Thesis for the Degree of Licentiate of Engineering

On Optimization of Plug-in Hybrid Electric Vehicles

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Abstract

The rising concerns about the global warming and emissions on one hand, and the limited sources of fossil fuels on the other hand, has made electrification of vehicles an interesting topic among researchers and companies. *Hybrid electric vehicles* (HEV) have been on market for several years. These vehicles proved to decrease the fuel consumption due to downsized engine, regeneration of the braking energy, and the higher efficiency gained from the extra freedom in choosing the engine operating points. Plug-in HEVs have the additional ability to store energy from the electricity grid using large capacity batteries. The extra source of energy in these systems opens new questions concerning both the energy management (the strategy that decides the power split between power sources) and sizing of the components.

The first part of the thesis is on energy management strategies for a PHEV. A trivial strategy is to run the vehicle on battery energy until the battery reaches a lower level and then keep the battery state of charge around that level. This strategy requires no information about the trip; however, it does not result in the best fuel economy. An energy management strategy is proposed for PHEVs which is based on minimizing an equivalent fuel consumption. To implement this strategy, some a priori information about the trip is required. The proposed strategy can improve the fuel economy considerably, even when using only information about the trip length, compared to the trivial discharge strategy. Increasing the information details about the trip results in fuel consumption close to the optimal, calculated by using dynamic programming, when full information about the trip is available.

The second part of the thesis focuses on design of PHEVs. The goal here is to design a vehicle that has low cost and low fuel consumption. An approach based on convex optimization is used for simultaneous optimization of component sizes and energy management for passenger PHEVs. The optimal sizes of key components, i.e. battery, electric motor, and engine/engine generator unit are obtained by minimizing a cost function, including operational and components costs. The effects of different performance requirement levels, change in prices of components and energy, and also driving pattern of different drivers, on the optimal design are studied. Since the result of the optimization depends highly on the driving cycle, a systematic way to generate driving cycles that reflect driving patterns of different drivers is given.

Keywords: Plug-in Hybrid Electric Vehicles, Energy Management, ECMS, Component Sizing, Driving Cycles.

Acknowledgments

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I am sincerely grateful to Nikolce Murgovski and Lars Johannesson who provided valuable feedbacks on parts of this thesis. I have also spent some time at Volvo cars as a part of the HyRange project, this was a great experience for me and I would like to thank the people in this project. Special thanks to Madeleine Persson, I recently realized that most of the favors that I asked her were not her responsibilities, and I never doubted anything!

I should say that I feel very lucky to be surrounded by so many great people. Every single day during last three years I came to the university with a great feel of joy, knowing I would be meeting and talking to you guys, Azita, Roozbeh, Mikael, Sahar, Viktor, Anna-Maria, Kasra, Mona, Marcus, Sajed, and many more. Last but not the least, I want to also thank my family, who have always been supporting and motivating me.

Mitra Pourabdollah
Göteborg, December 2012

List of publications

This thesis is based on the following appended papers:

Paper 1

Mitra Pourabdollah, Viktor Larsson, Lars Johannesson, Bo Egardt, PHEV Energy Management: A Comparison of Two Levels of Trip Information, *SAE World Congress, April 2012, Detroit, Michigan, USA.*

Paper 2

Mitra Pourabdollah, Nikolce Murgovski, Anders Grauers and Bo Egardt, Optimal sizing of a parallel PHEV powertrain, Accepted for publication in *IEEE Transactions on Vehicular Technology*.

Paper 3

Mitra Pourabdollah, Anders Grauers and Bo Egardt, Effect of Driving Patterns on Components Sizing of a Series PHEV, Submitted to *7th IFAC Symposium on Advances in Automotive Control , September 2013, Tokyo, Japan.*

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Part I

Introductory chapters

Chapter 1

Background

The development both in technology and economy on one hand, and the growing population on the other hand, has dramatically increased the mobility and transportation in the last decades. Although transportation has made life easier for people in many ways, it has raised concerns about the limited sources of fossil fuels and the impacts on the environment. The transportation sector is a major consumer of energy and emits a high amount of pollution [1]. Suggested solutions for this problem requires motivating higher use of public transportation and developing cleaner and more fuel efficient vehicles, including electrification of vehicles.

1.1 Electrified vehicles

Hybrid electric vehicles (HEV) are the first generation of electrified vehicles that, in addition to an *internal combustion engine* (ICE), have an *electric motor* (EM) and an electric energy storage. HEVs can improve fuel efficiency, because of the possibility of downsizing the engine, the ability to recover braking energy, the extra power control freedom gained by the two power sources, and the ability to stop the engine when idle.

In fact, electrified vehicles existed for more than hundred years. The first electric vehicle was built in 1939 by Robert Anderson. At the beginning of the twentieth century, electric vehicles were available in the market, as well as steam or gasoline powered vehicles, and actually, the electric vehicles were a more attractive choice to the customers, since they did not have the problem of unclean gasoline engines and long start up time of steam engines. In 1901, Ferdinand Porsche even developed the first gasoline-electric hybrid vehicle. However, the main problem with this vehicle was the heavy batteries, that could weigh up to 1.8 tones for a four passenger vehicle. Moreover, the invent of electric starters, along with the expansion of the roads, made longer range engine powered vehi-

Figure 1.1: Transportation has raised concerns about the impacts on the environment.

cles dominant products on the roads [2]. It was not until a hundred years later that the concerns about emissions and dependency on limited resources of fuels brought the electrified vehicles back on the market. In 1997, Toyota released the first series of Prius which was a hybrid electric vehicle, making it the top selling hybrid car, by selling more than 2.8 million Prius around the world through October 2012. Today, most of the car manufacturers have their hybrid version of vehicles in the market, for example Honda Civic Hybrid, Toyota Camry Hybrid and Insight, Ford Fusion and Escape Hybrid, Hyundai Sonata Hybrid, and Lexus CT 200h.

The improvements in battery technology and the reduction in cost and weight of the batteries on one hand, and the desire to become independent on the fossil fuels on the other hand, has made the second generation of the electrified vehicles, *Plug-in hybrid electric vehicles* (PHEV), interesting to the manufacturers. PHEVs have the additional ability to store energy from the electricity grid, using large capacity batteries. The stored energy can propel the vehicle on short trips, thereby reducing vehicle's dependency on petroleum and potentially CO_2 emissions. Today, there are several PHEVs available in the markets, like Tesla Roadster, Mitsubishi i-MiEV, Nissan Leaf, Chevrolet Volt, Ford Focus Electric, BMW ActiveE, Renault Fluence Z.E., Toyota Prius Plug-in Hybrid, Renault Kangoo Z.E., Coda, Tesla Model S, and Volvo V60 Plug-in Hybrid.

The extra source of energy in PHEVs has opened issues concerning the optimization of these systems. To maximize the benefits from PHEVs, they can be optimized at three different levels: first, the configuration level, where the best configuration is chosen; second, the design level where the optimal dimensions of different components for the vehicle with a fixed configuration are found; third, the energy management level, where the optimal power flow for the vehicle is decided [3].

Depending on how the power sources in a PHEV interact, they can be categorized into three main types: series, parallel, and series-parallel hybrids. Each of these configurations has its advantages in specific situations [4]. In this thesis, the optimization of series and parallel PHEVs at the energy management and design levels are studied.

The first part of this thesis is on optimization at energy management level. Energy management strategies decide the power split between the ICE and the electric machines, while meeting the power demand at the wheels. The main aim of the optimization is to minimize the total energy consumption while satisfying constraints in the system. For HEVs, the energy management minimizes the fuel consumption, while keeping the *battery state of charge* (SoC) within a specific range. Many different energy management strategies are proposed for HEVs (for example [5] and [6] using ECMS methods, [7] using model predictive control, and [8]) based on a combination of rules and ECMS) resulting in fuel consumption close to the optimum.

For PHEVs, since the electrical energy is cheaper than the fuel energy, it is optimal to run on the battery energy in short distances. In the absence of any information about the trip length, it is also best to run the vehicle on electricity first (depletion mode) and then keep the battery SoC around a lower level (charge sustaining mode). This strategy, called *charge depletion charge sustaining* (CDCS), does not guarantee the best fuel economy and performance for long trips, due to high internal battery losses during the depletion mode, and less power control freedom in charge sustaining mode. In [9], the tradeoff between the available information about the trip and the fuel consumption is shown by using a probabilistic model for the trip length; if the trip is perfectly known, the controller will choose a blended strategy that depletes the battery slowly until the end of the trip, but with increased uncertainty, the strategy will gradually tend towards CDCS. The best strategy is the one that can minimize the fuel consumption using the least possible information about the coming trip. In this thesis an energy management strategy is presented that is based on *telemetry equivalent consumption minimization strategy*, introduced for HEVs in [10]. The method is modified to be used in PHEVs, where it uses only the information about the trip length, along with general information from the driver's past trips. It is shown that the result is close to the optimal value and the method can reduce the fuel consumption considerably compare to CDCS, using relatively low level of detailed information.

The second part of the thesis focuses on the problem of designing electrified vehicles. This is an optimization problem, where the goal is to design a vehicle with low cost *and* energy consumption. Since the problem of energy management influences the performance of the vehicle, both the energy management and the component sizing should be included in the problem. This optimization problem is complex, since both the objective function and the constraints are nonlinear. Genetic algorithms have been used widely to solve this problem, for example in [11], [12], [13], [14] , [15], and [16]. However, these algorithms can not guarantee finding the global optimal solution and they do not scale well with complexity.

