Doctoral Thesis in Mechatronics

Computationally Efficient and Adaptive Energy Management Strategies for Parallel Hybrid Electric Vehicles

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Computationally Efficient and Adaptive Energy Management Strategies for Parallel Hybrid Electric Vehicles

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Academic Dissertation which, with due permission of the KTH Royal Institute of Technology, is submitted for public defence for the Degree of Doctor of Philosophy on Wednesday the 31st May 2023, at 1:30 p.m. in Gladan, Brinellvägen 83, Stockholm.
Only blood, sweat, and tear lead me toward success.

Bara blod, svett och tårar leder mig mot framgång.

惟有血，汗，泪引领我走向成功。

— Tong Liu
Abstract

Hybrid electric vehicles (HEVs) are irreplaceable in attaining sustainable development in contemporary society. Owing to the extra degree of freedom in supplying traction power, HEVs resort to appropriate energy management strategies (EMSs) to present their superiority over conventional internal combustion engine vehicles and pure electric vehicles.

Existing EMSs suffer from heavy computation overheads and excessive mode switches. This thesis proposes several novel methods for developing online EMSs for parallel HEVs that achieve both compelling fuel economy and excellent computation efficiency and adaptivity in online applications with uncertain driving conditions.

First, offline dynamic programming (DP) solutions are exploited to develop online EMSs for close-to-optimal control performances. The optimal speed profile serves as the reference in online control and the optimal value function (VF) is utilized to design control methods. To avoid the “curse of dimensionality”, tabular VFs are approximated by piecewise polynomials to substantially decrease computation and memory overheads in online usage.

Second, to reduce the search space for optimal control actions, two types of special internal combustion engine (ICE) configurations are adopted and analyzed. The first type forces the ICE to strictly operate at the optimal operation line (OOL), whereas the second one allows a narrow band around the OOL. The second one outperforms the first one because it contributes to more robust ICE operations with slightly higher computation complexity.

Third, a hierarchical architecture is proposed for online EMSs so that the transient powertrain mode and torque split scheme are optimized by different methods in sequence. To avoid the exponential complexity of finding the optimal trajectory of the powertrain mode, the optimal VF is leveraged for an optimal decision within one control period with the aid of simplified assumptions. Model approximations on the ICE and the electric motor are conducted so as to convert the complex torque split problem into a constrained quadratic programming problem. These methods dramatically facilitate the computation efficiency of each online EMS.

Fourth, learning-based adaptive control is introduced to mitigate the adverse effect caused by deviations between the model and reality. For this target, efficient learning algorithms are designed to iteratively update the coefficient matrix of approximated VF. Moreover, to avoid the pitfall of “cold start” and prompt a fast convergence, the coefficient matrix is initialized by the optimal VF from offline DP.

Finally, an event-triggered control mechanism is applied to the torque split control and presents its remarkable advantage in eliminating excessive computation overhead. At each time step, the efficient trigger algorithm
decides if the reference ICE torque is still valid or outdated. If it is valid, the EMS directly uses the reference value as the optimal output; otherwise, the optimization algorithm for torque split control is executed to calculate a new value and update the reference.

Performances of designed EMSs are tested by processor-in-the-loop simulations so that both numeric results and computation efficiencies can be obtained for quantitative analysis and comparisons. The testing results indicate that the proposed EMSs can rapidly adapt to real driving conditions and generate more than 90% fuel economy of the DP optimum, and more importantly, all these EMSs are real-time implementable on a portable microprocessor with limited onboard computation resources.

**Keywords:** Hybrid Electric Vehicle, Energy Management Strategy, Computation Efficiency, Value Function, Adaptive Learning, Processor-in-the-Loop Simulation
Sammanfattning

Elhybridfordon (HEV) är oersättliga för att uppnå en hållbar utveckling i dagens samhälle. Medelst den extra frihetsgraden för att tillhandahålla dragkraft, använder HEV:erna sig av s.k. energihanteringstrategier (EMS) för att kombinera fördelarna med konventionella förbränningsmotorfordon och rena elfordon.

Befintliga EMS lider av tunga beräkningskostnader och överdrivna lägesomkopplare. Denna avhandling flera nya metoder för att utveckla online-EMS för parallella HEV som uppnår både övertygande bränsleekonomi och utmärkt beräkningseffektivitet, samt god anpassningsförmåga i online tillämpningar med osäkra körförhållanden.

För det första utnyttjas offline dynamisk programmering (DP)-lösningarna för att utveckla online EMS för nära optimal reglerprestanda. Den optimala hastighetsprofilen tjänar som referens vid online-reglering och den optimala värdefunktionen (VF) används för att utforma reglermetoder. För att undvika ”dimensionaliteten förbannelse” approximeras tabellformat VF:er med bitvisa polynom för att avsevärt minska beräknings- och minneskostnader när de används online.

För det andra analyseras två typer av speciella förbränningsmotorkonfigurationer (ICE) vilket minskar sökutrymmet för optimala regleråtgärder. Den första typen tvingar ICE att arbeta strikt vid den optimala driftlinjen (OOL), medan den andra typen tillåter ett smalt band runt den. Den andra typen är bättre än den första eftersom den bidrar till mer robust ICE-drift, men med något högre beräkningskomplicerat.

För det tredje föreslås en hierarkisk arkitektur för online-EMS så att det transienta drivlinjeläget och vridmomentfördelningen optimeras med olika metoder i sekvens. För att undvika den exponentiella komplexiteten i att hitta den optimala banan för drivlinjeläget utnyttjas en VF grundad på förenklade antaganden, vilket leder till ett optimalt beslut inom en kontrollperiod. Modellförenklingar av både ICE och elmotorn genomförs för att omvandla det complexa problemet med vridmomentfördelning till ett begränsat kvadratiskt programmeringsproblem. Dessa metoder underlättar dramatiskt beräkningseffektiviteten för varje online EMS.

För det fjärde introduceras inlärningsbaserad adaptiv styrning för att mildra den negativa effekten som orsakas av avvikelser mellan modellen och verkligheten. För detta ändamål är effektiva inlärningsalgoritmer utformade för att iterativt uppdatera koefficientmatrisen för approximerad VF. Dessutom, för att undvika fallgropen ”kallstart” och föranleda en snabb konvergens, initieras koefficientmatrisen av den optimala VF från offline-DP.

Slutligen appliceras en händelseutlöst kontrollmekanism på vridmomentsv...
delningskontrollen och uppvisar sin anmärkningsvärda fördel när det gäller att eliminera alltför stora beräkningskostnader. Vid varje tidssteg avgör den effektiva triggeralgoritmen om referens-ICE-vridmomentet fortfarande är giltigt eller föråldrat. Om det är giltigt använder EMS referensvärdet direkt som den optimala utgången; annars exekveras optimeringsalgoritmen för vridmomentdelningskontroll för att beräkna ett nytt värde och uppdatera referensen.


**Nyckelord:** Elhybridfordon, Energihanteringsstrategi, Beräkningseffektivitet, Värdefunktion, Adaptiv Inlärning, Processor-in-the-loop
Acknowledgement

On the occasion of rounding off my doctoral thesis in KTH Royal Institute Technology, I would like to express my great appreciation to everyone who ever provided me with company, support, encouragement as well as criticism during my entire student life.

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安危他日终须仗，甘苦来时要共尝：
孤当与诸君风雨同舟，携手共进，养天地正气，法古今完人。

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母爱若水，父爱如山：
爱子心无尽，归家喜及辰；月明闻杜宇，南北总关心。

Last but not least, my heartfelt gratefulness and best wishes ought to be attributed to my previous mentors, Prof. Xiangmo Zhao and Prof. Huansheng Song, from my alma mater, Chang’an University, in distant China. I could not grow up from an innocent youth to a competent researcher without your cultivation, enlightenment, tolerance, and expectation. May happiness follow you everywhere just like we do.

三千雨露清，笙歌伴雁行；桃李满天下，春晖遍四方。

Tong Liu 刘童
Stockholm, Sweden, March 2023
List of papers

Paper A

*Increasing Fuel Efficiency of a Hybrid Electric Competition Car by a Binary Equivalent Consumption Minimization Strategy*

Tong Liu, Lei Feng, Mikael Hellgren, and Jan Wikander


Paper B

*A Binary Controller to Ensure Engine Peak Efficiency for a Parallel Hybrid Electric Car*

Tong Liu, Lei Feng, Mikael Hellgren, and Jan Wikander


Paper C

*Fuel Minimization of a Hybrid Electric Racing Car by Quasi-Pontryagin’s Minimum Principle*

Tong Liu, Lei Feng, and Wenyao Zhu

*IEEE Transactions on Vehicular Technology (TVT)*, vol.70, no.6, pp. 5551-5564, June 2021.

Paper D

*A Low-Complexity and High-Performance Energy Management Strategy of a Hybrid Electric Vehicle by Model Approximation*

Tong Liu, Wenyao Zhu, Kaige Tan, Mingwei Liu, and Lei Feng

Paper E

Computationally Efficient Energy Management for a Parallel Hybrid Electric Vehicle Using Adaptive Dynamic Programming

Tong Liu, Kaige Tan, Wenyao Zhu, and Lei Feng

Submitted to IEEE Transactions on Intelligent Vehicles (T-IV), 2023.

Paper F

Optimal and Adaptive Engine Switch Control for a Parallel Hybrid Electric Vehicle Using a Computationally Efficient Actor-Critic Method

Tong Liu, Kaige Tan, Wenyao Zhu, and Lei Feng

2023 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM), Seattle, WA, USA, 27 June 27 - 1 July 2023, accepted and to be published.

Other contributions by the author not included in the thesis.

Paper G

Computationally Efficient Energy Management for a Hybrid Electric Racing Car by Binary Model Predictive Control and Pontryagin’s Minimum Principle

Tong Liu, Lei Feng, and Shuo Fu

34th International Electric Vehicle Symposium and Exhibition (EVS34), Nanjing, China, 25-28 June 2021.

Paper H

Research Progress on Test Scenario of Autonomous Driving

Runmin Wang, Yu Zhu, Xiangmo Zhao, Zhigang Xu, Wenshuai Zhou, and Tong Liu

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<td>AC</td>
<td>Actor-critic</td>
</tr>
<tr>
<td>ADP</td>
<td>Adaptive dynamic programming</td>
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<tr>
<td>AVF</td>
<td>Approximated value function</td>
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<tr>
<td>BLDC</td>
<td>Brushless direct current</td>
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<tr>
<td>DDPG</td>
<td>Deep deterministic policy gradient</td>
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<tr>
<td>DNN</td>
<td>Deep neural network</td>
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<tr>
<td>DP</td>
<td>Dynamic programming</td>
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<td>DQN</td>
<td>Deep Q-network</td>
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<td>DRL</td>
<td>Deep reinforcement learning</td>
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<tr>
<td>ECMS</td>
<td>Equivalent consumption minimization strategy</td>
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<td>EES</td>
<td>Electric energy storage</td>
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<td>EM</td>
<td>Electric motor</td>
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<td>EMS</td>
<td>Energy management strategy</td>
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<td>EV</td>
<td>Electric vehicle</td>
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<tr>
<td>HIL</td>
<td>Hardware-in-the-loop</td>
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<tr>
<td>HEV</td>
<td>Hybrid electric vehicle</td>
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<tr>
<td>HJBE</td>
<td>Hamilton–Jacobi–Bellman equation</td>
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<tr>
<td>GA</td>
<td>Genetic algorithm</td>
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<tr>
<td>ICE</td>
<td>Internal combustion engine</td>
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<td>ICEV</td>
<td>Internal combustion engine vehicle</td>
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<td>LB-EMS</td>
<td>Learning-based Energy management strategy</td>
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<td>MINLP</td>
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<td>MPC</td>
<td>Model predictive control</td>
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<td>NRMSE</td>
<td>Normalized root mean square error</td>
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<td>OB-EMS</td>
<td>Optimization-based Energy management strategy</td>
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<tr>
<td>OCP</td>
<td>Optimal control problem</td>
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<td>OOL</td>
<td>Optimal operation line</td>
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<td>PIL</td>
<td>Processor-in-the-loop</td>
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<td>Abbreviation</td>
<td>Description</td>
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<tr>
<td>PMP</td>
<td>Pontryagin’s minimum principle</td>
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<td>PSO</td>
<td>Particle swarm optimization</td>
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<td>Q-value</td>
<td>State-action value</td>
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<td>RL</td>
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Chapter 1

Introduction

This chapter starts by introducing the significance of vehicular electrification on energy conservation and emission reduction, especially highlighting the distinctive merits of hybrid electric vehicles (HEVs). After exemplifying and analyzing the current research and development status of diverse HEV energy management strategies (EMSs) at great length, existing research gaps are highlighted and based on which research questions (RQs) are meticulously proposed. Then, the main contributions of this thesis are briefly summarized, followed by an outline of the remaining chapters. At last, the statement correlated to the Sustainable Development Goals raised by United Nations is provided.

