

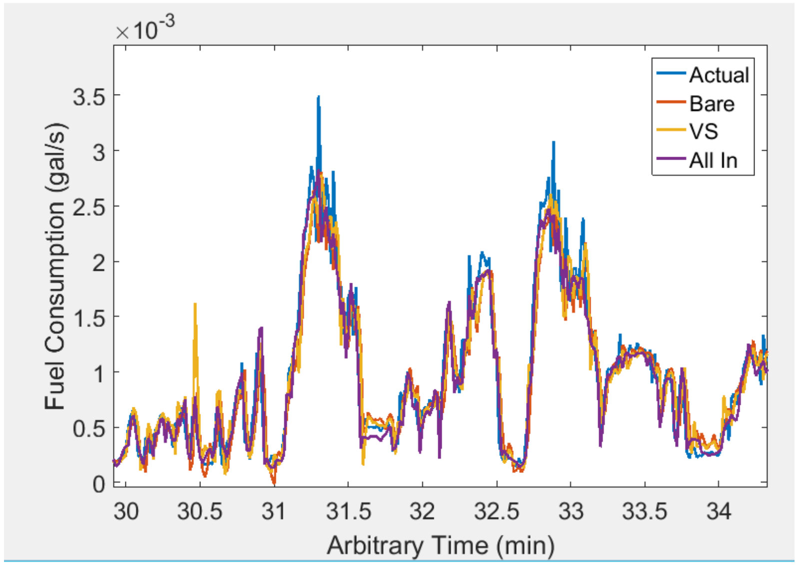


Figure 4: Predicted fuel consumption with varying input scenarios compared to actual measured fuel consumption values.

Length of Training Data

One could expect that the longer the training data, the better the NN fit and performance would be. Here, we examined the influence of four different training lengths from the OCBUS data on the ability of the NN model to predict fuel consumption. We find that the length of a dataset used to train a NN influences the performance of the model. Longer data sets produce smaller errors and vice versa (Table 4).

Table 4: NNs trained with varying lengths OCBUS datasets predict fuel consumption with associated percent errors.

Training Dataset Length (min)	Fuel Consumption % Error
4	1.50 %
8	3.30 %
17	2.24 %
35	0.46 %
70	0.12 %

Different Drive Cycles

NNs trained and tested with datasets from different drive cycles perform depending on the conditions of the training and testing datasets. A NN trained on a dataset without highway driving: OCBUS cycle, and tested with data with highway driving: Keisling cycle, yields a 13.08% error. A NN trained on a dataset with highway driving and tested with data without highway driving yields a 4.01% error. Time of year and different trucks may influence these errors. The test conditions for this instance is explored further in chapter 2.

Control System Settings

System on trained NNs can only accurately predict system on fuel consumption and system off trained NNs can only predict system off fuel consumption. Large errors (>10 %) occur when a network trained on one system setting attempts to predict fuel consumption from the opposite system setting (Table 5). This indicates that a NN model does not model control system settings that it was not trained to model.

Table 5: Percent error of aggregate fuel consumption from training and testing NNs with varying LH system on/off settings. OCBUS cycle used for testing and training.

NN Trained Data	Input Data	% Error
LH System On	LH System On	0.46 %
LH System On	LH System Off	14.81 %
LH System Off	LH System Off	1.07 %
LH System Off	LH System On	10.67 %

The LH system state can be set to more than on and off settings. A NN was built with the LH system set to TA and tested with data collected with the system set to TR.

The TR prediction, 1.56% error, performs worse than a TA prediction, 0.46% error, using a TA trained NN.

Emissions Models:

The NNs trained to predict emissions perform well for some outputs; notably well for HC and NO_X with errors <5 % (Table 6). Predictions of CO consistently create error of >10 % for most scenarios.

Table 6: Percent error of each predicted emission type over the length of the UPSUK cycle for system on and off and the 3 input scenarios.

Control System Setting / Emission % Error	System On			System Off		
	Bare	VS	All In	Bare	VS	All In
CO_2	0.87 %	2.13 %	7.26 %	1.29 %	4.11 %	11.31 %
CO	6.92 %	62.63 %	15.33 %	13.61 %	2.73 %	41.50 %
HC	1.72 %	2.02 %	0.27 %	0.27 %	1.91 %	1.38 %
NO_x	0.15 %	0.89 %	2.51 %	2.95 %	2.14 %	3.15 %
PM_{10}	0.37 %	0.48 %	7.23	1.59 %	2.00 %	6.06 %

Discussion

Training Inputs

Training NNs with different input scenarios shows that the Bare scenario that includes inputs of velocity and acceleration are the most influential variables. The addition of engine speed as an input variable only marginally improves predictions of fuel consumption (Figure 4).

Number of Neurons

For all tests, we used a NN with one hidden layer that included the number of neurons given by Eqn. 6. The number of neurons seemed to have small effect on model performance although our sensitivity studies suggest that the use of too few (e.g. 1 or 3) and too many (e.g. 48) results in marginally higher error. We hypothesize that too few or too many neurons may create a weak NN that cannot generalize (Figure 3). An intermediate amount of neurons creates stronger performing NNs. The number of neurons determined by Eqn. 6 trains a NN that performs well but this equation may not work for all applications. A NN trained with 12 neurons performs best among the 4 tested options but an equation or method has not been found to support this for this study.

Length of Training Data

The length of a dataset that trains a NN has profound effects on model performance. A substantial amount of data, as well as increased variability in captured drive cycles, improves the model. In Table 5, NNs with over 35 minutes of training data have error <1%. The NN trained with 4 minutes is the outlier with error of 1.50%, which produces less error than the 8 and 17 minute trained models.

Different Drive Cycles

Variability in drive cycle also trains a more accurate NN. The OCBUS cycle, being an inner city bus route, does not include higher speeds that would be found from driving on the highway. The Keisling trained NN model can predict the OCBUS cycle with error of 4.01% while the OCBUS NN model predicts the Keisling route with a higher error of 13.08%. Additional information for this case can be found in chapter 2.

Control System Settings

The models performed well with training from different LH system settings of controller on and off and torque addition and torque replacement. In each case of NNs built from data with different system settings than the data used for testing, predictions produced more error than when trained and tested with the same settings (Table 5). These instances of the models failing shows that the trained NNs are only trained for that specific controller setting. Control system settings directly affected performance of the NN model predictions. Extensive datasets that specify system settings would be able to predict fuel consumption in each control scenario. This would be invaluable in being able to determine the optimum controller setting to reduce fuel consumption.

Emissions Models

NNs trained to predict emissions have higher error and increasing the number inputs does not appear to improve performance (Table 6). This error may not be fully attributed to the inputs. The UPSUK data used to train NNs is approximately 8 minutes long; fuel consumption NNs trained on this length of data produced more error in their predictions than any other tested data length (Table 4). A longer emissions data input could benefit model performance. Separating each emission into its own model may also improve model training since fuel consumption models performed better overall while predicting only one output.

Conclusions and Future Work

NNs are likely a viable tool to model the fuel consumption from conventional gasoline and hydraulic hybrid vehicles. The error in the model predictions was less than 1% when training was performed over a long enough drive cycle and it is possible that the error can be further reduced through improved training strategies. While NNs may not replace lab dynamometer testing performed on characteristic drive cycles, they could complement traditional models in assessing and optimizing fuel consumption of vehicles in the future.

NNs can be further improved by capturing more drive cycle characteristics and having data from different drivers and road conditions. Different drivers could add more variability to the data since no two drivers have the exact same driving habits. Including vehicle curb weight, engine size, and make and model in the training could improve the NNs for specific vehicles. However, by adding this functionality, the models would be less generalized than predicting fuel consumption directly from a drive cycle velocity-time input.

NNs can also be improved with the exploration of optimizing the training process. The backpropagation algorithm used in this preliminary LH study is one of at least 2 others (Bayesian Regularization and Scaled Conjugate Regression) in the MATLAB Neural Time Series tool. Utilizing other NN training tools and techniques could lead to the discovery of an optimal training method for this application.

3. FUEL ECONOMY MODELS

NN models performed well in the preliminary LH applications. This chapter of the study trained NN models from real world, on-road data to predict FE for 2 production HEVs and explored methods to consistently create a NN model. These models were compared to physics-based models and measured data to demonstrate the strength of the method. The city and highway LH models are explored further in this chapter to justify the HEV tested drive cycles.

Methods

In this work, NN models were trained and evaluated to predict fuel consumption from a suite of hybrid electric and hybrid hydraulic vehicles. The training and evaluation were performed on data that were independently obtained across different drive cycles and on different days. For the hybrid electric vehicles, the performance of the NN model was also compared to the performance from physics-based models. The sections below describe the vehicles, routes and models used in our study.

Vehicles and Routes

This study employed three different hybrid vehicles: (i) one 2010 Toyota Prius, which is an HEV, (ii) one 2013 Chevrolet Volt, which is a plug-in HEV (PHEV), and (iii) 2013 and 2015 Ford E450 LH HHVs.

Custom routes were developed for tests with the HEV and PHEV. These were designed to mimic commuter driving and each consisted of a city and highway driving on roads in Fort Collins, CO (see Figure 5). Each vehicle was driven several times on the four cycles shown in panels a through d. These drive cycles incorporated a variety of driving conditions and included a mix of stops, accelerations, and portions of constant velocity while navigating through traffic. Four routes were created from a combination of one of the two city cycles and one of the two highway cycles so that each route has both city and highway driving conditions. Each route consisted of approximately 45 minutes of driving. A stair plot of the vehicle velocities for the four routes used for both vehicles is shown in Figure 6.

An established and a custom drive cycle were used to test the LH HHVs. The established drive cycle was the Orange County Bus (OCBUS) cycle was developed to mimic a transit bus cycle [56]. In this work, the OCBUS cycle was executed on a test track in 35 minutes. The custom drive cycle, henceforth referred to as the Keisling cycle, was an entire day (~9 hours) of shuttling senior citizens across town. The Keisling cycle included long durations of idling and a mix of city and highway driving. A velocity histogram of the HHV velocities for the OCBUS and Keisling cycles is shown in Figure 7.