An alternative is to use approximations and assumptions to formulate the problem as a convex optimization problem. Once the problem is formulated as a convex optimization problem, it is relatively straight forward to solve it [17]. The method is originally introduced in [18] to simultaneously optimize battery size and energy management for a plug-in hybrid bus. In this thesis, the method is extended to find the optimal size of battery, electric motor, and engine generator unit or internal combustion engine, simultaneously with the energy management, for series and parallel PHEVs. The effect of different factors, e.g., energy prices, battery price, and performance requirements on the optimal design of a PHEV are studied. Furthermore, to design vehicles that match drivers with different driving patterns, relevant driving cycles are generated, considering both the speed profile and the distance distribution of the trips. A Markov process with transition matrices trained by real data is used to generate speed profiles and a Weibull standard distribution function is used to approximate the trip distance distributions of different drivers.

1.2 Contribution

The main contributions of this thesis are:

- A modification of T-ECMS [10] is presented for energy management of PHEVs. The method is based on the idea to use the information about the trip length to discharge the battery close to the optimal discharge behavior, i.e., at a slower rate until reaching the destination. The algorithm is presented in Paper 1.

- An extension of the convex optimization method used for powertrain dimensioning in [19] is given for finding the optimal design of a PHEV. The method gives the optimal size of battery, electric motor and internal combustion engine, and the optimal energy management for both parallel and series PHEVs, over a predefined driving cycle. The method is presented in Paper 2 for a parallel PHEV, and it is used for dimensioning a series PHEV in Paper 3.

- A study of the influence of different levels of performance requirements, and battery and energy prices on the optimal design of a PHEV, presented in Paper 2.

- A method for generating driving cycles which represent real life driving patterns, including driving distance distributions of different drivers given in Paper 3.

1.3 Thesis outline

This thesis is presented in two main parts. Part I serves as a general introduction to the field and overview of the methods used in papers. In Chapter 2, the models of PHEVs and their main components, different driving cycles, and the performance requirements are presented. Chapter 3 gives an overview on different energy management strategies used in Paper 1. The chapter continues with an introduction on convex optimization problems and the approaches taken to use the method in Papers 2 and 3. A brief summary of the appended papers is provided in Chapter 4 and finally the conclusions are drawn in Chapter 5. In Part II of the thesis, the three publications are included.

Chapter 2

Modeling

This chapter gives a background on the vehicle model, powertrain configurations and component models, driving cycles, and performance requirements.

2.1 Model requirements

The vehicle model is simulated in Matlab/Simulink ® using quasi-static models. In a quasi-static model, instead of using more correct but complex mathematical descriptions of the system, most of the dynamics are neglected and speed dependent characteristics are obtained from stationary relations. Using quasi-static models reduces computational burden, while describing the system behavior well.

The simulations are run backward over known driving cycles. In the backward simulations, the tractive force required at the vehicle wheels, the required speed, torque, or power of each component are calculated from the known driving cycle. Since the calculation of the power is the opposite of the flow of power in real process, the simulation is called backward. This is different from forward simulation, in which a control loop is used to control the throttle position to follow the target speed.

2.2 Vehicle model

The longitudinal dynamics of a vehicle is affected by different forces acting on the vehicle, i.e., the aerodynamic losses, F_a, rolling friction losses, F_r, the uphill driving force, F_g, and the traction force from the prime movers, F_t, as shown in Fig. 2.1. Knowing the vehicle's speed, v, and the total mass, m_{tot}, the power demand can be calculated from the forces as

$$P_{dem} = F_t v = (m_{tot} d\frac{v}{dt} + F_r + F_g)v + F_a v \qquad (2.1)$$

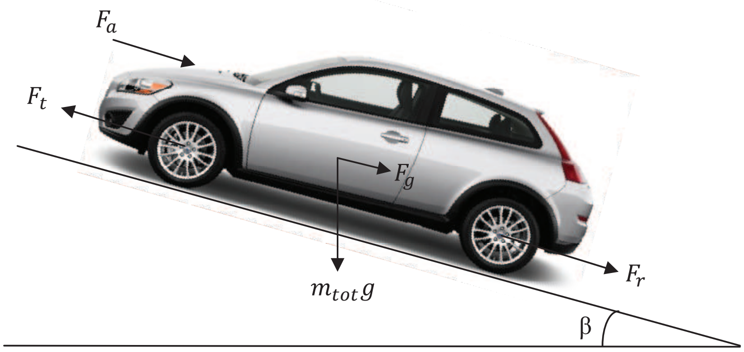

Figure 2.1: Different forces acting on a moving vehicle.

All the forces, except aerodynamic force, are dependent on the total mass of the vehicle, therefore, the power demand can be calculated as

$$P_{dem} = P_m m_{tot} + P_a. \tag{2.2}$$

2.3 Powertrain model

PHEVs have two or more power sources, usually a motor to convert the electrical energy and an engine to convert the fuel energy, in addition with an electrical energy storage. Dependent on how these power sources interact, PHEVs can be categorized into different types.

Series hybrid

In a series PHEV, as shown in Fig. 2.2, it is only the *electric motor* (EM) that powers the wheels. The *engine generator unit* (EGU) is the primary engine connected to a generator that produces electricity. The EM can be powered by the battery and/or the EGU. The battery can be charged by the EGU, from the braking energy, or from the grid. Series vehicles are suited for city drive, since the engine is not connected to the wheels and the EM, compared to the engine, has a better efficiency at low speeds and can deliver higher torque. The engine can be downsized to get a better efficiency and conventional mechanical transmission elements can be removed. However, series vehicles are slightly heavier and more expensive than parallel PHEVs, because in addition to a generator, they need a large battery and an EM that can provide the maximum power demand.
The power balance equations for a series PHEV are given by

$$T_{EM}\omega_{EM} + P_{brk} = P_{dem}, \tag{2.3}$$

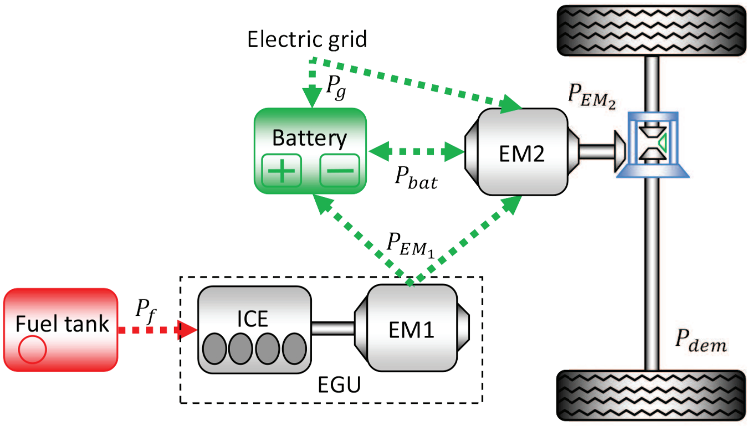

Figure 2.2: Configuration of a series PHEV (solid lines are the mechanical link and dashed lines are the electrical links).

$$P_{EM} = P_{EGU} + P_{bat} - P_{aux}, \tag{2.4}$$

where P_{dem} is the power demand; P_{brk} is the power dissipated at the friction brakes; T_{EM} and ω_{EM} are the torque and speed of the EM, P_{EM} is the electrical power of the EM; P_{bat}, P_{EGU}, and P_{aux} are the battery power, the electrical power of the EGU, and the electrical power used by auxiliary devices. The battery can be charged at charging occasions which gives

$$P_{bat} = -P_g \eta_g. \tag{2.5}$$

where P_g is the grid power (including the losses) and η_g is the charger efficiency. For simplicity, the rotational inertia of the wheels, the differential, the EM, and the EGU are neglected in the models.

Parallel hybrid

In a parallel PHEV, as shown in Fig. 2.3, both the EM and the *internal combustion engine* (ICE) are directly connected to the wheels, either on the same axle or different axles. Since both the EM and ICE are connected to the axles, they should have the same speed as the shaft. A parallel PHEV has no generator, but the motor functions as a generator during braking. Parallel vehicles are suited for highway driving, where the engine propels the vehicle with a good efficiency. Since the engine is directly connected to the wheels, the losses due to the conversion of energies, as in series PHEVs, will be omitted. The additional power for acceleration or climbing hills is provided by the electric motor. A drawback of the parallel configuration is the need for a clutch to mechanically disconnect the ICE during idling.

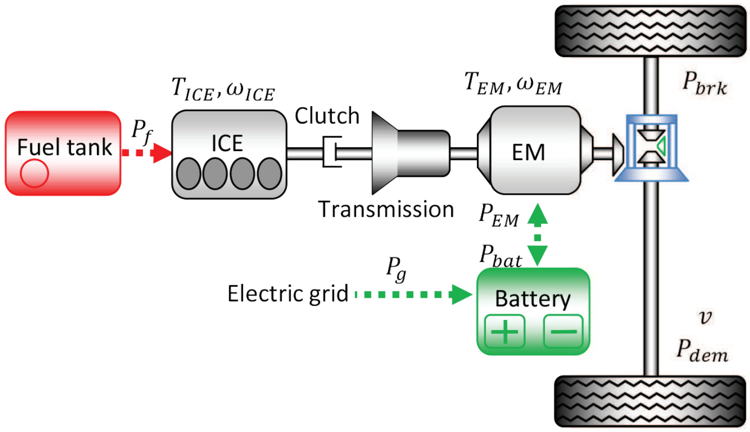

Figure 2.3: Configuration of a parallel PHEV (solid lines are the mechanical link and dashed lines are the electrical links).

