OPTIMIZATION OF A PLUG-IN HYBRID ELECTRIC VEHICLE

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OPTIMIZATION OF A PLUG-IN HYBRID ELECTRIC VEHICLE

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GLOSSARY

Symbol	Refers To
AER	All electric range in miles
A_f	Frontal area of vehicle in m^2
A-h	Amp hours
ANL	Argonne National Laboratory
C_D	Coefficient of drag
Capacity	Energy capacity of the battery pack in kWh
C_{max}	Rated battery pack capacity in A-h
$C_{needed,grade}$	Battery capacity needed in kWh to pass grade ability constraint
C_{nom}	Nominal capacity for battery type, Wh per cell
C_{used}	Current capacity of battery pack that has been used in A-h
C_{RR1}	First coefficient of rolling resistance
C_{RR2}	Second coefficient of rolling resistance
CVT	Continuously variable transmission
DOD	Depth of discharge
$E_{0\text{-}60}$	Peak engine power in kW in 0-60 mph acceleration test
$E_{50\text{-}70}$	Peak engine power in kW in 50-70 mph acceleration test
EPA	Environmental Protection Agency
EPRI	Electric Power Research Institute
F_d	Vehicle drag force in N
F_g	Vehicle gravitational force in N
F_r	Vehicle rolling friction force in N
F_{veh}	Total force on vehicle in N
$FE_{Electric,EPA}$	55%/45% EPA Weighted fuel economy (kWh/mile) in electric mode
$FE_{Gasoline,EPA}$	55%/45% EPA Weighted fuel economy (mpg) in gasoline only mode
$FE_{Highway,Electric}$	Fuel economy (kWh/mile) on HWFET cycle in electric mode
$FE_{Highway,Gasolin}$	Fuel economy (mpg) on HWFET cycle in gasoline only mode
$FE_{Urban,Electric,}$	Fuel economy (kWh/mile) on UDDS cycle in electric mode
$FE_{Urban,Gasoline,}$	Fuel economy (mpg) on UDDS cycle in gasoline only mode
FE_{EPA}	EPA weighted fuel economy (mpg)
FE_{Urban}	Fuel economy (mpg) in urban driving on UDDS cycle
$FE_{Highway}$	Fuel economy (mpg) in highway driving on HWFET cycle
GHG	Greenhouse gas
grade	Percentage grade in grade ability constraint
HEV	Hybrid electric vehicle
HWFET	EPA Highway Fuel Economy Test driving cycle
I	Current out of battery in amps
IC	Internal combustion
K	Number of cells in battery pack
Li Ion	Lithium ion battery type
m	Vehicle mass in kg
$M_{0\text{-}60}$	Peak electric motor power in kW in 0-60 mph acceleration test

$M_{50\text{-}70}$	Peak electric motor power in kW in 50-70 mph acceleration test
mpeg	Miles per gasoline equivalent gallon
mph	Miles per hour
MWP	Mileage weighted probability
NiMH	Nickel metal hydride battery type
Pb Acid	Lead acid battery type
$P_{acc,e}$	Electrical accessory load in kW
$P_{acc,m}$	Mechanical accessory load in kW
$P_{battery}$	Power out of battery in kW
P_E	Peak engine power in kW
P_{engine}	Power out of engine in kW
PHEV	Plug-in hybrid electric vehicle
PHEV20	Plug-in hybrid electric vehicle with 20 mile all electric range
P_M	Peak motor power in kW
P_{max}	Maximum discharging power of battery in kW
P_{motor}	Power out of the motor in kW
PNGV	Partnership for a New Generation of Vehicles
PSAT	Powertrain Systems Analysis Toolkit
P_{total}	Total required powertrain power output in kW
P_{veh}	Total vehicle power output at wheels in kW
$R_{int,min}$	Minimum internal resistance per cell in ohms
rpm	Revolutions per minute
SOC	State of charge of battery
SOC_{min}	Minimum allowable state of charge of battery
$SOC_{sustain}$	Charge sustaining state of charge
UDDS	EPA Urban Dynamometer Driving Schedule speed trace
V	Velocity of vehicle in m/s
V_{eff}	Voltage of the battery pack
V_{min}	Minimum terminal voltage
V_{nom}	Nominal voltage per cell
VOC_{max}	Maximum open circuit voltage per cell
ZEV	Zero emissions vehicle
$\$C_{BattAcc}$	Cost of battery accessories
$\$C_{Batt,LiIon}$	Cost of battery for lithium ion battery type
$\$C_{Batt,NiMH}$	Cost of battery for nickel metal-hydride battery type
$\$C_{Batt,PbAcid}$	Cost of battery for lead acid battery type
$\$C_E$	Cost of engine
$\$C_M$	Cost of electric motor
$\$C_{PE}$	Cost of power electronics
$\$C_{Total}$	Total incremental powertrain cost
ρ	Density of air at standard conditions in kg/m^3
$\eta_{battery,dis}$	Discharging efficiency of battery
$\eta_{drivetrain}$	Drivetrain efficiency
η_{motor}	Efficiency of electric motor

SUMMARY

A plug-in hybrid electric vehicle (PHEV) is a vehicle powered by a combination of an internal combustion engine and an electric motor with a battery pack. The battery pack can be charged by plugging the vehicle into the electric grid and from using excess engine power. A PHEV allows for all electric operation for limited distances, while having the operation and range of a conventional hybrid electric vehicle on longer trips.

The purpose of this study was to develop a methodology for optimizing a PHEV design using minimum drivetrain cost as a figure of merit and determine the optimum designs for an all electric range (AER) of 10, 20, and 40 miles. Design parameters, electric motor size, engine size, battery type, and battery capacity, are optimized to determine the least cost design that meets a fixed set of vehicle performance constraints. The performance constraints are: 0-60 miles per hour (mph) acceleration time, 50-70 mph acceleration time, 0-30 mph acceleration time in electric only operation, top speed, and grade ability. The design optimization was carried out for three different levels of all electric range between 10 and 40 miles.

Using Argonne National Laboratory's Powertrain Systems Analysis Toolkit (PSAT), a base vehicle with characteristics resembling a mid-sized sedan is constructed, powertrain components are defined and scaled, and vehicles with different design parameters are simulated to determine their performance. The costs of different PHEV components and present value of battery replacements over the vehicle's life are used to determine the design's drivetrain cost.

The resulting optimum PHEV designs are simulated for fuel economy through PSAT and the social impact in terms of gasoline use reduction and carbon emissions reduction are quantified.

The overall least cost optimum results are vehicle designs using lead acid battery type. The optimum vehicles have the minimum electric motor size that can meet the 0-30 mph acceleration time in all electric operation. For an AER of 40 miles, the optimum vehicle has a minimum engine size that is sufficient to meet the 0-60 mph acceleration performance constraint. For vehicle designs with an AER of 10 and 20 miles, the engine is sized to help with meeting the grade ability performance constraint. The resulting optimum battery capacity in all cases of AER is the minimum battery capacity required for the AER.

The social impact in terms of gasoline use reduction and carbon emissions reduction was determined for the optimum PHEV designs. The least cost PHEV10 design has an EPA weighted electric operation fuel economy of .233 kWh/mi and a gasoline operation EPA weighted fuel economy of 58.1 mpg. The PHEV20 and PHEV40 had similar but slightly lower fuel economies. The PHEV10 shows a gasoline reduction of 63% of the average sedan in the current vehicle fleet, while the PHEV20 and PHEV40 show gasoline reductions of 70% and 80% respectively. The PHEV10, PHEV20, and PHEV40 save 280, 312, and 356 gallons of gas respectively annually. For carbon emissions, the PHEV10 provides a 53% reduction including electric power plant carbon emissions. This translates to a reduction of 2,102 kg of CO_2 emitted per year over the average sedan. The PHEV20 has slightly more carbon emissions, only a 51%

reduction or 2,010 kg CO_2 emissions saved annually. The PHEV40 reduces carbon emissions by 1,844 kg CO_2 per year which is a 47% reduction over the average sedan.

At $2.50 per gallon gasoline and 9 cents per kWh electricity, the PHEV designs save $643 to $696 in fuel costs annually over the average sedan meeting the 27.5 mpg CAFE standard.

CHAPTER 1

INTRODUCTION

1.1 Background

As fossil fuel energy sources become more and more scarce, technologies that show possible potential for decreasing energy use are being evaluated. Since the transportation sector accounts for about two thirds of the gasoline consumption in the US, new transportation technologies are being looked at with increasing vigor. One such new technology is plug-in hybrid electric vehicle technology.

A plug-in hybrid electric vehicle (PHEV) is a vehicle powered by a combination of an internal combustion engine and an electric motor with a battery pack. The battery pack can be charged by plugging the vehicle into the grid and from using excess engine power. A PHEV allows for all electric operation for limited distances, while having the operation and range of a conventional hybrid electric vehicle on longer trips.

PHEVs have significant potential to reduce oil consumption and greenhouse gas (GHG) emissions. Using energy off the grid as a substitute for burning gasoline, PHEVs increase coal, natural gas, and nuclear energy use in power plants, but also increase our energy independence from oil.

There are an increasing number of prototype vehicles being developed. However, most of the prototype designs have been designed with the intent to prove the technology.

There have also been many examples of converting hybrid electric vehicles (HEVs) to PHEVs. However, a methodical design optimization has not yet been published.

1.2 Optimization Considerations

A vehicle design optimization presents many complexities. A vehicle presents a system of many components working together in very intricate ways. The powertrain of a hybrid electric vehicle (HEV) is a link of an internal combustion (IC) engine, electric motor, transmission, wheels and axles, and battery pack. Each component has several parameters and possible designs. For example, a battery pack can have different capacities, chemistries, and voltages. Varying a single parameter typically has an effect on the whole system design. Also, compatibility between different components with varying parameters must be checked. For example, it must be ensured that the battery pack has enough available power to supply the peak electric motor power and there must be a check to see if the transmission can withstand the torque from the motor and engine.

Also, there must be a way of evaluating the effectiveness of any given design. The vehicle design must adhere to a set of performance constraints, such as 0-60 mile per hour (mph) acceleration time and grade-ability constraints. Also, the vehicle design must be evaluated for cost to determine the minimum cost design. There could be many other figures of merit besides lowest cost, such as minimum gasoline consumption, minimum weight, or best performance.

1.3 Past Work

Much work has been done with HEV and PHEV technology in the past few years, however, HEV technology has been around over a century. In 1905, an American engineer named H. Piper developed and patented a powertrain with an electric motor augmenting an engine that could accelerate a vehicle to a scorching 25 mph in a mere 10 seconds[1]. However, better engine technologies eliminated the need for electric augmentation and the idea of the HEV sat dormant for about 60 years.

HEV interest was rekindled with the oil crisis in the early 1970's. The crisis led to funding and development of several experimental HEVs, but the development of the technology began to diminish as soon as oil became plentiful again.

The next big step in HEV technology development came in 1993. The federal government announced the creation of the Partnership for a New Generation of Vehicles (PNGV) consortium, consisting of the "Big 3" automakers: Ford, GM, and Chrysler, along with 350 smaller firms. PNGV outlined very aggressive goals and called for the development of zero emission vehicles (ZEVs) using plug-in and hydrogen technologies.

As a contrast to the PNGV objectives, development in Japan and Europe was more orientated towards developing modestly improved and more commercially viable charge sustaining HEV designs. This type of development led to the first commercially successful HEVs, the Honda Insight and the Toyota Prius.

Currently, conventional HEVs are gaining a greater share of the marketplace. R. L. Polk analyst Ronnie Williams[2] predicts that hybrid sales will top two million vehicles, over 10 percent of the market, in the next five years. However, the recent attention being paid to the energy crisis and oil peaking has caused a more detailed look at more extensive hybridization and at plug-in hybrids.

University of California Davis, the Electric Power Research Institute (EPRI), Argonne National Laboratory (ANL), and CalCars are the current front runners in PHEV research. UC Davis and CalCars have introduced many working prototypes and have demonstrated PHEVs' ability to reduce oil consumption and GHG emissions. Meanwhile, Argonne National Laboratory has developed a flexible and comprehensive advanced vehicle simulator, Powertrain Systems Analysis Toolkit (PSAT) [3], which has allowed for the modeling and testing of hybrid, plug-in hybrid, and fuel cell vehicle designs without the need to construct and prototype. EPRI has determined costs and impacts for PHEVs with different all electric ranges[4] (AERs).

Currently, with backing from such prominent figures as former CIA Director James Woolsey, PHEV research of some type is going on at many colleges, universities, laboratories, and in industry.

1.4 Purpose

The purpose of this study is to determine an optimum least cost PHEV design with base vehicle characteristics that meets a set of performance constraints. Knowledge of this optimum design will allow for better accuracy when using PHEV characteristics in estimating future energy consumption, emissions, and social impacts.

The vehicle design parameters engine size, electric motor size, battery pack capacity and battery types are optimized. A base vehicle platform resembling the characteristics of a mid-sized sedan is used. The least cost design that meets a set of performance parameters including 0-60 mph acceleration time, 50-70 mph acceleration time, 0-30 mph all electric acceleration time, sustained grade ability, and top speed, is determined for different values of all electric range. The social impact of the optimum designs are evaluated in terms of reduced carbon emissions and gasoline consumption.

The optimization construction and methodology is developed. The resulting methodology can be adapted for different vehicle technologies and performance constraints.

CHAPTER 2

PLUG-IN HYBRID ELECTRIC VEHICLE TECHNOLOGY

2.1 Overview of a Hybrid Electric Vehicle

A hybrid electric vehicle (HEV) uses both an internal combustion (IC) engine and an electric motor in the powertrain, and also uses a bank of batteries to recapture and store energy from braking. This combination of an electric motor and an IC engine is more efficient from a system viewpoint than a conventional powertrain.

There are many different configurations of hybrid electric systems, including series, parallel, and power-split platforms. All PHEVs in this study have a parallel hybrid configuration with a pre-transmission motor location and a continuously variable transmission (CVT). This configuration is shown in Figure 1.

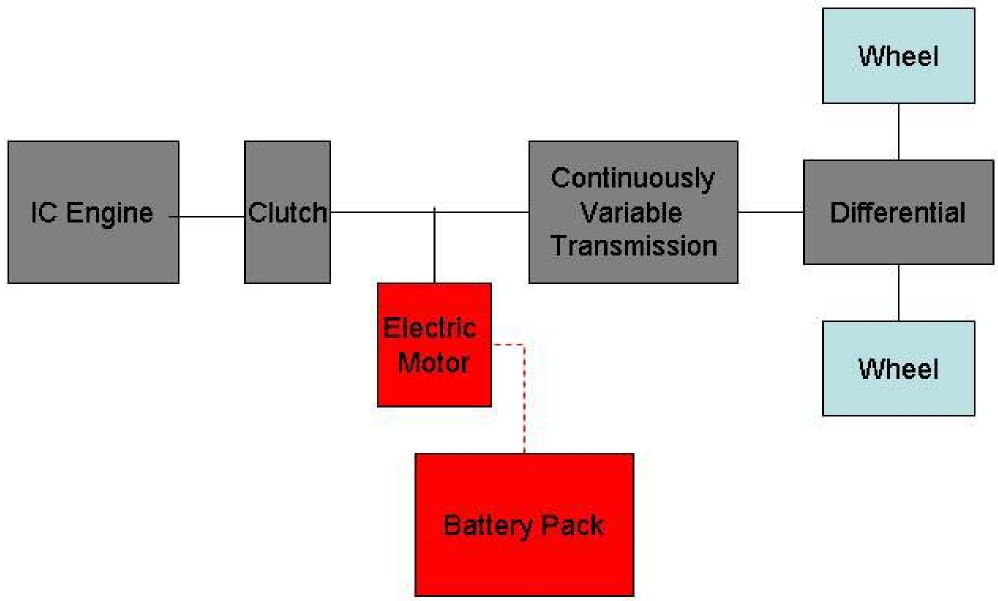

Figure 1. PHEV Parallel Pre-Transmission Configuration with CVT

The addition of HEV technology to a vehicle design improves efficiency primarily by four ways. First, the addition of the electric system allows the IC engine to operate in a more efficient range a greater amount of time. Typically, IC engines are more efficient at a higher load near wide open throttle. In a conventional vehicle, power requirements at cruising and idling are so low that the engine is forced to run at a lower than optimum loading. However, with a hybrid configuration, the IC engine can run at the most efficient load most of the time, using the excess power to charge the batteries. If the batteries are charged, the electric motor can provide the small amount of power required to propel the vehicle while the engine remains off.

Second, having the power of an electric motor at hand, it makes it possible to downsize the engine. Electric motors have higher torque at low rpm range while IC engines typically have high torque at high rpm range. This makes using an electric motor combined with an engine during acceleration, a time when the highest torque is needed, more efficient that using a larger equivalent torque IC engine. Also, having a smaller engine reduces the engine braking load, leaving more energy available to be recovered by regenerative braking.

Thirdly, having an electric motor allows the IC engine to completely shutoff instead of idling. The electric motor can simultaneously start the car moving and start the engine. Not having the engine idling while sitting at a traffic light significantly increases fuel economy in city driving. The Chevrolet Silverado incorporates this mild form of hybridization, and by simply eliminating engine idling, it has shown a 13% fuel economy increase in city driving.

Finally, the electric system allows for extensive recapture of the energy of braking. In conventional vehicles, deceleration is accomplished by friction between brake pads and rotors. The kinetic energy is dissipated in the form of heat. However, it is possible to recover a lot of this energy in useable form. By using the electric motor in reverse as a generator, the resistance created by the generation of electricity can be used to decelerate the vehicle and the electricity generated is used to charge the battery. Some estimates show it is possible to get almost 60% of the energy of braking back into useful electricity.

2.2 Hybrid Electric Vehicle Components

2.2.1 Battery Pack

The battery pack is the main electrical energy storage device. It is typically made up of a number of modules, connected in series with an open circuit voltage in the range of 100 to 300 volts, with the best designs at the higher end of this range. Each module is made of a number of cells.

Battery packs can be come in many different chemistries, but the most common are Nickel Metal Hydride (NiMH), Lead Acid (Pb Acid), and Lithium Ion (Li Ion). These are the chemistries considered in this study. Each chemical battery type has its own power, energy, and voltage characteristics.

