ITS in Energy Management Systems of PHEV’s

A Thesis

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By

James Wollaeger, B.S.

Graduate Program in Electrical and Computer Engineering

The Ohio State University

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Master’s Examination Committee:

Ümit Özgüner, Advisor
Giorgio Rizzoni
Simona Onori
Abstract

Intelligent Transportation Systems (ITS) is a broad category of research relating to new technologies that can improve systems in vehicles, such as safety or energy management. The studies in this thesis discuss how energy management systems can be improved with theories and information from ITS research areas. New types of vehicles are entering the marketplace now that include electric vehicles (EV’s), hybrid electric vehicles (HEV’s), and plug-in hybrid electric vehicles (PHEV’s). HEV’s and PHEV’s are a particular challenge to control engineers because of the flexibility of their powertrains. These vehicles contain two power sources, their internal combustion engine and their battery-powered electric motor. The powersplit control problem will be discussed and how optimal control theory can be implemented to optimize the powersplit resulting in lower fuel consumption.

Chapter 2 discusses the areas of ITS that are relevant to the PHEV control problem. These include sourcing geographic data such as road grade and computing the length and geometry of a route to be traversed. Chapter 3 covers the Challenge X vehicle simulator and the dynamic equations that form the vehicle model. The Challenge X vehicle was designed for the 2004 Challenge X competition sponsored by General Motors where student teams competed to convert a small SUV into a hybrid electric vehicle. This simulator was modified from its original form to reflect a prototype plug-in hybrid electric vehicle. This included modifying the battery model to include
more capacity and change the cell chemistry to lithium ion from nickel-metal hydride.

Chapter 4 includes the details of the powersplit control algorithm implemented, called the Adaptive Equivalent Consumption Minimization Strategy (A-ECMS). A new formulation called the finite horizon adaptive ECMS is introduced and its performance analyzed under varying road load conditions and compared with the global optimal solution from Dynamic Programming.
Acknowledgments

Upon completing my masters in Electrical and Computer Engineering, I would like to thank my family and friends for encouraging me to pursue my dreams. Thanks especially go to Kathryn Lookadoo, who has heard about every step of the way and motivated me to work as hard as I possibly could. I couldn’t have learned as much as I did without the help of Dr. Umit Ozguner (my advisor), Dr. Pinak Tulpule, Dr. Simona Onori, Dr. Giorgio Rizzoni, Dr. Enzo Marano, Dr. Keith Redmill, Dr. Lina Fu, and all my wonderful professors from Ohio Northern University which prepared me well for success.
Vita

July 29, 1987 .......................... Born - Mayfield Village, Ohio

May, 2010 .............................. B.S. Electrical Engineering, Ohio
Northern University

September, 2010-March, 2012 ............... Graduate Research Assistant,
The Ohio State University.

March, 2012 .............................. M.S. Electrical Engineering, The Ohio
State University

Publications

Research Publications

J. Wollaeger, S. Kumar, S. Onori, S. Di Cairano, D. Filev, U. Ozguner, G. Rizzoni
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Fields of Study

Major Field: Electrical and Computer Engineering
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Chapter 1: Introduction

1.1 Hybrid Vehicles

In a world where resources are becoming increasingly scarce, consumers are looking to purchase products made with new environmentally friendly materials that are powered by clean sources of power. In addition to this so called ”green movement”, consumers are also finding economic reasons to use non-traditional sources of power. A prime example of such a consumer movement is the development of hybrid electric vehicles (HEVs). The overall design goal of the HEV is to reduce the consumption of fossil fuels such as diesel or gasoline. The additional equipment required in a HEV often adds many thousands of dollars worth of equipment when compared with a traditional vehicle. This upfront cost can often be underwritten through the financial savings from the reduced fuel consumption of the HEV. Auto manufacturers and universities have been researching vehicle electrification since the advent of the automobile, but vehicles powered by fossil fuels were always more popular with consumers due to their longer driving range. As technology and batteries get progressively better and more reliable, while prices of fossils fuels climb due to increased world demand, auto manufacturers see a market opportunity to sell vehicles that use less fuel and
have a lower cost of ownership. Sections 1.1.1 and 1.1.2 describe two different HEV architectures that have been introduced to the marketplace in recent years.

1.1.1 Series Architecture Drivetrain

The first type of hybrid electric vehicle architecture is the series hybrid. In a series hybrid, the internal combustion engine (ICE hereafter) is not mechanically connected to the wheels driving the vehicle. Instead the ICE is used to power a generator which then powers the electric motor (EM) that is mechanically coupled to the drive wheels. Figure 1.1 shows the general powertrain layout of a series HEV. Because the EM is used to propel the vehicle, it must be sized appropriately to meet all velocity and acceleration design constraints. The advantage of the series hybrid is the disconnection between the ICE and the drive wheels. This disconnection allows the ICE to be smaller leading to fuel savings. During periods of higher power demand, energy from the battery is used to supplement the generator. The smaller ICE can operate with the more thermodynamically efficient Atkinson combustion cycle[6]. The Atkinson cycle is seldom used in traditionally powered vehicles because of the low torque produced at low engine speeds and low energy density. One disadvantage of the series hybrid is the large efficiency losses present when converting between mechanical power and electrical power. Mechanical transmissions can transmit approximately 95% of the rotational energy from the engine to the ground[14]. The inefficiencies of the generator, power electronics, and motor can bring the driveline efficiency down to near 80% depending upon the particular operating condition.
1.1.2 Parallel Architecture Drivetrain

The second general type of HEV architecture is the parallel hybrid. Parallel hybrids are distinct because they can drive the wheels directly with the EM and ICE at the same time. Figure 1.2 shows the general power transfer to the road for a parallel hybrid. There are many different ways to implement a parallel hybrid by coupling the EM at different points of the driveline, but those nuances are beyond the scope of this thesis. This thesis will concentrate on the parallel hybrid architecture chosen for the Challenge X Vehicle shown in figure 1.3. Figure 1.3 shows that the ICE is connected directly to the front axle by a 6-speed automatic gearbox and small integrated starter alternator (ISA) that can be used as a generator to directly charge the battery. The wheels on the rear axle are connected to an electric traction motor via a gearbox. The only changes to the Challenge X architecture when converting it to a Plug-in Hybrid Electric Vehicle (PHEV) for this study was the elimination of the engine electrical assist mode present in the original competition vehicle. The ISA for the Challenge X PHEV is used only for starting the engine and the regenerative braking on the
front axle. Parallel hybrids are advantageous because of their flexibility of operating modes, but the flexibility also creates complex control challenges. The Challenge X vehicle is termed a through-the-road parallel hybrid because the ICE and big EM on the rear axle are not mechanically connected via a torque split transmission. If power regeneration needs to take place while maintaining speed or accelerating, the ICE will be powering the front wheels with a positive torque command while the EM at the rear of the vehicle will be receiving a negative torque demand to recharge the battery pack. Obviously this can lead to drivability and traction concerns, but for the following studies in this thesis, it is assumed that the vehicle will not lose traction on the road.

