THESIS

IN-VEHICLE VALIDATION OF ENERGY CONSUMPTION MODELING AND SIMULATION

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ABSTRACT

IN-VEHICLE VALIDATION OF ENERGY CONSUMPTION MODELING AND SIMULATION

The Colorado State University (CSU) Vehicle Innovation Team (VIT) participated in the first Department of Energy (DOE) Advanced Vehicle Technology Competitions (AVTC) in 1988. Since then, it has participated in the next iterations of the competition as well as other advanced vehicle technology projects. This study aims to validate the mathematical modeling and simulation of electrical energy consumption of the EcoCAR 3 competition (academic years 2014-2018) as well as the testing methods used for validation. First, baseline simulation results are obtained by simulating a 0-60 mph wide open throttle (WOT, or 100% APP) acceleration event (AE) with the product being the electrical energy economy in Wh/mi. The baseline model (representing the baseline control strategy and vehicle parameters) is also simulated for 0-40 mph and 0-20 mph AEs. These tests are replicated in the actual vehicle, a 2016 P2 PHEV Chevrolet Camaro entirely designed and built by CSU's VIT. Next, the same AEs are again tested with a changed acceleration rate due to the APP being limited to 45%. The velocity profiles from these tests are used as feedback for the model and the tests are replicated in simulation. Finally, the baseline model is altered in 3 additional ways in order to understand their effect on electrical energy consumption: the mass is increased, then the auxiliary low voltage (LV) load is increased and then the transmission is restricted to only 1 gear. These simulations are again replicated in-vehicle in order to validate the model's capability in predicting changes in electrical energy consumption as certain vehicle parameters are changed. This study concludes that model can predict these changes within 6.5%, or ±30.2 Wh/mi with 95% confidence.

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1.0 Introduction

Battery Electric and Hybrid Electric Vehicles (BEV, HEV respectively) have the potential to consume less energy and emit less pollution compared to a traditional internal combustion engine (ICE) powered vehicle [6]. This technology is important for reducing the end-user greenhouse gas emissions within the transportation sector [20]. End-user energy consumption within the transportation sector contributes 23% of the US CO_2 emitted each year [8] and 60% of these emissions come from light duty vehicles [13].

Colorado State University (CSU) spent 2014-2018 designing and building a Plug-in HEV (PHEV) using a stock 2016 Chevrolet Camaro as part of the EcoCAR intercollegiate competition. This competition, part of a series funded and managed by the U.S. Department of Energy, is the next iteration of the Advanced Vehicle Technology Competitions (AVTCs) [4]. Its focus is to drive innovation in electrified vehicle technologies, provide education to students who are considering a career in the automotive industry and provide a platform for further automotive research. The EcoCAR competition requires extensive system modelling and simulation for the purpose of control system development as well as predicting performance changes given changes to that control system. One of the primary performance metrics that is evaluated is the energy consumption of the system.

The vehicle CSU designed is a P2 parallel PHEV. It is rear wheel driven. The fuel used in the internal combustion engine (ICE) is ethanol (E85). The electrical energy used to power the electric motor (EM) is stored in the Energy Storage System (ESS), which is mounted at the rear of the vehicle. The ESS is a battery with a nominal voltage of 348 V, a capacity of 12.6 kWh with 7 modules arranged with 2 parallel strings of 15 cells in series. The ESS serves to power the electrical propulsion system. The electrical propulsion system is comprised of a Remy HVH-250 3-phase permanent magnet electric motor rated for 150 kW which is controlled by a Rinehart Motion Systems PM250DZ inverter. This propulsion system is upstream of the transmission which allows it to potentially take advantage of the torque multiplying advantages of the transmission in lower gears.

This study focuses on the electrical energy consumption and does not consider the fuel use of the engine. Figure 1 demonstrates the vehicle architecture for this platform. In order to focus on the high voltage (HV) electrical system, all simulations and in-vehicle tests are executed with the Tilton Engine to Motor Clutch unlocked (or open) such that the electric motor is the only torque source driving the wheels of the vehicle. This operating mode is referred to as the Charge Depleting (CD) mode.

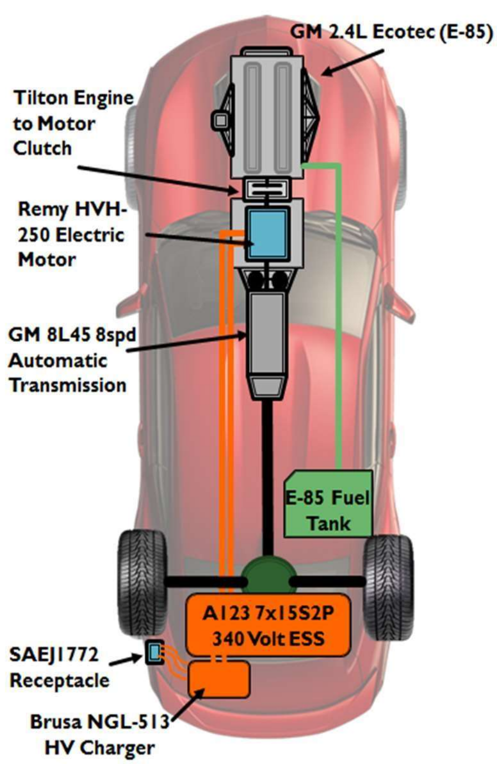

Figure 1: Propulsion system architecture of CSU's 2016 PHEV Chevrolet Camaro

The Vehicle Development Process (VDP) utilized during the acquisition cycle of this platform includes the development of the Hybrid Supervisory Controller (HSC) and all related control software. The vehicle is modeled using software developed in the Matlab Simulink simulation environment. The control software runs in real-time on a Woodward MotoHawk SECM112 automotive controller. This paper examines the validation of this model and considers the sensitivity of the platform's in-vehicle energy consumption to various vehicle parameters.

1.1 Background

1.1.1 Contributing Factors of Energy Consumption in Electric Vehicles

There are a wide variety of parameters, both physical and operational, that contribute to energy consumption within these systems. There are complex physical factors such as tire dynamics and aerodynamic efficiency that play a role in energy consumption regardless of the vehicle architecture [14]. There are simpler physical parameters such as vehicle mass and transmission gearing that also play a large role. These parameters are included in the existing vehicle model while tire characteristics and aerodynamic efficiency are highly simplified for modeling efficiency.

There are also operational and control parameters that affect the energy consumption of the vehicle. Examples that have been shown to have a large impact include the acceleration rate (or tip-in rate) AEs, the state of charge (SOC) of the ESS and the power electronic efficiencies of the inverter's conversion of DC current to AC as well as the EM itself [3].

Previous studies have shown that the propulsion control system itself also has a notable effect on energy consumption. One strategy is called optimal energy management (OEM) in which the HSC is constantly evaluating the efficiency of the ICE based on a mapping of engine speed and torque vs. known efficiency. This evaluation is executed using feedback via the vehicle's controller area network (CAN) bus, which is being updated with data from various sensors at varying rates, and reference to an onboard brake specific fuel consumption (BSFC) map [24]. The controller chooses the most efficient point (given the desired velocity based on accelerator pedal position, or APP) and commands that combination of torque/speed of the engine. This system is also applicable to systems without an ICE such as that utilized in this investigation. However, the power electronics have an efficiency of 90% or greater and generally have less variation in efficiency vs. torque and speed compared to ICEs, which generally have an efficiency of 17-30% [10].

A potential improvement to the OEM control strategy adds AE prediction as an input to the control system. This predictive optimal energy management (POEM) control strategy requires classification of AEs based on the desired end velocity. This strategy has previously shown potential for further reducing fuel consumption in HEVs when compared to an OEM control strategy [24]. Given that the foundation of the optimization remains the same, a POEM strategy is also expected to result in energy consumption improvements in an electrical propulsion system (although by smaller margins).

1.1.2 In-Vehicle Data Acquisition

With the rise in popularity of electronic controllers for various vehicle systems, most new vehicles sold in the U.S. since 1991 utilize a communication protocol called CAN-II [5]. This protocol was originally standardized by the Society of Automotive Engineers (SAE) in 1986 and also adopted by the International Organization of Standardization (ISO) in 1993. The primary driver for manufacturers to adopt this standard was its compatibility with the on-board diagnostics (OBD) standard which was made mandatory for all new vehicle sales in 1995 [29].

The specific architecture for a vehicle's CAN bus is left up to the manufacturer and is generally proprietary information. The standardized architecture includes factors such as number of nodes, length of nodes, bit size, baud rates and serial function [19]. Other factors, such as message identification and transmission rates, are controlled by the manufacturer and requires a database of identifying information to inform the controller how to interpret each signal. The signals contain important information for the function, development or diagnosis of the vehicle.

For example, the transmission control module (TCM) is constantly recording parameters such as input shaft rotational velocity, output shaft rotational velocity and temperature. The TCM uses these values to perform functions such as automated shifting, torque converter clutch control or cooling [7]. This investigation utilizes information on the CAN bus to evaluate the energy consumed during controlled AEs.

1.2 Purpose

The purpose of this investigation is ultimately to evaluate the validity of vehicle energy efficiency simulations compared to data collected in-vehicle. The desired product is a quantified confidence level regarding modeling results as well as a list of parameters that are shown to a have significant impact on energy consumption. This information is useful because it helps the development team to validate simulation results, identify parameters with high potential for optimization and identify confidence bounds such that modeling results within a certain confidence interval can be reliably replicated in-vehicle [22].

