Modelling of Chevy Volt Gen II Supervisory Controller in Charge-Sustaining Mode

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Abstract: In this paper, the modeling and validation process for the powertrain supervisory controller of Chevy Volt Gen II for charge sustaining operation is presented. To this end, three models are developed, including a control-oriented driver model, an artificial neural network (ANN) model to replicate vehicle mode selection, and a torque distribution model to determine torque allocation for electric motors and internal combustion (IC) engine for each operating mode of the vehicle. The developed models are based on experimental studies using data from vehicle operation for different drive cycles as well as real-world data of Chevy Volt driving at Michigan Technological University for different driving styles for different levels of aggressive driving behaviour. The results show that the ANN model can predict the vehicle operating mode with 99.3% accuracy. In addition, the validation results of the combined models for two US federal test procedures (FTP), namely UDDS and US06 drive cycles demonstrate that the overall model predicts the net energy consumption of the vehicle within 5% of the experimental data.

Keywords — Vehicle Supervisory Control, Hybrid Electric Vehicle, Torque Distribution, Neural Network Modeling

1-Introduction

The number of light-duty hybrid electric vehicles (HEVs), alternative fuel vehicles (AFVs), and diesel models offered by vehicle manufacturers in the US has almost tripled from 2010 (73 models) to 2019 (218 models) [1]. In particular, during the same period, the number of HEV models offered has increased more than 60 times [1]. This increase in model offerings necessitates extensive research and development (R&D) effort and investment by the automotive original equipment manufacturers (OEMs). This demands for model-based design and validation of HEVs to minimize development time and cost, while constantly improving vehicle performance. To this end, model-in-the-loop (MIL), software-in-the-loop (SIL), and hardware-in-the-loop (HIL) efforts are ever-increasing in the design of HEVs to minimize efforts in vehicle verification and validation (V&V) cycle. On related efforts at Michigan Technological University, our research team aims to reduce Chevy Volt Gen II (MY2017) vehicle energy consumption using vehicle-to-everything (V2X) connected data, and integrated powertrain and vehicle dynamics (PT&VD) controls. This is part of the NEXTCAR (Next-Generation Energy Technologies for Connected and Automated On-Road Vehicles) project sponsored by the U.S. Department of Energy (DOE). Table 1 shows general specification of Chevy Volt.

Table 1: Chevy Volt Gen II specifications

Parameters	Values
Engine type	1.5 L I-4 Ecotec engine, direct injection
Engine peak torque/power	140 Nm / 75 kW
Motor/Generator A (MGA) type	Distributed bar wound, Ferrite magnet
MGA unit peak torque/power	118 Nm / 48 kW
Motor/Generator B (MGB) type	Distributed bar wound, NdFeB magnet
MGB peak torque/power	280 Nm / 87 kW
Battery type	Li-ion, 2 parallel 96 series configuration
Battery Energy / peak capacity	18.4 kW-hr / 52 Ah
EV range	53 miles
Extended range	420 miles
Curb weight	160 kg
0-60 mph	8.4 seconds
Top speed	98 mph
Fuel economy	42 MPG / 106 MPGe (combined)

This paper presents part of the modelling efforts to develop a model to represent vehicle supervisory controller (SC); thus, proper MIL, and HIL platforms can be developed to assess our designed VD&PT control strategies in comparison to the baseline vehicle controller. In addition, the SC has become part of our NEXTCAR evaluation platform to develop control strategies for optimum vehicle speed profiling and platooning to determine vehicle energy consumption.

SCs are high-level controllers of a vehicle which for a given driving profile, decide on the power split between the Internal Combustion Engine (ICE) and the battery-electric-motor-generator operation to achieve optimal performance, including a trade-off between energy usage, requested speed profile tracking error, and drivability of the vehicle [3]. SCs are tasked with mode-selection, torque distribution, and making the connection between the driver and the powertrain. In general, HEVs bear with themselves more complex engineering systems than conventional vehicles due to an increased number of power sources. Therefore the SC modelling for HEVs is more complicated than conventional vehicles. One such complication is controlling the torque distribution among different power sources available based on the power request. For the Chevy Volt Gen II, the power sources are ICE, electric motor A (MGA) and electric motor B (MGB) which exchange energy with the vehicle battery. This vehicle has five operating modes including two charge depletion (CD) modes (EV1 and EV2), and three charge sustaining (CS) modes namely low extended range (LER), fixed gear (FG) and high extended range (HER) that will be discussed later in the paper. The SC selects the vehicle operating mode to achieve the best energy conversion efficiency while meeting drivability, emissions, noise vibration, and harshness (NVH) constraints.

There are few studies in literature describing the Chevy Volt Gen II SC structure in charge-sustaining mode. Conlon, B. et. al. [4] described the Voltec powertrain performance and efficiencies as well as the drive modes. The CS and CD operation logics were analyzed and the resulting data was used in our work for VS&PT model development. Kim, N. et. al. [5, 6] developed the Voltec powertrain model and studied vehicle performance under different operating conditions. They investigated key vehicle features at CS mode of operation. In [7], authors propose an adaptive supervisory controller, based on Pontryagin's Minimum Principle (PMP), for on-line energy management optimization of Chevy Volt Gen II. Using minimum driving information, such as the total trip length and the average cycle speed, the proposed algorithm depends on the parameter adaptation from SOC feedback. In [8], authors present the performance of the SC developed for a parallel HEV, in particular, their method of mode selection using a state machine and a torque distribution module using dynamic equations. For each state (i.e. operating mode) then, a dynamic control strategy associated with that operating mode is discussed to facilitate a smooth transition between modes (no sudden shocks to the prime movers) while satisfying the vehicle power request. Even though in their study, they focus on both CS and CD operation whereas in this study, the focus is on CS operation, the ideas for smooth torque blending is universal to both studies. In [9], which is a survey paper for SC control algorithms of HEVs and PHEVs, the authors classify different control algorithms for from parallel, series, and power split HEVs and PHEVs. For Chevy Volt Gen II, which is a compound power split, this information was of use.

Although different models are found in the literature to simulate and optimize HEVs, models to represent the SC of “production HEVs” for MIL and HIL applications are rarely discussed in the literature. This paper aims to address this gap by developing a model that simulates the main SC tasks of a production HEV electronic control unit (ECU) such as mode selection, torque distribution, and driver model development. The SC model is demonstrated for Chevy Volt Gen II, but the same methodology can be utilized for other HEVs.

The paper is organized as follows. Section 2 presents the modelling process step by step; first, we describe the VD&PT model components, then an overview of the SC is presented. Then the five vehicle drive modes are briefly explained and the designed ANN model to replicate the production vehicle SC for mode selection is introduced. Next, torque distribution, friction brake, and driver models are explained. In Section 3, the results of the two FTP drive cycle validations including vehicle velocity tracking error alongside energy consumption prediction errors are discussed. Finally, Section 4 concludes the paper by summarizing the findings from this work.

