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Predictive Control Strategies of Plug-in HEVs

MASTER'S THESIS

to achieve the university degree of

Master of Science

Master's degree programme: Mechanical Engineering and Business Economics

submitted to

Graz University of Technology

Supervisor

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The thesis cannot be made public until March 2024

Graz, March 2019

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Abstract

Plug-in Hybrid Electric Vehicles (PHEVs) are a kind of vehicles with two propulsion systems – internal combustion engines and electric drive. Besides charging the battery during driving, electric energy can also be supplied by plug-in at the stationary electric grid. They are one type of charming solution for increasingly CO_2 emission environment problem. PHEVs have generally lower total fuel consumption, which greatly depends on the overall power management and energy management strategy, that is represented as the control strategy in the Hybrid Control Unit (HCU). The thesis discusses control strategies towards a P4 topology PHEV and a P2 topology PHEV, whose existing HCUs implement Charge Depletion Charge Sustaining (CDCS) strategy and individually calculate power split ratio and select driving mode for the power distribution decision. Compared to the traditional non-predictive CDCS, control strategies with prediction information have the ability to further improve fuel economy. The thesis objective is to design predictive hybrid control strategies based on existing HCU for the P2 topology PHEV to improve fuel economy behavior. The designed predictive control strategies should be able to be applied for P4 HCU use, too.

Before the online models' development, offline global optimization with a deterministic Dynamic Programming (DP) is applied to analyze full-scale benefits mechanism of predictive strategies. Later two new predictive HCUs are developed. The main idea is to use a global horizon prediction model to determine the full-scale possibly optimal battery depletion strategy, which is tracked by an online Model Predictive Control (MPC) model or a Rating-Weighting model. The local predictive HCUs optimize power distribution between the two power sources on the local range. Two online control methods are designed to improve fuel economy while taking drivability and NVH/comfort aspects into consideration. These two proposed control methods are integrated into the existing HCU of the P2 topology PHEV and are fine-tuned through simulations. MPC method is compatible with the HCU of the P4 topology PHEV as well. Their effectiveness is evaluated by comparing simulation results of existing HCU of P2 topology PHEV with two created new prediction-based HCUs.

It was found that the two prediction-based hybrid control strategies can obtain improvements in fuel economy. But simulation results demonstrate the influence of driving cycles and future information know-in-advance degree to the final fuel economy improvements, which reveal that predictive strategies are not always beneficial.

Keywords: Plug-in Hybrid Electric Vehicle (PHEV), Predictive Control, Fuel Economy, Model Predictive Control (MPC)

Abstrakt

Plug-in-Hybrid-Elektrofahrzeuge (PHEVs) sind Fahrzeuge mit zwei Antriebssystemen - Verbrennungsmotoren und Elektroantrieb. Neben dem Laden der Batterie während des Fahrens kann elektrische Energie auch durch Verbindung mit dem stationären Stromnetz bereitgestellt werden. PHEV sind eine interessante Technologie, welche einen Beitrag zur Lösung des Problems der zunehmenden CO_2-Emissionen leisten kann. PHEVs haben im Allgemeinen einen niedrigeren Gesamtkraftstoffverbrauch, der jedoch stark von der Gesamtstrategie des Energiemanagements abhängt, die als Steuerungsstrategie in der Hybrid Control Unit (HCU) dargestellt wird. Die Master Thesis diskutiert verschiedene Steuerungsstrategien für PHEV mit P4-Topologie und PHEV mit P2-Topologie. Die für diese Topologien vorhandenen HCUs ermöglichen die Charge-Depletion-Charge-Sustaining-Strategie (CDCS-Strategie) berechnen das Power-Split-Verhältnis abhängig vom Fahrmodus. Verglichen mit einem herkömmlichen nicht-prädiktiven CDCS können Steuerungsstrategien mit Vorhersageinformationen die Effizienz des Antriebsstrangs weiter verbessern. Das Ziel dieser Master Thesis ist es, auf der Grundlage der vorhandenen HCU für die gegebenen P2- und P4-Topologie vorhersagende Hybridsteuerungsstrategien zu entwickeln, um den Kraftstoffverbrauch zu reduzieren.

Vor der Entwicklung der Online-Modelle wird die globale Offline-Optimierung mit deterministischer dynamischer Programmierung (DP) angewendet, um den Nutzen-mechanismus von Vorhersagestrategien zu analysieren. In der Folge werden zwei neue prädiktive HCUs entwickelt. Die Hauptidee besteht darin, ein globales Horizont-vorhersagemodell zu verwenden, um die möglicherweise optimale Energie-Managementstrategie der Batterie zu bestimmen, die auf einem Online-Modell der Model Predictive Control (MPC) oder einem Rating-Weighting-Modell basiert. Die lokalen prädiktiven HCUs optimieren die Energieverteilung zwischen den beiden Energiequellen im lokalen Bereich. Im Zuge der Untersuchungen der beiden Online-Steuermethoden zur Verbesserung der Kraftstoffeffizienz wurden auch Aspekte des Fahrverhalten und NVH / Komfort berücksichtigt. Die beiden entwickelten Steuerungs-strategien wurden anschließend in die vorhandene HCU der P2-Topologie integriert und durch Simulationsrechnungen optimiert, wobei die entwickelte MPC-Methode auch mit der HCU der P4-Topologie kompatibel ist. Durch einen Vergleich der Simulationsergebnisse bestehender HCU der PHEV mit P2-Topologie mit den beiden neuen, auf Vorhersage basierenden HCUs, kann das Potenzial der entwickelten Regelstrategien bewertet werden.

Im Rahmen der Potenzialbewertung konnte festgestellt werden, dass die beiden auf Vorhersagen basierenden Regelstrategien Verbesserungen im Kraftstoffverbrauch erzielen können. Simulationsergebnisse zeigen jedoch auch den Einfluss von Fahrzyklen und Informationsgehalt der Vorhersagedaten auf die Qualität der Regelstrategien zu Effizienzverbesserung – so konnte dargestellt werden, dass die auf Vorhersagen basierenden Strategien nicht unter allen Umständen von Vorteil sind.

Stichwort: Plug-in-Hybridfahrzeug (PHEV), Predictive Control, Kraftstoffverbrauch, Modell Predictive Control (MPC)

Acknowledgment

Above all, I would like to thank my supervisor Bhargav Adabala in AVL for his critical guidance and feedback every week. Special thanks go as well to my university supervisor at TU Graz, Mario Hirz, for his assistance and helpful discussions throughout this research.

I also present my gratitude to AVL colleagues, Jonathan Lindblom, who lay a great basement for my thesis's start. Thank you as well to other colleagues in my department, Simon, Thomas, Sundar and Kun for their professional answers and suggestions in the methodology, contents and presentation of this work.

Additionally, I also would like to thank AVL colleagues in the simulation department, Samuel, Stefan and Sander, for their technical support.

Finally, thank AVL for providing the opportunity and facilities to work on this fascinating topic.

Huan Chen

Graz, December 2018

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List of Abbreviations

ppm	Parts Per Million
EV	Electric Vehicle
NEDC	New European Drive Cycle
AER	All-Electric Range
PHEV	Plug-In Hybrid Electric Vehicle
HEV	Hybrid Electric Vehicle
V2V	Vehicle-To-Vehicle
V2I	Vehicle-To-Infrastructure
V2X	Vehicle-To-Everything
GPS	Global Position System
GIS	Geographic Information System
ITS	Intelligent Traffic System
ADAS	Advanced Driver Assistance System
AEB	Advance Emergency Brake
ACC	Adaptive Cruise Control
HCU	Hybrid Control Unit
CV	Conventional Vehicle
HF	Hybridization Factor
ICE	Internal Combustion Engine
EM	Electric Motor
EREV	Extended Range Electric Vehicle
EMT	Energy Management Task
PMT	Power Management Task
TCU	Transmission Control Unit
ECU	Engine Control Unit
ACU	Auxiliary Control Unit
EPS	Electric Power Steering
BMS	Battery Management System
ESP	Electronic Stability Program
ESS	Energy-Storage System
CS	Change-Sustaining
CD	Charge-Depletion
CDCS	Charge-Depletion and Change-Sustaining Strategy
SoC	State of Charge
GOP	Global Optimization
LP	Linear Programming
DP	Dynamic Programming
SP	Stochastic Programming
PSO	Particle Swarm Optimization
QP	Quadratic Programming
DDP	Deterministic Dynamic Programming
ROP	Real-Time Optimization
ECMS	Equivalent Consumption Minimization Strategy
MPC	Model Predictive Control
PMP	Pontryagin’s Minimum Principle

LTV-MPC	Linear Time-varying Model Predictive Control
eMPC	Explicit Model Predictive Control
sMPC	Stochastic Model Predictive Control
C/GMRES	Continuation and Generalized Minimum Residual
MINLP	Mixed-integer Nonlinear Programming
PI	Proportional-Integral
PID	Proportional-Integral-Differential
P4-HCU	HCU for the P4 topology PHEV
P2-HCU	HCU for the P2 topology PHEV
NVH	Noise, Vibration, and Harshness
R-W	Rating and Weighting method
BSFC	Brake Specific Fuel Consumption
BSG	Belt Driven Starter/Generator
FEAD	Front End Accessory Drive
ISG	Integrated Starter/Generator
AWD	All Wheel Drive
MIL	Mode-in-the-Loop
HIL	Hardware-in-the-Loop
SIL	Software-in-the-Loop
DCT	Dual Clutch Transmission
ConvDrv	Conventional Drive
AddBoost	Additive Boost
SubBoost	Substitute Boost
OptmGentn	Optimum Generation
MinGentn	Minimum Generation
IdleGentn	Idle Generation
EltlDrv	Electrical Drive
Recup	Recuperation
HWFET	Highway Fuel Economy Driving Schedule
UDDS	Urban Dynamometer Driving Schedule
FTP	Federal Test Procedure

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Chapter 1 Introduction

1.1 Background and Motivation

According to the statistical report, the number of cars sold worldwide in 2018 will be 81.5 million. The enormous vehicle industry satisfies the mobility requirements of people around the world, but generally has a conspicuous negative influence on the environment and society as well. Reports [1][2], which comprehensively conclude all the problems resulting from vehicles, all particularly emphasize vehicle exhaust emissions. Fuel combustion process of conventional vehicles directly or indirectly releases damaging pollutants into the atmosphere all the time, another main emission product CO_2, known as greenhouse gases, even accounts for global climate change. Reference [3] mentioned that CO_2 concentrations were 404 parts per million (ppm) in 2016. If no efforts are taken, the value is likely to increase to 1300 ppm by 2100, that will increase the planet mean surface temperature from 3.7℃ to 7.8℃.

Regarding this, governments created emission legislation to limit vehicle pollutant emissions and greenhouse gas emissions. Those increasingly strict legislations efficiently cause to vehicle industry reformation. Especially for the CO_2 emissions, various regions have already enacted targets until 2020 or 2025. The European Union even proposed a target for 2030, which decreases the averaged CO_2 output of the car fleet below a value of 67 g/km, see Figure 1.1.1. Thus, taking CO_2 emissions target into consideration, outstanding fuel economy behavior will be the persistent demand for vehicles. Among lots of methods to reduce fuel consumption, powertrain system electrification is popular and compelling. As shown in Figure 1.1.2, people analyze that switching to Electric Vehicles (EVs) earlier rather than exhausting the fuel potential of consumption-engine technologies, would reduce the costs of a 70 g/km (New European Drive Cycle, NEDC) CO_2 emissions target by €200 to €500 per vehicle in 2025 [4].

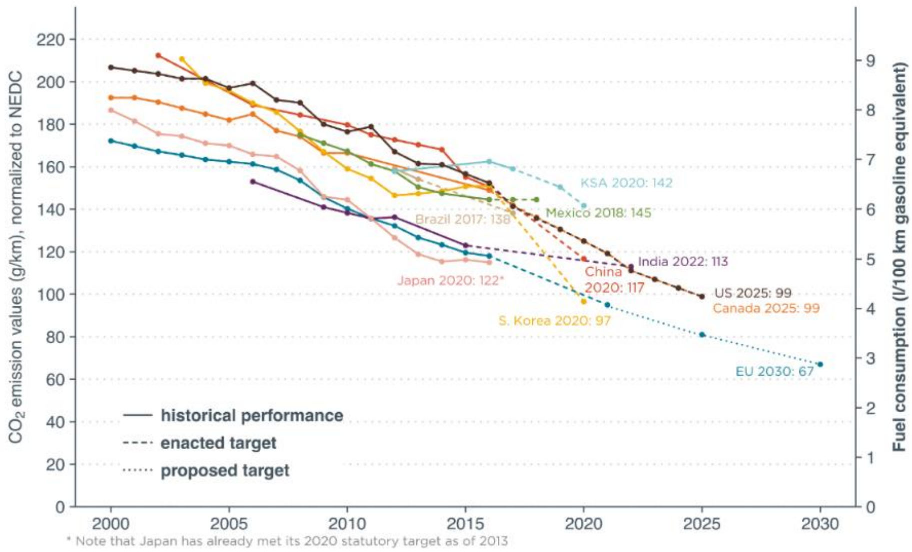


Figure 1.1.1: Passenger car CO_2 emissions and fuel consumption worldwide until 2030, normalized to NEDC [1].

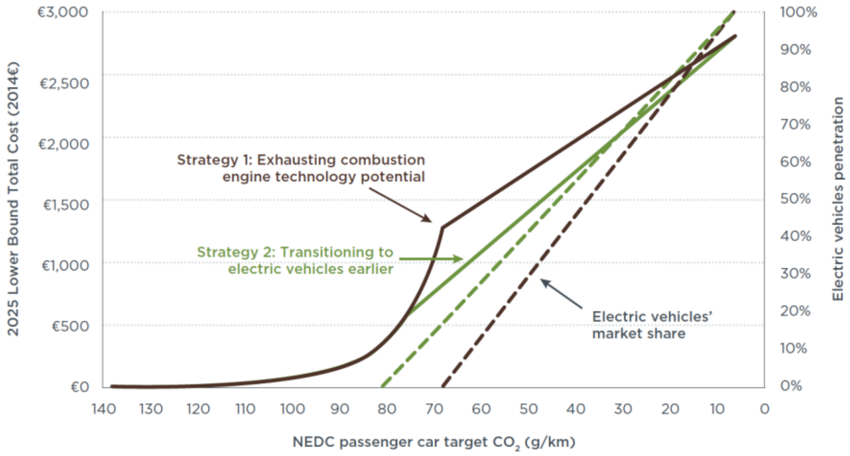


Figure 1.1.2: The lower bound of total incremental cost to reduce CO_2 emissions for each passenger car in EU by 2025, compared to the year 2014 baseline. Earlier transitioning to electric vehicles will bring less cost to reach the CO_2 emissions target compared to full deployment of combustion engine [4].

1.2 Plug-in Hybrid Electric Vehicle

Plug-in hybrid electric vehicle (PHEV) is one kind of vehicle with an alternative propulsion system with high electrification degree. Along with the target to reduce CO_2 emissions in stricter and stricter regulations, there will be more and more PHEVs in the future market. PHEV has a smaller combustion engine and a larger capacity battery compared to standard HEVs. Therefore, PHEV has the capability to drive vehicle with pure electricity, which is in most cases drawn from external electric energy resource. PHEV has All-Electric Range (AER), although it's shorter than the AER of pure EV, usually (20-50 km), the AER can support daily travel to the workspace, or occasional long-distance driving in regular hybrid mode, as shown in Figure 1.2.1 [5].

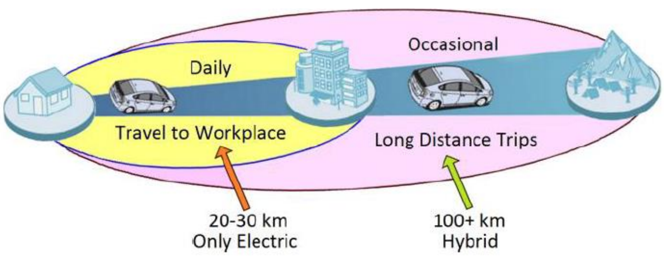


Figure 1.2.1: Travel range of a typical PHEV [5].

1.3 Predictive Information

Nowadays, advanced communication, sensing, information and computation technologies have been integrated into transportation infrastructure including cars, traffic signals, roadside sensor units, etc. [6]. Gradually, there is an increasing tendency of so-called internet-of-things in the traffic environment, e.g. vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I), vehicle-to-could. All kinds of prediction information from Global Position Systems (GPS), Geographic Information Systems (GIS), Intelligent Traffic Systems (ITS), V2X, cloud system or real-time intelligent traffic energy management center, etc. enable people to do lots of improvement in various aspects of traffic and environment. The improvement can be concluded into three aspects: safety, comfort and efficiency. Lots of Advanced Driver Assistance Systems (ADAS) contribute to one of three objectives, e.g. Advance Emergency Brake (AEB) for safety under the critical situation, or combination of several objectives, e.g. Adaptive Cruise Control (ACC) for safety and comfort, truck platooning for safety and efficiency.

Majority of ADAS functions nowadays can operate the vehicle in speed, acceleration, braking or steering; sometimes even an optimal velocity trajectory can be designed and tracked in order to save energy by avoiding unnecessary traffic congestion. However, in the term of long-distance trips, human driving is still actual, which means that the vehicle velocity is still strongly dependent on the driver's control.

In this case, the optimization of vehicle powertrain overall efficiency or intelligent usage of various energy sources under different traffic conditions still contributes mostly to energy efficiency aspects. Regarding hybrid electric vehicles (HEVs), engineers implement a lot in investigations of prediction-based control strategies. Lots of results show that predictive control strategies can significantly improve fuel economy compared to conventional pre-determinate control strategies [7][8].

1.4 Thesis Objective

The thesis research is based on two PHEVs with different configurations and their existing Hybrid Control Units (HCUs). The ultimate objective is to improve PHEVs overall fuel economy behavior by implementing predictive models into one of the HCUs, which might influence its existing power distribution decision. The developed method should be compatible with two existing HCUs.

1.5 Thesis Outline

The thesis outline includes: Chapter 1 describes the background of the thesis and presents the thesis' ultimate objectives. Chapter 2 starts with an introduction of all kinds of EVs, and discusses the advantages of PHEVs. Then the chapter mainly introduces the classification of PHEVs' control strategies and all kinds of prediction-based control strategies. Later the comparison reference, existing control strategy in two HCUs and their internal difference, are revealed. In the end, a more detailed research problem statement is proposed corresponding to the thesis objectives. In Chapter 3, a control-oriented model is going to be developed and validated. Chapter 4 is about global optimization creation for the use of prediction-based control strategies benefits mechanism analysis. Chapter 5 develops predictive control models and implements them into one of the existing HCUs. Chapter 6 is about simulation of developed prediction-based HCU and results analysis. Chapter 7 includes a summary, discussions and future possible improvement methods based on the thesis are recommended.

Chapter 2 Literary Research

2.1 Hybrid Electric Vehicles

HEVs are vehicles based on one or multiple power sources to ensure propulsion. The electrification degree is classified through a scale from 0 (conventional vehicle, CV) to 1 (pure electric vehicle) [9], see Figure 2.1.1. Generally, larger size Electric Motor, EM or smaller size of Internal Combustion Engine (ICE) means a higher degree of electrification. In order to represent how much is the share of electric power, a Hybridization Factor (HF) is defined [5]:

$$HF = \frac{Electric\ Motor\ Power}{Electric\ Motor\ power + Engine\ Power} \tag{2.1}$$

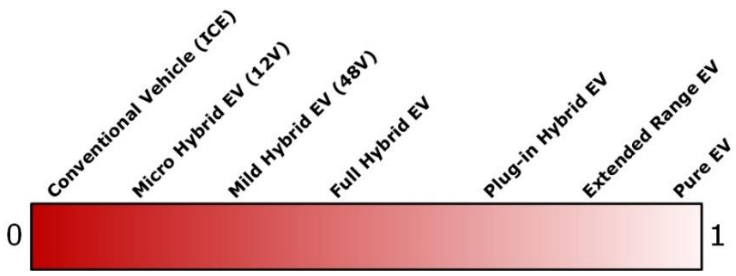


Figure 2.1.1: Degree of Electrification, 0 stands for a pure conventional drive with least degree of electrification, 1 stand for a pure electric vehicle with the highest degree of electrification [9]

HEV combines ICE with electric propulsion. The electricity source can be a battery, full cell systems or even solar energy. Micro HEV, mild HEV, and full HEV are classified according to Electric Motor's character. If equipped with an external charging system, HEVs are upgraded to Plug-in HEVs (PHEVs). ICE in HEV and PHEV can offer traction power to the vehicle directly, while just work as backup battery charging system in Extended Range EV (EREV). HEVs (including PHEVs) can also be sorted based on the configuration of the powertrain components, known as series, parallel and series-parallel (power split) hybrids. In another way, according to the position of EM in the powertrain system, there are P0-P4 HEVs. A more detailed comparison of HEVs and configuration combination can be found in Appendix 1.

PHEV is a kind of full HEV comprising a smaller combustion engine, a larger EM and a larger capacity battery, which can be charged externally [5]. It has the following advantages [9][10]:

- Compared to standard HEVs, electric energy can be gained from outside, thus zero fuel consumption is possible if the driving range is within AER. Additionally, larger EMs enable higher recuperation capability.
- There is no range anxiety for PHEVs usages compared to full EVs.
- Both types of traction source can be used, thus efficient energy distribution is possible compared to EREVs. Usually, EM is dedicated for in-city, low speed or

low-power demand scenarios, and ICE tends to be used under the highway, high speed or high-power demand conditions.

2.2 Control Strategies of PHEVs

The main challenge for the development of control strategies of HEVs is the coordination of mechanical and electrical power path. How the power split between these two paths is to be made during vehicle operation comprises a new control task: supervisory control. There are two main tasks of supervisory control [11]:

- **Energy Management Task (EMT):** Long term operation modes of the battery.
- **Power Management Task (PMT):** Short term power distribution decision of various power sources.

Potentially, the achievable fuel improvement of HEVs in the fuel economy range from 10% for mild hybrids to more than 30% for highly hybridized vehicles [12]. Sophisticated HCU with certain strategies are needed to realize this potential. HCUs of all PHEVs and HEVs utilize various input signals from other vehicle components and decide output signals with objectives of fuel economy, drivability, emission etc. As it is visible in Figure 2.2.1, there are lots of sub-controller for vehicle components. For example, human-machine interface with driver's demands, Transmission Control Unit (TCU), Engine Control Unit (ECU), Battery Management System (BMS), etc. These sub-controllers send components statues, all kinds of limitations and requests to HCU. With certain algorithm logic inside HCU, it can output target statues, response to the requests and vehicle state information for display.

On one side, many characteristics of HEVs HCUs have lots of overlap with PHEVs. For example, control strategies for HEVs and PHEVs can be all classified into: rule-based and optimization-based [12][16]. On the other side, as mentioned in 2.1, PHEVs are capable of all-electric driving within AER, which make zero emission possible. This added layer of operation makes the control strategies of PHEVs different from pure HEVs.

2.2.1 Battery Operation Modes in PHEVs

PHEVs usually have relatively large capacity batteries. How to maximize the potential of a high amount of electricity to better increase fuel economy must be addressed by HCU strategy. The SoC of the energy storage system (ESS) is usually used to influence the operation modes which are taken by HCUs. Nowadays, there are two SoC changing states in the long-distance range: Charge-Depletion (CD) and Change-Sustaining (CS). CD mode can be classified into pure electric vehicle (EV) mode or blended mode. But obviously, SoC depletes faster in EV modes since blended mode starts ICE in between. Various mode combinations compose common control strategies of PHEVs, as shown in Figure 2.2.2:

- **Pure electric drive mode within AER**: Since PHEVs have large size batteries and EM, the vehicle can be propelled electrically for a certain distance. This mode is trip distance dependent and will only be used within AER. In the situation where the size of battery capacity is increased, or the trip distance is reduced, the mileage (mileage of a vehicle is the number of miles that it can travel using one gallon or liter of fuel) of vehicle will increase, reaching a value of infinity when the distance is less than AER. Under this mode, SoC will decrease fastest [13].

- **CDCS strategy**: When the trip distance is larger than AER, CDCS is the most common strategy in PHEVs. The vehicle will first drive in electric drive mode and then shift to CS mode when SoC achieved a pre-defined value. So CDCS strategy sometimes is called EVCS as well. The trip distance where the vehicle drives in electric drive mode is exactly the AER. Under the CS trip segment, vehicle traction power is from ICE or hybrid, ICE and EM. But SoC variation band under CS mode is always narrow enough so that it can be considered that SoC is sustained in a long term. The CS mode continues until there is an external battery charge source. It's also noteworthy that ICE is allowed to start in EV mode range if the power demand is more than what battery and EM can provide maximumly [15].
- **Blended strategy**: This strategy means to deplete SoC throughout the whole trip. ICE will be started frequently in between to reduce the SoC depletion rate.