The power balance equations for a parallel PHEV are given by

$$T_{EM}\omega_{EM} + e_{on}T_{ICE}\omega_{ICE}\eta + P_{brk} = P_{dem}, \tag{2.6}$$

$$P_{EM} = P_{bat} - P_{aux}, \tag{2.7}$$

where T_{ICE} and ω_{ICE} are the torque and speed of the ICE, e_{on} is the engine on-off variable, and η is the transmission efficiency which depends on the choice of gear.

2.4 Powertrain components

In this section, the quasi-static models of the main components of PHEVs are described.

2.4.1 Battery

Batteries are one of the key components of HEVs. They can save the electrical energy in form of chemical energy and thus work as a reversible energy storage. Different technologies are used in the batteries of electrified vehicles, each having its characteristics. Some of the commonly used are lead-acid, nickel-cadmium, nickel-metal hydride, and lithium-ion. To capture the characteristics of different batteries and also the dynamic behaviors, a complex model is needed. However, to reduce the complexity in calculations, the battery is modeled as a steady state battery equivalent circuit, which is an open circuit voltage, V_{oc}, in series with an internal battery resistance, R, as shown in Fig 2.4.

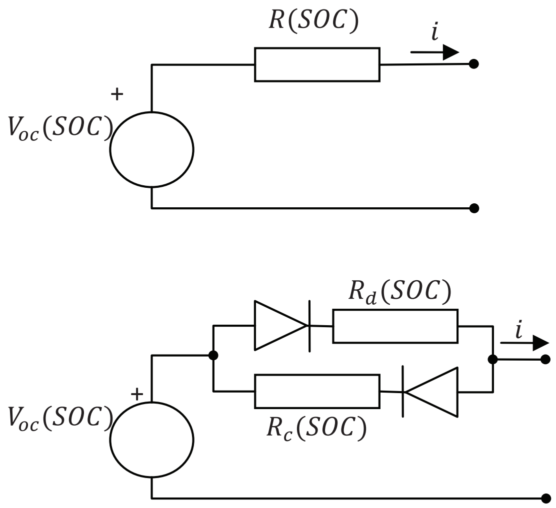

Figure 2.4: The battery equivalent circuit, as an open voltage in series with an internal resistance (upper); the resistance can have different values at charging or discharging modes (lower).

The battery current, i, can be calculated as:

$$i = \frac{V_{oc} - \sqrt{V_{oc}^2 - 4RP}}{2R}, \tag{2.8}$$

where P is the output power of the battery. For a battery with a capacity of Q, the SoC changes with

$$\frac{d}{dt}(SoC) = -\frac{i}{Q}. \tag{2.9}$$

Using the total capacity of the battery can deteriorate its lifetime, therefore only around 20% of the total battery capacity of HEVs and around 60-80% of the total battery capacity of PHEVs are used.

2.4.2 Electric motor

The electric motors used in electrified vehicles are mostly permanent magnet synchronous AC, due to their higher efficiency and power density. The EM is modeled by a static loss map which relates the electrical power to the mechanical power. The electrical power is hence

$$P_{EM} = T_{EM}, \omega_{EM} + P_{EM,loss}. \tag{2.10}$$

The losses, include copper (torque and speed dependent), iron, and winding (speed dependent) losses. For simplicity, it is assumed that the losses in the

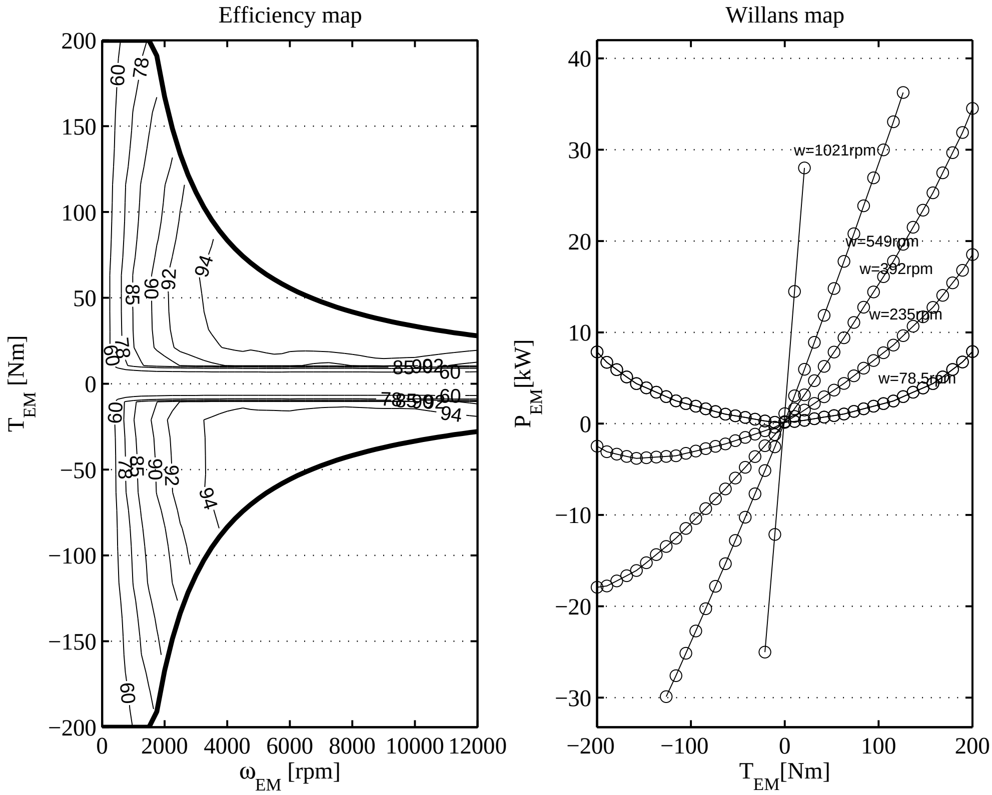

Figure 2.5: The efficiency map (left) and the Willans map (right) for a 35kW permanent magnet synchronous EM.

power electronics are also included in the EM losses. The EM model can be described by an efficiency map as a function of torque and speed, or by the electrical power as a function of torque at different motor speeds (known as Willans approach [20]):

$$\eta_{EM} = f_\eta(T_{EM}, \omega_{EM}) \tag{2.11}$$

$$P_{EM} = f_p(T_{EM}, \omega_{EM}). \tag{2.12}$$

The typical characteristics of these models are shown in Fig. 2.5. The Willans line can be approximated by a second order polynomial as

$$P_{EM}(\omega_{EM}, T_{EM}) = c_1(\omega_{EM})T_{EM}^2 + c_2(\omega_{EM})T_{EM} + c_3(\omega_{EM}). \tag{2.13}$$

where the coefficients c_1, c_2, and c_3 are functions of ω_{EM} and therefore are time dependent. These coefficients are calculated using least squares method for grids over ω_{EM} to fit the second order polynomial to the measured data.

To vary the size of the EM, the torque and the losses are assumed to scale linearly with a scaling factor, s_{EM} [21], [22]. Hence, given a baseline EM model, the losses of the scaled EM are calculated as

$$
\begin{aligned}
P_{EM,loss}(\omega_{EM}, T_{EM}) &= s_{EM} P_{EM,loss,base}(\omega_{EM}, T_{EM,base}) \\
&= s_{EM}\left(c_1(\omega_{EM}) T^2_{EM,base} + c_2(\omega_{EM}) T_{EM,base} + c_3(\omega_{EM})\right) \\
&= s_{EM}\left(c_1(\omega_{EM})\left(\frac{T_{EM}}{s_{EM}}\right)^2 + c_2(\omega_{EM})\frac{T_{EM}}{s_{EM}} + c_3(\omega_{EM})\right) \\
&= c_1(\omega_{EM})\frac{T^2_{EM}}{s_{EM}} + c_2(\omega_{EM}) T_{EM} + c_3(\omega_{EM}) s_{EM}.
\end{aligned} \tag{2.14}
$$

2.4.3 Internal combustion engine

The engines used in PHEVs are usually spark ignited gasoline or compression ignited diesel internal combustion engines. These engines can be described by a quasi-static model, which is either measured from engine experiments at steady-state or calculated by engine process simulation programs. The model gives the fuel consumption as a function of the engine torque and speed. The models are either given as an efficiency map, which is a function of engine torque and speed, or as the fuel power as a function of torque, at different engine speeds, called Willan's lines. The Willans lines can be approximated by a second order polynomial as

$$
P_{f,base}(\omega_{ICE}, T_{ICE,base}) = b_1(\omega_{ICE}) T^2_{ICE,base} + b_2(\omega_{ICE}) T_{ICE,base} + b_3(\omega_{ICE}) \tag{2.15}
$$

where the coefficients b_1, b_2, and b_3 are functions of ω_{ICE} and therefore are time dependent. The efficiency map of the ICE and the Willans map with the approximated second order polynomials are shown in Fig. 2.6 To vary the ICE size, we assume that the torque and the losses are scaled linearly with a scaling factor, s_{ICE}. Linear scaling has been used by many authors (e.g., in [21] and [23]). Linear scaling is valid for scaled sizes close to the baseline size and for an ICE with fixed number of cylinders. Assuming linear scaling, the efficiency of a scaled ICE, η_{ICE} is given by

$$
\eta_{ICE}(\omega_{ICE}, T_{ICE}) = \eta_{ICE,base}(\omega_{ICE}, \frac{T_{ICE}}{s_{ICE}}). \tag{2.16}
$$

Using (2.15), the fuel power of the scaled engine is calculated in a similar way as EM

$$
P_f(\omega_{ICE}, T_{ICE}) = b_1(\omega_{ICE})\frac{T^2_{ICE}}{s_{ICE}} + b_2(\omega_{ICE}) T_{ICE} + e_{on} b_3(\omega_{ICE}) s_{ICE}. \tag{2.17}
$$

The variable e_{on} is introduced to remove the idling losses b_3, when the ICE is off.

