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Improving Fuel Efficiency of Commercial Vehicles through Optimal Control of Energy Buffers

MOHAMMAD KHODABAKHSHIAN

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KTH School of Industrial
Engineering and Management
100 44 Stockholm
Sweden

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Abstract

Fuel consumption reduction is one of the main challenges in the automotive industry due to its economical and environmental impacts as well as legal regulations. While fuel consumption reduction is important for all vehicles, it has larger benefits for commercial ones due to their long operational times and much higher fuel consumption.

Optimal control of multiple energy buffers within the vehicle proves an effective approach for reducing energy consumption. Energy is temporarily stored in a buffer when its cost is small and released when it is relatively expensive. An example of an energy buffer is the vehicle body. Before going up a hill, the vehicle can accelerate to increase its kinetic energy, which can then be consumed on the uphill stretch to reduce the engine load. The simple strategy proves effective for reducing fuel consumption.

The thesis generalizes the energy buffer concept to various vehicular components with distinct physical disciplines so that they share the same model structure reflecting energy flow. The thesis furthermore improves widely applied control methods and apply them to new applications.

The contribution of the thesis can be summarized as follows:

- Developing a new function to make the equivalent consumption minimization strategy (ECMS) controller (which is one of the well-known optimal energy management methods in hybrid electric vehicles (HEVs)) more robust.
- Developing an integrated controller to optimize torque split and gear number simultaneously for both reducing fuel consumption and improving drivability of HEVs.
- Developing a one-step prediction control method for improving the gear changing decision.
- Studying the potential fuel efficiency improvement of using electromechanical brake (EMB) on a hybrid electric city bus.
- Evaluating the potential improvement of fuel economy of the electrically actuated engine cooling system through the off-line global optimization method.
- Developing a linear time variant model predictive controller (LTV-MPC) for the real-time control of the electric engine cooling system of heavy trucks and implementing it on a real truck.

Keywords: Energy buffer, Optimal control, Hybrid electric vehicle, Engine cooling system, Equivalent consumption minimization strategy, Model predictive control

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Mohamamd Khodabakhshian
Stockholm, December 2015

Contents

List of Appended Papers

Paper A

Mohammad Khodabakhshian, Lei Feng, Stefan Börjesson, Olof Lindgärde, Jan Wikander, "Reducing Auxiliary Energy Consumption of Heavy Trucks by Onboard Prediction and Real-time Optimization", in revision process and to be re-submitted to *Applied Energy*.

Jan provided feedback. Olof and Stefan provided data for section 5 (Real-time Implementation and Vehicle Testing). Lei developed the models, wrote section 2.6 (Driveline Torque and the Regenerative Brake), performed the global optimization and assisted in editing the paper. Mohammad developed the MPC controller, performed the simulations and analyses and wrote the major part of the paper.

Paper B

Mohammad Khodabakhshian, Lei Feng, Jan Wikander, "Fuel Saving Potential of Optimal Engine Cooling System", in *Proceedings of 12th International Symposium on Advanced Vehicle Control (AVEC)*, pp.271-276, 22-26 September 2014.

Lei and Jan provided feedback and assisted in editing the paper. Mohammad performed the research and wrote the paper.

Paper C

Mohammad Khodabakhshian, Lei Feng, Jan Wikander, "Predictive Control of the Engine Cooling System for Fuel Efficiency Improvement", in *Proceedings of the International Conference on Automation Science and Engineering (CASE)*, IEEE, pp.61-66, 18-22 August 2014.

Lei and Jan provided feedback and assisted in editing the paper. Mohammad performed the research and wrote the paper.

Paper D

Mohammad Khodabakhshian, Lei Feng, Jan Wikander, "Optimization of Gear Shifting and Torque Split for Improved Fuel Efficiency and Drivability of HEVs", SAE Technical Paper 2013-01-1461, April 2013.

Jan provided feedback. Lei developed the gearbox filters and also assisted in editing. Mohammad performed the research and wrote the paper.

Paper E

Mohammad Khodabakhshian, Lei Feng, Jan Wikander, "Improving Fuel Economy and Robustness of an Improved ECMS Method", in *Proceedings of 10th International Conference on Control and Automation (ICCA)*, IEEE, pp.598-603, 12-14 June 2013.

Lei and Jan provided feedback and assisted in editing the paper. Mohammad performed the research and wrote the paper.

Paper F

Mohammad Khodabakhshian, Lei Feng, Jan Wikander, "One-Step Prediction for Improving Gear Changing Control of HEVs", *Journal of Robotics and Mechatronics*, Vol.26, No.6, 2014.

Jan reviewed the paper. Lei provided feedback on structuring and editing the paper. Mohammad performed the research and wrote the paper.

Paper G

Mohammad Khodabakhshian, Jan Wikander, Lei Feng, "Fuel Efficiency Improvement in HEVs Using Electromechanical Brake System", in *Proceeding of Intelligent Vehicles Symposium (IV)*, IEEE, pp.322-327, 23-26 June 2013.

Lei and Jan provided feedback and assisted in editing the paper. Mohammad performed the research and wrote the paper.

List of Other Publications

Mohammad Khodabakhshian,“Improvement of Fuel Efficiency and Drivability Using Simple Prediction for Gear Changing”, in *Proceeding of Advances in Automotive Control (ACC)*, IFAC, pp.518-523, September 2013

Mohammad Khodabakhshian,“Application of Electromechanical Brake System in Hybrid Electric Buses”, *Technical Report*, TRITA-MMK 2012:02, ISSN 1400-1179, KTH Royal Institute of Technology, Stockholm, Sweden, January 2012

Daniel Frede, Mohammad Khodabakhshian, Daniel Malmquist, Jan Wikander, “A Survey on Safety-critical Vehicular Mechatronics”, in *Proceeding of International Conference on Mechatronics (ICM)*, IEEE, pp.176-181, April 2011

Daniel Frede, Mohammad Khodabakhshian, Daniel Malmquist, Jan Wikander, “A State-of-the-art Survey on Vehicular mechatronics Focusing on By-wire Systems”, *Technical Report*, TRITA-MMK 2010:10, ISSN 1400-1179, KTH Royal Institute of Technology, Stockholm, Sweden, October 2010

Acronyms

AC air conditioning

ADP approximate dynamic programming

CONVENIENT COmplete Vehicle ENergy-saving Technologies

DP dynamic programming

ECMS equivalent consumption minimization strategy

EMB electromechanical brake system

HEV hybrid electric vehicle

LTV-MPC linear time variant model predictive controller

MPC model predictive control

NL-MPC non-linear model predictive control

OASIS Optimization of Auxiliary Systems In hybrid heavy vehicleS

PMP Pontryagin's minimum principle

SA short answer

SOC state of charge

Nomenclature

α	road inclination angle
$\dot{E}_s$	stored energy
$\dot{m}_r$	air mass flow rate through the radiator
η_c	coulombic efficiency of the battery
η_f	fan efficiency
η_p	pump efficiency
$\mathit{\Gamma}$	cost to go
$\mathbf{G}$	a function used to define equality or inequality side-constraints
$\mathbf{S}_f$	set of final state constraints
$\mathbf{u}$	vector of control inputs
$\mathbf{v}$	vector of disturbance inputs
$\mathbf{x}$	vector of system states
$\boldsymbol{\lambda}$	vector of costate variables
$\mathit{\Omega}$	control constraint
ω_f	fan speed
ω_p	pump speed
$\mathit{\Omega}_s$	state constraint
$\omega_{e,max}$	maximum engine speed
$\omega_{e,min}$	minimum engine speed
$\omega_{em,max}$	maximum electric motor speed

$\omega_{em,min}$ minimum electric motor speed

ω_{em} electric motor speed

ω_{e} engine speed

$\omega_{f,max}$ maximum fan speed

$\omega_{f,min}$ minimum fan speed

$\omega_{p,max}$ maximum pump speed

$\omega_{p,min}$ minimum pump speed

ρ air density

τ_{e} engine torque

$\tau_{a,lb}$ minimum alternator torque

$\tau_{a,ub}$ maximum alternator torque

τ_{a} alternator torque

$\tau_{e,max}$ maximum engine torque

$\tau_{e,min}$ minimum engine torque

$\tau_{em,max}$ maximum electric motor torque

$\tau_{em,min}$ minimum electric motor torque

τ_{em} electric motor torque

τ_{e} engine torque

θ_{m} thermostat opening ratio

A frontal area of the vehicle

C_{w} drag coefficient

c_{1} cooling system model parameter

c_{2} cooling system model parameter

c_{3} cooling system model parameter

d tuning parameter

d_{1} tuning parameter

f state update function

F_d driving force

F_r resistance force

f_r rolling resistance coefficient

F_{ad} aerodynamic drag force

F_{br} braking force

F_{cr} climbing resistance force

F_{rr} rolling resistance force

g gravity acceleration

H hamiltonian

h_1 tuning parameter

h_2 tuning parameter

I_b battery current

$I_{b,max}$ maximum battery current

$I_{b,min}$ minimum battery current

K a function defining constraints on the final states

k_p tuning parameter

m vehicle mass

$P_{battery}$ battery power

P_{fuel} power from fuel

P_f fan power

P_{in} input power

P_l power loss

P_{out} output power

P_p pump power

Q_b battery capacity

Q_{in} heat power transmitted from the engine to the coolant

r_1 tuning parameter

r_2 tuning parameter

r_3 tuning parameter

SOC battery state of charge

SOC_{max} maximum allowable state of charge

SOC_{min} minimum allowable state of charge

SOC_{ref} reference SOC

t time

t_0 initial time

T_e coolant temperature at the engine outlet

t_f final time

T_a ambient temperature

$T_{e,max}$ maximum engine temperature

$T_{e,min}$ minimum engine temperature

u^* optimal control

U_b battery voltage

u_p coolant volumetric flow rate through the pump

v vehicle speed

Chapter 1

Introduction

Reduction of fuel consumption is vital for the automotive industry because of environmental concerns, market competition and legal regulations. The European Parliament has set a target of 5.6 l/100km for the average fuel consumption of new cars, to be introduced by 2015. The next target is 4.1 l/100km for 2020[1]. While the advancement in this area is beneficial for both private and commercial vehicles, it has larger economic and environmental benefits for commercial ones as they have much longer operational times and consume much more fuel than private cars. More than 30% of the total operational cost of a truck is spent on fuel [1].

1.1 Background

Automotive manufacturers use different methods to improve tank-to-wheel efficiency. The main intention in all methods is reduction of energy loss. The efforts in this field can be categorized into two areas. One is the efficiency improvement of different components in the vehicle, which for example includes the reduction of aerodynamic drag and rolling resistance. The other is the management of energy flow in the vehicle, i.e. control of the energy flows in order to optimize the use of (and interaction between) different energy sources, energy buffers and consumers in the vehicle. Usually a combination of different methods is used to improve fuel efficiency. An important part of this thesis deals with the control of energy flow through optimal control methods, through investigations of hybrid electric vehicles (HEVs), engine cooling systems and brake system. These applications are briefly explained in the following sub-sections.

1.1.1 Energy buffer concept

Mechatronic systems such as vehicles, manufacturing systems and airplanes typically contain several energy sources and consumers. An important aspect of de-

[1] http://www.unep.org/

veloping these systems is to design them to be as efficient as possible to decrease cost and wasted energy. A common attribute of these systems is that to fulfill the main tasks, substantial amounts of energy in various forms flow through different subsystems. The components of interest serve as energy source, consumer or storage. A particular component has different energy efficiency depending on working conditions. To minimize energy loss in individual components, they should all work under optimal conditions. However, this is generally not possible, hence it becomes an optimization challenge to control the energy flows such that energy losses at the system level are minimized. In order to achieve control of energy flows, we can temporarily store and release energy into and from components with buffering capacity. In this thesis, the emphasis is on the energy buffer control in vehicles.

Energy buffers can store energy in different forms depending on their structure. The vehicle chassis is an energy buffer which stores kinetic energy. The vehicle can accelerate before going up a hill and store the kinetic energy, and then release it during the uphill stretch. Any component with rotating or translating inertia can be considered an energy buffer.

Batteries store the energy in chemical form. Normally, the electrical energy in the vehicle is provided by an alternator which is driven by the engine. When the electrical energy from the alternator is not sufficient, the rest of the energy is provided by the battery. The battery can be charged when the alternator is producing more energy than the rest of the vehicle requires. When the vehicle is approaching an uphill stretch followed by a downhill stretch, the battery can be discharged going uphill to decrease the load on the engine during the climb. Going downhill, the batteries can be recharged.

One application of energy buffer control is in HEVs, where the controlled energy buffer is typically the battery. HEVs are discussed in Section 1.1.2. Another similar application is brake blending, where the controlled energy buffer is the same as in HEVs but the objective of optimization is both fuel consumption reduction and proper brake performance, i.e. acceptable braking distance. Brake blending is discussed in Section 1.1.4.

Engine and cooling system components can store the energy as enthalpy. Due to the heat generated during the combustion process, the engine temperature increases. The temperature is regulated by transferring some part of the generated heat to the environment using the engine cooling system. Before a high-load situation, the cooling system may spend extra effort to reduce the engine temperature. Hence, the cooling effort may be reduced during the high-load period. If the reduced cooling effort at high engine torque condition saves more fuel than the increased effort at low engine torque condition consumes, the total fuel consumption is decreased. In this aspect, the engine and the cooling system act as an energy buffer which temporarily stores the energy. An engine cooling system is presented in Section 1.1.3, where the energy buffers considered for optimization are the battery and the cooling system.

A schematic of the energy flow in a vehicle is presented in Fig. 1.1, where the energy buffers are battery, engine cooling system and chassis. Fuel is the main source of energy. The engine provides power for propelling the vehicle and runs the alternator which produces electrical energy for the electrical auxiliaries. When the vehicle moves, the propulsion energy is stored in the chassis in the form of kinetic energy which can be used to run the alternator and to charge the battery during braking. The electrical energy to drive vehicular electric loads comes from both the alternator and the battery. The generated heat in the engine is taken away using the pump and the fan.

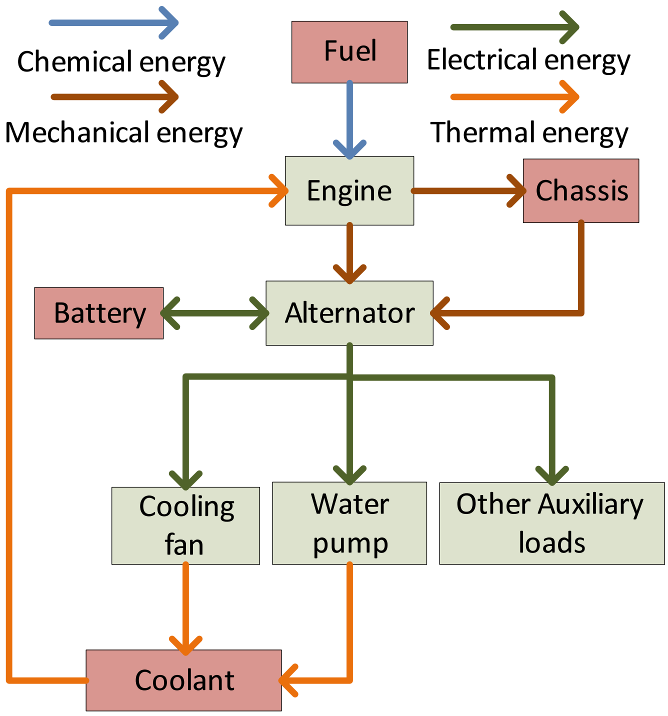

Figure 1.1: Energy buffers and energy flow in the vehicle considering battery, cooling system and chassis as energy buffers

1.1.2 HEVs

Hybridization of the powertrain system is a promising method to decrease fuel consumption [2]. In hybrid vehicles, at least two ways of storing energy are utilized. One is in the form of externally supplied energy, i.e. fuel. The other is used to both store and release energy during vehicle operation [3]. The primary energy source is usually an irreversible chemical energy storage (fuel) and the secondary energy source can be either mechanical (e.g. flywheel), pneumatic (e.g. compressed air energy storage), hydraulic (e.g. hydraulic buffers) or electric (e.g. battery). Primary and secondary energy sources, together or independently, provide the energy for consumers.

The most popular hybrid powertrain is hybrid electric and has shown substantial decrease in fuel consumption compared to a conventional powertrain [4, 5]. There are several architectures for hybrid electric vehicles, namely series hybrid, parallel hybrid and combined architectures. Each architecture has its own pros and cons and is suitable for specific applications [6, 2]. The schematic of one type of parallel hybrid electric powertrain used in this thesis is shown in Fig. 1.2. The engine and the electric motor are the prime movers. The engine converts the chemical energy of the fuel to mechanical energy, and the electric motor converts the electrical energy from the battery to mechanical energy and vice versa. At each instant, the control unit decides how much torque each prime mover should provide. When the vehicle is in braking mode, the energy can flow from the wheels to the electric motor. In this case, the electric motor acts as a generator and charges the battery.

