Czech Technical University in Prague

Faculty of Mechanical Engineering

Department of Automotive, Combustion Engine and Railway Engineering

Master's thesis

Development and optimization of a control algorithm for multi-mode hybrid powertrain

Supervisors:

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2020 Bc. Štěpán Pance

MASTER'S THESIS ASSIGNMENT

I. Personal and study details

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Study program:	**Master of Automotive Engineering**		
Branch of study:	**Advanced Powertrains**		

II. Master's thesis details

Master's thesis title in English:

Development and optimization of a control algorithm for multi-mode hybrid powertrain

Master's thesis title in Czech:

Vývoj a optimalizace řídicího algoritmu 'multi-mode' hybridního vozidla

Guidelines:

1. Focus the literature research on the optimal and heuristic HEV control algorithms and their development.
2. Study overall energy consumption minimization potentials for the multi-mode HEV powertrain using a kinematic (backward) simulation model with built-in optimal control methods in GT-Suite.
3. Prepare a modular dynamic (forward) simulation model of the multi-mode HEV in GT-Suite with a heuristic control algorithm, emphasizing the robustness of the algorithm.
4. Test and optimize the developed heuristic algorithm, using the experience gained by optimal control methods evaluation.

Note: part of SGS19/104/OHK2/2T/12 project

Bibliography / sources:

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Name and workplace of second master's thesis supervisor or consultant:

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Assignment valid until: ______________

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Supervisor's signature	Head of department's signature	Dean's signature

III. Assignment receipt

The student acknowledges that the master's thesis is an individual work. The student must produce his thesis without the assistance of others, with the exception of provided consultations. Within the master's thesis, the author must state the names of consultants and include a list of references.

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Annotation

Author:	Bc. Štěpán Pance
Title in English:	Development and optimization of a control algorithm for multi-mode hybrid powertrain
Title in Czech:	Vývoj a optimalizace řídícího algoritmu 'multi-mode' hybridního vozidla
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Supervisors:	Ing. Rastislav Toman Dr.Ir. Leonardo Gunawan
Abstract:	The main goal of this thesis is a methodology process of developing a heuristic control algorithm for a parallel hybrid vehicle from results of an optimal control simulation model, controlled by dynamic programming method.
Keywords:	Hybrid vehicle, Multi-mode hybrid, Heuristic control algorithm, Hybrid powertrain, GT-Suite
Number of pages:	84

Declaration

I hereby declare that I have completed this thesis independently and that I have listed all the literature and publication used in accordance with the methodological guidelines about adhering to ethical principles in the preparation of the final thesis.

In Prague, 14th of August, 2020

Bc. Štěpán Pance

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Table of Content

1. Reasons for HEV control algorithm

We are living in global world, where there is increasingly more focus on decreasing our CO_2 emissions which are often viewed to be the most responsible for the greenhouse effect. Transportation is currently producing 15% of global CO_2 emissions [1] and for states like California it can be even close to 50% of total CO_2 emissions [2] produced by humans. Greenhouse effect is considered to be the main reason for the currently increasing global temperature average which is causing many climate changes. Therefore, representatives of most political and economic unions lead up to significant lowering of emissions. For example, European Union has a goal to become climate neutral by 2050 and some other political groupings have similar targets. [3] Because of this, politicians and governments are pushing legislative towards strict emission limits including limits for passenger transportation. From 2021, phased in from 2020, the fleet average local CO_2 emissions of new vehicles need to be less than 95 g/km. That is equivalent to 4.1 l/100 km of petrol and 3.6 l/100 km of diesel, and in following years will be decreasing.

The segment of passenger cars has been dominated by the use of internal combustion engine (ICE) powertrains for decades, however, with today's legislation getting increasingly strict, purely ICE-powered cars start to fail fulfilling those regulations. To accomplish those, the manufacturers need to implement progressively more complicated, thus expensive, exhaust gas aftertreatment devices. Similarly, the manufacturers need to come up with more complicated control strategies and therefore they start to lean towards hybrid and even purely electric powertrains. Some manufacturers decided to leap directly to electric vehicles (EVs). Whether that is the right step or not, we cannot tell by now. In this thesis I am discussing mostly topics associated with hybrid electric vehicle (HEV) control system.

Control system algorithm is the key element to use hybrid powertrains to full potential and lower the emissions as well as improve drivability of the vehicle. The apparent reason for that is having two different torque sources – ICE and electric motor. The target is to find the operating point where the overall combined efficiency of the system is the highest, thus the fuel and energy consumptions are reduced. To successfully apply this strategy, energy control algorithm is needed. The first target of this thesis is to research all kinds of control algorithms of HEVs and their development. The following practical task is building a kinematic (backward) simulation model for a vehicle based on idea of Multi-Mode Hybrid – Series/Parallel Hybrid with two electric motors designed by Schaeffler. [13] For this purpose, optimal control methods built in GT-Suite simulation software, such as the dynamic programming and equivalent consumption minimization strategy, are used. The final task is to create a heuristic control algorithm and use it in the dynamic simulation model with some features and logic taken over from the backward simulation results.

In the following chapter, discuss the introduction to HEVs, the different architectures for HEVs as well as I list different topologies of parallel hybrids based on the location of the electric motor, and the classification based on the level of hybridization. The last part of this chapter is dedicated to the specific Multi-mode hybrid powertrain (proposed by Schaeffler [13]), the explanation of the logic for such a solution.

In the third chapter, I talk about the possibility to adjust the conventional ICE for its use in an HEV - what are the reasons at the first place, what are the solutions to do so and why similar engine could be used in models in following chapters.

In the fourth chapter, I introduce what a control strategy is, I list which control algorithms are used to control hybrid powertrains and their basic categorization - heuristic and optimal control. I also mention their use cases and limits of application in simulations or physical world.

In the chapter five, the description of the process of developing the kinematic model with implementation of dynamic programming optimal control for this powertrain and discuss its key outtakes for the heuristic control algorithm presented in the second half of the chapter five.

I explain the logic of the heuristic control algorithm for the Multi-mode hybrid vehicle, designed with the basic outtakes from the results of the dynamic programming, and describe the process of development of the dynamic model in which it can be implemented. Moreover, I run a few tests to confirm the correct function of the control algorithm and the dynamic model. The last section of chapter five presents the idea of methodology how to proceed with the development of the heuristic control based on the results from the optimal control.

2. Classification of hybrid electric vehicles

Different types of classification for hybrid electric vehicles (HEVs) is discussed in this chapter. First of all, the basic architectures of HEVs is introduced. Later the topic of their specific functions is presented to help understand the terminology in following chapters. After that, definition of classification according to topology and architecture is made. In the last subchapter, specific solution for multimode hybrid powertrain, the main topic of this thesis is introduced.

2.1. Basic architectures of HEVs

2.1.1. Series drivetrain

The series hybrid system is the simplest configuration, see *Figure 1*. The typical distinguishable feature of series system is that the electric motor and ICE are not mechanically connected and can operate independently at any speed. The ICE generally does not need to meet high power demands, instead, its main focus is to achieve the maximum efficiency. The high peak torque demands during driving mean that the electric motor(s) need to be powerful enough and for that reason, and as a general rule, the battery pack is larger than the one in parallel hybrids. The advantage of such a system is that the engine can be operated at its best efficiency operation curve. Furthermore, we need to keep in mind is that we also need to consider the efficiency of the generator. Example of a typical series hybrid electric vehicle (S-HEV) configuration is Karma Fisker. This has a powerful 2L turbocharged engine with max power of 190 kW and 20kWh battery. A special sub-category of S-HEV are vehicles equipped with range extender like BMW i3 REx. [4] [5]Range-extender vehicles are further discussed in 2.4.5.

Advantages	Disadvantages
ICE can work in optimal efficiency point	Lower efficiency of power transfer
Regenerative braking is possible	Need for large battery

Table 1 - Advantages and disadvantages of series architecture

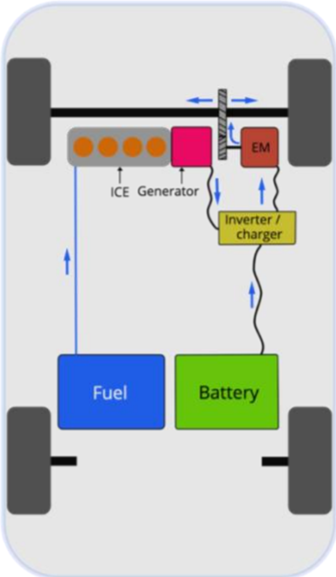

Figure 1 - Series hybrid

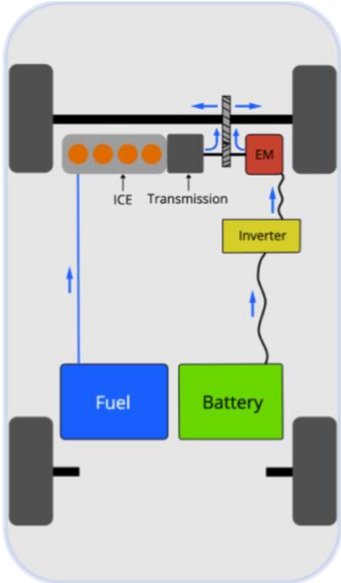

Figure 2 - Parallel hybrid

2.1.2. Parallel drivetrain

These hybrid systems are composed of ICE and EM which can usually both individually drive the car as well as been coupled and drive the car together. The common feature of parallel drive is that the rotational speeds of connecting axes between EM and ICE have the same speed and supplied torque from both is added together. If we want to use only one source of torque, the other one must rotate as well or be disconnected by clutch. As you can see in the Figure 2, parallel drivetrain is more similar to a conventional car drivetrain, where the main power source is the ICE. [4] [5]

Advantages	**Disadvantages**
High efficiency of mechanical part	Lower efficiency of electrical part
Possibility of power regenerative	
Engine working possibilities are better than in pure mechanical drive	

2.1.3. Combined drivetrain

The combined drivetrain, also known as Multi-mode hybrid, offers combination of both the series and parallel architectures in one drivetrain. That is enabled by mechanical devices like clutches or planetary gearsets. Although combined drivetrains are more complex than series or parallel drivetrains, they compensate it by increased efficiency and usability. Finally, they are capable of eliminating the necessity for a conventional transmission by replacing it by fixed gear solutions or set of planetary gears. Examples of combined drivetrains are Toyota hybrid system (*Figure 3*) or Twindrive solution for Multi-mode hybrid from Schaeffler - featured in this thesis.

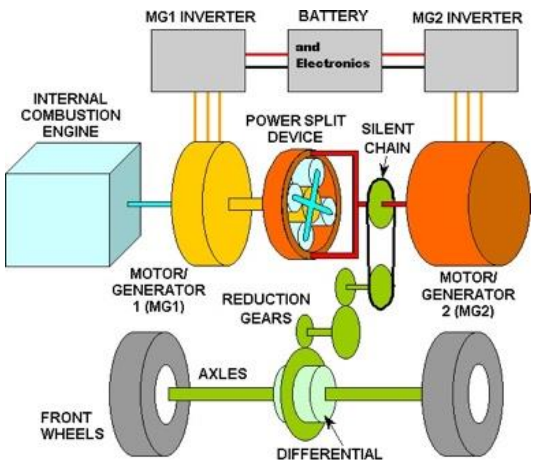

Figure 3 - Toyota Prius Hybrid Synergy Drive [32]

Advantages	Disadvantages
Series and parallel setup	Mechanical complexity of the setup
Capability of using each component (electric motors and ICE) to its full potential	Complex control strategies High cost due to its complexity

2.2. Drive modes functions of hybrid electric vehicles

Compared to a conventional vehicle, HEV can save fuel intentionally using and switching following functions depending on driving conditions.

2.2.1. Start Stop

Start-Stop system automatically switches off the ICE when the vehicle is stationary and the power from ICE is needed. When the power from ICE is needed (not only for propulsion, but also for HVAC* system and battery charging), starter motor starts the engine back on. After cold starts, when the temperature of ICE and catalytic converter is not high enough, the SS system is not activated. In HEV, this function can be provided by the built-in electric motor, if it is in P0 – P2 position. 2.3.1. - 2.3.3. In addition, the SS system can typically be manually turned off and uses 12 or 48V architecture.

**) Heating, ventilation, and air conditioning*

2.2.2. Load point shifting of the combustion engine.

The goal for the load point shifting (LPS) is to shift the operation point of the ICE to the highest possible efficiency point at specific moment of use. To do that we use electric motor as a generator, producing negative torque and charge the battery – LPS up *(Figure 4*). If we power assist the engine, the EM is producing positive torque, so we make the ICE to produce less torque – LPS down. The decision depends on power demand, battery SOC, and control strategy.

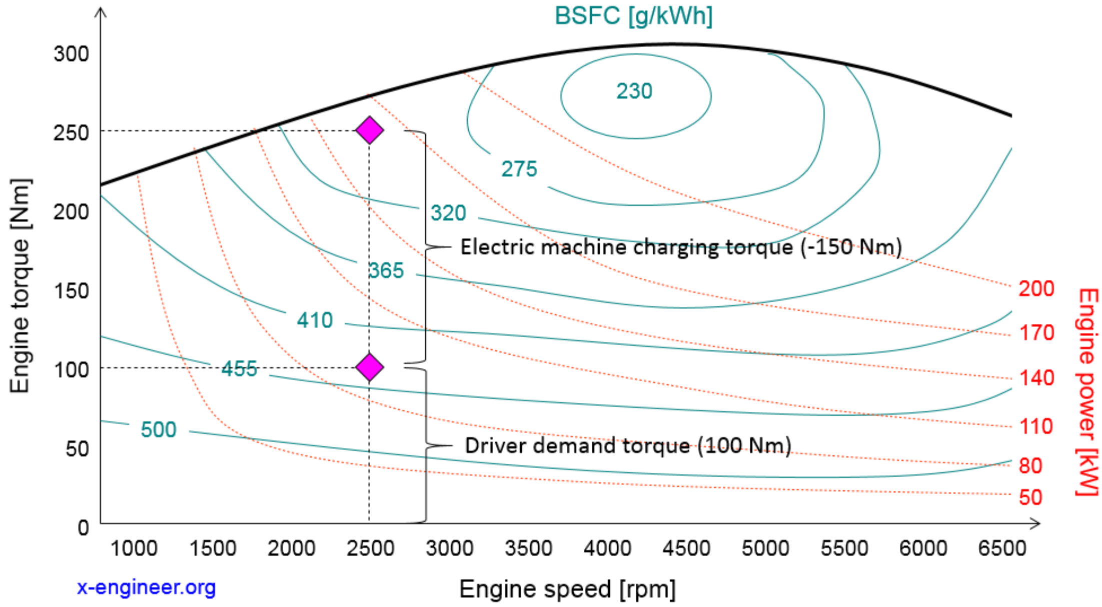

Figure 4 - Example of load point shifting up [6]

2.2.3. Regenerative braking

The regenerative braking (i.e. E-recuperation) is a mechanism for energy regeneration during slowing down the vehicle. With use of the traditional brakes, the kinetic energy is thanks to mechanical (friction) brakes transformed to heat which is considered as an energy loss. Therefore, regeneration braking contributes to higher efficiency but also to lower wear of the mechanical brakes.

The amount of the energy regeneration depends on the SOC of the battery and the maximum power of the generator at given time. For instance, when the battery is close to full charge, the regenerative braking is disabled, and the vehicle slows down by application of mechanical brakes. [7] One of the main issues of combination of electro-mechanical braking system is the control problem of intensive braking maneuver. The challenge is the cooperation of the regenerative braking and active driving safety systems (ADSS) - especially with the anti - lock braking system (ABS). At all events, there is a limit where the application of mechanical brakes is necessary. [7]

There are two primary approaches how to combine application of mechanical brakes and the regenerative braking, parallel and series braking strategy. (*Figure 5*)

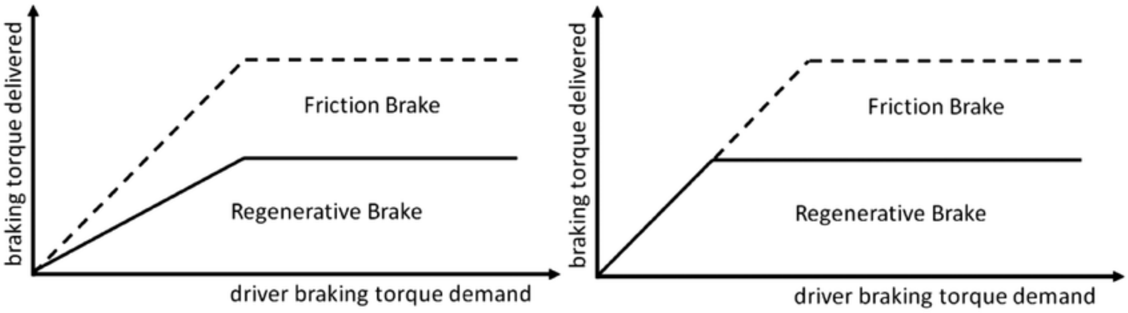

Figure 5 - Parallel (left) and series (right) regenerative braking actuation strategy [8]

Parallel braking strategy

This is the simplest implementation of the regeneration feature to the vehicle (*Figure 5 – left*). The strategy ensures that every time braking is applied, some part of the kinetic energy is regenerated, even at ADSS activity. The ratio of both braking architectures is usually constant, till the generator or battery regeneration limit is reached. One of the disadvantages is, that the parallel braking never uses the regenerative braking to its full potential because every time braking, fraction of braking is realized by mechanical brakes. [7]

Series braking strategy

The second strategy is series braking (*Figure 5 – right*). This strategy activates the regenerative braking first, after it achieves maximum regeneration, the friction brakes start to operate when we reach this threshold. Therefore, the series braking strategy is able to transform the most energy. [7]. Later, in the simulation models, it was considered that the vehicle is equipped by ADSS, capable of ABS when series braking by the EM2 is applied. Therefore, the mechanical brakes are applied when the braking power exceeds either battery or motor regeneration limit, and to get the vehicle to full stop.

2.2.4. Electric drive

Depending on the vehicle's architecture, there is a capability of HEV to travel certain distance in electric drive mode often referred to as an e-drive. The combustion engine is switched off, so it does not produce any local emissions, which is appreciated in in-city driving even though it may be not ideal from the efficiency standpoint.

2.2.5. Boosting / Power assist

In this mode, the ICE and electric motors work together in parallel mode to achieve the maximum power or throttle response in spite of efficiency. Due to instant torque input, electric motors reduce the effect of “turbo-lag” in vehicles equipped with turbocharged engines. This mode improves performance of the vehicle, drivability, may ad “sporty feeling” and most importantly also enhances safety of driving.

2.3. Classification of HEVs according to topology

2.3.1. Topology P0

As you can see in the *Figure 6* the electric motor in P0 topology is connected directly to the engine crankshaft typically via belt drive, thus it is not capable of any e-drive. This solution gives the motor a capability to replace a starter motor. The power of the motor is usually within a few kilowatts, therefore, the acceleration assist and regenerative braking is mild. For that reason, the effect on fuel efficiency (FE) is also low (<10%).[8][9] One of the disadvantages is that the EM is located at the very beginning of the drivetrain, so it is affected by all the drivetrain losses from ICE to wheels. [8][9]

2.3.2. Topology P1

The EM is placed right behind the engine, (i.e. in front of the clutch). Therefore, it shares most of the features with the P0 topology. In contrast to the P0, the notable difference is that the motor is not affected by the losses of the ICE. [8][9]

2.3.3. Topology P2

As in the P1 topology, the EM is located behind the engine. However, the difference is that it is connected to the transmission input shaft, (behind the clutch). Therefore, the EM can be fully decoupled from the ICE and allow for an e-drive. The additional clutch located between the EM and transmission allow its use for a Start/Stop. The power of the EM varies from 15 to 80 kW, while the FE gain is commonly in range of 10 – 30 %. [8][9]

2.3.4. Topology P3

The location of the EM in P3 position is behind the vehicles transmission where it can be joined right on the output shaft (P3a); or in case of rear wheel drive vehicle, it can be mounted to the end of the cardan shaft (P3b). The Start/Stop (SS) system has to be provided by P0 or by a conventional starter motor. The FE gains (10 – 30%) are similar to P2 design and the power of the EM is usually in the range of 15 – 50 kW. In contrast to previous solutions, the torque is delivered independently on shifted gear and without ICE and transmission losses. [8][9]

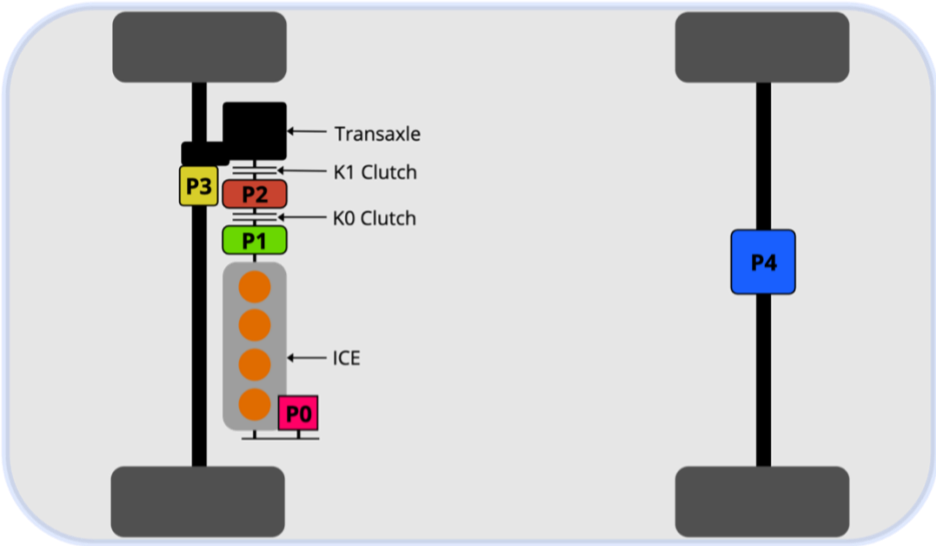

Figure 6 - P0 - P4 basic hybrid topologies

2.3.5. Topology P4

Finally, the P4 topology integrates the EM into the secondary axle as shown in *Figure 6*. This solution offers a full e-drive mode as well as the option to build a purely electric vehicle. Advantage of this placement is lowering the drive losses during EV driving and having an effective strong regenerative braking. The ICE needs to have a dedicated starter motor, and since both the EM and ICE propel different axels, the P0 topology is often added to create combined P0P4 topology. P4 is also an elegant solution to get an electric all-wheel drive (eAWD). The EM power differs significantly from 15 to 100 kW which translates to FE gain of 10 to 30 %. [8][9]

2.4. Classification according to level of hybridization

This classification is used to categorize hybrid powertrains based on the power portion coming from electric motors and drive modes the HEV is capable of. The graphic interpretation can be seen in *Figure 7* below. The charts list of features of each category starting with "micro-hybrid" which is the least electrified kind of hybrid and as we go on the chart the right side there is higher and higher percentage of electrification all the way to the right end to EV. The list of levels:

2.4.1. Micro – Hybrid

Micro-hybrids are actually not “real” hybrid vehicles. The EM is used exclusively for SS system which is described in more details in 2.2.1.

