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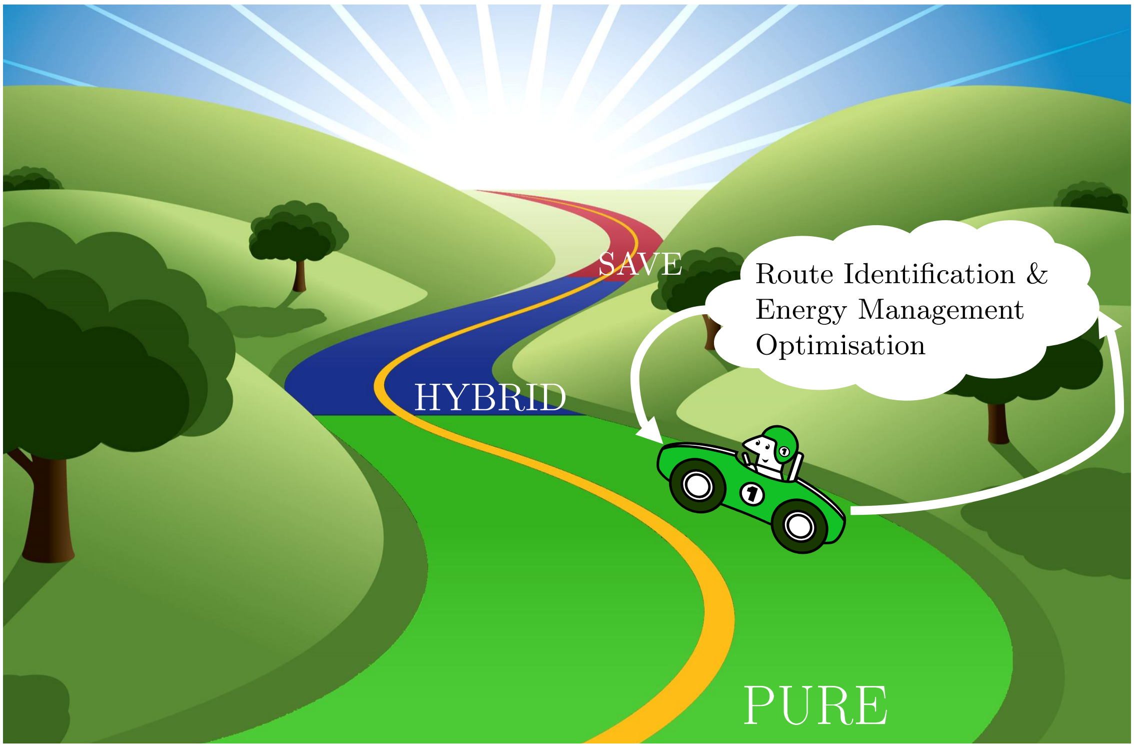

Development of a Route Identification and Energy Management Optimisation System for Plug-in Hybrid Electric Vehicles

Master's Thesis in *Systems, Control and Mechatronics*

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Department of Signals and Systems
Division of Automatic Control, Automation and Mechatronics
CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2013
Master's Thesis EX064/2013

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Cover:

Illustration of the mode selection algorithm developed in this thesis.

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The Devil is in the details

Abstract

Plug-in Hybrid Electric Vehicles (PHEV) are increasing in popularity and so is the research interest for them. One topic of research is how to best handle the flows of energy in the powertrain, which is done by the *energy management system*. However, to find an optimal energy management strategy is not a trivial task. Advanced techniques have been developed during the last decade, but have not received a widespread usage in the industry. One reason is the computational power required for the calculations, which is not present in modern vehicles. However, an increased connectivity between vehicles and the mobile network gives the possibility to transmit driving statistics and energy management strategies between the vehicle and a server, on which these calculations could be performed. This thesis aims to investigate and develop a structure of a server application where an optimal energy management strategy can be calculated.

To calculate an optimal strategy, a priori information about the upcoming driving mission is required. One way of obtaining a priori information is if the driver inputs the expected driving mission. However, this might not be desirable for the driver to do every day. Instead, the developed system identifies repetitive driving patterns, such as commuting routes, from raw GPS data. For each of these patterns an optimal energy management strategy is calculated.

To evaluate the developed system a study is performed on the Volvo V60 PHEV, which has a set of predefined driving modes. For a driver it is a non-trivial task to select a fuel optimal sequence of driving modes; a poor mode selection might even result in a heavily degraded fuel economy. In the study an algorithm that optimises the mode selection along a commuter route is developed. The algorithm is based on a sub-optimal Dynamic Programming developed in the thesis since conventional Dynamic Programming can result in a perceived counterintuitive mode selection for the driver. Simulation results indicate that an optimised mode selection can reduce fuel cost and increase the lifetime of the battery, but more detailed studies are required to estimate the actual savings.

Finally, the developed system is generic and can handle multiple users. The routines for the energy management optimisation are interchangeable and different vehicle models are easily treated.

Keywords: Plug-in Hybrid Electric Vehicle, Optimal Control, Dynamic Programming, Route Identification.

Preface

This thesis was written at the division of Automatic Control, Automation and Mechatronics at Chalmers University of Technology during the spring and fall of 2013. The key findings of the case study in this thesis are presented in the paper *Optimal Selection of Driving Modes along a Commuter Route for a Plug-in Hybrid Electric Vehicle*, which has been submitted to the 19th World Congress of the International Federation of Automatic Control.

Several people have contributed during my work with this thesis. First of all, I would like to express my gratitude to Professor Bo Egardt, thanks for giving me the opportunity to do this thesis. I am also grateful for the support you provided and that you gave me the possibility to present my findings in a paper. Furthermore, I would like to thank my supervisor PhD student Viktor Larsson for valuable guidance and support throughout the work as well as fruitful discussions, no matter how higgledy-piggledy they were the outcome was always good.

Thanks are also due to Volvo Car Corporation for making necessary vehicle data available for this thesis.

Andreas Furberg
Gothenburg, Saint Lucia's Day 2013

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Abbreviations and Symbols

Abbreviation	**Full text**
AER	All Electric Range
BSFC	Brake Specific Fuel Map
CDCS	Charge Depletion Charge Sustaining
DP	Dynamic Programming
ECMS	Equivalent Consumption Minimisation Strategy
EGU	Engine Generator Unit
EM	Electric Machine
EMS	Energy Management System
HEV	Hybrid Electric Vehicle
ICE	Internal Combustion Engine
ISG	Integrated Starter Generator
PHEV	Plug-in Hybrid Electric Vehicle
SoC	State of Charge

Symbol	**Name**	**Unit**
Δt	Sample Time	s
η	Efficiency	-
ω	Angular Velocity	rad/s
θ	Road Slope	rad
c_f	Fuel Price	SEK/kg
F	Force	N
J	Cost Function	-
m	Vehicle Mass	kg
$\dot{m}_f$	Mass Fuel Rate	kg/s
P	Power	W
Q	Nominal Battery Capacity	Ah
r	Ratio or Radius	- or m
S	Final Cost	-
T	Torque	Nm
V_{oc}	Open Circuit Voltage	V
v	Velocity	m/s
x	Optimisation State	-

Part I
Thesis and Hybrid Vehicle Introduction

1 Introduction

This chapter is intended to give the reader a brief background of the hybrid electric vehicle concept, followed by the purpose and problem framing of this thesis as well as its limitations. The chapter is finalised with a thesis outline.

1.1 Background

Due to global warming a worldwide reduction in yearly CO_2 emissions is a likely future scenario. Regulations to limit these emissions within the EU, US and China among others have therefore been stated [6, 7, 5]. These regulations do not only consider the global warming but also the problem with decreased air quality in larger urban areas. For the automotive industry these regulations imply that the development of a vehicle fleet with less CO_2 emissions and air polluting substances than today is crucial for companies to survive. The expected peak in oil production is also a factor steering the automotive industry from a purely oil based fleet. Major car companies have introduced Hybrid Electric Vehicles (HEV) and Plug-in HEVs (PHEV) into their fleets, some examples are; Toyota Prius, Honda Civic Hybrid, Ford Focus Electric, BMW ActiveE and Volvo V60 Plug-in Hybrid. Figure 1.1 shows the number of sold hybrid vehicles per year in the US between 1999 and 2012, as well as the corresponding fraction of all cars and trucks sold.

A hybrid electric powertrain has both an Internal Combustion Engine (ICE) and an Electric Machine (EM). Both the ICE and EM can provide traction power of the vehicle and therefore, there is a degree of freedom in how to supply this force; only by using the ICE or only the EM or a combination of both. In addition, the ICE can be used to simultaneously provide traction force and recharge the battery and the EM can recuperate the brake energy during braking instead of using friction brakes.

The main difference between a PHEV and a HEV is the battery size; a PHEV has a much larger battery since it is intended to be recharged with energy from the electric grid while an HEV only charges the battery by using the EM as a generator while driving. The focus of this thesis is on PHEVs.

The unit in the vehicle that decides how to use the ICE and the EM is denoted Energy Management System (EMS). Advanced techniques for optimal control of the EMS have been developed during the last decade. However, modern vehicles do not take advantage of these techniques since they require a priori information about the upcoming driving mission. In this context, a priori information is driving data such as velocity and altitude trajectories. Instead a simple strategy is used; drive on electrical energy as long as possible, then switch over to fuel. The strategy is known as Charge Depletion Charge Sustaining (CDCS) and is the optimal EMS strategy if future driving conditions are unknown.

If accurate a priori information is available, an optimal EMS strategy can be calculated. These strategies can lower the fuel consumption and extend the lifetime of the (in general) single most expansive part, the battery. The resulting behaviour from these calculations is that the electrical energy is only used when it is most profitable, e.g. when the electrical losses are small. Note that this is only a good strategy if the driving mission is longer than the All Electric Range (AER), i.e. the

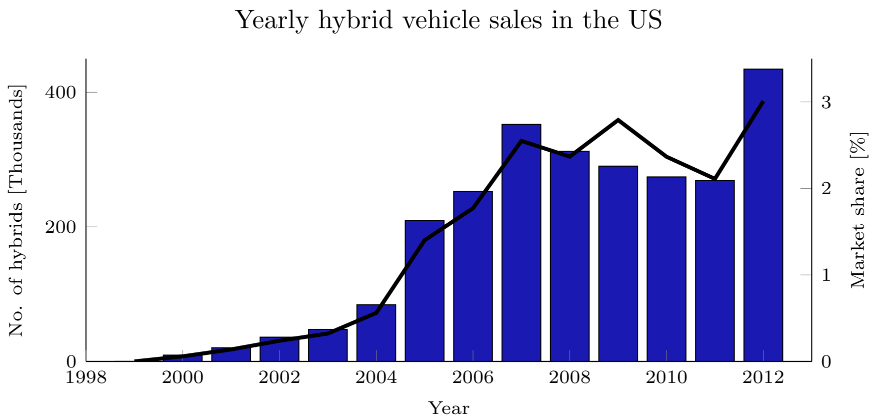


Figure 1.1: Bar diagram showing amount of hybrid vehicles sold per year in the US, in front is the total market share, i.e. fraction of all sold passenger cars and trucks, indicated. (Figures for hybrids: [4], total vehicle sales: [27].)

distance the vehicle can travel using electrical energy only. If the driving mission is shorter than the AER, there is no point of using the ICE unless the EM alone cannot meet the requested power. In Sweden, 11% of the labor force commuted longer than 30 km to work in the year of 2000; the median distance within this group was 50 km [22]. This indicates that a considerable amount of customers could benefit from an optimised strategy, if they commute by car and drive a PHEV.

There are different ways of obtaining a priori information about the upcoming driving mission. One way is to have the driver inputting the final destination and the anticipated driving path. However, this might not be a desirable procedure to perform every day. Another way of obtaining a priori information about the upcoming driving mission is to use historical driving data, which has been shown in [13]. From historical driving data, repetitive driving patterns can be identified and for each pattern an optimal EMS strategy can be calculated. Calculating an optimal EMS strategy is non-trivial and requires large computational power. The limited amount of computational power available in modern vehicles has therefore been a hold up for implementation of this kind of systems.

However, the introduction of cloud techniques in modern vehicles (such as *BMW ConnectedDrive* [3], *Volvo On Call* [25]) has made it possible to send data between the vehicle and a server. By taking advantage of this new functionality, a vehicle–server system for EMS optimisation could be developed.

1.2 Purpose and Problem Framing

Technology for such a vehicle–server system is available as well as the required main algorithms. Nevertheless, a system of this kind has not been introduced to the market. This thesis aims at developing a conceptual system architecture for the server, with the intention of increasing the possibility that this type of system is presented to the market in the near future.

To evaluate the system, a case study investigating *Optimal Mode Selection in*

Volvo V60 PHEV along different commuting routes is conducted. The Volvo V60 PHEV, as many other vehicles, has a set of predefined driving modes. Even though it is common practice to predefine different driving modes in vehicles, typically defined by heuristic[1] rules to satisfy perceived driveability constraints, the research within the academic community has mainly been focused on optimal energy management. The industry preference for predefined driving modes has therefore often been neglected, since the usage of heuristic modes is suboptimal in terms of fuel economy and incorporation of driveability constraints in sophisticated optimisation techniques is not straightforward.

The purpose of this thesis is to, at least partly, bridge the gap between academia and industry. This is done with a two-folded focus:

1. Develop a conceptual system architecture that emulates a server on which historical driving data is used for energy management optimisation of a PHEV.

2. Evaluate the system with a case study on the Volvo V60 PHEV, in which the system is tested on real driving data and an algorithm for using driving modes in the energy management optimisation is developed.