2-Modeling

Fig. (1) shows the overall model layout for the Chevy Volt Gen II. The model was developed in MATLAB/Simulink environment and the experimental data from Argonne National Laboratory (ANL) was used to validate the final SC model.

The two major subsystems of this model are the HEV SC model and the plant (VD&PT) model. The VD&PT plant model consists of submodels of the three power sources [7, 8], the traction power inverter module (TPIM) [9], battery and the vehicle dynamics. The VD&PT model predicts the vehicle performance in terms of vehicle speed and total energy consumed. The parameters of interest such as battery State of Charge (SOC), vehicle speed and engine speed are fed back to the controller which distributes the torque among three power sources and also controls the amount of friction braking needed during vehicle deceleration. The SC model consists of vehicle drive mode selection and the torque distribution algorithm. A driver model is also developed to make a link between requested vehicle speed and required axle torque.

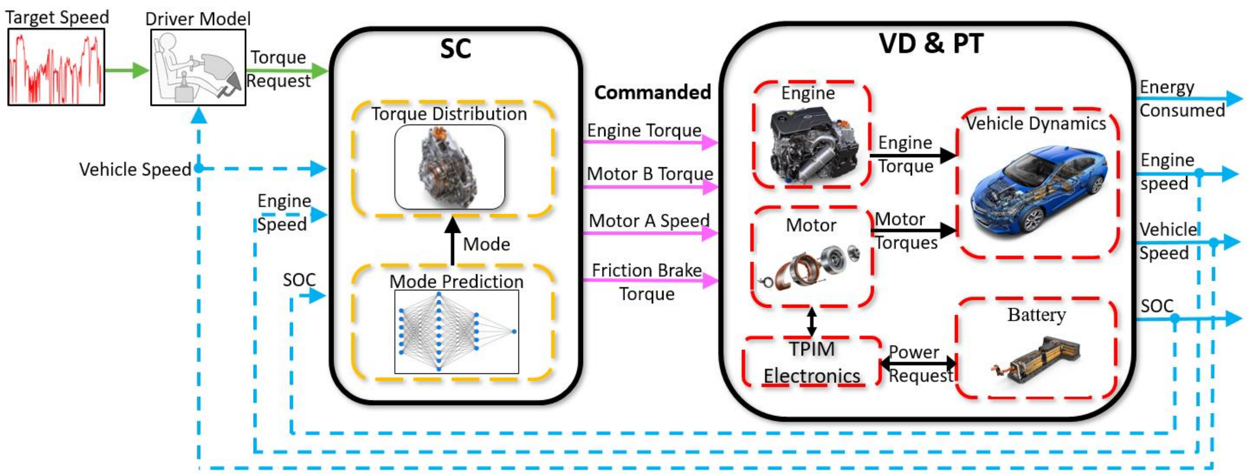

Figure 1: Overview of combined VD&PT and HEV supervisory controller (SC) model for Chevy Volt Gen II

2.1- VD&PT Model

A high-fidelity VD&PT model was developed [10, 11] to predict vehicle energy consumption using the inputs including commanded ICE torque, MGB torque, MGA speed and vehicle drive mode to determine vehicle velocity and energy consumption. Figure (2) shows a schematic of the developed VD&PT model. The torque requests for the ICE and MGB units and the speed request for the MGA unit from the SC are used to calculate the individual component speeds and torques based on kinematical equations for the two planetary gear set arrangement. Once the vehicle torques and speeds are determined, the performance maps are used to determine the overall battery power request for MGA and MGB. The ICE model was developed consisting sub-models of ICE dynamics including rotational and airflow dynamics with other subcomponents such as torque generation and exhaust gas recirculation (EGR) using the performance maps. The MGA and MGB models consist of efficiency maps extracted from [12]. The battery model consists of two circuits, one determining battery capacity and other with a series internal resistance and two RC circuits, encompassing battery thermal and electrical dynamics [11].

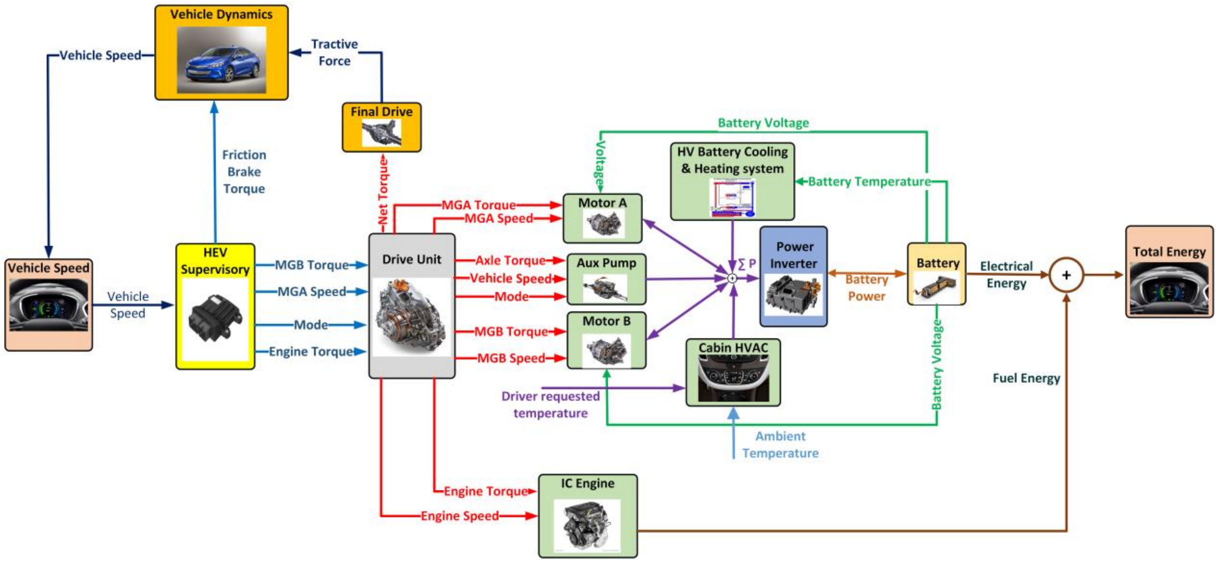

Figure 2: Designed vehicle dynamics and powertrain (VD&PT) model

The TPIM efficiency map was also incorporated to accurately determine electrical energy. In addition, a heating ventilation air conditioning (HVAC) model was created by modelling cabin, heaters, ICE coolant thermal model, compressor, heat exchangers between ICE coolant and the air coming from the cabin vent. The driver's set point temperature is the only input and the HVAC model determines the HVAC energy consumption.

In addition, for each simulation time step, the amount of fuel consumed for the operation is calculated using the developed ICE model. The total electrical energy consumed is calculated using the battery model, resulting in instantaneous energy consumption. Our model considers the fuel penalties associated with the cold start-up and catalyst heating for fast light-off. In order to calculate the net energy consumption, the vehicle plant model requires the inputs from the SC that will be explained in the followings.