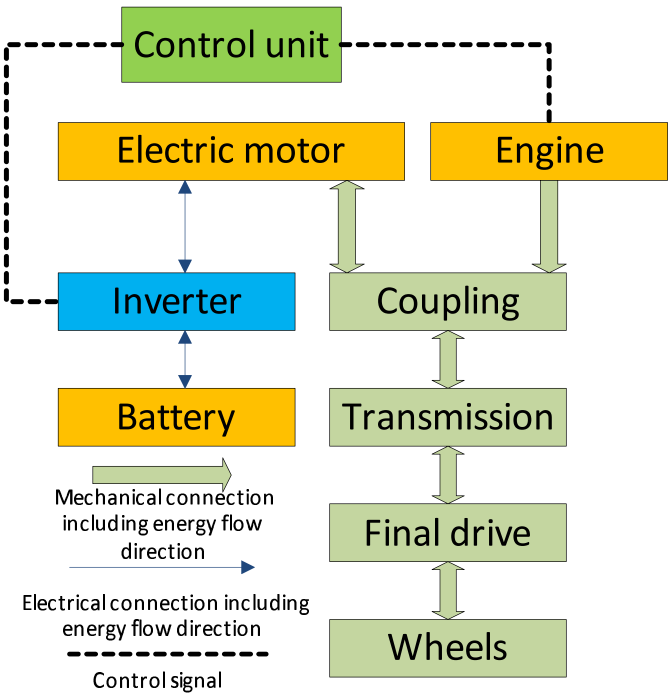

Figure 1.2: Schematic of parallel hybrid electric powertrain system

The battery in HEVs is charged by either the engine or the vehicle kinetic energy through braking by means of the electric motors. The most important factor that determines the performance of the hybrid electric powertrain is the power management strategy, which decides the torque split ratio between the engine and the electric motor. The energy management strategy is discussed extensively in different publications and several approaches exist [7, 8]. Each method has advantages and disadvantages determining its suitability for specific applications. One of the proposed energy management methods is the equivalent consumption minimization strategy (ECMS) [9, 10, 11]. In ECMS, the electrical energy is converted to equivalent fuel consumption using an equivalence coefficient. Then, a cost value is calculated for each time instant by adding the fuel rate and the equivalent fuel consumption supplied by the battery. The optimal torque split ratio between the engine and the electric motor is calculated by minimizing the cost at each instant. The equivalence coefficient is the core of the ECMS method. To maximize the fuel consumption reduction when using ECMS, it is essential to have proper values for the equivalence coefficient at each instant. Several methods are proposed by researchers to calculate this [12, 11, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22]. Most of the available methods need to be tuned for each specific driving cycle. However, it is desirable to increase the robustness of the ECMS to improve the fuel efficiency in all driving conditions without the need to re-tune the controller. The ECMS method is described in more detail in Section 2.3.

Furthermore, when designing a power management module for HEVs, the drivability should also be considered (to potentially improve it, or at least not degrade it). Otherwise optimization of torque split might result in a poor driving experience.

1.1.3 Engine cooling system

Regulation of engine temperature via the engine cooling system is an important aspect of combustion engines. About 35% of the total chemical energy (fuel) that enters an engine is converted to useful crankshaft work, and about 30% of the fuel energy is carried away in the exhaust flow in the form of enthalpy and chemical energy [23]. Thus, about one third of the total energy must be dissipated to the surroundings by heat transfer. Removing the heat is highly critical in keeping an engine and its lubricant from thermal failure.

The engine cooling system in conventional vehicles includes a radiator fan, water pump and thermostat. A schematic of a conventional thermal management system is presented in Fig. 1.3. The pump circulates the coolant in the cooling system. Some of the generated heat from the combustion process is transferred to the coolant. Depending on the coolant temperature, the thermostat leads the coolant either to the radiator to dissipate the heat or to the engine.

The design of the engine cooling system has not changed much in the last few decades. The engine cooling system component parameters are not usually optimized and the cooling systems have very conservative designs since they need to be very reliable [24]. Cooling systems in conventional vehicles are designed for maximum possible heat rejection, resulting in over-actuation of pump and fan [25, 26]. Consequently, unnecessary high demand on the pump and the fan increases parasitic load to the engine, hence increasing fuel consumption [27]. The radiator

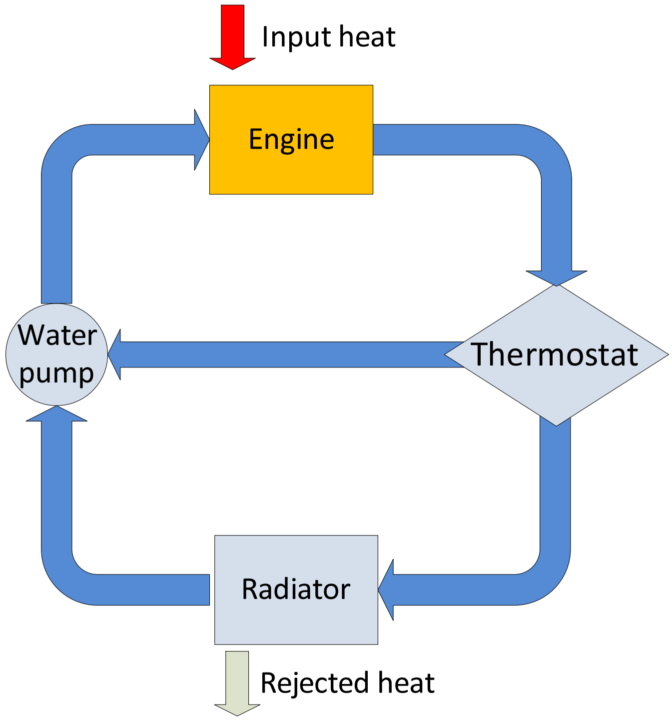

Figure 1.3: Schematic of engine cooling system

fan driven by the engine can consume as much as 10% of engine power in older engines [24]. The coolant pump is also engine driven in conventional trucks, so the flow rate is a function of engine speed. The thermostat opening ratio is only dependent on the coolant temperature. This cooling system design does not allow accurate control of the engine temperature.

Using an electric pump and fan instead of mechanically driven ones can decrease the waste energy in the cooling system [28, 29, 30, 31, 32]. The thermostat can also be replaced with a controllable electric valve [33, 34, 35]. The electrified engine cooling system has several potential benefits, namely reducing frictional losses, achieving a thermally optimized engine, increasing lubricant oil life, decreasing engine emissions, increasing engine life and system flexibility [25]. Application of electric pump and valve has been claimed to result in 2.8-5% reduction of fuel consumption according to [26, 36, 37]. This reduction is due to both reduced energy consumption in the pump and improvement of engine efficiency because of higher engine temperature. Chanfreau et al. [38] reports 3% reduction in fuel consumption due to electrification of both the pump and the fan. Application of controllable electric pump, fan and valve shows 2-3% improvement of fuel efficiency as discussed in [33]. Replacing mechanically driven actuators with electrical ones shows around 2-5% reduction of fuel consumption of the cooling system in all of the mentioned studies.

An important aspect of an electrified engine cooling system is the potential of employing advanced control methods which enable smart use of cooling system actuators to optimally regulate the enegine temperature and minimize the overall loss in the system and thereby increase the efficiency. Several control strategies have been proposed by researchers to control the engine cooling system. Some of these are introduced in Paper A.

Optimal control of the engine cooling system has been the subject of several different research studies [39, 40]. Most of the research has focused on regulating the temperature, but the effects on fuel consumption are usually omitted. Furthermore, the challenge of of the real time implementation of optimal engine cooling system control for real vehicles is rarely discussed.

1.1.4 Electromechanical brake system

Electromechanical brake systems (EMBs) use electromechanical actuators instead of hydraulic or electrohydraulic devices. They provide several benefits for the vehicle, offering better vehicle stability (thanks to faster and more accurate brake control by accurate control of electric motors of the brake caliper [41]) and they can easily be integrated to other subsystems (such as active safety systems). They can also reduce the braking distance compared to conventional hydraulic or pneumatic brake systems [42]. When EMB is used in HEVs, the accurate braking torque control is beneficial for the efficient usage of regenerative braking. Plus, due to elimination of hydraulic fluid in the system, EMBs are more environmental friendly [43] compared to hydraulic brake systems.

EMBs can be designed as self-enforced systems, thus decreasing the required energy for braking [44, 45, 46]. A schematic of EMBs is presented in Fig. 1.4. The input to the brake system is a signal from the brake pedal. Based on the required brake torque, the electric motor moves the wedge. The wedge moves the brake pad, which is then pressed against the brake disk. The electric motor regulates the brake torque according to the brake signal by controlling the force on the wedge. The actuator force on the wedge is reinforced by the brake friction force and thereby the required actuator size is reduced. When the brake pedal is released, the motor returns the wedge to its initial position.

Brake blending

A brake system in commercial vehicles consists of at least two sources of braking. The primary braking source (service brake) is the friction brake and the secondary brake can be a retarder of any kind, e.g. hydrodynamics, engine compression, engine exhaust or electromagnetic. Although the service brake can provide enough braking force, extensive application of the service brake especially in long periods of braking

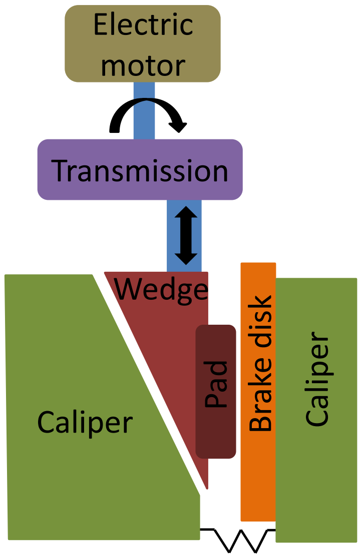

Figure 1.4: Schematic of EMB

such as downhill is not safe. This is due to the excess heat generation resulting in reduction of friction coefficient [47]. This also results in reducing the life span of the brake components [48]. In hybrid electric vehicles, part of the braking is done by the energy recuperation system, i.e. regenerative brake. So in hybrid electric vehicles, the aim of the brake system is to reduce the speed of the vehicle according to a brake command signal while maintaining vehicle stability and recuperating as much as possible of the kinetic energy to improve fuel efficiency. For efficient braking, it is clear that a proper strategy for brake blending is required.

EMB has good potential to improve fuel efficiency due to its low energy consumption. However, the fuel efficiency improvement of EMB for HEVs has not yet been extensively investigated.

1.2 Objectives and research questions

This thesis work has been performed as part of two different projects: OASIS (Optimization of Auxiliary Systems In hybrid heavy vehicleS) and CONVENIENT (COmplete Vehicle ENergy-saving Technologies). Our role in the OASIS project was to study the fuel efficiency improvement of heavy vehicles - particularly hybrid city buses - by simulating the implementation of a brake-by-wire system. In the CONVENIENT project, our role was to design a predictive thermal management controller for conventional heavy trucks to reduce the fuel consumption as well as meeting the engine cooling system requirements. The controller had to be implemented on a real truck for real world experiments. A preliminary work for the CONVENIENT project, which in this thesis is called Pre-CONVENIENT, placed emphasis on improvement of the ECMS method. Each project has different content, however they all aim to reduce fuel consumption in heavy vehicles.

The main scope of the thesis is to investigate applications of optimal control of energy buffers to reduce fuel consumption in heavy vehicles. According to the discussion in Section 1.1, the main objective can be broken down into the following research questions:

Q1 ECMS is a promising method for energy management in HEVs, however the performance is heavily dependent on the equivalence coefficient between electrical energy consumption and fuel consumption. If the coefficient is not tuned properly, the performance is not optimal over a range of driving situations. How can we increase the robustness of ECMS with respect to varying driving situations?

Q2 When designing a torque split controller in HEVs, the drivability is sometimes omitted. How can we consider both drivability and fuel consumption?

Q3 How much can the EMB increase fuel efficiency in HEVs?

Q4 What is the effect of the engine cooling system on fuel efficiency in heavy trucks?

Q5 How can we optimally control the engine cooling system in real time to reduce fuel consumption in heavy trucks?

1.3 Research process

The research in this thesis heavily depends on high fidelity simulation tools. Autonomie[2] is used as the simulation tool for the OASIS and the pre-CONVENIENT projects. A Simulink based simulation environment which is based on AVL cruise[3] and AVL boost[4] is used for the CONVENIENT project. The latter simulation environment is developed by Volvo[5], one of the project partners. The projects introduced in Section 1.2 are conducted in the framework of three studies. Short summaries of different phases of each study are explained. The driving cycles used for simulations are also described briefly.

[2]http://www.autonomie.net/
[3]https://www.avl.com/cruise
[4]https://www.avl.com/boost
[5]http://www.volvogroup.com/

1.3.1 Study I: Improvement of robustness of the ECMS method (pre-CONVENIENT)

This project started with a literature review on energy management strategies in hybrid electric vehicles. Based on the results from literature study, the ECMS method was investigated in more detail, and its limitations, especially regarding its robustness, were identified. The work then concentrated on improving ECMS using different methods and evaluating the proposed methods using simulation.

1.3.2 Study II: Optimal thermal management of conventional heavy trucks (CONVENIENT)

Different engine cooling system control strategies were studied during the literature review. Then the fuel saving potential of an optimal engine cooling system control strategy was investigated using dynamic programming (DP). For real time control of the engine cooling system, a controller based on a model predictive control (MPC) scheme was designed. The performance of the controller was evaluated using a high fidelity plant model. The controller was then evaluated on a real truck.

1.3.3 Study III: Application of an EMB system in hybrid electric city buses (OASIS)

The project was initiated by doing a literature study on EMBs and brake blending. Afterwards, different control strategies for brake blending were studied, and a straight forward control strategy was developed based on the requirements from the project partners (Volvo bus[6] and Haldex[7]). The selected control strategy was developed and evaluated in the simulation environment.

1.3.4 Driving cycles

Several different driving cycles are used in this thesis for evaluating performance and comparing different solutions. In Studies I and III, a wide range of driving cycles are used for simulation. They can be categorized into modal (polygonal) cycles [49] and actual cycles. Modal cycles are constructed using different constant acceleration and constant velocity situations. The modal ones used in this thesis include Japan10, ECE, NEDC and SORT1. In the actual cycles, an actual velocity profile is used. The actual cycles used in this thesis are US06, SC03, UDDS, Manhattan, Nuremberg bus route cycle and bus rte cycle. The latter 3 contain multiple stop and go situations and are good examples of normal city bus drive cycles. The actual cycles are usually more complex than the modal ones since they are based on real vehicle speed trajectories.

[6] http://www.volvobuses.com/
[7] http://www.haldex.com/

In study II, two driving cycles are used: (1) the KTH cycle- a virtual cycle which consists of one uphill-downhill situation and one acceleration-deceleration situation. This cycle is used to investigate the behavior of the cooling system and analyze the system behavior. And (2) the BLB cycle- a driving cycle which is a real route of 90 km between two towns in Sweden, namely Borås and Landvetter. This cycle is used for verification of the controller performance and to get quantitative results. The driving cycles used in this thesis are plotted in Appendix B.

1.4 Contribution

Application of optimal energy buffer control in vehicles is presented in this thesis work. Two case studies are discussed, namely, application of ECMS for HEVs and application of MPC for cooling system control. Several methods are presented for improvement of the ECMS method. Drivability is also considered when using the ECMS method. MPC is used for cooling system control to reduce fuel consumption while concurrently regulating the engine temperature. The application of EMB for HEVs is also investigated to evaluate its effects on fuel consumption. The contributions of the thesis are summarized as follows.

- Developing a new function to make the ECMS controller more robust.
- Developing an integrated controller to optimize torque split and gear number simultaneously for both reducing fuel consumption and improving drivability of HEVs.
- Developing a one-step prediction control method for improving the gear changing decision.
- Studying the potential fuel efficiency improvement of using EMB on a hybrid electric city bus.
- Evaluating the potential improvement of fuel economy of the electrically actuated engine cooling system through the off-line global optimization method.
- Developing a linear time variant model predictive controller (LTV-MPC) for the real-time control of the electric engine cooling system of heavy trucks and implementing it on a real truck.

1.5 Delimitation

In Study I, simulations are performed on diesel trucks of 40 and 60 metric tons respectively. Although most of the results are based on the simulations, some limited real world experiments have been performed on the truck. The simulation environment and the prediction module have been provided as a package by Volvo, so the main emphasis of this thesis is on design and evaluation of the controller.

The effects of engine temperature on its efficiency are not considered. Improvement of optimal control solvers are not studied in this thesis.

