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Model Advancement And Hil Setup For Testing A P2 Phev Supervisory Controller

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MODEL ADVANCEMENT AND HIL SETUP FOR TESTING A P2 PHEV SUPERVISORY CONTROLLER

by

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Advisor Date

DEDICATION

To family and friends.

ACKNOWLEDGEMENT

Firstly, thanks to my faculty advisor Dr. Jerry Ku's dedication. His advice and support has been very crucial for the successful completion of my master's thesis. My friends from the EcoCAR3 team have been very supportive and have contributed significantly to my thesis work. Last, but not the least, I am grateful to the Advanced Vehicle Technology Competition sponsors and organizers for providing me and several other students this great opportunity.

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CHAPTER 1 INTRODUCTION

Global environmental and economic factors have urged the automotive manufacturers and the government to find sustainable and environment friendly transportation solutions. EcoCAR3 is a premier collegiate Advanced Vehicle Technology Competition which is an effort to promote innovation and mould the future automotive leaders. The Wayne State University EcoCAR3 team is one amongst the sixteen North American Universities developing different Hybrid Electric Vehicle architectures for the Chevrolet Camaro. Wayne State University EcoCAR3 team is developing the Pre-transmission Parallel Plug-In Hybrid Electric Vehicle architecture.

The goal of the competition is to reduce the well-to-wheel Green House Gas (GHG) emissions, criteria tailpipe emissions and energy consumption, thereby improving overall efficiency while retaining the thrill and ride quality of the well engineered stock vehicle. This explains the importance of the Emissions and Energy Consumption event which is a dynamic event in the Final Competition. Teams spend considerable amount of time in testing the Hybrid Supervisory Controller code and optimizing the control strategy for better vehicle safety and reduced emissions and energy consumption to be successful in this event.

Model based development and rapid prototyping are necessary procedures in order to enable parallel controls development and optimization activities. Accurate vehicle plant model simulation is essential. A systematic and reliable approach has been taken in order to achieve the maximum possible accuracy with the available time and resources.

1.1 E AND EC EVENT

The EcoCAR3 Emissions and Energy Consumption event is a dynamic event. The participating team vehicles are driven around a circular track at different speeds at different locations of track for almost 100 miles. The difference between the fuel tank mass before and after the event is measured as the fuel consumption during the event. An emissions trailer towed by the car during the event measures the vehicle greenhouse gas emissions and criteria tail pipe emissions. The collected data is finally used to score the different vehicles. The main focus of the competition being the reduction of emissions and overall energy consumption, this is the single most weighted event in the entire competition. Figure 1 below shows the EcoCAR3 Y3 Emissions and Energy consumption event drive cycle. Energy consumption and emissions account for a significant portion of the score.

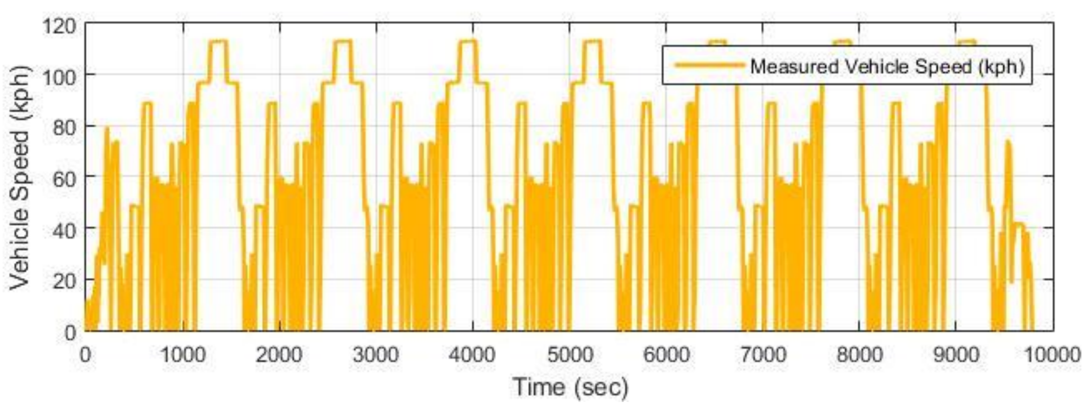

Figure 1. E and EC drive cycle

To be successful in this event the Hybrid Supervisory Controller's energy management functionality and diagnostic functionality has to be tested thoroughly. A robust control strategy is essential in order to ensure safety during the event.

CHAPTER 2 LITERATURE REVIEW

2.1 MODEL BASED DEVELOPMENT

The EcoCAR teams have benefitted in the past from Model Based Development and Rapid Controls Prototyping activities as it enables the faster development and refinement of the Hybrid Supervisory Controller software, eliminating the dependency on vehicle or component availability for simple testing activities.

In [1] Arizona State University's EcoCAR3 team member discuss about their team's plant model and supervisory controller development in Simulink. The team developed Pre-transmission parallel hybrid electric vehicle architecture for the Chevrolet Camaro. The vehicle model consists of a modified Chevrolet Camaro plant model with GM 2.4L LEA E85 engine and GKN AF-130 electric machine, just like ours. The electric machine is powered by an A123 7M15s3p pack with a capacity of 19.4Ah. The paper provides details regarding the vehicle plant model development and architecture selection during the initial phases based on the simulation results. The effect of adding a torque converter model has been discussed in detail. Moreover, the modeling approach has been mentioned to be based on data provided by the manufacturers. The authors state that many parameters have been assumed as the data is unavailable. The paper does not discuss or propose any approaches to improve or validate the model simulation accuracy. Moreover, there is no account that the model outputs were validated or compared against real world test data.

In [2], Ward describes the modeling and simulation of the Ohio State University EcoCAR3 team's hybridized Chevrolet Camaro. The architecture is a plug-in hybrid electric vehicle (PHEV). The modified powertrain consists of a Ford 2.0L GDI4 engine coupled to a Tremec T-5 five speed automated manual transmission. The electric counterpart to the ICE is a Parker-Hannifin 150kW electric machine powered by an A123 Systems 18.9kWhr energy storage system. The thesis discusses the initial Simulink based model development activities including the optimization of the model based on the controller testing requirements. The parameters used are mostly data from the manufacturers and the author mentions that the models are of low fidelity at multiple occasions. Moreover, the abstract mentions that the model will be continually improved throughout the four year competition. The author gives a brief estimation of which component or soft ECU models are expected to get more complex over the course of the competition and the estimates seem to be reliable.

Marquez [3] discusses the development of the Virginia Tech EcoCAR3 team's P3 Plug-in Parallel Hybrid Electric Vehicle model and controls development. The thesis discusses architecture selection, model development and component and vehicle testing activities in detail. The thesis shows a good idea of the initial stages of the vehicle architecture selection and controls development. However, the paper does not give a note on the model accuracy relative to the real world data. In [4], the author discusses the model development and validation for simulating a electric scooter energy consumption. The validation of the simulated model results have been discussed in detail in [4]. The test setup and component and vehicle testing requirements are discussed thoroughly.

In this thesis the vehicle plant model simulation accuracy is validated by comparing the simulated results with real world measurements.

2.2 MODEL FIDELITY AND ACCURACY

Model fidelity is determined by the application. Different modeling approaches for modeling and simulation of vehicles exist ([5] and [6]). Hofman et al. states that modeling of longitudinal vehicle dynamics alone in a Forward Dynamic modeling approach is desirable for energy consumption simulation accuracy. In Hofman et al. [5], the authors analyze three different engine models and evaluate the Forward Dynamic engine model accuracy by comparing the results with the other simulation results and test data. The paper gives an idea of the practically achievable accuracy with the various models. It has been mentioned that the forward dynamic model produces a relative error of 4.6%.

Equations for torque converter model are obtained from [7] which identifies the use of relationship between torque ratio, speed ratio and capacity factor to simulate the effect of torque converter in an automatic transmission. An example map of the torque converter efficiency with respect to speed ratio is also provided which can be used as a good starting point during initial model development when data is not available. Moreover, the article recommends alternative analytical model based on curve fitting which can replace these maps. Apart from providing the equations for more powertrain components models, the paper also briefly reassure the popular use of map based models for powertrain component efficiency simulations.

Evaluation of various battery circuit models [8] clearly shows the Dual Polarity (DP) circuit model accuracy is the highest among the battery equivalent circuit models. It can be seen from the plots in the paper that the Thevenin circuit model simulation results are closer to the DP model simulation results. Hybrid Pulse Power Characterization

(HPPC) test data from the Li-ion cell testing is obtained and used to validate the circuit models. The simulated results are compared to the HPPC data and the relative error is used to rank the model. The article provides a good baseline for the practically feasible SOC simulation accuracy. Further the paper provides the equations for all the circuit models under discussion.

Reference [4] shows the use of low fidelity map based models for energy consumption simulations. High fidelity models are required when the goal is to refine, fine tune or analyze the effects of the failure of one or more parts in a specific component. For instance, a high fidelity brake model might be essential to simulate the exact brake pedal feel, which is useful for improving the brake system effectiveness, ergonomics and driver comfort. Whereas, our application demands effective simulation of energy consumption while braking or deceleration, and this is affected only by the braking torque distribution between the conventional brakes and the regenerative torque from the electric machine. Therefore the braking system's internal dynamics can be assumed to be ideal.

In Wilhelm et al. [9], various driver behavior models are evaluated under different driving conditions in order to assess the effects of the driver model on simulation accuracy. It is claimed that the proposed driver model is capable of estimating fuel consumption with an average error of 1.9% and 1.5% standard deviation.

After thorough literature research the fidelity required in order achieve the desired accuracy has been determined. A combination of physics and map-based models is desirable for achieving decent accuracy with higher simulation speeds.

CHAPTER 3 OVERVIEW

3.1 PRETRANSMISSION PARALLEL PLUG-IN HYBRID ELECTRIC VEHICLE

The Wayne State University EcoCAR3 team is developing a Pre-transmission Parallel Plug-In Hybrid Electric Vehicle architecture for the EcoCAR3 team vehicle as shown in the figure. Figure below shows the high level P2 Hybrid Electric Vehicle powertrain architecture of the WSU EcoCAR3 team. The powertrain consists of a GM 2.4L LEA engine which runs on E85 and a 64kW GKN EVO AF130-4 electric machine coupled together coaxially. The electric machine is powered by a 10.7kWh energy storage system from Bosch. A 9.3 gallon fuel tank stores the E85 which is an alternative to the conventional gasoline.

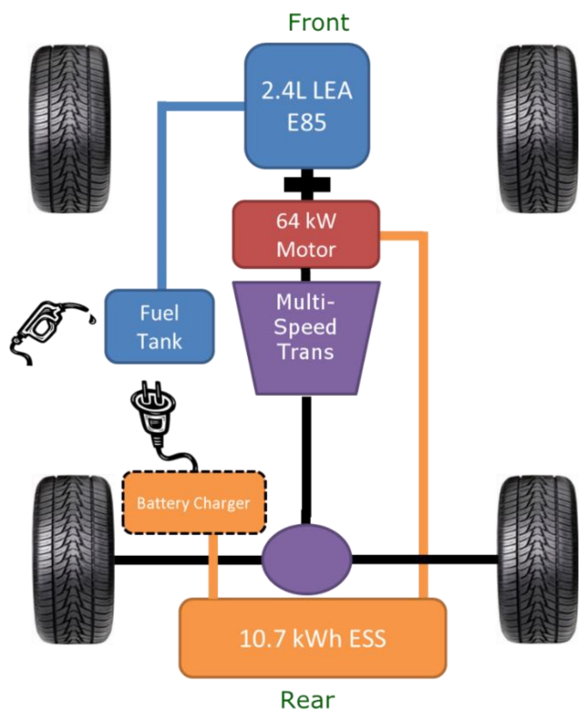

Figure 2. Pre-transmission Parallel Hybrid Electric Vehicle architecture

3.2 WORK FLOW

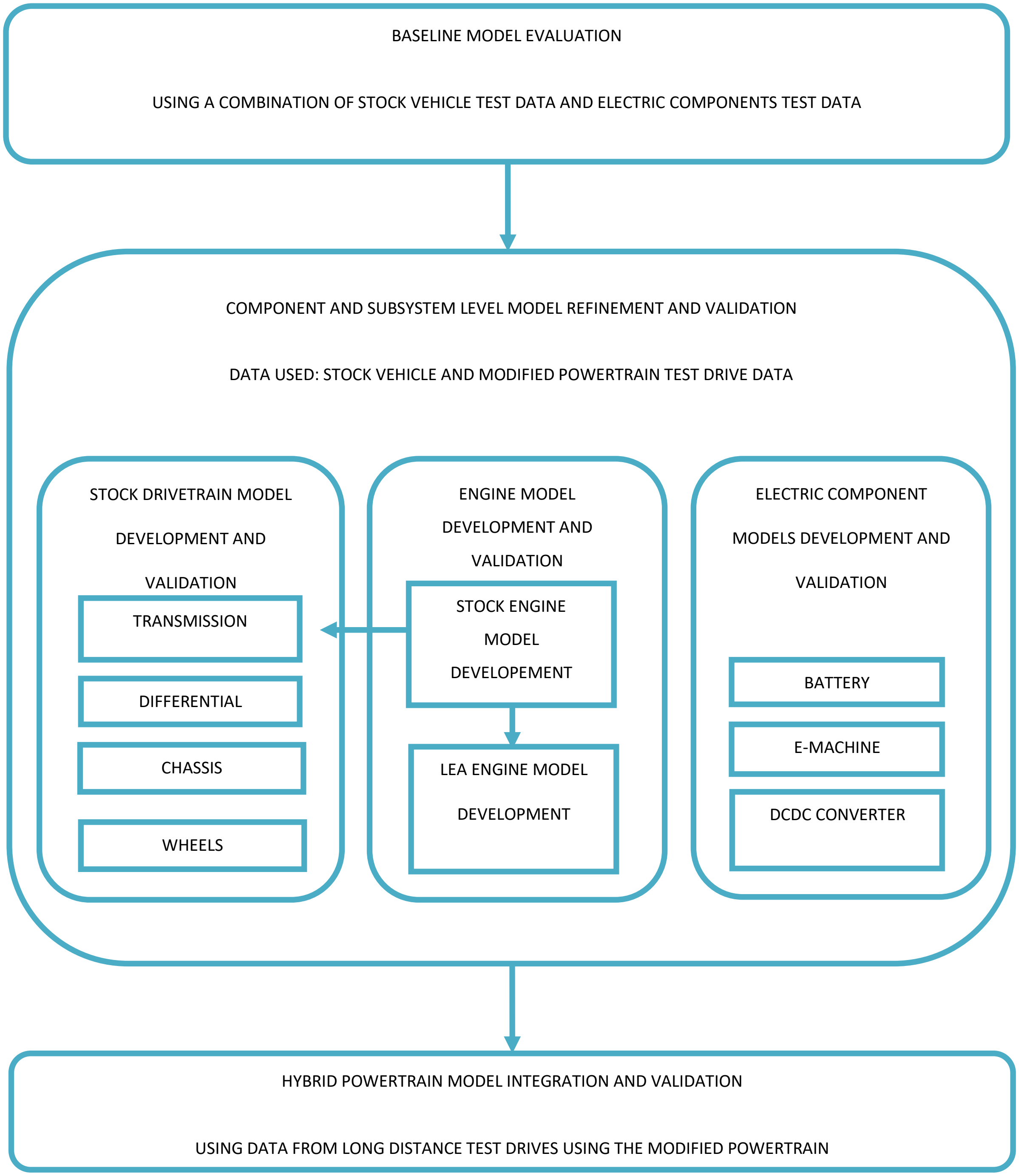

Figure 3. Detailed modeling workflow

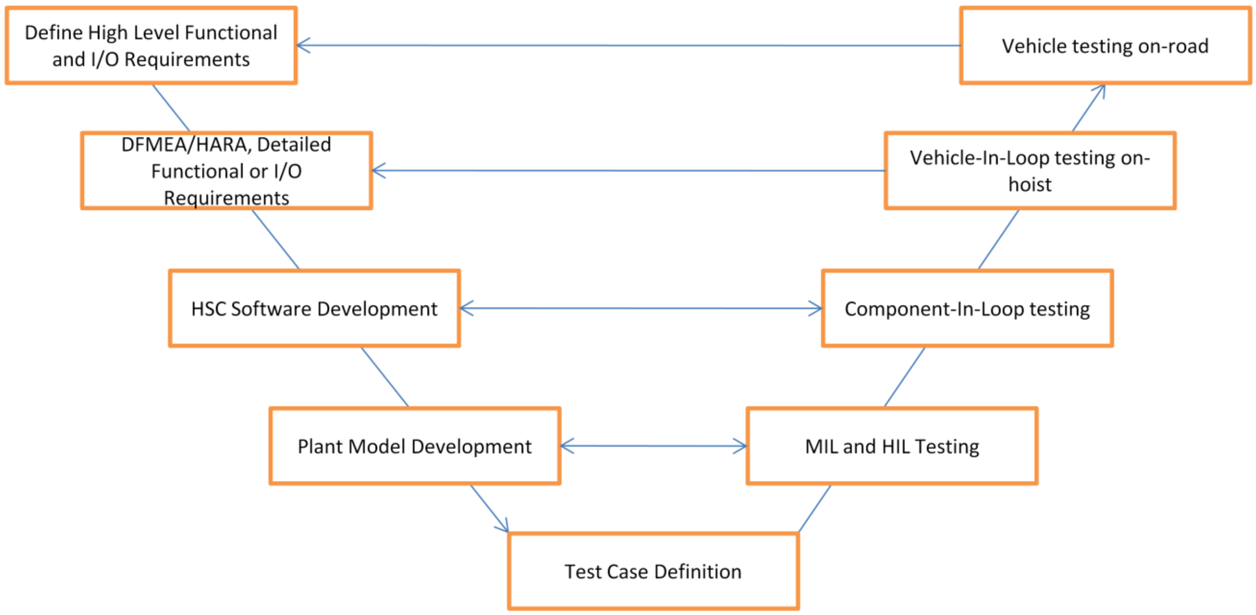

Figure 4. WSU EcoCAR3 Controls Development Cycle

Since most of the components were already integrated and were needed for testing activities demanded by the controls, mechanical and electrical teams during year 3, the measurements from test drives performed previously were used to validate the model. The overview of the plan of work is shown in the Figure 3. The available models and the data were audited initially. The following data were available as a result of the previous testing activities performed:

1) Stock vehicle test drive data: CAN logs from test drive of the stock vehicle, performed during year 2 is available. This is the most accurate test result available on the stock powertrain. The stock drivetrain components are used in the hybrid powertrain without any major modifications. Therefore the data from stock vehicle test drive logs can be used to validate the stock drivetrain components. A test bench to test the components downstream the torque converter upto the wheels and a chassis dynamics model can be used to test

these components. Moreover, the IC engine model fidelity can be validated using the stock IC engine parameters and this data. That is the IC engine model is parameterized to represent the stock IC engine and then validated using the inputs from the stock vehicle test drive logs. Later the IC engine will be replaced with the parameters for LEA engine and tested against the modified powertrain logs once the data is available.

2) Electric-only powertrain test drive data: During the Summer of 2016, the team extensively tested the electric-only powertrain. Since the IC engine was not installed in the vehicle at that time, it was a great opportunity to test the E-Machine and the battery pack in the electric-only mode. Data acquired during these tests is used to test the electric machine and the battery pack models. Moreover, the electric-only powertrain configuration that was used during these tests was built and tested in order to further ensure that the drivetrain models produce sane/expected results.

3) Modified hybrid powertrain test drive data: This data is used for validating the final modified pre-transmission parallel hybrid electric vehicle model. The new LEA engine model and the entire model in closed loop with the driver model is validated using the drive cycle data generated from the logged vehicle speed data. The model input is the drive cycle speed and the model outputs such as fuel consumption, electric energy consumption, transmission ratio and all related signals are calculated and compared with the values from the vehicle logs.

Initially, the baseline model developed by the previous team members is evaluated using the data from the CAN logs. Then the components from the stock vehicle are parameterized, refined and validated using data from the stock vehicle test drive. Models of the E-Machine, battery pack and other electric components newly installed are developed and validated based on data from electric-only configuration test drive logs. Finally the refined component models are integrated and validated in closed loop based on the modified vehicle test drive logs. Later the model is transferred to HIL platform and validated in the HIL platform with the actual Hybrid Supervisory Controller hardware in loop with the newly developed and validated pre-transmission parallel hybrid electric vehicle plant model.

3.3 DATA ACQUISITION

Development and refinement of vehicle plant model involves modeling activities at component, subsystem and system levels. Though it is ideal to setup component and subsystem level test benches in order to obtain more accurate measurements, in our situation this is not very easy because of limited resources. Moreover, most of the components were already installed in the vehicle during the start of the research work. Hence removing and reinstalling the components is a very tedious work as it involves too much manual labor and might interfere with the mechanical and electrical inspection activities which are equally important. Therefore very practical approaches have been taken in order to evaluate the model accuracies.

Data acquired using CAN loggers during vehicle test drives are used for validating the models. Since all the component models send enough information about the component outputs and inputs this data is sufficient for developing models with sufficient fidelity for energy consumption simulation. This enables the WSU team to work parallel on multiple tasks.

In some cases, the components were tested separately, that is still installed in the vehicle but disconnected and disengaged in terms of mechanical and electrical transmission. For instance, details regarding the Battery Management System (BMS) startup and shutdown sequence and response to commands were not readily available from the manufacturers and the information had to be obtained through component testing. Since the battery pack was already installed in the vehicle, the test had to be performed in the vehicle. Therefore, the battery pack was electrically isolated and tested in order to obtain the information needed.

3.4 MODELING PLATFORM

In the initial phases of the controls development process, MIL and SIL are the ideal platforms suited for the controls code development. Since these platforms avoid the additional complications arising due to the physical I/O wiring and signal latency which are a part of the real world, these platforms are ideal for initial code development. Once the code reaches a sufficient fidelity, then it is time to move on to HIL as it is time to address the complications arising due to signal latency and other real world failure scenarios. HIL is a more effective platform for testing the diagnostic functionalities of the HSC as the test cases can be simulated more accurately. Therefore initially the plant model is developed in the MIL environment and validated against test data for the simulation accuracy with minimal complications. Later the MIL model is adapted to the HIL platform.