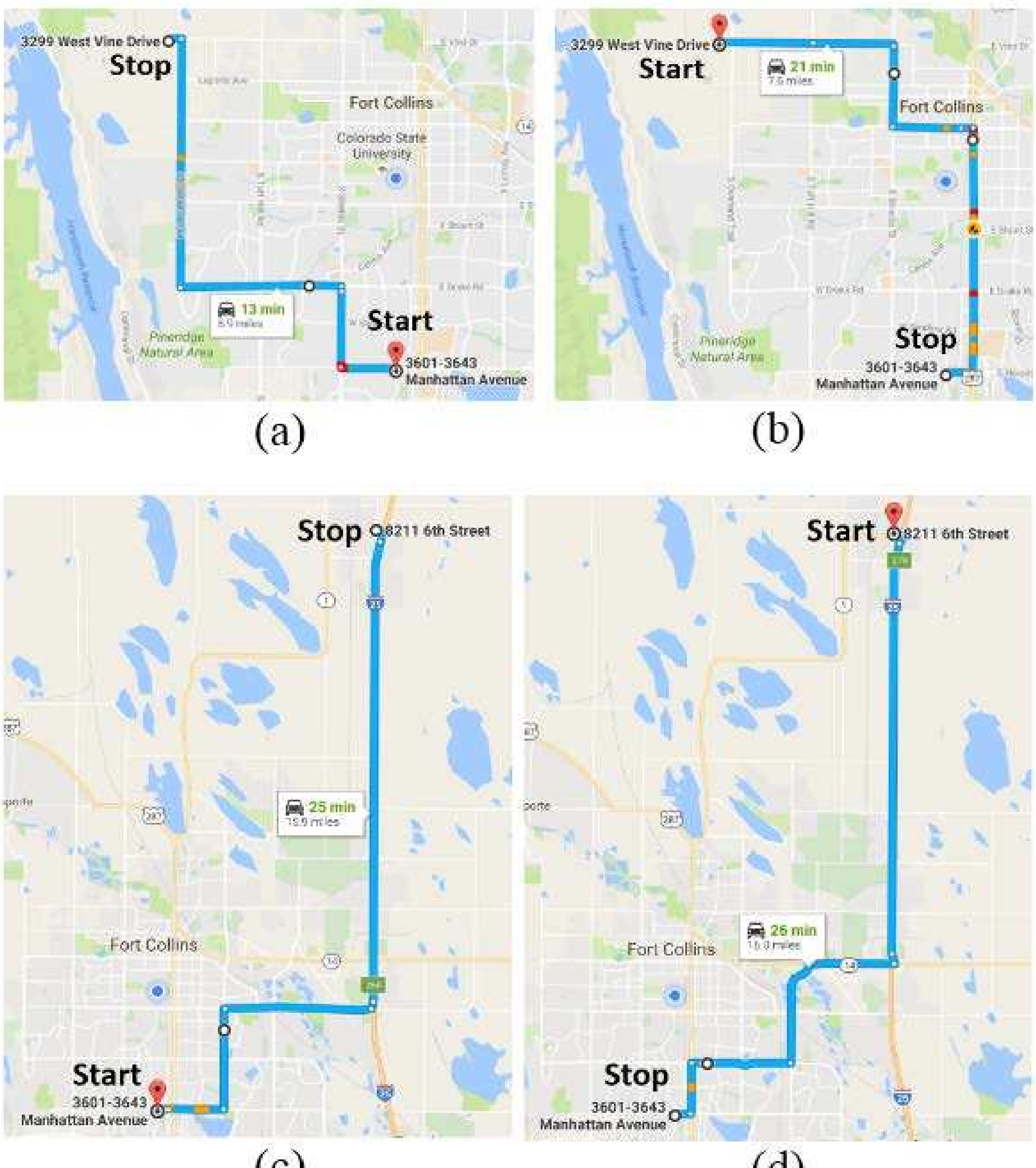


Figure 5: Maps of drive cycles captured in Ft. Collins, CO: a) city drive cycle 1, b) city drive cycle 2, c) highway cycle 1, and d) highway cycle 2. Credit: Google Maps

a)

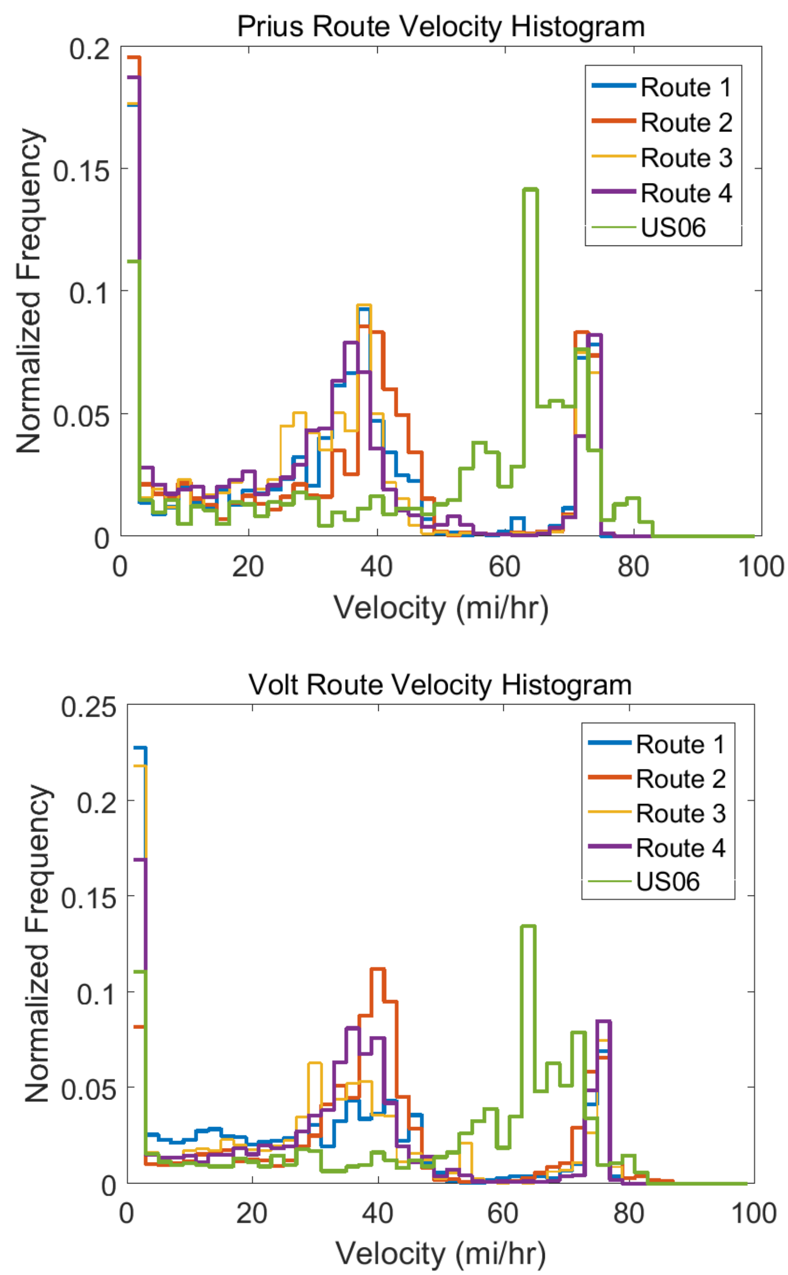


Figure 6: Vehicle velocity histogram of the 4 routes as driven with a 2010 Prius (a) and a 2013 Volt (b). Each drive route includes similar driving instance distribution and includes a mix of highway and city driving speeds. Training NNs with this data will produce a model that can anticipate all included driving speeds. The US06 cycle is also included for comparison.

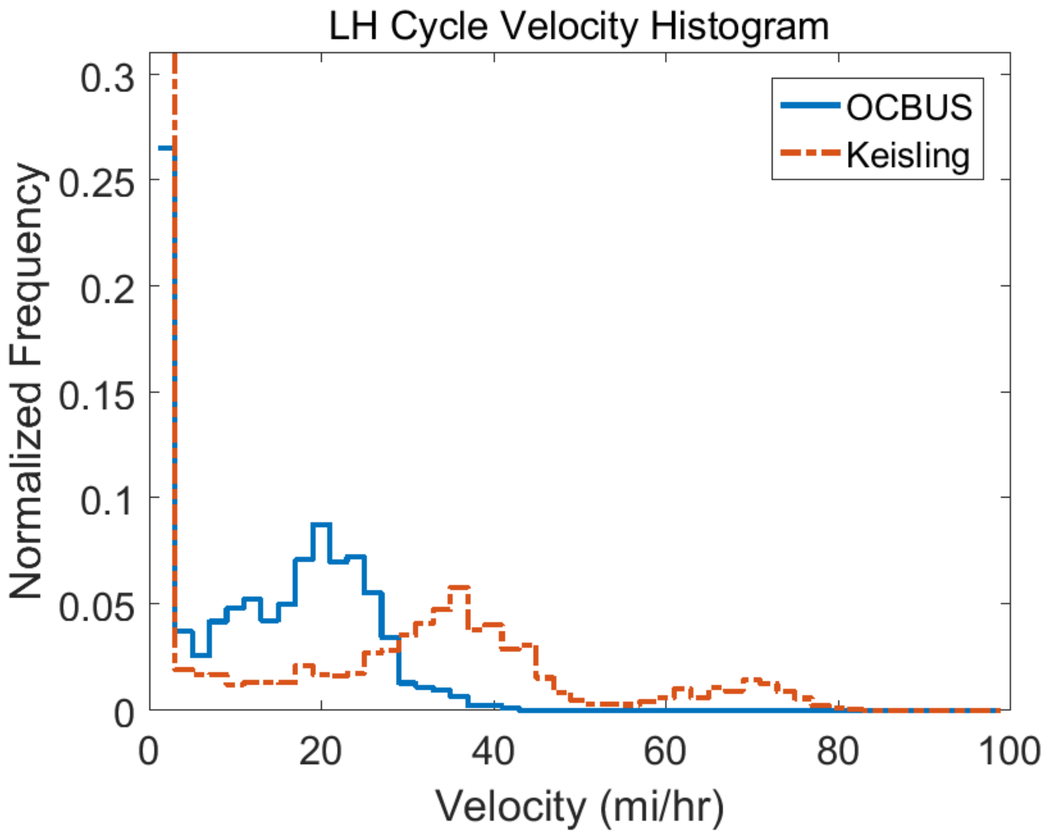


Figure 7: Vehicle velocity histogram of the Keisling and OCBUS drive cycles, as driven on LH trucks. The Keisling cycle includes highway driving while the OCBUS cycle is primarily city transit driving.

Data Acquisition

Velocity and fuel consumption data were collected using Controller Area Network (CAN) signals available through the On-Board Diagnostics (OBD-II) port. For the Toyota Prius HEV, the signals were recorded using an ELM327 based data logger connected to a cellphone through bluetooth. For the Chevrolet Volt, data was collected using a Kvaser CAN/USB connecter. GPS coordinates were also recorded. Unlike generic EPA drive cycles, which are executed under controlled conditions, the custom designed drive cycles produce data more consistent with real-world driving events.

Physics-Based Models

Autonomie and Modelica models for a 2010 Toyota Prius were developed based on information available from the literature. The Autonomie model was developed by modifying the public 2004 Toyota Prius model with the new BSFC map as shown in Figure 8 [44, 57]. Additional information for other subsystems was also incorporated based on information in the literature [58]. The Modelica model was entirely custom built by our research group at Colorado State University. Validation of the models was completed through comparison of chassis dynamometer FE data on the EPA drive cycles. Autonomie and Modelica models were developed for the Prius HEV and validated for EPA and on-road drive cycles. An Autonomie model of the Volt PHEV was also developed according to the methods referenced and FE values calculated [43].

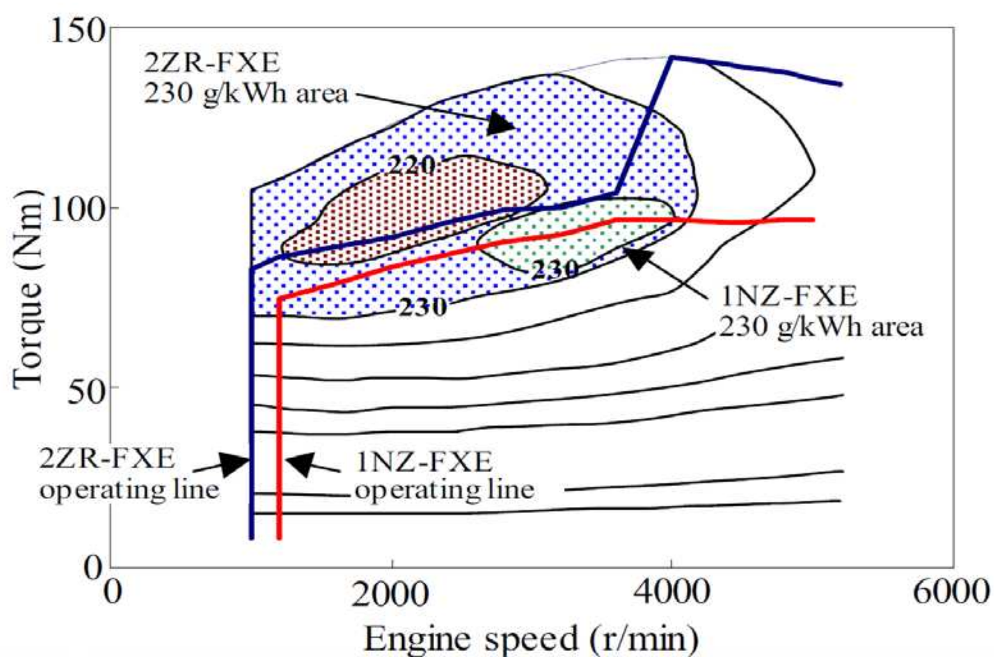


Figure 8: BSFC map with operation limits and ideal operating line information that must be incorporated manually in Autonomie and other simulation [44].