In Study II and Study III, the results are based on simulating a hybrid electric city bus. No real world experiment has been done and no on-board prediction of the driving conditions were used.

1.6 Thesis outline

This thesis work is organized as follows. The first chapter contains motivation and background followed by introducing the research questions, research process and the contributions. In chapter 2, the concept of energy buffer is discussed followed by a discussion regarding different control methods. Chapter 3 contains answers to the research questions by discussing and summarizing some of the results from the appended papers. The contributions discussed in Sec. 1.4 are also elaborated. In chapter 4, suggestions for possible future works are presented. A summary of the appended papers is presented in Appendix A.

Chapter 2

Introduction to energy buffer control

2.1 Definition of energy buffer

An energy buffer is a component (system) within an energy conversion system which in a controlled way store energy and release it, so that the energy conversion system has more chances of operating at high efficiency conditions. The definition of energy buffer in this thesis follows the terminology used in [50]. A general schematic of energy buffers is presented in Fig. 2.1. The input power P_{in} is distributed among output power P_{out}, power loss P_l and the change in the stored energy $\dot{E}_s$. Note that $P_{in} \geq 0$, $P_{out} \geq 0$, $P_l \geq 0$ and $\dot{E}_s$ can either be positive, zero or negative.

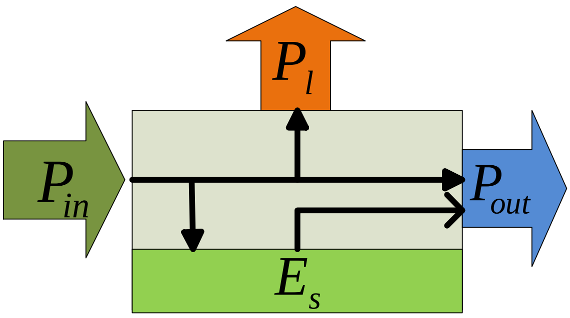

Figure 2.1: A general schematic of energy buffers

The general equation for energy buffers is

$$P_{in} = P_{out} + P_l + \dot{E}_s. \tag{2.1}$$

The input, output, stored and waste energies can be in different forms (e.g. chemical energy, kinetic energy). If $\dot{E}_s > 0$, the energy buffer is charged and if $\dot{E}_s < 0$, the energy buffer is discharged. If $\dot{E}_s = 0$, energy content of the energy buffer is unchanged. Depending on the charging or discharging status of an energy buffer, P_{in} or P_{out} may be 0.

If an energy conversion system contains at least one energy buffer, the energy storage of each buffer can be considered as a system state. The energy flow dynamics of the system is modeled by the state space equation

$$\dot{\mathbf{x}}(t) = f(\mathbf{x}(t), \mathbf{u}(t), \mathbf{v}(t), t),$$

where $\mathbf{x}(t)$ is the vector of system states, t is time, $\mathbf{u}(t)$ is the vector of control inputs and $\mathbf{v}(t)$ is the disturbance vector. The required wheel torque and wheel speed to follow a driving cycle with specified speed and altitude trajectory can be considered as disturbance.

A primary control objective for such a system is to minimize the input energy to the whole system. Minimization of the input energy can be described in the form of a standard optimal control problem [51] as finding a piecewise continuous control $u^* : [t_0, t_f] \to \mathit{\Omega} \subseteq \mathbb{R}^m$ that satisfies

$$\min_{\mathbf{u}(t)} (K(\mathbf{x}_{t_f}, t_f) + \int_{t_0}^{t_f} P_{in}(\mathbf{x}(t), \mathbf{u}(t), \mathbf{v}(t), t)\ \mathrm{d}t), \tag{2.2}$$

subject to

$$\dot{\mathbf{x}}(t) = f(\mathbf{x}(t), \mathbf{u}(t), \mathbf{v}(t), t),$$

$$\begin{cases} \mathbf{x}(t_0) = \mathbf{x}_0, \\ \mathbf{x}(t_f) \in \mathbf{S}_f, \end{cases}$$

$$\mathbf{x}(t) \in \mathit{\Omega}_x(t), \text{for all } t \in [t_0, t_f], \text{where}$$

$$\mathit{\Omega}_x(t) = \{\mathbf{x} \in \mathbb{R}^n | \mathbf{G}(\mathbf{x}, t) \leq 0; \mathbf{G} : \mathbb{R}^n \times [t_0, t_f] \to \mathbb{R}\},$$

where K is a function defining constraints on the final states $\mathbf{x}_{t_f}$, t_f is the final time, t_0 is the starting time, P_{in} is the function defining total input power to the system, f is the state update function, $\mathbf{x}_0$ is the initial state, $\mathbf{S}_f$ is the set of final state constraints, e.g. the final value of SOC when considering HEVs (Sec. 2.3), $\mathit{\Omega}_s$ is the set of state constraints, e.g. the physical limits on states, $\mathit{\Omega}$ is the set of control constraints, e.g. the physical limits of actuators, and **G** defines equality or inequality side-constraints. It is assumed that **G** is continuously differentiable. Eq. (2.2) follows the notation in [52]. From Eq. (2.2), we introduce a semi-formal definition of the energy buffer.

Let $P_i : R^n \to R$ be the natural projection of the Cartesian frame and let $|\mathbf{x}|$ represent the cardinality of the set $\mathbf{x}$. Any component whose state, x_i, is allowed to vary within a range during $[t_0, t_f]$ can be considered as an energy buffer, i.e. $x_i(t) \in P_i(\Omega_x(t))$, $|P_i(\Omega_x(t))| > 1$.

The implication is that if the energy storage content of a device is allowed to freely vary within a boundary, then there is a large number of possible trajectories of the state. Optimal control is about choosing the optimal state trajectory that minimizes the energy consumption. On the other hand, if the state must follow a fixed trajectory, there is no flexibility. In this aspect, the state with freely controllable trajectories stands in this thesis for an energy buffer.

Since the main focus of this thesis is automotive applications, a few common energy buffers in such applications are presented in this chapter.

2.1.1 Battery

A battery is a chemical energy storage. Different models can be used to describe the battery charging and discharging dynamics. This thesis uses an equivalent circuit model that simplifies the battery as an ideal voltage source and an internal resistance [2]. The equivalent circuit is shown in Fig. 2.2.

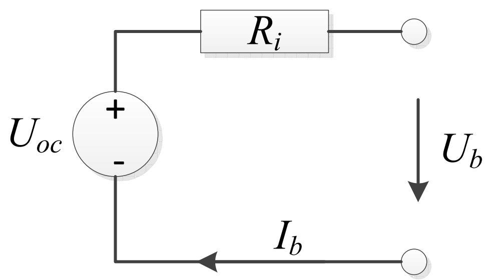

Figure 2.2: Battery equivalent circuit

The indicator of the energy content is the state of charge (SOC). The dynamics of the battery can be described as

$$S\dot{O}C = \frac{\eta_c I_b}{Q_b}, \tag{2.3}$$

where I_b is battery current, Q_b is battery capacity and η_c is the coulombic efficiency of the battery. If I_b is positive, the battery is charged and if it is negative, the battery is discharged. The output power of the battery is

$$P_{bat} = U_b I_b,$$

where U_b is closed circuit voltage. When there is current through the battery, some energy is dissipated in the form of heat as a result of the internal electrical resistance. The P_{in}, P_{out}, P_l and $\dot{E}_s$ for the battery are defined as

$$P_{in} = \begin{cases} U_b \cdot I_b & \text{if battery is being charged, i.e.} \quad I_b > 0, \\ 0 & \text{if battery is being discharged, i.e.} \quad I_b < 0, \end{cases}$$

$$P_{out} = \begin{cases} 0 & \text{if battery is being charged, i.e.} \quad I_b > 0, \\ -U_b \cdot I_b & \text{if battery is being discharged, i.e.} \quad I_b < 0, \end{cases}$$

$$P_l = f(\mathbf{z}),$$

where $\mathbf{z}$ is a vector of variables and battery parameters that affect battery internal resistance. Examples of $\mathbf{z}$ contents are temperature, SOC of battery [53] and battery current [54]. The $\dot{E}_s$ is calculated as

$$\dot{E}_s = U_b \cdot I_b - P_l.$$

2.1.2 Vehicle body

If the vehicle must exactly follow the given drive cycle, its speed cannot be considered as an energy buffer; however, if its speed is allowed to deviate from the drive cycle speed profile, it can be considered as an energy buffer to temporarily store vehicle kinetic energy. This is a popular topic of variable speed control to reduce vehicle fuel consumption [55]. Vehicle speed v can be considered as the state for the vehicle body. The dynamics of the vehicle can be described as

$$\dot{v} = (\frac{1}{m})(F_d - F_r), \tag{2.4}$$

where v is vehicle speed, m is vehicle mass, F_d is driving force and F_r is the resistance force which is calculated as

$$F_r = F_{rr} + F_{ad} + F_{cr} + F_{br}, \tag{2.5}$$

where F_{br} is braking force. F_{rr}, F_{ad} and F_{cr} are rolling resistance, aerodynamic drag and climbing resistance respectively and can be calculated as

$$F_{rr} = f_r mgcos\alpha, \tag{2.6}$$

$$F_{ad} = \frac{1}{2}\rho C_w A v^2, \tag{2.7}$$

$$F_{cr} = mgsin\alpha, \tag{2.8}$$

where f_r is rolling resistance coefficient, g is gravity acceleration, α is road inclination angle, ρ is air density, C_w is drag coefficient and A is frontal area of the vehicle. By combining Eq. (2.4)-(2.8) we have

$$m\dot{v} = F_d - fmgcos\alpha - \frac{1}{2}\rho C_w A v^2 - mgsin\alpha - F_{br},$$

and if we multiply it by v, we have

$$m\dot{v}v = F_d v - fmgvcos\alpha - \frac{1}{2}\rho C_w A v^3 - mgvsin\alpha - F_{br}v,$$

which can be rearranged to

$$m\dot{v}v + mgvsin\alpha = F_d v - fmgvcos\alpha - \frac{1}{2}\rho C_w A v^3 - F_{br}v,$$

and

$$vsin\alpha = \dot{h},$$

then we have

$$m\dot{v}v + mg\dot{h} = F_d v - fmgvcos\alpha - \frac{1}{2}\rho C_w A v^3 - F_{br}v, \tag{2.9}$$

so using Eq. (2.9) and the terms in Eq. (2.1) we have

$$E_s = \frac{1}{2}mv^2 + mgh,$$

then,

$$\dot{E}_s = mv\dot{v} + mg\dot{h},$$

$$P_{in} = F_d v,$$

$$P_l = fmgcos(\alpha) + 1/2\rho C_w A v^3 + F_{br}v,$$

$$P_{out} = 0.$$

If the input power from the engine is more than the power loss, the stored energy in the vehicle body will increase. The energy can be stored either due to climbing a hill, increasing the speed, or a combination of them. When P_{in} from the engine is less than the lost power, the stored energy in the vehicle body is decreasing. This reduction of the energy can be due to loosing altitude, speed reduction or a combination of them.

2.1.3 Cooling system

Different models are used in literature to describe the dynamics of the engine cooling system. A one-state model where the state is coolant temperature at the engine outlet is used in [40] and [56]. The heat dissipation from the radiator is formulated as a rational function. Nilsson et al. [39] also use a one state model where the heat rejection from the radiator is modeled as a lookup table. Setlur et al. [28] and Salah et al. [57] use a two-state model where the second state is the coolant temperature at the radiator outlet. A three-state model where the coolant temperature at the engine inlet is the third state is introduced in [35, 58].

This thesis employs the one-state rational function model [40, 56], where the state is coolant temperature at the engine output and the control inputs are pump speed and fan speed. Note that the thermostat is not replaced with a controllable valve. The time delays in the system and the heat transfer inside the engine are ignored. An important assumption is that the engine is the only source of the heat entering the coolant, and the coolant dissipates heat to the environment only through the radiator. A schematic of the engine cooling system is presented in Fig. 2.3. The coolant temperature in the pump output is relatively low. Most of the low temperature coolant goes through the engine and a small part of the coolant goes through coolers such as the transmission oil cooler. The high temperature coolant exiting the engine goes through the thermostat, and a small part of it goes through the heaters such as the cabin heater. The opening ratio of the thermostat is a function of coolant temperature.

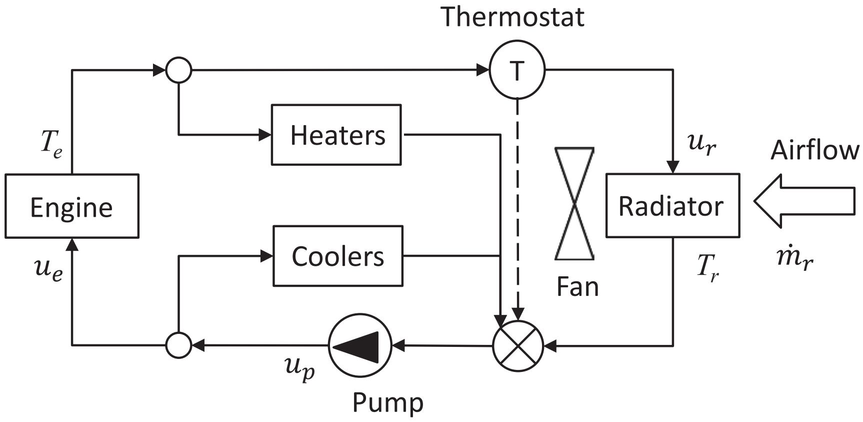

Figure 2.3: Schematic of the cooling system

The state equation of the cooling system can be described as

$$\dot{T}_e = c_1 Q_{in}(\tau_e, \omega_e) - \frac{\theta_m(T_e) u_p(\omega_p) \dot{m}_r(\omega_f, v)(T_e - T_a)}{c_2 \theta_m(T_e) u_p(\omega_p) + c_3 \dot{m}_r(\omega_f, v)}, \tag{2.10}$$

where T_e is coolant temperature at the engine outlet (or coolant temperature for simplicity), T_a is ambient temperature, Q_{in} is the heat power transmitted from the engine to the coolant, u_p is coolant volumetric flow rate through the pump, $\dot{m}_r$ is air mass flow rate through the radiator, and θ_m is the thermostat opening ratio. c_1, c_2 and c_3 are constant model parameters. The heat power Q_{in} is a function of the engine torque τ_e and the engine speed ω_e. The pump volumetric flow rate u_p is a function of the pump speed ω_p. The radiator mass flow rate is a function of both fan speed ω_f and vehicle speed v. The thermostat opening ratio θ_m is a function of the coolant temperature T_e.

When we consider the engine cooling system as energy buffer, the engine, pump and fan are considered as one system together. So the values for P_{in}, P_l, P_{out} and $\dot{E}_s$ should be calculated for the whole system, and not separately for the engine, pump and fan. These values are explained in more details here to clarify how the engine cooling system is considered as energy buffer.

