Look-Ahead Information Based Optimization Strategy for Hybrid Electric Vehicles

by

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ABSTRACT

The environmental impact of the fossil fuels has increased tremendously in the last decade. This impact is one of the most contributing factors of global warming. This research aims to reduce the amount of fuel consumed by vehicles through optimizing the control scheme for the future route information. Taking advantage of more degrees of freedom available within PHEV, HEV, and FCHEV “energy management” allows more margin to maximize efficiency in the propulsion systems. The application focuses on reducing the energy consumption in vehicles by acquiring information about the road grade. Road elevations are obtained by use of Geographic Information System (GIS) maps to optimize the controller. The optimization is then reflected on the powertrain of the vehicle.The approach uses a Model Predictive Control (MPC) algorithm that allows the energy management strategy to leverage road grade to prepare the vehicle for minimizing energy consumption during an uphill and potential energy harvesting during a downhill. The control algorithm will predict future energy/power requirements of the vehicle and optimize the performance by instructing the power split between the internal combustion engine (ICE) and the electric-drive system. Allowing for more efficient operation and higher performance of the PHEV, and HEV. Implementation of different strategies, such as MPC and Dynamic Programming (DP), is considered for optimizing energy management systems. These strategies are utilized to have a low processing time. This approach allows the optimization to be integrated with ADAS applications, using current technology for implementable real time applications.

The Thesis presents multiple control strategies designed, implemented, and tested using real-world road elevation data from three different routes. Initial simulation based results show significant energy savings. The savings range between 11.84% and 25.5% for both Rule Based (RB) and DP strategies on the real world tested routes. Future work will take advantage of vehicle connectivity and ADAS systems to utilize Vehicle to Vehicle (V2V), Vehicle to Infrastructure (V2I), traffic information, and sensor fusion to further optimize the PHEV and HEV toward more energy efficient operation.

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DEFINITIONS/ABBREVIATIONS

ADAS	Advanced Driver Assistance Systems
GIS	Geographic Information System
MPC	Model Predictive Control
DP	Dynamic Programming
FE	Fuel Economy
HEV	Hybrid Electric Vehicles
FCHEV	Fuel Cell Hybrid Electric Vehicles
PMS	Power Management Strategies
ECMS	Equivalent Consumption Minimization Strategy
SOC	The State of Charge
RB	Rule Based
HiL	Hardware In-the-loop
VHiL	Vehicle Hardware In-the-loop
MPG	Miles per Gallon
ICE	Internal Combustion Engine
EM	Electric Motor

1. INTRODUCTION

1.1. BACKGROUND

The question remains open on how to obtain the requisite information about the future driving conditions [1]. However, with the advancement of technology it has become possible to acquire future information of the trip through various means including cloud and GIS systems [2]. A look-ahead information strategy utilizes future information of the driving conditions. This information includes road grade, trip distance, traffic information (such as traffic lights and stop signs) to generate an optimization strategy for Hybrid Electric Vehicles (HEV). This research is more advantageous for a Plug-in Hybrid Electric Vehicle (PHEV) due to the extended electric range that allows recapturing more kinetic and potential energy along the route during deceleration and downhill.

The strategy also works for Fuel Cell Hybrid Electric Vehicles (FCHEV) [3] to increase fuel economy. For improved performance, by the PMS, the information about future driving conditions may be incorporated into its control strategy. This information may be facilitated by using the ‘drive pattern recognition’ method which uses the current driving conditions (speed, acceleration, braking) to decide the immediate or near future driving conditions.

Driver pattern recognition may be used to decide if the vehicle is following a highway or city drive pattern and allow for modification of the controls accordingly. Another method for incorporating future driving conditions is to study the upcoming grade conditions of the current route to a particular destination [4]. Furthermore, recent studies have shown that optimal PMS depends on knowing the driving conditions about to be encountered. The use of look-ahead preview information to optimize the PMS in FCHEV is currently unexplored.

On the other hand, different approaches were implemented in the literature using either full preview or partial preview for road only. The optimization is then integrated with PMS using Dynamic Programming (DP), Standard Equivalent Consumption Minimization Strategy (ECMS) or Rule Based (RB) strategy [4].

Different control strategies and optimization algorithms were used to provide optimal fuel economy. Global optimization approach was utilized as exact future velocity, and road elevations are known. The optimal power split ratio is then calculated to minimize the cost function. Different techniques utilized for developing energy management strategies implementing the look-ahead information are presented to create energy management strategy using DP and ECMS [4].

ECMS with partial preview was implemented to calculate the actual value of the fuel equivalence factor “s” that result in the minimum fuel use and render depending on equalizing the initial and final value of SOC. At the beginning of given drive cycle, *s* is initially guessed and then a numerical procedure is used to iterate to find *s* for the future power demand for the drive cycle, then compare the final SOC to the desired SOC and repeat the process until the final SOC is equal to the desired SOC.

The DP is a numerical optimization based method helping in achieving a significant increase in the fuel efficiency. For a future preview, two-scale DP can be utilized such that a higher level DP used to plan battery’s SOC for the entire trip while a lower level short horizon DP segmentally keep track of SOC trajectory found in higher level [5]. However, the DP was not suitable for real-time application because of its dependence on the driving cycle and massive computational demand.

The result shows road with varying road elevation with DP strategy implemented as illustrated in Figure 1. The ICE was used less frequently due to depleting the battery to its lower bound on uphill and recapturing the energy when facing downhill. The DP more predictively acts and charges the battery in short uphill intervals E–F and G–H. This is due to higher torque demands, so running the ICE is more efficient [4].

The experiment was conducted by use of seven elevation profiles. Three of the seven were simulated profiles. While the other four were real road profiles obtained from California. The road grade and the SOC at different instances are correlated, that reflect the optimization pattern. It was observed that an improvement of 0.8-28% was achieved in fuel efficiencies by implementing the look-ahead based information in the PMS.

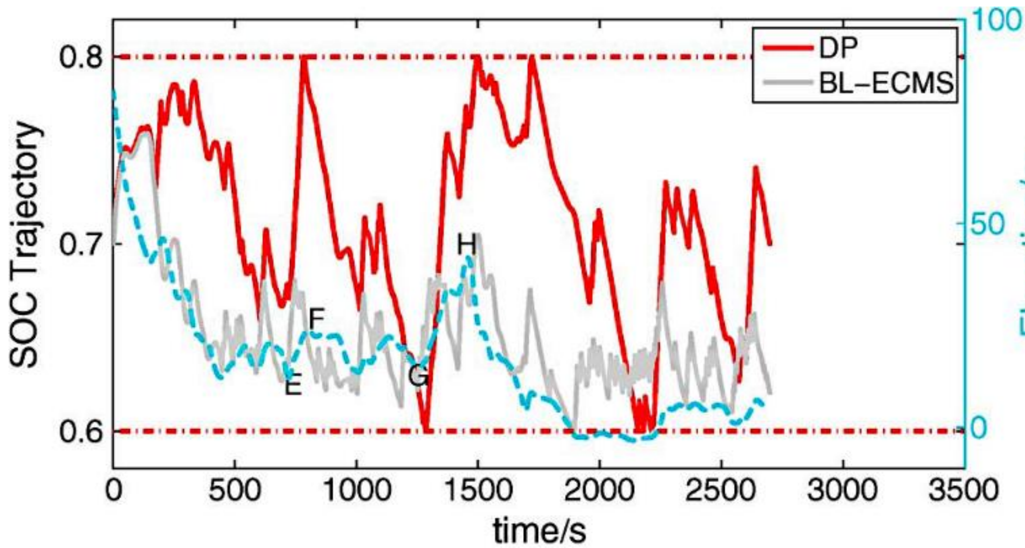

Figure 1. SOC Trajectory with Two Control Strategies (DP and BL ECMS) [4]

Global optimization is computationally intensive and requires all the information about the route before solving the optimization problem; this issue makes a tremendous challenge in integrating such optimization algorithms in vehicles giving the current hardware capabilities. Acquiring all the information about the route can also be challenging as well. This issue is a major motive in current technology to develop solutions so these systems can be utilized in vehicles, these solutions include sensor fusion, V2V, and V2I communication.

The cloud-based approach is a proposed solution to perform global optimization for computationally intensive applications [2]. In this method, the information of the destination and the current driving conditions are sent to a server as an input for the optimization algorithm. The server acquires the necessary information that includes, GPS maps, GIS data, and traffic information. The output of the optimization is then transmitted back to the vehicle where the supervisory controller uses these information to execute RB control scheme. The approach flow chart is shown in Figure 2.

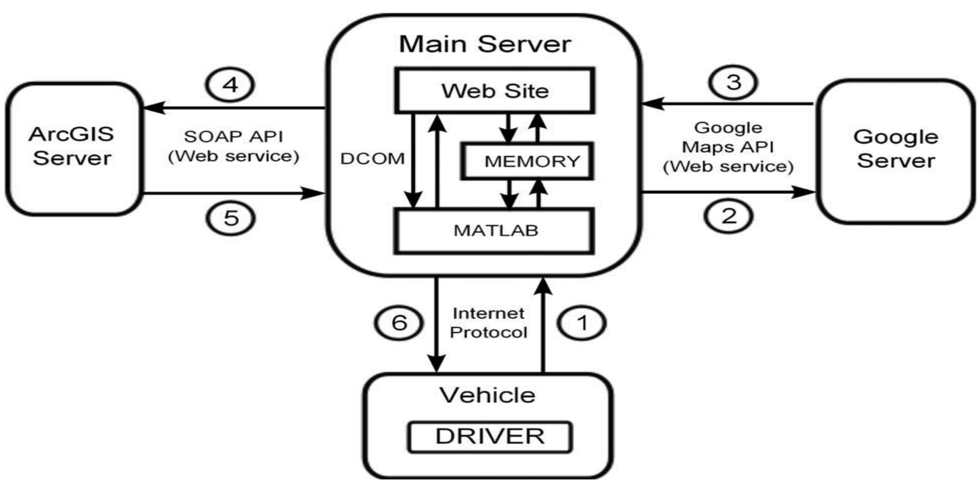

Figure 2. Cloud optimization approach

1.2. LITERATURE REVIEW OF CONTROL AND OPTIMIZATION FOR HEV AND PHEV

Unlike conventional ICE based vehicles it is apparent that HEVs perform better since they have the electric power that can reduce the amount of fuel used by ICE. Integrating electric powertrain components including an EM along with an electrical Energy Storage System (ESS) adds extra degrees of freedom to the system which can be leveraged to optimize the vehicle for better fuel economy. The electrical components can provide power and assist the ICE at high power demand situations [6].

Adding the electrical powertrain components reduce the load on the ICE and contribute to high efficiency operating conditions. Another advantage of an electrical powertrain component is recapturing the kinetic and potential energy that occurs during braking and going downhill respectively.

The inclusion of electrical powertrain components requires more complex Power-Management Strategy (PMS), to handle the extra degrees of freedom and the added complexity of the system. PMS will determine the torque split between the ICE and EM in the powertrain and find the optimal operating conditions for both components.

HEV/ PHEV power management strategies can be classified into two major categories: reactive and route-based control strategies. Reactive power management strategies use current driving information in their controller scheme; therefore they can only find the near optimal solution for the problem [7]. Those strategies include charge depleting, charge sustaining, and (ECMS).

RB control strategies are control systems that rely on the mode of operation. The rules are determined based on human intelligence and mathematical models and executed without knowledge of a defined drive cycle. Most of the described RB control strategies are based on IF-THEN type of control rules [8]. Some RB controllers perform load balancing which aims to operate the ICE at a high-efficiency region. This strategy performs better and results in good fuel economy at low torque and speed.

Deterministic RB control strategies are designed based on human desired characteristics. Heuristic rules, efficiency maps, and lookup tables are used to determine the power split between the ICE end EM based on the power flow in the powertrain and the torque demand. Charge sustaining RB control strategy aim to balance the SOC of the battery within specified range, this strategy mostly operate either the ICE or the EM alone giving the torque demand can be provided.

Charge depleting RB control strategy mainly use EM as the main source of torque in the powertrain and operate in pure EV mode if the SOC is higher than the lower limit and the EM can provide the requested torque. Other RB techniques can be used depending on the mode of operation, and the HEV architecture. Different rules can be utilized for parallel, series, and power-split HEV. PHEV RB control strategy have more flexibility in determining the mode of operation since the battery has greater capacity than HEV, this allows the vehicle to operate for longer range in pure EV mode before the need to turn on the ICE. Development of PHEV was motivated by increasing the electric power in vehicles and further decrease the amount of fuel consumed by ICE. This development contributes to reducing the HEV environmental footprint further.

Fuzzy Rule-Based (FRB) control strategy is a better possible approach to have higher efficiency than the RB control strategy. Unlike deterministic RB control, fuzzy logic can still be used to execute in real-time but find a more optimal power split between the ICE and EM. Fuzzy logic is chosen over the other methods because of the superiority it has to other conventional rule-based methods and is advantageous in robustness, adaptation, and flexibility [8].

Today’s hybrid vehicles are looking to be improved upon by looking into the supervisory controller algorithms. The current algorithms use information that is communicated internally in the vehicle's CAN network [9]. These parameters could be the battery SOC, current ICE and EM states, and the driver demand.

Optimization-Based Control Strategies can be used to decrease the cost functions of fuel consumption. Optimization algorithms can obtain global optimum solutions by optimizing over a fixed driving cycle. This cost function is highly dependent on the system variables at a given time. Local optimization algorithms can also provide a solution that is not globally optimal, but it can be utilized for real-time implementation.

Some strategies look to improve the basic design of RB to optimize the vehicle further by utilizing techniques like ECMS, Fuzzy Logic, Sequential Quadratic Programming (SQP) and Baseline Strategy (BS). All these algorithms usually aim at increasing the vehicle's efficiency in one type of drive cycle. However, this approach is realistic to what current vehicles undergo. The stochastic nature of real world driving makes the optimization process more challenging to predict the best drive cycle to optimize the controller.

The next approach is to use algorithms that can handle various real-time information as well as geographic information and provide the optimal power-split in real-time. Some parameters would be road grade, distance, traffic conditions, and internal vehicle parameters such as battery SOC, current ICE and EM states, and driver demand. However, these types of algorithms are computationally intensive and may not be possible to execute within the vehicle.

The solution to this problem is to off-board the calculations to a server that can receive the information from multiple sources and then provide the optimal torque split to the vehicle. The information would be sent out by using information collected by the vehicle supervisor controller from the internal CAN communication. Then be transmitted through Gateway General Packet Radio Service (GPRS) network nodes [9]. This approach the server can continuously learn the drive cycle that the vehicle is experiencing and optimize the vehicle for those conditions.

This method will increase the overall efficiency of the vehicle throughout a known travel route. It will also allow for the integration of V2V and V2I communication. Both communication systems can provide additional information that could be critical in improving the efficiency of the vehicle.

Dynamic Programming (DP) is used to find optimal control policies for multi-stage decision processes [8]. DP perform global optimization by dividing the problem into stages throughout the route. This approach is used to solve the optimization problem and find the best control output that will achieve an optimal fuel economy. DP can use with both linear and non-linear optimization problems and search for an optimum solution.

Linear Programming (LP) is the widely applied form of constrained optimization. LP optimization problems require high computational power to solve since the size of the problem, and the constraints can be enormous in such a complex system, but developing more advanced solvers and more powerful computer help solving complex problems faster than before [10].

Global Optimization techniques require the knowledge of the entire driving schedule. For example for DP, both initial and final value of the state variables have to be defined for the algorithm to stay within the feasible domain. To perform global optimization on HEV, different parameters would be required to solve the problem; those might include SOC, drive cycle, route information.

1.3. HEV ARCHITECTURE

HEV have different architectures and can also be classified based on the degree of hybridization. The degree of hybridization represent the power percentage, and the size of the electric powertrain components compare to the power and size of the ICE. In this category, HEVs are classified into Micro hybrid, Mild hybrid, Full hybrid, and PHEV.

PHEV have the same general architecture as HEV. However, PHEV batteries have a higher capacity which makes them capable of operation in pure EV mode for extended range. Also, PHEV batteries can be recharged through an external power source. Table 1 shows a comparison between different types of HEV.

Table 1. Hybrid Categorization

Type	Functionality	Regenerative Braking	Pure EV Mode	External Recharge
Micro Hybrid	• Shut off the ICE at idling.	NO	NO	NO
Mild Hybrid	• Shut off Engine during deceleration. • Electric assist.	Mild	NO	NO
Full Hybrid	• Smaller Engine and larger EM than before. • Electric assist and electric only lunch.	YES	Limited	NO
Pure EV	• NO ICE in the powertrain.	YES	YES	YES
Plug-in Hybrid	• Can operate as Pure EV or as Hybrid with a higher electric assist.	YES	YES	YES

HEV and PHEV are categorized based on the degree of hybridization and the architecture of the powertrain. The degree of hybridization and the architecture determine many factors of the operation including but not limited to fuel economy, emissions, and pure EV range.

Parallel HEV is the most common architecture available in the market. In this architecture, the ICE and EM are connected on the same line, and both of them provide torque to the wheels. Parallel HEV architecture is shown in Figure 3.

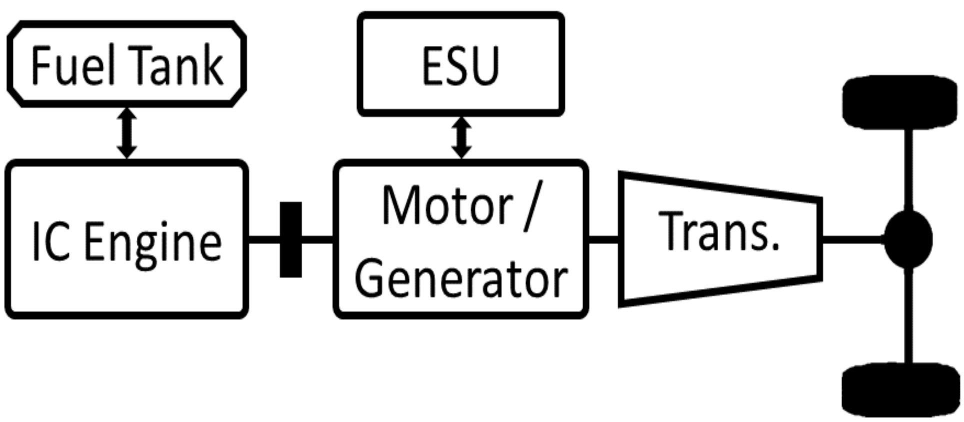

Figure 3. Parallel HEV architecture

In parallel HEV both ICE and EM may be connected to the same shaft and can provide torque either separately or together. If one of the components is providing torque, then the other component is either free spinning or disconnected by a clutch placed between ICE and EM. Parallel HEV can be further categorized by determining the dominant component to be either the ICE or EM; this can change the position of the clutch and transmission in the powertrain.