2.4.2. Mild – Hybrid

Vehicles are equipped with higher level of electrification in comparison to Micro-hybrids. However, they are still not capable of fully electric drive. Furthermore, it shares its feature of SS system with Micro-hybrids category while it is capable of regenerative braking and load point shifting (LPS). The EM instant torque helps with filling up torque gaps and improving throttle response. Electric motor is typically mounted in P0 or P1 position and uses 48V architecture. The mild hybrid solution recently became very popular in the VW group’s lineup.

Note: Having voltage architecture below 50 V is very desired across all HEVs. The major advantage is that technicians in most countries can manipulate with this system without having a special license for manipulating with higher circuit architectures than safe voltage limit of 50 V. If the 50V target cannot be met, the manufacturers automatically incline towards significantly higher voltages (300 or even 400 V).

2.4.3. Full – Hybrid

Vehicles use the combination of ICE and electric motors to its full potential. It is capable of fully electric drive (usually short distances – few kilometers and low speeds e.g. 50 km/h) as well as pure ICE mode and combination of both.

2.4.4. Plug – In Hybrid

The Plug-in hybrid vehicles (PHEV) are considered to be the highest level of hybridization among HEV. Its differentiation factors are the biggest battery capacity (among HEVs), providing a fully electric range for more than 30 km, the capability of relatively high speeds in e-drive mode (e.g. 100 km/h), and most importantly the presence of a charging socket adding the ability of charging from an electrical grid. The PHEV stands out thanks to its capability to link both the conventional fossil-fuel and electric powered vehicles, thus providing an enhanced efficiency and a variety of use cases. As an example, for short commutes, which consist mostly of in-city driving, the car (if the battery has high SOC) can be used in e-drive or with only minimum intervention of the ICE. This covers most populations commute to/from work so the vehicle can be operated as an EV. On the other hand, the ICE can be used conveniently for long-distance trips without the need for time consuming stops for charging as in case of EVs. Furthermore, during highway driving where the ICE can be used more in the range of its higher efficiencies (higher loads) it is more beneficial in comparison to e-drive. [9]

Because of the high battery capacity, the powertrain brings the biggest opportunity for optimization if appropriate energy control strategy is used [4]. Therefore, the proposed simulation model for Scheffler's Multi-mode powertrain [13] is intentionally assumed to have properties as a PHEV (relatively high-capacity battery, powerful EMs)

2.4.5. Range – Extender vehicles

The Range-Extender vehicles (REVs) are interesting fusion between PHEV and the battery electric vehicle (BEV). The common attributes are charging socket, and large battery pack. The main difference is the philosophy of use. In contrast to PHEV, the REV uses the series charging by a small capacity ICE which is used only if the battery state of charge (SOC) is low. Therefore, it can be categorized as a special example of S-HEV because the vehicle is propelled rigorously by EM. The battery capacity is comparable to BEV; hence it should be used as one. That means to charge it regularly from the electric grid and use the ICE only in need. However, this solution is not very popular among manufacturers of passenger cars. It is more often used in buses for public transportation.

2.4.6. Electric vehicles

In case of EVs, the electric motor (or motors), are the exclusive source of the driving power. In BEV, the energy is taken from a high-capacity battery. Meanwhile, in fuel cell electric vehicle (FCEV), the electric energy is extracted by electrochemical reaction in fuel cell from hydrogen. Example of FCEV production vehicle is Toyota Mirai. The level of hybridization (electrification basically) of EVs reaches 100 %, *Figure 7*, so technically they are no longer hybrid vehicles. [10] [11] [12]

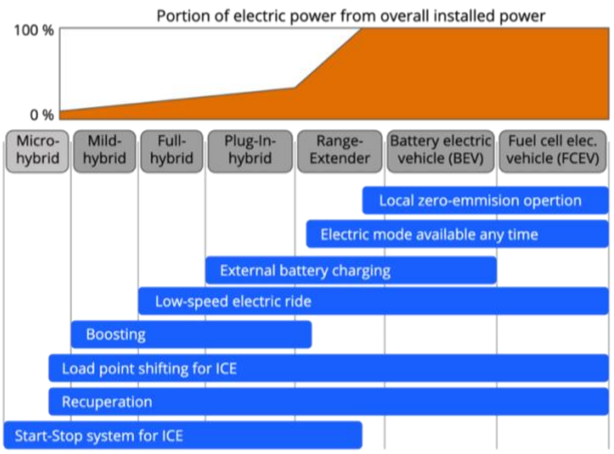

Figure 7 - Classification according to level of hybridization, (adjusted from [12])

2.5. Multi-mode HEV introduction

The inspiration for the model architecture comes from the Schaeffler Twindrive design which belongs to combined drivetrain architecture introduced above in 2.1.3. The presented idea of Schaeffler is to design a dedicated hybrid transmission which is implemented to the vehicle instead of a conventional transmission without many packaging differences. It brings an advantage of significantly lowering number of moving components in the transmission thus reducing complexity, cost and mechanical losses.

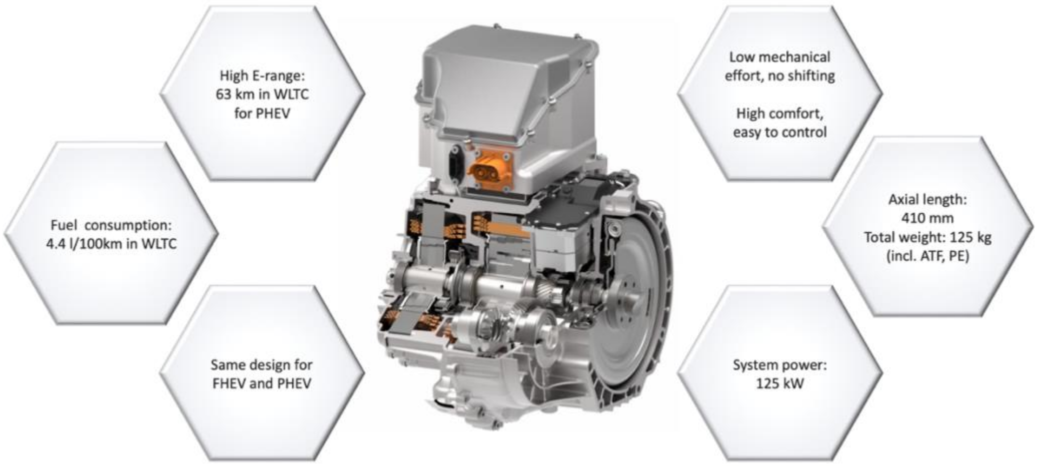

Figure 8 - Transmission for a Multi-mode HEV introduced by Schaeffler [13]

2.5.1. Components

The unit consists of two electric motors, two gear sets, and two clutches. The ICE is connected to the clutch RK, after RK clutch the first gear set follows and that is connected to the electric motor number 1 (EM1) which acts primarily as a generator and a starter. Between EM1 and electric motor number 2 (EM2) is mounted clutch K0. EM2 is the main propulsion power unit and it enables fully electric mode (e-drive) or series drive when the K0 clutch is open. If the clutch K0 (and RK) are closed, which happened only if speed limit conditions are met, the vehicle can operate in parallel mode. All the drive combinations are presented in *Table 2*

The use case of this unit is expected to be for P-HEV mid-size sedans, station wagons and SUVs where it can vindicate its potential higher complexity and cost of the battery.

Characteristics	
Max. System Data Output Power / Torque	125 kW / 2600 Nm
E-Motor EM 1 Peak Power / Max. Torque	110 kW / 100 Nm
E-Motor EM 2 Peak Power / Max. Torque	125 kW / 310 Nm
ICE Max. Power / Max. Torque	110 kW / 250 Nm
Weight / Length	125 kg / 410 mm
E-range (WLTC)	63.2 km @ 9 kWh

Figure 9 - Indicative powertrain specification [13]

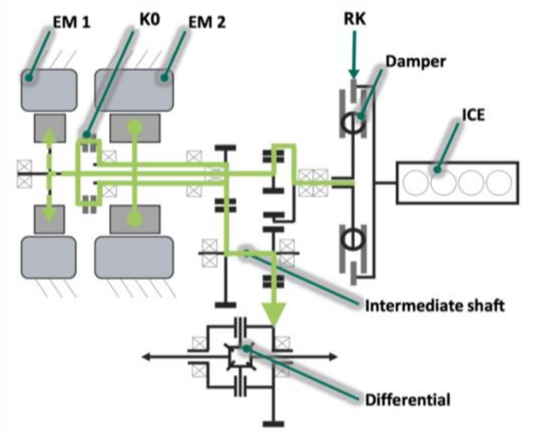

Figure 10 – Multi-mode HEV powertrain scheme [13]

	ICE	EM 1	EM 2	Clutch RK	Clutch K0
Electric mode	Off	Off	Driving	Closed	Open
Regeneration	Off	Off	Driven	Closed	Open
Series	Driving	Driven	Driving	Closed	Open
Parallel (+Boost)	Driving	Off/Boost	Driving/LPS	Closed	Closed
E-boost EM1+2	Off	Driving	Driving	Open	Closed

Table 2 - Multi-mode HEV powertrain logic

2.5.2. Application of components

As mentioned above, the EM2 is the main propulsion power unit which is in function every time the vehicle is on the move. The vehicle is limited by the design to operate strictly in e-drive or series mode under certain threshold speed values because there are only fixed gears ratios and therefore the operation of the of the ICE in parallel mode is theoretically possible speeds where it achieves at least its idle RPM. Since the efficiency of combustion engines are very low in speeds closely to idle speed, the more meaningful ICE speed limit for its use would be around 1300 RPM. Below that speed limit, the clutch K0 is strictly open.

Before the ICE is operated, first it needs to be started. Starting is provided always by EM1 with the clutch K0 opened and clutch RK closed. After the ICE is started, it is used either to act as a generator coupled with the EM1 in generator mode (series mode) with clutch K0 open, or to drive the vehicle in parallel mode with both of the clutches closed. The parallel mode is provided by cooperation of the ICE and the EM2 and EM1 is just freely spinning. The EM2 is responsible for load point shifting in the way it is explained in 2.2.2.

The last set of features is referred to as "Boost", where unlike in the previous modes the main focus is to provide the best performance preferably over the better efficiency. Even though Schaeffler denies this kind of use I mention it as a possibility of this powertrain and I also work with this ability in my simulation models.

Here we can distinguish two kinds of boost topologies. Firstly, pure e-boost mode where both EM1 and EM2 provide power and the ICE is off. To accomplish that, we need to have the clutch RK open and K0 closed. The maximum power output may not be limited by the power of the motors but by the power limit of the battery pack.

The second topology is parallel Boost mode where to both active electric motors, power from the ICE is also added, both clutches are closed, and the powertrain is working to its maximum power. This mode is also limited by the minimum engine speed in parallel mode mentioned earlier.

With the boost ability, this solutions from Schaeffler would enable manufacturers to allow or limit the Boost capabilities for variety of power outputs to distinguish between different car models specifications. For instance, the basic models with less power and smaller battery, would not offer boost modes in contrast with more expensive, sportier models with larger batteries with boost modes available.

Part	Function
Electric motor 2 (EM2)	The main power unit, responsible for Electric mode Load point shifting in Parallel mode Regenerative braking
Electric motor 1 (EM1)	Starter motor for the ICE Generator in Series mode E-boosting
ICE	Parallel mode – propelling the vehicle Series mode – electric power generation
RK Clutch	Open in EV boost mode Closed in all other modes, link between ICE and EM2
R0 Clutch	Open in EV, Series Closed in Parallel and e-boost mode

Table 3 - Functions of electric motors and combustion engine

3. Potential of combustion engine in HEV

In this section I would like to mention examples of adjustments which can be done to an ICE which is specifically modified for its use in HEV which are presented in [14]. I want to present the potential idea that a similar optimization process could be implemented to the ICE used in the Schaeffler Multi-mode hybrid introduced in section 2.5

3.1. Reason for the optimization

The philosophy behind this idea is that the ICEs in conventional vehicles are designed to be as versatile as possible e.g. operating smoothly from low to high engine speeds as well as providing very low torque or very high torque. Therefore, it is very difficult and expensive to design an ICE with a good efficiency covering such a broad range of operating points. On the other hand, in a HEV the ICE and electric motors are (or should be) managed in a way that they provide the same or even better driving experience than the conventional vehicle without using some of the operational spectrum of the ICE. That makes the used range of operation narrower and for that reason, the ICE can be better optimized for it. That can make the engine either more efficient, less expensive or both.

For this experiment 4-cylinder, turbocharged engine was used, EA211 1.5l TSI evo engine from VW, operating in the Miller cycle. In this article [14], 4 different potential approaches for lowering the brake specific fuel consumption (BSFC) of the ICE for hybrid vehicles were suggested, together with their hardware solutions. All those adjustments were designed and proposed for a full HEV, with capacity of its battery pack higher than 1 kWh, capable of fully electric drive. The properties of the base engine are presented in *Figure 11* and *Figure 12*. Effects of all four suggested ideas are presented in *Figure 13.*

Figure 11 - Variants and technologies EA211 1.5l TSI evo [14]

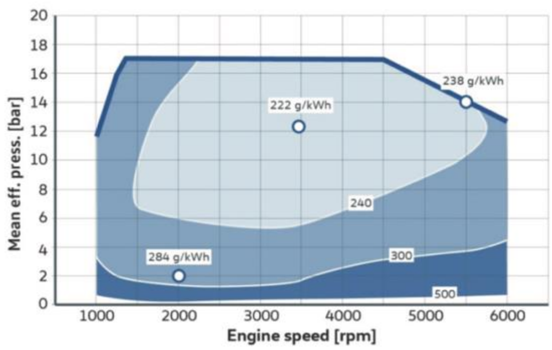

Figure 12 - Map of BSFC EA211 1.5l TSI evo 96 kW [14]

3.1.1. Potential for improvements

Elimination of low-end torque

The first hybrid specific potential improvement is elimination of low-end torque (LET) area. This means that if we want the engine to operate at low speeds but with high loads. Especially in turbocharged SI engines this area is limited by knock which is solved by the compression ratio decrease, or compressor boost limit. The solution to avoid this area is to use series mode in which the engine is decoupled from the wheels thus it can produce the wanted power at higher RPM, so it operates at highest efficiency operation line and produce electric energy for the electric motor.

Maximum engine speed limit

Another potential is to limit the maximum engine speed. This solution can be used for a series hybrid in vehicles equipped with variable transmission ratio. With this approach the dedicated engine design can limit the engine speed to where it reaches its maximum engine power.

Low load operation limit

The third potential is elimination of the engine use in low efficiency areas such as low load operations and idle. Those operation points can be replaced by electric motor in E-drive. Another option is to use load point shifting, discussed in chapter 2.2.2.

Operation targeting

Lastly targeting the engine operation in special phases. This is easily possible in vehicles which are capable of mechanical decoupling of the engine from the wheels. This way we can easily use series mode or specially defined phases for cold starts and efficient catalyst heating.

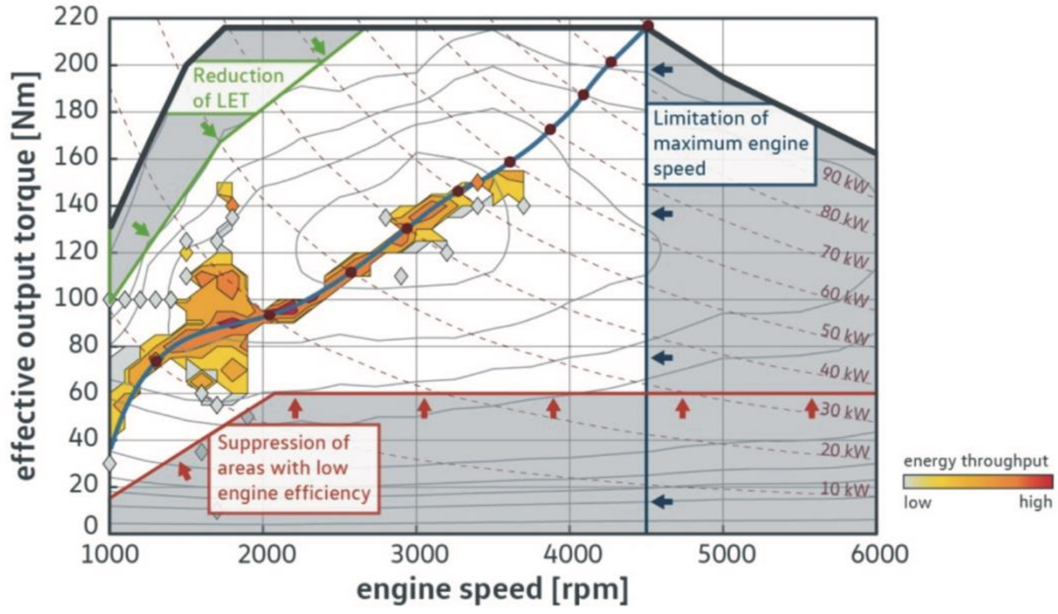

Figure 13 - Reduced engine operating map for hybrid powertrain [14]

The application of the four potential adjustments are shown in the *Figure 13* which represents the proposed reduced operating map of the ICE. Consequent adjustments to the engine to profit from the reduced operating map are discussed in the next sub-chapter.

3.1.2. Solutions to suggested improvements

Higher compression ratio

At first, the geometrical compression ratio (CR) thanks to the reduction of LET and use high quality RON98 fuel can be increased to up to 15.0:1, as well as the active cylinder deactivation (ACD) can be removed, because the low load areas were eliminated. More aggressive exhaust gas recirculation (EGR) can be implemented because the range of operating points was limited. Hand in hand with the increase in EGR goes increase the size of the variable turbine geometry (VTG) turbocharger to increase the mass flow.

Passive pre-chamber ignition system

The result of higher engine CR and aggressive EGR is high cycle to cycle variations (CCV) That causes rough operation. This problem can be solved by application of a passive pre-chamber ignition system. It improves CCV and operation smoothness significantly even with high CR and charge dilution. This kind of ignition is not usable for ICE in a conventional vehicle for reason of poor combustion performance in low loads and cold starts. However, in case of this ICE the pre-chamber ignition can be used because those operation regions are eliminated.

Optimization of the camshaft profile

For the engine with narrower engine speed range can be adjusted profiles of camshafts because they are mostly limited by optimization for higher engine speeds. Because of lower maximum engine speed proposed in this solution, the intake cam profile can be increased from 7 mm to 9 mm, meanwhile the valve opening duration was shortened from 150° to 145 °CA. The new intake valve-lift curve improves the knock resistance up to 3 °CA so therefore the ignition timing can be tweaked.

Optimization of valve timing and EGR rate

Lastly the valve timing and amount of external EGR rate were optimized for the whole engine operation map. Optimization of those parameters are crucial to gain the advantages from previous adjustments.

3.1.3. Results of the adjustments

This carefully designed engine delivers 6.5 gCO_2/km improvement over the original ICE in WLTC cycle. That is an improvement of approximately 7 % which can the deciding factor for the vehicle to pass the CO_2 emission limits. The BSFC and percentage difference maps of the adjusted ICE are shown in *Figure 14* and *Figure 15.* That proves that there are still ways how to improve efficiency of current ICEs as well as efficiency of the whole vehicle.

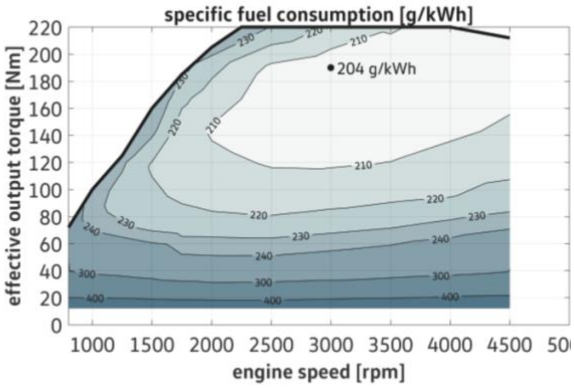

Figure 14 - Map of BSFC of the adjusted engine [14]

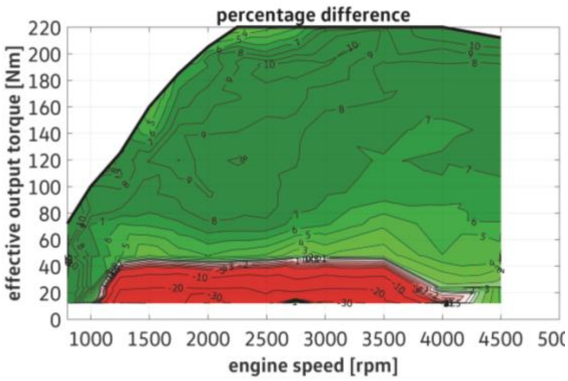

Figure 15 - Map of the percentage difference to the base engine [14]

4. Control strategy

In this chapter, introduction to control strategy is made and why they are necessary for HEVs. There is an overview of control algorithms which be used for control of hybrid powertrains. Furthermore, they are classified to one of the two basic categories - heuristic and optimal. At the end of the chapter the choice of the control strategies for further steps is made.

4.1. Introduction to control strategies

By a control strategy we mean a control system that decides, how each individual elements of the drivetrain work to meet the performance requirement with regard to the overall energy efficiency of the vehicle to reduce the overall energy consumption. At the same time, it needs to fulfill various physical restrictions - such as minimum/maximum ICE and EM speed or torque, battery power limit or gear selection. [4] [16] Terminology of types of control strategies:

Causal control strategies

The causal strategies rely on past and present events. This approach has to be used in cases where the driving profiles are not predictable in sense that exact speed, road profile as a function of time. [4]

Non-Causal control strategy

The non-causal detailed knowledge of future conditions as exact speed, road profile as *f(t)*. Those conditions are known for regulatory drive cycles or for some kinds of public transportation with route plans (e.g. subway or train). Non-Causal control strategy would also be suitable for autonomous vehicles if complete GPS data and on-line traffic information of the route would be accessible. [4]

Offline control strategy

The offline strategy aims at optimizing the use of power sources a known driving condition, known driving cycle. Offline control strategy aims to reach the global optimum, for example Dynamic Programming (DP).