P_{in} for the cooling system is the electrical power input to the pump $(P_p(\omega_p))$ and fan $(P_f(\omega_f))$ where ω_p is pump speed and ω_f is fan speed. For the cooling system we have

$$P_{in} = P_p + P_f. \tag{2.11}$$

Calculation of P_l and P_{out} are explained below. For an arbitrary pair of (ω_p, ω_f) at a certain vehicle speed v and heat power transmitted from the engine to the coolant Q_{in}, we calculate the corresponding change rate of the coolant temperature and denote it as $\dot{T}_e^o$ using Eq. (2.10). The arbitrary pair of (ω_p, ω_f) is just one of many possible combinations resulting in $\dot{T}_e^o$. We can find the optimal combination of (ω_p, ω_f) resulting in the minimal value of P_{in} as follows.

$$(\omega_p^*, \omega_f^*) = argmin_{(\omega_p,\omega_f)} P_p(\omega_p) + P_f(\omega_f), \tag{2.12}$$

subject to

$$\begin{gathered}\dot{T}_e = \dot{T}_e^o, \\ \omega_{p,min} \leq \omega_p \leq \omega_{p,max}, \\ \omega_{f,min} \leq \omega_f \leq \omega_{f,max}.\end{gathered}$$

So for all possible combinations of (ω_p, ω_f) it is always true that

$$P_p(\omega_p^*) + P_f(\omega_f^*) \leq P_p(\omega_p) + P_f(\omega_f),$$

and we can write

$$P_{l,1}(\omega_p, \omega_f) = P_p(\omega_p) + P_f(\omega_f) - P_p(\omega_p^*) - P_f(\omega_f^*).$$

$P_{l,1}$ is the power loss due to the non-optimal selection of ω_p and ω_f to reach the same cooling effect. Due to the efficiency of the pump and fan, some energy is also dissipated as

$$P_{l,2}(\omega_p, \omega_f) = (1 - \eta_p(\omega_p))P_p + (1 - \eta_f(\omega_f))P_f,$$

where η_p and η_f are pump and fan efficiency, respectively. So the lost power for the cooling system P_l is

$$P_l = P_{l,1}(\omega_p, \omega_f) + P_{l,2}(\omega_p, \omega_f). \tag{2.13}$$

The output power of the cooling system is the minimal power to keep the coolant temperature constant, i.e., $\dot{T}_e = 0$. Let $\dot{T}_e^0 = 0$ in Eq. (2.12). We have the optimal pair of pump and fan speeds as $(\omega_{p0}, \omega_{f0})$

$$(\omega_{p_0}, \omega_{f_0}) = argmin_{\omega_p, \omega_f}(P_p(\omega_p) + P_f(\omega_f)),$$

so $P_p(\omega_{p_0}) + P_f(\omega_{f_0})$ represents the minimum input power required for keeping the coolant temperature constant. In this case for the given heat injection Q_{in}, vehicle speed v, and ambient temperature T_a, the heat energy in the engine is unchanged, and all the input power is used for rejecting the engine heat to the environment and keeping the engine temperature constant. So the minimum power output of the cooling system is

$$P_{out}(\omega_{p0}, \omega_{f0}) = \eta_p(\omega_{p0})P_p(\omega_{p0}) + \eta_f(\omega_{f0})P_f(\omega_{f0}), \tag{2.14}$$

Given an arbitrary pair (ω_p, ω_f), the combination may result in non-zero $\dot{T}_e$ and the selection of the two speeds may not be optimal. The input electrical power is

$$P_{in} = P_p(\omega_p) + P_f(\omega_f).$$

The necessary output power to keep the coolant temperature constant at the given condition is $P_{out}(\omega_{p0}, \omega_{f0})$ as in Eq. (2.14) and the lost power is $P_l(\omega_p, \omega_l)$ as in Eq. (2.13). The difference between P_{in} and $P_{out} + P_l$ is the energy stored or retrieved from the electric cooling system

$$\dot{E}_s = P_{in} - P_l - P_{out}.$$

If a combination of (ω_p, ω_f) results in negative $\dot{T}_e$, then $\omega_p > \omega_{p0}$ or $\omega_f > \omega_{f0}$. The combination normally results in $P_{in}(\omega_p, \omega_f) > P_{out}(\omega_p 0, \omega_f 0)$ and $\dot{E}_s > 0$, i.e., the energy buffer is charged if the coolant temperature drops. There is, however, no general causal relationship between $\dot{T}_e$ and $\dot{E}_s$. If the combination (ω_p, ω_f) is significantly different from (ω_p^*, ω_f^*), the $P_l(\omega_p, \omega_f)$ may be so large that $P_{in} <= P_l + P_{out}$. The majority of the input power is lost by the poor selection of ω_p and ω_f. The same argument also applies to the case $\dot{T}_e >= 0$.

The analysis reveals that an important method to reduce the energy loss of the electric cooling system is to optimize the combination of ω_p and ω_f

$$\min_{\omega_p, \omega_f} \int_{t_0}^{t_f} P_{in}(t)\, \mathrm{d}t, \tag{2.15}$$

subject to

$$T_{e,min} \leq T_e(t) \leq T_{e,max}.$$

If we consider the regenerative brake, Eq. (2.15) becomes

$$\min_{\omega_p,\omega_f} \int_{t_0}^{t_f} P_{in}(t) r(t)\, \mathrm{d}t, \tag{2.16}$$

where

$$r(t) = \begin{cases} 1 & \text{if no regenerative brake exist at time } t, \\ 0 & \text{if regenerative brake exist at time } t. \end{cases}$$

During the regenerative brake, the cooling energy is free because the electricity is generated from the brake energy. The cooling energy can be stored as much as possible (without violating the constraints on T_e) during the regenerative brake. This usually corresponds to reduction of the engine temperature.

2.2 Energy buffer control

As discussed in Section 2.1, the main objective of energy buffer control is minimization of the energy loss of the system. In the vehicles using fuel for propulsion, this is equivalent to minimizing fuel consumption.

Several methods can be used to solve the optimal control problem formulated in Eq. (2.2). If a priori knowledge of the driving cycle is available, the problem can be solved using global optimization methods. A widely used method for solving optimal control problems is Pontryagin's minimum principle (PMP) [59]. PMP provides a set of necessary conditions for the optimality of an optimal control solution. Following the procedure in [52], the energy buffer control can be described as an optimal control problem where the final states are constrained to specified windows and the state trajectories satisfy time dependent constraints. Furthermore, the final time is fixed.

Application of PMP for energy buffer control is described here. The problem discussed in Eq. (2.2) includes several constraints. In the thesis we only consider the cases that the constraints are not active. A comprehensive discussion on how to consider the cases when the constraints are active is done in [52]. The Hamiltonian is calculated as

$$H(\mathbf{x}, \mathbf{u}, t) = P_{in}(\mathbf{x}(t), \mathbf{u}(t), t) + \boldsymbol{\lambda}(t)^T f(\mathbf{x}(t), \mathbf{u}(t), t). \tag{2.17}$$

where $\boldsymbol{\lambda}(t)$ is the co-state vector, i.e. vector of Lagrange multipliers [60]. The Lagrange multipliers are used to adjoin the constraints to the cost function.

Theorem [52]: Suppose that $\mathbf{u}^*$ is the optimal control for the problem in Eq. (2.2) and $\mathbf{x}^*$ is the corresponding state trajectory. The following conditions should be satisfied for $t \in [t_0, t_f]$:

1. $\mathbf{u}^*$ minimizes H for all $t \in [t_0, t_f]$,
2. $\mathbf{x}^*(t_0) = \mathbf{x}_0$ and $\mathbf{x}^*(t_f) = \mathbf{x}_f$,

3. $\dot{\boldsymbol{\lambda}}^*(t) = -\nabla_{\mathbf{x}} H|_*$ where $\boldsymbol{\lambda}^*(t)$ is the co-state trajectory. Then we have: $\dot{\boldsymbol{\lambda}}^*(t) = -\nabla_{\mathbf{x}} P_{in}(\mathbf{x}^*(t), \mathbf{u}^*(t), t) - [\frac{\partial f}{\partial \mathbf{x}}(\mathbf{x}^*(t), \mathbf{u}^*(t), t)]^T \boldsymbol{\lambda}^*(t)$,

4. $\mathbf{G}(\mathbf{x}^*(t), t) < 0$.

The calculation of co-state $\boldsymbol{\lambda}$ is usually a very complicated process depending on the system model. Furthermore, application of PMP requires a priori knowledge of the load trajectory. In some cases such as the ECMS method as discussed in Section 2.3, the calculation of co-state is straightforward, and the problem becomes an instantaneous optimization problem without the need for a priori knowledge.

Another method to solve the optimal control problems is dynamic programming (DP) [61] where the problem in Eq. (2.2) is discretized and solved using numerical methods. Application of DP for energy buffer control is described briefly here based on [2]. The integral and the state update constraint in Eq. (2.2) are discretized as

$$\min_{\mathbf{u}(k)} (K(\mathbf{x}_{t_f}, t_f) + \sum_{k=0}^{N-1} P_{in}(\mathbf{x}(k), \mathbf{u}(k), \mathbf{v}(k)) \cdot \Delta t), \tag{2.18}$$

subject to

$$\dot{\mathbf{x}}(k+1) = f(\mathbf{x}(k), \mathbf{u}(k), \mathbf{v}(k)).$$

The cost value from each point $(t, \mathbf{x})$ to the final point $(t_f, \mathbf{x}_f)$ is defined as the cost-to-go function $\Gamma(t, \mathbf{x})$. So the value of $\Gamma(t_0, \mathbf{x}_0)$ corresponds to the optimal value of the cost function which is searched for. In DP, the time and state variables are gridded. Γ is calculated for the grid points

$$t_k = k \cdot \Delta t, \quad k = 0, \dots, N,$$
$$\mathbf{x}_i = \mathbf{x}_{min} + i \cdot \Delta \mathbf{x}, \quad i = 0, \dots, p,$$

where $p = \frac{\mathbf{x}_{max} - \mathbf{x}_{min}}{\Delta \mathbf{x}}$. $\Delta \mathbf{x}$ is selected in a way that p becomes integer. The calculation of an optimal trajectory starts by

$$\Gamma(t_f, \mathbf{x}_i) = K(\mathbf{x}_i),$$

and the calculation continues backward in time to solve the recursive algorithm

$$\Gamma(t_k, \mathbf{x}_i) = \min_{\mathbf{u} \in V} \{\Gamma(t_{k+1}, \mathbf{x}_i + f(\mathbf{x}_i, \mathbf{u}, \mathbf{v}(t_k)) \cdot \Delta t) + P_{in}(\mathbf{x}_i, \mathbf{u}, \mathbf{v}(t_k), t) \cdot \Delta t\}.$$

The control variable $\mathbf{u}$ should belong to a feasible (i.e. within physical constraints) subset V, which is discretized to q values $\mathbf{u}_j, j = 1, \dots, q$. After calculation of $\mathbf{u}$, the values are stored in a look up table

$$U(t_k, \mathbf{x}_i) = arg\{\Gamma(t_k, \mathbf{x}_i)\}.$$

The function U is used to reconstruct the optimal trajectory $\mathbf{x}^*(t)$ and $\mathbf{u}^*(t)$ which can be used to calculate $P_l^*(t)$. We start the forward calculation from $k = 0$ and continue forward in time

$$u^*(t_k) = U(t_k, \mathbf{x}^*(t_k)),$$
$$\mathbf{x}^*(t_{k+1}) = \mathbf{x}^*(t_k) + f(\mathbf{x}^*(t_k), \mathbf{u}^*(t_k), \mathbf{v}(t_k)) \cdot \Delta t.$$

Since the state values $\mathbf{x}_i + f(\mathbf{x}_i, \mathbf{u}, \mathbf{v}(t_k)) \cdot \Delta t$ and $\mathbf{x}^*(t_k)$ usually do not match the points of the grids, the corresponding values of Γ and U should be interpolated using the values calculated for the closest points of the grid. A detailed discussion on different interpolation methods is presented in [2]. The computation load of DP increases with the number of states, discretized state values p, the number of control inputs, the number of discretized control input values q and the problem time N. Thus, DP is usually used for offline calculation and benchmarking. Furthermore, it is necessary to have a priori knowledge about the driving cycles if DP is to be used. However, access to the data from the whole driving cycle is not always available online. Hence, it is necessary to use other methods to solve the optimal control problem if PMP and DP are not applicable.

2.3 Equivalent consumption minimization strategy (ECMS) for HEVs

If P_{in} and f do not contain the states, the optimal control problem in Eq. (2.2) can be reduced to an instantaneous optimization problem. An example is when the only energy buffer is the battery, and the only state is SOC. In this case neither $P_{in} = \dot{m}_f(\tau_e, \omega_e)$ nor f (Eq. (2.3)) contains SOC. From the theorem we have

$$\dot{\lambda}^*(t) = -\nabla_{\mathbf{x}} H|_* = -\frac{\partial \dot{m}_f(t,u)}{\partial x} - \lambda^* \frac{\partial f(x^*, u^*)}{\partial x}$$

and

$$\frac{\partial \dot{m}_f(t,u)}{\partial x} = 0,$$

$$\frac{\partial f(x^*, u^*)}{\partial x} = 0,$$

so

$$\dot{\lambda} = 0,$$

and λ becomes a constant for the entire drive cycle (when constraints are not active). The physical interpretation of λ is the equivalent cost of electricity [9, 62, 11]. In other words, the electrical energy is converted to the equivalent fuel using an equivalence coefficient. This strategy is called equivalent consumption minimization strategy (ECMS). A popular application of ECMS is power management of HEVs. In parallel HEVs, a major control decision is to decide when and how much energy should the battery provide at each instant. Through the process explained in [63], Eq. (2.2) can be reduced to

$$\min_{T_{em}}(P_{in}), \tag{2.19}$$

where

$$P_{in} = P_{fuel} + \lambda \cdot P_{battery}, \tag{2.20}$$

and subject to

$$\begin{aligned} \tau_{e,min} &\leq \tau_e \leq \tau_{e,max}, \\ \tau_{em,min} &\leq \tau_{em} \leq \tau_{em,max}, \\ SOC_{min} &\leq SOC \leq SOC_{max}, \\ \omega_{e,min} &\leq \omega_e \leq \omega_{e,max}, \\ \omega_{em,min} &\leq \omega_{em} \leq \omega_{em,max}, \end{aligned}$$

where P_{fuel} is power from fuel, $P_{battery}$ is battery power, τ_e is engine torque, τ_{em} is electric motor torque, SOC is state of charge of the battery, ω_e is engine speed and ω_{em} is electric motor speed. Other indices are self explanatory.

The power management strategy of HEVs should be charge sustaining, i.e. the final SOC is equal to the initial SOC, so the net battery usage is zero. Any net battery charge will provide low cost energy in the future resulting in reduction of the fuel consumption. On the other hand, any energy consumption from the battery must be compensated in later phases. The compensation can be achieved either directly from the engine or indirectly using the electric motor to regenerate the electrical energy from the brake energy [9]. If the equivalence coefficient is too small, the battery net usage will not be zero at the end of the driving cycle, resulting in violation of the final constraint of SOC. On the other hand, if the equivalence coefficient is too large, the battery usage will be too conservative, resulting in non-optimal fuel consumption [62]. Different methods are introduced in the literature for calculation of the equivalence coefficient [12, 11, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22]. Our simulations on a hybrid electric city bus reveal that these methods cannot provide optimal solutions in all sorts of driving cycles as discussed in Paper E. The method presented in Paper E is to improve the robustness of the ECMS method.

2.4 Model predictive control (MPC) for the engine cooling system

Model predictive control (MPC) [64, 65] is a powerful method for solving optimal control problems involving many constraints. So MPC can be a suitable method for solving optimal control of energy buffers which usually comprise several constraints. Using the prediction data from prediction units which work based on external signals from different sensors can improve the performance of MPC. The MPC algorithm includes the following steps:

- Calculating a future trajectory
- Calculating a control sequence which minimizes a cost function over the prediction horizon

- Applying the first member of the control sequence to the system
- Getting state update, and then recompute

Different versions of MPC exist. In non-linear model predictive control (NL-MPC), the state update function is not linear. This method is used in Paper C. Another method is to linearize the state function at each instant and approximate the cost function by a linear or quadratic function. This method is called linear time variant MPC (LTV-MPC). The benefit of this method is that the cost function can be transformed into a linear programming or quadratic programming problem, which is possible to solve using efficient solvers. The algorithm of LTV-MPC is presented in Fig. 2.4. LTV-MPC is used in Paper A. Application of PMP for the cooling

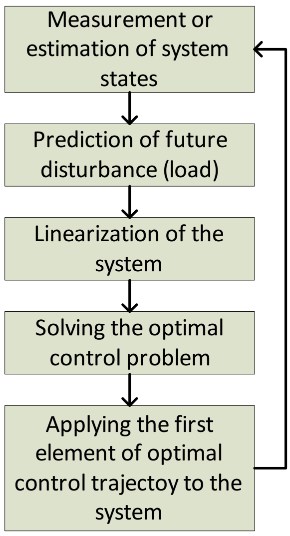

Figure 2.4: LTV-MPC algorithm

system can be cumbersome due to the difficulties in finding the co-state value. PMP has been used for cooling system control in [40] but the derivation of co-states is complex and approximate. The problem can be solved using simpler solutions. Different control methods have been used in literature for the engine cooling system. PI controllers are used in [66, 33, 36, 37, 29]. PID controllers are used in [67, 36]. In [68, 28, 57], a Lyapunov-based nonlinear control algorithm is proposed. In [38], a rule based controller is used to control pump and fan speed. In [69], a nonlinear back stepping robust controller is developed to regulate the engine coolant temperature. Al Tamimi and Salah [70] use a neural network-based optimal control strategy to regulate engine temperature using an electrified cooling system. These methods effectively regulate coolant temperature at the desired level and reject disturbances, but do not intend to reduce the energy consumption of the cooling system. Furthermore they do not utilize prediction of the future driving conditions.

Optimal control methods are used in [39, 40] to reduce the auxiliary load of the engine cooling system. Employing prediction for optimal control of the engine cooling system is studied in [39]. Convex optimization is used in [56] for the engine cooling system control. A predictive controller based on neural networks is used in [71] to control water pump and thermostat. However, the online implementation of optimal control of engine cooling systems is not studied in literature to the knowledge of author. The emphasis in this thesis is using convex optimization in the context of MPC using onboard prediction of the driving cycle to improve fuel efficiency by reducing the parasitic load of the electric cooling system and also using the regenerative brake.