The battery pack's energy capacity is given in amp-hours and its state of charge (*SOC*) is defined as:

$$SOC = \frac{(C_{\max} - C_{\text{used}})}{C_{\max}} \tag{2.1}$$

where C_{max} is the nominal rated C/3 capacity of the pack in A-h and C_{used} is the capacity of the pack in A-h that has been used since the pack was fully charged. C/3 is the capacity rating where the entire charge of the pack is discharged in 3 hours. The safe operating *SOC* range varies with different battery chemistries but is forced to stay over the constant range of 0.2 to 1 for this study. For most battery chemistries, the battery pack starts to be damaged at a *SOC* less than 0.2.

2.2.2 Electric Motor

The electric motor, often referred to as simply the motor, converts electrical energy from the battery pack to mechanical power into the CVT. The electric motor can also be used in reverse as a generator, converting mechanical energy from braking into electrical energy to be used to charge the battery pack.

There are two main types of electric motors used in HEVs. The first is permanent magnet motors, using a permanent magnet to create the magnetic field needed to produce power. The second is an induction motor, which uses current to create the magnetic field. This study investigates only permanent magnet motors, the more common of the two in HEV applications.

2.2.3 Power Electronics

Since the battery pack is basically a constant voltage device, a motor controller is needed to vary the current so that the motor produces the necessary torque. The power electronics are typically designed to the specific characteristics of the electric motor and are typically comprised of a microprocessor, power switching semiconductors, and a thermal management system.

2.2.4 Internal Combustion Engine

The internal combustion (IC) engine converts gasoline to mechanical engine to drive the wheels, and when needed to drive the motor operating as a generator to recharge the battery pack. There are many different types of engine designs, but in this study, a scaled version of the spark ignition 2001 1.5 L 60 kW Prius engine is used. Data for this engine is provided by ANL[19] and is shown in Appendix D.

2.2.5 Continuously Variable Transmission

The continuously variable transmission (CVT) is a belt driven transmission that provides continuous gear ratios to allow the IC engine and electric motor to operate at the most efficient or most powerful rpm over a range of vehicle speeds. The use of a CVT results in both better performance and better fuel economy over an automatic transmission.

2.3 PHEV Technology Considerations

The main aspect differentiating the PHEV from the HEV is the ability to plug the PHEV into the grid and charge the battery pack using grid electricity. A PHEV is rated by the all electric range (AER), which is the distance the vehicle can travel without the IC engine turning on over the EPA Urban Dynamometer Driving Schedule (UDDS) starting with an *SOC* of 1 and finishing with the smallest possible *SOC* that the battery pack can sustain without being damaged (assumed to be 0.2 in this study). Figure 2 shows the UDDS speed trace.

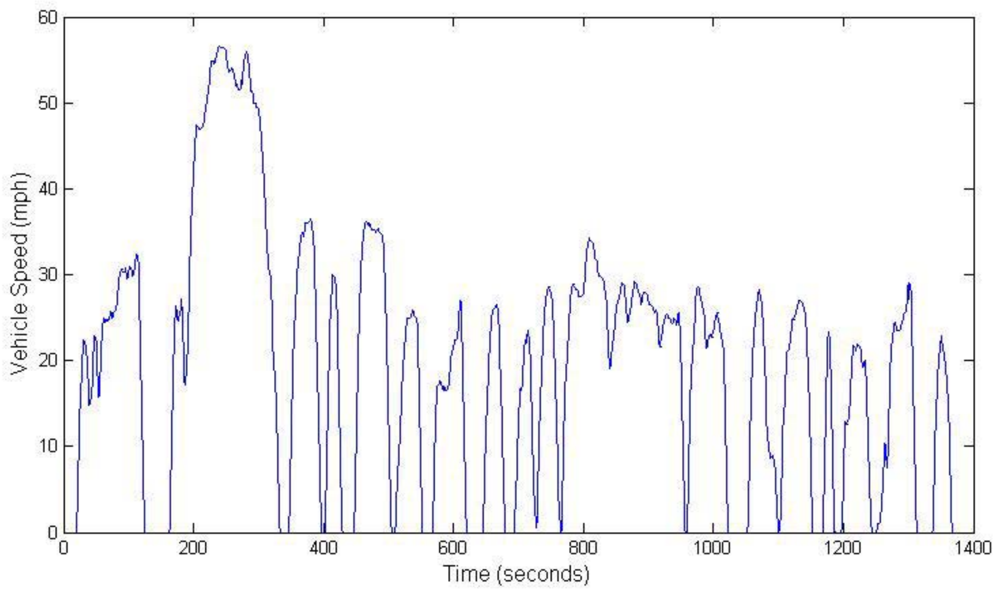

Figure 2. UDDS Driving Cycle

The UDDS cycle simulates urban driving and is part of the test procedure for determining EPA rated fuel economy. A PHEV that has an AER of 10 miles is designated as a PHEV10 and a PHEV that has an AER of 40 miles is designated as a PHEV40 and so on.

While a PHEV might have an AER of 40 miles, it might not necessarily have a control scheme that will use all electric operation for the first 40 miles of operation. PHEVs might use a control scheme that uses battery power to optimize fuel economy or to provide the most pleasant driving experience. While a PHEV might have the ability to travel a certain distance in all electric operation, in real world use, it could operate in all electric mode only for a certain speed range and torque demand. The engine could turn on any time the driver asks for a significant increase in torque, and prolonged all electric operation would be rare. Even so, fuel economy benefits could be realized whether or not the PHEV operates strictly in all electric mode. Different control schemes were not evaluated in this study.

The average light duty vehicle in the US is driven 40 miles per day[14]. However, some days, vehicles will travel longer distances than this, and some days, vehicles will travel shorter distances than this. ERPI[4] determined that a PHEV20 can drive 39% of its total miles driven in all electric mode awhile a PHEV40 can drive 61% of its total miles in all electric mode. Above a 40 mile AER, the benefits start to drop off, and at a 60 AER, 72% of the total miles would be driven in all electric mode. As a compromise between simulation time and ability to capture most of the miles driven in all electric mode, AERs of 10, 20, and 40 miles are chosen for this optimization.

CHAPTER 3

METHODOLOGY

3.1 Overview of Approach

In order to determine the least cost PHEV design that meets a set of performance constraints, the following steps are used:

- A base vehicle platform and base vehicle characteristics are established, such as drag coefficient and accessory loads.
- Design parameters are selected.
- Performance constraints are selected.
- Relationships between the design parameters are developed based on the performance constraints.
- Cost functions of the design parameters are developed.
- Design parameters are optimized using minimum cost as a figure of merit.
- Impacts of optimized designs are evaluated for gasoline consumption reduction and carbon emissions reduction.

The optimization steps are repeated for different all electric ranges (AERs) of 10, 20, and 40 miles. After the design parameters were optimized, the resulting vehicle design may have a different mass than the mass used during the optimization. Therefore, the masses of the resulting designs were calculated and the optimization was repeated for designs with the adjusted masses.

3.2 Powertrain Systems Analysis Toolkit

Argonne National Laboratory's Powertrain Systems Analysis Toolkit (PSAT)[3] is used extensively in this study. PSAT is a Matlab/Simulink based software that allows user specification of all specific vehicle components. Once the vehicle is specified, PSAT uses forward facing component dynamic models to simulate the vehicle operation along a specified speed trace or a specific performance test. From a specified road speed and grade, PSAT determines the power required at the wheels, determines the resulting driver response, and goes from driver, through the powertrain, including transient behavior and component efficiencies, and attempts to match the power required to meet the speed trace. Ultimately, PSAT will output fuel consumption, performance characteristics for specific powertrain components, and total cycle emissions for a given vehicle over a given driving cycle or performance test.

For all PSAT simulations in this study, a base vehicle platform is used and the design parameters are varied by scaling the sizes of the components of interest, and by changing the chemistry and scaling the size of the battery pack.

PSAT is first used to develop relationships between design parameters based on the performance constraints, determining the specific combinations of electric motor and engine sizes that will meet the 0-60 acceleration time and the 50-70 acceleration time performance constraints. PSAT is also used to determine the battery pack capacity required for the three battery types, NiMH, Li Ion, and Pb Acid, for the different AERs.

3.3 Component Costs

Component cost curves for engine size, motor size, and each of the three types of battery types are developed from various studies and industry estimates. The cost curves give a dollar amount per unit size of the design parameter, e.g., $ per kW peak motor power or $ per kWh battery capacity for a certain battery chemistry. Battery lifetimes are estimated, and battery replacement costs are discounted to present value and included in the battery costs.

Once the component cost curves are developed, it becomes possible to assign a PHEV an incremental powertrain cost for its various levels and types of components. Components that are the same for all types of PHEVs, i.e., chargers, vehicle frames, and CVTs, will have their costs ignored.

3.4 Optimization Approach

Once the performance curves and component cost curves are constructed, the vehicle design parameters are optimized to determine the least cost design. The optimization routine starts with a motor size and an engine size corresponding to a point that has sufficient power on a performance curve. Then, for each AER and for each battery type, the smallest acceptable kWh capacity of the battery pack is determined either from the AER range requirement, the peak electric motor power requirement, or to meet the grade ability performance constraint.

Once the component sizes are determined, the routine determines the drivetrain cost of the vehicle using the component cost curves. The least cost design for a given AER is then determined.

CHAPTER 4

BASE CHARACTERISTICS AND PERFORMANCE GOALS

4.1 Base Vehicle Platform

The base vehicle platform was chosen to resemble a typical midsized sedan. The following vehicle characteristics, taken from a 2001 study by Tony Markel and Keith Wipke[5], are used:

Table 1. Base Vehicle Characteristics

Frontal Area (A_f)	2.17 m^2
Coefficient of Drag (C_D)	0.33
First Coefficient of Rolling Resistance (C_{RR1})	0.007
Second Coefficient of Rolling Resistance (C_{RR2})	0.00012 s/m
Electric Accessory Load ($P_{acc,e}$)	500 W
Mechanical Accessory Load ($P_{acc,m}$)	700 W

All vehicles modeled in PSAT and all optimization results are for vehicles with the characteristics listed in Table 1.

4.2 Performance Constraints

The optimized vehicle is required to meet six performance constraints. Many of these are taken from PNGV goals when the consortium was created, while others are developed from examining what consumers want when purchasing automobiles. The performance constraints are:

1) 0-60 mph acceleration time in less than 12 seconds. This originated from the PNGV goals. The vehicle starts from rest with a *SOC* of 0.7 and accelerates to 60 mph. The 0.7 *SOC* is assumed to be average operating *SOC*.

2) 50-70 mph acceleration time in less than 8 seconds. Also a PNGV goal, 50-70 mph can be thought of as the "passing acceleration". The vehicle starts at 50 mph with an *SOC* of 0.7 and is accelerated to 70 mph.

3) 0-30 mph acceleration time less than 5 seconds in all electric operation. This is assumed to be the lower performance limit of a vehicle that is drivable in a city environment in all electric operation. The vehicle starts at rest with a *SOC* of 0.7 and the engine is not allowed to start at any time in the performance test.

4) 6.5% grade at 55 mph for 1200 seconds. This is a PNGV goal. The vehicle is allowed to use both engine and electric power. The initial *SOC* of the vehicle is 0.7 and the final *SOC* at the end of the test must be higher than 0.2.

5) Top speed at least 90 mph. The vehicle at 0.7 *SOC* must be able to go faster than 90 mph with both engine and electric power.

6) Vehicle must meet a specified all electric range (AER). The vehicle starts at a full *SOC* and must be able to run along the UDDS cycle for the specified number of miles without engine operation. The final *SOC* must be above 0.2.

There are many other performance qualities that consumers could want in a car. However, the optimization gets significantly more complicated as more constraints are added.

CHAPTER 5

VEHICLE MODELING

5.1 Approach

To determine that a given vehicle design meets the 0-60 mph acceleration, the 50-70 mph acceleration, the 0-30 mph all electric acceleration, and the AER performance constraints, the vehicle design's performance was simulated in Powertrain Systems Analysis Toolkit (PSAT). To determine that a given vehicle design passes the grade ability constraint, an analytical model was constructed. Both of these models require design parameter values, vehicle characteristics, and total vehicle mass as inputs.

The total vehicle mass input presents a problem because the mass of the optimum vehicle design resulting from the optimization may not be consistent with the assumed mass. To address this issue, a vehicle mass is input to the vehicle model, the optimization is performed, the new masses of the resulting designs are calculated, and these new masses are put back into the vehicle performance models and new optimum designs are calculated. This iterative process on total vehicle mass, while time consuming, had to only be performed for one iteration for the total masses of the resulting optimum designs to be within 1.5% of the masses used in the optimization.

The PHEV10 Pb Acid optimum design was assumed to have a total vehicle mass of 1,600 kg. All other designs with different AERs and different battery types have total vehicle masses different than 1,600 kg.

It was determined that all optimum design parameter values, e.g. electric motor size, engine size, etc., resulted from a single driving performance constraint. Therefore, it was only necessary to calculate the design parameter value that was the minimum value needed to meet the driving performance constraint for vehicles with different masses. So, while the first development of the vehicle models included all ranges of design parameter values, all following iterations on vehicle mass only calculated the minimum design parameter values necessary to meet the pertinent driving performance constraint.

5.2 Base Vehicle Setup

In order to simulate a vehicle in PSAT, one must first define the vehicle characteristics, the powertrain configuration, and specify the specific components. PSAT includes a library of configurations and components, and allows specific parameters to be modified and scaled as needed.

For the powertrain configuration, a parallel hybrid two wheel drive CVT configuration with the electric motor connected pre-transmission is used. Figure 3 shows the base configuration.

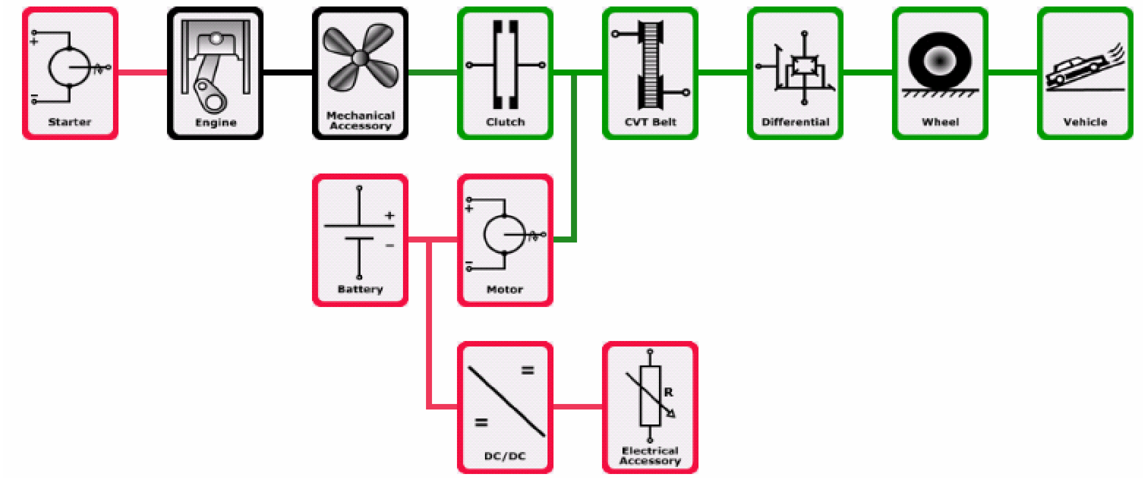

Figure 3. Base Hybrid Configuration in PSAT

The starter used is a standard 2 kW starter. It is conceivable that the electric motor can start the engine, however, this would add complexity in the modeling.

For the mechanical accessories, a constant 700 W loss is used. This is roughly the load of all the engine accessories on a conventional light duty vehicle, such as the water pump and the air conditioning compressor.

A simple clutch model is used, with a lock threshold of 5 rpm and a rotating inertia of 0.004 kg*m^2. This clutch can handle up to 150 N-m of torque.

The CVT used is a belt style CVT with a gear range of 0.42 to 2.40. The gear efficiencies are calculated in PSAT and the maximum efficiency is 92%. The CVT includes a hydraulic pump for transmission fluid and is included in the gearbox efficiency.

For the final drive, a 3.77 gear ratio was selected. This is the final gear ratio of the Ford Taurus.

For the wheels, a 14 inch rim diameter was selected and rolling coefficients were set to match the base vehicle characteristics from Chapter 4. The first rolling coefficient, C_{RR1} was set to 0.007 and is treated as a normal rolling friction coefficient. The second rolling coefficient, C_{RR2} was set to 0.00012. The coefficients are used in PSAT's wheel friction model to calculate rolling resistance by the following equation:

$$F_R = [C_{RR1} + C_{RR2} * V] * m * g \tag{5.1}$$

where F_R is the force on the vehicle from rolling resistance in N, V is the velocity of the vehicle in m/s, m is the mass of the vehicle in kg, and g is gravity, 9.81 m/s^2.

A 12V DC/DC power converter was selected with an efficiency of 0.95. The electrical accessory loss was set at a constant 500 W. This is to simulate loads such as the radio or the headlights.

A standard Ford Taurus vehicle platform was selected and then the characteristics were modified based on the vehicle characteristics in Chapter 4. The frontal area (A_f) was set to 2.17 m^2 and the coefficient of drag (C_D) was set to 0.33.

The entire vehicle mass was overwritten to 1,600 kg for the PHEV10 optimum design. For other designs, the mass of the actual design in PSAT was compared to the actual mass of the PHEV10 design, and the difference was added to 1,600 kg and the resulting mass was set for the vehicle. This process in effect resulted in using a base mass excluding the engine, motor, and battery pack of 1,277 kg.

5.3 Engine Platform and Scaling Procedure

The 2001 model year 1.5 L 60 kW spark ignition Toyota Prius engine was selected as the base engine platform. This engine is one of the more efficient of the newer engines in the marketplace today. The data for this engine was measured and compiled at ANL and is included with PSAT[19]. The data for this engine is shown in Appendix D. Figure 4 shows the efficiency map for the base engine.