1.1 Background

According to International Energy Outlook\footnote{https://www.eia.gov/outlooks/ieo}, the total world energy consumption will surge from 629 quadrillion Btu\footnote{1 quadrillion = $10^{15}$, Btu refers to British thermal unit, 1 Btu $\approx 1055$ joules} in 2020 to 911 quadrillion Btu in 2050, roughly a 45% increase. Although renewable energy accounts for a continuously larger share of the energy market, it cannot completely replace fossil fuels, including coal, natural gas, petroleum, and other liquids, in the foreseeable future. Since the majority of current road passenger and freight vehicles are powered by internal combustion engines (ICEs) consuming fossil fuels, the transportation sector consumes more than 50% of petroleum and other fossil fuels, and thus, contributes the second largest end-use energy consumption throughout the 30-year projection (following the industrial consumption but obviously ahead of residential and commercial ones). Correspondingly, the annual greenhouse gas emission is predicted
to reach 42.839 billion \textit{mt}\footnote{mt refers to metric ton, 1 mt = 1000 kg} in 2050 globally, implying a nearly 1% annual gain in average since 2020 with 31.5 billion \textit{mt} onward. 37% of this emission is from the transportation sector due to the highest reliance on fossil fuels among all sectors. In the meantime, road passenger and freight vehicles are responsible for at least 80% of the emission concerning transportation\cite{1}.

Such massive fossil fuel consumption and greenhouse gas emission incur serious energy crises, climate change, and environmental degradation in contemporary society. Statistical Review of World Energy 2022, issued by British Petroleum\footnote{https://www.bp.com/en/global/corporate/energy-economics.html} elucidates that the average crude oil price in 2021 bounced back to $70.91 per barrel\footnote{1 barrel = 42 U.S. gallons \approx 159 litres} second highest since 2015 and quadruple higher than that in 1998. Additionally, State of the Global Climate 2021, published by World Meteorological Organization\footnote{https://public.wmo.int/en/our-mandate/climate/wmo-statement-state-of-global-climate} solemnly warns that resulting from the accumulation of greenhouse gas, the global mean temperature in the most recent seven years, 2015-2021, has peaked on record, over 1.1\textdegree C above the pre-industrial average during 1850-1900. Disastrous consequences include the facts that the global mean sea level rose an average of 4.5\textit{mm} per year since 2013, the area of the Antarctic ozone hole reached up to 24.8\textit{million km}^2 in 2021, Summit Station, the highest point on the Greenland ice sheet with an altitude of 3216\textit{m}, experienced the first-ever recorded rainfall in 2021, etc. For a sustainable future of the global community, energy conservation and emission reduction become indisputable and imperative for the whole society, especially in the transportation sector.

Vehicular electrification is an effective approach to reduce fossil fuel consumption and greenhouse gas emission from road transportation due to the greatly improved “tank-to-wheel” energy efficiency. As revealed by the U.S. Department of Energy, a gasoline-powered internal combustion engine vehicle (ICEV) can only utilize about 25% of the fuel energy for supplying traction power whereas more than 40% is transformed into waste heat of exhaust gases and directly transmitted into the atmosphere\cite{2}, \cite{3}. By contrast, an electricity-empowered electric motor (EM) can manipulate as high as 75% of onboard electric energy to propel the vehicle. In this context, electric vehicles (EVs), driven by EMs, can attain an operation cost of $0.04 per mile, significantly lower than that of ICEVs of $0.10 per mile. Moreover, without the complex combustion process, EVs also hold the advantages of no emission\footnote{https://afdc.energy.gov/vehicles/electric_basics_ev.html}, less noise, and slight vibration on the way. Enjoying both economic and ecological benefits, EVs have acquired tremendous attention and vigorous popularization in the customer market over the last two decades.

However, existing EVs are confronted with several insurmountable issues
resulting from intrinsic shortcomings of their onboard electric energy storage (EES), namely electrochemical battery packs. Above all, the excessively low energy density of battery cells, ranging from 40 to 200 \( \text{Wh/kg} \), necessitates large battery packs to ensure sufficient onboard energy storage but introduces non-negligibly extra masses and volumes to the vehicles themselves [4]. Moreover, the specific power of battery cells is always strictly restrained for safety, and thus the recharging process usually lasts several hours [5]. The above two technical bottlenecks bring the “range anxiety” to EVs and limit them mainly severing for short-distance urban commutes rather than long-distance transportation. More importantly, around 50% of an EV cost is spent on battery systems because of their high prices and short lifetimes [6].

To overcome EV imperfections and retain eco-driving, hybrid electric vehicles (HEVs) become a promising solution. By combining the fuel path (containing the fuel tank and the ICE) and the electric path (containing the EES and the EM) into one powertrain, an HEV can enjoy the merits of an ICEV and an EV simultaneously [7]–[9]. A comparative study presented during Brighton to London Future Car Challenge shows that for a 57-mile urban/extra-urban driving route, the average energy consumption by various HEVs under testing was 1.14 \( M J/km \), higher than that by EVs of 0.62 \( M J/km \) yet lower than that by ICEVs of 1.68 \( M J/km \) [10], [11]. Nonetheless, taking the greenhouse gas emission into consideration, HEVs are regarded as the lowest emitters with half of them emitting less than 70 g/km, followed by EVs with an average value of 93 g/km [8] and ICEVs ranging from 67 g/km to more than 168 g/km. On the one hand, compared to ICEVs, HEVs can ensure ICEs always either work with high efficiencies or are switched off because EMs can provide supplementary torques to assist propelling or recuperate excessive torques to recharge EESs [12], [13]. By this means, fuel consumption and tailpipe emissions can be vastly decreased with better ride comfort yet without compromised driving performances [14], [15]. Moreover, ICEs can be downsized for further improvement in fuel economy after delicate optimization on powertrain architectures [16], [17].

On the other hand, unlike EVs, HEVs are free from the “range anxiety” or the long-time recharging [18], [19]. Thanks to the fuel path, an HEV does not need a large battery pack as the sole onboard energy storage since the EES can be flexibly recharged by the ICE on the road rather than merely by the power grid at the stop. In light of this, HEVs are more likely to realize higher “well-to-wheel” energy efficiencies than their counterparts through more rational and efficient utilization of fuel and electricity.

\[8\] Assume the grid average emission factor in United Kingdom is 542 g/kWh
1.2 EMS Survey

Even though HEVs possess remarkable superiority in balancing driving requirements and environmental profits, their actual performances have recourse to onboard energy management strategies (EMSs) \[7\], \[20\], \[21\]. Given that there are multiple types of onboard energy sources, the transient torque demand on the powertrain can be satisfied by the combination of ICE and EM with an infinite number of solutions in theory. Such an extra degree of freedom on energy supply necessitates appropriate EMSs that can intelligently split the torque demand into the fuel path and the electric path so as to attain improvements in fuel consumption, charge sustain, tailpipe emission, component aging, ride comfort, and satisfy all system constraints or predefined regulations.

During past decades, a myriad of novel EMSs have been proposed and published by researchers in academia and industry. Based on the generally accepted taxonomy, existing EMSs can be broadly classified into two types, namely rule-based (RB-) and optimization-based (OB-) EMSs \[22\]–\[25\]. Nevertheless, owing to rapid advances in machine learning and data mining in recent years, various innovative artificial intelligence techniques have been widely applied to the study of HEV energy management and thereafter given rise to a new type of EMSs, i.e., learning-based (LB-) EMSs \[26\]–\[28\].

1.2.1 RB-EMS

RB-EMSs, including thermostat (on/off) \[29\], \[30\], power follower \[31\]–\[33\], state machine \[34\], fuzzy logic \[35\]–\[38\], and so on, are the most direct and popular methods in practice owing to their simple logic, rapid execution, extensive applicability and component variability. Kim et al. proposed an RB-EMS integrating the traits of thermostat and power follower for a series HEV and obtained better fuel economy than the two methods individually utilized \[29\]. An adaptive state machine-based EMS for a multi-stack fuel cell HEV was designed by Fernandez et al. and its effectiveness was verified under different driving scenarios by hardware-in-the-loop (HIL) simulations \[34\]. Additionally, Phan et al. investigated the adoption of fuzzy logic control in HEV energy management and put forward an interval Type 2 fuzzy logic controller for a plug-in HEV for better fuel efficiency and longer battery life under uncertain road conditions than the traditional Type 1 fuzzy logic controller \[37\].

For all these RB-EMSs, predefined rules are extracted based on heuristic intuitions and/or engineering expertise rather than explicit dynamical models of HEV powertrains or complete prior knowledge of future driving.
As a result, they usually have to experience lengthy developing processes since their coefficients have to be carefully calibrated by tedious trial-and-error. In spite of this, they cannot ensure close-to-optimal or even robust performances, especially when multiple objectives should be accounted for. For this reason, the exclusive utilization of RB-EMSs ceases to be the mainstream of EMS study in recent years and but they often serve as benchmarks to verify the superiority of other EMSs.

1.2.2 OB-EMS

Unlike RB-EMSs, OB-EMSs usually formulate HEV energy management problems as optimal control problems (OCPs) and then employ various optimization approaches to search for optimal or suboptimal solutions with full respect to all system constraints and man-made rules. Depending on the reliance on future driving information, OB-EMSs can be further divided into offline and online subgroups.

Offline OB-EMSs aim to obtain the global optimum over a specific driving cycle by minimizing the predefined objective function without violating any constraint. To this end, they have to require a precise mathematical model of the HEV powertrain and prior knowledge of the complete driving cycle. Because future driving conditions cannot be expediently accessed or accurately predicted, this type of EMSs cannot be directly implemented in practice, and their solutions are treated as non-causal. More seriously, enormous computation overheads usually prevent them from online utilization with real-time constraints. Despite all these limitations, offline OB-EMSs are still extensively studied because they greatly facilitate the proliferation of online EMSs.

As the most effective approach to the global optimum, dynamic programming (DP) is the most prevalent benchmark method to verify the optimality of other EMSs and its solutions provide optimized references for the design of other EMSs. With the aid of smooth ICE set point trajectories derived by DP, fuel consumption, raw particular matter emissions, and raw nitrogen oxide emissions of a diesel HEV can be well balanced by the online EMS designed by Nüesch et al. Besides, Cipek et al. presented an EMS with a cascade architecture for a series-parallel HEV, wherein DP optimal outputs serve as a prior known input to a gradient-based optimization algorithm, achieving a close-to-optimal solution with much shorter time.

Apart from DP, other OB-EMSs, such as swarm optimization (PSO), genetic algorithm (GA), simulated annealing (SA), are also widely applied in the research of HEV energy management. Even though they cannot guarantee that their solutions are as optimal as that of DP, they enjoy obviously higher computation efficiencies than DP.
Hence, they are more suitable to solve energy management problems with multiple state and control variables. To simultaneously optimize energy management and gear-shifting, a PSO-based EMS with three inputs and two outputs was introduced by Chen et al. and can reduce energy consumption by about 50% compared with an RB-EMS \[57\]. Similarly, Liu et al. proposed a GA-based EMS, wherein GA is executed offline to search for optimal values for seven control actions referring to different driving conditions and the corresponding control action will be applied in online usage once the driving condition is identified. In addition, Chen et al. employed SA to search the optimal engine-on power and the maximum current coefficient for another controller to rapidly calculate the close-to-optimal torque split solution \[62\]. Furthermore, as the co-optimization of structural design and energy management becomes an emerging research topic, these strategies enable quasi-optimal coefficients of powertrain components for further improvements of HEV performances under diverse driving scenarios. For instance, Liu et al. employed GA and PSO, respectively, to find out the optimal sizing of the lithium-ion battery pack for a series hybrid military truck and based on which designed several online EMSs for better fuel economy \[13\], \[64\], \[65\].

In contrast to offline OB-EMSs, online OB-EMSs tend to convert a global energy management problem into a local one at each time step and seek a sequence of suboptimal solutions. In this way, the computation complexity is greatly reduced and complete future driving information is no longer necessary in advance. The most common online OB-EMSs are Pontryagin’s minimum principle (PMP) \[66\]–\[70\], equivalent consumption minimization strategy (ECMS) \[71\]–\[75\], and model predictive control (MPC) \[76\]–\[79\].

By formulating a constrained global optimization problem as a local Hamiltonian minimization problem, PMP can produce necessary but not sufficient conditions for an optimal solution. Jiang et al. proposed a PMP-based EMS for a hybrid bus that can obtain similar control performances on energy consumption and component durability as DP \[69\]. With the aid of real-time traffic information, the PMP-based EMS designed by Shi et al. can also achieve near-optimal fuel economy on various driving cycles \[70\].

To improve fuel economy and preserve the EES charge sustain, ECMS attempts to minimize the equivalent fuel consumption which is the sum of actual fuel consumption from the ICE and equivalent electricity consumption from the EES. Sun et al. developed an adaptive ECMS with velocity forecast that achieves a noticeable improvement in fuel economy and a more stable state of charge (SOC) trajectory than another ECMS without forecast \[71\]. In a recent publication by Chen et al., an NN is trained offline based on DP solutions and then predicts the optimal equivalence factor online for ECMS. In this way, the proposed ECMS gains competitive fuel
economy compared to DP at different driving cycles [75].

Since the one-step optimization horizon in PMP and ECMS limits the global optimality, MPC is motivated to seek a proper balance between the control performance and the computation power in practical online applications, thanks to its flexibility in selecting the length of the receding optimization horizon. The MPC-based EMS for a series hybrid electric tracked vehicle can realize a roughly 6% improvement in fuel economy over a well-calibrated RB-EMS and reach over 98% of DP optimality [76]. To further strengthen the advantage of MPC, Zhang et al. employed two machine learning methods to precisely predict the future vehicle velocity as a reference and applied sequential quadratic programming to accelerate the computation speed for optimal solutions. Testing results from HIL simulations demonstrate that this novel MPC can attain 95% of DP optimality but the average computation time at each step is only twice of that of an RB-EMS, charging-depleting-charging sustaining [79].

