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Ultracapacitor Assisted Powertrains: Modeling, Control, Sizing, and The Impact on Fuel Economy

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ULTRACAPACITOR ASSISTED POWERTRAINS: MODELING, CONTROL, SIZING, AND THE IMPACT ON FUEL ECONOMY

A Thesis
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Master of Science
Mechanical Engineering

by
Dean Rotenberg
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Accepted by:
Dr. Ardalan Vahidi, Committee Chair
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Dr. John Wagner

Abstract

This thesis investigates possible fuel economy gains attainable by a combination of high-power density ultracapacitors (also called supercapacitors) and an induction motor integrated into a conventional vehicle powertrain for power assistance.

Periods of quick acceleration require a much higher power output from an automobile than what is encountered under more typical driving conditions. A simple kinetic energy calculation can show that accelerating a 2000 kg vehicle (roughly the size of a Ford Explorer SUV) from 0 to 60 mph in 10 seconds requires almost 70 kW of power, in addition to the power needed to overcome road and air drag forces. Situations such as these consume a disproportionately high amount of fuel, and have a negative impact on the fuel economy of the vehicle. In conventional powertrains, the engine is typically sized much larger than is needed for steady-state operation, in order to meet these spikes in power demand. A larger engine is more expensive to manufacture and to operate. Such rapid transients in power may be better handled by the use of high power density ultracapacitors which represent the latest trend in electrostatic energy storage systems. While the total energy an ultracapacitor can store is typically ten times less than a battery of the same size, the ultracapacitor is capable of releasing or storing energy roughly ten times faster. The potential of this relatively new technology to assist the combustion engine during brief demand spikes, and to capture kinetic energy through regenerative braking, is the subject of this study.

A mild parallel hybrid powertrain is considered in which an ultracapacitor-supplied motor assists the engine during periods of high power demand, and the ultracapacitor may be recharged by the engine during periods of low demand, and through regenerative braking. A detailed simulation model of the powertrain is created to evaluate the fuel economy of the vehicle. The fuel economy gains are strongly dependent on how well the power split decision is made, that is the decision of how to distribute the power demand between the engine and the electric motor at each instant in time. To this end two forms of implementable control are designed to determine the power split between the engine and motor. A rule-based controller, which can

be quickly tuned and implemented, is applied for more exploratory simulations. Simplicity and expedience in both tuning and implementation make this method useful for testing the impact of different component combinations on fuel economy. After a suitable combination of engine, motor, and ultracapacitor sizes has been determined, an optimization-based power management strategy is created which shows a better overall performance. Various component sizing and control strategies tested consistently indicate a potential for 10 to 15 percent improvement in fuel economy in city driving with the proposed mild hybrid powertrain. This order of improvement to fuel economy was confirmed by deterministic dynamic programming (DDP) which finds the best possible fuel economy.

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Chapter 1

Introduction

Periods of quick acceleration require a much higher power output from an automobile than what is encountered under more typical driving conditions. A simple back-of-the-envelope kinetic energy calculation can show that accelerating a 2000 kg vehicle (roughly the size of a Ford Explorer SUV) from 0 to 60 mph (0 to 26.82 m/s) in 10 seconds requires almost 70 kW of power, in addition to the power needed to overcome road and air drag forces. Almost the same amount of additional power (70 kW) is needed during a 1 second accelerator pedal tip-in to increase the velocity of that same vehicle from 45 to 48 mph. Situations such as these may consume a disproportionately high amount of fuel, and have a negative impact on the fuel economy of the vehicle. In conventional powertrains, the engine is typically sized much larger than needed for steady-state operation, in order to meet these spikes in power demand. In addition to the higher cost of a larger engine, operating a large combustion engine at its most efficient torque-speed combination is less likely during normal cruise.

This problem is answered in part by the current generation of hybrid vehicles, which run their (typically smaller) combustion engines more efficiently by utilizing the assistance of electric motors and battery packs for energy buffers. In addition, by recovering a portion of their kinetic energy through the use of electromagnetic regenerative braking, they are able to make that energy available to assist propulsion of the vehicle, saving a considerable amount of fuel [10]. Among the remaining challenges in the field are the added cost and weight of large battery packs, the low cycle life of current available batteries, and the limited power release rate inherent in a battery, which makes a battery-powered electric motor unable to respond to large power demand spikes without drastically increasing battery size and cost [9].

It is believed that rapid transients in power demand will be better handled by the use of high power

density ultracapacitors [8, 9, 38], which represent the latest trend in electrostatic energy storage systems. A typical ultracapacitor is capable of releasing or storing energy roughly ten times faster than a battery of the same weight. The total energy which it can store, however, is typically ten times less than that same battery, meaning that an ultracapacitor provides an order of magnitude increase in power density at the cost of an order of magnitude of energy density [6, 7, 1]. The potential of this relatively new technology to assist the combustion engine during brief demand spikes, and to capture kinetic energy through regenerative braking, is the subject of this study.

An ultracapacitor shares several of the basic characteristics of a normal capacitor. Two electrodes are separated by a layer of dielectric material which keeps current from flowing between them, allowing an electric potential to develop. The electrodes are typically constructed by applying a layer of activated carbon to a layer of metal foil. The electrodes are submersed in an electrolytic fluid, and separated by a thin membrane of dielectric material. As charge builds up on the electrodes, ions from the solution are attracted to the surface of the activated carbon. This configuration is known as the electric double-layer capacitor. The powder-like carbon layer possesses a surface area far greater than that of a typical capacitor electrode, rising as high as $375000m^2$ for just 250g of carbon, and the membrane provides a charge separation which can be as low as a few nanometers [37]. These characteristics enable a capacitance on the order of $1000F - 5000F$ [6, 7, 38, 37], several orders of magnitude greater than that of a conventional capacitor. Despite this increased capacitance, the energy density of the ultracapacitor is still substantially lower than that of a battery. However, the serial resistance of an ultracapacitor is decades lower than a battery's resistance, typically less than $1m\Omega$ [8, 12, 18]. This low resistance allows for a much higher current to be drawn, giving an ultracapacitor a much higher power density. It is the combination of high power density and low energy density and their reliable [21] operation which makes the ultracapacitor well-suited to alleviating brief demand spikes from the engine. Other advantages of the ultracapacitor include a very high cycle life, on the order of more than 500,000 cycles [7, 9, 12, 18, 38], and the ability to operate over a wide range of temperatures, providing consistent performance at temperatures as low as $-40C$ [18]. As a developing technology, the performance characteristics of ultracapacitors have seen a significant improvement in the recent past [5] and are still improving further. Maxwell Technologies [1], a main provider of ultracapacitors in North America, has been introducing new models over the last few years that have higher power densities and reduced cost (See Figure 1.1).

Because of the properties which differentiate them from batteries, high power-density ultracapacitors may be integrated with vehicle powertrains (in a mild parallel hybrid configuration) to boost available

Figure 1.1: The 48 volt BMOD0140 Maxwell ultracapacitor module with capacitance of 140F (Dimensions $41.6 \times 19 \times 16$ cm, Mass ≈ 13.6 kg). While the maximum total energy stored is a mere 161kJ, this energy can be released in just a few seconds generating considerable power boost to a vehicle. The maximum power for this product is 4800W per unit mass or almost 65kW instantaneous maximum power. Newer products listed on Maxwell website [1] have even higher power densities.

power during vehicle acceleration and relax engine transients, making them an effective mechanism for reducing fuel consumption and emission levels without compromising vehicle agility [6, 7, 38]. Moreover, in many situations, regenerative braking alone may provide sufficient energy for this power boost [15]. The additional cost and weight of the ultracapacitor and electric motor may be justified by a downsized internal combustion engine and, since transients the engine is exposed to are reduced, even possibly a less costly catalytic converter.

While full hybrid vehicles, which rely on batteries for power leveling, have reached mass production, the use of ultracapacitors in mild hybrids remains a technology to explore. Most of the existing research on ultracapacitor hybrids is geared towards transit buses where their frequent stop-and-go cycle match the operational characteristics of ultracapacitors [11, 22, 3]. Some researchers have proposed use of ultracapacitors as a supplementary storage device to batteries in hybrid vehicles to help extend the battery life [33, 34, 29, 26]. In fuel-cell powered vehicles, ultracapacitors have been considered as an auxiliary power source which can assist the fuel cell during startup and fast power transients [27, 16, 36, 28]. A concept BMW X3 which was unveiled in 2006, had an ultracapacitor-powered electric motor integrated between the combustion engine and the transmission, helping to boost the engine when accelerating [2].

The objective of this study is to assess the extent to which an ultracapacitor, as a stand-alone power assist device, can improve the fuel economy of a mid-size passenger vehicle without sacrificing the vehicle's ability to follow a given velocity profile. In consistence with the literature, the hybrid configuration considered is a parallel mild hybrid powertrain. An induction motor powered by an ultracapacitor module assists

the combustion engine during acceleration power peaks, and is recharged back either by the engine during normal cruise, or through regenerative braking.

A detailed full-order model of the powertrain is developed to determine, through simulation, the impact of the proposed configuration and the power management scheme on fuel economy and vehicle performance. This is a causal, forward looking model which contains the dynamics of the ultracapacitor and transmission, and the longitudinal dynamics of the vehicle. The dynamics of the engine and motor are faster than the other dynamics in the powertrain, and they are treated as static systems. The performance of the proposed powertrain is assessed using the Urban Dynamometer Driving Schedule, or UDDS, shown in Figure 1.2. This driving cycle offers significant opportunity for regenerative braking, and contains numerous power spikes which are well suited to ultracapacitor-driven assistance. A rule-based power management strategy is also developed which can be quickly implemented and tuned for preliminary analysis and sizing of the system components. The rule-based strategy is used to compare the performance of the powertrain over the UDDS cycle, utilizing several different sizes of engine, motor, and ultracapacitor.

Due to the complexity of the full-order model, a representative reduced-order, single-state model of the powertrain is also created for the purpose of optimization-based control. This model is used for determining the optimal power management of the powertrain through dynamic programming, and then for the design of a model predictive controller. The purpose of dynamic programming is to estimate the full potential of the powertrain when optimally controlled [30]. Utilizing the results of the component comparisons simulated with the rule-based strategy, the model predictive controller is created for the most viable component combination, and is then implemented on the full-order model.