The model that has been developed to date is practical but of relatively low fidelity. For example, the transient nature of torque flow during gear changes is not modeled. Figure 2 illustrates this simplification. In reality, a gear shift takes roughly 0.25 seconds and during that time the torque and rotational velocity at the wheels is changing [1]. Those gear changes are simulated in the model as instantaneous step changes. This paper aims to determine whether this level of fidelity is sufficient for future control system development projects. The model is simulated using AEs of varying tip-in rates and final velocities. These tests are replicated in-vehicle. The results are then analyzed and compared.

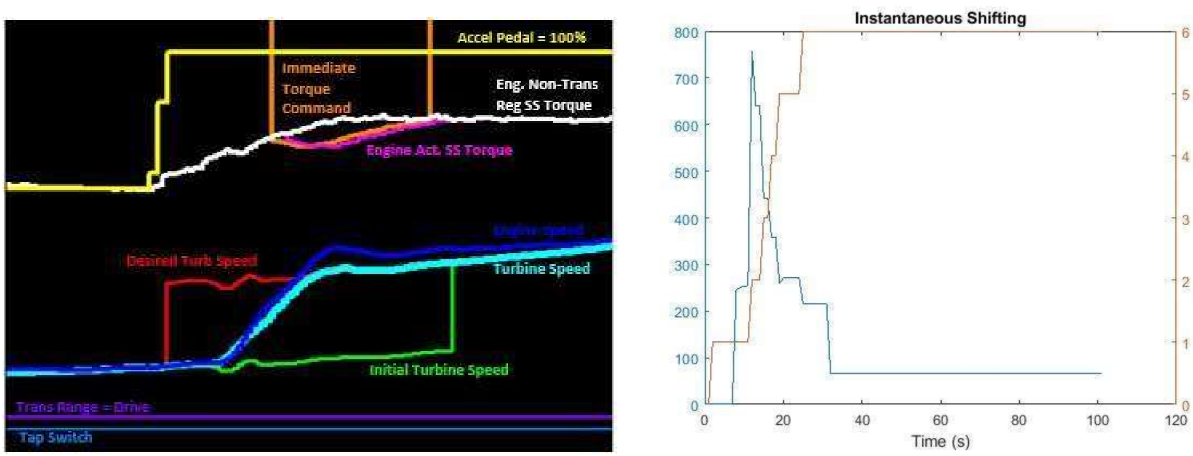

Figure 2: Close-up of the transient torque and speed response of a shift in-vehicle (left) vs. the instantaneous shifts simulated by this vehicle model

CSU VIT is currently involved with another advanced vehicle technology project called the Toyota Test Vehicle Platform (TVP). This project aims to implement a POEM control strategy in order to evaluate its impact on energy consumption when compared to an OEM control strategy. The results of this study are intended to inform future control system modeling and simulation activities as well as in-vehicle testing methods.

1.2.1 Research Questions

The products of this investigation will be useful during future development activities as will be better informed about what parameters actually have an effect on energy consumption, the extent of that effect as well as the extent such results can be replicated in-vehicle. The products are intended to answer the following questions:

1. Does the system model accurately predict the electrical energy consumption of the vehicle across a variety of AE scenarios?
2. Is the system model sufficiently sensitive to physical and operational changes such that its simulation can accurately predict changes in electrical energy consumption?
3. Are the testing methods and facilities of the CSU VIT adequate for consistently measuring the electrical energy consumption of a BEV or a PHEV/HEV in CD mode?

1.3 Novel Aspects of this Research

This study aims to validate the energy consumption model that was developed entirely by graduate and undergraduate members of CSU's VIT. This model, and further iterations of it, will be used for further control system development in the future as well as predicting the energy consumption of the system. Furthermore, this study validates this student-developed model using a student-developed vehicle. This vehicle arrived at CSU as a stock vehicle (ICE only) and was retrofitted with an all new powertrain (including numerous custom student designed parts) and control system [9].

With the results of this study CSU VIT will better understand the team's capability to model electrical energy consumption, collect in-vehicle electrical energy consumption data and quantify the uncertainties in the team's ability to predict electrical energy consumption via control system modeling and simulation. These results are intended to improve the team's modeling and testing methods for use in future AVTCs as well as other advanced vehicle technology projects, including the Toyota TVP.

1.4 Thesis Outline

This section outlines the structure of this thesis. Section 2 describes the simulation methodology, including the simulation environment as well as the team's confidence in the existing model. Section 3 discusses in-vehicle testing methodology, including replicating the simulation environment and the confidence in the data collected. The results of both the simulations and in-vehicle tests are recorded in Section 4 and further discussed in Section 5. Section 6 summarizes the conclusions that can be made from the acquired results as well as recommendations for future work.

2.0 Simulation Methods

This section defines the simulation environment, justifies the simulation results, identifies simplifications and shortcomings of the model, defines the scope of these specific simulations and gives an overview of the actual simulation methods.

2.1 Simulating Electrical Energy Consumption

The model requires the following values in order to simulate electrical energy consumption such that the simulation can be replicated in-vehicle:

- Vehicle velocity
- Current gear
- Auxiliary load
- ESS current
- APP
- Vehicle mass
- Distance driven
- ESS voltage

The model uses the desired velocity profile, called a drive cycle, as an input. Using data previously collected and validated, a subsystem of the model called the Driver Model determines the corresponding APP. This APP is then used as an input to the Controller Model of the inverter for the purpose of longitudinal propulsion, which is a typical application of driver modelling [28]. The output of this subsystem is a torque request that is calculated based on an efficiency map provided by the inverter manufacturer. The torque request is in turn used as an input to the Plant Model of the EM. The Plant Model is physics based and must obey relevant physical laws (such as the energy required to accelerate a mass at a certain rate) as well as limits of the modeled components (such as the maximum torque output of the EM). The resulting output is a torque command and is then used as an input to the Plant Model of the transmission in order to simulate gear changes. The resulting power is used as an input to the Plant Model of the ESS in order to calculate the required output current. The actual voltage of the ESS changes with the magnitude and duration of output current. This change is modeled using the output current of the ESS Plant Model, ESS impedance and the time steps of the simulation compared to a map of the voltage drop provided by the ESS module manufacturer [15]. This process is summarized by Figure 3 below.

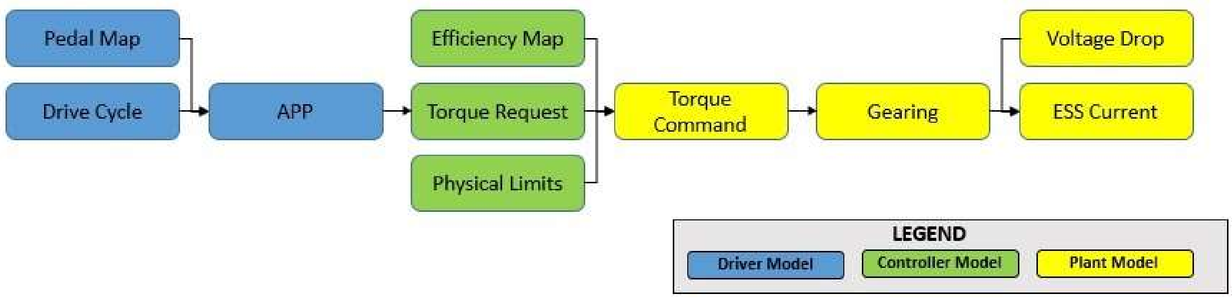

Figure 3: Electrical energy consumption overview

These all work in parallel with the rest of the physics-based model. The Plant Model also includes physical parameters such as the mass of the vehicle. This value is obtained by weighing the vehicle in its completed state, a process that is overseen by competition officials. It also includes wheel parameters such as total radius (with tire) and coefficient of friction but does not include dynamic characteristics such as the dynamic coefficient of friction with heating or tire pressure. The transmission is also simply modeled with the manufacturer specified gear ratios and manufacturer provided shift schedule. Finally, minor losses such as aerodynamic drag and shaft inertias are simply modeled using the manufacturer provided frontal area (which was not changed during the retrofit) and estimated inertial values.

2.1 Definition of Simulation Environment

Tables 1-3 define the initialization parameters of the model prior to simulation. Some of these parameters, such as vehicle mass or the transmission gear ratios, are relevant because these parameters can also be feasibly varied in-vehicle and thus replicated to validate the predicted change in energy consumption [16]. Others, such as the frontal area or component parameters, are not as feasibly varied in-vehicle but may still result in energy consumption changes and are required for successful execution of the model [21].

Table 1: Physical vehicle parameters considered in the system model

Vehicle Parameter	Value
Vehicle Mass	1805 kg
Frontal Area	2.56 m^2
Tire Radius	0.35 m
Coefficient of Drag	0.35
Final Drive Ratio	2.77
Transmission Gear Ratios	4.615, 3.007, 2.065, 1.671, 1.265, 1.00, 0.845, 0.652
Driveshaft Inertia	0.0015 kg-m^2
Half-shaft Inertia(s)	0.0015 kg-m^2
Auxiliary Load	1250 A

Table 2: Specifications and limits of the electric motor

Component Parameter	Value
EM Continuous Power	100 kW
EM Peak Power (30 sec.)	150 kW
EM Continuous Torque	215 Nm
EM Peak Torque (30 sec.)	400 Nm
EM Continuous Speed	4400 rpm
EM Peak Speed (30 sec.)	3500 rpm

Table 3: Specifications and limits of the energy storage system

Component Parameter	Value
Nominal Voltage	350 V
Capacity	12.6 kWh
Internal Resistance	0.242 Ohm
Initial State of Charge (SOC)	100%

2.2 Reliability of Simulation Results

It is important to establish a baseline model and baseline vehicle state in order to reliably compare changes to the system's energy consumption as vehicle parameters are varied [30]. For this purpose, the baseline model is the model initialized as described above. Simulation results from this model are compared to data recorded in-vehicle in order to justify the utility of this model.