3.5 TEST BENCH SETUP

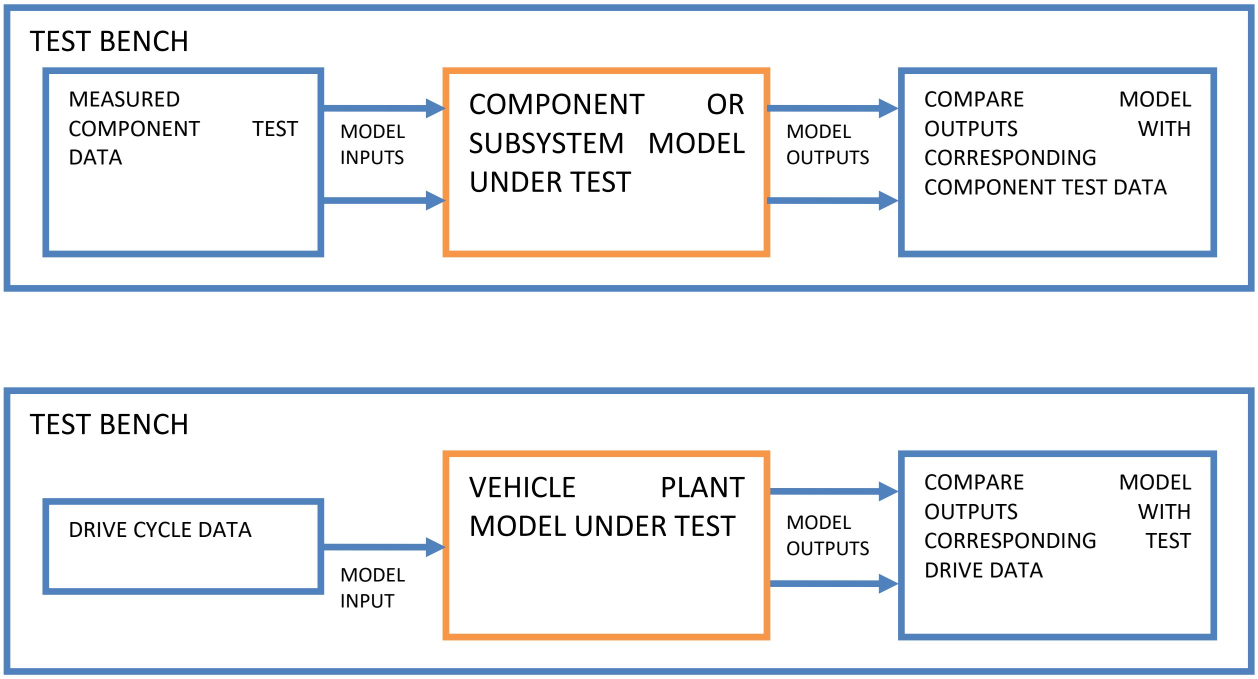

Figure 5. Test bench setup

Throughout the research work, several virtual test benches were setup in order to evaluate both the component and system level model accuracy. Though each component or system test bench is different in terms of the model inputs, outputs and test data used, the overall topology of the test benches can be basically classified into two types: 1) Feed forward type test benches for testing component and subsystem level models and 2) Closed loop system level model test benches.

All the component level and the system level models validations are initially performed using an open loop/ feed forward test bench. In this setup, the model inputs are corresponding real world test data acquired during component or vehicle testing. For instance, the battery pack test bench uses the battery current and ambient atmospheric temperature measured during component testing as the model input and the model outputs such as battery voltage and temperature rise due to the current flow is recorded and compared with the corresponding component test data. This way we are able to validate the component or subsystem behavior under the exact same condition as in the real world component.

The system level model test benches are similar to the actual vehicle plant model. The actual vehicle plant model is equipped with more measurement tools in order to monitor and optimize the parameters when working in a closed loop along with the other component/subsystem models. For the vehicle plant model validations, drive cycle data and the other environmental factors such as the ambient temperature, atmospheric pressure and road gradient are the model inputs. The driver model simulates the other subsystem level model inputs by comparing the drive cycle speed with the actual vehicle speed, as it would do in the actual drive cycle simulations. The entire simulation happens in closed loop and no measured data is used as a model input other than the vehicle speed and the environmental conditions.

3.6 ECOCAR3 HEV PLANT MODEL STATUS

P2_Parallel_MIL_Model_V1.2.slx, hereafter referred to as V1.2 model is the model developed by the previous EcoCAR3 team members. Though the model contained significant level of details to start model based development activities, it is not sufficient and have to be updated as in year 3 more model based testing and development activities are done. This continuous model update and validation is a routine process in the EcoCAR series of competitions as the information for modeling the components will be available only after testing the components. The model developed as a result of this thesis has been named as P2_Parallel_MIL_Model_Thesis.slx and made available to the EcoCAR3 team members. Table 1 on the following page shows the model status and improvements from the previous model.

Table 1. HEV plant model status

Models	P2_Parallel_MIL_Model_V1.2.slx	P2_Parallel_MIL_Model_Thesis.slx
IC Engine		
- Mechanical Model	Not validated	Validated
- Thermal Model	Not modeled	Not validated
Engine Control Module (ECM)		
- ECM I/O model	Not validated	Validated
- Engine torque control function model	Not validated	Not validated
Battery Management System (BMS)		
- Startup/Shutdown function sequence	Not modeled	Validated
- BMS I/O model	Not modeled	Validated
- Resistance measurement model	Not modeled	Validated
- Charge and Discharge limits map model	Not modeled	Not modeled
Energy Storage System (ESS)		
- Electrical model	Not modeled	Validated
- Thermal model	Not modeled	Validated
E Machine (IPMSM)		
- Electromechanical model	Not modeled	Validated
- Thermal model	Not modeled	Not validated
Motor Control Unit (MCU)		
- Torque control model	Not modeled	Not validated
- MCU I/O model	Not validated	Validated
- MCU thermal model	Not modeled	Not validated
Transmission		

- Mechanical model	Not validated	Validated
Transmission Control Module (TCM)		
- Shift Pattern model	Not modeled	Validated
- TCM I/O model	Not validated	Validated
- CAN based gear shift model	Not modeled	Not modeled
Torque converter model		
- Mechanical model	Not validated	Validated
Differential		
- Mechanical model	Not validated	Validated
Chassis Model		
- Physics model	Not validated	Validated
Fault Insertion Blocks	Not modeled	Modeled

CHAPTER 4 BASELINE MODEL EVALUATION

The baseline model developed by the previous teams is first evaluated. At the beginning of the year 3 when the baseline model evaluation was performed, the data from the modified powertrain testing was not yet available. However, due to the Figure 6 and 7 below shows the test bench setup for the baseline model evaluation.

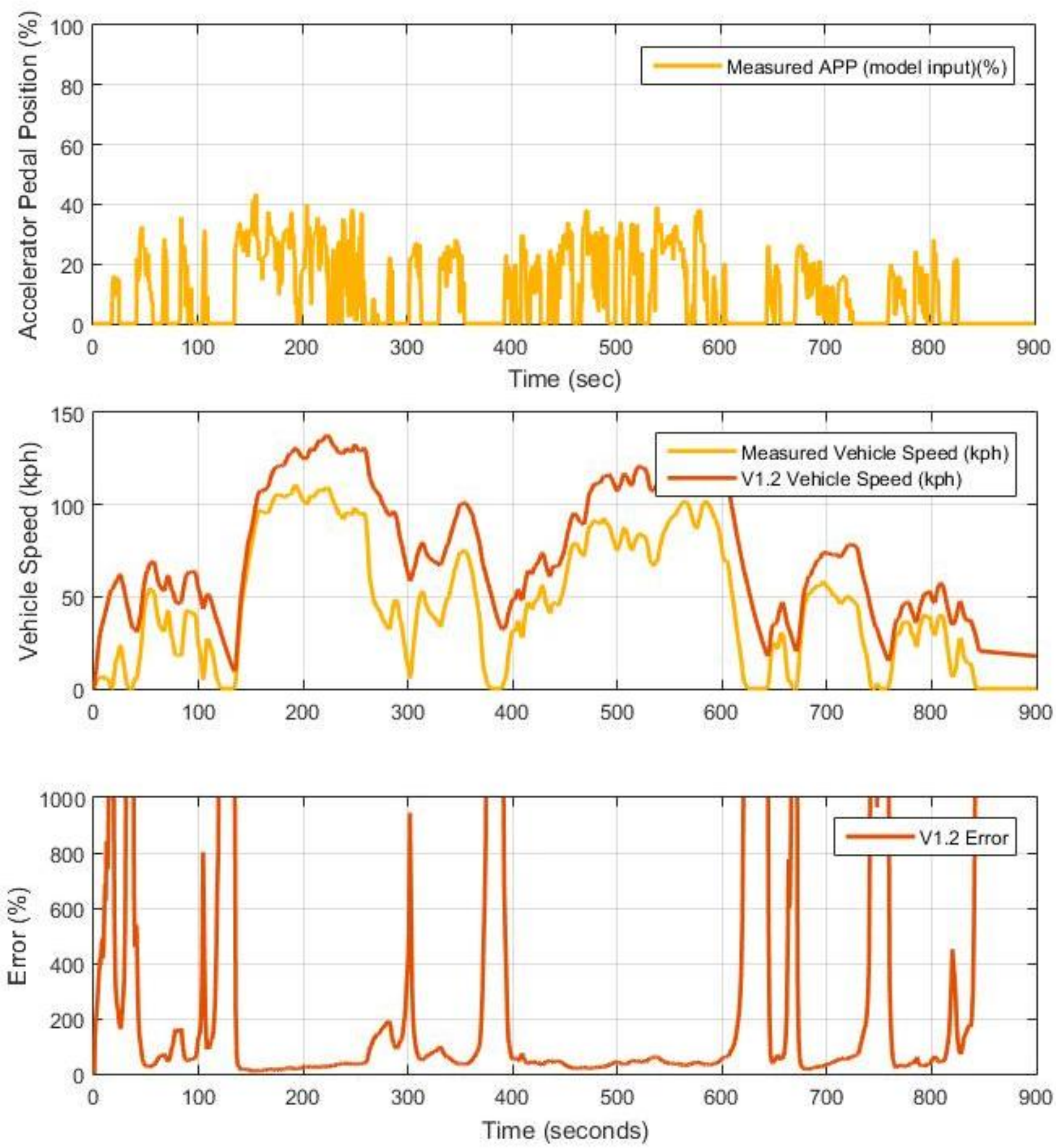

Figure 6. Baseline model evaluation results: Input accelerator pedal position and simulated vehicle speed

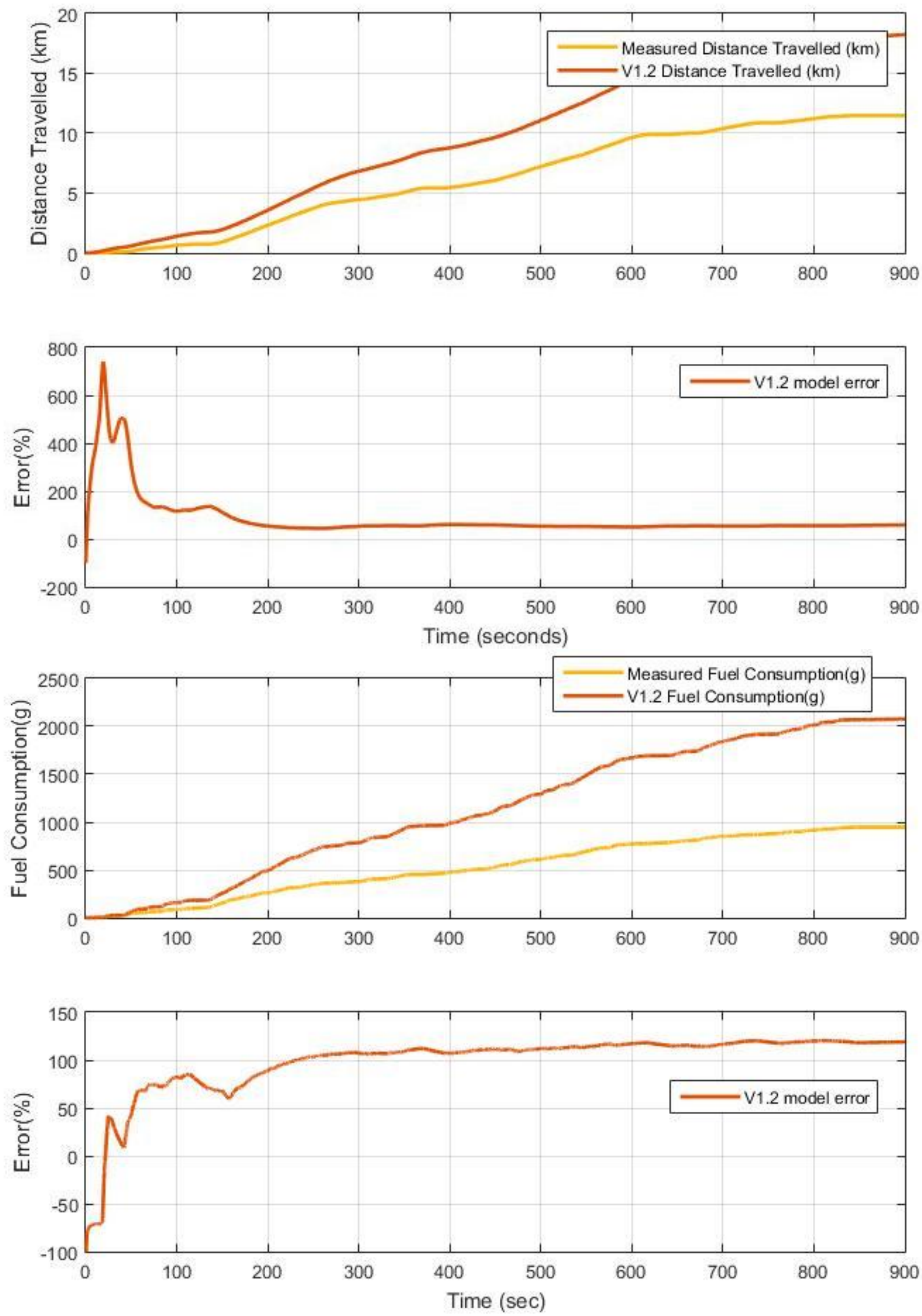

Figure 7. Baseline model evaluation results: Simulated distance travelled and fuel consumption

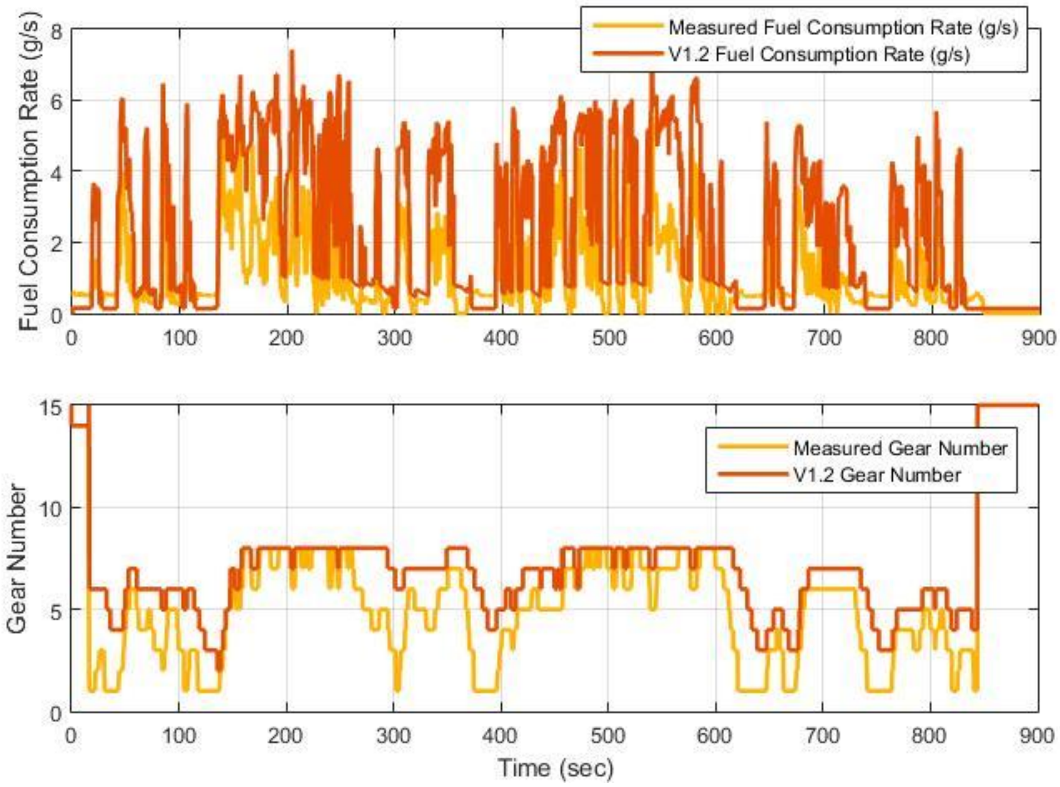

Figure 8. Baseline model evaluation results: Simulated fuel consumption rate and transmission gear number

CHAPTER 5 PLANT MODEL ADVANCEMENT

5.1 DRIVETRAIN, WHEELS AND CHASSIS MODELING

In this context the torque converter, transmission, Transmission Control Module (TCM) and differential subsystem models are collectively known as the drive train model. Transmission subsystem model consists of two component models internally, which are the torque converter model and the transmission model.

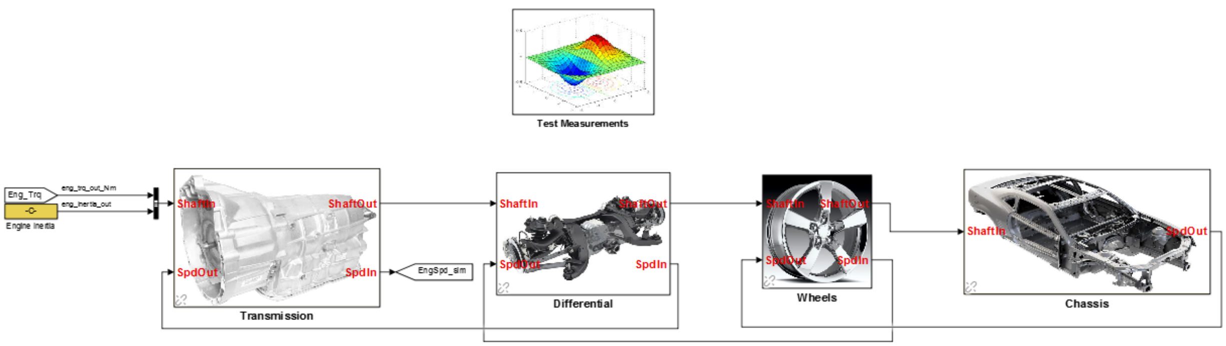

Figure 9. Drivetrain, wheel and chassis models test bench

5.1.1 TORQUE CONVERTER

The torque converter model in the original baseline model is not accurate. The newly modeled torque converter based on the reference determines the torque output based on a lookup table which gives the torque converter torque ratio based on the input and output speed ratio. This torque ratio used to calculate the instantaneous torque converter output torque which is the input to the transmission. Apart from this the torque converter model also contains a viscous loss model and a model to calculate the engine speed based on the residual torque and torque converter efficiency.

5.1.2 TRANSMISSION

The transmission model simulates the transmission output torque based on the gear ratio selected by the Soft TCM model and the transmission frictional and viscous losses. The transmission losses were initially not parameterized to represent the current vehicle accurately. Therefore a new model which simulates the transmission losses based on the output speed has been developed and optimized. The original model was super efficient, that in other terms the simulated losses were lower than in the real vehicle. The formulas from the original model have been retained with minimal modifications.

5.1.3 WHEELS

The wheel model calculates the wheel rolling resistance. Later the resultant of the linear force acting on the wheels due to rolling resistance and the wheel input torque is output as the wheel output force to the chassis model. The baseline model parameters, that is the coefficients of rolling resistance were incorrect and have been replaced with the data from manufacturers.

5.1.4 CHASSIS

Chassis Model simulates the force acting on the vehicle which is a resultant of the air drag, linear vehicle inertia, resistance due to grade and wheel output force and calculates the rate of acceleration at any instant, instantaneous velocity of the vehicle, distance travelled, wheel slippage and other associated functions. The model input is the horizontal wheel force. The model output is the linear velocity of the vehicle. The vehicle mass and the vehicle frontal area values were incorrect and data from the manufacturers is used.

5.1.5 SOFT TCM

The Soft TCM model simulates the transmission shift behavior based on the shift lever position, vehicle speed, APP and BPP. The baseline TCM model contained assumed shift pattern data based on a six speed transmission. The transmission shift pattern has been updated with the data from manufacturers. Figure 10 below shows the transmission gear numbers simulated during the transmission testing.

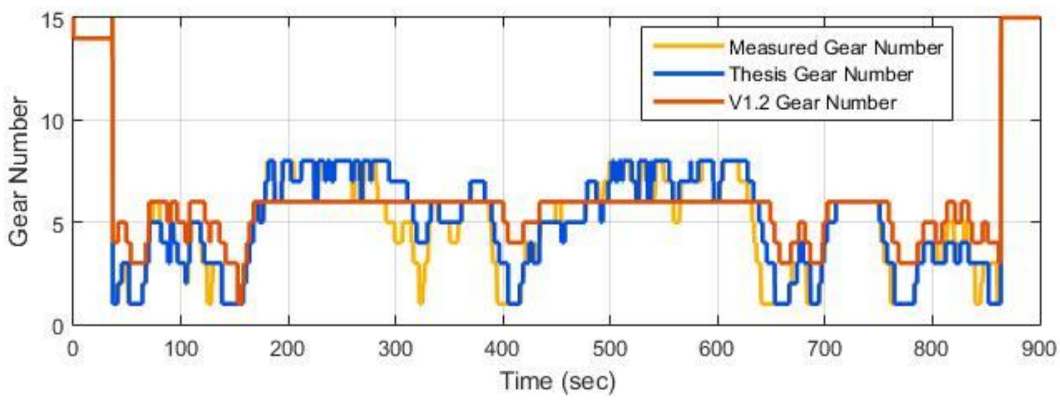

Figure 10. Soft TCM output validation results

5.1.5 DRIVETRAIN, WHEEL AND CHASSIS COMPONENT MODELS VALIDATION

Since the drivetrain from the stock vehicle is used as such, except for minor modifications to the propeller shaft, the CAN data from the stock vehicle test drive recorded by the previous teams have been used to optimize and validate these models. The original transmission and differential models were not parameterized to reflect the mechanical transmission losses of the stock vehicle accurate enough. The difference in the simulated vehicle speed produced during baseline model evaluation and the actual vehicle speed logged during on-road testing can be seen in the figure 11 below. The difference in the simulation is due to the lack of an accurate transmission losses model.

Initially, the transmission model parameters are assumed and then optimized after a few iterations comparing the results with the stock vehicle CAN log results.