Figure 1.2: Powertrain of a Parallel Hybrid[27]

1.1.3 Plug-In Hybrid Electric Vehicle

The new generation of vehicles that auto manufacturers are building that can take advantage of the electrical power grid while not restricting driving distances, are called plug-in hybrid electric vehicles. PHEV’s differ from conventional HEV’s because of
their increased battery pack capacity and ability to charge from the national power grid. The electrical power available on the power grid is attractive to customers because it is cheaper to purchase than gasoline. In some parts of the country, electrical power is even generated from renewable sources of energy such as hydroelectric dams, wind, and solar energy. These renewable power sources are capable of lowering the CO₂ footprint of the driver. Customers are becoming very environmentally conscious and want to minimize their carbon footprint on the world.

PHEV’s differ in operation from HEV’s because of the way the additional power source is used. In a PHEV the battery is considered a second primary energy source whereas in a HEV, the battery is only used as an energy buffer. An energy buffer provides the capability to recapture energy from braking action and the ability for the
EM to assist the ICE when extra power is requested during a hard acceleration. Due to this fundamental change in battery management strategy, the energy management systems of HEV’s and PHEV’s differ significantly. The energy management systems in HEV’s operate in a charge sustaining (CS) mode meaning the SOC is kept constant over a driving profile. PHEV’s energy management systems operate in a charge depleting (CD) mode, meaning it will try to use all the available energy in the battery pack over the course of a trip. By minimizing the SOC over a trip, a greater percentage of power provided by the electrical grid will be used. PHEV’s try to utilize the cheaper electrical power whenever possible to save the driver money in transit costs.

1.2 Brief Problem Statement

Hybrid vehicles are being bought by consumers in ever increasing numbers because of their ability to lower fuel consumption which impacts the cost of operation of a vehicle. While each powertrain architecture outlined previously has its own advantages, the overall goal of each is to minimize fuel consumption. More formally, this optimal control problem can be formulated as a cost function $J$ to be minimized.

$$J(x(t), \tau_{\text{ice}}(t), \tau_{\text{em}}(t)) = \int_0^{T_f} \dot{m}_f(\tau_{\text{ice}}, \tau_{\text{em}}) dt$$  \hspace{1cm} (1.1)

Equation 1.1 is subject to the constraints:

$$P_{wh} = P_{\text{em}} + P_{\text{ice}}$$

$$P_{\text{em}_{\text{min}}} \leq P_{\text{em}} \leq P_{\text{em}_{\text{max}}}$$

$$P_{\text{ice}_{\text{min}}} \leq P_{\text{ice}} \leq P_{\text{ice}_{\text{max}}}$$

Here, $\dot{m}_f$ is the mass fuel flow rate, $\tau_{\text{ice}}$ and $\tau_{\text{em}}$ are the torque commands for each power source, $T_f$ the trip end time, $x(t)$ the SOC, and $P$ the power of the wheel,
EM, and ICE. While the cost function is relatively straightforward, the mass fuel flow rate is highly dependent upon the specific velocity profile being driven. Various methods, such as dynamic programming, exist to evaluate the cost function for a set of torque splits resulting in a minimum fuel consumption, but a method that works in real-time is desired. One such method that can evaluate the cost function instantaneously is the equivalent consumption minimization strategy[11], hereafter ECMS. What this method does is assign an equivalent fuel cost to the battery power so that an instantaneous minimum cost can be found. A drawback to this method is its inability to adapt to velocity cycles that are very different than the ones used to tune the ECMS. This inflexibility has led to many different approaches to correct for different driving styles which include gain scheduling based on driving pattern recognition to a new variant of ECMS called Adaptive-ECMS[15] that takes into account the battery SOC when calculating the equivalence factor. Chapter 4 will detail the ECMS strategy that was implemented in the Challenge X PHEV simulator.
Chapter 2: Intelligent Transportation Systems Overview

2.1 What are Intelligent Transportation Systems?

Intelligent Transportation Systems, as defined by the constitution of the Intelligent Transportation Systems Society of IEEE, are systems that utilize synergistic technologies and systems engineering concepts to develop and improve transportation systems of all kinds[13]. All ITS systems covered in this thesis are applicable to the automotive research area. All ITS systems proposed in this thesis were not implemented on actual hardware, but simulation frameworks were created to feed the PHEV energy management system additional realistic information (such as grade and estimated velocity profile) that can be obtained in the real world by ITS technologies.

One of the core functionalities of ITS automotive systems is their inclusion of Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication systems. These communication systems enable a vehicle to communicate information such as global location, speed, and vehicle intentions to surrounding vehicles, transportation system infrastructure, and remote data repositories such as those connected to the internet. When all of these communication protocols are combined with one another, they form a vehicular ad hoc network or VANET. A VANET, as detailed in [26], is a collection of mobile ad hoc networks, that are characterized by their high speeds, persistent
mobility, and short-lived connections due to the range constraints of the wireless protocols such as the 500 meter range of the IEEE 802.11p standard. An example of a VANET is shown in figure 2.1. The emergency event in the figure can be broadcast to the other vehicles so the drivers can be alerted to potential hazard situations and emergency response units such as law enforcement and medics automatically called by the roadside base station.

![Figure 2.1: VANET][26]

### 2.2 ITS Information Used in Challenge X PHEV Simulator

The Challenge X PHEV Simulator used in the studies of this thesis implement a power management algorithm that is reliant upon the predicted energy consumption of the vehicle for a finite prediction window. In simulation, we as control engineers have access to a priori data, such as the upcoming velocity profile, which is input into the road load estimation block. The road load estimation block consists of
a backwards model of the Challenge X vehicle where velocity is input and energy consumption is output. For this system to be implemented in a real-time application, a velocity prediction must be made based upon the route selected, its geometry, and varied traffic laws on the route. Sections 2.2.1, 2.2.2, and 2.2.3 describe the data that must be used for such a velocity advisory algorithm.