Figure 4 compares the simulated velocity results of the first 505 seconds of the Urban Dynamometer Drive Schedule (UDDS) drive cycle with the desired velocity [12]. The difference between the simulated velocity and the desired velocity is, on average, -0.6%. The maximum difference is 0.22 mph. This result verifies that the model executes as expected.

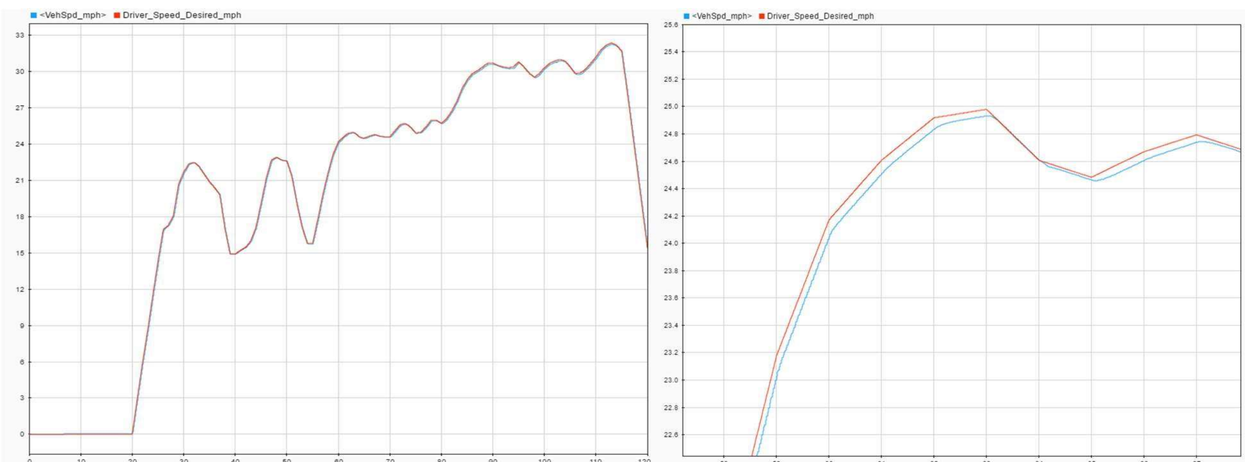

Figure 4: Comparison of the desired velocity from the drive trace (red) and the simulated velocity (blue)

The model is verified using only simulation results, but an in-vehicle comparison is required for validation. Ideally, the comparison is between a standard drive cycle that is simulated and executed in a highly controlled environment, such as on a chassis dynamometer in an environmentally controlled chamber [11]. However, this investigation focuses only on the vehicle when operating in CD mode and there is no historical in-vehicle data collected on a chassis dynamometer for the purpose of validation. Instead, the baseline results are a 0-60 mph

AE executed with the same initialization parameters described above. Figure 5 compares this simulated AE to in-vehicle data collected on a closed course.

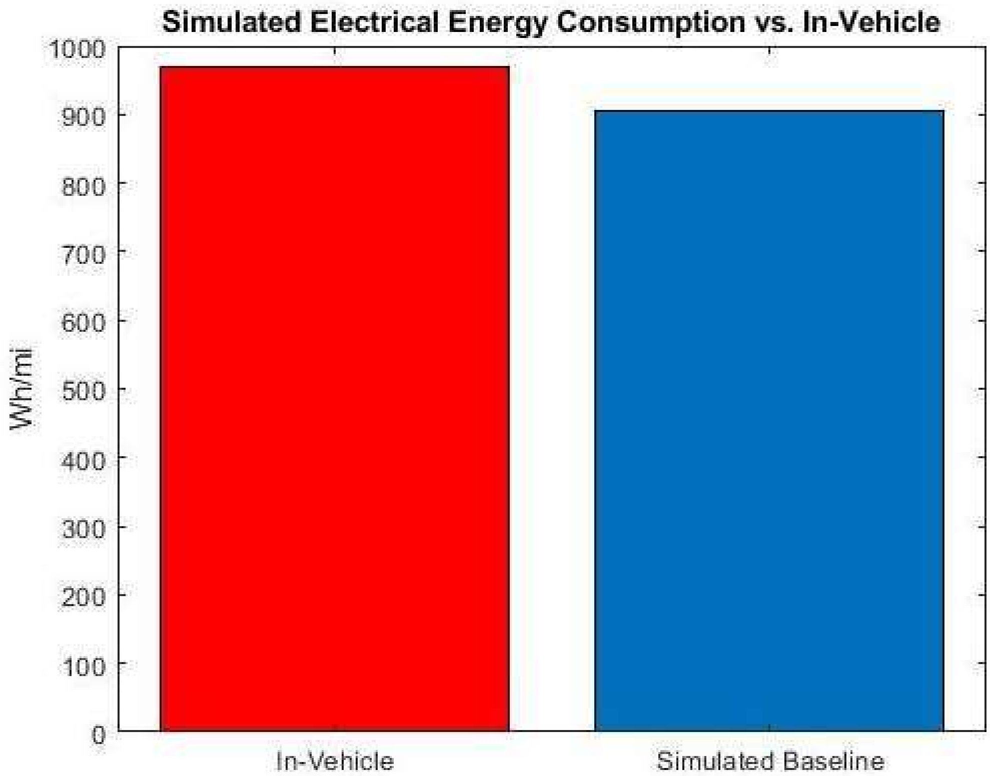

Figure 5: 0-60 mph AE and energy consumption, simulated (blue) vs. in-vehicle data (red)

The simulation predicts that the vehicle achieves 60 mph (in CD mode) in 20.1 seconds. In-vehicle data support this result, achieving 60 mph in 18.9 seconds on average. This instills confidence that the simulation is executed as expected and sufficiently models the real system. This model confidence is further validated by comparing the energy consumed during the same 0-60 mph AE. These differences are attributed to both modeling deficiencies and the environmental conditions under which the in-vehicle test was executed.

2.3 Simulation Simplifications

There are several factors that explain the difference of 1.2 seconds (about 6%) described in Section 2.2. The model does not account for ambient air temperature whereas the in-vehicle test was executed in southern California at temperatures above room temperature. The increased ambient air increases the power required to cool the HV components (EM, inverter and ESS). The cooling system itself is a low voltage (LV) system that includes 2 pumps, 3 large fans as well as 2 radiators fitted with 2 temperature sensors each. The power for these components is supplied by the 12V battery in the vehicle. The 12V battery is not supported by an alternator but by an Auxiliary Power Module (APM). The APM drives DC current from the HV ESS to the 12V battery after stepping the voltage down from the open circuit voltage to about 14V [27].

The model of the vehicle does account for the auxiliary load on the 12V battery that must be supported by the APM. The model uses a constant value of 1250 A to simulate this load. This value was selected after conducting an analysis on the LV auxiliary systems in order to determine the in-vehicle consumption of the major LV components (pumps, fans, controllers, etc.). The analysis shows that the in-vehicle auxiliary load is not a constant value. The HSC is programmed to turn certain pumps and fans on/off in order to keep cooled components within a range of temperatures. However, using a constant value within the model is sufficient for the purpose of controls development. This is because in order to accurately model a dynamic auxiliary load it would also be necessary to model each individual pump, fan, controller, actuator and sensor (every component powered by the 12V battery). This is another example where the baseline fidelity of the model is found to be sufficient and practical for controls development and trend level validation.

Other limitations of the model that may lead to discrepancies between simulation results and in-vehicle results include (but are not limited to) simplified tire slip models, an assumed 50/50 weight distribution and a static low voltage auxiliary load. The platform itself also offers reasons as to why in-vehicle results may differ from simulation results. Since it is running in real-time, data collection and the timing of serial communication is very important whereas this concern is absent in the modeling environment. For example, CAN messages are required to execute the control system in real-time but not when simulating the model. Messages that get dropped, are prone to noise or that are getting bad sensor information could all cause discrepancies in the results [2]. This investigation seeks to both identify and limit such problems.

There are other simplifications made in the model that can explain discrepancies between simulation and in-vehicle results. The vehicle is modeled using the Simple Tire block available in Matlab Simulink [25]. This model does not account for tire dynamics, material or pressure. Tires are well-known to have significant effects on a vehicle's acceleration performance and fuel economy [26]. This simplification is acceptable because the goal of controls development is to optimize energy consumption through the powertrain. If the in-vehicle tires are simply kept as a constant then a simple tire model still allows for trend level validation. Changes in energy consumption can be directly attributed to changes to the control system. There is no chance of dynamic tire conditions causing a change.

2.4 Scope Definition

This investigation aims to evaluate the utility of the mathematical model of the system in predicting the electrical energy consumption of the system during physical testing. The ability of the model to sufficiently predict energy consumption instills confidence in its utility for automotive controls development. This investigation focuses solely on the electrical energy consumption and disables the vehicle system that consumes chemical energy through the combustion of E85 fuel. Furthermore, traditional fuel economy and emissions are also outside of this investigation's scope.

WOT AEs are considered the baseline results of this investigation. Drive cycles are readily repeatable in-vehicle without the use of a dynamometer or professionally trained driver by using either WOT scenarios- the driver depresses the accelerator pedal as far as possible as quickly as possible- or a pedal block. The pedal block allows the driver to depress the pedal at the same rate as WOT but limits the level of actuation to 45% APP. This limit is considered ECO AEs. The AEs are of the following categories:

- 0-20-0 mph
- 0-40-0 mph
- 0-60-0 mph

Once baseline results are established each 0-60 mph test is additionally executed with the rate of acceleration held constant at WOT while changing the following parameters:

- Vehicle mass
- Available transmission gears (all gears or only 4th gear)
- Auxiliary load

A simple Design of Experiments (DOE) defines the iterations required to test each variable described above. Table 4 defines each run of this investigation. Each run is simulated 1 time and repeated in-vehicle 3-6 times. In-vehicle tests are executed at least 3 times and analyzed for normality. If the data is normal and falls within the determined confidence interval then testing of that category ends, otherwise testing continues until reasonably consistent results are obtained. The purpose of this procedure is to ensure a statistically meaningful sample result.