Series HEV consists of an additional electric generator, in this architecture, the ICE does not provide torque to the wheel. Instead, it spins the generator to provide electrical power. The electric power generated can either charge the battery or provide direct power to the EM which is the only source of torque for the vehicle.

Series HEV has high efficiency since the engine always operates at a high-efficiency region, since it is only spinning the generator with constant torque, also the EM have higher efficiency than ICE. Series HEV architecture is shown in

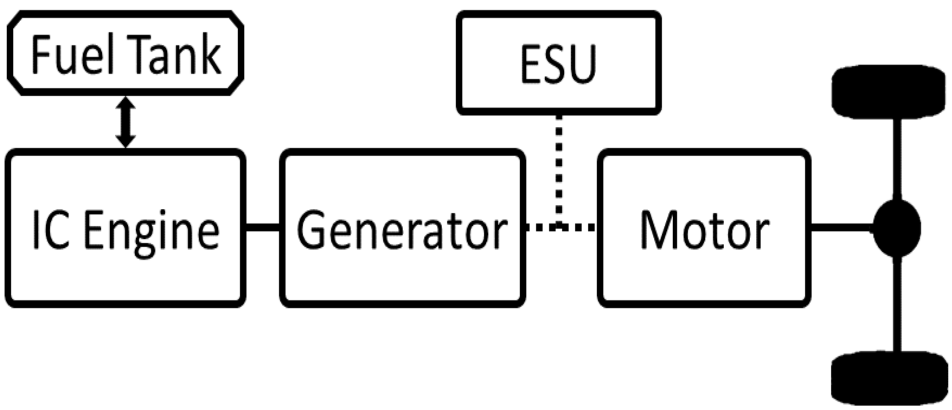

Figure 4. Series HEV architecture

Parallel through the Road Hybrid Electric Vehicle (PTTR-HEV) can provide four wheel drive option. The unique architecture consists of a conventional powertrain connected to the front wheels and an electric powertrain connected to the rear wheels. This architecture has less complexity since the two powertrains are not mechanically connected, it also requires simple and less complex PMS and control scheme. PTTR HEV architecture is shown in Figure 5.

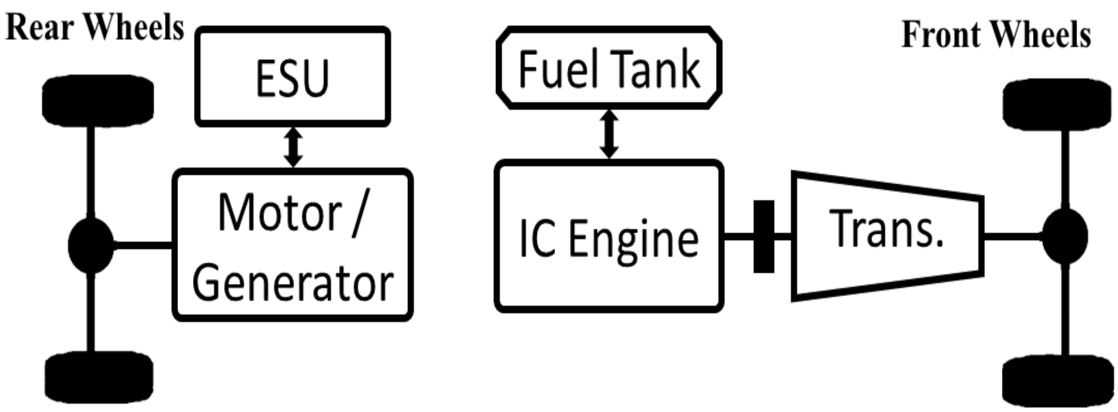

Figure 5. PTTR HEV architecture

1.4. MOTIVATION FOR LOOK-AHEAD OPTIMIZATION

Look-ahead optimization employs the use of 3D maps to extract road elevations. Knowing the future driving conditions can be utilized to optimize the supervisory controller of the vehicle. The power delivered from the vehicle to overcome an uphill can significantly increase the amount of fuel used by ICE which tremendously increases the overall expenditure for the vehicle. The fuel used to overcome an uphill will also substantially increase the greenhouse gas emission and negatively affect the environment.

Furthermore, the potential energy from driving downhill is significant and can be utilized to reduce the amount of fuel used by recapturing this energy through regenerative braking using the EM and the vehicle battery. The wasted potential energy on a downhill can be used to drive the vehicle on an uphill or a flat road. This process will reduce the amount of power delivered by the ICE. Also, this will improve the overall efficiency of the vehicle since the EM has a much higher efficiency than ICE.

This optimization of the control scheme aims to improve the fuel economy of HEVs. The approach utilizes look-ahead information to maximize the amount of energy recaptured on varying terrain route as shown in Figure 6. As the future information of the route is known, the optimization and the controller will prepare the vehicle for charging and discharging the battery during downhill and uphill, by following this approach the EM and the battery will be the main source of delivering power to drive the vehicle and reduce the load on the ICE.

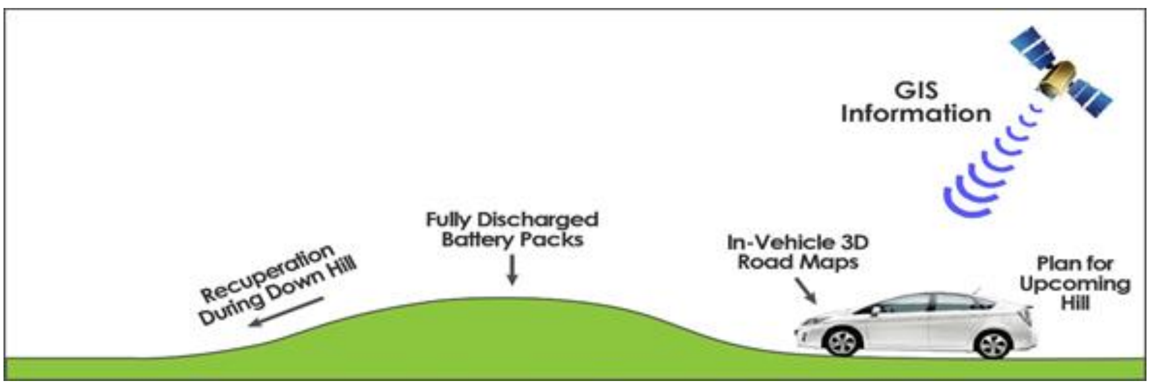

Figure 6. Terrain Preview for optimization strategy

The road grade has a significant measurable effect on the dynamic of the vehicle and the overall performance. The effect of the grade is reflected on the overall requested power from the powertrain. The amount of power required to overcome an uphill can very high for the vehicle to provide, vehicle gradeability test is performed to quantify the power required due to grade at certain speed, in most cases the vehicle can only overcome a high grade uphill on low speed.

The following figure shows a grade profile that was taken from a real route in San Francisco. Figure 7 highlights the power due to grade for positive power and grade (uphill) and the negative power and grade that can be utilized for regenerative braking (downhill).

The road grade is calculated based on the elevations acquired from the 3D GIS maps. Once the grade is computed, the vehicle dynamics are calculated, simulations are used to calculate the power requirement and the power delivered by the powertrain to overcome the grade and also to quantify and amount of energy that can be recaptured during downhill.

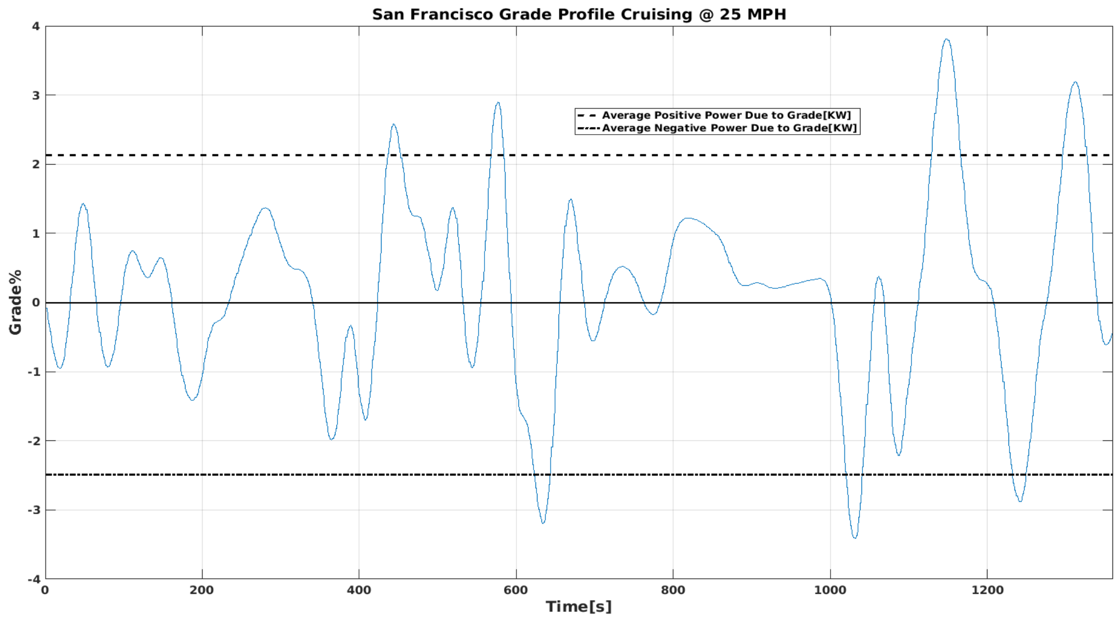

Figure 7. Positive and Negative average power due to road grade

The controller uses the future information to perform local optimization using RB control scheme that prioritize the power-split and prepare the vehicle for upcoming uphill and downhill to maximize the amount of energy harvested through regenerative braking. This optimization is performed considering two segments in the future so the information of the entire route is not required at this stage.

Global optimization is accomplished in the control scheme using DP based on the power requirement for entire route due to the terrain of the road to minimize the fuel consumption. Since DP optimized control scheme perform global optimization, the entire route information is required at the beginning of execution in pursuance of finding the optimum torque split between the ICE and EM. This controller will determine the operating mode and to either provide power or to operate in the regenerative braking mode as illustrated in Figure 8.

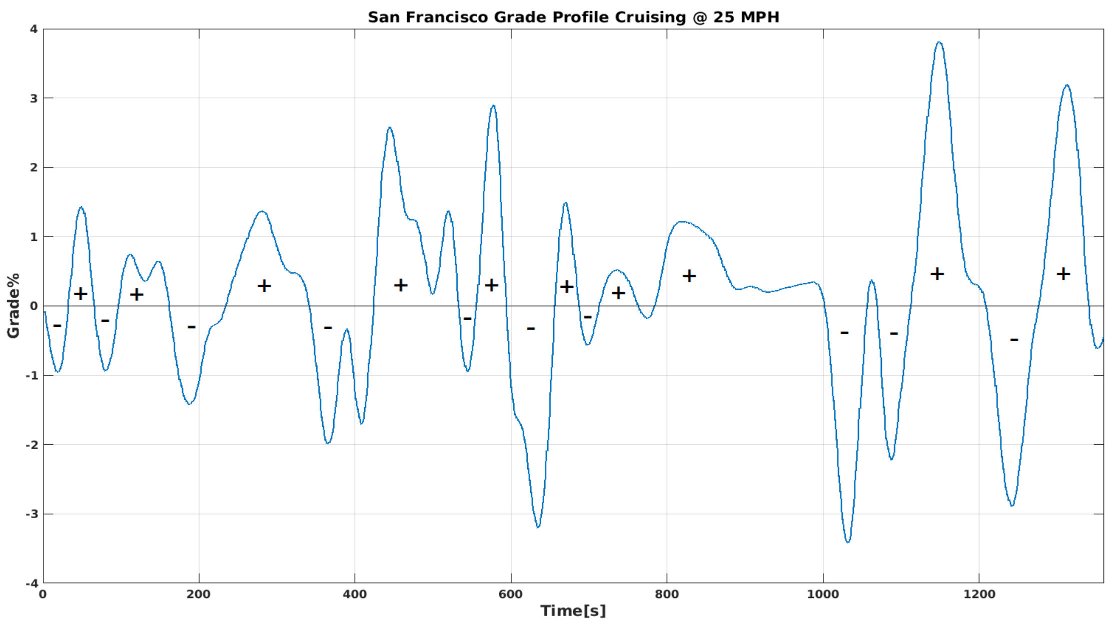

Figure 8. Positive and negative average power segmentation due to grade

1.5. OBJECTIVES OF THE RESEARCH

The objective of this research is to develop, design and integrate an optimized control scheme that utilize the future information of the route and prepare the vehicle for charge and discharge the battery in order to maximize the amount of energy recaptured through regenerative braking and reduce the amount of fuel consumed by the ICE. Reducing the environmental impact of the fossil fuels will have an enormous impact on global warming, this can be achieved through reducing the amount of fuel consumed by vehicles through optimizing the control scheme for the future route information.

The scope of this research involves integrating look-ahead information based optimization Strategy with other ADAS applications and intelligent sensors based applications [11].These systems include GIS 3D maps, traffic information, machine vision, and V2X communication. Integrating ADAS applications make this system more efficient by integrating it into the infrastructure which includes taking into account traffic information. With the possibility of implementing vehicle to vehicle communication and vehicle to the cloud and infrastructure communication [12]. Including the traffic congestion and other parameters into the optimization, that will make vehicles more efficient, safer and more convenient.

Several studies have shown the potential for optimizing hybrid powertrains to leverage grade information. This research presents a practical approach for real world elevation data that is used to validate the optimized control strategies. The implementation of these strategies is implemented in high fidelity model and tested in Hardware-In-The-Loop (HiL) simulation, this research focus on maximizing the improvement while minimizing the complexity and processing time.

The practical approach of RB optimization will accommodate for real-time data acquisition and processing. This approach will implement local optimization for the control scheme, so only certain amount of information for the next future segments is required at a certain time, while global optimization needs all the information of the entire route.

Global optimization makes a considerable challenge regarding in-vehicle implementation and real-time execution. RB optimized approach has the advantage of requiring less information and real-time execution so that can be integrated with other ADAS applications and the supervisory controller of the vehicle. By following this method, the system will be validated later using Vehicle Hardware-in-the-Loop (VHiL) and ultimately implemented in the vehicle.

Control strategies for HEV are mainly divided into two main categories, charge depleting with use the electric powertrain as the main source to provide the power requested by the driver. Thus this strategy depletes the battery to its lower limit [13]. This strategy aims to operate the vehicle in pure EV mode as long as the EM can provide the requested torque and the battery can provide the requested power. If the requested power in charge depleting more is higher than what the EM can provide the controller, operate the ICE but keep using the EM as the main source of power and keep depleting the battery until it reaches its lower limit.

The second one is charge sustaining which uses the ICE as the main power source to provide the requested power. Charge sustaining uses the EM to assist in providing the rest of the power that the ICE cannot provide [14]. This strategy aims to maintain the SOC of the battery within a small window to minimize the amount of the ICE operation and, the fuel consumption.

The optimized control strategy in this research uses a blended mode of charge depleting and charge sustaining in order to optimize the control strategy and minimize the fuel consumption. The blended mode depends on future information of the route to optimize the control scheme and maximize the energy harvested through regenerative braking. The SOC trajectory reflects the energy delivered and recaptured.

The SOC is the state variable for the optimization and the control scheme; it is used to determine the performance of the vehicle regarding optimization. The blended operation aims to extend the electric range of the vehicle. The blended strategy is shown in Figure 9.

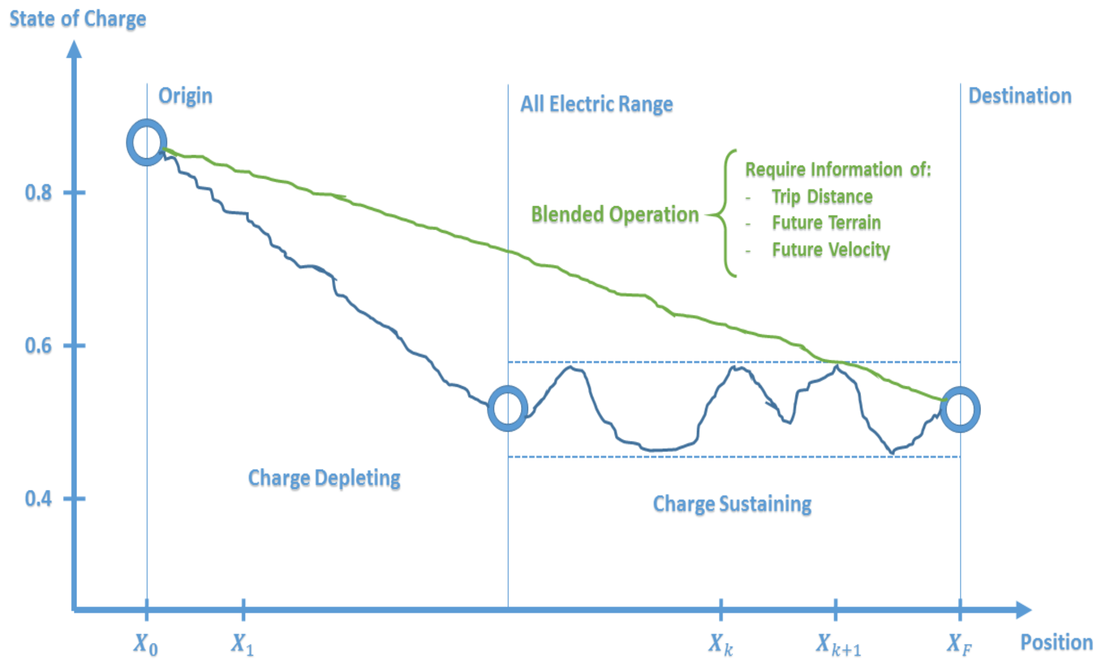

Figure 9. Look-ahead blended control strategy

The proposed controller top-level design is constructed such that it generates the optimization strategy and feeds the data to the supervisory controller in the vehicle. This design layout follows the industrial design on integrating Electronic Control Unit (ECU) to perform a specific task while communicating with the supervisory controller. The output of the look-ahead controller is translated as control torque command that the supervisory controller to implement in the powertrain.

The controller design layout is shown in Figure 10. Where x is the SOC of the battery which is the state variable of the optimization in the controller. u is the control command that ultimately represents the torque split ratio between the EM and ICE, and the goal of the controller is to find the most optimal control command. v is the modeled system input that represents the driver command.