2.2.1 Route

One of the most important factors effecting a velocity profile is the choice of the route from the origin to the destination. In most parts of the developed world, extensive road networks exist that a driver can use to travel freely from point A to point B. It is up to the personal preference of a driver to select a route based upon shortest time, shortest distance, or even lowest cost if toll roads can be travelled. Path search algorithms are in wide use today in modern automotive GPS units and by Geographic Information System (GIS) hosting services such as any online mapping tool like Google Maps. All mapping applications at the lowest level are driven by vector map data. This vector map data commonly exists in the form of digital line graphs (DLG files) that contain points of interest, called nodes, and lines connecting them signifying a length of road, or network connection. An example of this data is seen below in figure 2.2. Each point contains a set of information describing it. For example, the highlighted point in the figure is a node of Riverside Dr. and lists its respective latitude and longitude coordinates. DLG files such as the one shown in figure 2.2 can be obtained from mapping providers such as ESRI or sometimes state government agencies such as the Ohio Geographically Referenced Information Program[18].
The DLG files provided by mapping agencies contain the network information that is used by path search algorithms to find a path from point A to point B. Some examples of routing algorithms include breadth-first search, uniform-cost search, and depth-first search[21]. While each algorithm searches in slightly different ways, they all start the search by starting at the node for point A. The node at point A lists its connections to the other nodes and oftentimes the costs associated with that path. The costs are an empirical value related to distance travelled to get to the next node or an estimated travel time based upon speed limit. The algorithm will continue traversing the nodes of the search tree until the destination point B is found. The search algorithm chosen will determine what path is found to the destination because in real world problems, many paths can exist between two locations. For example the breadth-first search will always find the path to the destination with the fewest node transitions. Uniform-cost search will always find the path with the least cost associated with the transition from point A to point B. ArcGIS server, a software platform that uses the digital line graphs, can process these files and return routes based upon the required search criterion for minimum time or distance routing. A server containing this software has been set up in the Control and Intelligent Transportation Research Laboratory for V2I purposes.

### 2.2.2 Geography

Another impact factor that can play a large role in the energy consumption of the vehicle is the road grade that is encountered. As the vehicle changes elevations along a route, its potential energy is constantly changing relative to its original potential energy at the beginning of the route. In areas that contain significant elevation
Figure 2.2: DLG File of part of Franklin County on the OSU GIS Server
changes, the power demand profile for a particular road can be dominated by the
power required to lift the mass of the vehicle to a higher elevation. Incorporating
these grade changes into a power management strategy requires an elevation model
of the earth.

The elevation model that was loaded onto the OSU GIS server is from the United
States Geological Survey[8][7]. The data is in the form of a digital elevation model
that is made up of raster data. Raster data contains a numerical value for each
cell, oftentimes of equal size, for the entire coverage area. The data obtained from
the USGS has both 3 meter resolution and 10 meter resolution data. Ohio has been
widely surveyed recently and it’s entire land area has 3 meter resolution data available.
What this means is that the coverage area grid is made up of cells which represent an
elevation value for every 3 meter by 3 meter square of Ohio’s land mass. Figure 2.3
shows an example of DEM data that is stored on the OSU GIS server. The lighter
shades of grey correspond to areas of higher elevation.

2.2.3 Traffic Laws

Another influential factor effecting a vehicles movement patterns are the traffic
laws that drivers should follow. Knowing the traffic laws, such as speed limits, turn-
ing restrictions, and safe passing maneuvers, can allow a vehicle to predict drivers
intentions. Fusing together the road geometry and using knowledge of the allowed
maneuvers along that particular section of road can enable a short term road load
profile prediction to be used in the energy management systems of future automo-
biles, whether they be conventional vehicles or PHEV’s such as the one used in this
thesis. While a road load prediction algorithm can certainly be made, the aim of the
studies in this thesis are to ascertain what kind of energy management benefit that a
load prediction system can give to an automobile.

2.3 Expected Velocity Profile

2.3.1 Traffic Flow

When attempting to create an expected velocity profile of a vehicle, traffic is often
a limiting factor to a vehicle in urban environments. Today, different traffic flow
modeling methods exist, with the historical traffic database being the most common.
This database is constructed based upon measurements of the number of vehicles
travelled on a road. Of course traffic is very time dependent, so this information
can be looked up based upon the road being travelled, day of the week, and time
of day. One such company that provides this data is Navteq[17]. They are one of the world leaders in supplying the map data that fuels routing algorithms in many consumer GPS units. The traffic flow estimates included in these maps allow GPS units to calculate estimated travel time based on expected traffic flow in addition to the known legal speed limits.

2.3.2 V-2-V Communication

Another source of the expected velocity profile for the energy management system can be obtained from traditional ITS technologies such as vehicle-to-vehicle communication. Velocity profiles from each vehicle can be broadcast wirelessly so that any nearby cars traveling in the same direction have a rough estimate of an expected velocity profile. Much variability would be introduced in this method because of different driving styles, possible lane differences, and unexpected traffic events such as vehicles merging in and out of traffic. To help filter out unwanted velocity profiles, which would be important on a crowded roadway with multiple lanes, each vehicle must have an understanding of the world surrounding it. To do this, onboard computers would have to model the traffic around it, and choose the vehicle in front of it. Vehicles in other lanes should be ignored along with vehicles behind it. To ascertain which vehicle is directly in front of it, absolute world coordinates, such as GPS, would be critical. For the computer to rely upon GPS would mean equipping each vehicle with an expensive and more accurate GPS receiver than production vehicles have today. As the technology becomes more mainstream though, prices can be expected to drop and this technology to become commonplace.
### 2.3.3 V-2-I Communication

The last source of traffic flow speed estimation is from vehicle-to-infrastructure communication. In many larger cities today, traffic control systems exit to ease congested roadways during rush hour. These systems employ techniques to estimate how much traffic is present on roads by means of induction loops[2] or newer vision-based traffic identification systems[16]. Induction loops are the oldest sensing technology and work by sensing pulses caused by cars passing through them. These loops are often mounted in the roadway and require maintenance that closes roadways. Newer systems are being implemented that use video surveillance cameras and image processing software to detect vehicles for a vehicle count and estimated velocity. Both of these systems are often connected to traffic control infrastructure such as traffic lights. An economical way of passing a velocity prediction from roadside sensors to moving vehicles is to add wireless network access points alongside of busy highways. Many of the sensors are currently in place and would just need to be networked to broadcast their traffic estimation. A limitation of the V2I technology is waiting for the infrastructure to catch up to modern vehicles. While urban cities would see the most benefit to connecting cars to the infrastructure, many rural areas would have little incentive to install such infrastructure. Other means of velocity estimation would need to be used in those circumstances.
Chapter 3: Challenge X Vehicle Simulator