Nonetheless, performances of online OB-EMSs are dependent on the precision of HEV models and the reliability of predicted information [80–82]. More specially, their performances will seriously deteriorate or even be worse than those of RB-EMSs, if models of powertrain components for EMS design obviously deviate from actual dynamical features and/or predicted driving tracks fail to reflect truths in practice.

1.2.3 LB-EMS

More recently, a large proportion of research interest has been transferred to LB-EMSs because of their distinctive model-free property and outstanding self-improving capability. Unlike RB- and OB-EMSs that produce fixed control actions during online usage, LB-EMSs can iteratively upgrade their control policies according to actual feedback of state variables and energy consumption. Hence, after sufficient training in simulation and/or actual driving environment, they can achieve close-to-optimal performances with satisfactory robustness [83]. According to the difference in learning types, they can be sub-classified into supervised learning, unsupervised learning, reinforcement learning (RL), and deep reinforcement learning (DRL).

In supervised learning, a large amount of labeled training data are required to repeatedly train the target control algorithm until its outputs achieve the desired accuracy level corresponding to the training data. In this regard, Chen et al. took advantage of optimized results by offline DP to train two NN modules for online control and improved fuel economy of a power-split plug-in HEV on multiple driving cycles [84].

In unsupervised learning, unlabeled training data are organized by some deduced rules to minimize a redundancy-associated cost function. In view
of this, unsupervised learning is more suitable for mode classification rather than torque split in HEV energy management. Shi et al. applied the K-means clustering method with 10 selected features to effectively classify 16 typical driving conditions for a hybrid electric city bus. Compared to a conventional RB-EMS, the new method decreases the battery degradation and energy consumption by 13.89% [41].

All RL methods utilize exchanged information from the environment to train their control policies for maximizing the cumulative reward [85]. As the most fundamental technique in the RL domain, Q-learning is extensively applied in HEV energy management thanks to its conceptual simplicity [86]–[90]. It is an off-policy and model-free RL method that stores state-action values (Q-values) in a lookup table. Xu et al. conducted an investigation and revealed that the Q-learning-based EMS possesses strong adaptivity under different varying conditions and achieves the best fuel economy, compared with other RB- and OB-EMSs [91]. Nonetheless, due to the discretization of state and control variables, RL methods have to encounter truncation errors and the possible “curse of dimensionality” when handling complex problems of large state-control dimensions [92].

To deal with RL deficiencies, DRL-based EMSs are launched, which integrate deep learning (DL) methods with RL methods. To be specific, energy management problems are formulated and solved based on RL frameworks, while tabular models of value functions (VFs) and control policies are approximated by DL skills [93]. By replacing tabular Q-values with deep neural networks (DNNs), deep Q-network (DQN)-based EMSs enable continuous state variables as inputs and outperform Q-learning-based EMSs in terms of training time and convergence rate [94]. However, online control performances of DQN-based EMSs are still far from the optimum because of two reasons. First, since estimated and target Q-values are derived from the same DNN, overestimated Q-values may drive the agent into pitfalls of local optima. To mitigate the detriment of overestimation, double-DQN-based EMSs are invented that utilize two DNNs for interactive updates to generate unbiased estimates of Q-values [95]–[97]. Second, control actions from DQN agents are still discrete, and thus defects of RL methods cannot be fully solved. In view of this, actor-critic (AC)-based algorithms, containing soft actor-critic (SAC) [98]–[102], deep deterministic policy gradient (DDPG) [103]–[107], and twin delayed DDPG (TD3) [108]–[110], have become the current research hotspot in HEV energy management. In an AC method, the control policy is implemented by the actor-network that properly handles continuous state inputs and control outputs, and control actions are evaluated by several critic-networks that effectively mitigate the Q-value overestimation and strengthen the EMS robustness. Currently, Huang et al. developed a SAC-based EMS for a power-split HEV with a single planetary
1.3. MOTIVATION

gear set that can achieve 95.25% fuel economy of the global optimum \cite{102}. With the support of terrain information, the DDPG-based EMS proposed by Li et al. shortens the fuel efficiency gap with the DP baseline down to nearly 6.4% and reduces ICE restart times by around 76% \cite{104}. In addition, by adding two extra critic-networks to the DDPG framework, the TD3-based EMS designed by Huang et al. improves the training efficiency and the learning ability by 10.98% and 23.53%, respectively, compared with a DDPG-based strategy \cite{109}. Despite these consecutive advancements in DRL, there are still some demerits to be solved in future research, such as the trade-off between exploitation and exploration, the hyperparameter sensitivity, the “cold start”, the inefficient training, etc. \cite{111}–\cite{113}.

1.3 Motivation

Based on the literature review in the previous section, it can be concluded that EMSs for HEVs remain an attractive research subject up to date. Even though remarkable achievements are continuously emerging and enriching the repository, there still exist many challenges that inevitably hinder the practical implementation of published EMSs and consequently severely weaken the inherent advantages of hybridized powertrains. These challenges are listed as follows.

First and foremost, the conflict between performance optimality and computation efficiency cannot be appropriately accommodated in online applications. RB- and online OB-EMSs can satisfy the real-time requirement owing to their acceptable computation overheads, but cannot ensure the robustness of their expected performances in practice due to the lack of adaptivity. By contrast, under reasonable configurations, LB-EMSs can approach (quasi-)optimal solutions by iterative information interactions with surrounding environments, whereas intractable computation overheads and/or memory demands detrimentally prevent the majority of them from field testing in real embedded processors. More specially, the Q-learning and DQN methods suffer the “curse of dimensionality” stemming from discretized state and control variables, and the emerging TD3 algorithm requires six complicated DNNs along with a massive experience buffer to guarantee its superiority in terms of optimality and robustness over other DRL alternatives. For instance, in a recently developed TD3-based EMS, the experience buffer needs to store one million samples of eight items and all selected AC DNNs have pyramid structures of three hidden layers. The neuron numbers in each hidden layer of actor-networks are 128, 64, and 32, and those of critic-networks are 256, 128, and 64, respectively \cite{110}. Evidently, the compelling fuel economy of 97.45% of DP optimality by this EMS is gained at the expense of tremendous consumption of computation.
resources, which confines this novel EMS to simulation work as yet.

Second, efficient control methods on ICE on/off switches are lacking. ICE on/off switches have a decisive influence on the overall HEV performance because each on/off switch leads to non-negligibly extra energy consumption and corresponding clutch dis/engagement. They are especially crucial to HEVs with parallel powertrains, in which ICE spinning speeds are coupled with wheel speeds when ICEs are in working status. Proper ICE switches are beneficial to fuel conservation, tailpipe reduction as well as ICE longevity extension, while improper ones, usually reflected as frequent and/or rapid switches, will seriously deteriorate fuel economy, degrade driving comfort, and even destroy vehicular drivability. On account of this, a complete EMS should synchronously optimize both ICE switch actions and torque split solutions. However, the combination of binary and continuous control variables complicates the HEV energy management which becomes a mixed integer nonlinear programming (MINLP) problem. Thus, the majority of previous studies neglected this binary control or adopted heuristic rules to decide it [66], [108], [114], while only a small number of novel EMSs attempt to search optimal solutions by sophisticated algorithms [110], [115]. As a result, similar to the issue aforementioned, the former option will drive the HEV performance away from the optimum and the latter one will result in excessive computation burdens.

Third but not least, fixed control periods impede the improvement of online computation efficiency. Almost all published online EMSs adopt fixed periods to execute control algorithms and then update control actions. This time-triggered control mechanism is ubiquitous in all engineering fields and is generally approved by virtue of its logical simplicity and reliable performance. Intuitively, an EMS of a shorter period tends to generate a better and more robust solution but occupies more computation resources per time unit. To the best of our knowledge, short periods are always preferred in the majority of current research because the numeric results of an EMS are the most significant but the computation and memory overheads are always underestimated. In fact, the control period ought to be carefully chosen in online execution for a feasible balance between the control performance of a designated EMS and the computing power of a specific processor. Moreover, according to our investigation, the necessary update frequencies of control actions during a driving cycle may change constantly and unpredictably. More specially, when the powertrain torque demand dramatically varies, control actions should be frequently updated for an expected improvement on the optimization objective; however, when the torque demand remains stable, variations of optimized control actions are negligible over a lot of consecutive steps, inferring that multiple executions of the optimization algorithm cannot contribute to better performance.
but just expend computation resources. This phenomenon reveals that fixed control periods cannot efficiently utilize onboard computation resources, and their inability to complex driving scenarios will expedite the exploration of flexible control periods of online EMSs.

1.4 Research Questions

After an elaborate analysis of existing achievements and challenges in the field of HEV EMS, this thesis aims to develop computationally efficient EMSs that enable close-to-optimal fuel economy even under hostile driving conditions and can be executed as real-time controllers by embedded processors with limited computation resources.

For a reasonable scope, this thesis focuses on only one type of HEVs. Unlike series, power-split and multi-mode HEVs, in which ICE spinning speeds can be independent of wheel speeds, the control of ICE operation is more crucial to the comprehensive performances of parallel HEVs. Hence, an HEV with a parallel powertrain is selected as the research object. In addition, this thesis only aims to minimize the equivalent fuel consumption of the powertrain over specific driving cycles. The equivalent fuel consumption is the sum of fuel consumption by the ICE during driving and penalized fuel consumption for recharging the EES at the end. Other criteria, such as tailpipe emissions, component aging, and driving comfort, are out of the scope of this thesis.

In light of the aforementioned outlines, research questions (RQs) in this thesis are listed below.

- **RQ.1**: How to design an online EMS that can improve the fuel economy of a parallel HEV and satisfy the real-time requirement?
- **RQ.2**: How to obtain close-to-optimal fuel economy with robust operations on ICE on/off switches?
- **RQ.3**: How to design an implementable EMS for a target processor with limited computation resources, given the requirement in RQ.2?
- **RQ.4**: How to effectively reduce both the computation overhead and the memory occupation of an EMS without obviously degrading its control performance?
- **RQ.5**: How to rapidly adapt an EMS to uncertain driving conditions?
- **RQ.6**: How can a flexible control period further improve the EMS computation efficiency?
1.5 Main Contribution

For designing computationally efficient and adaptive EMSs for parallel HEVs, the main contributions of this thesis are briefly summarized below.

- Two types of special ICE configurations are adopted to simplify the OCP concerning HEV energy management. The first type strictly forces the ICE only operating at its OOL and thus converts the OCP into a binary programming problem; whereas the second one enables the ICE to operate within a narrow band around the OOL to balance the OCP complexity and the ICE utilization. Through PIL simulations, the second option is better because it can avoid excessive powertrain mode switches with an acceptable computation overhead.

- Optimized solutions by offline DP are intensively exploited to design online EMSs. First, DP solves the speed planning problem and provides an optimal speed profile as a reference for online EMSs. Second, the optimal control policy and VF obtained from DP solutions are flexibly utilized in online control algorithms for solving and/or evaluating optimal control actions. Moreover, the optimal powertrain mode profile from DP serves as a rational base to separate the complete driving cycle into several time-dependent segments for reducing the complexity of EMS design.

- Piecewise polynomials, instead of complicated NNs, are selected to approximate the VF. Unlike general methods that estimate the VF by NNs with complex structures, an efficient parametric approximation method is designed to estimate the VF by piecewise polynomials with concise structures. As a result, both real-time computation loads and onboard memory occupations are obviously reduced. In addition, to preserve the optimality and accelerate the convergence, AVF parameters are initialized by DP solutions.

- An event-triggered control mechanism is adopted to further improve the EMS computation efficiency. Since the most suitable execution period for the torque split control always changes with the variation of the powertrain torque demand, a fixed period cannot appropriately balance the trade-off between control performance and computation overhead. Therefore, an efficient trigger algorithm is designed to determine whether the transient ICE torque in hybrid mode can directly inherit the reference value or it has to be solved by the optimization algorithm. Testing results by PIL simulations verify that the flexible period can significantly decrease CPU utilization without obviously sacrificing control performances.


1.6. THESIS OUTLINE

- PIL simulations are selected to verify the advantages of proposed online EMSs, especially those concerning computation efficiency. The majority of existing research only focuses on the numeric performances of designed EMSs and a small number of published achievements merely present the EMS execution time in HIL simulations with high-performance processors. In view of this, the real-time computation efficiency, containing both online CPU utilization and onboard memory occupation, is regarded as a prominent evaluation index in our EMS design. For this target, a PIL simulation test bench based on a low-performance microprocessor is established to test the online performances of designed EMSs.

These aforesaid contributions are reflected by proposed EMSs, with design flows illustrated in Chapter 3 and full details introduced in Appended Papers. Table 1.1 lists the ICE configuration and relevant RQs that each appended paper studies and addresses. Because RQ.6 is a new topic that has not been interpreted in any submitted publication, the study for this topic is elaborated in Section 3.10 with corresponding evaluations presented in Section 4.7.