Table 4: Simplified DOE of acceleration events for evaluation

Acceleration Category	Run	Tip-in Rate	Mass	Available Gears	Auxiliary Load
0-20 mph	1	WOT	1805 kg	All	1250 W
	2	Eco	1805 kg	All	1250 W
0-40 mph	3	WOT	1805 kg	All	1250 W
	4	Eco	1805 kg	All	1250 W
0-60 mph	5	WOT	1805 kg	All	1250 W
	6	Eco	1805 kg	All	1250 W
	7	WOT	1936 kg	All	1250 W
	8	WOT	1805 kg	4th	1250 W
	9	WOT	1805 kg	All	1308 W

2.5 Modeling Environment

The model is developed using Matlab Simulink, a visual programming language which automatically generates the C code that is ultimately uploaded to the HSC. As a VPL, programming is done by connecting various “blocks” that each serve a unique function. There are blocks that are intended to be used within the system plant, such as the simple tire blocks which include tire radius and friction, the vehicle body itself which allows the user to define parameters such as frontal area or drag, clutches, torque sources, voltage sources and many others. Figure 6 shows an annotated diagram of the EM. The plant is responsible for mathematically representing the actuators and components that require control. The plant includes the ICE, EM, transmission, ESS and vehicle body.

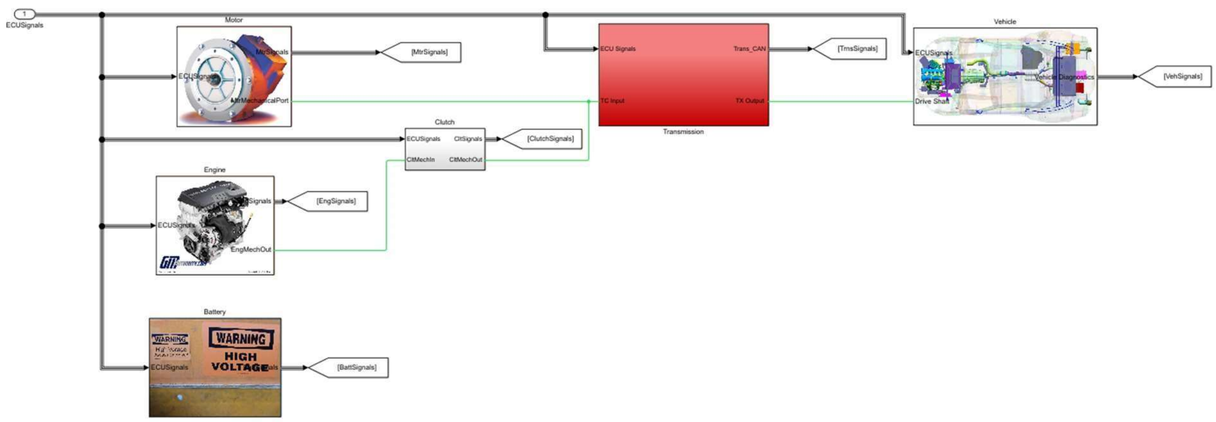

Figure 6: Snapshot of the Plant Model, developed in Matlab Simulink

There are other blocksets that are intended for use specifically in the system controller. The most important of these blocks is the StateFlow block. StateFlow allows the user to define system (or subsystem) states. One example of StateFlow within this simulation is the Vehicle Operating Mode (VOM) function. This function determines whether the vehicle should be off, on but in accessory mode (torque is not available) or run mode. Run mode also includes several sub-states, including the CD mode required for this investigation. The VOM StateFlow is illustrated in Figure 7. The controllers are responsible for actuating the various components as desired. Controllers request a certain amount of torque from torque sources, limit component outputs for safety and evaluate the driver’s requests based on the desired velocity and a reverse lookup table to determine the appropriate APP.

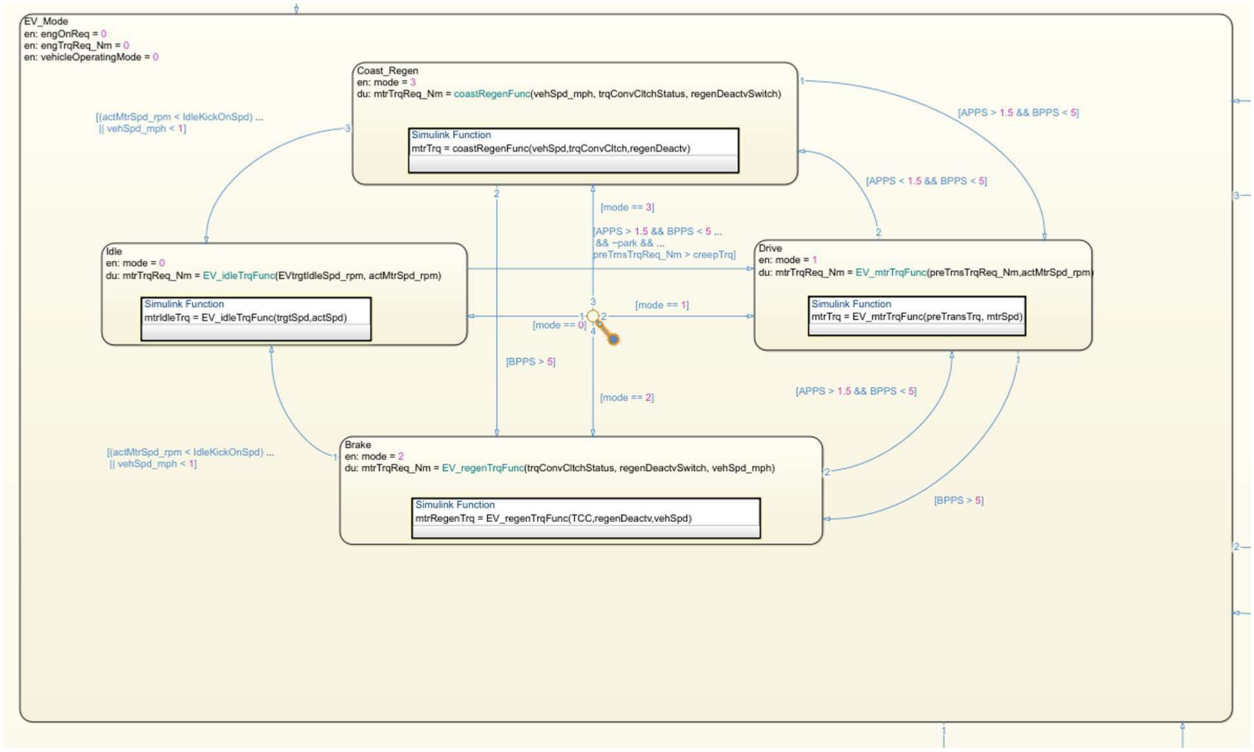

Figure 7: Model StateFlow diagram defining vehicle operational state

The driver of the vehicle is also considered part of the system. Lateral control is not accounted for as part of the model- every drive cycle is assumed to be driven in a perfectly straight line. The driver model uses a function that maps pedal position and instantaneous vehicle velocity to a desired velocity, and thus the energy required to achieve that velocity. The drive trace (such as the UDDS or a 0-60 mph AE) serves as the desired velocity and the model uses that value to determine the requisite APP.

3.0 In-Vehicle Methods

In-vehicle testing requires both a control algorithm and data acquisition (DAQ) tools that operate in real-time. In-vehicle testing differs from simulation in that regard. Simulations are not concerned with signal send rates, CAN timing or errors or the processing power available to the HSC. A simulation can execute a 60 minute drive trace in a matter of seconds whereas the drive trace would take the full 60 minutes to execute in-vehicle. This is an advantage of controls development in the Matlab Simulink environment but a challenge when validating the model. Another advantage of developing in both time domains is the ability to incorporate knowledge gained during real time in-vehicle testing to the controls development in software. This development process creates a feedback loop that allows for safe software integration to the vehicle and then software development calibration using in-vehicle results. This process increases confidence in the model without having to invest unnecessary resources to improving model fidelity for the same result.

3.2 Definition of Closed Course Environment

In-vehicle data is collected on a closed course. The closed course is Christman Airfield in Fort Collins, CO. This facility is a decommissioned take off/landing strip for small aircraft. It is approximately 0.75 miles in length, in a straight line that mimics the lack of lateral control within the model and is outdoors. It is exposed to the variable ambient temperature, pressure and humidity. The runway experiences a slight road grade, approximately 0.7% in the Southern direction, as demonstrated by Figure 8 [18]. In order to ensure that the road grade does not affect results, tests are only executed driving in the Northern direction, starting from a permanently marked starting line on the Southern end of the runway.