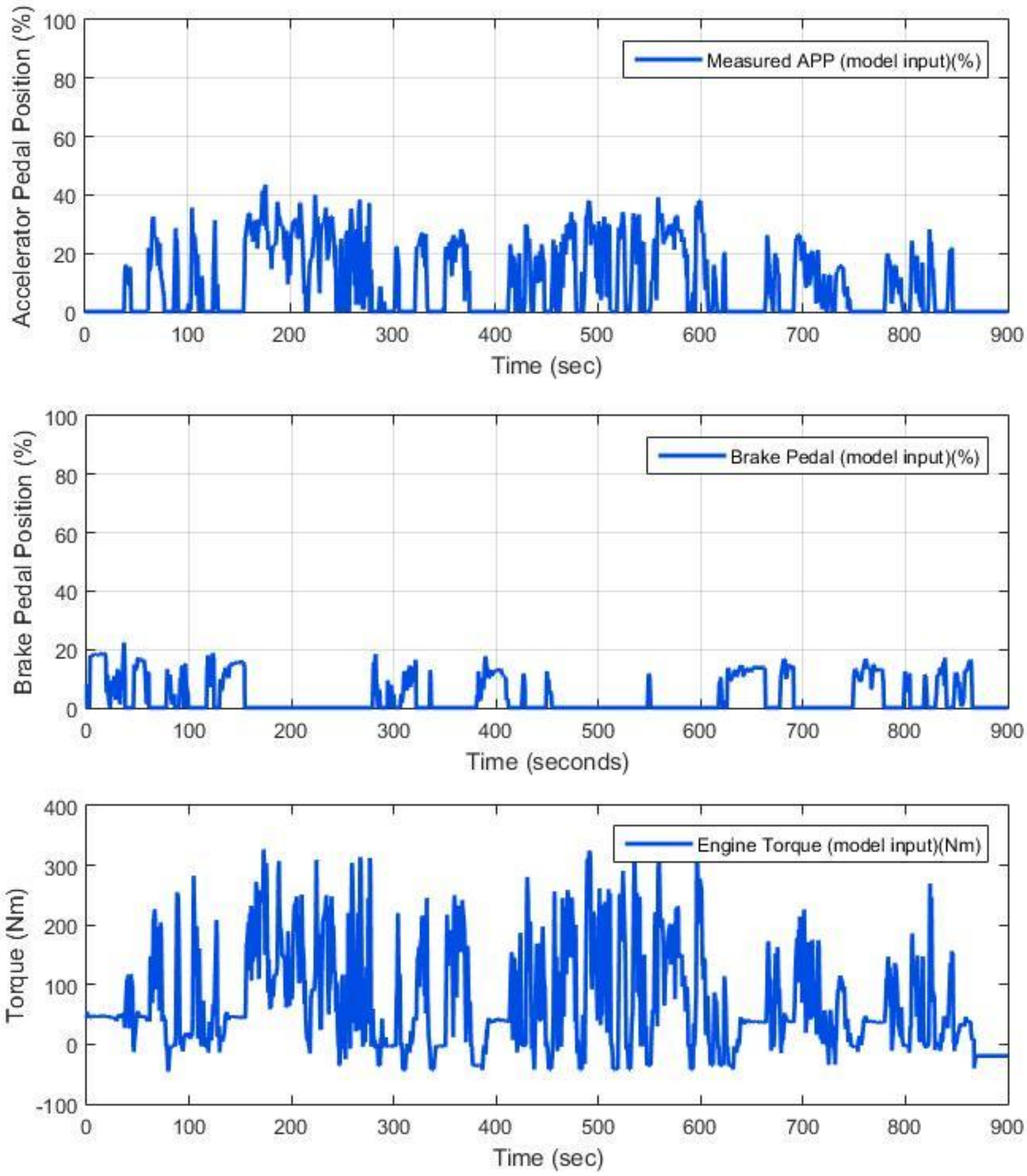

Figure 11. Drivetrain, chassis and wheels models validation results

The Figure 11 above shows the inputs to the transmission and wheel models. Engine torque and transmission output speed are the transmission model inputs. The engine torque data from the measured stock vehicle CAN logs is used in place of the output from the engine model. APP is an input to the Soft TCM model which determines the transmission shift pattern and the BPP is an input to the brake model which is inside the wheel subsystem model.

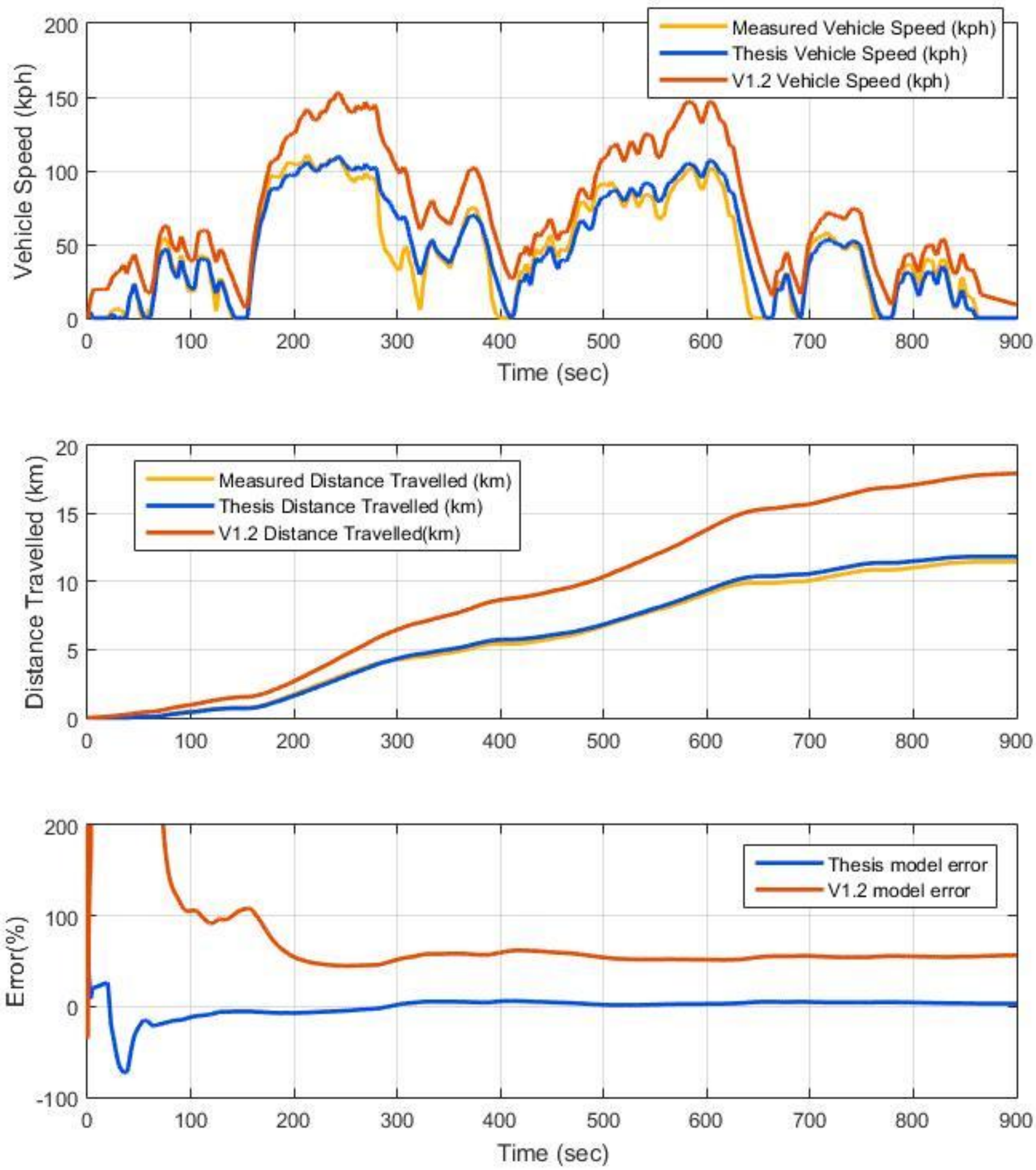

Figure 12. Drivetrain, chassis and wheels models validation results

5.3 IC ENGINE MODEL

5.3.1 MODEL ADVANCEMENT

An IC Engine plant model with a mean value manifold filling dynamics model as shown in [10] and map based torque, fuel consumption and emissions models is desirable fidelity for achieving accurate energy consumption simulation. The baseline model did not contain a manifold dynamics model and hence the simulated fuel consumption was far lower than the actual under closed loop testing and too high during open loop or feed forward testing.

IC Engine plant model currently developed consists of a manifold dynamics model used to calculate the manifold absolute pressure based on the throttle position and the engine speed. The output of this model is used to calculate the mass air flow into the combustion chamber using the Speed-Density equation [10], [11]. The volumetric efficiency of the engine is obtained from a lookup table based on the engine speed and the manifold absolute pressure. The dynamic engine torque is obtained from a lookup table based on the engine speed and the mass air flow into the engine. Later engine torque and engine speed are used to obtain the dynamic fuel consumption and emission values from lookup tables containing data from the manufacturer.

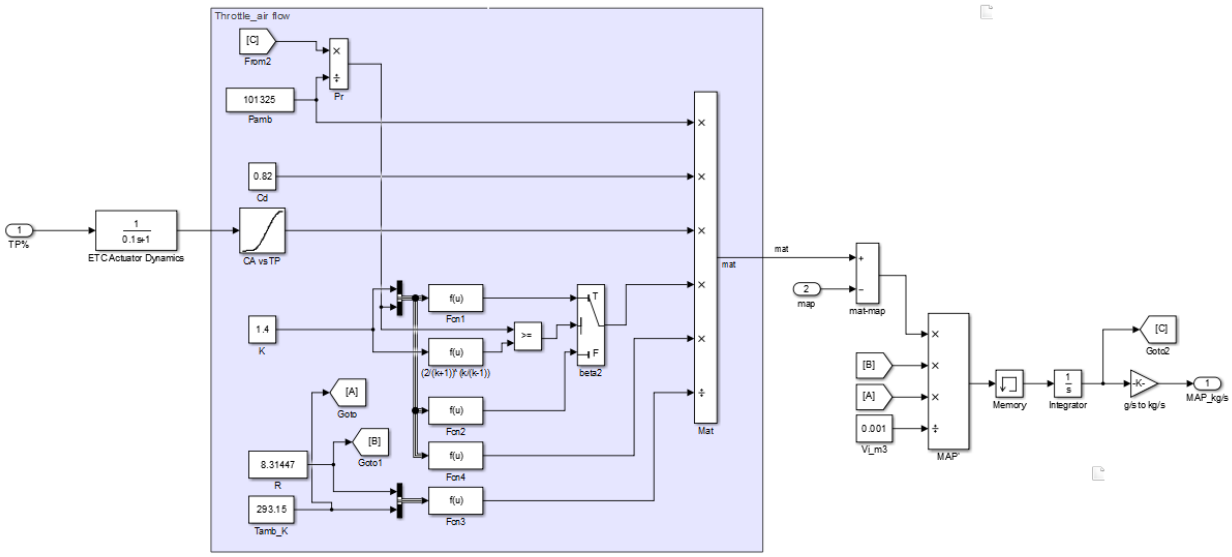

Figure 13. IC Engine intake manifold flow dynamics model

Equations used to calculate manifold air flow and manifold absolute pressure:

$$\dot{m}_i = \frac{N * V_{disp} * P_{map} * \eta_{vol}}{2 * R * T_{amb}} \qquad \text{Eq 1}$$

$$\dot{P_{map}} = \frac{RT_i}{V_{man}}(-\dot{m}_i + \dot{m}_t) + P_{map}\left(\frac{\dot{T}_i}{T_i}\right) \qquad \text{Eq 2}$$

$$\dot{m}_t = Th_{CA} * C_d * \frac{P_{amb} * \sqrt{K'}}{\sqrt{RT_{amb}}} * \beta_{2(map)} + \dot{m}_{t0} \qquad \text{Eq 3}$$

$$K' = 2K/(K-1) \qquad \text{Eq 4}$$

$$\beta_{2(map)} = \begin{cases} \sqrt{P_r^{2/K} - P_r^{(K+1)/K}}, if\ P_r \geq \left[\frac{2}{K+1}\right]^{\frac{K}{K-1}} \\ \sqrt{\left[\frac{1}{K'}\right]\left[\frac{2}{K+1}\right]^{\frac{K+1}{K-1}}}, \quad otherwise \end{cases} \qquad \text{Eq 5}$$

$$P_r = \frac{P_{map}}{P_{amb}} \qquad \text{Eq 6}$$

Where,

$\dot{m}_t$ = instantaneous air mass flow past throttle plate (kg/sec)

$\dot{m}_{t0}$ = previous air mass flow past throttle plate (kg/sec)

$\dot{m}_i$ = instantaneous air mass flow into intake port (kg/sec)

$\dot{P}_{map}$ = absolute manifold pressure derivative (N/m^2)

P_{map} = absolute manifold pressure (N/m^2)

P_{amb} = ambient pressure (N/m^2)

T_i = intake manifold temperature (K)

V_{disp} = Engine displaced volume (m^3)

V_{man} = manifold + port passage volume (m^3)

R = ideal gas constant

K = ratio of

Th_{CA} = throttle effective area, (m^2)

T_{amb} = ambient temperature, (K)

C_d = coefficient of discharge

η_{vol} = engine volumetric efficiency

N = engine speed, rad/sec

5.3.2 IC ENGINE MODEL VALIDATION

Baseline model does not contain the ECM strategy for maintaining engine idle speed. Thus the ECM logic to maintain engine idle speed was modeled. This has improved the fuel consumption accuracy significantly. Figures 14 and 15 show the validation results of the stock Camaro engine model based on the test drive data. Due to the unavailability of test data for the custom LEA 2.4L engine, the model fidelity is initially tested with the stock engine parameters.

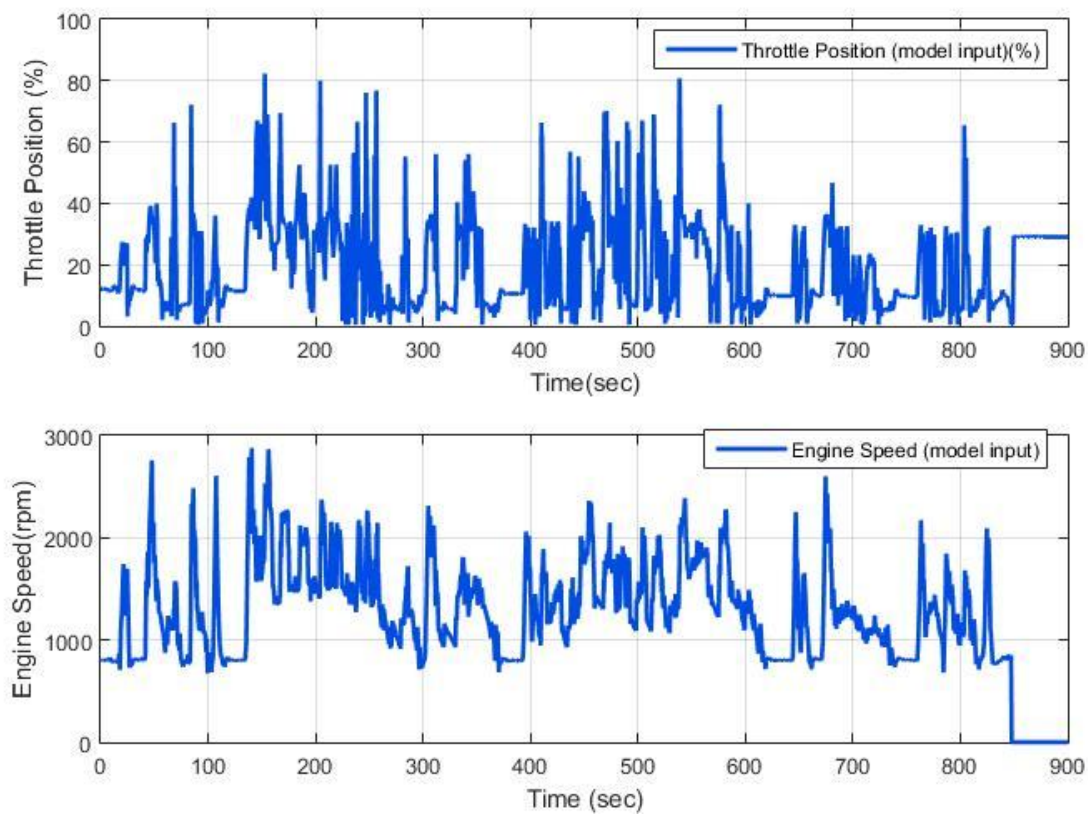

Figure 14. IC Engine model fidelity validation using stock engine parameters

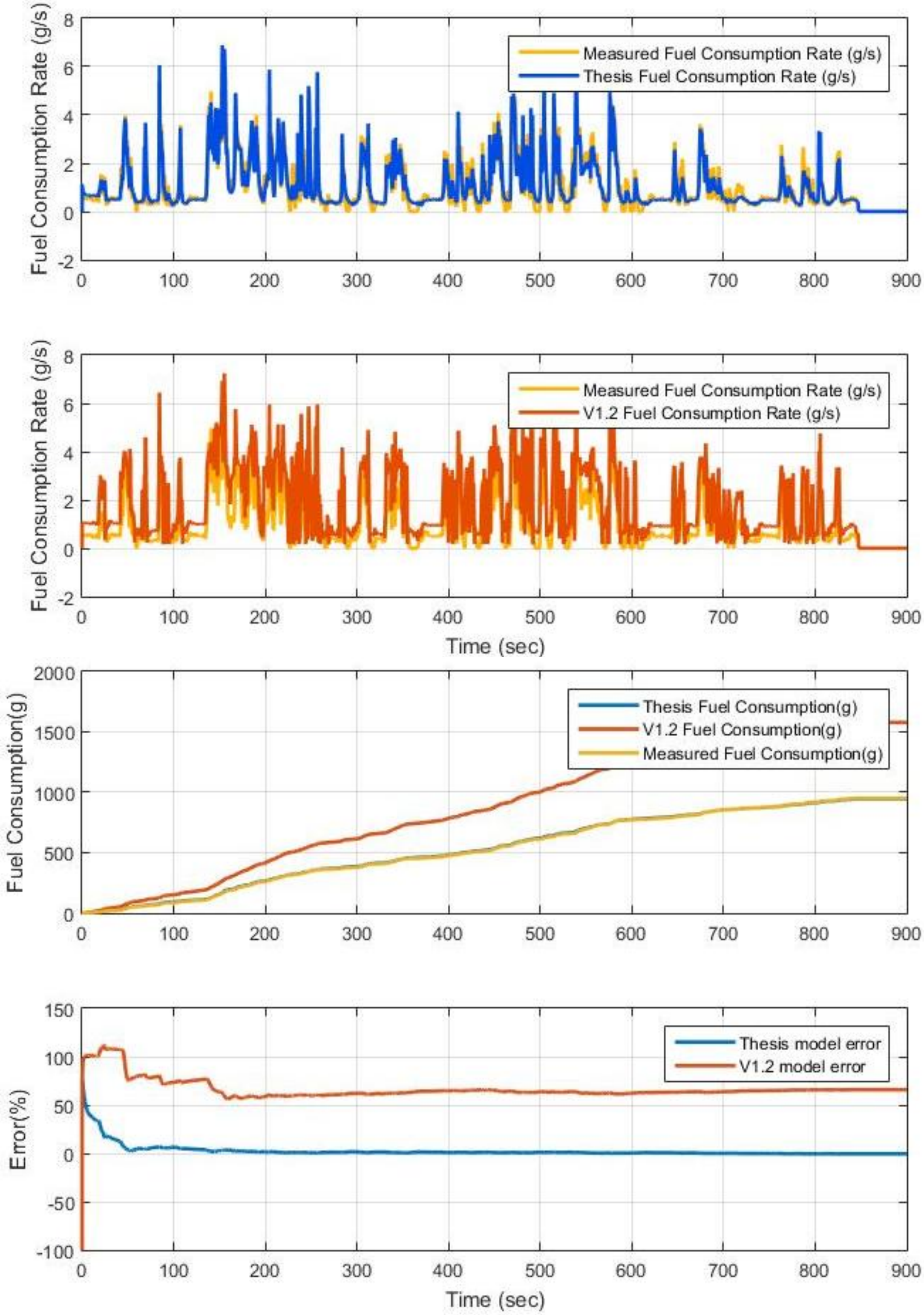

Figure 15. IC Engine model fidelity validation using stock engine parameters

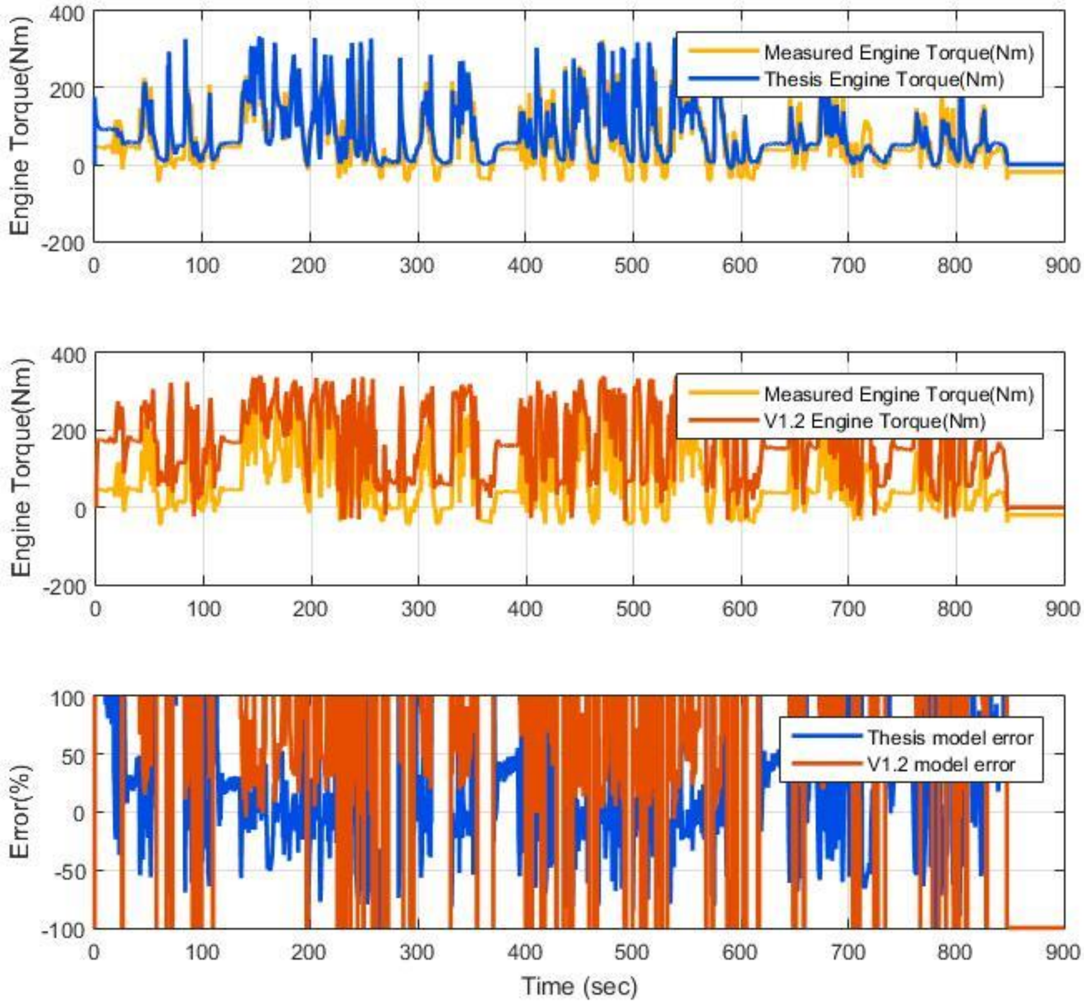

Figure 16. IC Engine model fidelity validation using stock engine parameters

Now, the model parameters are updated with the LEA2.4L engine parameters provided by the manufacturer and simulated. The simulation outputs are compared with the data from on-road testing of the vehicle with newly developed power train in engine-only mode. Figure 17. shows the validation results of the modified LEA 2.4L engine based on test data from on-road testing.