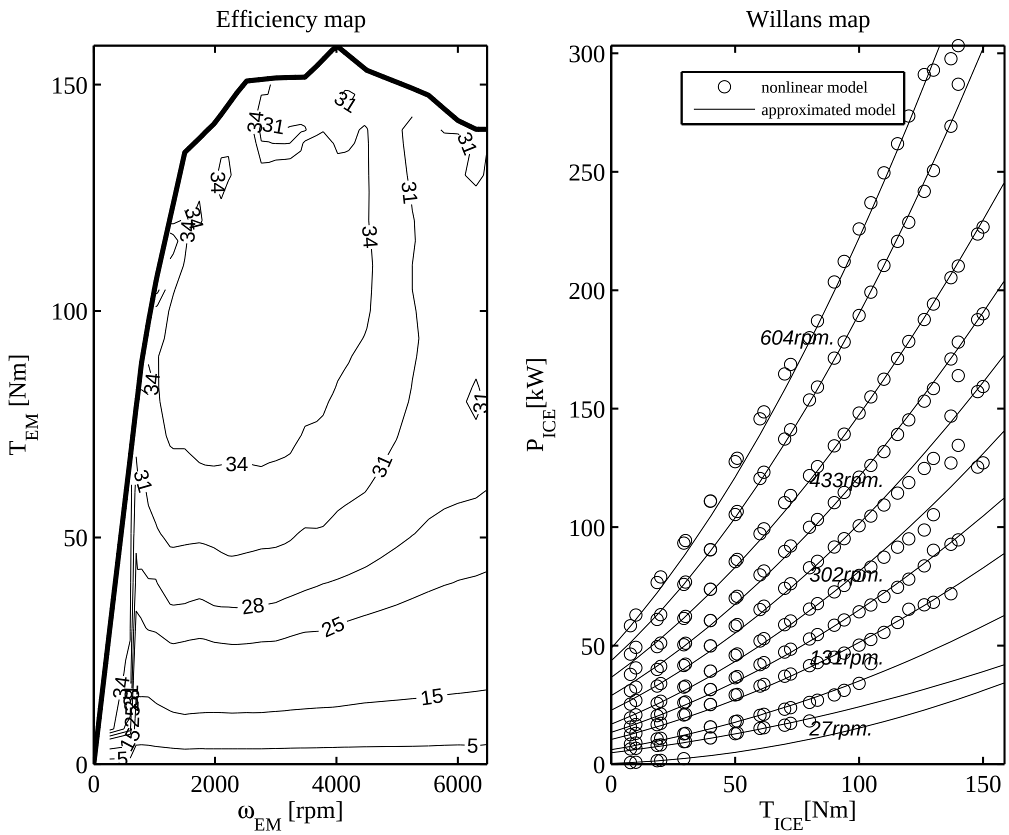

Figure 2.6: The engine efficiency as a function of engine speed and torque (left) and the fuel power as a function of engine torque for different engine speeds (right) as a function of the output power for a 65kW naturally aspirated spark ignited ICE.

2.4.4 Engine generator unit

An EGU is a combination of an engine connected electrically to a electric generator. Since the operating point of the EGU is not related to the output speed or torque at the wheels, it can be chosen in a way to maximize the total efficiency for every power demand [3]. The EGU model is the fuel power as a function of the output power, as shown in Fig. 2.7. The fuel power of an EGU can be approximated by a second order polynomial as

$$P_f(P_{EGU}) = a_1 P_{EGU}^2 + a_2 P_{EGU} + e_{on} a_3 \tag{2.18}$$

where the coefficients a_1, a_2, and a_3 are are found by least squares. Assuming linear losses, the fuel power of a scaled EGU is calculated similarly as for EM

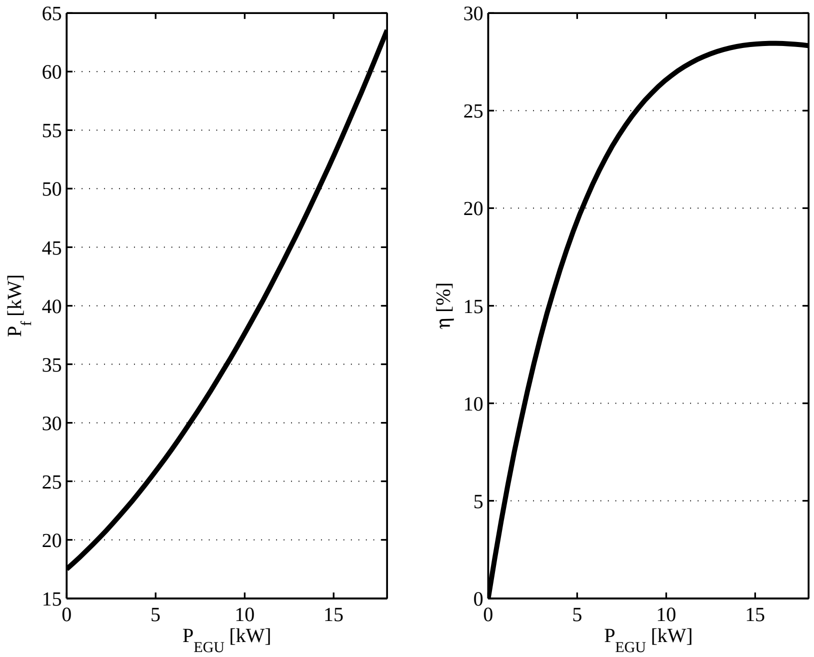

Figure 2.7: The map for a 18kW EGU.

and ICE as

$$P_f(P_{EGU}) = a_1 \frac{P_{EGU}^2}{s_{EGU}} + a_2 P_{EGU} + e_{on} a_3 s_{EGU}. \tag{2.19}$$

2.4.5 Transmission, final drive and clutch

Gear boxes are used in vehicles to transform the speed and torque on the differential side to the desired speed and torque on the engine side. This is because the speed range of the engine is very different compared to the speed range of the wheels. Moreover, the speed range of the engine where the torque and power are at the maximum is narrow.

To choose the gears at every time instant k, a gear shifting strategy is needed. There are different strategies based on torque, efficiency, or speed of the vehicle. Usually a hysteresis model is applied to prevent frequent gear changes. The gear shifting strategy can also be changed to either give a better fuel economy or a better performance.

Usually, in systems with two rotating parts, there is a need for a clutch. The clutch is used to connect the two shafts while they rotate with the same speed and decouple them when their speeds are different. We assume that the model does not allow any slip in the clutch at low speeds, and the PHEV is propelled by the EM. The dynamics of the gear box and the clutch are neglected in this thesis and the efficiency is assumed to be constant. Knowing the gear and the vehicle's speed, the angular speeds ω_{EM} and ω_{ICE} are calculated at every time instant.

2.4.6 Cost and weight models

The models of the key components of a PHEV are scalable, therefore, a model for the cost and weight of these components as a function of sizes is needed. For all the components, i.e. battery, EM, ICE, and EGU, we assume an initial cost, and linear cost and weight that increase with the sizes. In this way, the cost and weight models of these components are described by

$$\begin{aligned} cost &= cost_i + cost_s\, s \\ m &= m_s\, s. \end{aligned} \tag{2.20}$$

2.5 Driving cycle

Driving cycles are used as a reference to assess the performance of a vehicle, for example the fuel consumption or emissions. For conventional vehicles, the speed profile of the vehicle is used to asses the performance, however, for PHEVs, since the vehicle can be charged from the grid, the driving distance between charging occasions need to be considered. A driving cycle typically includes vehicle's velocity, v, possibly road's inclination, β, at each point of time, and charging times between the trips, with constant acceleration during a time step, h.

2.5.1 Speed profile

The speed profiles of driving cycles can be given by available standard driving cycles, logged data from real life driving, or generated driving cycles.

Standard driving cycles

Standard driving cycles are produced by organizations to make comparison of performances of different vehicles possible. However, since typical driving conditions varies among regions, specific driving cycles are made for different regions. Some of the most common driving cycles are new European driving cycle (NEDC), federal test procedure 75 (FTP75) from USA, Japanese 10.15 Mode, and CUEDC from Australia. The effect of using different standard driving cycles on fuel economy has been studied in [24], [25], [26], and [27].