Figure 1.2: Velocity profile of the UDDS driving cycle, used by the driver model to provide demands for the vehicle.

Chapter 2

Hybrid Powertrain Configuration and Models

2.1 Hybrid Configuration

A parallel hybrid configuration, shown in 2.1, was chosen in which the torques supplied by the engine and motor are additive. The configuration used in this study is known as a mild hybrid, because the engine has been sized large enough to meet the vehicle's power demands on its own, should the ultracapacitor be unable to assist [7]. This choice was made to account for the ultracapacitor's low energy density, which imposes a limit on the amount of assistance the motor can sustain between recharge cycles. For this study,

Figure 2.1: Overview of the structure of a Parallel Hybrid with Ultracapacitor Energy Storage.

the motor is placed before the transmission, and the rotational speeds of the engine and motor are assumed to

be the same¹. An advantage of this design is that it is simple for the motor to bring the shaft speed up passed the engine's idling speed. It will be seen later that this placement is also an advantage in the control design.

2.2 PSAT Model

The ultracapacitor hybrid concept was first evaluated using the PSAT (Powertrain Systems Analysis Toolkit) package [17, 25, 31] in order to ensure that the components, parameter values, and the model are realistic. PSAT, created by Argonne National Laboratory, allows the user to specify a desired powertrain configuration and select pre-existing models of the various powertrain components from an extensive library of production vehicles. The software then assembles the components into a Simulink model, attaches a rule-based control module for power management, and simulates the performance over a demand cycle selected from a library of standard driving cycles.

An existing model of a 2-wheel drive full-size SUV powertrain with a 6 cylinder, 4 liter, 160kW engine was selected as the baseline model, referred to as the conventional case. An induction motor was placed in a parallel torque configuration with the engine, and provided with an ultracapacitor as its only power source. This is the ultracapacitor-driven mild hybrid configuration. Different size motors were tested with a 93 volt ultracapacitor module of 78F capacitance. Initial simulation studies proved ultracapacitors promising for reducing fuel economy and encouraged a more rigorous study.

To that end, a simple control algorithm was needed which could be easily tuned and used in fuel economy evaluation of the ultracapacitor-equipped hybrid powertrain. Therefore, two new models of the powertrain were created. These models are based on the PSAT model, but they operate independently from the PSAT software. The first model is a full-order model created for simulation of the powertrain under various driving conditions, and contains three primary states. The second is a single-state model which captures the ultracapacitor's state-of-charge dynamics for use in control design, and is referred to as the reduced-order model.

2.3 Full-Order Model

The full-order model is designed to simulate the performance of the powertrain under the demands of standard driving cycles. It contains the vehicle velocity, the torque converter input speed, and ultracapacitor

¹Different speeds are possible through the addition of torque coupling, but that is not included in this study.

state-of-charge as its primary dynamic states. The full-order model is based on the PSAT model, using maps and parameters experimentally determined by Argonne for the simulation software. However, the signal structure of the model has been changed, with more computations being handled at the component level, and some of the components themselves have been simplified. The controller used by PSAT has been replaced with several different methods of control, discussed in later sections.

Figure 2.2: Overview of the structure of the full-order model.

An overview of the full-order model is shown in 2.2. The model receives the reference velocity and road grade as inputs. All other signals are calculated within the model. In order to determine its commands to the powertrain, the controller requires the shaft speed at the engine and motor, the velocity of the vehicle, the state-of-charge of the ultracapacitor, and the current rate of fuel consumption in the engine. The controller will compare the vehicle's current velocity to the reference velocity of the cycle, and convert the difference into a torque demand. It will then split this demand between the motor, engine, and friction brakes. The details of the controller itself will be discussed in the following chapters.

The full-order model is able to report a large amount of information about the powertrain after a simulation is run, but the outputs of primary importance are the fuel rate and the state-of-charge. These two signals are shown as outputs in 2.2 for this reason. A more detailed diagram of the plant for the full-order model is shown in 2.3. The commands from the controller are shown as inputs here, and the information communicated to the controller is shown as output.

This is a casual, forward-looking model, in which the motor and engine are considered to be the starting point, and the direction in which torque is communicated is referred to as the downstream direction.

Figure 2.3: Diagram showing the flow of information through the plant of the full-order model. Inputs are the torque demands to the motor, engine, and friction brakes. Outputs are the rate of fuel consumption, the shaft speed at the motor and engine, the velocity of the vehicle, and the state-of-charge.

The motor draws power from the ultracapacitor by means of a current demand. The ultracapacitor uses this information to determine the voltage drop seen by the motor. Note that in future work, it is recommended that a power converter be included between these two devices. The torque input seen by the torque converter is the sum of torques provided by the engine and the motor. As the engine and motor are both connected to the torque converter's input shaft, the rotational speed of the motor and engine are the same. The torque converter, gearbox, and final drive make up the transmission [13]. Each component makes an internal torque calculation, and communicates the torque to the next component.

The vehicle block converts the torque from the powertrain into a force at the wheels. It then uses a force balance on the vehicle's mass to calculate the current traveling velocity. This velocity is converted into a rotational speed at the axle, and this speed is communicated back to the transmission. Each component in the transmission makes an internal speed calculation, and communicates this information upstream, eventually calculating the shaft speed at the motor and engine. The details of each component are discussed in the following sections.

2.3.1 Ultracapacitor Model

The ultracapacitor provides electric power to the motor. The open-circuit voltage of the ultracapacitor is given by:

$$V_{uc,oc} = \frac{q_{uc}}{C_{uc}} \quad (2.1)$$

Figure 2.4: Contour plot which shows the capacitance (in F) as a function of temperature and current.

Figure 2.5: Contour plot which shows the line resistance, in Ω and scaled by a factor of 100, as a function of temperature and current.

$$C_{uc} = C_{uc}(T_{uc}, i_{uc})$$

where the capacitance, C_{uc} , varies slightly with the ultracapacitor's internal temperature and current. This relationship is given by a map (shown in Figure 2.4), rather than a closed-form equation, and these and other maps were obtained using empirical data taken from PSAT [17]. The charge dynamics of the ultracapacitor are given by:

$$\frac{dq_{uc}}{dt} = -i_{uc} \quad (2.2)$$

where i_{uc} is the current being drawn. Positive and negative current correspond to discharging and charging, respectively. The state-of-charge is a normalized parameter representing the amount of charge remaining in the ultracapacitor, defined as:

$$SOC = \frac{V_{oc,uc} - V_{min,uc}}{V_{max,uc} - V_{min,uc}} \quad (2.3)$$

where $V_{max,uc}$ and $V_{min,uc}$ are the maximum and minimum open-circuit voltages. The effective voltage provided by the ultracapacitor is:

$$V_{out,uc} = V_{oc,uc} - i_{uc}R_{uc} \quad (2.4)$$

$$R_{uc} = \begin{cases} R_{dis} & i_{uc} > 0 \\ R_{chg} & i_{uc} < 0 \end{cases}$$

R_{chg} and R_{dis} are the line resistances for charging and discharging, respectively. The two resistances are assumed to be the same, as is typically the case in an ultracapacitor [12]. This resistance varies with temperature and current, as shown in Figure 2.5. The current drawn from the ultracapacitor is determined from the power P_{uc} demanded by motor, using the simple relation:

$$i_{uc} = \frac{P_{uc}}{V_{out,uc}} \quad (2.5)$$

This power is bounded by the line losses in the ultracapacitor. The maximum charging and discharging power the capacitor can support are given as:

$$P_{max,dis} = \frac{V_{oc,uc}^2}{4R_{uc}} \quad (2.6)$$

$$P_{max,chg} = V_{oc,uc} \frac{V_{oc,uc} - V_{max,uc}}{R_{uc}} \quad (2.7)$$

Because the capacitance and line resistance are dependent upon temperature, the thermal dynamics of the ultracapacitor are modeled. The heat generated is given by the power losses in the system.

$$Q_{gen,uc} = \begin{cases} i_{uc}^2 V_{out,uc} & i > 0 \\ i_{uc}^2 V_{out,uc} - i_{uc} V_{out,uc} \times (1 - \eta_{uc}) & i < 0 \end{cases} \quad (2.8)$$

In this expression, η_{uc} is a charging efficiency of the ultracapacitor, separate from the line losses. The convective heat transfer between the case and the surrounding air is given by:

$$Q_{case,uc} = \frac{T_{air} - T_{uc}}{R_{therm,uc}} \quad (2.9)$$

with $R_{therm,uc}$ being the equivalent thermal resistance. T_{air} is the temperature of the air flowing across the

surface, which needs to be determined using terms from the previous time step.

$$T_{air,t+\Delta t} = T_{\infty} - \frac{Q_{case,uc}}{2\dot{M}_{air}C_{p,air}} \quad (2.10)$$

$\dot{M}_{air}$ and $C_{p,air}$ are the mass flow rate and heat capacity of the air, and T_{∞} is the ambient temperature, assumed to be constant. Using these two heat flux sources, and the mass and heat capacity of the ultracapacitor, the temperature dynamics are expressed,

$$M_{uc}C_{p,uc} \frac{dT_{uc}}{dt} = Q_{gen,uc} + Q_{case,uc} \quad (2.11)$$

2.3.2 Motor Model

The motor dynamics are much faster than those of the ultracapacitor, and so the motor is modeled as a static system. The losses in the motor are dependent on both the shaft speed and the motor's output torque, and include the losses of the motor controller as well. The efficiency map corresponding to these losses is shown in Figure 2.6. Rather than multiplying torque and speed, and adding a loss term, the electric

Figure 2.6: Contour plot which shows the efficiency (in %) of the motor as a function of motor torque and shaft speed.

power needed by the motor is mapped directly from the output torque and speed, with these losses taken into

account,

$$P_{uc} = P_{map,mot}(T_{mot}, \omega_{mot}) \quad (2.12)$$

The maximum electric power which can be supplied to the motor is limited by it's maximum allowable current, shown as:

$$P_{max,mot} = i_{max,mot} V_{out,uc} \quad (2.13)$$

Figure 2.7: Plot of peak and continuous torque and power of the motor, as functions of the shaft speed. The magnitudes represent both generating and propelling.