In most cases, engineers would like PHEVs to run out the electricity after a driving trip, where there is supposed to have an external charging source to offer electric energy for the battery again. In this case, more electricity is utilized, which means more fuel is saved.

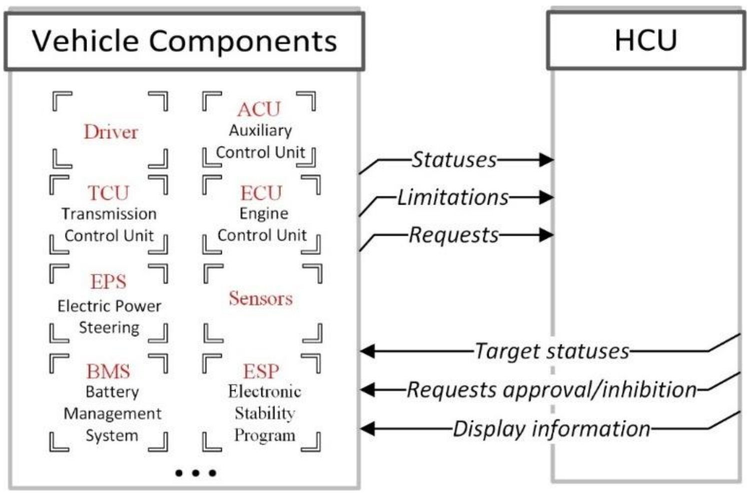


Figure 2.2.1: HCU utilizes various input signals from other vehicle components' sub-controllers and calculates output signals.

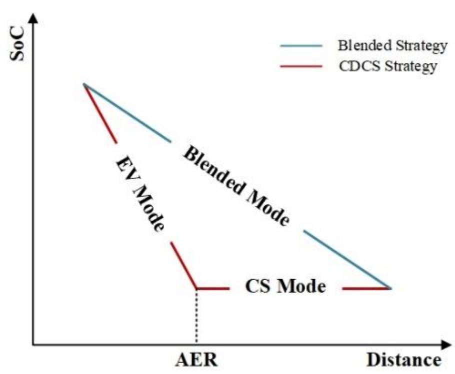


Figure 2.2.2: CDCS strategy and blended strategy of PHEVs

2.2.2 Rule-based Control Strategies

As mentioned before, control strategies can be divided into rule-based and optimization-based. Rule-based control strategies, also called heuristic-based strategies, are fundamentally consistent in the manner of producing output signals to the vehicle components sub-controller, based on a set of pre-defined rules [14]. These rules are usually designed based on heuristics, intuition, human expertise, experience or mathematical models without prior knowledge of the trip [17]. Nowadays, rule-based control strategies are still most commonly used due to their simplicity, low computational demand, real-time applications and good reliability. Under defined rules, look-up tables or simple logic, the vehicle can shift between various driving modes according to the current state of powertrain (e.g. SoC, speed, temperature, components limitation).

Rule-based control strategies can be further divided into deterministic and fuzzy rule-based strategies. Deterministic rule-based control strategies have all the pre-determined rules unchanged in real driving. The strategy calibration process accounts for behavior difference in various driving cycles. Since desired behavior differs under certain circumstances, it is obviously not always optimal for all the conditions.

PHEV system is a multi-domain, nonlinear and time-varying system [18]. Fuzzy rule-based strategies have more operation freedom compared to deterministic rule-based control strategies. Fuzzy logics have two advantages:

1) the solution to the problem can be cast in terms that human operators can understand, so that their experience can be used in the design of the controller [19];

2) Robustness to measurement noises and component variability with real-time adaption [20]. Rules can to some extent be modified in adaption methods based on future information, advanced algorithm or real-time traffic conditions [21][24], making fuzzy rule-based strategies get rid of typical drawbacks of rule-based strategies. However, fuzzy rule-based strategies are still strongly dependent on predefined rules and calibration processes.

2.2.3 Optimization-based Control Strategies

Due to all kinds of limitation in rule-based control strategies, optimization-based control strategies are developing continually. In these control strategies, output signals from HCU are calculated by minimization of a cost function representing all the desired optimization objectives. Optimization-based control strategies also need some rules defined in advance, but compared to the rule-based control strategies, they usually don't request strictly. The optimization cost function can balance the vehicle in various aspects and hard constraints on vehicle components are allowed. The optimization methods are classified into offline global optimization and online real-time optimization.

2.2.3.1 Offline Global Optimization

If optimization is implemented towards a whole driving cycle with power demands known in advance, a global optimal or sub-optimal energy management solution can be found. Offline global optimization (GOP) is 'non-causal' and has a heavy computation burden, and therefore has no ability to optimize the system in real-time. Simulated annealing, game theory, linear programming (LP), optimal control theory, dynamic programming (DP), stochastic programming (SP), genetic algorithms and particle swarm optimization (PSO) are several common methods to solve GOP [16][17]. With different solving methods, various optimum degree results can be computed. Generally, there are three main solution types [25]:

- **Static optimization** only optimizes strategy parameters of a rule-based energy management strategy with PSO, SP, etc.
- **Optimal optimization** formulates the energy management problem of HEVs as dynamic, nonlinear and constrained optimization problems. This type is usually solved by DP.
- **Simplified model approximation optimization** concludes HEVs control problems into a mathematical programming problem, such as quadratic programming (QP), where the problem is described as a quadratic function [26][27] and LP, where a non-linear system is simplified into a linear system.

Due to great simplification in first and third types, they don't offer optimal results even though all the future information is collected. But in another way, they are not only faster and easier to implement compared with the second type of GOP, but also still generally reveal benefits source once rough future power demands can be gained. In this case, they are good solutions for long (global) horizon prediction optimization, can better adapt to change of driving cycles in reality or even be used in real-time once for a while. Long-horizon prediction optimization is still not real-time, but they can modify the real-time controller online. For instance, Ref [28] used offline optimization to find the design routine for the online controller and an optimized rule-based controller was proposed.

The second type GOP in most case offers benchmarks for other casual control strategies because of its optimum results. Bellman's DP proposed in the 1950s [29] is the most widely applied solution for it. DP decomposes a dynamic optimization problem into a sequence of sub-problems by discretizing the original optimization problem over time - thus forming a cost-to-go function at each sample time [25]. The DP obtained accurate full knowledge of the future is also named deterministic DP (DDP). GOP with DDP not only offers an optimization direction for 'casual' real-time controller, but also reveals benefits mechanism. For example, the GOP showed the optimal feedforward power split control law corresponds to a real-time control design in ref [30]. Secondly, with the implementation of 'casual' online control strategies, lots of elements can account for their behavior difference in optimization objectives (e.g. with a same prediction-based control strategy of PHEVs, more detailed future information can bring more benefits in fuel economy). Based on this fact, GOP is also utilized as a tool to strictly compare and analyze all kinds of influence on vehicle behavior in desired aspects. Ref [31][32] used GOP to compare fuel economy and drivetrain efficiency between CV, HEV, PHEV. Ref [33] analyzed the influence and selection of charge depletion range with GOP. And the potential benefits were explored considering both fuel economy and emission in ref [34].

2.2.3.2 Online Real-time Optimization

Real-time Optimization, ROP approaches also formulate the control problem into a cost function and then use mathematic solutions to solve the minimum or maximum optimization. But unlike GOP, ROP obtains optimal solutions based on instantaneous or short-horizon cost functions. Obviously, for ROP is much less computation needed but the results are not globally optimal. For online real-time implementation, ROP is a good option.

The most well-known real-time optimization method is Equivalent Consumption Minimization Strategy (ECMS). ECMS was introduced by Paganelli in 1999 [35]. Except for the instantaneous optimal fuel consumption, the cost function of ECMS also takes instantaneous electricity energy into consideration. The instantaneous optimal control is based on the calculus of variations or Pontryagin's Minimum Principle (PMP) [36]. The battery energy is converted to the fuel energy by multiplying an equivalent factor. This kind of conversion makes sense, because the used electric energy currently is compensated with fuel in the future to some extent to charge the battery (recuperation can also be the case, but this is not generic to all trip conditions). Especially for HEVs, whose operation mode is usually charge-sustaining, the net overall electric energy flow of the battery is actually zero. For PHEVs, if the trip distance is out of AER, the more cost of electricity at first will bring in higher fuel consumption in the end. The instantaneous cost function of ECMS, also called the Hamiltonian function, is formulated as:

$$\min_t f(t) = m_{fuel,equiv}(t) = m_{fuel,ICE}(t) + \gamma(t) \cdot P_{ele}(t) \qquad (2.3)$$

Subject to: components constraints

$\gamma(t)$ is the equivalent factor, which defines the equivalence between fuel and electricity use, $P_{ele}(t)$ is instantaneous electricity power drawn or charged in battery. $\gamma(t)$ is the only parameter that needs to be tuned in ECMS. The change of $\gamma(t)$ can contribute to battery charge or discharge behaviour for each moment, and the overall $\gamma(t)$ trajectory obviously decides total fuel consumption. In this case, although ECMS is easy and direct to understand, the biggest problem during its implementation process is the tuning of $\gamma(t)$. The optimal initial value $\gamma(t_0)$ depends on the driving cycle, and ideally $\gamma(t)$ should adapt to real-time driving conditions itself. Therefore, simply to assume $\gamma(t)$ as a constant for a determined vehicle cannot lead to outstanding fuel economy behaviour. Based on that, adaptive ECMS is introduced, where $\gamma(t)$ changes in real-time according to certain rules.

2.2.4 Prediction-based Control Strategies

As simply mentioned in 1.3, future information can be used to modify current control variables. This part is about various prediction-based control strategies for real-time use. Hence, GOP is not introduced here in detail. The three main techniques to recognize future driving conditions are [37][38]: telematics-based prediction that uses information sources (e.g. GPS, ITS, GIS) to present speed, distance, slope, acceleration, etc.; statistic and cluster analysis-based prediction means to assume driving conditions in the future through historical driving parameters and current states; Markov Chain is mainly for stochastic process with Markov process theory defined as future condition that is dependent only on current state but independent of the past; artificial neural network as a kind of state-of-art method to predict information as well. The obtained prediction information can be used in different strategies. Here, several most commonly used strategies are introduced.

2.2.4.1 Model Predictive Control strategy

Model predictive control (MPC) strategy is an attractive method for solving constrained multi-input multi-output optimal control problem. ECMS is too short-sighted to gain global optimal results without any prediction function, while GOP has quite heavy computation effort and is dependent on prediction pretty much. MPC is then a good compromise between ECMS and GOP. Within a finite receding prediction window, MPC solves a time-finite optimization problem for each time instance. As shown in Figure 2.2.3, for current control variable $u(k)$, an optimization within the moving horizon window $(k+1, k+2, \dots, k+n)$ is calculated. To optimize vehicle response and behavior corresponding to certain control variables, a control-oriented vehicle model is implemented inside MPC, and MPC is therefore a kind of model-based control strategy. The results of optimization are n control variables $u(k+1), u(k+2), \dots, u(k+n)$ for next n time segments. But only the first output control variable $u(k+1)$ is applied. To sum up, MPC generally contains three steps [39]:

- Use of a vehicle model to predict future behavior or output over the prediction horizon;
- Minimize (maximize) cost function reflecting optimization objectives for a sequence of control variables;
- Apply the first control variable of the sequence to the plant.

This process is repeated by moving the horizon window one by one step forward. MPC also has the advantage to take all kinds of contradictory objectives into one optimization cost function (see Appendix 2). In most nowadays applications in hybrid vehicles, the simulation target is to minimize fuel consumption. The main idea behind is to influence the engine start-stop decision, modes selection and the optimum power split ratio in the corresponding driving environment of the controller.

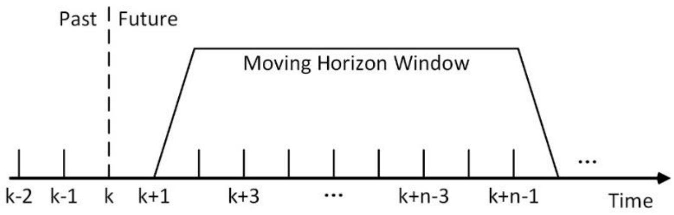


Figure 2.2.3: MPC moving horizon window

HEVs control problems are nonlinear and constrained problems. The most direct way for these problems is to develop MPC based on nonlinear dynamic models and nonlinear solvers. In this way, the MPC calculation accuracy can be promising, but the high computation effort makes it impossible for real-time implementation. So, simplification of MPC implementation, or with other words the trade-off between accuracy and real-time feasibility, is a huge topic for MPCs development. One method to solve the above problem is to linearize and discretize the model, so that cost functions can be formulated as quadratic functions. Then QP can be selected to solve the problem. In ref [40], with a novel velocity prediction method, QP was adopted to realize the rolling optimization. In ref [41], the cost function was formulated as a QP problem with a linear model and linear constraints. This is called a linear time-varying MPC (LTV-MPC). The LTV-MPC proved to achieve comparable results with a well-tuned controller [42]. Although this kind of simplification has advantages in simulation speed, further fuel economy improvement is desirable. Another kind of MPC that is easy to be implemented for real-time use is called explicit MPC (eMPC). This technique computes an optimal law or a set of function evaluations offline, which is stored in a state-dependent lookup table [43]. For eMPC, there is no need to use an optimization solver in real time, which significantly reduces computation time and satisfies limitations due to memory and computational power of automotive hardware. In ref [44], a near-optimal eMPC was firstly developed for a power-split Toyota Prius PHEV. The eMPC works well only for a system with fewer states, inputs and constraints. So, a quite easy control-oriented model was chosen although this power-split HEV is much more complicated than other series HEVs [45]. Aforementioned simplified MPCs (linear and explicit MPCs) fail to inspire most fuel economy potential of hybrid drivetrains. Therefore, lots of research were conducted as well to solve nonlinear model-based or even hybrid model-based MPC. Here DP is still a promising tool to solve the short-horizon optimization problem. To lighten the computation load, the dynamic characteristic of the vehicle can be neglected. A common and practical way is to take SoC as the only state variable, which results in a so-called 1-D static model. Relative implementations can be found in [46][47]. Another numerical computation method to solve the nonlinear MPC is the continuation and generalized minimum residual (C/GMRES). C/GMRES is used especially for the 2-D dynamic model to solve the MPC receding optimization problem. In Ref [48], an online iterative algorithm is developed based on C/GMRES for a dynamic power-split HEV model with speed and SoC as state variables. In ref [49], C/GMRES with forwarding difference approach is used to get the optimal battery power for a lower level controller. There are other solve methods for nonlinear MPC receding short-horizon optimization; e.g. in ref [50], a real-time distributed solution is presented in combination with a dual decomposition. The results show that the computational load is small and close to optimal in terms of fuel consumption; in ref [51], a PSO-based nonlinear MPC strategy is proposed and proved to decrease 10% in fuel consumption compared with CDCS strategies. More complicated procedures, like mixed-integer nonlinear programming (MINLP) is also possible to solve this problem [MINLP].

If taking certain discrete state, e.g. gear selection, engine start-stop decision, driving modes shifting into consideration, the optimal control problem will become a more complicated nonlinear hybrid control question [52], which can be expressed by a piecewise constant switching function $\sigma(t)$ [53]. Some creative MPC methods are conducted, e.g. in ref [1], the proposed algorithm solves a nonlinear hybrid optimal control problem, taking discrete decisions of gear choice and drive mode into consideration.

Above mentioned MPCs are classified according to the model type, because MPC is model-based. According to the prediction methods, they can be sorted into mainly two types: telematic-based MPCs, stochastic MPCs (sMPCs), learning-based MPC. The first type is easy to understand and commonly used because GPS, GIS, etc. devices are easy to access nowadays. sMPCs are proposed with a Markov chain model to prediction future information (e.g. required power). Markov chain combined with DP, which is so-called stochastic-DP is widely used in this type [54][55]. sMPCs can tackle the uncertainty that arises from the environment or the driver. The learning-based MPCs tend to use an artificial neural network for prediction of driving behavior and vehicle states change. Sometimes, the learning algorithm is only for partial prediction and another strategy is introduced for a whole MPC controller [56].

To sum it up, there are lots of MPC design works based on different model types or prediction methods. A variety of researches try to find an attractive trade-off between accuracy and real-time capability. But what is notable is that the real-time feasibility of MPC not only depends on vehicle models and solving methods, but also depends on prediction horizon length, discrete time sample and hardware conditions.

2.2.4.2 Predictive Adaption Strategies

When one or several parameters in ECMS or heuristic (rule-based) strategies are changing under certain online tuning process, these strategies are therefore adaptive.

This Section only introduces ECMS and heuristic strategies with adaptive parameters according to real-time prediction relative regulations.

As discussed in Section 2.2.3.2, battery equivalent factor $\gamma(t)$ is a tunable and significant value in ECMS strategy. To simply assume $\gamma(t)$ as a constant from the beginning to the end cannot lead to outstanding fuel economy behavior. A low $\gamma(t)$ favors the use of electricity and enables the system to deplete the battery. On the contrary a high value that marks high cost of electricity use might lead to higher fuel consumption and sustaining or SoC increase. Obviously, certaithe n relationship can be found between SoC change and battery equivalent factor. In HEV, researchers naturally find a method that adjusts the $\gamma(t)$ according to SoC target value. The SoC target in HEV is usually a constant number or narrow range due to the charge-sustaining operation mode in HEV [57][59]. As shown in Figure 2.2.4, between section 0-T, actual initial equivalent factor deviates from optimal a lot. The low value $\gamma(t)$ makes the battery to be discharged. Actual SoC would be far away from the sustaining level if there is no adaption process. On the contrary, if with adaptation to the value $\gamma(t)$, SoC can be kept around predefined nearly constant level [60]. Correspondingly, in the designs of ECMS for PHEVs, researchers try to find pre-defined SoC trajectories for the online tuning of the equivalent factor. For instance, in ref [61], a SoC trajectory is found by defining a mixed strategy between blended and CDCS strategies. The ahead 90% of first-time approximated distance implements a blended strategy where SoC changes linearly to the distance. If the actual distance exceeds this value, then charging sustaining is used. Another condition is that instead of using DP to directly search optimal $\gamma(t)$ of each time instant [62], the optimal SoC trajectory from DP calculation is followed by adapting the equivalent factor. Or like ref [63], that puts forward an offline pre-designed optimal $\gamma(t)$ map with DP, still at the same time a segmented SoC reference curve proposed dynamically according to the optimal SoC is followed. The control process based on the deviations from the defined SoC reference is called SoC feedback controller [60]. The most common feedback controller is (fuzzy) PI/PID controller [36, 58-61, 64].

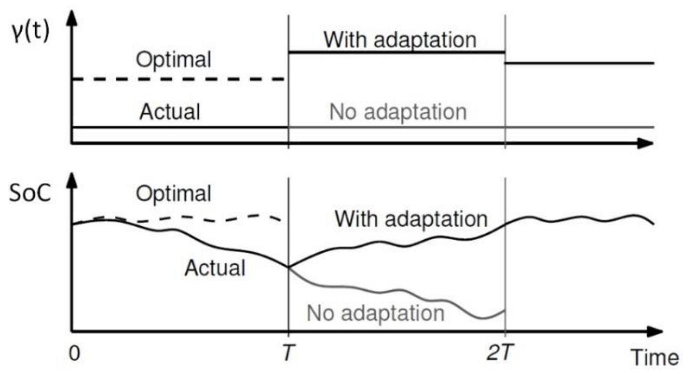


Figure 2.2.4: Adaptive ECMS concepts with SoC reference [60].

Although ECMS already discrete global optimization problem into each time instant, and adaptive ECMS in most cases can reach sub-optimal results, researchers still complain this group of strategies because they are too complicated and computationally intensive to be used in real-life applications. Lots of literary treats the proposed adaptive rule-based control strategies. Ref [66] takes DP to calculate optimal engine load points area and a recalibration method is implemented to improve the existing rule-based control strategy (as shown in Figure 2.2.5). Final Hardware-in-the-Loop (HIL) experiments show a reduction in both fuel and electricity consumption. Ref [67] presents an advanced rule-based modes selection strategy for a PHEV. DP is used to analyze the behavior of the optimal operating modes selection under various driving cycles and SoC values. Based on the conclusion, the machine learning method is adopted to create a predictive model control map for the existing rule-based control strategy. Ref [68] creates a blended rule-based control strategy for a PHEV. Figure 2.2.6 presents its working principle: with rough estimation regarding driving style and trip information in STAGE 1 and STAGE 2, energy demand can be estimated in STAGE 3. Adaptive part of this method is realized by calculating total available battery energy, with that control strategy is adjusted in real time in STAGE 4. Ref [11] introduces a PSO-based recalibration method that is developed for a rule-based control strategy. The recalibration method mainly tends to find a power demand threshold, under which pure electric drive is activated. The PSO-based recalibration process is not necessary to work in real time, while running offline (cloud computation) for each time sample is possible.

As discussed above, lots of literary works proved the feasibility and advantages of adaptive ECMS and adaptive rule-based control strategies. It's also inevitable that there are some drawbacks under different aspects. For adaptive ECMS, the fuel economy improvements rely too much on the offered SoC reference. There is actually no prediction process for the online use platform. ECMS is very sensitive to the change of the equivalent factor and its initial value at the beginning of trips. Unavoidably, adaptive ECMS cannot fit trip prediction deviations and real-time dynamic changes. As for the adaptive heuristic strategies, the aforementioned literary works provide information that only one parameter or one small part of the whole control models is adaptive online or offline. To sum it up, there is no general regulation that can be extracted from all of these analyzed adaptive rule-based strategies. Therefore, their universality towards drivetrain configurations and driving situations is not that ideal.

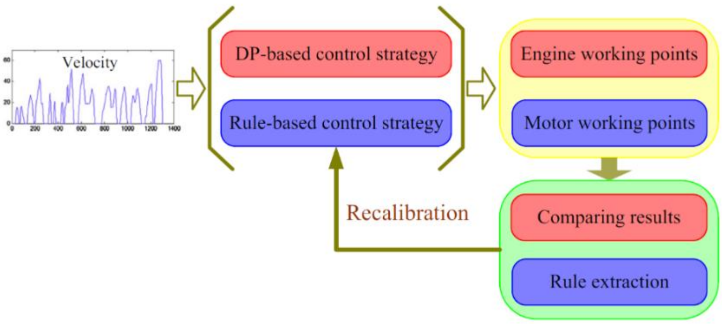


Figure 2.2.5: Optimization-based recalibration of the rule-based strategies [66].

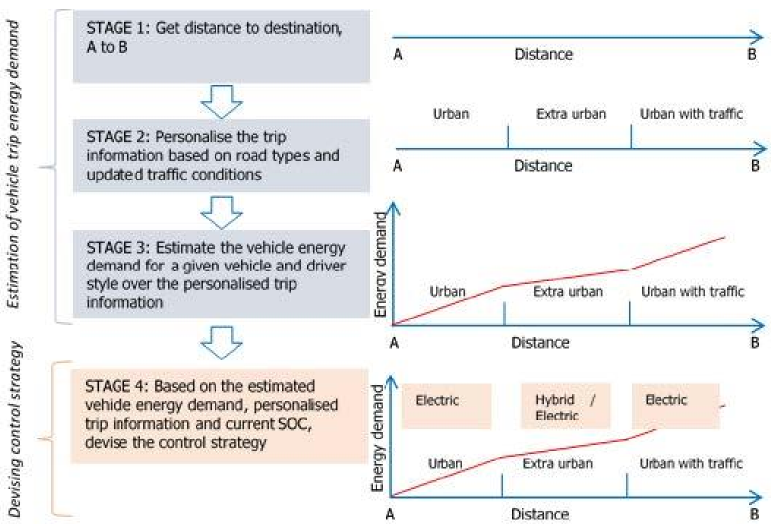


Figure 2.2.6: Working principle of the proposed blended rule-based control strategy [68].