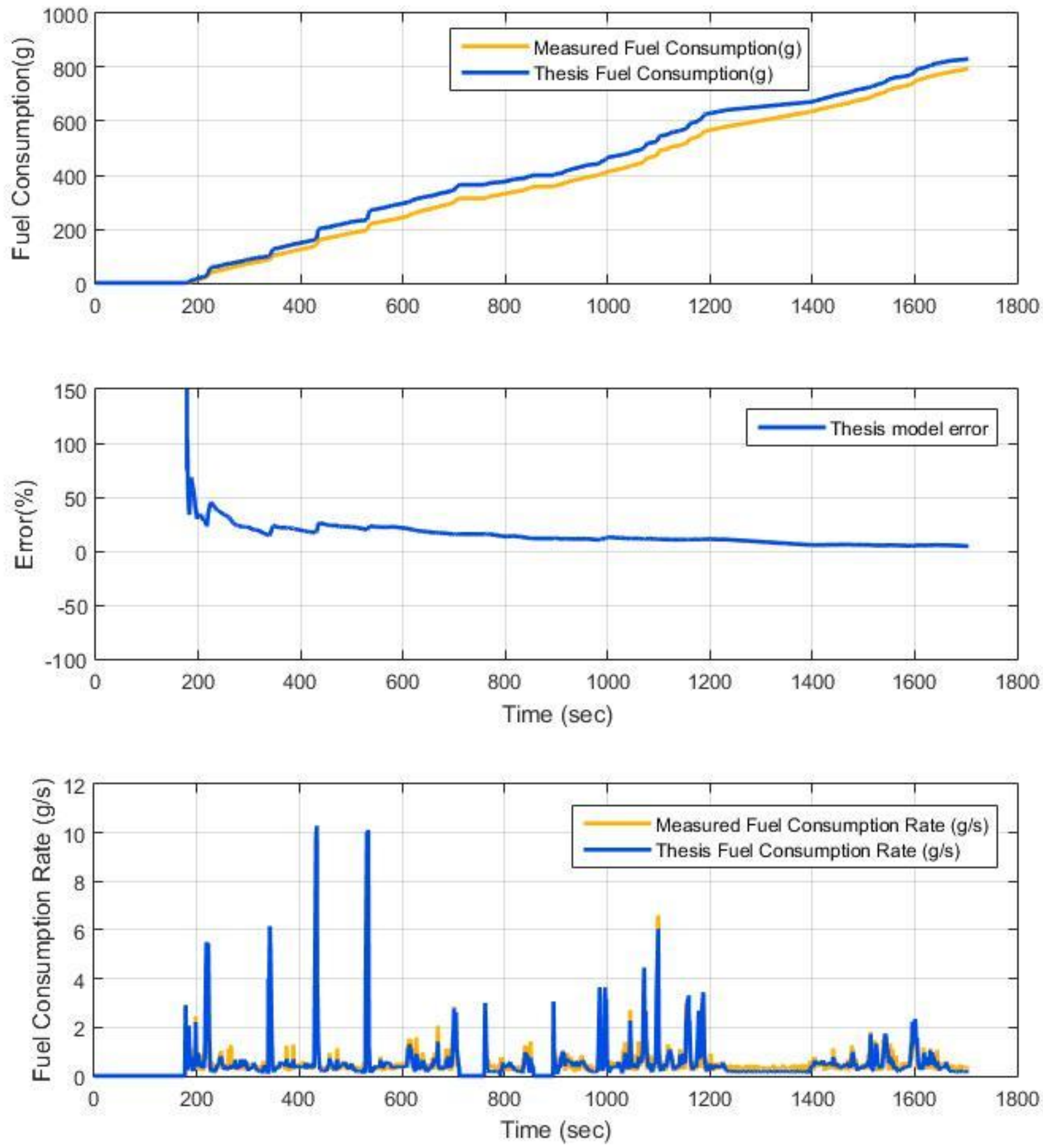

Figure 17. LEA engine model validation results

5.4 DRIVER MODEL

Key position, accelerator pedal, brake pedal and shift lever position are the inputs needed from the driver for normal driving. Modeling the driver behavior involves many factors including but not limited to road quality, turns, weather and driver psychology as shown in the [12], [9]. However for drive cycle simulations to calculate vehicle energy consumption the environmental data for simulating the vehicle dynamics are not available.

5.5 E-MACHINE MODEL

5.5.1 MODEL DEVELOPMENT

The E-Machine used in EcoCAR3 is GKN EVO AF130-4, an Internal Permanent Magnet Synchronous Electric machine (IPMSM). The sponsor donated electric machine is controlled by a Rinehart PM150DX Electric machine Control Unit (MCU), which will be discussed in a later section. A map based E-Machine model has been used to accurately simulate the IPMSM energy consumption at any point of the simulation. Since the purpose of the model is only to simulate the electric machine's energy consumption two maps defining the electric machine's peak torque curve and the electric machine' efficiency map are used to calculate the electric current consumed and the mechanical torque produced at any instant of the simulation with the following formulas. Figure 18 shows a view of the map based electric machine model.

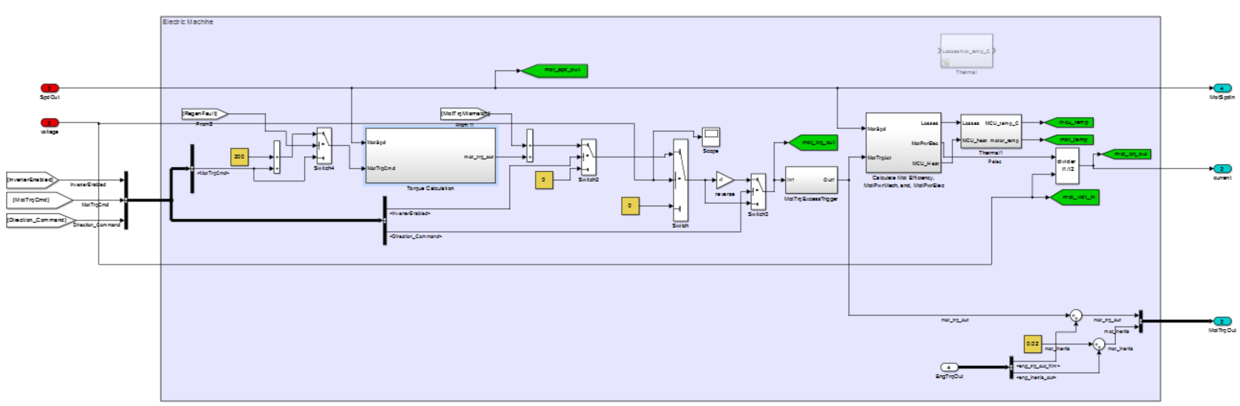

Figure 18. Inside the E-Machine model

In the efficiency map (Figure 19) produced using data from the manufacturers, it can be seen that at many points the electric machine's efficiency is zero. Though theoretically 0% efficiency is possible, the calculated electrical energy consumption cannot be infinite practically. Thus a value of 1% has been assumed to be the lowest possible efficiency in order to simulate logical values of electrical energy consumption at very low speed and torque regions. The inverter efficiency was modeled to be constant following data from the Rinehart document.

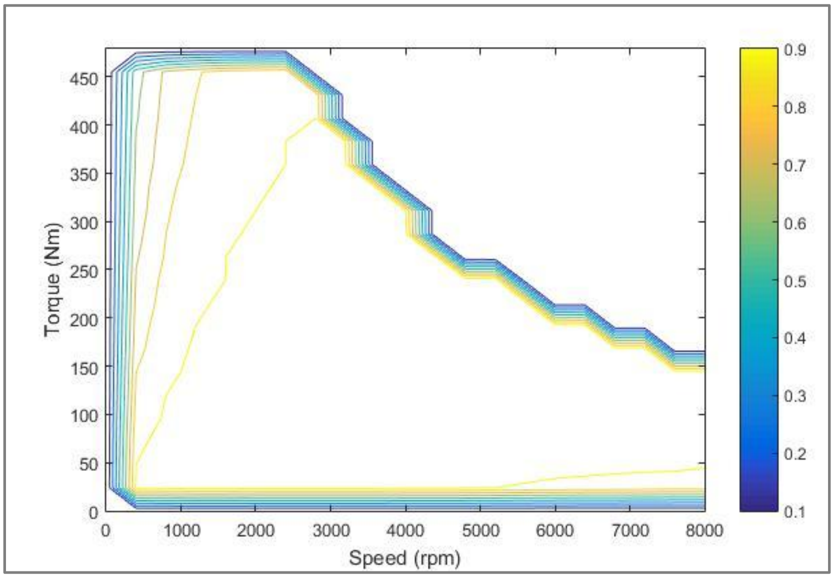

Figure 19. GKN EVO AF130-4 IPMSM efficiency map

Equations Used:

$$P_{mec\,h} = \frac{2\pi NT}{60} \qquad \text{Eq7}$$

$$P_{elec} = \begin{cases} \dfrac{P_{mec\,h}}{\eta_{mot\,(N,T)} * \eta_{mcu}}, & when\ motoring \\ P_{mec\,h} * \eta_{mot\,(N,T)} * \eta_{mcu}\,, & when\ regenerating \end{cases} \qquad \text{Eq 8}$$

$$i_{mcu} = \frac{P_{elec}}{V_{bat}} \qquad \text{Eq 9}$$

Where,

P_{mech} = Mechanical Power (W)

P_{elec} = Electrical Power (W)

$\eta_{mot\,(N,T)}$ = Instantaneous IPMSM Efficiency based on electric machine speed and torque (%)

η_{mcu} = Rinehart MCU Efficiency (%)

i_{mcu} = Instantaneous DC current consumed by the inverter (A)

V_{bat} = Instantaneous battery voltage (V)

N = Electric machine speed (rpm)

T = Electric machine torque (Nm)

5.5.2 E-MACHINE MODEL VALIDATION

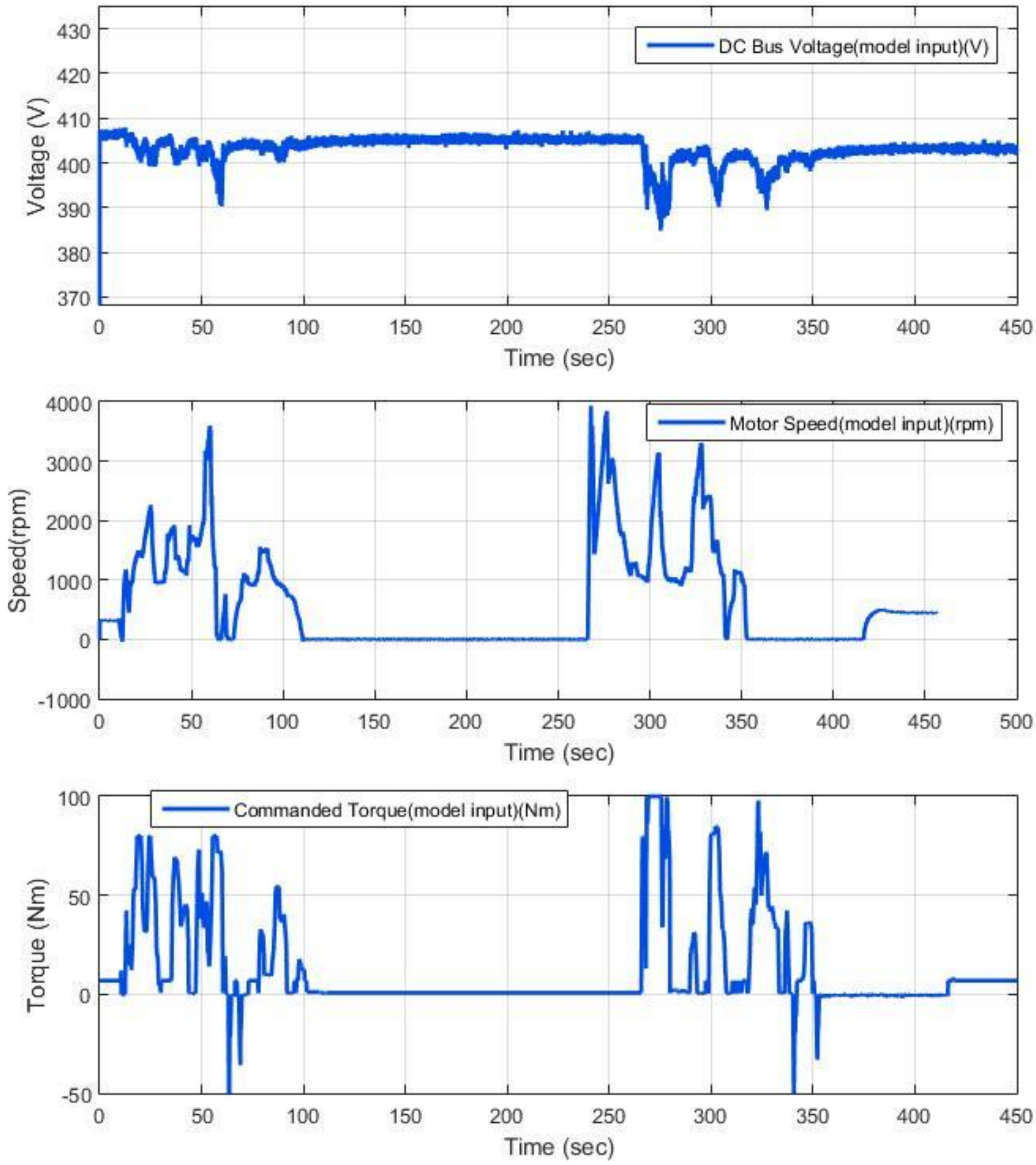

Figure 20. E-Machine model validation results

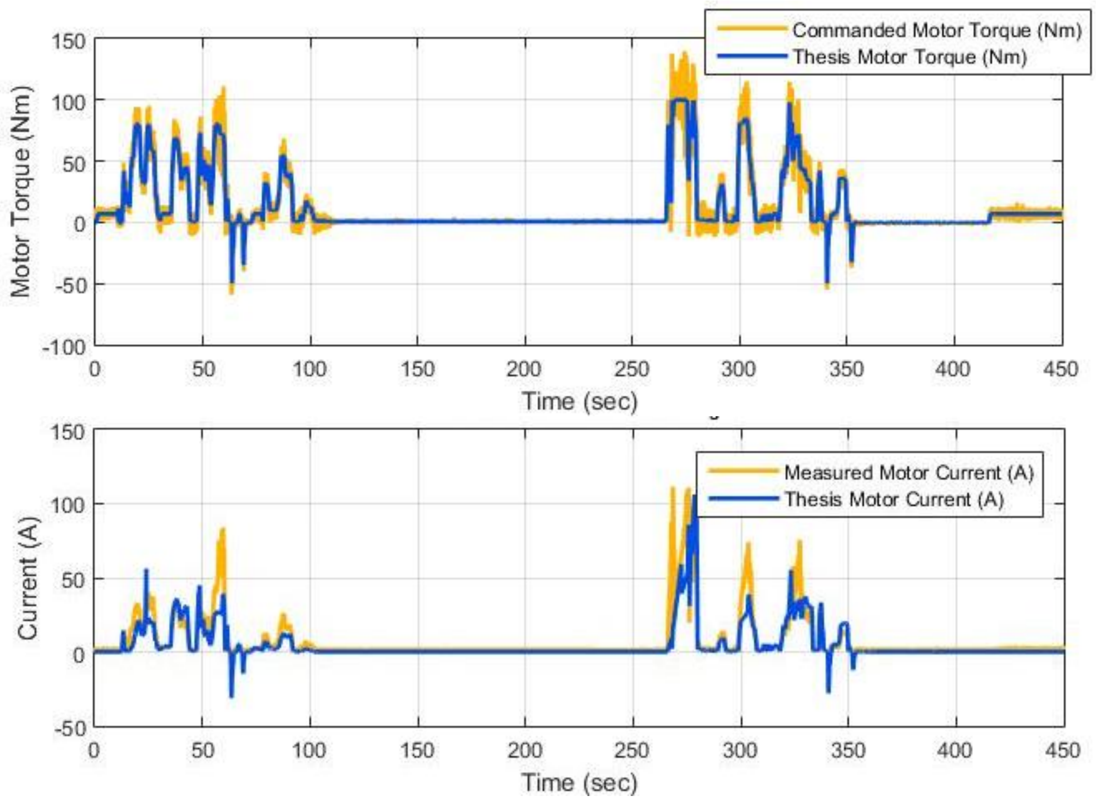

Figure 21. E-Machine model validation results

From the plots above it can be seen that there is considerable difference in the E-Machine model simulated torque feedback and current simulation. After thorough investigation it is identified that the current mismatch is due to torque control strategy of the MCU. The MCU currently ramps the torque at a rate of 1500Nm/s and use of a proportional integral controller is common in the E-Machine controller. A high fidelity MCU model is necessary in order to capture the effects of the MCU dynamics in a more detailed manner.

5.6 ENERGY STORAGE SYSTEM (ESS) MODEL

The Energy Storage System used by the team is a Li-ion battery pack from Bosch. Quasi-static circuit model of the pack is needed for obtaining accurate SOC prediction during drive cycle simulation. More accurate models based on battery electrochemistry can be developed but at the cost of simulation time. A Thevenin circuit model is developed after confirming its prediction accuracy through previous research work [8]. Though DP model is marginally more accurate than Thevenin circuit model, considering time allocation for the model and amount of work required to optimize the parameters the later is used.

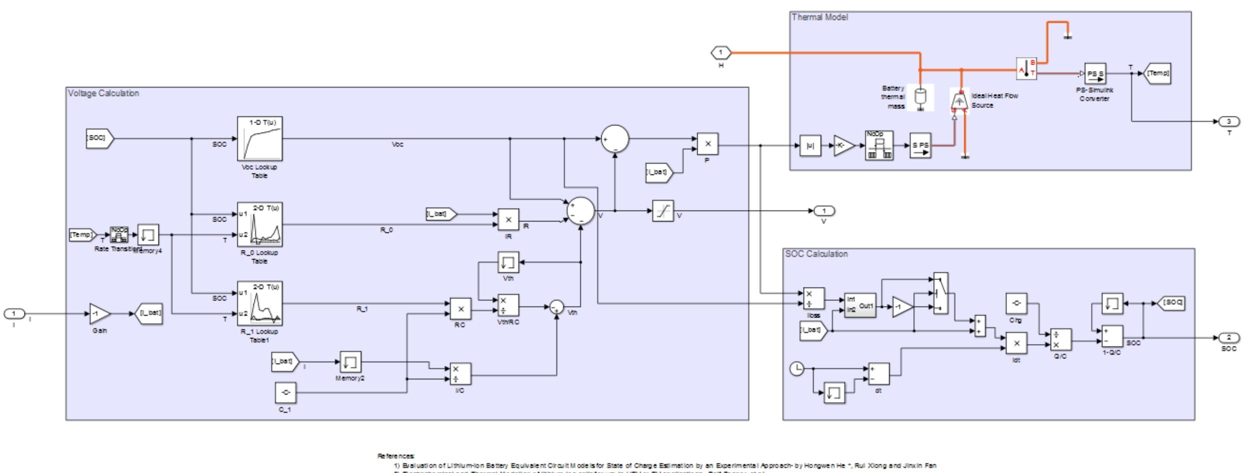

Figure 22. Equivalent circuit model of a single Li-ion cell

Lookup tables are used to determine the dynamic battery open circuit voltage, resistance and capacitance values based on the SOC and cell temperature. These parameters were identified based on the Li cell HPPC test data provided by the manufacturer. The Simulink parameter optimization tool was used effectively to automate the parameter optimization process. These values are used to calculate the instantaneous cell output voltage based on SOC and cell temperature. Later the cell voltage is scaled to the pack voltage. Figure shows a single Li-ion cell equivalent circuit model which has been modeled and parameterized based on input from Bosch.

Equations used:

$$V_{cell} = V_{oc(SOC)} - V_{drop} \quad \text{Eq 10}$$

$$V_{drop} = i_{cell} * R_{1(SOC,T)} + V_{th} \quad \text{Eq 11}$$

$$V_{th} = \frac{i_{cell}}{C} - \frac{V_{th0}}{R_{2(SOC,T)} * C} \quad \text{Eq 12}$$

$$Q = \int V_{drop} * i_{cell} \quad \text{Eq 13}$$

Where,

V_{cell} = cell voltage in V

i_{cell} = cell current in A

$R_{1(SOC,T)}$, $R_{2(SOC,T)}$ = Instantaneous Li-ion cell internal resistances with respect to SOC and temperature in Ohms

C = cell capacitance in F

$V_{oc(SOC)}$ = open circuit voltage corresponding to the current SOC V

Q = heat generated in the battery cell in J

Figure 23 below shows the component level validation results of the battery pack. The HPPC test data from Bosch is used to test the Li-ion cell model. The figure 25 shows the validation results of the battery pack.