NN Training Procedure Exploration and Model Testing

The MATLAB Neural Time Series tool was used to predict all networks with a 3 second time delay. This time delay produced accurate FE predictions while reducing the models' total training time. The time delay accounts for vehicle acceleration and momentum in the model. A NARX network architecture was used for all model trainings. Every network was trained with 10 neurons in 1 hidden layer (Figure 9 and Figure 10). Backpropagation algorithms were chosen on training performance for each vehicle. Networks were trained using the Bayesian Regularization backpropagation algorithm for the Prius and Volt and the Levenberg-Marquardt backpropagation algorithm for LH vehicles. The data sets were partitioned into training, validation, and testing segments of 70%, 15%, and 15% respectively for the NN training tool internal performance check. For each routes' data set, 10 to 20 NNs were trained and the NN with the most optimized R-value was used for each model. We chose to train multiple NNs for each model because the performance varies significantly from each attempt. This method did not consistently produce a high performing network within 50 trained models but instead produces a range of models with varying prediction errors as shown in Figure 9 and Figure 10 for the Prius and Volt, respectively. There is a chance of training a model with minimal prediction errors but training 50 NNs does not guarantee a strong model shown by the distribution of errors produced in Figure 11. A number of trained NNs above 50 was not attempted due to the increased training time for each attempt.

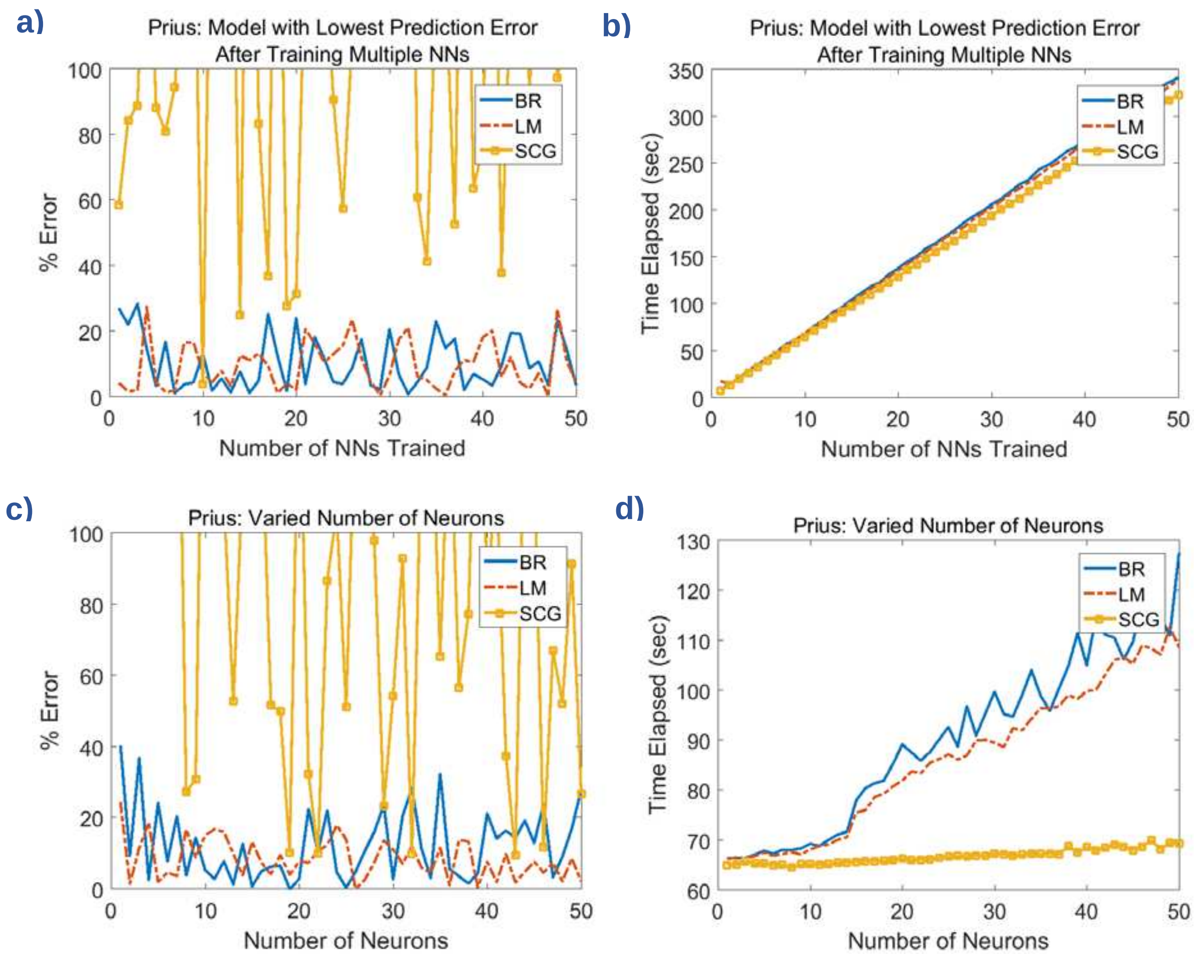


Figure 9: An exhaustive method for determining optimal training conditions in Prius FE NN models with 3 different backpropagation algorithms: Bayesian Regularization (BR), Levenberg-Marquardt (LM), and Scaled Conjugate Gradient (SCG). a) Percent error generated when training an increasing number of NNs trained with 10 neurons, b) length of elapsed training time when training an increasing number of NNs trained with 10 neurons, c) percent error generated when training with an increasing number of neurons; 10 networks trained for each amount of neurons, d) length of elapsed training time when training with an increasing number of neurons; 10 networks trained for each amount of neurons. Methods proved to be inconclusive considering the variability in error from 1 to 50 NNs trained and 1 to 50 neurons. This method is incapable of producing consistent NN models.

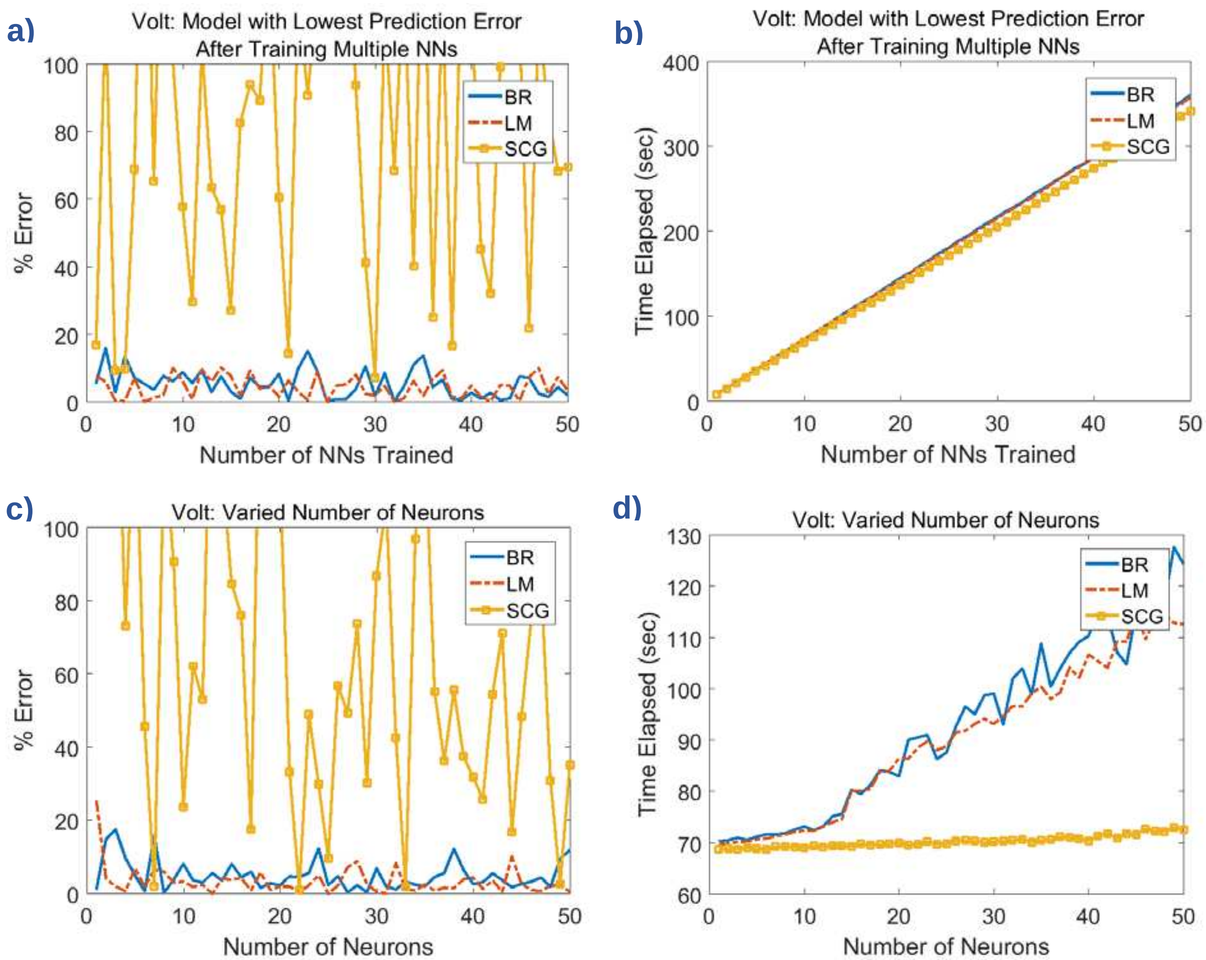


Figure 10: An exhaustive method for determining optimal training conditions in Volt FE NN models with 3 different backpropagation algorithms: Bayesian Regularization (BR), Levenberg-Marquardt (LM), and Scaled Conjugate Gradient (SCG). a) Percent error generated when training an increasing number of NNs trained with 10 neurons, b) length of elapsed training time when training an increasing number of NNs trained with 10 neurons, c) percent error generated when training with an increasing number of neurons; 10 networks trained for each amount of neurons, d) length of elapsed training time when training with an increasing number of neurons; 10 networks trained for each amount of neurons. Methods proved to be inconclusive considering the variability in error from 1 to 50 NNs trained and 1 to 50 neurons. This method is incapable of producing consistent NN models.

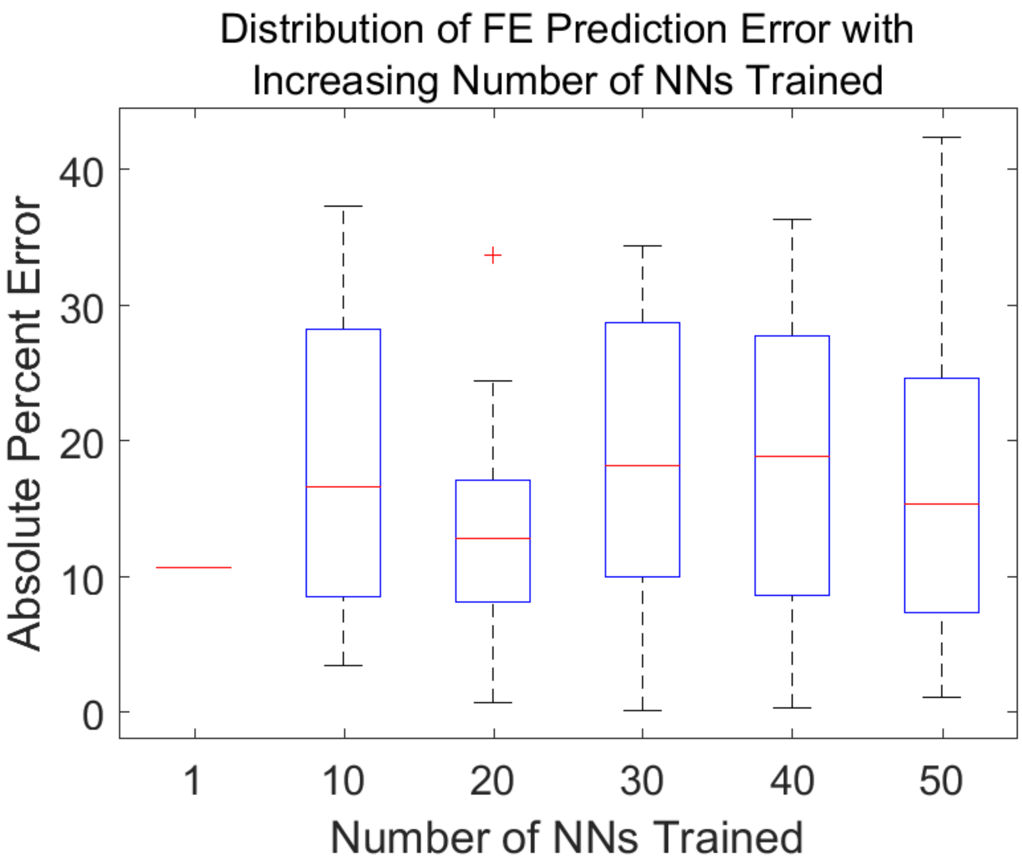


Figure 11: Increasing number of NNs trained with each attempt and their distribution of FE prediction error. Methods proved to be inconclusive considering the variability in error from 1 to 50 NNs trained. This method is incapable of producing consistent NN models but is capable of producing some models with very low prediction error.