Online control strategy

The online strategy is based on real time decision making, such as fuzzy logic, neural network or predictive driving.

4.1.1. Reasons for control strategies

In comparison to a conventional vehicle, HEV control problem is much more complex. Cause of that the HEV is a multi-energy source system (fossil fuel for ICE, electric power from battery for EMs). It can be also described as that parallel HEV's operation has one degree of freedom. The reason for that is the combination of 2 power sources, in acceleration – ICE and EM, and in deceleration – Conventional brakes and generator. [17]

It is typically used *u to* describe the power-split ratio between the ICE and EM as follows.

Powertrain action	Power split ratio
LPS up	$u > 1$
e-drive	$u = 1$
Pure ICE drive	$u = 0$
Power assist (LPS down)	$0 < u < 1$
Regenerative braking	$u < 0$

Table 4 - Power split ratio u for HEV control strategies

To control the power-split ration manually all the time would be overwhelming for the driver. Hence the HEV needs to be equipped with an automated control strategy which takes care of managing all power sources in the vehicle independently on the driver. If the control strategy is well designed, it can save fuel for the following reasons.

- The HEV may store part of the vehicle's kinetic energy in a battery regenerative braking as described in 2.2.3.
- ICE can be designed specifically for use in HEV vehicles as I talked about in chapter 3.
- The correct HEV control strategy may ensure that the ICE operates at its maximum efficiency or in the optimum operating line by controlling the power of the EM. [15]

4.1.2. Conditions for control strategies

One of the basic principles is that the ICE should be used predominantly in situations when it can operate under high loads (in relatively high efficiencies), otherwise the electric motor should be prioritized. The modes which can be implemented (e.g. LPS, e-drive or SS system) are described in sub-chapter 2.2.

The second condition is the battery SOC, which should stay in predetermined value interval. If the SOC is approaching or gets bellow bottom threshold, the charging mode is activated. If the SOC is approaching or gets above upper threshold, the regeneration is usually disabled, electric mode is prioritized. Other conditions can be given by temperatures of components like, cold catalyst, overheated electric motor, cold or overheated battery pack etc.

4.2. Heuristic control strategies

This strategy is based on intuitive control strategies derived from experience, experiments, and optimal strategy simulations. The focus of heuristic strategies is their relative simplicity, robustness, and realistic implementation to commercial vehicles. Heuristic control strategies provide solution to causal control problem where the decision making needs to be done in real time.

4.2.1. Rule-based (RB)

Rule based control strategy is based on fulfilling combinations of conditions for some event to happen. The system consists of predefined rules, which is expressed by the "if-else" language, conditions and commands.

$$\textbf{If } v_{vehicle} < 50\frac{\text{km}}{\text{h}} \textbf{ and } P_{driver} \leq 20\text{ kW} \textbf{ then } \text{P}_{gen} = 5\text{ kW} \tag{1}$$

$$\textbf{If } v_{vehicle} < 50\frac{\text{km}}{\text{h}} \textbf{ and } 20\,kW < P_{driver} < 50\text{ kW} \textbf{ then } \text{P}_{gen} = 15\text{ kW} \tag{2}$$

$$\textbf{If } v_{vehicle} < 50\frac{\text{km}}{\text{h}} \textbf{ and } P_{driver} \geq 50\text{ kW} \textbf{ then } \text{P}_{gen} = 20\text{ kW} \tag{3}$$

One of the weak points of the rule-based system can be that once we are adding more and more rules, the system will become confusing and therefore any maintenance or rule changes becomes challenging. Therefore, for more sophisticated management with more sets of rules, the fuzzy logic or even neural network would be more suitable control system. [17]

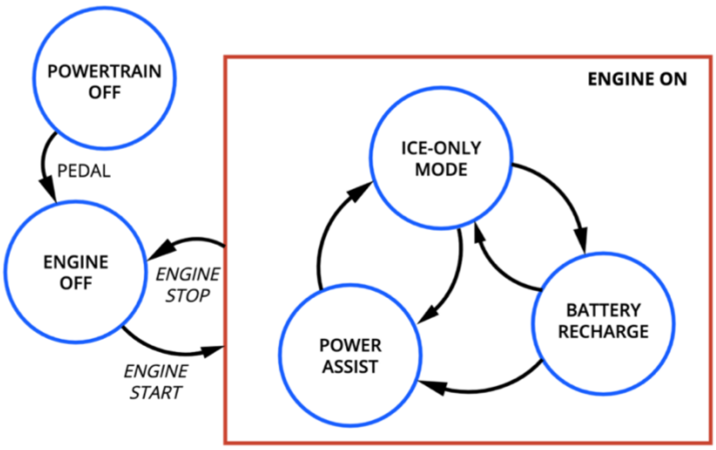

Figure 16 - Scheme of an example of rule-based control for HEV (adjusted from [4])

4.2.2. Map based

Map based algorithm is an approach where the control variable, e.g. torque split u or shifted gears i are predefined in 2D, 3D or multi-dimensional maps so the output setpoints are clearly defined based on the values of input variables such as vehicle speed, power demand or SOC. The maps are prepared offline based on results of optimal solutions from different cycles and then they can be implemented for online control. This control is often used among manufacturers. In the *Figure 17* are presented examples of gear selection map and torque-split map where the λ_τ is ratio between provided torque and maximum torque available for the EM at that speed. [16] [17]

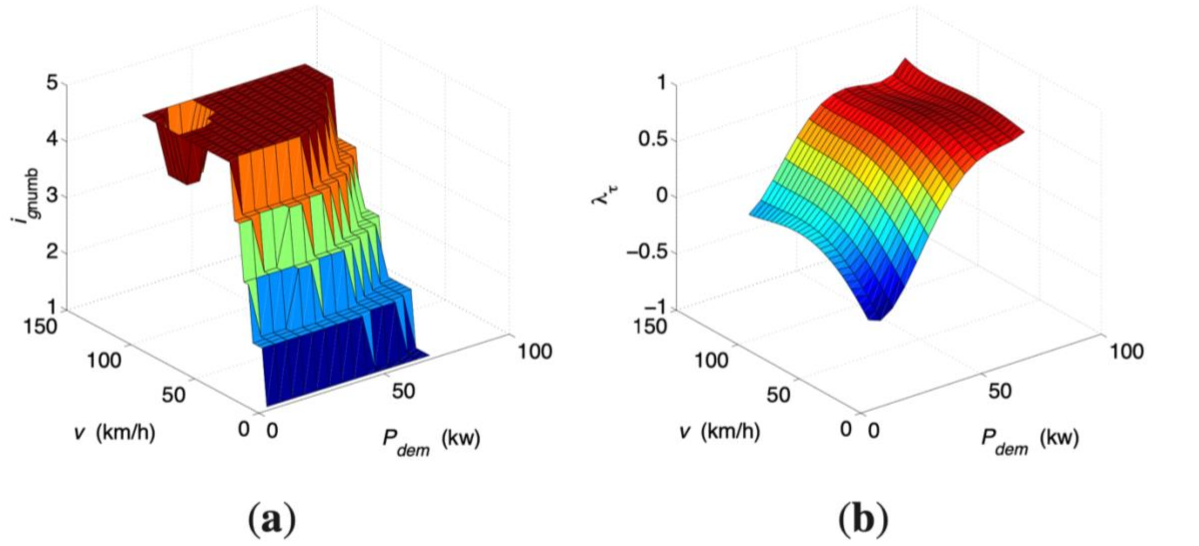

Figure 17 - (a) Gear number map; (b) torque-split ratio map [17]

4.2.3. Fuzzy logic

Fuzzy logic can be used for a control algorithm with reasonable number of variables. Input variables for fuzzy logic can be for example: driver power command P_{driver}, SOC and EM speed. The basic idea of the fuzzy logic controller (FLC) is to represent human logic, knowledge and distribution which can be represented as *if – then (and)* rules, in a way which is applicable to computers. It uses simple Boolean logic – "And", "Or" and "Not". At the very beginning we need define what the input from the real environment mean define fuzzy sets (e.g. P_{driver} is low or high) and define membership function for each fuzzy set - *Figure 18*. After that, *if – then* rules are defined. [19] For instance:

If SOC is "optimal" **And** P_{driver} is "low" **then** P_{gen} is 5 kW (4)

After the fuzzy sets and membership function are defined the controller can process data like this:

1) Fuzzification takes the crisp (input) values and transfers it to fuzzy values and their degree of membership. As an example, for a driver request of 45 kW. As can be seen in Figure 18, the equivalent fuzzy values of 45kW are 0.25 - normal and 0.75 - high.

Figure 18 - Membership function of Driver Power Request (adjusted from [19])

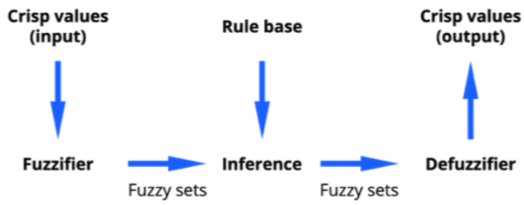

Figure 19 - Outline of the fuzzy logic system [19]

2) Degree of truth for the antecedents of each rule is calculated which determines to which degree is each rule valid.
3) Inference – implements the if – than rules to which are modified by multiplying the consequent by the degree of antecedent validity from step 2.
4) Aggregation – the results of the inference step are combined by weights average into a single fuzzy set value which represents a decided action for each controller output.
5) Defuzzification which transfers the results of fuzzy sets to get exact - crisp values as an output. For example, power of the generator - P_{gen} = 7.65 kW.

Fuzzy logic may seem complicated; however, it is not that difficult to build, and allows us to relatively easily calibrate the system by changing the values of the membership functions. The values in these functions are crucial for the correct function of the controller. [19]

4.2.4. Neural network

Neural network (NN) form base of deep learning, which is a subfield of machine learning, where the algorithms are inspired by the structure of human brain. The NN takes in the data, and trains itself to recognize some data patterns, and finally, predict the outputs for similar data. [20]

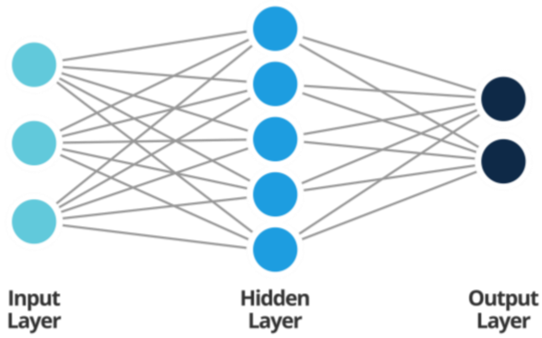

Figure 20 - Artificial neural network architecture [19]

The algorithm is classified into three basic layers, input layer which takes data we want to process, hidden layer (can consist of number or even hundreds of layers) in which most of computations and learning process take place, and finally, output layer that predicts the output. Each layer consists of cells called neurons, which are virtually connected to all neurons in other layer. Connections are called channels. Each channel has assigned a numerical value – weight w_i which is multiplied with the neuron value. Weights define the amount of importance of individual neurons in each layer. Then sum of the results is sent to the neuron in the next layer and we add bias b_i to it. The process continues till it reaches the output layer. [19] [20] [21]

$$a_0^{(1)} = Sigmoid\left(w_{0,0}\, a_0^{(0)} + w_{0,1}\, a_1^{(0)} + \cdots + w_{0,n}\, a_n^{(0)} + b_0\right) \tag{5}$$

We can rewrite the equation of the whole system in a compact matrix formula.

$$a^{(1)} = \sigma\left(Wa^{(0)} + b\right) \tag{6}$$

Number of hidden layers depends on the application and approach to the solution. The output of the NN algorithm are probabilities of predefined output neurons similarly to fuzzy inference step in fuzzy logic. In case of control strategy for a HEV, the output could be the power-split ratio u, which would be influenced by the driving conditions. Process of taking input data and providing output data can be identified as *Forward Propagation.* The quality of the output data depends on how much is the NN trained (i.e. how precise and correct are the weights). For calibration of the algorithm, training process can be performed called *Backward Propagation.* [19] [20] [21] Backward propagation is reversed process, where the NN after providing an incorrect output is given the correct output and it adjusts the weights accordingly. The training data need to be obtained by different method. In the case of HEV control, data would be obtained from optimal control strategies. [24]

4.2.5. Combination of heuristic control strategies

Combination of NN and fuzzy logic are used where artificial NN calibrates the membership function thus improves results and saves 90% of computational power.[26] Also, very common combination is Rule-based and map-based control strategies.

4.3. Optimal control strategies

The optimal control strategies have intentions to reach the very optimum result (i.e. find the optimal power split ratio for the lowest energy or fuel consumption). The optimal results can be evaluated from two different perspectives - local optimal, or global optimal. [4]

Local optimal (i.e. sub-optimal) strategies find the control solution for optimum energy consumption at each point in time without context to the overall maneuver. With high-enough computational power they are applicable in real life driving. The discussed strategies of this type are Equivalent Consumption Minimization Strategy (4.3.1) and predictive control (4.3.2).

Global optimal solutions on the other hand find the optimal control for the whole maneuver. The optimal solution might not be locally optimal but at the end results in minimal energy consumption at the end of the maneuver. Listed global strategies are game theory (4.3.3) and dynamic programming (4.3.4).

4.3.1. Equivalent Consumption Minimalization Strategy

Equivalent Consumption Minimization Strategy (ECMS) is specifically designed to be used for control strategy of parallel HEVs. This idea was introduced by Paganalli [23]. The initial assumption is that the condition of the driving power demand P_d is always fulfilled by the combination of the power from ICE (P_{ICE}) and the power from electric motor (P_{EM}). [22]

$$P_d(t) = P_{ICE}(t) + P_{EM}(t) \tag{7}$$

The philosophy of ECMS is to minimize the instantaneous sum of mass fuel rates – the real mass fuel rate of combustion engine ($\dot{m}_{f\_ICE}$) and the imaginary mass fuel rate consumed by electric motors ($\dot{m}_{f\_EM}$) titled as equivalent fuel consumption cost which is related to the battery SOC variation.

$$\boldsymbol{\dot{m}_{f\_total}(t) = \dot{m}_{f\_ICE}(t) + \dot{m}_{f\_EM}(t)} \tag{8}$$

$$\dot{m}_{f\_EM}(t) = \frac{s(t)}{H_{LHV}} \cdot \frac{P_{EM}(t)}{\eta_{trans}(t)} \tag{9}$$

Where $H_{LHV}[kj/kg]$ is lower heating value of the fuel consumed by ICE, $P_{EM}(t)$ is power provided by electric motors, $\eta_{trans}(t)$ includes efficiencies of the battery, inverter and motor/generator ($\eta_{trans}(t) = \eta_{bat}(t) \cdot \eta_{inv}(t) \cdot \eta_{EM}(t)$ and finally, $s(t)$ is an equivalence factor, all at investigated time).

Equivalence factor

The equivalence factor s is a fictional constant which enables us to convert battery power to an equivalent fuel power. Hence it enables us to compare two completely different power sources and based on that provide charge-sustaining. Charge-sustaining is a mode where the battery SOC may fluctuate but on-average is maintained at defined value. As was discovered during work on the heuristic control algorithm in chapter **Error! Reference source not found.**, the evaluation of equivalence factor (EF) is a challenging task. It depends on many parameters like final and current SOC, vehicle speed, drive cycle or road condition as well as on vehicle drive architecture. There is no rigorous way to calculate it, so different approaches can be made. [33]

The simplest way to evaluate EF is to determine the average EF for given vehicle and given cycle. This is meaningful to do only for simulation purposes or if we try to optimize the control strategy for a specific cycle. The exact value of the EF may be calculated for some topologies from results of global optimization strategies (e.g. Dynamic programming) or can be determined using iterative method to maintain charge-sustaining during the cycle. This approach was used in [24] where the EFs were determined for multiple driving cycles and compared to results from dynamic programming. The research [25] shows the approach of using EF in dependency on battery SOC. *Figure* 21

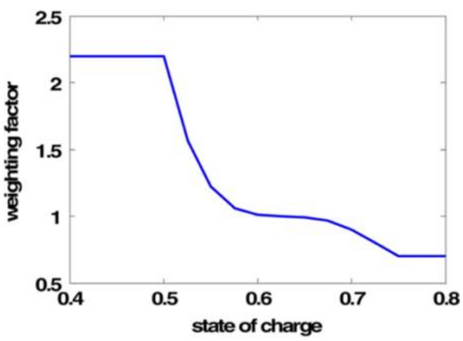

Figure 21 - Dependency of the equivalence factor s(t) on the SOC [-] [25]

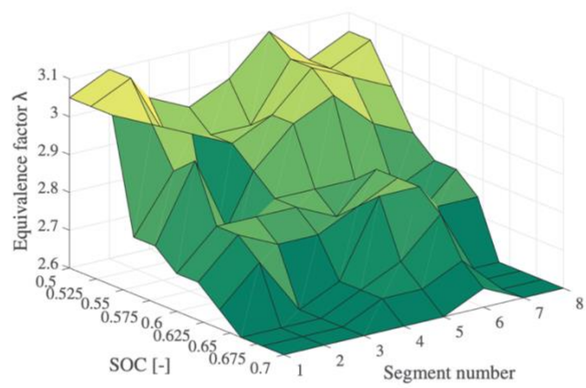

Figure 22 - 3D look-up map of EF related to SOC and road segment number [26]

The most complex but yet versatile approach is creating a 3D look-up map with dependency of the EF on SOC and route segment. The route segments are described based on the distance and speed in the segment which can be also used in a different order, so they cover also different routes. Example of such use can be found in [26].
Both examples ([25][26]) are considered to be stochastic (i.e. online) ECMS because they make possible to work in real time without knowing the exact cycle beforehand.

From the properties listed above can be concluded that ECMS is considered to be a sub-optimal management strategy which is capable to work in real time without knowing the future driving profile, however it is not capable to provide us with global optimum but only locally optimal result.

4.3.2. Predictive control

The predictive control is a hybrid solution between online and offline method. Similarly, as ECMS - 4.3.1, predictive control is considered to also return a sub-optimal solution. The information about the whole maneuver is not known nonetheless for the of predictive control is considered that GPS and navigation data can be received. As well as data from surrounding cars or vehicles sensors. That can give us information about the upcoming events is sufficient advance (*Figure 23* and *Figure 24*). That give known driving conditions for a short-term horizon t_f. With this information and sufficient computing power we can get optimal control strategy for $t_c < t_f$. [4] Based on the information about future for the know period and based on the vehicles speed, target speed and SOC the P_m is estimated. The optimal control is gained by Dynamic programming discussed in section 4.3.4. For example, if we know that there is downhill coming, the SOC can be gained there by regenerative braking or LPS. The opposite way, if we know that the vehicle is coming to a traffic gam, it is advantageous to have as much SOC as possible at the point it arrives there and use the electricity in the bump to bump traffic. [28] Predictive control is to some degree an applicable solution in real traffic. [17]

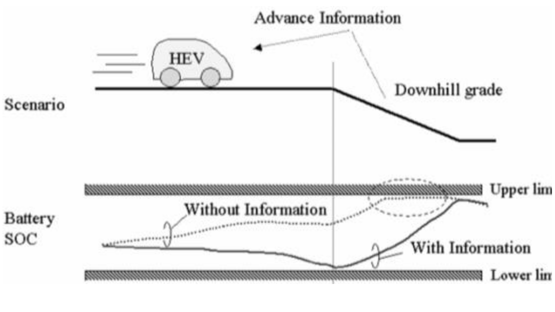

Figure 23 - Upcoming slope declination [28]

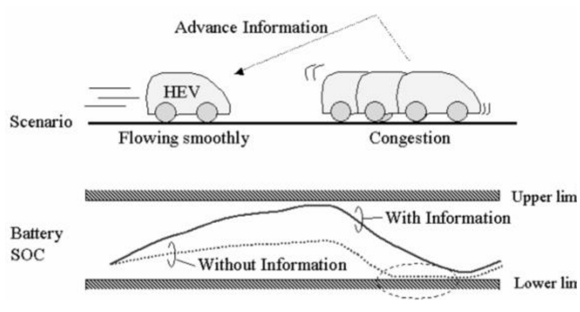

Figure 24 - Upcoming dense traffic [28]

4.3.3. Game theory

Game theory is applicable in many modern studies from economics to biology. Applied to a HEV energy management control, we can say that the state of the system is influenced by decisions of two „players“ playing a non-cooperative game. Driver is the first player, leader, who selects his move, operating variables such as wheel speed or torque request - $w(t)$. The second player called follower, in HEV example powertrain, selects its move or action $u(t)$ – powertrain control variables. The state of the system at this step is $x(t)$ which represents the battery SOC and $x(t+1)$ SOC in the following stage. The game is considered to be played in its horizon which consists of $H+1$ stages.

$$x(t+1) = f(x(t), u(t), w(t)) \tag{10}$$

The action of the second player is a reaction to the action of the leader. To evaluate the quality of the decision cost function of the second player action cost function is introduced which can determine the optimality of the move at each stage. By minimizing the cost function, similarly as in Dynamic programming discussed in the next chapter, we get the optimal control. [29]

4.3.4. Dynamic Programming

Dynamic programming is a numerical method dealing with optimization of dynamic tasks which can be described as solving process control tasks taking place in time. [4]

Approach of DP is using recursive functional relations and leaning on Principle of Optimality introduced by Richard E. Bellman in [30]. Application of this approach requires partition of a complex problem to many simple step subproblems, solving optimally each task individually, then combine results of all steps back together, find the all solutions to the problem and finally, get the optimal solution. DP deals with the situations of decision-making process at each stage, with goal to minimize (or maximize) the output – mathematical expression of a cost function J and fulfill all constrains. Equation 17 represents the final form of the total cost function.[22]

In our application it means that DP algorithm calculates every possible combination of ICE and battery power at each time step, ensuring that the algorithm reaches the global optimum, also fulfilling our set constrains – as a general rule, maximal and minimal acceptable SOC and final SOC. Examples of outputs seek to be minimized are fuel consumption or emission production. [31]

Computing time

At the first step, discretization of time, state and control variables needs to be done. Discretization length highly influences computational time and accuracy of the result. For more accurate result we can make the discretization length smaller or add more state or control variables. Nonetheless, that increases the computational time. Number of state and control variables increases comp. time exponentially, discretization of values (linearly). N is number of time steps p and q are the numbers of possible state and input values (value discretization), n is the number of states and m is number of control inputs.[4]

$$T_{comp} = O(N \cdot p^n \cdot q^m) \ [4] \tag{11}$$

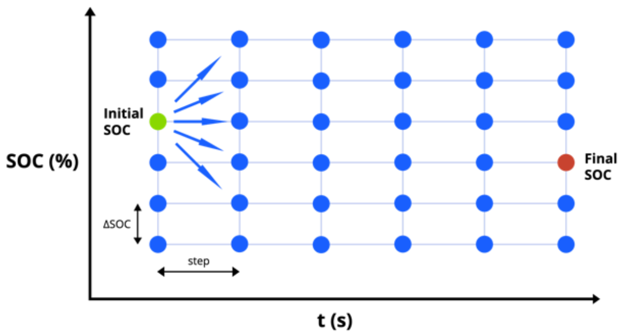

Figure 25 - Discretization of the grid, and possible cost to go function J from x_0 to x_1

In the first step of the process, a grid of state variables and time we want to analyze, is created. The system can be described as follows:

$$x_{k+1} = f(x_k, u_k, w_k) \tag{12}$$

Where state variable x_k is the SOC, u_k is a power split factor (and w_k is the speed of the vehicle at time step k and x_{k+1} is SOC at time step $k + 1$.