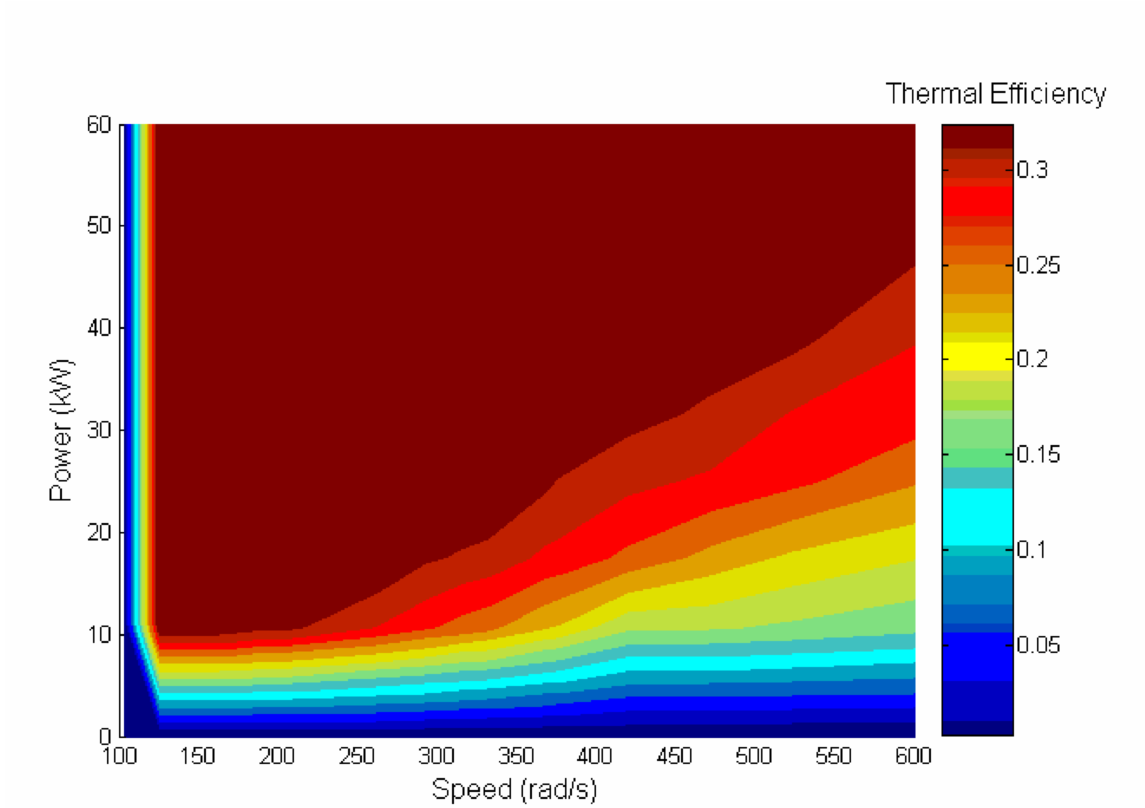

Figure 4. Base 60 kW Engine Efficiency Map

The engine is scaled by maximum power rating using a linear engine scaling algorithm that comes with PSAT. The scaling file linearly scales the fuel map so that the engine efficiency is constant with scaled power. Figure 5 shows the efficiency map of the base engine scaled to 30 kW.

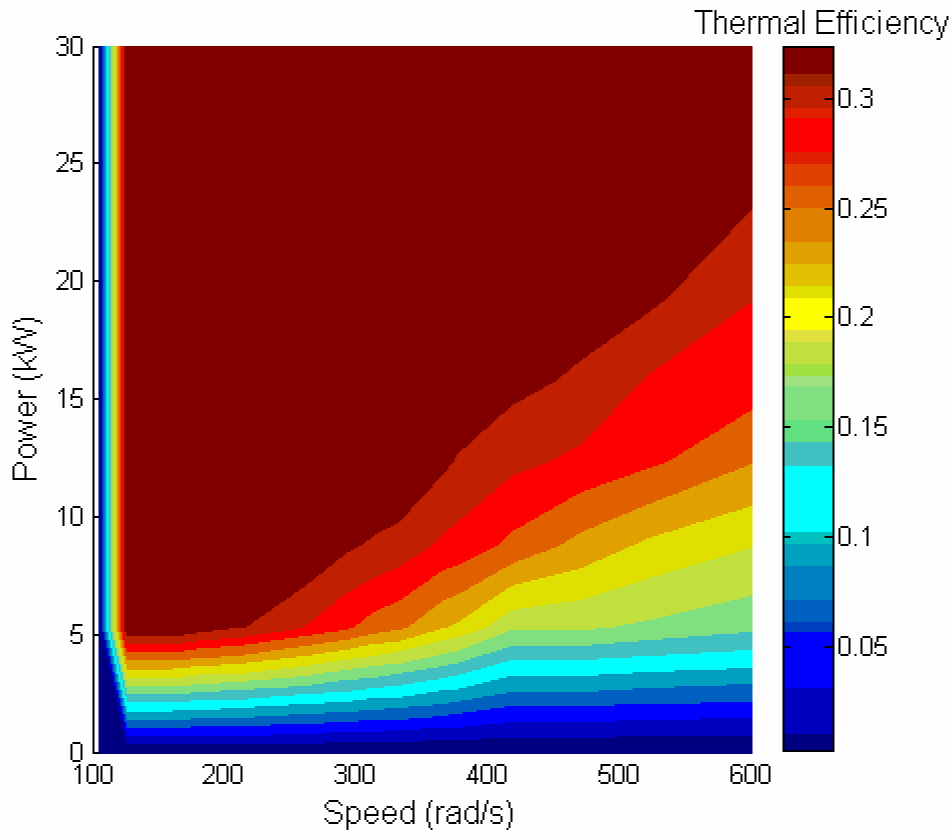

Figure 5. 30 kW Scaled Engine Efficiency Map

The engine is scaled over a wide range, 10 to 60 kW. The accuracy of the constant efficiency with varying maximum power is reduced as the engine power gets further away from the nominal 60 kW. It is estimated that the engine efficiency might vary as much as 20%[15] at 10 kW from the assumed efficiency at 60 kW.

5.4 Motor Platform and Scaling Procedure

The motor used is a 49 kW continuous 49 kW peak permanent magnet motor developed by Honda. The effective torque map comes from Honda R&D America and is included with PSAT[20]. Data for this motor is shown in Appendix D.

The motor is scaled by peak power using PSAT's linear motor scaling algorithm, similar to the engine scaling algorithm.

5.5 Battery Packs and Battery Pack Scaling

A commercial example of a battery pack was selected for each type of battery chemistry from the battery packs in PSAT. The pack size was scaled linearly by manually adding to the number of modules and at the same time, linearly increasing the nominal rated A-h capacity. This method linearly increases the voltage and thus the power capability of the pack and at the same time linearly increases the A-h capacity of the pack by the same percentage. The internal resistance characteristics of the batteries remained the same for each chemistry. For any performance tests, the initial *SOC* was set to 0.7 and the minimum *SOC* was set to 0.2, except for all electric range simulation, which the initial *SOC* was set to 1.

For the NiMH battery pack, a 60 A-h 300 cell Ovonics battery pack[16] with a nominal voltage of 1.2 volts/cell was chosen and scaled. The internal resistance and open circuit voltage data was provided by Ovonics and came with PSAT and is shown in Appendix C.

For the Pb Acid battery pack, a Johnson Controls 28 A-h 150 cell pack[17] with a nominal voltage of 2.0 volts/cell was selected and scaled. The data for this pack was provided by the University of Illinois and comes with PSAT and is shown in Appendix C.

Finally, for the Li Ion pack, the only available choice was a 6 A-h 75 cell battery pack with a nominal voltage of 3.6 volts/cell developed by Saft[18]. The data for this pack comes with PSAT and includes resistance and charging efficiency data based on temperature and a thermal model. This is shown in Appendix C. The pack was scaled with the same method as the other two chemistries.

5.6 Control Schemes

For performance tests in which the engine is allowed to operate, a parallel HEV control strategy is used in which preference is given to performance over fuel economy. For the acceleration tests, this strategy allowed for both the engine and the motor to run wide open at maximum power throughout the test.

For tests in which the engine wasn't allowed to operate, a fuel consumption orientated parallel HEV control strategy is used. To insure that the engine doesn't start, the engine was set to turn on only when the wheel power demand was greater than 10^{12} kW. After the tests for all electric operation, it was verified that the engine did not turn out through the entirety of the test.

For tests to determine fuel economy, the electric-only control strategy was used for the full charge tests simulating electric only fuel economy and a parallel hybrid consumption strategy was used for the partial charge tests simulating gasoline only fuel economy. For the partial charge tests, the charge sustaining SOC was set at 0.7 and the engine was allowed to start when there was more power required than the electric motor could provide and also when the battery state of charge went below 0.65. This control strategy assured that there was no significant battery drain between the start and ending of the cycle, which would skew the resulting gasoline only fuel economy.

5.7 Determining the Minimum Electric Motor Size

It was found that the performance constraint of 0-30 mph acceleration in less than 5 seconds determined the minimum acceptable electric motor size. Using the all electric setup control scheme, different scaled levels of the electric motor are tested in an acceleration run. During the all electric acceleration tests, the battery pack was purposely oversized to ensure that the pack provided sufficient power for the test and that the motor was able to produce peak power.

An iterative approach was used to determine the minimum electric motor size that would pass the 0-30 mph acceleration constraint. It was determined that a car with the base vehicle characteristics and the base PSAT setup with a mass of 1,600 kg needs at least a 44 kW motor to accelerate from 0-30 mph in 5 seconds in all electric operation. For designs with larger masses, the minimum electric motor size was found by the same method.

5.8 Acceleration Performance Curves Development

Acceleration as a function of motor size and engine size was developed to represent a constant acceleration time. The two acceleration curves developed are the curve for 0-60 mph in 12 seconds and the curve for 50-70 mph in 8 seconds. These curves represent the acceptable combinations of motor and engine sizes that will meet the performance goal, see Figure 8 on page 32. These curves were developed for a 1,600 kg vehicle. For designs other than 1,600 kg, it was only necessary to develop the left endpoints of these curves, as the optimum designs were found to lie on these endpoints.

Starting at the minimum acceptable electric motor size for a 1,600 kg vehicle, 44 kW, an iterative approach is used to determine the corresponding engine size that meets the performance goal. Engine sizes were adjusted and the acceleration test was rerun until the resulting acceleration time was within .1 second of the performance constraint. Once the corresponding engine size is found, the electric motor size is adjusted by a 1 kW step size and the process is repeated.

For designs with vehicle mass other than 1,600 kg, only the corresponding engine size needed to accompany the minimum electric motor size to meet the 0-60 mph and 50-70 mph performance constraints was determined.

Common logic would suggest that the power from the electric motor and engine would be directly additive, and thus the performance curves would resultantly be straight lines. However, this is not the case because the IC engine and the motor have different torque curve shapes. Figure 6 shows the wide-open throttle (WOT) engine torque curve.

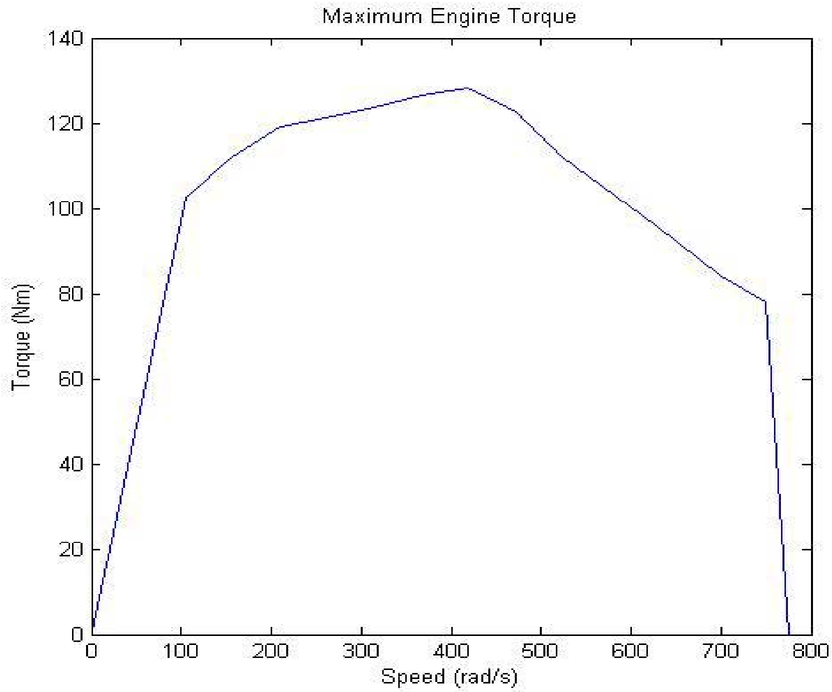

Figure 6. Base WOT Engine Torque Curve

The engine produces its highest torque at its mid RPM range. However, the electric motor produces its best torque at its low range of RPM. Figure 7 shows the base electric motor torque curve.

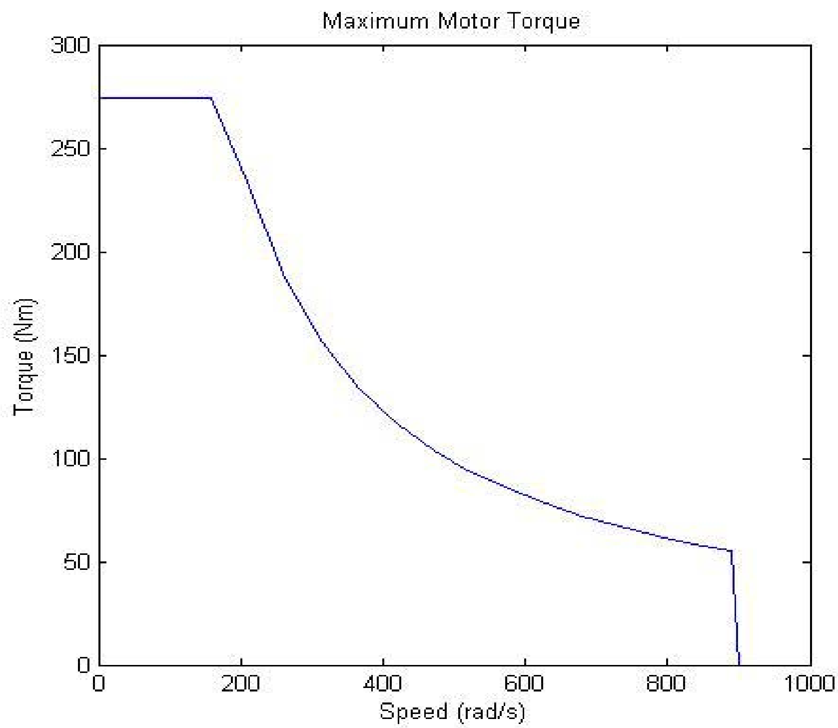

Figure 7. Base Electric Motor Torque Curve

For the acceleration performance constraints, the drive-train goes over a wide range of rpm (albeit, less of a range with the use of a CVT) and by increasing the electric motor size, the drivetrain torque is increased during the beginning of the test when the drivetrain is at a low rpm range, and by increasing the engine torque, the drivetrain torque is increased more at the higher range of rpm. This effect is more pronounced in the 0-60 mph acceleration test than the 50-70 mph acceleration test because it is over a wider range of rpm.

Once a number of tests are run and acceptable combinations of electric motor size and engine size are determined for each acceleration test, the points are curve fitted to get a smooth function. The 0-60 acceleration time performance curve is curve fitted with a second order polynomial while the 50-70 acceleration time performance curve is fitted with a linear equation. Figure 8 shows the performance curves and the curve fits.

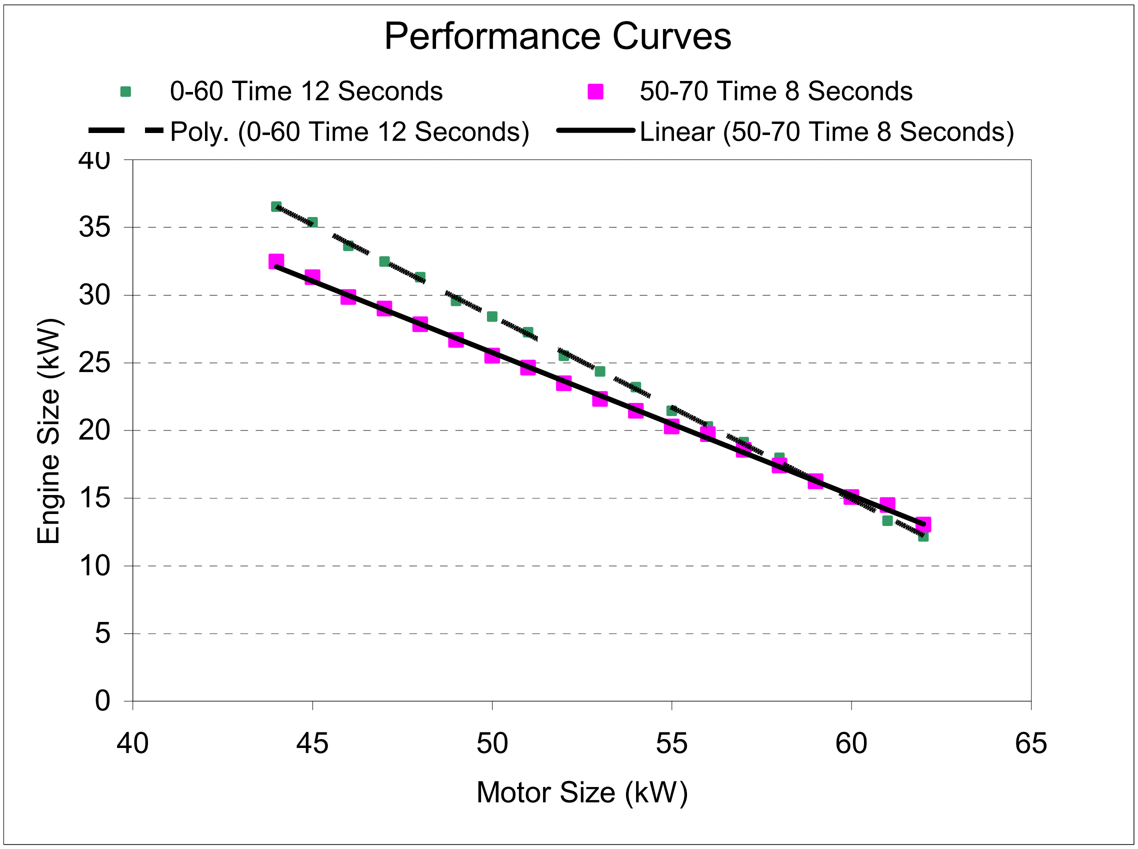

Figure 8. Performance Curves

Figure 8 is for a total vehicle mass of 1,600 kg. The total drive train power required in both cases decreases as the electric motor size increases.

The smooth function for the 0-60 mph time in 12 seconds for a 1,600 kg vehicle is given by:

$$E_{0-60} = -.0002 * M_{0-60}^{\ 2} - 1.327 * M_{0-60} + 95.32 \text{ (kW)} \tag{5.2}$$

where $M_{0\text{-}60}$ is the motor size in kW and $E_{0\text{-}60}$ is the engine size in kW, and the combination of $M_{0\text{-}60}$ and $E_{0\text{-}60}$ at any point along the 0-60 performance curve provides the power needed to propel the vehicle from 0-60 mph in 12 seconds. $M_{0\text{-}60}$ is valid from 44 kW to 62 kW, and correspondingly, $E_{0\text{-}60}$ is valid from 36.5 kW to 12 kW.