The vehicle should be able to meet the driver demand by providing the requested torque and match the input velocity request which in the model is the drive cycle. The controller and the behavior of the model are determined by the ability of the vehicle to follow the trace of the input drive cycle with minimal error. y is the model output that is calculated in the vehicle based on the control command.

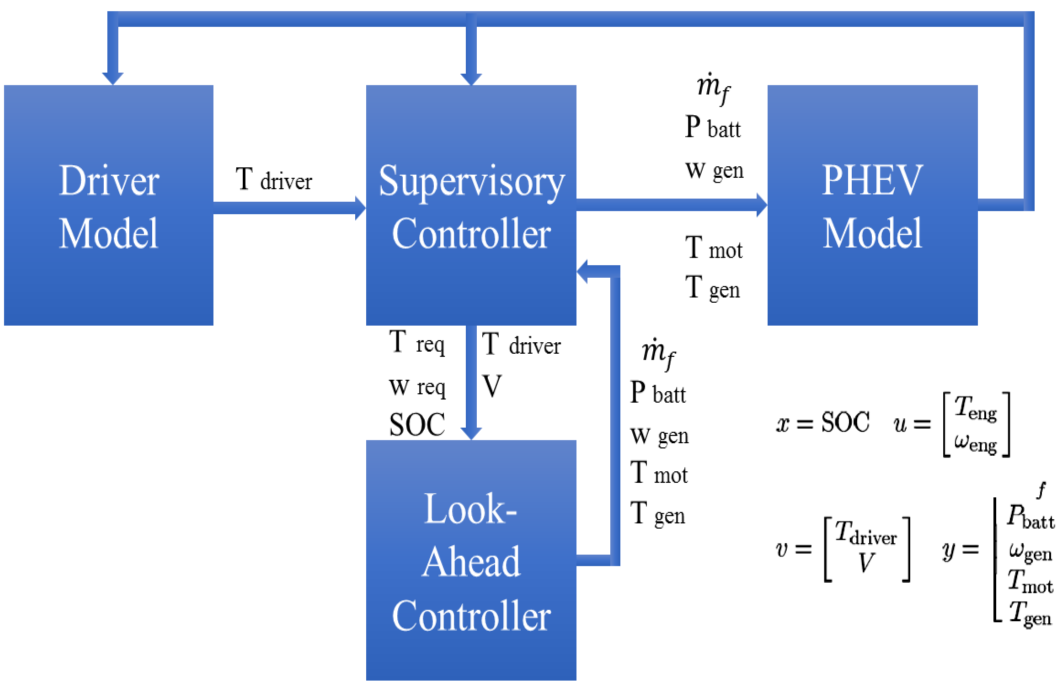

Figure 10. The proposed controller top-level design

2.1. DATA ACQUISITION

The algorithm acquires the road elevation, divide the path into segments and analyze these segments. The analysis considers two segments at a time to feed to the controller as shown in Figure 11. The algorithm analyzes the distribution of the elevation and the grade values to determine if in the next two segment the vehicle is either approaching an uphill or downhill.

RB optimized perform local optimization which determines the process of data acquisition since only two segments of future information is required to solve the optimization at a certain time. This approach does not require knowing the information of the entire route like DP, also account for the data acquisition and processing time. When integrated with other ADAS systems and the vehicle, this implementation strategy will reduce implementation issues and computational processing time.

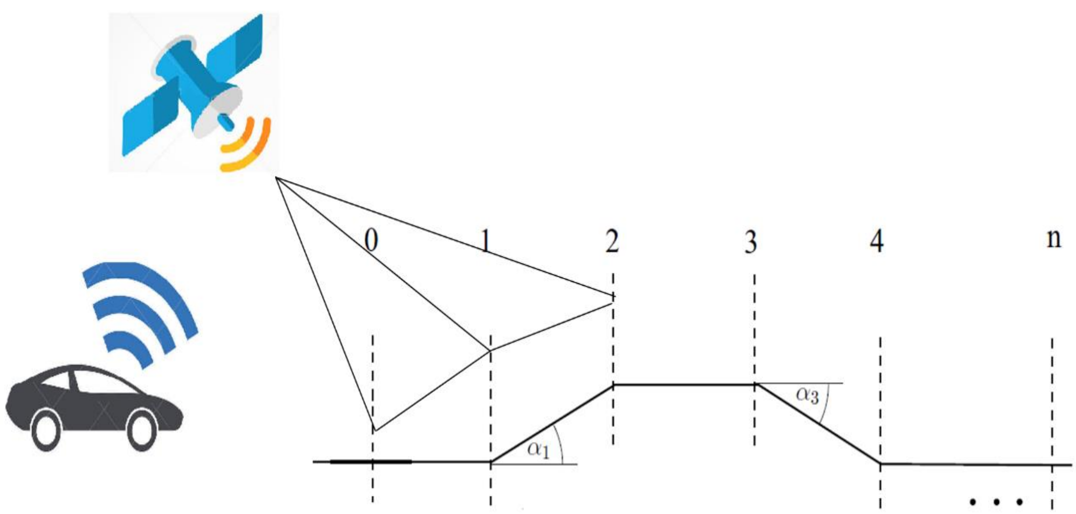

Figure 11. Road Terrain Segments Optimization

The road elevation profile acquisition is achieved using Google Earth to view and select the route. The routes have been chosen based on different variations of road elevations. The first route selected has a smooth transition between uphill and downhill over an extended period of time. This smooth transition limit the high dynamic disturbance in the model which result if vehicle meeting speed trace of input drive cycle with no fluctuation due to grade.

The second route has steeper uphill and downhill and with more positive grade than negative grade, the nature of this route induce more disturbance in the model and limit the amount of regenerative braking since the negative grade is much less than positive grade throughout the route. The third route has very high variations in elevation and grade compare to the first and second route, where the vehicle is constantly switching between an uphill and downhill. This route was selected to test further the behavior of optimized control scheme and the vehicle undergoing the frequent grade changes.

The problem faced is that Google Earth does not provide data extraction for the elevation data. As a solution for the data acquisition, Geocontext-Profiler and Google Maps JS API was utilized to acquire the elevation profile for a defined route. Google Maps Elevation API return the elevation for a single point, and the accuracy level might vary along the route. The routes that were selected are shown in Figure 12 from San Francisco, the routes selected are approximately 9.066 kilometers long. The grade for the model is then calculated using Equation 6, shown below, for each step.

Figure 12. Selected Route

$$Grade = \frac{Rise\ (Vertical\ Distance)}{Run\ (Horizontal\ Distance)} \tag{11}$$

The grade profile can have some inconsistent variations as a result of inaccurate elevation readings from to Google Elevation API. A smoothing API is used to correct the data [15], this is a critical component of the process since this noise can cause a high dynamic disturbance in the controller and vehicle model. Some GIS system has a low resolution that can reach 1 data sample per 10 meters, a sample of noise road elevation data along with the grade is shown in Figure 13.

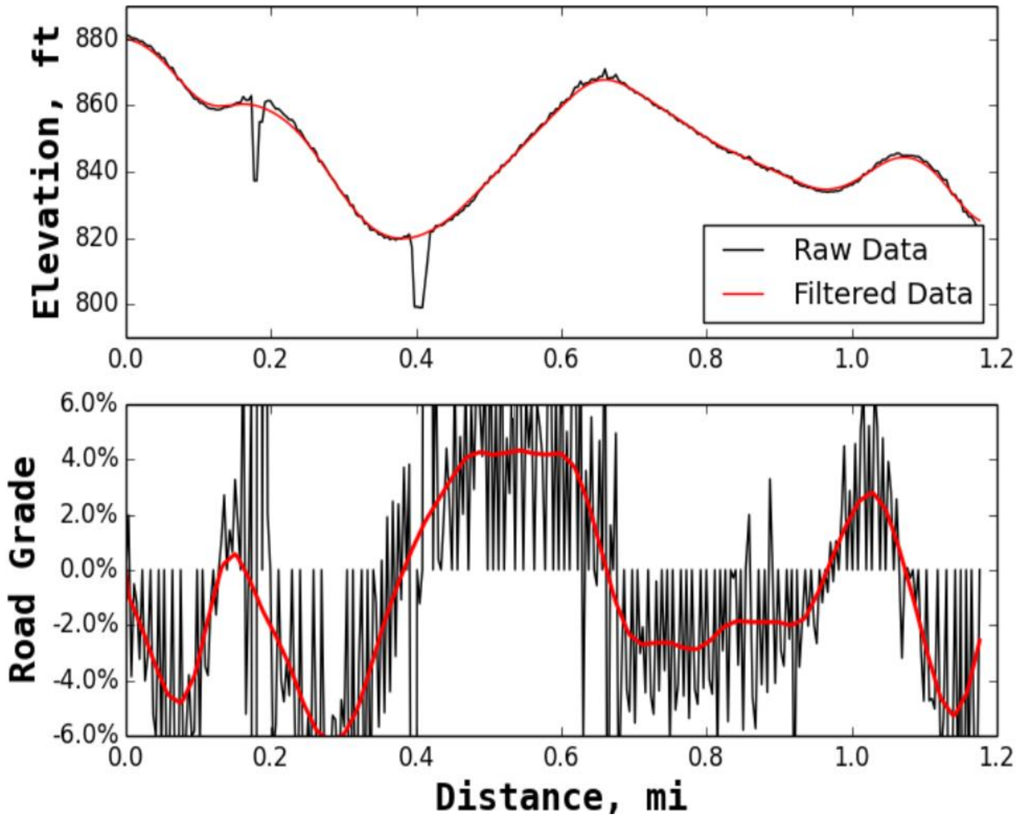

Figure 13. Road elevation and grade correction [15]

This noise is corrected using smoothing functions. The correction was performed to eliminate outlying incorrect data from affecting the behavior of the vehicle model. Performing the data correction using smoothing API result in a more accurate representation of the actual road elevation, it also reduces the high dynamic variation of grade values that is essentially a disturbance for the plant model and the controller. The resulted elevation profiles for the three routes are shown in Figure 14.

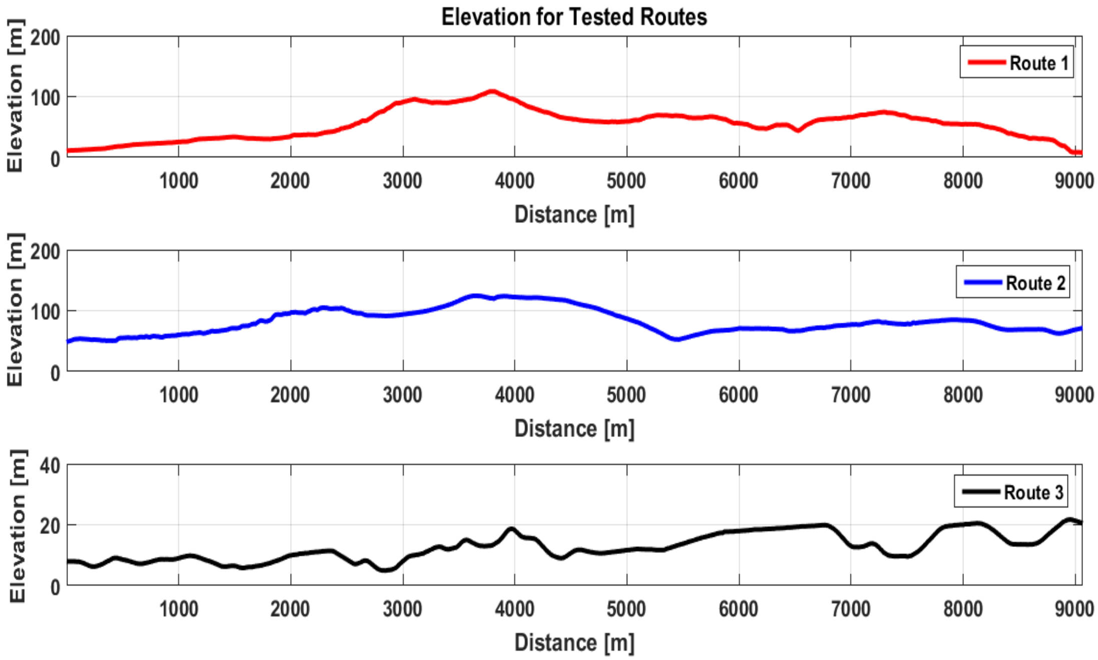

Figure 14. Elevation Profiles

Th vehicle model input is the drive cycle which represents the demand of the driver and the desired speed value that the vehicle should follow. Standard test drive cycles are used to test and validate vehicle model but since those drive cycles designed for zero grade roads they were only used to test the fidelity of the model.

To setup the test model undergoing the road elevations extracted from GIS maps, a drive cycle was created based on the speed limits provided by Google Maps Roads API. Based on the speed limits, the drive cycle was designed to start from zero, accelerate over an extended period of time and cruise at a maximum speed of 26 mph and the end of the route, the vehicle decelerates to zero, as shown in Figure 15.

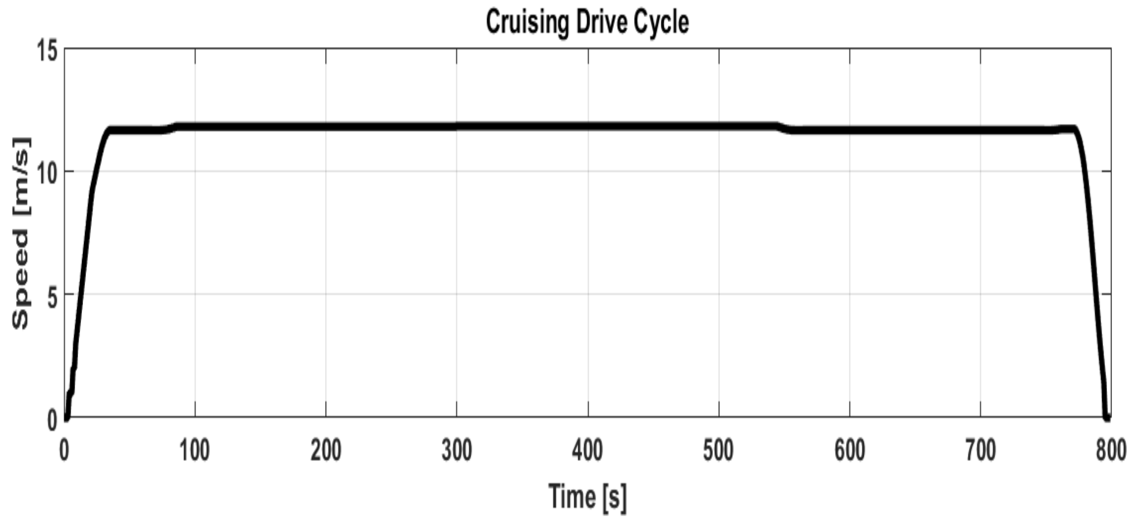

Figure 15. Drive Cycle

To test the fidelity and the performance of the model, Environmental Protection Agency (EPA) introduced standard testing drive cycles. Drive cycles consists of data points that represent speed value taken as an input for the model, so the vehicle follows the trace of the drive cycle, the speed calculated in the model is compared to the input speed to assess the behavior of the plant model undergoing the control scheme.

The nature of the drive cycle determines the power flow in the powertrain since it represents the power command of the driver that the vehicle powertrain components should be able to provide. Drive cycles are also used to quantify the fuel consumption of the vehicle and test the effect of different control strategies. Another use of drive cycles is to measure the gas emissions of the vehicle. Different drive cycles are designed to test certain properties of the vehicle performance. US06 drive cycle was used to test the performance the fidelity of the model. US06 combine both highway and city driving as shown in Figure 16.

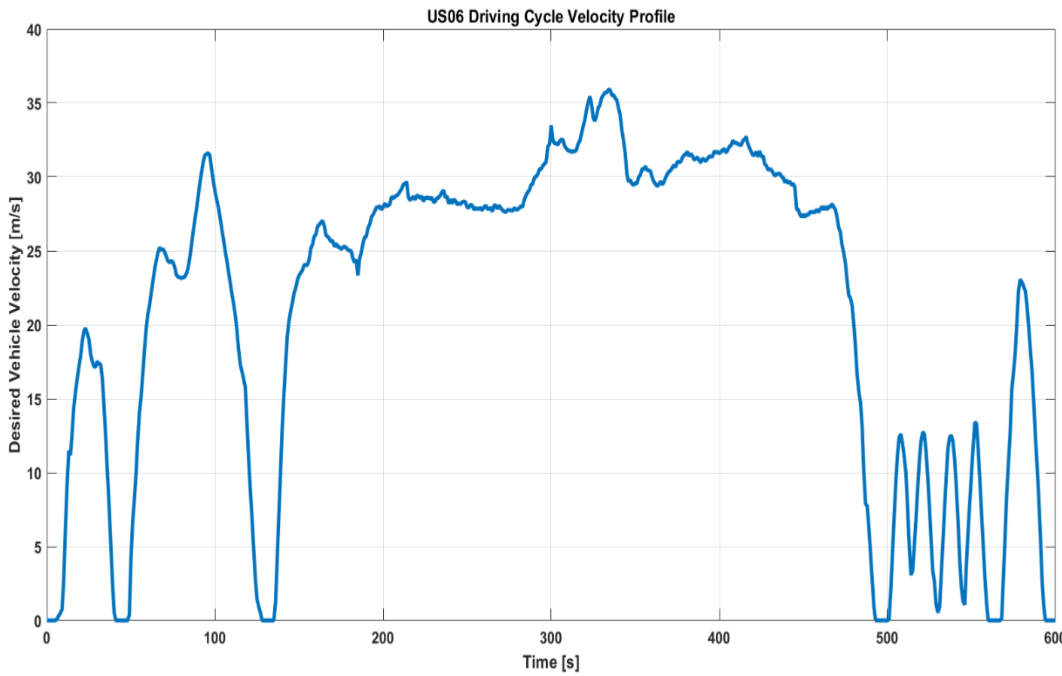

Figure 16. US06 Drive Cycle

2.2. PLANT MODEL

HEVs are more complex than conventional vehicles as they incorporate an electrical powertrain and require more complex control scheme and have the potential for optimization since HEVs have more degrees of freedom, thus a high fidelity model was built using MATLAB/Simulink. The model was developed to reflect an actual vehicle with all the sub-systems of the powertrain to simulate the operation PHEV and analyze the power flow throughout the ICE, EM, battery, transmission, and other components. The specifications for the modeled vehicle are shown in Table 1.