All training inputs are in the form of a velocity-time trace. Given only an input of a velocity-time trace, the NNs were trained to output fuel consumption. Other vehicle parameters could also be included to improve predictions. Parameters like HEV battery state of charge (SOC) and engine speed were not included to test the minimal amount of data required to train a NN model. This minimalistic approach was explored since velocity is readily acquired data through CAN signals or location derived data acquired through GPS locators. The networks were built using the real world, on-road data sets.

Both the Prius and Volt networks were trained on the collected routes 1 through 4 and the LH vehicles were trained both on the OCBUS and Keisling cycles. (Table 7).

Table 7: Vehicles and available data sets for modeling and testing

Vehicles	Drive Cycle Data Sets	
2010 Toyota Prius and 2013 Chevrolet Volt	Route 1 Route 2 Route 3 Route 4	*Each route is a combination of a city cycle and highway cycle from Figure 5. Each route is a unique sample of driving data
Lightning Hybrids Hydraulic Hybrid Ford E450	OCBUS Cycle Keisling Cycle	

The LH tests accounted for NN tests across different drive cycles, vehicles, and data collected across different seasons of the year at different elevations. The OCBUS cycle and the Keisling cycles were captured by two different vehicles with the same make and model but model years 2013 and 2015, respectively. The operating loads of each vehicle also varied depending on the amount of passengers. The OCBUS cycle was collected in the summer at approximately 5000 ft elevation and the Keisling cycle was collected in the winter at approximately sea level.

The Prius and Volt NN models were each tested with the collected 4 routes' data (Fort Collins, CO elevation of ~5000 ft) and data for 3 EPA drive cycles from ANL (collected at ~700 ft). The data from Fort Collins and ANL were collected from different vehicles with the same make and model and year. All NN models were tested with additional data and not just data used for training. These NN models were then compared to results from the physics-based models for all cycles.

Results

<u>LH HHV Model Results</u>

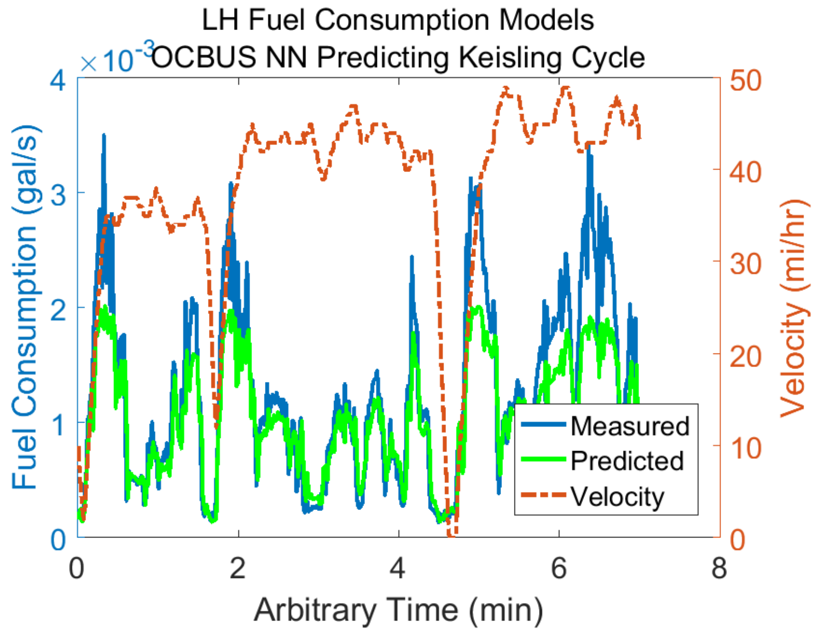
Two NN models were trained using two different drive cycles' data sets provided by LH. The performance of each model was tested with the drive cycle that it was not trained with. The NN models generated from the on-road training cycle predicted FE with varying accuracy. The OCBUS model has no training inputs over 35 mph. This caused the model to under-predict when input with the Keisling cycle which contains many instances at highway speeds (>75 mph) (Figure 12). The LH NN models depict 2 unique training conditions and are reflected in predictions .The Keisling trained model performed well with all tested drive cycle instances. This was anticipated since the speeds in the OCBUS are present in the lower speeds of the Keisling cycle. Models appeared to over-predict the fuel consumed during lower fuel consumption rates and can be seen during accelerations at 0, 1.6, and 4.6 minutes in Figure 12.

The LH NN models produced less error in the Keisling model than the OCBUS model (Table 8).

Table 8: Comparison of the ability of each modeling technique to accurately predict real world fuel economy for LH vehicles. Shown in parentheses is the error in predicted FE compared to the measured. Negative error depicts over-estimating FE and positive error depicts under-estimating.

Drive Cycles / **Models**	**Keisling Shuttle**	**OCBUS**
Real World	8.53 mpg	7.87 mpg
NN Keisling Trained	N/A	7.57 mpg (3.8 %)
NN OCBUS Trained	9.59 mpg (-11.1 %)	N/A

a)



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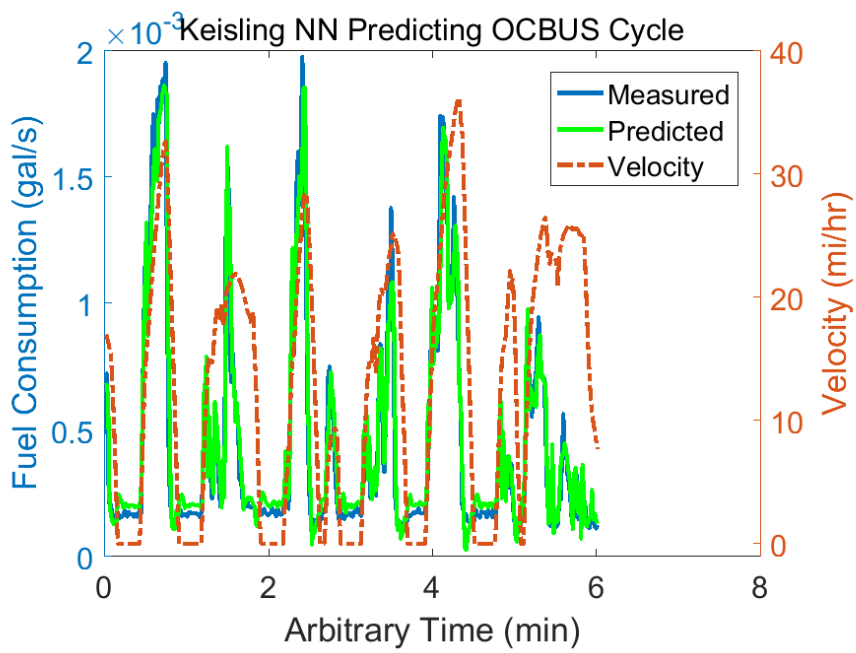

Figure 12: Testing LH NN models: a) Model trained on OCBUS cycle and tested with Keisling cycle. b) Model trained on Keisling cycle and tested with OCBUS cycle. OCBUS model is incapable of predicting instances of higher fuel consumption (during highway segments). Vehicle velocity included in plots to show the trend with fuel consumption.

Prius and Volt HEV Model Results

All Prius and Volt models' cumulative fuel consumption predictions were plotted against the measured values for Route 1 and the 3 EPA cycles Figure 13 and Figure 14 respectively The Prius and Volt NN models performed well for each cycle. The Autonomie Prius model over-predicted on-road collected data. The Autonomie and Modelica Prius model predicted total fuel consumptions similar to measured values for UDDS, HWFET and US06 but deviated in instantaneous fuel consumption predictions. The errors in the physics-based models in the middle of the data sets were higher than the aggregate fuel consumption. The physics-based models are designed to estimate total FE and not the time dependent fuel consumption. This is evident when comparing the cumulative fuel consumption to the physics-based models' predicitons.

Calculated fuel economy from total distance driven over the cycle per the amount of fuel consumed yielded mixed results. The Prius NN outperformed the physics-models in predicting on road data (Table 9). The Volt models had similar performance with the EPA cycles and the NN model produced FE with less error than the Autonomie model for on road test cycles (Table 10). A comparison of the error produced by each model is in Figure 15.

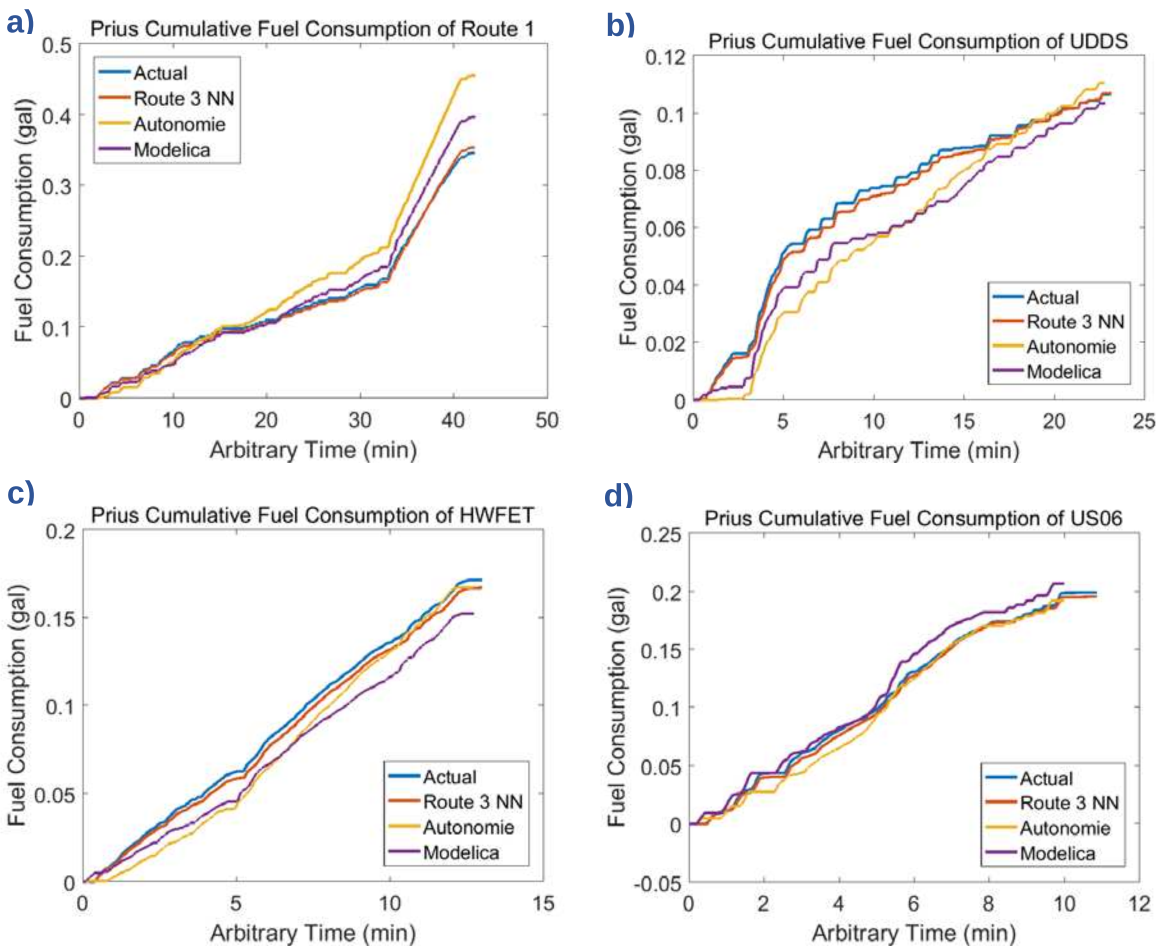

Figure 13: Prius cumulative fuel consumption comparison plots for Route 3 Trained NN, Autonomie, and Modelica with 4 tested drive cycles: a) On-road Route 1, b) UDDS Cycle, c) HWFET Cycle, and d) US06 cycle.