Figure 3.1: Architecture of Original Challenge-X Vehicle [4]

3.1 Simulator Overview

The vehicle simulator used during the studies contained in this thesis is based off of a power-flow based model of the Ohio State Universities’ Challenge X competition
vehicle[4]. This simulator was developed as a complement to the original experimentally validated Simulink Model to simplify the complexity of the calculations, reduce simulation time, and eliminate the issue of velocity tracking error by eliminating the driver block. The driver block was eliminated by implementing a backwards simulator that calculates the power required to track the velocity profile that is supplied as the input to the system. The power that is necessary to accelerate the vehicle to the velocity setpoint is supplied to the wheels by the internal combustion engine (ICE) and the lithium battery powered electric motor.

![Figure 3.2: Power Flow Diagram of Simulator](image)

The specifications of the slightly modified Challenge X vehicle are shown in table 3.1. The original vehicle was designed as a standard hybrid electric vehicle for the Challenge X competition. Since it was not originally a PHEV, the battery pack was increased in size to 9.34 kWh and has been changed to a lithium-ion chemistry cell.

Current production PHEV’s include the 2012 Chevrolet Volt, 2012 Toyota Prius Plug In, and preproduction models of the 2013 Ford C-Max Energi. The 2012 Chevrolet Volt is a series hybrid while both the Prius and C-Max are parallel hybrids. As of this writing, the Prius has only been launched in 12 US states and the Ford C-Max
### Table 3.1: Vehicle Specifications.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicle</td>
<td>Chevrolet Equinox SUV</td>
</tr>
<tr>
<td>Total Mass</td>
<td>2090 Kg</td>
</tr>
<tr>
<td>Fuel</td>
<td>B20 Biodiesel Blend</td>
</tr>
<tr>
<td>Engine</td>
<td>Fiat 1.9L 4-cylinder</td>
</tr>
<tr>
<td>Nominal Electrical System Voltage</td>
<td>270 Volts</td>
</tr>
<tr>
<td>Belted Starter Alternator</td>
<td>10.6 kW Permanent Magnet motor</td>
</tr>
<tr>
<td>Rear Axle Motor</td>
<td>67 kW peak, 3 ph AC Induction motor</td>
</tr>
<tr>
<td>Transaxle</td>
<td>6 Speed Automatic</td>
</tr>
<tr>
<td>Battery</td>
<td>9.34 kWh A123 ANR 26650 Li-ion</td>
</tr>
</tbody>
</table>

will be officially launched in late 2012. All three vehicles feature lithium ion batteries as replacements to the nickel metal hydride batteries of their HEV predecessors. Utilizing this new battery technology allows more capacity to be added because the new packs are between 25-30% more compact and 50% lighter than the old NiMH batteries[9]. The Volt operates by running in an all electric charge depletion mode until the state of charge reaches a minimum when the ICE starts to maintain the SOC above the minimum threshold. The C-Max can operate in a similar fashion but also has extra modes that are available to the driver so that EV now, EV later, and auto charge depletion modes can be selected. Of the two cars in production, the Prius has the smallest battery pack size of 4.4 kWh and the Volt has the largest at 16 kWh. Thus, the approximately 9 kWh battery pack size chosen for the Challenge X simulator will allow for a range similar to early production PHEVs.
3.1.1 Modeled Vehicle Dynamics

To attain the desired speed, the following equations are used to model the system dynamics of our vehicle:

\[ F_{req} = F_{roll} + F_{aero} + ma + F_{grade} \]  \hspace{1cm} (3.1)

\[ F_{roll} = (C_{r0} + C_{rv}v^{2.5}) \times mg \]  \hspace{1cm} (3.2)

\[ F_{aero} = 0.5\rho_{air}A_fC_dv^2 \]  \hspace{1cm} (3.3)

\[ F_{grade} = mgsin(\theta) \]  \hspace{1cm} (3.4)

where:

m = mass of the loaded vehicle

a = acceleration of the vehicle

\[ C_{r0} = \text{Stationary Rolling Resistance} \]

\[ C_{rv} = \text{Rolling Resistance Coefficient due to Velocity} \]

v = Velocity of the Vehicle

\[ \theta = \text{Angle of the Road Grade in Radians} \]

3.1.2 Modeled Battery Dynamics

The battery model that was added to the original Challenge X simulator is a simplified version of the A123 ANR26650 lithium ion cylindrical cell model developed by Y. Hu et al[28]. The model was created using the identification algorithm detailed in section four of the paper. First the open circuit voltage was found by starting with a fully charged cell in equilibrium and measuring the terminal voltages. Then
the battery was discharged at a very low rate, for example C/20 (with C being the capacity of the battery), and a voltage reading was taken. Then the battery was discharged to the next SOC level and another voltage reading taken after the battery was given time to reach electrochemical equilibrium. After running the experiments, the resultant data was fit to the following circuit equivalent battery model shown in figure 3.3. The modeled circuit represents the discretized equivalent circuit with modeled internal resistance and n series connected parallel RC circuits.

![Circuit model of ANR26650 Battery Pack](image)

Figure 3.3: Circuit model of ANR26650 Battery Pack

To further simplify the battery model for the energy-based Challenge X simulator used for PHEV studies, the battery model shown in figure 3.3 has been replaced by a resistance lookup table containing $R_{eq}$. $R_{eq}$ is the equivalent resistance of the battery pack that was measured by parameter identification of the battery model used in the studies of [28]. Using only the equivalent resistance which is dependent on load and SOC, the ohmic losses of the battery, shown in equation 3.5, are calculated.
While this battery model, shown in figure 3.4, doesn't take into account the higher order effects of the original battery model, it has sufficient resolution for energy-based control simulations.

\[
P_{BattLost} = (I_{load})^2 R_{eq}
\]

\[
V_{batt} = V_{OC} - I_{load} R_{eq}
\]

where \(V_{OC}\) is equal to the open circuit voltage given by the battery manufacturer.