1.3 Limitations

This thesis does not aim to develop a full-scale system and therefore some parts are simplified, mainly data storage and communication. The modes used in the case study of the V60 PHEV are approximations, made by the author, of the modes implemented in the vehicle. Furthermore, the thesis is limited to investigate logged driving data from roads where a repetitive driving behaviour can be identified; roads where driving conditions change significantly from day to day are therefore considered outside of the scope.

1.4 Thesis Outline

The thesis is outlined as:

Part I - Thesis and Hybrid Vehicle Introduction

1, *Introduction*, gives the reader a brief background of the hybrid electric vehicle concept, followed by the purpose and problem framing for this thesis as well as its limitations.

2, *Hybrid Vehicles and Energy Management*, introduces the reader to the two most common hybrid electric vehicle configurations, series and parallel, and the energy management problem.

[1]Heuristic (Greek: ”find” or ”discover”) refers to experience-based techniques for problem solving, learning, and discovery that give a solution which is not guaranteed to be optimal. Where the exhaustive search is impractical, heuristic methods are used to speed up the process of finding a satisfactory solution. Examples of this method include using a rule of thumb, an educated guess, an intuitive judgement, stereotyping, or common sense. [20]

Part II - System Design, Modelling and Optimisation.

3, *System Design*, presents an overview of a conceptual system followed by the design of the implemented system and an implementation overview.

4, *Vehicle Modelling*, presents the components considered in the vehicle model as well as the quasistatic model of them. A description of the inverse simulation approach finalises the chapter.

5, *EMS Optimisation* formulates the EMS as an optimal control problem, after which three different optimisation techniques are presented.

Part III - Case study: Optimal Mode Selection in Volvo V60 PHEV.

6, *Case Introduction* presents the case study and introduces the driving modes in the Volvo V60 PHEV. The chapter is ended with an overview of the system implementation for the case study.

7, *Modelling of Volvo V60 PHEV* presents the modelling of the vehicle configuration and driving modes of the Volvo V60 PHEV.

8, *Optimal Mode Selection*, the first part of this chapter introduces the reader to the concept of decision points. The major part of the chapter is then spent on developing an algorithm that, identifies the optimal mode selection for each decision point along a route while considering the predictability of the vehicle.

9, *Results* presents the identified routes as well as a comparison between the optimal mode selection and a CDCS strategy along the routes.

Part IV - Discussion, Conclusions and Future Work.

10, *Discussion*, findings and implications of the thesis are discussed.

11, *Concluding Remarks*, concluding remarks of the thesis and identified topics for future work.

2 Hybrid Vehicles and Energy Management

This chapter introduces the reader to the two most common hybrid electric vehicle configurations, series and parallel, as well as the energy management problem.

2.1 Hybrid Vehicle Configurations

Several different hybrid vehicle configurations exist and the two predominant configurations on the market are the series and parallel configurations. The main focus of this thesis is on the parallel configuration since the vehicle used in the case study (Volvo V60 PHEV) is a parallel hybrid.

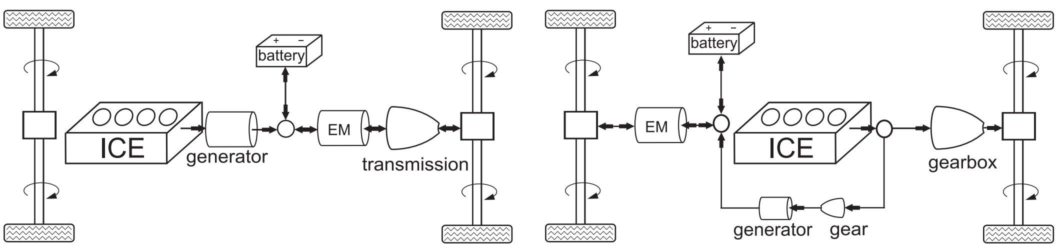
2.1.1 Series Hybrid

In a series hybrid the ICE generates mechanical power, which is transformed by the generator into electrical power. The EM is then supplied with power from the generator or power drawn directly from the battery. The combination of the ICE and the generator is usually denoted Engine Generator Unit (EGU). The battery is rechargeable by recuperating break energy with the EM or by using power from the EGU. An illustration of a series hybrid configuration is shown in Figure 2.1a.

A series configuration is desirable if the main usage is city driving, where the average speed is low and conventional vehicles have a poor performance. This is because the operating point of the ICE can be chosen freely, since it is mechanically decoupled from the wheels. This configuration is however not well suited for highways where the average velocity is high and the average power demand is high. The poor performance on highways is due to the large increase of EGU power losses for increased power demand. Another drawback with the series configuration is that the EM needs to be sized to meet the peak power.

2.1.2 Parallel Hybrid

In a parallel hybrid both the ICE and the EM are mechanically connected to the wheels, where the ICE is mostly placed on the front axle while the placement of the EM varies. A configuration with the EM placed on the rear axle is depicted in Figure 2.1b. The main advantage with the parallel configuration compared to



(a) Series (b) Parallel

Figure 2.1: Schematic overview of the two predominant PHEV configurations. (Figures found in [16].)

the series is that the ICE can deliver power directly to the wheels, giving a better highway performance. On the other hand, it is not possible to freely choose the ICE operating point, which gives a low performance for city driving. Another advantage with the parallel configuration is that neither the EM, nor the ICE is required to be sized to be able to meet the peak power. Smaller components can therefore be chosen, resulting in a lower cost and weight of the vehicle.

2.2 Energy Management

Since there are two sources of energy available in a hybrid vehicle, there is a degree of freedom in how to supply the traction force of the vehicle. A hybrid vehicle configuration therefore offers several ways to decrease the fuel consumption compared to a conventional vehicle, such as:

- The ICE can be downsized from being able to meet peak power to only meet the average power.
- The ICE can be turned off during idling.
- Brake energy can be recuperated and stored in the battery.

These are three quite intuitive ways to decrease the fuel consumption and they are only dependent on the physical properties of the hybrid vehicle configuration.

However, the fuel consumption can be reduced further by optimising the individual usage of the power sources. The controller that decides the amount of power from each source is, as mentioned, denoted Energy Management System (EMS). The objective when optimising the EMS strategy is to reduce the fuel consumption. A reduction in fuel consumption is obtained by only using electrical energy when it is preferable, for example at low speeds where the electrical power losses are low and the ICE in general has a poor performance. At high speeds or during heavy accelerations, the electrical losses are much higher and the ICE efficiency is usually high why a low usage of electrical power, in general, is desired during these driving conditions.

Another positive effect from using the electrical energy wisely is the reduced wear and tear of the battery, which is achieved by lowering the Ah throughput and C-rate[2].

2.2.1 Discharge Strategies

In a vehicle energy management context the State of Charge (SoC) is used to denote the fraction of available energy in the battery [10], where SoC = 1 equals a fully recharged battery and SoC = 0 a completely depleted battery. The SoC trajectory for a PHEV along a driving mission can be interpreted as a discharge strategy, i.e. how fast the EMS should deplete the battery. Since the electrical energy is assumed to be much cheaper than the fuel energy a low final SoC is desirable.

For a PHEV there are two distinct scenarios for a driving mission; either is the mission within the All Electric Range (AER) or not. If it is within the AER the

[2]C-rate: Charge or discharge rate equal to the capacity of a battery in one hour.

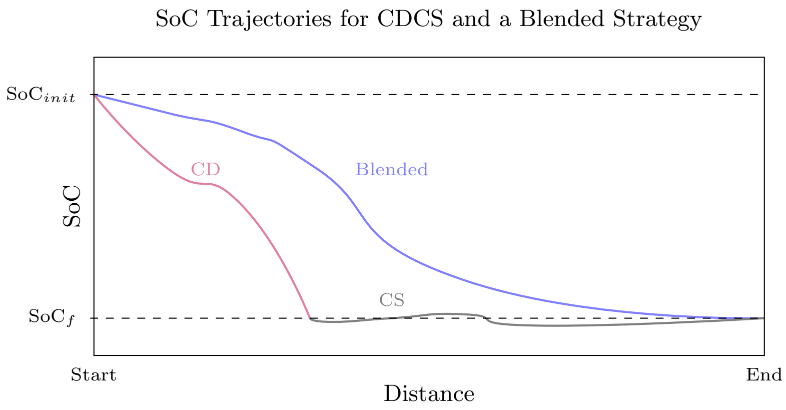


Figure 2.2: Schematic illustration of CDCS and a blended strategy.

electrical energy is enough for the vehicle to drive purely on electricity, unless the vehicle is a parallel hybrid and a combination of the ICE and EM power is required to meet the peak power. A more interesting scenario is therefore when the driving mission is longer than the AER, which gives a degree of freedom in how to deplete the battery. How to optimally use this freedom depends on the available a priori information.

2.2.2 CDCS Strategy

If no a priori information is available the Charge Depletion Charge Sustaining (CDCS) strategy results in the optimal fuel consumption [10]. This is a very simple strategy, where the battery is discharged as long as energy is available and the ICE is turned on once the SoC level reaches a lower limit. An illustration of a SoC trajectory from a CDCS strategy is depicted in Figure 2.2, note that the CDCS trajectory is coloured different in the CD and the CS phase for illustrative purpose.

The drawback with the CDCS strategy is that for trips longer than the AER the electrical energy is most likely used in a sub-optimal manner.

2.2.3 Blended Strategy

If there is a priori information about the driving mission the EMS can calculate when to use the ICE and when to use the EM. This will lower the ohmic losses as well as decreasing the time where the ICE is operated with bad performance, thus giving a lower fuel consumption than the CDCS strategy. A schematic SoC trajectory from a blended strategy is illustrated in Figure 2.2.

Numerous studies have investigated the benefits of blended strategies, see for example [17, 8, 23]. The results indicate that the fuel cost reduction of a blended strategy compared to a CDCS strategy varies significantly. Factors affecting the cost reduction are; powertrain model, drive cycle, trip length in relation to the AER among others.

Part II
System Design, Modelling and Optimisation

3 System Design

This chapter presents an overview of a conceptual system followed by the design of the implemented system and an implementation overview.

3.1 Conceptual System

The intention with presenting a full-scale conceptual system is to introduce the reader to the expected working environment of the implemented system. This gives a better understanding of the design implementation and simplifications.

The system consists of a unit in the vehicle and a cloud server that communicates with each other, for example when the vehicle is parked. During driving, the unit in the vehicle stores the driving data, i.e. GPS coordinates, altitude- and velocity trajectories. Once the vehicle is parked and turned off, the data is sent to the server for processing. Note that both the logging of GPS data and uploading of the data on a server is possible with *Volvo On Call* [25].

The new driving data is compared to the historical data and if enough new information has been encountered an update of the stored routes is performed. A route is considered as being a driving trajectory between two locations which is frequently occurring. For every route an optimal EMS strategy is calculated and sent to the vehicle.

Next time the vehicle is to be driven along one of these routes the corresponding strategy is used and the driver can enjoy a fuel economic drive along the route. A schematic overview of the system is illustrated in Figure 3.1 and summarised below.

1. Driving data is collected during driving.
2. When the vehicle is parked the data is sent to the server.
3. The new driving data is compared to the stored data and if enough new information is obtained the affected route is updated.
4. An optimal EMS strategy is calculated for the updated route.
5. The EMS strategy is sent to the vehicle.
6. Next time the vehicle is driven along a route it uses the corresponding EMS strategy and the driver can enjoy a fuel economic drive along the route.

3.2 Implemented System

The implemented system has focused on the server features and hence some simplifications are done in the implemented system compared to the conceptual system.

The largest simplification is the communication between the vehicle and the server. In a real application this is a crucial part that requires a large engineering effort. However, in this context it is a valid assumption to assume that data is able to move between different parts of the system. In this thesis the sending and receiving of data is therefore simplified to function calls in MATLAB. Another simplification

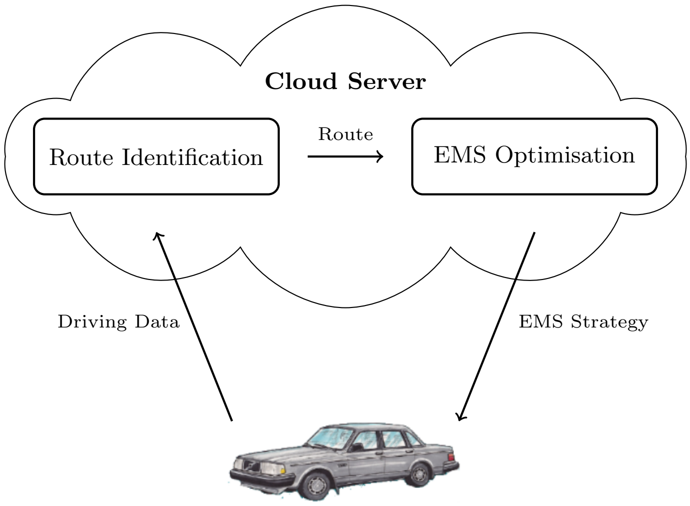


Figure 3.1: Schematic overview of the system.

is that the system does not recognise by itself if an update of available routes should be done. Instead, the user is required to manually send a route update request to the server. The system is evaluated with a simulation study in which the automatic detection of the route that is to be driven, e.g. *from home* or *to work*, has not been implemented.

With these simplifications the implementation represents the conceptual system proposed in Chapter 3.1, *Conceptual System*. The implemented system consists of three major parts where each part consists of multiple Matlab routines.

Vehicle Model: Simplified model of a vehicle, used to compute an optimal EMS strategy and to simulate the driving of a vehicle along a route for evaluation.

Route Identification: Processing of logged GPS data for identification of routes.

EMS Optimisation: Calculation of optimal EMS strategy for a vehicle model on a route.

A flowchart illustrating the major parts and flows of the system is depicted in Figure 3.2.