The future trajectory is in this thesis assumed calculated by onboard prediction of the future vehicle speed and engine torque. The cost function is approximated as a quadratic function. The control problem for the engine cooling system can be formulated as

$$\min_{\mathbf{u}_{0|k},\cdots,\mathbf{u}_{H_p-1|k}} \sum_{i=0}^{H_p-1} \dot{m}_f[\tau_{ei|k}(\mathbf{u}_{i|k},\mathbf{w}_{i|k}),\omega_{ei|k}], \tag{2.21}$$

subject to

$$\begin{aligned}
x(k+1) &= f(x(k),u(k),w(k)),\\
T_{e,min} &\leq T_e(k) \leq T_{e,max},\\
SOC_{min} &\leq SOC(k) \leq SOC_{max},\\
\omega_{p,min}(k) &\leq \omega_p(k) \leq \omega_{p,max},\\
0 &\leq \omega_f(k) \leq \omega_{f,max},\\
I_{b,min} &\leq I_b(k) \leq I_{b,max},\\
\tau_{a,lb}(k) &\leq \tau_a(k) \leq \tau_{a,ub}(k),\\
SOC(N) &= SOC(0),
\end{aligned}$$

where T_e is engine temperature, ω_p is water pump speed, ω_f is fan speed, I_b is battery current and τ_a is alternator torque.

Using the procedure explained in Paper A, the problem can be transformed to

$$\min_{\mathbf{u}_{0|k},\cdots,\mathbf{u}_{H_p-1|k}} \sum_{i=0}^{H_p-1} (\frac{1}{2}\mathbf{u}_{i|k}^T H_{i|k}\mathbf{u}_{i|k} + \mathbf{f}_{i|k}^T\mathbf{u}_{i|k}) + \xi SOC_{H_p}, \tag{2.22}$$

subject to all inequality constraints and the state update equation in Eq. (2.21). ξ is a negative tuning parameter to compensate the SOC at the end of the prediction horizon. Eq. (2.22) can be solved using standard quadratic programming methods as discussed in Paper A.

2.5 Real time aspects of the energy buffer control methods

One of the important aspects of energy buffer control is real time implementation of control methods. If a control method is not applicable in real time, it can be used only for benchmark in simulation. The presented method, namely DP, PMP and MPC can all be considered as real time controllers. However, the need for a priori knowledge for both DP and PMP and heavy computational load for DP, make them inappropriate for real time implementations. On the other hand, ECMS and MPC are both suitable methods for real time implementation since they do not require knowledge of the whole driving scenario. Another aspect when designing a controller for energy buffers is the implementation of the controllers on real vehicles. Although a proposed control method may provide acceptable results in simulation environment, it might be difficult to implement it on a real vehicle. MPC and ECMS require quadratic programming and numerical optimization solvers respectively. Implementation of MPC and ECMS on real vehicles is straightforward thanks to the already available commercial toolboxes.

Chapter 3

Discussion and results

The objective of this thesis is to use optimal control of energy buffers to improve the fuel efficiency of commercial vehicles. The objective is broken down into different research questions as explained in Section 1.2. This chapter presents answers to the research questions. Each question is followed by a short answer (SA) and a longer explanation.

3.1 Answer to the Research Question 1

Q1 ECMS is a promising method for energy management in HEVs, however the performance is heavily dependent on the equivalence coefficient between electrical energy consumption and fuel consumption. If the coefficient is not tuned properly, the performance is not optimal over a range of driving situations. How can we increase the robustness of ECMS with respect to varying driving situations?

SA The equivalence coefficient can be calculated at each instant using a function that considers both the change rate of SOC of the battery and the current SOC.

The robustness of the ECMS method can be improved by designing proper functions for calculating the equivalence coefficient. The functions should be able to change the equivalence coefficient based on driving conditions. In Paper E, two different functions are used for calculating the equivalence coefficient, firstly Equation 13 in Paper E states that

$$s = k \cdot tan(a \cdot SOC(t) + b) + m, \tag{3.1}$$

where

$$
\begin{aligned}
a &= \frac{-\pi}{SOC_{max} - SOC_{min}},\\
b &= \frac{\pi}{2} - a \cdot SOC_{min},\\
k &= k_p \frac{cos^2(a \cdot SOC_{ref} + b)}{a},\\
m &= s_{ref} - k \cdot tan(a \cdot SOC_{ref} + b),
\end{aligned}
$$

where SOC_{max}, SOC_{min} and SOC_{ref} are maximum allowable, minimum allowable and reference values of SOC, respectively. s_{ref} is reference value for equivalence coefficient and k_p is tuning variable. And secondly, Equation 19 in Paper E states that

$$
s = \begin{cases} k_1 \cdot tan(a_1 \cdot SOC(t) + b_1) + d_1 \cdot (\frac{r_1 - \dot{SOC}(t)}{r_2 - r_3})^{d+1} + h_1 & \text{if } \dot{SOC}(t) < 0,\\ k_1 \cdot tan(a_1 \cdot SOC(t) + b_1) + h_2 & \text{if } \dot{SOC}(t) \geq 0, \end{cases} \tag{3.2}
$$

where k_1, a_1 and b_1 are calculated similar to k, a and b in Eq.(3.1). d_1, r_1, r_2, r_3, d, h_1 and h_2 are tuning parameters.

Both Eq.(3.1) and Eq.(3.2) are functions of current SOC and Eq.(3.2) is also a function of the change rate of SOC. When the change rate of SOC suddenly decreases, the penalty for SOC will increase in the cost function. On the other hand, if the SOC is changing slowly, or if it increases, no extra penalty is considered. Using the change rate of SOC, the ECMS method proactively protects overuse of the battery by accordingly increasing the value of the equivalence coefficient. This results in better overall fuel efficiency.

In Paper E, results from simulations using Eq.(3.1) and Eq.(3.2) for calculating the equivalence coefficient are compared. Two groups of driving cycles are selected. Group 1 includes ECE and NEDC and Group 2 includes Nurenburg bus route and UDDS. Eq.(3.1) is used as benchmark for comparison.

Three sets of simulations are considered. In each set, simulations are performed on all of the cycles from both groups. For the first set, Eq.(3.1) is tuned for the Group 1 cycles. For the second set, Eq.(3.1) is tuned for UDDS cycle. For the third set, Eq.(3.2) is used and tuned for UDDS cycle. The results are presented in Table 3.1. The increase or decrease in fuel consumption values are relatively small since they are compared with a controller which is already tuned. The main point of presenting fuel consumption values is to show the robustness of the presented method rather than quantitative values of fuel consumption improvement. Obviously, tuning Eq.(3.1) for one group does not ensure satisfactory performance for the other drive cycles. On the contrary, tuning Eq.(3.2) for only one cycle improves the fuel efficiency in the other group (or at least does not decrease the efficiency). The results show that considering the change rate of SOC results in more robust function for calculation of the equivalence coefficient.

Table 3.1: Fuel consumption (FC) ($l/100km$) using different equations in different driving cycles

Driving cycle	**FC using Eq.(3.1) tuned for ECE and NEDC**	**FC using Eq.(3.1) tuned for UDDS (% increase(+) or decrease(-) in FC)**	**FC using Eq.(3.2) tuned for UDDS (% increase(+) or decrease(-) in FC)**
ECE	21.01	21.21 (0.9)	20.99 (-0.1)
NEDC	35.35	35.47 (0.3)	35.24 (-0.3)
Nurenburg bus route	26.46	27.11 (2.5)	26.11(-1.3)
UDDS	24.89	23.85 (-4.1)	24.72 (-0.7)

The SOC trajectory using Eq.(3.2) during ECE is shown in Fig.3.1. The equivalence coefficient trajectories in the ECE cycle for both equations are shown in Fig. 3.2. Using Eq.(3.2) results in a more responsive equivalence coefficient calculation. This responsiveness is beneficial when the SOC is changing fast. In some instances, such as the period of 120-130 seconds where the SOC drops fast, Eq.(3.2) adapts the equivalence coefficient quicker than Eq.(3.1).

As discussed in Paper E, the fuel consumption improvement using the presented method is limited. However, the presented method can reduce the tuning effort due to its robustness. The parameters can be tuned for one representative cycle and then be applicable for many similar drive cycles without degrading performance. A more detailed discussion on this topic is presented in Paper E.

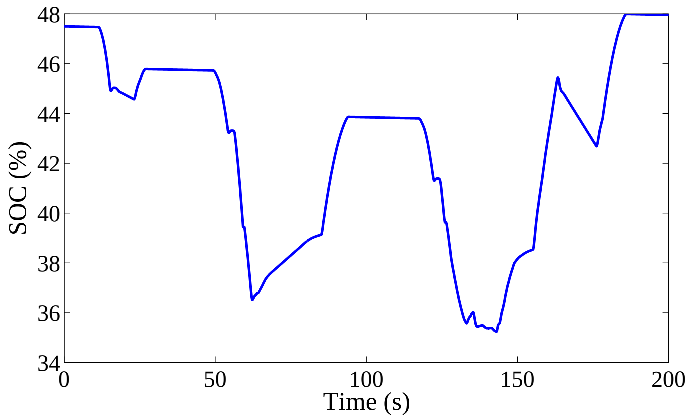

Figure 3.1: SOC trajectory in ECE using Eq.(3.2)

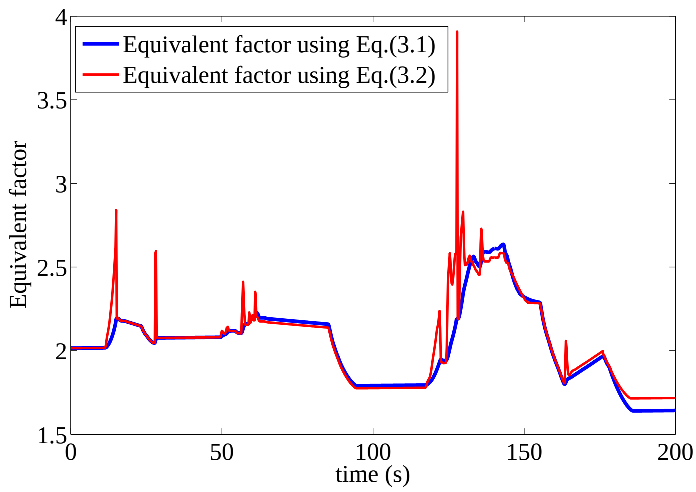

Figure 3.2: Equivalence coefficient trajectory in ECE using both Eq.(3.1) and Eq.(3.2)

3.2 Answer to the Research Question 2

Q2 When designing a torque split controller in HEVs, the drivability is sometimes omitted. How can we consider both drivability and fuel consumption?

SA The number of gear changing events can be considered as one of the main drivability criteria. A controller which integrates the torque split controller and gearbox controller can be used to consider fuel consumption minimization and drivability at the same time.

Paper D presents a literature review on different methods of considering drivability. The number of gear shifting, engine on/off events and the cumulative error between the demanded torque from the driver and the delivered torque to the wheels are considered as drivability criteria. The ECMS method is used in a controller to decide the torque split ratio between the electric motor and the engine. The gear changing decision is formulated as an optimal control problem where the objective is minimization of fuel consumption, and the control variables are gear number and the torque from the electric motor. Due to the fast dynamics of driving conditions, the gear calculated by the gear changing controller may vary frequently, resulting in poor drivability or even infeasible gear number demand. To solve this problem, smart filters are employed after the gear changing controller to stabilize the gear number command. The heuristics for the filters are explained in Paper D. The torque split controller and the gearbox controller are used in a single integrated controller.

In paper D, a set of simulations has been performed on four different driving cycles. A summary of results is presented in Table 3.2. Using the integrated controller for controlling torque split and gearbox number, both fuel efficiency and drivability are improved. Fuel consumption is decreased by 0.5-4.6%. The number of gear changing events is decreased by 55-61%. The trajectories of gearbox number demand for a rule based controller (provided by Autonomie and called "default controller" here) and the optimal controller are presented in Fig. 3.3. Note that the improvement can not be achieved without implementing the gearbox filters after the gearbox controller. The effect of gearbox filters is presented in Fig. 3.4 where gearbox demand before and after employing the filters is shown. Although engine on/off was not considered during the optimization, the number of on/off events could be reduced by up to 72%. The cumulative torque error between the torque demand and the torque on the wheels is reduced 21-43%. A more detailed discussion on this topic is presented in Paper D.

Table 3.2: Comparison of default gearbox controller and optimized gearbox controller considering fuel efficiency, gear event and engine event in Sort 1, ECE, UDDS and Manhattan driving cycles

Driving cycle		SORT1	ECE	UDDS	Manhattan
Default	Fuel consumption (l/100km)	24.95	22.03	25.01	30.29
	Gear event	23	23	197	193
	Engine event	6	7	32	36
Optimal	Fuel consumption (l/100km)	24.11	21.01	24.89	27.34
	Gear event	10	9	89	75
	Engine event	6	6	12	10

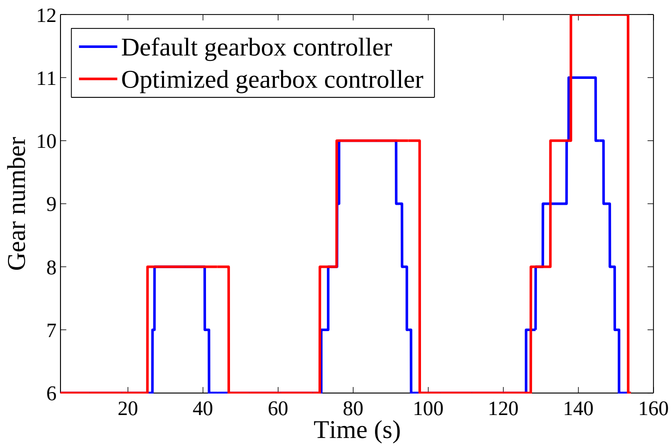

Figure 3.3: Gearbox demand from default gearbox controller and optimized gearbox controller in SORT1 driving cycle

To further improve the drivability, a one-step prediction of the driving cycle is used in the gearbox controller as discussed in Paper F. To evaluate the performance improvement, simulations are done in eight different driving cycles. There is always a time delay between the instant the gearbox receives the gear changing command and implements the command. In some cases, the required gearbox number demand after the time delay might differ from the calculated gearbox number, i.e. the time delay may cause non-optimal gearbox number in some cases. The time delay can be compensated by calculating the required gearbox number for an instant one time step ahead. This can be achieved by using predicted values of the feedback signals from the vehicle to the controller. The predicted vales are calculated using derivatives of the feedback values. In other words, the gearbox controller is using

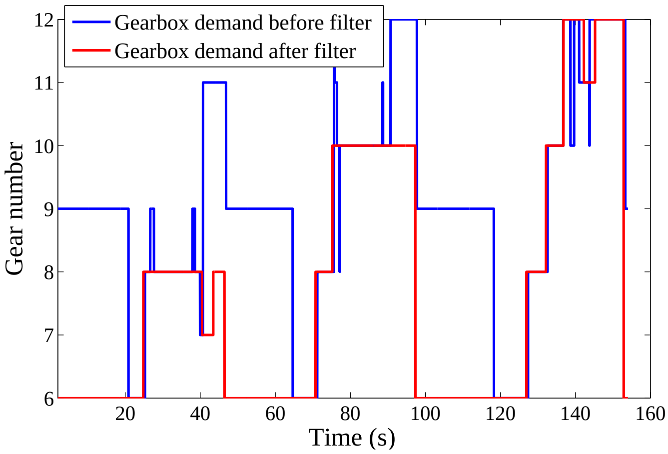

Figure 3.4: Gearbox demand before and after filter in SORT1 driving cycle

a one-step prediction. The prediction does not complicate the controller, and can be used without changing the controller structure.

The results are presented in Table 3.3. Using the one step prediction could improve the fuel efficiency by 0.6-5.6%. The number of gear changing events decreased up to 32%. The effect of one step prediction is discussed briefly here using the results from the Manhattan cycle. A more detailed discussion is elaborated in Paper F. The trajectory of gear changing events is presented in Fig.3.5. The number of gear changes is decreased when one step prediction is used. This results in better drivability as discussed in Paper D. The reason of this reduction in gear changing events is that the input to the controller is one step ahead of the current state. The current and the predicted vehicle speed and equivalence coefficient for a short period of time are presented in Fig.3.6 and Fig.3.7 respectively. As can be seen in Fig.3.6, the vehicle speed is calculated one second ahead of the real vehicle speed. Fig.3.7 shows that using prediction, the equivalence factor is calculated one second earlier compared to when the prediction is not used.