Table 1.1: Research Objects of Appended Paper

<table>
<thead>
<tr>
<th>Appended Papers</th>
<th>ICE Configuration</th>
<th>RQ.1</th>
<th>RQ.2</th>
<th>RQ.3</th>
<th>RQ.4</th>
<th>RQ.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Paper I</td>
<td>Binary Control</td>
<td>•</td>
<td>•</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Paper II</td>
<td>Binary Control</td>
<td>•</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Paper III</td>
<td>Binary Control</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Paper IV</td>
<td>Continuous Control</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td></td>
</tr>
<tr>
<td>Paper V</td>
<td>Continuous Control</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
</tr>
<tr>
<td>Paper VI</td>
<td>Continuous Control</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
</tr>
</tbody>
</table>

1.6 Thesis Outline

The remainder of this thesis is organized as follows. Chapter 2 introduces the research platform, including the HEV model, the selected driving cycles, and the simulation test bench. Chapter 3 formulates the HEV energy management and articulates the design process of each proposed EMS. Chapter 4 systematically summarizes all contributions covered by this thesis. Chapter 5 responds RQs, draws conclusions, and raises future work.
1.7 Sustainable Development Goals

To a great extent, the research and development of HEVs have been facilitating the reduction of fossil fuel consumption and exhaust emission concentration for the ultimate targets of carbon peak and neutrality as well as adequately satisfying the transportation and travel demands in nowadays society. As aforementioned in Section 1.2, practical HEV functionalities highly rely on control performances and computation efficiencies of onboard EMSs, which are exactly the research topics of this thesis. To this end, this research directly contributes to the following 5 of the 17 Sustainable Development Goals issued by United Nations 9

- **No.7 Affordable and Clean Energy** – Ensure access to affordable, reliable, sustainable and modern energy for all;

- **No.9 Industry, Innovation and Infrastructure** – Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation;

- **No.11 Sustainable Cities and Communities** – Make cities and human settlements inclusive, safe, resilient and sustainable;

- **No.12 Responsible Consumption and Production** – Ensure sustainable consumption and production patterns;

- **No.13 Climate Action** – Take urgent action to combat climate change and its impacts.

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9[https://sdgs.un.org/goals](https://sdgs.un.org/goals)
Chapter 2

Research Platform

This chapter illustrates the research platform for this thesis. It starts with the control-oriented dynamical model of the parallel HEV under investigation, then presents three driving cycles for designing and testing online EMSs, and finally exhibits the PIL simulation test bench.

2.1 HEV and its Powertrain Dynamics

The HEV under investigation is a lightweight prototype for research and education and has a parallel powertrain depicted by Figure 2.1. This powertrain contains two independent propelling components, namely a gasoline-driven ICE in the fuel path and a brushless directly current (BLDC) motor in the electric path. Since the large specific power is more important to this HEV than the large specific energy, a supercapacitor (SC) instead of a battery pack is selected as the onboard EES. During driving, the powertrain has two working modes, namely electric mode and hybrid mode. In either mode, clutch 2 must be engaged so that the traction torque generated by the ICE and/or the EM can be delivered to the driving wheels. In the electric mode, the ICE is switched off, clutch 1 is disengaged, and the HEV is propelled only by the EM; whereas in the hybrid mode, the ICE is switched on, clutch 1 is engaged, and the ICE cooperates with the EM to provide the traction torque for HEV mobility. Essential parameters concerning HEV driving dynamics are listed in Table 2.1.

Since the most significant optimization objective is the accumulated fuel consumption over a driving cycle, the quasi-static modeling method is employed to analyze energy flows across the ICE, the EM, and the SC. Details of fast dynamics on powertrain components, such as shifts of ICE and EM operation points, clutch dis/engagements, and ICE on/off switches, are ne-
CHAPTER 2. RESEARCH PLATFORM

neglected since they have negligible impact on the overall fuel economy of a long-time driving.

Table 2.1: Essential Parameters of the HEV

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Sign</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>HEV gross mass</td>
<td>M</td>
<td>216</td>
<td>kg</td>
</tr>
<tr>
<td>Gravitational acceleration</td>
<td>g</td>
<td>9.81</td>
<td>kg·m·s⁻²</td>
</tr>
<tr>
<td>Rotational mass conversion ratio</td>
<td>δ</td>
<td>1.04</td>
<td>/</td>
</tr>
<tr>
<td>Driving wheel radius</td>
<td>r</td>
<td>0.26</td>
<td>m</td>
</tr>
<tr>
<td>Windward area</td>
<td>A_f</td>
<td>1.05</td>
<td>m²</td>
</tr>
<tr>
<td>Air drag coefficient</td>
<td>c_d</td>
<td>0.15</td>
<td>kg·m⁻³</td>
</tr>
<tr>
<td>Rolling resistance coefficient</td>
<td>c_r</td>
<td>0.011</td>
<td>/</td>
</tr>
<tr>
<td>ICE gear ratio</td>
<td>R_ICE</td>
<td>1.23</td>
<td>/</td>
</tr>
<tr>
<td>EM gear ratio</td>
<td>R_EM</td>
<td>1.06</td>
<td>/</td>
</tr>
<tr>
<td>Differential gear ratio</td>
<td>R_p</td>
<td>10</td>
<td>/</td>
</tr>
<tr>
<td>Lumped efficiency in drive shaft</td>
<td>η_d</td>
<td>0.9</td>
<td>/</td>
</tr>
<tr>
<td>Lumped efficiency to recharge SC</td>
<td>η_Rc</td>
<td>0.25</td>
<td>/</td>
</tr>
<tr>
<td>SC average efficiency</td>
<td>η_sc</td>
<td>0.98</td>
<td>/</td>
</tr>
<tr>
<td>SC terminal voltage</td>
<td>V_sc</td>
<td>40-50</td>
<td>V</td>
</tr>
<tr>
<td>SC nominal capacitance</td>
<td>C_sc</td>
<td>107</td>
<td>F</td>
</tr>
<tr>
<td>SC nominal charge capacity</td>
<td>Q_sc</td>
<td>5350</td>
<td>C</td>
</tr>
<tr>
<td>Average auxiliary power</td>
<td>P_aux</td>
<td>10</td>
<td>W</td>
</tr>
<tr>
<td>ICE maximum torque</td>
<td>T_max</td>
<td>3.1</td>
<td>Nm</td>
</tr>
<tr>
<td>ICE maximum power</td>
<td>P_max</td>
<td>1.5</td>
<td>kW</td>
</tr>
<tr>
<td>EM maximum torque</td>
<td>T_em</td>
<td>11</td>
<td>Nm</td>
</tr>
<tr>
<td>EM maximum power</td>
<td>P_em</td>
<td>3.55</td>
<td>kW</td>
</tr>
</tbody>
</table>

2.1.1 HEV Longitudinal Model

The total driving time $t_f$ of a driving cycle can be uniformly divided into $N$ steps with identical interval $t_s = t_f / N$. At the $k^{th}$ step, $k \in \{0, 1, 2, \ldots, N-1\}$, the net traction torque on driving wheels, $T_{t,k}$, can be expressed by,

$$T_{t,k} = r \left[ \delta M a_k + \frac{1}{2} A_f c_d v_k^2 + M g (c_r \cos \alpha_k + \sin \alpha_k) \right], \quad (2.1)$$

$$a_k = \frac{v_{k+1} - v_k}{t_s}, \quad (2.2)$$

where $a$, $v$, and $\alpha$ denote the HEV acceleration, the HEV speed, and the road slope angle in the longitudinal direction.

In this parallel powertrain, $T_{t,k}$ can be supplied individually by the ICE
2.1. HEV AND ITS POWERTRAIN DYNAMICS

(a) HEV Picture

(b) Parallel Powertrain Architecture

Figure 2.1: HEV Prototype under Investigation
or the EM, or jointly by both, written as,

$$T_{t,k} = R_p \left( T_{ce,k} R_{ce,k} \eta_d + T_{em,k} R_{em} \eta_d^{\text{sign}(T_{em,k})} \right),$$

(2.3)

where $T_{ce}$ and $T_{em}$ denote the ICE and EM torque outputs. The sign of $T_{em}$ indicates the working mode of EM. A positive value means the actuator mode and a negative value means the generator mode.

### 2.1.2 ICE Model

The transient fuel consumption by the ICE during one time-step $t_s$ consists of two parts: one is the actual fuel consumption $m_{ce}$ during the combustion process for generating driving torque output $T_{ce}$, and the other one $m_{sw}$ is the equivalent fuel consumption during the powertrain mode switch for ICE ignition/flame-out and clutch dis/engagement.

The first part, $m_{ce}$, can be calculated by,

$$m_{ce,k} = t_s \dot{m}_{ce,k},$$

(2.4)

$$\dot{m}_{ce,k} = \frac{P_{ce,k}}{Q_f} = \frac{T_{ce,k} \omega_{ce,k}}{Q_f \cdot \eta_{ce}(T_{ce,k}, \omega_{ce,k})},$$

(2.5)

$$\omega_{ce,k} = \frac{R_p R_{ce}}{r} v_k,$$

(2.6)

where $\dot{m}_{ce}, P_{ce}, \omega_{ce}, \eta_{ce}(\cdot)$ are the transient ICE fuel consumption rate, power consumption, spinning speed, and net efficiency, respectively; $Q_f$ is the gasoline lower heating value. In a quasi-static model, $\eta_{ce}(\cdot)$ is expressed as an explicit 2-dimension (2D) lookup table based on sampling points from field testing, with $T_{ce}$ and $\omega_{ce}$ as inputs, shown in Figure 2.2.
The second part, $m_{sw}$, can be determined by,

$$m_{sw,k} = \begin{cases} 0; & s_{ce,k} = u_{ce,k} \\ m^*; & s_{ce,k} \neq u_{ce,k} \end{cases},$$

(2.7)

$$s_{ce,k+1} = u_{ce,k},$$

(2.8)

where $m^*$ denotes the equivalent fuel consumption for one powertrain mode switch, $s_{ce} \in \{0, 1\}$ is a binary state variable indicating the current ICE on/off status ("0" refers to off and "1" to on), and $u_{ce} \in \{0, 1\}$ is a binary control variable representing the ICE on/off instruction.

It is noteworthy that the actual energy consumption and the duration time for one mode switch vary a lot under different operation conditions [16]. Additionally, the energy consumption for restarting the ICE is obviously larger than that for halting the ICE. For simplification, $m^*$ is the average equivalent fuel consumption of two modes under different operation conditions. Moreover, $t_s$ should be long enough, at least 1 s, to ensure that one switch can be fully completed within it.

The admissible range of $T_{ce}$ pertains to both $\omega_{ce}$ and $s_{ce}$. To be specific, if the ICE is off, i.e., $s_{ce} = 0$, $T_{ce}$ must be 0; otherwise, $s_{ce} = 1$, its upper limit $T_{ce}^{max}$ is determined by $\omega_{ce}$, further coupled with $v_k$.

$$s_{ce,k} = 0 \Rightarrow T_{ce,k} = 0$$

(2.9)

$$s_{ce,k} = 1 \Rightarrow T_{ce,k} \in [0, T_{ce}^{max}(v_k)]$$

(2.10)

### 2.1.3 EM Model

The transient electric power consumption by EM, $P_{em}$, is relevant to the EM working mode and written as,

$$P_{em,k} = \frac{T_{em,k}\omega_{em,k}}{\eta_{em}(T_{em,k}, \omega_{em,k}) \text{sign}(T_{em,k})},$$

(2.11)

$$\omega_{em,k} = \frac{R_p R_{em}}{r} v_k,$$

(2.12)

where $\omega_{em}$ and $\eta_{em}(\cdot)$ are the transient EM spinning speed and net efficiency. Similar to $\eta_{ce}(\cdot)$, $\eta_{em}(\cdot)$ is modeled as a 2D lookup table as well, with $T_{em}$ and $\omega_{em}$ as inputs, shown in Figure [2.3]

### 2.1.4 SC Model

An SC is selected as the sole onboard EES to support all onboard electric appliances mainly by virtue of its long cycle life, free maintenance, insen-

---

1ICE brake is not considered in this HEV because the high specific power of SC can be fully utilized to recuperate all braking power from the powertrain.
sitivity to the environment temperature variation, and high specific power \cite{3,116}. For simplification, define $P_{aux}$ as the average value of electric power to all auxiliary devices during driving and $\eta_{sc}$ as the average value of lumped efficiency including the SC and the DC/DC converter. The net power across SC, $P_{sc}$, is the combination of $P_{em}$ and $P_{aux}$. Consequently, the SC dynamics can be expressed as,

$$P_{sc,k} = \frac{P_{em,k} + P_{aux}}{\eta_{sc}},$$

$$V_{sc,k} = -\frac{P_{sc,k}}{C_{sc} \cdot V_{sc,k}},$$

$$V_{sc,k+1} = V_{sc,k} + t_s \dot{V}_{sc,k},$$

$$SOC_k = \frac{C_{sc}}{Q_{sc}} V_{sc,k}.$$ 

The EES SOC is the most significant state variable in EMS design and evaluation. However, the real value of the transient SOC of an onboard EES during driving cannot be directly measured. Thanks to the linear relation between $V_{sc}$ and SOC of the SC, $V_{sc}$ is selected as the indicator of SOC in this thesis hereafter.

Nonetheless, the SC suffers the low specific energy. As a result, its charge sustainability should be carefully preserved. Overcharging results in serious safety hazards while over-depletion causes extremely inefficient operations. Furthermore, unlike plug-in HEVs that have external chargers, this HEV cannot use the grid power to recharge the SC. As a consequence, when the HEV completes a driving task and stops, if the SC terminal voltage is lower than its initial value, clutch 1 ought to be engaged, clutch 2 ought to be

Figure 2.3: EM Efficiency Map
2.2 DRIVING CYCLES

Disengaged, and then the ICE has to be ignited to recharge the SC. The extra fuel consumption for SC recharging, $m_{rc}$, is calculated by,

$$m_{rc} = \frac{C_{sc}}{2\eta_{rc}Q_f} \left( V_{sc,0}^2 - V_{sc,N}^2 \right),$$  

(2.17)

where $V_{sc,0}$ and $V_{sc,N}$ indicate the initial and final values of SC terminal voltage before and after a driving task.