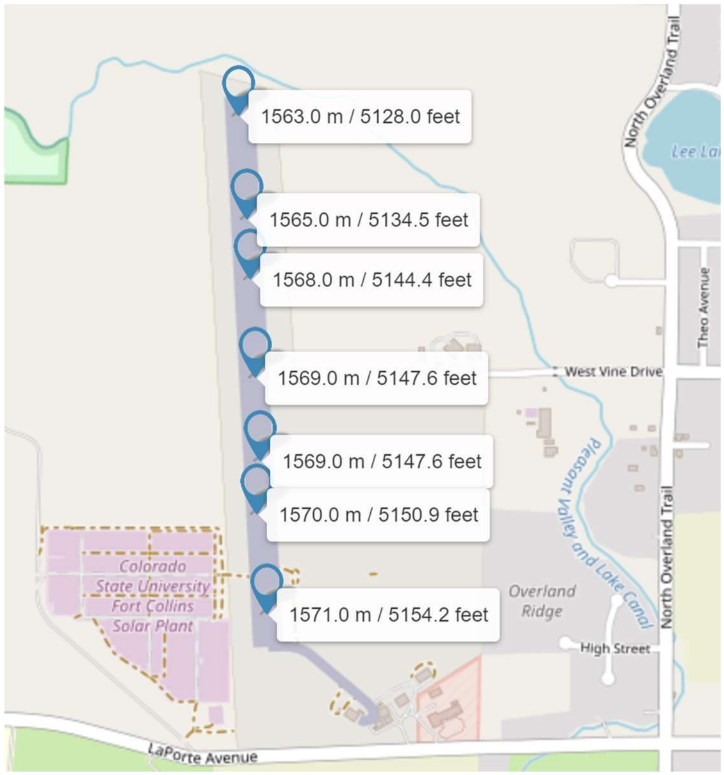

Figure 8: Elevation change along the runway at Christman Airfield

3.2 In-Vehicle Data Collection

As stated in Section 2.1, the software baseline is the vehicle model as it existed at the end of the EcoCAR 3 competition. Similarly, the baseline vehicle is the state of the vehicle exactly as it existed at the end of the EcoCAR 3 competition. No modifications to the vehicle mass, shift schedule or APP map exist in the baseline vehicle (or model). This investigation inserts changes to these parameters in order to determine the effects on both the model and the physical system.

In-vehicle DAQ is executed using a Vector GL1000 CAN Logger. This device logs every transmitted and received CAN signal as they occur in real time to a memory card for post processing. All the relevant data (velocities, current, voltage, speed, torque, etc.) are reported on the CAN bus from various sensors and controllers. There are 2 relevant CAN channels for the purpose of this investigation: one channel facilitates communication between all the hybrid components and the other channel facilitates communication between the transmission and other stock vehicle controllers. It is the responsibility of the HSC to facilitate this communication and the responsibility of the Vector GL1000 to log all of this communication.

Data analysis follows EPA methods originally developed for the analysis of particulate matter in 1999. This study aims to achieve Data Validation Level I. This includes proper data file identification, the inclusion of field notes, instrument performance checks as well as the review of unusual events and the identification of atypical values (when compared to the rest of the dataset) [23]. Data analysis and post-processing is done using Vector CANoe software and Matlab. Vector CANoe is used for data management, performance checks and the review of unusual events. Matlab is used for statistical analysis to identify atypical values (in addition to all calculations required).

3.3 In-Vehicle Methods

Closed course testing begins with closing the course from bystanders and potential hazards. This course is closed by scheduling the airfield for use as well as signage and barriers to prevent entry by unintended personnel. Aggressive driving is defined as a WOT scenario. The APP is thus limited to 100%. The driver is expected to tip-in from 0% to the requisite APP as fast as possible during the aggressive driving style testing. ECO driving follows the same tip-in rate but actuation is limited to 45%. The remaining parameter variations are discussed in detail in the following section.

3.3.1 Inserting Parameter Changes

The parameters intended for evaluation regarding predicting changes in electrical energy consumption are acceleration rate, vehicle mass, auxiliary load and available gears. Inserting these changes in the model is as simple as changing a single number within the model, respectively. This section outlines how these changes are replicated in-vehicle.

The baseline acceleration rate is a WOT scenario where the APP is immediately 100% in order to request the most torque as possible from the electrical propulsion system throughout the AE. In order to predict a change in electrical energy consumption caused by the acceleration rate, an ECO AE is defined as acceleration to the desired velocity at 45% APP. Achieving this controlled APP is accomplished by using a simple pedal block. The pedal block is constructed out of a piece of wood of the same width as the accelerator pedal itself and taped to the underside of the pedal using abrasion resistant Tesa tape. Each test is executed in succession so that differences in position or attachment method do not cause unintended changes to results. Before starting each test, the APP limit of 45% is verified using real-time CAN monitoring software Vector CANoe. The resulting drive trace is then fed back to the model so that the same velocity profile can be simulated.

The increase in vehicle mass is achieved by loading bags of sand into the rear seat of the vehicle. The sandbags are weighed and found to be 21.8 kg each. With 6 bags used, the total increase in mass is rounded to 131 kg. The downside of this method is that there is nowhere besides the rear seat of the vehicle to load this mass. As a rear wheel drive vehicle, increasing the mass at the front of the vehicle rather than the wheel could affect the tractive power available at the wheel. This simplification is accepted because the system model does not include front-to-rear weight ratios within its physics so the in-vehicle location of the added mass is still comparable.

The auxiliary load is increased by 58 W by turning every available auxiliary load to its highest setting (which were all turned off in baseline and subsequent testing). The vehicle's stock alternator was removed and replaced with an APM. This component takes HV power from the ESS, reduces the voltage to 14 V and uses the current to keep the LV battery charged. The systems that are turned on include:

- Headlights, set on the bright setting
- AC fans, set to the highest setting
- Seat warmer, set to the warmest setting
- Steering wheel warmer
- Front and rear windshield defrosters
- Radio, set to the highest volume
- Hazard lights

Finally, the gear ratios are controlled by inserting a communication fault between the TCM and the Engine Control Module. By limiting communication between these two controllers a diagnostic trouble code (DTC) is triggered which limits the transmission to only using 4^{th} gear. This gear is the closest to 1:1 available in this transmission and is meant to protect the transmission in the event of a larger problem such that the driver can get the car to a mechanic for repairs. Since the rest of the electrical propulsion system is on the custom CAN channel it is acceptable that a DTC is active on the second CAN channel.

3.3 Scope Definition

The scope of in-vehicle testing and evaluation is limited by the closed course requirement. Standard drive cycles are not an option. The scope of the simulation investigation is limited to tests that are reliably repeatable at Christman Airfield. The 9 categories of AEs outlined in Section 2.4 are repeated until the results are verified as normal. A DOE is useful for defining each VIL test that must be executed [17]. The resolution of this DOE is coarse. Trend level validation requires results from at least 2 extremes in variability. As such, each variable and AE scenario will only have 2 states: high and low. Table 4 in Section 2.4 illustrates the details of this DOE.

4.0 Results

This section summarizes the results of both simulation and in-vehicle testing. Simulation results include both the raw electrical energy consumption and energy economy, which is electrical energy consumption per mile. However, the in-vehicle results are truncated to only energy economy.

4.1 Simulation Results

Table 5: Simulation results from the DOE outlined in Section 2.4

Category	Simulation EC (Wh)	Simulation EC (Wh/mi)
0-60 mph WOT	190.4	906.7
0-60 mph ECO	192.7	856.4
0-60 mph +MASS	242.6	1102.7
0-60 mph +AUX	193.2	772.8
0-60 mph +TRANS	185.8	807.8
0-40 mph WOT	82.7	1333.2
0-40 mph ECO	83.7	1288.2
0-20 mph WOT	33.1	4141.3
0-20 mph ECO	30.1	3344.4

4.2 In-Vehicle Results

4.2.1 Wide Open Throttle

In-vehicle results from WOT testing of each category are summarized and compared to simulation results in Table 6. The percent error (calculated using the simulation EC as the expected value) are categorized as less than 10% (green), between 10% and 20% (yellow).

Table 6: WOT results for 0-60, 0-40, 0-20 mph AEs

Category	SIL EC [Wh/mi]	VIL EC [Wh/mi]	Error (%)	CI [Wh/mi]	Mean EC [Wh/mi]	%Error of the Mean	Abs. Error [Wh/mi]
		996.3	9.9%				
		892.3	-1.6%				
0-60mph WOT	906.7	954.8	5.3%	(885.9, 1040.5)	968.2	6.8%	61.6 (+72.3, -82.4)
		991.4	9.3%				
		911.9	0.6%				
		1302.7	-2.3%				
		1378.9	3.4%				
0-40mph WOT	1333.2	1471.5	10.4%	(1258.3, 1491.2)	1400.1	5.0%	66.9 (+91.1, -141.8)
		1396.7	4.8%				
		1450.9	8.8%				
		4078.0	-1.5				
0-20 WOT	4141.3	4141.9	0.0	(3856.0, 4200.1)	4028.0	-2.7%	-113.2 (+172.1, -172.0)
		4001.7	-3.4				

4.2.2 ECO-Driving

In-vehicle results from eco-driving testing of each category are summarized and compared to simulation results in Table 7. Eco-driving for these tests is defined as an aggressive tip-in to 45% APP. A constant 45% APP is achieved using a pedal block calibrated such that the accelerator pedal cannot be depressed beyond the desired APP. The percent error (calculated using the simulation EC as the expected value) are categorized as less than 10% (green) and between 10% and 20% (yellow).