3.2.1 Vehicle Model

For every type of vehicle that uses the system a vehicle model is stored in a database on the server. The models are of as low complexity as possible to keep the computational time for the EMS optimisation short as well as keeping down the required amount of data storage. Chapter 4, *Vehicle Modelling* presents how a vehicle is modelled for this purpose.

Each vehicle that uses the system is assigned an ID to match the driven trips with the vehicle model. This means that a vehicle can only access the trips that it has logged itself, unless access to other trips is manually given.

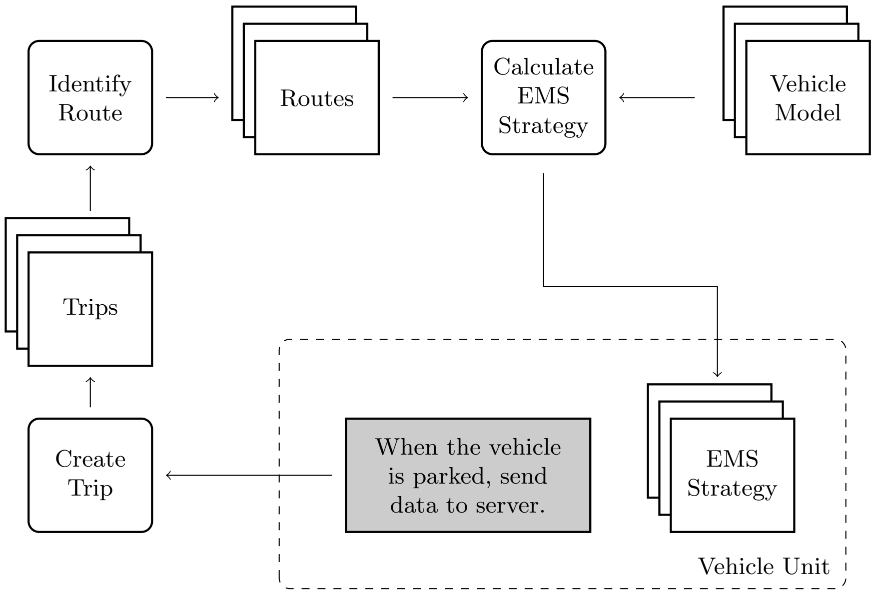


Figure 3.2: Schematic overview of the system.

3.2.2 Route Identification

The GPS unit in the vehicle is assumed to log the instant velocity of the vehicle, the longitudinal and latitudinal coordinates as well as the road altitude at every time sample. However, data from some samples might be missing or incorrect, a preprocessing is therefore performed where unrealistic values are removed using low pass filtering. Once the driving data has been preprocessed, all the data required to create a trip is available. In this thesis a trip is defined as:

> *Trip Definition:* A trip is the driving between two consecutive parking periods irrespective of the parking period.

The definition is chosen to match the logged GPS data available for this thesis.

Given several trips, routes are identified using the clustering algorithm proposed in [15] which is appended in Appendix C, *Route Clustering*. In this thesis a route is defined as:

> *Route Definition:* A route is a large enough number of trips, starting and ending within the same geographical area, and going roughly along the same path.

This is a quite open definition and it is intentionally chosen, so that for example parking at a different parking spot at work should not lead to the definition of a new route. The velocity trajectory for the route is found by choosing the most representative trajectory of all the trips related to the route, as done in [15].

The data used in this thesis is taken from the Swedish Car Movement Database, see [12]. The database consists of driving data collected from vehicles driven in the county of Västra Götaland and the Kungsbacka municipality, in the southwest part of Sweden. Trips created from this data is divided into a set of training data, *optimisation trips*, and a set of validation data, *simulation trips*. There is no practical difference between these, but the distinction is made so that the system can be evaluated without gathering more driving data. Optimisation trips are used to identify routes for which an optimal EMS strategy is calculated. The simulation trips are used to simulate drives along identified routes. By using different data for the optimisation and simulation, the system response to every day changes in driving behaviour is captured.

3.2.3 EMS Optimisation

Given a vehicle model and a route, an optimal EMS strategy can be calculated. The EMS optimisation routine in the system is an interchangeable part where the choice depends on the preferences of the system designer. In Chapter 5, *EMS Optimisation* different EMS optimisation techniques are presented.

3.3 Implementation

The system design has been influenced by the object oriented way of thinking, since it defines objects with different properties and how objects interact with each other, e.g. a vehicle can be driven along a route. Objects in the system have been identified as *Trip*, *Route*, *Vehicle Model*, and *EMS Strategy*.

Figure 3.3 illustrates how each object relates to the each other. In the figure one Vehicle Model is considered along with its Trips. From some of the Trips are a couple of Routes identified, for readability only one Route is depicted in the figure. It can be seen that a Vehicle Model owns the Trips created from its driving data and the Routes that have been identified from the Trips. A Route owns the clustered Trips and the EMS Strategy that is calculated using the Route and corresponding Vehicle Model.

The implemented system is divided into different folders and each object is represented by a MATLAB *struct* stored as a .mat file. Table 3.2 gives an overview of the folders and a short description of the contents in each of them. In the database folder sub-folders are used to store Vehicle Models, GPS data, Trips, Routes and EMS Strategies. Within these sub-folders, an additional layer of sub-folders is used to keep the data from different users separated.

To keep track of which Trips belong to which Vehicle Model, a Trip is assigned with the Vehicle ID and the Vehicle Model with a reference to its Trip database. The Vehicle Model also has a reference to all Routes identified from the Trips. A Route has the property *Representative Trip ID*, which is the Trip that given a set of features, such as time with velocity above 90 km/h, is the Trip that best represents the Route, see [15] for a detailed presentation of all features. A distance offset is calculated from each Trip to the Representative Trip, and this offset is stored as a property in the Route.

All objects and their properties are summarised in Table 3.1.

Table 3.1: Objects in the system and their properties.

Objects in System	
Object	**Properties**
Vehicle Model	Vehicle ID, Trip Database ID, Route list, EM, ICE, EGU, Generator, Battery, Transmission, Parameters.
Trip	Vehicle ID, Trajectories: velocity, altitude, slope, longitude, latitude.
Route	Route ID, Optimisation Trip IDs, Simulation Trip IDs, Vehicle ID, Representative Trip ID, distance offset from Representative Trip to all other Trips.
EMS Strategy	Route ID, EMS Strategy.

Table 3.2: Description of folders in the implemented system.

Folders in System	
Folder	**Description**
Database	Individual databases for each user with; GPS data, Trips, Routes, Vehicle Model and EMS Strategies.
EMS Optimisation	Functions to calculate an optimal EMS Strategy.
Route Identification	Functions for processing GPS data, creating Trips and Routes, finding torque trajectories etc.
Vehicle Model	Functions modelling the vehicle, such as fuel consumption.

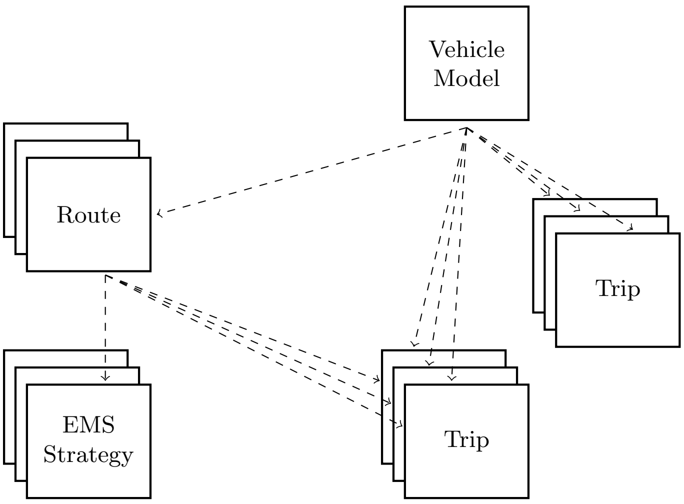


Figure 3.3: Illustration of the owner relation between objects in the system. In the figure one Vehicle Model is considered along with its Trips and Routes. Trips logged by the vehicle which are not part of any Route are illustrated in a separeate heap.

4 Vehicle Modelling

This chapter presents the components considered in the vehicle model as well as the quasistatic model of them. A description of the inverse simulation approach finalises the chapter.

4.1 Quasistatic Model

Modelling all aspects of a vehicle is a complex process and requires large computational power. However, for fuel consumption modelling, only a few components are necessary to take into account. To further decrease the complexity of the vehicle model, a quasistatic model is used for each component. In a quasistatic model the complexity is reduced by neglecting most of the dynamic aspects and speed dependent characteristics are obtained from stationary relations. Using quasistatic models reduces computational burden, while describing the system behaviour well [9].

The following chapters describes the quasistatic model of the components considered in the vehicle model.

4.1.1 Chassis

The longitudinal force on a vehicle can be found by approximating the vehicle as a point mass and use Newton's second law of motion

$$F_{\text{traction}} = F_{\text{acceleration}} + F_{\text{drag}} + F_{\text{gravity}} + F_{\text{rolling}}, \tag{4.1}$$

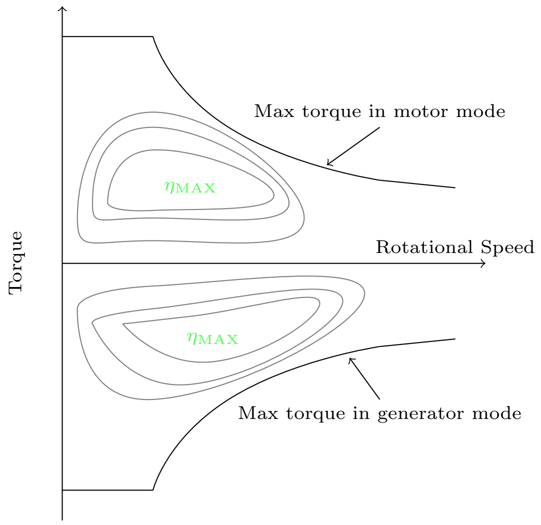
which explicitly is

$$\frac{T_{\text{wheels}}}{r_{\text{wheels}}} = m_e a + \frac{\rho_{\text{air}}}{2} c_d A_f v^2 + mg\sin(\theta) + mgc_r\cos(\theta). \tag{4.2}$$

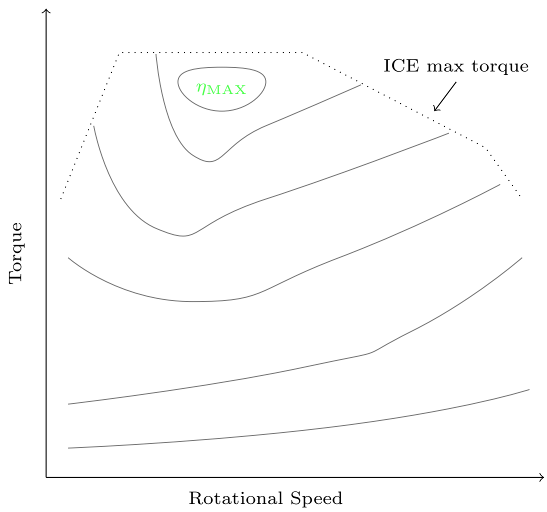
where m is the mass of the vehicle, m_e equivalent vehicle mass, i.e. including moments of inertia of the rotating parts, a is the vehicle acceleration, v is the vehicle velocity, θ is the road slope, ρ_{air} is the density of air, g is the acceleration of gravity, r_{wheels} is the wheel radius, A_f is the vehicle frontal area, c_d is the aerodynamic drag resistance coefficient which is assumed constant, c_r is the rolling friction coefficient and T_{wheels} is the torque applied on the wheels [10].

4.1.2 Electric Machine

The EM is typically a permanent magnet machine. It is often modelled using a black box approach where the EM torque and speed are the inputs and the electric power loss is the output. Dynamic effects due to temperature and internal moment of inertia are neglected. The electrical power losses can be found by linear interpolation in loss maps based on data from steady state measurements, see Figure 4.1a for an example. Another approach is to approximate the losses as a polynomial with speed dependent coefficients. The polynomial coefficients are found by linear least square fitting of a set of angular speeds in the EM loss map. A good presentation of this method is found in [21].



(a) Schematic illustration of a two-quadrant measured efficiency map for a typical EM. (Original figure found in [10])



(b) Schematic illustration of a BSFC for an ICE. (Original figure found in [16])

Figure 4.1: Illustration of an EM efficiency map and a BFSC map of an ICE.

4.1.3 Internal Combustion Engine

The ICE is either a spark ignited gasoline engine or a diesel engine. These are often modelled using a black box approach with crankshaft torque and speed as inputs and the fuel mass rate as the output. As in the case of the EM the dynamic and temperature effects are neglected, and the maximum ICE torque is assumed to depend only on the crankshaft speed. The mass fuel rate can be found by linear interpolation in Brake Specific Fuel Consumption (BSFC) maps constructed from steady state measurements in engine test stands. Another approach is to approximate the losses as a polynomial where the coefficients are speed dependent and determined by linear least squares from the BSFC map. This is done in the same manner as for the EM, an example of a BSFC map is depicted in Figure 4.1b.

4.1.4 Engine Generator Unit

For a series hybrid configuration the ICE is, as mentioned earlier, coupled with a generator. This combined component, the EGU, can be modelled in the same manner as the EM since a generator is an EM with a reversed torque.