2.2.4.3 Application of Offline Prediction Models

The existing P2-HCU of the present project is obviously real-time capable, which means it can solve the PMT and EMT problems online (here offline models mean these models whose calculation cannot be finished real time in actual vehicle hardware). In the area of prediction-based control strategies, offline models are commonly applicated as well. These offline models are in most cases designed for a quite long horizon even up to global horizon prediction. Due to the explosive increase of information and calculation effort towards a quite long distance, these offline long horizon models always suffer heavy computation and therefore they are unfeasible on online platforms. Nevertheless, predictive online models like MPCs are even too short-sighted, don't even mention predictive adaption ECMS or rule-based control strategies. It is also straightforward that local optimization never leads to globally optimal results. Based on these cognitions, offline prediction models, that means long horizon prediction models, always appear in combination with the online prediction control models. One method to utilize the information from offline models is to create maps before the start of a trip. This application is commonly used with deterministic global optimization, which offers an optimal solution but is only suitable for a boundary condition - fixed situation. Another limitation for this offline deterministic global optimization is that accurate information for a whole trip is not available in reality. Nowadays, cloud computation offers a brand new possibility of offline models. Since future information of the whole trip is hard to obtain at the beginning of a trip, offline long horizon calculation models can update themselves in the cloud computing platform, leading to correct information prediction and recalculation for certain time segments.

The interface between offline long horizon models and online models can be detailed by control strategies directly. If the long horizon prediction process is accurate enough, of course researchers will see improved behaviors in the online simulation. However, as mentioned above, it's not advisable to rely on the prediction too much. Online control models should always have some freedom to adjust actual PMT solutions. Instead of direct control solutions, a SoC reference trajectory is the most common interface between offline long horizon models and online models. There is no prediction in these online models (e.g. ECMS), short horizon prediction (e.g. MPC) or quite simple long horizon prediction (e.g. trip traffic segments, traffic lights, distance). These online models have the ability to face dynamic deviations. The way to combine offline long horizon prediction models with online models through a long term SoC reference trajectory is named 'two-stage control architecture' [11]. As shown in Figure 2.2.7, global energy management is the long horizon calculation model, local power management is the online models, SoC_{ref} is the value taken from SoC rethe ference trajectory for each time instant. Overall prediction-based control model (supervisory control system in Figure 2.2.7) is comprised of an offline long/global horizon model (global energy management in Figure 2.2.7) and an online model (local power management in Figure 2.2.7).

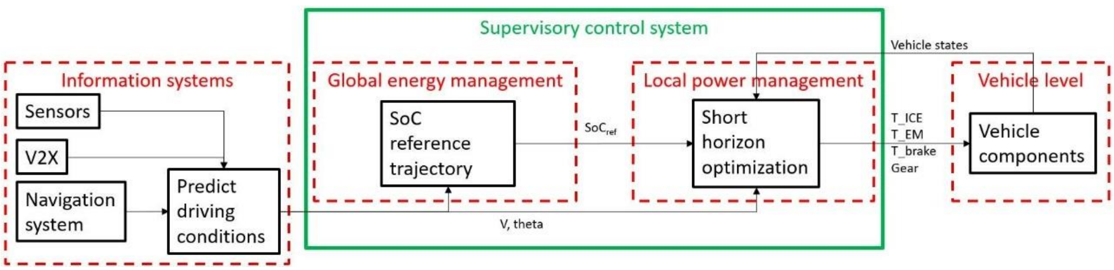


Figure 2.2.7: Two-stage control architecture with SoC reference trajectory as interface [11].

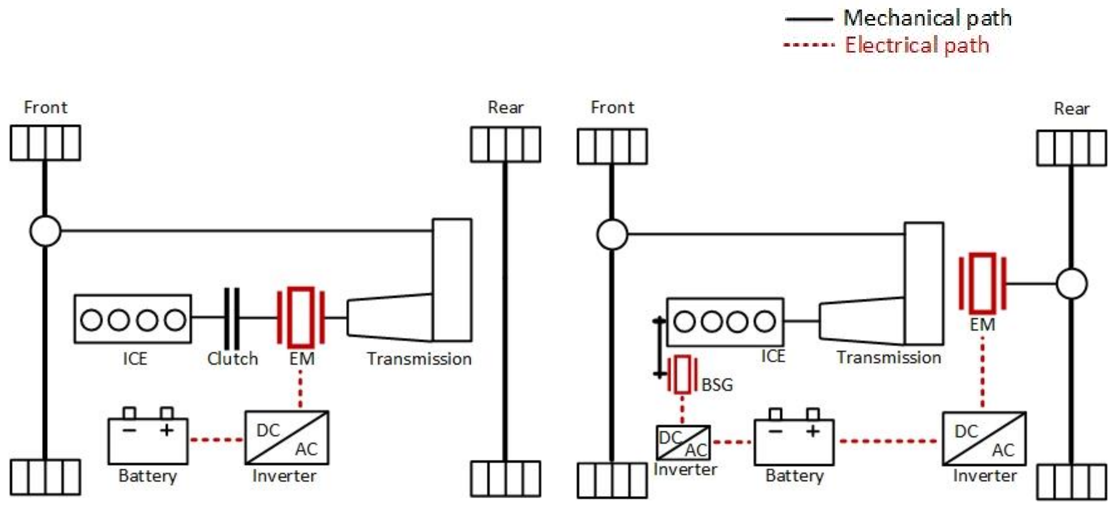
2.3 Preliminary

This part is to clarify the basement and further motivation of the thesis under consideration of the above mentioned literary research and discussion of potential methods.

2.3.1 P2, P4 PHEVs

As mentioned in Section 2.1, PHEVs are one type of vehicles with alternative propulsion, which has some special advantages. In the present work, there are a P2 PHEV and a P0+P4 PHEV (simplified as P4 in the following part) existing as reference configurations. The topologies of them are shown in Figure 2.3.1. As discussed in A 1.3, P4 PHEV combines the benefits of P0-P4 configuration. Compared to P2 PHEV, although P4 PHEV is more complicated and costlier, ICE is more possible to work on optimum load points. This is because (Belt Driven Starter/Generator) BSG is not in the driveline, it's freer to offer an electric boost for ICE or generate electricity with redundant energy from ICE to charge the battery. The load points of single EM in P2 PHEV are limited to some extent to avoid influence on vehicle drivability and safety.

In the baseline of the project, the two HCUs for P2 and P4 (simplified as P2-HCU and P4-HCU) all adopt conventional CDCS without prediction. CDCS is easy to design and has a low computational burden. Nevertheless, blended operation mode, which allows to gradually deplete battery for the whole trip, reaching SoC lowest boundary, turns to be much more optimal in fuel economy [69-72]. It's not difficult to find out that the adoption of blended mode needs information about future driving circumstances. For instance, trip distance should be available to know where SoC can reach the lowest boundary. A perfect blended operation mode is to distribute electric energy from the perspective of the whole trip. Electric drive covers all the relatively low power demand road segments with a constraint of running out the battery from beginning to the destination. The rest of the road segments driving modes are engine-dominated, which means that ICE is always on but only works on optimal load points with electric boost or optimal generation. The perfect blended strategy is not realistic because whole trip information is rarely available and the global optimization problem is impossible for real-time use. Nevertheless, prediction-based control strategies are still more attractive compared to conventional CDCS and sometimes closer to optimal behavior. All in all, prediction-based strategies are worthwhile to explore most fuel economy potential of existing P2 and P4 PHEV.



(a) P2 PHEV (b) P0+P4 PHEV

Figure 2.3.1: P2 PHEV and P0+P4 PHEV topology

2.3.2 Existing HCUs

The two existing HCUs stem from standard automotive applications (offered by AVL), both generally have following sub-models inside:

- **Observer** model receives all the signals from vehicle components controller (e.g. ECU, TCU, as shown in Figure 2.2.1) and does some simple calculations.
- **Torque (power) demand calculation** model determines necessary traction torque (power) needed from powertrain components, including driver demand, cruise control demand, vehicle stability, etc.
- **Torque (power) distribution** model implements core decisions regarding PMT and EMT. P2-HCU and P4-HCU employ torque (power) distribution in different ways. The former selects optimum driving modes while the latter calculates the power split ratio. Although there are some relationships between driving modes and power split ratio, a particular design is needed in the prediction-based model design for P2-HCU.
- **Engine start/stop management** model decides to start or stop ICE after torque (power) distribution decision. All kind of constraints, e.g. clutch state, SoC value, temperature, are regarded. Due to the difference in power distribution decision in P2-HCU and P4-HCU, there are two matching engine start/stop management models individually for them.
- **Dynamic control model** mainly takes care of coordinated dynamics of the requests and seamless transitions between each state.

An overview of P2-HCU and P4-HCU configuration comparison is presented in Figure 2.3.2. Basically, they have a similar structure. Different parts lay on torque distribution models and the corresponding engine start/stop management models. As shown in Figure 2.3.2, P2-HCU selects mode and has output variables as demanded ICE, EM torque (green part) and speed. P4-HCU calculates power split ratio and controls torque and speed of ICE, EM and BSG (blue part). Model-in-the-loop (MIL) tests of HCUs also ask for input definition stimulation where all the boundary conditions are defined e.g. speed, road inclination, environment temperature, initial SoC value, and plant model, which offers a high-fidelity vehicle model. It's not advisable to develop totally new prediction-based HCUs, while prediction-based control models, which just influence the output of torque (power) distribution model, are sufficient enough. Simulations and comparisons are conducted for newly developed of prediction-based HCUs and existing HCUs. Due to technical reasons, an online simulation of P4-HCU is temporarily impossible, thus all the following work is going to be finished in P2-HCU. The thesis will also discuss theoretical differences between them and the final created methods that should be able to easily be changed to suit P4-HCU as well.

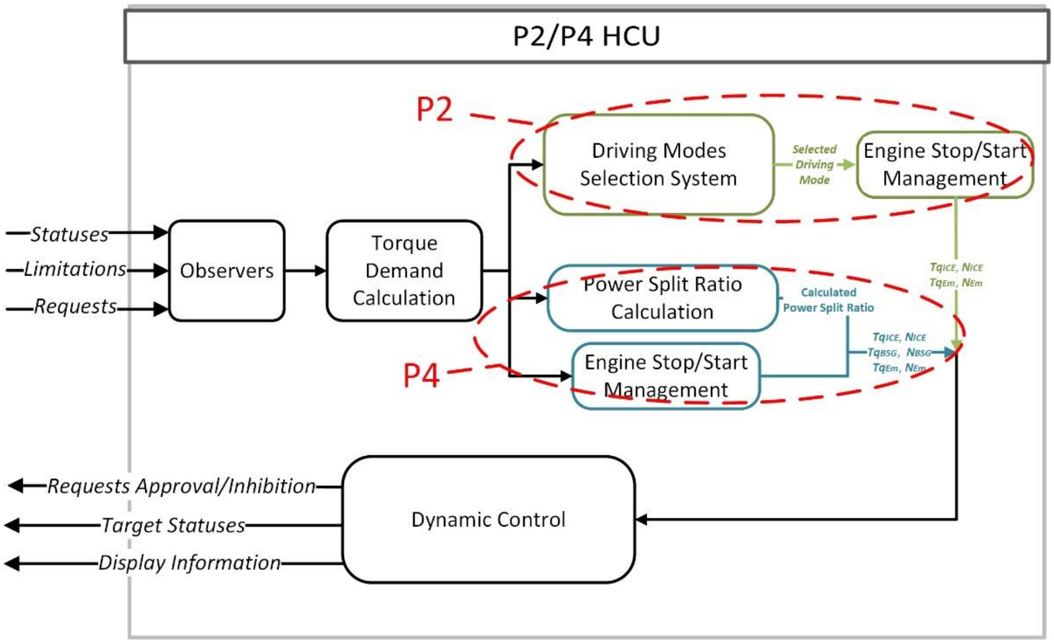


Figure 2.3.2: Overview of P2-HCU and P4-HCU configurations comparison

2.3.3 Further Problem Statement

The ultimate research objective was proposed in Section 1.4: improve PHEVs overall fuel economy behavior by implementing predictive models into one of the HCUs, which will influence its existing power distribution decision. The developed method should be compatible with two existing HCUs. This Section is to select appropriate prediction-based strategies and solving solutions for the ultimate objective. The precondition of this thesis is that trip distance is longer than AER, where predictive control strategies are not trivial anymore.

Predictive strategies adopted in this thesis can be classified into offline and online strategies. The offline GOP, discussed in 2.2.3.1, have a prior of the whole trip. GOP with DDP as solving solution is an excellent tool to analyze why information prediction improves overall fuel economy. And fuel consumption results from GOP are also benchmarks for online simulation results, which reveal the potential of online strategies. GOP with DDP as the solving solution is implemented in this research to better design the online controller. Another kind of offline models created in this work is global horizon prediction models. Global horizon here means to extend long horizon to the whole trip, but the information obtained inside these global horizon models can be estimated or simplified prediction information. Definitely, these global horizon models' outcomes are not optimal and still unfeasible in vehicle local hardware. They are assumed to run in cloud platform and only output SoC_{ref} values to online control models.

P2-HCU selects driving modes for torque distribution of each time sample. As said in Section 2.2.4.1, driving modes shifting decision is a discrete optimization problem and leads to a hybrid vehicle model. The hybrid control problem needs to solve modes shifting time, shifting numbers, modes sequence. However, optimization-based including GOP strategies are unable to solve the issue, which can be applied to the P4-HCU since power split ratio can be a continuous control variable. (Adaptive) Rule-based control strategies are the easiest way. For instance, in the thesis work of Jonathan, another master student, a 'rating and weighting' (R-W) method for the P2-HCU was developed [73]. This R-W method is compatible with the hybrid control problem and is theoretically quite close to adaptive-ECMS without constraints. But it has some common drawbacks as shown in Section 2.2.2, e.g. no strict constraints, too many rules, complicated calibration and tuning process, etc. Furthermore, R-W method is unable to be used in P4-HCU later. As a result, this research decides to create an optimization-based control strategy for the P2-HCU. Adaptive-ECMS will not be developed in this thesis because similarity with R-W and less optimality compared with MPC. The relationship between driving modes and power split ratio is deliberated and an DDP-based algorithm is designed to switch discrete driving modes into continuous variables. The DDP-based solver can be used for GOP that finds optimal results and a MPC model is proposed, which is shown to be a promising advanced optimal-close method for supervisory control problem. Real-time implementation of MPC turns to be a huge topic and can be even extended to another research topic. This thesis is going to simply accelerate simulation speed with proper tuning of some key parameters (e.g. prediction horizon). At the meantime, drivability and comfort objectives will be taken care inside online MPC instead of being sacrificed too much due to fuel economy targets. This prediction and optimization-based GOP and MPC can be easily transformed for P4-HCU use. The existing R-W strategy will be modified and discussed in the thesis as well. To sum up, the thesis includes the following main steps:

- Control-oriented model development and validation in Chapter 3.
- DP-based solver creation, offline global optimization calculation and analysis in Chapter 4.
- MPC model design, R-W modification and their integration with the existing P2-HCU under Simulink environment in Chapter 5.
- Simulation and results analysis in Chapter 6.

Chapter 3 Vehicle Control-oriented Model

For the present investigations, a basis simulation model was provided by the industrial partner. The high-fidelity model existing in the plant is detailed at a high level. With this detailed and accurate model, various HCUs behavior can be compared and evaluated under Model-in-the-Loop (MIL) simulation. In this way, the provided plant model is an excellent basement for prediction-based HCUs simulation and analysis performed in the course of the present master thesis project.

As mentioned in the last chapter, MPC is model-based and therefore it needs a vehicle model for prediction of system response to control variables and environment variations. This vehicle model for predictive control is a so-called control-oriented model. Existing high-fidelity (plant) model and HCU consider vehicle dynamic characteristic. Vehicle behavior during transient driving is also modeled, e.g. gear shift process, ICE intake and exhaust systems. The dynamic model (or 2-D model) is not ideal for online MPC model use, because it brings huge computational burden and needs complicated numerical solving solutions (e.g. C/GMRES introduced in 2.2.4.1). To compare fuel economy results of various HCUs, fuel consumption of ICE and electric energy state of battery should be noted while dynamic characteristics can be ignored. For a control-oriented model, a quasi-static model (1-D) is sufficient enough to maintain the vehicle physical causality [12][69].

Because following predictive strategies are created for P2-HCU, in this chapter, a quasi-static vehicle model is created for the P2 PHEV. It will be validated to have sufficient accuracy in energy consumption estimation compared to high-fidelity vehicle plant model. Moreover, various driving modes on P2 PHEV are introduced in the end.

3.1 Vehicle Parameters

The vehicle topology is shown in Figure 2.3.1(a). All the parameters of the investigated P2 PHEV for the following components models are supplied by AVL. Some important parameters are listed in Table 3.1.1.

Table 3.1.1: Components parameters of the P2 PHEV model

Vehicle total mass	1750 kg
Vehicle frontal area	2.35 m*m
ICE maximum power	102 kW under 5500 rpm
EM maximum power	94 kW
Battery capacity	14.7 kWh
Battery nominal voltage	350 V
Battery useable SoC range	20%-95%
Transmission	7-speed dual-clutch

3.2 Components Models

3.2.1 Longitudinal and Drivetrain Models

With the longitudinal model, the future power demand can be calculated with some prediction information. The force analysis of vehicle longitudinal model is shown in Figure 3.2.1.

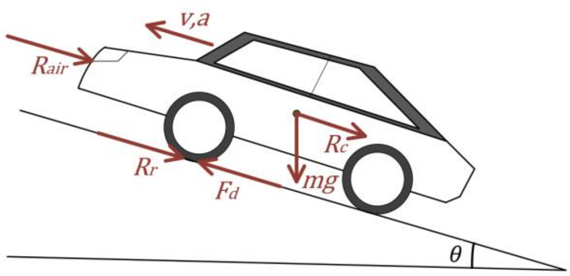


Figure 3.2.1: Longitudinal model force analysis

F_d equals to the sum of resistive forces: aerodynamic drag R_{air}, rolling resistance R_r and the force of the road inclination. R_c is the sum of all the inertial forces. v is vehicle velocity, a is acceleration. The power demand P_d can be given by:

$$P_d = (R_{air} + R_r + mgsin\theta + R_c) * v \tag{3.2a}$$
$$= \left(\frac{1}{2}\rho AC_d v^2 + mgcos\theta C_r * sign(v) + mgsin\theta + m_{ine} * a\right) * v \tag{3.2b}$$

ρ is the air density, A is the frontal area, C_d is the aerodynamic drag coefficient, m is vehicle mass, C_r is rolling resistance coefficients, m_{ine} is generalized vehicle mass and θ is the inclination angle, v is the current vehicle speed.

As for the drivetrain model, the friction loss of the complete drivetrain is dependent on rotational speed, torque and actual gear. Since gear selection is automatically decided by the transmission control unit (TCU), gear selection optimization problem is not discussed in this research. The thesis just selects a group of proper and reasonable gear numbers for all the simulation and calculation), that is:

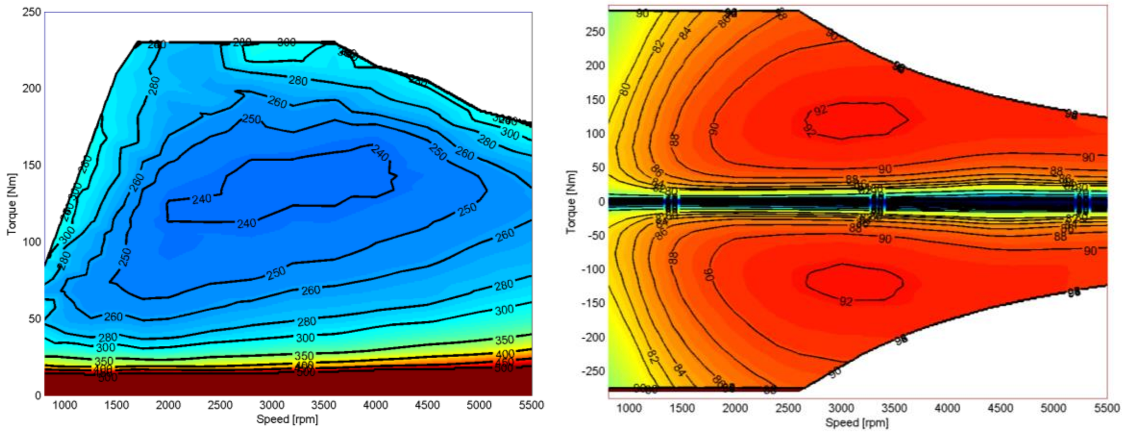
$$T_{loss} = f(\omega_{driv}, T_{driv}, G_{driv}) \tag{3.3}$$

3.2.2 ICE and EM Models

The fuel consumption characteristics of ICE, $m_{fuel,ICE}$, is decided by engine rotational speed and torque. The information is described in a 2-D MAP, which is usually called brake specific fuel consumption (BSFC) map. Similarly, the efficiency of inverter and EM, τ_{EM}, is calculated based on EM rotational speed and torque according to a 2-D MAP. These two 2-D MAPs are shown in Figure 3.2.2. And the equations are:

$$m_{fuel,ICE} = f(\omega_{ICE}, T_{ICE}) \tag{3.4a}$$

$$\tau_{EM} = f(\omega_{EM}, T_{EM}) \tag{3.4b}$$



(a) ICE BSFC [g/kWh] (b) EM and inverter efficiency [%]

Figure 3.2.2: ICE BSFC MAP, EM and inverter efficiency MAP

3.2.3 Battery Model

Thevenin-based model is more applicated in hybrid powertrains [74] and is sufficiently accurate. The Thevenin-based equivalent electric circuit configuration is shown in Figure 3.2.3.

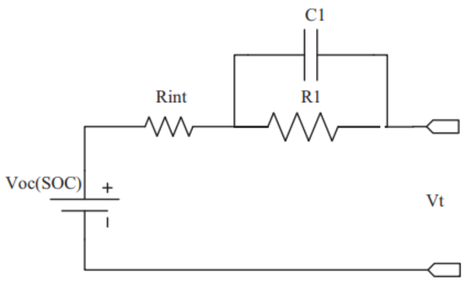


Figure 3.2.3: Thevenin-based equivalent electric circuit configuration [74]

The model consists of open-circuit voltage (V_{oc}), internal resistance (R_{int}), over-voltage resistance (R_1) and a capacitor (C_1). All parameters are related to the SoC, whose variations are calculated by the integration of the battery current (I_{Bat}). Q_0 is the nominal battery capacity, R_{in} is the resistance altogether. For the sake of battery health, there is a minimal and maximal boundary of SoC: [20%, 95%].

$$\Delta SoC = -\frac{1}{Q_0} I_{Bat} * \Delta T \tag{3.5a}$$

$$I_{BAT}(k) = \frac{V_{OC} * SoC - \sqrt{V_{OC} * (SoC)^2 - 4R_{in} * SoC * P_{EM}}}{2R_{in} * SoC} \tag{3.5b}$$

3.3 Driving Modes in P2-HCU

Several following hybrid modes are defined for P2 PHEV. The P2-HCU has a model to generate the quasi-stationary request for ICE, EM and drivetrain configuration. These requests are calculated in parallel for each hybrid mode. All the modes are shown as follows:

- **Conventional Drive (**ConvDrv**):** ICE is the only propulsion source.
- **Additive Boost (**AddBoost**):** This mode can satisfy driver demand when the demanded traction torque exceeds maximum ICE torque under current engine speed. It is notable that AddBoost can be enabled within AER, where the PEHV initially intends to drive electrically. Under AddBoost, EM works as torque reserve without downshifting the ICE.
- **Substitute Boost (**SubBoost**):** This mode doesn't exist in the actual P2-HCU, but it's actually a kind of common driving mode. When the demanded torque is relatively high, part of torque is going to be offered by EM, thus ICE can work on optimal efficient position without upshifting load point.
- **Optimum Generation (**OptmGentn**):** OptmGentn increases ICE load point to a more fuel economy position under the same speed. EM works as a generator for battery re-charging with leftover energy from the ICE.
- **Minimum Generation (**MinGentn**):** MinGentn is designed for battery health. It can keep SoC above a lower threshold. ICE creates more energy than driver demand, EM works as a generator to charge high voltage battery and prevent too deep depletion.
- **Idle Generation (**IdleGentn**):** When the vehicle is standing still and SoC drops below a lower SoC threshold. The ICE idles and charges the battery through EM. No power is transferred to the wheel.
- **Electrical Drive (**EltlDrv**):** Here EM is the only source of propulsion. EltlDrv is the most commonly used mode in PHEV. The battery offers propulsion energy, therefore SoC decreases quickly under this mode. The ICE is turned off, or at least not connected via the clutch. Electric creep for low velocities range is included in this mode as well.
- **Recuperation (**Recup**):** This function regenerates mechanical brake energy into electric energy by putting EM into generator mode. Thanks to a large capacity battery and a large size EM in this P2 PHEV, most recuperation energy can be utilized to charge the battery.
- **Stop/Standstill:** Vehicle's stop state is defined as that vehicle is not moving and ICE is turned off. The main functionality is to enable ICE stop and EM speed control at standstill, which activates a transmission oil pump for dual clutch transmission (DCT) control.