Table 7: ECO results for 0-60, 0-40, 0-20 mph AEs

Category	SIL EC [Wh/mi]	VIL EC [Wh/mi]	Error (%)	CI [Wh/mi]	Mean EC [Wh/mi]	%Error of the Mean	Abs. Error [Wh/mi]
0-60 ECO	856.4	778.7	-9.1%	(745.5, 844.4)	802.0	-6.4%	-54.4 (+42.4, -56.6)
		826.2	-3.5%				
		770.6	-10.0%				
		840.9	-1.8%				
		793.7	-7.3%				
0-40 ECO	1288.2	1223.2	-5.0%	(1219.2, 1450.5)	1338.6	3.9%	50.4 (+111.9, -119.4)
		1403.9	9.0%				
		1370.6	6.4%				
		1355.8	5.3%				
		1339.4	4.0				
0-20 ECO	3344.4	3405.3	1.8	(3204.5, 3550.9)	3330.2	-0.4%	-14.2 (+220.7, -125.7)
		3288.2	-1.7				
		3297.1	-1.4				

4.2.3 Driving Under Parameter Variation

In-vehicle results indicate that the data gathered follows a normal distribution and that each AE category can successfully be executed in-vehicle such that the mean percent error is less than 10%. Given the standard deviation between percent error of WOT testing (5.3%) and ECO testing (0.7%), the results from each AE category are considered valid. For this reason, further VIL testing of the remaining variables (mass, auxiliary load and available transmission gears) is only executed in the 0-60 mph AE category. The data from each additional 0-60 mph AE test is truncated to both 0-40 mph and 0-20 mph in order to minimize time spent testing in-vehicle. Results from these tests are summarized in Table 8.

Table 8: In-vehicle results using physical parameters of mass, auxiliary load and available gears as variables

Category	SIL EC [Wh/mi]	VIL EC [Wh/mi]	Error (%)	CI [Wh/mi]	Mean EC [Wh/mi]	%Error of the Mean	Abs. Error [Wh/mi]
0-60 mph +mass	1102.7	1020.7	-7.4%	(996.59, 1063.7)	1030.1	-6.6%	-72.6 (+33.6, -33.5)
		1024.1	-7.1%				
		1045.6	-5.2%				
0-60 mph +aux	772.8	762.4	-1.3%	(573.6, 837.6)	705.6	-8.7%	-67.2 (+132.0, -132.0)
		697.4	-9.8%				
		657.1	-15.0%				
0-60 mph +trans	807.8	697.5	-13.7	(659.2, 712.3)	685.8	-15.1%	-122.1 (+26.5, -26.6)
		683.2	-15.4				
		676.6	-16.2				

4.2.4 Model Error

The model error for each AE category is summarized in Table 9. The model overestimates energy consumption for 6 of the 9 AE categories. The minimum absolute total error is 14.2 Wh/mi for the 0-20 mph ECO category which also has the largest confidence interval. The maximum total error is 122.1 which also has the smallest confidence interval.

Table 9: Model error and associated confidence interval (95% confidence)

Category	Model Abs. Error [Wh/mi]	Confidence Interval [Wh/mi]	Model %Error
0-60 mph WOT	61.6	+133.8 -20.8	-6.4%
0-60 mph ECO	-54.4	OUT	6.8%
0-60 mph +MASS	-72.6	OUT	7.0%
0-60 mph +AUX	-67.2	+64.8 -199.2	9.5%
0-60 mph +TRANS	-122.1	OUT	17.8%
0-40 mph WOT	66.9	+158.0 -74.9	-4.8%
0-40 mph ECO	50.4	+162.3 -69.0	-3.8%
0-20 mph WOT	-113.2	+58.9 -285.3	2.8%
0-20 mph ECO	-14.2	+206.5 -139.9	0.4%

4.2.5 Experimental Error

It is also important to consider the experimental error in order to validate the testing methods. Table 9 summarizes these experimental errors. The overall average relative error is 2.8%, or 40.7 Wh/mi. The average relative error for baseline tests is 3.0% (62.9 Wh/mi). The average relative error for all ECO tests is 2.7% (40.5 Wh/mi). This result agrees with the WOT vs. ECO error compared to simulation. The standard deviation of relative error between the remaining parameter variations (2.5%) further reinforces that the in-vehicle data collected for these categories are considered valid and the main source of error compared to simulation results is modeling shortcomings. These results are summarized in Table 10.

Table 10: Average experimental error of each AE testing category

Category	Avg. Experimental Error [Wh/mi]	CI [Wh/mi]	Avg. Relative Error [%]
0-60 mph WOT	39.4	+72.3 -82.4	4.1
0-60 mph ECO	25.2	+42.4 -56.6	3.1
0-60 mph +MASS	31.3	+33.6 -33.5	3.0
0-60 mph +AUX	37.8	+132.0 -132.0	5.4
0-60 mph +TRANS	7.8	+26.5 -26.6	1.1
0-40 mph WOT	48.8	+91.1 -141.8	3.5
0-40 mph ECO	46.2	+111.9 -119.4	3.4
0-20 mph WOT	81.9	+172.1 -172.0	2.5
0-20 mph ECO	50.1	+220.7 -125.7	1.5

4.2.6 Total Error

Total error encapsulates both the model error (Sections 4.2.1-4.2.3) and experimental error (Section 4.2.4). The function of the total error is to determine the bounds within which results can be considered valid as well as inform the tester whether a simulation result can be replicated in-vehicle. The total error is summarized in Table 11:

Table 11: Total error, from both model and experimental error

Category	Total Error [Wh/mi]
0-60 mph WOT	±90.1
0-60 mph ECO	±74.8
0-60 mph +MASS	±99.5
0-60 mph +AUX	±91.0
0-60 mph +TRANS	±160.1
0-40 mph WOT	±96.8
0-40 mph ECO	±72.6
0-20 mph WOT	±157.0
0-20 mph ECO	±19.5

5.0 Discussion

5.1 Comparing Simulation and In-Vehicle Results

On average, across all evaluation categories, the vehicle model and simulation results are able to predict the electrical energy consumption of the vehicle within 6.5%, ignoring experimental error. These results indicate that the model is sufficient for predicting electrical energy consumption changes that are within ±30.2 Wh/mi. Changes to the system that result in a modeled change in electrical energy consumption that is less than ±30.2 Wh/mi cannot be reliably replicated in-vehicle. These results are summarized in Figure 9.

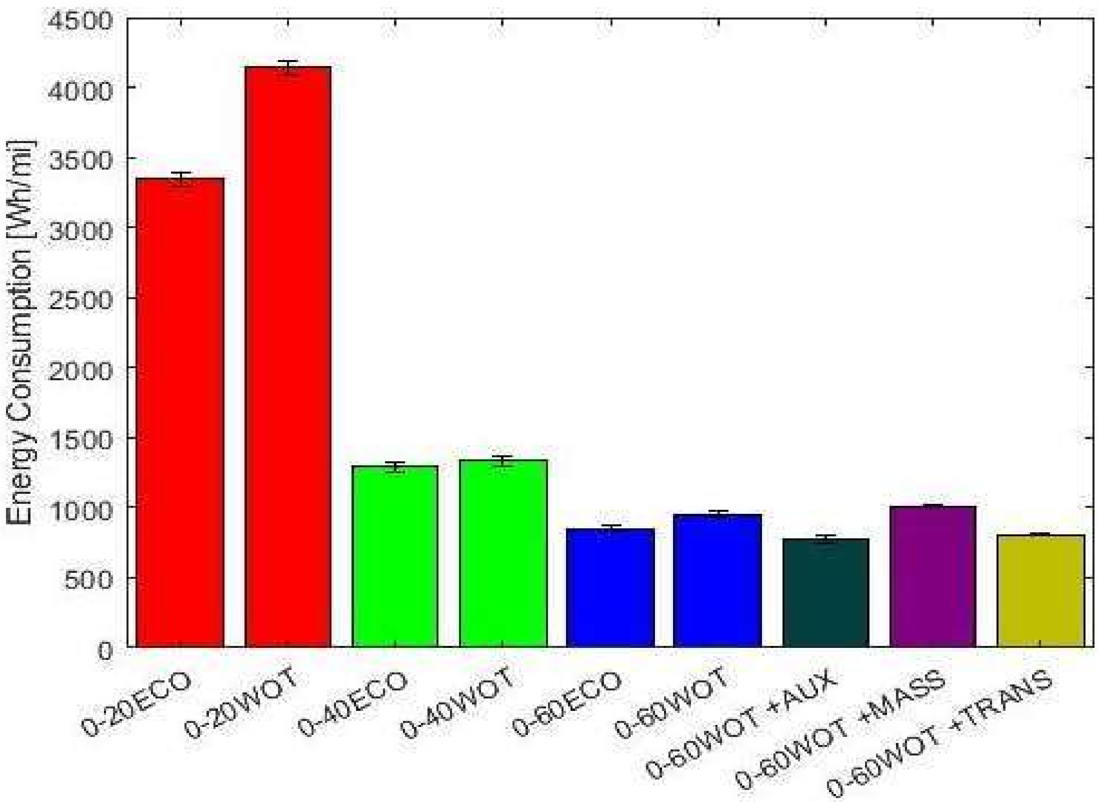

Figure 9: Energy consumption per mile, with standard error bars

Results indicate a trend showing that low speed simulated AEs are more reliably replicated in-vehicle. The average error for 0-20 mph AEs, between WOT and ECO scenarios, is 2.3%, or ±54.2 Wh/mi. The average errors for 0-40 mph and 0-60 mph AEs (WOT and ECO scenarios) are 5.9% (±38.3 Wh/mi) and 5.3% (±21.4 Wh/mi), respectively. The increase in error at greater velocities can be explained by the closed course testing facility available to the VIT and the increase in error as ΔElevation increases. However, it is important to also consider the error caused by in-vehicle experimentation in the model's ability to predict electrical energy consumption to fully comprehend the model's ability to predict changes in electrical energy consumption.