The smooth function for the 50-70 mph time in 8 seconds for a 1,600 kg is given by:

$$E_{50-70} = -1.0563 * M_{50-70} + 78.577 \text{ (kW)} \tag{5.3}$$

where $M_{50\text{-}70}$ is the motor size in kW and $E_{50\text{-}70}$ is the engine size in kW, and the combination of $M_{50\text{-}70}$ and $E_{50\text{-}70}$ along the 50-70 performance curve provides the power needed to propel the vehicle from 50-70 mph in 8 seconds. $M_{50\text{-}70}$ is valid from 44 kW to 62 kW, the same range as in the 0-60 mph performance curve. If more demanding performance constraints were used, these curves could be developed over a wider range of engine and motor sizes.

It was determined that in cases of large AERs, the optimum engine size value is at the left endpoint of the 0-60 performance curve. Therefore, while it was necessary to develop these curves for a single vehicle mass in order to find out the location of the optimum point along the curve, it was only necessary to find the left endpoint for different vehicle masses.

5.9 Simulating Top Speed

The power required for a 90 mph top speed was determined using PSAT simulation. It was found that all vehicles designs that could pass the 0-30 mph acceleration test also had a top speed greater than 90 mph in all electric mode only. Thus, any combination of electric motor size and engine size that uses a motor greater than or equal to the minimum motor size is sufficient to pass the top speed performance constraint. The top speed performance constraint did not drive any design parameter optimum values. If a more demanding top speed constraint had been used, it might have had an impact on the optimization.

5.10 Simulating All Electric Range

To determine the battery capacity required for a certain level of all electric range and battery type, the base vehicle was simulated with PSAT. Running in all electric mode, the vehicle was run on the UDDS cycle for a specified distance (10, 20, and 40 miles). The simulation was set to stop whenever the *SOC* of the battery pack dropped below 0.2. The battery capacity was scaled iteratively until the simulation stopped at the desired distance. This battery capacity iteration was repeated for all three battery types and was also repeated during the vehicle mass iterations to arrive at the final vehicle mass.

The smallest possible electric motor was used as previously determined by the 0-30 mph time performance constraint. The use of a larger electric motor allows for more regenerative braking energy to be captured, and can result in lower battery capacity required for a given AER. Since it would be very time consuming to optimize the electric motor size versus battery capacity for different vehicle weights and battery types, and because it would not be expected to have a significant effect on the results, the effect of motor size on battery capacity was ignored. Consequently, all the results of the AER modeling are for the smallest motor and largest battery capacity design possibility. The accuracy of this assumption is investigated later.

The maximum instantaneous power of the battery pack is checked to determine if the electric motor gets sufficient power over the simulation. The maximum discharging power is determined from a battery circuit in which the internal resistance is set to the minimum internal resistance of the cell, $R_{int,min}$, and the terminal voltage is set at the minimum cell voltage provided by the battery manufacturer. Then, after some algebra on a voltage loop and a current loop equation, the maximum power output of the battery pack, P_{max}, is given by:

$$\mathrm{P}_{\max} = \frac{(VOC_{\max} - V_{\min}) * V_{\min}}{R_{\mathrm{int,min}}} * K \text{ (W)} \tag{5.4}$$

where VOC_{max} is the maximum open circuit voltage per cell and is given by the battery manufacturer as a map indexed by *SOC* and the battery pack temperature. VOC_{max} is 1.35 volts/cell for NiMH[16], 2.4 volts/cell for Pb Acid[17], and 3.9 volts/cell for Li Ion[18]. V_{min} is the minimum cell voltage at the terminals and is 0.7 volts/cell for NiMH, 1.5 volts/cell for Pb Acid, and 3.2 volts/cell for Li Ion. $R_{int,min}$ is the minimum internal resistance per cell in ohms and is given by the battery manufacturer as a map indexed by SOC and battery pack temperature. $R_{int,min}$ is 0.000625 ohms/cell for NiMH, 0.001167 ohms/cell for Pb Acid, and 0.00493 ohms/cell for Li Ion. K is the number of cells in the battery pack. Using Equation 5.4, the maximum power for NiMH, Pb Acid, and Li Ion battery types are 0.728 kW/cell, 1.156 kW/cell, and 0.454 kW/cell respectively.

Even with the least power dense battery type, Li Ion, the corresponding maximum available power corresponding to a 10 mile all electric range was sufficient to power the minimum electric motor size. However, for larger motor sizes, the battery pack power was checked to ensure that it was sufficient to power the electric motor. Table 2 shows the required battery capacities for each battery pack for each AER for vehicles with the final vehicle masses.

Table 2. Battery Capacities Required for AERs

AER (miles)	Battery Capacity (kWh)		
	NiMH	*Pb Acid*	*Li Ion*
10	3.51	3.57	2.81
20	6.85	6.94	5.45
40	13.64	13.78	10.81

These packs all have different voltages and different A-h capacities. Table B.1 in Appendix B shows all the characteristics for these packs. The Li Ion packs require significantly less energy capacity because of a higher charging and discharging efficiency and because of a lighter optimum vehicle design.

Table 3 shows the corresponding maximum pack powers corresponding to the required pack capacity for the AER.

Table 3. Battery Maximum Power for Packs with Specified AER

AER (miles)	Maximum Pack Power (kW)		
	NiMH	*Pb Acid*	*Li Ion*
10	88.0	107.5	44.8
20	123.0	157.9	62.4
40	174.7	222.5	88.0

5.11 Modeling the Grade Ability Performance Constraint

Simulating the grade constraint for many different configurations of vehicles with PSAT would be tedious and time consuming, so an analytical approach was used. From a force balance, the vehicle power is calculated, and then the motor power is calculated. From the motor power, the battery capacity needed to make the 6.5% grade restraint at 55 mph for 1200 seconds is calculated.

The force required, F_{veh}, to move the vehicle up a constant grade at a constant speed is given by:

$$F_{veh} = F_g + F_d + F_r \tag{5.5}$$

where F_g is the gravity force, F_d is the drag force, and F_r is the frictional rolling resistance force, all in N.

The gravitational force component, F_g, is given by:

$$F_g = m * g * \sin(\tan^{-1}(grade/100)) \tag{5.6}$$

where m is the mass of the vehicle, g is the gravitational constant, and $grade$ is the road grade, 6.5 %.

The drag force, F_d, is given by:

$$F_d = \frac{\rho * C_D * A_F}{2} * V^2 \tag{5.7}$$

where ρ is the density of air, 1.29 kg/m^3, C_D is the coefficient of drag, 0.33, A_F is the frontal area, 2.17 m^2, and V is the velocity of the vehicle, 24.58 m/s (55 mph).

The force of rolling resistance, F_R, is given by:

(5.8)

$$F_R = [C_{RR1} + C_{RR2} * V] * m * g$$

where C_{RR1} is the first coefficient of rolling resistance, 0.007, and C_{RR2} is the second coefficient of rolling resistance, 0.00012 s/m.

Next, the power required, P_{veh} is calculated:

(5.9)

$$P_{veh} = F_{veh} * V$$

Next, the total drivetrain power required is calculated by adding in drivetrain efficiencies and accessory loads:

(5.10)

$$P_{total} = P_{acc,m} + P_{acc,e} + \frac{P_{veh}}{\eta_{drivetrain}}$$

$P_{acc,m}$ is the mechanical accessory load, 0.7 kW, $P_{acc,e}$ is the electrical accessory load, 0.5 kW, and $\eta_{drivetrain}$ is the drivetrain efficiency, which is assumed to be 0.8.

Once P_{total} is determined, the corresponding power out of the motor and out of the battery pack is determined. The motor power, P_{motor}, is given by:

(5.11)

$$P_{motor} = P_{total} - P_{engine}$$

where P_{engine} is the maximum power of the engine. The power out of the battery, $P_{battery}$ is given by:

(5.12)

$$P_{battery} = \frac{P_{motor}}{\eta_{motor} * \eta_{battery,dis}}$$

where η_{motor} is the efficiency of the motor, normally a weak function of rpm and load, but assumed constant and estimated to be 0.95. The battery discharge efficiency, $\eta_{battery,dis}$, is a weak function of *SOC* and battery temperature, but is assumed constant and estimated to be 0.95.

Once the battery power is known, the necessary capacity to pass the grade ability performance constraint, $C_{needed,grade}$, can be calculated in kWh. The current out of the battery, I, is given as:

$$I = \frac{P_{battery}}{V_{eff}} \tag{5.13}$$

where V_{eff} is the voltage of the battery pack, and is calculated with the following equation:

$$V_{eff} = \frac{V_{nom} * C_{needed,grade}}{C_{nom}} \tag{5.14}$$

where V_{nom} is the nominal voltage per cell, and C_{nom} is the nominal capacity in kWh per cell. Table 4 shows the nominal voltages and nominal capacities used for each battery type.

Table 4. Nominal Voltages and Capacities[16,17,18]

Battery Type	V_{nom} (Volts/cell)	C_{nom} (Wh/cell)
NiMH	1.2	72.0
Pb Acid	2.0	56.0
Li Ion	3.6	21.6

Data from Table 4 comes from battery manufacturer information that is included with PSAT.

The battery energy capacity needed is calculated with the following:

$$I * V_{eff} * t = (SOC_{sustain} - SOC_{\min}) * C_{needed,grade} \tag{5.15}$$

where t is the time for the grade ability test, 1/3 hour, $SOC_{sustain}$ is the charge sustaining SOC, specified as 0.7 in the performance constraints, and SOC_{min} is the minimum allowed SOC, 0.2.

Performing a little algebra, the necessary battery energy capacity, $C_{needed,grade}$, is simplified to:

$$C_{needed,grade} = \frac{P_{battery}[\text{kW}] * t[\text{h}]}{SOC_{sustain} - SOC_{\min}} \tag{5.16}$$

The battery energy capacity is calculated for each battery type, AER, and motor/engine size combination.

CHAPTER 6

COMPONENT COST MODELING

6.1 Component Costing Approach

Since many of PHEV components use new and developing technologies, concrete cost estimates are difficult to determine. However, there has been significant study on HEV costs. Mainly, two studies from the Electric Power Research Institute[4, 6] (EPRI) and industry examples are used in determining vehicle component costs.

The EPRI studies were done in a partnership with an industry working group with representatives from all the major automobile manufacturers. The cost estimates include manufacturing materials and manufacturing volume considerations. The costs in this study are estimated for a volume of 100,000 units per year.

6.2 Component Costs

6.2.1 Engine Size

The engine size cost estimate is taken from an EPRI study[4] and is based heavily on feedback from industry representatives. Only a 4 cylinder engine in a front wheel drive configuration is considered, consistent with the engine used in the PSAT modeling in the previous chapter. The cost for the engine, $\$C_E$, is calculated with the following equation:

(6.1)

$$\$C_E = \$12.00 * P_E + \$424$$

where P_E is the peak power of the engine in kW. This equation is stated to be valid up to peak engine powers of around 90 kW, at which point the engine would become a six cylinder engine with a different cost function.

6.2.2 Electric Motor Size

The cost of the electric motor also comes from an EPRI study[4]. EPRI, along with help from the representatives from industry, estimate the cost of the electric motor as:

(6.2)

$$\$C_M = \$13.7 * P_M + \$190$$

where $\$C_M$ is the cost of the electric motor and P_M is the peak power of the electric motor in kW. This is for a brushless permanent magnet motor with a manufacturing volume of 100,000 units per year.

In addition to the cost of the electric motor, the PHEV also needs power electronics to control the electric motor. For a typical pulse width modulation controller with thermal management system included, the cost of the power electronics, $\$C_{PE}$, was estimated by EPRI to be:

(6.3)

$$\$C_{PE} = \$8.075 * P_M + \$235$$

and the total cost associated with the electric motor size design parameter is $\$C_M$ added to $\$C_{PE}$.

6.2.3 Battery Pack Cost

The battery pack cost is comprised of the cost of the batteries, the hardware and mounting, and of the thermal management. The EPRI studies are used to determine the cost of the battery accessories[4] and the cost of NiMH batteries[6]. A UC Davis study is used to determine the cost of Pb Acid batterys[7] and an industry example is used to estimate the cost of Li Ion batteries[8].

For NiMH batteries, EPRI[6] estimates the cost of "energy batteries" used in all electric vehicles at $235 per kWh and "power batteries" used in conventional HEVs at $400 per kWh. NiMH batteries used in PHEVs would be somewhere between these two numbers. Corresponding to EPRI's estimate of the NiMH battery cost for a PHEV20, $320 per kWh is used in this study. Equation 6.4 gives the cost of NiMH batteries:

$$\$C_{Batt,NiMH} = \$320 * Capacity \text{ [kWh]} \tag{6.4}$$

where $\$C_{Batt,NiMH}$ is the cost of the NiMH batteries and *Capacity* is the energy capacity of the battery pack in kWh.

For Pb Acid batteries, the UC Davis study[7] uses a similar battery pack as used in the PSAT modeling, and estimates its cost with a 100,000 units per year manufacturing volume at $120 per kWh. For Pb Acid batteries, the following equation is used:

$$\$C_{Batt,PbAcid} = \$120 * Capacity \text{ [kWh]} \tag{6.5}$$

where $\$C_{Batt,PbAcid}$ is the cost of the lead acid batteries.

Since Li Ion batteries are a very new and developing technology, the prices for large scale HEV use are very difficult to obtain. As a compromise, an industry estimate based on small scale consumer use is used[8], which is \$650 per kWh for Li Ion batteries. This might be a relatively high estimate and as production volumes increase and technology develops, this estimate could be reduced substantially. For Li Ion batteries, the following equation is used:

$$\$C_{Batt,LiIon} = \$650 * Capacity \text{ [kWh]} \tag{6.6}$$

where $\$C_{Batt,LiIon}$ is the cost of the Li Ion batteries.

For the cost of the battery pack accessories an EPRI study[4] estimate developed in cooperation with industry is used. For the hardware, the tray, and the thermal management, the following equation is used:

$$\$C_{BattAcc} = \$1.2 * Capacity\text{[kWh]} + \$680 \tag{6.7}$$

where $\$C_{BattAcc}$ is the cost of all the battery pack accessories.

6.2.4 Battery Replacement Costs

Battery life is a complicated function of charging and discharging cycles, depths of discharge (DOD), driving frequency, climate, battery type, and varies greatly between different battery pack designs. No attempt was made to include all of these factors in the battery life estimation.

From literature review, certain trends for each battery type have been shown. A current estimate of the battery life of current technology NiMH, Pb Acid, and Li Ion are 1,500, 450, and 1,200 cycles at depths of discharge of 0.8 respectively[9]. However, advanced NiMH and Pb Acid designs have been shown to have the potential of 2,000 cycles[6] and certain Li Ion battery pack designs have shown to have as much as 9,000 cycles[10]. EPRI has shown that 2,000 cycles on a PHEV20 roughly translates to 100,000 vehicle miles.

For a 15 year, 150,000 mile vehicle life, this study estimates that Li Ion and NiMH will have a battery replacement at 100,000 miles (year 10) and Pb Acid will have a battery replacement every 50,000 miles (year 5 and year 10). Only the battery cost is added on, not the battery accessories. The battery replacement costs are discounted with the economic present value equation:

$$PV = \frac{FV}{(1+i)^N} \tag{6.8}$$

where PV is the present value cost in dollars, FV is the future value cost in dollars (from the battery cost equations), i is the interest rate, assumed to be 7% to estimate inflation and the return consumers expect on their money, and N is the number of years. The present value of all future battery replacements is included in the battery cost $\$C_{batt}$ when determining total incremental powertrain cost.

6.2.5 Incremental Powertrain Cost

The total incremental powertrain cost, $\$C_{Total}$, is given by:

$$\$C_{Total} = \$C_E + \$C_M + \$C_{PE} + \$C_{Batt} + \$C_{BattAcc} \tag{6.9}$$

$\$C_{Total}$ is not the total cost of the powertrain; it is only the total cost of the powertrain that is dependent on the design parameters. The combination of design parameters that produces the lowest $\$C_{Total}$ while still meeting all the performance constraints is the optimum least cost design.

CHAPTER 7

OPTIMIZATION ROUTINE AND VEHICLE MASS ITERATION

7.1 Optimization Approach

An optimization routine was written (Appendix B) that optimizes the design parameters for a given battery type and AER. The optimization routine inputs a range of engine sizes and motor sizes, adjusts the engine and motor size to meet the performance acceleration constraints, and then determines the battery capacity. The battery capacities required for the AER constraint, to provide the peak motor power, and to meet the grade ability constraint are calculated and the minimum battery capacity that will satisfy all three constraints is selected.

The cost of the combinations of electric motor size, engine size, and battery capacity is determined from the cost functions. Finally, the least cost combination is determined. This is repeated for each battery type, and then the whole process is repeated for each AER.

Since PSAT requires a total vehicle mass input which is not varied in the optimization routine, these calculations are at a fixed mass. The masses of the resulting vehicle designs are calculated. These masses are used as the assumed vehicle masses in the next vehicle mass iteration. For each vehicle mass iteration, the PSAT simulations the optimization is repeated. Vehicle mass iterations were done for each battery type.

7.2 Design Parameter Drivers

It was found that the optimum value of any given design parameter is determined by a single performance constraint. Thus, for all successive iterations on vehicle mass, only the design parameter values that were needed to pass the pertinent performance constraint were calculated. The following is a list of the design parameters and their controlling performance constraint.

7.2.1 Electric Motor Size

The 0-30 mph acceleration in 5 seconds in all electric operation determines the electric motor size. There is nothing in the optimization driving the electric motor to be any larger than this.

7.2.2 Battery Capacity

In all cases of AER, the optimum battery capacity is the minimum battery capacity required to pass the AER performance constraint while using the minimum electric motor size. The battery capacity is the most sensitive (most expensive) design parameter and all other design parameters are adjusted so that the vehicle can have the smallest battery capacity possible and still meet the performance constraints.

7.2.3 Engine Size

The smallest engine size that meets the 0-60 mph in 12 seconds performance constraint when paired with the minimum electric motor size is the optimum value except in cases where the battery capacity is insufficient to meet the grade ability performance constraint which occurs at AERs of 10 and 20 miles. At these AERs, increasing the engine size costs less than increasing the battery capacity, therefore, the optimum engine size is the one that allows the vehicle to pass the grade ability performance constraint while having the smallest battery capacity possible.