The maximum torque output of the motor is limited both electrically and mechanically. The mechanical torque limit is calculated by:

$$T_{max,mech,mot} = T_{peak,mot} - HI \times [T_{peak,mot}(\omega_{mot}) - T_{cont,mot}(\omega_{mot})] \quad (2.14)$$

$T_{cont,mot}$ and $T_{peak,mot}$ are the continuous and peak torques, which depend upon the current shaft speed, as shown in figure 2.7. The heat index, HI , is a term constructed to adjust the available torque between the peak and continuous torques during operation, and its dynamics are given by:

$$\frac{dHI}{dt} = \frac{0.3}{t_{max,mot}} \left(\left| \frac{T_{mot}}{T_{cont,mot}} \right| - 1 \right) \quad (2.15)$$

where $t_{max,mot}$ is a time constant of the motor. In general terms, the motor will be able to operate near the peak torque after resting, but will be forced towards the continuous torque limit during sustained operation.

The output torque is also limited by the electrical power available to the motor, and this constraint is shown as:

$$T_{max,elec,mot} = P_{map,mot}^{-1}(P_{max,mot}, \omega_{mot}) \quad (2.16)$$

where $P_{map,mot}^{-1}$ denotes an inverse of the map used earlier, calculating torque from inputs of shaft speed and electric power. The maximum torque, $T_{max,mot}$, that the motor can provide at any given moment, will be the more restrictive of the mechanical or electrical limitations.

2.3.3 Engine Model

The engine dynamics are also much faster than the relevant dynamics of this study, and are not considered. Instead, the *fuel consumption rate* of the engine is determined from engine torque and shaft speed, using a static map obtained from empirical data. A contour plot of this map is shown in 2.8, and the relationship is written as:

$$\dot{M}_{fuel} = \dot{M}_{fuel}(T_{eng}, \omega_{eng}) \quad (2.17)$$

The constraints on engine torque and power are empirically mapped from the engine speed, shown in 2.9. The mechanical losses of the engine are assumed to be constant, and are represented by the term $P_{loss,eng}$.

Figure 2.8: Contour plot which shows the fuel consumption rate (in g/sec) of the engine as a function of engine torque and shaft speed.

Figure 2.9: Plot of the maximum and minimum torques and powers generated by the engine. The lower boundary refers to the case in which no fuel is consumed.

The net engine output torque is thus defined as:

$$T_{eng,out} = T_{eng} - \frac{P_{loss,eng}}{\omega_{eng}} \quad (2.18)$$

Because this study focuses on evaluating fuel economy, the particulate emissions of the engine are not modeled.

2.3.4 Torque Converter Model

In the proposed configuration, both the engine and the motor are directly connected to the torque converter. Therefore, the torque supplied by the engine and motor are additive, and the same rotational speed is shared between them.

$$T_{in,tc} = T_{mot} + T_{eng,out} \quad (2.19)$$

$$\omega_{mot} = \omega_{eng} = \omega_{in,tc} \quad (2.20)$$

The rotational dynamics of the torque converter are characterized by:

$$J \frac{d\omega_{in,tc}}{dt} = T_{1,tc} - T_{loss,tc} \quad (2.21)$$

where J is the rotational inertia upstream of the torque converter, $\omega_{in,tc}$ is the torque converter's input speed, and $T_{1,tc}$ is the torque at the impeller of the torque converter. The loss in the torque converter, $T_{loss,tc}$, is mapped as a function of $T_{in,tc}$, $\omega_{in,tc}$, and the slip ratio ω_{ratio} , defined as:

$$\omega_{ratio} = \frac{\omega_{out,tc}}{\omega_{in,tc}} \quad (2.22)$$

where $\omega_{out,tc}$ is the rotational velocity of the powertrain downstream of the torque converter. The torque behavior of the converter is modeled differently under different circumstances, and these circumstances are represented by three different modes. The torque converter is considered to be in "idle" mode when the rotational speed upstream is near the idling speed of the engine. In this mode, the torque behavior is expressed

by:

$$T_{1,tc} = T_{in,tc} - T_{2,tc} \quad (2.23)$$

$$\begin{aligned} T_{2,tc} &= T_{in,tc} \times (T_{in,tc} > 0) \frac{\omega_{in,tc} - \omega_{idle,eng}}{100} \\ 0 &\leq (\omega_{in,tc} - \omega_{idle,eng}) \leq 25 \end{aligned} \quad (2.24)$$

where $\omega_{idle,eng}$ is the idling speed for the engine, and $T_{2,tc}$ is the torque at the turbine of the torque converter. The second representative mode is the "quasi-static" mode. The torque converter is considered to be in this mode when operating near steady state, providing that the conditions for idle mode are not met:

$$T_{1,tc} = T_{ratio}(\omega_{ratio}) \frac{\omega_{in,tc} |\omega_{in,tc}|}{K^2(\omega_{ratio})} \quad (2.25)$$

$$T_{2,tc} = T_{in,tc} - \frac{T_{1,tc}}{T_{ratio}(\omega_{ratio})} \quad (2.26)$$

Here, T_{ratio} is the torque ratio, and K is called the "capacity factor." Both parameters are mapped functions of the slip ratio ω_{ratio} . When the conditions for neither of the above two operating modes are met, the torque converter is considered to be in "transient" mode, and its behavior is described by:

$$\begin{aligned} T_{1,tc} &= |T_{in,tc}| \frac{\omega_{goal} - \omega_{in,tc}}{25} \\ -0.01 |T_{in,tc}| &\leq T_{1,tc} \leq 0.75 |T_{in,tc}| \end{aligned} \quad (2.27)$$

$$T_{2,tc} = (T_{in,tc} - T_{1,tc}) \times T_{ratio}(\omega_{ratio}) \quad (2.28)$$

where ω_{goal} is an intermediate variable described by:

$$\begin{aligned} \omega_{goal} &= \sqrt{|T_{in,tc}|} \times K(\omega_{ratio}) \\ \omega_{idle,eng} + 20 &\leq \omega_{goal} \leq 310 \end{aligned} \quad (2.29)$$

The turbine torque $T_{2,tc}$ is also the torque applied by the torque converter to the gearbox:

$$T_{out,tc} = T_{2,tc} \quad (2.30)$$

2.3.5 Gearbox Model

The gearbox is modeled as a gear ratio and a loss term. The torque supplied by the gearbox to the driveline is given by:

$$T_{out,gb} = G_t \times (T_{out,tc} - T_{loss,gb}) \quad (2.31)$$

where $T_{loss,gb}$ is mapped as:

$$T_{loss,gb} = T_{loss,gb}(\omega_{out,gb}, T_{out,tc}, G_t) \quad (2.32)$$

and the input speed is determined as:

$$\omega_{in,gb} = \omega_{out,gb} G_t \quad (2.33)$$

during most of the cycle. However, directly after a gear shift, the input speed is passed through a simple filter, to avoid large instantaneous changes in speed which could cause numerical errors during simulation. This filter is represented as a transfer function.

$$\omega_{in,gb,filtered} = \frac{1}{0.2s + 1} \omega_{in,gb} \quad (2.34)$$

The gear ratio, G_t , is determined by the same shifting strategy that PSAT uses in its simulations. This shifting strategy was not optimized specifically for the use of ultracapacitor energy storage, and shifting strategy can have a noticeable impact on fuel economy [23]. In the future, work shifting can be treated as an extra degree of freedom, in order to maximize the fuel economy improvement.

2.3.6 Final Drive Model

The wheel torque and gearbox speed are also influenced by the final drive ratio:

$$T_w = g_f \times T_{out,gb} - T_{loss,fd} \quad (2.35)$$

$$\omega_{out,gb} = \omega_w \times g_f \quad (2.36)$$

where the final drive ratio g_f , and the loss term $T_{loss,fd}$, are constants.

2.3.7 Vehicle Model

The vehicle longitudinal dynamics are obtained by the simple application of Newton's second law of motion:

$$M \frac{dv}{dt} = \frac{T_w}{r_w} - F_{grade} - F_{drag} - F_{brake} \quad (2.37)$$

where M and v are the mass and velocity of the vehicle, r_w is the wheel radius, and F_{grade} is the force due to weight and road grade, calculated as:

$$F_{grade} = [\sin(\theta) + (\mu_1 + \mu_2 \omega_w) \cos(\theta)] Mg \quad (2.38)$$

where μ_1 and μ_2 are friction coefficients [14], and θ is the road grade. The aerodynamic drag force is:

$$F_{drag} = Cv^2 \quad (2.39)$$

where C is a scaled drag coefficient [14]. Assuming no wheel slip, the rotational speed of the axle is calculated from the vehicle velocity by:

$$\omega_w = \frac{v}{r_w} \quad (2.40)$$

The friction brake force at the wheels is represented by F_{brake} . The friction brakes themselves are not modeled, and it is assumed that they can provide any demand that the cycle will require of them.

Table 2.1: Values of constant parameters used in full-order model

η_{uc}	0.9958	$P_{loss,eng}$	700W
μ_1	0.009	$R_{therm,uc}$	$0.8864 \frac{K}{W}$
μ_2	0.00012	T_{inf}	20C
C	$0.6203 \frac{kg}{m}$	$T_{loss,fd}$	8Nm
$C_{P,air}$	$1009 \frac{J}{kg-K}$	$V_{min,uc}$	3.7V
$C_{P,uc}$	$1200 \frac{J}{kg-K}$	$V_{max,uc}$	92.5V
J	$0.204 kg-m^2$	g_f	3.27
$\dot{M}_{air}$	$0.014 \frac{kg}{s}$	$i_{max,mot}$	140A
M	2117.8kg	r_w	0.367m
M_{uc}	35.4645kg	$t_{max,mot}$	180s