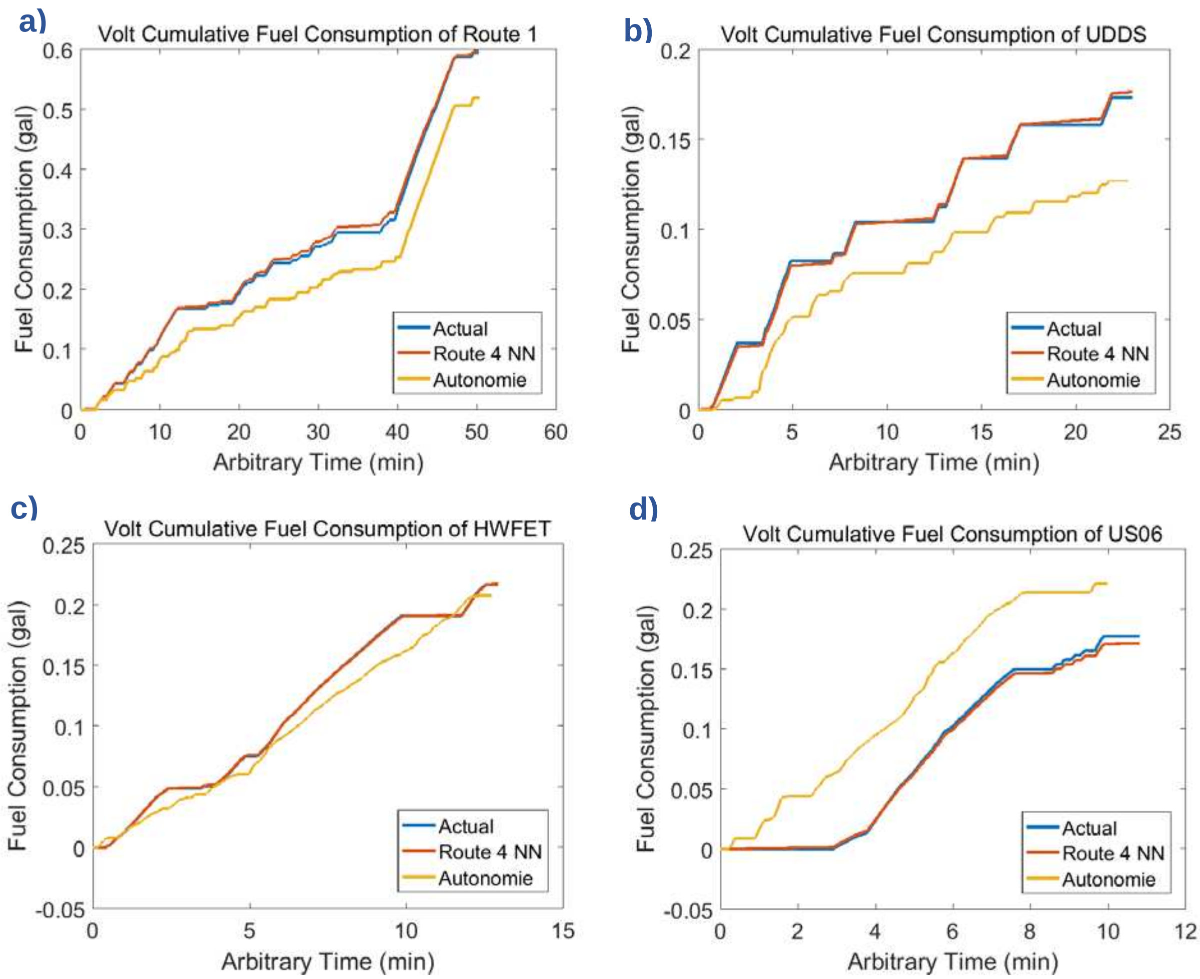

Figure 14: Volt cumulative fuel consumption comparison plots for the Route 4 trained NN, Autonomie, and Modelica with 4 tested drive cycles: a) On-road Route 1, b) UDDS Cycle, c) HWFET Cycle, and d) US06 cycle.

Table 9: Comparison of the percent error of FE for each modeling technique and tested cycle for a 2010 Toyota Prius. Negative error depicts over-estimating FE and positive error depicts under-estimating. Measured FE in MPG is given in the first row of data. All 4 NN models labeled by what training data was used. Error highlighted in yellow is 5-10% absolute error and red is greater than 10%.

Prius FE Models \ Tested Drive Cycles		Route 1	Route 2	Route 3	Route 4	UDDS	HWFET	US06
Measured FE		65.33 MPG	64.24 MPG	71.91 MPG	78.14 MPG	69.89 MPG	63.27 MPG	41.61 MPG
Percent Error	**Route 1 NN**	-1.42 %	-1.27 %	-3.66 %	-5.15 %	-6.04 %	3.54 %	5.49 %
	Route 2 NN	-4.86 %	-4.66 %	-7.46 %	-9.29 %	-9.70 %	-0.99 %	3.15 %
	Route 3 NN	-2.36 %	-2.51 %	-4.39 %	-5.55 %	-0.42 %	2.15 %	1.08 %
	Route 4 NN	-4.63 %	-4.63 %	-8.31 %	-10.9 %	-16.9 %	2.22 %	6.84 %
	Autonomie	23.2 %	22.0 %	28.9 %	35.0 %	3.74 %	2.78 %	-0.86 %
	Modelica	11.8 %	9.39 %	19.4 %	23.5 %	-3.33 %	-7.27 %	3.73 %

Table 10: Comparison of the percent error of FE for each modeling technique and tested cycle for a 2012 Chevrolet Volt. Negative error depicts over-estimating FE and positive error depicts under-estimating. Measured FE in MPG is given in the first row of data. All 4 NN models labeled by what training data was used. Error highlighted in yellow is 5-10% absolute error and red is greater than 10%.

Volt FE Models \ Tested Drive Cycles		Route 1	Route 2	Route 3	Route 4	UDDS	HWFET	US06
Measured FE		38.64 MPG	40.35 MPG	42.29 MPG	46.15 MPG	43.04 MPG	48.18 MPG	38.76 MPG
Percent Error	**Route 1 NN**	-2.49 %	-1.70 %	-3.31 %	-4.12 %	-5.24 %	-3.57 %	-1.27 %
	Route 2 NN	4.65 %	2.44 %	4.03 %	2.75 %	7.69 %	-0.95 %	1.66 %
	Route 3 NN	-2.71 %	-1.13 %	-3.26 %	-3.57 %	-6.69 %	-2.58 %	-1.47 %
	Route 4 NN	-0.66 %	0.86 %	-0.95 %	-1.17 %	-1.71 %	-0.16 %	4.29 %
	Autonomie	-15.7 %	-15.2 %	-9.60 %	-2.80 %	-37.8 %	-3.48 %	5.54 %

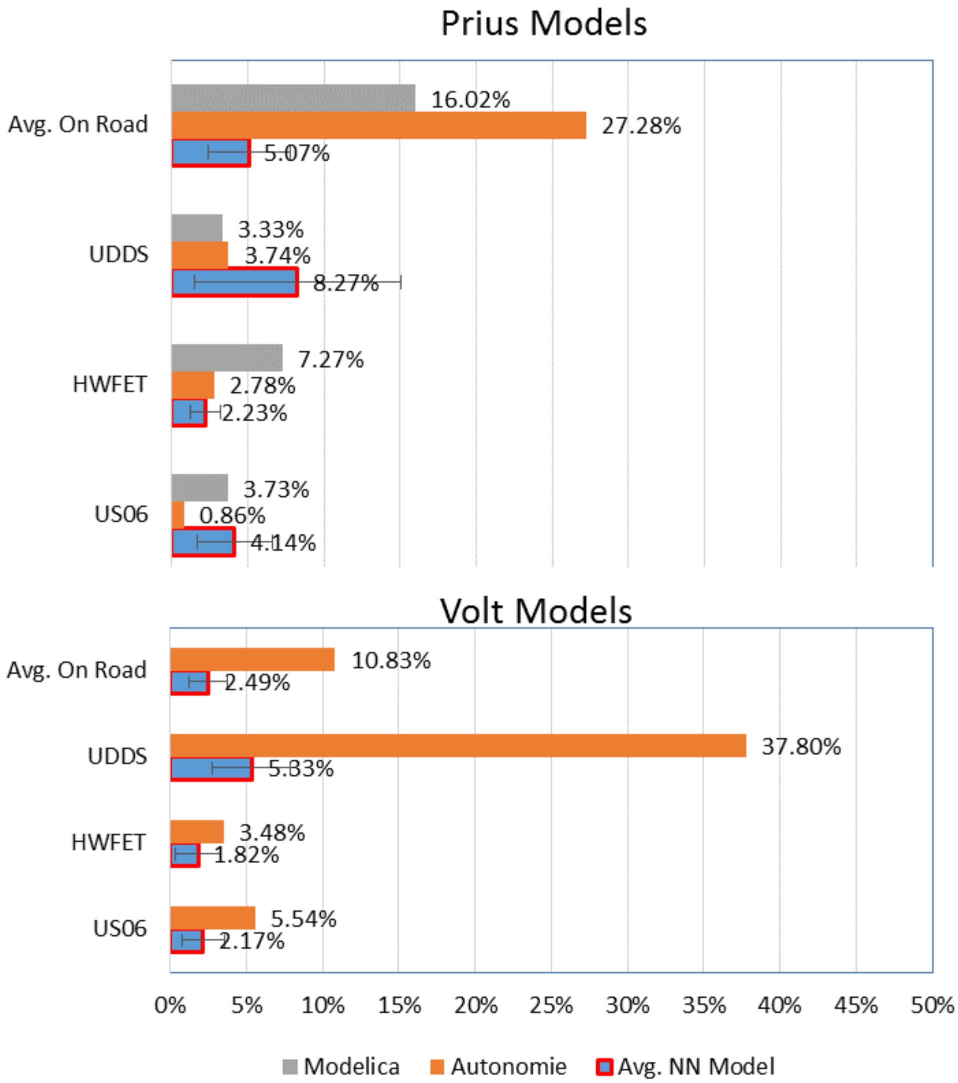

Figure 15: Comparison of the 3 Prius models and 2 Volt models tested with the various cycles. The 4 NN model errors are averaged for each cycle. Errors from the 4 on-road routes are averaged in 1 on-road error. Error bars for 95% confidence is also included.

Overall, the NN models predicted all drive cycles more accurately and consistently than the physics-models. The Route 4 trained NN from the Volt performed strongest with on-road data and EPA data yielding correlation coefficients of 0.977, 0.977, 0.981, and 0.970 for Route 1, UDDS, HWFET, and US06 cycles respectively (Figure 15).