The expression of the cost function used in GT-Suite software for cost of policy u at initial condition x_0, is

$$J_\pi(x_0) = g_N(x_N) + T_N(x_N) \dots + \sum_{k=0}^{N-1} L_k, (x_k, u_k(x_k)) + p_k(x_k) \tag{13}$$

Where $g_N(x_N) + T_N(x_N)$ represents value of the final cost. Terminal state penalty (T_N) acts like an additional penalty function which is needed, because we are using constrained values of state variables $x(t) \in [x_{min}, x_{max}]$. The range of available SOC.

$$T_N = \gamma \times (SOC_{grid} - SOC_{target})^\beta \tag{14}$$

The function $L_k, (x_k, u_k(x_k))$ is the cost of applying at step k and $p_k(x_k)$ is the penalty function of applying the limited state variables x_k at step k where k goes from 0 to $N - 1$, the control policy in the first N steps is $u = u_0, u_1, u_2, \dots, u_{N-1}$, N is the final step.

Penalty function p_k is defined as follows.

γ	Terminal State Penalty Weight
β	Terminal State Penalty Exponent
SOC_{grid}	Value of SOC on the grid
SOC_{target}	Target (final) SOC
SOC_{max}, SOC_{min}	Max./Min. allowed SOC on the grid
λ	Penalty Function Weight
α	Penalty Function Exponent (*Figure 26*)

Table 5 - Table of "constraints on state" variables for DP [33]

$$p(SOC) = \lambda \times \left(\frac{SOC(t) - SOC_{des}}{(SOC_{max} - SOC_{min})/2} \right)^{\alpha} \tag{15}$$

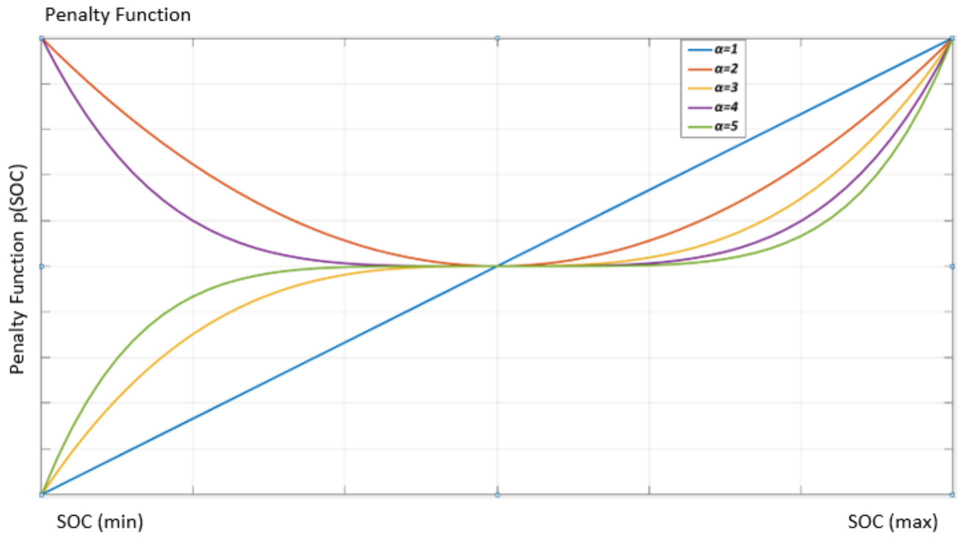

Figure 26 - Coefficient α for dynamic programming [31]

All the transitional cost values are saved during the forward in time marching calculation process creating a transitional cost matrix. This part of the process takes majority of the computational time (> 95%).

During backward marching process happens evaluation of the cost to go function values $J_k\left(x^i\right)$ for all allowed values of state variable x at each time step k and state index i. For the last step, end cost calculation is used:

$$J_N\left(x^i\right) = g_N\left(x^i\right) + T_N\left(x^i\right) \tag{16}$$

Then all the possible solutions of the final total cost policy are calculated.

$$J_k\left(x^i\right) = \min_{u_k \in U_k}\{ L_k\left(x^i, u_k\right) + p_k\left(x^i\right) \ldots + J_{k+1}\left(f_k\left(x^i, u_k\right)\right)\} \tag{17}$$

Optimal control is reached when the right-hand side of the equation 17 is minimized for all k going from $N-1$ *to* 0. This process takes the rest of the computational time. The results of equation 17 are stored and create an optimal control map where using forward marching process in time again, the optimal solution is found within seconds. [33]

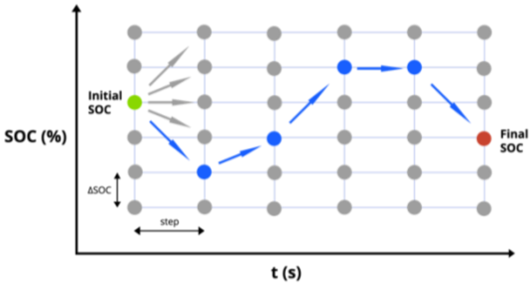

Figure 27 - Optimal solution of dynamic programming

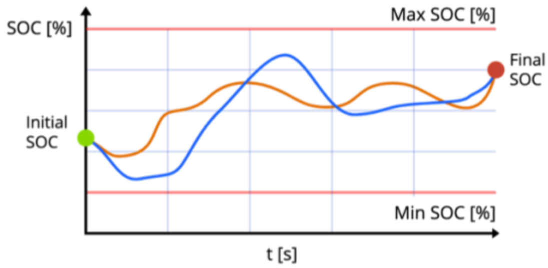

Figure 28 - Example solutions of SOC during maneuver

4.4. Choice of control strategies

For the purpose of the following steps in this thesis, the Dynamic Programming is applied in the kinematic model of the Multi-mode HEV.

Despite of, indisputable superior results of controls such as neural networks, their complexity and difficult development is incomparable to rule-based or map-based solutions. Therefore, I made a choice for combination of rule-based and map-based control, because of their easy ability of cooperation and ability of implementation in GT-Suite for heuristic control. Based on a set of rules, will select a control map for a component. [16] [17]

5. Multi-mode HEV simulation models

In the following chapters the knowledge from previous four chapters is used. In this chapter I talk about steps that lead to successful building of two simulation models. The first one is the kinematic (backward) simulation model and the second one is dynamic (forward) simulation model. Both models are built in GT-Suite software. The dynamic model is controlled by heuristic control algorithm which was built with elements from Dynamic Programming gained in the kinematic model. Kinematic model was tested in 4 different cycles to obtain globally optimal results. From those results, conclusion of applicable control approaches for heuristic control were made. Based on the experience from the dynamic programming, the heuristic control algorithm was designed. The focus was on versatility and usability for any cycle. The heuristic control is presented in chapter 5.4.4.

5.1. Vehicle components

In this section, the choice of model components is introduced, together with optimization of some of the model's parameters.

5.1.1. Component definition

In this section I want to describe the hardware components which both the KM and following dynamic model consist of. The choice of our components was led mostly by available components data maps.

ICE

The choice of the ICE is different than the one proposed by Schaeffler. We decided to use Volkswagens 4-cylinder neutrally aspirated unit - EA211 1.5l MPi 81kW. The reason for this choice was that we had access to all necessary control maps for this ICE. In our models, the ICE is represented by Map-Based Engine Model, which describes engine performance, fuel consumption heat rejection, emissions and other characteristics. The quantities are found in the maps imported to the model.
Note: ICEs in HEVs are used differently than in conventional cars so they can be adjusted to more specific use as was discussed in Chapter 3. Because of the lowered maximum engine speed of 4500 RPM, the adjusted EA211 1.5l TSI evo would be a perfect candidate for this model. Unfortunately, we do not have the necessary operation maps.

Hybrid Transmission

As was described in chapter 2.5.1, the transmission consists of two electric motors, two gear sets and two clutches. The choice

EM1

The choice of the base efficiency map for the EM1 is based on Bosch machine. The map is adjusted and limited to replicate the motor proposed by Schaeffler [13]. The motor functions mainly as a generator so the important values are the negative values of torque. I set the minimum limit of min. continuous torque to -100 Nm, min. peak torque limit to -140 Nm and maximum torque to 200 Nm, which can be theoretically used in e-boost mode. See maximum and minimum torque-line map in Attachment

EM2

The choice for the EM2 was a map of electric motor GKN-AF130. I followed the same process as for EM1. Since the EM2 is the main power source, it has higher limits than EM1. Its peak max. and min. torque are 310 Nm, -310 Nm respectively, till 4500 RPM and maximum speed of 13500 RPM. The limit for negative torque is never reached at any point of the operation because the regenerative effect is often limited by maximum charging power of the battery. See maximum and minimum torque-line map in Attachment 1: Performance maps of electric motors EM1, EM2

Note: Neither of those electric motor models does not contain invertor loss map which is unknown for us so after discussion with my supervisor the invertor efficiency was set to be 100%. That is a potential for future improvement for specification of our results. We consider that it does not greatly influence the methodology which is also the focus of this thesis.

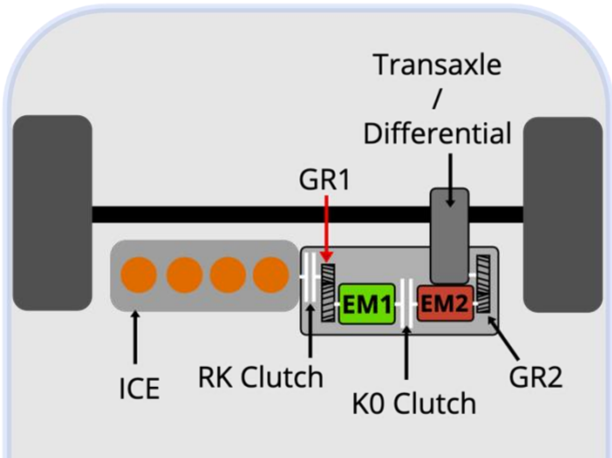

Figure 29 - Scheme of a simplified layout of the Multi-mode HEV

Gear sets

There are only two gear sets in the transmission. The first gear set with gear ratio i_1 (GR1) is located between the ICE and the EM1, and the second gear set with gear ratio i_2 (GR2) is located between EM2 and differential before the output from the transmission. The mechanical efficiencies of the gear sets are counted in retarding forces which are applied to the vehicle as one. Optimization and definition of used gear sets ratios is described in section 0.

Clutches

There are two clutches located in the model, RK and R0. Both clutch setups in the model are identical, with static torque limit of 300 Nm and Coulomb friction model.

HV Battery

The battery pack for the model consists of 104 cells in series, 37Ah with result output voltage of 400 V and capacity of 14.8 kWh.

Vehicle parameters	**Value**
Engine type	EA211 1.5l MPi 81kW
Maximum torque T_{max}	141 Nm at 4000 min-1
Total vehicle mass m	1576 kg
Vehicle limited v_{max}	180 km/h @ approx. 4500 RPM
Radius of the wheel R_{wheel}	0.3069 m
Air temperature T_{air}	297 K
ICE to EM1 gear ratio i_1	0.34
EM1 and EM2 to final drive gear ratio i_2	2.02
Differential gear ratio i_D	4
Maximum battery capacity C_{batt}	14.8 kWh
Retarding force $F = A + Bv + Cv^2$ A / B / C	90.8 N / 0.484 Nh/km / 0.0382 Nh^2/km^2

Table 6 - Basic vehicle parameters

5.1.2. Parametric optimization of components

Series operation line

Another challenging task was to determine series operation line of the ICE and EM1 as a motor generator unit. Series operation line (SOL) is a line of the highest efficiency of an ICE (or system consist of more units) as a dependency of power or torque and ICE speed. The reason why it is useful is that the SOL is imported to the model to control the ICE speed accordingly to the power demand from the ICE in series mode. This saves a lot of computational power in KM with DP because there is one less parameter to be optimized at each step. The same SOL is implemented.

The idea was inspired by the by article [14], where determination of the SOL for the EA211 1.5l TSI evo was made. I apply this SOL concept to the ICE-EM1 unit which considers both, efficiency of ICE and efficiency of EM1. Since this is pretty computationally demanding task. I developed a MATLAB script which also enables me to change the input parameters like gear ratio between the ICE and EM1, its efficiency and most importantly also the efficiency maps of the ICE and the EM1. This feature makes it useful to prepare the SOL for any model of HEV operating in series mode with arbitrary ICE and generator. The important steps of the script are listed below.

Note: The condition for the input maps is that it needs to be in a column form in order: ICE speed [RPM], Torque [Nm], BSFC [g/kWh]for the ICE and for the generator in order: EM1 speed [RPM], Torque [Nm], Efficiency [-]

Operations with efficiency maps

It imports the efficiency maps which can have different sizes, sort them from low to high speeds, and multiply the EM1 speed and divide the EM1 torque by the gear ratio to get maps with the same speed range for its use in next steps.

BSFC to efficiency conversion

Conversion of BSFC to brake efficiency for ICE:

$$\eta_f = \frac{1}{BSFC \cdot Q_{LHV}} \tag{18}$$

Calculation of power

Brake effective torque to brake effective power calculation for both ICE and EM1

$$P_e = n_{rpm} \cdot \frac{\pi}{30} \cdot \frac{T_e}{1000} \tag{19}$$

Interpolation of values

Interpolation of values to the grid defined by user. The user can choose the step size of the output array for ICE speed (100 rpm) and for ICE power (2 kW). Maps defined in columns are transformed to a Mash format which enables interpolation to the defined grid. Size of both maps are comparable now, so efficiencies can be multiplied to get the map of the system ICE-EM1 efficiency. The result ICE-EM1 efficiency map can be seen in *Figure 30.*

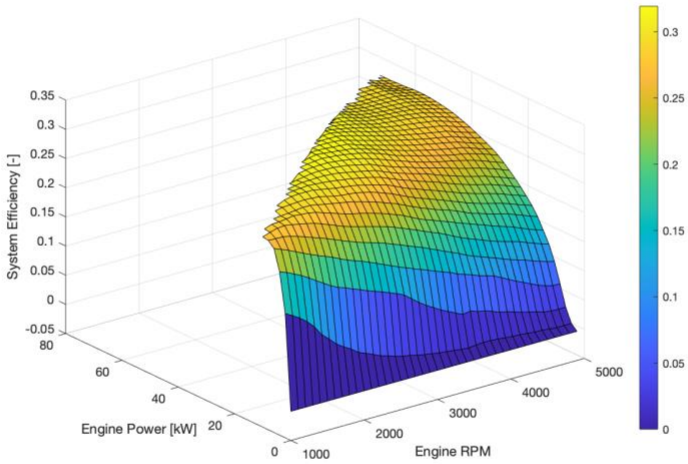

Figure 30 – The ICE-EM1 power efficiency map

Finding SOL

The next and final step is to extract the best efficiency operation speed for each ICE power step, and we get the result of the SOL for the ICE-EM1. I manually adjust the ICE speed for the low power demand (from 0 to 8 kW) because I keep in mind the potential noise vibration and harshness (NVH) of the ICE in relatively high loads and low speeds.

The result of this process is presented in *Table 7* and in *Figure 31*.

The gear ratio used in this script is taken from result of the sensitivity analysis of gear ratios presented in the next section 0.

Generator power demand [kW]	ICE speed [RPM]
0 - 4	1200
6	1300
8	1300
10	1500
12	1500
14	1700
16	1800
…	…
66	4600
68	4800
70	4900
72	5100

Table 7 - Output array of SOL of the ICE-EM1 for KM and DM

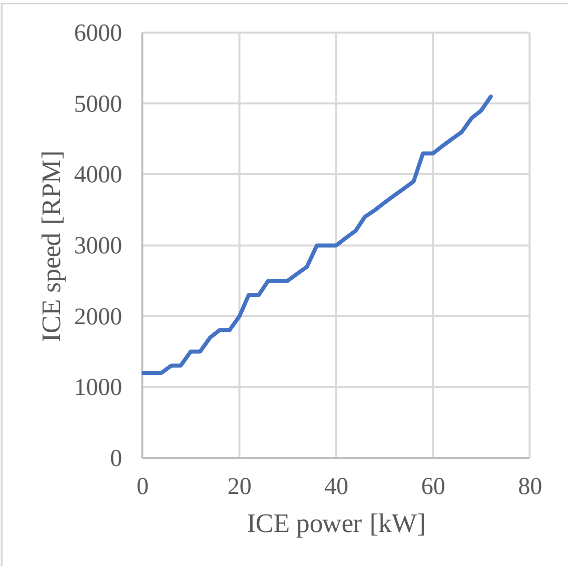

Figure 31 - Output SOL of the ICE-EM1 for the KM and DM

I consider this MATLAB script to be also a really valuable output of my work on this thesis. Therefore, I also submit it in attachments of this thesis.

Gear ratios determination

In this section I describe my steps, how I determine gear ratios i_1 for the ICE to EM1 gear set and gear ratio i_2 for the EM2 to the differential. The calculation is made based on conditions:

Differential gear ratio i_D (fixed)	4
Target maximum speed limit v_{max}	180 km/h
Maximum ICE/EM2 speed at v_{max}	4500 / 13500 RPM

Table 8 - Condition for gear ratios i_1 and i_2

Step 1) ICE to wheel (i_T) and EM2 to wheel (i_{EM2}) gear ratio calculations from the maximum speed.

$$i_T = \frac{n_{ICE\ max}}{n_{wheel\ max}} = \frac{4500}{\frac{v_{max} \cdot 1000}{120 \cdot \pi \cdot r_{wheel}}} = \frac{4.5 \cdot 120 \cdot \pi \cdot 0.3069}{180} \doteq 2.89 \tag{20}$$

$$i_{EM2} = \frac{n_{EM2\ max}}{n_{wheel\ max}} = \frac{13500}{n_{wheel\ max}} \doteq 8.68 \tag{21}$$

Those values are the limit gear ratios. When we consider the differential, we get the upper limit for i_2 = 2.17 and i_1 = 0.33. The value of i_1 gear ratio depends on i_2.

Step 2) Based on the results in step 1), 10 different pairs of GRs which gives the desired 2.89 gear ratio (*Table 9*). Evaluation of the GRs was made from two different perspectives (efficiency of ICE – EM1 generator, vehicle acceleration time)

i_1	0,26	0,28	0,30	0,32	0,34	0,36	0,38	0,40	0,42	0,44	0,46
i_2	2,79	2,59	2,42	2,27	2,13	2,02	1,91	1,81	1,73	1,65	1,58

Table 9 - pairs of gear ratios i_1 and i_2

Firstly, for each GR i_1, SOL was generated using the MATLAB script introduced in section 5.1.2. From the output data arithmetic mean efficiencies of ICE-EM1 couple can be find for each i_1. The difference in efficiencies for different ratios are presented in *Figure 32.*

Secondly, the theoretical acceleration of the vehicle was calculated based solely on vehicle resistances. Results

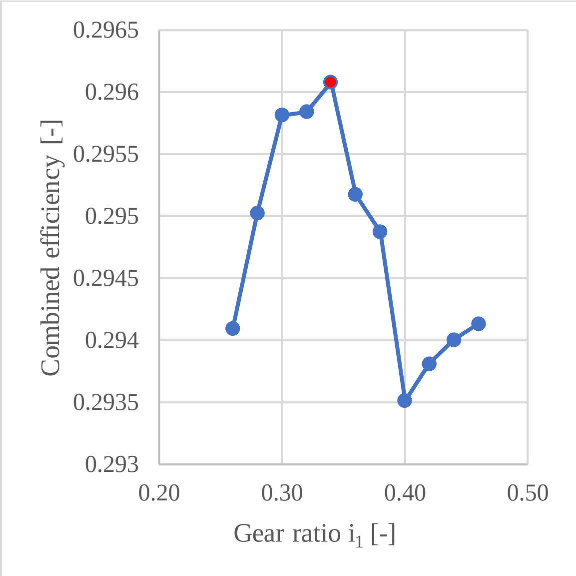

Figure 32 – Mean efficiency of ICE-EM1generator for different i_1

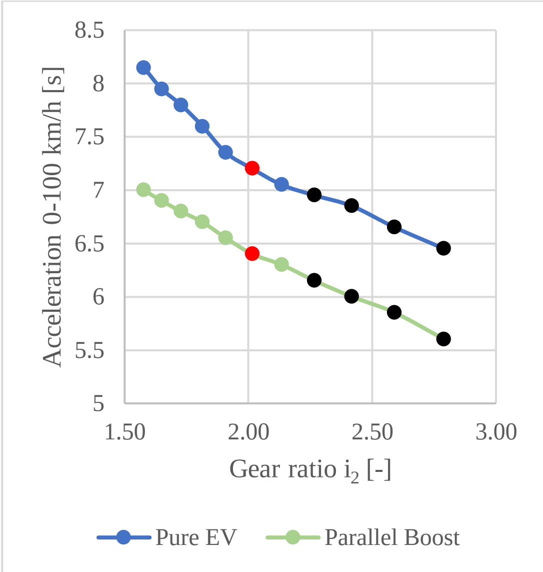

Figure 33 – Acceleration of the vehicle for different i_2

Step 3) From the results, three different pairs of gear ratios are selected which fulfill the requirements the best. I decided to not aim exactly for the prescribed 180 km/h target, but slightly higher, which also add some safety factor for ICE and EM2.

	i_1	i_2	i_T	v_{max}
G1	0.34 (2.94)	2.02	2,74	194 km/h
G2	0.34 (2.94)	2.13	2,90	183 km/h
G3	0.32 (3.13)	2.13	2.74	183 km/h

Table 10 - Pairs of gear sets G for DM analysis

The highlighted gear solution is implemented in the KM, the other two potential gear ratio pairs are used for comparison in the DM. The black-highlighted gear ratios i_2 do not fulfill the requirements of the 180 km/h for EM2.