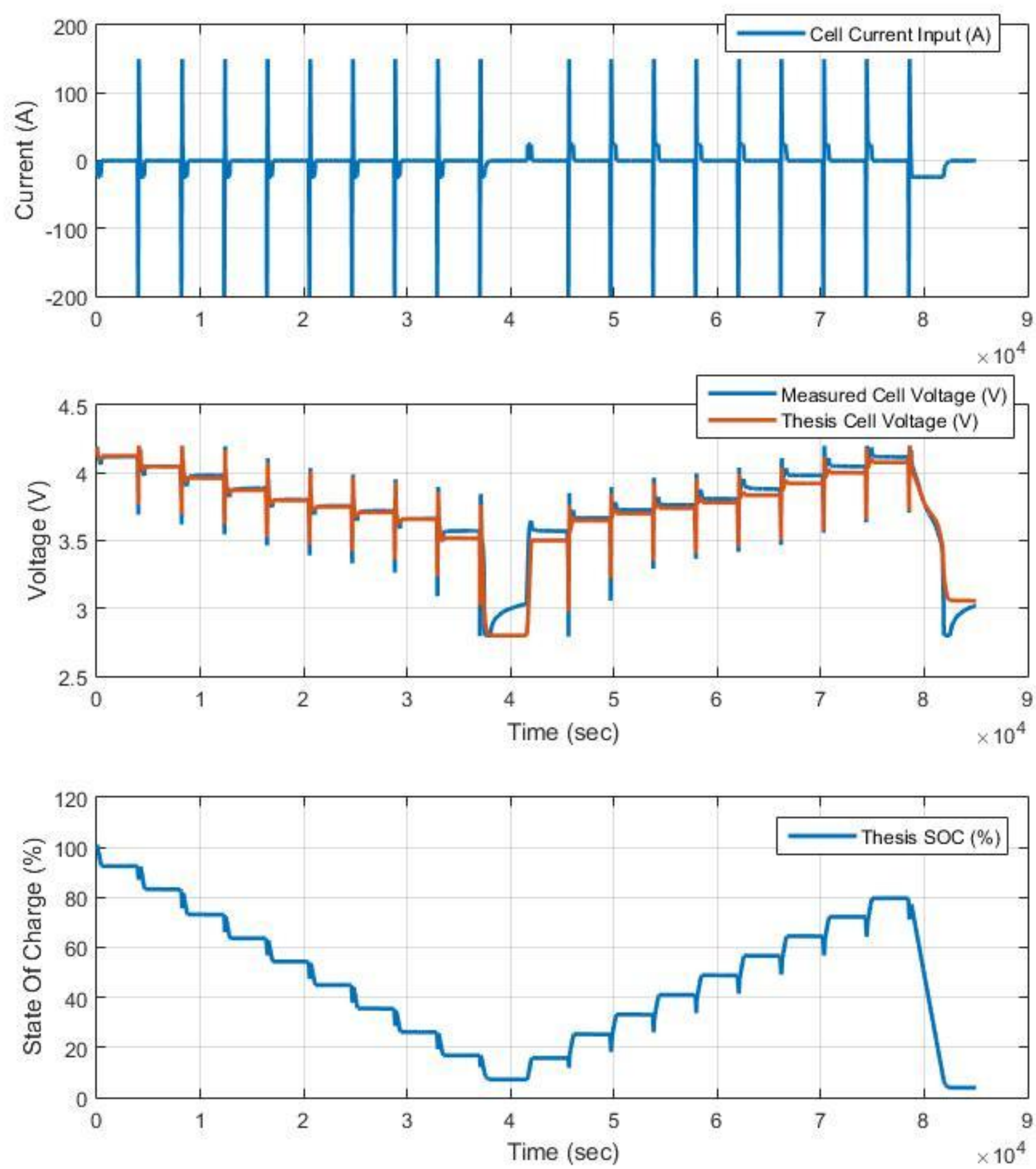

Figure 23. Single Li-ion cell model validation results

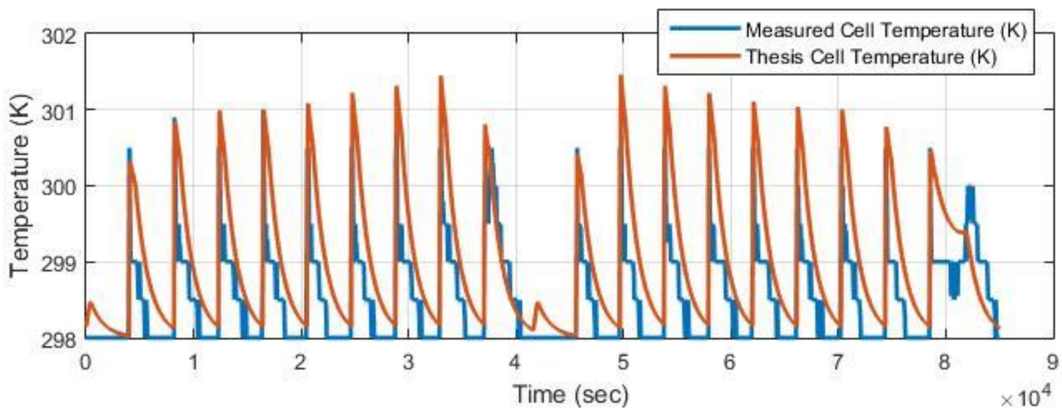

Figure 24. Single Li-ion cell model validation results

The figures 23 and 24 show the results of Li cell model testing. As seen the simulated voltage and temperature values are considerably accurate and correlate with the test data. A large difference can be seen in the voltage prediction because of the sudden change in the battery voltage at low charge condition. Hence more data points are needed for low battery SOC voltage simulation. The battery SOC at the point of major error was around 10%. Since we never expect to go below 15% SOC which is the manufacturer's recommendation, the current model accuracy is sufficient for predicting the energy consumption. The figure 25 below shows the battery pack validation results.

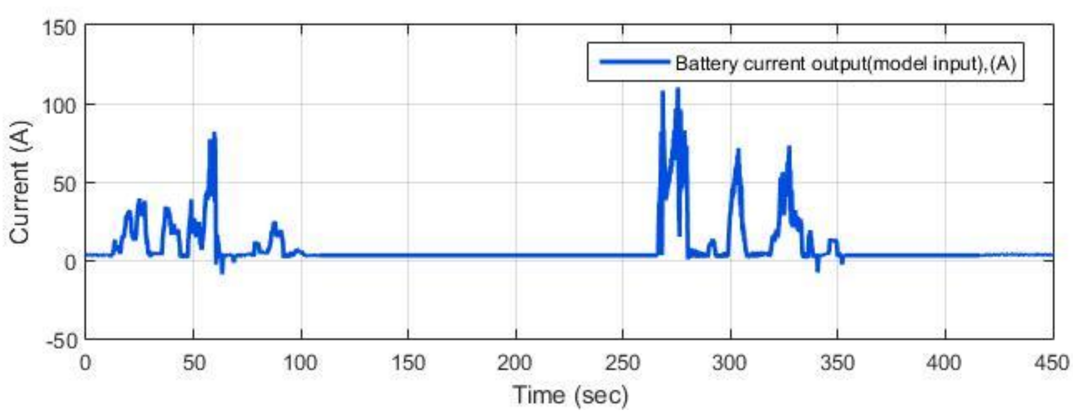

Figure 25. Battery pack model validation results

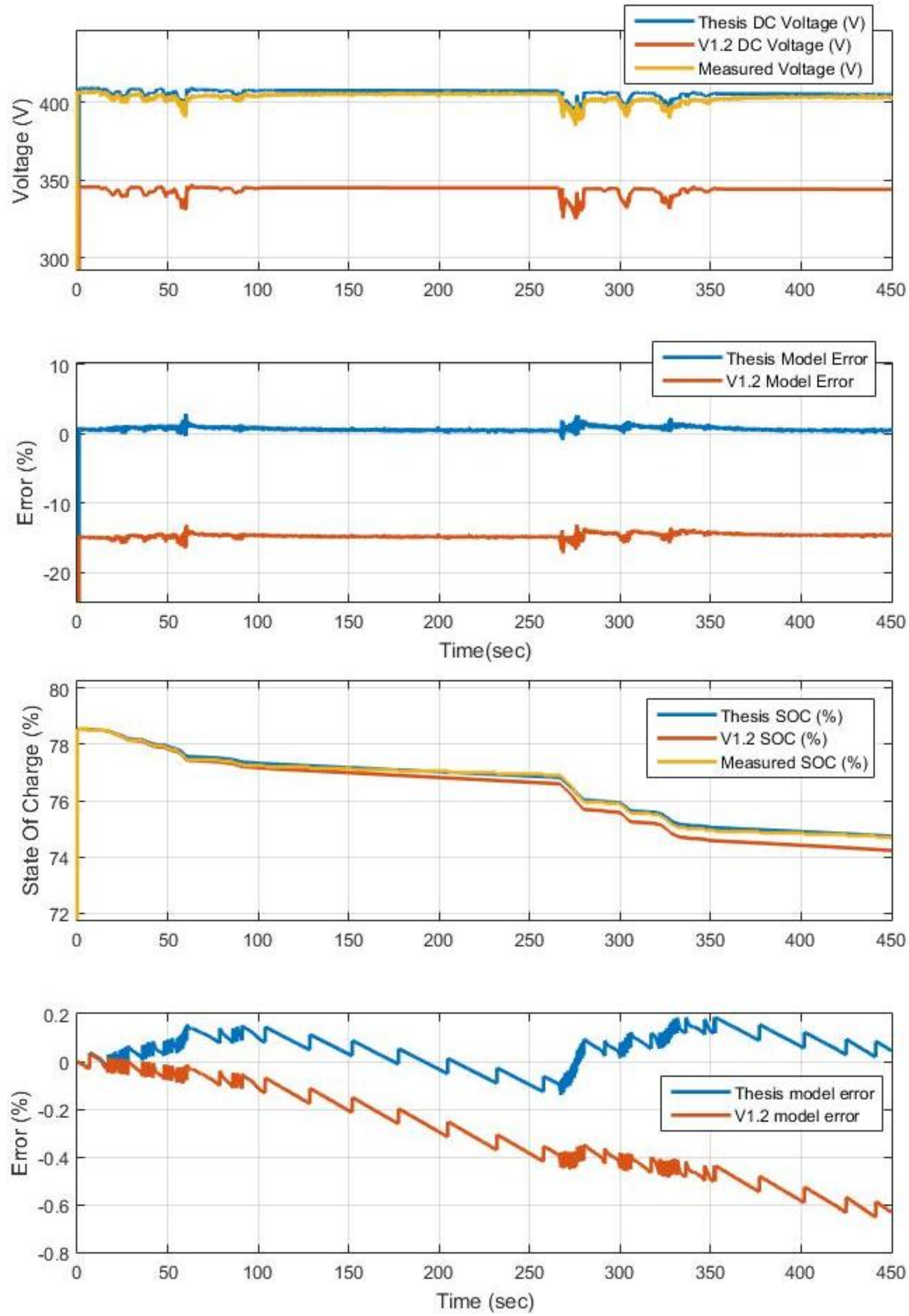

Figure 26. Battery pack model validation results

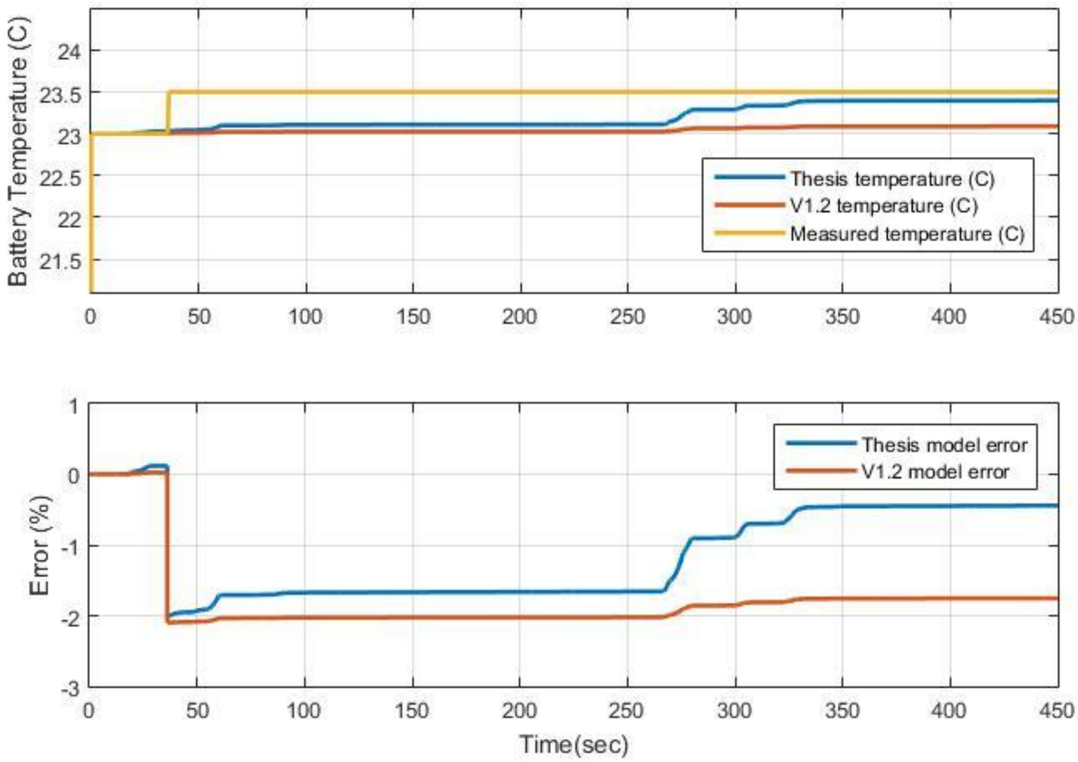

Figure 27. Battery pack model validation results

Significant improvement in the SOC and voltage prediction accuracy can be seen from the previous model. SOC prediction error has been reduced to 0.2% peak for the given drive cycle, whereas the previous model's accumulated error is around -0.6%. Voltage prediction accuracy improved significantly because the V1.2 model was not parameterized correctly and contained assumed parameters from another battery pack. Also note that the voltage prediction directly impacts current consumption as the electric machine model uses the voltage output of the battery to calculate the current consumption and this is feedback directly. Therefore any inaccuracy in voltage prediction will result in a huge difference in the overall energy consumption simulation.

5.6 ACCESSORY LOADS MODEL

Accessory load model includes AC Compressor, electrical actuators, Soft ECU loads and LV electrical equipment such as the instrument cluster on the vehicle dashboard. Due to insufficiency in time to test every individual electrical component and develop a model, a constant accessory loads model is currently assumed. At present, the model does not account for the AC compressor load. Though this is desirable, more testing is needed before the AC compressor dynamic load model can be updated. Current consumption of the DCDC converter has been assumed to 3A in the current model [12].

5.7 SOFT BMS MODEL

Lithium ion batteries have gained popularity over the past decade due to its superior power ratings and capacities, when compared to the other popular battery chemistries. Though Lithium ion batteries are used in many production EVs and HEVs, they still are known for their unstable nature beyond the safe operating limits. To address the safety concerns of the battery pack which may arise due to overcharge, over-discharge, battery internal or external short circuit or ground fault the manufacturer has implemented a Battery Management System (BMS) which continuously monitors the pack and controls the pack output contactors based on the HSC request and charge or discharge current limits. In order to develop the HSC code to control the BMS, it is ideal to have a Soft BMS model with all the functionalities of interest.

The main functions of the BMS are: to monitor the battery SOC, terminal voltage, current and temperature and check if these values are within limits; detect battery internal failure or ground fault; and communicate the battery status to the other components such as the HSC. The BMS continuously sends information about the maximum dynamic charge and discharge current limits based on the battery's condition over the CAN. It is essential to maintain the current consumption within this range. If the battery output current exceeds this range the BMS will open contactors without further notice as a safety measure to prevent significant damage to the battery and the user. The dynamic charge limit is mapped by monitoring the current limit signal from the BMS while charging the battery. The discharge limit is mapped based on data obtained during on-road test.

Since details about the BMS behavior to the command signals are not provided, the BMS was tested and the startup, shutdown and most of the safety critical functionalities are studied and a moderate fidelity Soft BMS model has been developed based on the component testing.

5.8 SOFT MCU AND SOFT BCM MODELS

These models have been retained from the V1.2 model developed during the previous years. Except for a few minor changes such as inclusion of a saturation block in the MCU to simulate the MCU's internal torque limit functionality which cannot be accessed through CAN signals. Since the clutch model was removed during year 3, the clutch model functionality which was modeled along with the MCU model by the previous team members was removed. The peak torque and continuous torque maps were updated with the latest data from the manufacturers.

CHAPTER 6 FULL VEHICLE MODEL VALIDATION

Data from hybrid electric vehicle testing has been used to validate the model simulation accuracy. Since the drive cycle has to be long enough to estimate the model accuracy level, the only two sets of test data are available to validate the model accuracy. The newly developed thesis model simulation results clearly show significant improvements in fuel consumption and State of Charge (SOC) prediction accuracy. Table below shows the average prediction error values for the fuel consumption and state of charge simulations.

Table 2. Full vehicle model validation results

	Thesis model error	V1.2 model error
Average fuel consumption error	-5.5%	-27.2%
Average State Of Charge error	-2%	-26.55%
Average distance travelled error	-0.7%	-0.4%

Despite significant improvements in the accuracy of the energy consumption simulation, the model still has errors. As discussed earlier, the stock vehicle model has been validated with stock vehicle test drive data. So, the possibility of increased vehicle resistance due to modified powertrain and mechanical assembly issues are being investigated. The brakes have not been calibrated recently and since we have had significant number of Diagnostic Trouble Codes from the ABS system in the past, calibration issues with the ABS is suspected. Moreover, misalignment in the Torque Converter or coupling shaft can produce more resistance. A quick fix for this issue is to recalibrate the model efficiency and losses to match the current powertrain. However, this is undesirable and will be fixed before moving further.

6.1 HYBRID MODE VALIDATION RESULTS

The results of vehicle tests in Hybrid mode are used to validate the model. The HSC was in charge sustaining mode during the test. Figure 28 shows the drive cycle, fuel consumption and SOC simulation vs. test result plots for the drive cycle derived from the CAN logs.

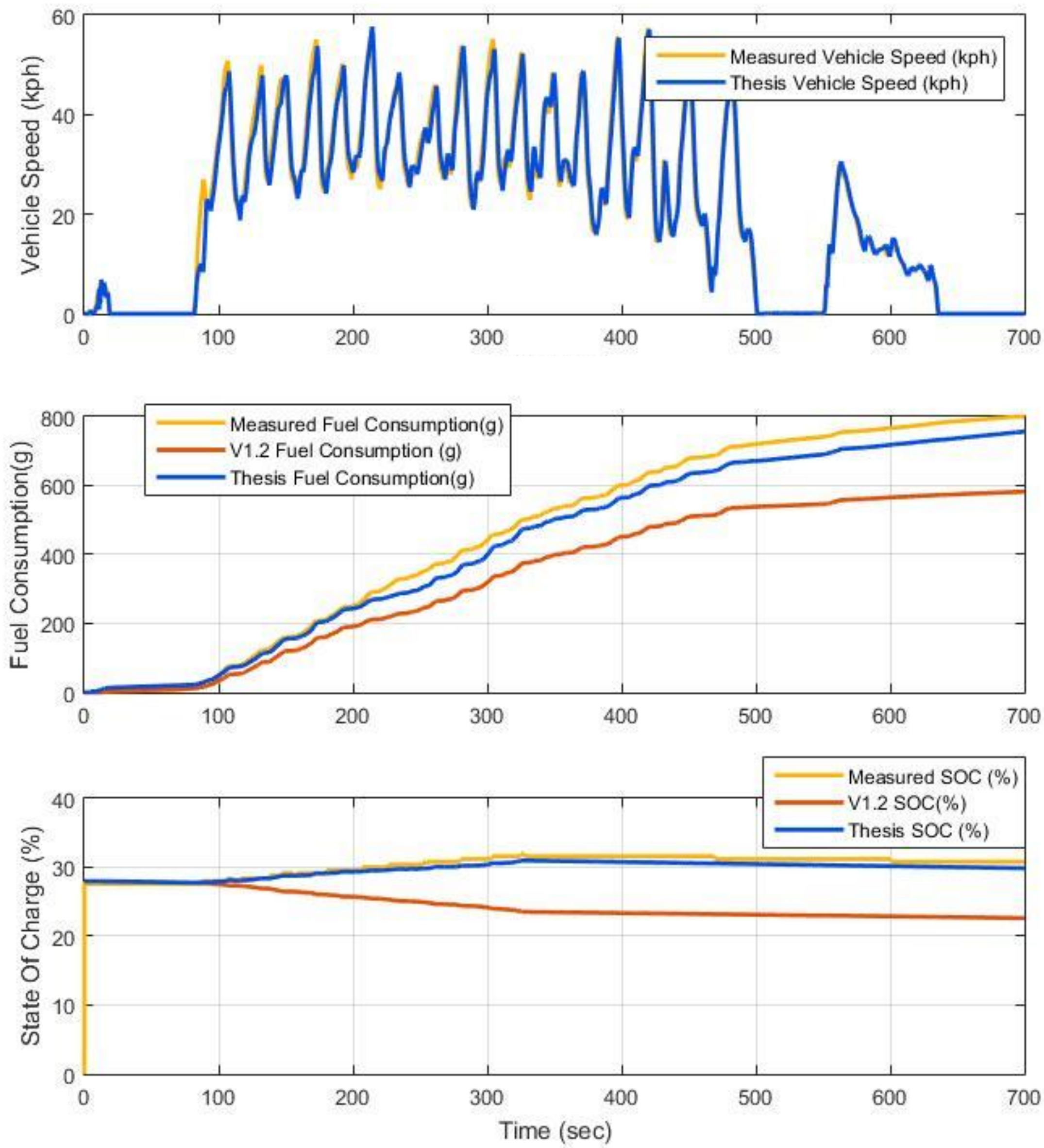

Figure 28. Full vehicle model CS mode validation results

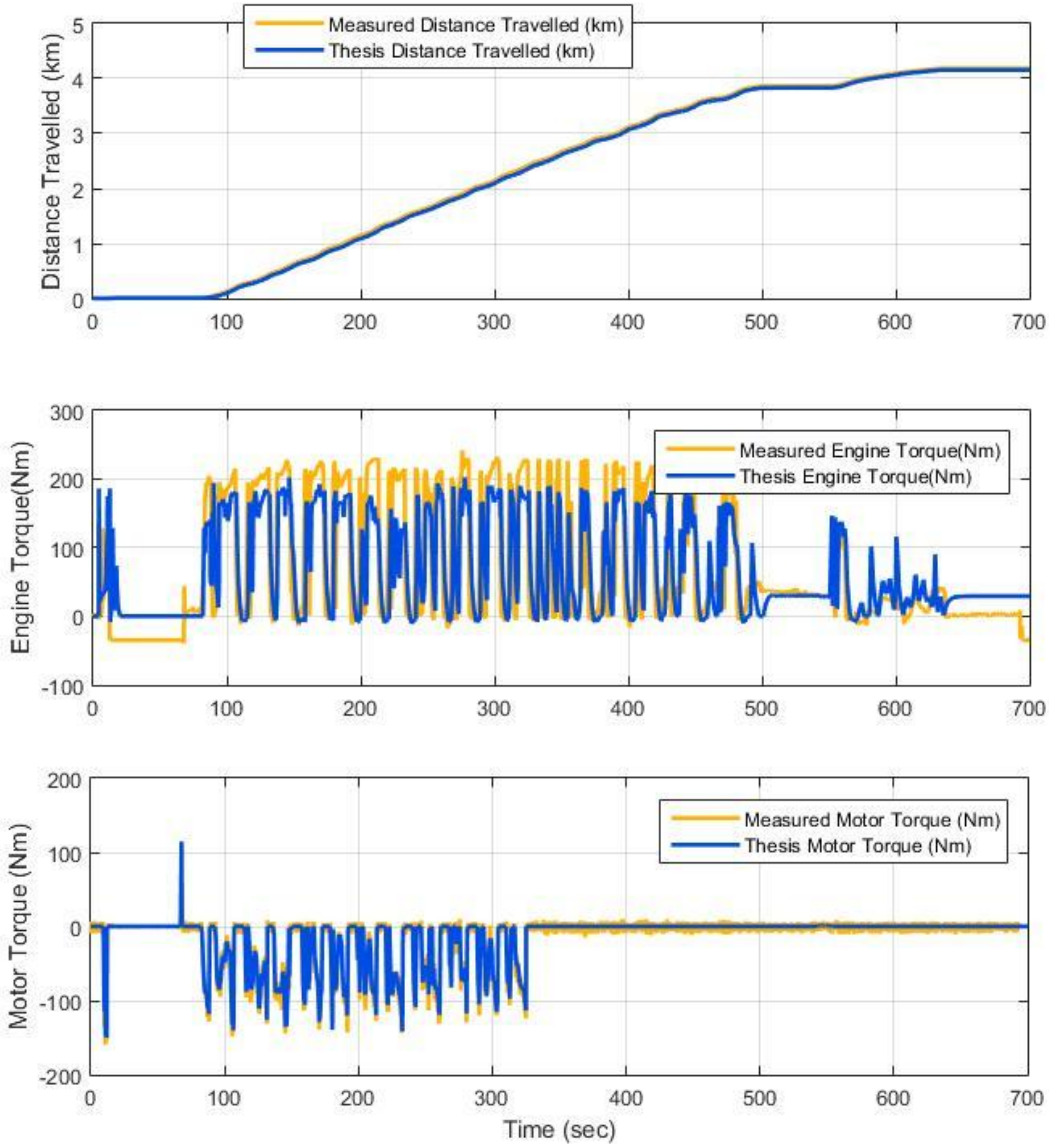

Figure 29. Full vehicle model CS mode validation results

Since the HSC model keeps changing due to testing requirements, the command signal sent from the HSC to the E-Machine or engine cannot be modeled very accurately without the knowledge of the model used during testing. Hence one of the inputs is fed to the model from the CAN logs. In this case, the Motor Torque command is fed from the CAN signal from the Rinehart MCU recorded in the logs. Whereas, the Accelerator Pedal Position Input to the Engine goes from the Driver model which is in a closed loop.