7.3 Vehicle Mass Iteration

Once the optimum designs for a vehicle with an assumed mass are known, and the controlling performance constraints for each of the design parameters are determined, the assumed mass of the vehicle is set equal to the mass of the vehicle with the resulting design parameters. The design parameter values that meet the controlling performance constraint with the new assumed vehicle mass are calculated.

The optimum PHEV10 Pb Acid vehicle design was set to a total vehicle mass of 1,600 kg. All the masses of the other vehicle designs are determined by comparing them with the PHEV10 design using linear scaling of component mass with respect to size in PSAT. The mass of the final optimum design is calculated and compared to the total vehicle assumed mass to determine if another iteration on mass is necessary. Table 5 shows the resulting masses for each vehicle design and vehicle mass iteration.

Table 5. Masses of Vehicle Designs

AER (miles)	Battery Type	First Design Mass	Final Design Mass	% Difference
10	Pb Acid	1,600	1,600	0.0%
10	NiMH	1,520	1,513	0.5%
10	Li Ion	1,514	1,501	0.8%
20	Pb Acid	1,724	1,750	1.5%
20	NiMH	1,567	1,562	0.3%
20	Li Ion	1,556	1,544	0.8%
40	Pb Acid	1,976	1,981	0.2%
40	NiMH	1,658	1,658	0.0%
40	Li Ion	1,637	1,653	1.0%

The difference between the initial assumed mass and the resulting vehicle mass based on the optimum design was as much as 25% in the cases of larger AERs. However, the vehicle mass converged very quickly. After only one vehicle mass iteration, the greatest difference in assumed mass and calculated mass was only 1.5%. This was determined acceptable and no other iterations on vehicle mass were carried out.

7.4 Determining Impact of Optimum Design

Current proponents of PHEVs predict that near term economically viable PHEVs will most likely have AERs in the range of 10-20 miles[11]. This is also in the range that a lot of vehicles are driven daily. This study determines the possible impact of the optimum PHEV designs for 10, 20, and 40 mile AERs.

To determine the fuel economy of the optimum PHEV designs, the EPA combined cycle test is simulated in PSAT and a weighting factor is used to estimate the time driven in all electric operation versus the time driven on charge sustaining mode. For a conventional vehicle, the EPA rated fuel economy is calculated with:

$$FE_{EPA} = \frac{1}{\frac{.55}{FE_{Urban}} + \frac{.45}{FE_{Highway}}} \tag{7.1}$$

where FE_{EPA} is the EPA rated fuel economy in mpg, FE_{Urban} is the fuel economy in mpg on the UDDS Driving Schedule simulating urban driving, and $FE_{Highway}$ is the fuel economy in mpg on the Highway Fuel Economy Test (HWFET) Driving Schedule simulating highway driving. However, for a PHEV, FE_{Urban} and $FE_{Highway}$ have to be adjusted to represent driving in all electric mode using grid electricity and driving in charge sustaining mode using gasoline. The fuel economies, weighted for 55% urban driving and 45% highway driving, are calculated for driving both in all electric operation on grid electricity and for driving in charge sustaining mode on gasoline.

A method developed by an EPRI[4] study is used to determine the percentage of total miles the vehicle travels in all electric operation. A mileage weighted probability (MWP) is determined. MWP is the statistical probability that a vehicle is driven less than or equal to its AER in a day. To calculate the MWP, data from the 1995 National Public Transportation Survey[12] was used to determine the probability that a given car will drive a certain amount of miles. Assuming that the PHEV is charged nightly, the miles that will be driven in all electric operation are calculated. For a PHEV20, EPRI calculates an MWP of 0.39, i.e. 39% of the miles driven on a PHEV20 will be in all electric operation. The other 61% of the miles are assumed to be in charge sustaining gasoline only operation. For a PHEV10, EPRI calculates an MWP of 0.22 and for a PHEV40, EPRI calculates an MWP of 0.61[4].

Once the fuel economies in all electric mode and charge sustaining mode in both highway and urban driving are determined, the impact of the optimum design is calculated. From Oak Ridge National Laboratory's Transportation Energy Data Book[13] the average passenger vehicle drives 12,200 miles per year. The CAFE average fuel economy for 2004 model passenger cars using the same EPA rating procedure is 27.5 miles per gallon. This is for an average 1,570 kg, 136 kW, car running on gasoline[14]. Gasoline consumption of both the average vehicle and the PHEVs are quantified and compared. Also, using national grid upstream CO_2 emissions (0.607 kg CO_2 per kWh) from the grid energy used by the PHEVs, the annual CO_2 emissions for the PHEV and for the average passenger car are calculated and compared. It should be noted that there will be an increased use in power plant fuels, coal, natural gas, and nuclear fuel for the PHEVs. However, this study focuses on the reduction of gasoline use because of the imported oil issue, while coal, nuclear, and natural gas are all 100% domestic fuels.

The annual fuel costs of the average vehicle and the PHEVs was also calculated and compared. A \$2.50 per gallon gas price is assumed. The national average residential electricity rate of 8.97 cents per kWh is used[21]. It should be noted that this is a high estimate for the cost of electricity, because a lot of PHEVs would be charged at night and would benefit from off-peak prices of electricity.

CHAPTER 8

RESULTS, DISCUSSION, AND CONCLUSIONS

8.1 Final Results

The optimization process produced the final optimum least cost designs. Table 6 shows the optimum PHEV designs for each AER.

Table 6. Optimum PHEV Designs

AER (miles)	Motor Power (kW)	Engine Power (kW)	Battery Capacity (kWh)	Battery Type	Cost
10	44	42.0	3.57	Pb Acid	$3,947
20	46	38.0	6.94	Pb Acid	$4,845
40	49	38.8	13.78	Pb Acid	$6,752

These are the least cost PHEV designs that meet the AER and all the performance constraints. All the optimum designs used Pb Acid battery type. The cost in Table 6 is only the cost of the engine, motor, and battery pack. Table 7 shows the cost breakdown for each design.

Table 7. Cost Breakdown of Optimum Designs

AER (miles)	Engine	Motor	Power Electronics	Battery and Replacements	Battery Accessories	Total
10	$928	$793	$590	$952	$684	$3,947
20	$880	$820	$606	$1,850	$688	$4,845
40	$890	$861	$631	$3,673	$697	$6,752

The total cost in Table 7 is not the total drivetrain cost, but only the incremental drivetrain cost above a constant baseline cost that is a function of the vehicle design parameters. The battery and battery replacement costs were the largest cost in the optimization. While Pb Acid had one more replacement that the other two battery types, it still produced the least cost design.

The second least expensive battery type was designs using NiMH battery type. Table 8 shows the optimum vehicle designs restricted to NiMH battery type.

Table 8. Optimum Designs for NiMH Battery Type

AER (miles)	Motor Power (kW)	Engine Power (kW)	Battery Capacity (kWh)	Battery Type	Cost
10	42.5	39.6	3.51	NiMH	$4,628
20	43.5	35.9	6.85	NiMH	$6,222
40	45.0	36.0	13.64	NiMH	$9,541

Table 9 shows the cost breakdown for the NiMH optimum vehicle designs.

Table 9. Cost Breakdown for NiMH Optimum Designs

AER (miles)	Engine	Motor	Power Electronics	Battery and Replacements	Battery Accessories	Total
10	$899	$772	$578	$1,694	$684	$4,628
20	$855	$786	$586	$3,306	$688	$6,222
40	$856	$807	$598	$6,584	$696	$9,541

Once again, the battery and battery replacement cost were the largest part of the total cost.

The Li Ion battery type produced the most expensive optimum designs. Table 10 shows the optimum vehicle designs for Li Ion battery type.

Table 10. Optimum Designs for Li Ion Battery Type

AER (miles)	Motor Power (kW)	Engine Power (kW)	Battery Capacity (kWh)	Battery Type	Cost
10	40.0	38.7	2.81	Li Ion	$5,623
20	40.5	35.3	5.45	Li Ion	$8,184
40	41.0	32.8	10.81	Li Ion	$13,427

Table 11 shows the cost breakdown for the Li Ion optimum designs.

Table 11. Cost Breakdown for Li Ion Optimum Designs

AER (miles)	Engine	Motor	Power Electronics	Battery and Replacements	Battery Accessories	Total
10	$888	$738	$558	$2,755	$683	$5,623
20	$848	$745	$562	$5,343	$687	$8,184
40	$818	$752	$566	$10,598	$693	$13,427

8.2 Discussion

In all cases, the resulting optimum value for the design parameter was driven by a single constraint. For most of the values of AER, the controlling performance constraint was the same for each design parameter.

For the electric motor size, the minimum motor size required to meet the 0-30 mph acceleration in all electric mode was the optimum value. This is the smallest acceptable motor size.

For the engine size, the optimum value is the engine size needed to pass the 0-60 acceleration constraint when combined with the minimum acceptable motor size. There are two exceptions to this. In cases of small AER, 10 miles and 20 miles, the optimum value of engine size needed was the size needed to pass the grade constraint with the minimum battery capacity needed to provide the AER. It was ultimately less expensive to add a bigger engine to charge the batteries in the grade constraint than to add more batteries.

In all cases, the lead acid battery type was the optimum battery type, even with one more battery replacement over the vehicle life. Lead acid is much cheaper than its competitors and in applications that need a lot of batteries, less expensive triumphs over better battery performance.

Most current consumer HEV designs use NiMH batteries rather than lead acid batteries. A distinction should be made here between HEV designs using batteries selected for high power output and a PHEV design using batteries selected for high energy storage. The discharge cycle of an HEV battery pack is much more demanding than a PHEV battery pack, and lead acid battery life characteristics are unsuitable. In order to use lead acid batteries in an HEV application, the battery pack would have to be sized above the necessary power and energy requirements to have an acceptable battery life. This adds weight and cost. Also, it should be noted than for small battery pack capacities required in HEVs, the cost of the batteries are much less than the cost of the battery hardware which is insensitive to battery capacity. This means that different battery chemistries do not play as large of a role in the overall battery pack cost in HEVs as in PHEVs.

In all cases, the optimum value for battery capacity is the minimum battery capacity required for the AER. Basically, the battery capacity is set at the minimum to pass the AER and all other optimization parameters are varied to pass all the other performance constraints.

While the driving force behind each optimum value is relatively straight forward, the effect of increasing mass with increasing component sizes is also quite dramatic. As AER increases, the added batteries add mass to the vehicle and more power is needed from the engine and electric motor, which adds more mass. Meanwhile, more batteries need to be added because the now heavier vehicle needs to meet the AER.

It was at first thought that since the Li Ion battery type designs weighed so much less than the other designs that they might be the optimum battery chemistry because of the smaller battery capacity, engine size, and motor size required for smaller vehicle masses. However, the higher cost of Li Ion batteries caused the lead acid battery vehicle designs to be the least cost optimum designs.

8.3 Sensitivity of Motor Size to AER

The smallest acceptable electric motor size was used when determining the battery capacity required for a given AER. However, the use of a larger electric motor allows for more energy from regenerative braking to be captured, and thus less battery capacity is required for the AER. To determine electric motor sizes effect on AER, the capacity needed for a given AER was simulated for 4 values of electric motor size. A lead acid 1,600 kg vehicle with an AER of 20 miles was used. Figure 9 shows the effect of electric motor size on battery capacity required for a given AER.

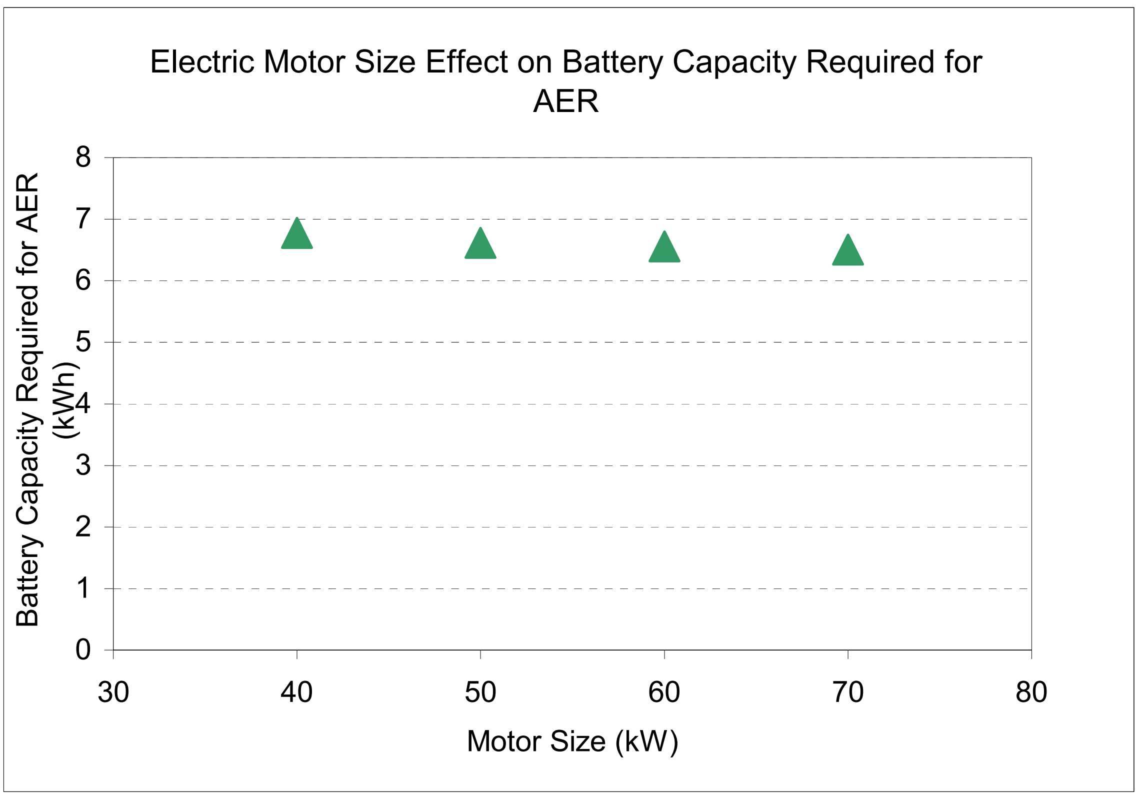

Figure 9. Electric Motor Size Effect on Battery Capacity Required for AER

Figure 9 shows that the battery capacity needed for a given AER is only a weak function of motor size.

The cost of the designs described in Figure 9 were calculated by pairing the electric motor size with an optimum engine size from the controlling performance constraint, i.e., either the 0-60 mph performance constraint or the grade ability performance constraint as described in the previous section. Figure 10 shows the effect of electric motor size on the optimum incremental drivetrain cost.

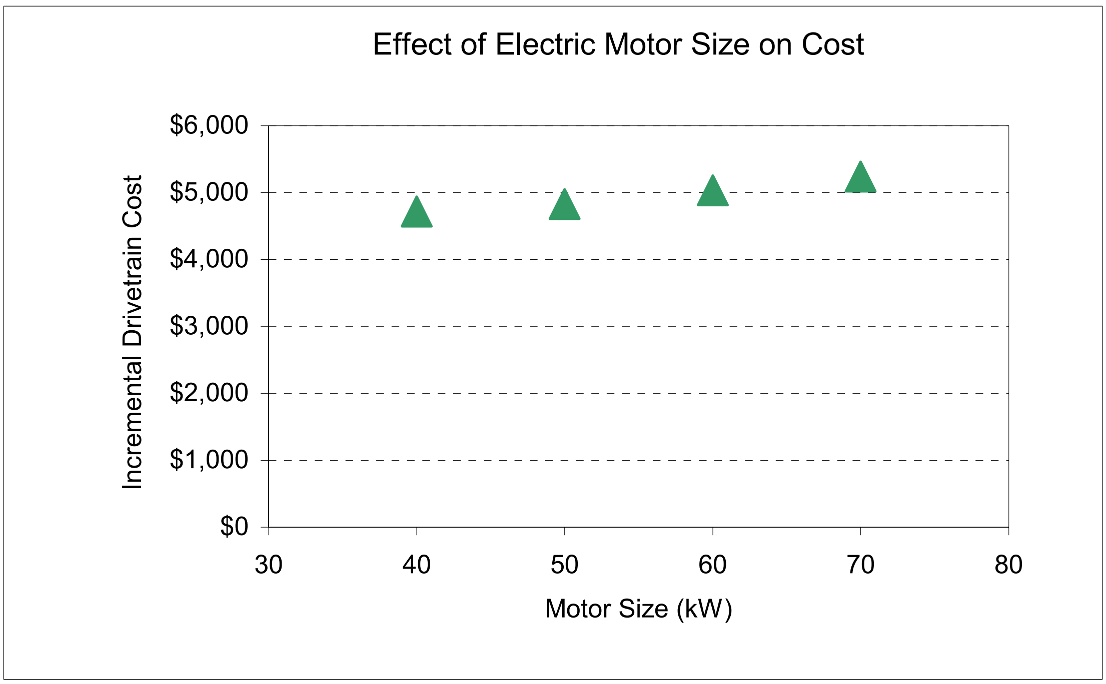

Figure 10. Effect of Electric Motor Size on Drivetrain Cost

Figure 10 shows that increasing the motor size increases the overall incremental drivetrain cost even though it decreases the optimum battery capacity required for the AER performance constraint. The additional cost of the electric motor is more than the savings from the reduced battery cost. Therefore, the assumption of using the minimum acceptable electric motor size when simulating the battery capacity required for the AER is not expected to have an effect on the optimization results.

8.4 Impact of Optimum PHEV Designs

Using the methodology for determining impact outlined in Chapter 7, the optimum Pb Acid design for the PHEV10 was simulated and has the following fuel economies:

Table 12. Fuel Economies for PHEV10 Optimum Design

PHEV10	EPA Weighted 55/45	
Electric Operation (kWh/mi)	.233	
Gasoline Operation (mpg)	58.1	
	UDDS	HWFET
Electric Operation (kWh/mi)	.235	.231
Gasoline Operation (mpg)	56.2	60.5

Table 13 shows the fuel economies found for the optimum PHEV20 design.

Table 13. Fuel Economies for PHEV20 Optimum Design

PHEV20	EPA Weighted 55/45	
Electric Operation (kWh/mi)	.262	
Gasoline Operation (mpg)	56.5	
	UDDS	HWFET
Electric Operation (kWh/mi)	.271	.253
Gasoline Operation (mpg)	54.3	59.5

Finally, Table 14 shows the fuel economies for the optimum PHEV40 design.