2.2- Supervisory Control (SC) Model

Fig. (3) shows the overview of the SC model that determines the required torque and speed inputs to the three power sources, including ICE, MGA, and MGB. There are three major subsystems within this controller. These subsystems include a friction brake model, mode selection model, and torque distribution model.

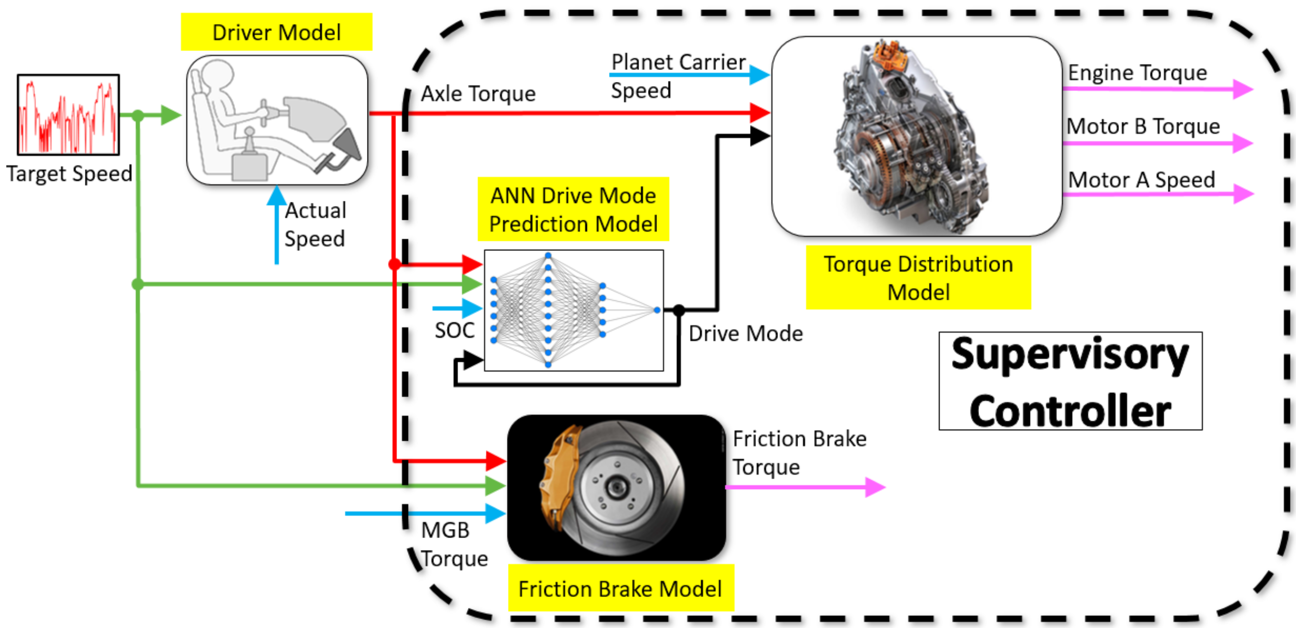

Figure 3: HEV supervisory controller (SC) model developed in this work

The vehicle is able to decelerate the vehicle by using the regenerative braking as well as the conventional friction brakes. The controller modelled here is designed to command braking in such a way that results in the largest recovered energy based on the capacity of MGB and the amount of friction braking depends on the regeneration capacity of MGB unit since MGA is not involved in regenerative braking. The excess energy is dissipated by the friction braking as heat. The generated friction brake torque is then sent to the vehicle dynamics block in the plant model. The other two subsystems, namely, the drive mode selection model and the torque distribution model are discussed in the following subsections.

2.2.1-Vehicle Drive Modes

The Chevy Volt Gen II operates in five drive modes, two EV modes, and three range extender modes. Depending on battery SOC, the vehicle operates as an EV up to 53 miles using the fully charged 18.4 kWh Li-ion battery pack. The range extender modes are in action as soon as the battery SOC drops below 18%. This threshold SOC value also depends on the wheel power at that moment and thus can vary [5]. Fig. (4) shows the schematic of the vehicle drive unit. The ICE and MGA are connected through the planetary gear set 1 (PG1) through ring and sun gears, respectively. A one-way clutch (OWC) is used to engage the engine when the vehicle executes range extender modes. The MGB is placed in connection to the unit through the planetary gear set 2 (PG2) through sun gear. The planet carrier of both sets is attached to the wheels. The three clutches, shown in Figure 4, creates five distinct modes in Volt Gen II.

(a) One motor EV (1EV) mode

Fig. (4)-a shows the 1EV power flow (shown by red lines). This mode is activated at low axle torque loads. To operate this mode, the clutch 2 is closed and clutch 1 is open and the OWC is unloaded; thus, the MGB unit is engaged to drive the vehicle as well as for regeneration.

(b) Two motor EV (2EV) mode

Fig. (4)-b shows the power flow in 2EV operation. This mode is engaged every time the vehicle starts, irrespective of whether the vehicle is in CD or in CS mode. This mode is primarily used at higher loads. Clutch 2 remains closed, the OWC is now engaged to fix the ring gear of (PG1) and thus MGA unit is also used to support the power demands.

(c) Low Extended Range (LER) mode

Fig. (4)-c shows the power flow when the vehicle executes LER mode. This mode is activated when both clutch 1 is open and 2 is closed and the OWC is freewheeling, thus allowing the engine to support power requirements. This mode is the first of the range extender operation and is operated for high loads at speeds up to 60 kph.