2.2 Driving Cycles

To verify the effectivity and generality of designed EMSs, three driving cycles are selected for designing and testing proposed EMSs and benchmark methods. A driving cycle contains a sequence of vehicle speed along a trip and the corresponding profile of road slope angle [117]. Although there are many standard cycles, such as Artemis urban/extra urban/highway, FHDS, FUDS, Japan 10-15, NEDC, and US06, none of them is utilized in this thesis. The reasons are twofold. Above all, these standard cycles only provide speed profiles without corresponding topographic information. In addition, these standard cycles are suitable for commercial HEVs on the market rather than this lightweight prototype. To obtain a more realistic and reliable estimation of fuel consumption for this specific HEV, we developed the following three driving cycles by ourselves.

2.2.1 SEM16

The first driving cycle is a racing track from Shell Eco-marathon. Exhibit in Figure 2.4, this track contains a polygon trajectory of 2240 m long with several uphills and downhills of varying slope angles. As displayed in Figure 2.4(a), the HEV must finish 8 laps of this track within 43 min, and a compulsory stop with ICE flame-out after each lap is required. Hence, the designated speed profile in Figure 2.4(c) ought to ensure that the HEV can finish one lap in around 305 s.

It is noteworthy that there are two slope angle profiles in Figure 2.4(b). The green dashed curve is smoother and represents a low-fidelity estimation of the real profile, depicted by the red solid curve full of apparent ups and downs. To verify the robustness and adaptivity of designed EMSs against uncertain conditions, the low-fidelity estimate is applied to design online EMSs whereas the real profile is adopted in the simulation environment to test their performances. Besides, the real profile can be exploited by offline deterministic DP to find a theoretical optimum as the benchmark. This principle is also applied for the next two cycles.

CHAPTER 2. RESEARCH PLATFORM

(a) Road Map

(b) Estimated and Real Slope Angle Profiles

(c) HEV Speed and Acceleration Profiles

Figure 2.4: Driving Cycle SEM16
2.2.2 STHLM

Illustrated by Figure 2.5, the second cycle is a section of public road in the outskirt of Stockholm Region and thereby is named STHLM for convenience. This route is roughly 5200 m long and contains many steeper uphills and downhills than SEM16. As a result, both the speed and acceleration profiles present much more frequent and dramatic variations over the 700 s driving time.

(a) Road Map

(b) Estimated and Real Slope Angle Profiles

(c) HEV Speed and Acceleration Profiles

Figure 2.5: Driving Cycle STHLM
2.2.3 KTH
The third cycle is around 2300 m long and provided by the project AD-EYE.\textsuperscript{3} It is named KTH because it is extracted from the university campus of KTH Royal Institute of Technology. Due to the rugged terrain, the HEV has to experience several drastic accelerations and decelerations during the 340 s driving time.

![Road Map](image)

(a) Road Map

![Slope Angle Profiles](image)

(b) Estimated and Real Slope Angle Profiles

![Speed and Acceleration Profiles](image)

(c) HEV Speed and Acceleration Profiles

Figure 2.6: Driving Cycle KTH

\textsuperscript{3}https://www.adeye.se/open-kth
2.3 PIL Simulation Test Bench

To test control performances of designed EMSs in the form of generated object code on the target processor and measure onboard computation resources consumed by these EMSs, a test bench for performing PIL simulations is established, shown in Figure 2.7. This test bench consists of three modules, namely a target processor to execute the tested EMS, a host PC to run the HEV model, and a USB cable for real-time communication.

To quantitatively illuminate the superiority of proposed EMSs on computation efficiency, a portable microprocessor with limited computation resources, STM32L476RGT6 (ARM® Cortex®-M4 32-bit RISC core with up to 80 MHz frequency, 1 Mbyte flash memory and 128 Kbyte of SRAM), is selected as the target processor. The complete system model, including the HEV dynamics, actuator controllers, and digital sensors, is built in MATLAB/Simulink. It should be noted that various sensor noises and actuator disturbances are introduced into the system model to test the robustness of designed EMSs against unpredictable perturbations. In this context, an online EMS should be converted into executable C code by Embedded Coder, then imported into the integrated development environment Keil µVision for compiling, and finally downloaded to this STM32 microprocessor for real-time execution.

At each time step, the microprocessor receives real-time state variables \(v\) and \(V_{sc}\) and fuel consumption \(m_{ce}\) and \(m_{sw}\) from the host PC. Afterward, it sends out correspondingly optimal control actions, containing \(u_{ce}^*, T_{ce}^*\), and \(T_{em}^*\). The communication between the EMS and the system model is realized by serial communication following the standard USART protocol.

\[\text{Control Action: } u_{ce}^*, T_{ce}^*, T_{em}^*\]

\[\text{State and Cost Feedback: } v, V_{sc}, m_{ce}, m_{sw}\]

\[\text{HEV & Powertrain Model in MATLAB/Simulink}\]

Figure 2.7: PIL Simulation Framework

Chapter 3

EMS Design

This chapter elaborates on the overall design process of each proposed EMS. First, the energy management problem concerning this specific parallel HEV is formalized as an MINLP problem. Then, a special ICE configuration is adopted to ensure its peak efficiency and simplify the OCP. Subsequently, a hierarchical architecture is employed for online EMS design so that the optimal powertrain mode and torque split solution are successively computed. In this premise, various computationally efficient and adaptive EMSs are proposed for improving the equivalent fuel efficiency.

3.1 OCP Formulation

The target of designed EMSs for this parallel HEV is to minimize fuel consumption over a specified driving cycle under all system constraints and predefined regulations. As mentioned in Section 2.2, there are 3 customized driving cycles for EMS design and test. However, at the very beginning, we only have distance-based profiles of road slope angles but not time-based speed profiles. Consequently, the original OCP is naturally a co-optimization problem containing not only energy management but also speed planning. Besides, since the total driving time $t_f$ is not a constant but a constrained variable to be optimized, the accumulated driving distance $y$ rather than the accumulated driving time $t$ is selected as the free variable.

Evenly divide a complete driving track of distance $Y$ into $N^*$ stages of identical length $y_s = Y/N^*$, and denote by $\bar{x}$ and $\bar{u}$ the state and control vectors. For all $j \in \{0, 1, 2, \cdots, N^*-1\}$, the HEV powertrain dynamics is re-written below.

\[
\begin{align*}
\bar{x} &= \begin{bmatrix} v \ t \ V_{sc} \ s_{ce} \end{bmatrix}^T, \\
\bar{u} &= \begin{bmatrix} u_{ce} \ T_{ce} \ T_{em} \end{bmatrix}^T,
\end{align*}
\]  

(3.1)
with respect to (2.3), (2.11)-(2.14) and the followings,

\[
x_0 = \begin{bmatrix} 0 & 0 & V_{sc,0} \\ 0 & 0 \end{bmatrix}^T, \quad (3.1a)
\]

\[
a_j = \frac{1}{\delta M} \left[ \frac{T_{t,j}}{r} - \frac{1}{2} A_f c_d v_j^2 - M g (c_r \cos \alpha_j + \sin \alpha_j) \right], \quad (3.1b)
\]

\[
v_{j+1} = \sqrt{v_j^2 + 2 y_s a_j}, \quad (3.1c)
\]

\[
\Delta t_j = \frac{2 y_s}{v_j + \sqrt{v_j^2 + 2 y_s a_j}} \quad (3.1d)
\]

\[
t_{j+1} = t_j + \Delta t_j, \quad (3.1e)
\]

\[
\dot{V}_{sc,j+1} = V_j + \Delta t_j \dot{V}_{sc,j}, \quad (3.1f)
\]

\[
s_{ce,j+1} = u_{ce,j}, \quad (3.1g)
\]

where \( \bar{x}_0 \) expresses initial values of all state variables, indicating that the HEV starts from the resting state with the ICE off and the SC voltage charged to \( V_{sc,0} \); \( \Delta t \) is the required time to drive across the distance \( y_s \) at the corresponding stage. Similar to the time-based model, it is also assumed that one powertrain mode switch can be finished within one stage.

Then, the optimization objective \( J \) can be derived as below.

\[
J(\bar{x}_0) = \sum_{j=0}^{N^* - 1} \left[ m_{ce}(\bar{x}_j, \bar{u}_j) \Delta t_j + m_{sw}(\bar{x}_j, \bar{u}_j) \right] + m_{rc}(\bar{x}_{N^*}), \quad (3.2)
\]

subject to (2.5)-(2.7), (2.9), (2.10) and the following,

\[
0 \leq v_j \leq v_{j}^{\text{max}}, \quad (3.2a)
\]

\[
0 \leq t_j \leq t_j^{\text{max}}, \quad (3.2b)
\]

\[
V_{sc, \text{min}} \leq V_{sc,j} \leq V_{sc, \text{max}}, \quad (3.2c)
\]

\[
V_{sc, N^*} \leq V_{sc, \text{min}} \leq V_{sc, \text{max}}, \quad (3.2d)
\]

\[
\omega_{ce,j} < \omega_{ce}^{\text{idle}} \Rightarrow s_{ce,j} = 0, \quad (3.2e)
\]

\[
T_{em, \text{min}}(v_{j}) \leq T_{em,j} \leq T_{em, \text{max}}(v_{j}), \quad (3.2f)
\]

where the superscripts max and min indicate the upper and lower bounds of each corresponding variable; \( V_{sc, \text{min}} \) is a special lower bound for \( V_{sc} \) at the end, typically close to \( V_{sc,0} \) and much larger than \( V_{sc, \text{min}} \) to preserve the charge sustain; \( \omega_{ce}^{\text{idle}} \) denotes the ICE idle speed and the ICE must be off if \( \omega_{ce} \) is less than \( \omega_{ce}^{\text{idle}} \).

The formulated OCP (3.2) is a complex MINLP problem containing 4 state variables and 3 control variables, among which \( v, t, V_{sc}, T_{ce} \) and
$T_{cm}$ are continuous while $s_{ce}$ and $u_{ce}$ are discrete. Owing to the excessive computational complexity, this OCP is difficult to be solved even by offline DP. Hence, some approximation methods ought to be taken to simplify this OCP and thereafter design computationally tractable online EMSs.

### 3.2 Special ICE Configuration

Operation efficiencies of ICEs in conventional ICEVs vary a lot during driving when transient torque demands on powertrains dramatically change. For this reason, ICEVs often encounter deficient fuel efficiencies, especially when driving routes are hilly. This flaw can be effectively alleviated by powertrain hybridization so that ICEs can collaborate with powerful EMs to provide traction torques for HEV mobility. In this way, ICEs can either always work with (close-to-)peak efficiencies when torque demands are huge or simply be switched off without fuel consumption when torque demands are small or negative. Accordingly, EMs can supply complementary driving or braking torques due to their rapid response capability. Consequently, HEVs can enjoy this double benefit that improves overall fuel economy meanwhile satisfying volatile powertrain torque demands.

Inspired by this unique merit of hybridized powertrains, a special ICE configuration is proposed to not only ensure the ICE peak efficiency but also simplify the OCP (3.2), i.e., the ICE can only operate on its optimal operation line (OOL) after switched on, shown in Figure 3.1. In this case, $T_{ce}$ is not an independent control variable anymore, but subject to $s_{ce}$ and $\omega_{ce}$, expressed as,

$$s_{ce,j} = 1 \Rightarrow T_{ce,j} = T_{ce}^0(\omega_{ce,j}),$$  \hspace{1cm} (3.3)

where $T_{ce}^0(\omega_{ce})$ is the ICE torque with peak efficiency at $\omega_{ce}$.
Then, the control vector is reduced to \( \bar{u} = [u_{ce} \ T_{em}]^T \), and DP is employed to solve this OCP offline. Optimized solutions include distance-based optimal profiles of all state variable \( \bar{x}^*(j) \), the optimal control policy \( \bar{u}_j = \pi(\bar{x}_j, y_j) \), and a 5D VF \( V(\bar{x}, y) \). With the aid of optimal time profile \( t^*(j) \), other distance-based profiles can be converted to correspondingly time-based ones serving as references for online EMS design, including \( v^o(t_k), V_{sc}^o(t_k), \) and \( s_{ce}^o(t_k) \).

### 3.3 Hierarchical EMS Architecture

In spite of the special ICE configuration, the simplified OCP \( (3.2) \) is still computationally complex and cannot be rapidly solved in online applications. One effective approach for this issue is to decompose this complicated OCP into several sequentially correlated sub-problems so as to significantly reduce the overall complexity to satisfy the real-time requirement of the target processor. The essence of this strategy is to decouple the co-optimization problem into two parts and then optimize the speed planning problem offline. Hence, online control only focuses on the energy management problem. For this target, the sub-problems are defined as 1) finding the optimal HEV speed profile; 2) selecting the optimal powertrain working mode; 3) splitting the torque demand between ICE and EM. Accordingly, a hierarchical architecture for EMS design is outlined in Figure 3.2. In this figure, the optimal solution to the first sub-problem concerning speed planning is obtained by solving the OCP \( (3.2) \) with DP \( [118], [119] \). This solution serves as the reference for the second and third ones concerning energy management, which are iteratively solved online according to the real-time feedback in actual driving scenarios. Moreover, the solution to the second sub-problem directly influences that to the third one because it decides whether or not the ICE provides the driving torque to the powertrain.