5.2 Sources of Model Error

Chirstman Airfield has an upward grade of roughly 0.7%, or a change in elevation of 26.2 ft. over 0.7 miles, when traveling in the Southern direction. The 0-20 mph AEs cover a distance of roughly 2-5% of a mile, or a maximum of 264 ft. The 0-20 mph AE experiences a change in elevation of only 0.21 - 0.24 ft. In contrast, a 0-40 mph AE experiences an elevation change of 1.41 - 1.65 ft. and a 0-60 mph AE experiences a change of 5.24 - 6.55 ft. The vehicle model is simulated at 0% grade. This means that the model does not account for the increased energy required to travel up a hill or the reduced energy required to travel down a hill. The relative lack of elevation change experienced during 0-20 mph AEs corresponds to lower average model error. Accordingly, the AE categories that require a longer distance to travel correspond to a greater average error between simulation and experiment. The outlier is AEs executed in a single gear (0-60 mph +trans). These conclusions are summarized in Table 12.

Table 12: Error between simulation and experimentation compared to change in elevation caused by travel distance

Category	ΔElevation (ft)	Average %Error of the Mean
0-60 MPH	1.29	6.6%
0-40 MPH	0.51	4.5%
0-20 MPH	0.03	1.6%
0-60 mph +mass	1.57	6.6%
0-60 mph +aux	1.58	8.7%
0-60 mph +trans	0.26	15.1%

Across all evaluation categories, the average model error in prediction of energy consumption is 6.5%, or a standard error of ±30.2 Wh/mi. However, the results show that modeling and simulation struggles more to predict changes in EC with changes to physical vehicle parameters. The baseline results show that the model predicts EC, with 95% confidence, within 4.8%. Modeling the driver in ECO driving scenarios results in an average error of 4.98%. However, the average model error increases when varying the physical parameters considered in this study. The average error when the mass is increased is 6.6%, when the auxiliary load is increased, is 9.2%. When the transmission is limited to 1 gear the model error is 15.1%.

This study confirms the model is capable of predicting the change in electrical energy consumption when mass is increased. The baseline 0-60 mph WOT test resulted in an average consumption of 968.2 Wh/mi. Increasing the mass by 130.6 kg correlates to an increase invehicle of 61.9 Wh/mi. The model is able to predict this increase within 6.6%, or ±8.6 Wh/mi. This result is in line with the standard error of the model as well. This is useful for the TVP project because the mass of the vehicle is expected to increase as the vehicle is electrified because additional components outweigh those that may be removed.

The model is also adequate in predicting the change in electrical energy consumption as the auxiliary load increases, although with slightly greater error than the other AE categories. This category shows that the model predicts this electrical energy consumption to within 9.2%, or ±53.1 Wh/mi. While this result is still in line with the overall standard error found in the model, the increased error indicates the Plant Model of the accessory power module could be improved.

Finally, the model shows the most error in predicting electrical energy consumption when the vehicle is limited to a single gear. On average, the model predicts a change in energy consumption that is 15.1% greater than what is recorded in-vehicle, or 122 Wh/mi. While the error is greatest in this category, the data collected in-vehicle is normal and resulted in the smallest standard deviation across all AE categories tested. These results indicate that this error may be due to a shortcoming of the model. Since the Controller Model of the TCM simply models the shift schedule and gear ratios of the transmission, it is most likely that this error stems from the Plant Model of the transmission itself. The Plant Model is more complex with models of each transmission clutch, inertial losses and it interacts with the efficiency map of the EM. It is plausible that such losses are overestimated when only operating in a single gear or that the efficiency map itself is slightly inaccurate. However, experimental error must also be considered with context to fully understand how well the model is able to predict in-vehicle changes to electrical energy consumption.

5.2 Experimental Error

Average experimental error across all AE categories is 3.0%, or ±41.2 Wh/mi. The primary drivers of experimental error in this study are test execution and environmental factors such as headwind or temperature. Test execution includes the starting location of each AE, the direction of travel, the tip-in rate of the APP and the amount of lateral control of the vehicle. In order to minimize this error each test must begin at the same location and travel in the same direction. The tip-in rate must also be consistent. Finally, the ideal test is executed in a perfectly straight line. This methodology should improve the consistency of energy consumed and distance traveled for each AE.

Environmental factors are harder to control. A headwind (wind blowing in the opposite direction as travel) increases energy consumption compared to no wind or a tailwind (wind blowing in the same direction as travel). A higher ambient temperature also increases the burden on component cooling systems. As discussed in Section 2.3, increasing this burden increases total overall energy consumption because the APM is required to supply more 14V current to the LV battery. In order to better control this source of error it is important to include environmental measurements in the field notes of each test (Section 3.2). Doing so allows the tester to identify environmental conditions that may cause abnormal results and to select when environmental conditions are appropriate for testing.

Average experimental error is smallest when executing the 0-60 WOT +TRANS AE category at 1.1%. This is most likely because of the dynamic nature of executing transmission shifts in-vehicle. The model simulates these shifts consistently (shifts consistently occur at nearly the exact same time and vehicle velocity under baseline conditions). However, in-vehicle the shifting is not as consistent. The shift from 1-2 occurs between 8-14 mph, 2-3 occurs between 23-28 mph, 3-4 occurs between 35-43 mph and the shift between 4-5 may not occur until 57 mph. Restricting the transmission to 1 gear eliminates this variability, thus minimizing experimental error.

Testing with increased mass results in the next greatest average experimental error under parameter variation at 3.0%. The mass of the vehicle, when properly secured, is not dynamic. Even though the model does not account for front/rear mass ratio the mass of the vehicle as a system does not change during an AE. Executing tests with increased mass can be executed repeatedly in-vehicle with little variability.

Experimental error is greatest, however, when executing the 0-60 mph +AUX AE category with 5.4% error. This is most likely caused by the dynamic nature of an auxiliary load. Auxiliary components- such as fans, heaters or the radio- are inherently reactionary to the current voltage of the battery. The APM controller aims to keep the LV battery at a certain voltage (13.5V in this study). As the auxiliary load changes during any given AE, especially with an increased load on the LV battery, the APM must react via PID control. Imperfect PID control, or lacking CAN transmission rates, leads to increased variability in APM functionality [27].

5.3 Total Error

The total error gives a final view as to how well the model can predict electrical energy consumption given both the errors driven by discrepancies between modeling and in-vehicle results as well as errors driven by experimental factors. Across all AE categories the average total error is 95.7 Wh/mi. This result indicates that, when considering both modeling and experimental errors, simulated changes to electrical energy changes less than |95.7 Wh/mi| cannot be reliably replicated in-vehicle.

The results when considering both sources of error as total error paint a different picture. The greatest sources of total error are the vehicle parameters that are varied for testing (mass, auxiliary load and available gears). The 0-60 mph +TRANS AE category results in the greatest total error at 17.8%. This error is primarily driven by simulation shortcomings in dynamically modelling shifts. Results from 0-60 mph +MASS testing results in the next greatest total error at 7.7%. Testing 0-60 mph +AUX results in the greatest total error, 10.9%. This error is, again, driven by the lack of dynamic auxiliary load modelling.

The next greatest total error results from executing the baseline WOT tests (5.6%). This error is most likely attributed to the variability noted in Section 2.2. Variations in the total distance traveled directly result in errors of electrical energy consumed per mile. This variation is also a result of variation in shift timing. This explains why ECO tests result in less error (4.7%). ECO tests showed a smaller window for executing gear changes, more closely matching what is simulated.

5.4 Implications for Toyota Test Vehicle Platform and Future Work

This study is intended to inform future development of an ongoing project by the VIT. This project, the Toyota TVP, is aimed at implementing predictive propulsion control of a P3 PHEV 2018 Toyota Tacoma in order to reduce energy consumption during AEs. The results of this study indicate that the most efficient manner of reducing energy consumption can be achieved by controlling the acceleration rate of the vehicle via the APP. If the TVP is approaching a known AE the best way to reduce electrical energy consumption is to limit the APP to a less aggressive position no matter how the physical APP as actuated by the driver. On average, ECO driving saves 308.5 Wh/mi compared to WOT scenarios. The model is able to predict this change within 2.7%.

The methodology discussed in this investigation is also applicable to the Toyota TVP project. This project will also use Christman Airfield for closed course testing and, as shown in Table 8, the road grade of the runway introduces greater error to the ability of the model to predict energy consumption. For Toyota TVP testing, it is important for the team members to begin each test from the same location and execute them in the same direction. It also indicates that including road grade in the system model could help to reduce model error.

The greatest amount of error resulted from the Plant Model of the transmission and propulsion through the transmission using only 1 gear. Predicting electrical energy consumption during this AE scenario results a total error of 122.3 Wh/mi. Further work in modeling transmission dynamics and shift schedules could reduce this error. This would be beneficial moving forward with advanced vehicle technologies as electrification becomes more prominent. Furthermore, the Toyota TVP involves a P3 propulsion system architecture in which the EM is downstream of the transmission. As such, the EM's torque and speed will not be changing the same way a torque source upstream of the transmission does.

Improved modeling of power losses through the powertrain could also help to improve the validity of the model, especially when modeling changes to the physical parameters discussed in these studies. Among the AEs tested with increased mass, increased auxiliary load and limited available gears all results showed that the model over-predicted the change in electrical energy consumption. All data from these in-vehicle tests resulted in energy consumption lower than that predicted by the simulations. Improving the Plant and Controller modeling of these subsystems (such as the vehicle body, accessory power module and transmission) could help to reduce the overall error of the model and reduce the value of change in energy consumption required to confidently replicate the change in-vehicle. In order to accomplish this, the model could include front/rear mass distribution in order to more accurately represent the tractive force at the driving wheel or include dynamic auxiliary loads as various auxiliary components (primarily cooling pumps and fans) turn on or off. This work is relevant to the Toyota TVP project because this study showed an increase in model error when testing increased auxiliary loads when compared to baseline, ECO and increased mass results. Having a clear understanding of the effects of the auxiliary load on energy consumption is vital for the TVP as that is one possible parameter that could be optimized when AEs are predicted.