4.1.5 Battery

The battery in a PHEV consists of several battery cells connected in series and/or in parallel. Complex chemical models are required to model these accurately, which requires large computational effort for simulation. They are also more accurate than required for the purpose of energy management. The battery is instead modelled as an equivalent circuit with a constant internal resistance, shown in Figure 4.2. The

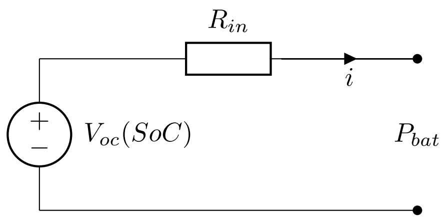


Figure 4.2: Equivalent circuit.

open circuit is assumed affine in the state x, i.e. SoC,

$$V_{oc} = a_0 x + a_1. \tag{4.3}$$

The battery dynamic is thus given by,

$$\frac{\mathrm{d}x}{\mathrm{d}t} = -\frac{i}{Q} = -\frac{V_{oc}(x) - \sqrt{V_{\mathrm{oc}}(x)^2 - 4R_{in}P_{bat}}}{2R_{in}Q}, \tag{4.4}$$

where R_{in} is the internal resistance of the battery which is assumed to be constant, Q is the nominal battery capacity, i is the battery current and P_{bat} is the power supplied or drawn from the battery terminals.

A final note is that throughout this thesis Li-Ion batteries are assumed since it is the cell chemistry predominantly used for PHEVs.

Since the battery is perhaps the single most expensive component of a PHEV, it is desirable that its lifetime is consistent with the lifetime of the vehicle. There are several factors affecting the battery lifetime. For example, cell temperature, Ah throughput, C-rate and the SoC interval in which the battery is operated [26]. A PHEV is usually limited to only operate within approximately 15 – 85 % of the battery capacity, since the wear and tear of the battery is significantly larger outside this interval. Temperature effects are for simplicity not treated in this thesis.

4.1.6 Power Electronics and Auxiliary Systems

Power electronics are either assumed part of the electric machine map or modelled as a constant efficiency factor. The auxiliary system is assumed to have a constant request of electrical power.

4.1.7 Transmission, Final Drive and Clutch

The efficiency of a transmission and final drive is assumed constant. The clutch is modelled lossless and without dynamics.

4.1.8 Friction Brakes

The friction brakes are assumed to be instantaneous and are only used when; the EM is saturated during regeneration, to avoid violating the upper SoC constraints or during heavy breaking.

4.2 Inverse Simulation Approach

To calculate the requested traction torque at the wheels, T_{wheels}, an inverse simulation approach is used. Given the road slope, θ, and velocity, v, the requested torque can be calculated by solving equation (4.2) for T_{wheels}. This is a non-causal method since the resulting velocity is used to find the required torque. The main advantage with this approach is that it only requires a small amount of computational power.

Once T_{wheels} is found for all samples along the route, the EMS is used to decide how much torque should be applied by the ICE, T_{ice}, and the EM, T_{em}. The exact relation between the torques depends on the actual vehicle configuration but the total torque applied on the wheels from the EM and the ICE must equal the requested torque.

5 EMS Optimisation

This chapter formulates the EMS as an optimal control problem, after which three different optimisation techniques are presented.

5.1 EMS as an Optimal Control Problem

When formulating the EMS as an optimal control problem the objective is to minimise the fuel cost under constraints formed by the vehicle architecture. By using a quasistatic vehicle model combined with an inverse simulation approach, both described in Chapter 4, *Vehicle Modelling*, the input signals to the system are the velocity trajectory, v, road slope trajectory, θ, and the gear shifting sequence, $gear$. The only state, x, is SoC and the control signals are the torques from the EM, T_{em}, and the ICE, T_{ice}. For easier notation, the input signals are compiled into an input signal vector, z, and the control signals into a control vector, u.

If the future driving conditions are fully known (v and θ) the optimal (deterministic) control problem is to find a feasible control signal, u, that minimises the cost criterion J i.e. the fuel cost. In this context, a feasible u is a signal that ensures that the requested torque at the wheels, T_{wheels}, is met in every sample.

The optimal control problem along a route can then be formulated as

$$
\begin{aligned}
J^* = \min_{u \in U} \quad & S(x(t_f)) + c_f \int_{t_0}^{t_f} \dot{m}_f(t, u(t)) \, \mathrm{d}t \\
\text{s.t.} \qquad \dot{x}(t) &= f(x(t), u(t)) \\
&= -\frac{V_{oc}(x(t)) - \sqrt{V_{oc}(x(t))^2 - 4R_{in}P_{bat}(u(t))}}{2R_{in}Q} \\
x(t) &\in [x_{\min}, x_{\max}] \\
u(t) &\in U(z(t), x(t)) \\
\text{where} \qquad & \\
u(t) &= [T_{em}(t), T_{ice}(t)] \\
z(t) &= [v(t), \theta(t), gear(t)].
\end{aligned}
\tag{5.1}
$$

In the cost criterion, S is the final cost. It penalises low final states and represents the cost to recharge the battery at the end of the route. The parameter c_f translates the fuel consumption into fuel cost by multiplication with the integral of the fuel mass rate $\dot{m}_f$. The gear selection is not treated as a control signal but is instead calculated using a gear shifting strategy based on the vehicle velocity and acceleration. This approach is used to reduce the complexity of the problem.

The problem formulation is a nonconvex nonlinear and mixed integer optimisation problem and it can hence, in general, not be solved analytically.

5.2 Optimisation techniques

There exists several different optimisation techniques to solve the EMS control problem defined by the equation system (5.1). The three predominant techniques are; convex optimisation, dynamic programming and ECMS.

5.2.1 Convex Optimisation

For some vehicle configurations it is possible to make a convex approximation of the equation system (5.1) and solve it using convex optimisation. This method has been investigated in [18, 14] among others. Defining the problem as a convex problem can reduce the computational burden significantly. However, rewriting the minimisation and its constraints as a convex problem is not always obvious and it might require unwanted approximations. Another drawback with the convex optimisation approach is that it cannot handle integer decisions meaning that gear decision and engine on/off must be predecided or found by iterating.

5.2.2 ECMS

The Equivalent Consumption Minimisation Strategy (ECMS) is perhaps the most common way to solve the EMS problem if future driving conditions are largely unknown. It is derived from the Pontryagin Principle, see for example [19]. The main idea in ECMS is to find the control signal u that, in every time sample, minimises the cost function

$$J(t,u(t)) = \dot{m}_f(t,u(t)) \cdot H_{\text{LVH}} + \lambda(t) \cdot P_{\text{bat}}(u(t)), \tag{5.2}$$

where $\dot{m}_f$ represents the fuel mass rate of the ICE, H_{LVH} is the lower heating value of the fuel used and P_{bat} is the power supplied by the battery. Here λ is the equivalence factor which translates battery energy into equivalent fuel energy. Hence, at each time sample, t, the value on λ affects if it is favourable to use the ICE and/or the EM [10].

Theoretically, for a given vehicle and a drive mission with full a priori information, it is possible to find a constant scalar value on λ that ensures that the final SoC is reached. For the given trip an optimal EMS strategy is then found by the ECMS with the usage of this scalar value. Unfortunately, a constant λ is only possible to find if the open circuit voltage of the battery is assumed constant or with a very small voltage dependence which is not always a valid assumption.

One example of a proposed implementation is that a look-up table with equivalence factors could be calculated and sent to the vehicle, see [13]. The equivalence factor is then given by the current SoC level and distance travelled. The advantage with this solution is that the trip does not need to be fully known, good approximative information is enough for the EMS to be stable for external disturbances.

5.2.3 Dynamic Programming

Dynamic Programming (DP) is a powerful technique used to solve nonlinear, non-convex and mixed integer optimisation problems. It is based on *Bellman's principle of optimality*:

> *The Principle of Optimality:* An optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision [1].

Illustrated by a simple example; if the shortest distance between the points A and D is defined by the sequence A – B – C – D, the shortest distance between B and D must be defined by the sequence B – C – D. For the EMS problem defined in this thesis, DP guarantees finding the global optimal solution [2].

DP is a numerical technique and hence a discretisation is required for the state (x), time (t), input signal (z) and control signal (u). The running time of DP algorithms increases linearly with the number of time steps but exponentially with the number of states and control signals. It is therefore preferable to keep the discretisation resolution of the state and control signal low to obtain a short computation time, however a too sparse grid results in a degraded solution.

Assume that the state is discretised into m points, $x_1, ..., x_m$ and that the time is discretised into N samples, $t_1, ..., t_N$. The state dynamics are discretised using the one step Euler method with a sample time Δt, meaning that the SoC dynamic is given by,

$$x(t_{i+1}) = x(t_i) + \Delta t \cdot f(x(t_i),u(t_i)) \tag{5.3}$$

The DP algorithm for the EMS problem can then shortly be described as follows:

1. For the last sample of the driving mission, $t = N$, assign an end value, S, for $x \in [x_1, ..., x_m]$; where $S(x \geq x_{\text{final}})$ corresponds to the cost of recharging the battery from x back to x_{init} and $S(x < x_{\text{final}}) = M$ where M is a large number to ensure that the final SoC is not below the desired final value, x_{final}.

2. At the previous sample, $t = N - 1$, use electric and/or fuel energy to minimise J_{N-1} = stage cost + S, where stage cost is the fuel cost from $t = N - 1$ to $t = N$.

3. For the remaining samples, $t \in [1,\, N - 2]$, continue in the same manner to choose the combination of electrical and fuel energy that minimises J_t.

The decision to use fuel or electric energy at sample t can be expressed as the following recursive equation,

$$J_t(x(t)) = \min_{u(t) \in U} \quad \{c_f \dot{m}_f(u(t))\Delta t + J_{t+1}(x(t+1)) + \Gamma(x(t+1))\}\,, \tag{5.4}$$

where Γ is a penalty function to keep the solution within the allowed SoC region, c_f is the fuel cost, $\dot{m}_f$ is the mass flow rate of fuel and Δt is the sample time.

The main advantage with the DP solution is that the cost matrix $J \in \mathbb{R}^{m \times N}$ contains the optimal cost for the remaining part of the drive mission for all SoC grid points. J can therefore be used to implicitly give a state feedback,

$$u^*(t) = \arg \min_{u(t) \in U} \{c_f \dot{m}_f + J_{t+1}(x(t+1))\}. \tag{5.5}$$

Thanks to this feedback, external disturbances are easily treated by DP since every element in J only considers the future irrespectively of past values; recall the simple distance example presented earlier. However, the usage of the cost matrix in a real time implementation requires good a priori information about the trip. If not, the consequence might be a feedback law that is far from optimal. DP is therefore mainly used as a reference to evaluate other techniques to solve the EMS problem. But, there are EMS formulations where the DP algorithm is very useful, which is seen in the case study.

Part III
Case study: Optimal Mode Selection in Volvo V60 PHEV.

6 Case Introduction

This chapter presents the case study and introduces the driving modes in the Volvo V60 PHEV. The chapter is ended with an overview of the system implementation for the case study.

6.1 Driveability and Predictability

Driveability is an important concept for automotive manufacturers, as it is very noticeable for the customer and the overall driving experience. It is therefore common practice to predefine different driving modes, e.g. *Sport, Eco, Electric Drive, Charge Sustaining*. These are usually defined by heuristic rules to satisfy perceived driveability constraints defined by the manufacturer. The idea is that the vehicle should behave consistently within each mode, so that the driver can anticipate the behaviour reasonably well. Typically, it is up to the driver to decide the driving mode. However, for a PHEV it is not a trivial task to select a fuel optimal sequence of driving modes, e.g. when to drive in *Electric Drive* or in *Charge Sustaining* mode. Consequently, a poor selection of driving modes can easily result in an increased fuel consumption.

The research perspective within the academic community has mainly been focused on optimal energy management; the industry preference for predefined driving modes has not been considered since usage of heuristic modes is suboptimal in terms of fuel economy and incorporation of driveability constraints in sophisticated optimisation techniques such as convex optimisation, DP and ECMS is not straightforward. Therefore, driveability has often been neglected by academia and the developed methods have therefore not received widespread usage in industry. The aim of this case study is to, at least partly, bridge this gap between academia and industry. The main idea is to consider the Volvo V60 PHEV and its driving modes that decide torque split and engine state, and identify the most fuel economic sequence of modes along different routes.

Moreover, to ensure some form of predictability for the driver, the driving mode is only allowed to change at a limited number of points along the route, denoted *decision points*. The decision points are placed at positions along the route where the driving conditions change, e.g. from urban to highway driving or from uphill to downhill. With this approach it is possible to obtain the best possible fuel economy while using the rule-based modes, defined to ensure driveability and predictability.

6.2 Driving Modes in Volvo V60 PHEV

In the Volvo V60 PHEV there are three principal driving modes; *Pure, Hybrid* and *Power*. In addition it is possible to activate *Save* which is not defined as a mode by the manufacturer. It can, however, in an energy management context also be considered as a mode. *Power* is not treated in this paper since it emphasises performance, e.g. acceleration and vehicle dynamics, rather than fuel economy. The driving modes considered in this thesis are by Volvo [24] described as follows :

Pure
"The diesel engine shuts off, letting the electric motor do all the work, (...) so that you can drive in silence with zero tailpipe emissions."

Hybrid
"Both the engine and the electric motor work in symbiosis for you. (...) Letting you appreciate the journey, without unnecessary stops and interruptions."

Save
"The diesel engine will recharge the battery to a level where you will be able to drive up to 20 km on pure electricity at a later occasion."

6.3 System Implementation for Case Study

For this case study, a modified version of the generic system described in Chapter 3, *System Design*, is used. The implemented system is illustrated in Figure 6.1. By comparing this system with the generic system, depicted in Figure 3.2, a few differences can be noted:

- The system is used for optimisation as well as simulation.
- The vehicle model has been assigned three driving modes.
- The EMS strategy is either a version of CDCS or mode selection calculated with a modified DP presented in Section 8.2.2, *A Suboptimal DP Algorithm.*

The system treats one Route at a time according to:

1. The Route is loaded from the Route database.
2. If the Route does not exist a processing of the GPS data and clustering of resulting Trips are performed. If the Route is not found after this, the system returns an error message.
3. Trips included in the Route are divided into trips for optimisation and simulation.
4. Decision points are identified and an EMS Strategy for the Route is computed and stored.
5. A simulation using the Vehicle Model, its Modes and the EMS Strategy for mode selection as well as CDCS is performed on all simulation Trips.
6. Results are stored as .txt files and .png figures in a database.