If the HEV can strictly follow \( v^o(t_k), k \in \{0, 1, \cdots, N\} \), optimal profiles of HEV acceleration and net traction torque, \( a^o(t_k) \) and \( T_t^o(t_k) \), can be calculated by \( (2.1) \) and \( (2.2) \). Under this condition, neither \( v \) nor \( t \) is a free state variable, and \( T_{em} \) is not independent but associated with \( s_{ce} \). Thus,

![Figure 3.2: Hierarchical EMS Architecture](image-url)
3.3. HIERARCHICAL EMS ARCHITECTURE

the OCP concerning HEV energy management is formulated as

\[ J(x_0) = \sum_{k=0}^{N-1} \left[ m_{ce}(x_k, u_k) + m_{sw}(x_k, u_k) \right] + m_{rc}(x_N), \]  (3.4)

subject to (2.1)-(2.15) except (2.10), and the following,

\[ x_k = \begin{bmatrix} V_{sc,k} & s_{ce,k} \end{bmatrix}^T, \]  (3.4a)

\[ u_k = u_{ce,k}, \]  (3.4b)

\[ x_0 = \begin{bmatrix} V_{sc,0} & 0 \end{bmatrix}^T, \]  (3.4c)

\[ V_{sc}^{\min} \leq V_{sc,k} \leq V_{sc}^{\max}, \]  (3.4d)

\[ V_{sc,N}^{\min} \leq V_{sc,N} \leq V_{sc}^{\max}, \]  (3.4e)

\[ \omega_{ce,k} < \omega_{ce}^{idle} \Rightarrow s_{ce,k} = 0, \]  (3.4f)

\[ s_{ce,k} = 1 \Rightarrow T_{ce,k} = T_{ce}^{\circ}(\omega_{ce,k}), \]  (3.4g)

\[ T_{em}(v_k) \leq T_{em,k} \leq T_{em}^{\max}(v_k), \]  (3.4h)

Since the only control variable \( u_{ce} \) is binary and the online control task at each step is just to determine the powertrain working mode, the searching space is greatly reduced and thereby an online EMS is able to rapidly solve this binary OCP with a limited computation overhead.

In practice, the actual HEV speed \( v_k \) always deviates from its optimum \( v^\circ(t_k) \) because of various system uncertainties and external perturbations. Thus, a speed regulator is designed to calculate an “up-to-date” \( T_{i,k} \) by which the HEV attempts to catch up with \( v^\circ(t_k+1) \). According to (2.1), \( T_{i,k} \) is determined by \( \alpha_k, v_k, \) and \( a_k \), among which \( \alpha_k \) can be acquired from prior knowledge and \( v_k \) from the onboard sensor. The most direct way to obtain \( a_k \) is to rewrite (2.2), i.e.,

\[ a_k = \frac{v_{k+1} - v_k}{t_s}. \]  (3.5)

However, \( a_k \) calculated by (3.5) is very sensitive to the sensor noise imposed on \( v_k \) and is prone to the numerical oscillation, especially when \( t_s \) is small. To tackle this issue, a PID controller with saturation limits is instead selected to calculate \( a_k \), expressed by,

\[ \Delta v_k = v_{k+1}^\circ - v_k, \]  (3.6)

\[ a_k = K_p \Delta v_k + K_i \sum_{i=0}^k \Delta v_i + K_d(\Delta v_k - \Delta v_{k-1}), \]  (3.7)
where $\Delta v$ is the difference between the actual HEV speed presently $v_k$ and the optimal one at the next step $v^o_{k+1}$; $a^*$ is an intermediate result bounded by the upper and lower limits of HEV acceleration, $a_{\text{max}}$ and $a_{\text{min}}$, for safety and feasibility concerns; $K_p, K_i,$ and $K_d$ are three tunable parameters of the PID controller.

In the following sections, several online EMSs of various innovative methods are introduced one by one. To balance the computation load and the control performance, the control periods for powertrain mode selection and torque split control are set as 1 s and 0.1 s, respectively. Although they adopt different algorithms to compute control actions, they all (except the DP-based EMS) comply with this fundamental architecture in online usage.

### 3.4 Binary ECMS-based EMS Design

As one of the most promising online EMS methods, ECMS unifies the fuel consumption by ICE and the electricity consumption by EM into a single optimization variable representing the gross HEV fuel economy by means of introducing a properly selected equivalence factor [82]. As a result, ECMS enables an instantaneous optimization that minimizes the equivalent fuel consumption at each step and meanwhile maintains the EES SOC. On account of this, an ECMS-based controller is designed for the OCP [3.4]. Owing to the binary feature of control variable $u_{ce}$, this method is named binary ECMS.

At the $k^{th}$ step, $k \in \{0,1,\cdots,N-1\}$, the transient equivalent fuel consumption, $m_{eq,k}$, is defined as,

$$m_{eq,k} = m_{ce}(x_k,u_k) + m_{sw}(x_k,u_k) + s(x_k) \cdot t_kP_{sc}(x_k,u_k),$$  \hspace{1cm} (3.9)

where $s$ is the equivalence factor that dominates the ECMS performance. A small value infers a low cost of electricity while a large one causes more fuel consumption.

In previous ECMS applications, $s$ can be either constant or variable. Nevertheless, when charge sustainability is a critical constraint in energy management, a dynamic $s$ usually outperforms a constant one. To be specific, when the EES is continuously discharged, a sharply increasing $s$ adds a severer penalty on this trend, and the reverse is also true when the EES keeps on being recharged [120], [121]. It is unlikely to gain an adaptation
3.5. **DP-BASED EMS DESIGN**

function of the absolutely optimal equivalence factor in practice. Tangent-

shape functions, however, can effectively fulfill the requirement and thus

have been extensively adopted [122], [123]. For this ECMS, \( s \) is derived

from the deviation between the transient \( V_{sc,k} \) and the initial one \( V_{sc,0} \),

\[
s(x_k) = r_n \cdot \tan \left( r_a \cdot (V_{sc,0} - V_{sc,k}) + r_b \right) + r_m
\]

(3.10)

where \( r_n, r_a, r_b, \) and \( r_m \) are tunable parameters, among which the first three

are positive and the last one is negative. In this way, when \( V_{sc} \) approaches

\( V_{sc}^{\text{max}} \), \( s \) is close to 0 and the electric energy is “free of charge”; conversely,

before \( V_{sc} \) drops to \( V_{sc}^{\text{min}} \), \( s \) has become extremely large to prevent the SC

from over depletion.

After \( s \) is calculated, \( u^*_{ce} \) is determined by,

\[
u^*_{ce,k} = \arg\min_{u_{ce,k} \in \{0, 1\}} m_{eq,k}
\]

(3.11)

According to \( T_i \) and \( s_{ce} \), the torque split control can calculate \( T^*_{ce} \) and

\( T^*_{em} \) by (2.9), (3.4g), and (2.3).

This ECMS-based EMS is designed for and tested on the driving cycle SEM16, with details presented in Paper A. Simulation results showcase

that this EMS can obtain about 90% of optimal fuel economy with little

computation overhead. However, there is a nontrivial shortcoming for this

EMS, concerning robustness and feasible operations of ICE on/off switches.

On this 305 s driving cycle, the ICE is switched too many times, and some-
times it just works for several seconds after once restart. This issue mainly

stems from the adaptation function of \( s \), which only attempts to maintain

\( V_{sc} \) around \( V_{sc,0} \) but completely overlooks the effect of driving scenarios in

the foreseeable future. Therefore, despite the high computation efficiency,

this EMS cannot be directly implemented in field testing. It hence moti-

vates the following EMS design, in which future driving information plays

an irreplaceable role.

### 3.5 DP-based EMS Design

The special ICE configuration introduced in Section 3.2 ensures the ICE
peak efficiency and reduces the OCP complexity at the expense of extremely
limiting the ICE operating region. A potential risk for this configuration
is the loss of optimality of designed EMSs. To confirm the effectiveness
of this special ICE configuration, two DP-based online EMSs are designed
to compare the performance of an HEV with this specially configured ICE
with that of the same HEV with a generally configured ICE, whose torque
can be freely selected within its admissible range, expressed by (2.10). Al-
though DP is an offline optimization algorithm, its optimized solutions can
be used for constructing online EMSs in the form of lookup tables, mapping the real-time state feedback $\mathbf{x}_k$ and the accumulated distance $y_k$ to the correspondingly optimal control action(s), $\mathbf{u}_k^* = \pi(\mathbf{x}_k, y_k)$.

To explore the best possible fuel economy under different ICE configurations, online EMSs are designed based on optimal solutions to the co-optimization problem (3.2) so that equivalent fuel efficiencies are obtained with the aid of optimal speed profiles. For the first EMS referring to the special ICE configuration, in which $T_{ce}$ is not an independent control variable but complies with (3.3), the state and control vectors, $\mathbf{x}_1$ and $\mathbf{u}_1$, are defined as,

$$
\begin{align*}
\mathbf{x}_1 &= [v \ t \ V_{sc} \ s_{cc}]^T \\
\mathbf{u}_1 &= [u_{ce} \ T_{em}]^T.
\end{align*}
$$

(3.12)

The second EMS for the general ICE configuration should have been obtained by solving the OCP (3.2). However, as aforementioned, this multi-dimensional OCP is too complex to be directly solved by DP even offline. As a compromise, a heuristic rule is introduced to simplify this MINLP problem to a general nonlinear programming problem with continuous variables. That is, the ICE should be kept on as long as $\omega_{ce}$ is larger than $\omega_{idle}^{ce}$ after clutch 1 is engaged. Hence, $s_{ce}$ is fully dependent on $v$ rather than $u_{ce}$, and thereby $u_{ce}$ is useless in the simplified OCP. Accordingly, the state and control vectors, $\mathbf{x}_2$ and $\mathbf{u}_2$, are defined as,

$$
\begin{align*}
\mathbf{x}_2 &= [v \ t \ V_{sc}]^T \\
\mathbf{u}_2 &= [T_{ce} \ T_{em}]^T.
\end{align*}
$$

(3.13)

The generated online EMS for the HEV with the special ICE configuration includes two 5D lookup tables for $u_{ce}^*$ and $T_{em}^*$, respectively. At the $k^{th}$ step in online usage, the five inputs are real-time feedback of the four elements in $\mathbf{x}_1^T$ as well as $y_k$. Similarly, the EMS for the generally configured ICE contains two 4D lookup tables for $T_{ce}^*$ and $T_{em}^*$, with $v_k$, $t_k$, $V_{sc,k}$, and $y_k$ as inputs.

Details of designing and testing these two DP-based EMSs are demonstrated in Paper B, including some novel methods to further improve the DP computation efficiency. Simulation results on driving cycle SEM16 show that the HEV with the special ICE configuration outperforms its counterpart in terms of equivalent fuel efficiency, and thus verify the advantage of this ICE configuration. Nonetheless, it should be noted that suffering from the “curse of dimensionality” of high-dimension lookup tables, these DP-based EMSs are only tested in the MATLAB/Simulink simulation environment but cannot be executed in the selected STM32 microprocessor. Since the primary target of this proposed EMS is to explore the superiority of this special ICE configuration, high-dimension VFs obtained by offline
3.6 Quasi-PMP-based EMS Design

To overcome the shortcoming of DP-based EMS that can hardly be implemented on the target microprocessor and to pursue close-to-DP control performances in online applications, PMP is employed to design online EMSs. As another approach for constrained global optimization problems, the most outstanding strength of PMP over DP lies in its capability of converting a global OCP into an instantaneous Hamiltonian minimization problem. Hence, it has much fewer computation loads than DP and can satisfy the real-time requirement in online execution. To general PMP-based EMSs, the only tunable parameter for a specific driving cycle is the initial costate associated with the EES SOC, which has a crucial influence on the overall control performance, particularly on the EES sustainability [23], [24].

There are two deficiencies that impair the performances of PMP-based EMSs in practice. The first one is the unavailable optimum of the initial costate, which must take complete prior knowledge as a prerequisite. The second one is the inability to the OCP with discrete state variables because the evolution of a costate is subject to the partial derivative of Hamiltonian with respect to the associated state, written as

$$\lambda_k^* = \frac{\partial \mathcal{H}_k}{\partial x_k} \bigg|_{u_k^*},$$  \hspace{1cm} (3.15)$$

where $\mathcal{H}$, $L(\cdot)$, $\lambda$ denote the Hamiltonian, the instantaneous cost, and the costate vector, respectively.

To tackle these two issues, a quasi-PMP-based EMS combing the optimal VF from DP and the high computation efficiency of PMP is designed to determine the real-time powertrain mode and torque split solution.

Aiming at the OCP (3.4), the Hamiltonian for a discrete-time PMP is expressed as,

$$\mathcal{H}_k = m_{ce}(x_k, u_k) + m_{sw}(x_k, u_k) + \lambda_{1,k+1} V_{sc,k+1}(x_k, u_k) + \lambda_{2,k+1} s_{ce,k+1}(x_k, u_k),$$  \hspace{1cm} (3.16)$$

$$\lambda_k = L(x_k, u_k, t_k) + \lambda_{k+1}^T \cdot x_{k+1},$$  \hspace{1cm} (3.14)$$

$\lambda_{k+1}$ is the initial costate, which has a crucial influence on the overall control performance, particularly on the EES sustainability [23], [24].
where $\lambda = [\lambda_1 \lambda_2]^T$ is the costate vector.