The simulated engine torque is lower than the measured engine torque for majority of the time. Though the drivetrain losses model has been validated thoroughly based on stock vehicle data, the modified vehicle losses are higher than the stock vehicle. Due to this the engine torque needed to reach the vehicle speed is higher than in the stock vehicle. Therefore the model has to be parameterized to account for the new modifications made. The details of this issue are still being investigated and will be studied in the future.

Similarly the deviation in the fuel consumption simulation accuracy is partly due to the lower torque production in the engine. Since the fuel consumption map is based on engine torque and the mass air flow rate calculated by the manifold dynamics model, the reduction in APP request directly impacts the fuel consumption too.

6.2 ENGINE ONLY MODE VALIDATION RESULT

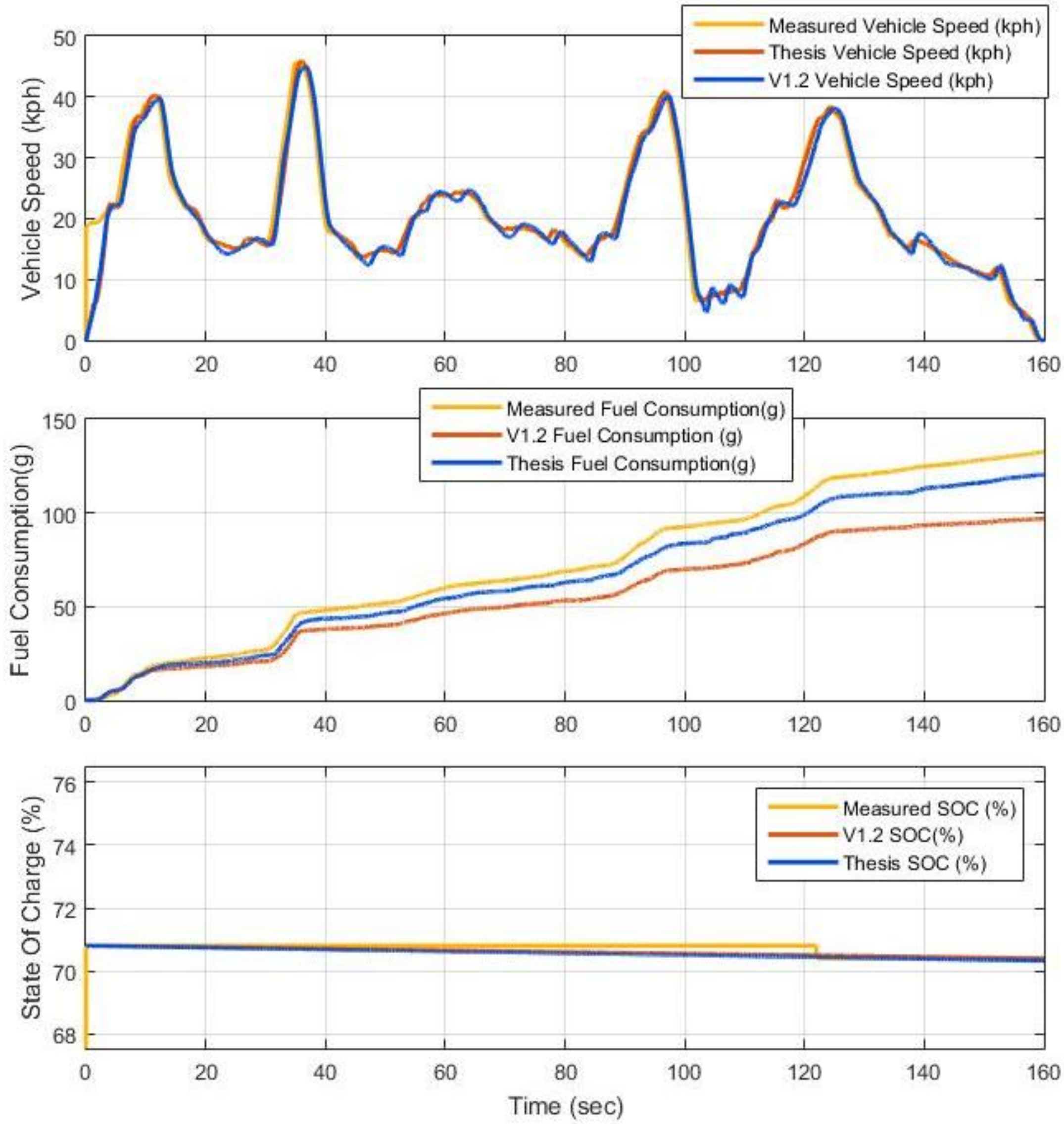

Figure 30. Engine-only mode validation results

During Engine-only mode the simulated results the SOC simulation accuracy in both models are significantly comparable as the electrical losses are negligible. Again the difference in the fuel consumption is due to the additional losses in the modified powertrain, which was not witnessed earlier. This will be accounted for in the future.

CHAPTER 7 HIL SETUP

Economic and safety factors have been vital in promoting the use of HIL as a testing platform for controls development. HIL validation reduces the testing time significantly as the code reaches satisfactory level of maturity during HIL simulation, thereby allowing us to do final code refinements and during vehicle testing. However, the model fidelity is the determining factor in HIL simulation. Figure 31 below shows the HIL setup for validating the EcoCAR3 team's Hybrid Supervisory controller functionalities.

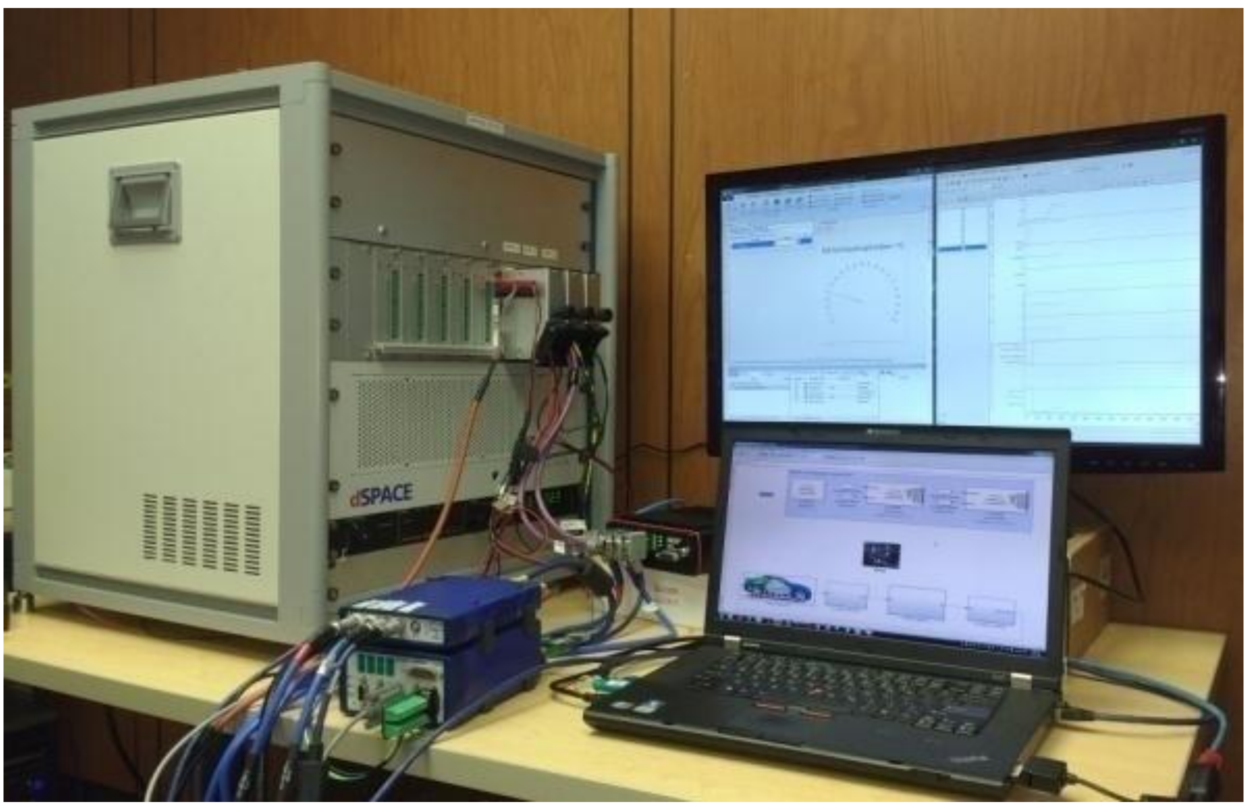

Figure 31. HIL Setup

The HIL setup has been carefully designed in order to replicate the actual vehicle in every possible aspect. Accuracy of the plant model and the HIL physical setup, which are the two main factors governing the validity of the HIL simulation has been considered and constantly improved as per testing requirements. Plant model accuracy is improved by validating the individual component models with data obtained from manufacturers and obtained through various component tests.

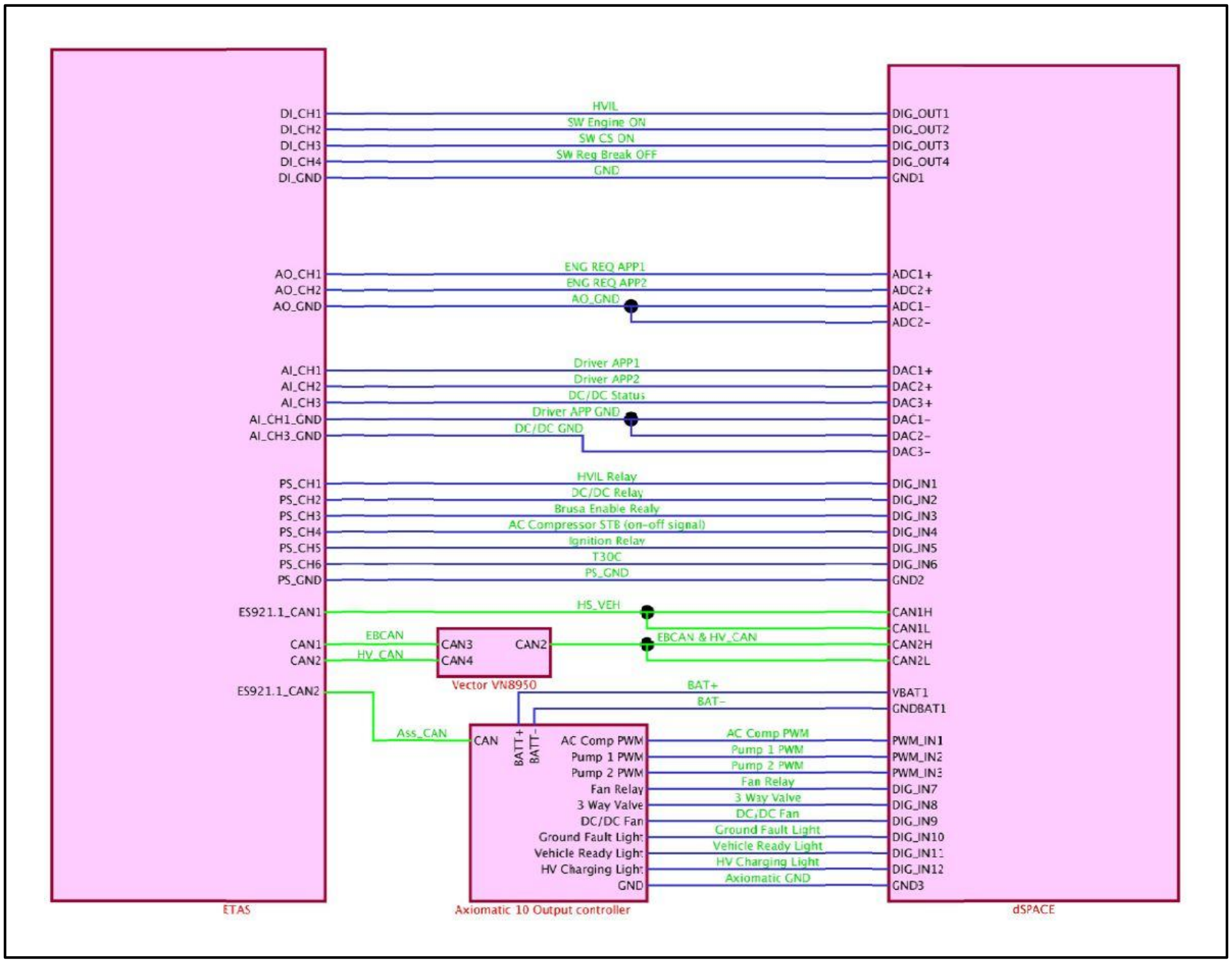

Figure 32. HIL Layout

7.1 HARDWARE AND SOFTWARE TOOLS

7.1.1 COMPONENTS UNDER TEST

ETAS ES910.3 is our HSC hardware in EC3 and consists of 2 CAN terminals. This along with the 2 CAN terminals on ES921.1 CAN extension module makes up for the four CAN terminals needed for the HSC. The ES930.1 consists of the analog and digital I/Os which are controlled by the HSC. The HSC code for the module is developed using the INTECRIO block set in Simulink and compiled. The compiled code in .a2l format is then flashed to the device using INCA.

Figure 33. ETAS Modules and the Axiomatic output controller

Axiomatic Output Controller (additional IO expansion device): Axiomatic Output Controller (AX021210) is used to simulate Digital IOs. The device which communicates with the HSC using Low speed CAN at 250kbps, can be controlled using a CAN message. Each signal bit of this message controls one digital output. The technical document on the Axiomatic output controller is “TDAX021210.pdf”. The dbc file containing the CAN message ID and output signals is “Axiomatic-output.dbc”.

ETAS INCA is the software tool used to configure the ETAS ES910.3 Rapid Prototyping module. Axiomatic output controller does not need any software setup and just executes the CAN signal commands sent through a particular message ID.

7.1.2 COMPONENTS SIMULATING THE VEHICLE

Figure 34. dSPACE Midsize Simulator (left); Vector VN8910A (right)

The dSPACE DS1006 processor based Mid-Size simulator in the EC3 garage is made up of a DS2202 I/O board, which is a low cost alternative to the standard DS2211 I/O board mentioned in most of the technical documents. Though there are minor differences between the two I/O boards, the DS2202 is sufficient for the testing activities performed by the team.

Vector VN8910 (with four CAN piggyback modules): This is a CAN measurement device with standalone operation capability. The HSC uses four different CAN buses to communicate with the real vehicle. The WSU EcoCAR3 team’s HIL simulator has only two CAN terminals. The VN8910A is used to gateway messages from the one CAN terminal of dSPACE to two CAN terminals of the HSC.

ControlDesk and AutomationDesk were used to configure and load the plant model to the dSPACE midsize HIL simulator. Vector CANoe is used to setup the VN8910A gateway and measurement configuration successfully. Screenshots of the software configuration windows can be found in the Appendix.

7.3 HIL SETUP CHALLENGES

The main challenges faced with the HIL setup are managing signal latency, message ID conflict issues and bandwidth limitation issues while gatewaying messages from the CAN2 bus output of dSPACE to the three CAN buses of the ETAS module using the Vector VN8910A interface module. To reduce signal latency and increase the bandwidth, the baud rate of the EBHVAD_CAN bus is increased to 1000kb/s. This way the messages are transmitted in almost half the time to the Vector module and since most of the messages are cyclic, the bus offered sufficient bandwidth for transmission of triggered DTC messages. Figure 32 shows a schematic layout of the current HIL setup, whereas the shows a detailed wiring diagram of our HIL setup, which will be used once more functionalities are added to the current model.

Message ID conflicts which occurred due to queuing messages from two CAN channels through EBHVAD_CAN are dealt by simulating the conflicting messages under different IDs in EBHVAD_CAN and then gatewaying them with the respective original message IDs in the EB_CAN and HV_CAN respectively. For example, the HSC transmits messages with the same ID 0x3A6 on both EB_CAN as well as HV_CAN. One of these two conflicting messages with the same ID is transmitted as 0x78E while merging the two CAN channels on the EBHVAD_CAN, in order to avoid ID conflicts. ADAS_CAN is not configured at this point, but a CAN port on the Vector module is allocated to add it in the future.

7.3 MODEL PORTABILITY

MIL, SIL and HIL portability is an important aspect of any vehicle plant model that is intended for use in software development. Simple factors such as model signal names, data type conversions could matter a lot when changing platforms. The thesis model is developed such that the model can be easily transferred between MIL and HIL platforms. Since version control systems are not used by the team, the model has to be updated manually and hence specific instructions are given to the team members on updating the model. If a new signal is added the signal is added in HIL first and transferred to the MIL model. New functionalities are added in MIL tested before transferring to HIL. This way the model is made consistent across all platforms.

7.4 HSC DIAGNOSTICS TESTING IN HIL

The HIL system has been used extensively for testing the HSC functionality for several possible fault scenarios that were identified through DFMEA. Once the appropriate fault is inserted the Supervisory Controller's performance has been validated in MIL environment, the model is transferred to the HIL platform. The HSC software is then flashed in the ETAS and the plant model is compiled and loaded on the dSPACE and the fault insertion control variables are controlled through INCA.

7.4.1 COMMON FAULT SCENARIOS

The fault scenarios tested in HIL can be broadly classified into:

1) Signal out of range fault: When the input signal is not in the logical range. This can occur due to two reasons: 1) if there is a fault in the wiring, the external noise can produce such issues, 2) if the component producing the signal is

malfunctioning. Example: pedal position out of range fault, shift lever position out of range fault,

2) Signal redundancy check fault: For critical inputs from driver such as accelerator pedal position, two sensors are used for redundancy checks. The signal redundancy check is essential in order to see if the sensor wired to the HSC is functioning properly.
3) Signal over limit fault: When the component signals are over the recommended limits. This may be similar to out of range faults, except for the fact that the range here is defined based on engineering knowledge and manufacturer recommendation. Example: over voltage fault, over current fault, over temperature fault, over speed fault and high voltage battery ground fault detection.
4) Command and feedback mismatch fault: When a HSC request or command is not acknowledged by the respective component. Example: Motor Torque mismatch and Engine Torque Mismatch

These faults can occur due to multiple reasons. However the HIL system should be capable of producing these faults in order to sufficiently test the Hybrid Supervisory Controller functionalities under these scenarios.

7.4.2 FAULT INSERTION IN HIL

There are two ways to insert fault in the current HIL setup: 1) Hardware fault insertion through the Fault Insertion Unit provided on the dSPACE HIL system and 2) Model fault insertion using the fault insertion variables as done during MIL testing. The choice of fault insertion method depends on the test performed. Model based fault insertion has been used extensively and it is sufficient for testing the fault scenarios tested by the team.

7.4.3 HSC DIAGNOSTICS HIL VALIDATION RESULTS

Below are the HIL testing results for over voltage fault detection and mitigation functionality of the Hybrid Supervisory Controller.

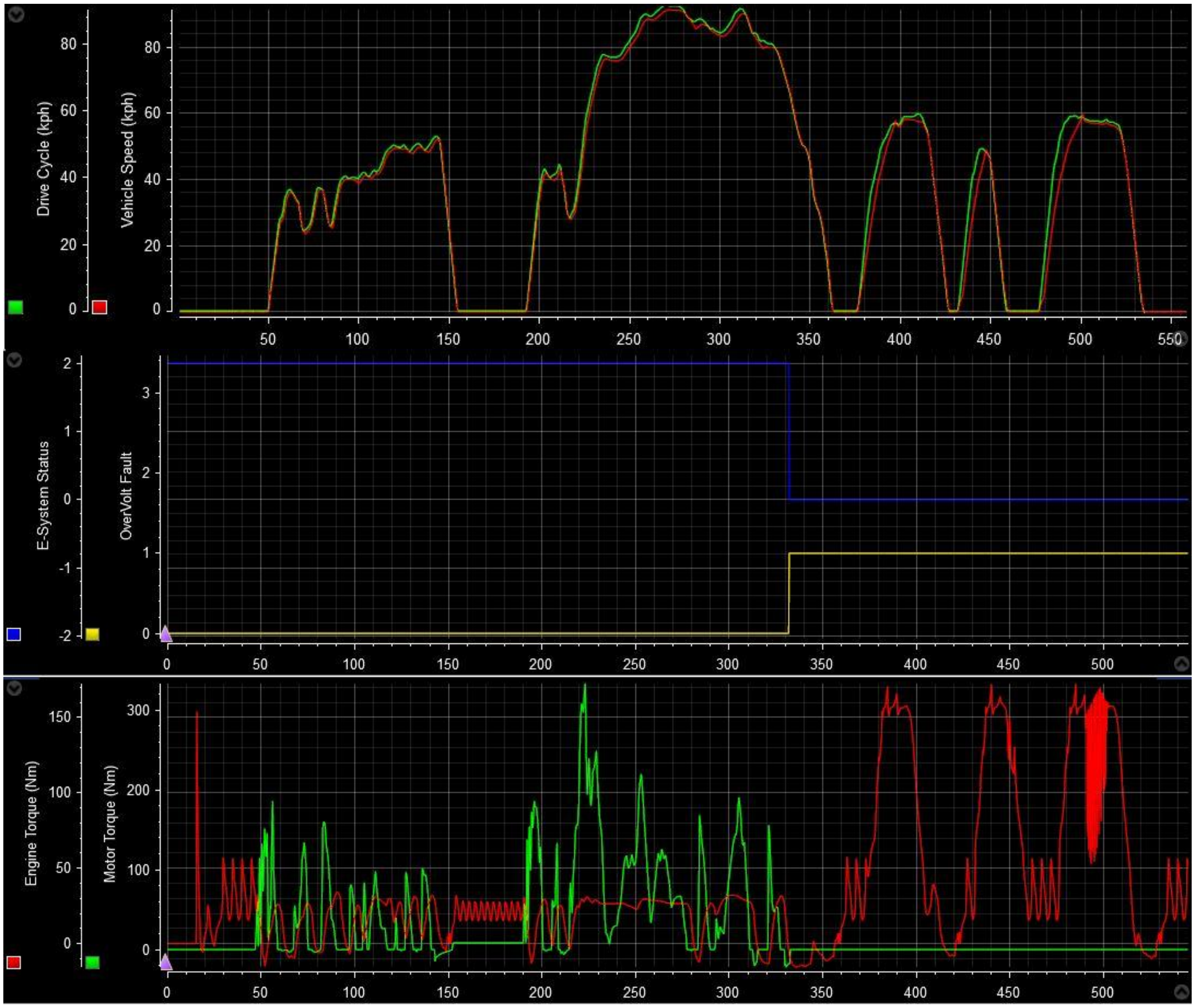

Figure 35. HSC over volt fault diagnostics testing in HIL

The fault was inserted in the voltage output signal from the energy storage system model using a fault insertion block. The fault values are set in HIL model using Simulink and when the model is compiled and loaded on to ETAS the fault is triggered at a preset time as modeled in the fault insertion lookup table. In this case the fault is inserted at approximately 340sec from the start of the simulation. The fault can be inserted manually using a variable in the ControlDesk environment too, but the former method is preferred as it is easier for automation.