It's not difficult to find that, under generation modes (OptmGentn, MinGentn and IdleGentn), EM always works as a generator by taking energy from ICE to charge the battery. However, MinGentn and IdleGentn are only selected when SoC is under a certain low threshold. Compared with OptmGentn, these two emergent generation modes cannot promise ICE to work on efficient load points. Two emergent modes are probably selected when the trip distance is close to AER or out of AER. For boost modes (AddBoost and SubBoost), EM and ICE cooperate to offer total traction torque. The difference is that under AddBoost, ICE works on maximum torque setpoints, while in optimal torque setpoints under SubBoost. Without regard to negative or zero demanded torque trip ranges, ConvDrv, EltlDrv and OptmGentn are most frequently selected. And an optimal sequence selection of these three modes can lead to optimal fuel economy behavior of the P2 PHEV.

3.4 Model Validation

Although control-oriented models can put vehicle dynamic characteristics aside, its accuracy of static energy consumption estimation will still influence the optimality of predictive control strategies. The ultimate target of prediction-based control strategies is to maximize fuel economy, which means fuel consumption of ICE should be simulated accurate enough. Furthermore, SoC change to some extent reveals energy consumption conditions and SoC is the only state variable in this quasi-static model. So, cumulative fuel consumption and battery SoC are the key variables of interest and thus require the highest prediction accuracy. Validation results will mainly be evaluated regarding these two aspects. To calculate SoC change and fuel consumption accumulation trajectories, two main inputs are needed: trip information (speed time series, road gradient time series) and a sequence of selected driving modes. In this part, the high-fidelity model is used to evaluate the developed control methods, which has been extensively tested and validated on the actual real-world vehicle. To fairly compare the control-oriented model and high-fidelity model, same inputs to vehicle model are applied.

By applying parameter fitting to minimize the errors between the control-oriented and high-fidelity model and focusing on the general trends and steady-state behavior of the fuel consumption and battery SoC, highly accurate predictions with respect to the fuel economy of the vehicle can be achieved. How fuel consumption and SoC change are estimated by this control-oriented model is shown in Figure 3.5.1. With trip information, the longitudinal model calculates torque demanded in the wheel side ($Tq_{d,wheel}$), after drivetrain model torque demanded in crankshaft ($Tq_{d,crank}$) is known. With another input selected mode, detailed torque distribution between ICE and EM decision is made. Demanded torque from ICE side (Tq_{ICE}) and EM side (Tq_{EM}) are used in Engine model and EM/Battery model. The final outputs of this process are SoC change trajectory and fuel consumption accumulation condition.

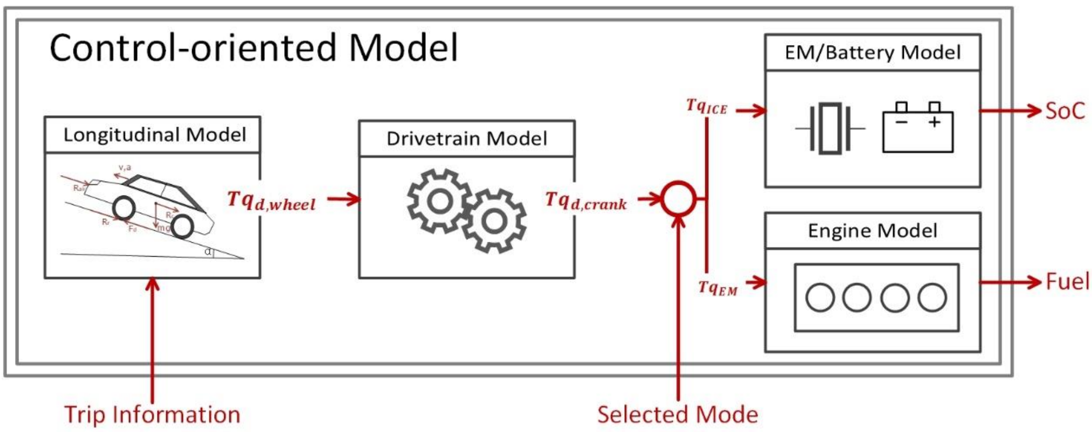


Figure 3.4.1: Control-oriented model to estimate fuel consumption and SoC change

A driving cycle commonly represents a set of vehicle speed points versus time. It is used to assess fuel consumption or pollutants emission of a vehicle in a normalized way. There are two kinds of driving cycles, modal cycles (e.g. NEDC) and transient cycles (e.g.

FTP-75). The driving cycle used here for the validation is the NEDC cycle. The NEDC cycle, as a modal cycle, is more compilation of straight acceleration and constant speed periods thus can help to reduce energy consumption differences caused by too many transient processes. AER of the considered P2 PHEV is 64 km in the NEDC cycle. A single NEDC cycle has a distance of 11 km. Therefore, 6-repeated NEDC (6-NEDC) are simulated so that the battery can be depleted from full to empty. The velocity profile of 6-NEDC cycle is shown in Figure 3.4.2.

The validation method is to run existing P2-HCU simulation with the 6-NEDC driving cycle at first. Then a sequence of driving modes selection is extracted (with 1s time sample), which should mainly follow CDCS strategy predefined in the existing P2-HCU calibration file. 6-NEDC cycle information and the sequence of extracted driving modes are then implemented into the created control-oriented model. To evaluate SoC and fuel consumption estimation function of the control-oriented model individually, two scenarios are used. The first one is to run the 6-NEDC cycle with full battery (95% SoC), and then to run the 6-NEDC cycle with empty battery (20% SoC). The SoC depletion trajectory comparison with full battery and fuel consumption accumulation comparison with empty battery are shown respectively in Figure 3.4.3 and Figure 3.4.4. From the sake of the whole 6-NEDC cycle, SoC and fuel consumption difference are ignorable. The more objective comparison is displayed by two different trajectories, which is calculated in this way: calculation results of the control-oriented model deduct simulation results of the existing P2-HCU. In Figure 3.4.3, it can be found that the SoC difference oscillates between -0.3% to 0.2%. In Figure 3.4.4, fuel consumption difference changes between 50 mL to 30 mL, which is maximumly 1.1% percent of the total fuel consumption (around 4500 mL). Sudden dynamic transient activities, e.g. acceleration, deceleration or gear shift, or some parameters simplification could lead to the differences. But they are all in an acceptable range. Based on these comparisons, it is concluded that the applied control-oriented model is accurate enough and can be used in the following chapters.

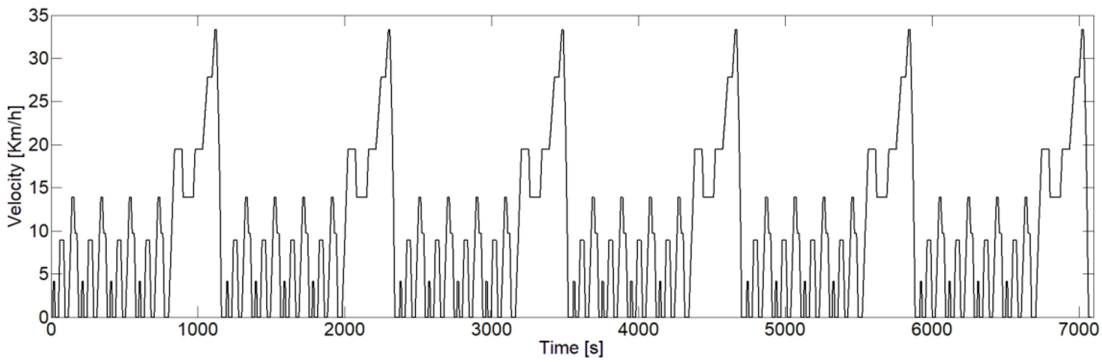


Figure 3.4.2: Velocity profile of the 6-NEDC driving cycle.

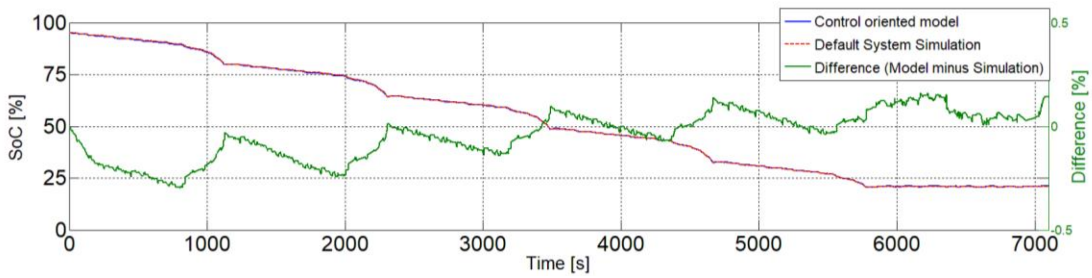


Figure 3.4.3: SoC depletion trajectories comparison with a full battery in the 6-NEDC cycle.

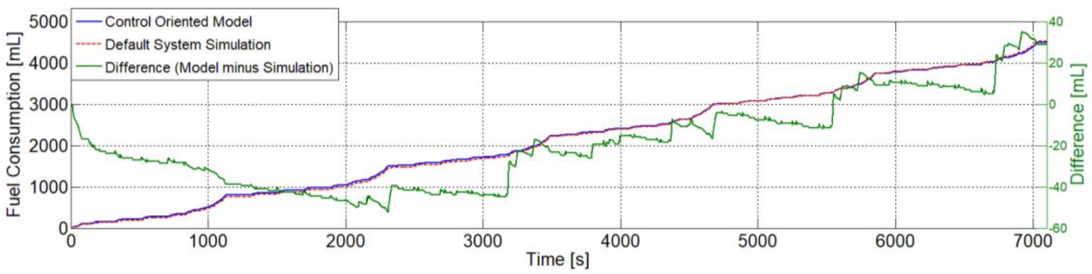


Figure 3.4.4: Fuel consumption accumulation comparison with an empty battery.

Chapter 4 GOP with a DDP-based Solver

As discussed in Section 2.2.3.1, GOP requires to know information about the whole (future) driving cycle. A long-horizon prediction covers all trip distances that are demanded. Even though, global optimization is not always capable to deliver an optimal solution. Several reasons account for it: 1) accurate future information for a whole driving range is rarely available; 2) there are some model simplifications or static methods implemented, as mentioned in Section 2.2.3.1; 3) the solving solution is not deterministic; stochastic DP is a classic example. The GOP implemented in this Chapter is based on a quasi-static vehicle model created in Chapter 3, with a DDP-based method to solve the mathematical optimization problem. The calculation result of this GOP is quite close to the theoretically best power distribution solution, which can reveal benefits mechanism of predictive strategies and offer an upper benchmark for online prediction-based models.

The P2-HCU has to decide driving modes for each time sample. Unlike P4-HCU, which provides a typical continuous optimization problem, this kind of hybrid discrete optimal control is hard to solve. One method is to convert driving modes selections into the power split ratio calculation. Based on this idea, a DDP-based solver, especially for this P2 PHEV, is designed in this Chapter. With the GOP solution, predictive strategies benefit mechanism analysis and initial SoC value influence on fuel economy improvement analysis are executed. All the work in this Chapter is finished offline within Matlab.

4.1 DDP-based Solver

4.1.1 DDP

DP, dynamic programming is a numerical technique that can be applied to any problem that requires decisions to be made in stages with the objective of finding a minimal penalty decision pathway [75]. DP asks for an underlying discrete-time system and a cost-to-go function that is additive over time and initialized at the final time step, which is described as [76][77]:

$$x_{k+1} = f_k(x_k, u_k),\ \ k = 0, 1, \ldots n-1. \tag{4.1}$$

$$g = g(x_n) + \sum_{k=0}^{n-1} g(x_k, u_k) \tag{4.2}$$

$$\underset{u(k)}{Minimize}:\ \ g = g(x_n) + \sum_{k=0}^{n-1} g(x_k, u_k) \tag{4.3}$$

k indexes discrete time; x_k is the state variable; u_k is control variable. In DP calculation, the overall optimization problem, defined as (4.3), is discretized into n sub-optimization steps, and a sequence of optimal control variables, $\pi = \{u_0{}^*, u_1{}^*, \ldots, u_{n-1}{}^*\}$, is found

based on the principle of optimality. The principle of optimality is created by Bellman, who contributed to the popularization of DP and its transformation into a systematic tool [77]. The principle states a rather obvious fact: an optimal policy has the property that whatever the initial state and decision are, the remaining decisions must constitute an optimal policy with regards to the state resulting from the first decision [78]. In this work, only a deterministic problem is considered, which means that there is no stochastic uncertainty. A backward deterministic DP developed in ref [79] is applied. Generally speaking, DP works in several main steps starting from the final state:

1) Define boundary conditions: initial and final state variable, discrete steps number and grid.
2) From step n-1 to n-2, calculate and compare step costs of each control variable option. Save minimum costs into the cost-to-go function and record this outstanding control variable $\boldsymbol{u_{n-1}}^*$.
3) According to the principle of optimality, $\boldsymbol{u_{n-2}}^*$ can be found by minimizing the cost-to-go function from step n-2 to n-3, instead of starting from finthe al step n-1 again.
4) The same process is conducted until reaching to the initial state. $\boldsymbol{u_0}^*, \boldsymbol{u_1}^*, \dots, \boldsymbol{u_{n-1}}^*$ are all found, and cost-to-go function value is the ultimate answer for the overall optimization in (4.3).
5) Run one-time forward from the initial step, DP implements the sequence of optimal control policy $\boldsymbol{\pi} = \{\boldsymbol{u_0}^*, \boldsymbol{u_1}^*, \dots, \boldsymbol{u_{n-1}}^*\}$ into the system model, which is found though backward calculation. Overall optimal state change trajectory and cost accumulation trajectory is exported.

For the vehicle quasi-static system, SoC is the state variable. Control variables are power split ratio in P4 PHEV and driving mode in P2 PHEV. For global fuel consumption minimization, the discrete-time PHEV system and overall optimization problem are described as formula (4.4) and formula (4.5). Control policy regarding power split ratio (driving mode) needs to be found under various constraints from each component. The thesis assumes that the destination of the driving cycle is known in advance. Among these constraints, (4.6a) - (4.6e) need to be satisfied all the time. (4.6f) is a constraint for the final SoC value and (4.6g) is the boundary defined for SoC value at the beginning (SoC_{init}). Ideally, for a driving cycle out of AER, SoC should change from maximum SoC_{max} value (95%) to minimum SoC_{min} value (20%) in the end. Here in GOP calculation, SoC_{init} is set as 95%, $SoC_{n,min}$ is 20%, $SoC_{n,max}$ is 21%.

$$SoC_{k+1} = f_k(SoC_k, u_k),\ k = 0,1, \dots n-1. \tag{4.4}$$

$$\underset{u(k)}{Minimize}:\ \ m_{fuel} = \dot{m}_{fuel}(SoC_n) + \sum_{k=0}^{n-1} \dot{m}_{fuel}(SoC_k, u_k) \tag{4.5}$$

$Subject\ to$:

$$T_{ICE,min,k} < T_{ICE,k} < T_{ICE,max,k} \tag{4.6a}$$

$$T_{EM,min,k} < T_{EM,k} < T_{EM,max,k} \tag{4.6b}$$

$$I_{Bat,min,k} < I_{Bat,k} < I_{Bat,max,k} \tag{4.6c}$$

$$SoC_{min} < SoC_k < SoC_{max} \tag{4.6d}$$

$$u_{min,k} < u_k < u_{max,k} \tag{4.6e}$$

$$SoC_{n,min} < SoC_n < SoC_{n,max} \tag{4.6f}$$

$$SoC_0 = SoC_{init} \tag{4.6g}$$

4.1.2 Driving Modes and Power Split Ratio

As it is discussed in Chapter 2, driving modes selection in P2-HCU leads to a hybrid optimal control problem. Traditionally, DP is only compatible with continuous time control variable like the power split ratio in P4-HCU. Obviously, the driving modes in P2-HCU have a certain relationship to the power split ratio. Therefore, a method to convert driving modes into power split ratios is found. Power split ratio μ is defined as follows:

$$T_d \geq 0, \quad \mu = \frac{T_{EM}}{T_d}, \quad \mu \geq 0 \tag{4.7a}$$

$$\mu = -\frac{T_{EM}}{T_{EM,min}}, \quad \mu < 0 \tag{4.7b}$$

$$T_d < 0, \quad \mu = -\frac{T_{EM}}{T_d}, \quad \mu < 0 \tag{4.7c}$$

$$Subject\ to: \quad \mu \in [-1, 1] \tag{4.7d}$$

T_{EM} is the torque output of EM. EM works as gena erator to charge the battery when T_{EM} is negative. $T_{EM,min}$ is the EM maximum negative torque. T_d is the total demanded torque at the crankshaft.

Torque distribution between ICE and EM of three driving modes is shown in Figure 4.1.1. These modes are AddBoost, SubBoost and OptmGentn. ICE maximum torque load points and optimal load points divide the whole possible vehicle overall load points area (demanded speed and torque) into three parts. Where AddBoost is allowed is the area upper ICE maximum torque load points, the area for SubBoost is between maximum and optimal load points. For AddBoost and SubBoost, traction torque is mostly offered by ICE with certain assista from EM; these two modes are named electric boost (eBoost). According to the power split ratio definition, power split ratio values of eBoost are between 0 to 1. For OptmGentn, whose operation area is under ICE optimal load points, EM works as a generator to charge the battery. The power split ratio for OptmGentn is between -1 to 0. Under modes SubBoost and OptmGentn, ICE works on optimal load points. The load point move process of ICE is the so-called load point shift. In traditional vehicles, ICE suffer high fuel consumption under low efficiency load points. Load point shift process including eBoost in actions HEVs have EM as an assist to enable ICE work on optimal load points. In PHEV, where usually a large size EM is used, ICE downsize design is possible [80]. Likewise, the power split ratio range of other modes can be calculated, all the driving modes and corresponding power split ratio can be found in Table 4.1.1.

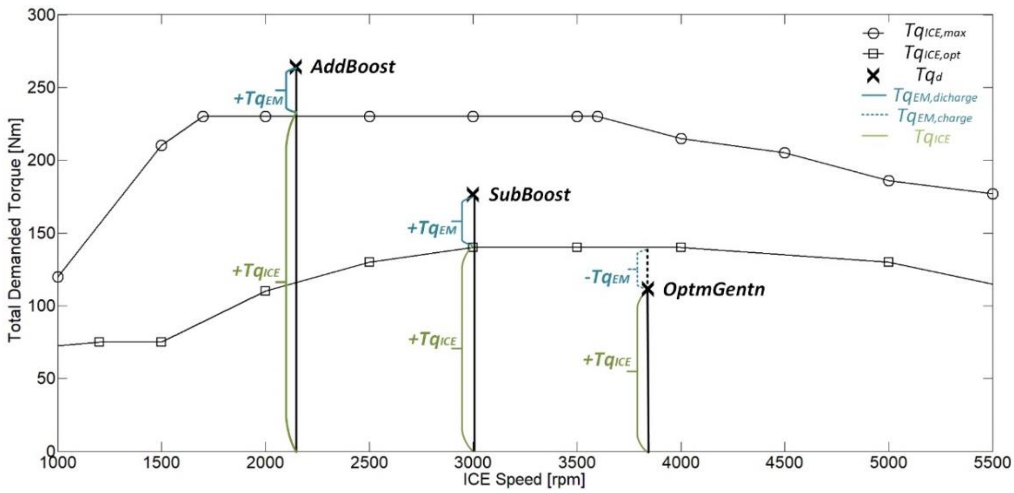


Figure 4.1.1: AddBoost, SubBoost and OptmGentn and corresponding torque distribution between ICE and EM.

Table 4.1.1: Driving modes and corresponding power split ratio

Driving Modes	Power split ratio
ConvDrv	$\mu = 0$
AddBoost	$0 < \mu < 1$
SubBoost	$0 < \mu < 1$
OptmGentn	$-1 \leq \mu < 0$
MinGentn	$-1 \leq \mu < 0$
IdleGentn	$-1 \leq \mu < 0$
EltlDrv	$\mu = 1$
Recup	$\mu = -1$
Stop/Standstill	$\mu = -1/1$

4.1.3 Free and Fixed Segments

In HEV optimization problems, it's not necessary to find the optimal control variable for each time step. There are mainly two types of operation segments: free segment and fixed segment. Fixed segments consist of all the discrete time range where SoC change is explicit and purely determined by driver or diving cycle. Free segments include time intervals where power distribution decision must be made by HCU. This kind of category is also used in ref [81]. The classification also helps to lighten the computation burden of DP since there is no need to search the optimal control variable for the free segments.

For P2 PHEV, driving modes are sorted according to free and fixed segments definition. In addition, two emergent modes are classified into another category. Because they are designed for emergent situations where SoC is very close to the lowest boundary. The driving modes categories according to free and fixed segments definition can be found in Table 4.1.2.

- **Fixed segments**: Driving modes assigned in this group are stop/standstill, Recup and AddBoost. It's easy to understand why stop/standstill is included here. For recuperation mode, an assumption is made that recuperation energy can always be taken full advantage. In this case, the energy in the electric path is explicit, which is used to charge the battery after a certain loss in each component. Due to the large capacity of this battery, the calibration file in P2 PHEV the defined SoC range for recuperation is 94%-21%. The battery overcharge phenomenon due to recuperation only happens when a very deep steep downhill driving situation is encountered when the battery is full, which doesn’t happen in all the driving cycles used in this thesis. AddBoost mode is selected when demanded torque is beyond ICE maximum torque under a certain speed. ICE maximum torque is known in advance and works as a component limitation in the whole system. As shown in Figure 4.1.1, the torque distribution of this mode is explicit already. SubBoost is not used in this P2 PHEV, all the range (between ICE maximum load points and optimal load points, as shown in Figure 4.1.1) originally use SubBoost is replaced by ConDrive or EltlDrv (when SoC is up lowest boundary).

- **Free segments**: Free segments include ConDrive, EltlDrv, OptmGentn and SubBoost. For time steps where demanded torque is positive, it is crucial to decide the energy distribution problem. There are two sources of energy on PHEVs: electricity and fuel. ConDrive and EltlDrv individually stand for taking demanded energy from a single path. It would be perfect if the load point shift is always possible whenever ICE is started. But in contrast, OptmGentn and SubBoost are not enabled all the time in reality due to other constraints or objectives, e.g. stability, NVH. For the P4 PHEV, with additional BSG beside the ICE, load point shift is freer. For the P2 PHEV, SubBoost, unfortunately, is not allowed. And the OptmGentn is more limited since ICE is always connected to the driveline, therefore has much less freedom.
- **Emergent Modes**: IdleGentn and MinGentn are referred to as emergent modes. These two modes are selected when the battery SoC is close to the lowest boundary. They are good for battery health, but the ICE under these two modes are usually not working on efficient positions.

Table 4.1.2: Driving modes categories

category	**operation modes**	**power split ratio**
Free Segments	ConDrive	$\mu = 0$
	OptmGentn	$-1 < \mu < 0$
	EltlDrv	$\mu = 1$
Not Used	SubBoost	$0 < \mu < 1$
Emergent Modes	MinGentn	$-1 \leq \mu < 0$
	IdleGentn	$-1 \leq \mu < 0$
Fixed Segments	AddBoost	$0 < \mu < 1$
	Recup	$\mu = -1$
	Stop/Standstill	$\mu = -1/1$

4.1.4 Power Split Ratio Range for P2 PHEV

As discussed in last Section 4.1.2, the detailed energy distribution of fixed segments is explicit, while ConvDrv, EltlDrv, OptmGentn and SubBoost these four modes should be selected in free segments. Except for AddBoost in fixed segments category, all the time steps, where demanded torque (power) is positive, are sorted into free segments. To find global minimum fuel consumption, or in other words, to solve the optimal GOP problem, DDP needs to search optimal modes selection for all these free segments. Here is this work, the situation where demanded torque (power) equals to negative or zero is not discussed. Two emergent modes are not considered as well. And all the power split ratio values are calculated with positive demanded torque (power).

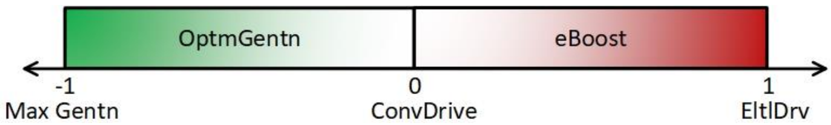
In the torque (power) distribution model of P4 PHEV, the power split ratio can be any value between -1 to 1, as shown in Figure 4.1.2(a). Load point shift actions up to EM maximum negative torque $T_{EM,min}$ or up to EM maximum positive torque $T_{EM,max}$ is allowed. Although final real power split ratio for P4 vehicle system doesn't cover the whole range between -1 to 1 due to components limitation, e.g. when ICE load points are very close to optimal position, it's not wise to start EM due to quite low efficiency. The final implemented power split ratio in P4 vehicle is roughly estimated as a shorten range between -1 to 1, as shown in Figure 4.1.2(b). The area with dark downward diagonal filling is the not used range. The direct output of DDP solver is continuous power split ratio. To make the output power split ratio compatible with driving modes in P2 PHEV, all the limitation on power split ratio should be regarded.