Table 2. Vehicle specification

Engine	3.4L V6 Gasoline
Motor Maximum Power	60 kW
Motor Maximum Torque	180 Nm
Battery Capacity	23.4 kWhr
Transmission	6 speed Automatic Transmission
Vehicle weight	2000 Kg

In the simulation, the vehicle is tested undergoing a drive cycle to evaluate the behavior and the response of each subsystem. The top level of the full vehicle model consists of the driver model which take the drive cycle as an input and calculate the driver command that is represented by accelerator pedal and brake pedal. The controller of the vehicle take the driver command the calculate the torque request by mapping the accelerator pedal to the maximum torque that the vehicle can provide through both ICE and EM.

The controller then calculates the torque split ratio and determine the torque command for the ICE and EM. The powertrain components respond to the driver command and provide the requested torque to the wheels. The tractive force acting of the vehicle is calculated by multiplying the torque delivered to the wheels by the tire radius. The tractive force is then taken into the vehicle dynamics model.

The vehicle dynamics model take the tractive force delivered by the powertrain to the wheels and calculate the net force acting on the vehicle by subtracting the force losses that include rolling resistance, aerodynamic drag, and grade force. The acceleration is then calculated by dividing the net force by the mass of the vehicle. The acceleration is then integrated to calculate the vehicle speed.

The vehicle speed is sent back to the driver model to construct a closed loop feedback controller and adjust the accelerator and brake pedal based on the error between the desired and actual speed. The top-level of the model is shown in Figure 17.

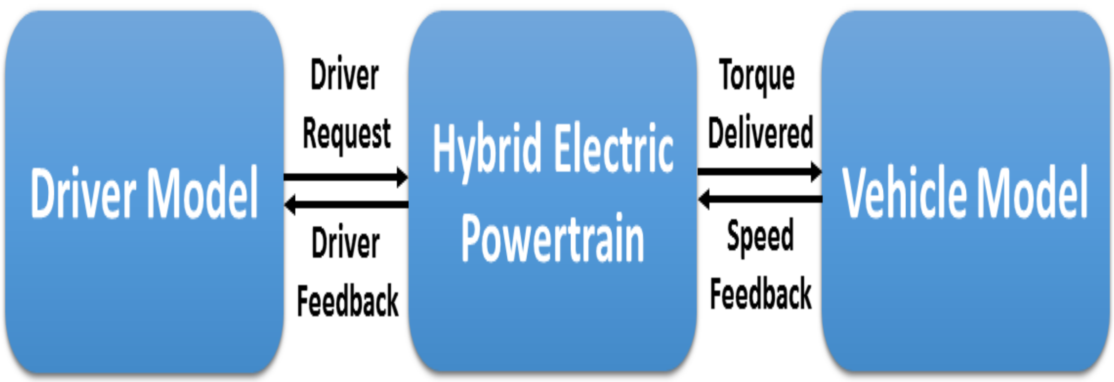

Figure 17. Top level of the HEV model

The MATLAB/Simulink model represent a PHEV model. The model reflects a PTTR-HEV architecture. In this model, the ICE based conventional powertrain that consist of ICE with fuel tank, the ICE is connected to the transmission through a clutch, the resultant torque provided is equal to the torque of the ICE multiplied by the gear ratio of the transmission. The ICE based powertrain components are connected to the front axle. The electrical powertrain that consists of the EM and the battery are connected to the rear axle. The torque at the rear axle is equal to the torque of the EM multiplied by the constant gear ratio of the EM transmission.

This architecture requires less complicated control scheme to determine the power split and power flow since there is no mechanical connection between the ICE and EM. The supervisory controller along with the powertrain components are shown in Figure 18.

Unlike parallel HEV, PTTR-HEV power flow is handled differently since there is no direct mechanical connection between the ICE and EM. Because of this difference, the speed of which the ICE operate on is different from the speed of the EM. In parallel HEV both the ICE and EM will have to spin at the same speed, this constraint make the powertrain power flow harder to manage, and it limits the optimization of the powertrain.

In PTTR-HEV, both the ICE and EM are connected to different axel with their transmission. In this configuration the EM spin by the same speed of the vehicle divided by the rear axle gear ratio. This constraint is caused by the absence of a clutch and a torque converter of the rear axle, it also limits and the optimization of the EM since it is constraints by the speed.

On the other hand, the ICE can operate at a different speed than the EM, which makes the optimization of the ICE operating in a more efficient region easier. This optimization is reflected on the fuel consumption and the MPG of the vehicle.

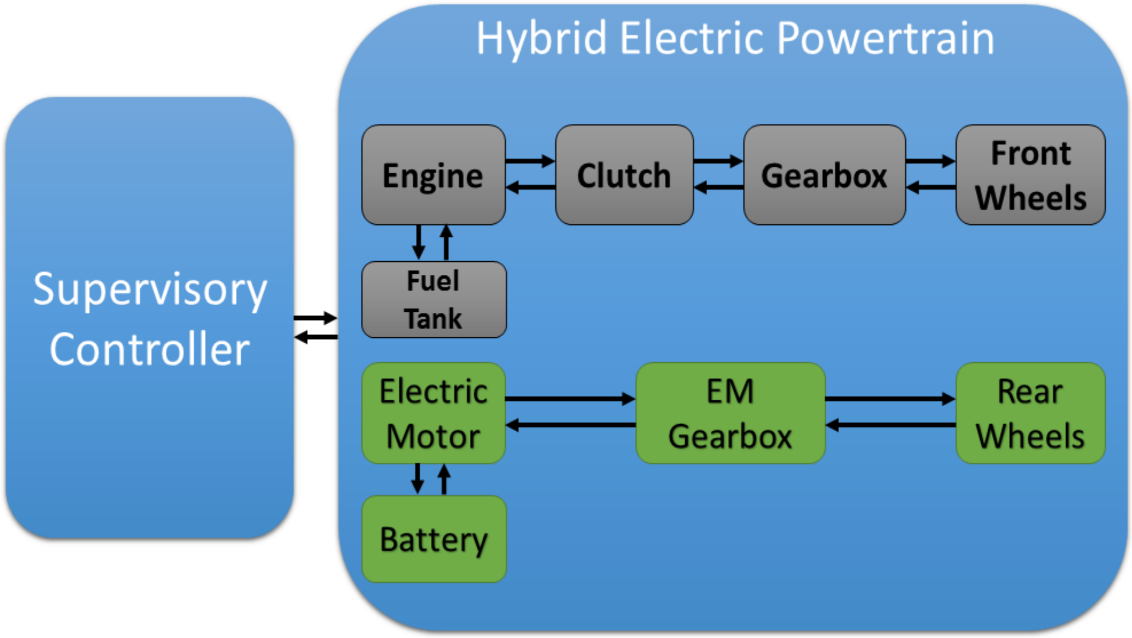

Figure 18. Powertrain components and controller

2.3. DRIVER SUB-MODEL

In order to test a model and analyze the response of the vehicle model, different drive cycles are applied to the model as a drive input. These drive cycles are desired speed values. The driver is simulated as a PID controller with an output of acceleration and braking pedals [16]. Vehicle model layout highlighting the driver model is shown in Figure 19.

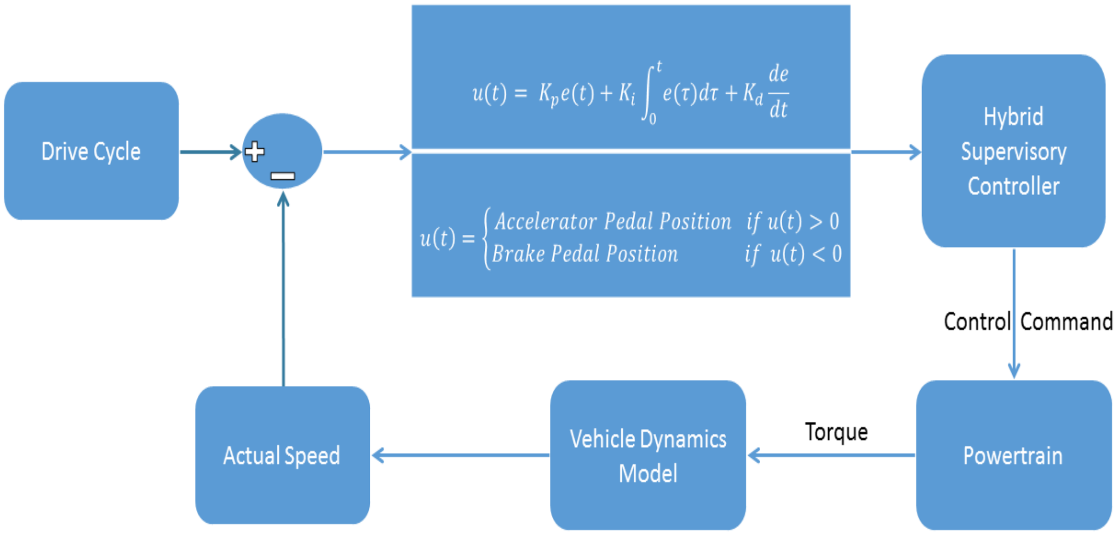

Figure 19. Driver Model

Driver Model consists of a PID controller. The input of the controller is the error signal which is the difference between the desired speed and the actual speed calculated in the model. The output control signal of the controller is calculated according to the following equation:

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau)d\tau + K_d \frac{de}{dt} \tag{6}$$

$$e(t) = V_{desired} - V_{actual} \tag{7}$$

$$u(t) = \begin{cases} Accelerator\ Pedal\ Position & if\ u(t) > 0 \\ Brake\ Pedal\ Position & if\ u(t) < 0 \end{cases} \tag{8}$$

Manual tuning of the PID was performed with the purpose of achieving the best speed matching between the desired speed and the actual speed. Taking into account, that the grade induced high dynamics.

The grade is essentially considered as output disturbance for the system. The result of the manual tuning is 0.65 for K_p, 0.03 for K_i and zero for K_d.

The output of the PID is a result of the difference between the desired speed (drive cycle) and the actual speed of the vehicle calculated in the model. Manual tuning of the PID is performed in order to have a perfect match between the drive cycle and the actual speed in the model.

2.4. ENGINE SUB-MODEL

ICE is modeled using the Kinematic approach. The backward kinematic approach uses the engine data provided by the manufacturer [17], this data include torque and speed map, fuel consumption map indexed by torque and speed and efficiency map. The outputs of the ICE model are torque, speed, and fuel flow rate for each time step of the executing the model.

The efficiency map of the engine is utilized to analyze the performance of the ICE and help optimize for more efficient operation. Figure 20 shows the ICE efficiency map indexed by the torque and speed, the highest efficiency of the engine is approximately 35%.

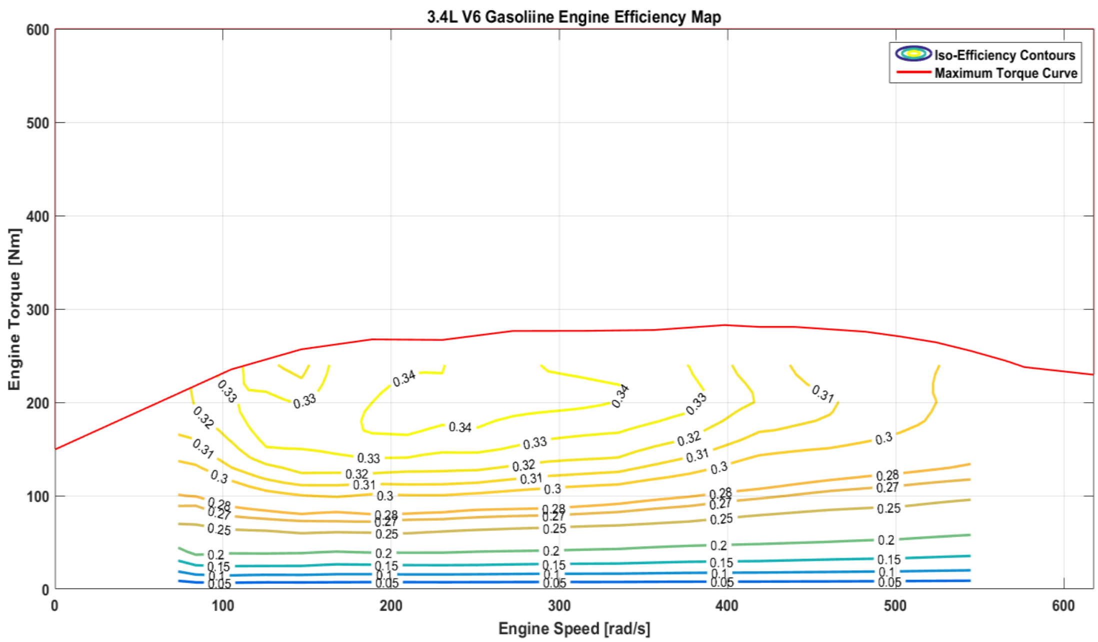

Figure 20. ICE efficiency map

The engine model takes the torque command input from the controller and calculates the mass flow rate of the fuel. Also, the efficiency of the engine is considered in deciding the operating condition. An efficient operation includes operating the ICE at a high-efficiency region in the efficiency map. Figure 21 shows the ICE fuel consumption map indexed by torque and speed. The contour lines show the fuel flow rate in g/s.

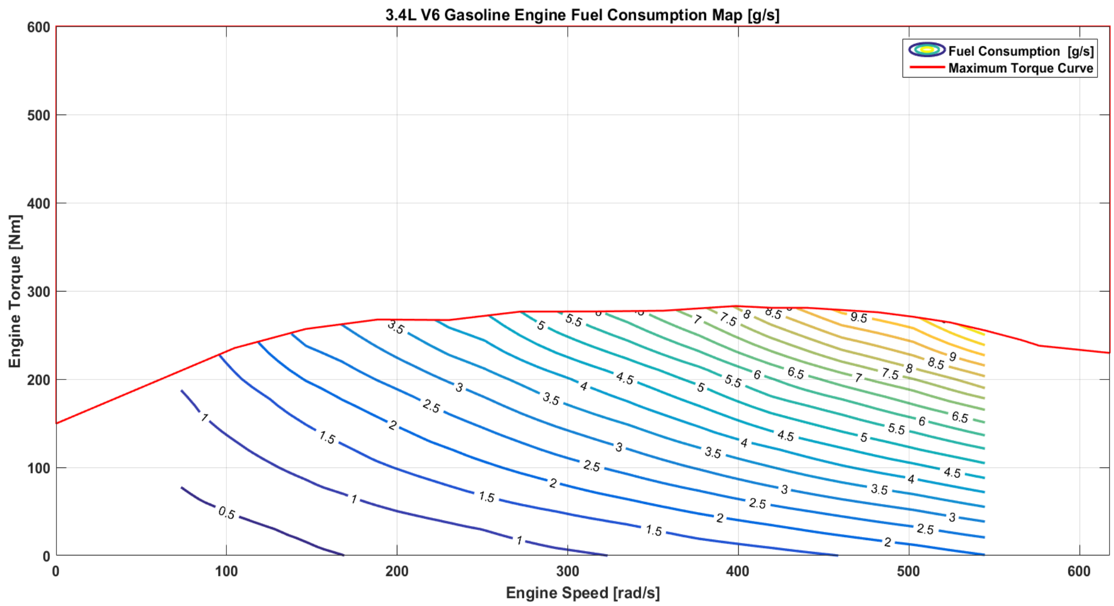

Figure 21. ICE fuel consumption map

2.5. ELECTRIC MOTOR SUB-MODEL

The EM is this model constructed using the data provided by the manufacturer. This approach uses the torque-speed map and the efficiency map [18]. The output of EM along with its gearbox is the torque, speed, and efficiency of the model. The response and efficiency of the EM are studied and considered in determining the best operating range of the EM. The EM model accepts the torque command from the controller and output the actual torque and calculates the efficiency, while the speed of the EM is calculated in its gearbox model.

Figure *22* shows the EM efficiency map indexed by its torque and speed. The red lines are the maximum and minimum torque that the EM can provide, and the blue dashed line is the torque limit that depends on the energy stored in the battery at each time step of execution. To optimize the EM operation, the efficiency of the EM is analyzed to check the operating conditions, the analysis indicates the operating points of the efficiency map and helps further optimize the EM. The controller will make the decision for the torque split aiming to operate at the highest efficiency region.

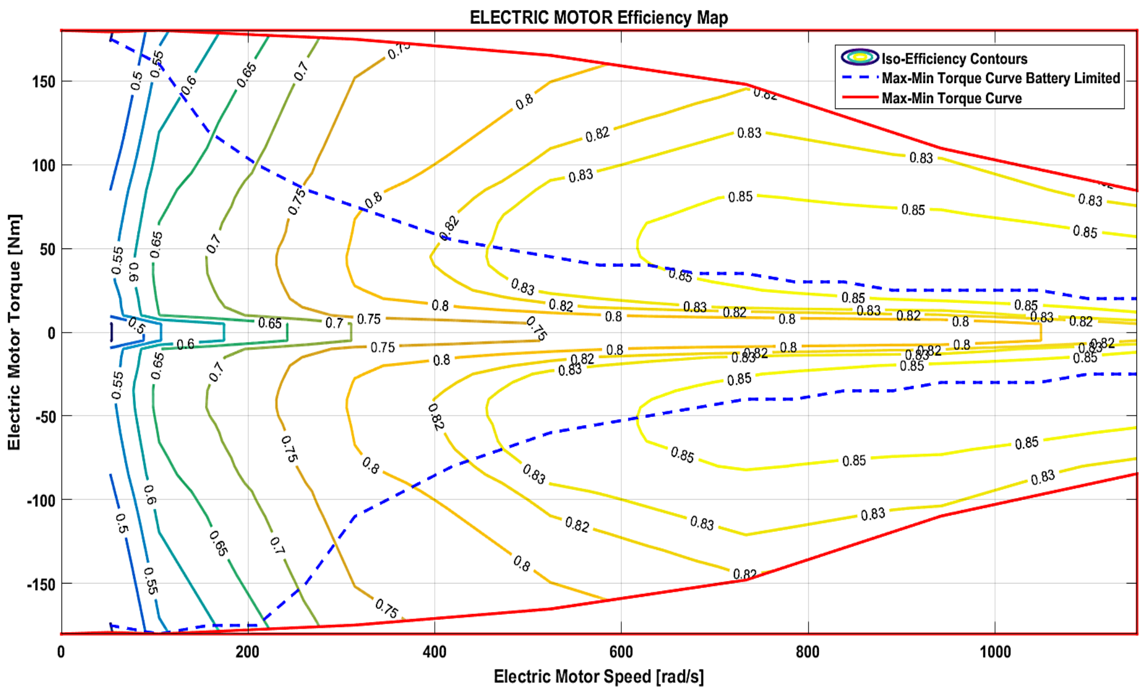

Figure 22. EM efficiency map

2.6. VEHICLE DYNAMICS SUB-MODEL

The vehicle dynamics are modeled to consider the load on the vehicle and calculate the power delivered to the wheels [19], the vehicle dynamics model accept the tractive force from the drivetrain, the resistive forces include the aerodynamic drag force, grade, force, rolling resistance. The model was properly adjusted to, count for the force balance then include the impact of grade on the vehicle using the following equations.

$$F_{tractive} = F_{rolling} + F_{\text{drag}} + F_{grade} + M_{eff}\frac{dv}{dt} \tag{9}$$

$$F_{tract} = (C_r mg\cos(\theta)) + \frac{1}{2}\rho C_d A_f V^2 + mg\sin(\theta) + mM\frac{dv}{dt} \tag{10}$$

Where ρ is density of air, A_f is frontal area, C_d is Drag Coefficient, C_r is Coefficient of rolling resistance, M_{eff} is the effective mass of the vehicle which is the mass factor (m) multiplied but vehicle mass (M). The resistive forces are subtracted from the tractive force delivered to the wheels which result in the net force acting on the vehicle. The vehicle dynamic parameters are in Table 3.