Table 3.3: Fuel consumption and gear events in different cycles for predictive and non-predictive methods

	Non-predictive method		predictive method	
Driving cycle	Fuel consumption (l/100km)	gear change event	Fuel consumption (l/100km)	gear change event
Japan 10	17.46	12	16.48	9
ECE	17.24	10	16.63	11
US06	16.02	55	15.92	42
SC03	20.89	37	20.46	37
Manhattan	29.75	105	28.8	89
Nurenburg	26.21	113	25.94	100
Bus rte	37.37	111	37.07	100

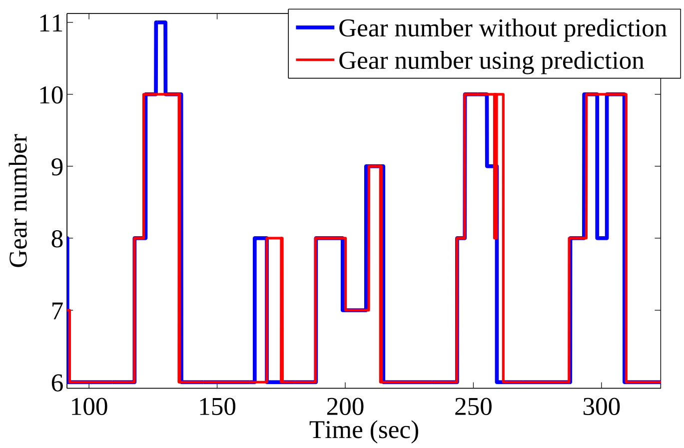

Figure 3.5: Gear changing in Manhattan cycle using predictive and non-predictive methods for 95-320 seconds

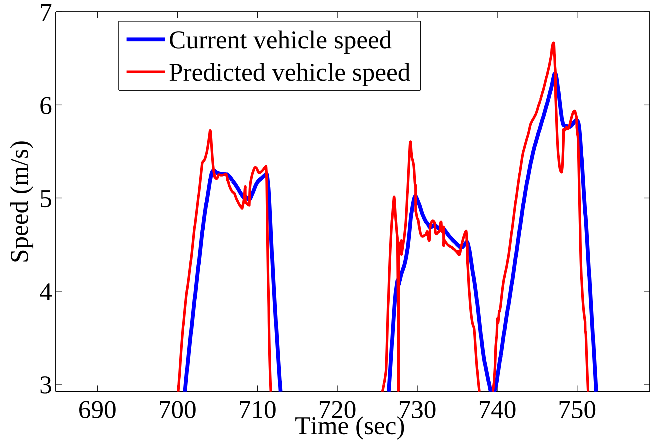

Figure 3.6: Current and predicted vehicle speed in Manhattan cycle for 685-760 seconds

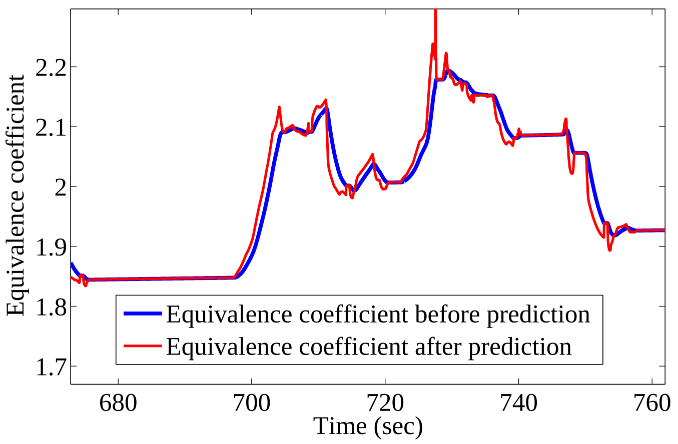

Figure 3.7: Current and predicted equivalence factor in Manhattan cycle for 670-760 seconds

3.3 Answer to the Research Question 3

Q3 How much can the EMB increase fuel efficiency in HEVs?

SA EMB can improve fuel efficiency by 0.5-1.5% in a hybrid electric city bus, depending on the driving cycle.

Paper G studies an EMB system installed on a hybrid electric city bus to investigate the potential fuel efficiency improvement. A rule based controller is used for brake blending. The controller blends the regenerative brake through electric motors and the mechanical brake which includes the engine brake and EMB. The rules in the controller are mostly based on the SOC of the battery and the required braking torque. While making sure that physical constraints are not violated the controller tries to meet the brake torque requirements by brake blending including as much regenerative braking as possible. Results from simulations on the SORT1 driving cycle are discussed briefly. A more detailed discussion is presented in Paper G. The energy consumption of the conventional brake system and the electromechanical brake system are plotted in Fig.3.8 and Fig.3.9, respectively. Although both EMB and the conventional brake are following the same operational trajectory, the energy consumption of the EMB is much smaller than the conventional brake system. The air compressor is the main energy consumer of the conventional brake system. In this study, a 6kw compressor with 18% duty cycle is used, i.e. on average around 1 kW power consumption. The EMB only requires a small amount of energy for position control of the wedge in the brake caliper. The results show a noticeable improvement of 0.5-1.5% fuel efficiency. The results heavily depend on the type of driving cycle that is used in the simulations. So in the cycles with many stop-go situations, more improvement could be seen. The relatively small value of fuel efficiency improvement is because most of the braking is done by the secondary brake system (retarders) and the regenerative brake. It is expected to gain more efficiency improvement if similar simulations are performed on a conventional city bus. The reason is that in conventional buses, the regenerative brake does not exist, so the service brake is more engaged in braking compared to hybrid electric buses, i.e. some part of the braking torque which is produced using the regenerative brake in the hybrid electric buses is in conventional buses performed using the service brake.

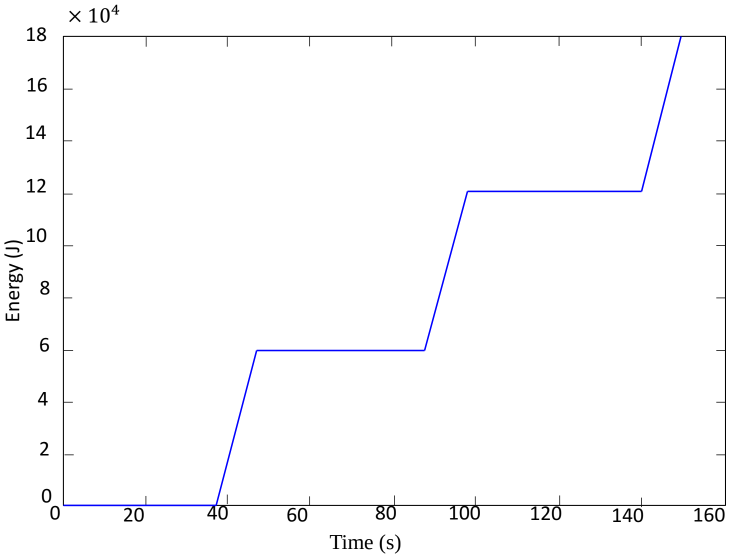

Figure 3.8: Energy consumption of the conventional brake system

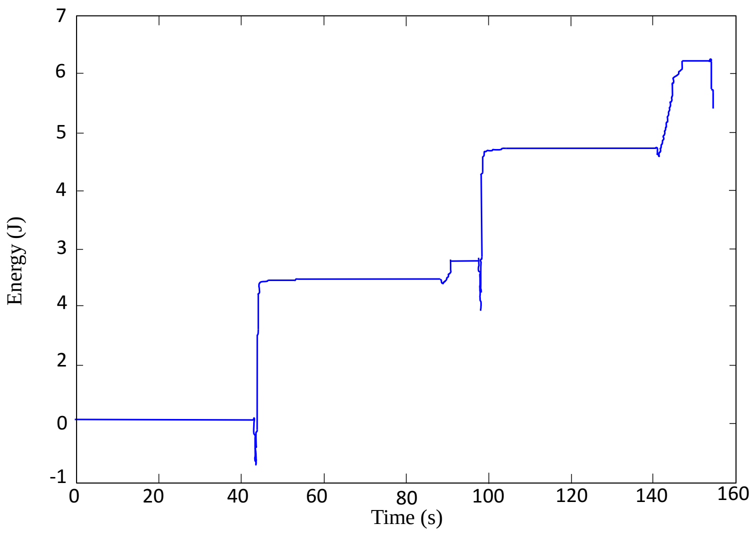

Figure 3.9: Energy consumption of the electromechanical brake system

3.4 Answer to the Research Question 4

Q4 What is the effect of the engine cooling system on fuel efficiency in heavy trucks?

SA The engine cooling system contributes to the parasite load on the engine. Optimal control of the engine cooling system shows 1.2-1.6% improvement in fuel efficiency of a conventional heavy truck depending on the driving cycle.

Dynamic programming (DP) is used in Paper B to investigate the potential fuel saving of optimal engine cooling system control in a heavy truck with conventional power train. The optimal controller achieves fuel efficiency improvement of 1.2-1.6% (depending on the driving cycle) compared to a state feedback controller which tries to stabilize the engine and radiator temperature to reference values using pole placement. The control variables in both DP and state feedback controller are pump and fan speed. The improvement values are based on comparison with a two states state-space model which has been used at the initial stages of the CONVENIENT project. The reduction of fuel consumption is related to the ability of the optimal controller to run the coolant pump and radiator fan when their operation adds least amount of energy on the engine. This results in a pre-cooling effect. Before the high load situations, e.g. before an uphill or before large acceleration, the cooling system decreases the engine temperature. Compared to an already warm engine, a cool engine requires less actuation of the pump and the fan for cooling during the high load conditions, resulting in reduction of the extra load on the engine from the cooling system.

Furthermore, the optimal controller decreases the overall usage of the actuators, hence, saving some fuel. As an example, the driving cycle and engine temperature trajectory for a test cycle are plotted in Fig.3.10. The trajectory of coolant volumetric flow rate through the pump is plotted in Fig.3.11. In two time instances, namely around 200 seconds and 800 seconds, the temperature drops and the demand from the pump is high. These two segments are just before climbing uphill and just before starting the high acceleration phase, respectively. The engine cooling system cools down the engine just before these two high load demand situations, so the alternator load on the engine is reduced during the high load conditions. Our study finds that the reduced energy consumption by allowing the temperature to rise during the high load situations outweighs the additional energy consumption during the pre-cooling segments.

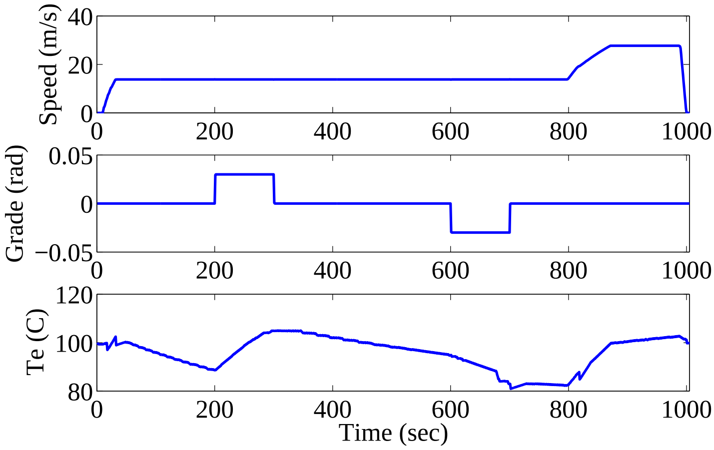

Figure 3.10: Engine temperature trajectory in KTH driving cycle

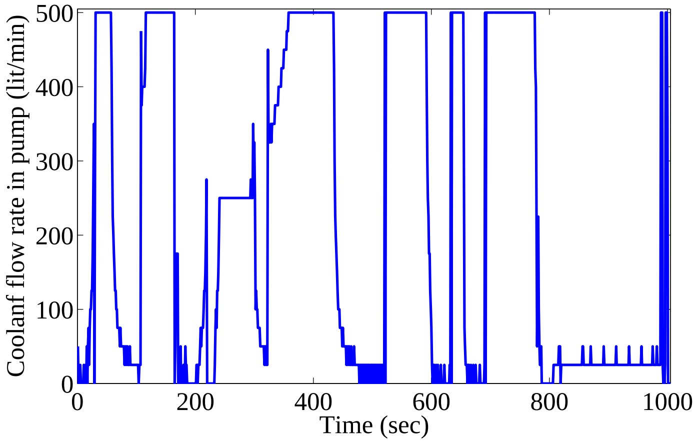

Figure 3.11: Trajectory of coolant volumetric flow rate through the pump in KTH driving cycle

3.5 Answer to the Research Question 5

Q5 How can we optimally control the engine cooling system in real time to reduce fuel consumption in heavy trucks?

SA A linear time variant model predictive control method can be used for real time optimal control of the engine cooling system.

Optimal control of the engine cooling system using model predictive control (MPC) is presented in Paper C and Paper A. The main objective of the controller is to increase fuel efficiency by decreasing the parasitic load of the electric cooling system. In Paper C, non-linear MPC is presented and the control variables are coolant pump speed and radiator fan speed. The results clearly show a pre-cooling effect similar to the global optimal control solution as discussed in the answer to research question 4.

In Paper A, LTV-MPC is used for controlling the engine cooling system. The control variables are coolant pump speed, radiator fan speed and battery current. The calculated battery current signal is input to the battery's dynamic model to obtain the required battery voltage, which calculates the required battery voltage, used for controlling the alternator.

All the components in the system are approximated by quadratic functions using curve fitting methods on measured data. The quadratic component cost functions result in a quadratic optimization cost function indicating the total fuel consumption of the truck. For simulations, the cost function is minimized using the standard quadratic programming solver of Matlab [72], "`quadprog`". The problem has also been solved using DP for developing a benchmark for evaluating the results from the MPC controller. A non-predictive PI-controller is also used for comparison between the optimal controller and the non-optimal controller. A brief summary of the results is discussed here using the results from simulations on the KTH driving cycle which was introduced in Sec. 1.3.4. A more detailed discussion about the results from simulation on other driving cycles are presented in Paper A.

The trajectory of coolant temperature at the engine output is shown in Fig.3.12 for the global optimal solution, the MPC controller and the PI controller. The temperature trajectory is similar in both the global optimal solution and the MPC controller. This confirms reasonable thermal behavior of the MPC controller. The higher temperature is advantageous in two ways. First, the energy consumption of the cooling system can be reduced and second, the engine's internal friction is reduced, resulting in higher engine efficiency.

The coolant pump speed demand is plotted in Fig.3.13. The overall behaviors of the DP and MPC solutions are very similar except a few deviations. The MPC controller demands less pump speed compared to the PI controller. In 1-1.5 km, due to the regenerative brake, the electrical energy from the alternator is more than the required energy for charging the battery. Thus, the pump demand is relatively large to reduce the coolant temperature in advance with free energy. A similar

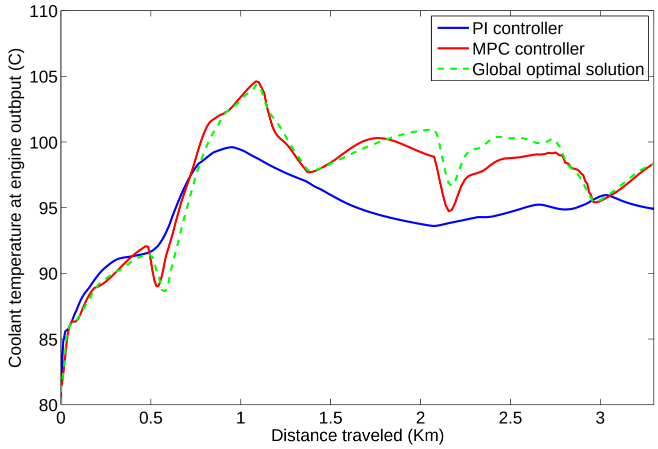

Figure 3.12: Trajectory of of the coolant temperature in KTH cycle

effect can be seen after 2.6 km. The trajectory of the radiator fan demand is shown in Fig.3.14. During the braking, the fan demand is at maximum since the fans can reduce the coolant temperature using the recovered brake energy. Overall fan speed demand in both DP and MPC is less than that of the PI controller.