Load point shifting map development

The process of the LPS map development was very similar to the one described in the SOL development. The basic of the MATLAB code from the SOL solution was used as the starting point since the processes use basically identical data processing.

The mathematical processes will not be described, but the final step is to minimize the right side of the equation 22. It does evaluate the right side of the equation and finds the combination of power from the ICE and power from the EM for each possible operation point and for each possible combination of powers from EM and ICE. The value with the minimal solution is saved in form of ratio – torque split (or power split) ratio u presented in *Table 4* in section 4.1

$$m_{eq} = \frac{BSFC \cdot P_{ICE}}{3.6} + \frac{S_{eq} \cdot 1000}{Q_{LHV}} \cdot \frac{P_{EM}}{\eta_{EM}} \tag{22}$$

$$X = u = \frac{P_{EM}}{P_{demand}} \tag{23}$$

$X = 1$ … EM2 motor is providing all of the power demand

$0 < X < 1$ … Power assist mode (LPS down)

$X = 0$ … ICE is providing all of the power demand

$X < 0$ … the electric motor is producing negative torque, charges the battery and makes the engine more loaded (LPS up).

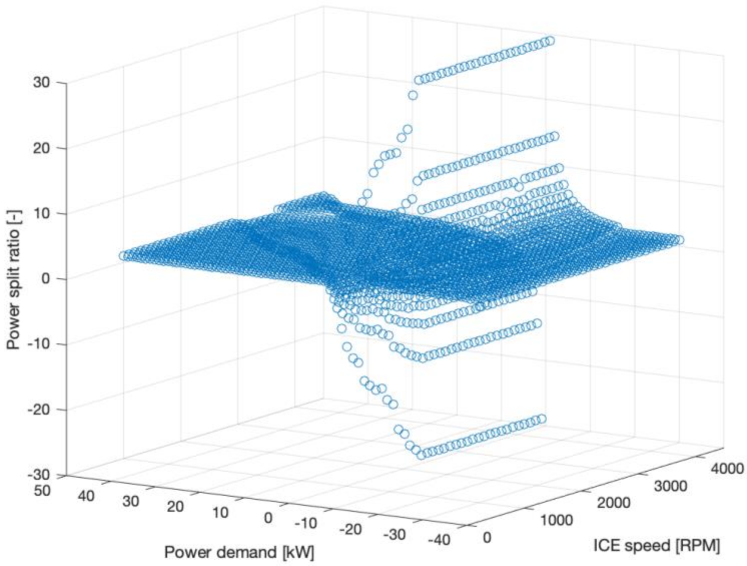

Figure 34 - Example of LPS map, for S_{eq} = 3 and i_1 = 0.34

5.2. Kinematic model development

5.2.1. Introduction

The KM follows principles of kinematics, where the model takes into account quantities such as displacement, velocity and acceleration of moving components and the vehicle without taking into account factors which cause the motion. Therefore, it enables us to apply optimal management strategies like DP or ECMS.

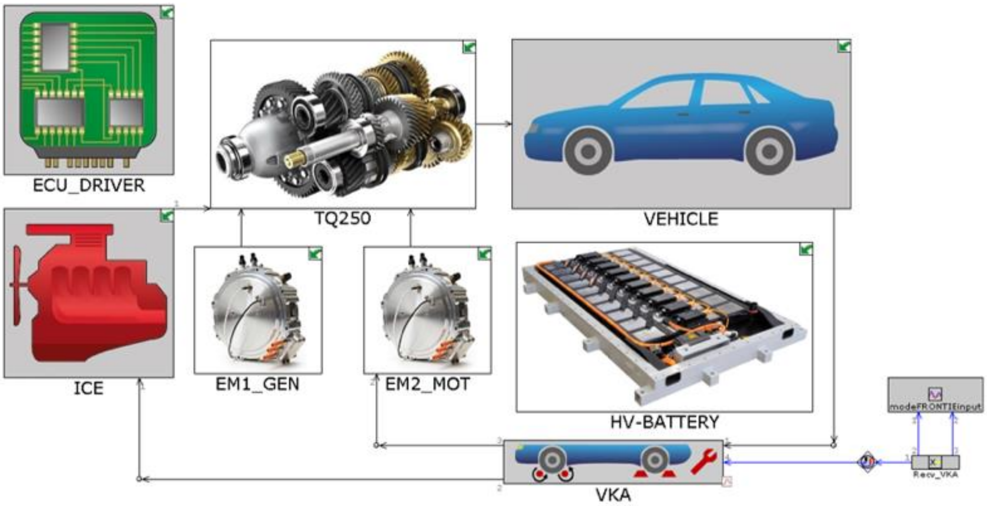

Figure 35 – Modular GT-Suite kinematic model of the Multimode Twindrive HEV

The KM was built in GT-Suite software *Figure 35*. I started with a partially built kinematic Multi-mode model provided by my supervisor Ing. Rastislav Toman. As a part of the internship this thesis is part of, the first task was to troubleshoot the model, research and understand the potential of DP (since it is a new feature of the 2020 version). Furthermore, make sensitivity analysis of DP settings and optimize some of the component's parameters for their best use in the model.

Model modularity

One of the assignment requirements was to build both models (KM and DM) in modular architecture. Modularity of models means, that it consists of individual sub-models which represent a component, logic (control) components or "mathematical component". As can be seen, both models fulfill the assignment requirement of modularity (*Figure 35* and *Figure 39*). Model displayed in *Figure 35* consists of following blocks of components.

Firstly, hardware components like EM1, EM2, ICE, Transmission and Vehicle which represent real components with all their behavior.

Secondly, ECU is representing logic, control components.

Finally, Vehicle Kinematic Analysis (VKA), mathematical component. This component activates the kinematic analysis mode which can implement the backward or forward-facing optimization strategies like DP and ECMS.

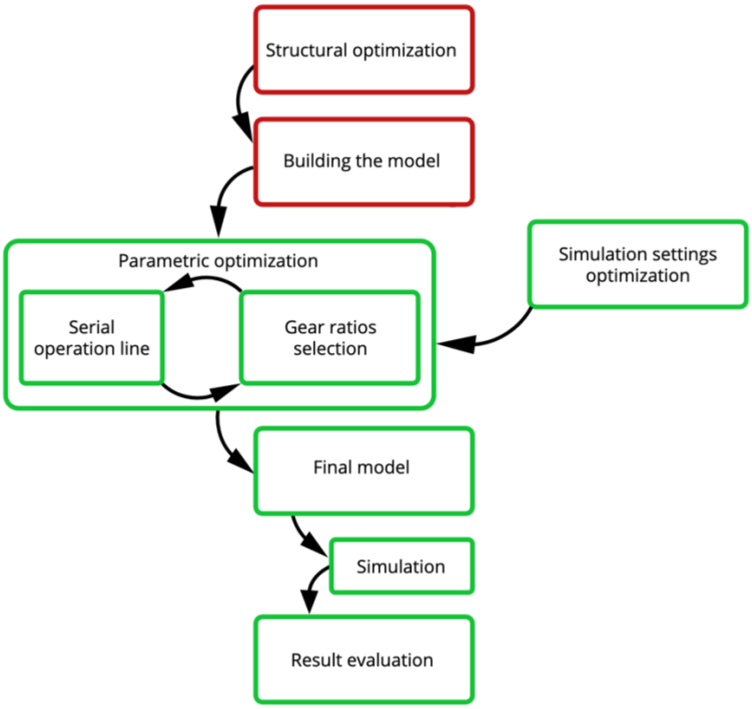

Figure 36 - KM workflow chart, Red - did not participate, Green - participate

5.2.2. Simulation settings of Dynamic Programming

Before the model could be used for simulation to get some serious data, the next step was to make a sensitivity analysis of DP on value "constraint of state" variables. Which are listed in the chapter about DP (4.3.4) in *Table 5.* The selection of values influences behavior and decision-making process of dynamic programming. After several simulation and data analysis, some coherence of results on values of variables were found.

α – Enforces SOC convergency to the SOC_{target}, during the maneuver. Higher α value allows higher SOC deviation than low value α from the SOC_{target}.

λ - It multiplies the effect value α.

β – Enforces SOC convergency to the SOC_{target} by adding high value to the cost function in the last time step of the simulation.

γ - It multiplies the effect value β

To make a reference, for the penalty function calculation. Relatively high values of α (e.g. α = 10) allow the DP wider interval of SOC during the cycle in contrast to low values of α (e.g. α = 2) where the DP follow the value of SOC_{target} more closely. The value of λ just multiplies this effect. The bigger interval of operation gives the DP more freedom in its decision and that should translate to lower fuel consumption. For that reason, values of $\alpha = 10$ and $\lambda = 4$ are chosen for the final simulation.

Similarly, for the terminal (i.e. final) state penalty function, high values of β (e.g. β = 10) allow the DP to finish the maneuver with high deviation and vice versa. Again, the value of γ just multiplies this effect. Naturally, it is desired to finish the maneuver with none or low deviation of SOC. Therefore, values of $\beta = 2$ and $\gamma = 250000$ are chosen for the final simulation.

Note: Default values in GT-Suite are: β = 2; γ = 50000 and α and λ are not defined.

α	10
λ	4
β	2
γ	250000

Table 11 - Final values of "constraints on state" variables for DP

At this point, the KM is finished and ready to run the simulation.

5.3. Kinematic model simulation results

In this section, drive cycles used in simulation process are introduced, together with all important simulation settings .

5.3.1. Definition of drive cycles:

After studying the challenges of the heuristic control strategy development from the optimal strategy in chapter 4, decision of setting up individual cycles for simulation was made. The goal is to have the most varied set of cycles to run in the KM simulation. The reason for that is to gain the most information about the decision-making process of the optimal control.

Therefore, five different simulation cycles are used. WLTC, CC1, CC2 and CC3 are used for the KM. All five cycles, together with Evaluation cycle, are used in representation results of heuristic control.

Simulation cycles

The cycles were built with individual cycles which can be found in GT-Suite library.

Overview of simulated cycles	Cycle composition	Individual cycle duration [s] / Avg. speed [km/h]	Cycle duration [s] / Avg. speed [km/h] / Distance [m]
WLTC	WLTC Class 3	-	1800 / 46.5 / 23266
Custom cycle 1 (CC1)	FTP75kph HWY WLTC Medium	1874 / 34.1 765 / 77.7 433 / 39.4	3072 / 45.7 / 39031
Custom cycle 2 (CC2)	HWY WLTC Low 460 NYCC	765 / 77.7 460 / 22.6 598 / 11.4	1823 / 41.9 / 21298
Custom cycle 3 (CC3)	2 x WLTC Extra High WLTC Low 460 WLTC Medium	2 x 323 / 91.7 460 / 22.6 433 / 39.4	1539 / 56.5 / 24157
Evaluation cycle	2 x LA92DDS cycle	2 x 1435 / 39.76	2870 / 39.76 / 31700

Table 12 – Specification of drive cycles for KM and DM

The cycles were defined from already existing cycles, but in completely random manner. For graphic overview of the speed profiles of the cycle, see Attachment 3: Speed profiles of applied cycles or results in the next section.

Simulation settings:

Case	Maneuver (Cycle)	Initial /Target SOC [-]	SOC_{DP_min} [%]	SOC_{DP_max} [%]	SOC_{disc} [%]
1	WLTC	0.3 / 0.5	20	60	2
2	WLTC	0.5 / 0.5	40	60	4
3	WLTC	0.7 / 0.5	40	80	2
4	CC1	0.3 / 0.5	20	60	4
5	CC1	0.5 / 0.5	40	60	2
6	CC1	0.7 / 0.5	40	80	4
7	CC2	0.3 / 0.5	20	60	2
8	CC2	0.5 / 0.5	40	60	4
9	CC2	0.7 / 0.5	40	80	2
10	CC3	0.5 / 0.5	40	60	4

Table 13 - Settings of DP for the final simulation

Note: The discretization length of the net grid for the battery SOC in Case 4 and 6 meant to be 2 instead of 4. This can lead to a really small inaccuracy by making the net grid less dense the but by no means it influences the verity of the result.

Results evaluation

To make comparable results between ***identical cycles and initial SOC but different*** $\boldsymbol{\Delta SOC_{final}}$ possible, the equivalent fuel consumption is introduced. This method is primarily used for evaluation of fuel consumption in heuristic control optimization process but it needs to be calculated from results of dynamic programming.

Calculation of total energy consumption per cycle:

$$\boldsymbol{FC_{eq} = E_{eq} \cdot \frac{360000}{D_{dist} \cdot \rho_{fuel} \cdot Q_{LHV}}} \tag{24}$$

Where the definition of equivalent energy consumption is as follows:

$$E_{eq} = E_{Total} + (S_{eq} \cdot \Delta SOC_{final}) \cdot C_{batt} \tag{25}$$

$$E_{Total} = E_{chem} + E_{el} \tag{26}$$

Where E_{chem} and E_{el} can be expressed as:

$$E_{chem} = FC_{L/100km} \cdot \frac{D_{dist} \cdot \rho_{fuel} \cdot Q_{LHV}}{360000} \tag{27}$$

$$E_{el} = (SOC_{Init} - SOC_{final}) \cdot C_{batt} \quad (28)$$

The E_{chem} can be only positive or 0 since there is a non-reversible chemical reaction of the fuel and air taking place in the ICE. On the other hand, E_{el} can take values positive as well as negative. If the battery SOC_{final} is lower than SOC_{Init}, the value of E_{el} is positive (i.e. the energy is used for propulsion), if SOC_{final} is higher than SOC_{Init}, E_{el} is negative because the battery was recharged during the cycle.

And also need to make a comparison between the same cycles with different ΔSOC_{final}. Mean equivalence factor for the whole cycle comparing the results:

$$S_{eq} = \frac{E_{Chem\,30/50} - E_{Chem\,50/50}}{SOC_{final} - SOC_{Init}} \cdot \frac{1}{C_{batt}} \quad (29)$$

For each cycle I get slightly different result: $S_{eq\_WLTC} = 2.33$, $S_{eq\_CC1} = 2.46$ and $S_{eq\_CC2} = 2.56$. Since there is only result for charge-sustaining in CC3, I cannot calculate S_{eq} for it. I take the average of the values $\boldsymbol{S_{eq\_mean} = 2.45}$**,** since the differences in S_{eq} are small and the ΔSOC_{final} are also small values so the inaccuracies are negligible.

Physical quantities	**Unit**
Energy $E_{Total}, E_{chem}, E_{el}, E_{eq}$	kWh
Fuel consumption $FC_{L/100km}$ and FC_{eq}	$\frac{l}{100}km$
Length of the cycle, distance D_{dist}	km
Density of fuel ρ_{fuel}	kg/l
Lower heating value of fuel Q_{LHV}	kJ/kg
State of charge SOC	$[-]\ (from\ 0\ to\ 1)$
Battery capacity C_{batt}	kWh

Table 14 - Units of physical quantities for FC_{eq}, E_{eq} and S_{eq} calculation

5.3.2. Kinematic model simulation results

Case	Maneuver (Cycle)	Initial /Target SOC [-]	Avg. fuel consump. [l/100 km]	ΔSOC_{final} $[-]$	Energy from fuel E_{chem} [kWh]	Energy from battery E_{el} [kWh]	Total energy consumption [kWh]	**Equivalent energy consumption [kWh]**
1	WLTC	0.3 / 0.5	6.41	-0.0076	13.65	- 2.84	10.80	**11.08**
2	WLTC	0.5 / 0.5	3.30	-0.0073	7.02	0.11	7.13	**7.40**
3	WLTC	0.7 / 0.5	0.55	-0.0070	1.17	3.06	4.23	**4.49**
4	CC1	0.3 / 0.5	4.30	-0.0187	15.35	-2.68	12.67	**13.34**
5	CC1	0.5 / 0.5	2.45	-0.0092	8.76	0.13	8.90	**9.22**
6	CC1	0.7 / 0.5	1.02	-0.0095	3.64	3.1	6.74	**7.08**
7	CC2	0.3 / 0.5	6.41	-0.0072	12.49	-2.85	9.64	**9.90**
8	CC2	0.5 / 0.5	2.67	-0.0077	5.19	0.11	5.31	**5.59**
9	CC2	0.7 / 0.5	0.70	-0.0077	1.35	3.07	4.43	**4.71**
10	CC3	0.5 / 0.5	3.99	-0.0075	8.82	0.11	8.94	**9.21**

Table 15 - Results of dynamic programming

Case number	1	2	3	4	5	6	7	8	9	10
FC_{eq}[L/100 km]	5.20	3.47	2.11	3.74	2.58	1.98	5.08	2.86	2.41	4.17

Table 16 - Equivalent fuel consumption for cycles of DP

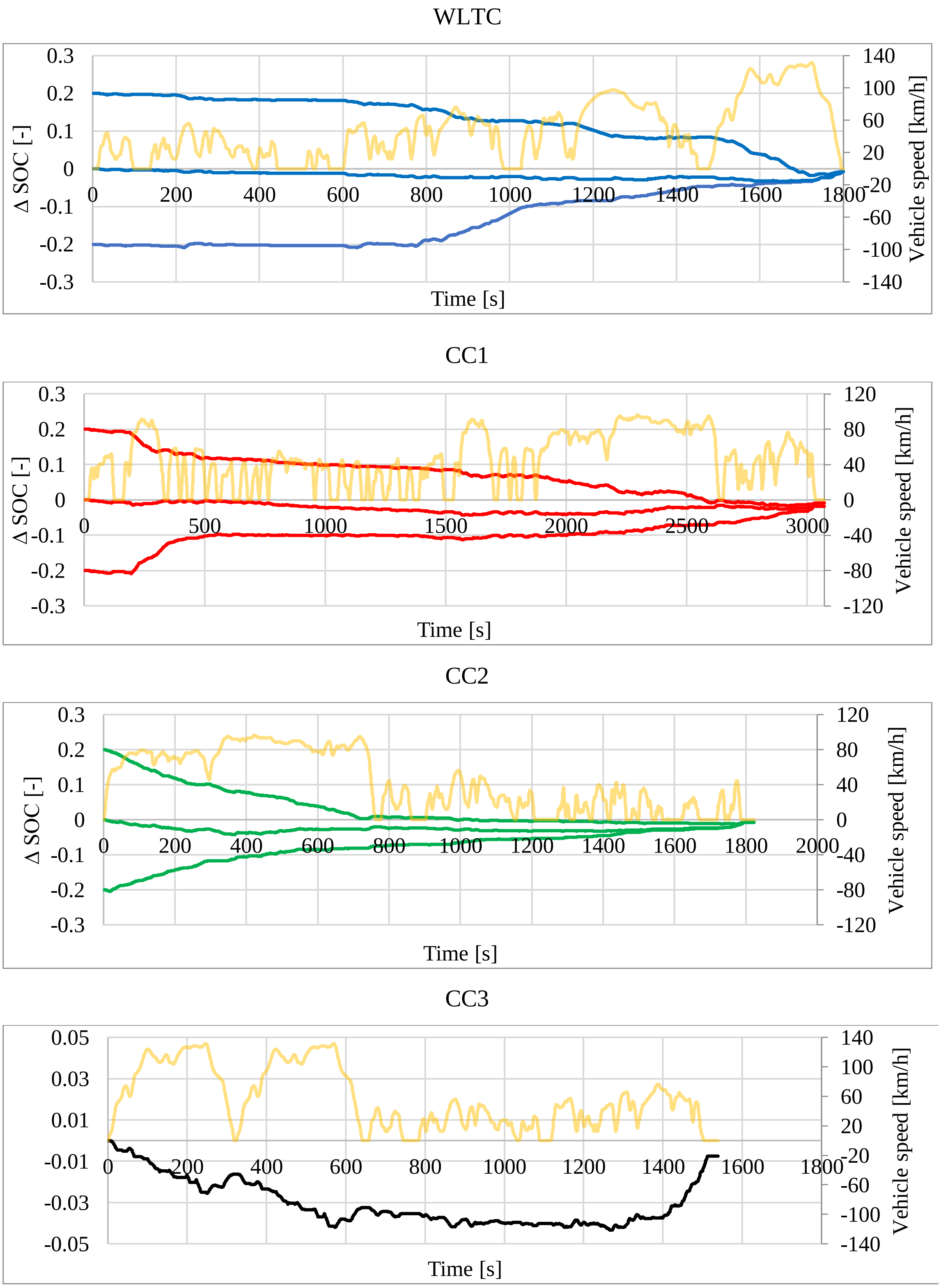

Figure 37 - Results of DP for WLTC, CC1, CC2 and CC3 cycles

As can be seen in *Table 16*, the result fuel consumption of the DP optimal control is fantastic. The most telling result is Case number 2, which represents WLTC cycle in charge-sustaining mode. The WLTC cycle is one of the most used cycles measurement of vehicle's fuel consumption and emissions. By using the method of equivalent fuel consumption introduced in previous section, the value of 3.47 l/100 km was defined from the average fuel consumption (3.3 l/100km) during the cycle. This approach is used for any fuel consumption comparison.

Reasons for good results of the KM

Series mode, when charging, is operating the engine at almost full load, where it has high efficiency, but from NVH perspective that is not ideal.

The difference in SOC_{final} are not negligible. In the mentioned case 2, the equivalent fuel consumption for charging the battery to SOC_{final} it is around 0.17 l/100 km.

When LPS is applied, the ICE highly loaded by the electric motors.

There are no losses of power electronics of EMs.

There is no fuel consumption taken into account when starting on or shutting off the ICE. There is no power consumption of the onboard electronics

5.3.3. Evaluation of optimal control strategy results.

Since the heuristic control algorithm is based on the DP results, also a lot of other data were analyzed. It was quickly realized, that the decision of DP depends on individual cycles, initial SOC and target, vehicles topology and is also influenced by settings of the DP (5.3.1). Therefore, the analysis was done more on the macroscopic level.