In Appendix A, *MATLAB Guide* all MATLAB files for the implementation are summarised and described. Note that this appendix is not intended to be a manual but rather an introduction and overview.

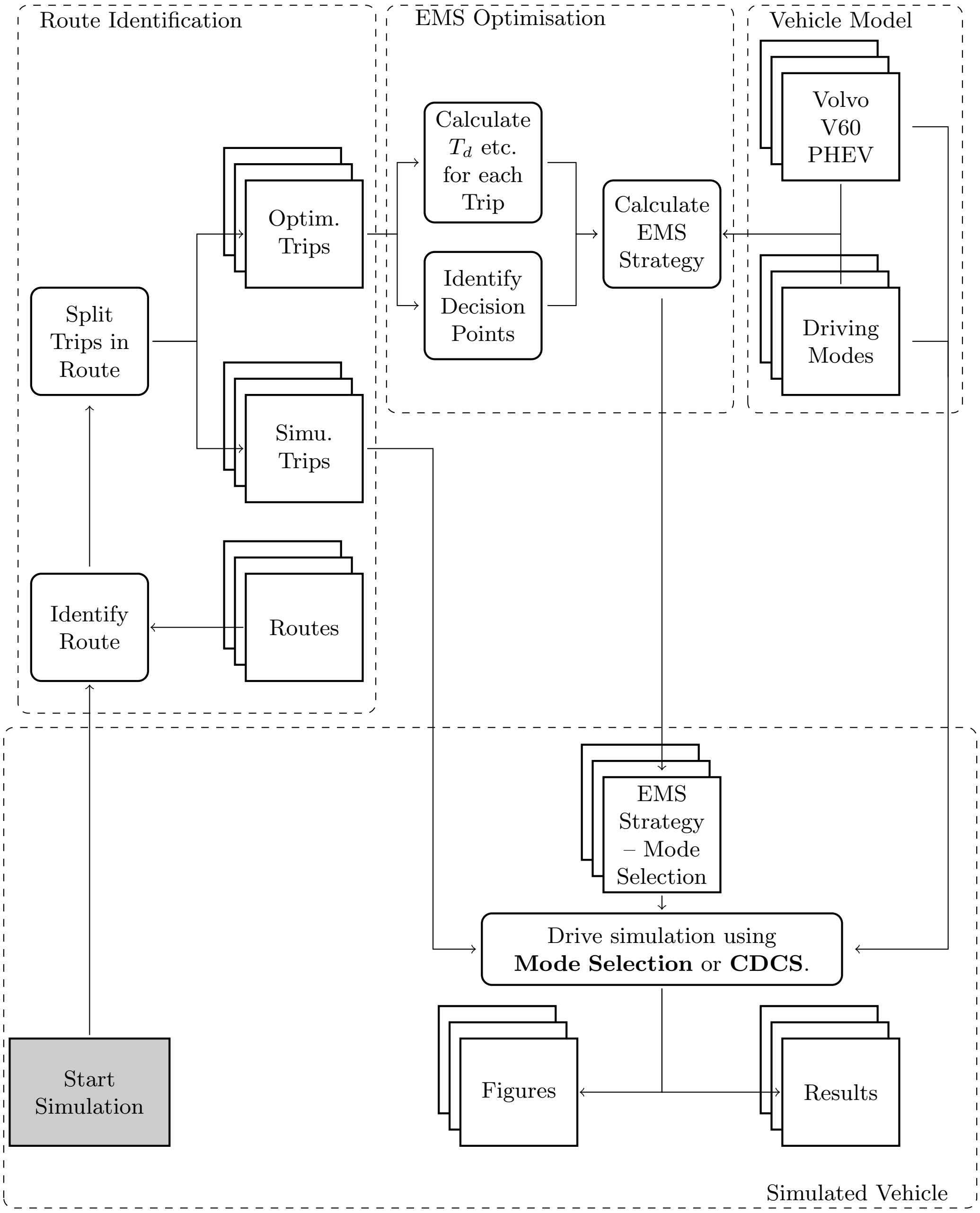


Figure 6.1: System implementation for case study (c.f. Figure 3.2).

6.4 Case Study Data

Logged driving data from six different drivers, in the county of Västra Götaland and the Kungsbacka municipality in the southwest part of Sweden, are investigated. The data corresponds to approximately two months of driving and is taken from the Swedish Car Movement Database, see [12]. However, the data has been preprocessed and is stored as *structs* in MATLAB where the latitude, longitude, velocity and altitude data are stored as separate vectors.

These six drivers have been manually selected since they are all commuters with a distance from home to work within an interval of 47 – 87 km. For the Volvo V60 PHEV this corresponds to routes slightly longer than the AER and up to twice the AER. The routes investigated in this case study fulfil the following requirements for both directions, i.e. to work and from work,

- All Trips included in a Route differ less than 1.5 km from the median value of all Trips in the Route.
- A Route must consist of 5 Trips for optimisation and at least 5 Trips for simulation.
- For Routes with 15 or more Trips, 40 % of the Trips are used for optimisation.

7 Modelling of Volvo V60 PHEV

This chapter presents the modelling of the vehicle configuration and driving modes of the Volvo V60 PHEV.

7.1 Vehicle Configuration

Volvo V60 PHEV is a parallel hybrid, where the electric motor powers the rear axis while the diesel engine powers the front axis. At high speeds the EM can be declutched from the powertrain, which decreases the drag losses. The ICE can also be used to power the generator and thereby recharge the battery. A schematic illustration of the configuration is depicted in Figure 7.1a, and the key powertrain components are summarised in Table 7.1.

7.1.1 Engine

At a given angular speed, ω_{ice}, the mass fuel rate, $\dot{m}_f$, of the ICE is assumed affine in torque

$$\dot{m}_f = (c_0(\omega_{ice})T_{ice} + c_1(\omega_{ice}))e_{on}, \tag{7.1}$$

where e_{on} is the binary engine state. The coefficients $c_{0:1}$ are speed dependent and are determined by linear least squares from the BFSC map.

7.1.2 Electric Motor

The EM is placed at the rear axis and is modelled jointly with the inverter; the combined electrical power is assumed quadratic in motor torque

$$P_{em} = d_0(\omega_{em})T_{em}^2 + d_1(\omega_{em})T_{em} + d_2(\omega_{em}). \tag{7.2}$$

The coefficients $d_{0:2}$ are speed dependent and are determined by linear least squares from the power loss maps of the EM and the inverter. The torque is defined positive in motoring mode and negative in generator mode.

7.1.3 Integrated Starter Generator

The generator (or Integrated Starter Generator - ISG) is modelled jointly with its inverter; the combined electrical power is assumed quadratic in generator torque

$$P_{isg} = e_0(\omega_{isg})T_{isg}^2 + e_1(\omega_{isg})T_{isg} + e_2(\omega_{isg}). \tag{7.3}$$

The coefficients $e_{0:2}$ are speed dependent and are determined by linear least squares from the power loss maps of the ISG and the inverter. Furthermore, the ISG is assumed to only operate in generator mode, i.e. $T_{isg} \leq 0$.

Table 7.1: The main vehicle data.

Chassis	
Mass/Air res.	1930kg, 0.74
Gearbox ratios	4.1, 2.4, 1.6, 1.2, 0.9, 0.7
Final gear ratio	1.9 (front), 9.2 (rear)
Aux. load.	325W
Battery	**Li-Ion**
Voltage/Capacity	380V, 11kWh
Engine	**5 Cyl. Diesel**
Max Power/Torque	158kW, 440Nm
Electric Motor	**Permanent Magnet**
Max Power/Torque	50kW, 200Nm
ISG	**Permanant Magnet**
Max Power/Torque	21kW, 54Nm

7.1.4 Battery

The battery is modelled as an equivalent circuit with a constant internal resistance in series with a voltage source, c.f Figure 4.2. The open circuit voltage is assumed to be linear in the state, x. The battery state dynamic is thus given by equation (4.4), revisited here for simplicity,

$$\frac{dx}{dt} = -\frac{I}{Q} = -\frac{V_{oc}(x) - \sqrt{V_{oc}(x)^2 - 4R_{in}P_{bat}}}{2R_{in}Q}. \tag{4.4 revisited}$$

The battery power is given by

$$P_{bat} = P_{em} + P_{isg} + P_{aux}, \tag{7.4}$$

and the battery power limits are imposed as speed dependent torque constraints on the EM and ISG.

7.1.5 Transmission

1. *Front Axis:* The final drive has a gear with fixed ratio r_{fw} and a constant efficiency η_{fw}. The gearbox has fixed gear ratios $r_{gb,i}$, $i = 1, ..., 6$, with torque losses that are given by a look-up-table, $T_{gb,loss}(\omega_{wh}, r_{gb.i}, e_{on})$. The vehicle is assumed to follow the predefined gear shifting strategy depicted in Figure B.1.

2. *Rear Axis:* The final drive has a fixed gear ratio r_{rw} and a constant efficiency η_{rw}. The mechanical drag losses are given by a look-up table, $T_{drag,rear}(\omega_{wh}, c_{rw})$, where c_{rw} represents the clutch state at the rear axis.

3. *ICE – ISG:* The coupling has a fixed gear ratio r_{isg} and a constant efficiency η_{isg}.

7.1.6 Main Powertrain Equations

The forces acting on the powertrain are calculated using an inverse simulation approach, as described in Chapter 4.2, *Inverse Simulation Approach*. This means that the torque demanded at the wheels, T_{wheels}, is to follow a given velocity and road slope trajectory determined by equation (4.2), revisited here for simplicity,

$$\frac{T_{\text{wheels}}}{r_{\text{wheels}}} = m_e a + \frac{\rho_{\text{air}}}{2} c_d A_f v^2 + mg\sin(\theta) + mgc_r\cos(\theta), \qquad \text{(4.2 revisited)}$$

where r_{wheels} represents wheel radius, v velocity, a acceleration, θ road slope, m vehicle mass and m_e equivalent vehicle mass, i.e. including moments of inertia of the rotating parts. Hence, the main torque equation is

$$\begin{aligned} T_{\text{tot}} &= T_{\text{wheels}} + T_{gb,loss,i} + T_{drag,rear} = \\ &\eta_{rw} r_{rw} T_{em} + \eta_{fw} r_{fw} r_{gb,i}\left(T_{ice} + \frac{r_{isg}}{\eta_{isg}} T_{isg}\right). \end{aligned} \tag{7.5}$$

It is assumed that if the ICE is on, the input torque to the transmission is positive, i.e. $T_{ice} + \frac{r_{isg}}{\eta_{isg}} T_{isg} \geq 0$.

7.2 Driving Modes

The modelling of the modes are based on assumptions made by the author and is intended to imitate the behaviour of the modes described in Chapter 6, *Case Introduction*. Note that the modelled modes do not reflect the exact behaviour of the actual modes in the Volvo V60 PHEV.

7.2.1 Pure

Both the engine and the generator are declutched and the electrical motor delivers all traction torque,

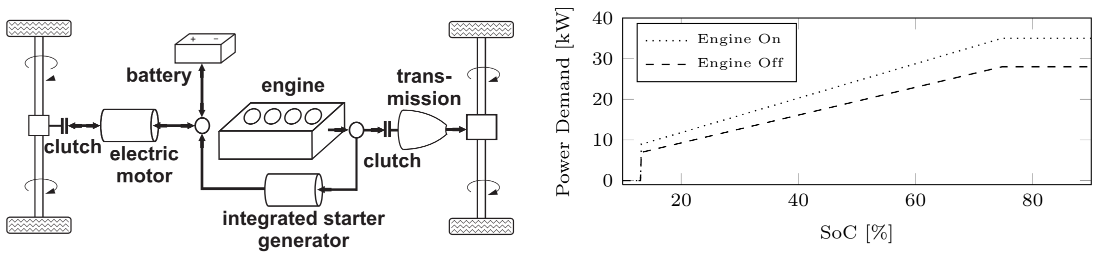
$$\begin{aligned} e_{on} = 0 &\implies T_{ice} = 0,\, T_{isg} = 0 \\ T_{em} &= \begin{cases} \frac{T_{\text{tot}}}{r_{rw}} \cdot \frac{1}{\eta_{rw}} & \text{if } T_{tot} \geq 0 \\ \frac{T_{\text{tot}}}{r_{rw}} \cdot \eta_{rw} & \text{if } T_{tot} < 0. \end{cases} \end{aligned} \tag{7.6}$$

If the EM cannot meet the torque request the mode switches to *Hybrid*.

7.2.2 Hybrid

The engine is started when the power request exceeds a higher threshold value; the engine is then kept on until the power request drops below a lower threshold value. Note that the hybrid behaviour is imitated by turning the engine on and off for different power requests and not by calculating a torque split. The engine state $e_{on}(t)$, at a time sample t, is thus given by,

$$e_{on}(t) = \begin{cases} 1 & \text{if } P_d \geq P_{on}(x) \\ 1 & \text{if } e_{on}(t-1) = 1 \text{ and } P_d \geq P_{off}(x) \\ 0 & \text{if } P_d \leq P_{off}(x) \\ 0 & \text{if } e_{on}(t-1) = 0 \text{ and } P_d \leq P_{on}(x) \end{cases} \tag{7.7}$$



(a) Volvo V60 PHEV. (b) Power thresholds for *Hybrid*.

Figure 7.1: Illustration of the Volvo V60 PHEV configuration and demanded power thresholds for engine on/off in *Hybrid*.

where P_d is the current power demand. P_{on} and P_{off} are the power thresholds for turning the engine on and off; the values are SoC dependent and illustrated in Figure 7.1b.