Table 2.2: Descriptions of variable parameters used in full-order model

θ	Road Grade	R_{uc}	Line Resistance
ω_{eng}	Engine Speed	T_{air}	Air Temperature
$\omega_{in,gb}$	Gearbox Input Speed	$T_{cont,mot}$	Motor Continuous Torque
$\omega_{in,gb,filtered}$	Filtered Input Speed	T_{eng}	Engine Torque
$\omega_{in,tc}$	Torque Converter Input Speed	$T_{eng,out}$	Output Shaft Torque
ω_{mot}	Motor Speed	$T_{in,tc}$	Torque Converter Input Torque
ω_{ratio}	Torque Converter Speed Ratio	$T_{loss,gb}$	Gearbox Loss
$\omega_{out,gb}$	Gearbox Output Speed	$T_{loss,tc}$	Torque Converter Loss
$\omega_{out,tc}$	Torque Converter Output Speed	$T_{max,elec,mot}$	Electrical Torque Constraint
ω_w	Wheel Speed	$T_{max,eng}$	Maximum Engine Torque
C_{uc}	Capacitance	$T_{max,mech,mot}$	Mechanical Torque Constraint
F_{brake}	Friction Brake Force	$T_{min,eng}$	Minimum Engine Torque
F_{drag}	Drag Force	T_{mot}	Motor Torque
F_{grade}	Road Grade and Wheel Resistance Force	$T_{out,gb}$	Gearbox Output Torque
G_t	Gear Ratio	$T_{peak,mot}$	Motor Peak Torque
HI	Motor Heat Index	T_{uc}	Internal Temperature
$\dot{M}_{fuel}$	Fuel Consumption Rate	T_w	Wheel Torque
$P_{max,chg}$	Maximum Charging Power	$V_{out,uc}$	Output Voltage
$P_{max,dis}$	Maximum Discharging Power	$V_{uc,oc}$	Open-Circuit Voltage
$P_{max,mot}$	Maximum Electrical Power	g_f	Final Drive Ratio
P_{uc}	Electrical Power	i_{uc}	Current
$Q_{case,uc}$	Heat Transfer	q_{uc}	Charge
$Q_{gen,uc}$	Heat Generation	soc	State-Of-Charge
R_{chg}	Charging Line Resistance	v	Vehicle Velocity
R_{dis}	Discharging Line Resistance		

2.3.8 Model Validation

The full-order model was tested for consistency against its parent PSAT model by replacing the controller portion of the model with forcing functions developed from PSAT simulation results. The powertrain

Figure 2.10: Percent error in fuel consumption between the original PSAT simulation results and those obtained from the full-order model, applied over the UDDS cycle with no grade and a 2% grade.

in the full-order model was thus subjected to the same demands that had been seen by the PSAT powertrain

model during various simulations, and its open-loop output was compared with the results of these simulations. Simulations were run for three different combinations of motor sizes: induction motors of 110kW, 70kW, and 40kW were combined with the 160kW engine. The results of this comparison are shown in Figure 2.10. The relative error of the full-order model is less than 1.2 percent.

2.4 Reduced-Order Model

The details incorporated into the full-order model make it a reliable tool for simulation, but they also make it too complex for use in model-based control design. In order to simplify the control design process, a reduced-order model of the powertrain is developed, containing the ultracapacitor state-of-charge as its only state. This model is simplified to a backward-looking model, as opposed to the causal and forward-looking full-order model. The torque converter, transmission, and the vehicle longitudinal dynamics are external to the reduced-order model, and the full-order model is used to calculate the engine and motor speeds, as well as the torque demand upstream of the torque converter. Because the controller only determines the power split

Figure 2.11: Diagram showing the flow of information through the plant of the reduced-order model. Inputs are the torque demands and shaft speed of the motor and engine. Outputs are the rate of fuel consumption, and the state-of-charge.

ratio between the engine and the motor, it uses the torque demand and speed upstream of the torque converter as inputs. Backward-looking modeling facilitates this approach. Figure 2.11 shows the signal flow in the reduced-order model. The motor model calculates the power demanded from it, which is simply:

$$P_{motor} = T_{motor}\omega_{motor} \quad (2.41)$$

and then communicates this power and the motor efficiency to the ultracapacitor model, which uses the

information to calculate the state-of-charge.

The ultracapacitor dynamics of the reduced-order model are mathematically very similar to those of the full-order model, save that the influence of temperature is dismissed. The effective voltage provided by the ultracapacitor is:

$$V_{out} = V_{oc} - i_{uc}R \quad (2.42)$$

$$R = \begin{cases} R_{dis} & i_{uc} > 0 \\ R_{chg} & i_{uc} < 0 \end{cases}$$

where V_{oc} is the open-circuit voltage of the ultracapacitor, i_{uc} is the current drawn from the ultracapacitor, and R_{chg} and R_{dis} are the line resistances for charging and discharging, respectively. In the reduced-order model, it is assumed that the line resistance R and capacitance C are independent of internal temperature of the ultracapacitor and are constant. The temperature-dependent changes in the internal resistance of the ultracapacitor may be significant [18], however, and controller performance might be improved in the future by adding them to this model. The state-of-charge is defined as:

$$soc = \frac{V_{oc}}{V_{max}} \quad (2.43)$$

where V_{max} is the maximum open-circuit voltage of the ultracapacitor at full charge. The ultracapacitor charging or discharging current is given by:

$$i_{uc} = \frac{P_{mot}}{\beta V_{out}} \quad (2.44)$$

where P_{mot} is the motor power. The coefficient β , is:

$$\beta = \begin{cases} \eta_{discharge} & \text{while discharging} \\ 1/\eta_{charge} & \text{while charging} \end{cases} \quad (2.45)$$

where η_{charge} and $\eta_{discharge}$ represent the motor efficiency when charging and discharging the ultracapacitor.

Combining (2.42)-(2.44), i_{uc} can be calculated as:

$$i_{uc} = \frac{socV_{max} - \sqrt{(socV_{max})^2 - \frac{4RP_{mot}}{\beta}}}{2R} \quad (2.46)$$

Utilizing (2.43) and (2.46), the governing equation for the state-of-charge dynamics is:

$$\frac{dsoc}{dt} = -\frac{i_{uc}}{CV_{max}} = \frac{-socV_{max} + \sqrt{(socV_{max})^2 - \frac{4RP_{mot}}{\beta}}}{2RCV_{max}} \quad (2.47)$$

The full derivation for (2.47) and (2.46) can be found in [35], in which it is shown that there are actually two physical solutions for i_{uc} ; the solution chosen is that which corresponds to lower resistive losses, and this choice can be enforced by the motor controller.

In the reduced-order model, the engine fuel consumption rate and motor efficiencies are modeled algebraically, using the Willan's line method:

$$\dot{m}_f = \frac{aT_{eng}\omega_{eng} + b\omega_{eng} + c\omega_{eng}^3}{\bar{a} + \bar{b}\omega_{eng} + \bar{c}\omega_{eng}^2} \quad (2.48)$$

$$\eta_{mot} = \frac{e_{mot}T_{mot}\omega_{mot}}{T_{mot}\omega_{mot} + P_{loss,mot}} \quad (2.49)$$

where ω_{eng} , ω_{mot} , T_{eng} , and T_{mot} are the rotational velocities and output torques of the motor and engine, respectively. η_{mot} is the energy efficiency of the motor, and $\dot{m}_f$ is the mass consumption rate of fuel. The other parameters (e_{mot} , $P_{loss,mot}$, a , b , c , $\bar{a}$, $\bar{b}$, and $\bar{c}$) are determined numerically from the characteristic maps of the selected engine and motor available in the PSAT database.

Chapter 3

Rule-Based Supervisory Control

3.1 Introduction

The power management strategy plays a critical role in fuel economy of a hybrid vehicle. In a conventional vehicle, the transmission provides a degree of freedom for shifting the operation of the engine to a more efficient operating point. In a hybrid vehicle, the electrical propulsion system, together with the energy storage system, provides an additional degree of freedom for optimizing energy use. The benefit of this is strongly dependent on how well the power split decision is made, that is the decision of how to distribute the power demand between the engine and the electric motor at each instant in time.

In a simple but intuitively appealing design, the power split decision can be made based on "if-then-else" rules and use of statically optimized efficiency maps. Depending on the power demand, the rules help determine the mode of operation (engine only, motor only, regeneration, combined operation) and the power split ratio. Various rule-based strategies have been proposed in the past and can be found in the literature [20]. Due to relative simplicity and ease of implementation, rule-based methods have been the most widely used power management approach in mass-produced hybrid vehicles.

The consequence of this simplicity, however, is that a rule-based method will not find the optimal power management policy, and therefore it cannot guarantee the best possible fuel economy, though at its best and if carefully designed it can result in fuel economies close to optimal. Therefore, many research groups have focused on developing optimization-based power management strategies that find the optimal or close-to-optimal power management policy. When the power management problem is posed as an optimal control problem, its nonlinear nature and several hard constraints render an analytical solution impractical.

A contribution to numerical solution of this problem has been the use of Bellman’s optimality principle through dynamic programming (DP) [19]. While DP assumes knowledge of future driving conditions, and is therefore neither causal nor real-time implementable, it provides valuable insights about best possible achievable fuel economy. Sub-optimal methods have also been proposed which are more suitable for real-time implementation, and among these, ECMS (Equivalent Consumption Minimization Strategy) methods and their derivatives are the most popular [24, 32]. Model predictive control can be a next step in this evolving trend because, while predictive in nature, it is causal and therefore real-time implementable [36]

In this study, the full spectrum of these approaches is explored, beginning in this chapter with the development of a simple rule-based strategy for power management. Simplicity and expedience in both tuning and implementation make this method useful for testing the impact of different component combinations on fuel economy. With a suitable combination of engine, motor, and ultracapacitor sizes having been determined through simulation, the following chapter focuses on the use of optimal control techniques. Dynamic programming is used to present an estimate of the best possible fuel economy, and then the design process for a model predictive control strategy is presented and implemented. The performance of this control strategy is then compared with those of the rule-based strategy and the dynamic programming results.

3.2 Power Management Strategy

A simple, rule-based power management strategy was designed to test the capability of the ultracapacitor assisted powertrain. The controller is tuned using a power threshold, P_{ref} . During propulsion, the rule-based algorithm commands the motor to assist the engine when the power demand is greater than this threshold, and commands the engine to charge the motor when the demand is less. The value of P_{ref} is dependent on the current shaft speed at the engine, and is obtained from the engine’s most efficient power curve, multiplied by a gain. It is this gain which provides the actual tuning parameter for the controller, and the reliance on this single degree of freedom which allows the rule-based strategy to be tuned quickly for a given system. The controller receives the ultracapacitor state-of-charge as an input, and enforces upper and lower boundaries of $soc_{max} = 0.9$ and $soc_{min} = 0.5$, respectively. Because the state-of-charge is a dynamic state, it may not be able to be strictly enforced by a high-level controller. The imposed upper boundary of 0.9 provides a buffer between the physical state-of-charge boundary and that which the controller attempts to enforce. The lower boundary of 0.5 is chosen for efficiency of operation, because the primary power loss in the ultracapacitor is proportional to the square of the current (Equation 2.4), and a lower state-of-charge results

in a lower output voltage (Equation 2.43), requiring a higher current to be drawn for a given power demand (Equation 2.5). The magnitude of the motor's power demand in either direction (generating or propelling) is scaled by the distance of the state-of-charge from its enforced boundaries, according to equations 3.1 and 3.2. This scaling keeps the motor demand from changing abruptly when one of the state-of-charge boundaries is reached.