Table 3. Vehicle dynamic parameters

Vehicle mass	2000 Kg
Gravitational acceleration	9.81 m/s^2
Coefficient of rolling resistance CRF	0.012
Tire radius	0.3305 m
Frontal area	2.82 m^2
Coefficient of aerodynamic drag	0.416

The vehicle acceleration is calculated based on the net force acting on the vehicle taking into consideration the effective mass of the vehicle. The actual speed of the vehicle is calculated by integrating the acceleration value. The actual vehicle speed is taking as a feedback signal to the driver model. Distance traveled is calculated by integrating the vehicle speed. Vehicle dynamic model is shown in Figure 23.

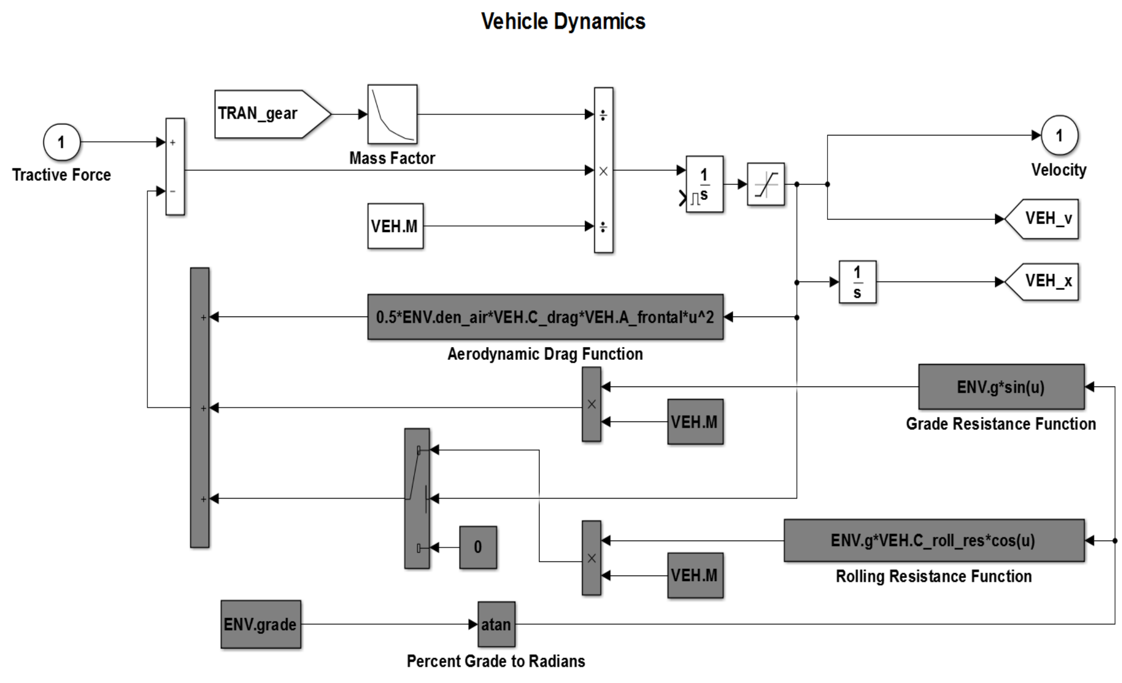

Figure 23. Vehicle dynamics model

2.7. RULE BASED CONTROLLER

RB controller is constructed using heuristic logic rules that are based on the desired mode of operation. Logic based controllers are often not the most optimal option, but they provide a robust fast solution for real-time applications. In the vehicle model, the RB controller is used to determine the torque split between the ICE and EM based mainly on the torque demand. The heuristic logic rules are determined based on the mode of operation, the speed of the vehicle, and the SOC of the battery which corresponds to how power can be delivered by the EM. The RB control scheme is shown in Figure 24.

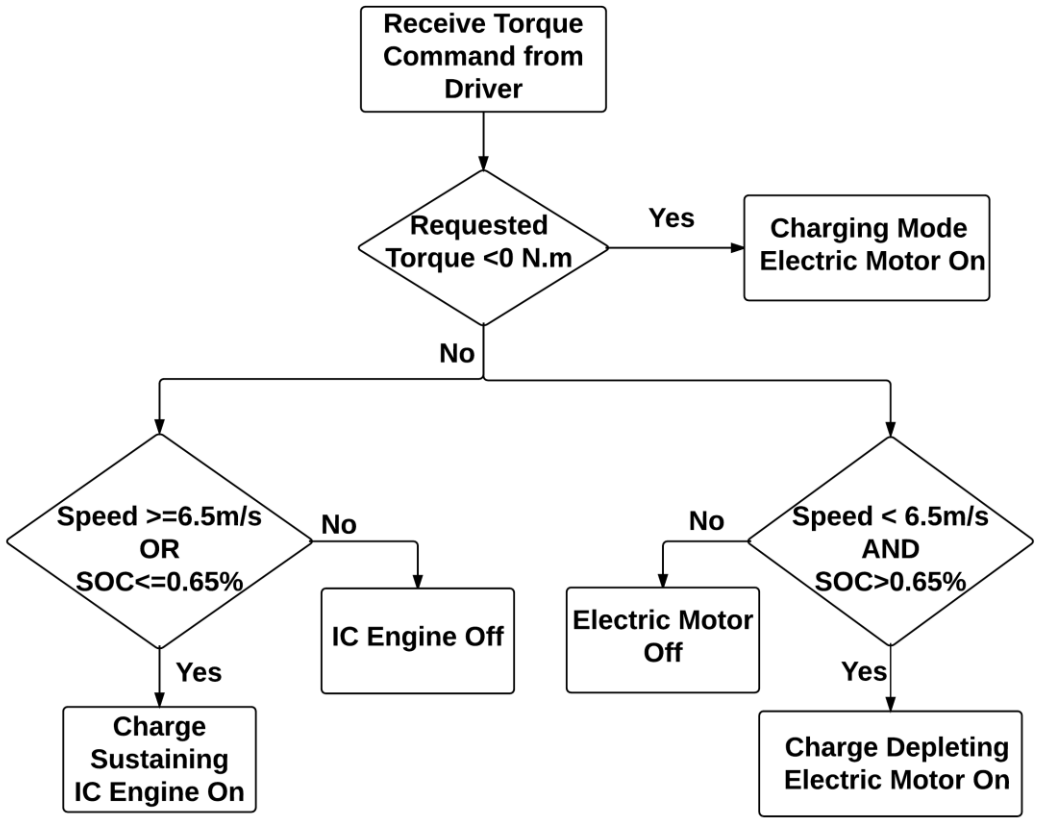

Figure 24. RB Control Scheme

First, the controller checks if the torque request is negative which mean that the vehicle is either braking or going downhill, in this case, the negative torque goes to the EM as regenerative braking. If the requested torque is positive, then the controller check the speed and SOC of the battery to determine the operating mode. The speed of the vehicle correspond to how much power need to be delivered by the powertrain, and since the ICE can deliver higher torque than the EM, then the ICE operate at higher torque demand.

The SOC of the battery reflects how much torque or power the EM can provide so if the SOC is high and the torque demand is less than the maximum torque of EM then the vehicle operate in charge depleting mode. If the SOC is below the set value for the charge depleting mode, then the ICE provide the requested torque, and the vehicle operates in charge sustaining mode.

2.8. HARDWARE-IN-THE-LOOP

The model is developed in MATLAB/Simulink, and it was tested to inspect the fidelity of the model and the performance of all the sub-systems. HiL is used to execute and test the model in real-time using target hardware that interface signals between the model in a virtual environment and real components. HiL executes and interfaces the model on an embedded target computer to test the plant under control, in this setup, the plant under control is the vehicle model along with the control scheme.

Simulation Interface Toolkit (SIT) that is developed by National Instrument is used to compile the model in MATLAB/ Simulink into C code and generate Dynamic-Link Library (DLL), the DLL is then imported in LabVIEW and SIT recognize the mapped signals from the Simulink model. Host VI is built in LabVIEW to interface and visualize the signals to monitor the execution of the model and send the receive signals through the input-output (I/O) module. Figure 25 shows the process of compiling and interfacing model for SIT.

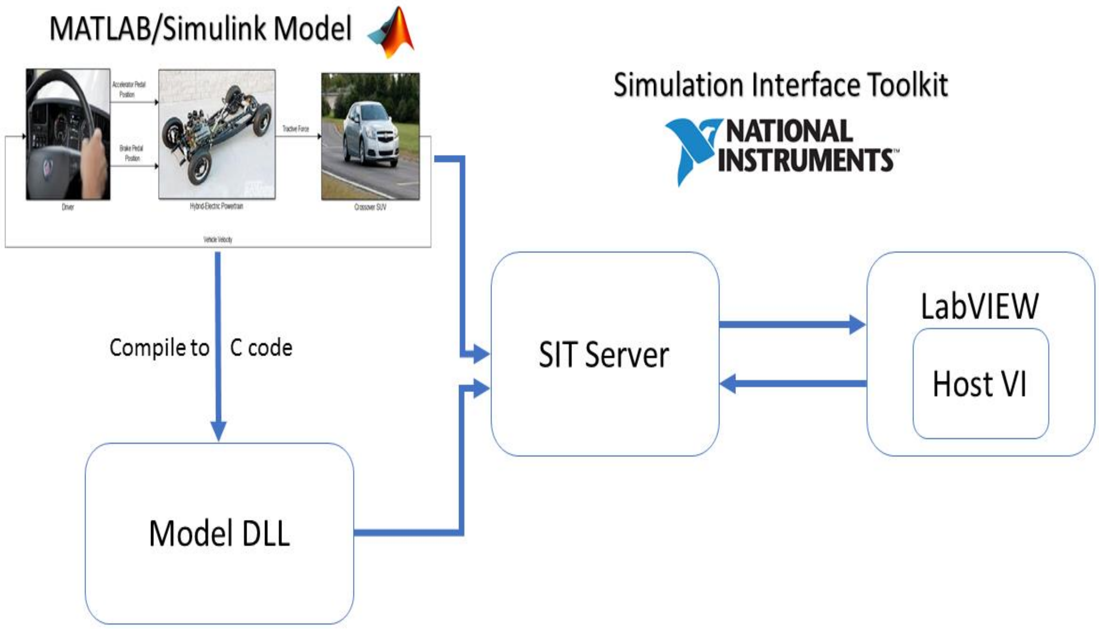

Figure 25. Simulation Interface Toolkit

The SIT server use TCP/IP to transmit signals and send new parameters between the model and the Host VI, also the SIT server manage signal transmission between the Host VI and I/O module, where the new parameters are transmitted back to execute model blocks.

The Host VI is built to interface the signal from the model. Graphs, indicators, and gauges are incorporated in the front panel of the Host VI in LabVIEW to visualize the signals and monitor execution. The front panel of the Host VI is shown in Figure 26.

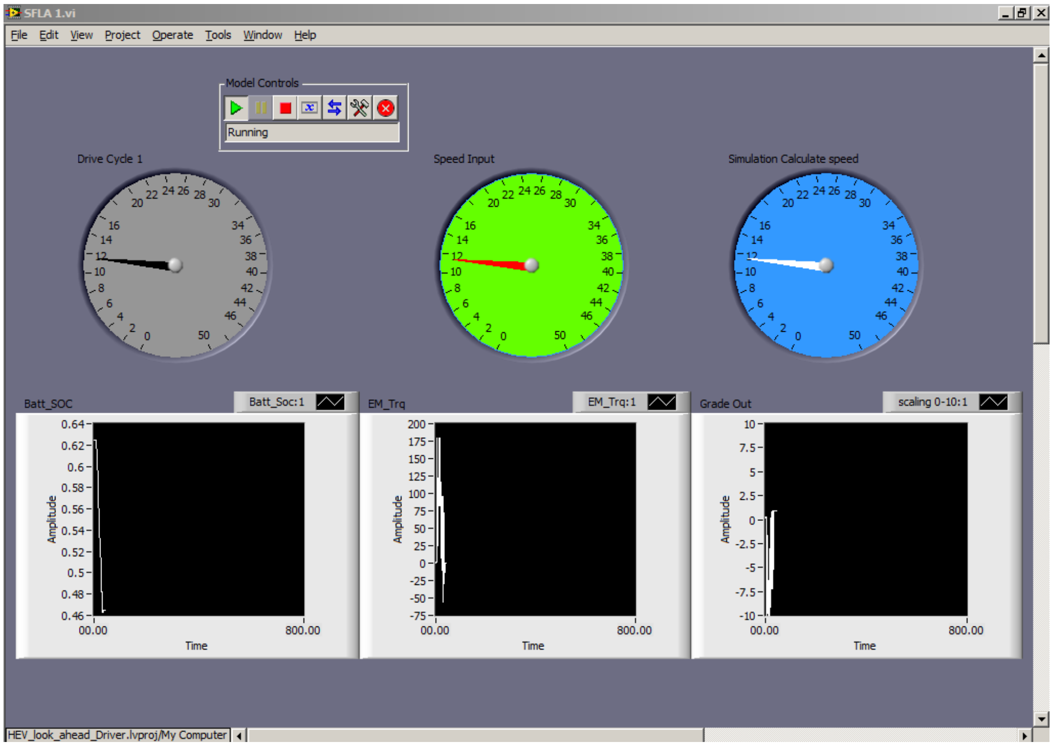

Figure 26. Host VI Front Panel

The target computer for the HiL test is NI PXIe-1071 chassis, which is a high-bandwidth controller that support high-performance test applications. NI PXIe-1071 interface with NI PXIe-6341 Multifunction Data Acquisition (DAQ) device that supports high-speed data acquisition through PCI Express bus, it provides 16 analog inputs, 2 analog outputs, 24 digital I/O lines, and 4 32-bit counter/timers for PWM. Host VI has the configuration for SIT signals mapping with DAQ I/O module. The HiL setup is shown in Figure 27.

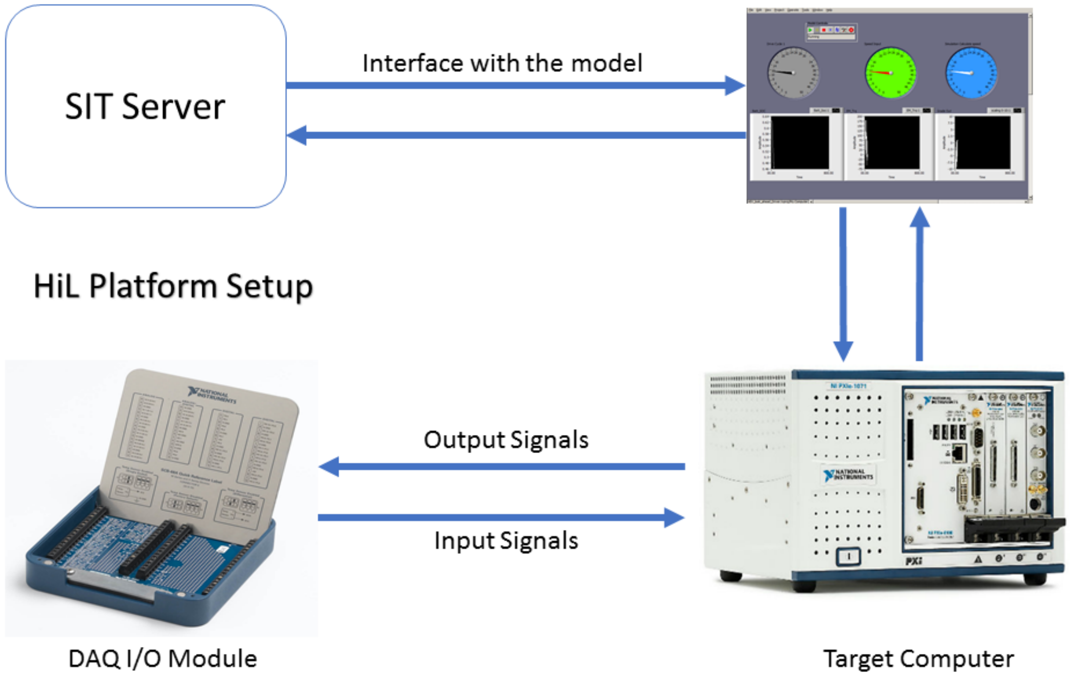

Figure 27. HiL Platform Setup

3.1. COST FUNCTION MATHEMATICAL MODEL

In order to minimize the cost function which is the fuel consumption, the supervisory controller determines the optimal torque split based on the future terrain on the route. The control scheme takes into consideration several subsystems to operate the vehicle. This derivation includes both the electrical components of the powertrain as well as ICE and the other mechanical elements of the vehicle. The main objective to achieve is the driver command, the driver demand is a constraint for the optimization algorithm and is considered as the input command for the controller.