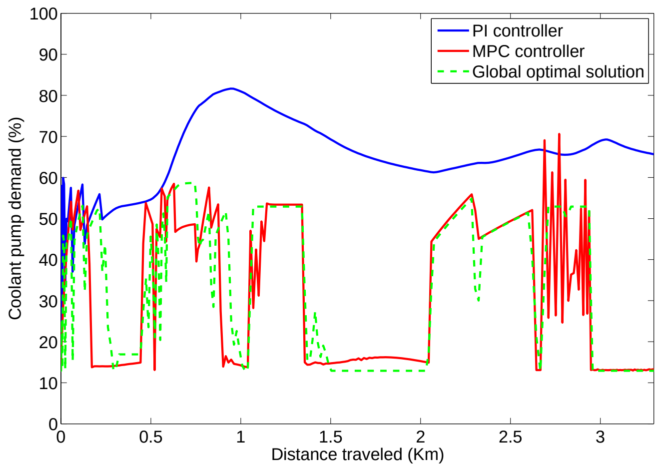

Figure 3.13: Trajectory of the coolant pump demand in KTH cycle

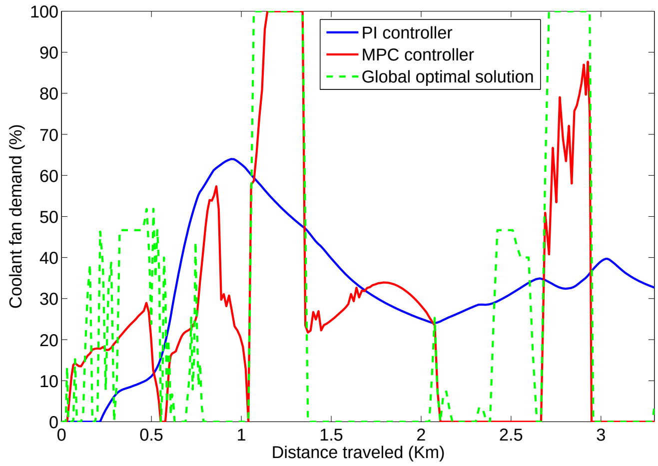

Figure 3.14: Trajectory of radiator fan demand in KTH cycle

Battery SOC and current are plotted in Fig.3.15 and Fig.3.16 respectively. MPC and DP give similar behavior. The SOC of the battery is decreased until start of the downhill at around 1.1 km. During the downhill until around 1.4 km, the major part of the recovered brake energy is used to charge the battery. Afterward, the battery is discharged again until beginning of the deceleration phase at around 2.6 km. During the brake phase, the battery is charged again. Since the control strategy is charge sustaining, the final SOC is close to the initial one. As opposed to the PI controller which only tries to ensure the sustainability of SOC, both DP and MPC actively use the energy from the battery to supply the electric cooling system. The battery is discharged when the regenerative brake is not available, in order to reduce the fuel consumption of the alternator, e.g. during 0-1 km and 1.5-2.5 km. During the regenerative brake, at 1-1.5 km and 2.5-3 km the battery is charged using the kinetic and potential energy of the truck. In normal driving, the energy for the cooling system and other electrical auxiliaries is from the battery and the alternator. By consuming less energy from the alternator, the torque on the engine will reduce, hence, the overall parasitic load on the engine is reduced and this results in less fuel consumption. The trajectory of the alternator torque is shown in Fig.3.17. Except the regenerative brake periods, the two optimal controllers almost always add less torque load to the engine. When there is regenerative braking, the alternator is driven by the vehicle kinetic energy which is transmitted from the wheels to the alternator through the driveline.

Table 3.4 compares the three cooling system controllers on various energy consumption values. Note that the driveline fuel consumptions of DP, MPC and PI are not the same. To evaluate the effect of the optimal engine cooling system controller

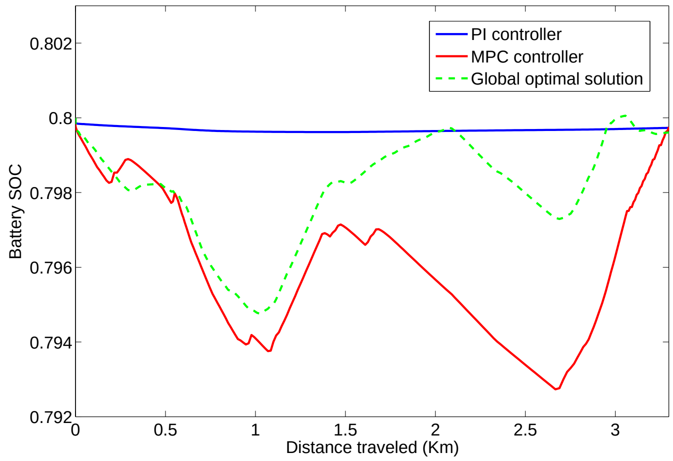

Figure 3.15: Trajectory of battery SOC in KTH cycle

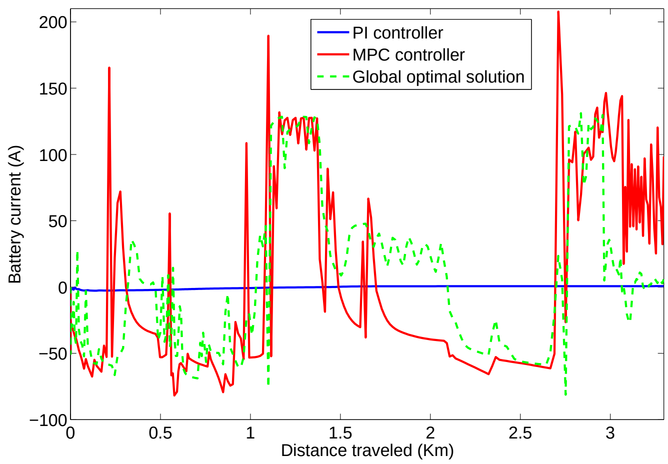

Figure 3.16: Trajectory of battery current in KTH cycle

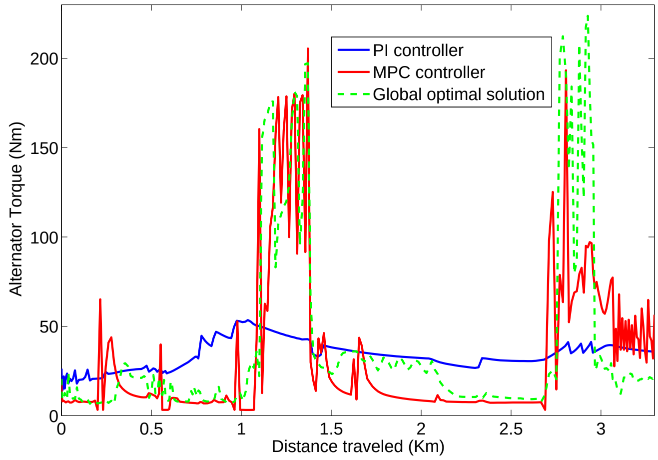

Figure 3.17: Trajectory of the alternator torque in KTH cycle

on fuel consumption, the controller should not affect the driveline torque or the vehicle speed profile. For fair evaluation of the performance of the controller, the fuel consumption of the driveline and the alternator need to be calculated separately. For better comparison, we calculate the mechanical power input to the alternator when there is no regenerative brake. This mechanical power is from the engine and increases the fuel consumption. These values are presented in Table 3.4. The alternator fuel consumption for both MPC and DP are reduced compared to the PI controller.

In summary, the MPC controller achieves 41% reduction in the alternator fuel consumption compared to the PI controller. This is equivalent to around 0.91% reduction in total fuel consumption. The control demands from the MPC controller are very close to the control demands from global optimal solution.

The MPC controller is implemented on a dSPACE MicroAutoBox, which is integrated into the experimental truck for *rapid control prototyping*. The "`quadprog`" solver which is used in the simulations is not applicable on MicroAutoBox, so FORCES Pro [73], is used as the solver. Results from simulations using FORCES Pro and "`quadprog`" are compared in Figs. 3.18, 3.19, and 3.20 for the first 46km of the BLB cycle. Apart from some deviations specially on the water pump during regenerative braking, the result from both solvers are consistent, which guarantees the consistency of results from simulation (using "`quadprog`") and experiment (using Forces Pro).

The trajectory of computation time for the Forces Pro on the MicroAutoBox measured on the first 46 km of the BLB cycle is presented in Fig. 3.21. The computational resources of the electronic control unit (ECU) of the truck is similar

Table 3.4: Energy consumption values for KTH cycle for a 40 tons truck

	MPC	**DP**	**Simple**
Total FC (lit)	2.1751	2.1438	2.1904
Driveline FC (lit)	2.1465	2.1158	2.1418
Alternator FC (lit)	0.0286	0.028	0.0486
$\frac{\text{Alternator FC}}{\text{Total FC}} \times 100\%$	1.31%	1.34%	2.22%
Reduction of the total FC	0.69%	2.1%	0
Reduction of the alternator FC	41%	42.4%	0
Reduction of the total FC due to the reduction of the alternator FC	0.91%	0.94%	0
MW from the engine to the alternator (kJ)	489.65	472.04	786.65
Total engine mechanical work (MJ)	32.7	32.6	33
Reduction of alternator MW	37.75%	40%	0

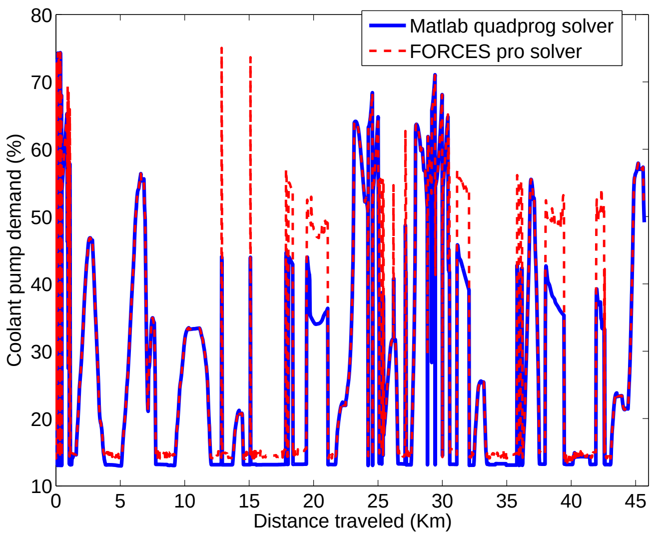

Figure 3.18: Comparison of pump demand from two solvers

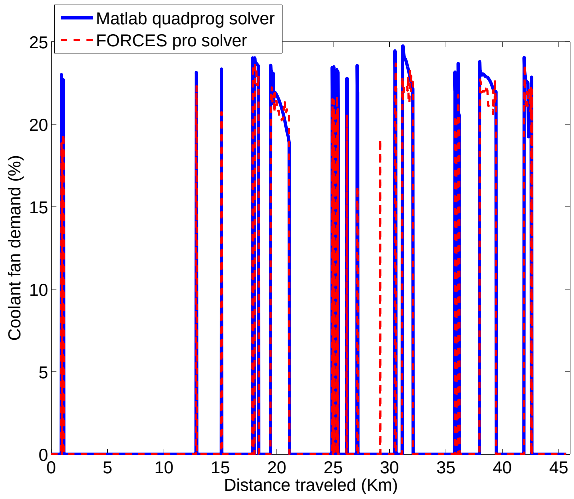

Figure 3.19: Comparison of fan demand from two solvers

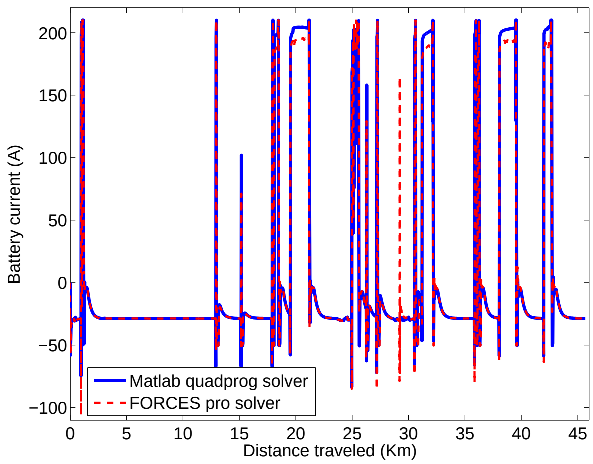

Figure 3.20: Comparison of battery current from two solvers

to the MicroAutoBox. The average solving time is 1.5 seconds and the maximum value is 2.5 seconds. In the experiment on the truck, the computation period for solving the optimization problem is 10 seconds, the prediction horizon is 100 seconds and the prediction step is 1 second. Every second, the control inputs are sent to the cooling system. After each solution of the optimization problem, the trajectory of control commands is stored and are sent to the actuators consecutively at each second for the next 10 seconds.

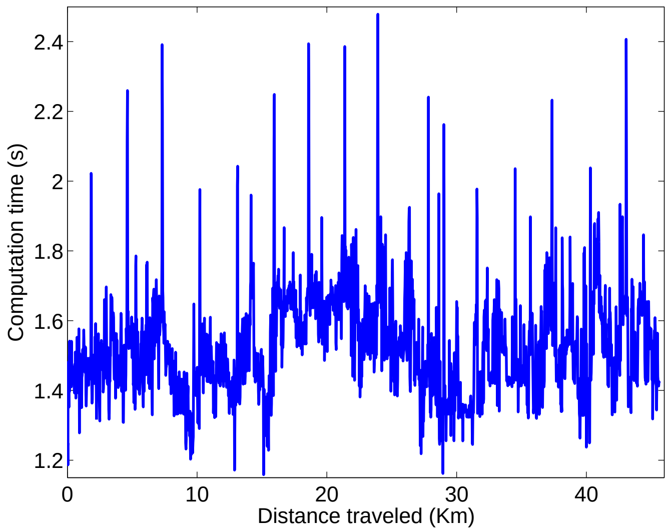

Figure 3.21: Computational time of FORCES Pro at each step

Chapter 4

Future work

The work in this thesis can be extended in several directions. Several ideas have evolved during the thesis which can be the subjects of future research. The ideas are categorized into six headings.

4.1 Energy buffer

The concept of energy buffer control can be used for controlling other subsystems such as the cabin air conditioning (AC) system. Furthermore, the overall energy flow in the vehicle can be managed in a central controller. In this case, all energy buffers are controlled in a single controller using a holistic view. Other control variables such as gear number can also be included as optimization variable.

More components of the engine cooling system can be controlled to potentially decrease the fuel consumption more than the presented values in this thesis. One of the main candidates is the grill shutter. Optimal control of the grill shutter would result in fuel consumption reduction by reducing drag force as well as smart use of ram air effect which minimizes the fan usage.

4.2 ECMS

In this thesis, one-step prediction is used to improve the performance of the ECMS method, however, application of multi-step prediction or Kalman predictors can also be investigated. Furthermore, the on-board prediction can be used to calculate the equivalence coefficient. This can improve the robustness of the controller. More research can be done to develop even more robust methods for calculation of the equivalence coefficient. Control of engine on/off can also be included in the optimization process. This can improve both drivability and fuel consumption.

4.3 MPC

The MPC controller can be improved for better performance by investigating the effect of varying control horizon, prediction horizon, resolution of prediction step and resolution of linearization. Longer prediction horizon may improve the performance of the controller but also increases the computational load.

The model used in this thesis for the MPC controller of the engine cooling system can be improved. The parameters for the current model need to be tuned for different driving cycles to reflect the correct behavior of the system, i.e. the current model is not robust enough. More advanced system identification methods can be implemented to improve model accuracy. Neural network is a candidate method to develop a more accurate model of the engine cooling system. Online system identification methods can also be used in the controller.

Apart from LTV-MPC, other types of MPC can be used for energy buffer control. NL-MPC [74] and explicit MPC [75] are the two main candidates. Although NL-MPC is used in Paper C, it can be developed for better performance. The main advantage of NL-MPC is that the controller performance is not degraded due to the linearization process. Explicit MPC can decrease the real time computational load significantly. Hence, longer prediction horizon can be used. Furthermore, the time delay between calculation of control signal and the actual implementation of the control signal is reduced, thus the overall performance can be improved.

4.4 Other control strategies

There are other control methods suitable for energy buffer control. Approximate dynamic programming (ADP) [61] is an option which can be investigated. This method benefits from the advantages of dynamic programming and reduces the computational load to be small enough for real time computation. Non-model-based methods such as fuzzy control [76] can also be implemented for the energy buffer control. Using fuzzy controllers can simplify the modeling process if the combination of energy buffers becomes too complex.

4.5 Real time performance improvement

The real time performance of the controller can be improved in terms of calculation efficiency. Alternative solvers can be selected to achieve better performance of the real time MPC controller. In this thesis, the formulation of matrices for MPC is intended for the Matlab solver “`quadprog`”, hence, all the variables are in one large vector, i.e the solver solves the problem for the entire prediction horizon in one stage. The embedded solver “Forces Pro” provides the opportunity to consider multistage formulation where the large vectors are replaced with smaller vectors. This formalism has the potential to decrease the calculation time by solving several optimization problems with small number of variables instead of one optimization problem with large amount of variables, hence, improving the performance of the controller. Investigation of multistage formalism of MPC is part of the future research.

4.6 Brake blending

More advanced controllers can be used for brake blending. The brake blending in HEVs can be unified with the torque split controller for more accurate control of braking as well as improvement of fuel efficiency. Furthermore, the brake blending effects on fuel consumption in conventional vehicles can be studied for possible fuel consumption improvement. Other electromechanical subsystems such as steering can be considered for fuel consumption reduction. By substituting different mechanical and hydraulic subsystems with electrical ones and totally remove the hydraulic and pneumatic subsystems, fuel consumption can be reduced considerably.