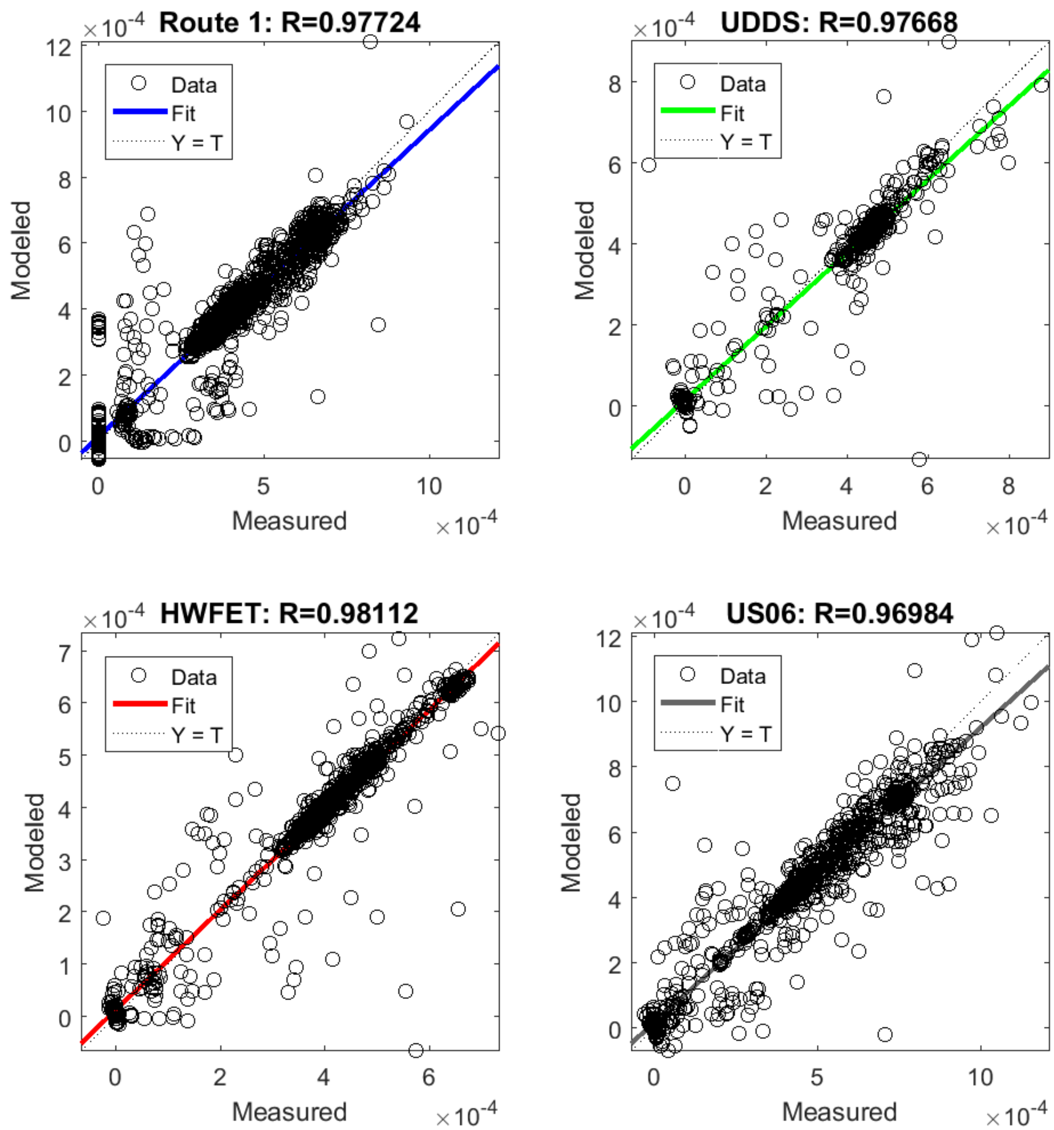

Figure 15: Correlation plots of Volt NN trained on Route 4 tested with Route 1, UDDS, HWFET, and US06 cycles with R values of 0.977, 0.977, 0.981, and 0.970 respectively.

The standard deviation of the absolute error in FE was calculated for both the Prius and Volt. Absolute percent errors from all 4 NNs and respective unique testing routes were used (routes used for training were not used to test that route's network in this calculation, for example the Route 1 trained NN was not tested with Route 1 data). The standard deviation in absolute error for the Prius and Volt were 2.43% and 1.43% respectively. This produced absolute error ranges of 2.54% to 7.40% for the Prius and

1.11% to 3.97% for the Volt. 83% of the Prius predictions fall within one standard deviation with both outliers occurring in the UDDS cycle predictions. 75% of the Volt predictions fall within one standard deviation with all 3 outliers occurring in the UDDS cycle predictions.

Discussion

LH HHV Model Discussion

The two LH models showed that there was minimal error resulting from drastically different elevation and seasonal weather conditions. The OCBUS cycle was collected at approximately 5000 ft during the summer and the Keisling at sea level during the winter. This is seen in the FE prediction error from testing the OCBUS cycle on the Keisling trained NN model in Table 8.

The LH NN models and their predictions provided insight on what occurs when training cycles fail to capture the tested drive cycle. The OCBUS trained network did not include any highway driving and resulted in being unable to predict highway fuel consumption in the Keisling cycle (Figure 12). The Keisling model accounted for more diverse drive cycle instances and had less error in its predictions. NN models trained on more driving applications, that capture more variability, produced higher performing predictions. This result was reinforced with the higher FE percent error in the OCBUS NN model than in the Keisling model (Table 8).

Prius and Volt HEV Model Discussion

The neural network models generally predict fuel economy within 7.40% and 3.97% for the Prius and Volt models respectively when trained and tested with the on-road collected data. The source of this error could be due to several factors. The NN models tend to over-estimate the FE but not extensively as seen with the under-estimation in the NN model trained with route 2 on the Volt. The NN models predict fuel economy with an absolute percent error of 16.9% and 7.69% for the Prius and Volt models respectively when trained with the on-road collected data and tested with EPA cycle data. This higher error appears to be caused from a disparity between the on-road collected data and the EPA collected data.

The UDDS cycle produced more error in the Prius and Volt NN models than any other drive cycle. Unless the error was a result from strange weather or data acquisition conditions, there could have been a certain combination of drive cycle instances in the UDDS that were not included in the training cycles. The latter seems more likely considering the LH models performed well with significantly different elevations and seasonal conditions. It is possible that the nature of the UDDS cycle could be more artificial or manicured when compared to real-world on-road driving. The UDDS cycle is in some aspect unlike the other two EPA cycles since the NN models perform well with those cycles. NN models designed to predict on-road data would perform worse when tested with data that does not exhibit real world cycles. There could be some change in battery SOC since the NN model is not designed to include this parameter.

The physics-based models performed well in predicting FE in all EPA cycles with an exception in the Volt Autonomie model predicting the UDDS cycle. The Prius models under-estimated in the on-road test cycles with FE error in excess of 10-35 % for both the Autonomie and Modelica models with the Autonomie model producing >30% error in one case (Table 9). These models can predict overall FE well but deviate in the instantaneous predictions and are not always accurate throughout the duration of the entire data set as seen in Figure 13 and Figure 14. These models could be well used in studying optimal vehicle system velocities and optimal powertrain control but did not appear to be suited for on-road FE predictions for HEVs. These models took significant effort to construct and verify. Autonomie could be best used for investigating specific vehicle control processes. Creating a custom model such as the Modelica model was very time consuming and perhaps was adept for exploring specific vehicle component and environmental processes which are not as easily manipulated in Autonomie. The NN models performed well at predicting FE consumption and can be created from easy to use NN toolboxes.

All NN models trained have been tested with data that was collected in conditions drastically different from the data used to train. All Volt and Prius NN models were trained with data collected at approximately 5000 ft yet the largest absolute error generated of cycles tested was 16.9%. This error could be attributed to the slower highway speeds in the EPA cycles as shown in Figure 6 with the US06 cycle. The NN models are not trained to include the US06 highway speeds as frequently as the real-world data highway speeds. This error could also be attributed to the difference in quality of data between the ANL data and the road collected data or from the 5000 ft elevation difference. However, it appears to be the former due to similar test conditions between the LH drive cycle data sets. The LH HHVs collect data using LH’s control systems for all explored data sets. The same cannot be claimed for the Prius and Volt HEVs since the ANL data was collected on a chassis dynamometer and the on-road data collected from the OBD-II port.

Conclusions

Predictive FE models do not all perform similarly, therefore should not be used for the same applications. Physics-based models would be suited for comprehensive research on vehicle dynamics and performance considering their computationally and financially costly nature. Physics-based models are optimized for the EPA cycles and predict on-road data with increased error. These models would benefit from optimization on on-road data also.

NN models can predict FE quickly and accurately when vehicle drive data is available. This method for predicting FE has been shown to be viable when trained from just a velocity-time trace. The training method explored here is not yet optimized to produce a strong model with every attempt. Including parameters like battery SOC and engine speed could improve model accuracy and improve the uniformity of model training.

4. HYBRID ELECTRIC VEHICLE EMISSIONS MODELS

Methods

This portion of the study trained NN models from real world, on-road emissions data to predict mass flow rates of CO_2, CO, HC, and NO_X for a 2013 Chevrolet Volt and explored methods to consistently create a NN model. PM_{10} emissions were not collected due to receiving updated information from the PEMS manufacturer advising against the collection of particulate from gasoline engines. These models were compared to measured data to demonstrate the error generated in the method. Data from the PEMS is primarily to capture trends of emissions produced during real world driving and not to study instantaneous measurement values. The data will need to be explored further and compared with supplemental Volt emissions data inaccessible at the time of this study.

Vehicles and Drive Cycle Development

This study utilized real world, on-road driving data from a 2013 Chevrolet Volt in full hybrid mode. Driving data was not collected for battery only operation. Custom drive cycle development was required to capture real world driving characteristics. Drive cycles and combined routes were the same as the on-road routes used in the FE modeling portion of the study. Again, each route was approximately 45 minutes long. The probabilistic velocity composition of the Volt routes can be seen in Figure 6. The 4 routes driven are shown to include driving instances at city and highway speeds with comparable frequencies. The Volt was driven and PEMS data collected by the author.

PEMS Data Acquisition

Emissions data was recorded for routes 1-4 using the PEMS device. The PEMS was allowed to heat up for at least 30 minutes prior to data collection for all testing. The PEMS was calibrated to manufacturer methods at the time of data collection. Data recording practice consisted of starting and stopping a “bag” in the PEMS UI at the start and stop of each cycle in order to partition data. This improved post processing data manipulation and ease of use. A background was collected before each cycle to zero the background air throughout the day of testing. Portions of the city drive cycles were modified by taking side streets to avoid areas of Ft Collins, CO where residents were having open bonfires. These emissions noticeably affected the background recorded by the PEMS before each cycle.

NN Training Procedures and Model Testing

The MATLAB Neural Time Series tool was used to predict all networks with a 3 second time delay. This time delay is the same used in the FE portion to produce accurate FE models while reducing total training time. The time delay accounts for vehicle acceleration in the model. A NARX network architecture was used for all model trainings. Backpropagation algorithms and number of neurons in the hidden layer were chosen on training performance for each vehicle (Figure 16). Each network was trained with 10 neurons in 1 hidden layer for CO_2, CO, HC, and NO_X. These parameters were chosen from the errors generated in Figure 16. All NNs were trained using the Bayesian Regularization backpropagation algorithm for NO_X, and PM_{10}. The data sets were partitioned into training, validation, and testing segments of 70%, 15%, and 15% respectively for the NN training tool internal performance check. For each NN model, 10 to 20 NNs were trained and the NN with the most optimized R-value was used for each model. The variations in number of models trained are resultant from inconsistent NN performance from each attempt. This produced a method that does not consistently produce a high performing network within 50 trained models but instead produces a range of models with varying prediction errors as shown in Figure 16. There is a chance of training a model with minimal prediction errors but training 50 NNs does not guarantee a strong model shown by the distribution of errors produced in Figure 11 for the FE modeling. A number of trained NNs above 50 was not attempted due to the increased training time for each attempt.