The current HSC mitigation strategy for over volt fault detection is to turn off the high voltage system, which means the electric machine will not be functional anymore. It is clear from the plot that the electric system status (E System Status) switches to zero as soon as the Over-volt fault is detected. Therefore the HSC switches from the Hybrid Charge Depleting mode of operation to Engine-only safe mode in order to ensure safety. There are three levels of over volt fault and this is just the result of lowest level of fault, wherein the battery voltage is within limits for safe operation of the battery, but the voltage is higher than the recommended MCU input voltage. More HSC diagnostic functionalities have been tested and some of these test results can be found in the Appendix.

7.5 E and EC DRIVE CYCLE HIL TESTING RESULTS

The table and figure 36 below shows the screenshot of the E and EC drive cycle HIL simulation results recorded using ControlDesk software.

Table 3. E and EC HIL Simulation Results

Vehicle Electric Energy Consumption, CD mode	207.36 Wh/km
Vehicle Fuel Energy Consumption, CD mode	329.15 Wh/km
Vehicle Fuel Energy Consumption, CS mode	775.9Wh/km

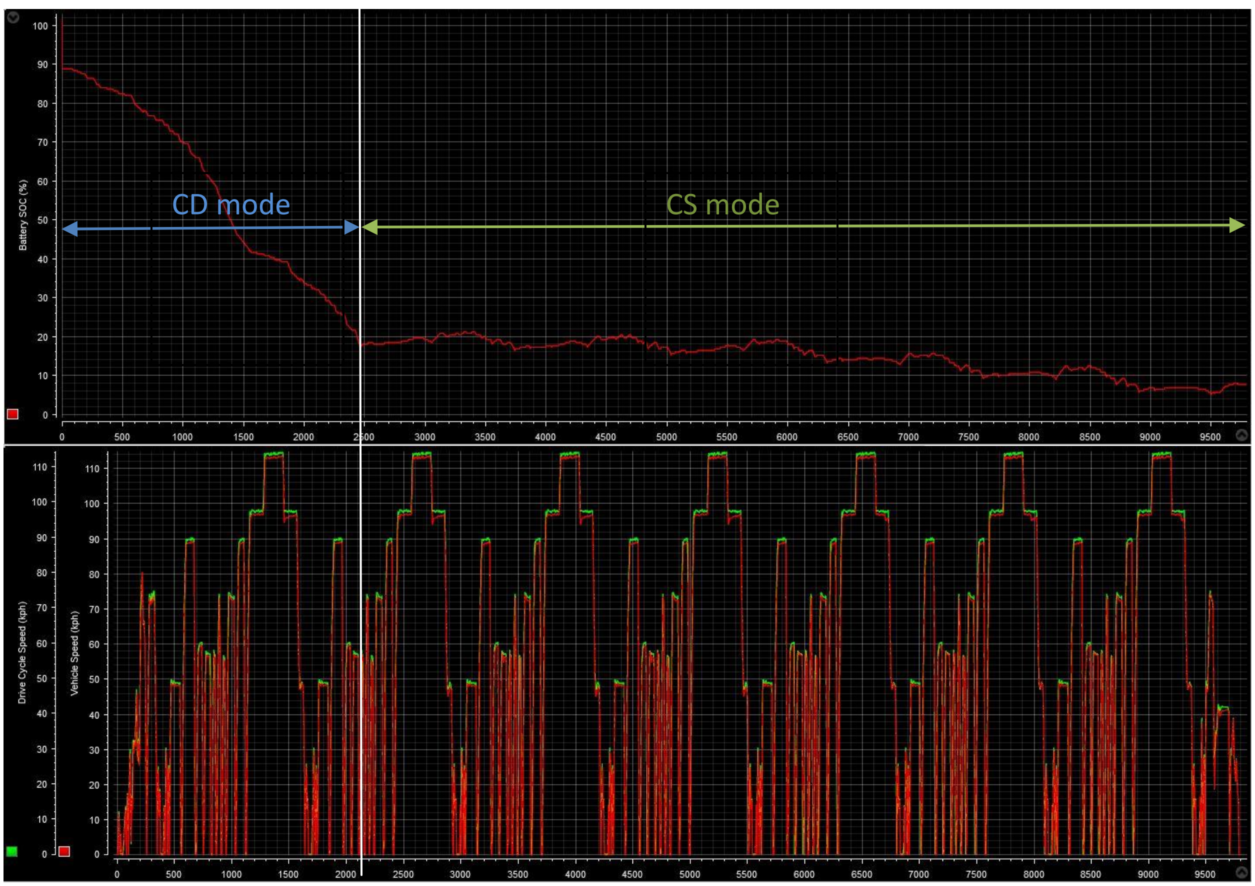

Figure 36. E and EC HIL simulation results

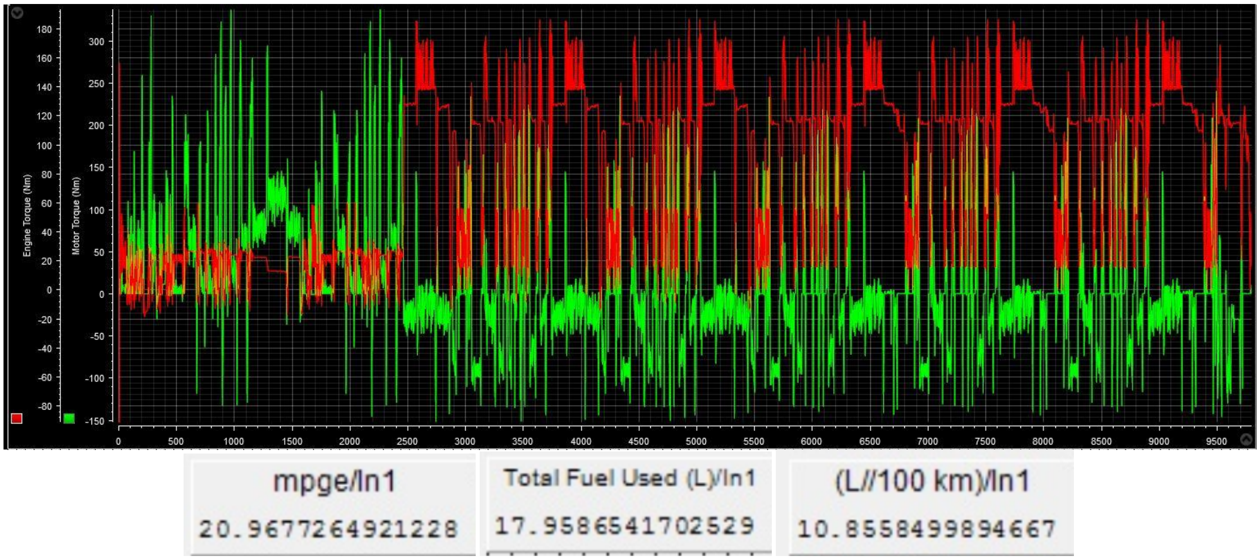

Figure 37. E and EC HIL simulation results

Though the same models were used in both SIL and HIL simulations, it can be seen that the Battery SOC keeps dropping even in the Charge Sustaining mode. This behavior was not noticed in SIL and might be because of the CAN signal latency. This is being investigated and will be resolved in the future. However, this issue unraveled a flaw in the controls code, which helped us fix it before going to the final competition. The Hybrid Supervisory Controller functionality to prevent battery discharge beyond 15% was not modeled correctly. It was never noticed in MIL or SIL environments as this issue never happened in those platforms. However in HIL after this issue happened the software has been revised to account for this scenario.

CHAPTER 8 RECOMMENDATIONS BASED ON RESEARCH

8.1 CHARGE AND DISCHARGE CURRENT LIMITS (SOFT BMS)

Due to the lack of information on the battery pack behavior, the current model does not contain accurate charge and discharge limits map. These are important in order to simulate the BMS behavior while driving. Without enough details any hybrid strategy that is developed based on these maps is unreliable. The hybrid supervisory controller has been programmed to stay within the limits sent through the CAN signals from the battery pack. In the real world if these limits are crossed, the BMS will open contactors in order to prevent damage. Without having a better idea of these charge and discharge maps, model based controls optimization is impossible. The results of a controls code developed based on assumed values may differ significantly from real world testing results.

8.2 DYNAMIC ACCESSORY MODELS

Accessory loads include cooling pump, AC compressor, component ECUs and other stock vehicle electrical and electronic components that draw power from the 12V battery. [12] shows that accessory loads contribute to a significant part of the energy consumed in a HEV. Therefore model accuracy will significantly improve the Energy consumption prediction of the model. Since on-road test data with the current thermal loops and accessories was not available until recently, the accessory load models have been assumed to consume constant power irrespective of the operating mode and the cooling required. In the future more data will be available from test drive at the GM's Milford Proving Ground, which can be used to develop and optimize a dynamic accessory load model. Map based models offer sufficient fidelity for cooling pumps, AC compressor and the Inverter.

8.3 SIMULATION STEP SIZE

The finalized code was tested with the same drive cycle, application and hardware settings, but different solver configuration settings. Different Simulink solvers and time steps are tested and the ODE1 solver with the fixed step size of 0.01sec is found to be fast and accurate for simulating the thesis plant model.

8.4 EMISSIONS SIMULATION VALIDATION

The combined score for reducing criteria tailpipe emissions and well-to-wheel greenhouse gas emissions has the highest impact in the emissions and energy consumption event of EcoCAR3. However, there is no way to measure or validate the emissions simulation accuracy before going to the final competition. Therefore it is recommended that in the future team members may use the data from the year final competition to validate this part.

8.5 TRANSMISSION CAN BASED SHIFTING MODEL

As per the manufacturers, the donated TCM is capable shifting when commanded using a specific set of CAN signals which are provided by the manufacturers. However, this functionality has not been realized to this day. Therefore the exact mechanism of CAN based shifting is still not known. This is essential for controlling the shift pattern in order to tap the maximum efficiency from the hybrid powertrain. Therefore it is recommended that this be studied thoroughly and implemented in the future models.

8.6 ECM TORQUE REQUEST MODEL

The Torque request model is needed in order to realize direct torque control of the engine. However, more details and testing is needed in order to develop a better model. Without sufficient details the model functionality developed is meaningless. Future teams may work towards realizing this functionality of the Engine Control Module. This is also essential for the hybrid electric vehicle control strategy development.

8.7 REGRESSION TESTING SETUP

Currently the model has reached a decent level of maturity and the diagnostics will be tested in the vehicle soon. It is recommended that the AutomationDesk for regression testing be setup for the critical diagnostic functionalities of the HSC. It is estimated that the majority of time in year 4 will be spent on software calibration and testing. Therefore automating processes such as HIL testing will be beneficial.

CHAPTER 9 CONCLUSION

In this thesis the advancement and validation of the Pre-transmission Parallel Plug-In Hybrid Electric Vehicle model for sufficiently testing the Hybrid Supervisory Controller's energy management and diagnostic functionalities has been discussed. Model fidelity and accuracy requirements were judged based on the test requirements and the necessary improvements are made. The new model is then validated by comparing the simulated results with the results from real world test drive data. The HIL setup and testing activities are also discussed in detail, which was a major development during year 3. Based on the research, recommendations have been made to the future team members in order to add more functionality to the existing model and facilitate better controls testing.

REFERENCES

1) Kumar, S., West, M., Conter, J., Cawley, M., Maady, R., & Mayyas, A. (2015). Vehicle plant model and supervisory control development for a parallel pre-trans plug-in hybrid electric Vehicle. IFAC-PapersOnLine, 28(15), 139-146. DOI: 10.1016/j.ifacol.2015.10.020

2) Ward J., Jason, 2015, “Modeling and Simulating a Performance Hybrid Electric Vehicle,” M.S. thesis, The Ohio State University, Ohio, USA.

3) Marquez, E., “Model and Control System Development For a Plug-In Parallel Hybrid Electric Vehicle,” 2015, The Virginia Polytechnic Institute and State University, Virginia, USA.

4) Lord, N., “Simulation Tools for Predicting Energy Consumption and Range of Electric Two-wheelers”, M.S. thesis, 2016, The Ohio State University, Ohio, USA.

5) Hofman, T., van Leeuwen, D. and Steinbuch, M. (2011) ‘Analysis of modelling and simulation methodologies for vehicular propulsion systems’, Int. J. Powertrains, Vol. 1, No. 2, pp.117–136.

6) Hendricks, E. and Sorenson, S., "Mean Value Modelling of Spark Ignition Engines," SAE Technical Paper 900616, 1990, doi:10.4271/900616.

7) Onori, S., Serrao, L., Rizzoni, G., “Hybrid Electric Vehicles, Energy Management Strategies”, Springer-Verlag London, 2016, doi: 10.1007/978-1-4471-6781-5, pp. 19-21.

8) He, H.; Xiong, R.; Fan, J. Evaluation of Lithium-Ion Battery Equivalent Circuit Models for State of Charge Estimation by an Experimental Approach. *Energies* 2011, *4*, 582-598.

9) Wilhelm, T., Okuda, H., Levedahl, B., Suzuki, T., "Energy Consumption Evaluation Based on a Personalized Driver-Vehicle Model", IEEE Transactions On Intelligent Transportation Systems, 2016, doi: 10.1109/TITS.2016.2608381.

10) Hendricks, E., Chevalier, A., Jensen, M., Sorenson, S. et al., "Modelling of the Intake Manifold Filling Dynamics," SAE Technical Paper 960037, 1996, doi:10.4271/960037.

11) Mean-Value Internal Combustion Engine Model with MapleSim: www.maplesoft.com/view.aspx?SF=35158/0/Maplesim_mean_valu.pdf, Accessed on: 5/3/2017.

12) Badin, F., Le Berr, F., Briki, H., Dabadie, J-C., Petit, M., Magand, S., Condemine, E., "Evaluation of EVs energy consumption influencing factors, driving conditions, auxiliaries use, driver's aggressiveness", Electric Vehicle Symposium and Exhibition (EVS27), 2013, Barcelona, Spain.

13) Arnett, M., "Modeling and Simulation of a Hybrid Electric Vehicle for the Challenge X Competition", 2005, The Ohio State University, Columbus, Ohio, USA.

14) Snyder, L., K., "Advancement And Validation Of A Plug-In Hybrid Electric Vehicle Model Utilizing Experimental Data From Vehicle Testing", M.S. Thesis, 2015, Wayne State University, Detroit, Michigan, USA.

15) Gao, W., D., Mi, C., Emadi, A., "Modeling and Simulation of Electric and Hybrid Vehicles", Proceedings of the IEEE, Vol. 95, No. 4, April, 2007, doi: 10.1109/JPROC.2006.890127.

16)Pukrushpan, T., J., Peng, H., Stefanpoulou, G., A., "Control-Oriented Modeling and Analysis for Automotive Fuel Cell Systems", Transactions of ASME, Vol. 126, March 2004, doi: 10.1115/1.1648308.

17)Wei, X., "MODELING AND CONTROL OF A HYBRID ELECTRIC DRIVETRAIN FOR OPTIMUM FUEL ECONOMY, PERFORMANCE AND DRIVEABILITY", Dissertation, 2004, The Ohio State University, Ohio, USA.

18)Schwager, L., Tüysüz, A., Zwyssig, C., Kolar, W., J., "Modeling and Comparison of Machine and Converter Losses for PWM and PAM in High-Speed Drives", IEEE Transactions on Industry Applications, Vol. 50, No. 2, pp. 995-1006, 2014, doi: 10.1109/TIA.2013.2272711.

19)Mapelli, L., F., Tarsitano, D., Mauri, M., "Plug-In Hybrid Electric Vehicle: Modeling, Prototype Realization, and Inverter Losses Reduction Analysis", IEEE Transactions On Industrial Electronics, Vol.57, No.2, 2010, doi: 10.1109/TIE.2009.2029520.

20)Schlegel, C., Hösl, A., Diel, S., "Detailed Loss Modeling of Vehicle Gearboxes", Proceedings 7th Modelica Conference, Sep. 20-22, 2009 Como, Italy.

21)Ni, D., Henclewood, D., "Simple Engine Models for VII-Enabled In-Vehicle Applications", 2007, University of Massachusetts, Amherst, Massachusetts, USA.

22) Shankar, R., Marco, J., Assadian, F., "The Novel Application of Optimization and Charge Blended Energy Management Control for Component Downsizing within a Plug-in Hybrid Electric Vehicle", Energies, 2012, 5, 4892-4923; doi:10.3390/en5124892

23) Wang, J., Besselink, I. J. M., & Nijmeijer, H. (2015). Electric vehicle energy consumption modelling and prediction based on road information. 1-12. Paper presented at 28th International Electric Vehicle Symposium and Exhibition (EVS 28), May 3-6, 2015, Goyang, Korea , Goyang, Korea, Republic of.

24) Horrein, L., Bouscayrol, A., Delarue, P., Verhille N., J., Mayet, C., “Forward and Backward simulations of a power propulsion system”, L2EP, Universite Lille, France.

25) Gao, Y., Ehsani, M., “Hybrid Electric Vehicle: Overview and State of the Art”, IEEE International Symposium on Industrial Electronics, 2005, Dubrovnik, Canada.