There is two main difference in P2 PHEV compared with P4 PHEV: there is no SubBoost, the area supposed to use SubBoost is replaced by ConDrive or EltlDrv; OptmGentn is rather limited due to the vehicle structure. As shown in Figure 4.1.2(c), which is the schematic diagram of power split ratio range in the P2 system, AddBoost is the only possible mode under eBoost and possible range for OptmGentn is narrower due to less ICE load point shift freedom. AddBoost is classified into fixed segments as discussed in last Section 4.1.3. There are three modes left inside free segments in the end, which can be solved by DDP. The power split ratio is displayed in Figure 4.1.2(d): 0 (ConvDrive), 1 (EltlDrv) and limited negative range (OptimGentn).

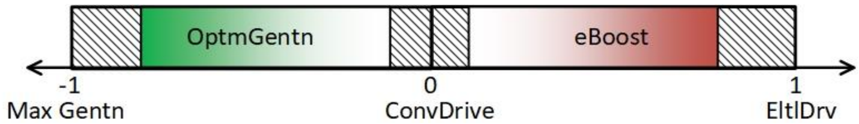
A special design here is to split the power split ratio between 0 to 1 by ConvDrv and EltlDrv. The way to deal with the narrow power split ratio range is to define: when power split ratio is negative, an ICE optimal load points look-up table is used to find ICE torque under a certain speed. If an irrational torque value is found, e.g. negative value or not a number then add significant value to the cost-to-go function. In this way, all the negative power split ratio out of the look-up table can be avoided. This special definition is listed in Table 4.1.3.

Someone may argue that there is no need to calculate power split ratio, e.g. once get a negative power split ratio, then select OptmGentn. But the truth is that OptmGentn is actually not allowed under this time step due to components freedom limitation. It's maybe EltlDrv that is implemented in the end, which accounts for inaccurate results from GOP calculation.

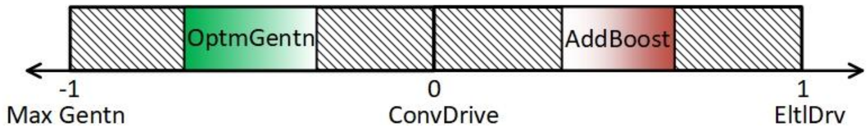
In the end, the DDP is chosen as solver from which the reasonable power split ratio for free segments is obtained. According to the sequence of optimal power split ratio, optimal modes within free segments can be selected. A power split ratio comparison example between the DDP-based for P2 PHEV and original DDP results is shown in 4.1.3. Original solution is spread between -1 to 1 while DDP designed for the P2 PHEV only selects 0 (ConvDrv), 1 (EltlDrv) and certain negative values (OptmGentn).



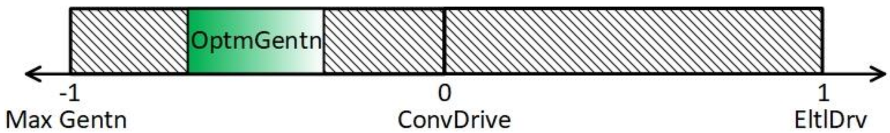
(a) Theoretical power split ratio range of P4 PHEV



(b) Final implemented roughly shortened range power split ratio of P4 PHEV



(c) Limited power split ratio range of P2 PHEV



(d) Power split ratio of three modes inside the free segments category of P2 PHEV

Figure 4.1.2: Power split ratio range differences

Table 4.1.3: New Definition of power split ratios for modes of free segments

Power split ratio	Selected Mode	Tq_{EM}	Tq_{ICE}
$0 \leq \mu \leq 0.5$	ConDrive	0	Tq_d
$0.5 < \mu \leq 1$	EltlDrv	Tq_d	0
$\mu < 0$	OptmGentn	$Tq_d - Tq_{ICE,Opt}$	$Tq_{ICE,Opt}$, look-up table

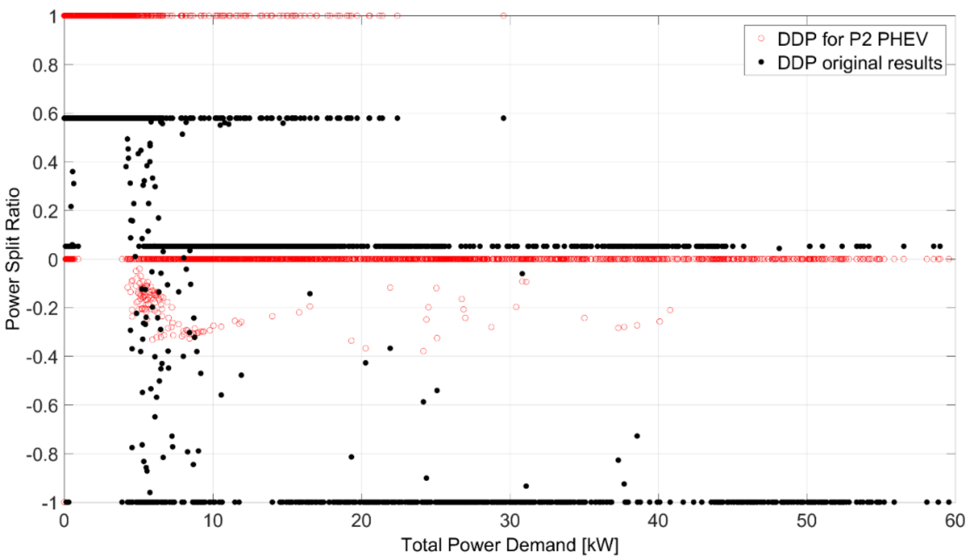


Figure 4.1.3: Power split ratio results comparison between original DDP and P2 PEHV specialized DDP.

4.2 GOP Boundary Conditions Definition

In Section 4.1, a DDP-based solver for the treated P2 PHEV configuration is created. This DDP-based solver can find a list of optimal driving modes for the whole driving range. After a one-time forward calculation, optimal fuel consumption and SoC trajectory are available as well. As a result, GOP can work as a tool to do some analysis in the following work. This Section clarifies some boundary conditions for following offline calculation.

The driving cycle used in this Chapter is the Graz cycle, which is a transient driving cycle defined by AVL. There are lots of velocity and altitude fluctuations in each range, therefore it’s a highly dynamic cycle unlike NEDC. Whole Graz cycle consists of four ranges: city cycle, highway cycle, rural cycle and city cycle. The overall distance is around 53 km within 4445s (1.235 hours). Graz cycle is quite typical long journey driving situation in Europe, its velocity and altitude profile is displayed in Figure 4.2.1.

The comparison for GOP reference here is the existing P2-HCU simulation results. Fuel consumption comparison directly shows if the predictive strategy can behave better in fuel economy in the Graz cycle. SoC trajectory and selected diving modes reveal individual operation or explain why predictive strategy behave better or vice versa. In Figure 4.2.2, the SoC trajectory of P2-HCU simulation with 95% initial SoC value is shown. It is clear that the existing trajectory implements CDCS operation mode. This strategy uses no predictive information and always tends to put EltlDrv in the highest priority when SoC is within a certain range. Another parameter that has to be clarified here is the auxiliary power. Except for power demand from the driver, there are lots of other energy consumption devices in the vehicle. These auxiliary systems are for vehicle safety or comfort consideration, e.g. lights, infotainment device. In reality, the value of auxiliary power can change under various driving conditions [82]. Here in this work, auxiliary power consumption is simplified as a constant 500W in GOP, which is the default setting for the existing P2-HCU simulation. To sum it up, all the boundary conditions of offline GOP are listed in Table 4.2.1.

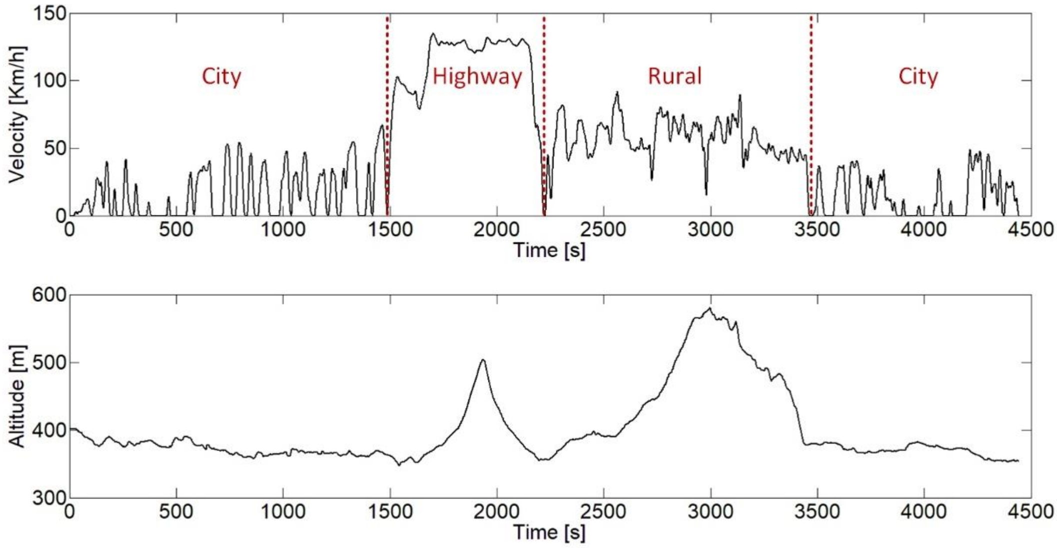


Figure 4.2.1: Velocity and altitude profile of the Graz cycle.

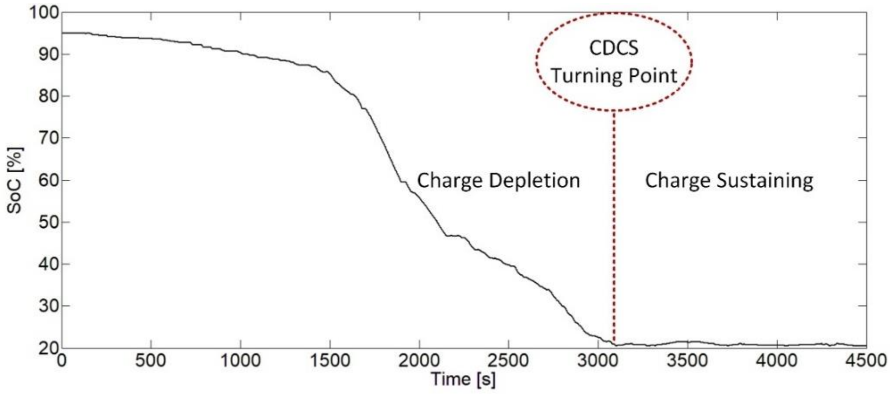


Figure 4.2.2: Existing P2-HCU shows CDCS behavior (SoC_{init} = 95%)

Table 4.2.1: Offline GOP boundary conditions

Driving Modes	**Power split ratio**
Cycle information	Graz cycle (53 km/4445s)
Control variable	Power split ratio, $u(k)$
State variable	Battery SoC, $X(k)$
Solver	DDP
Vehicle model	(1-D) quasi-static model
Predictive information	Velocity, distance, altitude
Auxiliary power	500 W

4.3 Predictive Strategies Benefits Analysis

Table 4.3.1 provides the numerical results of the P2-HCU simulation and offline GOP solution. It is clear to see that with the same initial SoC value (SoC_{init} = 75%), GOP saves 209.5mL/12.7% fuel compared to the existing CDCS strategy. It is of interest for online predictive models' design if the nature of this improvement is found. This part is going to summarize and analyze the results from three main aspects: recuperation, energy distribution for the whole range and emergent generation modes.

Table 4.3.1: Fuel economy improvement with GOP

Graz cycle, SoC_{init} = 75%	**Existing P2-HCU**	**GOP**
Final SoC (%)	20.86	20.24
Fuel Consumption (mL)	1648.3	1438.80
Fuel Economy Improvement	/	209.5 mL/12.7%

4.3.1 Recuperation

There is a classic example when people talk about why predictive strategies can improve HEVs fuel economy. As shown in Figure 4.3.1, the HEV with slope preview takes a prescient strategy, which is to use more electric energy before downhill to avoid battery SoC is too high to receive all the recuperation energy. This phenomenon is named as 'maximize recuperation potential'. Except for gravitational change environment, recuperation energy can also come from braking processes. For both of them, the main idea to improve fuel economy from recuperation point of view is to deplete the battery in advance, so that SoC upper boundary is just right reached after the recuperation process. The requirements for road slope information or braking prediction are what traditional non-predictive strategies fail to satisfy.

The function of 'maximize recuperation potential' in predictive strategies is really significant for fuel economy improvements, especially for HEVs with small battery capacities. However, in the case of the present P2-HCU, CDCS strategy always selects EltlDrv until SoC reaches a quite low boundary. Whenever there is a downhill or deceleration range, CDCS strategy itself already depletes battery as much as possible. Based on that, predictive strategies will not behave better in recuperation aspect. Furthermore, the battery size of the P2 PHEV is 14.7 kWh at 350V, which is large enough to save maximum recuperation energy under most SoC ranges. The large size EM in this PHEV also enables the recuperation process with high efficiency compared to pure HEVs, as discussed in Section 2.1.

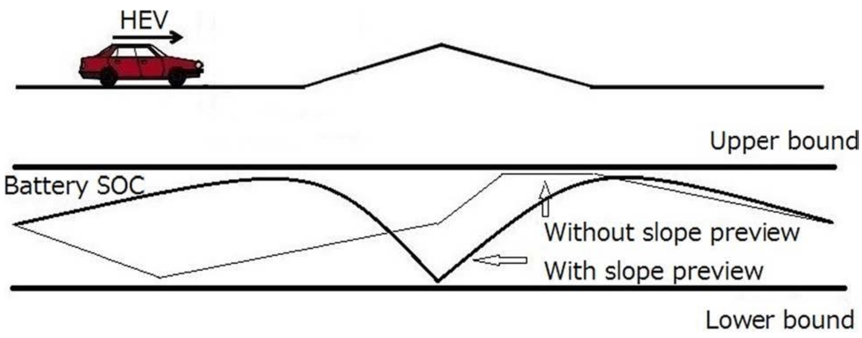


Figure 4.3.1: An example shows how predictive strategy enables a HEV to maximize recuperated energy by slope information [83].

4.3.2 Energy Distribution for the Whole Driving Range

As mentioned in 2.2, one of the main functions of HCU is long-term energy management. The energy management for the whole driving range reveals the electricity distribution strategy for the whole trip. The existing CDCS strategy put electricity use at the highest priority, which means most of the time (before SoC reaches the low boundary) selected driving mode is always EM-oriented, that's why SubBoost is not used in P2 PHEV, where ICE dominates when electricity is still available. In GOP, the search for this strategy is actually about solving a mathematic minimization question.

To show the strategy difference, an existing P2-HCU simulation and GOP calculation are finished with 75% initial SoC in the Graz cycle. Figure 4.3.2 shows the comparison results regarding SoC depletion, fuel consumption and modes selection. SoC depletion trajectory of existing HCU is typical CDCS type, while GOP depletes SoC from 75% to 20.24% (listed in Table 4.3.1), adopts perfect to blended operation strategy. The numerical fuel economy comparison listed in Table 4.3.1 is also presented in the fuel consumption accumulation trajectory in Figure 4.3.2. Existing HCU simulation generally consumes fuel consistently after the 2400s, where SoC begins to sustain. The GOP 'blue' fuel consumption trajectory dramatically increases between the 1700s to 2000s; after 3000s there is no fuel consumption anymore. Selected modes under various timesteps are displayed in Figure 4.3.2 as well. First of all, there is almost no difference in stop/standstill and Recup selection. As described above, P2-HCU use lots of EltlDrv at first, then mainly ConvDrv and OptmGentn are selected under battery sustaining condition. EltlDrv is still selected once for a while; therefore SoC always oscillates around pre-defined low boundary value. Regarding GOP modes selection, there is a significant and obvious phenomenon that GOP uses lots of ConvDrv in highway range where the velocity is the highest or rural range where the velocity is second highest. For other trip ranges, where the velocity is quite low or relatively low, EltlDrv is implemented.

The main unique behavior with GOP can be summarized as: to start ICE in high-velocity ranges and fully use existing electric energy for all the other low-velocity ranges. This behavior is exactly what blended operation asks for. The substantial reason behind this is that ICE works more on optimal position with GOP compared to existing P2-HCU. Figure 4.3.3 shows that ICE load points positions on BSFC MAP, the 'redpoints' which present ICE load points with GOP, located mostly in the center region within 250 g/kWh BSFC. ICE load points in existing P2-HCU simulation locate on the left region, which is unfortunately much less optimal.

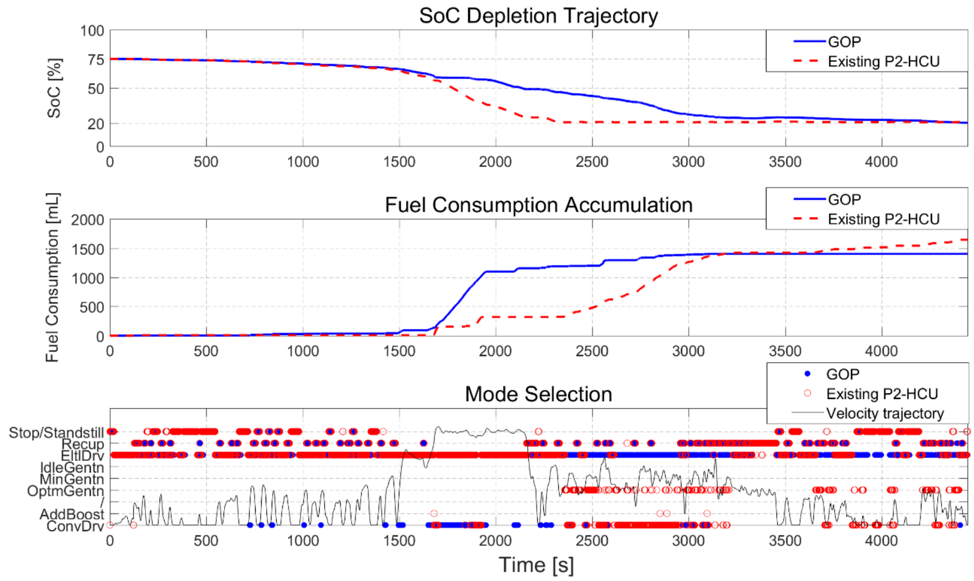


Figure 4.3.2: SoC trajectory, fuel consumption and driving modes selection comparison between P2-HCU and GOP, with initial SoC value as 75% in the Graz cycle

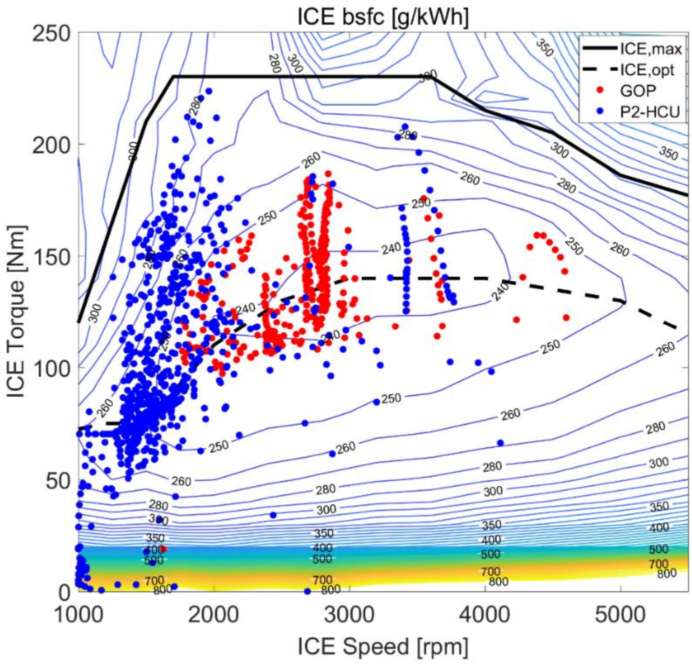


Figure 4.3.3: ICE load points comparison

4.3.3 Emergent Generation Modes

Another aspect that can slightly contribute to GOP fuel economy improvement is the existence of emergent generation modes. As mentioned before, emergent generation modes contain MinGentn and IdleGentn. Figure 4.3.4 displays the SoC ranges definition in the P2-HCU calibration file for various driving modes selections. The SoC range for selection of these two emergent modes is 20% to 20.3%. OptmGentn is selectable between 20.3% to 22%. SoC range for EltlDrv and AddBoost is defined from 21% to 95%. In this case, in charge sustaining process of the existing P2-HCU, two emergent modes will not be selected unless SoC at the beginning of this trip is really low or the trip distance is much longer than AER. The SoC mainly oscillates between 20.3% to 22%, the common situation is from 20.5% to 21.5%. For example, the numerical result in Table 4.3.1 shows that final SoC with P2-HCU simulation is 20.86%. This design in the calibration file is reasonable due to possibly much less optimal ICE load points under two emergent modes. Furthermore, if the final destinations of trips are always unknown without any prediction information, it is smart to design these two emergent generation modes for the sake of battery health in long term. However, GOP always knows where is the end of a single trip. Mathematics calculation inside GOP enables that SoC depletes accurately from 75% to the low boundary. As shown in Table 4.3.1, the final SoC value is 20.24% with GOP, that means more electricity is used and correspondingly an amount of fuel is saved.

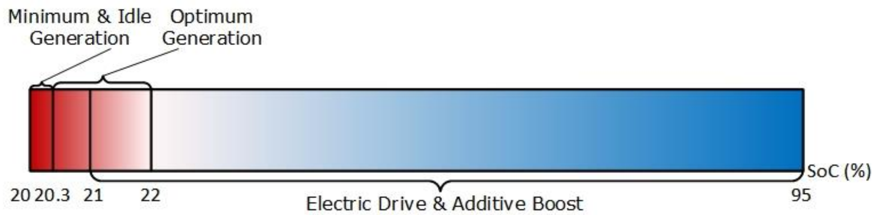


Figure 4.3.4: SoC range for various driving modes

4.4 The Influence of Initial SoC Values

Initial SoC value stands for existing useable electric energy at the beginning of the trip. The last Section 4.3 only presents a comparison of results when SoC_{init} is 75%. It's not hard to imagine that SoC_{init} is one of the boundary definitions - therefore can influence fuel consumption results no matter in P2-HCU simulation or GOP calculation. When SoC_{init} is 75%, fuel economy improvement with GOP is huge. Although these are only offline calculation results, they at least reveal the potential of online predictive control models. This part is to explore two questions: 1) Does GOP always behave better in fuel economy with various SoC_{init} compared to the existing P2-HCU; 2) If the answer is 'yes' for the first question, how does SoC_{init} influence fuel economy improvements.

Table 4.4.2 lists fuel consumption for P2-HCU simulation and GOP offline calculation with various SoC_{init}. Four groups, where SoC_{init} is individually set as 95%, 75%, 50%, 25%, can generally present different level SoC_{init} within the whole SoC usable range is (95%-20%). The final row in Table 4.4.2 shows that GOP can improve fuel economy for each group. However, the improvements don't monotonically increase or decrease along with the change of SoC_{init}. To explain the comparison results, the following work is going to compare modes selection of several groups. Mode selection of each instance is short term PMT solution; all the PMT solutions for the whole trip lead to long term EMT strategy. Or in other words, modes selection can explicitly explain the difference in fuel consumption and account for SoC depletion and fuel consumptions trajectory as well.

Figure 4.1.1 shows modes selection differences with 75% SoC_{init} and 50% SoC_{init}. GOP adopts the same strategy in these two groups; the only distinction is that with 50% SoC_{init}, more ConvDrv modes are selected in highway range because of less available electric energy. As shown in Figure 4.1.1, two green dash lines display the turning points of CDCS, where the battery enters into sustaining range. The existing P2-HCU has sustaining range in rural cycle with 75% SoC_{init}, while coincidently in the mid of highway range with 50% SoC_{init}. ICE is coincidently started in the mid of highway range under 50% SoC_{init}. It's not hard to imagine that SoC_{init} can influence turning points position, after which ICE will be used frequently. If ICE can be used in part of the highway cycle (high-speed cycle), then what GOP can do will be less important. This explains the great fuel economy improvement value difference (can be found in Table 4.4.1: 209.5 mL with 75% SoC_{init}, 87.4 mL with 50% SoC_{init}) for these two groups.