As you can see in *Figure 37,* three conclusions can be made about the optimal control behavior. Each cycle consists of three segments:

Charge approaching

The first part of the cycle always consists of the SOC(t) charge "approaching" to the area of 0 to approx. 0.1 SOC below the SOC_{Target} This can be said about almost every cycle and every initial SOC. The process can take: from almost half of the cycle (CC2 and CC3) to 95% of the cycle (WLTC).

Charge-sustaining below target SOC

In the second part of the drive cycle, the DP tends to charge-sustaining and stay below the SOC_{final}. This process can take from almost no time (WLTC) to half of the cycle (CC2 and CC3).

Charging to target SOC

Finally, the last section where the algorithm tends to charge the battery. That is usually done by both, aggressive series charging and kinetic energy regeneration by regenerative braking. This process usually takes place in the last 5% of the cycle.

All three sections can be noticed better in *Figure 38* which was made for the same vehicle, but with five times smaller battery.

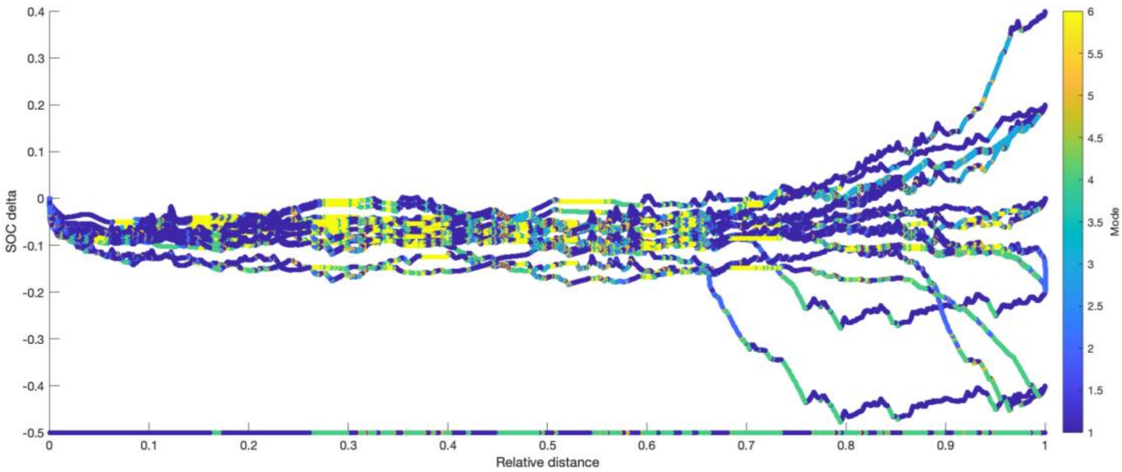

Figure 38 - results of DP for smaller battery capacity

5.3.4. Observations from DP

The key observations from the optimal control done by DP are based on the three described operation regimes. The goal for the heuristic control development is to mimic the actions described in 5.3.3. Firstly, get the kind of charging/discharging behavior at the beginning of the cycle and to reach the charge-sustaining section.

Once the value of SOC gets close from bellow to the value of the SOC_{Target}, start the charge-sustaining section.

And finally, at the end of the cycle, charge the battery as close to the target value as possible. The accuracy of 0.02 SOC would be acceptable.

The heuristic method solution of those observations is described in 3-step process in: Use of observations from DP.

And lastly focus on calmer behavior of the control algorithm. That means less changes in drive topologies. The heuristic method solution is described in 3-step process in the section 5.4.4

5.4. Dynamic model development

In this chapter, the steps necessary for development of dynamic model discussed, differences with the kinematic model are talked about and finally the heuristic control is introduced.

5.4.1. Introduction

The dynamic model follows the physical sequence of events. In other words, the action and reaction of the system are in chronological order. Therefore, when it comes to developing a dynamic model, it is the most important thing to keep in mind. The main difference between the KM and DM is in the way of control. In case of DM of a vehicle in GT-Suite the vehicle is controlled by a "Driver controller" which imitates actions of a real driver. It controls the accelerator position and brake pedal position. In case of a vehicle with a manual transmission, it can change gears and operate the clutch.

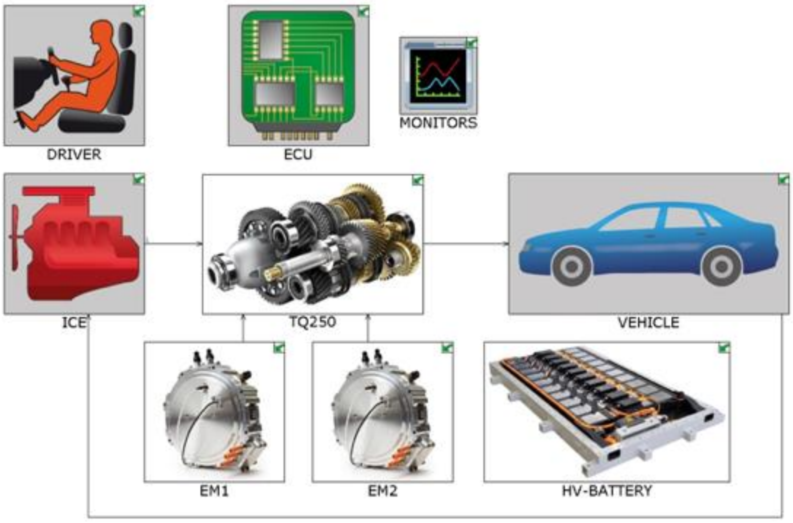

Figure 39 - Modular GT-Suite dynamic model of the Multimode Twindrive HEV

5.4.2. Building dynamic model

For the process of building a dynamic model, it is recommended to build the dynamic model from a simple model of electric vehicle. After that, adding building blocks of components as well as logic blocks, is recommended. Later, some of the concepts of the heuristic control algorithm can be added to the model. Model presented in this thesis was built in following steps.

Basic model of EV

In the first step of the building process, it is recommended to start with building an EV model, or some of template models in GT-Suite can be used as well. In my case, a model of EV truck was provided by my supervisor. It was a simple, single motor architecture, so a complete rebuilt to twin-motor EV was done.

E-drive and recuperation functions

The next step was to make the vehicle function in basic e-drive and braking by the electric motor. After that, cooperation of mechanical brakes and regenerative braking was the next step.

Series boost mode

When the fully functional model was built, realization of series boost mode was relatively straightforward.

Implementation of ICE

After having fully functional model of EV, ICE could be added. In the case of this multi-mode hybrid, use of the ICE was implemented only for series charging at first. Later, after solving logic of clutch switch, parallel mode was added.

ICE starting

Probably the most challenging task of the model development process was the function of starting the ICE by the EM1 generator at every possible scenario. After all, it was successfully finished and the model was ready for the first testing.

Parallel boost mode

After the model optimization and troubleshooting, parallel boost mode was added. Correct function of the starting process was yet another challenge as a consequence of this step, but was successfully solved and the model was ready for heuristic control development.

An example of parallel boost acceleration can be found in Attachment 4: 9.4

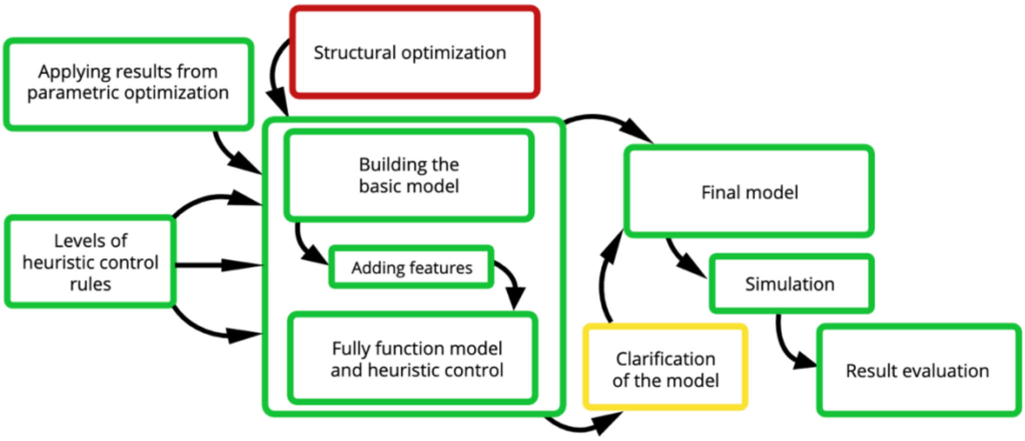

Figure 40 - DM workflow chart, Red - did not participate, Yellow - optional, Green - fully participate

5.4.3. Logic blocks of the ECU

Task of the ECU in DM

As discussed before, the system follows chronological order of action and reaction. As an example, the output data from the driver and all components (ICE, EM1, EM2, battery, clutches and mechanical brakes.) are sent the ECU, where it acts as an input for the logical process decided by sets of rules. Those sets of rules can be called the heuristic control algorithm. When the rules are applied based on the input data, the output (control) data are sent back to the driving components. The components make an action according to the inputs, and driver can “sense” the reaction, and makes reaction if necessary. At that point, the next step cycle starts.

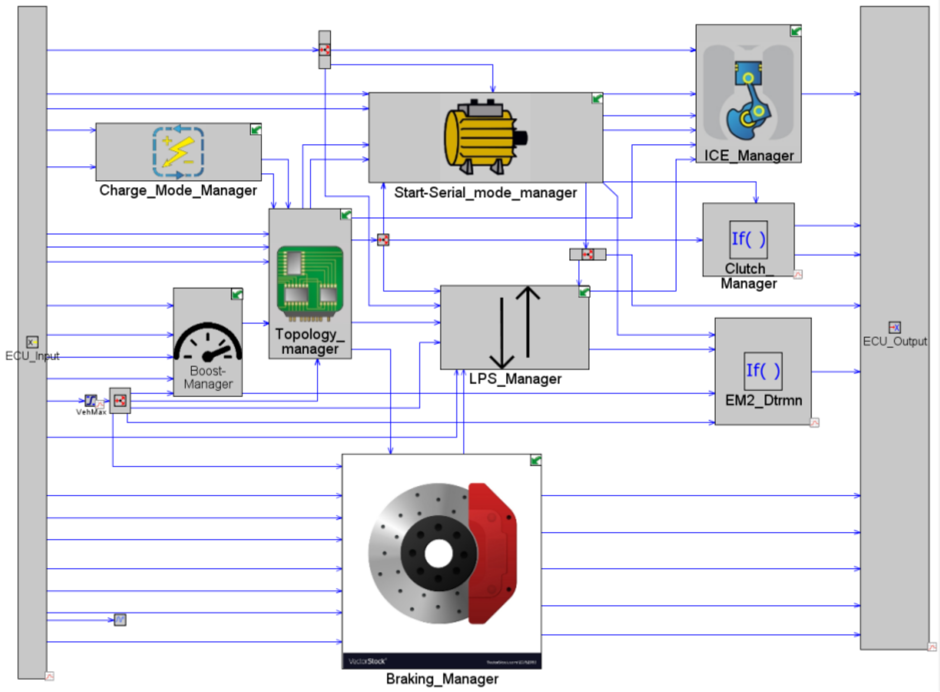

Figure 41 - Structure of the ECU

Charge mode manager (CMM)

The input data for the CMM are the current $SOC(t)$ and the traveled distance. The CMM takes care of definition of the charging mode, which has very decisive weight on the behavior in the next steps. The charge mode is decided solely based on $SOC(t)$, with exception of “charge coefficient” C. It is described in more detail chapter 5.4.4 about the heuristic control algorithm. The output of the CMM are the $SOC(t)$ and value of charge mode CH. Those values ale sent to Topology manager.

Boost manager (BM)

Based on the driver power requirement, power limit of the EM2, battery power limit and vehicle speed, the boost mode is defined. The boost function can be switched off externally by simple 0-1 switch. The output of the boost manager is power of each drive component and boost mode value is sent to the topology manager.

Boost manager			**Topology manager**	
Boost mode	Parameter value	Boost ON/OFF	Topology mode	Parameter value
			e-drive	1
EM2	1	OFF	Series mode	2
EM2 + ICE	2	OFF	Parallel boost	3
EM2 + EM1	3	ON	Parallel LPS	4
EM2 + EM1 + ICE	4	ON	e-drive boost	0

Table 17 - Table of values for BM and TM

Topology manager (TM)

The TM makes the most decision-making. The selection of drive mode is made based on the input from CMM, BM and values of drive limiters *v, p, a* (see: *Charge-sustaining below target SOC*

Secondly, when the battery SOC is within the range of CH3, it does not leave, with one exception. (When the vehicle is coming to a stop at the end of the cycle, thanks to the regenerative braking it charges above the hysteresis of the CH3. It is intentionally mentioned, because it is what happened to the result with highest efficiency of the WLTC. It is presented in the next chapter.)

Charging to target SOC

And finally the battery SOC should reach to the SOC_{Target}. For this action, charging coefficient C was defined:

$$C = \frac{D_{maneuver}}{D_{maneuver} - D_t} \cdot \left(SOC_{target} - SOC_t\right) \tag{30}$$

The coefficient C is sensitive to the $SOC_{target} - SOC_t$ at the end of the cycle and when it reaches a specific value, it overwrites the value of CH to 5 and starts intensive serial charging if necessary to reach the SOC_{Target}. For the coefficient to be effective, the cycle distance and SOC_{Target} needs to be known. See the atta

). The value of drive mode defines the driving architecture of the hybrid vehicle. The drive mode, power demands for each driving component and ICE ignition are the outputs of the TM.

Starter and series mode charging manager (SSM)

The task for the SSM is to apply starting process of the ICE by EM1, according to drive mode. When the motor is started, and series mode activated, it determines the charging RPM of the ICE according to charging power demand. That is done by the series operation line which was defined in (5.1.2 - *Finding SOL*). The output is sent to the ICE manager, Clutch manager, EM2 determination block and directly to the EM1.

LPS manager

Based on the input drive mode from TM, speed of the ICE and power demand, the LPS is done. For that process, a 3D lookup map from section 5.1.2 - Load point shifting map development which returns the torques split ratio U, and LPS manager decodes it into the EM2 and ICE power output.

ICE manager

It receives input data from TM, SSM and LPS manager and based on the drive mode, it selects which data to use to operate. If the drive mode is parallel, it proceed LPS, if the drive mode is series, it does SOL charging.

Braking manager

The braking manager is responsible for decisions between application of mechanical brakes and regenerative braking. It takes inputs from the driver, vehicle body and from EM2. The mechanical brakes are used for the complete stop procedure or braking when the limit of recuperation is crossed. The output parameters are sent to vehicles brakes and to EM2.

Clutch manager (CM)

According to the import values of the drive mode and starting mode from TM and SSM respectively, the position of clutches is selected. The output values are sent to clutches which are in the TQ250 transmission.

EM2 determination

Based on the input values from the SSM, LPS manager and Braking manager, the power demand of EM2 is defined.

5.4.4. Heuristic control strategy

Major features of heuristic control strategy are presented and discussed in this section. The main goal of this thesis was to build a heuristic control algorithm based on some key observations made from results of the optimal control strategy - dynamic programming (presented in details in

0 - 5.3.4). The rest of the strategy was built based on experience and knowledge gained from research in chapters 2 - 4.

Drive mode limiters

First of all, I define drive mode limiters which are used as an input to Topology manager (TM). Drive mode limiters are values which have direct impact on topology selection in Topology manager (TM). I define three different limiters *v*, *p*, and *a*:

- *v* is derived from vehicle speed and it relates to vehicle threshold of e-drive speed limit
- *p* is derived from power demand and it relates defined threshold value
- *a* is derived from vehicle acceleration and defined threshold value

Drive mode limiters gain values 1 or 2. That is based on their underlying value (i.e. velocity, power and acceleration) against threshold. Transient between the values is done with hysteresis to prevent oscillation. Mean values (MV) can be changed in the Case setup.

	T_1	**MV**	**T_2**
v	MV - 2 km/h	50 km/h	MV + 2km/h
p	MV - 1 kW	15 kW	MV + 1 kW
a	MV - 0.1 m/s^2	0.25 m/s^2	MV + 0.1 m/s^2

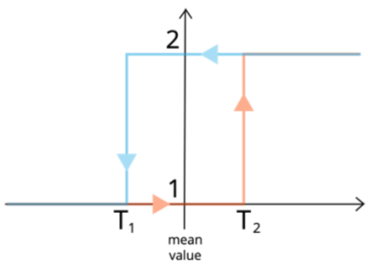

Figure 42 - Drive mode limiters values and their hysteresis thresholds

Charge mode CH

The main feature and idea of the proposed heuristic control strategy is the charge mode parameter CH. The parameter CH divides the range of battery SOC to 5 fields, presented in *Figure* 43. Boundaries between charge mode transitions are “softened” by 2% hysteresis section, identically to the *Charge-sustaining below* target SOC

Secondly, when the battery SOC is within the range of CH3, it does not leave, with one exception. (When the vehicle is coming to a stop at the end of the cycle, thanks to the regenerative braking it charges above the hysteresis of the CH3. It is intentionally mentioned, because it is what happened to the result with highest efficiency of the WLTC. It is presented in the next chapter.)

Charging to target SOC

And finally the battery SOC should reach to the SOC_{Target}. For this action, charging coefficient C was defined:

$$C = \frac{D_{maneuver}}{D_{maneuver} - D_t} \cdot \left(SOC_{target} - SOC_t\right) \tag{30}$$

The coefficient C is sensitive to the $SOC_{target} - SOC_t$ at the end of the cycle and when it reaches a specific value, it overwrites the value of CH to 5 and starts intensive serial charging if necessary to reach the SOC_{Target}. For the coefficient to be effective, the cycle distance and SOC_{Target} needs to be known. See the atta

. The used parameters of SOC limits are presented in *Table* 18.

	SOC [-]
SOC_{HIGH}	0.9
SOC_{Target}	0.5
$SOC_{Difference}$	0.07 - 0.1
SOC_{LOW}	0.2

Table 18 - defining values of SOC for charge modes this simulation

The main reason for introducing the charge mode is to successfully implement observations from the dynamic programming. The important action happens in the CH 2, CH 3 and CH 4 sections. The 3 important observations from the DP need to be fulfill.

Use of observations from DP

From the experience with dynamic programming, the consistent behavior was observed and summarized in 5.3.4.

Charge approaching

First, in the heuristic model, if the $SOC_{Initial}$ is below the SOC_{Target}, that means that it is in CH4, the heuristic control has the tendency to charge the battery. The reason for that is a rule that the battery is charged all the time. If the drive mode limiter *v* returns value of 1, the battery is charged serially by predefined power and the engine is operated on the SOL defined in *Finding SOL*. If the vehicle speed exceeds the e-drive limit, *v* returns value of 2 and LPS mode is applied according to results of *Load point shifting map development.*

If the $SOC_{Initial}$ is above SOC_{Target}, charge mode CH 2 is applied and the vehicle operates in e-drive mode or it can be set to operate in LPS mode, when the power demand is above certain threshold. For that reason, the CH2 from its nature, is a charge-depleting mode as it is wanted.

If the $SOC_{Initial}$ is identical to SOC_{Target}, it is in the middle of hysteresis between the CH 3 and CH 2. CH 3 is designed to be charge-sustaining, the CH 2 is designed to be charge - depleting. The battery SOC has the tendency to stay in between its limits. After some time, the battery SOC reaches values of CH3 and charge sustaining process takes place.

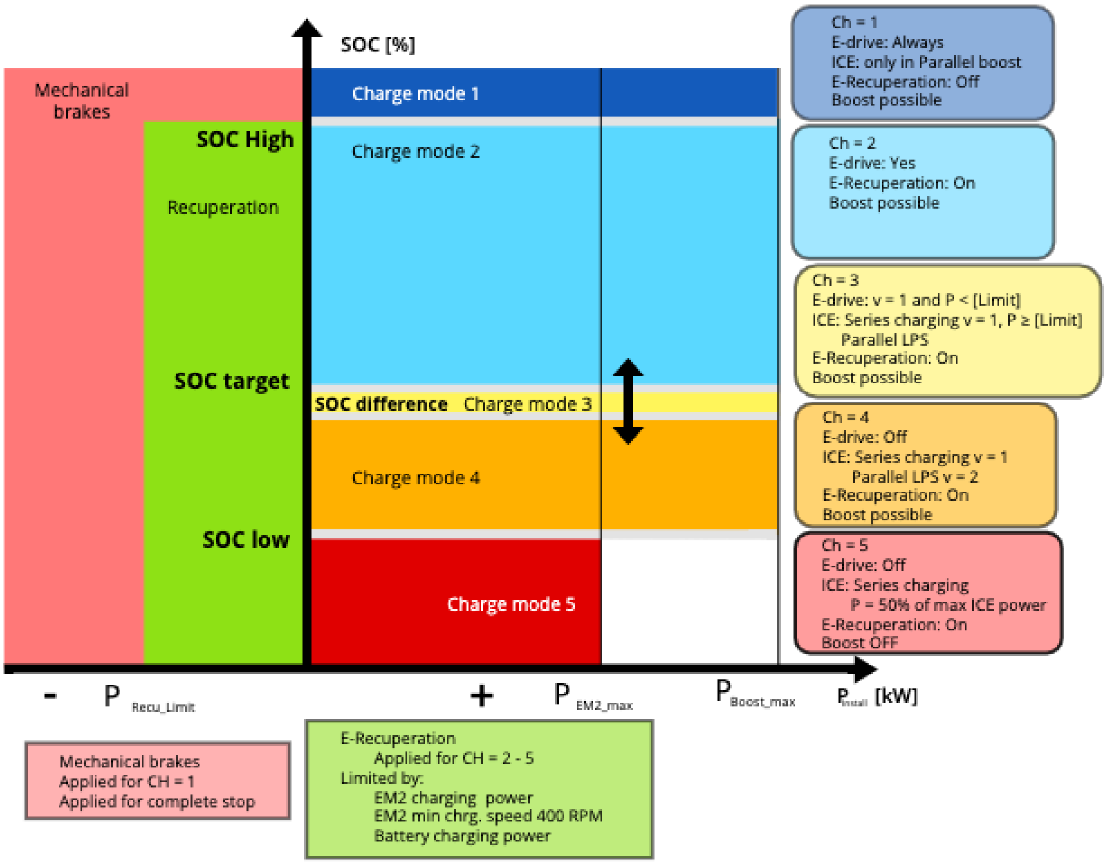

Figure 43 - Heuristic control strategy chart

Charge-sustaining below target SOC

Secondly, when the battery SOC is within the range of CH3, it does not leave, with one exception. (When the vehicle is coming to a stop at the end of the cycle, thanks to the regenerative braking it charges above the hysteresis of the CH3. It is intentionally mentioned, because it is what happened to the result with highest efficiency of the WLTC. It is presented in the next chapter.)