For the most part, existing PMP-based EMSs either choose heuristic methods to estimate $\lambda^*$ [67, 69, 124] or resort to complex optimization methods to deduce $\lambda^*$ [62, 68, 70]. The former can only get sub-optimal solutions and the latter might result in enormous computation overheads. To obtain a quasi-optimal $\lambda$ during online control without tediously iterative searches, the Hamiltonian-Jacobi-Bellman equation (HJBE) is utilized to connect the VF $V(V(\cdot))$ from DP and the costate $\lambda$ in PMP along the optimal trajectory $x^*$.

As aforementioned in Section 3.2, the 5D VF $V(x, y)$ is obtained through solving the distance-based OCP (3.2) by DP. Along optimal profiles $v^*(j)$ and $t^*(j)$, a 3D VF $V(x, y)$ can be extracted out for deriving the transient $\lambda^*$ in online control.

$$\lambda^*_k = \frac{\partial V(x, y)}{\partial x_k} \bigg|_{x^*_k},$$  \hspace{1cm} (3.17)

where the transient state value (V-value), $V(x_k, y_k)$, can be acquired by performing interpolation on the 3D lookup table $V(x, y)$.

More details about this EMS design are exhibited in Paper C. Among them, $\lambda^*_1$ can be directly calculate by (3.17), but $\lambda^*_2$ cannot because of the non-derivable property of $s_{ce}$. As a result, $\lambda^*_2$ has to be approximated by the difference of $V(\cdot)$ at $s_{ce} = 0$ and $s_{ce} = 1$, expressed as,

$$\lambda^*_{2,k} \approx \frac{V(V_{sc,k}, 1-s_{ce,k}, y_k) - V(V_{sc,k}, s_{ce,k}, y_k)}{1 - 2s_{ce,k}}$$ \hspace{1cm} (3.18)

The computing process for $T^*_{ce}$ and $T^*_{em}$ is as same as that in the binary ECMS-based EMS.

The reasons that this EMS is named quasi-PMP are twofold. The first one is that $\lambda^*$ is calculated by the HJBE (3.17) rather than the general recursive equation (3.15). The second one is that the difference operation (3.18) is utilized to approximate $\lambda^*_2$ coupled with the binary state $s_{ce}$.

Thanks to the particular computing method, this EMS has much less computation overhead than general PMP-based EMSs and significantly smaller tabular VF than the DP-based EMS. Thus, it can be implemented on the target STM32 microprocessor and tested by the PIL simulation.

### 3.7 MPC&PMP-based EMS Design

Although the quasi-PMP-based EMS is real-time implementable, there are still several imperfections for further improvement. Above all, the ICE has to be ignited five times during the 5 min driving cycle SEM16, one switch per minute on average. This switching frequency is obviously too high for...
ordinary ICE usage and definitely adverse to preserving the ICE lifespan. Another potential risk stems from the adoption of tabular VF, leading to the complete EMS occupying nearly half of the maximal flash memory provided by the target \textit{STM32} microprocessor. Therefore, it is likely that this microprocessor cannot support this EMS designed for long-distance driving cycles. Accordingly, more advanced approaches ought to be developed to upgrade both the HEV configuration and the EMS performance.

These excessive powertrain mode switches mainly result from the special ICE configuration. The binary ICE control lacks the flexibility to quickly adapt to the time-varying torque demand on the powertrain. The contribution of this special ICE configuration mainly lies in the highly reduced OCP complexity, which is verified by PIL simulations. The average CPU utilization of the quasi-PMP-based EMS is just 4.72\%, implying that this target microprocessor is competent to cope with more complex optimization algorithms for better control performance and thereof inspiring a more robust ICE configuration to balance the OCP complexity and the ICE utilization. Exhibited in Figure\ref{fig:3.3}, this new ICE configuration does not force the ICE to operate only on the OOL but within a narrow band around the OOL with high efficiency. The upper and lower bounds for ICE torque output at a given $\omega_{ce}$ are defined as,

\begin{align}
T_{ce,k}^{\text{max}} &= T_{ce}^o(\omega_{ce,k}) + \frac{\Delta T}{2}, \\
T_{ce,k}^{\text{min}} &= T_{ce}^o(\omega_{ce,k}) - \frac{\Delta T}{2},
\end{align}

where $\Delta T$ is the width of the high-efficiency narrow band.

By this way, $T_{ce,k}$ becomes an independent control variable when $s_{ce} = 1$. Hence, \ref{eq:3.4b} and \ref{eq:3.4g} should be hereafter updated as,

\begin{equation}
\mathbf{u}_k = [u_{ce,k} \ T_{ce,k}]^T, \tag{3.4b*}
\end{equation}

\begin{equation}
s_{ce,k} = 1 \Rightarrow T_{ce,k} \in [T_{ce,k}^{\text{min}} \ T_{ce,k}^{\text{max}}]. \tag{3.4g*}
\end{equation}

The newly updated OCP \ref{eq:3.4} cannot be rapidly solved online because of its hybrid variables and nonlinear dynamics. To address this issue, the hierarchical EMS architecture illustrated in Section\ref{sec:3.3} is adopted to solve the two control variables separately, i.e., a constrained MPC is designed to quickly determine the optimal powertrain mode, and then a value-based PMP optimizes the torque split scheme in the hybrid mode.

General MPC methods can solve the mode selection problems with limited horizons, but they need high-performance processors to satisfy the real-time requirement and will consume a large number of onboard computation resources. To improve the computation efficiency, two operational
Figure 3.3: ICE with Narrow Operation Range

constraints are introduced to restrict the ICE operation for a rapid execution of the MPC algorithm.

1. The interval between two mode switches must last at least 5 s, implying that the ICE can be restarted at most once in a 10 s period.

2. In the hybrid mode, $T_{ce}$ is assumed always equal to $T^*_ce(\omega_{ce})$. Hence, $u = u_{ce}$.

The first constraint aims to prevent the ICE from rapid switches and the second one simplifies the MINLP problem as a binary one just like the previous special ICE configuration. Note that this simplification is only valid for the powertrain model selection. The actual ICE torque output in the hybrid mode, $T^*_ce$, should be calculated by the subsequent PMP algorithm.

Owing to the binary characteristic of $u_{ce}$, the total number of possible control sequences over a receding horizon is $2^K$. Among them, the vast majority of these sequences are inadmissible because they violate the first constraint and thus must be discarded; and only the admissible ones will be used to calculate their corresponding costs over the receding horizon. The sequence concerning the minimal cost is treated as the optimal one, whose first item is the ultimate output of MPC at the current step.

When the powertrain works in the hybrid mode, the torque split control employs a value-based PMP algorithm to split $T_t$ into the fuel and electric paths. Unlike the quasi-PMP in Section 3.6, this PMP only optimizes a continuous variable $T_{ce}$ in the hybrid mode and does not need to consider $m_{sw}(\cdot)$. Thus, the Hamiltonian is written as

$$H_k = \dot{m}_{ce}(x_k, u_k) + \lambda_k \dot{V}_{sc,k}(x_k, u_k) = \frac{P_{ce}(x_k, u_k)}{Q_f} - \lambda_k \frac{P_{sc}(x_k, u_k)}{C_{sc} V_{sc,k}}, \quad (3.21)$$

where $\lambda$ here is a scalar associated with $V_{sc}$. 

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Similar to the quasi-PMP, this PMP also exploits the VF from offline DP to derive $\lambda^*$. The only difference lies in that, this PMP requires a 2D VF with $V_{sc}$ and $y$ as inputs along the profile of $s_{ce}(j) = 1$, written as $V^1(V_{sc}, t)$. Hence, $\lambda^*$ can be calculated by,

$$
\lambda^*_k = \frac{\partial V^1(V_{sc,k}, y_k)}{\partial V_{sc,k}}
$$

(3.22)

Afterward, $T^*_{ce}$ and $T^*_{em}$ can be solved successively.

A complete online EMS can be established by combining the above constrained-MPC and value-based PMP together. Testing results from PIL simulations show that this EMS can generate close-to-optimal fuel efficiency with acceptable computation and memory overheads.

To further improve the computation efficiency, two significant methods are taken to simultaneously reduce the computation and memory overheads. The first one approximates the tabular VF as piecewise polynomials. Due to complex dynamical characteristics, the surface of $V^1(\cdot)$ is not smooth and cannot be directly fitted by simple expressions. Through careful explorations and comparisons, we found that $s_{ce}$ imposes the most profound influence on the evolution of $V(\cdot)$ because the switching points on $s_{ce}^*(j)$ well match the most obvious turning edges on $V^1(\cdot)$. This discovery motivates us to divide $V^1(\cdot)$ into several segments according to variations of $s_{ce}^*(j)$ along $y$, and then fit each segment by polynomials of different orders.

After many attempts, linear polynomials are ultimately selected to fit $V^1(\cdot)$, expressed as,

$$
V^1(V_{sc,k}, y_k) = w^n_{2} V_{sc,k} + w^n_{1} y_k + w^n_{0}
$$

(3.23)

where $w^n_{2}$, $w^n_{1}$, $w^n_{0}$ are parameters for the $n^{th}$ segment, $n \in \{1, 2, \cdots, N_{md}\}$. $N_{md}$ is the number of divided segments for a specific driving cycle.

The second method is the model approximation that estimates $P_{ce}$ and $P_{sc}$ as quadratic polynomials. Because of complex nonlinear characteristics of 2D lookup tables $\eta_{ce}(\cdot)$ and $\eta_{em}(\cdot)$, shown in Figures 2.2 and 2.3, online computation processes for $u_{ce}^*$ and $T_{ce}^*$ are very time-consuming, and these two lookup tables occupy fairly large onboard memory spaces. Inspired by preceding achievements [125]–[127], quadratic polynomials with $T_{ce}$ and $T_{em}$ at different $\omega_{ce}$ and $\omega_{em}$ are selected to fit $P_{ce}$ and $P_{sc}$, respectively. The relevant formulas are written as,

$$
P_{ce,k} = p_2(\omega_{ce})T_{ce,k}^2 + p_1(\omega_{ce})T_{ce,k} + p_0(\omega_{ce})
$$

(3.24)

$$
P_{sc,k} = q_2(\omega_{em})T_{em,k}^2 + q_1(\omega_{em})T_{em,k} + q_0(\omega_{em})
$$

(3.25)
where $p_2(\omega_{ce})$, $p_1(\omega_{ce})$, and $p_0(\omega_{ce})$ are fitting coefficients on the fuel path for a specific $\omega_{ce}$, and $q_2(\omega_{em})$, $q_1(\omega_{em})$, and $q_0(\omega_{em})$ are those on the electric path for a specific $\omega_{em}$.

Approximation results for several different $\omega_{ce}$ and $\omega_{em}$ are displayed in Figure 3.4. Compared with explicit values in Figures 2.2 and 2.3, NRM-SEs of approximates on the fuel and electric paths are 2.68% and 4.88%, respectively.

Owing to the nonlinear item $\eta_d^{sign(T_{em})}$ in (2.3), $T_{em}$ cannot be expressed by a simple function of $T_{ce}$. A heuristic rule is thus introduced to tackle this issue. If $R_p R_{ce} \eta_d \cdot T_{ce}(\omega_{ce})$ is smaller than $T_t$, $T_{em}$ is assumed positive with $sign(T_{em}) = 1$; otherwise, $T_{em}$ is regarded as negative, leading to $sign(T_{em}) = -1$. This method can tremendously reduce computation overheads for executing MPC and PMP algorithms. Especially to the latter one, the complex nonlinear $\mathcal{H}$ is converted into a constrained quadratic

Figure 3.4: Power Approximation by Quadratic Polynomials
programming problem and reformulated as,
\[ H_k = \begin{cases} a_1 T_{ce,k}^2 + b_1 T_{ce,k} + c_1; & R_p R_{ce} \eta_d \cdot T_{ce}^\circ (\omega_{ce,k}) < T_{t,k} \\ a_2 T_{ce,k}^2 + b_2 T_{ce,k} + c_2; & R_p R_{ce} \eta_d \cdot T_{ce}^\circ (\omega_{ce,k}) \geq T_{t,k} \end{cases}, \] (3.26)

where
\[ a_1 = \frac{p_2(\omega_{ce}) - \lambda_k q_2(\omega_{em}) R_{ce}^2}{Q_f C_{sc} R_{em}^2 V_{sc,k}}, \] (3.26a)
\[ b_1 = \frac{p_1(\omega_{ce}) R_{ce}}{Q_f} + \lambda_k \frac{R_{ce}^2}{C_{sc} V_{sc,k}} \left( \frac{2 q_2(\omega_{em}) T_{t,k}}{R_{em}^2 R_p \eta_d} + q_1(\omega_{em}) \frac{R_{em}}{R_p} \right), \] (3.26b)
\[ a_2 = \frac{p_2(\omega_{ce}) - \lambda_k q_2(\omega_{em}) R_{ce}^2}{Q_f C_{sc} V_{sc,k}} \eta_d^2, \] (3.26c)
\[ b_2 = \frac{p_1(\omega_{ce}) R_{ce}}{Q_f} + \lambda_k \frac{R_{ce}^2}{C_{sc} V_{sc,k}} \left( \frac{2 q_2(\omega_{em}) T_{t,k} \eta_d^3}{R_{em}^2 R_p} + q_1(\omega_{em}) \eta_d^2 \right). \] (3.26d)

In (3.26), \( a_1, b_1, a_2 \), and \( b_2 \) are four intermediate variables, and \( c_1 \) and \( c_2 \) are two constants independent of \( T_{ce} \).

This upgraded EMS is also tested by PIL simulations on the same driving cycles. All details involving its design process and testing results are presented in **Paper D**.