Real-life driving cycles

Although using standard driving cycles is a good way to compare the performance of different vehicles, in general the results are limited since these cycles are short and they do not represent real-life driving behaviors. Therefore, it is sometimes necessary to use measured driving data to assess the performance. In this thesis, two data bases of real-life driving data are used. The first database [1] contains data collected from two Volvo V70 plug-in hybrids driven as private cars by 16 families each for some weeks in Gothenburg during year 2010. In total there are 3617 trips in this database. The second database [2] contains driving data from 500 privately cars, each driven at least for 30 days [28]. The data is logged using equipment containing GPS units and includes time, position, velocity, and number and id of the used satellites.

Driving cycles generated by Markov chains

Markov Chains can be used to capture the features of real-life driving in a compact form and to then generate representative driving cycles [29]. This method of generating driving cycles gives flexibility in constructing arbitrary driving cycles with desired lengths. The procedure is as follows: first, real life driving cycles are sorted based on desired characteristics, for example trip distance. For each group of these data, the information is extracted in form of a probability matrix. This so called transition matrix includes probabilities of moving from one state to another (the state is characterized by the velocity v and the acceleration a), defined as

$$P_k(V_{k+1} = v_{k+1}, A_{k+1} = a_{k+1} | v_k, a_k). \tag{2.21}$$

The probabilities are saved in the transition matrix for all the possible combinations of v_k and a_k. From the transition matrix corresponding to a desired characteristic, the driving cycle can be synthesized.

2.5.2 Driving distance distribution

To determine the performances of PHEVs in general, in addition to the speed profile of a driving cycle, it is also important to know how often the driver has access to a charging station, or how far he/she drives between two charging occasions. Therefore, to assess the performance of PHEVs, one needs to model the driving distance distribution. In this thesis, to model the driving distance distribution real-life data is first used to study how different people drive. It is worth mentioning that in the database, trips are separated if the data is missing

[1] provided by ETC Battery and FuelCells Sweden AB
[2] provided by the Test Site Sweden (TSS) project

for more than 10 seconds. However, for PHEVs, the trips should be separated by the charging occasions. Considering the availability of charging stations, and sufficient parking time to charge the battery, we can assume different minimum charging time to separate the trips. For simplicity, we consider only daily charging which is a realistic assumption, because it is more likely that the owner of a PHEV has a charger at home with which he can charge the vehicle at nights for around 8 hours.

Usually, the trip length distribution is given for all drivers and over one day, as in [30], [31], [32], [33], and [34]. However, if vehicles are to be designed to match different drivers, it is important to know how each vehicle is driven during its life-time, due to the very different driving behaviors of individual drivers.

We approximate a standard Weibull distribution function to the trip length distribution functions of different drivers. Weibull distribution is defined as

$$f(x, \lambda, k) = \begin{cases} \frac{x}{\lambda}(\frac{x}{\lambda})^{k-1}e^{-(\frac{x}{\lambda})^k}, & x \geq 0, \\ 0, & x < 0, \end{cases} \tag{2.22}$$

with k as shape parameter and λ as scale parameter [35]. Weibull distribution function is widely used in life data analysis due to its versatility. For example, by changing the shape parameter to 1 or 2, the distribution gives the exponential distribution or the Rayleigh distribution. The cumulative distribution function, which represents the probability that the trips have shorter distance than x, is given by

$$f(x, \lambda, k) = 1 - e^{-(\frac{x}{\lambda})^k}. \tag{2.23}$$

By using Weibull distribution functions with different values of λ and keeping k constant, behavior of drivers with different trip distance distributions are approximated. The distributions are shown for several different values of λ in Fig. 2.8.

To generate a mix of stochastic driving cycles, the trip distances for a specific driver are chosen from the Weibull curves, uniformly on the probability/y-axis in a way that a similar distance distribution function is obtained. To get a smooth curve as the Weibull CDF curves, the number of trips chosen on the y-axis should be quite high. However, to reduce the computation time, we choose only 10 trips. Choosing higher number of points does not effect the result a lot. Knowing the trip distances, the corresponding Markov transition matrix is used to generate the driving cycle.

2.6 Performance requirements

Performance requirements are in general more demanding than normal driving, but crucial for commercial success. Some of the important performance requirements are top speed, acceleration at different speed or 0-100km acceleration

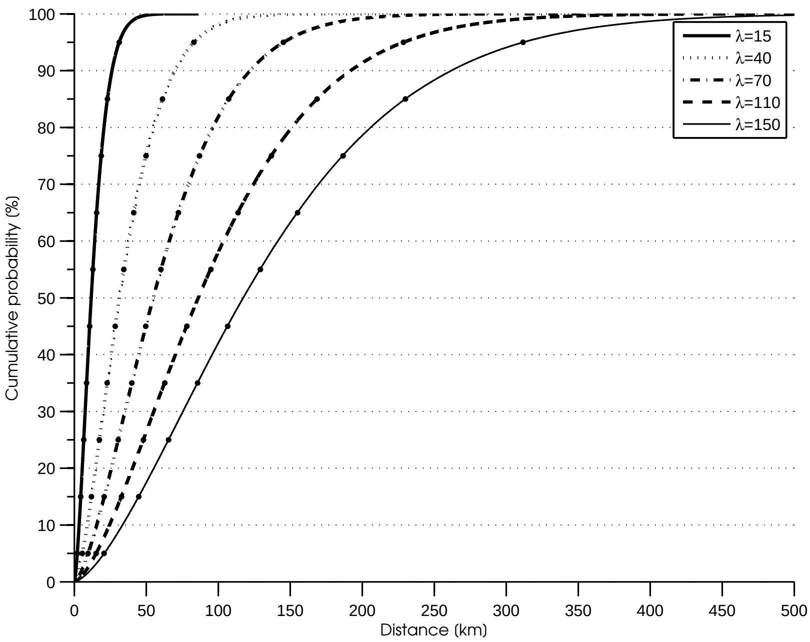

Figure 2.8: Weibull cumulative distribution function for different values of λ and $k = 1.5$.

time, uphill driving, and all electric range for PHEVs. In a series PHEV, since only the EM is directly connected to the wheels, the minimum power of the EM for fulfilling the top speed and uphill driving can be directly calculated. The requirement on acceleration is usually defined as the time the vehicle accelerates from 0 to 100 kph. The EM power also determines the sum of the battery and EGU power.

For a parallel PHEV, since there are two sources providing the power to the wheels, a different way to define the performance requirements is needed. A possible way is to first define a normalized net traction force as a function of speed as shown in Fig. 2.9. The normalized net force is simply the force needed to give the vehicle the required acceleration (or ascent capability), divided by mass. A performance cycle is then made, with speed from zero up to the maximum speed, and accelerations taken from the normalized net force curve. This performance cycle can be added to the driving cycle. The optimization solver finds the components sizes so that they can provide the torque and power to manage the performance requirement.

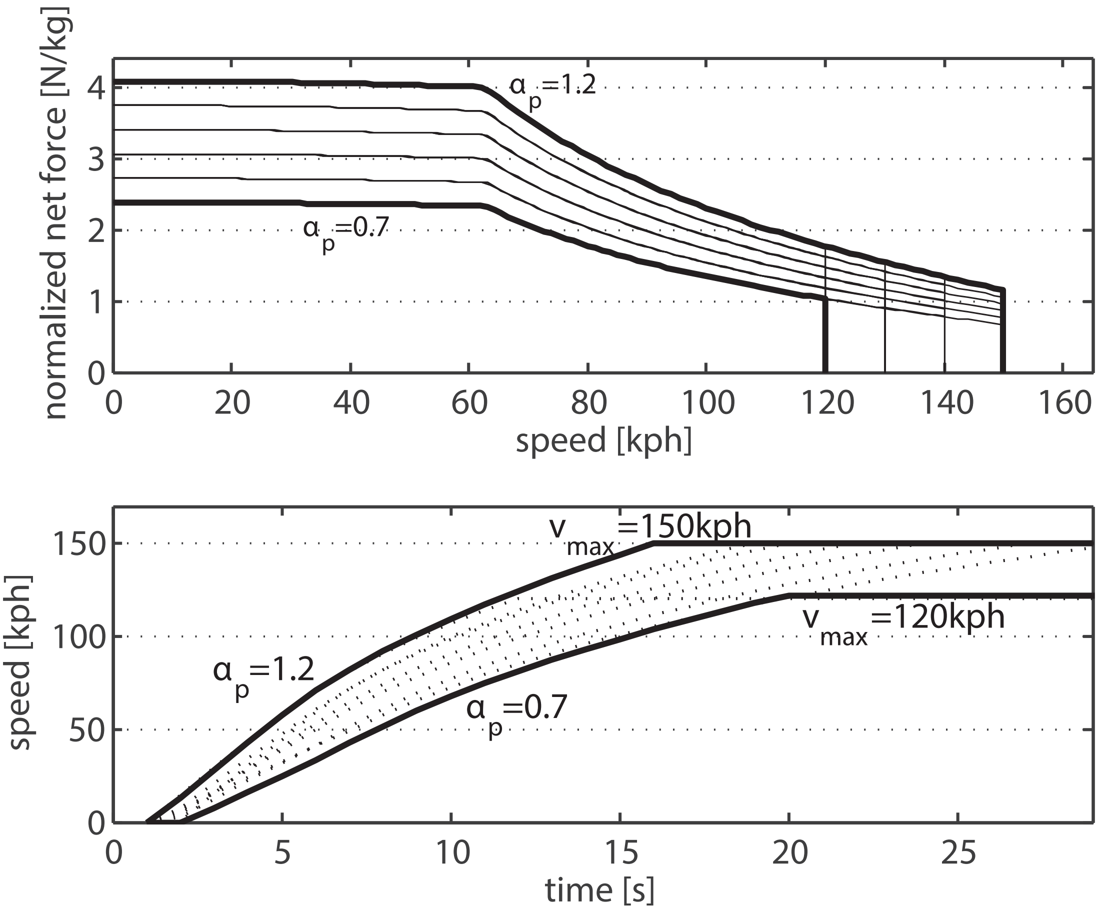

Figure 2.9: Normalized net force as a function of speed (upper), and the generated performance cycles for different levels of performance reqiurements (lower).