![Battery Model of Challenge X PHEV Simulator](image)

Figure 3.4: Battery Model of Challenge X PHEV Simulator

When converting the Challenge X simulator to a PHEV, a design constraint was set such that the new vehicle could drive for 20 miles on electricity alone, also known as all electric range (AER). It was determined that a pack with approximately 9 kWh capacity was needed to satisfy this AER constraint. Further dictating the total battery capacity are the number of cells needed to build a pack that matches voltage and current ratings of the electric drive system. The new A123 cells have a nominal voltage of 3.3 volts, so 82 batteries in series yielded the 270 volts needed by the power electronics. Then by adding parallel strands, it was determined that 15 strands were
<table>
<thead>
<tr>
<th>Battery</th>
<th>A123 ANR22650</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chemistry</td>
<td>Lithium Ion</td>
</tr>
<tr>
<td>Nominal Battery Voltage</td>
<td>270.6 Volts</td>
</tr>
<tr>
<td>Series Batteries</td>
<td>82</td>
</tr>
<tr>
<td>Parallel Strings</td>
<td>15</td>
</tr>
<tr>
<td>Actual Capacity</td>
<td>9.34 kWh</td>
</tr>
</tbody>
</table>

Table 3.2: Battery System Specifications.

needed to bring the battery capacity slightly above the 9 kWh design goal. Table 3.2 shows the details of the new A123 Li-Ion battery pack. Figures 3.5 and 3.6 show the discharging and charging efficiency, respectively, of the simplified battery model. The battery pack itself is able to supply up to 100 kW (7.5 C discharge rate) of power for a sustained time, but the power electronics and motor in the PHEV can only handle 67 kW. The battery pack is able to be recharged by regenerative braking in the PHEV and can be safely charged at rates up to 150 amperes (10 A per strand). 150 A equates to a maximum charge rate of 40 kW which was set as the highest charging rate in the energy management system.

3.2 Power Split Control

With the added flexibility of being able to provide traction power from two different sources of energy in this parallel hybrid, a new and complex control problem has been introduced. An algorithm needs to be formed such that the power requirements for the vehicle satisfy the total tractive force of equation 3.1 and the following constraints:

\[ P_{req} = F_{req} v(t)_{req} \]
Figure 3.5: Discharging Efficiency of the proposed A123 Battery Pack Model

Figure 3.6: Charging Efficiency of the proposed A123 Battery Pack Model
\[ P_{wh} = P_{em} + P_{ice} \]
\[ P_{min} \leq P_{em} \leq P_{max} \]

where \( P_{min} \) and \( P_{max} \) are the minimum and maximum power, respectively, of the electric motor. Several different methods have been created and modified over the past few years by researchers at OSU CAR. The most widely used power split algorithm on OSU projects has been an algorithm called the Equivalent Consumption Minimization Strategy[15][19][24]. This power split algorithm, and its slightly modified successor, the Adaptive Equivalent Consumption Minimization Strategy, are discussed further in chapter 4.

The power split control in a hybrid electric vehicle is closely related to the battery SOC. As a higher proportion of the torque load is provided by the electric motor, the deviation of the SOC will be more extreme. While the same can be said of the ICE and the fuel tank, the higher energy storage capacity of the fuel tank (due to the high energy content per gallon) allows for a few hundred hundred miles of driving range on a single tank of petroleum. While battery technology is improving, the energy storage density of batteries is much lower than fossil fuels thereby limiting the amount of electrical power available from the national electric grid in the vehicle.

### 3.3 Measures of Energy Consumption Performance

When measuring the overall performance of the PHEV, there are two sources of energy to account for. The first source of energy is the fuel tank which contains a twenty percent blend of biodiesel in the case of the Challenge X vehicle. The second source of energy is the battery pack that contains energy from the electrical power grid. While it is relatively straightforward to account for the fuel burned by the
ICE, it is more difficult to account for the energy used from the battery pack in the optimal control problem formulation from equation 1.1. When comparing the energy consumption of the vehicle, it is useful to have a metric that can be used for both energy sources. In [22], several different methods of comparison are proposed. Some of the proposed metrics include the total monetary cost of the fuel, energy equivalent gallon metric, and finally the metric chosen for this thesis, total CO$_2$ production. All non-renewable energy sources ultimately have a carbon dioxide contribution to the atmosphere. For fair comparisons of total energy consumption, it is desirable to calculate the amount of CO$_2$ produced by the combustion of diesel and the burning of various fuels at power plants such as coal or natural gas. In [22], the amount of CO$_2$ generated by the consumption of 1 gallon of B20 biodiesel is 9.09 kilograms. Using the 2008 US standard power generation mix shown in table 3.3, it was calculated by Argonne National Laboratory in [3] that .567 kilograms of CO$_2$ is produced per kWh. By totaling up the amount of CO$_2$ generated by the burnt diesel and spent electricity from the power grid, we are able to measure the quantity of total emissions for the PHEV over a particular driving profile. Therefore, the metric used in assessing the control strategy in this thesis is minimizing the total CO$_2$ production over a route.
### Table 3.3: 2008 Standard Generation Mix

<table>
<thead>
<tr>
<th>Fuel</th>
<th>Percentage of Electricity Generated</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coal</td>
<td>51%</td>
</tr>
<tr>
<td>Nuclear</td>
<td>19%</td>
</tr>
<tr>
<td>Natural Gas</td>
<td>15%</td>
</tr>
<tr>
<td>Hyrdroelectric</td>
<td>9%</td>
</tr>
<tr>
<td>Oil</td>
<td>4%</td>
</tr>
<tr>
<td>Other</td>
<td>2%</td>
</tr>
</tbody>
</table>

Chapter 4: ECMS

4.1 Equivalent Consumption Minimization Strategy

The Equivalent Consumption Minimization Strategy (ECMS) was developed by Paganelli [11] and was developed as a solution to determine the optimal power split for a parallel hybrid vehicle with two different power sources. In his original publication[11], Paganelli compared his new ECMS algorithm to existing power split optimization algorithms such as the loss minimization strategy[23] and a variant of simulated annealing[25]. The simulated annealing algorithm is widely known and is not a method which can be used in a real-time implementation, but was included as a benchmark by which to compare the other control strategies to. In this thesis, a similar approach was taken by using a dynamic programming algorithm to obtain the global optimal solution to compare the new variant of ECMS to.

The ECMS algorithm solves the optimal control problem by applying Pontryagin’s minimum principle. [19] states that if an optimal control, \( u^*(t) = u(\tau_{\text{ice}}, \tau_{\text{em}}) \), is found then the following conditions have been satisfied:

1. \( u^*(t) \) minimizes at each instant the Hamiltonian of the optimal control problem:

\[
H(x, u, \lambda) \geq H(x, u^*, \lambda), \forall u(t) \neq u^*(t) \tag{4.1}
\]
where the Hamiltonian is defined as

\[ H(x, u, \lambda) = \lambda(t) \cdot f(x, u) + \dot{m}_f(u) \quad (4.2) \]

with \( \lambda(t) \) an auxiliary variable called the co-state of the system.