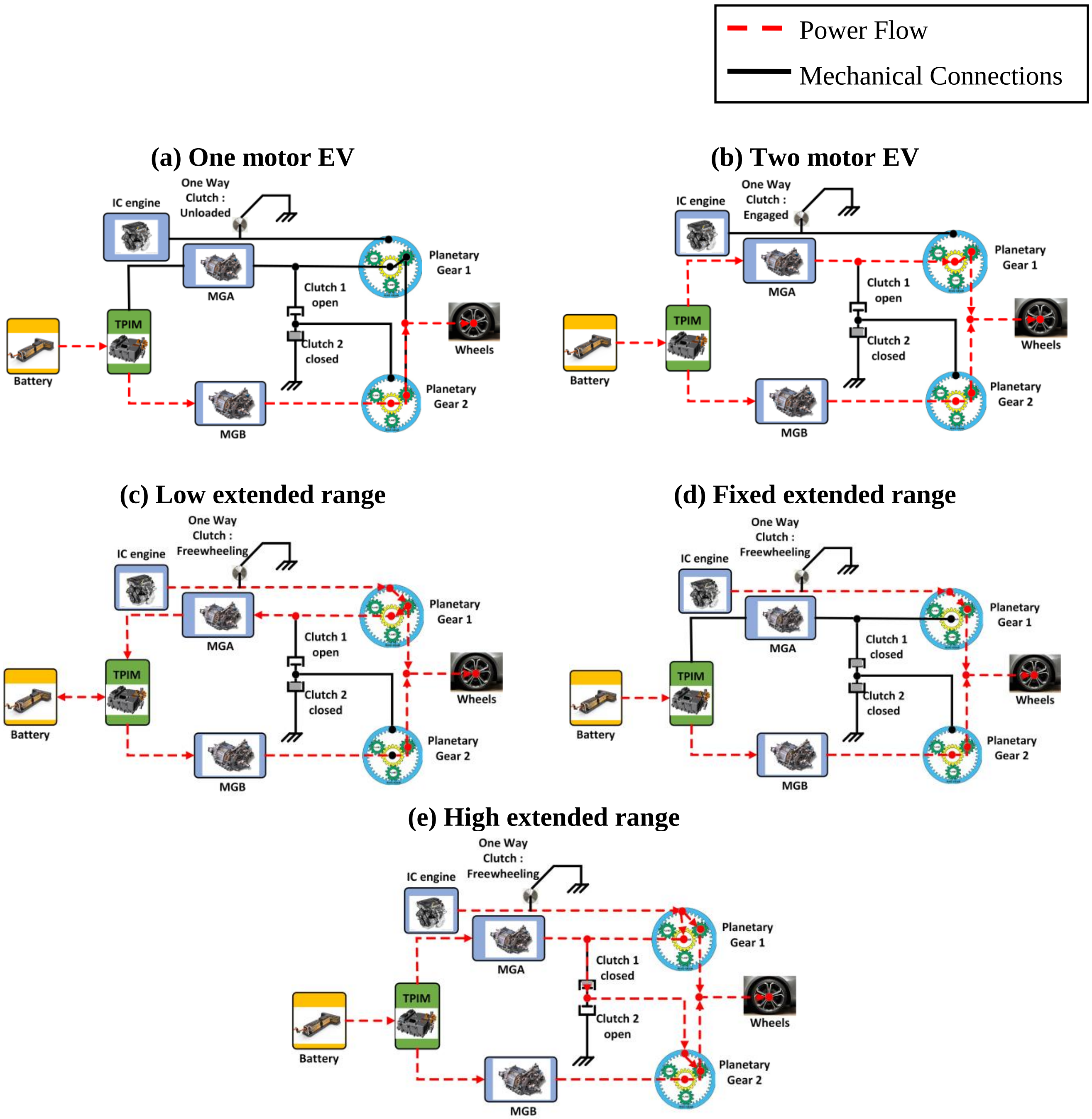

Figure 4: Chevy Volt Gen II drive modes

(d) Fixed Extended Range (FER) mode

This mode mechanically connects the IC engine to the wheels. Fig. (4)-d shows the power flow for this mode. With respect to LER mode, both the clutches are closed as MGA unit is not performing any operation and all the engine power is sent to wheels. This mode operates at higher vehicle speeds above 60 kph to 110 kph with higher torque demands than those in LER.

(e) High Extended Range (HER) mode

As the name suggests, for any higher torque demands and at higher speeds than 110 kph, this mode is used. Fig. (4)-e shows the power flow for this mode. This mode performs the compound power split of engine power by distributing engine power at PG1 through planet carrier, sun gear and clutch 1. In this case, the clutch 1 is closed again and clutch 2 is opened to transit the engine power through PG2.

2.2.2- ANN Mode Prediction Model

The first thing that ECU should decide is which mode to command in order to meet the power request. Since there are five distinct modes of operation for the Chevy Volt in CS operation, a five-class classification machine learning platform is designed. This approach was chosen over surface-response approaches because surface-response methods highly depend on hand-crafted decision- boundaries separating the different classes which were found to be highly subject-specific and also prone to visualization error (the last data plotted had more impact on plotting the decision boundaries) however the machine learning approach was fast in closed-loop simulation environment as well as free from visualization error or dependency on human intervention to define decision boundaries. Multiple learning algorithms were tested such as KNN (K-nearest neighbors), decision trees, support vector machine (SVM) using MATLAB classification toolbox, and the most suitable algorithm was found to be ANN which has been extensively deployed in complicated classification problems [13].

An ANN was trained to select a mode of operation based on the following features. The feature vector includes 1. Axle torque: this is one of the most informative features when it comes to mode selection, since modes are designed for different levels of axle torque at the first place. Axle torque directly affects power request, hence was included as the first element of the feature vector, 2. Vehicle speed: this feature is also an important feature because the vehicle speed determines the vehicle kinetic energy, which correlates with the mode (higher modes are associated with higher vehicle kinetic energy since there has been more energy input to the vehicle as the operating mode is going towards HER). In addition, the kinematic constraints of the vehicle depend on the vehicle speed and to be in certain modes, a specific range of speeds is a necessity for the realization of the kinematic constraints. 3. SOC: In charge sustaining mode where the SOC is comparatively low, it was found out that the SOC level is affecting operating mode. Lower SOCs are associated with battery inefficient regions of operation and higher chances of battery aging, hence the ECU of the vehicle is “SOC-conscious” when selecting modes to be using more ICE when SOC drops in CS mode, 4. Acceleration: Higher accelerations correlate with higher power request, which is a fundamental mode-selection parameter. After looking at the raw data of accelerations, the decision was made to include this feature which contains the footprint of the operating mode, 5. Battery power: This feature is correlated with total power request, and helps in two ways. First, it can help in distinguishing between EV1 and EV2 modes, as they are associated with different levels of battery power. Second, it includes the effect of regenerative braking in the feature vector, which is hard to include using the other features such as speed or acceleration. When regen is at the place, there is a high chance that the vehicle is going to experience a “lower mode” towards 1EV, 6. Previous mode: The logic behind adding this was that the real ECU works based on hysteresis margins and it was necessary to account for this effect in simulation.

ANL researchers conducted extensive chassis dynameters for this vehicle. More than 12 CS experiment recording was chosen which included UDDS, US06, HWFET, zero grade passing, and other drive cycles [6]. The data was combined and shuffled as a routine practice in machine learning in order to enhance the generalizability of the learning algorithm. Then this data was used for training and validation purposes. The training data was 70% of all the data mentioned previously, and 15% was used for validation and 15% was used to test the performance of the developed tool. The data for each signal was normalized based on the minimum and maximum values observed throughout the tests obtained by ANL, so the numbers fed to ANN were between -1 and 1. This was an important step which resulted in higher than 99% accuracy for the ANN for test data, as ANNs are sensitive to the outliers.

The architecture of the ANN was a three-layer fully connected network with 10 neurons at the hidden layer. The reason for the architecture was our inputs (or feature vector) were highly representative of each mode and the need for a deeper ANN was not felt. In addition, our higher than 99% accuracy for test data assured that the developed ANN had acceptable performance when working with static data.