During braking, the motor charges the ultracapacitor, and is subject to the same state of charge restrictions as during propulsion. Friction brakes are assumed to be engaged any time the demanded power falls outside of the motor's lower power limit. The motor is also restricted from charging the ultracapacitor while the engine speed is below the idling speed. A graphic representation of the rule-based control algorithm is given in Figure 3.1, with the terms used described in Table 3.1.

Figure 3.1: Flow chart showing the decision tree of the rule-based control algorithm.

Table 3.1: Description of terms used in rule-based control algorithm flow chart.

P_{eng}	Engine Power Demand	P_{max}	Maximum Motor Power
P_{mot}	Motor Power Demand	P_{min}	Minimum Motor Power
P_{brake}	Friction Brake Demand	K_{chg}	Charge Coefficient
P_{dem}	Total Power Demand	K_{dis}	Discharge Coefficient
P_{ref}	Desired Engine Power	soc	State of Charge

$$K_{chg} = \frac{SOC_{max} - SOC}{SOC_{max} - SOC_{min}} \quad (3.1)$$

$$K_{dis} = \frac{SOC - SOC_{min}}{SOC_{max} - SOC_{min}} \quad (3.2)$$

Figure 3.2: Overview of the signal structure of the rule-based controller.

The rule-based power management algorithm receives the total power demand at the wheels as an input. This power demand is calculated by a vehicle and driver model, shown in 3.2. This model uses the velocity, reference velocity, and road grade to calculate the power demanded at the wheels, and is based on the longitudinal dynamics of the full-order model. The driver is modeled as a simple proportional controller and calculates a desired acceleration proportional to the difference between the vehicle velocity v , and the pre-determined cycle velocity V_{ref} :

$$\dot{v}_{dem} = K_{driver}(v_{ref} - v) \quad (3.3)$$

The torque demand at the wheels is a function of this desired acceleration and the forces due to drag and road grade:

$$T_{dem} = [\dot{v}_{dem}(J + Mr_w) + [F_{grade} + F_{drag}]r_w] \quad (3.4)$$

where the terms F_{grade} and F_{drag} are the same as those shown in equations 2.39 and 2.38. The constant J represents the rotational inertia of the powertrain, and is given by:

$$J = J_w + G_t^2(J_{eng} + J_{mot}) \quad (3.5)$$

where J_w , J_{eng} , and J_{mot} are the rotational inertias of the motor, engine, and wheels, respectively. The gear ratio, G_t , is the same as was shown in Section . Using the provided rotational velocity of the wheels, the required torque calculated in 3.4 is converted into the power demand for the rule-based control algorithm.

$$P_{dem} = \omega_w T_{dem} \quad (3.6)$$

3.3 Simulation Results

The fuel economy was evaluated by simulations using the full-order model controlled by the rule-based power management strategy. Shown in Figures 3.3, 3.4, and 3.5 is a time history of several of the performance characteristics of the powertrain over the UDDS cycle with no road grade, using the 160kW engine and a 110kW electric motor. This simulation showed a fuel economy improvement of slightly more than 9.57% over the conventional powertrain.

Figure 3.3: Time history of power provided by the motor and the engine during propulsion of the vehicle over UDDS cycle with zero percent road grade, using a 160kW engine and 110kW motor.

Figure 3.4: Time history of power provided by the motor and the friction brakes during braking of the vehicle over UDDS cycle with zero percent road grade, using a 160kW engine and 110kW motor.

For this cycle, it appears that a smaller motor and engine would be sufficient. For the majority of the cycle, the ultracapacitor is able to meet its demands without reaching the charge limits imposed upon it. The results also indicate that the energy provided by regenerative braking is more than sufficient to sustain the motor's assistance to propulsion for these driving conditions, and that the motor is only utilizing a portion of the available braking energy.

Figure 3.5: Time history of vehicle velocity and ultracapacitor state-of-charge over UDDS cycle with zero percent road grade, using a 160kW engine and 110kW motor.

Next, to determine the effect of component sizing, the performance of different sizes of motor and ultracapacitor were simulated with the full-order model and rule-based controller. Induction motors with maximum power of 110kW, 70kW, and 40kW were combined with three sizes of ultracapacitors. Tables 4.3.2 and 3.3 summarize the components used.

Table 3.2: Different motor sizes tested.

Max. Power (kW)	Continuous Power (kW)	Weight (Kg)
40	21	30
70	35	115
110	75	92

Table 3.3: Different ultracapacitor sizes tested.

Voltage (V)	Cap (F)	Energy (Wh)	Weight (Kg)
93	78	93.7	35.46
93	156	187.4	70.92
93	234	281.1	106.38

The fuel economy of each case was compared to that of the conventional vehicle in full-order model simulations. Figures 3.6 and 3.7 summarize the fuel economy improvement for UDDS cycle tests applied over 0 and 2 percent road grades, respectively. The hybrid powertrains were able to produce the results shown while still following the cycle velocity. Comparative velocity plots are not shown, because the velocity profiles are indistinguishable from those of the conventional case. As seen in these Figures, the smaller 40kW motor gives the best fuel economy results of the three, making it a better choice than the original chosen 110kW motor. Looking at Figure 3.3, notice that the motor's assistance is rarely much higher than

10kW, meaning that the larger motors provide no real extra benefit to offset their increased weight. In light of this information, the 40kW motor was chosen for future simulations.

On a flat road (zero percent grade) the larger ultracapacitor modules result in better fuel economy than the 93V 78F ultracapacitor, but on a 2-percent road grade the advantage of larger ultracapacitor sizes seem to diminish. One likely explanation is the increased weight of the larger devices, which has a much larger impact in the presence of the road grade. Another consideration is that the presence of an uphill road grade reduces the amount of braking energy available for use by the ultracapacitor. Moreover, the larger sizes ($> 100\text{Wh}$) may not be an economically viable alternative to batteries according to [7]. Therefore, the 93V 78F ultracapacitors seems to be the most appropriate of the three sizes compared, and is used in further simulations.

Figure 3.6: Percent increase in fuel economy between conventional powertrain and hybrid powertrain with various motor and ultracapacitor sizes, applied over the UDSS driving cycle with no road grade.

Figure 3.7: Percent increase in fuel economy between conventional powertrain and hybrid powertrain with various component sizes, applied over the full-order model with UDSS driving cycle and a 2% road grade.

To investigate the expected benefits of downsizing the combustion engine in the ultracapacitor assisted powertrain, a number of tests were run with a smaller 120kW engine chosen from the PSAT database. Table 3.4 shows the fuel economy improvement over the conventional powertrain for the 120kW and 160kW engines (both with the 40kW motor and the 93V, 78F Ultracapacitor).

Table 3.4: Percent fuel economy improvement with different engines.(UDSS cycle, 40kW motor, 93V, 78F UC)

	0% grade	2% grade
120kW engine	+14.4%	+7.4%
160kW engine	+13.2%	+9.5%

The vehicle with the downsized 120kW engine was able to follow the UDDS cycle on both 0 and 2 percent grades, and the fuel economy was better than the conventional powertrain. With no road grade, the 120kW engine consumed less fuel than the hybrid with 160kW engine, but this relationship was reversed in the presence of a 2 percent road grade. This may be due to several factors, 1) the smaller engine having to overwork on the 2 percent grade, 2) the limitations of the rule-based algorithm, and its sensitivity to its choice of parameters 3) the gear shifting strategy, which is not optimized for the mild hybrid powertrain. The superiority of the 120kW engine for the UDDS cycle without road grade was confirmed with a more general comparison, shown in Table 3.5. The smaller engine achieved a better fuel economy for most combinations of motor and ultracapacitor size. A new ultracapacitor was included in this study as well, and this new 196V 39F ultracapacitor module contains the same number of individual ultracapacitor cells as the 93V 156F module. Because of this, the two modules would be of roughly the same size, weight, and cost. The inferior performance of the 196V module suggests that increasing the capacitance of the ultracapacitor is more effective than increasing the voltage. These observations call for a more detailed analysis of engine downsizing in the future. It is important to note that, due to the limited overall energy stored in the ultracapacitor, it may be very difficult to ensure that the motor will always have an energy supply to assist with during power spikes. Because of this, it may not be viable to size the engine below that which could meet the driver's power demands on its own.

Figure 3.8: Contour plot which shows the fuel efficiency of the 160kW engine as a function of engine torque and shaft speed. The fuel efficiency is defined as the power (kW) over the fuel consumption rate (g/sec).

Figure 3.9: Contour plot which shows the fuel efficiency of the 120kW engine as a function of engine torque and shaft speed. The fuel efficiency is defined as the power (kW) over the fuel consumption rate (g/sec).

Table 3.5: Comparison of the fuel economy increase achieved by various engine, motor, and ultracapacitor size combinations, run over the UDDS cycle with no road grade.

engine 120kW		Ultracapacitor			
		93V 78F	93V 156F	93V 234F	186V 39F
	40kW	14.91%	15.31%	17.28%	15.09%
motor	70kW	12.03%	14.05%	13.85%	13.66%
	110kW	11.34%	12.38%	12.18%	11.44%
engine 160kW		Ultracapacitor			
		93V 78F	93V 156F	93V 234F	186V 39F
	40kW	12.84%	15.38%	15.66%	13.60%
motor	70kW	11.48%	13.06%	13.66%	11.95%
	110kW	9.57%	11.96%	12.62%	11.46%

Chapter 4

Optimization Based Supervisory Control

4.1 Introduction

The rule-based power management strategy is simple to tune, real-time implementable, and for the most part, intuitive. The power management logic of most production hybrid vehicles is rule-based for these same reasons, among several others. While a rule-based scheme can be perfected by excessive tuning and reliance on statically optimized-maps, however, its optimality can not be guaranteed for every driving condition. The reason is large variations of vehicle operating conditions from one driving cycle to another, and the limitations of a rule-based control scheme by the structure of its rules. If instead, the vehicle's power management is formulated as a dynamic optimization problem, the fuel economy potential of the hybrid at its best may be determined. This is challenging, however, as such optimization problems are typically highly nonlinear and subject to several dynamic constraints of the engine, motor, energy storage, and vehicle. Though analytical solutions to power management do not exist in general, attempts have been made to cast and solve these problems in a standard optimal control framework. The primary obstacle to this approach is a lack of information about upcoming driving conditions. Numerical solutions to the optimal control problem are the most widely used, and among these, Dynamic Programming (DP) is a particularly powerful technique. Assuming known future driving conditions, DP can find the power management policy which results in the best fuel economy for a given driving cycle. In this chapter, the fuel economy potential of the ultracapacitor hybrid is first determined by DP applied to the UDDS driving cycle. Since DP is non-causal and not implementable in real-time, the optimization is then cast in a Model Predictive Control (MPC) framework, which can produce near-optimal solutions in a causal manner. An MPC optimization can be

converted to a Quadratic Program (QP), which can (under certain conditions) be efficiently solved online in polynomial-time.