Chapter 3

Optimization

This chapter is devoted to studies of optimization problems for a PHEV. These optimization problems can be formulated at three different levels; finding the best configuration; finding the best design or component sizes for a given configuration; and finding the best energy management strategy for an existing vehicle [3]. In Section 3.1, different energy management strategies for a given PHEV are briefly discussed. Energy management strategies decide how the power flows in the system in real time, and the optimization at this level aims at minimizing the total energy consumption for a fixed design of a vehicle.

The second part focuses on the design level optimization. PHEVs have the potential to reduce fuel consumption, but this depends highly on the sizing of the key mechanical and electrical components and the controller splitting the power flow between these components. The simultaneous optimization of component sizes and energy management makes the optimization problem complex, but it turns out that it is possible to pose the problem as a convex optimization problem. The advantage with using convex optimization is that once the problem is formulated as convex, the global optimal solution is obtained by using very effective solvers. The steps taken to formulate the problem of simultaneous optimization of component sizes and energy management as a convex problem are presented in Section 3.2.

3.1 Energy management

As mentioned earlier, the potential fuel consumption savings of a given PHEV depends on the energy management strategy that decides how the power should be split between the power sources. This is an optimal control problem, where the fuel consumption is minimized while respecting some constraints on e.g. the battery SoC or EM and ICE torque. The controller can use some a priori information about the trip, provided by the driver or identified by an algorithm.

Depending on the level of a priori information about the trip, different energy management strategies can be used. The three most common methods are presented in this section.

3.1.1 Charge depletion charge sustaining

One of the simplest energy management strategies used in PHEVs is charge depletion charge sustaining (CDCS). In this strategy, the vehicle first runs on the electrical energy in the battery until the battery is discharged to a lower level. After that and if the trip length is longer than the *all electric range* (AER) of the vehicle, the battery SoC is kept around this lower level. Since electrical energy is cheaper than fuel energy, CDCS is the best strategy in short trips, or in the absence of a priori information about the trip. However, because of high battery losses during the charge depletion mode and less freedom during the charge sustaining mode, this strategy does not guarantee the best fuel economy and performance for trips longer than the AER of the vehicle.

3.1.2 Equivalent consumption minimization strategy

The *equivalent consumption minimization strategy* (ECMS) represents the real-time implementation of the optimal control problem mentioned earlier. In this strategy, an equivalent fuel power is introduced as

$$J_{f,eq}(t) = P_f(t) + s(t)P_{bat}(t), \tag{3.1}$$

where $s(t)$ is an equivalence factor used to convert the electrical power to an equivalent fuel power. At every time instant, the torque is split between the two power sources in a way that $J_{f,eq}(t)$ is minimized. The optimal equivalence factor varies with the driving conditions. Therefore, the equivalence factor that is suitable for one driving cycle may lead to poor performance or even no charge sustaining conditions for another. In reality, the value of the equivalence factor is not known in advance; however, $s(t)$ can be assumed to be constant or tuned online [6]. Different methods to find the equivalence factor are described in [5].

ECMS is originally applied to HEVs to sustain the SoC around a constant level and therefore it needs to be modified to be used in PHEVs to use the energy in the battery. In Paper 1, a method based on *telemetry equivalent consumption management strategy* (T-ECMS) originally introduced for HEVs in [10], is modified to be used for PHEVs.

3.1.3 Dynamic programming

Dynamic programming (DP) is a method to solve optimal control problems numerically, based on the principle of optimality [36]. DP is used to find the global

Table 3.1: Fuel consumption from three energy management methods, CDCS, T-ECMS, and DP

Method	Fuel consumption	Difference from DP
CDCS	943.7	5.2%
T-ECMS	903.2	0.7%
DP	896.7	0%

optimal control input, u, by minimizing a cost function, J, while satisfying constraints. In automotive applications, DP is used by many authors to find the optimal energy management which minimizes the fuel consumption, while satisfying the constraints on the SoC level and the powertrain models (for example in [37], [38], [39], [40], [41], and [42]).

The advantage with dynamic programming is that it can handle complex constraints on inputs and states [3]. However, the computation time which increases exponentially with the number of states, is still an issue despite the efforts that has been done to reduce the burdens [43], [44]. In addition, to use the deterministic DP, the complete trip needs to be known in advance. Therefore, DP is mostly used as a tool to provide a benchmark for assessment of different controllers. For example, in Fig 3.1 the battery SoCs, resulting from the implementation of the method in Paper 1, CDCS, and DP are shown. The fuel consumption of these three methods are also given in Table 3.1.

3.2 Convex optimization

Convex optimization can be used to find the optimal design of a PHEV. The objective function in this problem is a weighted sum of the fuel and electrical energy consumption, in addition to the components costs. The equations governing the power flows in the system act as constraints together with maximum component ratings. The variables in the problem are the component sizes as well as the complete control trajectory of the energy management system. The main challenge in using the convex optimization approach is in formulation. Once the problem is formulated as a convex optimization problem, effective solvers can solve the problem in a straight forward way.

In a general form, a convex optimization problem can be written as

$$\begin{aligned} \inf_x \quad & f_0(x) \\ \text{subject to} \quad & f_i(x) \leq 0, i = 1, ..., m, \\ & h_j(x) = 0, j = 1, ..., p, \end{aligned} \tag{3.2}$$

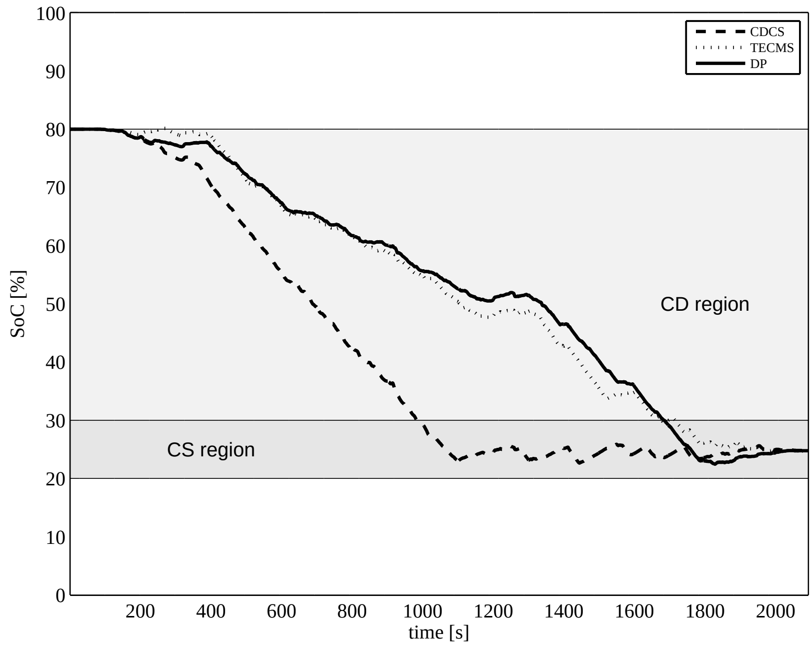

Figure 3.1: The battery SoC from the three energy management strategies, CDCS, T-ECMS, and DP.

where the cost function $f_0(x)$ and the constraints $f_1, ..., f_m : R^n \rightarrow R$ are convex and $h_1, ..., h_p : R^n \rightarrow R$ are affine functions [17]. To formulate the problem as convex, several steps must be taken. As mentioned before, the cost function is the sum of operational and component costs. The operational cost over a discretized driving cycle is calculated considering the consumed fuel and electric power, using the energy prices. The component costs are calculated as the depreciation over the driving cycle, taking the yearly interest rate into account.

3.2.1 Heuristic decisions

As mentioned, in a convex optimization problem, all the functions need to be convex (or even affine). Since the set of integer variables is not convex, they need to be found outside the problem by heuristics. Deciding these variables, the rest of the problem is formulated and solved as a convex optimization subproblem. The integer decision variables in our problem are the engine on-off variable and the gear ratio for parallel PHEVs. The engine on-off decision is decided based on the baseline power demand, $P_{dem,base}$, required by the vehicle when following a driving cycle. The baseline mass, m, used to calculate $P_{dem,base}$, is the mass of the vehicle with the baseline component sizes. It is shown in [19] that the error due to this on-off heuristics is below 1% for a series powertrain.