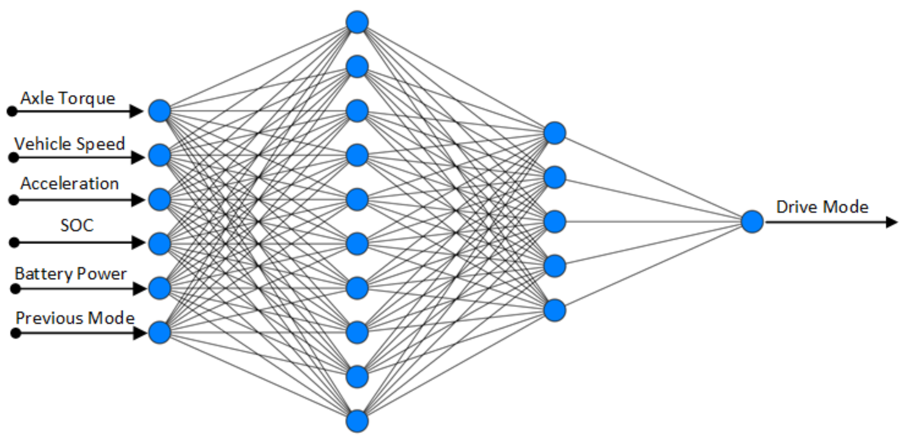

Figure 5: ANN architecture to predict vehicle drive mode

Table 2: Error in training mode selector ANN

Training Accuracy = 99.3%		True Class				
		1EV	2EV	LER	FER	HER
Predicted Class	1EV	10386	31	1	0	0
	2EV	34	1157	19	0	0
	LER	4	8	2114	12	4
	FER	5	8	16	2694	8
	HER	0	0	0	2	5585

Table 2 shows the training error of the ANN which demonstrates an interesting pattern. For each class (mode), the highest number of false predictions are adjacent modes, e.g. for mode LER, even though the ANN predicts the mode accurately more than 98% of the instances, its false predictions are mainly FER and 2EV. This can be explained by the fact that the transitioning modes, e.g. LER to FER, were not considered as “classes” and introduce confusion to the learning algorithm; however, the rate of false prediction is very low (less than 2%), as shown in Table 2.

2.2.3-Torque Distribution Model

Once the drive mode of the vehicle is selected by the ANN, the distribution of the torque requested among the three power sources is done by using the logics identified and developed using the ANL experimental data. Kim et al. [5, 6] investigated vehicle operating points for standard FTP drive cycles as shown in Fig. (6). The vehicle shifts into CS drive mode of operation usually at battery SOC below 18% as shown in Fig. (6)-a. The engine start points also wary based on the battery SOC [5, 6].

If the SOC is below 15%, then the engine is turned on during wheel power demands as low as 10 kW as shown in Fig. (6)-a. In addition, as shown in Fig. (6)-b, it was found that the vehicle keeps the engine rotating and cut off the fuel when the vehicle speed is above 40 mph. If the speed is lower than 40 mph, the ECU commands the engine to stop. During 2EV drive mode, the vehicle operates the MGB and MGA drive units with an average torque distribution of 90:10, i.e. 90% of the vehicle power demand is covered up by the MGB unit and the rest is provided by the MGA. The LER and HER drive modes work almost similarly with the engine being working in very narrow and efficient operating region, around 25 kW to 35 kW with the rest of the power demand or excess energy directed to the MGB. This is evident in Fig. (6)-c where, even at high loads, the ECU tries to keep the engine running in an efficient region with power output below 35 kW. The MGA in these drive modes works closely with ICE to control the engine speed and to charge the battery when the excess power is available.

In the FER mode, the ICE goes into direct mechanical connection with the wheels, with a high amount of energy provided by the engine and the rest is provided by the MGB. During this drive mode, the MGA charges the battery whenever necessary but the instances are rare as the SC sends all the engine power to the wheels. In addition, Fig. (6)-d shows the operating regions of these modes, which suggests that these different drive modes are designed to supply power at specific loads and speeds. These control strategies from references [5,6] along with ANL and our vehicle test data were used to develop the torque distribution model in this work.

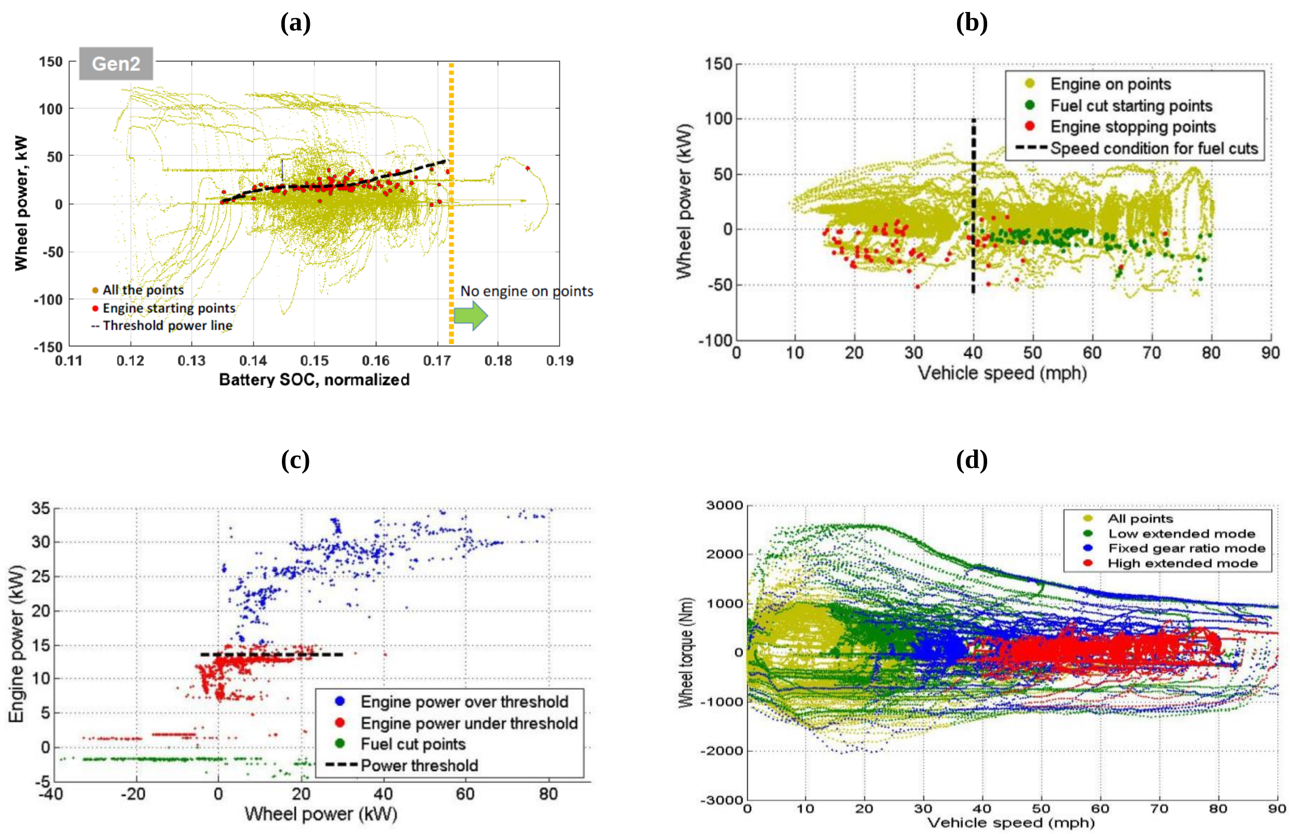

Figure 6: Chevy Volt Gen II Powertrain operating points [5,6] (a) Engine starting points for CS operation, (b) Fuel cut-off and engine stopping conditions, (c) Engine power with respect to power threshold, (d) Axle torque and speed operating points for CS drive mode