Table 14. Fuel Economies for PHEV40 Optimum Design

PHEV40	EPA Weighted 55/45	
Electric Operation (kWh/mi)	.291	
Gasoline Operation (mpg)	54.5	
	UDDS	HWFET
Electric Operation (kWh/mi)	.315	.267
Gasoline Operation (mpg)	52.2	57.7

The fuel economy is relatively similar for each of the three designs; however, it decreases as AER increases because of the increased mass of the designs. The miles driven in all electric operation and in gasoline operation were calculated for each design and the annual gasoline consumption and CO_2 emissions were calculated.

The PHEV10 is able to operate on average 22% of its miles in all electric operation when charged nightly. Driven 12,200 miles per year, it will operate 2,684 miles in all electric operation using grid electricity and 9,516 miles on gasoline as a charge sustaining HEV. Using the fuel economies from Table 12 and using the EPA weighting, 55% urban and 45% highway miles, the PHEV10 will use 163.9 gallons of gasoline and 625.7 kWh grid electricity per year. The upstream power plant CO_2 emissions and the tailpipe CO_2 emissions come out to total 1,833 kg of CO_2 per year.

Similarly, the PHEV20, operating 39% of its miles using grid electricity, will operate 4,758 miles in all electric mode and 7,442 miles in gasoline only mode. Using fuel economies from Table 13, the PHEV20 will use 131.6 gallons of gasoline and

1247.6 kWh grid electricity per year. The total CO_2 emissions for the PHEV20 are 1,925 kg per year.

The PHEV40 design operates 61% of its miles in all electric mode. 7,442 miles will operate on electricity and 4,758 miles will operate on gasoline each year. Using fuel economies from Table 14, the PHEV40 will use 87.3 gallons of gasoline and 2169 kWh of grid electricity annually. The total CO_2 emissions for the PHEV40 are 2,091 kg per year.

Using 8.97 cent per kWh electricity and $2.50 per gallon gasoline, the annual fuel costs for the PHEV10, PHEV20, and PHEV40 are $466, $441, and $413 per year respectively. It should be noted that the PHEV10 has a fuel cost of 2.09 cents per mile when operating on electricity and a fuel cost of 4.30 cents per mile operating on gasoline, so there is a financial incentive for PHEV owners to plug their PHEV into the grid. The other optimum PHEV designs had similar fuel costs per mile.

By contrast, today's CAFE average car getting 27.5 mpg, driven the same amount of miles uses 444 gallons of gasoline per year and produces 3,935 kg of tailpipe CO_2 emissions. The average car has an annual fuel cost of $1,109 per year. Table 15 shows the percentage reduction in gasoline consumption and CO_2 emissions and the annual fuel savings for each of the optimum PHEV designs over today's average car.

Table 15. Gasoline Consumption, CO_2 Reduction, and Fuel Savings of PHEVs

	Gasoline Saved (gallons/year)	% Gasoline Reduction	CO2 Reduced (kg/year)	% CO2 Reduction	Fuel Savings ($/year)
PHEV10	279.8	63%	2,102	53%	$643
PHEV20	312.0	70%	2,010	51%	$668
PHEV40	356.4	80%	1,844	47%	$696

Gasoline savings increase as AER increases, however, CO_2 emissions also increase as AER increases because the vehicle is using more grid electricity that comes mainly from coal combustion. Even the PHEV10 with a moderate cost premium provides a 63% gasoline consumption reduction. This has the potential to significantly reduce our dependence on foreign oil.

8.5 Conclusions

The design optimization methodology and optimum results for a plug-in hybrid electric vehicle has been presented and certain trends have been observed. Most of the design parameters are driven by a single performance constraint. The main findings are as follows:

- Lead Acid battery type produces the least cost design for AERs of 10, 20, and 40 miles. The vehicle cost is most sensitive to battery capacity and the optimum value of battery capacity is always the capacity required for the vehicle to meet the all electric range.
- Electric motor size is driven by the 0-30 mph acceleration in all electric operation constraint. The smallest size electric motor that can meet the 0-30 mph constraint is optimum in all cases of all electric range.
- Engine size is driven by the 0-60 mph acceleration constraint except in cases of small all electric ranges, 10 miles and 20 miles, in which it is driven by the grade ability constraint. For cases of all electric range higher than 20 miles, the smallest engine size combined with the minimum electric motor size that can make the vehicle pass the 0-60 mph acceleration constraint is the optimum engine size. For

the cases of small electric range, the optimum engine size is the engine size needed to pass the grade ability constraint while using the minimum battery capacity to provide the all electric range.

- The EPA weighted fuel economy for the PHEV10 design is 58.1 mpg in gasoline only operation and .233 kWh/mi in electric operation using grid electricity. The fuel economy is similar for all the optimum designs; however, it decreases slightly as AER increases because vehicle mass also increases.
- The PHEV10 optimum design provides a 63% reduction in gasoline consumption and a 53% reduction in CO_2 emissions over the CAFE average car. The 53% reduction in CO_2 emissions includes power plant emissions. This translates to a savings of 280 gallons of gasoline and 2,102 kg of emitted CO_2 per year.
- The PHEV20 optimum design provides a 70% reduction in gasoline consumption and a 51% reduction in CO_2 emissions including power plant emissions. This translates to a savings of 312 gallons of gasoline and 2,010 kg of emitted CO_2 per year.
- The PHEV40 optimum design provides an 80% reduction in gasoline consumption and a 47% reduction in CO_2 emissions including power plant emissions. This translates to a savings of 356 gallons of gasoline and 1,844 kg of emitted CO_2 per year.
- The percentage of gasoline reduction increases and the percentage of CO_2 reduction decreases as AER increases. However, all optimum PHEV designs have demonstrated over a 60% gasoline consumption reduction and at least a 45% CO_2 reduction over the average car in the current vehicle fleet.

- For $2.50 per gallon gas and 8.97 cents per kWh electricity, the fuel cost of the optimum PHEV designs is $643 to $696 per year less than the fuel cost of the average sedan meeting the 27.5 mpg CAFE standard.

8.6 Future Work

This was a first attempt at a PHEV design optimization and many aspects that could have been considered and probably should have been considered in retrospect were not. These include using more demanding consumer orientated performance goals and putting values on floating performance metrics.

The resulting optimum designs are vehicles with low performance compared to average fleet vehicle. The 12 second 0-60 mph time and the 5 second 0-30 time simulates a relatively underpowered car (about 80 kW total drivetrain power). For future studies, higher performance constraints might be considered in order to result in vehicle designs that might appeal to a wider consumer audience.

In order to find the market optimum design, consumer needs and values would have to be investigated. If dollar amounts were put on performance metrics such as acceleration time and fuel economy, and the vehicle was optimized to maximize value rather than minimizing cost, the resulting designs would be more market orientated. However, this approach would add complexity and a lot of estimates and assumptions based on economics would be required.

Overall, this optimization approach is outlined and is encouraged to be used as a base to build on. The method has been outlined and assumptions can easily be changed and approaches can be modified for different vehicle types and technologies.

APPENDIX A

PSAT MODELING POINTS

Table A.1. 0-60 mph Acceleration Time

Motor Size (kW)	Engine Size (kW)	Total Power (kW)	0-60 Time (seconds)
44	36.52	80.52	12
45	35.36	80.36	12
46	33.63	79.63	12
47	32.47	79.47	12
48	31.31	79.31	12
49	29.57	78.57	12
50	28.41	78.41	12
51	27.25	78.25	12
52	25.51	77.51	12
53	24.35	77.35	12
54	23.19	77.19	12
55	21.45	76.45	12
56	20.29	76.29	12
57	19.13	76.13	12
58	17.97	75.97	12
59	16.23	75.23	12
60	15.07	75.07	12
61	13.33	74.33	12
62	12.17	74.17	12

Table A.1 is for a 1,600 kg vehicle.

Table A.2. 50-70 mph Acceleration Points

Motor Size (kW)	Engine Size (kW)	Total Power (kW)	50-70 Time (seconds)
44	32.47	76.47	8
45	31.31	76.31	8
46	29.86	75.86	8
47	28.99	75.99	8
48	27.83	75.83	8
49	26.67	75.67	8
50	25.51	75.51	8
51	24.64	75.64	8
52	23.48	75.48	8
53	22.32	75.32	8
54	21.45	75.45	8
55	20.29	75.29	8
56	19.71	75.71	8
57	18.55	75.55	8
58	17.39	75.39	8
59	16.23	75.23	8
60	15.07	75.07	8
61	14.49	75.49	8
62	13.04	75.04	8

Table A.2 is for a 1600 kg vehicle.

APPENDIX B

OPTIMUM BATTERY PACK DESCRIPTIONS

Table B.1. Battery Pack Descriptions for Designs with AER

Battery Type	AER (miles)	Capacity (kWh)	Pack Zero Load Voltage (V)	A-h Capacity	Mass (kg)
NiMH	10	3.51	145	24.2	47
	20	6.85	203	33.8	92
	40	13.64	286	47.7	183
Pb Acid	10	3.57	299	11.9	125
	20	6.94	417	16.7	244
	40	13.78	587	23.5	484
Li Ion	10	2.81	233	12.0	42
	20	5.45	325	16.8	82
	40	10.81	457	23.6	162

APPENDIX C

OPTIMIZATION CODE

```
%PHEV Optimization Routine
% Sam Golbuff "Optimization of a Plug-In Hybrid Electric Vehicle"
% Georgia Institute of Technology, Strategic Energy Initiative

function PHEV(Batt_type,AER)

%Batt_type='LiIon' %NiMH, LiIon, or PbAcid
%All electric range in miles, 10 20 30 40 50 or 60

P_m_min=43; %kW  minimum motor size
P_m_max=100; %kW maximum motor size
P_e_min=10; %kW minimum engine size
P_e_max=100; %kW maximum engine size

for P_m=P_m_min:1:P_m_max
    for P_e=P_e_min:1:P_e_max
        i=P_e-P_e_min+1; %index for engine loop
        P_e_in(i)=P_e;
        P_m_in(i)=P_m;

[P_m_out(i),P_e_out(i),C_batt_out(i),Cost_Tot_out(i)]=PHEVoptim(P_m,P_e
,Batt_type,AER); %runs for set P_m

    end
    Cost_Tot_min_k=min(Cost_Tot_out);
    %find pointing row
    for r=1:1:(P_e_max-P_e_min)
        if Cost_Tot_min_k == Cost_Tot_out(r)
            pointer=r;
        end
    end
    P_e_out_optim_k = P_e_out(pointer);
    P_m_out_optim_k = P_m_out(pointer);
    C_batt_out_optim_k = C_batt_out(pointer);

    k=P_m-P_m_min+1; %index for motor loop
    Cost_Tot_min(k)=Cost_Tot_min_k;
    P_e_out_optim(k)=P_e_out_optim_k;
    P_m_out_optim(k)=P_m_out_optim_k;
    C_batt_out_optim(k)=C_batt_out_optim_k;
end

Cost_min=min(Cost_Tot_min)
for l=1:1:(P_m_max-P_m_min)
    if Cost_min == Cost_Tot_min(l)
        pointer=l;
```

```
    end
end
P_e_optim_final=P_e_out_optim(pointer)
P_m_optim_final=P_m_out_optim(pointer)
C_batt_optim_final=C_batt_out_optim(pointer)




%   Plug In Hybrid Electric Vehicle Optimization Code
%   Sam Golbuff,  Georgia Institute of Technology, Strategic Energy
%   Initiative

function [P_m,P_e,C_batt,Cost_Tot] = PHEVoptim(P_m,P_e,Batt_type,AER)
%inputs: P_m motor power in kW, P_e engine power in kW, Batt_type
battery
%type, AER all electric range in miles
%outputs P_m motor power than meets constraints, P_e Engine power that
%meets constraints, C_batt batter capacity in A-h, Cost_Tot total cost
of
%drivetrain



% First, determine if P_m and P_e meet acceleration constraints

P_m_0_30 = 44; %Minimum electric motor power needed in kW to pass 0-
30mph in 5 seconds for 1,600 kg vehicle

if P_m >= P_m_0_30;
else
    P_m=P_m_0_30;
end                        % This will redefine P_m is less than 44 kW

P_e_0_60 = -.0002*P_m^2-1.327*P_m+95.32; %Minimum Engine Power for 0-60
in 12 seconds

if P_e >= P_e_0_60;
else
    P_e=P_e_0_60;
end                        % This will redefine P_e if doesnt meet 0-60
requirement

P_e_50_70 = -1.0563*P_m+78.577; %Minimum Engine Power for 50-70 in 8
seconds

if P_e >= P_e_50_70;
else
    P_e=P_e_50_70;
end                        % This will redefine P_e if doesnt meet 50-70
requirement

% Now P_e and P_m meet all acceleration requirements

% Next, determine battery capacity
```

```
        % Finding A-h Capacity needed for AER for 1,600 kg vehicle
        Batt_Type_list={'NiMH';'PbAcid';'LiIon'};
        Batt_Type_funct = strcmp(Batt_Type_list, Batt_type);
        if Batt_Type_funct(1) == 1 %NiMH
            C_AER_list=[24.6;34.5;42;48;52.8;57.6];  %A-h  required  for
AER, 10 20 30 40 50 60
        end
        if Batt_Type_funct(2) == 1 %PbAcid
            C_AER_list=[17.3;25;30.2;34.7;39.2;42.6];
        end
        if Batt_Type_funct(3) == 1 %LiIon
            C_AER_list=[7.8;11.3;13.9;16;17.5;19.2];
        end
        C_AER_pointer=AER/10;
        C_AER=C_AER_list(C_AER_pointer); %Capacity required in A-h for
AER


        % Finding A-h Capacity needed for motor power requirement
        P_Nominal_list=[.541;.771;.447];   %nominal   kW   per   cell   of
different battery types
        C_Nominal_list=[.2;.186666;.08];  %nominal   A-h   per   cell   of
different battery types
        if Batt_Type_funct(1) == 1 %NiMH
            P_Nominal=P_Nominal_list(1);
            C_Nominal=C_Nominal_list(1);
        end
        if Batt_Type_funct(2) == 1 %PbAcid
            P_Nominal=P_Nominal_list(2);
            C_Nominal=C_Nominal_list(2);
        end
        if Batt_Type_funct(3) == 1 %LiIon
            P_Nominal=P_Nominal_list(3);
            C_Nominal=C_Nominal_list(3);
        end
        K_power=P_m/P_Nominal; %Number of cells for power requirement
        C_P=C_Nominal*K_power; %Required Capacity (A-h) by the motor


        %Finding A-h Capacity needed for Grade Ability Requirement
        P_req_grade = 45.7; %total kW needed for 6.5% grade at 55 mph
for 1,600 kg vehicle
        P_m_grade = P_req_grade-P_e;
        if P_m_grade < 0
            P_m_grade = 0;
        end
        eta_motor = .95; %effiency of motor
        eta_batt_dis = .95; %efficiency of discharging battery
        P_batt_grade = P_m_grade/(eta_motor*eta_batt_dis);
        V_Nominal_list  =  [1.2;2.0;3.6];  %Volts/cell  for  different
battery types
        if Batt_Type_funct(1) == 1 %NiMH
            V_Nominal=V_Nominal_list(1);
        end
        if Batt_Type_funct(2) == 1 %PbAcid
```

```
            V_Nominal=V_Nominal_list(2);
        end
        if Batt_Type_funct(3) == 1 %LiIon
            V_Nominal=V_Nominal_list(3);
        end
        t = 1200/(60*60); %seconds of the gradeability test
        SOC_sustain = .7; %Charge Sustaining SOC
        SOC_min = .2; %Minimum Allowable SOC
        C_grade                                                 =
((1000*P_batt_grade*C_Nominal*t)/(V_Nominal*(SOC_sustain-SOC_min)))^.5;
        %  C_grade  is  the  minimum  capacity  A-h  to  make  the  grade
requirment

        %Final Battery Capacity
        C_list=[C_AER;C_P;C_grade];
        C_batt=max(C_list);   % This is the battery capacity that meets
the power, grade, and AER constraints

% Now, P_m, P_e, Batt_type and C_batt are specified
 % Next, find the incremental cost of the power-train
 P_m;
 P_e;
 Batt_type;
 C_batt;
 int=.07;
 Cost_e = 12.00*P_e+424;  % Cost of engine ($)
 Cost_m = 13.7*P_m+190;   % Cost of motor ($)
 Cost_pe = 8.075*P_m+235;   % Cost of Power Electronics ($)
    if Batt_Type_funct(1) == 1 %NiMH
        Cost_batt = 97*C_batt+(97*C_batt/(1+int)^10); % Cost of battery
($) for NiMH
    end
    if Batt_Type_funct(2) == 1 %PbAcid
        Cost_batt =
36*C_batt+(36*C_batt/(1+int)^5)+(36*C_batt/(1+int)^10); % Cost of
battery ($) for PbAcid
    end
    if Batt_Type_funct(3) == 1 %LiIon
        Cost_batt = 195*C_batt+(195*C_batt/(1+int)^10);  % Cost of
battery ($) for LiIon
    end
 Cost_batt_acc = 4*C_batt+680; % Cost of battery accessories ($)
 Cost_Tot=Cost_e+Cost_m+Cost_pe+Cost_batt+Cost_batt_acc; %Total Cost of
Powertrain
```

APPENDIX D

BATTERY PACK DATA

The battery pack data is included in PSATv6.0 in different initialization files in Matlab code.