4.2 Dynamic Programming

The fuel economy potential of the ultracapacitor hybrid powertrain was first estimated using Dynamic Programming, with details provided by Rotenberg et al. in [30]. In collaboration with the third author of [30], DP was applied to the reduced-order model of the powertrain equipped with the 160kw engine and 110kw motor. The system was subjected to a power demand history corresponding to the UDDS driving cycle with no road grade. The fuel economy of the powertrain was calculated for the case in which the motor demand, P_{mot} , was determined by optimization. This case was compared with a representation of conventional case, estimated by setting $P_{mot} = 0$ under the same conditions, and by imposing a lower bound on the engine speed to represent the engine's idle speed. Figure 4.1 shows the trajectory of the state-of-charge over the drive cycle, and Figure 4.2 provides a history of the difference in fuel consumption rate between the two cases compared. The optimally controlled powertrain achieved a fuel economy which was 15.0% better than that of the conventional case. This estimate provides a useful basis of comparison for evaluating the performances of the implementable control strategies discussed in this thesis.

Figure 4.1: Trajectory of the ultracapacitor state-of-charge when P_{mot} is optimally controlled, applied over the UDDS driving cycle with no road grade. Pointwise-in-time constraints on soc are shown by the dashed lines.

Figure 4.2: Percent difference in fuel flow rate between the case when $P_{mot} = 0$ and when P_{mot} is optimally controlled, applied over the UDDS cycle with no road grade.

For the purpose of comparison, the rule-based power management algorithm was simulated using

the reduced-order model. The purpose of these simulations was to compare the performance of the rule-based controller to that the Dynamic Programming results, and to ensure the algorithm was free of errors before implementation on the more complex full-order model. This simulation was run using the same components and cycle as the DP optimization. The rule-based controller was able to achieve a fuel economy improvement of 5.72% over the $P_{mot} = 0$ case, a mere fraction of the estimated improvement potential of 15%. Based on these results, an optimization-based controller was designed using Model Predictive Control, discussed in the next section.

4.3 Model Predictive Control

4.3.1 General MPC

Model Predictive Control is a model-based optimal control methodology. Its *finite*-horizon cost function and use of a discrete-time internal model allow it to be formulated as a finite-dimensional optimization problem, meaning a finite number of control inputs are determined at each optimization window. The benefit is that the control of complex systems with input and state constraints, nonlinearity, time-delays, and other complicating factors may be expressed in a form for which standard and effective optimization techniques exist.

In this work, a linearized model and constraints, along with a quadratic cost function, are used for the purpose of control design. The linearized discrete-time model of the plant is given as:

$$\begin{aligned} x_{k+1} &= Ax_k + Bu_k \\ y_k &= Cx_k \end{aligned} \tag{4.1}$$

and the input and output constraints present are expressed as:

$$\begin{aligned} u_{min,i} &\leq u_i \leq u_{max,i} \\ y_{min,i} &\leq y_i \leq y_{max,i} \end{aligned} \tag{4.2}$$

where k denotes the sample time. The following finite-horizon quadratic cost function is defined:

$$J = \sum_{i=k}^{k+P-1} \left[x_{i|k}^T Q x_{i|k} + u_i^T R u_i \right] + x_{(k+P)|k}^T S x_{(k+P)|k} \tag{4.3}$$

in which P is the prediction horizon, and the term $x(i|k)$ shows the predicted (by equation 4.1) value of x for instant i based on its initial value at instant k . The matrices Q , R , and S are positive definite or semi-definite symmetric penalty weights. At instant k the goal is to find the sequence of optimal control inputs $U = [u_k \ u_{k+1} \ \cdots \ u_{k+P-1}]^T$ which minimizes the cost function (Equation 4.3) subject to the system dynamics (Equation 4.1) and the constraints (Equation 4.2). Recursive use of the discrete-time state space equation (4.1) yields:

$$x_{i|k} = A^i x_k + \sum_{j=0}^{i-1} [A^j B u_{i-1-j}] \quad (4.4)$$

and by substituting this result into Equation 4.3, the cost function can be written as a quadratic function of the unknown control sequence U and the value of the states at the current time step x_k :

$$J = \frac{1}{2} U^T H U + x_k^T C U + \frac{1}{2} x_k^T Y x_k \quad (4.5)$$

subject to the constraints re-written as:

$$GU \leq W + Sx_k \quad (4.6)$$

In this expression, known as a quadratic programming formulation [4], the time-invariant matrices H , C , Y , G , W , S are calculated to maintain mathematical equivalence to Equations 4.2 and 4.3. The cost function is optimized by finding the set of values U which will minimize this expression. Once this optimal value of U is found, the corresponding value of u_k is applied by the controller as its input to the plant at the current time step. The rest of the values of $U = [u_{k+1} \ \cdots \ u_{k+P-1}]^T$ are discarded, and the entire set of calculations will be repeated at the next time step, which will then be considered the new u_k point. This method, known as a receding horizon approach, lends robustness to the MPC, but also gives it the disadvantage of being computationally intensive. The size of the optimization problem can be reduced if, in the sequence U , only the $N < P$ inputs are assumed to be free optimization variables, where N is referred to as the control horizon. That is, $U = [u_k \ u_{k+1} \ \cdots \ u_{k+N-1}]^T$ are considered degrees of freedom for optimization. All of the remaining values of $U = [u_{k+N} \ \cdots \ u_{k+P-1}]^T$ will be set to zero.

In many cases, it is necessary to track a reference, rather than simply to regulate the states. The tracking problem can be handled by augmenting the states of the system as $\bar{x}(t) = [x(t) \ y_{ref}(t) \ u(t)]^T$, where y_{ref} is the reference curve for the outputs. The original system of Equation 4.1 is re-written to represent the tracking case, utilizing the augmented form of the states, and assuming that the reference signal is constant

over the future horizon:

$$\begin{bmatrix} x_{k+1} \\ y_{ref,k+1} \\ u_k \end{bmatrix} = \begin{bmatrix} A & 0 & B \\ 0 & I & 0 \\ 0 & 0 & I \end{bmatrix} \begin{bmatrix} x_k \\ y_{ref,k} \\ u_{k-1} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ I \end{bmatrix} \Delta u_k \quad (4.7)$$

$$\begin{bmatrix} \bar{y}_k \end{bmatrix} = \begin{bmatrix} C & -I & 0 \end{bmatrix} \begin{bmatrix} x_k \\ y_{ref,k} \\ u_{k-1} \end{bmatrix} = \bar{C} \bar{x}_k$$

By following substitutions to Equation 4.3,

$$\bar{y}^T Q \bar{y} = \bar{x}^T \bar{C}^T Q \bar{C} \bar{x} = \bar{x}^T \bar{Q} \bar{x} \quad (4.8)$$

$$\bar{x}^T \bar{C}^T S \bar{C} \bar{x} = \bar{x}^T \bar{S} \bar{x} \quad (4.9)$$

The cost function can be adapted to represent the tracking problem, subject to the appropriate constraints:

$$J = \sum_{i=k}^{k+P-1} \left[\bar{x}_{i|k}^T \bar{Q} \bar{x}_{i|k} + \Delta u_i^T R \Delta u_i \right] + \bar{x}_{(k+P)|k}^T \bar{S} \bar{x}_{(k+P)|k} \quad (4.10)$$

$$\begin{aligned} \Delta u_{min} &\leq \Delta u_k \leq \Delta u_{max} \\ \bar{y}_{min} &\leq \bar{y}_k \leq \bar{y}_{max} \end{aligned} \quad (4.11)$$

The cost function can then be converted into a quadratic program, and solved numerically.

4.3.2 MPC for Power Management

A model predictive approach to power management requires an internal model representing the HEV plant. This model will be linearized and placed in state-space form for use in linear MPC design. The full-order model is too complex for this purpose, containing heavy use of look-up tables, logical switches, and several dynamic states. These complexities would create problems during linearization, and the resulting high-order linear system would result in prohibitively large optimization computations for use in real-time. With the full-order model being too complex to be practical, the reduced-order model is used instead, having

been designed with this purpose in mind. In order to be used for linear MPC, the reduced-order plant is linearized around a representative operating point which corresponds to a region in which the motor and engine are propelling, and the ultracapacitor is discharging. For this specific region, the line resistance in the ultracapacitor and the efficiency of the motor are assumed to be constant:

$$R = R_{dis} \quad (4.12)$$

$$\beta = \eta_{discharge}$$

Linearizing the reduced-order model around an operating point yields the following single-state linear state-space system:

$$\begin{aligned} [\dot{\tilde{x}}]_{1 \times 1} &= [A]_{1 \times 1} [\tilde{x}]_{1 \times 1} + [B]_{1 \times 3} [\tilde{u}]_{3 \times 1} \\ [\tilde{y}]_{4 \times 1} &= [C]_{4 \times 1} [\tilde{x}]_{1 \times 1} + [D]_{4 \times 3} [\tilde{u}]_{3 \times 1} \end{aligned} \quad (4.13)$$

where $\tilde{x}$, $\tilde{y}$, and $\tilde{u}$ denote the deviation of each signal from its value at the operating point. The states, inputs, and outputs are defined as:

$$\begin{aligned} x &= [soc] \\ u &= [T_{eng} \quad T_{drive} \quad \omega_{shaft}]^T \\ y &= [soc \quad \dot{M}_{fuel}]^T \end{aligned} \quad (4.14)$$

Here, the ultracapacitor state-of-charge is the only dynamic state, and the only manipulated input (control input) is the engine torque T_{eng} . The other two inputs, torque demand and engine shaft speed, are imposed by the driving cycle and treated as measured disturbances.