2. the co-state variable satisfies the following dynamic equation:

\[ \dot{\lambda}(t) = -\frac{\partial H}{\partial x} = -\frac{\partial f(x, u)}{\partial x} \quad (4.3) \]

The above conditions are necessary for an extremal solution. If the optimal solution exists for the problem, then the solution is also extremal. If the minimum principle gives only one extremal solution, and we know the optimization problem has only one unique solution, then the extremal solution is the optimal solution. Pontryagin’s minimum principle stated above is used to find solutions by minimizing the Hamiltonian function such as equation 4.2 mentioned above. The hamiltonian in our fuel minimization problem can be interpreted as the equivalent fuel consumption written as

\[ H(x, u, \lambda) = m_{\text{equiv}}(x, u, s) = s(t) \cdot \frac{E_{\text{batt}}}{Q_{\text{lhv}}} \cdot f(x, u) + \dot{m}_f(u) \quad (4.4) \]

where \( E_{\text{batt}} \) is the total capacity of the battery, \( Q_{\text{lhv}} \) is the lower heating value, or energy density per unit mass, of the biodiesel, and \( s(t) \) the equivalence factor which relates the cost of battery energy to fuel energy. The equivalence factor is written:

\[ s(t) = \lambda(t) \cdot \frac{Q_{\text{lhv}}}{E_{\text{batt}}} \quad (4.5) \]

The equivalence factor is a tunable parameter that controls the optimization of the power split. In past works of ECMS, this optimization was implemented on a standard
HEV where the $SOC(t_0) = SOC(t_f)$. The equivalence factor was usually tuned by finding a value of $s(t)$ such that for typical driving profiles, the final SOC didn’t deviate from the constant target SOC. To improve the robustness of the strategy, a penalty weight was proposed in [10], in the form of a function such as the one shown in figure 4.1. As the SOC of the battery approaches the set limits, the selected ECMS factor will be penalized so that the battery doesn’t become overcharged or over-depleted. When a certain driving style, or even route causes the battery to become over-depleted or overcharged, the power split is not operating effectively and will result in higher fuel consumption. Further studies on the topic of ECMS have resulted in an Adaptive form of ECMS, discussed in section 4.3 that take into account different driving styles and routes.

![Figure 4.1: ECMS Penalty Weight](image)

Figure 4.1: ECMS Penalty Weight
4.2 Optimal Charge Depletion Profile

The dynamic programming (DP) algorithm was used to find the benchmark solutions for all the energy management studies in this paper. DP can be used to find the benchmark solution because the technique utilizes the principle of optimality\[5\]. The principle of optimality states that a larger problem can be broken down into many different subproblems and the set of solutions of the subproblems is the optimal solution of the overall problem. This principle can be applied to a PHEV fuel minimization problem by discretizing the problem into a finite number of states and finding the path through the state space that results in the lowest fuel consumption.

When solving the optimal control problem explained in section 1.2, it is important to discretize the problem with a high enough resolution that the global optimal solution is found. When setting up the state space for the dynamic programming algorithm for PHEV fuel minimization, we are ultimately interested in finding the SOC profile that will result in the least fuel consumption over the driving cycle. This SOC profile dictates the optimal power split between the EM and ICE power sources. The resolution of the power split is very small in real world applications, but for these studies a resolution of 500 watts was used in the DP code. Having the resolution set at 500 watts resulted in approximately 40,000 possible SOC states per time step after taking into account the upper and lower SOC limits. The state space then scales up linearly based upon the length of the driving profile. Because of the large state space of possible solutions, the Ohio Supercomputing Center was used to solve this optimization problem due to the long run time and large amount of runtime memory needed.
Much research has been done before related to finding the optimal SOC profile for a PHEV[20]. The vehicle simulator used for the dynamic programming study in that paper was the same Challenge X vehicle. What Tulpule et al. found was that as the battery size of the PHEV increased, the optimal SOC profile showed a higher correlation coefficient to a linear fit. This correlation is shown in figure 4.3.

### 4.2.1 Battery Size Case Study

To show the charge depletion rate changes mentioned by [20], simulations were run to show how the size of the battery directly effects the optimal SOC profile along the same route. A standard driving cycle published by the US Environmental Protection Agency, called the Urban Dynamometer Driving Schedule, was chosen for this study. Figure 4.4 shows the velocity and length of the driving profile. As per the simulation...
Figure 4.3: Linear correlation with respect to Battery Capacity[20]

standards, the cycle was repeated six times so a total distance traveled of just over 40 miles was reached. Figure 4.5 shows how as the size of the battery increased, the SOC profile showed less deviation from a linear charge depletion.

4.2.2 DP results for 315 North Case Study

The research team at CAR has maintained a server with recorded velocity profiles of a few vehicles which were part of the SMART@CAR program. A driving profile from the CAR Toyota Prius was used as an example profile that mixes suburban and intercity driving profiles. The route begins at CAR and heads north on Kenny Rd till making a right on Ackerman Rd to merge onto 315 North. After a small segment of the highway was driven, the driver got off at W North Broadway St. and continued to their residence. Grade data was added to the profile after it was driven by looking up the elevation (shown in figure 4.7) on the CITR GIS server mentioned in chapter 2. To simulate a round trip from this location, the velocity and grade profiles were reversed and repeated so that there was no gain in elevation over the route. The round trip route was repeated 4 times to simulate a total distance of about 40 miles. This
Figure 4.4: EPA’s Urban Dynamometer Driving Schedule

Figure 4.5: Optimal SOC profile for Different Battery Capacities
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trip Length</td>
<td>40.63 Miles</td>
</tr>
<tr>
<td>Trip Time</td>
<td>2.7 Hours</td>
</tr>
<tr>
<td>Average Moving Velocity</td>
<td>23.1 MPH</td>
</tr>
</tbody>
</table>

Table 4.1: 315 North Route Statistics

length was necessary to ensure that the car operated in blended mode with sufficient ICE power contribution to cause measurable fuel consumption. The resultant SOC profile of the DP shows that the optimal state of charge trajectory is roughly linear with respect to distance. Therefore, the linear SOC equation,

$$SOC_{ref}(k) = SOC_{init} - \frac{Dist_{k+T}}{Dist_{trip}} \cdot (SOC_{init} - SOC_{min})$$  \hspace{1cm} (4.6)

is used as the linear reference SOC generator, where $SOC_{init}$ is the initial state of charge of the battery, $Dist_{k+T}$ is the total traveled distance plus the expected distance to be covered in prediction $T$, and $Dist_{trip}$ the total distance of the trip. In these studies, it was assumed that the battery started fully charged at 95% SOC and was considered empty at 25% SOC.