More work in automating testing would also be beneficial for the workflow of the team, both in simulation and in-vehicle. Automating simulation testing will decrease the total time required to simulate control strategy and parameter changes. Instead of manually changing the desired parameters or subsystems, a script can be written to automatically do so and minimize the need for simulation downtime. Automating in-vehicle testing can be accomplished by giving the HSC control of the APP. This strategy eliminates the need for a pedal block as well as the testing issue of tip-in rate while conducting more complex testing of acceleration rate. This method also reduces the need for operator training or inconsistent execution of tests as it is not necessary for the operator to watch/memorize a velocity trace while executing a test. Future work on the Toyota TVP will include naturalistic driving scenarios, which are difficult to reliably and consistently replicate with a human driver. Automating in-vehicle testing would result in more consistent execution of complex drive cycles, more reliable data and less work or resources lost.

6.0 Conclusions

The vehicle modeling, simulation and testing methodologies discussed in this study are sufficient for practical control system development for CSU's VIT in future AVTCs and the Toyota TVP project. The vehicle testing methodology employed and resulting better understanding of the limitations in predicting energy consumption through modeling and simulation will improve the team's future VDPs.

The modeling and simulation methods discussed result in an average total error of 5.2%, or ±83.4 Wh/mi. This result indicates that simulation results that do not result in a change of greater or less than 83.4 Wh/mi then the team cannot say with 95% confidence that the change can be reliably replicated in-vehicle. Understanding this limitation allows the team to streamline the workflow such that unnecessary and unfeasible in-vehicle tests can be omitted.

Furthermore, the in-vehicle testing methodology is better informed for obtaining consistent and statistically relevant results. It is feasible to measure changes in electrical energy consumption without the use of expensive equipment such as chassis dynamometers or additional sensors such as high resolution current measurement systems. It is important for the team to begin tests at a consistent starting point and travel in a consistent direction. It is also important for the team to understand the limitations of the testing facility available to them, Christman Airfield. This facility has a slight positive grade in the Southern direction and has limited availability. Understanding these limitations allows the team to more efficiently execute tests in-vehicle such that the resulting data is reliable and relevant.

This study is also useful for many other automotive engineering projects with access to an in-vehicle CAN bus. This method of communication and data acquisition is adequate for relaying all necessary sensor information and reliably logging such data. Even without access to the manufacturer's CAN database, it is feasible to construct a custom CAN channel for control and data acquisition of non-stock electrical propulsion systems.

References

[1] M. Schang, "8LXX Transmission Communications," 03-Oct-2017.

[2] K.W. Tindell, H. Hansson, A.J. Wellings, "Analysing Real-Time Communications: Controller Area Network (CAN)," University of Uppsala, SW Department of Computer Systems, University of York, EN Department of Computer Science, 1995.

[3] D. A. Trinko, Z. D. Asher, and T. H. Bradley, "Application of Pre-Computed Acceleration Event Control to Improve Fuel Economy in Hybrid Electric Vehicles," WCX SAE World Congress Experience, 2018, pp. 2018-01–0997.

[4] AVTC, "AVTC I Advanced Vehicle Technology Competitions - The heart of automotive ingenuity working towards future mobility solutions."

[5] CAN in Automation, "CAN in Automation (CiA): History of the CAN technology."

[6] Union of Concerned Scientists, "Cleaner Cars from Cradle to Grave (2015)."

[7] Clemson University Vehicular Electronics Laboratory, "CVEL: Electronic Transmission Control."

[8] International Energy Agency, "CO2 Emissions from Fuel Combustion Highlights 2016."

[9] G.C. DiDomenico, J. Bair, V.K. Kukkala, T.H. Bradley, "Colorado State University EcoCAR 3 Final Technical Report," WCX SAE World Congress Experience, 2019, pp. 1-2.

[10] T. Gustafsson, A. Johansson, "Comparison between Battery Electric Vehicles and Internal Combustion Engine Vehicles fueled by Electrofuels- From an energy efficiency and cost perspective," Master's Thesis in Sustainable Energy Systems, Chalmers University of Technology Department of Energy and Environment, pp. 24-26, Feb. 2015.

[11] L. Pelkmans, P. Debal, “Comparison of On-Road Emissions with Emissions Measured on Chassis Dynamometer Test Cycles,” Transportation Research Part D: Transport and Environment, vol. 11, no. 4, pp. 233-241, Jul. 2006.

[12] U.S. Environmental Protection Agency, “Dynamometer Drive Schedules,” EPA Vehicle Chassis Dynamometer Driving Schedules (DDS)

[13] U.S. Environmental Protection Agency, “EPA and NHTSA Set Standards to Reduce Greenhouse Gases and Improve Fuel Economy for Model Years 2017-2025 Cars and Light Trucks.”

[14] C. M. Silva, T. L. Farias, H. C. Frey, and N. M. Rouphail, “Evaluation of numerical models for simulation of real-world hot-stabilized fuel consumption and emissions of gasoline light-duty vehicles,” Transportation Research Part D: Transport and Environment, vol. 11, no. 5, pp. 377–385, Sep. 2006

[15] C.E. Holland, J.W. Weidner, R.A. Dougal, R.E. White, “Experimental Characterization of Hybrid Power Systems Under Pulse Current Load,” Journal of Power Sources, vol. 109, no. 1, Jun. 2002, pp. 32-37.

[16] S. Pagerit, P. Sharer, A. Rousseau, “Fuel Economy Sensitivity to Vehicle Mass for Advanced Vehicle Powertrains,” SAE World Congress & Exhibition, 2006.

[17] C.R. Hicks, “Fundamental Concepts in the Design of Experiments,” New York, NY: Holt, Rinehart and Winston, 1964.

[18] T. Johnson, “Implementation and Evaluation of Backward Facing Fuel Consumption Simulation and Testing Methods,” Master’s Thesis in Mechanical Engineering, Colorado State University Department of Mechanical Engineering, pp. 34, Jun. 2019.

[19] ISO, “ISO 11898-1:2003 Road Vehicles – Controller Area Network (CAN) – Part 1: Data Link Layer and Physical Signaling,” 2003.

[20] C. Samaras, K. Meisterling, “Life Cycle Assessment of Greenhouse Gas Emissions from Plug-in Hybrid Vehicles: Implications for Policy,” Environ. Sci. Technol., vol. 42, no. 9, pp. 3170–3176, May 2008.

[21] Y. Oh, J. Park, J. Lee, M. Do Eom, S. Park, “Modeling Effects of Vehicle Specifications on Fuel Economy Based On Engine Fuel Consumption Map and Vehicle Dynamics,” Transportation Research Part D: Transport and Environment, vol. 32, Oct. 2014.

[22] G. Paganelli, Y. Guezennec, G. Rizzoni, “Optimizing Control Strategy for Hybrid Fuel Cell Vehicle,” SAE Transactions, vol. 111, no. 3, pp. 398-406, 2002.

[23] J. Homoloya, J. Rice, “Particulate Matter ($PM_{2.5}$) Speciation Guidance- Final Draft,” U.S. EPA Monitoring and Quality Assurance Group, Office of Air Quality Planning and Standards, ed. 1, Oct. 1999

[24] Z. D. Asher, D. A. Baker, and T. H. Bradley, “Prediction Error Applied to Hybrid Electric Vehicle Optimal Fuel Economy,” IEEE Transactions on Control Systems Technology, vol. 26, no. 6, pp. 2121–2134, Nov. 2018.

[25] MathWorks, “Tire (Simple),” Matlab & Simulink.

[26] H. Pacejka, E. Bakker, L. Nyborg, “Tyre Modelling for Use in Vehicle Dynamics Studies,” SAE International, Paper No. 870421, Feb. 1987.

[27] V.K. Kukkala, T.H. Bradley, S. Pasricha, “Uncertainty Analysis and Propagation for an Auxiliary Power Module,” IEEE Transportation Electrification Conference and Expo, Jun. 2017.

[28] C.C. Macadam, “Understanding and Modeling the Human Driver,” International Journal of Vehicle Mechanics and Mobility, vol. 40, no. 1-3, Aug. 2010.

[29] U.S. Environmental Protection Agency, "Vehicle Emissions On-Board Diagnostics (OBD)"- 1995 Final Rule," Federal Register, vol. 60, no. 153, pp. 2-25, Aug. 1995

[30] A. Engel, "Verification, Validation and Testing of Engineered Systems," Hoboken, JN: Wiley, 2010

LIST OF ABBREVIATIONS

AE	Acceleration Event
APP	Accelerator Pedal Position
AVTC	Advanced Vehicle Technology Competition
APM	Auxiliary Power Module
BEV	Battery Electric Vehicle
BSFC	Brake Specific Fuel Consumption
CD	Charge Depleting
CSU	Colorado State University
CAN	Controller Area Network
DAQ	Data Acquisition
DOE	Design of Experiments
DTC	Diagnostic Trouble Code
EM	Electric Motor
ECO	Energy Economic Driving
ESS	Energy Storage System
HV	High Voltage
HEV	Hybrid Electric Vehicle
HSC	Hybrid Supervisory Controller

ICE	Internal Combustion Engine
ISO	International Organization of Standardization
LV	Low Voltage
OBD	On-board Diagnostics
OEM	Optimal Energy Management
PHEV	Plug-in Hybrid Electric Vehicle
PID	Proportional, Integral, Derivative
POEM	Predictive Optimal Energy Management
SAE	Society of Automotive Engineers
SOC	State of Charge
TVP	Test Vehicle Platform
TCM	Transmission Control Module
UDDS	Urban Dynamometer Drive Schedule
VDP	Vehicle Development Process
VIT	Vehicle Innovation Team
VOM	Vehicle Operating Mode
WOT	Wide Open Throttle (100% APP)