All training inputs are in the form of a velocity-time trace. Given only an input of a velocity-time trace. The NNs were trained to output mass flow rates of CO_2, CO, HC, and NO_X. Other vehicle parameters could also be included to improve predictions. Parameters like HEV battery state of charge (SOC) and engine speed were not included to test the minimal amount of data required to train an emissions NN model. This minimalistic approach was explored since velocity is readily acquired data through CAN signals or location derived data through GPS locators. The networks were built using the real world, on-road data sets. The Volt NNs were trained on the collected routes, 1 through 4.

All NN models were tested with separate data sets from data used for training. The Volt NN models were each tested with the collected 4 routes' data (Fort Collins, CO elevation of ~5000 ft) and compared to measurement. The error calculations were performed by taking the absolute value of Equation 5 and averaged over all tested routes. This was done since the NN models can under and over estimate. An average absolute error produced depicts performance of the models without taking under and over estimations into account.

Results

The carbon related measurements for all tested routes were collected and g/mi calculated to compare to standards (Table 11). The measurements produced results that trended well with velocity of the vehicle. Figure 17 shows the measurements for CO_2, CO, and HC with velocity and predicted values from the Route 1 trained NN model. The Route 1 NN models produce predictions with R-values of 0.9989, 0.9982, and 0.9989 for CO_2, CO, and HC respectively. All NN models trained with Routes 1 through 4 trend with variability in the measured values and major deviations in some models (Figure 18).

Table 11: Maximum average measured emissions compared to emissions standard for CARB super ultra-low emission vehicles (SULEV20) and CAFE standard for 2025 [10, 59]. SULEV20 is the lowest emitting standard (most restrictive) for a vehicle of this weight as of early 2017.

Measurement & Standard / Emission	Maximum Mean Measured (g/mi)	CAFE 2025 (g/mi)	SULEV (g/mi)
CO_2	$8.50*10^{-7}$	163	N/A
CO	$2.34*10^{-10}$	N/A	1.0
HC	$1.22*10^{-9}$		0.020
NO_X	$8.01*10^{-10}$		0.020

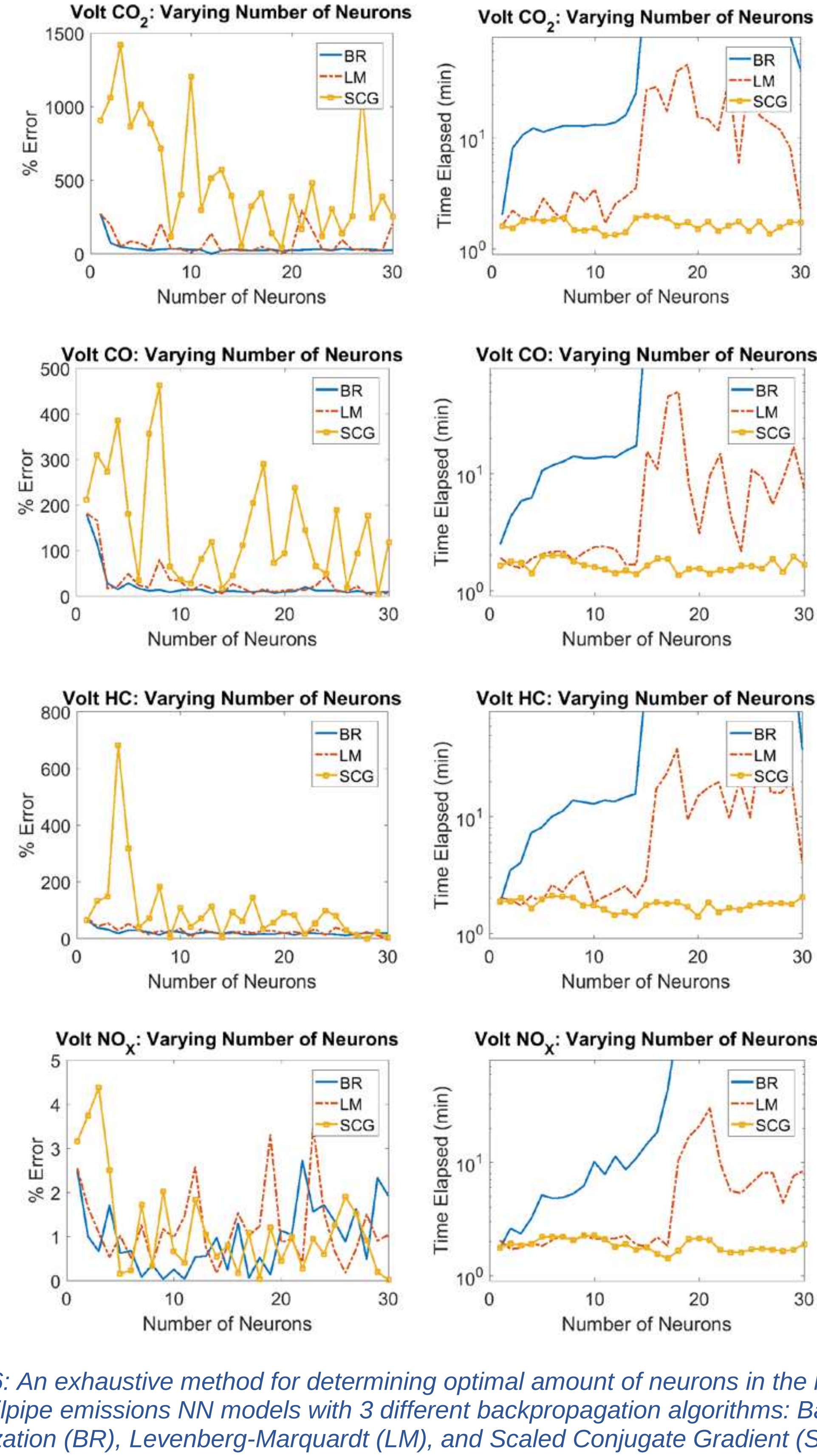

Figure 16: An exhaustive method for determining optimal amount of neurons in the hidden layer in Volt tailpipe emissions NN models with 3 different backpropagation algorithms: Bayesian Regularization (BR), Levenberg-Marquardt (LM), and Scaled Conjugate Gradient (SCG).

Percent error generated when training with an increasing number of neurons and length of elapsed training time when training with an increasing number of neurons is plotted for each emission. 10 networks trained for each amount of neurons and the lowest error model reported. Half of the route 1-4 data used to train networks and the other half used to test and produce prediction errors. Methods proved to be inconclusive for training consistent models considering the variability in error from 1 to 50 NNs trained and 1 to 50 neurons.

The NO_X measurements for all tested routes were collected and produced results that trended well with velocity of the vehicle. Figure 19 shows the measurements for NO_X with velocity and predicted values from the Route 1 trained NN model. The R values and correlation plots are also shown. NO_X model predictions perform well with R value of 0.9912. NN models trained with routes 1 & 4 trend well with the measured values with major deviation in models trained with routes 2 & 3 (Figure 20).

Models were tested with the 4 routes and have average cumulative errors ranging from 1.51-100%, 0.01-70.86%, 24.35-68.19%, and 2.36-31.63% for CO_2, CO, HC, and NO_X respectively (Figure 21). Models were tested with the 4 routes and average cumulative errors calculated.

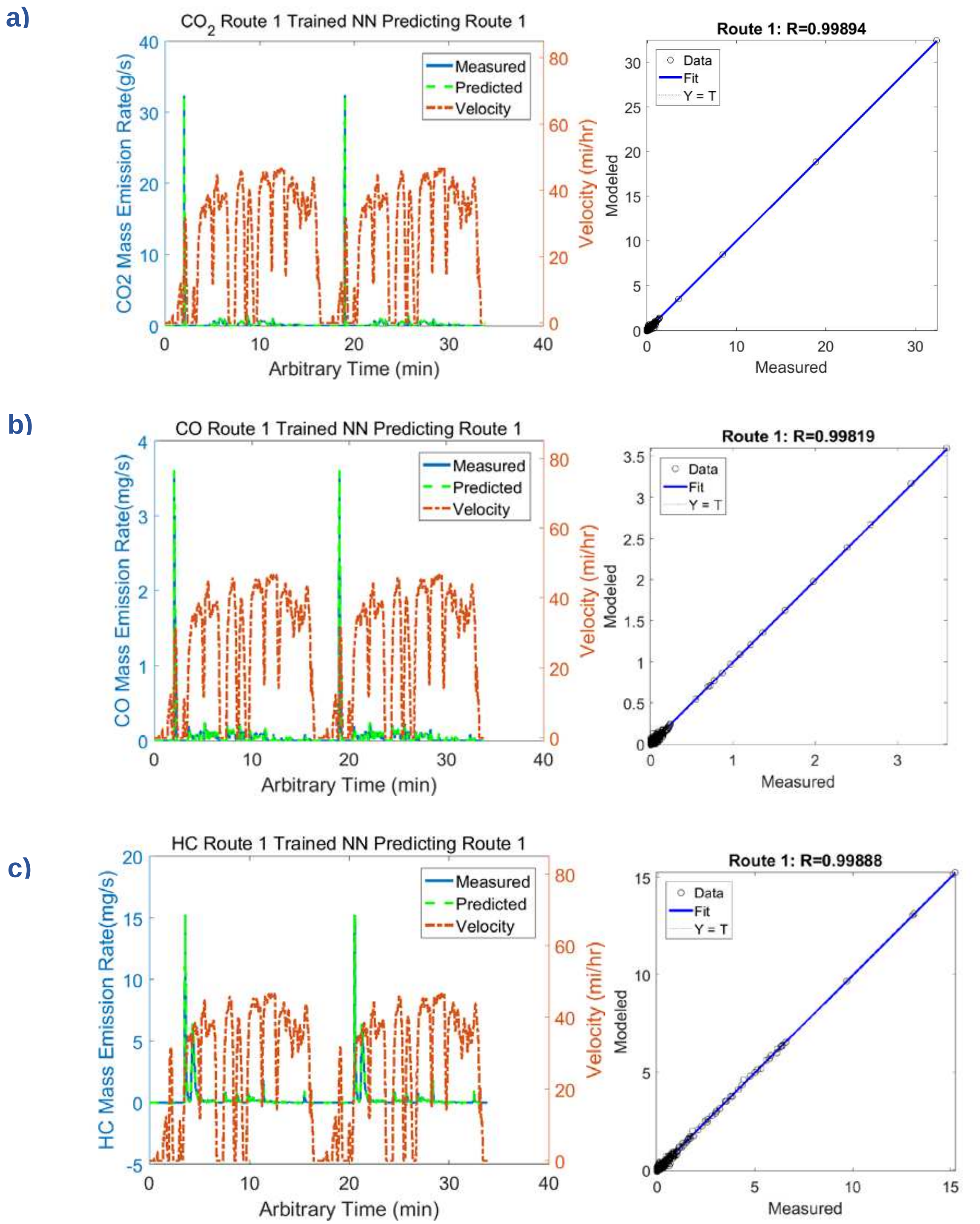

Figure 17: Measurements from Route 1 for CO_2 (a), CO (b), and HC (c) with velocity and predicted values from the Route 1 trained NN model. A correlation plot and R value for predicted and measured values are also included.