Table 4.4.2: Fuel consumption comparison under various SoC_{init} in Graz driving cycle

SoC_{init}	95%	75%	50%	25%
Existing P2-HCU fuel consumption [mL]	666.3	1648.3	2766.1	4105.7
GOP fuel consumption [mL]	512.8	1438.80	2678.7	3850.1
Fuel economy improvement [mL]	153.5	209.5	87.4	255.6

According to the above analysis, fuel economy improvement with 25% SoC_{init} should be less than 87.4 mL. Because with less existing electric energy, CDCS turning point with 25% SoC_{init} should locate even earlier compared to 50% SoC_{init}. In this case, highway range in the mid of Graz cycle is more used by ICE. It is the truth that, according to Table 4.4.2, fuel economy improved by GOP is highest with 25% SoC_{init} (the value is 255.6 mL as listed in Table 4.4.2). Figure 4.4.2 shows modes selection differences with 50% SoC_{init} and 25% SoC_{init}. CDCS turning points with 25% SoC_{init} is around 1000s position, much earlier before entering into highway range. So as analysed, existing P2-HCU with 25% SoC_{init} behaves even better in taking advantage of high-speed range compared to 50% SoC_{init}. As shown in Figure 4.4.2, existing P2-HCU almost selects ConDrive all the time in highway range (around 1500s to 2250s). Figure 4.4.3 shows the fuel consumption trajectories comparison between GOP and P2-HCU with 25% SoC_{init}. It is clear that fuel consumption increasing trajectories are the same in highway range. The deviation appears after 3500s, which is within the final city cycle range. Comparing P2-HCU modes selection between 50% and 25% SoC_{init} within final city cycle range in Figure 4.4.2 (inside two green circles) it becomes visible that much more OptmGentn and ConDrive are selected with 25% SoC_{init}, where GOP still use the EltlDrv most of time.

On one hand, the conclusion here is to only take care of high-speed range is not enough, sufficient electric energy needs to be saved for low-speed range as well. If the vehicle has few available electric energy at the beginning of trips, a relatively high-speed instance in low-speed (city) ranges should be utilized in order to use EltlDrv in other lower-speed moments. This is rarely available in reality, due to the requirement for all trip accurate information. On the other hand, it can be summarized that, taking GOP as benchmark, the existing P2-HCU fuel economy behavior difference with different SoC_{init} is the cooperation of lots of random elements, e.g. battery size, power demand, traffic condition. SoC_{init} actually has no regular influence on fuel economy improvements. In the following Chapter, it is enough to choose one SoC_{init} value for all the simulation analysis and there is no need to compare simulation results with different SoC_{init} values anymore.

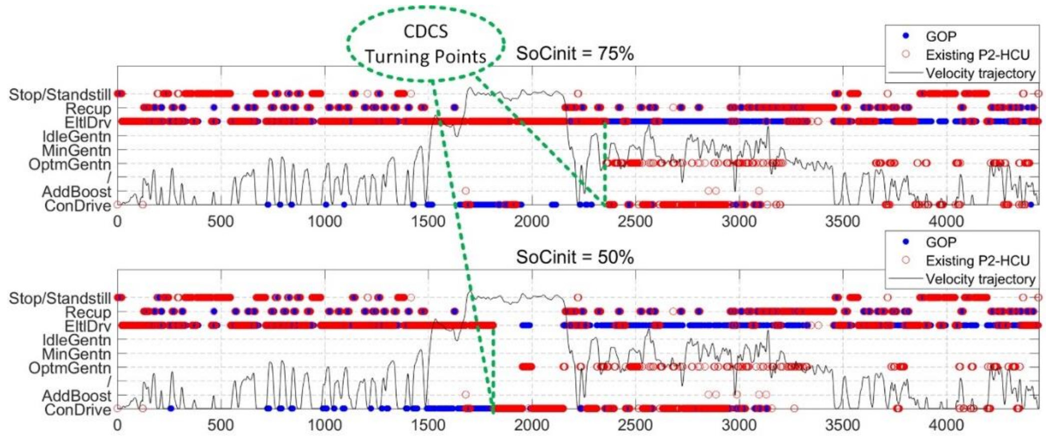


Figure 4.4.1: Modes selection comparison with 75% and 50% SoC_{init}.

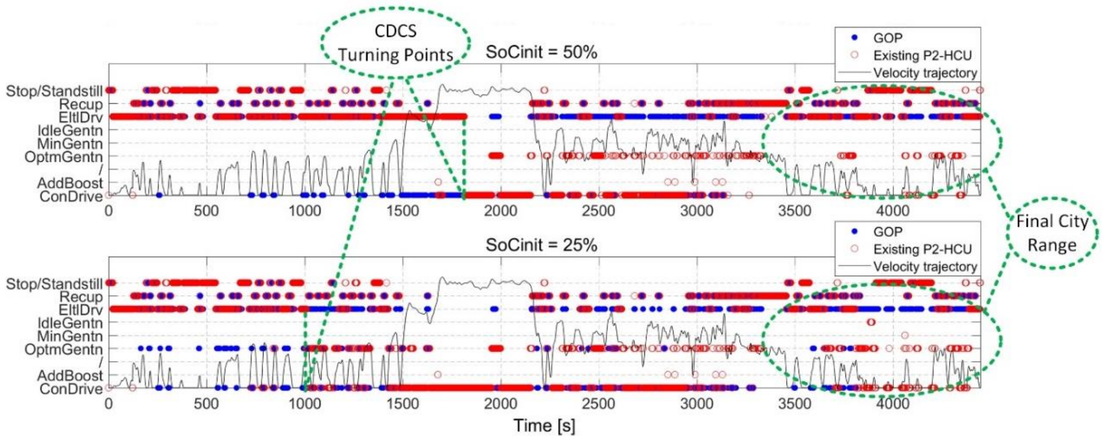


Figure 4.4.2: Modes selection comparison with 50% and 25% SoC_{init}.

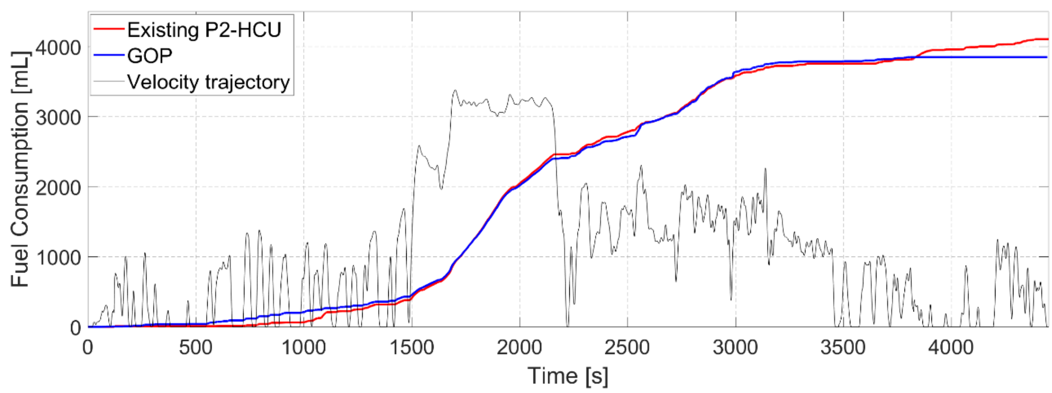


Figure 4.4.3: Fuel consumption accumulation comparison between GOP and existing P2-HCU with 25% SoC_{init}.

Chapter 5 Predictive HCUs Development

The last Chapter introduces GOP calculation with a DDP-based solver. The method assumes to know all the information about a trip and can find the globally optimal driving modes selection sequence. Nevertheless, this offline deterministic GOP method has no possibility to be used for the online controller due to its heavy computation effort. The significant job of this Chapter is to investigate two new predictive HCUs on the basis of the existing P2-HCU. During the design process of predictive models, conclusions from Chapter 4 are implemented. As widely discussed in Section 2.2.4, state-of-art predictive control models combine long term horizon models with online (short term horizon) models. In this Chapter, long term horizon is extended into a global horizon. In this case, the SoC reference trajectory is calculated towards the whole trip. In reality, the SoC reference can be recalculated and updated for every certain time step on the cloud calculation platform. Here in this thesis, to simplify the research process, SoC reference trajectories from these global horizon prediction models are only created once at the beginning of trips. Regarding the online predictive control models, the design process is discussed together with their later integration into the existing P2-HCU. As mentioned in Section 2.3.2, the existing P2-HCU is a quite mature product. There is no need to create a brand new HCU, but it is intended to influence the power distribution decisions of the corresponding model in the existing P2-HCU. In this Chapter, two online predictive control models have created: MPC and R-W method. R-W is easy to design and implement, but it is not the optimal choice nowadays and cannot be used in the P4-HCU. MPC, as the state-of-art predictive choice recently, presents an outstanding upper benchmark after GOP and has the potential to work in real time. Both of them should be integrated into the existing P2-HCU to perform as two new predictive HCUs.

5.1 Global Horizon Prediction Models

Global horizon prediction models, unlike GOP with DDP-based solver, have more freedom to create SoC reference. The key point is a balance between optimality and detailed degree of prediction information. Based on that, there are four kinds of global horizon prediction models discussed here. According to the available information, they are classified as follows:

- **Distance information:** distance information is easy to obtain for a destination-fixed trip. Or even not, an approximate distance can be simply estimated through navigation systems at the beginning of a trip. For PHEVs, the existence of CDCS operation mode is reasonable. Because lots of commute trips are shorter than AER the electric driving-dominated mode can reduce the use of ICE to most extent overall. However, when a long trip is a case, CDCS is no longer an ideal option. Even though only an estimated distance is available, SoC reference trajectory can be found. The common way is to distribute the battery energy linearly over the trip. $\boldsymbol{SoC_{ref}}(\mathbf{t})$ is formulated as:

$$SoC_{ref}(t) = SoC_{init} - \frac{SoC_{init} - SoC_{end}}{D_{total}/D(t)} \tag{5.1}$$

$\boldsymbol{SoC_{init}}$ is SoC value at the beginning of a trip, $\boldsymbol{SoC_{end}}$ is SoC value at the end of a trip, 20% is used in this thesis. $\boldsymbol{D_{total}}$ is the overall distance, $\boldsymbol{D(t)}$ is distance at time $\boldsymbol{t}$.

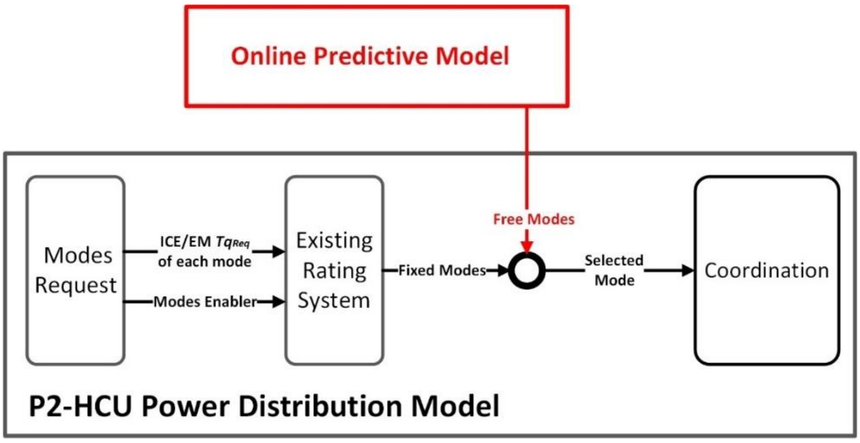
- **Distance, velocity limitation and altitude:** except distance information, altitude is not hard to obtain with the installation of a GIS in modern vehicles. Moreover, navigation systems can clearly show traffic conditions in each segment of a pre-designed route. At least, the control system can get rough information about trip environment types (e.g. city, highway, rural). Although detailed power demand is still unknown, with common sense got from Chapter 4 that to start ICE in high-speed road ranges and fully use pure electric drive mode in low-speed city cycle, it is reasonable to heuristically define rules for the whole range. What is defined in the present thesis, is to save 5% SoC for each final 5 km city cycle. At the same time, ICE is utilized in the highway cycle.
- **Distance, estimated/accurate velocity and altitude:** if velocity limitation is further detailed predicted (estimated), it is possible for the global horizon prediction model to estimate the future power demand according to the vehicle longitudinal model. Once future power demand is known, same DDP-based solver created in the last Chapter can be used to find SoC reference trajectories. It is not realistic to get a fully accurate velocity profile except for some test trips. SoC trajectories calculation with accurate velocity would be the same with the GOP used in Chapter 4. This kind of SoC trajectories should not be an option for real HCUs design, but they can offer a fair comparison basement in research analysis. More application will be discussed in the next Chapter. Estimated velocity is more realistic and surely will not bring an optimal SoC reference.

5.2 Requirements for Online Predictive Models

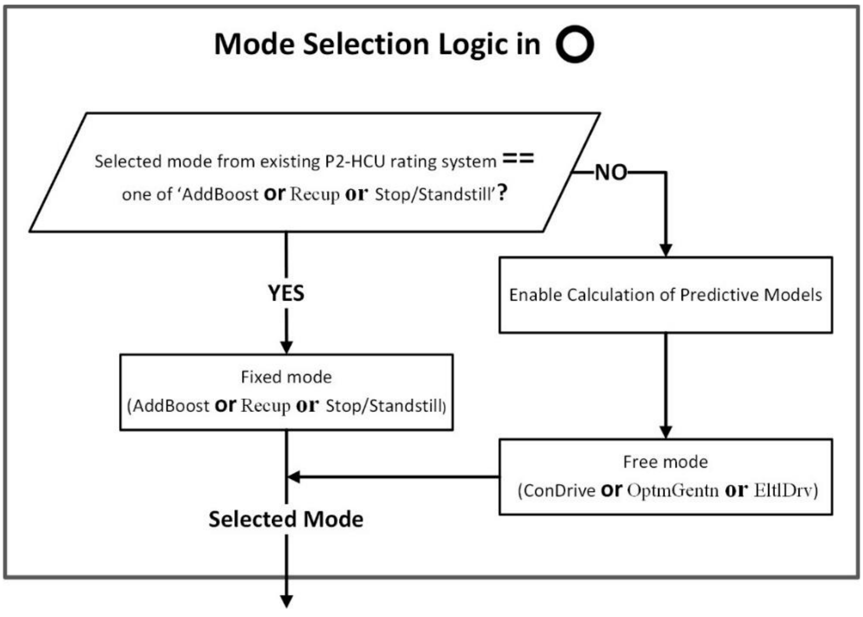
Before the creation of online predictive control models starts, it is significant to define the structure of these two new predictive P2-HCUs. In this way, input and output variables for two predictive control models will be defined.

As mentioned before, the only influence of created predictive models is the output of the existing power distribution model, that is defined by the selected mode for the P2-HCU. Figure 5.2.1(a) presents the structure of an existing power distribution model and how online predictive models are integrated with it. At first, all modes requests are solved in the 'Modes Request' model, inside which the torque requests Tq_{Req} of ICE and EM under all modes are calculated. Except that, 'Modes Enabler' is a significant tool to filter modes. 'Enabler' mainly presents the definition of a calibration file; the modes enabled SoC range displayed in Figure 4.3.4 is one example. Besides, there are detailed definitions for each mode regarding vehicle velocity, clutch state, transmission state and some other limitation lookup tables. In the 'Existing Rating System', a simple rating with modes priority definition is operated, after which only one mode with the highest score will be chosen. The 'Coordination' plays a character of a final check of the selected mode to promise that a reasonable mode is used in the vehicle. In the end accordingly, torque Tq_{Req} and speed N_{Req} of ICE and EM requested by the selected mode are output variables of this P2-HCU.

This part of the thesis designs the implementation process of online predictive models. First of all, the fixed and free segments classification used in Chapter 4 is used here as well. Free segments whose power distribution will be decided by predictive control models, have modes selection between ConvDrv, OptmGentn and EltlDrv. On the contrary, fixed segments that include AddBoost, Recup and Stop/Standstill can take the output of modes selection from existing P2-HCU. At first, with the calculated power demand from the power demand calculation model, the system will simply judge the present time instance that belongs to the fixed segment or free segment. Furthermore, once AddBoost, Recup and Stop/Standstill are selected, the output from the predictive control models will be forbidden. There are several reasons to explain this definition: 1) MPC model has much more computation burden than rule-based control strategies. It will accelerate the simulation process by removing free segments calculation; 2) The real judgment conditions are much more complicated than a theoretical definition. There are lots of relative boundary definitions in the P2-HCU regarding AddBoost, Recup and Stop/Standstill selection. It is safer to let a more sophisticated system decide between these three modes. For example, P2-HCU will select Stop/Standstill mode instead of Recup mode in some time segments with negative power demand. The design principle is reasonable that it is not necessary to operate in recuperation mode when the negative power demand value is under a certain threshold due to low efficiency. 3) AddBoost is kept here to fully satisfy driver's demand in case that predictive control models select EltlDrv to improve fuel economy while sacrificing drivability too much. The overall integrated structure is shown in Figure 5.2.1 (a) and the core logic of the selection between fixed modes and free modes is displayed in Figure 5.2.1 (b). The overall predictive HCUs work configuration is summarized in Figure 5.2.2.



(a) Structure of existing P2-HCU power distribution model and integration of predictive models



(b) The logic of mode selection between the existing rating system and predictive models

Figure 5.2.1: Integration of new predictive models with existing P2-HCU

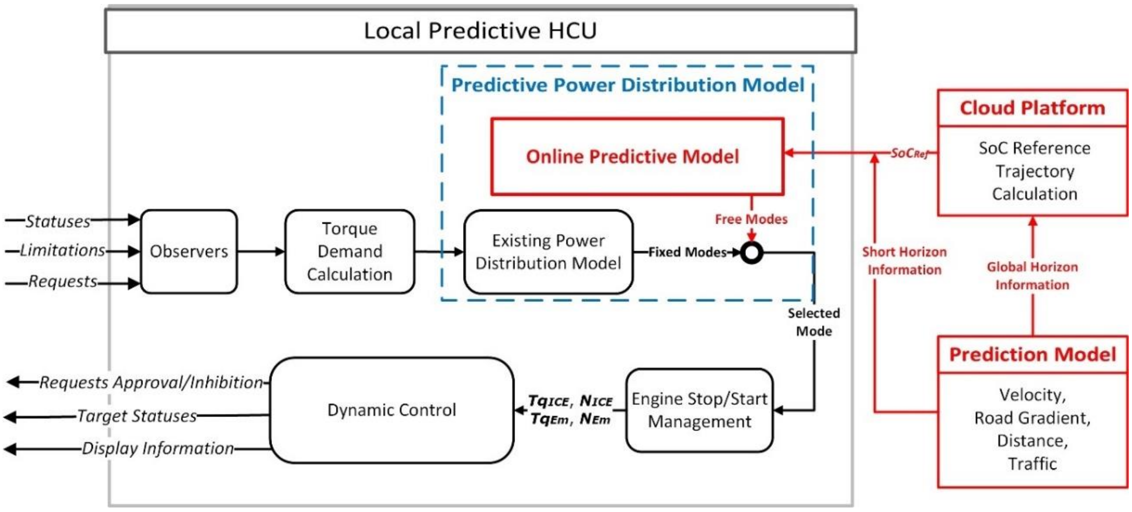


Figure 5.2.2: Local predictive HCU overall structure

Still, there are lots of request for a qualified controller of a PHEV. The requirements are listed and explained as follows:

- **Minimize short term total fuel consumption:** This is the ultimate objective of the ongoing designed predictive HCU. Although to minimize short-term fuel consumption is not equal to a minimization of overall fuel consumption, this process is still necessary to flexibly face uncertainty in reality.
- **Track SoC reference:** Online predictive models only have short horizon prediction (MPC) or quite simple predictive information (R-W) - thus are short-sighted. SoC reference trajectories given by global horizon prediction models can help online predictive models to avoid the drawback. It is promising to keep small deviations from the SoC reference, if global horizon prediction is accurate enough.
- **NVH/Comfort:** Regardless of the gear shift and clutch operation processes, too frequent ICE start or driving modes shift should be avoided for the sake of vehicle NVH characteristics. It is not advisable to follow SoC reference too close or too frequent. Moreover, each ICE start process consumes certain fuel and similarly, each mode shift operation wastes some energy.
- **Abandon 'Modes Enabler':** As mentioned above, all kinds of components constraints are defined in the calibration file of the existing P2-HCU. The 'Modes Enabler' is the part of the Simulink model to present all these definitions, including the CDCS strategy. Although it is convenient to use 'Modes Enabler' to add components constraints, blended mode of the P2 PHEV is impossible under the control of SoC threshold and priority definitions in the calibration file.
- **Drivability:** A good controller should not sacrifice drivability too much for fuel economy. The measure applied here to handle this issue includes the use of AddBoost, as mentioned above.

5.3 Predictive R-W HCU

As presented in Figure 5.2.1 (a), in the existing P2-HCU, a simple rating system, 'Mode Enablers' and priority definition altogether decide the selected driving mode. Similarly, the R-W method created based on reference [84] is a kind of a rule-based unconstraint control strategy. It is the easiest way to solve a hybrid optimal control problem. In reference [73], the R-W method combined with a prediction strategy is created for this P2-HCU. A score of each mode is calculated as follows:

$$S_{final}(\mathrm{i}) = S_{rat}(i) * S_{wei}(i) * S_{pen}(i) * E(i) \tag{5.2}$$

i presents the ID for one mode. S_{final}, S_{rat}, S_{wei} and S_{pen} are final calculated scores, rating score, weighting score and penalty score for one mode. $E(i)$ means to use the existing 'Modes Enabler' to filter un-allowed modes under the constraints from the existing P2-HCU calibration file. There are three aspects regarding rating and weighing process for each mode: fuel consumption, SoC reference track and drivability. The formula is:

$$\begin{aligned} S_{rat}(i) * S_{wei}(i) = S_{rat,fuel}(i) * S_{wei,fuel}(i) + S_{rat,SoC}(i) * S_{wei,SoC}(i) + S_{rat,dri}(i) \ldots \\ * S_{wei,dri}(i) \end{aligned} \tag{5.3}$$

The rating scores and weighting scores for each mode are given by searching pre-designed lookup tables. Here, fuel consumption rating should be mentioned as an example. Total instantaneous fuel consumption for all the driving modes are calculated. The fuel consumption equivalent parameter $\gamma(k)$ under k time instant is a constant at first, and if any generation modes are used, then it changes as follows [84]:

$$\gamma(\mathrm{k}) = \frac{\gamma(k-1) * SoC(k) + bsfc(k) * \Delta SoC(k)}{SoC(k) + \Delta SoC(k)} \tag{5.4}$$

Accordingly, the total equivalent instantaneous fuel consumption $\dot{m}_{fuel,equiv}(k)$ is:

$$\dot{m}_{fuel,equiv}(k) = \dot{m}_{fuel,ICE}(k) + \gamma(\mathrm{k}) * \dot{P}_{battery}(k) \tag{5.5}$$

$\dot{P}_{battery}(k)$ is the battery power change value. Fuel sub-rating value $S_{rat,fuel}(i)$ for one mode is:

$$S_{rat,fuel}(i) = \mathrm{map}(\dot{m}_{fuel,equiv}(k)) \tag{5.6}$$

It is reasonable that a mode with less equivalent fuel consumption gets a higher score. More design information can be found in ref [84]. This part of the work mainly explains the implemented changes based on this method. Section 5.2 discusses all the requirements for online predictive models. The first and second requirements 'minimize short term total fuel consumption' and 'track SoC reference' are satisfied through fuel sub-rating and SoC sub-rating. In the simulation, the original drivability sub-rating and sub-weighting models are removed since it should be sufficient if proper AddBoost selection is promised. This change also enables to get rid of two drivability lookup maps tuning processes, which usually takes lots of time. The third requirement 'NVE/Comfort' is the topic of the penalty model, where ICE start number and mode shift number in each 1 second are limited. And according to the common conclusion from Chapter 4, an additional positive score is given to the ConDrive mode in case of high-velocity driving range beyond 120 km/h. Especially, a PI controller is designed in the SoC rating model to enable that the system will not follow SoC trajectory too close and too frequent. In the end, 'Modes Enabler' is removed here. It is understandable to use enabler to add components constraints to the mode selection process. Nevertheless, the existence of SoC range that is specially designed for CDCS will forbid the blended operation mode. And it is decided to use the R-W model to only select three free modes, whose selection process mainly presents the energy management strategy. Components constraints, by the way, are integrated with lookup maps design processes. The structure of the updated R-W model is shown in Figure 5.3.1, among which grey parts are removed models from the original R-W structure.