Fig. 7 shows the part of torque distribution algorithm used in the SC. Based on the drive mode selected by ANN model, various torque distribution rules are used to determine component torques and speeds. The distribution is also checked to see if it follows the kinematic constraints of the drive unit. The distribution between the power sources is dependent on the power demand, torque request and battery SOC. For example, if the vehicle is in LER mode, and if the wheel power demand is low, engine is still run at higher power, the excess of which is used to charge the battery through MGA unit. This ensures that the engine always operates in the most efficient region even though the demand of power is low. In addition, when the vehicle is in FER mode, the torque of the engine is fixed in the efficient operating region and all the power is sent to wheels and no battery charging through MGA unit.

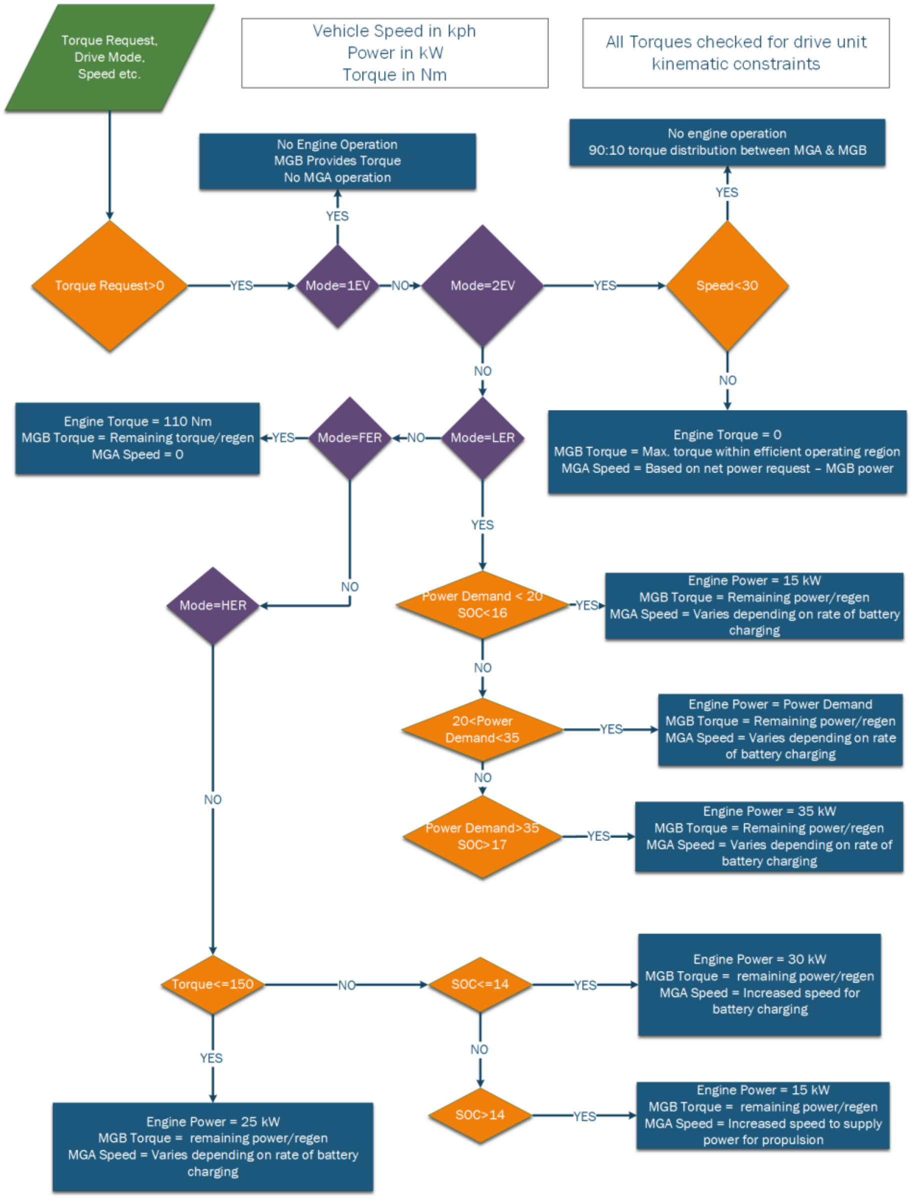

Figure 7: SC torque distribution algorithm for vehicle acceleration

2.3- Control-Oriented Driver Model

The driver model provides the necessary control input to the supervisory controller for knowing the requested axle torque based on vehicle acceleration and deceleration. The driver model is thus affected by the target speed set by speed limits and driver demand as well as the feedback of actual vehicle speed. This is a classic tracking problem, therefore, PIDs are good candidates to consider for this task. By comparing the target speed and actual speed, the driver decides to accelerate or decelerate the vehicle. Powell et. al. [14] developed a PI-based driver model which generates vehicle acceleration or braking command based on the comparison of target and actual speed. There are various driver models developed based on the control inputs required as described in reference [15]. Since the SC works on just one control input i.e. the axle torque request, the driver is required to perform a tracking task to match the actual speed to the target speed.

In this work, a PI control was used to minimize the speed tracking error by commanding the required axle torque to the SC. Therefore, a particular set of PI gains can be correlated to particular driving behavior, representing different levels of aggressive driving. Figure (7) shows the implemented driver model. The target vehicle speed and actual vehicle speed are compared and the difference is fed to the PI controller, which produces an axle torque request. The gains of the PI control, the K_i and K_p, are tuned to represent a particular driving behavior. A report by National Renewable Energy Lab (NREL) [16] found a general trend of increased average fuel consumption for higher acceleration rates and observed that vehicles in city traffic moving very slowly also resulted in higher fuel consumption. To this end, the effect of driving behaviour on vehicle total energy consumption was investigated.

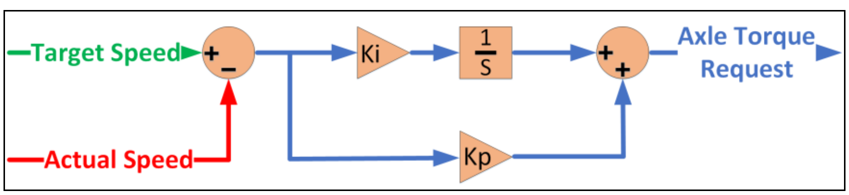

Figure 8: PI-based driver model in this study

A number of experiments were conducted at Michigan Technological University to capture acceleration rates for driver executing two different aggressive driving for a near step increase in vehicle speeds. Using these recorded speed profiles, the PI was tuned to mimic the driving behavior of two drivers.