APPENDIX

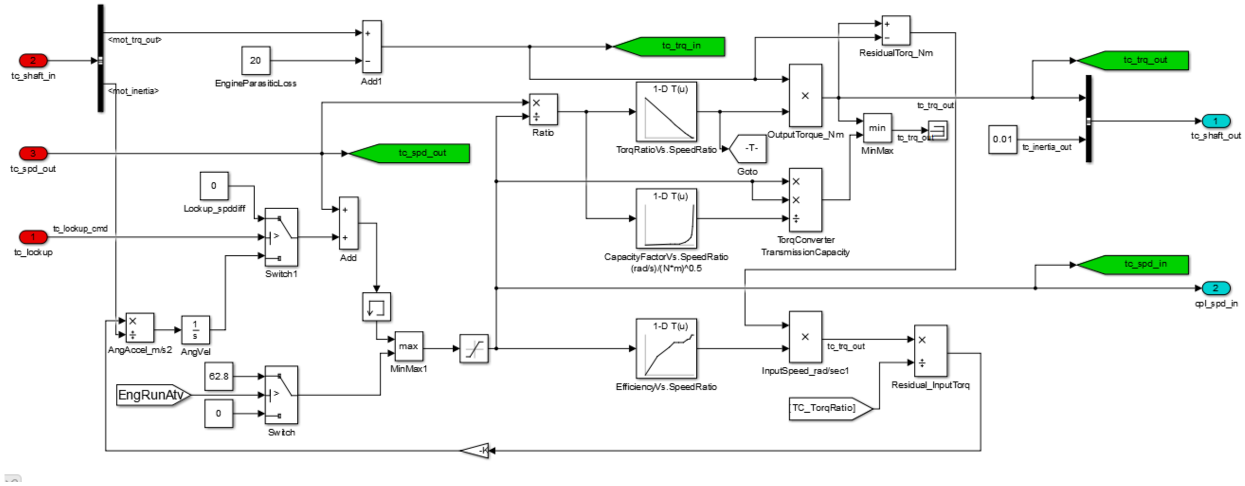

Figure 38. New torque converter model

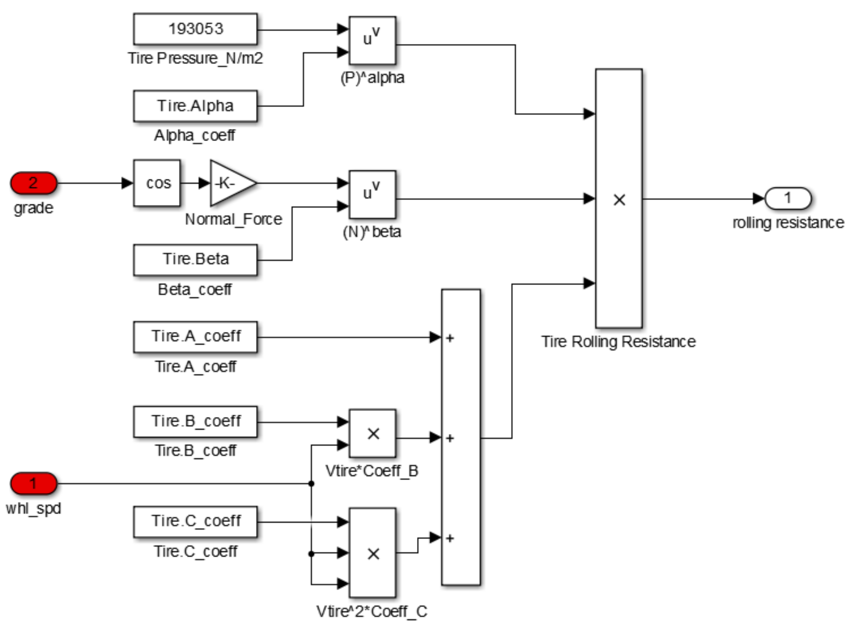

Figure 39. New tire rolling resistance model

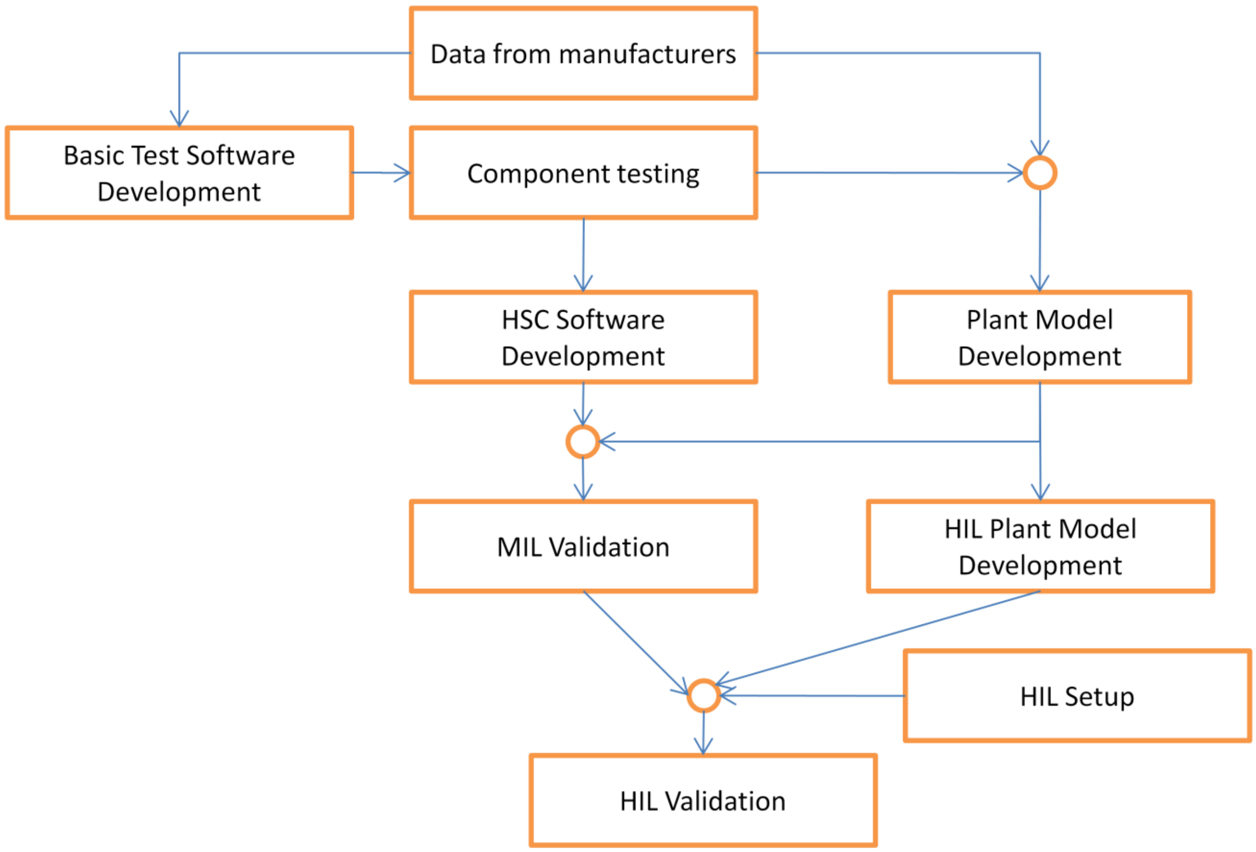

Figure 40. Detailed MIL and HIL testing work plan

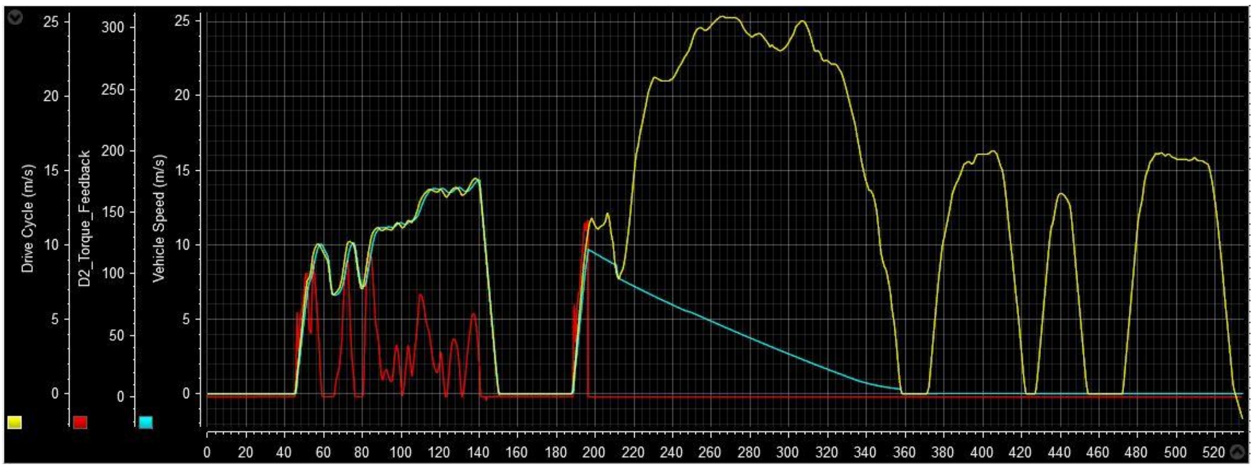

Figure 41. HSC APP mismatch diagnostics testing results in HIL

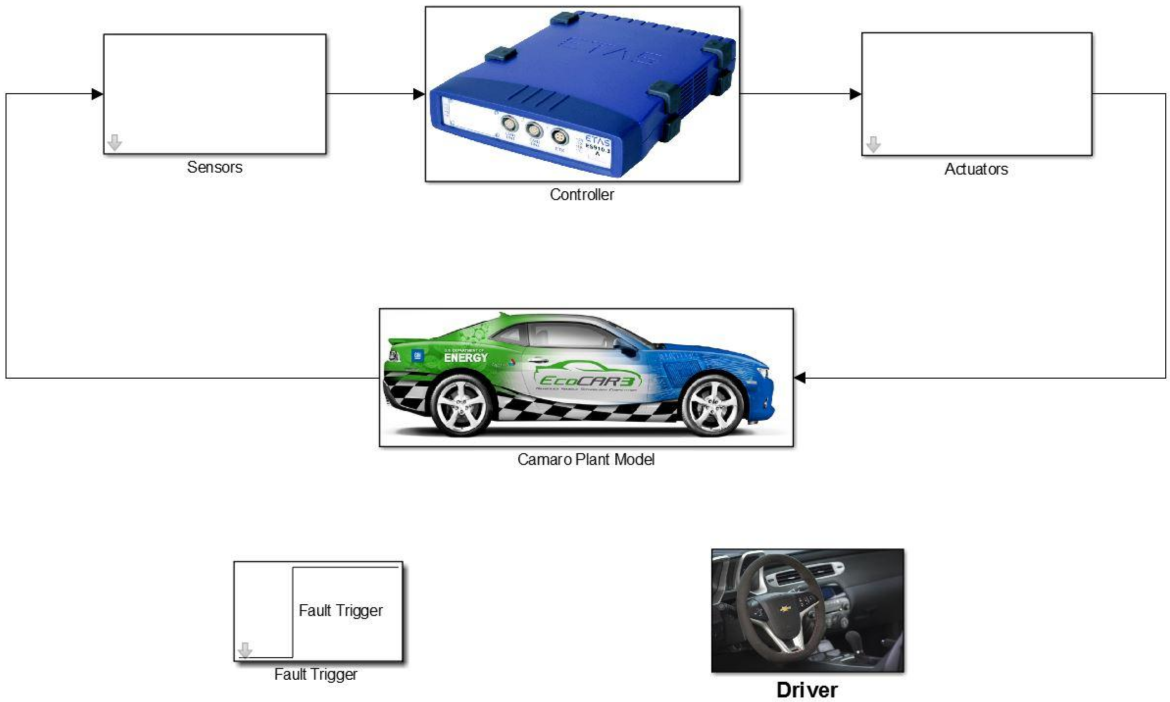

Figure 42. Thesis MIL model

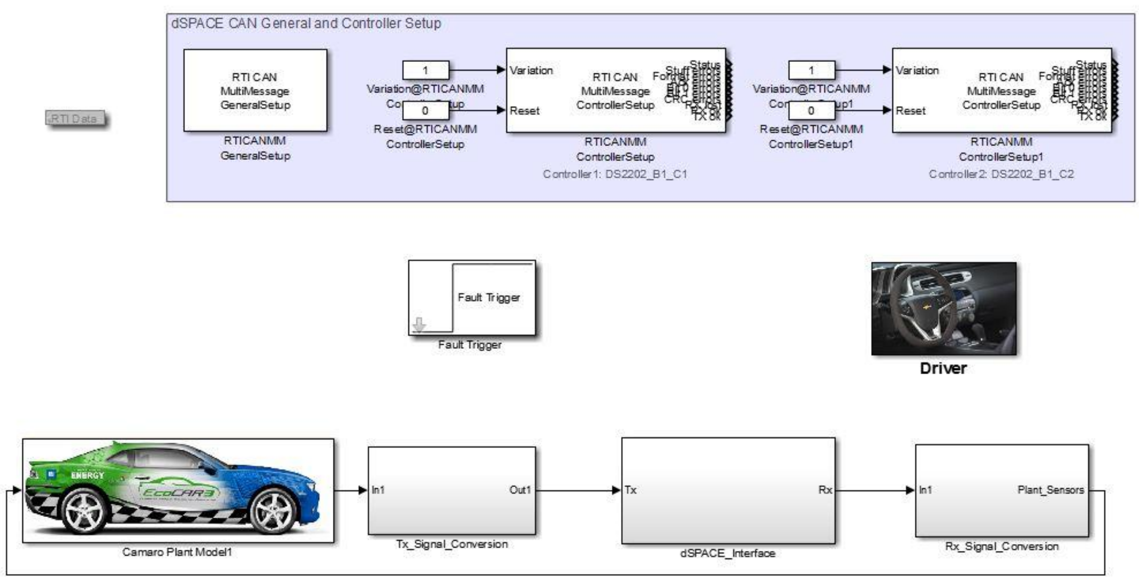

Figure 43. Thesis HIL vehicle model

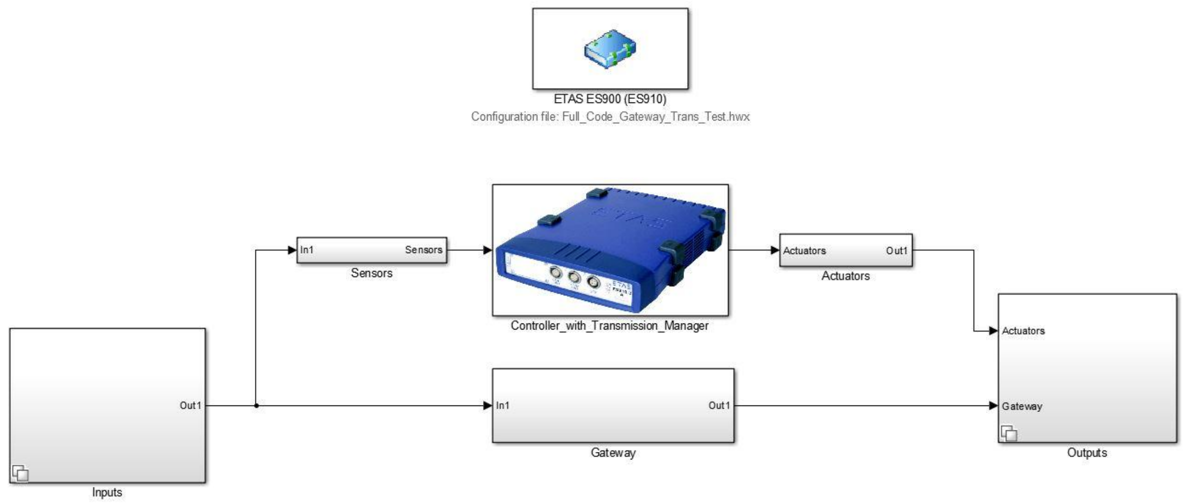

Figure 44. HSC software model for HIL testing

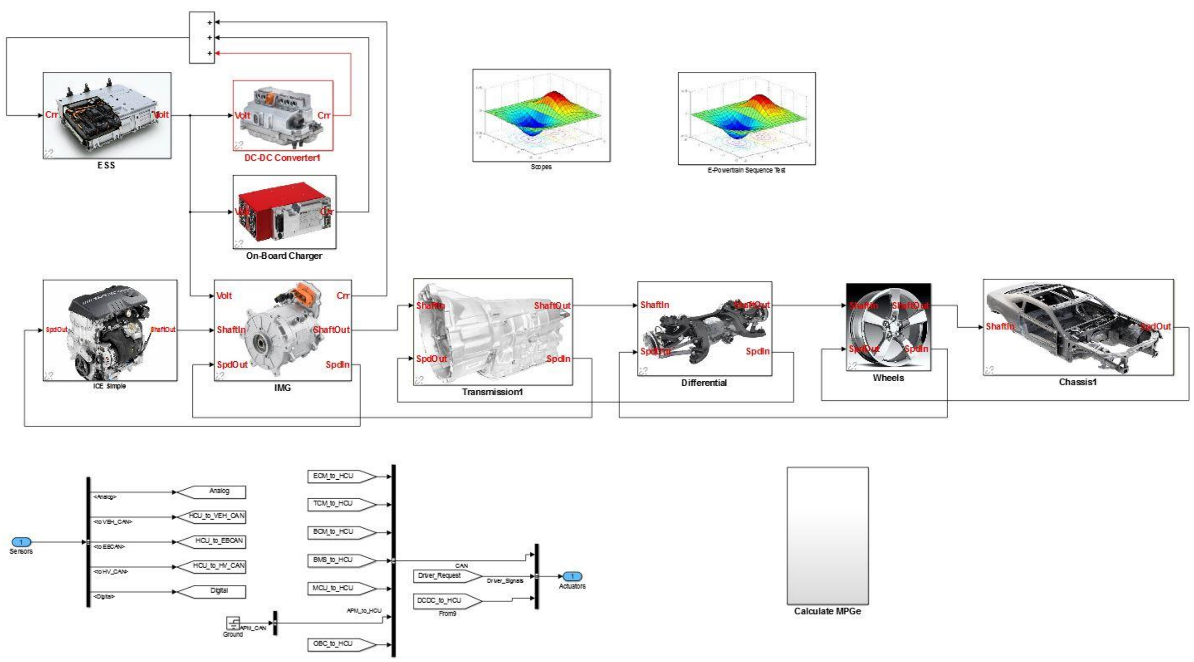

Figure 45. Inside the new plant model

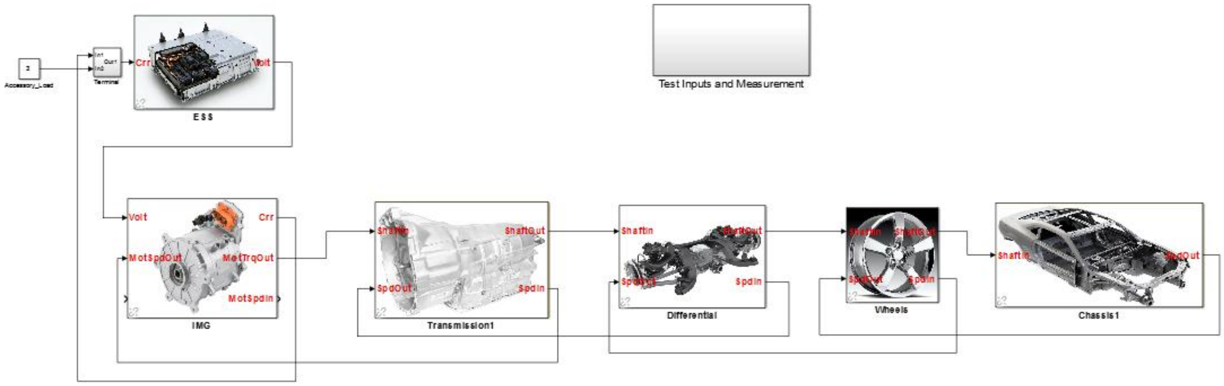

Figure 46. Electric powertrain test bench

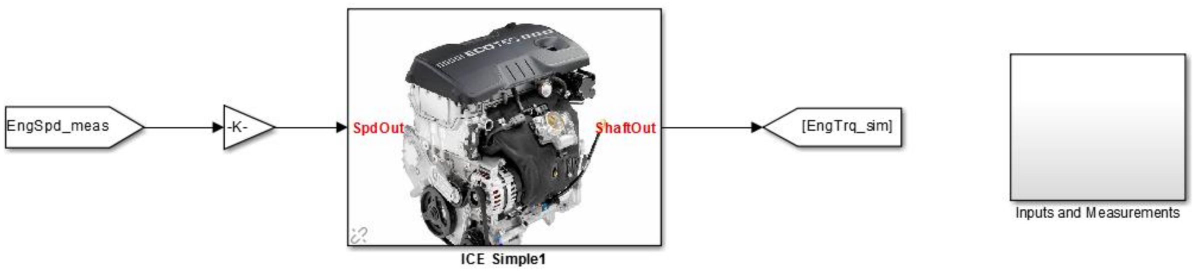

Figure 47. IC Engine test bench

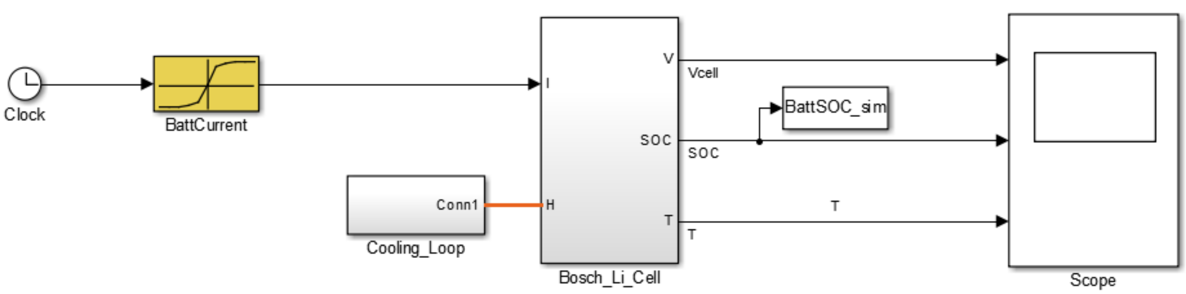

Figure 48. Energy Storage System(ESS) single Li-ion cell test bench

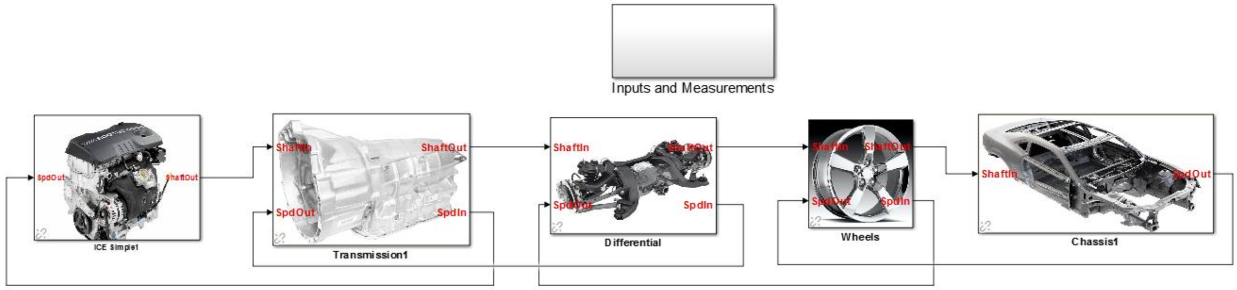

Figure 49. Stock powertrain test bench

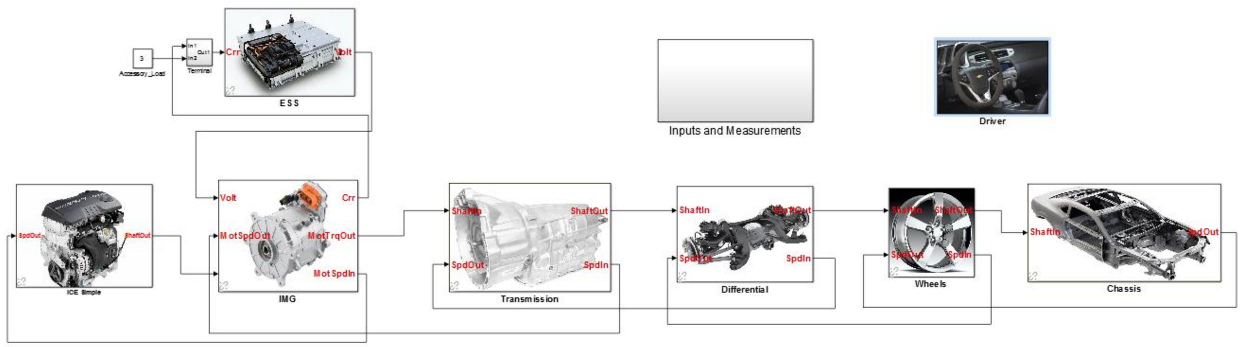

Figure 50. Full vehicle model test bench

ABSTRACT

MODEL ADVANCEMENT AND HIL SETUP FOR TESTING A P2 PHEV SUPERVISORY CONTROLLER

by

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May 2017

Advisor: Dr. Jerry Ku

Major: Mechanical Engineering

Degree: Master of Science

Teams participating in Advanced Vehicle Technology Competitions such as EcoCAR3 are often bound by limited time and resources. Moreover, vehicle and component downtime due to mechanical and electrical issues reduce the time available for testing activities demanded by the Controls/Systems Modeling and Simulation teams. Therefore, the teams would benefit from identifying new approaches and being more pragmatic and productive in order to achieve satisfactory progress in the competition. This thesis summarizes the approach taken to improve the simulation accuracy of the Wayne State University EcoCAR3 team's Pre-transmission Parallel Hybrid Electric Vehicle plant model and HIL setup. Focus is on testing the Hybrid Supervisory Controller energy management and diagnostic functionality to be successful in the emissions and energy consumption event. After thorough literature research it is determined that a varying fidelity forward dynamic HEV plant model can produce accurate energy consumption simulation results. Initially, data obtained from

manufacturers is used to model the components such as IC Engine, Electric Machine, Energy Storage System (ESS), transmission, differential, chassis and the ECUs. Later, test benches are setup to optimize and refine the individual model parameters by comparing the simulated results with the actual results obtained from component testing and on-road vehicle testing. Finally, the total vehicle plant model is validated by comparing the simulated results with the P2 PHEV on-road test data. The accuracy of the plant model determines the ability to optimize the Hybrid Supervisory Controller code to achieve maximum energy efficiency. Apart from model accuracy improvement, the Hardware In Loop (HIL) test setup is also discussed. HIL system is essential for validating the Hybrid Supervisory Controller's functionalities in real time. The challenges during modeling and HIL setup are discussed and more improvements that can be done during the final year are recommended based on the research.

AUTOBIOGRAPHICAL STATEMENT

Sajjan Balakrishnan is currently pursuing his graduate studies in Mechanical Engineering at Wayne State University. He has a Bachelors degree in Mechatronics Engineering from Anna University, India.

Sajjan was the Wayne State University EcoCAR3 team's Systems Modeling and Simulation Co-Lead during the year 3 competition. He also has professional experience as a Mechanical Design Engineer and developed several industrial automation solutions for diverse applications. He is interested in product development, mechanical design, systems modeling and simulation and controls development.