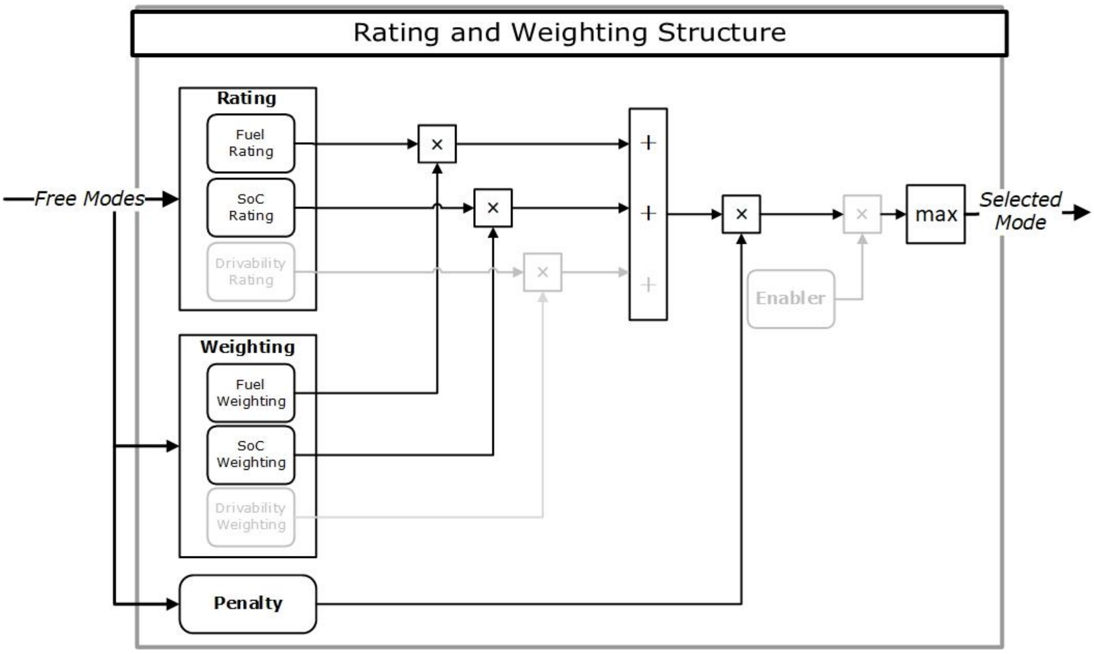


Figure 5.3.1: The structure of the updated R-W method (the grey parts are removed)

5.4 MPC-based HCU

The applied R-W method is quite effective and the SoC sub-rating and sub-weighting process enable it similar to the adaptive ECMS method. It has common drawbacks as rule-based control strategies, e.g. without hard constraints and complicated calibration processes. In the present application of the P2-HCU, the R-W method works properly due to its fit into the hybrid control problem. Taking the P4-HCU into consideration, MPC is created here to solve both modes selection and power split ratio calculation process. As analyzed in Section 2.2.4.1, MPC is a quite advanced control strategy. It offers sub-optimal solutions by splitting the global optimization problem into small sections. The length of each section is called a prediction horizon, the cost function is defined as:

$$\underset{u(k)}{Minimize}: \ f = \sum_{i=1}^{i=n} \left\{ \dot{m}_{fuel,ICE}\big(k+i, \varphi(k+i)\big) + w1 \cdot \left[SoC_{ref}(k+i) - SoC(k+i)\right]^2 \right\} \\ \ldots + \ w2 \cdot \delta_{ICE,started}(k+1) \tag{5.2}$$

$$Subject\ to: \quad SoC_{k+n,min} < SoC_{k+n} < SoC_{k+n,max} \\ \text{Constraints defined in (4.6)} \tag{5.3}$$

The present time instant is k, to find the power distribution solution for $k+1$, a cost function with three aspects of fuel consumption, SoC reference tracking, and ICE start limitation between $k+1$ to $k+n$ is minimized. $w1$ and $w2$ are the weighting values. With

DDP-based solver created in the last Chapter, the outcome of this function minimization is a sequence of n selected modes for future n time instants. In the end, only the first selected mode is implemented. Therefore, $\delta_{ICE,started}$ is positive only if the calculated mode of $k+1$ time instant is ConvDrv or OptmGentn, while the utilized mode of k time instant is EltlDrv, Recup or Stop/Standstill.

Chapter 6 Simulation and Analysis

In this Chapter, a predictive R-W HCU and a MPC-based HCU are created based on the cognitions made in Chapter 5 and used for simulation. Actually, it takes some effort to tune the key parameters in the controllers, e.g. weighting values, lookup tables, initial fuel consumption equivalent value, etc. Besides, MPC suffers heavy computation effort compared to the predictive R-W HCU and existing CDCS rule-based P2-HCU. It is necessary to find a proper prediction horizon length, which is defined as the 60s in this thesis. During the long tuning process, it is found out that the predictive R-W HCU and MPC-based HCU can be tuned to obtain similar fuel economy improvements compared to the existing P2-HCU. Prediction strategies generally can save fuel consumption by distributing fuel and electric energy optimally. But lots of elements decide the final improvement results. The type of predictive strategy is one factor, boundary conditions like vehicle components (e.g. battery size), initial SoC value, driving conditions, detail degree of prediction information, etc. are other factors. Some literary works, of course, try to create a predictive strategy by balancing drivability, NVH and feasibility, see in Appendix 2. In this way, 3 or 4 kinds of predictive strategies are created and compared under consideration of these aspects. These proper requirements are already taken into consideration in two predictive strategies that are designed in Chapter 5. The main objective of simulation and analysis in this Chapter is not to compare these two predictive strategies, but to explore the various driving cycles and prediction information's influence on the contribution level to fuel economy improvements. These simulations were designed based on a simple question regarding the research of predictive strategies: Do predictive strategies always behave better in fuel economy compared to existing CDCS rule-based strategies?

6.1 The Influence of Driving Cycles

The Graz cycle is used in Chapter 4, which is kind of typical long-distance driving cycle in Europe with lots of fluctuations in velocity and altitude. Graz cycle contains four driving elements: city, highway, rural and city. To exhibit the influences of the driving cycles and the contribution nature of predictive strategies, a highway cycle and a city cycle is introduced here. The former is the highway fuel economy driving schedule (HWFET), the latter is the urban dynamometer driving schedule (UDDS) that is also called FTP-72 (FTP, Federal Test Procedure) [85]. Single HWFET cycle and UDDS cycle velocity profiles are shown in Figure 6.1.1. To fairly compare three driving cycles, 4-HWFET and new 6-UDDS cycles are created here. 4-HWFET means to repeat a single HWFET cycle four times. New 6-UDDS cycle repeats the UDDS cycle six times, but the relative high-speed range (around 200-400s) is removed. The velocity profiles of these two newly created driving cycles are shown in Figure 6.1.2. The accumulated distance of the 4-HWFET and the new 6-UDDS cycle are all round 66km, longer than AER of the P2 PHEV investigated in this work. The distance of the Graz cycle is around 53km, and an altitude profile is included (can be found in Figure 4.2.1). It is obvious that the 4-HWFET cycle has a high-velocity overall the entire trip, and the new 6-UDDS cycle has a low velocity below 50km/h and lots of sudden stop states due to typical city traffic conditions.

To compare fuel consumption improvements with the 4-HWFET cycle, the new 6-UDDS cycle and the Graz cycle, SoC reference trajectories calculated by use of the GOP tool designed in Chapter 4 are sent to the online MPC model. Although it is not realistic for practical applications, this definition promises the same detailed degree of information prediction. And as concluded in Section 4.4, SoC_{init} doesn't have a mathematically regular influence on the fuel improvements by predictive strategies. So, there is no problem to set SoC_{init} as 75% for all the simulations. All the prediction horizons used in MPC are 60s.

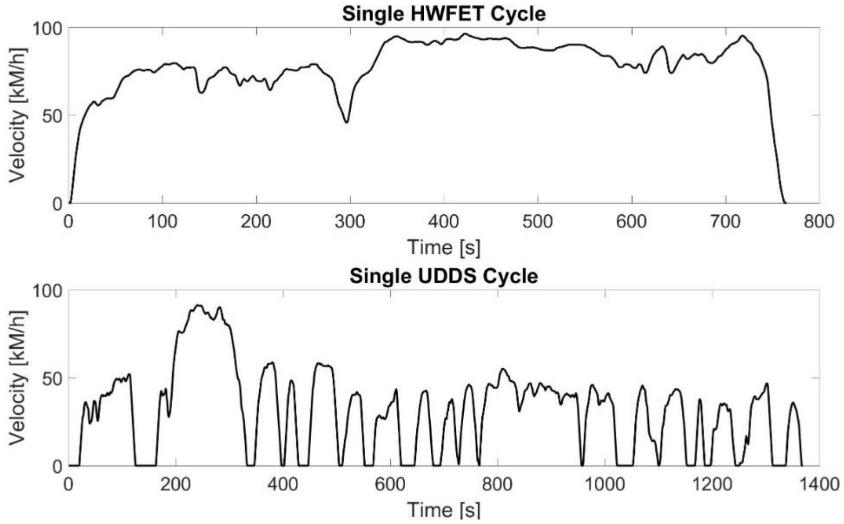


Figure 6.1.1: Single HWFET cycle and UDDS cycle velocity profiles [85].

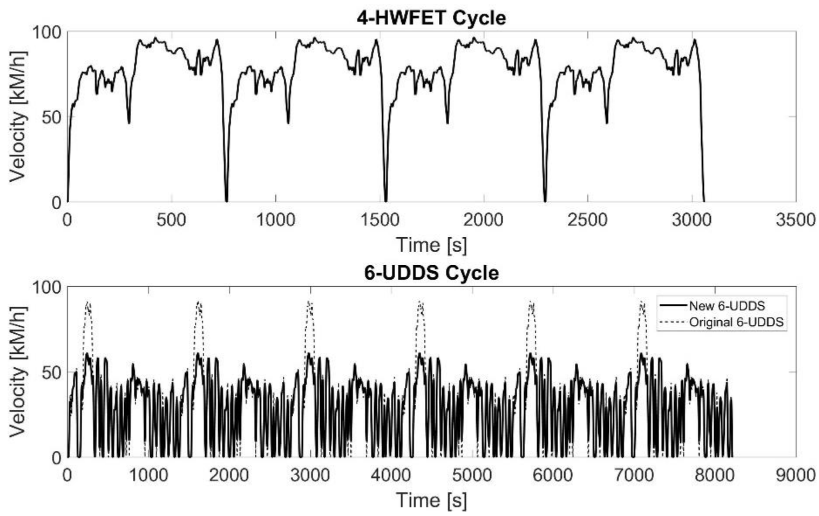
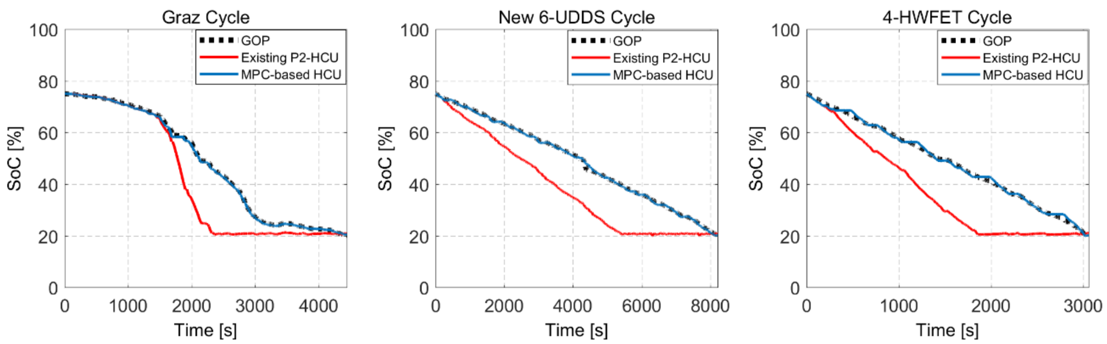


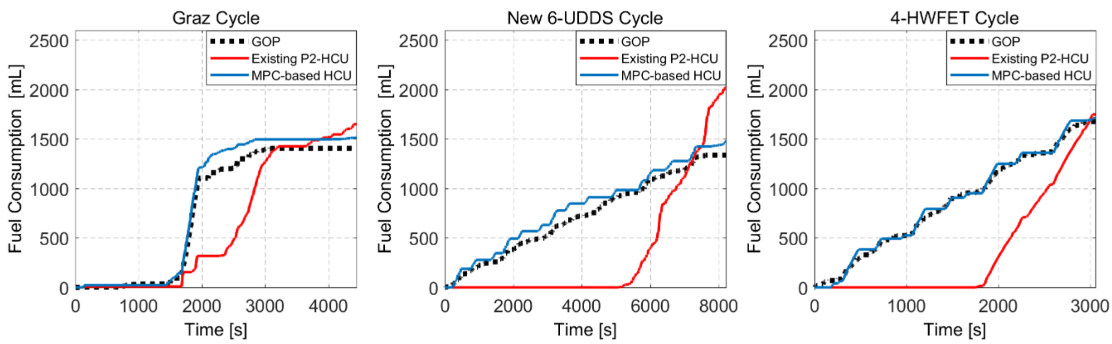
Figure 6.1.2: 4-HWFET cycle and 6-UDDS cycle velocity profiles.

The simulation results are displayed in Figure 6.1.3 (a) that shows the SoC depletion trajectories in the three cycles. Existing P2-HCU still operates in the CDCS mode, as clearly displayed in Chapter 4 Graz cycle's SoC trajectory is not that 'linear' as those of the new 6-UDDS cycle and the 4-HWFET cycle because of the altitude existence and a mix of various driving ranges. The created MPC-based HCU can follow the SoC reference trajectories offered by GOP well, which represent 'blended' mode as they should be. Figure 6.1.3 (b) shows fuel consumption accumulation trajectories in the three cycles. The final overall fuel consumption values of the existing P2-HCU in the three cycles are all between around 1500mL to 2000mL, which mainly owns to a similar distance design of the driving cycles. The discovery that the total distance to some extent reveals total energy demand also explains why researchers design global SoC depletion trajectory linearly changes along with distance. Of course, cycles with altitude like the Graz cycle are an exception. MPC-based HCU cannot reach the same contribution level as offline GOP calculation. It is reasonable because the actual online simulation velocity always has deviations from the target velocity. And offline GOP ignores lots of dynamic constraints; thus it only achieves a theoretically or potentially least fuel consumption. It is not difficult to find in Figure 6.1.3(b) that the fuel consumption accumulation trajectories of MPC-based HCU are all similar to GOP. The existing P2-HCU always has a fuel consumption accumulated in the later cycle range because of the EltlDrv-dominated mode selection until SoC reaches the lowest boundary. In this way, fuel consumption of the existing P2-HCU always goes beyond the fuel consumption trajectories of the MPC-based HCU in the final 1000s of the three cycles. Especially for the new 6-UDDS city test cycle, the fuel consumption of the existing P2-HCU dramatically increases during the battery sustaining process.

Numerical overall fuel consumption comparison results are recorded in Table 6.1.1. Properly tuned MPC-based controller and predictive R-W method have similar results. In the new 6-UDDS cycle, fuel economy improvement with predictive control strategies can reach up to 26%. In the 4-HWFET cycle, the value is around 1%-2%, and the Graz cycle's fuel economy improvement is around 8%, in between the highway cycle and the city cycle. It can be concluded that driving in the city cycle with the empty battery could be a disaster in view of fuel consumption reduction. This situation is exactly the long-distance driving case with CDCS strategy. From this aspect, predictive strategies are absolutely necessary. In another aspect, it is also clear that predictive strategies have no outstanding advantage in the highway cycle. However, it is meaningless to discuss the improvement in single short-term cycles. Generally speaking, predictive strategies are advantageous to improve fuel economy for PHEVs that are going to be used in all kinds of driving cycles for longer driving distances.



(a) SoC depletion trajectories comparison of the three driving cycles



(b) Fuel consumption accumulation trajectories comparison of the three driving cycles

Figure 6.1.3: Simulation results comparison of the three driving cycles.

Table 6.1.1: Numerical fuel consumption results comparison of the three driving cycles.

Cycle Type		Existing P2-HCU	MPC-based HCU	Predictive R-W HCU	Offline GOP
Graz	Fuel consumption	1648.3 mL	1511.8 mL	1512.8 mL	1405.9 mL
	Improvement	/	136.5mL/8.28%	135.5mL/8.22%	242.4 mL/14.7%
New 6-UDDS	Fuel consumption	2022.8 mL	1493.7 mL	1478.5 mL	1336.6 mL
	Improvement	/	529.1 mL/26.16%	544.3 mL/26.91%	686.2 mL/33.9%
4-HWFET	Fuel consumption	1748.5 mL	1713.1 mL	1729.8 mL	1676.2 mL
	Improvement	/	35.4 mL/2.02%	18.7 mL/1.07%	72.3 mL/4.13%

6.2 The Influence of Prediction Information

This Section is going to compare the influence of prediction information on the fuel economy improvements. As said above, the prediction horizon of MPC used in this thesis is 60s. The prediction is sufficiently short to have an assumption that prediction information in the 60s is accurate enough. In the created predictive R-W HCU, the only model that needs prediction information is ‘Penalty’, which is related to short-term velocity or long-term general traffic information. As a conclusion, prediction information used in online predictive models can be considered to be accurate enough. On the contrary, prediction information for the global horizon could be quite rough and inaccurate. Even though the cloud platform can update SoC reference frequently, the SoC reference has a great possibility to be suboptimal or non-optimal due to really long driving distances of the whole trip and absence of detailed long horizon prediction. Based on that, a detailed degree of prediction process only lays influence on the SoC reference trajectory calculation model (cloud platform/global horizon prediction). In the present work, the Graz cycle is used for simulation and analysis. And SoC_{init} is still set to 75%.

Section 5.1 listed three kinds of global horizon predictions: 1) pure distance information. 2) distance, velocity limitation and altitude. 3) distance, estimated/accurate velocity and altitude. In the first and third situation, a SoC reference trajectory is calculated individually. With only distance information available, the SoC value can deplete linearly along with the distance. With distance and altitude, accurate or non-accurate prediction information available, the SoC trajectory can be calculated due to the known power demand of each moment. The accurate velocity and estimated velocity profiles used for simulations are presented in Figure 6.2.1. The principle to design the estimated velocity is to follow the general shape of accurate velocity. In this way, the velocity in the highway range is relatively more accurate while the estimated velocity, especially in the city cycle, is hard to follow the peaks. Besides, lots of sudden stops are assumed to be traffic lights positions, that is always predictable with navigation guidance on board. Figure 6.2.2 presents the SoC reference trajectories for the first and third prediction situations. Although the estimated velocity is not accurate enough, its calculated SoC reference trajectory has a similar profile with the SoC reference trajectory calculated based on the accurate velocity. Figure 6.2.3 uses the SoC depletion trajectory to explain the heuristic rule defined in this thesis if only distance, velocity limitation (traffic condition) and altitude information are available. From 75% SoC_{init}, the controller selects EltlDrv at first. Later in the highway range, ConDrive is used. In the end of the highway range, where is the beginning of the rural range, the vehicle adopts to EltlDrv again until SoC reaches the boundary of 25% (as said in Section 5.1, for each final 5 km city cycle, 5% SoC is saved). Later in the final city range, pure electric drive is used. The final SoC of this case is 21.44%, which obviously is not low enough. Because as analysed in the last Chapter, a perfect blended operation mode is to run out of the battery at the end of the trip.

Table 6.2.1 lists all the numerical fuel consumption results with various predictive information. The fuel consumption of the existing P2-HCU is 1648.3 mL (can be found in Table 6.1.1), which is the basis for fuel consumption improvements. It is obvious that more predictive information leads to higher improvements. The first condition, that with accurate velocity, has 8.28% improvements, which is the closest to the offline GOP calculation result. The second condition, with estimated velocity, has around 6% improvements. As a conclusion, the predictive velocity is not necessary to be perfectly accurate, but just has to reveal general power demand of each short term trip section. The third condition designed with a heuristic rule according to the common set from Chapter 4 also has a fuel economy improvement of 3.54%. But it is a critical point to decide where to start ICE during the highway driving range. If the start position is at the beginning of the highway range, then the final fuel consumption is even worse due to too long-term high-power demand requirements. It can be assumed in this case, that the mid highway range could be a good choice, but this might be not optimal for other cycles. The last condition with only distance information does not show any fuel economy improvement. As a summary, predictive strategies cannot always promise better fuel economy. It is better to obtain the accurate or estimated power demand for each time interval.

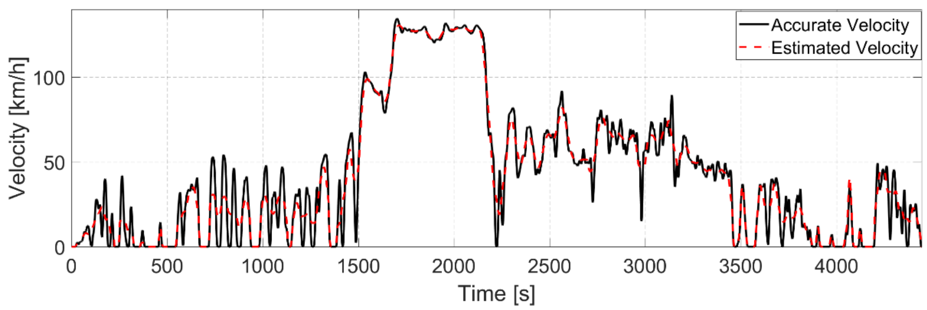


Figure 6.2.1: Accurate and estimated velocity of the Graz cycle used for simulations.

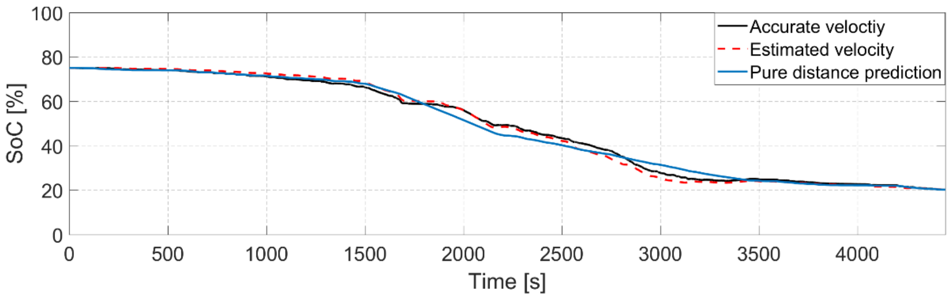


Figure 6.2.2: SoC reference trajectories with various prediction information.

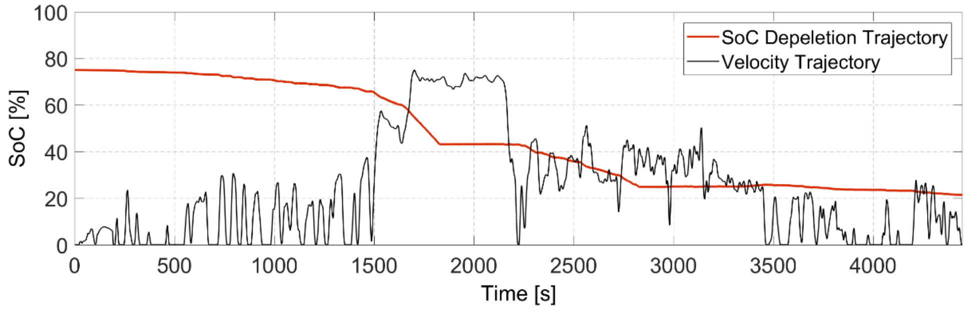


Figure 6.2.3: SoC depletion trajectory with a self-defined heuristic rule.

Table 6.2.1: Numerical fuel consumption results comparison with various predictive information

Prediction Information		**MPC-based HCU**	**Predictive R-W HCU**
Distance Accurate Velocity Altitude	Fuel consumption	1511.8 mL	1512.8 mL
	Improvement	136.5mL/8.28%	135.5mL/8.22%
Distance Estimated Velocity Altitude	Fuel consumption	1551.0 mL	1544.7 mL
	Improvement	97.3 mL/5.90%	103.6 mL/6.29%
Distance Velocity Limitation Altitude	Fuel consumption	1590.0	
	Improvement	58.3 mL/3.54%	
Distance	Fuel consumption	1721.7 mL	
	Improvement	-73.4 mL/-4.45%	

Chapter 7 Summary and Recommendation

This part summarizes the outcomes of the thesis and recommends some future improvements based on an objective discussion.