The gears for a parallel PHEV can be chosen by heuristics based on known variables, e.g., the vehicle's speed and power demand.

3.2.2 Optimization variables

The decision variables of the optimization problem include, firstly, the component scaling factors, s_{bat}, s_{EM}, and s_{ICE}/s_{EGU}, which are all dimensionless scaling parameters. The second group consists of optimization variables which are related to the energy management and are determined for every time instant. These variables vary for different configurations of PHEVs. For a series PHEV, the variables are: the EM and ICE torques, T_{EM} and T_{ICE}, battery current, $\tilde{i}$, battery state of energy, E_b, grid power, P_g, and braking power, P_{brk}. For a parallel PHEV, the variables are: the EM torque, T_{EM}, EGU power, P_{EGU}, battery current, $\tilde{i}$, battery state of energy, E_b, grid power, P_g, and braking power, P_{brk}.

The constraints in (3.2) are the equations governing the power flow in the system, the component models, and the limitations of the components, e.g., the maximum torque of EM and ICE or the maximum current of the battery. Most of the equations introduced in Chapter 2 are convex functions of the decision variables, but some need modification to be formulated as convex functions. The steps taken to formulate the optimization problem of series and parallel PHEVs as a convex problem are given in the next section.

Steps to formulate the problem as convex optimization problem

Since multiplication of variables does not result in a convex function, the output battery power given by

$$P_{bat} = s_{bat}(V_{oc}i(k) - Ri^2(k)). \tag{3.3}$$

will not result in a convex function. A change of variable as $\tilde{i} = s_{bat}i$ is needed, which gives the convex function of

$$P_{bat} = V_{oc}\tilde{i}(k) - R\frac{\tilde{i}^2(k)}{s_{bat}}. \tag{3.4}$$

for positive value of s_{bat}.

Moreover, the result of the optimization gives a real value for s_{bat}, instead of an integer number of cells. This will introduce a rounding error but has a small influence on the optimal result, because either the cell capacity can be considered very small to give large number of cells, or the result can be interpreted as an indication of the optimal pack capacity.

Since a quadratic over linear function $f(x,y) = \frac{x^2}{y}$ is convex for $y > 0$ and a second order polynomial function $f(x) = px^2 + qx + r$ is convex for $p \geq 0$, the

Table 3.2: Convex optimization problem for a series PHEV

Variables	$T_{EM}^N, P_{EGU}^N, P_{brk}^N, \tilde{i}^N, E_b^{N+1}, P_g^{N_c}, s_{bat}, s_{EGU}, s_{EM}$
minimize	$cost(P_f, P_g)$
subject to	$P_{EM}(k) = P_{bat}(k) - P_{aux} + P_g(k)\eta_g$
	$P_{bat}(k) = V_{oc}\tilde{i}(k) - R\frac{\tilde{i}^2(k)}{s_{bat}}$
	$E_b(k+1)(k) = E_b(k) - h(k)V_{oc}\tilde{i}$
	$P_f(k) = a_1\frac{P_{EGU}^2(k)}{s_{EGU}} + a_2P_{EGU}(k) + e_{on}a_3s_{EGU}$
	$P_{EM}(k) >= c_1(k)\frac{T_{EM}^2(k)}{s_{EM}} + c_2(k)T_{EM}(k) + c_3(k)s_{EM}$
	$E_b(k) \in [E_{b,min}, E_{b,max}]$
	$P_g(k) \in [P_{g,min}, P_{g,max}]$
	$P_{EGU}(k) \in [P_{EGU,min,base}, P_{EGU,max,base}]s_{EGU}$
	$T_{EM}(k) \in [T_{EM,min,base}(\omega_{EM}(k)), T_{EM,max,base}(\omega_{EM}(k))]s_{EM}$
	$\tilde{i}(k) \in [\tilde{i}_{min}, \tilde{i}_{max}]$
	$s_{bat} \in [s_{bat,min}, s_{bat,max}]$
	$s_{EM} \in [s_{EM,min}, s_{EM,max}]$
	$s_{EGU} \in [s_{EGU,min}, s_{EGU,max}]$
	$\forall k \in \{0, \ldots, N-1\}$

second order polynomial models for the EM power, fuel power result in convex functions of the optimization variables.

Combining the power balance equations and the equation over the battery power gives a second order constraint function. Since having an equality sign in a second order polynomial constraint does not result in convex formulation, we change the equality sign into inequality. This does not effect the results, since the optimal P_{EM} will satisfy the inequality with equality. This is so, because otherwise energy would be wasted, making the result not optimal.

The convex formulation of the problems are summarized in Table 3.2 and Table 3.3 for series and parallel PHEVs.

As examples of the results obtained using the method for sizing of PHEVs, two results are given. The first one illustrates the optimal operational and component costs of a series PHEV, driven over a 700 km long driving cycle. Since the problem is a Multi-objective optimization problem (the component cost versus the operational cost), the conflicting objectives can be scaled to formulate a single objective optimization problem. The parameter used to scale the problem is in reality related to the lifetime driving distance of a car. By altering this weighting parameter, a so called Pareto front can be obtained as shown in Fig 3.2. The optimization is done for different level of performance requirements considered in the problem.

The second example gives the result of the optimization for a series PHEV. As

Table 3.3: Convex optimization problem for a parallel PHEV

Variables	T_{ICE}^{N}, T_{EM}^{N}, P_{brk}^{N}, $\tilde{i}^{N}$, E_{b}^{N+1}, $P_{g}^{N_c}$, s_{bat}, s_{ICE}, s_{EM}
minimize	$cost(P_f, P_g)$
subject to	$P_{dem}(k) - P_{brk}(k) = T_{EM}(k)\omega_{EM}(k) + e_{on}(k)T_{ICE}(k)\omega_{ICE}(k)\eta(k)$
	$P_{EM}(k) + P_{aux}(k) \leq P_{bat}(k) + P_g(k)\eta_g$
	$P_{EM}(k) = c_1(k)\frac{T_{EM}^2(k)}{s_{EM}} + c_2(k)T_{EM}(k) + c_3(k)s_{EM}$
	$P_{bat}(k) = V_{oc}\tilde{i}(k) - R\frac{\tilde{i}^2(k)}{s_{bat}}$
	$E_b(2:k+1) = E_b(1:k) - h(k)\tilde{i}(1:k)V_{oc}$
	$T_{EM}(k) \in [T_{EM,min,base}(\omega_{EM}(k)), T_{EM,max,base}(\omega_{EM}(k))]s_{EM}$
	$T_{ICE}(k) \in [0, T_{ICE,max,base}(\omega_{ICE}(k))]s_{ICE}$
	$\tilde{i}(k) \in [i_{min}, i_{max}]s_{bat}$
	$E_b(k) \in [SoC_{min}, SoC_{max}]V_{oc}Q$
	$P_g(k) \in [0, P_{g,max}(k)]$
	$s_{bat} \in [s_{bat,min}, s_{bat,max}]$
	$s_{EM} \in [s_{EM,min}, s_{EM,max}]$
	$s_{ICE} \in [s_{ICE,min}, s_{ICE,max}]$
	$\forall k \in \{0, \ldots, N-1\}$

mentioned earlier, the length of the driving cycle highly influences the optimal sizing. To clearly show this, the optimization is done over driving cycles with lengths from 1 to 180 km. For each trip length, 10 different stochastic driving cycles are generated by Markov chains, and the mean (μ) and standard deviation (σ) of the optimal component sizes, in addition to the energy demand of the trip and available battery energy are shown in Fig 3.3.

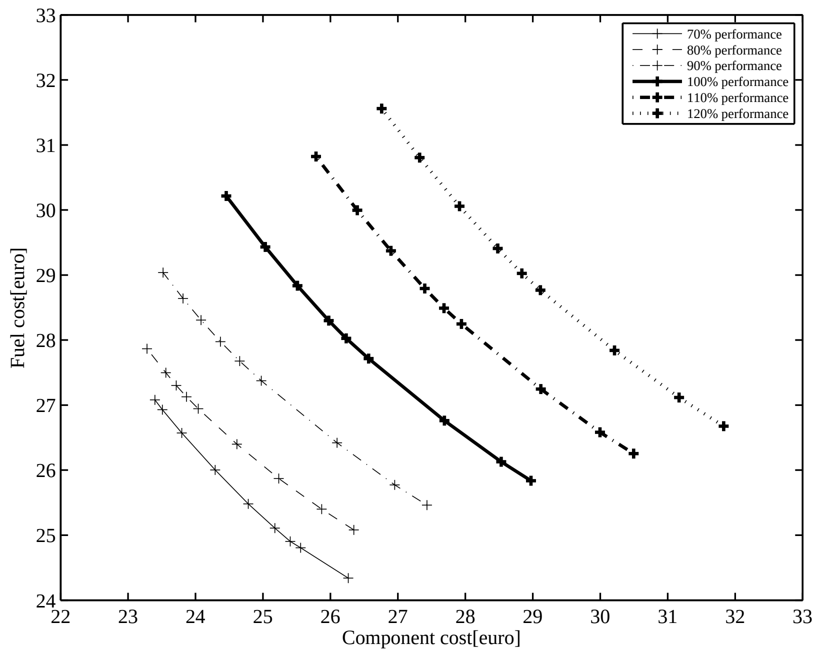

Figure 3.2: Set of pareto points obtained by using different weighting factors between fuel cost and component cost