When the engine is on, $e_{on}(t) = 1$, the operating points are:

$$\begin{aligned} T_{isg} &= \frac{0.2 - \min(\max(x{,}0.1), 0.2)}{0.1} T_{isg}^{\min} \\ T_{ice} &= \frac{T_{\text{tot}} - \frac{r_{isg}}{\eta_{isg}} T_{isg}}{\eta_{fw} r_{fw} r_{gb,i}} \\ T_{em} &= 0 \end{aligned} \tag{7.8}$$

where $T_{isg}^{\min}$ is the ISG lower torque constraint. Note that the ISG will recharge the battery if the SoC drops below 20 %, thus ensuring a charge sustaining behaviour around the lower SoC limit. The EM is declutched for speeds above 120 km/h.

When the engine is off, $e_{on}(t) = 0$, the operating points are:

$$\begin{aligned} &T_{isg} = 0, \quad T_{ice} = 0 \\ &T_{em} = \begin{cases} \dfrac{T_{\text{tot}}}{r_{rw}} \cdot \dfrac{1}{\eta_{rw}} & \text{if } T_{tot} \geq 0 \\ \dfrac{T_{\text{tot}}}{r_{rw}} \cdot \eta_{rw} & \text{if } T_{tot} < 0. \end{cases} \end{aligned} \tag{7.9}$$

7.2.3 Save

The EM is declutched at all times which decreases drag losses at the rear axis but instead prohibits regeneration from braking and downhill driving. The torques are given by,

$$\begin{aligned} e_{on} &= 1 \implies T_{em} = 0 \\ T_{ice} &= \frac{T_{\text{tot}} - \frac{r_{isg}}{\eta_{isg}} T_{isg}}{\eta_{fw} r_{fw} r_{gb,i}} \\ T_{isg} &= \frac{0.4 - \min(\max(x{,}0.1), 0.4)}{0.3} T_{isg}^{\min}. \end{aligned} \tag{7.10}$$

Note that the ISG will recharge the battery if the SoC drops below 40 %, this to ensure that up to 20 km of electrical driving is possible once *Save* is de-activated.

8 Optimal Mode Selection

The first part of this chapter introduces the reader to the concept of decision points. The major part of the chapter is then spent on developing an algorithm that identifies the optimal mode selection for each decision point along a route, while considering the predictability of the vehicle.

8.1 Decision Points along a Route

Consider a commuter that drives along the same route to work every day. One could argue that it would be intuitive for the driver, if the driving mode changes only at points along the route where the driving conditions tend to change. For example, it would make sense to stop electric driving and start the engine when entering a steep uphill segment or when leaving a sub-urban area to enter a highway. In this thesis, positions along the route where either the speed profile or the road slope changes are denoted *decision points*. More specifically, three velocity and three road slope classifications are defined, as indicated in Table 8.1. If the vehicle is only allowed to change driving mode at the decision points a repetitive behaviour from day to day is obtained, giving the vehicle a good predictability along the route.

Identifying decision points is roughly done in five steps, where all trips along a route is considered.

1. Resample each trip from a second basis to a 100 m basis to keep the computation time down.
2. Assign a velocity and road slope classification according to Table 8.1, for each sample in every trip.
3. Identify the most frequently occurring velocity and road slope classification for each sample, this is the route classification.
4. Samples where the route classification changes are identified as decision points.
5. If two decision points are within 500 m, the decision point identified with the road slope classification is prioritised.

An illustration of the velocity and road slope classification as well as identified decision points along a route is given in Figure 8.1.

Table 8.1: Classification values for velocity and road slope.

Property	Decision Point Classification			Unit
	Urban	Highway	Motorway	
Velocity	< 50	$50 - 90$	> 90	km/h
	Downhill	Flat	Uphill	
Road Slope	$<$ -1	-1 – 1	$>$ 1	%

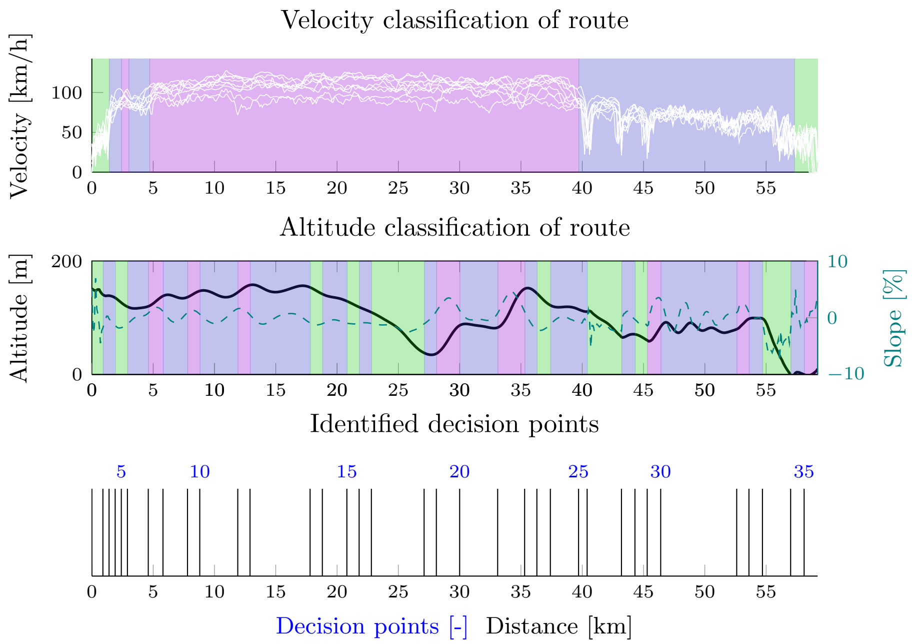


Figure 8.1: Illustration of identified decision points along a route.

8.2 Optimal Driving Mode Selection

Given a route with N decision points, the optimal mode selection problem can be formulated as the following optimisation problem

$$
\begin{aligned}
J^* = \min_{u_{1:N}} \quad & S(x(t_{N+1})) + \sum_{k=1}^{N} L(t,u_k) \\
\text{s.t.} \quad & x(t_{k+1}) = x(t_k) + \int_{t_k}^{t_{k+1}} f(x(t),u_k)\ \mathrm{d}t, \quad \forall\ k \in [1,N] \\
& x(t_1) = x_{\text{init}} \\
& x(t) \in [x_{\min}, x_{\max}] \\
& u_k \in \{Save, Hybrid, Pure\}
\end{aligned}
\tag{8.1}
$$

where

$$
\begin{aligned}
L(t,u_k) &= c_f \int_{t_k}^{t_{k+1}} \dot{m}_f(t,u_k)\ \mathrm{d}t \\
f(x(t),u_k) &= -\frac{V_{oc}(x(t)) - \sqrt{V_{oc}(x(t))^2 - 4R_{in}P_{bat}(u_k)}}{2R_{in}Q}.
\end{aligned}
$$

L represents the fuel cost incurred over the route segment between two consecutive decision points and c_f denotes fuel price. Note that L is completely defined by the driving mode as the operating points of the ICE, EM and ISG are decided by heuristic rules within each mode. The final cost is given by S, which penalises low final states and represents the cost to recharge the battery at the end of the route.

By comparing this equation system with equation system (5.1) two main differences can be noted. In equation system (5.1) the minimisation is done in every time sample, while it is done over a segment in equation system (8.1). Further, the control signal is the active mode over a segment instead of the torques T_{ice} and T_{em} in every sample. This decreases the computational burden significantly compared to the EMS problem presented in Section 5.1, *EMS as an Optimal Control Problem*.

8.2.1 Solution with Dynamic Programming

The optimal control problem defined above is a sequential problem with N steps, representing the decision points along the route where it is allowed to change driving mode. Furthermore, it is an integer decision problem, as the control signal u is the choice of driving mode. The optimisation technique Dynamic Programming (DP), introduced in Chapter 5.2.3, *Dynamic Programming*, is well suited to solve this type of sequential problem formulation. To solve the problem with DP the SoC state, x, is gridded into m points, x_1,...,x_m, and the time intervals between the decision points are time discretised with a sampling time of one second.

Starting at the end position of the route, $k = N + 1$, the cost-to-go matrix J is initialised with the final cost S; the DP equation is thereafter solved recursively backwards over the decision points and the gridded values of the state,

$$J_k(x_i) = \begin{cases} S(x_i), & k = N+1 \\ \min\limits_{u_{k,i}} \Big\{ L(u_{k,i}) + J_{k+1}\big(x_i + \tilde{f}_k(x_i,u_{k,i})\big) \Big\}, & k \in [1, N] \end{cases} \tag{8.2}$$

where $i = 1,...,m$ and $\tilde{f}_k(x_i,u_{k,i})$ represents the change in the state between two consecutive decision points. Thus, at each decision point k the cost-to-go is represented by a vector J_k, which is defined over the gridded values of the SoC state, $x_{1:m}$.

Figure 8.2 depicts the optimal driving mode, as obtained by

$$u^*_{k,i} = \arg\min_{u_{k,i}} \Big\{ L(u_{k,i}) + J_{k+1}\big(x_i + \tilde{f}_k(x_i,u_{k,i})\big) \Big\}, \tag{8.3}$$

at the different decision points along the route. The results show that a specific mode is not necessarily optimal over a connected set with respect to the SoC state. This behaviour can be explained mainly by the final penalty function S and the limited freedom in terms of control decisions; i.e. the torque split decision is given by heuristic rules and the number of decision points along the route is limited. Thus, to avoid a too low final state and a high final cost, the optimal mode selection might be quite intricate.

For a driver the optimal driving mode, as given by equation (8.3), might be experienced as counterintuitive. For example, consider a vehicle that is driven regularly along a commuter route. Assume that, at some day, the vehicle reaches a decision point at 50% SoC and *Pure* is selected as the optimal mode, i.e. electric driving. The following day the vehicle could reach the same decision point at a higher SoC value and *Save* might be selected as the optimal mode; thus meaning that the engine will be turned on at a higher SoC than the previous day when electric driving was selected. This is not a predictable driving behaviour, as most drivers would expect the engine to be turned on, only if the SoC is lower than at the previous day.

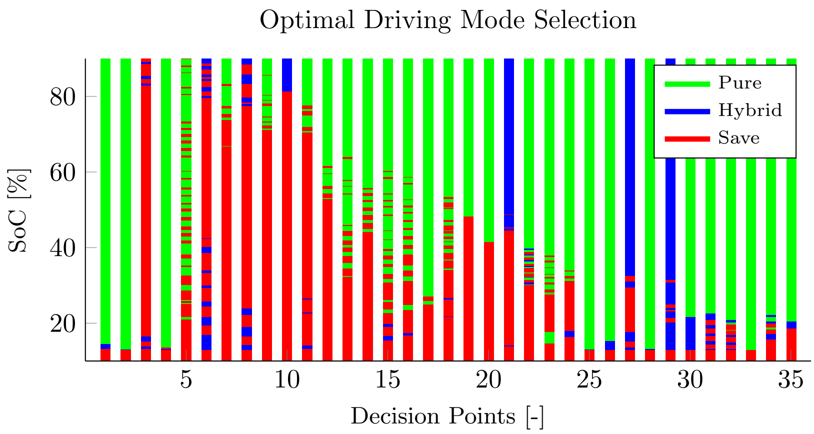


Figure 8.2: The optimal driving modes at the different decision points along the route illustrated in Figure 8.1 for one of the trips. The result is obtained with Dynamic Programming.

8.2.2 A Suboptimal DP Algorithm

To ensure some form of predictability for the driver, a slightly suboptimal mode selection algorithm is proposed. The algorithm ensures that a driving mode is "optimal" over a connected set with respect to SoC, at each decision point. Furthermore, the mode sequence with respect to the state is fixed: *Save* at low SoC values, *Hybrid* at intermediate values and *Pure* at high values; i.e. use of the engine should be favoured as SoC decreases. The optimisation variables in the proposed algorithm are the SoC threshold values, i.e. the SoC values where the driving mode changes for all given decision point.

The algorithm is described by the following steps:

1. At the end of the route initialise the cost-to-go with the final cost S

$$\hat{J}_{N+1}(x_i) = S(x_i) \ i = 1,...,m \tag{8.4}$$

2. For all decision points $k = N,\ N-1,...,1$ compute

$$\bar{J}_k^j(x_i) = L(u^j) + \hat{J}_{k+1}(x_i + \tilde{f}_k(x_i,u^j)), \tag{8.5}$$

i.e. equation (8.2) but without minimisation with respect to u; thus forming three intermediate cost-to-go vectors, one for each mode $j \in \{Save,Hybrid,Pure\}$.