The dynamics of the battery state of charge (SOC) is the key source of reference for the optimization. The system is modeled by the open circuit voltage (OCV) in series with a constant internal resistance [20].

$$\frac{d}{dt}SOC = \frac{-I}{C} = -\frac{V_{\mathrm{oc}} - \sqrt{V_{\mathrm{oc}}^2 - 4P_{\mathrm{batt}}\mathrm{R}}}{2RC} \tag{1}$$

Where V_{oc} is the OCV of the battery, P_{batt} is the electrical power at the output side. R is the internal resistance of the battery, and the connecting wires and C is the battery capacitance. The ICE fuel rate is modeled by lookup tables mapped by the engine torque and the engine speed.

$$\dot{m}f = f(T_{eng}, \omega_{eng}) \tag{2}$$

In the same manner, the battery power is modeled by lookup tables to relate the mechanical power to the motor speed.

$$P_{\text{batt}} = g(P_{\text{m}}, \omega_{\text{m}}) \tag{3}$$

Positive $P_{\text{batt-dmd}}$ means the battery is charging and negative $P_{\text{batt-dmd}}$ means the battery is discharging, so the total power demand.

$$P_{\text{dmd}} = P_{\text{drv-dmd}} + P_{\text{batt-dmd}} \tag{4}$$

Where $P_{\text{drv-dmd}}$ is the power demanded by the driver, the demanded torque T_{dmd} is then calculated based on an optimized map for different operating regions and then calculate the optimal torque and speed split for the hybrid powertrain. Different optimal control strategies use minimized the cost of function J_{f} which is for hybrid vehicles is a function of the fuel flow rate and the state of charge of the battery [4].

$$J_{\text{f}} = \int_{t0}^{tf} \dot{m}_{\text{f}}\,(t, u)dt + \phi(SOC_{\text{i}}, SOC_{\text{f}}) \tag{5}$$

The powertrain constraints are SOC, torque, and speed. The equations may be simplified to minimize the instantaneous fuel flow rate. This optimization is achieved simply by determining the optimal torque split between the ICE and the electric motor, EM. This approach maximizes the kinetic energy captured through regenerative braking.

This system will produce more energy efficient vehicles through advanced control algorithms, but it requires enormous computational power, this implicates that the method of the control strategy has to be real-time implementable which presents an immense challenge.

3.2. RULE BASED OPTIMIZATION

HEV uses an EM and generator along with the ICE, which adds more degrees of freedom to the system and makes control systems for these vehicles more complex by providing more margin for optimization regarding utilization of the resources onboard. Different optimization strategies are utilized with varying complexity for various control strategies. The most common control schemes for HEVs are RB control strategies. RB mainly consider the mode of operation based on certain rules derived using human intelligence, heuristics, and mathematical models [8]. Deterministic RB control strategy is implemented in this model.

This strategy is based on heuristic analysis of energy flow and determines the torque split between the ICE and the EM. The optimization approach is essentially prioritizing the resources on board to minimize the fuel flow rate and maximize the amount of kinetic energy that is utilized through regenerative braking. Road grade changes the load balance for the model since the model is essentially built for flat roads with zero grade.

In order to include look ahead optimization in the model, an algorithm was constructed to calculate a statistical function to add in the controller. The function returns a negative value when approaching uphill and a positive value when facing downhill. The function also implements a curve fitting algorithm, this allows the function to cope and eliminate highly dynamic variations that might destabilize the controller. In turn potentially destabilizing the dynamics of the vehicle. These calculations are applied to two segments of the road at each step in the model to count for short range and long range look-ahead information in the future. In this case, the controller can optimize for the current state of the road with longer range taken into consideration. The calculation is then performed using the following equations.

$$\frac{n}{(n-1)(n-2)}\sum\left(\frac{x_i-\bar{x}}{s}\right)^3 \tag{12}$$

In Equation 12, n represents the number of elements in the array, $\bar{x}$ is the mean of the array and *s* is the standard deviation. Smooth spline curve fitting is used to eliminate highly dynamic variations. Controlling quick changes that may destabilize the controller and the dynamics of the vehicle. This is controlled by Equation 13.

$$p\sum_i w_i(y_i-s(x_i))^2+(1-p)\int\left(\frac{d^2s}{dx^2}\right)^2\ dx \tag{13}$$

Where *S* is the smoothing spline, *p* is the smoothing parameter and *w* is the specified weight for *x* input and *y* output. The result of this algorithm for the routes defined above is shown in Figure 28.

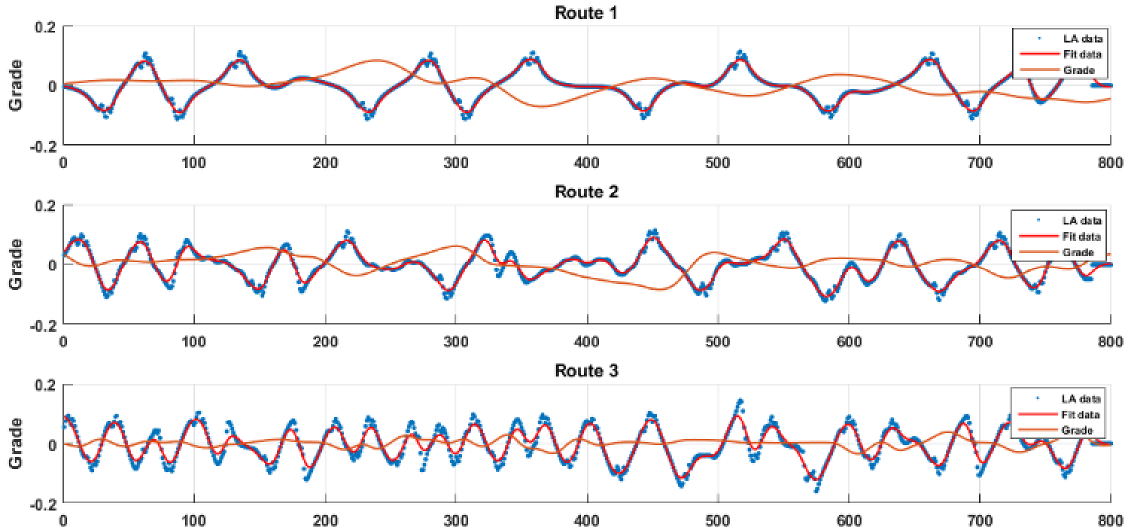

Figure 28. Look-ahead algorithm result

Deterministic RB control strategy is implemented in a full hybrid vehicle model including the algorithm for look-ahead optimization. This process is shown in the flow chart in Figure 29. The control scheme starts with acquiring the road grade for two segments ahead and check the grade distribution based on the mean and standard deviation to check if the vehicle is approaching downhill or uphill to prepare the vehicle for charging and discharging respectively.

Deciding the mode of operation is either case will always be restricted by the SOC of the battery and also by the torque demand. So when approaching uphill, the vehicle operate in charge depleting mode as long as the SOC is higher than the lower limit. Otherwise, the vehicle will operate in charge sustaining where the ICE is the main source of power. On the other hand, when approaching downhill, the vehicle take the negative torque through regenerative braking harvesting the maximum about of potential energy.

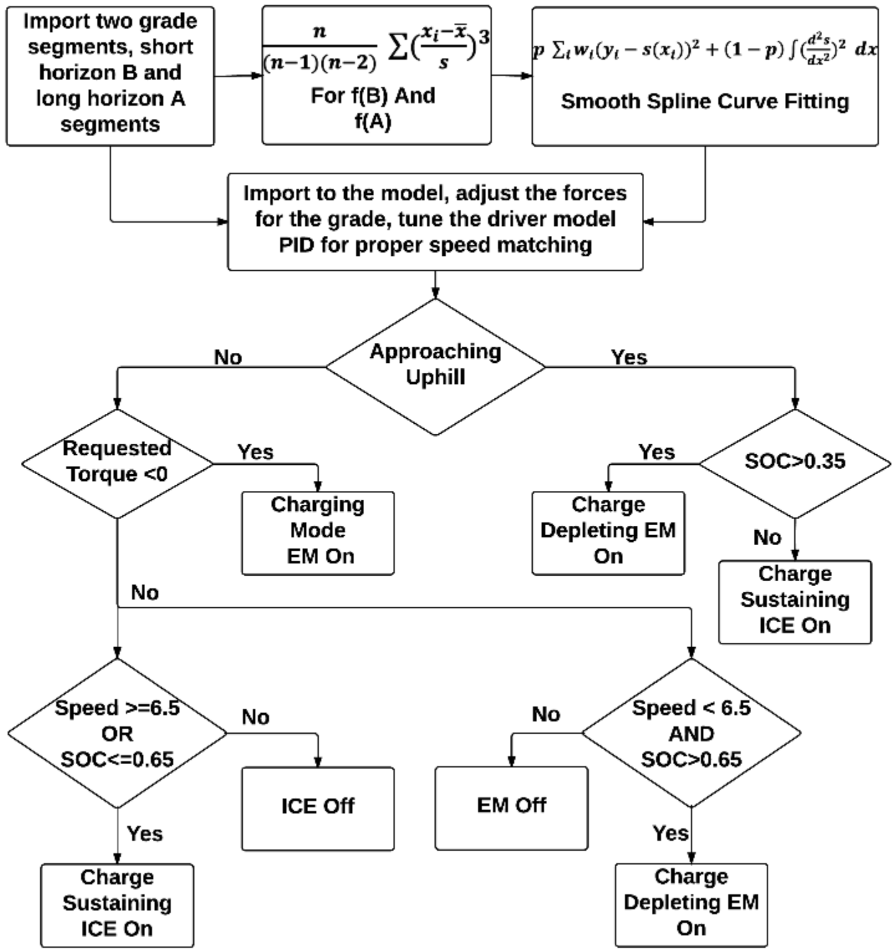

Figure 29. Rule Based Optimized Control Strategy

For RB approach, HiL was utilized to validate the control strategy in real time. VHiL will also be used to integrate and validate the inclusion of look-ahead control into an existing conventional ICE-based powertrain using VHiL methodology tested on the rolling test bench (Chassis Dynamometer) [21].

The integration of hybrid electric module to an existing platform can be validated the control strategy during the development stage using this concept. Mayyas et al. were the first to use VHiL approach to test and validate the control strategies for an HEV [22].

3.3. DYNAMIC PROGRAMMING OPTIMIZATION

DP algorithms were developed to find the optimal control strategy for multivariable multi-stage systems [8]. DP involves an optimization problem utilizing a backtracking approach. It divides the bigger problem into smaller sub-divisions and finds the optimal solution for the smaller subsystems. Once all the subsystems are solved, they are sorted to find the optimal solution. Integration of the sub-solutions together then provides insight to the larger problem.

Bellman's principle of optimality approach is used, such that, the entire journey is divided into an equal number of subdivisions [23]. At each subdivision, the fuel consumption by the ICE has to be minimized.

The backtracking starts from the destination endpoint. The minimal fuel path to the previous point (time step) is obtained from all the possible paths and is reserved or stored as the minimal fuel path. This approach is continued backward until the initial starting point is reached. All the minimal fuel paths are integrated starting from the endpoint to the initial point giving the overall route for optimal fuel consumption.

DP implementation using Bellman's principle of optimality approach aims to minimize the cost through global optimization. Minimizing the cost is implemented through finding the most efficient path by minimizing the cost function of each stage from the initial until the final point as illustrated in the following figure.

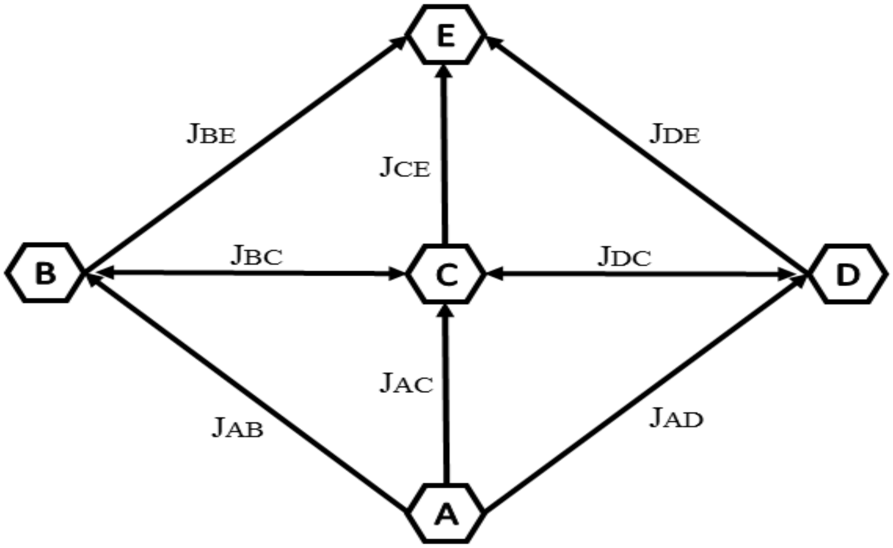

Figure 30. DP path optimization

The objective function of an optimization problem demonstrates the end goal to be achieved, in this case, it is the cost function. If the goal is to get from point A to point E, then the cost function is the summation each segment's cost. If we assume that the most optimal path is from A through B to E, then the cost of this path is: Cost = $J_{AB} + J_{BE}$

DP approaches the larger problem by subdivision of possible routes between two points. By dividing the bigger problem into N stages on the horizontal axis. On the vertical axis, there is the control function. In this case, power from the ICE is a control function. The values of the control function on the vertical axis will be equally spaced from zero to the maximum power capacity of the ICE. All the possible connections between the nodes of two consecutive stages are given.

To achieve the optimization of the control scheme, it is important that the power from the ICE or the EM can be changed from zero to any other possible value or vice versa within the time equal to the difference between the two stages. The DP approach stage diagram with four stages is shown in Figure 31. The proposed algorithm uses a similar approach utilizing more stages [24]. In between each stage, the energy consumption from the ICE is calculated by taking an average of the ICE power at the two stages and multiplying it with the time interval of the stage. Hence, the cost for each subdivision that is to be minimized.

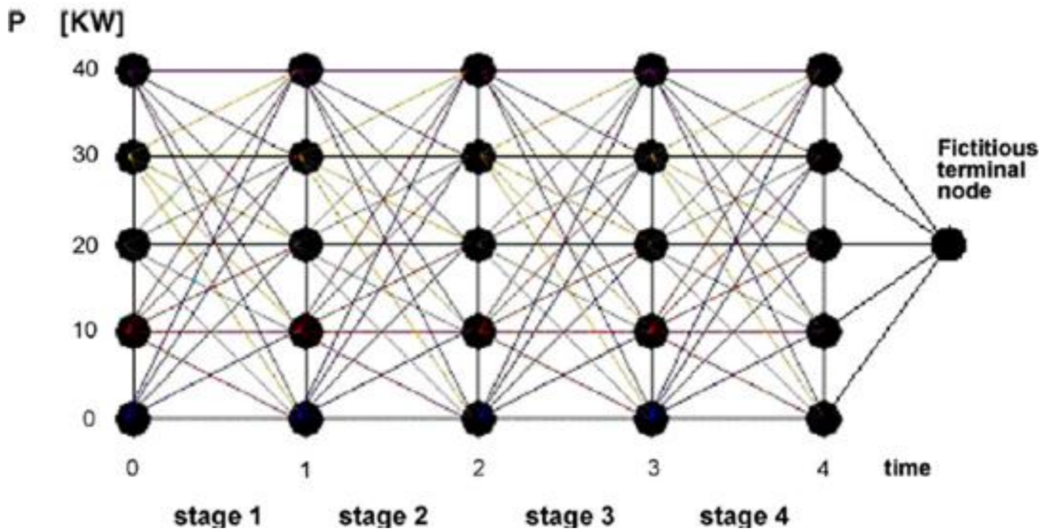

Figure 31. Dynamic programming diagram for a 4 stage problem *[1]*

Table 4. Nomenclature for DP Model

$P_{ICE}(k)$	Power of the ICE (KW)
$P_{EM}(k)$	Power of the EM (KW)
$P_{req}(k)$	Total power required (KW)
$P_{ICE\ max}$	Maximum power that can be delivered by the ICE (KW)
$P_{EM\ max}$	Maximum power that can be delivered by the EM (KW)
X_k	State of charge
X_{min}	Minimum state of charge
X_{max}	Maximum state of charge
N	Total number is time steps
k	Time step index
I(k)	Current of the battery
Q_n	Battery capacity

Total power required is supplied, by the collective power of ICE and EM. In reality, the efficiencies of ICE and EM also act upon engine and motor respectively. Unlike the energy consumed by the ICE the power of electrical motor can also be negative when the regenerative brake is applied when the power is supplied from the EM, the resultant power driving the vehicle will be lesser due to the practical losses by a factor of efficiency. In the case of regenerative braking, the kinetic energy of the vehicle is not entirely converted into electrical energy. The power recaptured is reduced by the factor of efficiency. So the negative power of EM indicates that it is being charged and the amount of inward charge is less than the change in kinetic energy of the vehicle.

SOC is the state of charge of the electrical storage system, which is the state variable for the optimization problem. The optimization constraint of the scheme includes the power of ICE. The power can only vary between the minimum (zero) and its maximum output power. The power of the EM can vary between its minimum value and maximum value for negative and positive power, state of charge can also vary only between the given minimum and the maximum value.

Objective Function: Minimize $$f = \sum_{k=0}^{N-1} \dot{m} f \tag{14}$$

Such that:

$$X(k+1) = \frac{-I(k)}{Q_n} + X(k) \tag{15}$$

$$X(0) = 0.55 \tag{16}$$

$$0 \leq P_{ICE}(k) \leq P_{ICE\ max} \tag{17}$$

$$P_{EM\ min} \leq P_{req}(k) - P_{ICE}(k) \leq P_{EM\ max} \tag{18}$$

$$X_{min} \leq X(k) \leq X_{max} \tag{19}$$

The main goal of DP is to reduce the fuel consumption, thusly the cost function is directly associated with the total fuel consumption. The cost function is calculated for the entire route and is minimized [25]. The cost function accounts for the amount of fuel being consumed each time step. The fuel flow rate then is related to the power produced by the ICE. The torque split between the ICE and the EM is then determined to minimize the cost function.

Road grade has a significant impact on fuel economy. The impact may have a positive or negative effect due to the grade of the road. Unlike conventional vehicles, HEVs utilize road grade to recapture the kinetic energy while also dissipating energy through friction braking. While the road grade effects are well understood, the majority of conventional vehicle drive cycles do not integrate road elevation or grade information [26]. Due to change in road grade, the power required to accommodate for that change varies based on the grade of the route.

The simulation was performed using MathWorks MATLAB and Simulink. For the rule-based model for look ahead optimization, the response of the model shows the SOC with the road grade, the power split between the ICE and EM, the cumulative MPG for the RB, and the RB optimized strategy, the result for route one is shown in Figure 32.