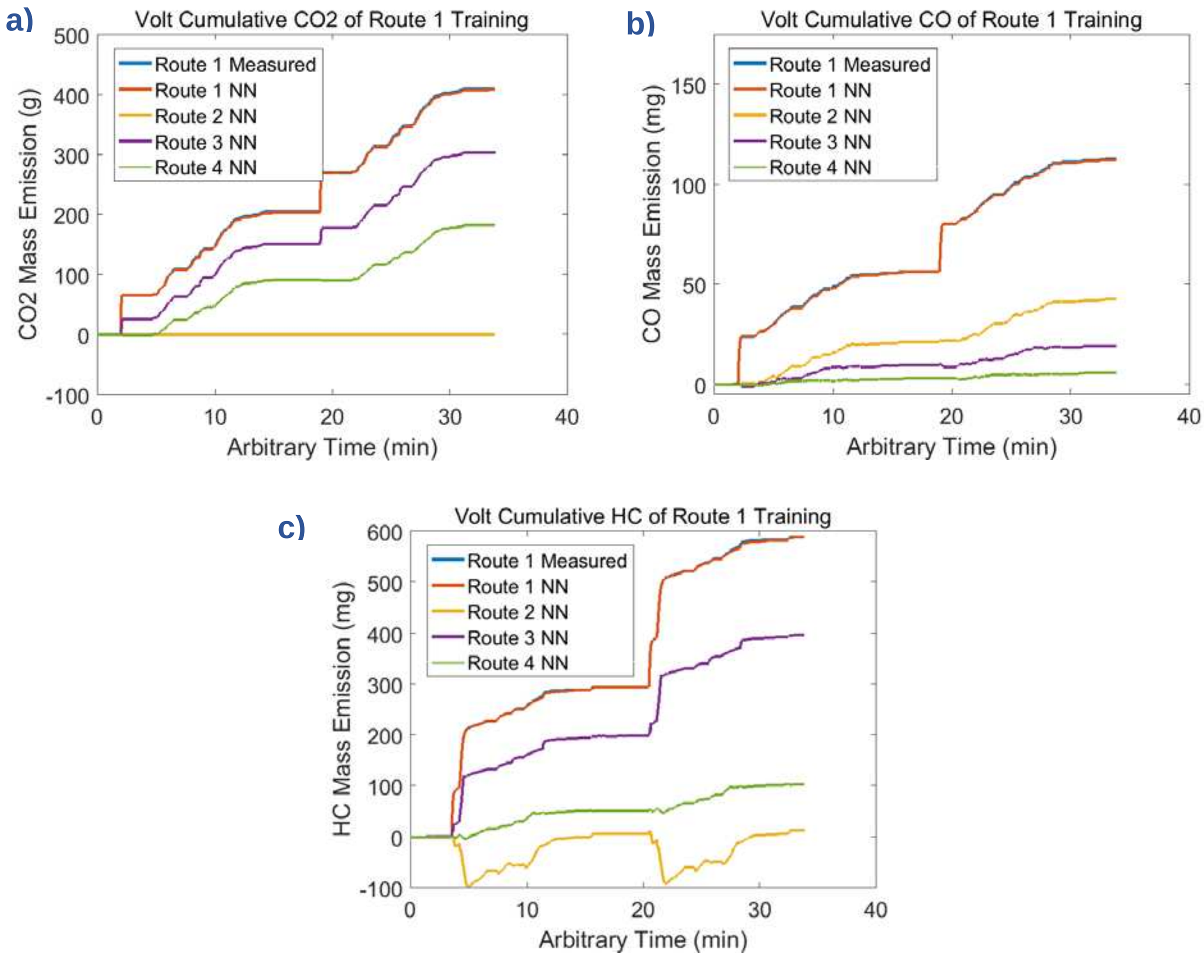

Figure 18: Route 1 cumulative emissions measurements from on-road drive data and predictions from NN models trained with routes 1 through 4 for CO_2 (a), CO (b), and HC (c).

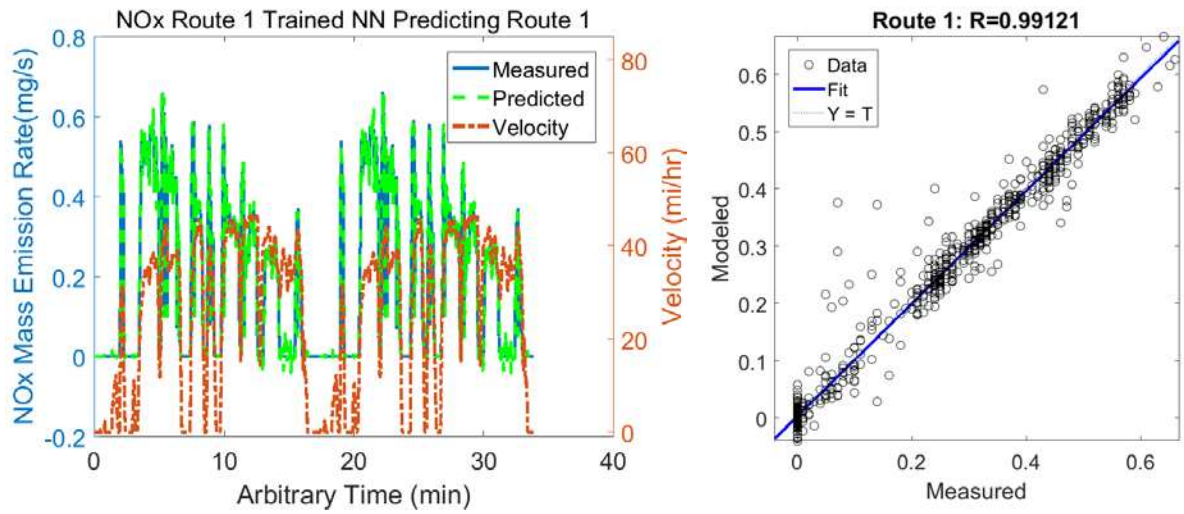

Figure 19: Measurements from Route 1 for NO_X with velocity and predicted values from the Route 1 trained NN model. A correlation plot and R value for predicted and measured values are also included.

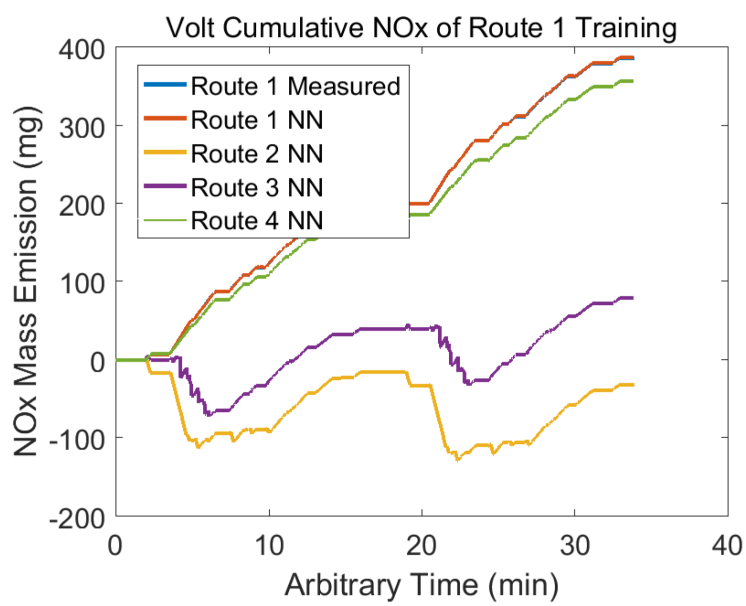

Figure 20: Route 1 cumulative emissions measurements from on-road drive data and predictions from NN models trained with routes 1 through 4 for NO_X.

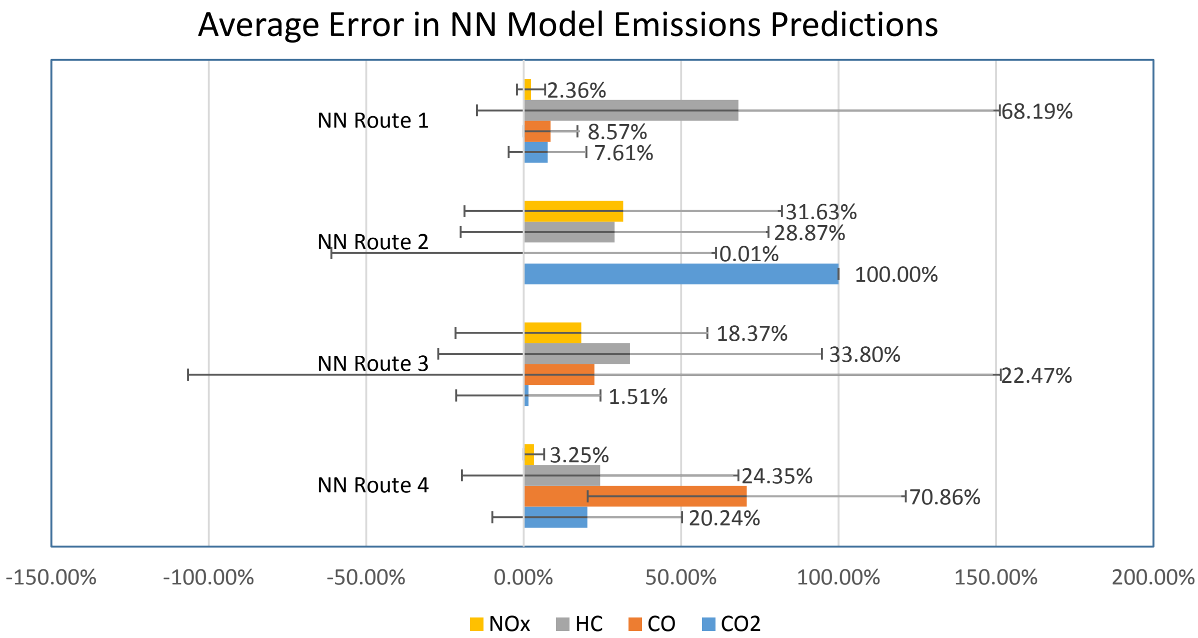

Figure 21: Average of error in model predictions over all 4 Routes for NO_X, HC, CO and CO_2 using NN models trained on Routes 1 through 4. Error bars for 95% confidence is also included.

Discussion

All average emissions in g/mi are at least 7 orders of magnitude less than the compared emission standard (Table 11). The Chevrolet Volt could emit this amount of pollutants but a more likely source for the large difference is from an error in calculating the gram per mile with raw data from the PEMS. A delay of undetermined amount between the recorded velocity and the measured pollutant offsets the gram per mile calculation. This delay could be different for each measured pollutant and will require further investigation to produce reliable gram per mile calculations.

The carbon based NN models predicted well when tested with the training data (Figure 17). When tested with data from other routes, there was less correlation in prediction trends (Figure 18) and greater error in predicting (Figure 21). Upon further inspection of the data, there appears to be discrepancies in the route 2 data with a CO_2 mass flow measurements stagnant at 0 for the entirety of the route. This could have affected the rest of the carbon measurements considering they all share a sensor module within the PEMS. The CO average prediction error of 0.01% appears to be coincidence since the confidence interval is greater than +/- 50% for the 4 routes. This could be an artifact of operator or equipment error in data collection or an artifact of the HEV. Recording on-road emissions data from a larger fleet of vehicles could remedy this issue.

The NO_X NN models performed well for all routes. However, there appears to be more error generated in route 2 again. Further investigation in collecting on-road emissions data will be required as mentioned previously. The NO_x models appear to predict with less error. This is most evident in the models trained on routes 1 and 4 with average error of 2.36% and 3.25%, respectively, and confidence intervals less than 5%.

Conclusions

On-road data models for emissions could be a viable technique for the explored emissions with data from more vehicles. Results could improve for conventional gasoline vehicles. HEV NN emissions models can predict well but this is not always the case. Most notably, NO_x NN models perform well in some instance with the average error less than 5%. Results could be improved with the addition of engine and energy system variables such as battery state of charge and various engine temperatures and pressures.

5. FUTURE WORK

Real world, on-road data trained NN models could be implemented in control system modeling to determine optimal powertrain controls settings in HEVs. This would lead to the improvement of HEV fuel efficiency thus reducing overall consumer fuel costs [12]. In turn, NN models could be used to improve the consumer experience with HEVs by predicting the range of the vehicle with greater accuracy. Vehicle range can be affected by normal operating conditions such as the state of the cabin environmental controls, entertainment system, and other energy consuming, non-drivetrain related amenities in the vehicle. The HEV's energy control system could factor these conditions when making range predictions with a NN model. This could be done in near real time since the model requires minimal computing resources. Overall, NNs can be utilized in HEV FE models using data from on-road operation.

If explored, NN modeling could create more comprehensive vehicle emissions models. This would improve the emissions inventories of transportation sources since on-road emissions can be significantly higher than what the EPA regulates in some cases [26]. This experiment will need revisiting with a larger data set in order to be confident in NN emissions models.

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