Charging to target SOC

And finally the battery SOC should reach to the SOC_{Target}. For this action, charging coefficient C was defined:

$$C = \frac{D_{maneuver}}{D_{maneuver} - D_t} \cdot (SOC_{target} - SOC_t) \tag{30}$$

The coefficient C is sensitive to the $SOC_{target} - SOC_t$ at the end of the cycle and when it reaches a specific value, it overwrites the value of CH to 5 and starts intensive serial charging if necessary to reach the SOC_{Target}. For the coefficient to be effective, the cycle distance and SOC_{Target} needs to be known. See the atta

Cycle	Threshold of C
WLTC	20
CC1	50
CC2	50
CC3	50
Evaluation cycle	50

Table 19 - Values of the charging coefficient for different cycles

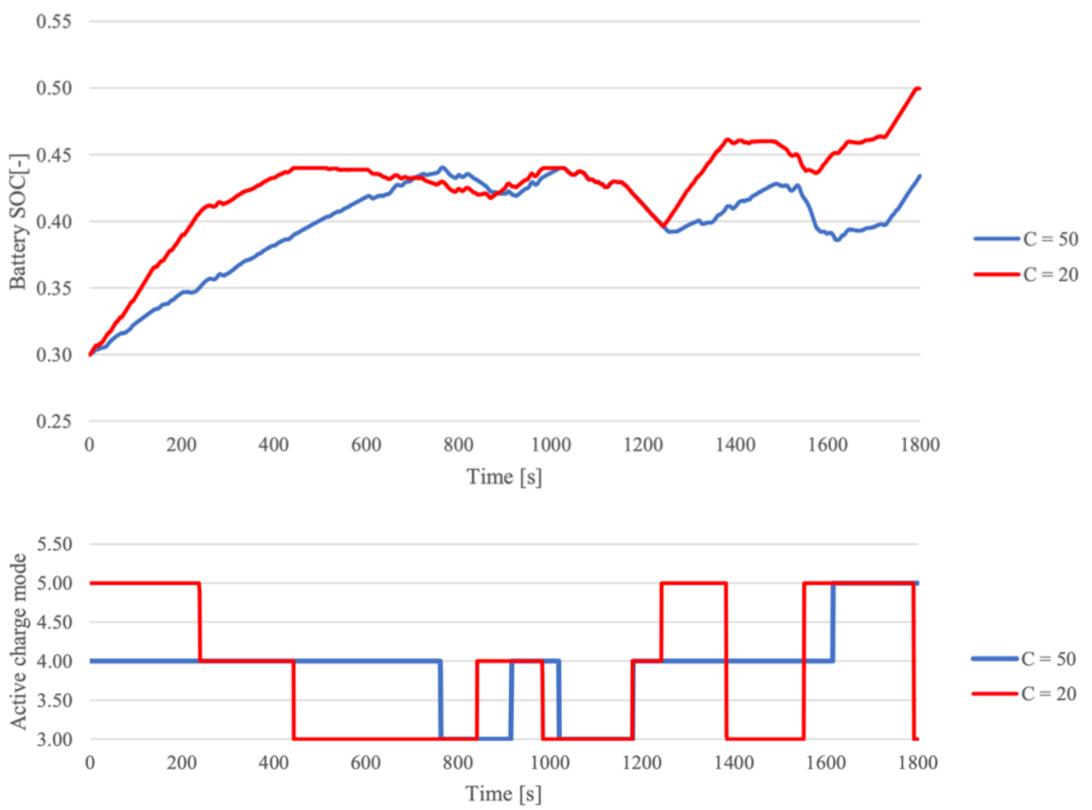

Figure 44 - Sensitivity analysis of charging coefficient C in WLTC cycle

5.5. Dynamic model simulation results

In this section I present results of sensitivity analysis steps which lead to optimization of heuristic control. The simulation of DM is done with the same set of cycles as KM (*Table 12*). Analysis steps are each time evaluated with use of different combination of drive cycles. For instance, gear ratios selection use all the steps, p limiter with battery only charging mode of CC1 and charge-sustaining CC 3 etc. and The results are compared based on the equivalent fuel consumption FC_{eq} value, introduced in *Results evaluation*.

5.5.1. Sensitivity analysis

Gear ratios selection

In this section, ideal gear ratio analysis is made. There are 3 different pairs of gear sets to compare, defined in *Table 10*

The simulation was done for all 10 cases, identical *Table 12*. From the results of fuel consumption and ΔSOC_{final}, the FC_{eq} was calculated. Since the same cycles were used for each pair of gears, the mean average of FC_{eq} for all cycles could be made. As can be seen in Figure 46 and Figure 47, the differences of fuel consumption of both comparisons are small. Based on the best performance of G2 pair, the next simulations use the gears $i_1 = 0.34$ and $i_2 = 2.13$. *Table* 10

From the results of WLTC Class3 cycle the average and equivalent fuel consumption is mentioned for reference: $FC_{avg} = 5.49 \frac{l}{100} km$ and $FC_{eq} = 5.37 \frac{l}{100} km$ $\Delta SOC_{final} = 0.0052$.

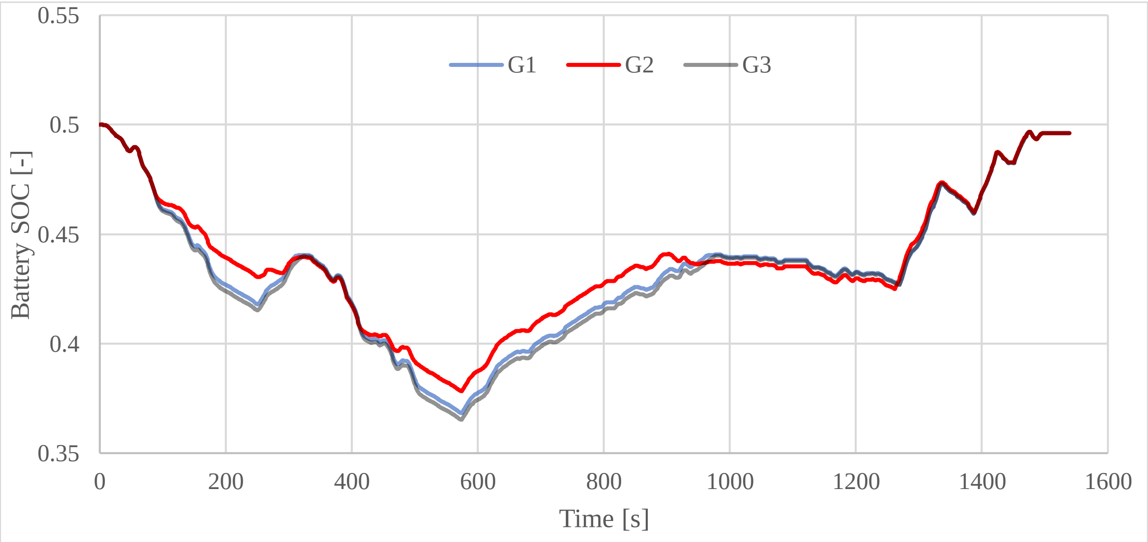

Figure 45 - Charge-sustaining mode in CC3 cycle for 3 different pairs of gear sets

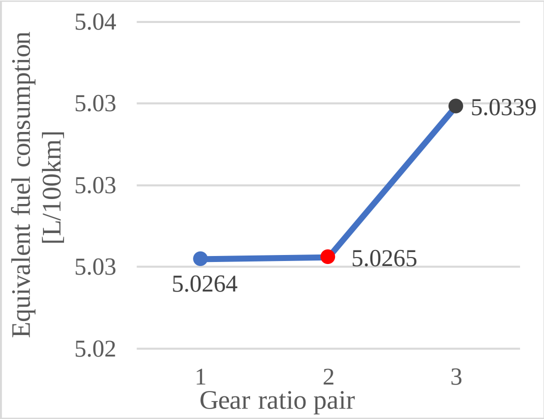

Figure 46 – Average FC_{eq} of ALL cycles for different pairs of gear sets

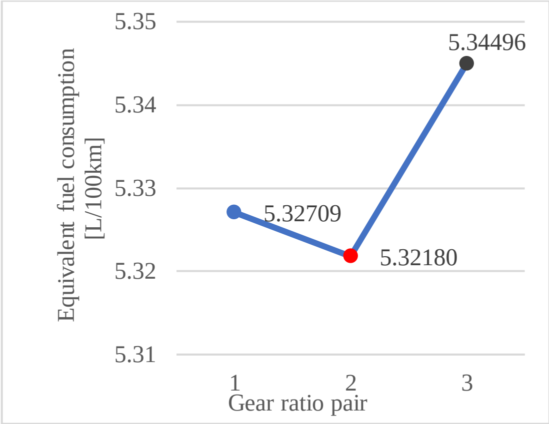

Figure 47 - Average FC_{eq} of all charge-sustaining cycles for different pairs of gear sets

Sensitivity on drive mode limiter

The sensitivity of fuel consumption result on drive mode limiter *p*. The drive mode limiter defines at which power demand (5, 10, 15 kW), the Topology manager (TM) should switch between parallel LPS and serious charging with higher load. The result is completely intuitive, because, with lower value of *p*, the parallel LPS mode (with equivalence factor 2.5) uses the engine less efficiently than serial charging set to minimum of 15 kW. In the values of the minor Axes you can see the applied drive mode decided by the Topology manager.

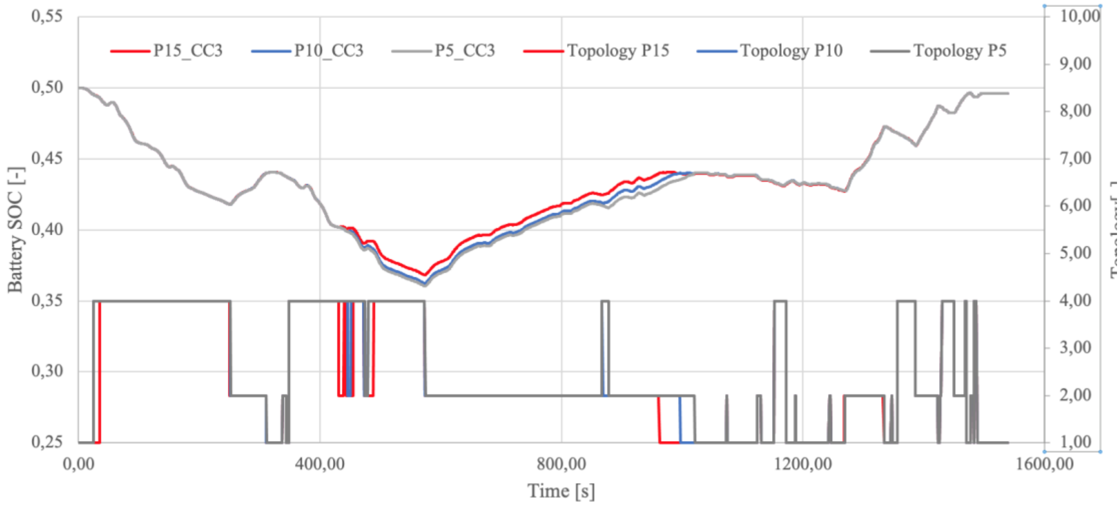

Table 20 - Evaluation of different values of parameter p in charge-sustaining cycle CC1

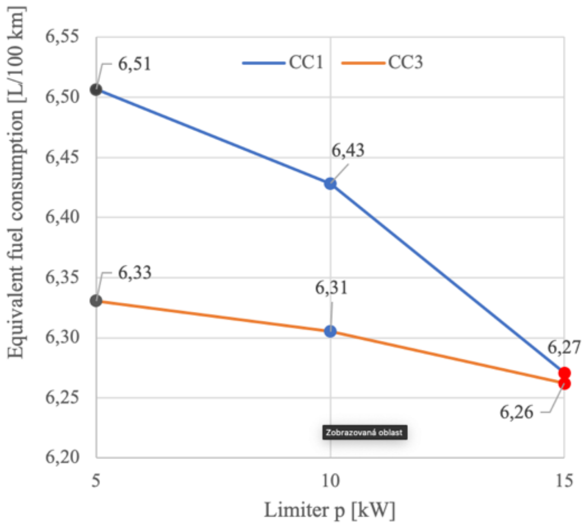

Table 21 - Influence of the parameter p on equivalent fuel consumption in CC1 and CC3

Sensitivity on equivalence factor

The value of equivalence factors influence the behavior of the LPS significantly. That is the consequence of the different control maps which the equivalence factor changes completely. It can be also noticed that the new LPS maps can influence the charge sustaining ability, so the further development of the heuristic control algorithm would be possible. That would probably lead to further improvement in efficiency of the dynamic model

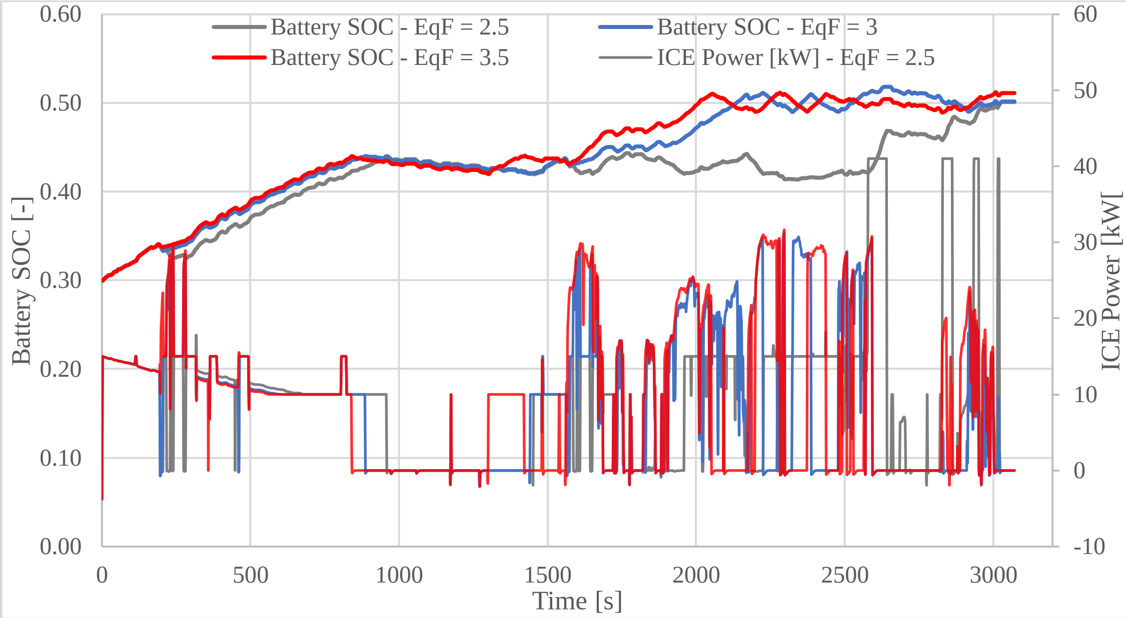

Figure 48 - CC1 cycle with 3 different LPS equivalence ratios

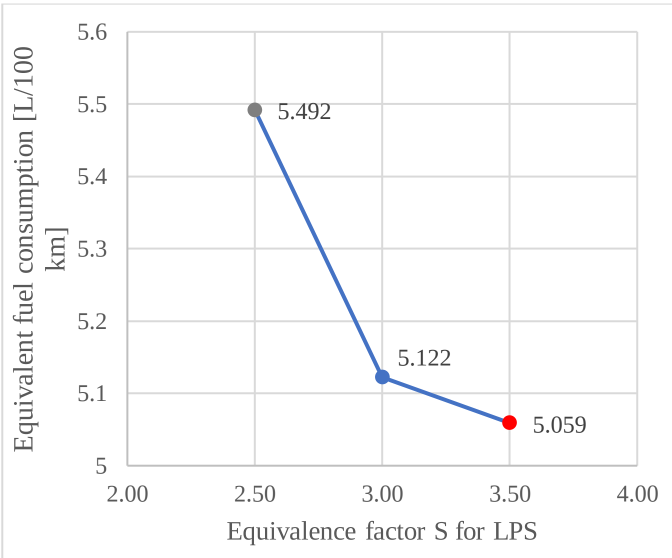

Figure 49 - Fuel consumption sensitivity to different equivalence factors

5.5.2. Evaluation of heuristic control

Application on random evaluation cycle

For reason, that the development and testing of both models was made on the same cycles, the proof of the correct function on different cycle is made. The evaluation cycle was chosen randomly from the GT-Suite library. It is two-times repeated LA92DDS cycle. The used settings were the best performing ones in the previous optimization:

p	i_1	i_2	S_{eq}
15	0.34	2.13.	3.5

Table 22 - Optimized settings for the dynamic model

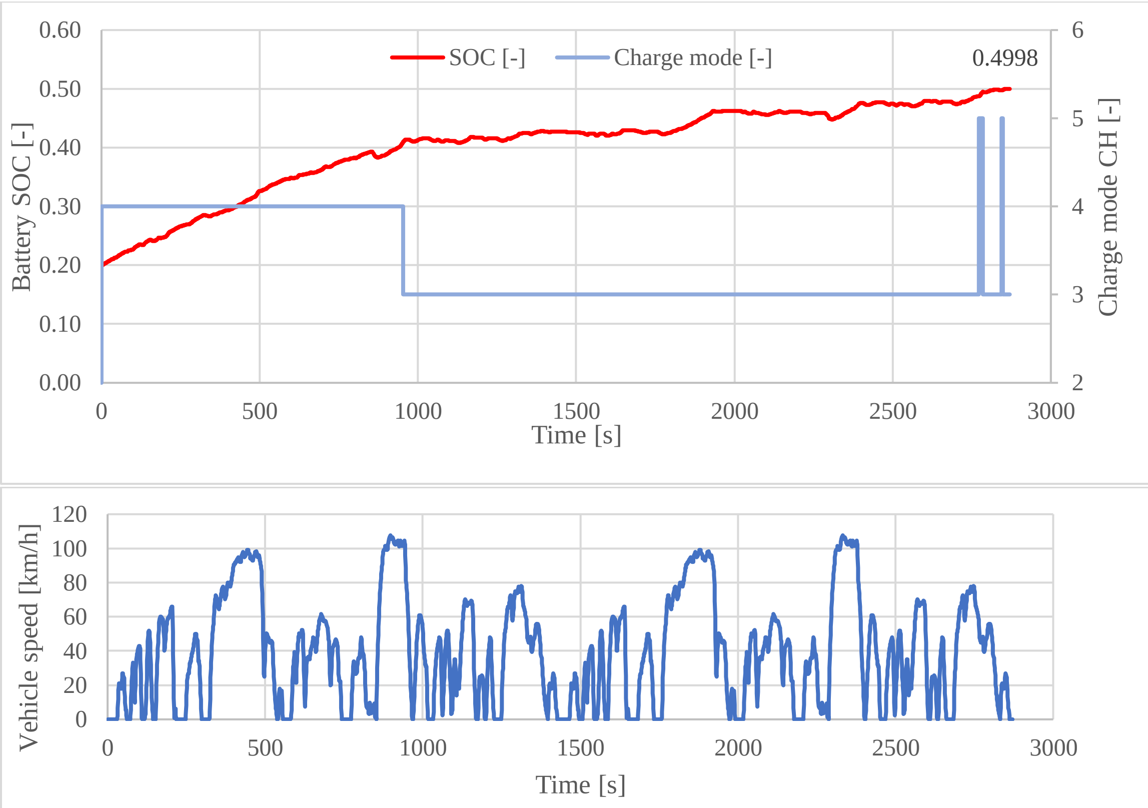

Figure 50 - Evaluation cycle simulation with heuristic control algorith

Charge-sustaining simulation of WLTC Class3

As the final result, the WLTC Class3 with the setting from previous optimization (Table 22) are used. The improvements in fuel consumption before and after parameter optimization is significant. Also, the frequency of switching drive modes is significantly lower with the designed optimal control in comparison to solutions of dynamic programming.

WLTC Class3	FC_{avg} [l/100 km]	FC_{eq}[l/100]	ΔSOC_{final}
Before optimization	5.49	5.37	0.0052
After optimization	4.91	4.57	0.0141

Table 1Table 22 - Optimized settings for the dynamic model

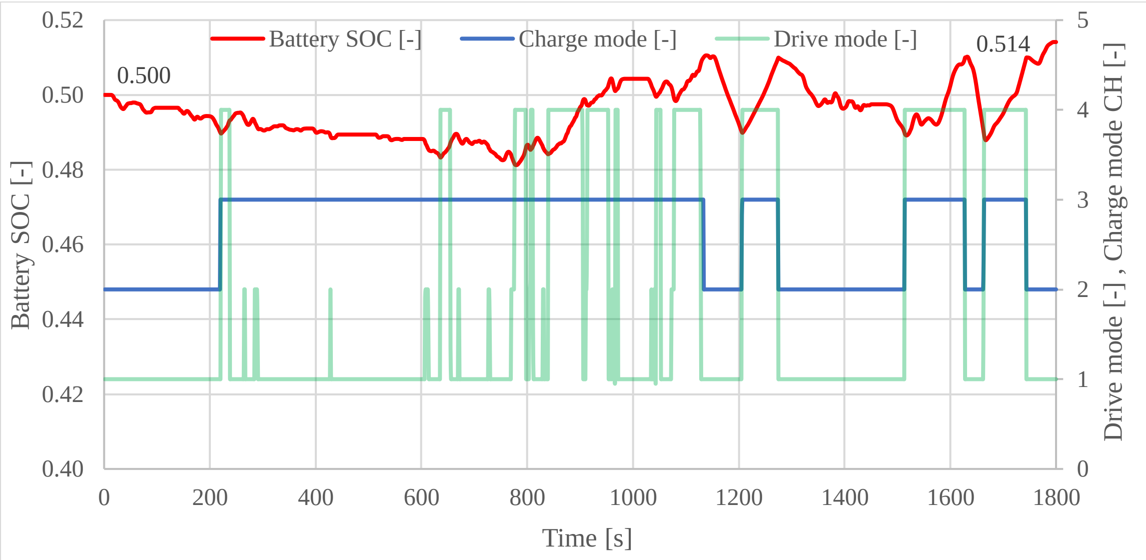

Figure 51 - Final WLTC Class3 cycle simulation of DM controlled heuristically

5.6. Methodology for heuristic strategy development

The last task of this thesis is to monitor major steps of the control strategy development and define a process of developing heuristic control algorithm for HEV in general.