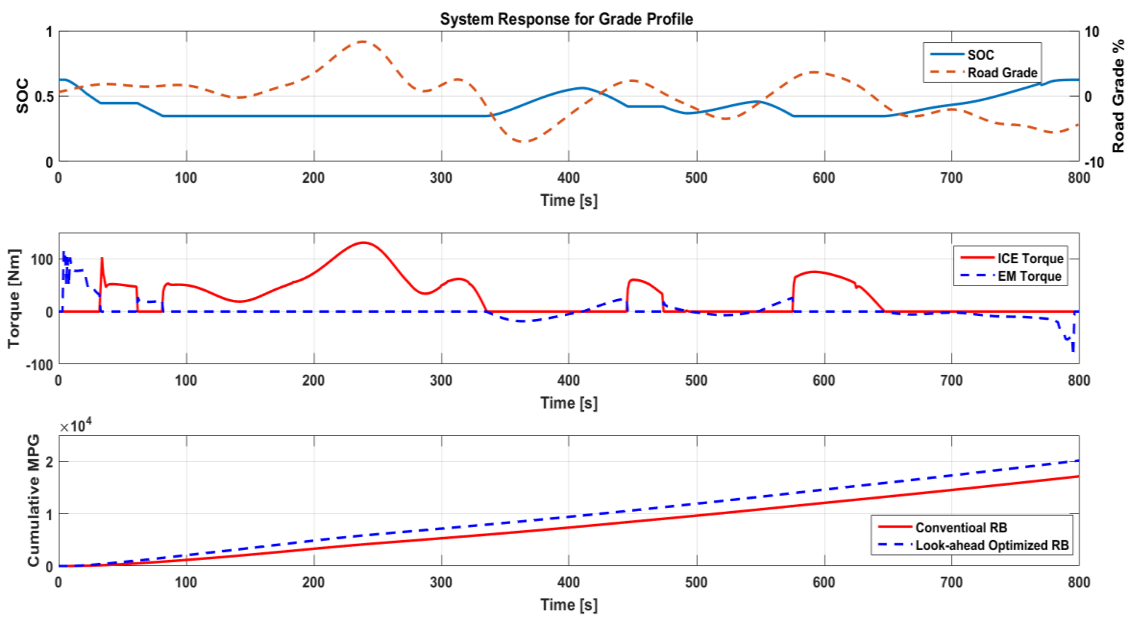

Figure 32. Route 1 results

The first plot in Figure 32 show the SOC and the grade, this shows the charging and discharging of the battery as the vehicle face an uphill or downhill. The second plot shows the torque split between the ICE and the EM as a result of the optimized controller. With look ahead optimization the model was able to capture more kinetic energy from regenerative braking. 17.64% improvement in cumulative MPG compare to baseline RB strategy without look-ahead optimization; this reflects in the third plot in the figure. The result for route 2 and 3 are shown in the following figures.

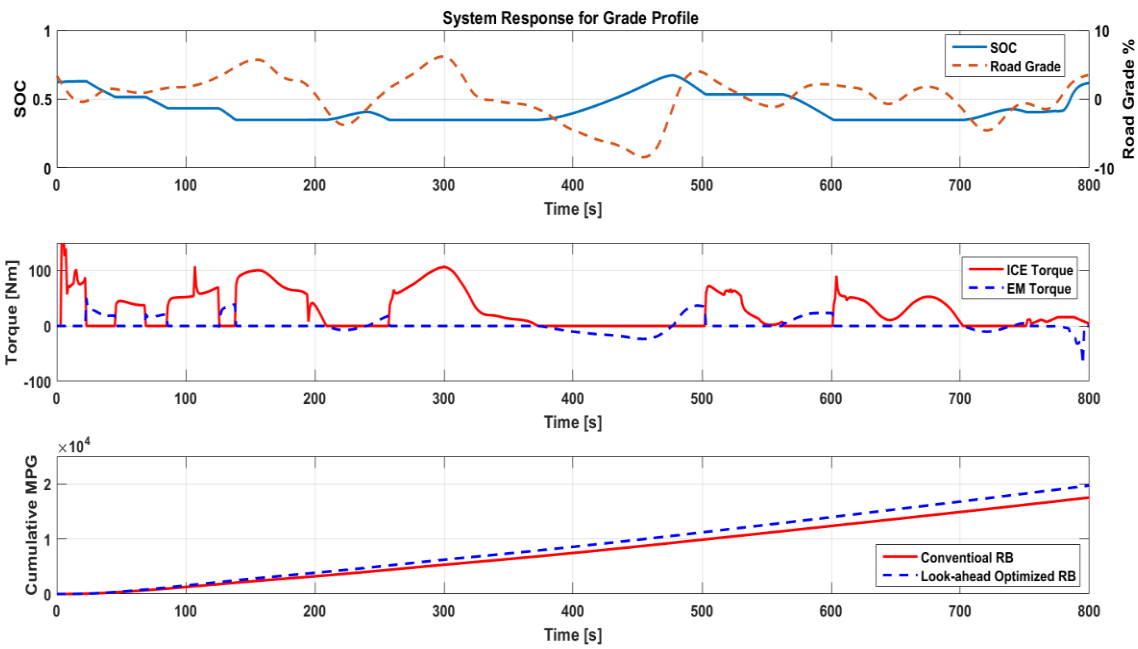

Figure 33. Route 2 results

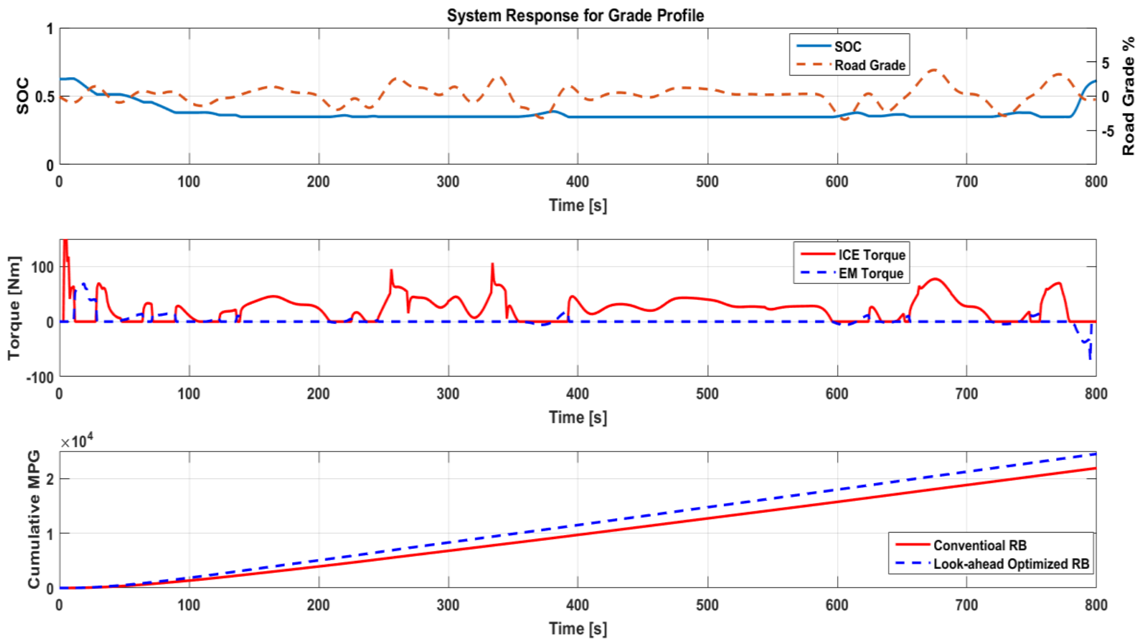

Figure 34. Route 3 results

Implementing look ahead optimization reflected on MPG and resulted in improvement of 12.45% and 11.84% for route 2 and route 3 respectively.

Bellman's principle of optimality was implemented to solve the DP control scheme. The performance of the algorithm was very fast in solving the problem despite the enormous size of the grid. The response of the model shows the state of charge with the road grade, the power split between the ICE and EM and the fuel consumption for the RB, the look-ahead optimized strategy, and the DP as shown in Figure 35.

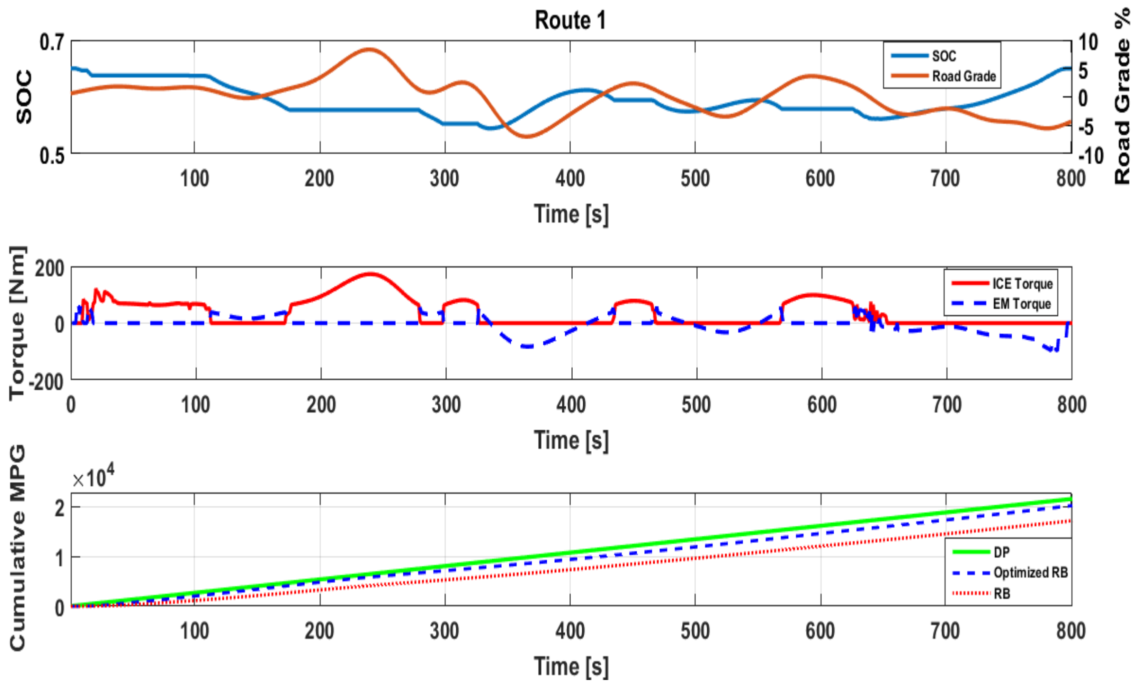

Figure 35. Route 1 dynamic programming results

Figure 35 shows the result of the first route using DP to optimize the control scheme and determine the power split for the ICE and EM. From the first part of the plot if can be noticed that the SOC trajectory is consistently correlated with the road grade, the SOC decrease as the vehicle go uphill.

When approaching an uphill, the EM is the main source of providing torque to the vehicle resulting in depleting the battery. As the vehicle goes on a downhill, the EM take the negative torque through regenerative braking and recharge the battery which results in increasing the SOC of the battery.

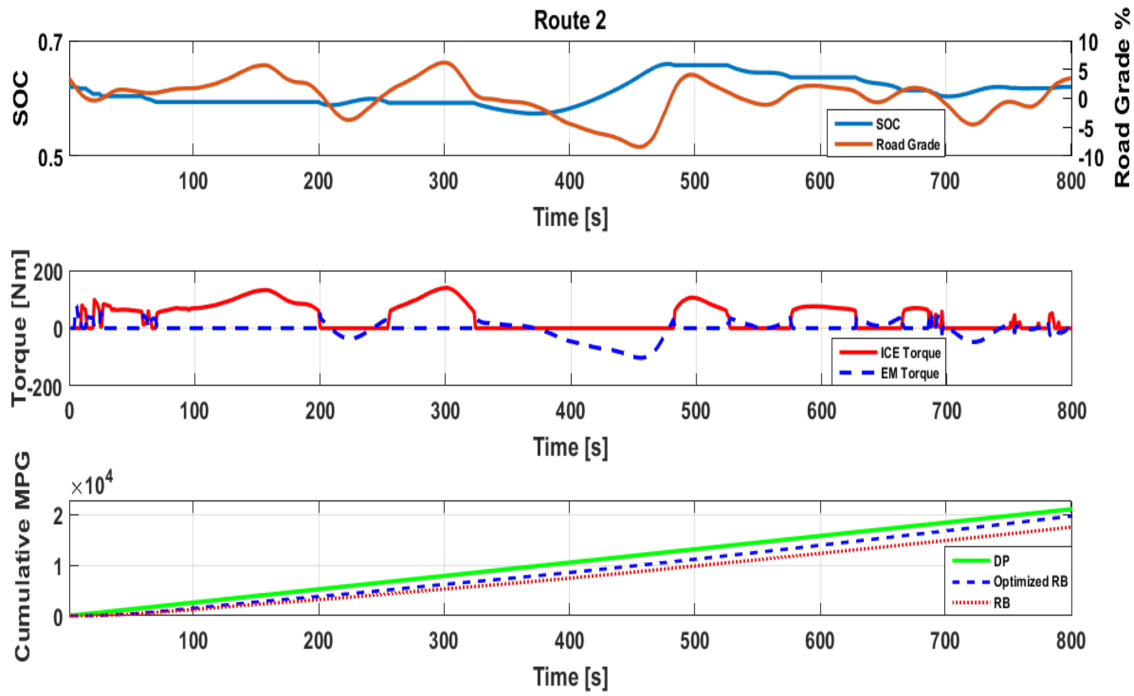

Figure 36. Route 2 dynamic programming results

Figure 36 shows the result for the second route using DP to optimize the control scheme. This route has steeper uphill than the first route. Also, the route has more positive average grade than negative grade compares to the first route which results in less regenerative braking. The difference in the nature of the route compared to the first route result in less improvement. It can be noticed that the MPG improvement for DP is still higher then optimized RB and higher than baseline RB without look-ahead optimization.

Figure 37 shows the result for the third route. This route has very high variations in elevation and grade compare to the first and second route, where the vehicle is constantly switching between an uphill and downhill. Due to the high grade variation, the optimal SOC trajectory was limited to smaller range compare to the other routes.

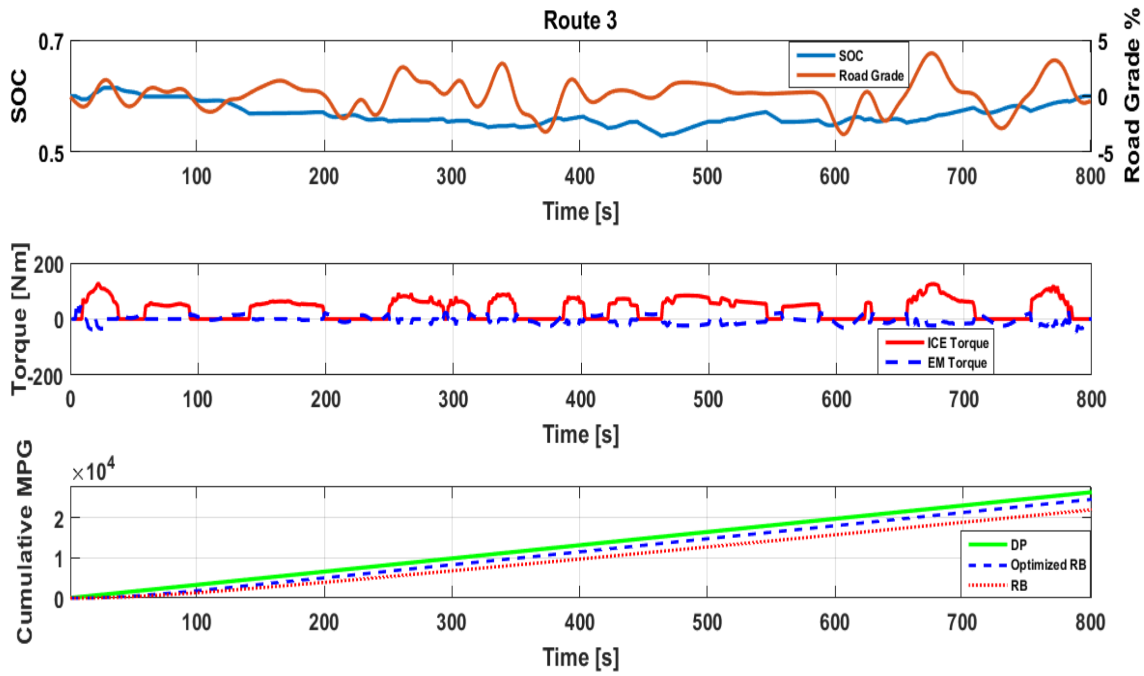

Figure 37. Route 3 dynamic programming results

To quantify the MPG improvement and compare the result between optimized RB and DP, the initial and final conditions of the state variable which in this case is the SOC, are set to be the same throughout both models for all the tested routes. Setting the initial and final conditions of both models to be the same result in more reliable compression of MPG improvement. The DP approach resulted in significant improvement in MPG throughout the experiment, the increase in is measured compared to the baseline RB strategy for routes 1, 2 and 3 respectively.

Table 5 shows the improvement percentage for both Optimized RB and DP. These improvements are measured compared to baseline RB strategy without look-ahead optimization, all baseline RB, optimized RB, and DP were tested and evaluated under the same conditions.

Table 5. Optimization Improvement

	Optimized RB	DP improvement
Route 1	17.63%	25.5%
Route 2	12.41%	20.3%
Route 3	11.83%	19.95%

The HiL testing was performed to ensure real-time execution and high fidelity model performance. The model was constructed in a way that reflects the hybridization symptoms in order to perform VHiL and test on a conventional vehicle. The test is planned as a validation for hybridizing design. Since the vehicle will be tested on a dynamometer, the road grade will be reflected on the vehicle using the rollers, also in this setup, the EM assist is also combined with the grade and reflected on the vehicles through the rollers.

The Host VI consist of signals mapping where the grade was an analog output, and the speed is an analog input that the model executes and follow the trace of the input command. Graphs and gages are used to visualize and show the signals during execution. The drive cycle is what the input signal should match, and the actual velocity is calculated in the model. The 3 signals of velocity are shown in Figure 38.