The linearized model is causal but not strictly causal, as the D matrix in Equation 4.13 is non-zero. Standard MPC formulations require a strictly-causal internal model, and this was achieved by augmenting 3 very fast first-order filters to the linearized model. Each input $\tilde{u}$ was approximated by its filtered version $\hat{\tilde{u}}$ as follows:

$$\hat{\tilde{u}} = -\frac{1}{\tau} \hat{\tilde{u}} + \frac{1}{\tau} \tilde{u} = \frac{1}{\tau} (\tilde{u} - \hat{\tilde{u}}) \quad (4.15)$$

This is an exponentially stable system, in which the value of $\hat{u}$ will approach δu at a rate controlled by the size of τ . To this end, τ is chosen to be 1000 times faster than eigenvalue of the A matrix in Equation 4.13. This ensures that the effect of the filters on the speed of the control response is minimal. These filtered inputs are augmented onto the states of the system to obtain:

$$\begin{bmatrix} \dot{\tilde{x}} \\ \dot{\hat{u}} \end{bmatrix}_{4 \times 1} = \begin{bmatrix} [A] & [B] \\ 0 & -\frac{1}{\tau} \\ 0 & -\frac{1}{\tau} \\ 0 & -\frac{1}{\tau} \end{bmatrix} \begin{bmatrix} \tilde{x} \\ \hat{u} \end{bmatrix}_{4 \times 1} + \begin{bmatrix} 0 & 0 & 0 \\ \frac{1}{\tau} & 0 & 0 \\ 0 & \frac{1}{\tau} & 0 \\ 0 & 0 & \frac{1}{\tau} \end{bmatrix} \begin{bmatrix} u \end{bmatrix}_{3 \times 1} \quad (4.16)$$

$$\begin{bmatrix} \tilde{y} \end{bmatrix}_{4 \times 1} = \begin{bmatrix} \begin{bmatrix} C \end{bmatrix} \\ \begin{bmatrix} D \end{bmatrix} \end{bmatrix} \begin{bmatrix} \tilde{x} \\ \hat{u} \end{bmatrix}_{4 \times 1}$$

Equations 4.13 and 4.16 can be used when the operating point is chosen at the system equilibrium. In the power management problem considered here, however, the chosen operating point is not an equilibrium of the system, because as long as the motor power is non-zero, state of charge dynamics will not reach equilibrium even with constant inputs¹. In order to handle the transience of the state at the operating point, x and y are tracked instead of $\tilde{x}$ and $\tilde{y}$:

$$\begin{aligned} \dot{x} &= \dot{\tilde{x}} + \dot{x}_{op} \\ y &= \tilde{y} + y_{op} \end{aligned} \quad (4.17)$$

where $\dot{x}_{op}$ shows the time rate of change of the state at the chosen operating point. By introducing another fast first-order filter:

$$\dot{\hat{x}}_{op} = -\frac{1}{\tau} \hat{x}_{op} + \frac{1}{\tau} \dot{x}_{op} \quad (4.18)$$

¹ State of charge is an integrating state and therefore a rigid mode.

the state-space Equation 4.16 can be rewritten in terms of x and y .

$$\begin{bmatrix} \dot{x} \\ \dot{u} \\ \dot{\hat{x}}_{op} \end{bmatrix}_{5 \times 1} = \begin{bmatrix} [A] & [B] & 1 \\ 0 & -\frac{1}{\tau} & 0 & 0 & 0 \\ 0 & 0 & -\frac{1}{\tau} & 0 & 0 \\ 0 & 0 & 0 & -\frac{1}{\tau} & 0 \\ 0 & 0 & 0 & 0 & -\frac{1}{\tau} \end{bmatrix} \begin{bmatrix} \tilde{x} \\ \hat{u} \\ \hat{x}_{op} \end{bmatrix}_{5 \times 1} + \begin{bmatrix} 0 & 0 & 0 & 0 \\ \frac{1}{\tau} & 0 & 0 & 0 \\ 0 & \frac{1}{\tau} & 0 & 0 \\ 0 & 0 & \frac{1}{\tau} & 0 \\ 0 & 0 & 0 & \frac{1}{\tau} \end{bmatrix} \begin{bmatrix} \tilde{u} \\ \dot{x}_{op} \end{bmatrix}_{4 \times 1} \quad (4.19)$$

$$\begin{bmatrix} y \end{bmatrix}_{4 \times 1} = \begin{bmatrix} C \\ D \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \begin{bmatrix} \tilde{x} \\ \hat{u} \\ \hat{x}_{op} \end{bmatrix}_{5 \times 1} + y_{op}$$

Figure 4.3: Diagram of the signal structure of the MPC. Measured disturbances are the torque demand, shaft speed, and rate of change of the state-of-charge at the operating point. Measured outputs are the ultracapacitor state-of-charge and the rate of fuel consumption. Control Input is the engine torque.

The above linearized system is used as the internal model for MPC design. Figure 4.3 shows a schematic block diagram of the closed-loop system. The two primary outputs are the ultracapacitor state-of-charge and the fuel consumption rate of the engine. The total positive torque demand and the engine shaft speed are imposed by the driving cycle and are therefore treated as measured disturbances. The rate of change of the state-of-charge at the operating point is known and also treated as a measured disturbance to the model. The manipulated (or control) input is the engine torque, and motor torque is found by simply

taking the difference between demand torque and engine torque:

$$T_{mot} = T_{drive} - T_{eng} \quad (4.20)$$

The response of the linear model, at several candidate operating points, was compared to that of the parent nonlinear model. The operating point which resulted in the least amount of disparity (observed qualitatively) was chosen for use in MPC design. The inputs and outputs at the selected operating point are:

INPUTS

$$T_{eng,op} = 31.9033Nm \quad T_{dem,op} = 41.9033Nm \quad \omega_{eng,op} = 171.7902 \frac{rad}{sec} \quad soc_{op} = -5.314 \times 10^{-3}$$

OUTPUTS

$$soc_{op} = 0.7 \quad \dot{M}_{fuel,op} = 5.8717 \times 10^{-4} \frac{kg}{sec}$$

The objective is to minimize the total fuel consumption while also respecting the pointwise-in-time constraints on engine torque, motor torque and state-of-charge. With this in mind, a finite-horizon cost function is formed which penalizes fuel use $\dot{M}_f$, deviation of state-of-charge from its reference value soc_{ref} , and engine torque T_{eng} :

$$J = \sum_{t=t_k}^{t_k+P} \left(q [soc_{ref} - soc(t)]^2 + r [\dot{M}_{fuel}(t)]^2 + s [T_{eng}(t)]^2 \right) dt \quad (4.21)$$

where $t_{k+1} = t_k + \Delta t$, and Δt is a fixed sampling time. P is the prediction horizon, and the scalars q , r , and s represent the penalty weights. These weights can be adjusted, along with soc_{ref} , to shape the performance of the MPC power management scheme. The cost function in Equation 4.21 should be minimized with respect to the control input T_{eng} while enforcing the system dynamics in Equation 4.19 and the inequality constraints shown in Figures 2.7 and 2.9:

$$\begin{aligned} 0 &< T_{eng} < T_{eng,max}(\omega_{eng}) \\ -T_{mot,max}(\omega_{mot}) &< T_{mot} < T_{mot,max}(\omega_{mot}) \\ 0.5 &< soc < 0.9 \end{aligned} \quad (4.22)$$

This constrained optimization problem (converted to a quadratic program) is solved at each sample time: The optimization variables are a sequence of the next N control inputs:

$$[T_{eng}(t_k) \quad T_{eng}(t_{k+1}) \quad \cdots \quad T_{eng}(t_{k+N-1})]$$

The parameter $N \leq P$ represents the number of optimization variables, and is called the control horizon. The optimization is solved in a receding horizon manner; that is only the first calculated control input of a sequence is applied to the plant and at a next step the optimization window is moved forward and the optimization process is repeated.

In simulated implementation, the MPC power management scheme is tested on both reduced- and full-order nonlinear models of the plant. The MPC controller is used only in propulsion mode (positive power demand). During braking (negative power demand) no optimization is necessary; regenerative braking should be given first priority as long as the motor and ultracapacitor charge limits allow, and beyond this the service brakes are activated. Therefore, the rule-based strategy is used to control regeneration during negative power demand.

4.3.3 MPC results

It was found that a step size of $\Delta t = 0.05\text{sec}$ was needed in order for the MPC to properly react to the dynamics of the system. Before implementing the MPC controller for power management, its tracking performance was tested. In this test scenario only deviation from reference state of charge was penalized in the cost function and fuel consumption rate was not penalized. This test configuration was used to track a

Figure 4.4: Inputs used for the tracking case, motor+engine torque and shaft speed, along side their respective operating points. The bias represents the centerline of the input, to illustrate the average distance from the operating point.

state-of-charge reference of 0.6 from an initial state of 0.7 (Figure 4.5) in the presence of sinusoidal torque and speed inputs (Figure 4.4). The centerlines of the inputs were chosen some distance away from the operating point, in order to examine the robustness of the controller. Four different prediction horizons were used, and the results show a drastic decrease in transients as the prediction horizon is increased. However, larger

prediction horizons also result in a slight increase to steady-state error, and will also increase the computation time of the controller as well.

Figure 4.5: Example of the model-predictive controller tracking a reference state-of-charge in the presence of disturbances in torque demand and shaft speed. The controller was applied with four different prediction horizons. Top: Full response. Bottom: Sectioned Views.