D.1 Ovonics NiMH

ess_nimh_60_300_ovonics.m[16]

```
%% File description
% Name : ess_nimh_60_300_ovonic
% Author : A.Rousseau - ANL
% Description : Initialize the parameters used in the Ovoniv M108 NiMH
% Capacity = 60Ah, Cell number = 300
% Cell type = M108
% Nominal Voltage = 12V
% Nominal Capacity (C/3) = 60Ah
% Dimensions (L * W * H) = 385mm X 102mm X 119mm
% Weight = 11.6kg
% Volume (modules only) = 5L
% Nominal Energy (C/3) = 750 Wh
% Peak Power (10s pulse @ 50%DOD @ 35 deg. C) = 4.9kW
% Data provided by  : Dennis Corrigan, Vice President of EV Battery
Systems, Ovonic
% Model : lib_ess_generic_map
% Technology : nimh

%% File content
ess.list.init = {'soc_min','soc_max','soc_init','num_cell'};
ess.init.soc_init = 0.7;
ess.init.element_per_module = 12;
ess.init.num_module = 25; % value for number of modules, this number is
scaled linearly with capacity
ess.init.num_cell = ess.init.num_module * ess.init.element_per_module;
ess.init.volt_nom = 1.2;
ess.init.volt_min = 0.7;
ess.init.volt_max = 1.35;
ess.init.mass_module = 11.6; % (kg), mass of a single ~6 V module
ess.init.mass_cell = ess.init.mass_module/ess.init.element_per_module;
ess.init.soc_min = 0.3; % This is overwritten to be .2
ess.init.soc_max = 1.0;
```

```
% LOSS AND EFFICIENCY parameters
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

ess.init.soc_index = [0:.1:1];  % SOC RANGE over which data is defined
ess.init.temp_index = [0 22 40];  % Temperature range over which data
is defined (C)
ess.init.cap_max_map = [60  60  60];    % (A*h), max. capacity at C/5
rate, indexed by ess.init.temp_index, scaled linearly with number of
modules
ess.init.eff_coulomb = [0.975   0.975   0.975]; % average coulombic
(a.k.a. amp-hour) efficiency below, indexed by ess.init.temp_index

% module's resistance to being discharged, indexed by
ess.init.soc_index and ess.init.temp_index
ess.init.rint_dis_map =

 1.167  0.905  0.851  0.792  0.775  0.76   0.75  0.768  0.823  0.881  0.839
 1.167  0.905  0.851  0.792  0.775  0.76   0.75  0.768  0.823  0.881  0.839
 1.167  0.905  0.851  0.792  0.775  0.76   0.75  0.768  0.823  0.881  0.839

*10/1000/ess.init.element_per_module; % (ohm)

% module's resistance to being charged, indexed by ess.init.soc_index
and ess.init.temp_index
ess.init.rint_chg_map = fliplr(ess.init.rint_dis_map);% (ohm), no other
data available

% module's open-circuit (a.k.a. no-load) voltage, indexed by
ess.init.soc_index and ess.init.temp_index
ess.init.voc_map =

  12.5   12.8   13.1   13.3   13.4   13.4   13.5   13.6   13.7   13.9   14.2
  12.5   12.8   13.1   13.3   13.4   13.4   13.5   13.6   13.7   13.9   14.2
  12.5   12.8   13.1   13.3   13.4   13.4   13.5   13.6   13.7   13.9   14.2

/ess.init.element_per_module; % (V)

% Max current and power when charging/discharging
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
ess.init.curr_chg_max = -max(max((ess.init.volt_max-ess.init.voc_map)
./ess.init.rint_chg_map));
ess.init.curr_dis_max = max(max((ess.init.voc_map-ess.init.volt_min)
./ess.init.rint_dis_map));

%to check the ess.calc.pwr_chg & ess.calc.pwr_dis because they're a
vector and in the database for the plot we need maps
ess.calc.pwr_chg = -max((ess.init.volt_max-ess.init.voc_map)
.*ess.init.volt_max./ess.init.rint_chg_map);%per cell
ess.calc.pwr_dis = max((ess.init.voc_map-ess.init.volt_min)
.*ess.init.volt_min./ess.init.rint_dis_map);%per cell
```

```
ess.init.pwr_chg = -max(max((ess.init.volt_max-ess.init.voc_map)
.*ess.init.volt_max./ess.init.rint_chg_map));%per cell
ess.init.pwr_dis = max(max((ess.init.voc_map-ess.init.volt_min)
.*ess.init.volt_min./ess.init.rint_dis_map));%per cell

% battery thermal model
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
ess.init.therm_on = 1;
% --     0=no ess thermal calculations, 1=do calc's
ess.init.therm_cp_module = 830;
% J/kgK  ave heat capacity of module (estimated for NiMH)
ess.init.temp_reg = 35;
% C  thermostat temp of module when cooling fan comes on
ess.init.area_mod = 1.6*(ess.init.mass_module/11)^0.7;
% -- if module dimensions are unknown, assume rectangle shape and scale
vs PB25
ess.init.area_module = 2*(0.385*0.119+0.102*0.119);
% m^2 total module surface area exposed to cooling air (typ rectang
module)
ess.init.flow_air_mod = 0.01;
% kg/s   cooling air mass flow rate across module (20 cfm=0.01 kg/s at
20 C)
ess.init.mod_flow_area = 0.005*2*(0.385+0.102);
% m^2 cross-sec flow area for cooling air per module (assumes 10-mm gap
btwn mods)
ess.init.case_thk = 2/1000;
% m  thickness of module case (typ from Optima)
ess.init.therm_case_cond = 0.2;
% W/mK  thermal conductivity of module case material (typ polyprop
plastic - Optima)
ess.init.speed_air =
ess.init.flow_air_mod/(1.16*ess.init.mod_flow_area);
% m/s  ave velocity of cooling air
ess.init.therm_air_htcoef = 30*(ess.init.speed_air/5)^0.8;
% W/m^2K cooling air heat transfer coef.
ess.init.therm_res_on =
((1/ess.init.therm_air_htcoef)+(ess.init.case_thk/ess.init.therm_case_c
ond))/ess.init.area_module; % K/W  tot thermal res key on
ess.init.therm_res_off =
((1/4)+(ess.init.case_thk/ess.init.therm_case_cond))/ess.init.area_modu
le; % K/W  tot thermal res key off (cold soak)
ess.init.flow_air_mod = max(ess.init.flow_air_mod,0.001);
ess.init.therm_res_on =
min(ess.init.therm_res_on,ess.init.therm_res_off);

clear ess.init.area_module ess.init.mod_flow_area ess.init.case_thk
ess.init.therm_case_cond ess.init.speed_air ess.init.therm_air_htcoef
ess.init.area_mod

% Battery density
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
ess.init.pwr_dis_nom = max(max((ess.init.volt_nom-ess.init.volt_min)
.*ess.init.volt_min./ess.init.rint_dis_map));%per cell
ess.init.pwr_density = ess.init.pwr_dis_nom/ess.init.mass_cell;
ess.init.energy_density =
mean((ess.init.volt_nom*ess.init.cap_max_map))/ess.init.mass_cell;
```

<u>D.2 Johnson Controls Pb Acid</u>

ess_pb_28_150.m[17]

```
%% File description
% Name : ess_pb_28_150
% Author : A.Rousseau - ANL
% Description : Initialize the parameters used in the Johnson Controls
lead-acid battery
% Capacity = 28Ah, Cell number = 150
% These parameters describe the Johnson Controls 12-95 lead-acid
% battery.  This data was provided by the University of Illinois
% Urbana/Champaign under subcontract #XCB-5-15296-01 to NREL.
% Model : lib_ess_generic_map
% Technology : pb

%% File content
ess.list.init = {'soc_min','soc_max','soc_init','num_cell'};
ess.init.soc_init = 0.7;
ess.init.element_per_module = 6;
ess.init.num_module = 25; % value for number of modules, scaled
linearly with capacity
ess.init.num_cell = ess.init.num_module * ess.init.element_per_module;
ess.init.volt_nom = 2;
ess.init.volt_min = 1.5;      % caution, this value may be too
low(compared with other lead acid batteries)
ess.init.volt_max = 2.4;
ess.init.mass_module = 11.8;                              % (kg), mass
of entire pack(including fan,ecu,case) divided by 40 modules
ess.init.mass_cell = ess.init.mass_module /ess.init.element_per_module;
ess.init.soc_min = 0.404; % overwritten to be .2
ess.init.soc_max = 1.0;

% LOSS AND EFFICIENCY parameters
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

ess.init.soc_index = [0:.2:1]; % SOC RANGE over which data is defined
ess.init.temp_index = [0 22 40]; % Temperature range over which data is
defined(C)
ess.init.cap_max_map = [28   28   28]; % (A*h), max. capacity at C/5
rate, indexed by ess.init.temp_index, scaled linearly with number of
modules
ess.init.eff_coulomb = [.9   .9   .9];   % average coulombic (a.k.a.
amp-hour) efficiency below, indexed by ess.init.temp_index

% module's resistance to being discharged, indexed by
ess.init.soc_index and ess.init.temp_index
ess.init.rint_dis_map =

                  0.038 0.024 0.007 0.007 0.007 0.011
                  0.038 0.024 0.007 0.007 0.007 0.011
                  0.038 0.024 0.007 0.007 0.007 0.011

/ess.init.element_per_module; % (ohm)
```

```
% module's resistance to being charged, indexed by ess.init.soc_index
and ess.init.temp_index
ess.init.rint_chg_map = ess.init.rint_dis_map; %no other data available

% module's open-circuit (a.k.a. no-load) voltage, indexed by
ess.init.soc_index and ess.init.temp_index
ess.init.voc_map =

                   6.0   8.9   11.8   12.0   12.3   12.6
                   6.0   8.9   11.8   12.0   12.3   12.6
                   6.0   8.9   11.8   12.0   12.3   12.6

/ess.init.element_per_module; % (V) voc at low soc seems low compared
with other lead acid batteries, use with caution

% Max current and power when charging/discharging
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
ess.init.curr_chg_max = -max(max((ess.init.volt_max-ess.init.voc_map)
./ess.init.rint_chg_map));
ess.init.curr_dis_max = max(max((ess.init.voc_map-ess.init.volt_min)
./ess.init.rint_dis_map));

%to check the ess.calc.pwr_chg & ess.calc.pwr_dis because they're a
vector and in the database for the plot we need maps
ess.calc.pwr_chg = -max((ess.init.volt_max-ess.init.voc_map)
.*ess.init.volt_max./ess.init.rint_chg_map); % per cell
ess.calc.pwr_dis = max((ess.init.voc_map-ess.init.volt_min)
.*ess.init.volt_min./ess.init.rint_dis_map); % per cell
ess.init.pwr_chg = -max(max((ess.init.volt_max-ess.init.voc_map)
.*ess.init.volt_max./ess.init.rint_chg_map)); % per cell
ess.init.pwr_dis = max(max((ess.init.voc_map-ess.init.volt_min)
.*ess.init.volt_min./ess.init.rint_dis_map)); % per cell

% battery thermal model
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
ess.init.therm_on = 1;
% -- 0=no ess thermal calculations, 1=do calc's
ess.init.therm_cp_module = 660;
% J/kgK  ave heat capacity of module (typical Pb bat - from Optima)
ess.init.temp_reg = 35;
% C thermostat temp of module when cooling fan comes on
ess.tmp.area_mod = (ess.init.mass_module/11)^0.7;
% -- if module dimensions are unknown, assume rectangle shape and scale
vs PB25
ess.tmp.area_module = 0.2*ess.tmp.area_mod;
% m^2 total module surface area exposed to cooling air (typ rectang
module)
ess.init.flow_air_mod = 0.01;
% kg/s cooling air mass flow rate across module (20 cfm=0.01 kg/s at 20
C)
ess.tmp.therm_flow_area_module = 0.005*ess.tmp.area_mod;
% m^2 cross-sec flow area for cooling air per module (assumes 10-mm gap
btwn mods)
```

```
ess.tmp.case_thk = 2/1000;
% m thickness of module case (typ from Optima)
ess.tmp.therm_case_cond = 0.20;
% W/mK thermal conductivity of module case material (typ polyprop
plastic - Optima)
ess.tmp.speed_air =
ess.init.flow_air_mod/(1.16*ess.tmp.therm_flow_area_module);
% m/s  ave velocity of cooling air
ess.tmp.therm_air_htcoef = 30*(ess.tmp.speed_air/5)^0.8;
% W/m^2K cooling air heat transfer coef.
ess.init.therm_res_on =
((1/ess.tmp.therm_air_htcoef)+(ess.tmp.case_thk/ess.tmp.therm_case_cond
))/ess.tmp.area_module; % K/W  tot thermal res key on
ess.init.therm_res_off =
((1/4)+(ess.tmp.case_thk/ess.tmp.therm_case_cond))/ess.tmp.area_module;
% K/W  tot thermal res key off (cold soak)
ess.init.flow_air_mod = max(ess.init.flow_air_mod,0.001);
ess.init.therm_res_on =
min(ess.init.therm_res_on,ess.init.therm_res_off);

if isfield(ess,'tmp')
ess = rmfield(ess,'tmp');
end

% Battery density
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
ess.init.pwr_dis_nom = max(max((ess.init.volt_nom-ess.init.volt_min)
.*ess.init.volt_min./ess.init.rint_dis_map));%per cell
ess.init.pwr_density = ess.init.pwr_dis_nom/ess.init.mass_cell;
ess.init.energy_density =
mean((ess.init.volt_nom*ess.init.cap_max_map))/ess.init.mass_cell;
```

D.3 Saft Li Ion

Ess_li_6_75_saft.m[18]

```
%% File description
% Name : ess_li_6_75_saft
% Author : A.Rousseau - ANL
% Description : Initialize the parameters used in the Saft Li-ion
% Capacity = 6Ah, Cell number = 75
% Model : lib_ess_generic_map
% Technology : liion

%% File content
ess.list.init = {'soc_min','soc_max','soc_init','num_cell'};
ess.init.soc_init = 0.7;
ess.init.element_per_module = 3;
ess.init.num_module = 25; % value for number of modules, scaled
linearly with battery capacity
ess.init.num_cell = ess.init.num_module * ess.init.element_per_module;
ess.init.volt_nom = 3.6;
ess.init.volt_min = 3.2;
ess.init.volt_max = 3.9;
ess.init.mass_module = .37824*3; % (kg), mass of a single module
ess.init.mass_cell = ess.init.mass_module/ess.init.element_per_module;
ess.init.soc_min = 0.3; % This is overwritten to .2
ess.init.soc_max = 1.0;

% LOSS AND EFFICIENCY parameters
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

ess.init.soc_index = [0 10 20 40 60 80 100]/100; % SOC RANGE over which
data is defined
ess.init.temp_index = [0 25    41];  % Temperature range over which
data is defined (C)
ess.init.cap_max_map = [5.943 7.035 7.405]; % (A*h), max. capacity at
C/5 rate, indexed by ess.init.temp_index, scaled linearly with number
of modules
ess.init.eff_coulomb = [0.968 0.99 0.992]; % average coulombic (a.k.a.
amp-hour) efficiency below, indexed by ess.init.temp_index

% module's resistance to being discharged, indexed by
ess.init.soc_index and ess.init.temp_index
ess.init.rint_dis_map =

    0.041900 0.028800 0.022100 0.014000 0.014500 0.014500 0.016200
    0.072000 0.015150 0.008390 0.004930 0.005050 0.005524 0.005722
    0.053500 0.013300 0.008200 0.005900 0.005900 0.006000 0.006300

% (ohm)
```

```
% module's resistance to being charged, indexed by ess.init.soc_index
and ess.init.temp_index

ess.init.rint_chg_map =

     0.021     0.018    0.0177    0.0157    0.0138    0.0138    0.015
    0.0124    0.0068  0.005426   0.00442   0.00463   0.00583  0.00583
    0.0104    0.0079    0.0072    0.0064    0.0059    0.0058    0.006

% (ohm)

% module's open-circuit (a.k.a. no-load) voltage, indexed by
ess.init.soc_index and ess.init.temp_index
ess.init.voc_map =

      3.44     3.473     3.496     3.568     3.637     3.757     3.896
     3.124     3.349     3.433     3.518     3.616     3.752     3.898
     3.128      3.36      3.44     3.528     3.623     3.761     3.899

% (V)

% Max current and power when charging/discharging
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
ess.init.curr_chg_max = -max(max((ess.init.volt_max-ess.init.voc_map)
./ess.init.rint_chg_map));
ess.init.curr_dis_max = max(max((ess.init.voc_map-ess.init.volt_min)
./ess.init.rint_dis_map));

% to check the ess.calc.pwr_chg & ess.calc.pwr_dis because they're a
vector and in the database for the plot we need maps
ess.calc.pwr_chg = -max((ess.init.volt_max-ess.init.voc_map)
.*ess.init.volt_max./ess.init.rint_chg_map); % per cell
ess.calc.pwr_dis = max((ess.init.voc_map-ess.init.volt_min)
.*ess.init.volt_min./ess.init.rint_dis_map); % per cell

ess.init.pwr_chg = -max(max((ess.init.volt_max-ess.init.voc_map)
.*ess.init.volt_max./ess.init.rint_chg_map)); % per cell
ess.init.pwr_dis = max(max((ess.init.voc_map-ess.init.volt_min)
.*ess.init.volt_min./ess.init.rint_dis_map)); % per cell

% battery thermal model
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
ess.init.therm_on = 1;
% -- 0=no ess thermal calculations, 1=do calc's
ess.init.therm_cp_module = 795;
% J/kgK  ave heat capacity of module (estimated for NiMH)
ess.init.temp_reg = 35;
% C thermostat temp of module when cooling fan comes on
ess.tmp.area_module = .032;
% m^2 total module surface area exposed to cooling air (type rectangle
module)
```

```
ess.init.flow_air_mod = .07/12;
% kg/s cooling air mass flow rate across module (20 cfm=0.01 kg/s at 20
C)
ess.tmp.mod_flow_area = .0011;
% m^2 cross-sec flow area for cooling air per module (assumes 10-mm gap
btwn mods)
ess.tmp.case_thk = .001;
% m thickness of module case (typ from Optima)
ess.tmp.therm_case_cond = 15;
% W/mK thermal conductivity of module case material (typ polyprop
plastic - Optima)
ess.tmp.speed_air = ess.init.flow_air_mod/(1.16*ess.tmp.mod_flow_area);
% m/s  ave velocity of cooling air
ess.tmp.therm_air_htcoef = 30*(ess.tmp.speed_air/5)^0.8;
% W/m^2K cooling air heat transfer coef.
ess.init.therm_res_on =
((1/ess.tmp.therm_air_htcoef)+(ess.tmp.case_thk/ess.tmp.therm_case_cond
))/ess.tmp.area_module; % K/W  tot thermal res key on
ess.init.therm_res_off =
((1/4)+(ess.tmp.case_thk/ess.tmp.therm_case_cond))/ess.tmp.area_module;
% K/W  tot thermal res key off (cold soak)
ess.init.flow_air_mod = max(ess.init.flow_air_mod,0.001);
ess.init.therm_res_on =
min(ess.init.therm_res_on,ess.init.therm_res_off);
ess = rmfield(ess,'tmp');

% Battery density
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
ess.init.pwr_dis_nom = max(max((ess.init.volt_nom-
ess.init.volt_min).*ess.init.volt_min./ess.init.rint_dis_map)); % per
cell
ess.init.pwr_density = ess.init.pwr_dis_nom/ess.init.mass_cell;
ess.init.energy_density =
mean((ess.init.volt_nom*ess.init.cap_max_map))/ess.init.mass_cell;
```