3. The new cost-to-go vector, at a decision point k, is obtained by concatenating three segments of the $\bar{J}_k^j$'s. The concatenation points are given by

$$(\hat{a},\hat{b}) = \underset{(a,b)}{\arg\min}\Big\{\sum_{i=1}^{a}\bar{J}_k^{Save}(x_i) + \sum_{i=a+1}^{b}\bar{J}_k^{Hybrid}(x_i) + \sum_{b+1}^{m}\bar{J}_k^{Pure}(x_i)\Big\}. \tag{8.6}$$

This gives the cost-to-go vector as

$$\hat{J}_k^*(x_i) = \begin{cases} \bar{J}_k^{Save}(x_i), & \text{if } x_i \in [x_1,x_{\hat{a}}] \\ \bar{J}_k^{Hybrid}(x_i), & \text{if } x_i \in [x_{\hat{a}+1},x_{\hat{b}}] \\ \bar{J}_k^{Pure}(x_i), & \text{if } x_i \in [x_{\hat{b}+1},x_m]. \end{cases} \tag{8.7}$$

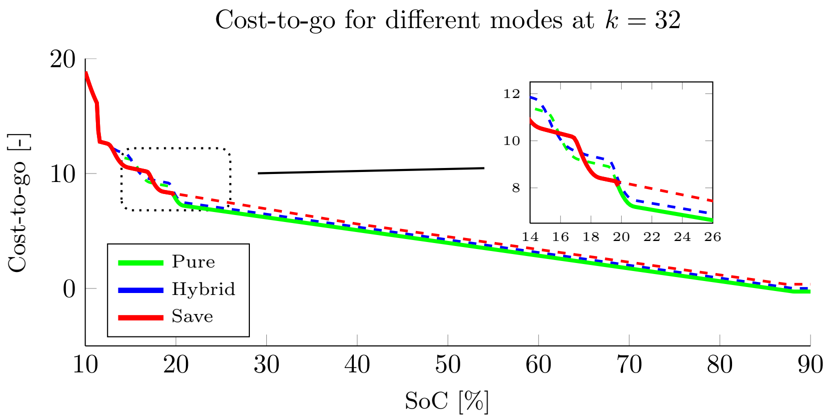


Figure 8.3: Dotted lines represent the intermediate cost-to-go vectors, $\bar{J}_k^j$. The solid line illustrates the cost-to-go that minimises the area below the curve, $\hat{J}_k^*$.

The optimal driving mode at decision point k is thus given by

$$\hat{u}_k^*(x) = \begin{cases} \mathit{Save}, & \text{if } x \in [x_1{,}x_{\hat{a}}) \\ \mathit{Hybrid}, & \text{if } x \in [x_{\hat{a}}{,}x_{\hat{b}}) \\ \mathit{Pure}, & \text{if } x \in [x_{\hat{b}}{,}x_m]. \end{cases} \tag{8.8}$$

Step 3, i.e. equation (8.6), can be interpreted as minimising the area below a curve defined by three separate segments; each corresponding to an interval in one of the three intermediate cost-to-go vectors, $\bar{J}_k^j$. This is illustrated in Figure 8.3, where the three intermediate cost-to-go vectors are depicted at a specific decision point. The conventional DP algorithm, given by equation (8.2), is in this case equivalent to minimising the same area, but without any restriction on the number of segments, as is seen in Figure 8.2. However, despite the restrictions imposed on the cost-to-go, the suboptimal DP algorithm only increases the cost marginally, as seen in Figure 8.4. This implies that overall fuel cost should not be affected very much by the suboptimal DP algorithm.

The final EMS strategy for mode selection along the route illustrated in Figure 8.1 is obtained by computing the optimal mode selection (c.f. Figure 8.2) for each trip. At each decision point k; the optimal mode selection is determined by averaging over the results obtained for the individual trips. Figure 8.5 illustrates the final EMS strategy. In the figure it can be seen that the majority of the SoC values gives either *Save* or *Pure*. Exceptions are for some intermediate values and at a few decision points where *Pure* cannot meet the requested power demand and it is not desirable to keep a constant SoC with *Save*. This implies that the heuristic rule used for engine on/off in *Hybrid* is not optimal in terms of fuel economy.

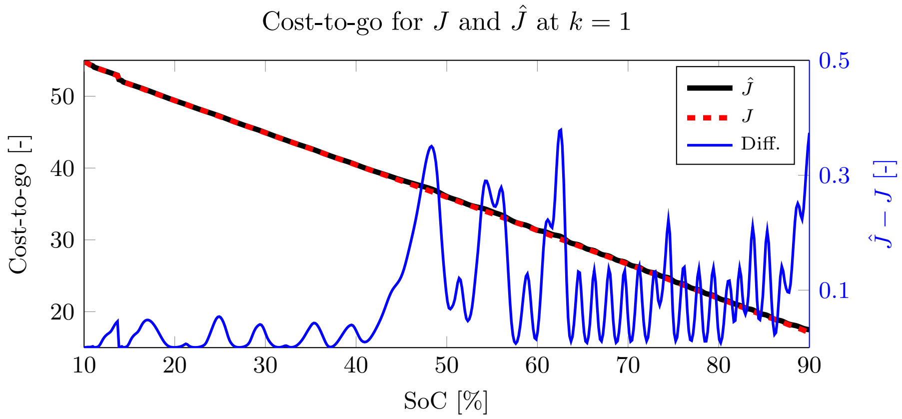


Figure 8.4: Optimal and sub-optimal cost-to-go at $k = 1$.

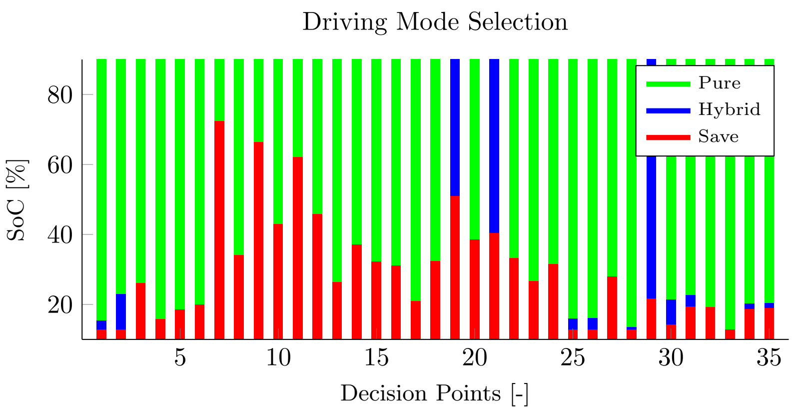


Figure 8.5: Driving modes at each decision point along the route shown in Figure 8.1, given by the suboptimal DP.

9 Results

This chapter presents the identified routes as well as a comparison between the optimal mode selection and a CDCS strategy along the routes.

9.1 Identified Routes

The system identified five of the six commuting routes in the investigated data. The identified routes are illustrated in Figure 9.2 and summarised in Table 9.2.

9.2 Simulation Results

To investigate the benefits with a route optimised mode selection, a comparison is made with CDCS. The CDCS is here implemented by *Pure* followed by *Hybrid*, when SoC drops below 20 % for the first time.

Since the Volvo V60 PHEV can be charged at home and work, an initial SoC corresponding to a fully charged battery, $x_{\text{init}} = 0.8$, is investigated. Figure 9.1 shows SoC trajectories for each route, either to or from work, when using the mode selection EMS strategy. Note that even though the velocity is close to constant during long segments for some of the routes, several decision points are identified on those segments. These are identified from the road slope, which is not shown in the figures due to space limitations. Table 9.3 summarises the average fuel consumption, final SoC, Ah-throughput and C-rate along each route for the mode selection and CDCS.

Route A – From Work is depicted in Figure 9.1a. It can be seen that the mode selection is quite predictable, in the sense that a similar sequence of modes is chosen along the route. At 25 of the 35 decision points the same mode is selected for all simulations. *Pure* is the predominant mode, since the fuel cost is minimised if the battery is depleted at the end of the route. However, *Save* is favoured during high power demands, clearly seen around 27 – 35 km, where there is uphill driving at high speed. The altitude profile for this route can be seen in Figure 8.1. In the figure it can be seen that the mode sometimes changes from *Pure* to *Hybrid* between two decision points; this occurs if the power demanded at the wheels cannot be satisfied in *Pure*, i.e. the driving is more aggressive than anticipated. Except for these instances, around 5 km for example, *Hybrid* is almost never selected. This further motivates the reasoning in Section 8.2.2, *A Suboptimal DP Algorithm*, in which it is concluded that the heuristic rule used for engine on/off in *Hybrid* is not optimal in terms of fuel economy.

Route C – To Work, depicted in Figure 9.1c, further illustrates that *Hybrid* is not fuel optimal. This can be seen by the rather high final SoC, around 27 % in mean value with an extreme value of 40 %. Notable is that when driving from work, the numbers are clearly in favour for the mode selection. Mode selection is better from work since the power request is considerable smaller in the end of that direction and *Pure* can be used to empty the battery. CDCS is a better strategy when driving to work since it is allowed to switch between *Pure* and *Hybrid* without regard to decision points. When the vehicle is in the CD phase: *Hybrid* is activated during segments where *Pure* cannot meet the power request and *Pure* is then switched back,

Table 9.1: Economic impact over a year per route.

Route	kg/route	litre/year	kWh/route	kWh/year	SEK/year	
A	0.17	31.64	0.33	74.75	$474 + 67$	$= 541$
B	0.04	7.86	0.30	67.57	$118 + 61$	$= 179$
C	-0.13	-23.59	1.19	267.05	$-353 + 240$	$= -113$
D	0.02	0.41	0.14	32.42	$6 + 29$	$= 36$
E	0.03	4.92	0.43	97.02	$74 + 87$	$= 161$

thus ensuring that the battery is depleted at the end of the route while meeting the power request throughout the route. Note that the distribution of decision points are not worse for *Route C* than any other route. It is therefore reasonable to believe that a more sophisticated algorithm for identifying decision points would not (or only marginally) change the outcome for *Route C*.

That *Hybrid* is not fuel optimal can also be seen by inspecting *Route B*. The benefits for this route arises from the combination of *Pure* and *Save* over smaller segments at the end of the route when driving from work.

Table 9.1 presents the potential economic gain over a year for each route, if the driver works 225 days, the fuel price is 15 $^{\text{SEK}}/_{\text{l}}$, the weight of diesel is 0.832 $^{\text{kg}}/_{\text{l}}$ and the electricity price is 0.9 $^{\text{SEK}}/_{\text{kWh}}$. *Route A* and *B* are the routes that have SoC trajectories closest to the blended trajectory depicted in Figure 2.2 and their economic gains are also the largest, in accordance with the theory presented in Section 2.2, *Energy Management*. Meanwhile, the SoC trajectories for *Route E* are very similar to a CDCS solution, c.f. Figure 2.2, and the economic gain is mainly due to the benefits of using a combination of *Save* and *Pure* instead of using *Hybrid*, which the CDCS is restricted to.

As mentioned in Section 2.2.3, *Blended Strategy*, the length of the route in relation to the AER (all electric range) affects the benefits of a blended strategy compared to CDCS. This is indicated by *Route D*, which has a length close to the AER and thus a low fuel consumption and thereby a small economic gain. *Route E*, on the other hand, is a quite long route and would therefore be assumed to have a large potential. However, the number of identified decision points are relatively low and there are two long segments without decision points, which limits the possibility for the mode selection to affect the fuel consumption. A more sophisticated algorithm for identifying decision points is therefore believed to increase the performance along *Route E*.

It can be seen in Table 9.1 that the economic gain from using the mode selection is small for all routes, and even negative for *Route C*. However, the results do not take the economic impact of the changed lifetime of the battery package into account. Table 9.3 indicates that the lifetime is increased when using the mode selection instead of CDCS, thanks to a lowered Ah-throughput and C-rate.

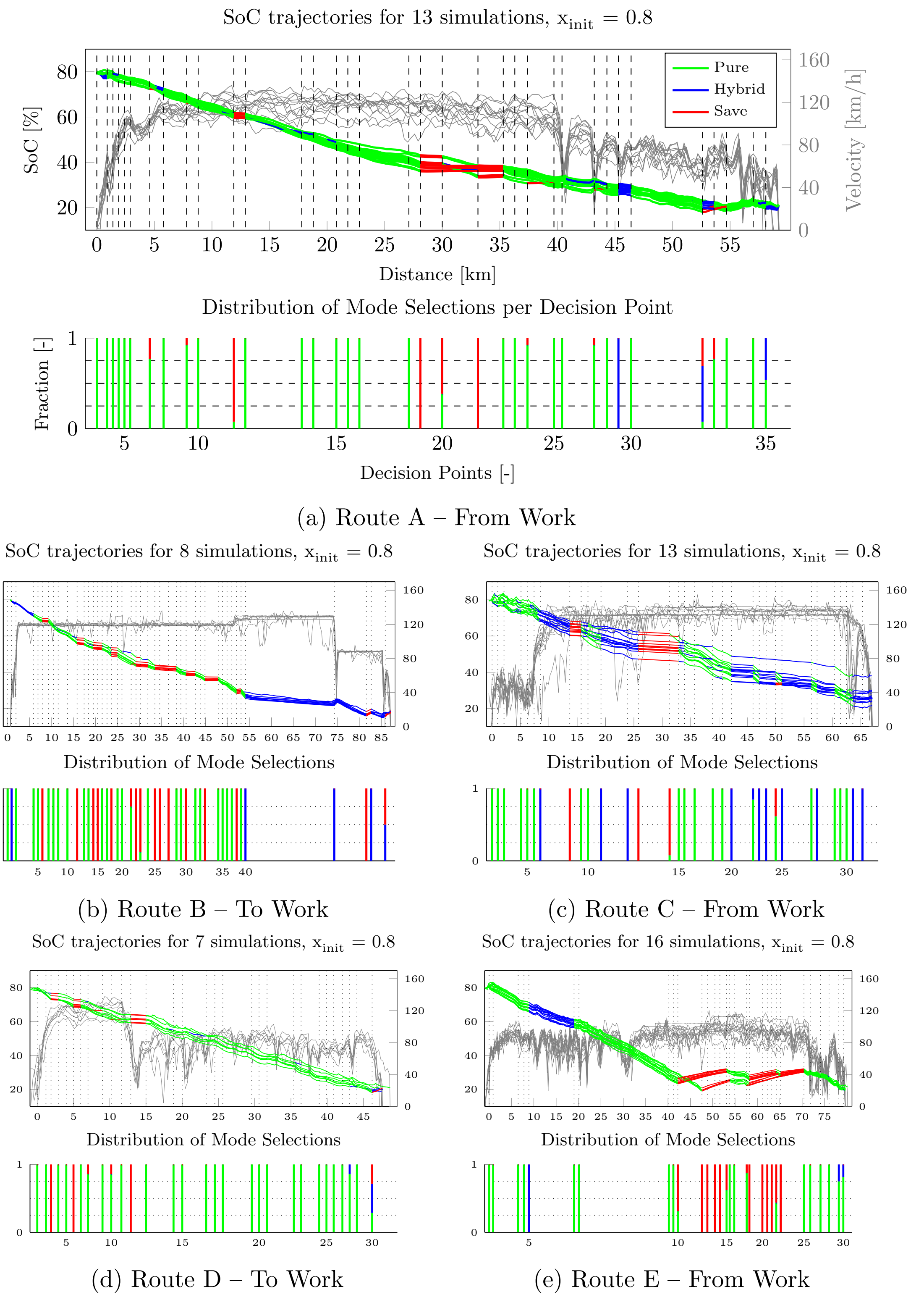


Figure 9.1: SoC trajectories for simulations along different routes with the distribution of the mode selections at every decision point illustrated by the bar diagrams. Note that the legends and labels are identical for all subfigures but only shown in subfigure (a) due to space limitations.