7.1 Summary

PHEVs offer promising solutions for the more and more serious CO_2 emission problem. They are one of the main categories in the electrification process of the automotive industry. With additional large size battery and EM, PHEVs can greatly improve the fuel economy of vehicles. The improvement effectiveness strongly relies on the control strategy in the HCU. Predictive control strategies are developed a lot recently due to generally mature navigation and communication devices and sensors. And trip velocity, distance and altitude profile are more or less available today. Lots of literature works prove predictive strategies can improve the fuel economy of HEVs. The basement of the thesis are a P4 PHEV and a P2 PHEV. The ultimate objective of the thesis is to improve fuel economy by reforming the existing HCUs into predictive HCUs. The existing P2-HCU and P4-HCU Simulink models have similar inner structures. They all operate with traditional non-predictive CDCS strategies which use electric drive almost completely from the start sections of trips. The main difference inside is the power distribution model, where the P2-HCU decides particular driving modes and the P4-HCU calculates the power split ratio. The CDCS strategy is not advantageous anymore when the trip distance is out of AER. Obviously, the later created predictive HCU should be evaluated by comparing simulation results with existing traditional HCUs simulation. P4-HCU has some problem in the Simulink simulation, thus predictive HCUs are created based on the P2-HCU. The simulation results of the existing P2-HCU is the comparison reference in the whole thesis.

The thesis is not about to create a brand new HCU, but to research the influences of outcomes of the power distribution decision, that includes the different driving modes in the P2-HCU. Target is to better understand how predictive strategies behave in saving fuel when the trip is out of AER. The thesis firstly develops a GOP tool to obtain a globally optimal solution. The most difficult design in this part is to make the traditional DDP solver be compatible with the hybrid control problem for the selection of driving modes. With this solver, the thesis finds out smart power distributions for a global scale that contributes most to the fuel economy improvements. But one commonly discussed element, the fully utilizing of recuperation potential doesn't contribute to the benefits. The offline GOP calculation work also draws a conclusion that SoC initial value doesn't regularly influence the fuel economy improvements.

With the conclusions of offline GOP calculation part, the thesis later develops a global SoC reference trajectory model and two online predictive models based on the MPC and R-W method. The design process reasonably takes the drivability and NVH/comfort requirements into consideration instead of sacrificing too much for the sake of fuel economy. Later, two predictive models are integrated with the power distribution model in the P2-HCU. In the case, there are a MPC-based HCU and a predictive R-W HCU available. The R-W method is similar to the ECMS, but actually a kind of heuristic strategy. It is noteworthy that the R-W method is not compatible with the P4-HCU. MPC, on the contrary, is a state-of-art method for predictive control and can be used in the P4-

HCU. In this thesis, with the self-designed DDP solver, it can work in the P2-HCU as well.

In the end, Simulink simulations are finished to observe how the driving cycles and predictive information influence the fuel economy improvements with predictive strategies. The conclusion is that road segments, which have lots of low velocity and sudden stop time instants, lead to a dramatical increase in fuel consumption. On one hand, highway cycles without this case cannot reveal the advantages of predictive strategies. City cycles, on the other hand, witness considerable decreasing in fuel consumption with predictive strategies. An exemplary applied Graz city cycle is some case in between, where predictive control strategies show numerical fuel economy improvements. As for the influence of predictive information, it can be stated that of course, the information is more accurate and abundant, the results are better. Once the power demand is available, which at least asks for an estimated velocity trajectory, predictive control strategies show the greatest potential.

7.2 Recommendation

7.2.1 Discussion

When people talk about predictive control strategies, there is a common doubt that predictive control strategies always are beneficial compared to the most common CDCS strategies in PHEVs. With the question in mind, the thesis does not only create a predictive HCU to improve the fuel economy but also targets to clarify in which kind of cases predictive strategies cannot promise benefits in fuel economy behavior. First of all, the thesis discusses the recuperation situation, which is talked about a lot in the typical example: to use more electric energy if prediction shows that there is a downhill driving section ahead. The thesis proves that this aspect is necessary for HEVs that have a small capacity battery, but not significant for PHEV implementing the CDCS mode. Secondly, in the final simulation results, it is clear that in pure highway driving cycles, predictive strategies are not advantageous anymore. This can clearly answer another frank question: what predictive strategies can do if there is a vehicle driving in the highway cycle with constant speed. The answer is 'nothing'. Thirdly, it is not so easy to squeeze saved fuel even with predictive strategies. The final results also depend on the detailed degree of predictive information. Even though lots of literary works show that with only distance information to obtain the linear change of SoC reference, still there is some fuel economy improvement. This is not always right according to the results of the simulations in this thesis. It is shown that it is better to use future power demand information even though the velocity profile is only an estimated one.

One important motivation behind all the works of the thesis leads to one main issue that is different from other master thesis work about predictive control strategies used in HEVs or PHEVs. The thesis didn't create and compare the real-time behavior, feasibility and some other behaviors of all kinds of predictive control strategies. Generally speaking, nowadays MPC is quite hard to be implemented into HCU for the real-time constraints. Literary works usually use it as a kind of upper-level benchmark after GOP, and creates predictive rule-based control strategies with real-time capability. This is also one reason why the thesis didn't verify the MPC-based HCU in HIL tests in Appendix 3. The HIL test in this thesis is not complete and more time would be needed to gather solid results.

7.2.2 Recommendations for future work

Based on the discussion part, there are some recommendations for future works:

1). All the simulations are finished based on the P2-HCU, it is also necessary to verify all the predictive methods created in this thesis for the P4-HCU. The predictive R-W method is an exception to that.

2). The thesis already clarifies that predictive control strategies are valuable. More types of predictive strategies should be created and compared.

3). It is important to improve the MPC in its real-time behavior.

4). A complete HIL test should be performed to prove the blended SoC trajectory and to compare the results with the simulation results of this thesis.

5). As for the global prediction model of the SoC reference trajectory calculation, more creative use of cloud platforms in predictive control could be an interesting topic.

6). It is still necessary to reduce the dependence on predictive information (quantity and quality). Statistics methods to estimate velocity or average velocity profiles and more intelligent methods, e.g. machine learning offer more solutions for that topic. These methods also may help to improve the controller real-time ability because nowadays optimization-based control methods still suffer regarding computation burden.

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Appendices

Appendix 1. HEVs Configuration Classification

A 1.1 Micro, Mild and Full HEVs

As discussed in Section 2.1, according to the degree of electrification, there are micro HEVs, mild HEVs, full HEVs, PHEVs and EREVs except for conventional vehicles and pure EVs. Micro, mild and full HEVs are standard HEVs without external charging source.

For most cases, the power size and the functions of EMs mounted in HEVs are used to distinguish micro, mild and full HEVs, as shown in Table A.1 [6]. As known, compared to CVs, HEVs have additional special functions to save fuel energy. The first function, engine start-stop, means to stop ICE during vehicle idling or low efficient speed range. Sometimes, a relatively higher power EM in a mild HEV can start/stop the ICE automatically whenever it's necessary. A further increase in fuel economy comes from energy recuperation, while vehicle deceleration or downhill scenarios. Another function that doesn't exist in micro HEV, is an electric boost, which realizes ICE load points shift to work on optimum setpoints of the combustion engine. From mild HEV to full HEV, electric boost is updated to electric traction. In this case, the vehicle can be propelled by the EM alone.

Table A.1: Comparison of micro, mild and full HEVs [5]

HEV Type	Micro HEV	Mild HEV	Full HEV
ICE	Conventional	Downsized	Downsized
EM Power	3-5 kW	7-15 kW	> 30 Kw
EM Voltage	12V	60-200 V	200-600 V
Fuel Saving	5-10%	20-30%	30-50%
Functions	Start/Stop Recuperation Accessories Charging	Start/Stop Recuperation Electric Assist	Start/Stop Recuperation Electric Traction
Example	BMW 1 and 3 series Ford Focus	BMW 7 Series Honda Civic Insight Hybrid	Toyota Prius Chevrolet Tahoe Hybrid
Relative Cost	Low	Medium	High

It seems like micro, mild and full HEVs all have functions of ICE start/stop and energy recuperation. However, the function realization extent is mostly decided by the EM power size. For example, energy recuperation is only possible to a very small extent in micro HEVs. Full HEVs can save fuel energy to the most extent, nevertheless, a larger size EM and battery brings to much higher cost compared to micro and mild HEVs. Thus, it's hard to simply conclude that full HEV is the best. There should be a compromise between fuel economy, cost, functionality and safety. A popular example is the mild 48V hybrid system, which has a potential of achieving competitive fuel economy with significantly lower incremental costs [78, 87, 88].

A 1.2 Series, Parallel and Series-parallel HEVs

There are three types topologies of HEVs based on the powertrain components configuration: series, parallel and series-parallel. In series HEVs, ICE is usually equipped with an electric generator for charging battery rather than driving the wheels. Parallel HEVs, however, contain two parallel traction paths: electrical path and mechanical path. Series-parallel is the combination of series and parallel configuration. Lots of literature outcomes explain and compare these three HEV types, e.g. [5, 6, 78, 87-90], the thesis will not unfold this part.

A 1.3 P0-P4 HEVs

One another traditional classification of HEVs topologies are based on the position of the EM in the powertrain system. There are 5 types, as illustrated in Figure A.1 [88]:

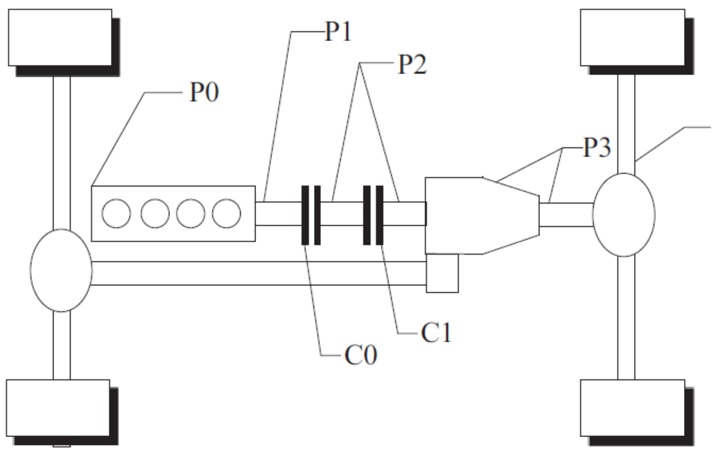

Figure A.1: Configurations of HEVs as a function of the EM positions [88][89]

P0 features a Belt Driven Starter/Generator (BSG) directly coupled to the ICE, which will have a significant impact on the design of Front-End Accessory Drive (FEAD). P0 HEVs ask high level of belt tension to offer start torque or regenerate energy efficiently. The main disadvantage of P0 layout is the low efficiency [91] due to the belt drive design and sustaining ICE drag torque.

P1 has the EM mounted on the crankshaft, known as integrated starter/generator (ISG). Compared to belt drive in P0, P1 has relatively higher drivetrain efficiency. However, P1 configurations have more impact on the existing vehicle architecture, EM needs to be designed more delicately. In P0 and P1 HEVs, electric traction is possible but not a smart choice, thus usually only medium or small power size electric systems are equipped.

P2 has EM side mounted on the gearbox input, after the clutch. Clutch 0 (C0) is the normal and essential clutch in all P0-P4 powertrains. Clutch (C1) is the optional clutch only for P2 HEV. The obvious advantage of P2 layout is high efficiency without ICE drag torque loss. And when ICE is disconnected to EM, pure electric drive is possible. Moreover, EM can match well to the drive demand with the better-designed gearbox. In P0, P1 and P2 HEV, EM works as ICE starter, thus conventional ICE starter can be removed.

P3 has an EM at the gearbox output and P4 at the driving axle, connected to wheels all the time. Without drag torque of ICE and gearbox, P3 and P4 layout have the highest efficiency during driving or recuperation. However, it should be noticed that the EM is always connected to the wheels, which means these two layouts do not provide the ability to generate electricity by the ICE for the consideration of vehicle stability and safety. P3 and P4 HEVs also lose the potential to optimize ICE load points without electric boost function. Additionally, EM speed and torque range need to cover the whole vehicle speed and torque range. Especially for P4 HEV, All Wheel Drive (AWD) is possible.

To allow the most integration of vehicle platforms, PX+P4 is a popular layout nowadays. As it is shown in Figure A.2 [91], PX means another EM besides the ICE. 'Pure P4' layout separates the two axles into an electric axle and a conventional axle, an additional EM on the conventional axle can keep the functions of ICE start/stop, direct battery charging, electric boost. The most popular 48V mild P0+P4 hybrid system almost combine all the benefits of P0-P4 configurations [87][91].

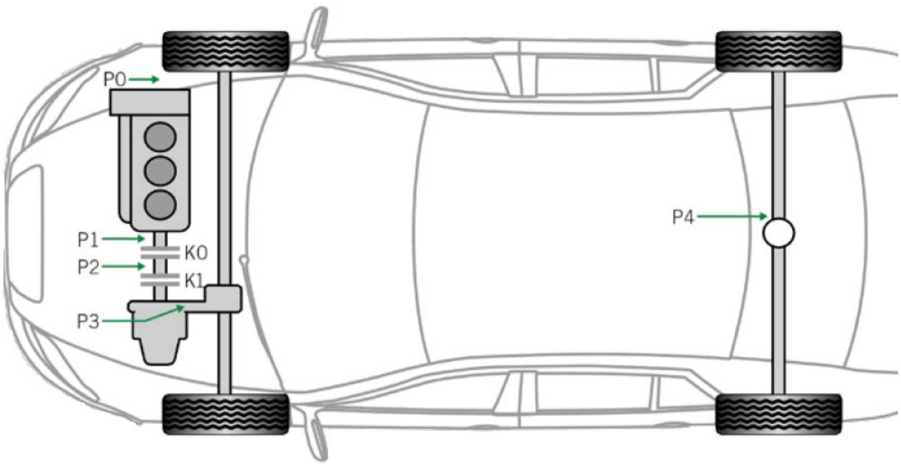

Figure A.2: Schematic diagram of different hybridization variants [91]

Appendix 2. Optimization Objectives of MPC

Within the HCU, MPC is used in various aspects for several main objectives. Due to the contradiction between these objectives, it is normally tried to optimize one or two objectives instead of all of them at once. Therefore, it's necessary to confirm the optimization objectives before the development of predictive control starts for a detailed hybrid vehicle configuration.

The most common and urgent goal is to minimize fuel consumption, which is the main advantage of HEVs or PHEVs compared to traditional vehicles. There are lots of researches and practice results for that. The main idea behind them is to influence the engine start-stop decision, modes selection or the optimum power split ratio in the corresponding driving environment of the controller. In Ref [92], authors take the extra fuel consumption cost of the engine one-time start as a constant number. Then two predictive fuzzy control methods are implemented to reduce the engine starts and stops. Also, some papers only focus on the engine start-stop system, for example, in Ref [93], a MPC-based controller is proposed to make the engine start quickly and smoothly. This result contributes a lot in an urban area with numerous engines idling and restarting states. Directly deciding the engine start-stop is one way, implementing MPC to select the operation modes or calculate the ideal power split ratio is another. Taking future information into consideration, like the road grade, vehicle speed, traffic flow even potential route change, etc. MPC-based energy management controllers can select the best strategy for the whole cycle or for a short period. All in all, ideally, they will choose the right strategy at right time to prepare for the future and make full use of recuperation.

Besides the engine, the battery is another important component in HEVs or PHEVs. For a one-time cycle, we would like to take full advantage of electric energy to reduce fuel consumption. But in the long run, it's also important to concern about the battery-aging and battery-fading issue. Based on this consideration, some researches use the MPC-based controller to reduce the battery over-discharging. Traditionally lots of control strategies restrict the scope of adding batteries SoC upper and lower thresholds or creating the ideal temperature environment. But in ref [94], a predictive algorithm is created to prepare the engine advanced start for providing desired power in the future. Also, the proposed algorithm is validated under different battery temperature environments. Fuel consumption is not optimized here obviously.

Because of nowadays strict emission regulation around the world, to hybridize the vehicle into HEVs or PHEVs is a popular choice for automotive manufacturers. The reduction of engine working time, optimum engine efficient operating points, the recuperation of energy during braking or downhills can all contribute to decreasing the overall emissions. However, under certain circumstances, we still need to pay additional attention to engine emission optimization. A classic situation is that the internal combustion engine in the hybrid vehicle is a diesel engine instead of the gasoline engine. As we can see in Ref [95], the authors take care of the performance of after-treatment systems. A control model is implemented, which is the integration of HEV superior control models and after-treatment thermal dynamic models. The integrated model can simulate the temperature dynamics of the after-treatment system. And through early and late post injections, the catalysts warm-up function is specially offered.

Comfort and drivability could be two critical properties of a vehicle, from the customers' side. In ref [96], researchers look into modes shifting process of a dual planetary power-split hybrid electric bus and analyze the reasons for the occurrence of system jerk. Based on that, a MPC-based dynamic coordination strategy is implemented to eliminate system jerk, thus improving comfort property. In ref [97], a MPC-based controller is designed to smooth the coupling during the transition between pure electrical mode and hybrid mode of a P12-configuration hybrid powertrain. Drivability is defined as the ability to supply the desired torque demand in a short time interval [98], it can be optimized through dynamics optimization of the propulsion machine.

As a summary, most of the MPC-based optimization objectives are within these five topics: fuel consumption, battery lifespan, tailpipe emission, comfort and drivability. It's unrealistic to gain the best results in every aspect. While we can find some examples to optimize two or three aspects. For example, multi-layer or integrated MPC strategy [95][98], longer prediction horizon to gain better trade-off [99]. Among these multi-objective MPC-based control strategies, selection of fuel consumption and battery lifespan altogether as the ultimate goal is quite popular [99-101].

Appendix 3. Hardware-in-the-loop Test

All the Simulink simulation processed in the computer represents some kind of model-in-the-loop (MIL) test. Such simulation tests cannot promise real-time performance constraints to be met in an embedded device with real-world I/O for each sample time [15]. Hardware-in-the-loop (HIL) is an important process of software development. HIL test allows the control algorithm to be verified before the test in the vehicle, which is much more expensive and time-consuming. The automotive controller includes a plant to be controlled, which is real and accurate in HIL tests. In MIL tests, the controller hardware is still not available, therefore only its Simulink model is used. HIL tests, on the contrary, have the actual hardware connected. With the HIL tool, researchers can test it repeatedly early in the design progress and reasonably tune some calibration parameters. The HIL simulation of automotive electronic control units (ECUs) is suitable for all kinds of the automotive controller, from the engine, transmission to HCU etc. All in all, HIL tests are an effective approach for rapid prototyping and evaluation. In the main content of the thesis, the predictive controller is simulated and evaluated in a MIL simulation in Matlab/Simulink. Here the additional part, HIL test is adopted. Due to some reasons, the HIL test was not fully successful, which leads to some simple but not complete conclusions. The following step of MIL is software-in-the-loop (SIL), where all the HCU Simulink models are transferred into a C-code through dSPACE software or an embedded C-code generator of Matlab. In SIL tests, coding bugs are easy to be found. In the course of the present project, the HIL device is offered by AVL, with a real HCU, a real TCU, real solenoids and a virtual plant model in the loop. The virtual models within HIL can capture dynamic characteristics accurately and run in real time. The TCU is designed by another department. The HCU is the integration of the existing P2-HCU C-code with the created predictive R-W model generated C-code. The MPC HCU is not tested in HIL due to the restricted thesis time schedule and code generation complexity. Moreover, the heavy computation requirements of MPC HCU make it impossible to run real time in the HIL device. More design or simplification jobs need to be finished in the MPC HCU. The simulation cycle used in the HIL system is the Graz cycle. The HIL device only tests with the NEDC cycle, which actually cannot promise the success of the Graz cycle. Because, as discussed in Section 3.5, NEDC is a kind of modal cycle, while the Graz cycle with lots of sudden changes in the velocity profile is a kind of transient cycle. To compare all kinds of simulation results, a fair basis that follows the Graz target velocity should be promised. Otherwise, simulation results are not comparable due to various power demands in each simulation case. This is exactly the problem met in one-week HIL test finished in December 2018. The huge velocity deviations of various simulation cases can be found in Figure A.3. The reason leads to this could be an incompatibility between the HCU and the TCU. No matter what it is, more time is needed to fix the problem, which is out of the time schedule of the thesis. In this case, the finished HIL test is not sufficient to prove if the predictive R-W model can improve fuel economy. But it is still clear to find out that the predictive strategy implements typically blended operation modes and the fuel consumption accumulates most in highway range as shown in Figure A.4. The phenomenon is exactly the same as shown in the MIL simulation results in Chapter 6.

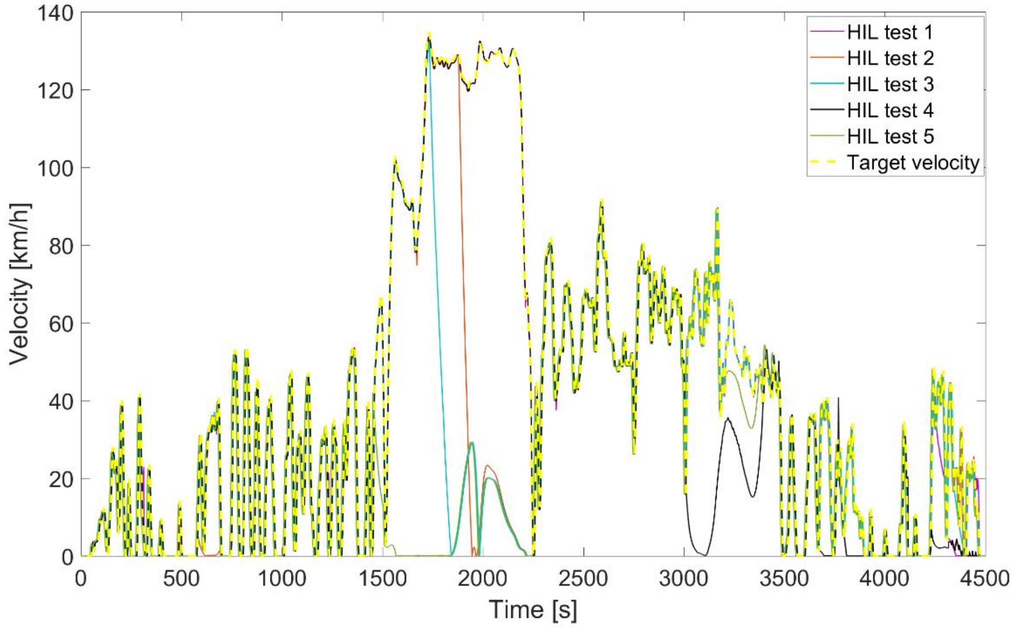

Figure A.3: Velocity of five HIL tests. Test 2, test 3, test 5 show considerable velocity deviations from the target velocity trajectory.

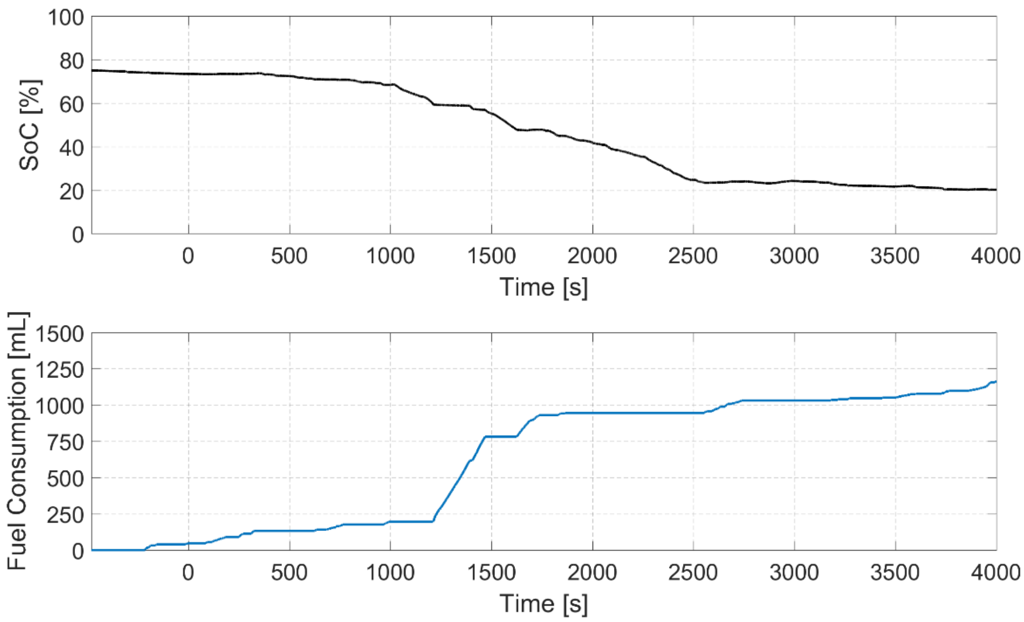

Figure A.4: SoC and fuel consumption trajectory of the predictive HCU HIL test.