4.3 Adaptive-ECMS

Adaptive-ECMS was formulated because of the need for a better way to manage a power split under varying driving conditions. As roads change between urban, suburban, and highway, the optimal power split between the electric motor and ICE varies. Different methods exist such as gain scheduling by driving pattern recognition [12], using a Kalman filter to predict future speeds and solve for optimal equivalence factor by receding horizon techniques [1], and lastly a SOC feedback controller[19].
Figure 4.6: SMART@CAR 315 North Case Study Route
Figure 4.7: Elevation along route from NED Database

Figure 4.8: Global Optimal SOC for 315 North Case Study
The variant of A-ECMS implemented in the Challenge X PHEV simulator is similar to the SOC feedback formulation. The equivalence factor in this type is A-ECMS is equal to:

\[ s_{k+1} = 0.5(s_k + s_{k-1}) + k_p(SOC_{ref}(k) - SOC(k)) \]  

(4.7)

where \( s_k \) is the equivalence factor at the current time step \( k \), \( SOC_{ref} \) the reference SOC, and \( k_p \) the adjustable gain of the controller. Graphically this equation can be pictured by figure 4.9. The \( SOC_{error} \) is multiplied by the gain, \( k_p \), and added to the average of the previous two equivalence factors. For our implementation, the equivalence factor was recomputed every second. The update frequency can be decreased to lower computational complexity for online adaptation though. The A-ECMS update formula is only updated while the vehicle is in motion. When the vehicle is not in motion, no energy can be either drawn or stored in the battery. Updating the equivalence factor while stopped would result in large SOC deviations leading to sub-optimal performance.

4.3.1 Finite Horizon A-ECMS

To further enhance the performance of the energy management strategy, a predictive control framework was wrapped around the vehicle model. Figure 4.10 shows how the velocity prediction was input into the vehicle model for a prediction of \( T \) seconds and the optimum equivalence factor calculated the by the A-ECMS update equation. In the simulations, prediction error was eliminated by making the prediction equal to the next \( T \) seconds of the actual velocity profile. While access to this data is unrealistic in the real world, prediction algorithms can be made increasingly accurate with the aid of ITS technologies such as V2V and V2I communication.
Figure 4.9: A-ECMS Calculation Description

Figure 4.10: Structure of Finite Horizon A-ECMS
4.3.2 Tuning the A-ECMS

The A-ECMS was tuned by taking two sample velocity profiles into consideration. The most common types of driving that a vehicle usually sees is driving in an urban environment and driving on the highway at sustained high speeds. The Urban Dynamometer Driving Schedule (UDDS) and the Federal Highway Driving Schedule (FHDS) are standard velocity profiles that reflect operation in these respective conditions. The velocity profile for the urban setting can be seen in figure 4.4 and the highway in figure 4.11. When tuning the A-ECMS, a gain sweep was performed in Matlab by running the simulation multiple times with different gains and comparing the resultant SOC profiles and mean squared error of the SOC profiles. Both driving profiles caused the A-ECMS to exhibit the same behavior where as the gain got higher, the SOC profile more closely tracked the $SOC_{ref}$.

Figures 4.12 and 4.14 show how the state of charge profile changes as the gain is increased. Low gains in the A-ECMS mean that the equivalence factor is not allowed to change quickly enough for accurate tracking of the $SOC_{ref}$ profile. Figures 4.13 and 4.15 show how low gains lead to slow adaptation of the equivalence factor. As an example of how the equivalence factor changes during a driving profile event, figure 4.15 has a declining equivalence factor at the end of the simulation because the vehicle is entering a deceleration state at the end of a highway causing the regenerative braking system to push electrical energy back into the battery pack for future use. The equivalence factor is becoming lower during this event because the extra energy in the battery pack is causing the SOC to become greater than the desired $SOC_{ref}$. If the vehicle were to continue driving after this point, the lower EQF would cause...
the power split to dedicate a larger power request to the EM than the ICE to lower the SOC back to the level of the \( SOC_{\text{ref}} \).

Figure 4.11: EPA’s Federal Highway Driving Schedule

It can be seen in figures 4.12 and 4.14 how the effect of increased gain allowed for closer tracking of the \( SOC_{\text{ref}} \) profile. When measuring the tracking error of the profiles, it is helpful to have a quantitative measure that sums up the error over the entire driving profile. The mean squared error is a measure of how closely the \( SOC_{\text{ref}} \) profile is tracked at each instant. From figure 4.16 we can conclude that a gain of greater than 2 is desirable for an urban route and from figure 4.17 a gain of greater than 1 is desirable for minimum error on a highway route. It is pretty intuitive that higher gains will be desired to track driving profiles which have conditions that are
Figure 4.12: SOC profile of UDDS Gain Sweep Study

Figure 4.13: Equivalence Factor of UDDS Gain Sweep Study
Figure 4.14: SOC profile of FHDS Gain Sweep Study

Figure 4.15: Equivalence Factor of FHDS Gain Sweep Study
Figure 4.16: Mean Squared Error of SOC - UDDS Gain Sweep

Figure 4.17: Mean Squared Error of SOC - FHDS Gain Sweep
changing at quick rates such as urban driving. From these MSE graphs, a $K_p = 2$ was chosen as the ECMS gain for the remainder of the studies in this thesis.

### 4.3.3 Finite Horizon A-ECMS results for 315 North Case Study

After tuning the A-ECMS, the effect of the prediction horizon was studied. The finite time horizon can be varied in length from 0 to $T$ seconds. In this study, no prediction algorithm was used because in a simulation environment, the actual velocity data can be input to the simulator. This is advantageous because no prediction error will be introduced into the control problem. As the prediction length $T$ was increased, the control algorithm gained accuracy at the cost of computational complexity. The additional computation is the result of calculating the power required for the next $T$ seconds at each time step. The memory footprint of the algorithm goes up linearly with respect to prediction length $T$, as all computations are vectors of size $T$.