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Appendix A

Summary of appended papers

A.1 Paper A: Reducing Auxiliary Energy Consumption of Heavy Trucks by Onboard Prediction and Real-time Optimization

The paper presents a linear time variant MPC for engine cooling system control of a truck. A review of different engine cooling system control methods is presented, and the importance of optimal control of the engine cooling system is described. The paper presents a model of the cooling system as well as its linearization. All the components are approximated by quadratic fits, and the optimal control problem is formulated as a quadratic programming problem. The performance of the controller is evaluated by simulating a high fidelity model which is validated by real truck test data. The results are compared to a state feedback controller and a global optimal solution. Final results show fuel efficiency improvement of the truck using the optimal thermal management system. The simulations are performed for two different cycles. The influence of prediction horizon is also investigated briefly. Usage of an alternative solver which enables us to implement the controller for real-time execution on a dSPACE MicroAutoBox is also briefly explained.

A.2 Paper B: Fuel Saving Potential of Optimal Engine Cooling System

The paper studies the potential fuel saving of an optimal engine cooling system control. The concept of energy buffer control is explained and a holistic view on energy buffer control is introduced. This concept is used to motivate how the optimal engine cooling system control can increase fuel efficiency. The nonlinear state-space models of the vehicle and its engine cooling system are described. Dynamic programming is used for global optimization to find the maximum efficiency that can be gained by an optimal engine cooling system control. A state feedback controller based on pole placement method is developed as a benchmark to compare with the results from global optimization. The results have shown notable improvement in the fuel efficiency. The rationale for the improvement of fuel efficiency is also explained, and the concept of pre-cooling of the engine is introduced.

A.3 Paper C: Predictive Control of the Engine Cooling System for Fuel Efficiency Improvement

Following paper B, the paper presents a non-linear MPC controller for real time implementation. The controller employs DP in every step of MPC to solve the optimal control problem within the prediction horizon. The controller performance is evaluated on a two states state-space model of the engine cooling system. The results are compared with a state-feedback controller and the global optimal solution. The results show fuel efficiency improvement by optimal control of the engine cooling system using non-linear model predictive control.

A.4 Paper D: Optimization of Gear Shifting and Torque Split for Improved Fuel Efficiency and Drivability of HEVs

The paper demonstrates that fuel efficiency and drivabiltiy are optimized in an integrated optimization process. In this paper, the drivability is evaluated using the number of gear shifts, engine on/off events and cumulative error between the demanded torque from the driver and the delivered torque to the wheels. The controller is designed in two parts, namely, the torque split controller and the gearbox control. Furthermore, the integration of the the two controllers is discussed. The integrated controller is optimizing the torque split and the gear number in one step. Proper filters for the gearbox controller are introduced to improve the efficiency of the controller in terms of drivability. The performance of the controller is evaluated using simulations on different driving cycles. Fuel consumption, gear event, engine event and cumulative torque demand are calculated for the case of using a non-optimal gearbox controller and the presented controller. The results show improvement in both drivability and fuel efficiency for all driving cycle situations.

A.5 Paper E: Improving Fuel economy and Robustness of an adaptive ECMS Method

The paper introduces different approaches to calculate the equivalence coefficient in the ECMS method. Based on the tangent function method used in [19], a new method is developed which uses the rate of change of SOC of the battery. Two different equations for calculation of the equivalence coefficient are proposed based on this method. The performance of the proposed method is evaluated in simulation environment. The simulations are performed on four different driving cycles. The presented method has shown better fuel efficiency compared to the normal tangent function. Also, it does not require the re-tuning of the controller for different cycles, thus, it is more robust compared to when normal tangent function is used.

A.6 Paper F: One-Step Prediction for Improving Gear Changing Control of HEVs

The paper proposes a one-step prediction strategy to improve the gear changing control by compensating the gear change delay. The aim is to improve fuel efficiency and drivability. The control structure is based on the ECMS method. The global optimal solution is also presented as a benchmark. Multiple representative driving cycles are categorized to distinguish distinct driving tasks, such as urban driving and highway cruising. The categorization reveals the dependency of control performance of the proposed controller on driving tasks. The results for predictive and non-predictive methods are then compared. Final results show improvement in both fuel consumption and drivability.

A.7 Paper G: Fuel Efficiency Improvement in HEVs Using Electromechanical Brake System

The paper studies the fuel consumption reduction potential of using an electro-mechanical brake system in a hybrid electric city bus. The conventional brake system in heavy vehicles is reviewed and an electro-mechanical brake system is introduced. A model of the brake system is presented which is used for simulations. A rule-based brake blending strategy is also presented. The control strategy and the brake system are then evaluated using simulation on different cycles. The results have shown limited but notable improvement of fuel efficiency.

Appendix B

Driving cycles used in the thesis work

The driving cycle explained in Sec. 1.3.4 are plotted here.

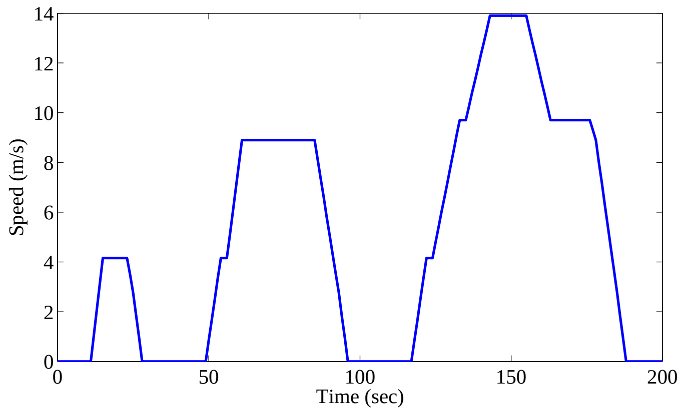

Figure B.1: ECE driving cycle

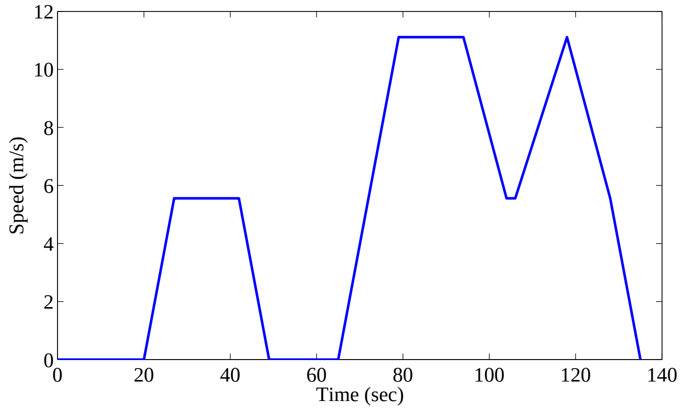

Figure B.2: Japan10 driving cycle

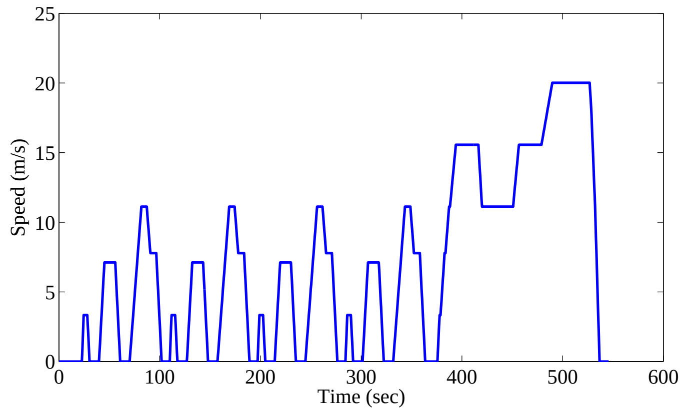

Figure B.3: NEDC driving cycle

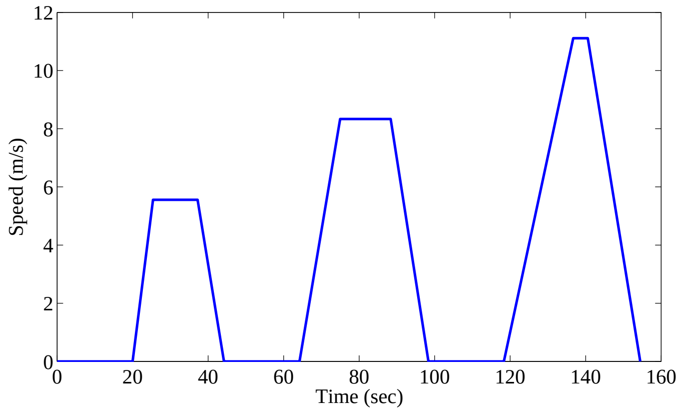

Figure B.4: SORT1 driving cycle

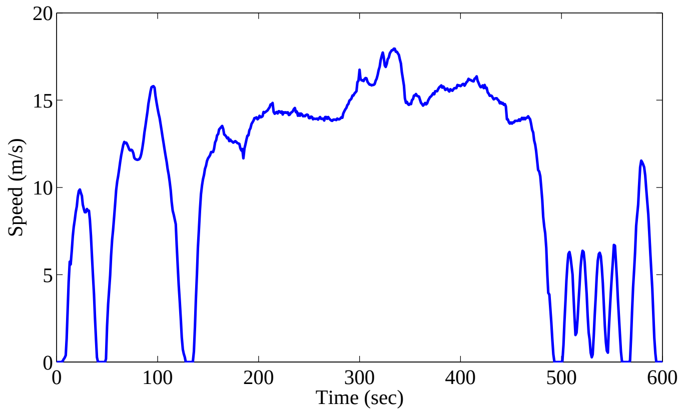

Figure B.5: US06 driving cycle

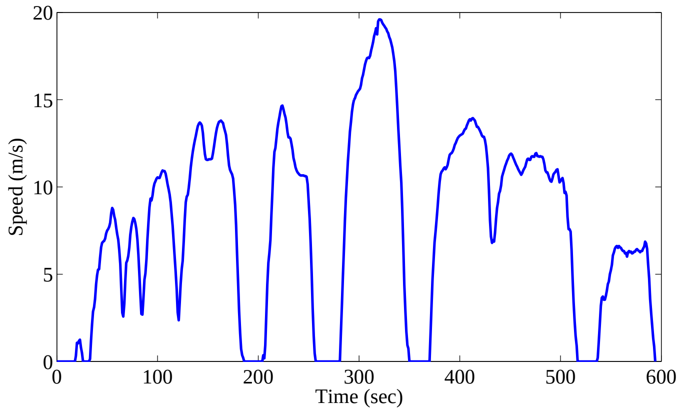

Figure B.6: SC03 driving cycle

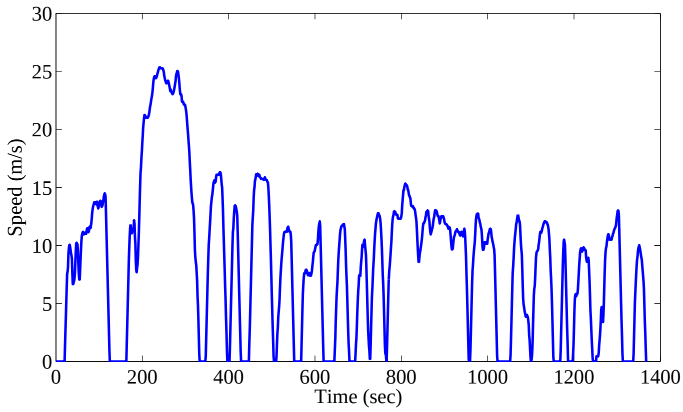

Figure B.7: UDDS driving cycle

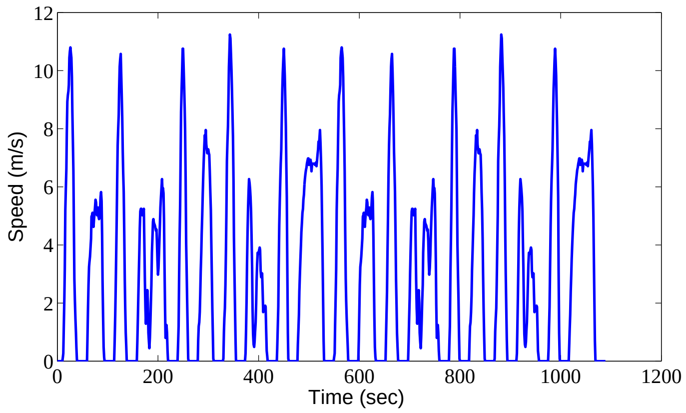

Figure B.8: Manhattan driving cycle

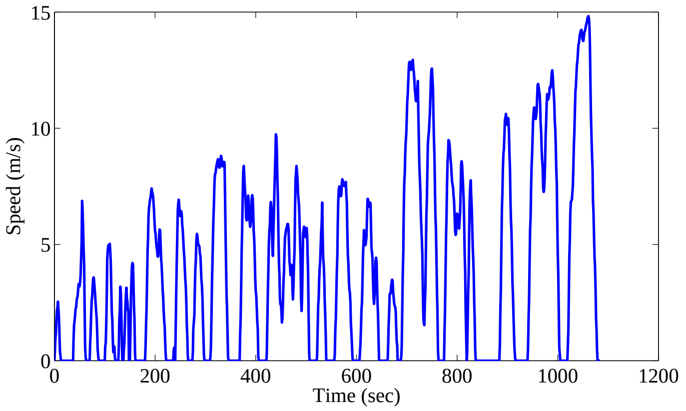

Figure B.9: Nuremberg bus route cycle driving cycle

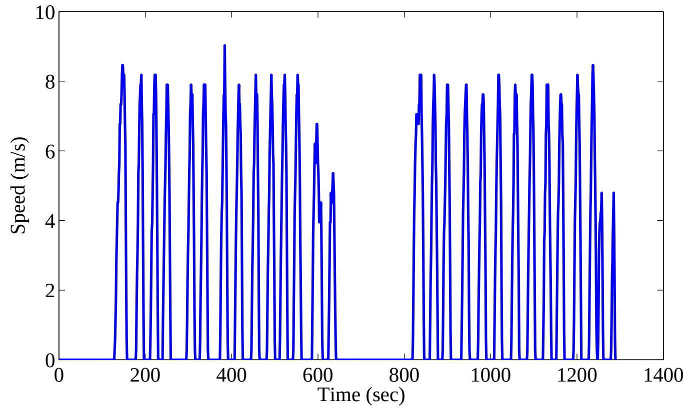

Figure B.10: bus rte cycle driving cycle

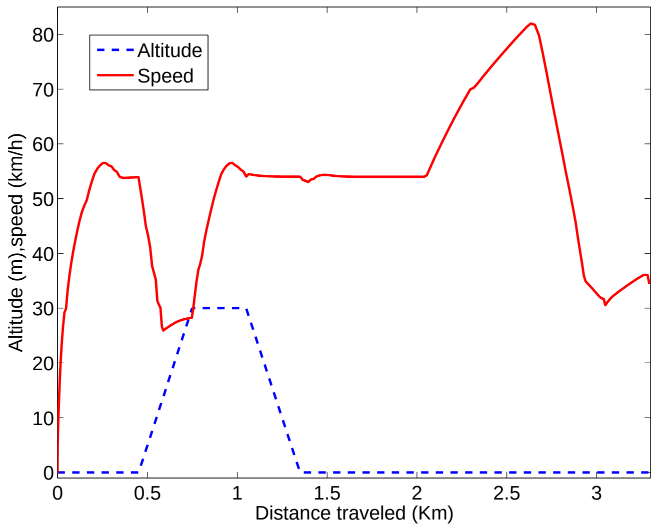

Figure B.11: The KTH Cycle

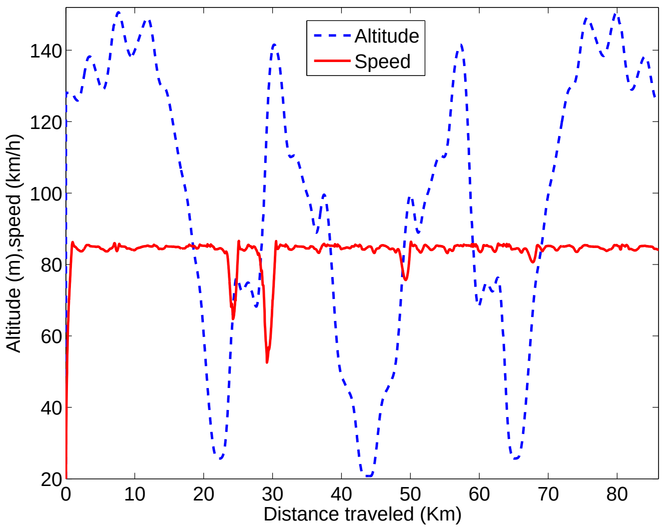

Figure B.12: The BLB Cycle