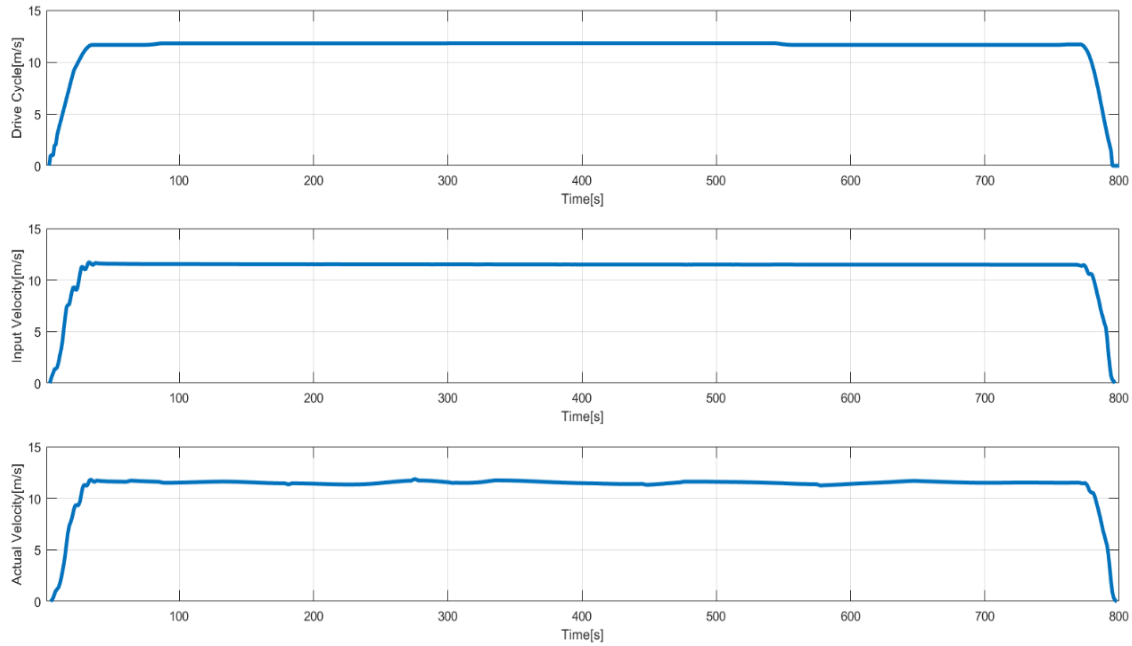

Figure 38. Drive Cycle, Input Velocity, and Actual Velocity

In the figure, the simulated speed input to HiL PXIe platform matches the drive cycle. The speed calculated in the model follow the trace of the input speed as shown in the third part of the figure. The trace was achieved with a minimal error that is approximately one percent.

The EM torque is a critical component of HiL testing since it reflects the amount of energy recaptured through regenerative braking, it also reflects the electric assist that will be supplied by the powertrain. The EM torque for the HiL test is shown in Figure 39.

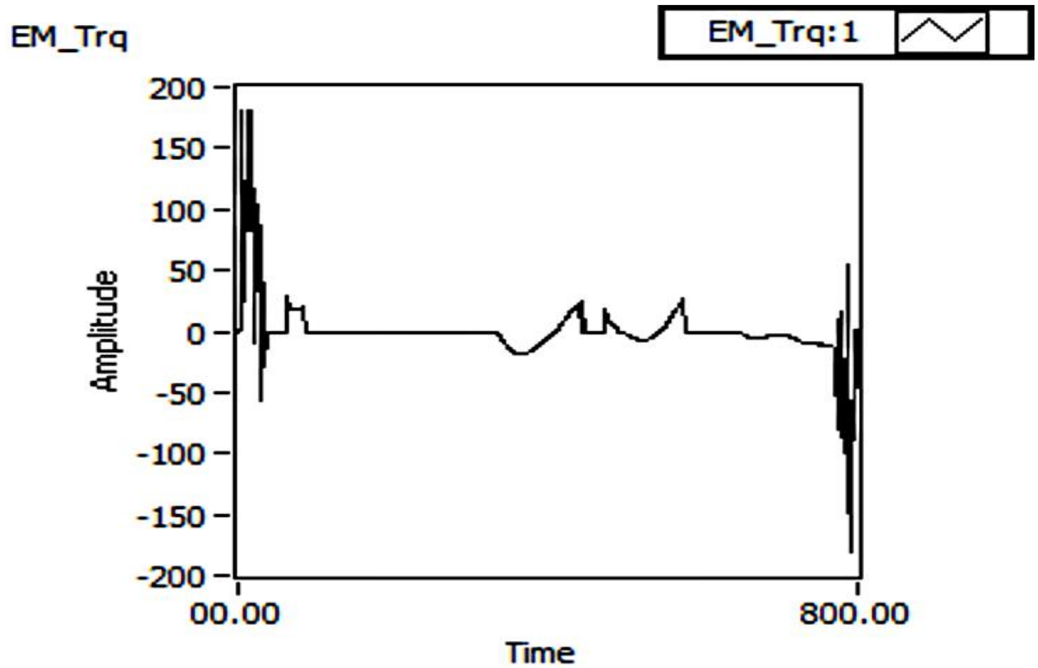

Figure 39. HiL EM Torque

SOC is the state variable of the control scheme and the optimization since it reflects the energy delivered by the battery and the energy recaptured through regenerative braking. SOC is also used by the controller to determine the mode of operation of the vehicle to be either charge depleting or charge sustaining. SOC was recorded in the HiL test as shown in Figure 40.

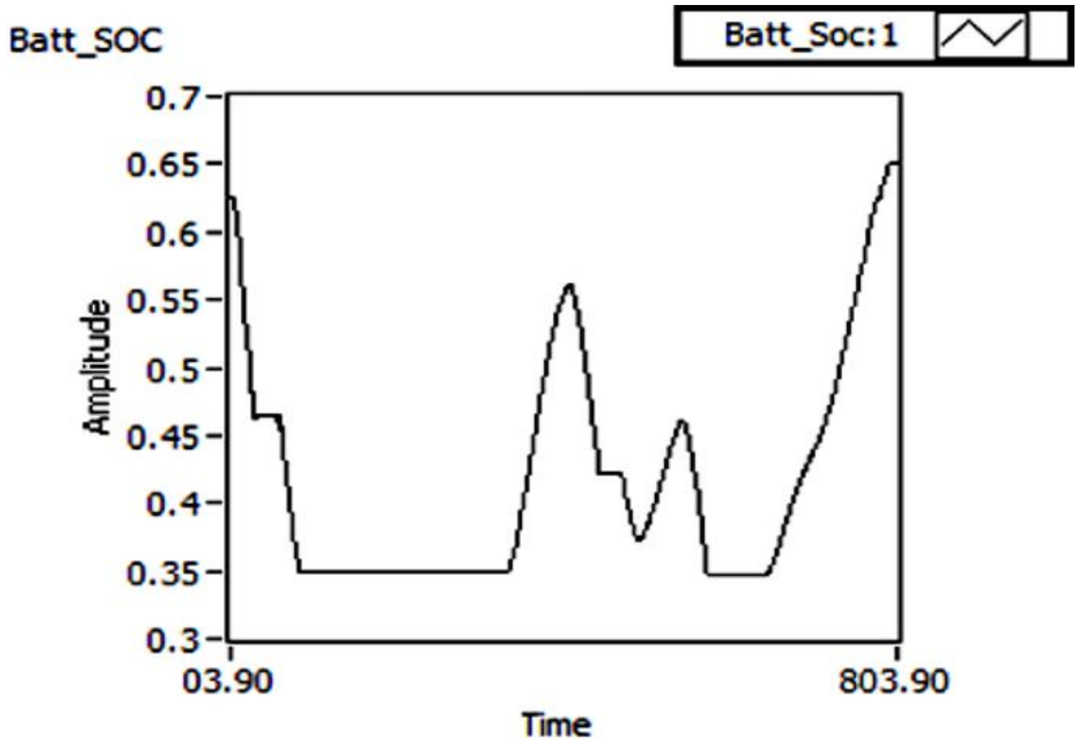

Figure 40. HiL SOC trajectory

The SOC signal shown above reflect the pattern of the road elevation and grade, the rise of SOC represent the regenerative braking from going downhill. The decrease of SOC represent the depleted power by the battery; this power is supplied by the EM to the powertrain.

The grade signal that is transmitted as an analog output through the DAQ is recorded. The grade signal is composed of two components, the road grade of the actual route acquired through GIS maps and the grade equivalent of the EM torque assist generated in the model. The road grade output signal is shown in Figure 41.

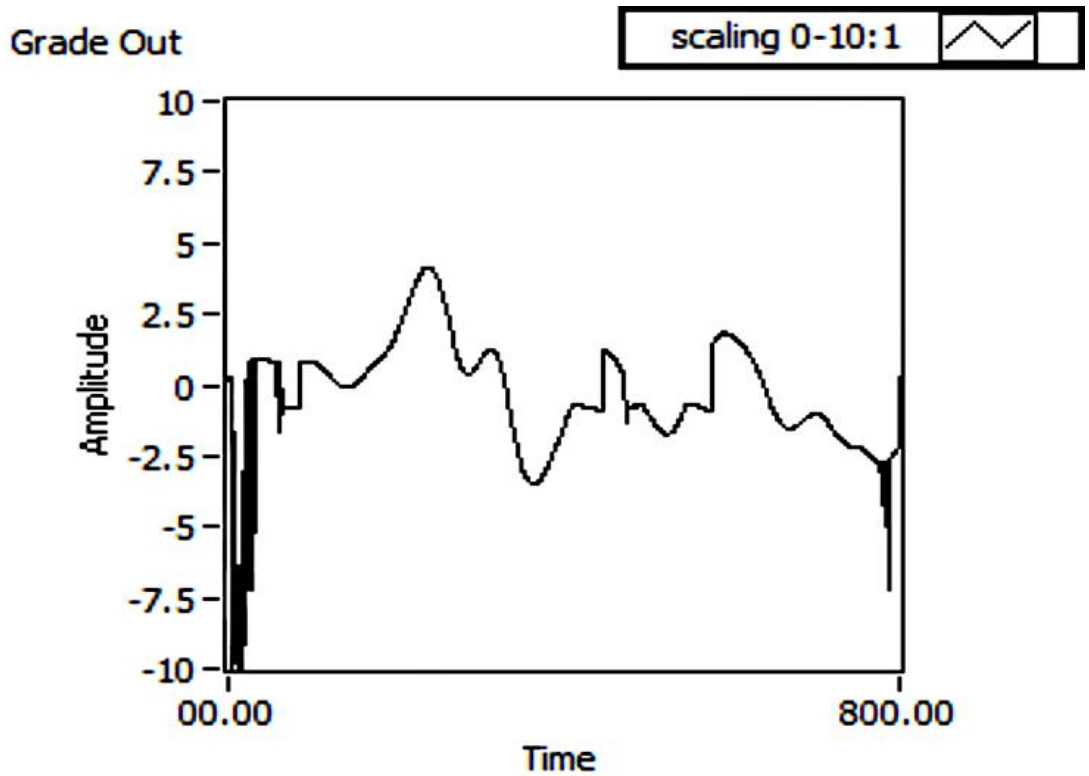

Figure 41. HiL road grade output signal

The HiL experiment was executed, and the model was able to control the vehicle and optimize the RB control scheme in real-time along with the plant model. The recorded data was evaluated and compared with the behavior of the model and actual vehicle dynamics to quantify the performance of the controller.

5. CONCLUSION

This thesis presents different control strategies for HEVs that take into consideration the impact of road grade on the vehicle and the possibility to utilize look ahead control strategies. In order to, minimize the fuel consumption and maximize MPG over multiple routes. The research focus was on maximizing the improvement while reducing the complexity and processing time. HiL tested was performed to ensure real-time execution of optimized RB control strategy.

This practical approach will accommodate for real-time data acquisition and processing that can be integrated with other ADAS application and the supervisory controller of the vehicle. The simulation was accomplished using data from real world routes from San Francisco, California. The acquisition of the elevation data and the speed profiles were achieved using Google API's.

In this research, two look-ahead control strategies were examined and compared to the baseline RB strategy. Optimized RB was able to run in real time and introduced MPG improvement that ranges from 11.84% to 17.64% over the tested routes.

Optimized RB is a real-time implementable strategy and computationally inexpensive compared to other strategies. DP was also implemented to find the optimal solution, in order to minimize the fuel consumption, thus achieving a significant increase in MPG that ranges from 19.95 to 25.5 percent. The developed algorithm for DP was able to solve the problem in a very reasonable timeframe despite the enormous grid size of the model.

Nevertheless, it is still a computationally heavy method. Requiring the information of the full route to solve it.

Future work will include utilizing VHiL in order to quantify the FE improvement where a complete vehicle system will be tested on the roller bench test (vehicle test bed) and look-ahead preview energy management algorithm will dictate the operation of ICE & EM to minimize the fuel consumption to validate the result.

REFERENCES

1. Sciarretta, Antonio, and Lino Guzzella. "Control of hybrid electric vehicles." *Control systems, IEEE* 27, no. 2 (2007): 60-70, doi:10.1109/mcs.2007.338280.

2. Ozatay, Engin, Simona Onori, James Wollaeger, Umit Ozguner, Giorgio Rizzoni, Dimitar Filev, John Michelini, and Stefano Di Cairano. "Cloud-based velocity profile optimization for everyday driving: A dynamic-programming-based solution." *IEEE Transactions on Intelligent Transportation Systems*15, no. 6 (2014): 2491-2505.

3. Han, J., D. Kum, and Y. Park. "Impact of hilly road information on fuel economy of FCHEV based on parameterization of hilly roads." *International Journal of Automotive Technology* 15, no. 2 (2014): 283-290.

4. Zhang, Chen, Ardalan Vahidi, Pierluigi Pisu, Xiaopeng Li, and Keith Tennant. "Role of terrain preview in energy management of hybrid electric vehicles."*Vehicular Technology, IEEE Transactions on* 59, no. 3 (2010): 1139-1147, doi:10.1109/tvt.2009.2038707.

5. Zhang, Chen, and Ardalan Vahidi. "Route preview in energy management of plug-in hybrid vehicles." *Control Systems Technology, IEEE Transactions on*20, no. 2 (2012): 546-553, doi:10.1109/tcst.2011.2115242.

6. Ramaswamy, Nikhil. "Development of control strategies to optimize the fuel economy of hybrid electric vehicles." (2014).

7. Vajedi, Mahyar, Amir Taghavipour, Nasser L. Azad, and John McPhee. "A comparative analysis of route-based power management strategies for real-time application in plug-in hybrid electric vehicles." In *2014 American Control Conference*, pp. 2612-2617. IEEE, 2014.

8. Safeera, N., and K. Chitharanjan. "Survey on Intelligence Based Electric Vehicle Control Strategies."

9. Daowei, Zhu, and Xie Hui. "Control strategy optimization of the hybrid electric bus based on remote self-learning driving cycles." In *2008 IEEE Vehicle Power and Propulsion Conference*, pp. 1-5. IEEE, 2008.

10. Luathep, Paramet, Agachai Sumalee, William HK Lam, Zhi-Chun Li, and Hong K. Lo. "Global optimization method for mixed transportation network design problem: a mixed-integer linear programming approach." *Transportation Research Part B: Methodological* 45, no. 5 (2011): 808-827.

11. Koehler, Stefan, Alexander Viehl, Oliver Bringmann, and Wolfgang Rosenstiel. "Optimized recuperation strategy for (hybrid) electric vehicles based on intelligent sensors." In *Control, Automation and Systems (ICCAS), 2012 12th International Conference on*, pp. 218-223. IEEE, 2012.

12. Hu, Jia, Yunli Shao, Zongxuan Sun, Meng Wang, Joe Bared, and Peter Huang. "Integrated optimal eco-driving on rolling terrain for hybrid electric vehicle with vehicle-infrastructure communication." *Transportation Research Part C: Emerging Technologies* 68 (2016): 228-244.

13. Markel, Tony, and Andrew Simpson. "Energy storage systems considerations for grid-charged hybrid electric vehicles." In *2005 IEEE Vehicle Power and Propulsion Conference*, pp. 6-pp. IEEE, 2005.

14. Paganelli, Gino, Gabriele Ercole, Avra Brahma, Yann Guezennec, and Giorgio Rizzoni. "General supervisory control policy for the energy optimization of charge-sustaining hybrid electric vehicles." *JSAE review* 22, no. 4 (2001): 511-518.

15. Wood, Eric, E. Burton, A. Duran, and J. Gonder. "Appending High-Resolution Elevation Data to GPS Speed Traces for Vehicle Energy Modeling and Simulation." *National Renew Energy Lab* (2014).

16. Liu, Jinming. "Modeling, configuration and control optimization of power-split hybrid vehicles." PhD diss., The University of Michigan, 2007.

17. Millo, Federico, Luciano Rolando, and Maurizio Andreata. *Numerical simulation for vehicle powertrain development*. INTECH Open Access Publisher, 2011.

18. De Santiago, Juan, Hans Bernhoff, Boel Ekergård, Sandra Eriksson, Senad Ferhatovic, Rafael Waters, and Mats Leijon. "Electrical motor drivelines in commercial all-electric vehicles: a review." *IEEE Transactions on Vehicular Technology* 61, no. 2 (2012): 475-484.

19. Zuo, Lei, and Pei-Sheng Zhang. "Energy harvesting, ride comfort, and road handling of regenerative vehicle suspensions." *Journal of Vibration and Acoustics* 135, no. 1 (2013): 011002.

20. Heppeler, Gunter, Marcus Sonntag, and Oliver Sawodny. "Fuel efficiency analysis for simultaneous optimization of the velocity trajectory and the energy management in hybrid electric vehicles." *IF AC Proceedings Volumes*47, no. 3 (2014): 6612-6617.

21. Mayyas, AbdelRaouf, Robert Prucka, Pierluigi Pisu, and Imtiaz Haque. "Chassis Dynamometer as a Development Platform for Vehicle Hardware In-the-Loop “VHiL”." *SAE International Journal of Commercial Vehicles* 6, no. 1 (2013): 257-267, doi: 10.4271/2013-01-9018.

22. Mayyas, Abdel Raouf, Robert Prucka, Imtiaz Haque, and Pierluigi Pisu. "Model–based automotive system integration: using vehicle hardware in–the–loop simulation for an integration of advanced hybrid electric powertrain."*International Journal of Electric and Hybrid Vehicles* 5, no. 3 (2013): 215-232, doi:10.1504/ijehv.2013.057606.

23. Yuan, Zou, Liu Teng, Sun Fengchun, and Huei Peng. "Comparative study of dynamic programming and Pontryagin’s minimum principle on energy management for a parallel hybrid electric vehicle." *Energies* 6, no. 4 (2013): 2305-2318.

24. Pérez, Laura V., Guillermo R. Bossio, Diego Moitre, and Guillermo O. García. "Optimization of power management in an hybrid electric vehicle using dynamic programming." *Mathematics and Computers in Simulation* 73, no. 1 (2006): 244-254, doi:10.1016/j.matcom.2006.06.016.

25. Sinoquet, Delphine, Gregory Rousseau, and Yohan Milhau. "Design optimization and optimal control for hybrid vehicles." *Optimization and Engineering* 12, no. 1-2 (2011): 199-213, doi: 10.1007/s11081-009-9100-8.

26. Lopp, Sean, Eric Wood, and Adam Duran. *Evaluating the Impact of Road Grade on Simulated Commercial Vehicle Fuel Economy Using Real-World Drive Cycles*. No. NREL/CP-5400-64544. NREL (National Renewable Energy Laboratory (NREL), 2015.