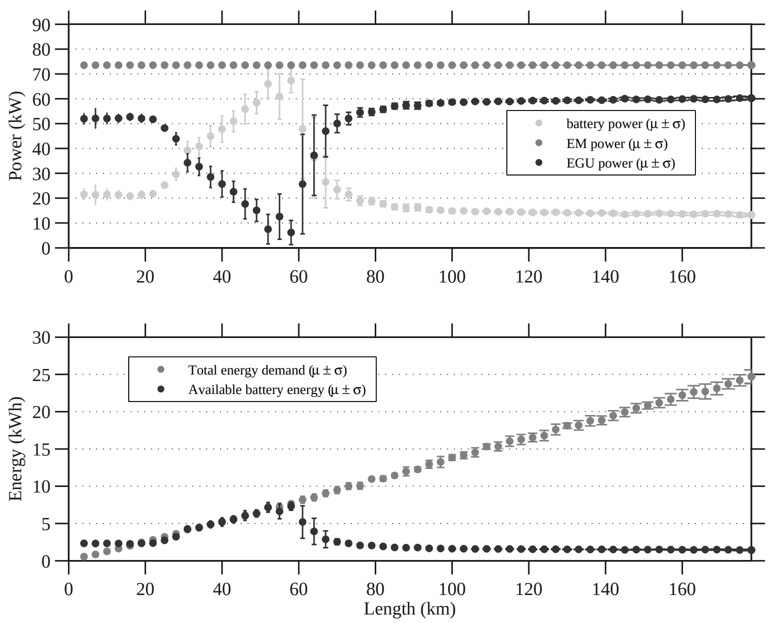

Figure 3.3: Optimal mean battery, EM, and EGU size with the standard deviations, for single trips with different lengths (upper figure); the available battery and demanded energy versus trip distance (lower figure).

Chapter 4

Summary of included papers

In this chapter, a brief summary of the appended papers is provided. Full versions of the papers are included in Part II.

Paper 1

> Mitra Pourabdollah, Viktor Larsson, Lars Johannesson, Bo Egardt, PHEV Energy Management: A Comparison of Two Levels of Trip Information, *SAE World Congress, April 2012, Detroit, Michigan, USA.*

Plug-in hybrid electric vehicles need a controller to split the power between the two power sources. In the absence of any information about the trip, the best strategy is to first deplete the battery and then, if the trip is longer than the all electric range of the vehicle, to sustain the battery state of charge around a lower level. However, fast discharging results in higher battery losses, and therefore does not give the best fuel economy on long driving distances. The optimal energy management is obtained using dynamic programming, knowing the driving cycle fully. This means that there is a tradeoff between improved fuel economy and the need for a priori information. In this paper, a new method for discharging the battery is proposed which is based on telemetry equivalent consumption minimization strategy. The proposed method requires only some general information, in addition to the information about the trip distance.

The results of implementing this method, considering two different levels of detailed information, are compared with the result of implementing charge depletion charge sustaining and dynamic programming methods. The proposed strategy improves the fuel economy considerably compared to charge depletion charge sustaining strategy. More detailed a priori information reduces the fuel consumption, very close to the optimal value.

Paper 2

Mitra Pourabdollah, Nikolce Murgovski, Anders Grauers and Bo Egardt, Optimal sizing of a parallel PHEV powertrain, Accepted for publication in *IEEE Transactions on Vehicular Technology*.

Paper 2 presents a method to find the optimal sizes of the key components , of a parallel PHEV, i.e., the battery, the electric motor, and the internal combustion engine, simultaneously with the energy management. To solve this problem, it is casted as a convex optimization problem. The objective function to be minimized is a weighted sum of the operational cost, i.e., fuel and electricity, and the cost of the key components. The constraints are given by equations governing the power flow in the system and the component models, and by the maximum component ratings. The results of the optimization are the global optimal energy management at every time instant over a given driving cycle and optimal component sizes. The comparably fast computation time of the method allows the use of a long driving cycle, including different driving patterns of a driver over 20 days.

This method can be used as a tool to understand how the optimal cost and design of a PHEV is influenced by different factors, e.g., performance requirements, charging behavior, driving cycle, battery type, energy and component costs, and gear shifting. For example, it is shown that the vehicle cost is more affected by the acceleration requirements, than the requirements on top speed and all electric range. Moreover, with the current price of energy and battery cells, the optimal AER is not very long.

Paper 3

Mitra Pourabdollah, Anders Grauers and Bo Egardt, Effect of Driving Patterns on Components Sizing of a Series PHEV, Submitted to *7th IFAC Symposium on Advances in Automotive Control, September 2013, Tokyo, Japan.*

Paper 3 presents a method to find the optimal design of a series PHEV that matches the driving pattern of a driver. To model the driving pattern of a driver, a driving cycle is needed, that includes not only the speed profile of the driving cycles, but also the distance driven between two charging opportunities. The speed profile of these driving cycles are generated by Markov processes, whose transition matrices are trained by real-life data. Using Markov process enables us to make stochastic combinations of driving cycles with different distances that represent the real life behavior of drivers. To model the driving distance distribution, Weibull standard distribution is used. By changing the parameters, the distribution is altered, to fit the driving distance distributions of different drivers.

The optimal size of the battery, electric motor, and engine generator unit are found over the generated driving cycles, using convex optimization method presented in Paper 2. The objective function to be minimized is the component costs and operational costs over the defined driving cycles. The optimization gives the optimal components sizes simultaneously with the optimal energy management.

The results show that the sizes of the components vary much for different distance distributions, however, are not very sensitive to the speed profiles. For drivers driving mostly short distances, the optimal vehicle has a small battery, but a big EGU to provide the power needed for performance requirements. For drivers who drive in average longer routes, the battery size increases, because more electrical energy is needed for longer driving cycles. However, if the driver drives mostly on very long routes, then the optimal vehicle design is more like an HEV, with a small battery and a big EGU.

Chapter 5

Concluding remarks

In this thesis optimization problems for PHEVs are studied at two different levels, energy management and sizing.

The first part focuses on energy management strategies for PHEVs. This is an optimization problem aiming at finding the best power split in terms of the fuel consumption, using available information about the trip. The trivial strategy is to fist use the battery energy, and in case the battery reaches a lower level, sustain the SoC around this level. This strategy is the best for short distances and also if no a priori knowledge about the trip is available. However, for trips longer than the all electric range of the vehicle, a strategy that can discharge the battery gradually to reach the lower level at the end of the trip decreases the internal battery losses and hence the fuel consumption and emissions. The method presented in Paper 1 is based on telemetry equivalence consumption minimization strategy for HEV, and is therefore modified to be used for PHEVs. This strategy can improve the fuel consumption using only the trip distance provided by the driver and general information including expected energy demand and braking energy per kilometer. The results show that the proposed method can decrease the fuel consumption considerably compared to the trivial strategy. The fuel consumption improves by increasing the level of information details. In other words, if the information is calculated considering only the trips driven on the same route as the current trip, the fuel consumption improves slightly compared to the case when all the trips over different routes are considered.

There are different ways to provide the information on trip length. One way is that the driver provides the estimate manually. An alternative is to use smart algorithms like route recognition algorithms to estimate the trip information. The method is robust to the general information, but is rather sensitive to the trip distance. This means that if the trip length given by the driver is over or under estimated, the battery will be discharged less or sooner than needed.

In the second part of the thesis, convex optimization is used for dimensioning a passenger PHEV. Its relatively fast computations makes it possible to consider variables of component sizing simultaneously with the variables of the energy management over a long driving cycle. The optimization is done for both parallel and series PHEVs, for which a cost function including the components and operational costs are minimized. To cast the models as convex functions, approximations, variable changes, and assumption must be done. For example, convex second order polynomial models are approximated to the power characteristics of the engine, the engine-generator unit and the electric machines, and the battery model assumes quadratic losses.

The method can be used as a tool to study the effect of different factors, like component and energy prices, driving and charging patterns, and different configurations, on optimal sizing. For example, it is shown that the cost is more affected by the acceleration requirements than the requirements on the top speed or the all electric range. Moreover, with the current price of energy and battery cells, the optimal AER is not very long. In addition, a systematic way to generate series of driving cycles which represent life time driving pattern of different drivers is presented, and the corresponding optimal design of the vehicles are given. The results shows, as expected, that the optimal battery size for a driver driving mostly short distances is small, but it increases if the driver drives longer distances more often, up to some point. If the driving cycles are very long, the optimal battery size decreases again.

The main drawback of the method is that the integer variables can not be included in the convex problem. Therefore, variables like the engine on-off and gear ratio needs to be decided by heuristics outside the convex problem. Future work needs to address the limitations and improve the heuristics.

Future work

First, the convex optimization method can be used to study different scenarios of changing battery type, fuel and battery price and performance requirements in more details. A more detailed battery model including the wear model and SoC dependent battery voltage need to be considered in the problem. Moreover, the problem can be extended to vehicles with different components, such as super capacitors, flywheels or fuel cells. Finally, future work has to address the limitation that is posed by the need to fix the integer control variables (gears and engine on-off) prior to the optimization.

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