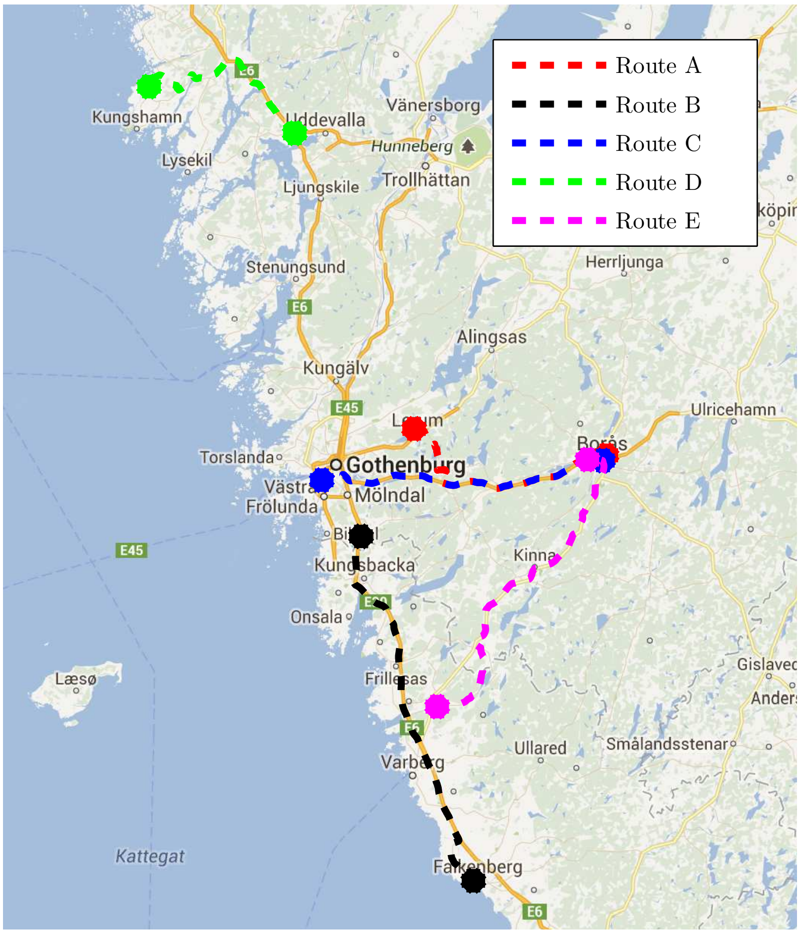


Figure 9.2: Routes identified in the case study.

Table 9.2: Summary of identified routes.

Route		Optimisation		Simulation		D-points
		Trips	Dist. [km]	Trips	Dist. [km]	
A	To Work	11	59.0	16	58.8	38
	From Work	9	59.2	13	58.8	35
B	To Work	6	87.1	8	86.3	44
	From Work	5	87.2	5	86.7	46
C	To Work	11	66.9	13	66.6	32
	From Work	6	67.2	7	68.1	38
D	To Work	8	47.0	10	47.8	31
	From Work	6	47.2	7	48.1	30
E	To Work	11	79.5	16	80.0	30
	From Work	6	77.5	8	77.4	28

Table 9.3: Summary of simulation results along the identified routes.

Route		Strategy	Fuel Cons. [kg]	Final SoC [%]	Ah-Through. [Ah]	C-rate [-]
A	To Work	CDCS	1.145	17.33	25.92	1.181
		Mode	1.191	20.54	24.18	1.103
			+4.0%		-6.7%	-6.6%
	From Work	CDCS	0.980	20.71	26.03	1.163
		Mode	0.765	20.52	25.93	1.160
			-21.9%		-0.4%	-0.3%
B	To Work	CDCS	2.670	15.37	26.85	1.053
		Mode	2.715	17.91	23.71	0.929
			+1.7%		-11.7%	-11.8%
	From Work	CDCS	2.797	18.90	24.91	0.970
		Mode	2.710	19.09	23.69	0.923
			-3.1%		-4.9%	-4.8%
C	To Work	CDCS	1.208	18.77	26.59	0.982
		Mode	1.114	22.33	24.52	0.907
			-7.8%		-7.8%	-7.6%
	From Work	CDCS	2.055	19.80	25.76	1.119
		Mode	2.275	27.03	22.97	0.966
			+10.7%		-10.8%	-13.7%
D	To Work	CDCS	0.291	21.18	25.15	1.256
		Mode	0.247	20.49	25.83	1.290
			-15.1%		+2.7%	+2.7%
	From Work	CDCS	0.285	18.35	25.71	1.258
		Mode	0.327	20.35	24.50	1.198
			+14.6%		-4.7%	-4.8%
E	To Work	CDCS	1.265	18.65	30.46	0.953
		Mode	1.285	20.98	26.59	0.832
			+1.6%		-12.7%	-12.7%
	From Work	CDCS	1.642	18.54	32.24	0.940
		Mode	1.596	20.13	35.25	1.029
			-2.8%		+9.3%	+9.5%

Part IV
Discussion, Conclusions and Future Work.

10 Discussion

The system developed in this thesis consists of a small set of algorithms, most of them are found in standard textbooks for optimal control and data mining. Even though the algorithms are considered as well known within their respective field their combined potential is large. This thesis has shown that for four out of five investigated driving patterns an energy management optimisation system can lower the fuel consumption. It also indicates that the lifetime of the battery can be extend. However, a more detailed study with more sophisticated models of the driving modes are required to estimate the actual savings.

The implemented system can handle several different users, which was shown in the case study, where six users with individual logged driving data where treated. Given historical driving data as raw GPS data, the system has proven to be able to create trips and identify commuting routes without the need of digital maps. However, the system only detected commuting routes for five of the six drivers.

One downside with the relative simplicity of the implemented route identification routine is that routes, on which minor detours are common, are not identified. This is due to the inability to combine trips into longer trips in combination with the trip definition, *a trip is the driving between two consecutive parking periods irrespective of the parking period.* This downside was illustrated in the case study for one of the drivers, where a route *From Work* could not be identified; the driver sometimes stopped to do errands, for example shopping at the local grocery store, before parking at home.

Furthermore, the system is generic and different EMS optimisation routines can be used without modifying the overall structure of the system. This in combination with the possibility to use different vehicle models should make the system interesting for a car manufacturer, since it can be developed for one model and easily extended to cover the whole vehicle fleet. It is here worth stressing that the case study in this thesis only illustrates one example.

Finally, the techniques left out of this thesis such as gathering GPS data and server communication is today possible to do with systems such as *Volvo On Call* and *BMW ConnectedDrive*. Therefore, developing a commercial system with the same architecture as the system developed in this thesis should not be too expansive.

11 Concluding Remarks

The case study performed in this thesis has shown that the developed system is able to identify commuting routes from GPS data and calculate an optimal EMS strategy for each identified route.

The main conclusions of this thesis are:

- The developed system is generic and can handle multiple users and EMS strategies.
- The route identification is good enough for this thesis but needs to be improved for a full scale system.
- Historical driving data is well suited as a priori information.
- The developed mode selection system has a potential to improve the fuel economy and increase the lifetime of the battery package.
- The modified DP presented in the thesis considers driveabilty and predictability and is only slightly sub-optimal compared to conventional DP.

11.1 Future Work

Two major improvements on the route identification are believed to give a better overall system performance, namely:

- The possibility to combine trips, e.g. identifying a stop at the local grocery store as a minor detour from the route.
- A more sophisticated method for identifying decision points.

Interesting topics for further system development and simulations has been identified as:

- Modifying the system to handle increasing amount of GPS data, i.e. how are the routes and EMS strategies affected by new GPS data.
- Use ECMS as EMS optimisation technique.

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Part V
Appendix

A MATLAB Guide

This chapter gives an overview of the .m files used in this thesis.

A.1 EMS Optimisation

Function	Description
classify_route	Identify decision points along a Route
DP_modes	Calculate the optimal EMS Strategy for mode selection along a Trip for a Vehicle Model
find_optimal_mode_matrix	Calculate the optimal EMS Strategy for mode selection along a Route for a Vehicle Model
optimal_mode_sequence	Identify the optimal sequence of modes over a SoC interval at a decision point

A.2 Route Identification

Function	Description
cluster_routes	Cluster Trips into Routes
divide_gps_into_trips	Create Trips from stored GPS data
format_trip	Format a trip, i.e. resample trajectories and calculate the T_{wheels} trajectory
load_route	Load a Route
process_device_trips	Function used in cluster_routes, performs the actual clustering

A.3 Vehicle Model

Script	Description
mode_hybrid	Modelling the behaviour of *Hybrid*
mode_pure	Modelling the behaviour of *Pure*
mode_save	Modelling the behaviour of *Save*
prepare_data_volvo_v60_phev	Calculation of vehicle property trajectories such as, coefficients for fuel consumption. Pre-calculation of gear shifting.

A.4 Simulation

Function	Description
save_results	Store the simulation results as a .txt file in a specified folder
simulate_modes	Simulate a drive along a Trip with a Vehicle using the mode selection EMS Strategy for modes
simulate_modes_CDCS	Simulate a drive along a Trip with a Vehicle Model using CDCS for modes
simulate_route	Simulate a drive along all simulation Trips in a Route, using mode selection and CDCS

A.5 Plot Functions

Function	Description
crop	Crop a specified figure
exportfig	Export a MATLAB figure to a figure in a specified format
main_script_plot	Main script for running plot functions and storing the figures
plot_cdcs_mode	Create a plot comparing CDCS and Mode Selection for a Trip
plot_decision_points	Create a figure with velocity trajectories and altitude trajectory of a Route and the identified decision points along the Route
plot_gear_strategy	Plot the gear strategy used
plot_google_maps	Plot a Trip on an interactive Google map (requires internet connection)
plot_hybrid_limits	Plot the *Hybrid* power thresholds
plot_mode_matrix	Plot the mode selection matrix when calculated with the modified DP
plot_mode_matrix_holes	Plot the mode selection matrix when calculated with DP
plot_soc_trajectories	Plot SoC trajectories when simulating several Trips along a Route as well as the mode distribution per decision point
plot_sub_vs_optimal	Plot the difference in the Cost function for mode selection when calculating it with DP and the modified DP
zoomPlot	Create a zoom in an existing MATLAB figure

B Gear Shifting Strategy

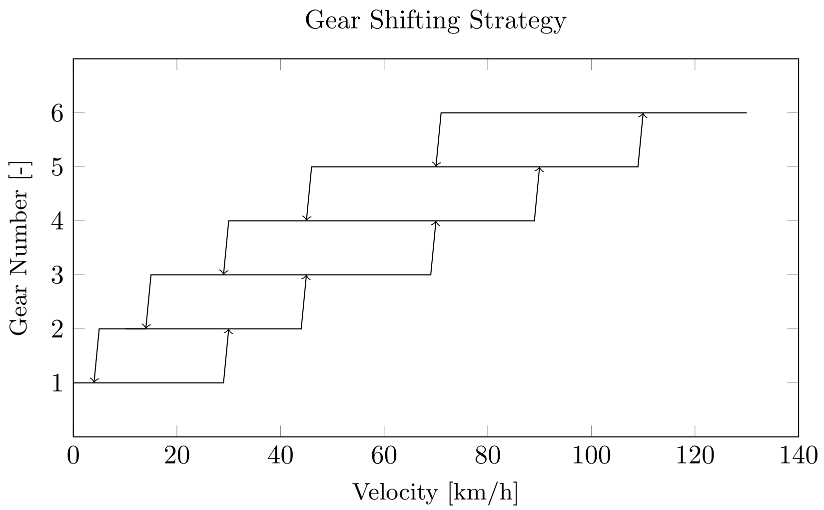

Figure B.1: Illustration of the gear shifting strategy used in this thesis.

C Route Clustering

Given several trips, routes are identified using the algorithm proposed in [15] which shortly can be described as,

1. For each of the k logged trips create a vector with q features where a feature might be; total part of trip with high acceleration, GPS coordinates after a certain fraction of the trip, max velocity etc.
2. Combine the vectors into a feature matrix $\Theta \in \mathbb{R}^{k \times q}$.
3. Create a trip distance matrix $D \in \mathbb{R}_+^{k \times k}$ with the standard euclidean distance between every trips features and all other trips features.
4. Perform a hierarchical agglomerative clustering[3] to find trips similar enough to create a route. Routes are defined by clusters containing at least ρ^* number of trips where the clusters are found using a distance criterion.
5. Find the trip that is most similar to the trips (i.e. the trip with a feature vector in the middle of the room spanned by all trip's feature vector) in the cluster. This trip is denoted the representative trip and is used as benchmark for the route.

[3]See [11] for a detailed presentation of the clustering algorithm.