Figure 4.18 shows a subset of the SOC profiles of different prediction lengths, $T$, when the 315 North Case Study profile from section 4.2.2 was used with the simulator. It is seen that as the length of the prediction gets longer, the higher the accuracy of tracking the linear SOC reference profile. After a certain point though, a longer prediction horizon doesn’t improve the tracking, but rather causes the SOC of the vehicle to enter an oscillatory state. The result of these oscillations around the $SOC_{ref}$ can be seen with higher mean squared error shown in figure 4.19. From this bar chart, it is shown that a prediction length of $T=60$ seconds has the least MSE with $K_p = 2$ when compared to other prediction lengths.

To compare the overall energy management of the Finite Horizon A-ECMS, it is important to measure the total energy consumed by the vehicle over the given route.
The result of the CO\(_2\) analysis outlined in section 3.3, is shown in figure 4.20. As the prediction horizon of the A-ECMS increased, the fuel consumption decreased. More importantly however, the total CO\(_2\) emissions were lower resulting in an overall savings of energy. This savings of energy is the result of the optimized power split between the ICE and EM in the PHEV.

![Figure 4.18: Effect of Prediction Length on Actual SOC Trace](image)

**4.4 PHEV Charge Depletion Strategy Comparison**

Thus far, the A-ECMS control strategy has tracked a linear charge depletion profile mimicking the result of the optimal solution computed by the dynamic programming algorithm. This linear charge depletion trend is dependent on the vehicle knowing the total distance to be travelled between plug-in charging opportunities. If this trip
Figure 4.19: Mean Squared Error for Different Prediction Lengths

Figure 4.20: Fuel Consumption and Emissions for Different Prediction Lengths
length information wasn’t known, the vehicle would operate in a charge depleting mode and then switch into a charge sustaining mode once the minimum SOC was reached. This electric vehicle/charge sustaining (EV/CS) mode is how current plug-in hybrids, such as the 2012 Toyota Prius, manage their power split. Oftentimes, this loss of trip information causes a drop in fuel economy. Figure 4.21 shows the result of the 315 North Case study with grade included to match all previous studies in this chapter. Interestingly, with this grade included in the trip profile, the EV/CS mode of charge depletion is not significantly worse than the control strategy with no velocity prediction. But as expected, the fuel consumption got lower as the prediction length was increased. Figure 4.23 shows the result of the same study on 315 North, but without the grade taken into account. Without the grade, the additional information of trip distance helped conserve fuel and lower emissions by approximately 11 percent. The added prediction velocity of 30 and 60 seconds improved emissions by 15 and 19 percent respectively when compared to the EV/CS baseline of today’s automobiles. Why the grade caused the EV/CS case to become roughly equivalent to a case with prediction information is not clear and warrants further research into studying the impact factor of grade on the gain $K_p$ of the Finite Horizon A-ECMS.
Figure 4.21: Charge Depletion Profiles
Figure 4.22: Fuel Consumption and CO₂ Emissions
Figure 4.23: Fuel Consumption and CO₂ Emissions No Grade
Chapter 5: Contributions and Future Work

5.1 Contributions

The work in this thesis details the important intricacies of modeling a PHEV for energy management control studies. Chapter one outlined the different types of hybrid vehicles and how they differ from one another. Their differences greatly impact the control strategies that can be implemented in their energy management systems. Chapter two outlines the research area of Intelligent Transportation Systems that can provide data to these energy management systems. An ITS system that was implemented for these studies was the road grade information that was set up on a server. Chapter four is about the ECMS control strategy and the differences in implementations that have been made over the years for various student projects.

The finite horizon A-ECMS control strategy covered in section 4.3.1 is a new variation of A-ECMS and exhibits excellent fuel consumption characteristics in simulations. The studies contained in this thesis detail the first implementation studies of the Finite Horizon A-ECMS control strategy on a Plug-In Hybrid Electric Vehicle. Based upon the results of the 315 North Case Study in section 4.2.2, it has been shown that a near-linear charge depletion profile is the optimal solution for a PHEV to attain minimum fuel consumption on relatively flat roads. To follow this linear
Table 5.1: 315 Prediction Results Summary

<table>
<thead>
<tr>
<th>Prediction Length</th>
<th>CO₂ Produced</th>
<th>Improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 Sec</td>
<td>164 g/mi</td>
<td>-</td>
</tr>
<tr>
<td>15</td>
<td>154 g/mi</td>
<td>-6.1%</td>
</tr>
<tr>
<td>30</td>
<td>152 g/mi</td>
<td>-7.3%</td>
</tr>
<tr>
<td>60</td>
<td>148 g/mi</td>
<td>-9.8%</td>
</tr>
<tr>
<td>90</td>
<td>146 g/mi</td>
<td>-11.0%</td>
</tr>
</tbody>
</table>

charge depletion profile requires the use of control strategy, like A-ECMS, to change the powersplit in real-time. A-ECMS adapts the equivalence factor to regulate the SOC around the $SO_{Cref}$ profile by SOC feedback. Section 4.3.3 shows how a velocity prediction can further enhance the performance of the real-time control strategy by lowering fuel consumption and CO₂ emissions. Table 5.1 contains a summary of how longer velocity predictions are beneficial to the energy management control strategy. A 90 second prediction of the upcoming velocity profile can lower total CO₂ emissions by 11%.

5.2 Future Work

For the control strategy outlined in this thesis to be implemented, a velocity prediction mechanism must be generated for real world applications. V2V communication can deliver an approximate velocity profile to a vehicle, but driving styles differ between drivers, so a statistical method based on past driving history might yield results that are closer approximations to a specific drivers behavior. Fusing this prediction algorithm together with other ITS technologies such as V2I communication can enable access to road geometry and traffic updates for more accurate predictions.
Further work that can be done to expand this work is to measure the robustness of the above control strategy to prediction error. Preliminary studies have shown the strategy to be fairly robust, but more detailed studies need to be done before drawing any final conclusions.

5.3 Conclusions

This thesis has shown that the Finite Horizon A-ECMS control strategy is successful in minimizing the fuel consumption in plug-in hybrid electric vehicles that have no velocity prediction error. In a world where more data is made available every day, tomorrows vehicles should be designed to take advantage of it to optimize fuel consumption by advanced energy management control systems. As more telecommunications equipment is installed as standard equipment in production vehicles, the development of V2I and V2V technologies is not a question of ”if”, but ”when”. Utilizing off-board data has been shown to be important to the energy management system and will for sure be a part of tomorrow’s fuel efficient vehicles.
Bibliography