APPENDIX E

ENGINE AND ELECTRIC MOTOR DATA

E.1 Base Engine Data

Eng_si_1500_52_USprius.m[19]

```
%% File description
% Name : eng_si_1500_52_USprius
% Author : F.Besnier - ANL
% Description : Initialize the 1.5L 60 kW MY01 US Prius gasoline engine
% Data provided by ANL APRF using in-situ engine torque sensor
% Remarks : The engine start speed is not compatible with
% other powertrain configurations.
% Model : lib_eng_map_hot
% Technology : si

%% File content
eng.list.init   =
{'warmup_init','tau','dn','inertia','spd_str','fuel_density_val','spd_i
dle'};

eng.init.fuel_mass = 50.0;   % Capacity of tank in kg
eng.init.mass = 108 + 6 + 10; %block + radiator + tank
eng.init.inertia = 0.1598;
eng.init.tau = 0.2; % 0 to 100% of max torque in 200ms
eng.init.dn = 0.05; % 100% of max to 0 torque in 50ms
eng.init.spd_idle =
conversion_calc('rotational_speed','rpm','rad/s',970); % rad/s
(default)
eng.init.spd_str =
conversion_calc('rotational_speed','rpm','rad/s',800);
eng.init.warmup_init = 0; % This should normally by 0
eng.init.pwr_max = 52000; % Watts
eng.init.pwr_max_eff = 50000; % Watts

%Fuel parameters for premium gasoline
eng.init.fuel_density_val = 0.749; % kg/L
eng.init.fuel_heating_val = 43000000; % (J/kg)Specific LHV
eng.init.fuel_carbon_ratio = 0.86; % (% Carbon by weight)
eng.init.co2_init = 0;

% Baseline engine parameters
eng.init.displ_init = 1500.0; % cc
eng.init.num_cyl_init = 4;
eng.init.bore_init = 8.3; % mm
```

```
eng.init.stroke_init = 8.32; % mm
eng.init.comp_ratio_init = 11.5;


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% maximum curves at each speed (closed and wide open throttle)
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% hot max wide open throttle curves
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
eng.init.spd_max_hot_index = [0  104.72   157.08  209.44  261.80
314.16  366.52  418.88  471.24  523.60  628.32  700  750 775    780];
eng.init.trq_max_hot_map = [0  85.3844   93.4610   99.23   101.1538
103.0768   105.3844   106.9228  102.3036  93.4610  80  70  65 0 0]*1.2;
% hot wide open throttle torque

% hot max closed throttle curves
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
eng.init.spd_min_hot_index =[ 0    10    20    30    40    50    60
70];
eng.init.trq_min_hot_map =[ -2.2266  -35.0633  -49.4566  -53.5278
-53.1965  -52.1803  -51.9947  -51.9537]

% Mid speed is used in logic to limit closed and wide open torque
curves
eng.init.spd_avg = 0.5 * (eng.init.spd_max_hot_index(1)+
eng.init.spd_max_hot_index(length(eng.init.spd_max_hot_index)));

eng.init.spd_fuel_hot_index = [104.72 126.386 157.08 164.3015 184.162
209.44 261.80 292.493 314.16 332.215 366.52 375.547 418.88 471.24
523.60 600 650];
eng.init.trq_fuel_hot_index = [11.5380 15.3840 17.6916  22.3076 25.3844
27.6920 31.5380 35.3840 40  44.6152  50.7688 60 66.154 71.5380 80
85.3844 93.0764 ];
```

```
%  efficiency
eng.init.eff_hot_map =

15.0 17.5 20.0 22.5 25.0 26.0 28.0 29.0 30.5 32.0 33.0 34.0 34.5 35.0 34.0 35.0 35.0
17.5 20.0 22.5 25.0 26.0 27.5 28.0 30.0 31.0 32.5 33.0 35.0 35.0 35.0 35.0 35.0 35.0
16.5 19.0 22.0 23.0 25.0 26.0 27.5 29.0 30.0 31.0 32.5 34.0 35.0 35.0 35.0 35.0 35.0
16.0 19.0 21.0 23.0 25.0 26.0 27.5 29.0 30.0 31.0 32.5 34.0 35.0 35.0 35.0 35.0 35.0
16.0 18.0 20.0 22.5 25.0 26.0 27.5 28.0 30.0 31.0 32.5 34.0 35.0 35.0 35.0 35.0 35.0
15.0 17.5 20.0 22.5 24.0 25.5 27.5 28.0 30.0 31.0 33.0 34.0 35.0 35.0 35.0 35.0 35.0
14.0 15.0 18.0 22.0 24.0 25.0 27.5 28.0 30.0 31.0 32.5 34.0 35.0 35.0 35.0 35.0 35.0
13.0 14.0 17.5 20.0 23.0 25.0 27.0 28.0 29.5 31.0 32.0 33.0 34.0 35.0 35.0 35.0 35.0
13.0 14.0 15.0 20.0 22.5 24.0 26.0 27.5 29.0 30.5 31.5 33.0 34.0 35.0 35.0 35.0 35.0
13.0 14.0 15.0 17.5 22.5 23.0 26.0 27.5 29.0 30.0 31.5 33.0 34.0 35.0 35.0 35.0 35.0
13.0 14.0 16.0 18.0 20.0 22.5 25.0 26.0 27.5 29.0 30.5 32.0 33.0 33.5 34.5 35.0 35.0
13.0 14.0 16.0 18.0 20.0 22.5 25.0 26.0 27.5 29.0 30.5 31.5 32.5 33.0 34.0 35.0 35.0
13.0 14.0 17.0 19.0 19.0 20.0 23.0 25.0 27.0 28.0 29.0 31.0 32.5 33.0 34.0 34.5 35.0
13.0 14.0 17.0 19.0 19.0 20.0 22.5 24.0 26.0 28.0 29.5 31.0 32.0 33.0 34.0 34.0 32.5
13.0 14.0 17.0 19.0 19.0 20.0 22.5 23.0 25.0 27.5 29.5 30.0 31.0 33.0 33.5 34.0 32.5
13.0 14.0 17.0 19.0 19.0 20.0 22.5 23.0 25.0 27.5 29.0 30.0 30.5 32.0 33.0 34.0 32.5
13.0 14.0 17.0 19.0 19.0 20.0 22.0 22.5 24.0 27.0 28.0 29.0 30.0 31.0 32.0 33.0 32.5

/100;
 % These are the numbers for the engine efficiency map

eng.init.fuel_hot_map =
eng.init.spd_fuel_hot_index'*eng.init.trq_fuel_hot_index
/eng.init.fuel_heating_val./(eng.init.eff_hot_map);%now in kg/s

% engine torque for fuel rate kg/s
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
eng.init.spd_zero_fuel_hot_index = eng.init.spd_min_hot_index;
eng.init.trq_zero_fuel_hot_index = 1.5*eng.init.trq_min_hot_map;

%Emissions in percentage of fuel rate (kg/s)
eng.init.spd_co_hot_index = eng.init.spd_fuel_hot_index;
eng.init.trq_co_hot_index = eng.init.trq_fuel_hot_index;
eng.init.co_hot_map =
zeros(length(eng.init.spd_co_hot_index),length(eng.init.trq_co_hot_inde
x));

eng.init.spd_hc_hot_index = eng.init.spd_fuel_hot_index;
eng.init.trq_hc_hot_index = eng.init.trq_fuel_hot_index;
eng.init.hc_hot_map =
zeros(length(eng.init.spd_hc_hot_index),length(eng.init.trq_hc_hot_inde
x));
```

```
eng.init.spd_nox_hot_index = eng.init.spd_fuel_hot_index;
eng.init.trq_nox_hot_index = eng.init.trq_fuel_hot_index;
eng.init.nox_hot_map =
zeros(length(eng.init.spd_nox_hot_index),length(eng.init.trq_nox_hot_in
dex));

eng.init.spd_pm_hot_index = eng.init.spd_fuel_hot_index;
eng.init.trq_pm_hot_index = eng.init.trq_fuel_hot_index;
eng.init.pm_hot_map  = zeros(length(eng.init.spd_hc_hot_index),
length(eng.init.trq_nox_hot_index));


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% O2
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
eng.init.spd_o2_hot_index = eng.init.spd_fuel_hot_index;
eng.init.trq_o2_hot_index = eng.init.trq_fuel_hot_index;
eng.init.o2_hot_map =
zeros(length(eng.init.spd_fuel_hot_index),length(eng.init.trq_fuel_hot_
index));


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% exhaust table
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% HOT
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
eng.init.spd_equiv_hot_index = eng.init.spd_fuel_hot_index;
eng.init.trq_equiv_hot_index = eng.init.trq_fuel_hot_index;

eng.init.equiv_hot_map =
zeros(length(eng.init.spd_equiv_hot_index),length(eng.init.trq_equiv_ho
t_index));
% Heat rejection variable Presid data table
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
eng.init.spd_htrej_hot_index = eng.init.spd_fuel_hot_index;
eng.init.trq_htrej_hot_index = eng.init.trq_fuel_hot_index;
eng.init.htrej_hot_map  = zeros(17,17);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Heat Transfer
%the following is a new thermal model of the engine
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
eng.init.spd_ex_gas_flow_hot_index =   eng.init.spd_fuel_hot_index;
eng.init.trq_ex_gas_flow_hot_index =   eng.init.trq_fuel_hot_index;
eng.init.ex_gas_flow_hot_map       =   eng.init.fuel_hot_map *(1+20);
% g/s  ex gas flow map:  for CI engines, exflow=(fuel use)*[1 + (ave
A/F ratio)]
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%eng.init.v0x\fuel use, thermal and emissions\thermal\fc heat net
calculation
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
eng.init.ex_pwr_map =
eng.init.spd_fuel_hot_index'*eng.init.trq_fuel_hot_index;
eng.init.ex_temp_map =
eng.init.ex_pwr_map./(eng.init.ex_gas_flow_hot_map *1089/1000) + 20;  %
W   EO ex gas temp = Q/(MF*cp) + Tamb (assumes engine tested ~20 C)
eng.init.spd_ex_temp_index = eng.init.spd_fuel_hot_index;
eng.init.trq_ex_temp_index = eng.init.trq_fuel_hot_index;

eng.init.temp_operating = 90;
eng.init.ex_temp_operating = mean(mean(eng.init.ex_temp_map));

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%Calculations
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% maximum and minimum calculations
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
eng.init.trq_hot_max = max(eng.init.trq_max_hot_map); % N-m
eng.init.spd_hot_max =
max(eng.init.spd_max_hot_index(max(find(eng.init.trq_max_hot_map>0))));
% rad/s
eng.init.pwr_hot_max = max(eng.init.spd_max_hot_index.*
eng.init.trq_max_hot_map); % W
eng.init.pwr_max_hot_map = eng.init.spd_max_hot_index.*
eng.init.trq_max_hot_map; % W

% Calculate the max engine efficiency in within the max torque curve
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
eng.init.eff_hot_map =
eng.init.spd_fuel_hot_index'*eng.init.trq_fuel_hot_index/eng.init.fuel_
heating_val./(eng.init.fuel_hot_map);
eng.tmp.max_trq =
interp1(eng.init.spd_max_hot_index,eng.init.trq_max_hot_map,eng.init.sp
d_fuel_hot_index);
eng.tmp.max_trq =
eng.tmp.max_trq(:)*ones(1,length(eng.init.trq_fuel_hot_index));
eng.tmp.max_trq = (eng.init.trq_fuel_hot_index(:) *
ones(1,length(eng.init.spd_fuel_hot_index)))' > eng.tmp.max_trq;
eng.init.eff_hot_map(eng.tmp.max_trq) = 0;
eng.init.eff_max = max(max(eng.init.eff_hot_map));

eng = rmfield(eng,'tmp');
```

E.2 Base Motor Data

Mc_pm_49_49_Honda.m[20]

```
%% File description
% Name : mc_pm_49_49_Honda
% Author : A.Rousseau - ANL
% Description : Initialize a permanent magnet electric motor from Honda
% Continuous Power = 49kW, Peak Power = 49kW
% Data provided by Anil Paryani (Honda R&D Americas)
% Model : lib_mc_map_Pelec_funTW_volt_in,lib_mc_map_Pelec_funTW_pwr_in
% Technology : pm

%% File content
mc.list.init = {'inertia','tau','coeff_regen','curr_max','volt_min'};

mc.init.inertia = 0.0507;
mc.init.coeff_regen = 1;
mc.init.volt_min = 60; % (V), minimum voltage allowed by the controller
and motor
mc.init.tau = 0.05; % from 0 to 100 % of the torque in 50 ms
mc.init.t_max_trq = 180; % Time the motor can remain at max torque
mc.init.mass = 45 + 15; % (kg), mass of motor and controller
mc.init.curr_max = 400; % (A), maximum current allowed by the
controller and motor
mc.init.spd_base =
conversion_calc('rotational_speed','rpm','rad/s',1500); % rad/s

mc.init.spd_cont_index =
conversion_calc('rotational_speed','rpm','rad/s',[0:500:8500 8600
8700]);
mc.init.trq_cont_map = [274.4    274.4   274.4   274.4  233.8 187.0
155.9 133.6 116.9 103.9 93.5 85.0 77.9 71.9 66.8 62.3 58.4 55.0 0 0]; %
(N*m)

mc.init.spd_max_index = mc.init.spd_cont_index;
mc.init.trq_max_map = mc.init.trq_cont_map;

mc.init.spd_min_index = mc.init.spd_max_index; % rad/s
mc.init.trq_min_map = -mc.init.trq_max_map;

mc.init.spd_eff_index =
conversion_calc('rotational_speed','rpm','rad/s',[0:500:8500]);
```

```
mc.init.trq_eff_index = [0.0  19.6    39.2    78.4    98.0    117.6
137.2 156.8 176.4 235.2 274.4];
mc.init.eff_trq_map = 0.01*

  63    87.7   84.7   79.4   78.09  76.5    75    73.89  71.3   63.8   59.7
 63.07  87.76  84.71  79.49  78.1   76.56  75.09  73.9   71.33  63.88  59.75
 80.23  85.98  86.96  87.34  86.64  85.45  84.73  84.03  83.26  80.81  77.35
 80.24  87.45  88.53  89.23  89.37  88.36  88.08  87.98  87.33  85.65  82.47
 81.05  90.54  90.31  90.33  90.42  90.38  90.13  89.86  89.38  87.95  87.25
 83.52  88.41  91.83  91.51  91.56  91.43  91.28  91.02  91.23  90.67  90.67
 84.9   90.61  91.38  92.36  92.29  92.35  92.16  92.12  93.52  93.61  93.61
 84.92  90.37  92.79  93.59  94.31  94.42  94.68  95.24  95.42  95.42  95.42
 86.24  93.14  94.56  95.69  95.67  96.02  96.07  95.88  95.88  95.88  95.88
 85.7   90.78  93.73   96    96.13  96.39  96.23  96.23  96.23  96.23  96.23
 82.22  89.23   93    95.29  96.05  96.05  96.05  96.05  96.05  96.05  96.05
 81.37  87.75  92.89  95.47  95.83  95.83  95.83  95.83  95.83  95.83  95.83
 80.69  86.69  92.47  95.18  95.4   95.4   95.4   95.4   95.4   95.4   95.4
 79.83   86    92.05  95.06  95.48  95.48  95.48  95.48  95.48  95.48  95.48
 78.99   85    91.13  94.5   94.7   94.7   94.7   94.7   94.7   94.7   94.7
 77.41  84.26  90.75  94.21  94.21  94.21  94.21  94.21  94.21  94.21  94.21
 76.08  82.89  90.31  93.49  93.49  93.49  93.49  93.49  93.49  93.49  93.49
 75.97  82.22  89.96  93.17  93.17  93.17  93.17  93.17  93.17  93.17  93.17

% These are the numbers for the motor efficiency map

mc.init.spd_prop_cont_index = [-fliplr(mc.init.spd_cont_index(2:end)) -
eps 0 eps mc.init.spd_cont_index(2:end)];
mc.init.trq_prop_cont_map = [-fliplr(mc.init.trq_cont_map(2:end))  -
mc.init.trq_cont_map(2) mc.init.trq_cont_map(2) mc.init.trq_cont_map(2)
mc.init.trq_cont_map(2:end)];
mc.init.pwr_prop_cont_map =
mc.init.spd_prop_cont_index.*mc.init.trq_prop_cont_map;

mc.init.spd_prop_max_index = [-fliplr(mc.init.spd_max_index(2:end)) -
eps 0 eps mc.init.spd_max_index(2:end)];
mc.init.trq_prop_max_map = [-fliplr(mc.init.trq_max_map(2:end))   -
mc.init.trq_max_map(2) mc.init.trq_max_map(2) mc.init.trq_max_map(2)
mc.init.trq_max_map(2:end)];
mc.init.pwr_prop_max_map =
mc.init.spd_prop_max_index.*mc.init.trq_prop_max_map;

mc.init.spd_reg_cont_index = [-fliplr(mc.init.spd_cont_index(2:end)) -
eps 0 eps mc.init.spd_cont_index(2:end)];
mc.init.trq_reg_cont_map = [fliplr(mc.init.trq_cont_map(2:end))
mc.init.trq_cont_map(2) -mc.init.trq_cont_map(2) -
mc.init.trq_cont_map(2)  -mc.init.trq_cont_map(2:end)];
mc.init.pwr_reg_cont_map =
mc.init.spd_reg_cont_index.*mc.init.trq_reg_cont_map;
```

```
mc.init.spd_reg_max_index = [-fliplr(mc.init.spd_max_index(2:end)) -eps
0 eps mc.init.spd_max_index(2:end)];
mc.init.trq_reg_max_map = [fliplr(mc.init.trq_max_map(2:end))
mc.init.trq_max_map(2) -mc.init.trq_max_map(2) -mc.init.trq_max_map(2)
-mc.init.trq_max_map(2:end)];
mc.init.pwr_reg_max_map =
mc.init.spd_reg_max_index.*mc.init.trq_reg_max_map;

mc.init.spd_eff_index = [-fliplr(mc.init.spd_eff_index(2:end))
mc.init.spd_eff_index];
mc.init.trq_eff_index = [-fliplr(mc.init.trq_eff_index(2:end))
mc.init.trq_eff_index];
mc.init.eff_trq_map = [flipud(fliplr(mc.init.eff_trq_map(2:end,2:end)))
flipud(mc.init.eff_trq_map(2:end,:));fliplr(mc.init.eff_trq_map(:,2:end
)) mc.init.eff_trq_map];
```

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