McLaughlin et. al. studied human response time and found that more than 90% of the drivers are able to respond as quickly as 2.25 seconds or less [17]. This response time is used for tracking vehicle speeds in the generic drive cycle that corresponds to driving conditions (legal speed limits, traffic conditions, etc) near Houghton and Hancock, MI area as will be discussed later in Section 3.

Table 3: Controller gains obtained from experimental data for two different driving behaviour

Control Parameter	Driver A	Driver B
Proportional Gain (N.s)	10	60
Integral Gain (N)	1	30

3.-Results and Discussion

Two representative FTP drive cycles were used to validate the overall model: namely UDDS and US06 as shown in Fig. (9). The performance of the model for predicting vehicle energy consumption is presented in Table 4. The results in Fig. (9) and Table 4 confirm: 1) Model is able to follow reference trajectory with an average error of less than 0.5 kph, 2) Predicted vehicle energy consumption is within 5% of that of the experimental data**.**

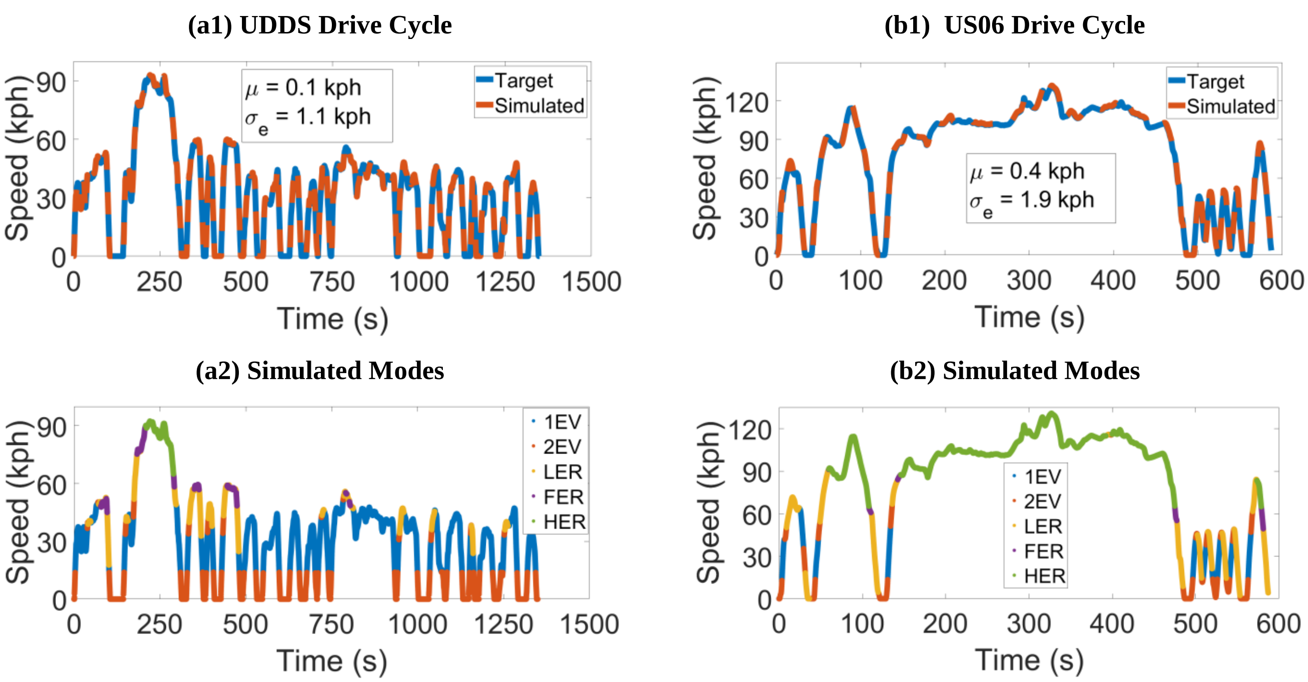

Figure 9: Model performance for UDDS and US06 drive cycles

Table 4: Predicted vehicle fuel and electrical energy consumptions against vehicle experimental data*

Cycle	Model Simulation			Experimental Data			Error (%)
	Fuel (MJ)	Electrical (MJ)	Total (MJ)	Fuel (MJ)	Electrical (MJ)	Total (MJ)	
UDDS	15.54	1.79	17.33	17.83	0.16	17.99	-3.67
US06	2.50	0.58	22.08	22.87	-0.29	22.58	-2.21

*Driver variation effect has not been taken into account in the reported data since the focus of this comparison is to assess the developed SC performance.

After characterization of the driver model, the driving behavior for the generic drive cycle was simulated. Fig. (9) shows the driver A and driver B performance in tracking the reference velocity trajectory. It was observed that in order to achieve the increased speed limit, both drivers are overshooting to reach the target with as high as 110 kph for the more aggressive driver. In addition, the more aggressive driver (driver B) was able to achieve the targeted speeds with more accuracy than the less aggressive driver (driver A). During the time taken by the driver A to reach a target speed, a new speed target was already given to the driver. Thus, poor tracking performance is observed for the driver A because of slow response time.

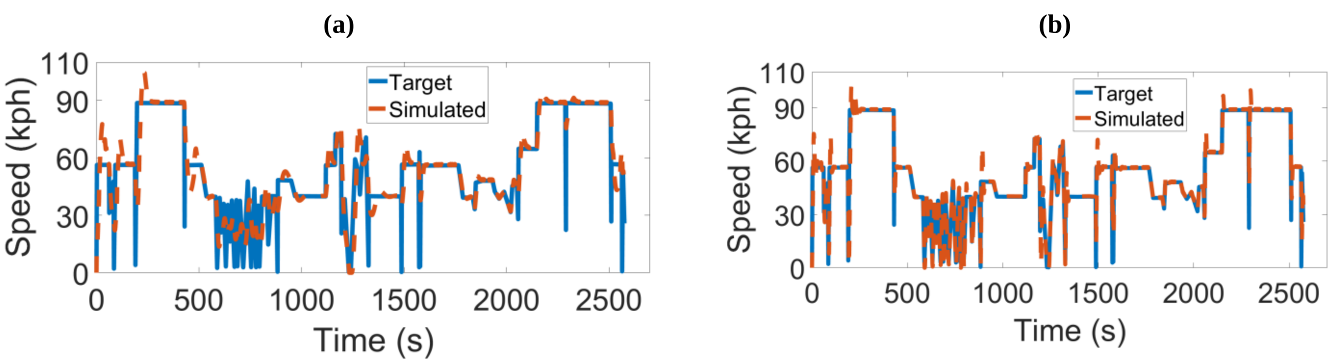

Figure 10: Effect of driver for tracking target vehicle speed in a generic drive cycle with intensive transient operating conditions

The total energy consumption for both drivers is shown in Table 5. Driver B is found to be using 6% more energy than the less aggressive driver, due to its higher acceleration and consequently a higher overshoot on target for most time instances. The main energy difference here is due to the peak acceleration rate of driver B, which requires the vehicle to use both the engine as well as the battery to support this excessive power request. As the SC restricts the ICE operation to be in most efficient brake specific fuel consumption (BSFC) region, the MGB is commanded by the ECU to provide the excess power request which, in result, increases the vehicle electrical energy consumption.