Once the tracking ability of the MPC on the reduced-order model was established, the controller was subjected to the UDDS cycle, and the design parameters were tuned to optimize fuel economy. The initial values of the design parameters were chosen as:

$$soc_{ref} = 0.7 \quad q = 1 \quad r = 1000 \quad s = 0 \quad P = 100 \quad N = 1 \quad \Delta t = 0.05sec$$

Recall that P and N are the prediction and control horizons, respectively. During the tracking experiments, it was found that higher prediction horizons and lower control horizons produced better results. However, a prediction horizon of 100 was determined to be too computationally intensive to be practical during the tuning of the other parameters, and a $P = 30$ was found to be the lowest prediction horizon which did not produce an extreme drop in fuel efficiency from the $P = 100$ case. The values of q , r , and s represent the penalty weights on state-of-charge, fuel consumption rate, and engine torque respectively. Because the values

of fuel rate seen under typical driving conditions are small (in kg/sec), this parameter was given a much larger weight than was applied to the state-of-charge. During initial investigation, the performance of the controller was seen to be extremely sensitive to the state-of-charge reference, and the initial value of $soc_{ref} = 0.7$ was varied until it was determined that $soc_{ref} = 0.65$ produced the highest fuel economy. Keeping this value of soc_{ref} fixed, the penalty on state-of-charge was tuned to $q = 0.45$. The resulting set of design parameters is shown below,

$$soc_{ref} = 0.65 \quad q = 0.45 \quad r = 1000 \quad s = 0 \quad P = 30 \quad N = 1 \quad \Delta t = 0.05sec$$

Initially, a weight on engine torque was not present, as it was considered to be redundant with the weight on fuel consumption. However, it was found that adding a non-zero value of s could increase performance, and $s = 0.004$ produced the highest fuel economy. Fixing this value of s and the previously-obtained value of q , the fuel consumption weight $r = 250$ was found to give the best results. Now that the weights in the cost function had been considered, the state-of-charge reference value was re-visited, due to its importance. With the rest of the parameters fixed, it was found that lower reference values performed better, even down to $soc_{ref} = 0$. In order to avoid excessive violations of the imposed lower boundary of $soc = 0.5$, a value of $soc_{ref} = 0.5$ was chosen for the final control configuration. With a satisfactory set of design parameters having been reached, the prediction horizon was raised back to $P = 100$, producing:

$$soc_{ref} = 0.5 \quad q = 0.45 \quad r = 250 \quad s = 0.004 \quad P = 100 \quad N = 1 \quad \Delta t = 0.05sec$$

This final configuration of the model predictive controller was able to obtain a fuel economy increase of 9.59% over the $P_{mot} = 0$ case, out-performing the rule-based strategy by 3.87%, but still falling far short of the DP-estimated 15% potential. This result gives indication that further improvements can be made to the power management strategy of the proposed hybrid powertrain.

The validity of the MPC power management strategy had been confirmed on the reduced-order model, and the controller was implemented on full-order model for a more accurate measure of performance. Based on the earlier sizing experiments, the 40kW motor and 78F ultracapacitor were used in conjunction with the 160kw engine. The design parameters which had been previously optimized were taken as an initial

Figure 4.6: Time history of power provided by the motor and the engine during propulsion of the vehicle over UDDS cycle with zero no road grade, using a 160kW engine, 110kW motor, 93V 78F ultracapacitor, and the model-predictive controller for power management. Simulated using the reduced-order model.

Figure 4.7: Time history of power provided by the motor and the friction brakes during braking of the vehicle over UDDS cycle with no road grade, using a 160kW engine, 110kW motor, 93V 78F ultracapacitor, and the model-predictive controller for power management. Simulated using the reduced-order model.

Figure 4.8: Time history of ultracapacitor state-of-charge over UDDS cycle with no road grade, using a 160kW engine, 110kW motor, 93V 78F ultracapacitor, and the model-predictive controller for power management. Simulated using the reduced-order model.

guess, and the prediction horizon was once again reduced to 30. With the penalty weights held fixed, the state-of-charge reference was varied to produce $soc_{ref} = 0.6$ as the most effective reference. Fixing the state-of-charge reference at this value, it became immediately apparent that the optimal weights from tuning on the reduced-order model were too far from their optimal values on the full-order model to provide a practical starting point. With this in mind, the original starting point was used, and the fuel rate penalty was varied with the other weights fixed at $q = 1$ and $s = 0$ to obtain $r = 500$ as an optimal value. From this point, the process was repeated to obtain $s = 0.005$, followed by $r = 50$. It is interesting to note that the previously obtained reference of $soc_{ref} = 0.6$ was still found to produce the most effective results, yielding:

$$soc_{ref} = 0.6 \quad q = 1 \quad r = 50 \quad s = 0.005 \quad P = 100 \quad N = 1 \quad \Delta t = 0.05sec$$

These parameters were used in the cost function shown in Equation 4.21, with the prediction horizon once again set to a value of 100. Under these conditions, the powertrain was able to achieve a fuel economy increase of 13.1% over the conventional case. Time histories of this simulation are shown in Figures 4.9, 4.10, and 4.11. The MPC displays a much higher utilization of braking energy than that of the rule-based controller, owing to a lower state-of-charge at the beginning of each braking sequence. This fact is consistent with the controller's behavior during the tuning process, which resulted in a state-of-charge reference near the lower constraint of $soc = 0.5$.

Figure 4.9: Time history of power provided by the motor and the engine during propulsion of the vehicle over UDDS cycle with zero no road grade, using a 160kW engine, 40kW motor, 93V 78F ultracapacitor, and the model-predictive controller for power management. Simulated using the full-order model.

Figure 4.10: Time history of power provided by the motor and the friction brakes during braking of the vehicle over UDDS cycle with no road grade, using a 160kW engine, 40kW motor, 93V 78F ultracapacitor, and the model-predictive controller for power management. Simulated using the full-order model.

Figure 4.11: Time history of vehicle velocity and ultracapacitor state-of-charge over UDDS cycle with no road grade, using a 160kW engine, 40kW motor, 93V 78F ultracapacitor, and the model-predictive controller for power management. Simulated using the full-order model.

Chapter 5

Summary and Future Work

Summary

The mild ultracapacitor hybrid powertrain concept proposed in this thesis proved promising in improving the fuel economy of passenger vehicles in city driving. The potential for improvement was assessed in simulations using a detailed model of the powertrain. Two different power management strategies, a rule-based and an optimization-based approach were tested. Various component sizing and control strategies tested consistently indicate a potential for 10 to 15 percent improvement in fuel economy in city driving with the proposed mild hybrid powertrain. This order of improvement to fuel economy was confirmed by deterministic dynamic programming (DP), which finds the optimal power management strategy numerically.

The simple-to-tune rule-based strategy was employed to determine the fuel economy gains with different sizes of motor and ultracapacitor. It was determined that, of the sizes considered, a 40kW motor along with 93V, 78F ultracapacitor was a reasonable and viable choice. After extensive tuning of the rule-based approach, an improvement of nearly 12.9% in fuel economy was demonstrated with this size of components. When the combustion engine was downsized from 160kW to 120kW, it was shown that drivability was not sacrificed, and that the fuel economy was better with the smaller engine in some scenarios but not all. More research is necessary to determine the potential of downsizing the engine, in terms of improved fuel economy and reduced engine cost, and this is relegated to future work.

Minimization of fuel used is by nature an optimization problem, and therefore a part of this research focused on formulating and solving the power management problem in an optimization-based framework. To facilitate the design of an optimization-based strategy, a reduced-model of the powertrain was developed.

Application of dynamic programming to this reduced-order model over the UDDS cycle revealed a gap between the calculated best possible fuel economy and what could be achieved with rule-based method. To that end, the reduced-order model was used to develop a real-time optimization-based controller by applying the method of Model Predictive Control (MPC), which was able to reduce fuel consumption more effectively than the rule-based strategy. Finally, the model predictive controller was used to manage the power split between the 160kW engine, and the 40kW motor and 78F ultracapacitor. After tuning, this configuration was able to achieve a fuel economy increase of 13.8%.

Future Work

The mild ultracapacitor hybrid powertrain has been shown to improve the fuel economy under urban driving conditions, without having any impact on the vehicle's demand response. However, the performance of the powertrain may be further improved. The dynamic programming results indicate that improvements to the implemented control strategy may be possible. Several possible improvements to both power management strategies are discussed here.

The rule-based strategy was shown to be inferior to the model predictive controller, but the computational demands of model predictive control may make a rule-based controller more desirable. The algorithm used in this study was only a first iteration of the concept. One likely improvement to the rule-based controller is the adaptation of a more sophisticated curve for the desired engine power (seen as P_{ref} in 3.1). This is the curve to which the controller compares the current engine power demand, in order to calculate the desired motor power. Another potential improvement is to explore different possible functions for K_{chg} and K_{dis} , shown in Equations 3.1 and 3.2. These are the functions which keep the motor demand from cutting off suddenly at the imposed state-of-charge boundaries of the ultracapacitor.

The model-predictive controller which produced the results in the above sections is also only one potential MPC design. The cost function for this controller, shown in Equation 4.21, places penalties on fuel consumption rate and engine torque, in addition to the deviation of state-of-charge from its reference value. This cost function discourages use of the engine, but does not contain information about the engine efficiency, which is shown in Figures 3.8 and 3.9 to vary widely throughout the potential operating region of the engine. By modeling engine efficiency within the MPC, the controller may be able to use the engine more effectively, rather than simply using it less. Another possible improvement would be to provide a state-of-charge reference which is a function of current driving conditions or demands, rather than simply a

constant.

Another important aspect of the MPC to consider is the reduced-order model on which it is based. The Willans model currently being used to approximate the motor has proven adequate for the MPC to produce a fuel economy increase, but was intended for a DC motor, and is not the most appropriate model available for an induction motor. Likewise, the use of a constant line resistance and capacitance to approximate the ultracapacitor may be improved by adding a temperature input to the model, and allowing for temperature-dependent approximations. Despite the simplifications inherent in the reduced-order model, the MPC was able to perform with this plant as a base, and it is likely that improvements to the MPC itself will be more productive than improvements to the plant.

The rule-based controller was used to estimate the effects of placing a power converter between the ultracapacitor and the motor. This addition may be necessary in order to apply the mild ultracapacitor hybrid concept in a physical prototype. While the addition of this component, by itself, was found to have a negligible effect on the fuel economy in simulations, the effects of a power converter on the aspects of control and component sizing have not been explored.

Another consideration for improvement of fuel economy is the shifting strategy used for the transmission. The strategy currently used has not been optimized for this specific powertrain configuration, and the behavior of the ultracapacitor-based assistance may have a noticeable impact on the appropriate gear ratio of the transmission.

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