Structural optimization of the vehicle

Firstly, I discuss the evaluation of the manufacturers (i.e. customers) requirements for the vehicle. Generally, requirements include the target parameters of the vehicle, such as performance, cost, or most importantly (as is mentioned in the introduction of this thesis), vehicles fuel consumption and CO_2 emissions. Together with the requirements, the structure of the vehicle is usually given as well. That can include components, such as the type of ICE, electric motor(s) and transmission; or parameters, such as the battery size, vehicle weight as well as the hybrid architecture and topology. If there are no such requirements, decision making process, to choose such components, needs to be carried out.

Parametric optimization of components

Secondly, parametric optimization of the applied components needs to be made. That can be done mostly before the simulation models are built. It can be done by analytical methods, experiments, or by engineering experience. The result of the parametric optimization can be, ideally, displayed as operation maps for a component or a system of components. Example of the parametric optimization process in this thesis are the production of SOL look-up table, LPS map and definition of pairs of used gear ratios.

The parametric optimization can take place simultaneously with the modular kinematic and dynamic model development. Modularity of the model provides the ability to adjust or change the major components relatively easily and makes the implementation of optimization results simple.

Building kinematic and dynamic models

The building process of both models can be more or less parallel. It is advised to build both models modularly and define parametrically as much as possible. Therefore, adjustments to the vehicle are significantly simplified.

When building both simulation models, it is important to understand the differences between them. The kinematic model is controlled by optimal control methods (e.g. ECMS or DP) which do not follow the physical sequence of events but lead to optimal control solution. The dynamic model is controlled by heuristic control and it follows the physical sequence of events. That makes the dynamic model complex and usually takes longer to develop. Therefore, building process of both models can be more or less parallel.

It is advised to build both models modularly and define parametrically as much as possible. Therefore, adjustments to the vehicle are significantly simplified.

After the parametric optimization of components is done, the kinematic model can be finished. Before the final simulation of KM, it is advised to do a sensitivity analysis of settings of the control algorithm (ECMS or DP).

Meanwhile, dynamic model can be finished, and from this point, the sensitivity analysis can be made at any time of the development.

Kinematic model simulation

The final simulation of KM can be carried out. The target heuristic control should be efficient not only in standardized cycles, but also for real-world driving. For that reason, it is advised to simulate as many cycles as possible. It is ideal to also use some real world driving data. With results from optimal control algorithm, development of the heuristic control can start.

Heuristic control algorithm

Results of optimal control data are used for heuristic control development. As a result of big amount of data, analysis can be a lengthy process. The goal is to find some decision making pattern or consistent behavior of the controller. For instance, connecting or disconnecting the ICE from the EM (or vice versa), switching between modes and application of load point shifting. When the relationships are found, the style of implementation into the heuristic control needs to be find as well.

The important thing to keep in mind is, that the DP and ECMS optimal control do not take into account any limits of "sensible" drivetrain control. Therefore, their behavior would be unacceptable in real-life use of the vehicle. The usability and reliability is the key thing to take into account, when designing the heuristic control.

When the heuristic control algorithm is finished and built into the dynamic model, the function and efficiency can be evaluated in arbitrary cycle.

6. Conclusion

The main goal of this thesis was to evaluate a development process of an heuristic control algorithm based on simulation results from optimal control strategy. At the beginning, the research about control strategies had to be done and is presented in chapter 4. After that, two simulation models of the same vehicle were built in the GT-Suite software. The models are based on the proposal of Multi-mode hybrid vehicle, done by Schaeffler [13]and is described in chapter 2.5.

The first model of the vehicle was the kinematic (backward) simulation model and the second one was dynamic (forward) simulation model. The kinematic model was controlled by dynamic programming which is kind of optimal control algorithm which secures the optimal solution data. My task was to do the parametric optimization of dynamic programming setting, chapter 5.2.2.

Another valuable outcome of this thesis are two MATLAB scripts which serve to development of series operation line of a pair: ICE – electric motor. The second MATLAB script can create a load point shifting map which is implemented to the dynamic simulation model and act as an important part of the heuristic control strategy.

The proposed heuristic control strategy was successfully implemented to the dynamic model and set of optimization simulations was done. The proposed control strategy achieves a fuel consumption of 4.91 l/100 km in WLTC Class3 cycle with extra 1.4 % of battery SOC. According to my supervisor, a comparable vehicle with a double clutch gearbox achieves 5.60 l/100 km.

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8. List of abbreviations

ICE	Internal combustion engine
EV	Electric vehicle
ECMS	Equivalent consumption minimalization strategy
HEV	Hybrid electric vehicle
P-HEV	Plug-in hybrid electric vehicle
BEV	Battery electric vehicle
FCEV	Fuel cell electric vehicle
DP	Dynamic programming
RB	Rule based
SOC	State of charge
LPS	Load point shifting
ADSS	Active driving safety systems
ABS	Anti-lock brake system
FLC	Fuzzy logic controller
LET	Low-end torque
ACD	Active cylinder deactivation
EGR	Exhaust gas recirculation
VTG	Variable turbine geometry
CCV	Cycle to cycle variation
KM	Kinematic model
DM	Dynamic model

9. Attachments

9.1. Attachment 1: Performance maps of electric motors EM1, EM2

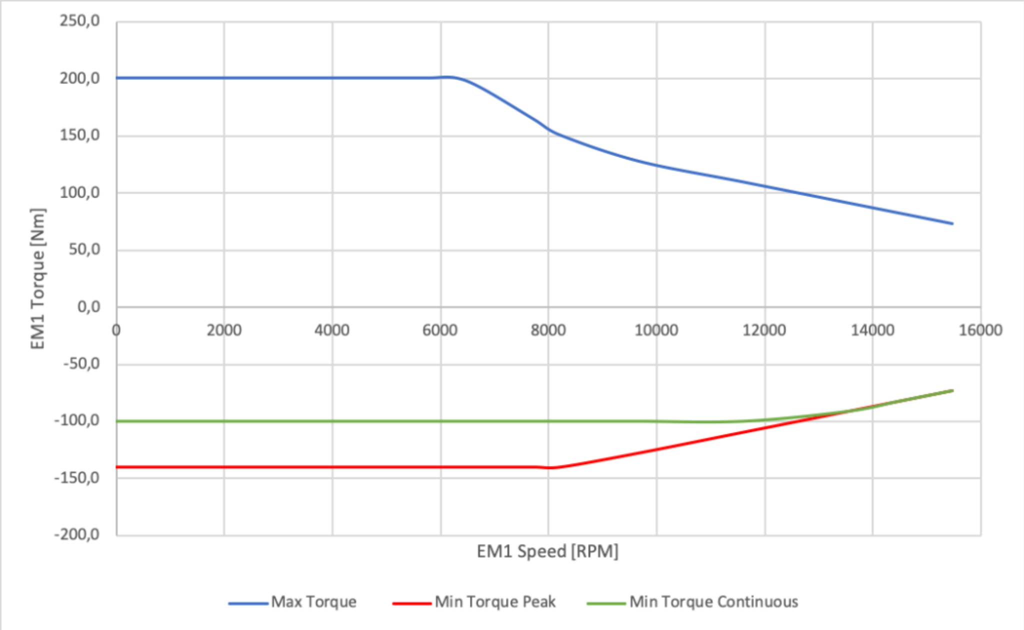

Figure 52 - Torque map of EM1

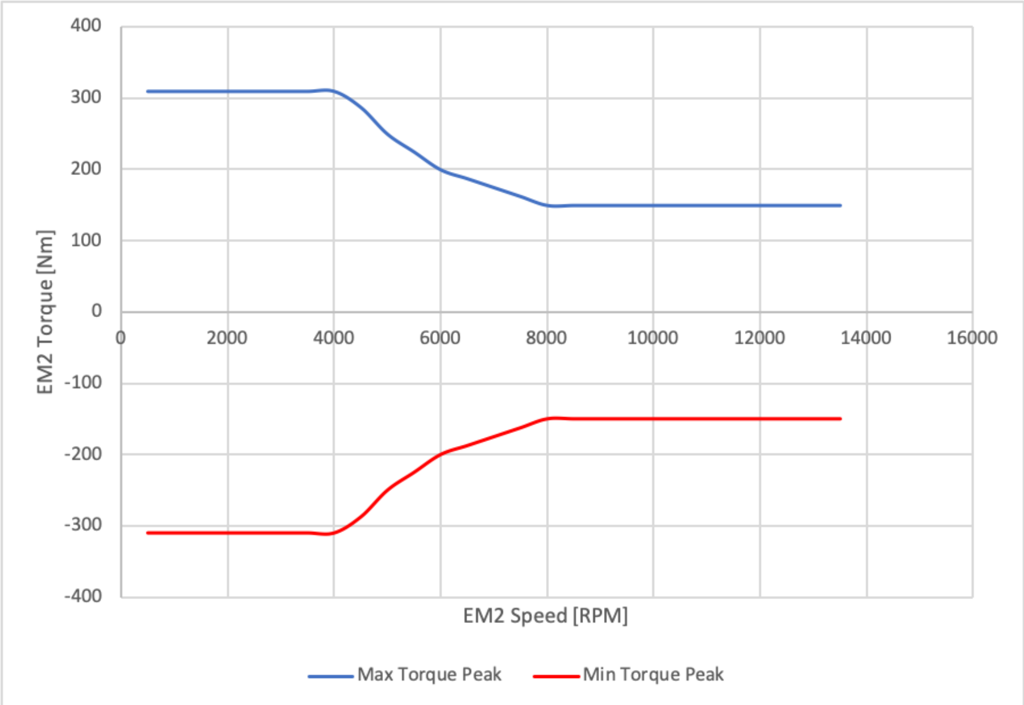

Figure 53 -Torque map of EM2

9.2. Attachment 2: Table of vehicle specifications for simulation

Notation	Meaning	Value
M_{Total} [kg]	Total vehicle mass	1576
M_{base} [kg]	Base vehicle mass	1226
M_{EM1} [kg]	Additional EM1 mass	30
M_{EM2} [kg]	Additional EM2 mass	30
M_{batt} [kg]	Additional HV Battery mass	150
M_{driver} [kg]	Additional driver mass	80
M_{trans} [kg]	Additional Transmission mass	60
Retarding force	Aerodynamics + losses	$F = A + B \cdot v + C \cdot v^2$
A[N]	Coefficient A	90.8
B[Nh/km]	Coefficient B	0.484
C[Nh^2/km^2]	Coefficient C	0.0382
g[m/s^2]	Gravity acceleration	9.81
T_{batt}[K]	Battery temperature	300
R_{wheel}[m]	Wheel radius	0.3069
J_{axle}[kgm^2]	Axle moment of inertia (including wheels and tires)	1.046
J_{shaft}[kgm^2]	Shaft moment of inertia	0.01
J_{EM1}[kgm^2]	EM1 moment of inertia	0.0179
J_{EM2}[kgm^2]	EM2 moment of inertia	0.025
J_{ICE}[kgm^2]	Engine moment of inertia	0.19377
i_1[-]	ICE to EM1 gear ratio	1 / 2.94 (0.34)
η_1[-] (Neglected when retarding forces are used)	ICE to EM1 gear ratio efficiency	0.98
i_2[-]	EM2 to Drive shaft ratio	2.02
η_2[-] (Neglected when retarding forces are used)	EM2 to Drive shaft ratio efficiency	0.98
i_D[-]	Differential gear ratio	4
η_{FD}[-]	Final differential gear ratio efficiency	1
Engine	EA211 1.5l MPi, R4, 81kW	
P_{max}[kW]	Maximum engine power	82 at 6000 min^{-1}
T_{max}[Nm]	Maximum torque	141 at 4000 min^{-1}
V[cm^3]	ICE displacement	1498
Q_{LHV}[kJ/kg]	Fuel lower heating value	43950
C_c[Ah]	Battery capacity	37
n_{cells}[-]	Number of Series/Parallel cells	104/1
C_{batt}[kWh]	Battery pack capacity	14.8

Table 23 - Complete vehicle specifications

9.3. Attachment 3: Speed profiles of applied cycles

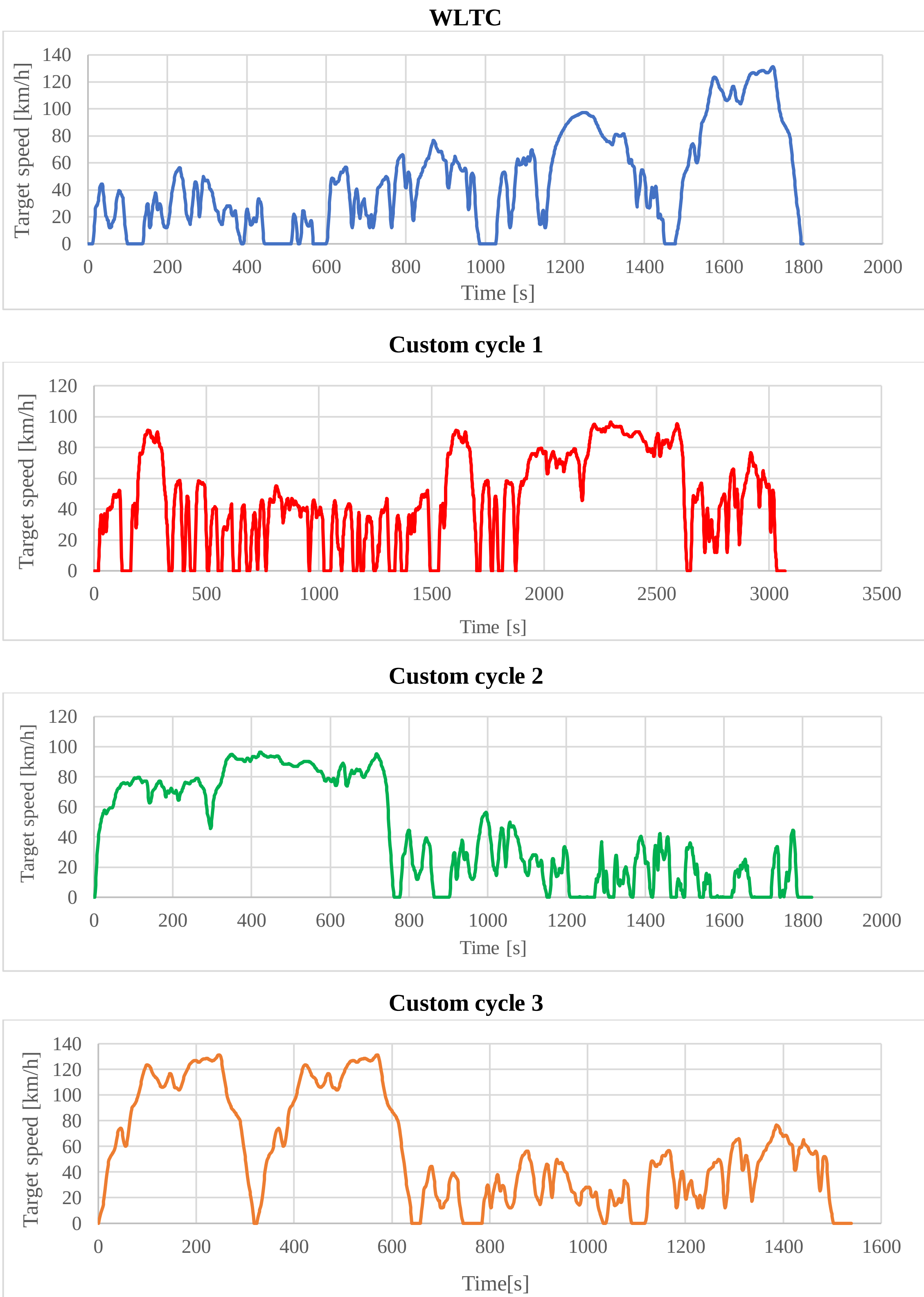

Figure 54 - Speed profiles of simulation cycle

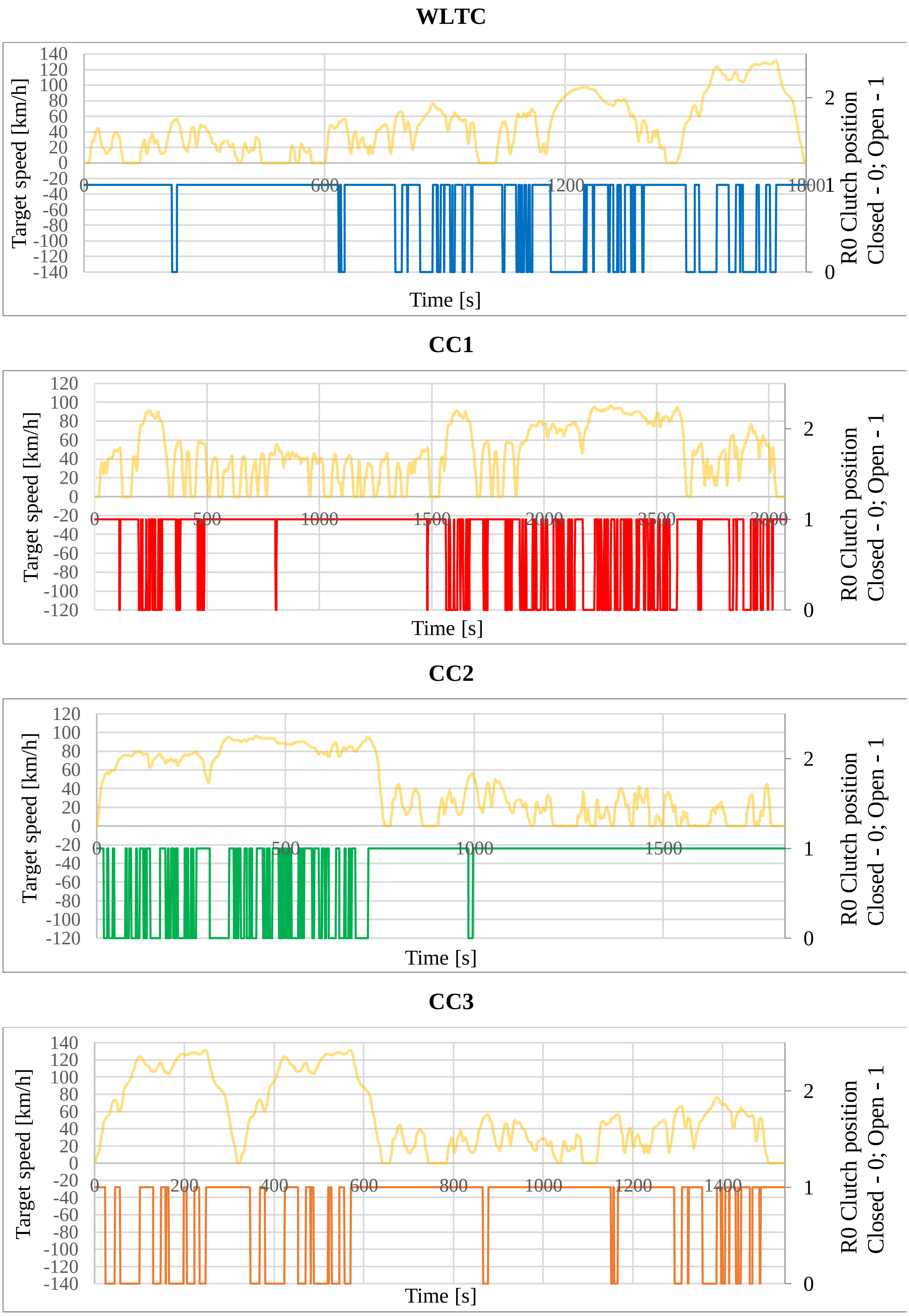

Figure 55 - Clutch R0 activation by dynamic programming

9.4. Attachment 4: Parallel boost acceleration

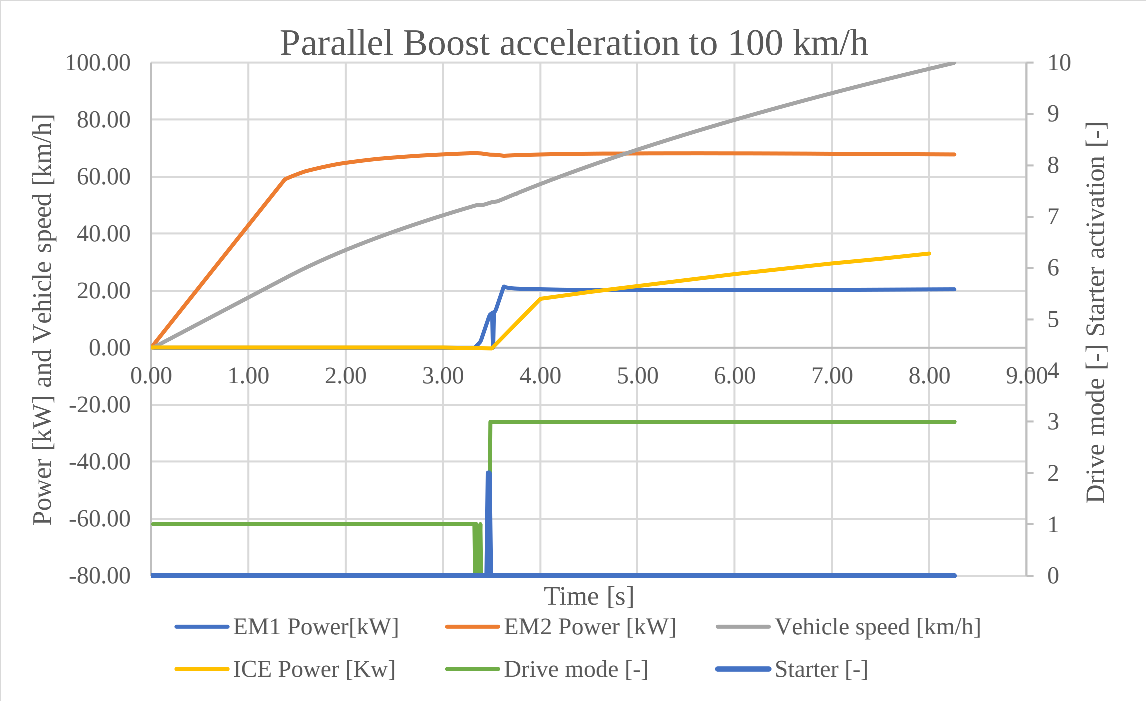

Figure 56 - Parallel boost mode of dynamic model