Table 5: Energy consumed for the two simulated driving behavior

Driver	Model Simulation			Energy Difference (%)
	Fuel (MJ)	Electrical (MJ)	Total (MJ)	
Driver A	59.21	0.87	60.09	-
Driver B	60.14	3.99	64.14	+6.73

4. - Summary & Conclusions

An SC model was developed for Chevy Volt Gen II powertrain that predicts total vehicle energy consumption within 5% of the experimental data. The SC includes an ANN model to select vehicle drive mode by using the most informative powertrain data. After determination of the operating mode, an empirical rule-based torque distribution model was developed to distribute required axle torque between ICE and two electric motors. In addition, a PI control-based driver model was developed to simulate driver acceleration speed profile. This model along with road gradient load provides inputs to the SC model. The experimental validation results for two US driving cycles showed that the developed model is able to simulate vehicle energy consumption for actual on-road conditions with less than 5% prediction error. The effect of driver acceleration speed profile was also investigated and showed that the vehicle energy consumption can change by over 6% for the conditions investigated, depending on how aggressive the driver was.

The developed model is of great utility to develop MIL and HIL platforms to simulate vehicle performance and also provide a benchmark to assess the performance of different designed controllers in comparison to the vehicle control strategies embedded in the production vehicle ECU.

5.-Acknowledgements

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References:

1. U.S Department of Energy, Energy Efficiency and Renewable Energy, “https://afdc.energy.gov/" accessed on April 13th, 2019.
2. Montevechi, JAB., Leal, A., “Application of Design of Experiments On the Simulation of A Process in an Automotive Industry”, Proceedings of 2007 Winter Simulation Conference, 2007.
3. Uthaichana, K., Bengea, S., and DeCarlo, R., “HEV Modelling for A Supervisory Level Power Control Problem”, IFAC Proceedings, Volume 38, Issue 1, 2005, Pages 271-276.
4. Conlon, B., Blohm, T., Harpster, M., Holmes, A., Palardy, M., Tarnowsky, S. and Zhou, L., 2015, “The Next Generation “Voltec” Extended Range EV Propulsion System,” SAE Technical Paper 2015-01-1152.
5. Jeong, J., Choi, S., Kim, N., Lee, H. et al., “Model Validation of the Chevrolet Volt 2016,” SAE Technical Paper 2018-01-0420,2018, doi:10.4271/2018-01-0420.
6. Kim, N., Choi, S., Jeong, J., Vijayagopal, R., Stutenberg, K., Rousseau, A., 2018, "Vehicle Level Control Analysis for Voltec Powertrain", *World Electric Vehicle Journal*, 9(2),29.

7. Onori, S., and J. Tribioli, L.., 2015, “Adaptive Pontryagin’s Minimum Principle supervisory controller design for the plug-in hybrid GM Chevrolet Volt”, Journal of Applied Energy, Volume 147, Issue 1, 2015, Pages 224-234
8. Phillips, AM., Jankovic, M., and Bailey, KE., 2000, “Vehicle System Controller Design For A Hybrid Electric Vehicle,” Proceedings of the 2000 IEEE International conference on Control Applications, cat no:00CH37162 .
9. Malikopoulos, AA., 2014, “Supervisory Power Management Control Algorithms for Hybrid Electric Vehicles: A Survey,” IEEE Transactions on Intelligent Transportation Systems, volume 15, issue 5, Pages 1869-1885.
10. Yadav, Rajeshwar, "Modeling and analysis of energy consumption in Chevrolet Volt Gen II Hybrid electric vehicle", Campus Access Master's Thesis, Michigan Technological University, 2018
11. Surresh, Kaushik,”Modelling and Analysis of Chevy Volt Gen II Hybrid Vehicle in Electric Mode”, Open Access Master’s Thesis, Michigan TechnologicalUniversity, 2018.
12. Sinisa Jurkovic, Khwaja Rahman, Nitin Patel, and Peter Savagian. “Next Generation Voltec Electric Machines; Design and Optimization for Performance and Rare-Earth Mitigation". SAE Int. J. Alt. Power, doi:10.4271/2015-01-1208, 2015.
13. Hemmati, S. and Wade, E., Optimally Selected Features Detect and Predict Freezing of Gait in Parkinson’s Disease, In proceedings of Biomedical Engineering Society (BMES), Minneapolis, MN, 2016.
14. B. K. Powell, K. E. Bailey and S. R. Cikanek, "Dynamic modeling and control of hybrid electric vehicle powertrain systems," in IEEE Control Systems Magazine, vol. 18, no. 5, pp. 17-33, Oct. 1998. doi: 10.1109/37.722250
15. Day, T. and Metz, L., "The Simulation of Driver Inputs Using a Vehicle Driver Model," SAE Technical Paper 2000-01-1313, 2000, https://doi.org/10.4271/2000-01-1313.
16. National Renewable Energy Laboratory (NREL), 2011,”Final Report on the Fuel Saving Effectiveness of Various Driver Feedback Approaches”, Milestone Report No. NREL/MP-5400-50836.

17. McLauglin, S., Hankey, J., Dingus, T., “A method for evaluating collision avoidance systems using naturalistic driving data”, Accident Analysis and Prevention, Volume 40, Issue 1, 2008, Pages 8-16, ISSN 0001-4575.
18. Jocsak, J., White, D., Armand, C., and Davis, R., 2015, “Development of the Combustion System for General Motors' High-Efficiency Range Extender Ecotec Small Gas Engine,” SAE Technical Paper 2015-01-1272.

Nomenclature:

1EV	1 Motor Electric Drive
2EV	2 Motor Electric Drive
AFV	Alternative Fuel Vehicles
ANL	Argonne National Laboratory
ANN	Artificial Neural Network
ARPA-E	Advanced Research Projects Agency-Energy
CD	Charge Depleting
CS	Charge Sustaining
FER	Fixed Extended Range Drive
FTP	Federal Test Procedures
GM	General Motors
HER	High Extended Range Drive
HEV	Hybrid Electric Vehicle
HIL	Hardware In the Loop
LER	Low Extended Range Drive
MGA/B	Motor Generator A/B
MIL	Model In the Loop
NEXTCAR	Next Generation Energy Technologies for Connected and Automated On-road Vehicles
OEM	Original Equipment Manufacturer
OWC	One Way Clutch
PHEV	Plug-in Hybrid Electric Vehicle

SC	Supervisory Controller
SIL	Software In the Loop
SOC	State of Charge
TPIM	Transmission Power Inverter Module
UDDS	Urban Dynamo meter Driving Schedule
V2X	Vehicle to Everything
VD&PT	Vehicle Dynamics & Powertrain