### 3.8 ADP-based EMS Design

As illustrated in Section 1.2, in spite of tractable computation loads, online OB-EMSs cannot ensure their robust performances in practical field testing because of the inability to adaptive learning, whereas model-free LB-EMSs are inflicted by restraints from the “cold start” and the architectural complexity. In view of this, an adaptive dynamic programming-(ADP-) based EMS is proposed to integrate the efficient computation of online OB-EMSs and the favorable adaptivity of LB-EMSs.

As a variation of the deterministic DP method for online usage, ADP has been successfully applied to HEV energy management by some innovative scholars \[45, 49, 128\]. By contrast to its primitive, ADP possesses two pivotal merits, namely the approximated value function (AVF) that eliminates the “curse of dimensionality” and the adaptive learning mechanism that relieves the model reliance. However, up to this day, ADP is not as prevalent as ECMS, MPC, and DRL in the field of HEV EMS design. The most prominent defect of ADP is the inefficient computing process, during which the tedious value or policy iteration has to be conducted at each step to search for the optimal solution. In addition, similar to DRL employing
DNNs to estimate real-time Q-values, common ADP methods also approximate VFs by complex NNs to ensure numeric accuracy, leading to enormous computation overheads when updating NNs in online applications. For a computationally efficient ADP-based EMS, the following three methods are adopted to surmount these obstacles.

The first method is to initialize the AVF by the VF from offline DP. It is common sense that the “cold start” will exert ineffective exploration and/or inefficient learning on any RL and DRL method, especially in the preliminary training stage. An effective countermeasure is to introduce “expert knowledge” for securing feasible operations and promoting the convergence process. In this thesis, “expert knowledge” refers to the 3D VF $V(x, t)$ obtained by calling for DP to solve the OCP (3.4). Although non-causal are DP solutions, numeric errors stemming from deviations between the model and reality can be mitigated during the subsequent online training.

The second method is to use piecewise polynomials rather than complicated NNs to represent the AVF. For easy fitting, the 3D VF $V(x, t)$ is separated into two 2D ones with different $s_{ce}$ values, i.e., $V^0(V_{sc}, t)$ for $s_{ce} = 0$ and $V^1(V_{sc}, t)$ for $s_{ce} = 1$. Following the same method adopted in the MPC&PMP-based EMS design, the two VFs are separated into $N_{md}$ time-dependent sections according to the optimal profile $s_{ce}(t_k)$. Polynomials of different orders have been tried to fit VFs on several testing routes and relevant results are listed in Table 3.1. After a cautious comparison, 3rd order polynomials are selected to fit tabular VFs for a balance of numeric accuracy and computation loads, expressed as,

$$
\tilde{V}_W^1(V_{sc}, t) = w_1^n V_{sc}^3 + w_2^n V_{sc}^2 \cdot t + w_3^n V_{sc} \cdot t^2 + w_4^n t^3 + w_5^n V_{sc} + w_6^n V_{sc} \cdot t + w_7^n t^2 + w_8^n V_{sc} + w_9^n t + w_{10}^n,
$$

(3.27)

$$
\tilde{V}_W^0(V_{sc}, t) = w_{11}^n V_{sc}^3 + w_{12}^n V_{sc}^2 \cdot t + w_{13}^n V_{sc} \cdot t^2 + w_{14}^n t^3 + w_{15}^n V_{sc} + w_{16}^n V_{sc} \cdot t + w_{17}^n t^2 + w_{18}^n V_{sc} + w_{19}^n t + w_{20}^n,
$$

(3.28)

where $\tilde{V}_W^1(\cdot)$ and $\tilde{V}_W^0(\cdot)$ denote the AVFs parameterized by the coefficient matrix $W$. $w^n = [w_1^n, w_2^n, \cdots, w_{20}^n]$ is the coefficient vector of $n^{th}$ section, and all $w^n$, $n \in \{1, 2, \cdots, N_{md}\}$, constitute $W = [w^1; w^2; \cdots; w^{N_{md}}]$.

The third method is to assume $T_{ce} = s_{ce} \cdot T_{ce}'(\omega_{ce})$ when determining the powertrain mode $u_{ce}^*$ so as to simplify the OCP. With the aid of $\tilde{V}_W^1(\cdot)$ and

<table>
<thead>
<tr>
<th>Polynomial Order</th>
<th>1st</th>
<th>2nd</th>
<th>3rd</th>
<th>4th</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficient Number</td>
<td>6</td>
<td>12</td>
<td>20</td>
<td>30</td>
</tr>
<tr>
<td>Average NRMSE</td>
<td>3.54%</td>
<td>2.32%</td>
<td>1.33%</td>
<td>1.18%</td>
</tr>
</tbody>
</table>
\[ V^0_W(\cdot), \] the global optimization object can be described as the approximated V-value at current step \( V_W(x_k, t_k) \), which is the instant cost plus the approximated cost-to-go by one-step lookahead approximation. Accordingly, \( u^*_{ce} \) targets at minimizing \( \tilde{V}_W(x_k, t_k) \), written as,

\[
\tilde{V}_W(x_k, t_k) = m_{ce}(x_k, u_k) + m_{sw}(x_k, u_k) + \tilde{V}_W(x_{k+1}, t_{k+1}|x_k, u_k), \quad (3.29)
\]

\[
u^*_{ce,k} = \arg\min_{u_{ce,k}} \tilde{V}_W(x_k, t_k), \quad (3.30)
\]

subject to the same constraints declared in the OCP \((3.4)\), where \( m_{ce}(\cdot) \) and \( m_{sw}(\cdot) \) make up the instant cost.

Thanks to the binary property of \( u_{ce} \), the OCP \((3.30)\) can be rapidly solved by a binary search rather than burdensome iterations. Subsequently, \( T^*_{ce} \) and \( T^*_{em} \) can be calculated by the torque split control, which employs a value-based PMP algorithm, same to that in the MPC&PMP-based EMS.

To overcome the adverse effect on \( \tilde{V}^0_W(\cdot) \) and \( \tilde{V}_W(\cdot) \) from the system deviation and then lift the control performance toward the optimum, an adaptive learning algorithm is designed to iteratively update \( W \) according to real fuel and electricity consumption by temporal difference (TD) learning and batch gradient descent.

This ADP-based EMS is tested on two driving cycles SEM16 and STHLM through PIL simulations, and its performances are compared with several benchmark EMSs for different targets, respectively. Details about the design process and test results of this EMS can be referred to Paper E.

### 3.9 AC-based EMS Design

As analyzed in Section \[1.3\], the overall HEV performance not only pertains to torque split solutions between the fuel and electric paths but also relies on ICE on/off switches. However, the simultaneous optimization of hybrid variables (continuous torque split ratio and binary ICE switch action) will bring in intractable computation complexity in online applications. In view of this challenge, an ADP-based EMS is proposed to separately solve these two variables in a hierarchical control architecture so that the computation and memory overheads are reduced to a large extent. To further reduce the reliance on the system model, an AC method is designed to regulate powertrain mode switches. Unlike general AC methods that formulate actors and critics as complex NNs and can only provide continuous control actions, this AC method employs concise piecewise polynomials instead of NNs for efficiently solving the optimal binary action. Besides, DP solutions are fully exploited to initialize the parameters of actor and critic before online training for rapid convergences.
CHAPTER 3. EMS DESIGN

Similar to the DP-based EMS introduced in Section 3.5, DP solutions to the OCP (3.4) contain not only the VF \( V(x, t) \) and the optimal profile \( s_{ce}(k) \), but also the optimal policy on mode switch \( u_{ce,k}^* = \pi(x_k, t_k) \). For any fixed pair of \( s_{ce,k} \) and \( t_k \), the value of \( u_{ce,k}^* \) is determined by a threshold value of \( V_{sc,k} \). Hence, \( u_{ce,k}^* = \pi(x_k, t_k) \) can be illustrated by the following inequalities,

when \( s_{ce,k} = 0 \),

\[
u_{ce,k}^* = \begin{cases} 
0; & V_{sc,k} \geq V_{sc,k}^0(t_k) \\
1; & V_{sc,k} < V_{sc,k}^0(t_k) 
\end{cases}
\]  

(3.31)

when \( s_{ce,k} = 1 \),

\[
u_{ce,k}^* = \begin{cases} 
0; & V_{sc,k} > V_{sc,k}^1(t_k) \\
1; & V_{sc,k} \leq V_{sc,k}^1(t_k) 
\end{cases}
\]  

(3.32)

where \( V_{sc,k}^0(\cdot) \) and \( V_{sc,k}^1(\cdot) \) are threshold values of \( V_{sc} \) for the electric and hybrid modes, respectively.

The policy \( \pi(\cdot) \) and the VF \( V(\cdot) \) from DP solutions are used to formulate and initialize the actor and the critic. Since both \( \pi(\cdot) \) and \( V(\cdot) \) are too complex to be directly fitted by simple polynomials, the profile \( s_{ce,k}^0(t_k) \) serves as a basis to separate them into \( N_{md} \) time-dependent segments, as it did beforehand in Section 3.7. Hence, the tabular \( V(\cdot) \) of explicit values in the critic are fitted by \( \hat{V}_{w}^1(\cdot) \) and \( \hat{V}_{w}^0(\cdot) \), expressed by (3.27) and (3.28).

Since the output of a general actor should be continuous and differentiable but \( u_{ce} \) is binary, \( \pi(\cdot) \) expressed by (3.31) and (3.32) cannot be directly implemented by the actor. To solve this issue, \( \pi(\cdot) \) is reformulated as logistic functions of \( V_{sc} \) and \( t \), written as,

\[
\pi(x_k,t_k) = \begin{cases} 
1 - \frac{1}{1+e^{-(v_{sc,k}^0-v_{sc,k}^0(t_k))}}; & s_{ce,k} = 0 \\
1 - \frac{1}{1+e^{-(v_{sc,k}-v_{sc,k}^1(t_k))}}; & s_{ce,k} = 1 
\end{cases}
\]  

(3.33)

Logistic functions (3.33) ensure that the value of \( \pi(\cdot) \) is always within the range \((0, 1)\). If \( V_{sc} \) is larger than its reference \( V_{sc}^0(\cdot) \) or \( V_{sc}^1(\cdot) \), indicating more electric energy than the reference is stored in the SC, \( \pi(\cdot) \) is smaller than 0.5; if \( V_{sc} \) is smaller, inferring more electric energy compared to the reference is consumed, \( \pi(\cdot) \) is larger than 0.5; otherwise when \( V_{sc} \) is identical to its reference, \( \pi(\cdot) \) is exactly equal to 0.5. Accordingly, the optimal action \( u_{ce}^* \) can be determined by the value of \( \pi(\cdot) \), written as,

\[
u_{ce,k}^* = \begin{cases} 
1; & \pi(x_k,t_k) > 0.5 \\
0; & \pi(x_k,t_k) < 0.5 \\
s_{ce,k}; & \text{otherwise}
\end{cases}
\]  

(3.34)
Subsequently, $V_{sc}^0(\cdot)$ and $V_{sc}^1(\cdot)$ are approximated by piecewise cubic polynomials at each segment. The relevant formulas are given below.

\begin{align}
\tilde{V}_{sc,F}^1(t_k) &= f_1^n t_k^3 + f_2^n t_k^2 + f_3^n t_k + f_4^n, \\
\tilde{V}_{sc,F}^0(t_k) &= f_5^n t_k^3 + f_6^n t_k^2 + f_7^n t_k + f_8^n,
\end{align}

where $\tilde{V}_{sc,F}^1(\cdot)$ and $\tilde{V}_{sc,F}^0(\cdot)$ are the approximations of $V_{sc}^1(\cdot)$ and $V_{sc}^0(\cdot)$ parameterized by the coefficient matrix $F$. $f^n = [f_1^n, f_2^n, \ldots, f_8^n]$ is the coefficient vector of $n^{th}$ section, and all $f^n$, $n \in \{1, 2, \ldots, N_{md}\}$, compose $F = [f^1; f^2; \ldots; f^{N_{md}}]$.

During online control, the critic and actor coefficient matrices, $W$ and $F$, are iteratively updated through interactive information with the HEV powertrain. Similar to the ADP-based EMS, TD learning is employed to update $W$. The gradient vector of critic $\Delta_c \in \mathbb{R}^{20}$ is written as,

$$\Delta_{c,k} = \frac{\partial l_k}{\partial w^n}.$$ 

(3.37)

The update of $F$ aims to minimize the cumulative fuel consumption. Thus, gradient descent is carried out along the direction to reduce the Q-value $Q(x, u, t)$, written as,

$$\Delta_{a,k} = \frac{\partial Q(x_k, u_k, t_k)}{\partial u_{ce,k}} \cdot \frac{\partial \pi_W(x_k, t_k)}{\partial f^n}$$

(3.38)

where $\Delta_a \in \mathbb{R}^{8}$ is the gradient vector of $Q(\cdot)$ in terms of $f^n$.

For robust training, updates of $W$ and $F$ follow the batch gradient descent method.

$$w^n \leftarrow w^n - \beta_c \sum_{k \in K} \Delta_{c,k},$$

(3.39)

$$f^n \leftarrow w^n - \beta_a \sum_{k \in K} \Delta_{a,k}.$$ 

(3.40)

where $\beta_c$ and $\beta_a$ are the learning rates of critic and actor, respectively.

The torque split control in this EMS is realized by the value-based PMP algorithm, which is introduced in Section 3.7.

The performance of this AC-based EMS is tested on the driving cycle KTH through PIL simulations and compared with an RB-EMS with tabular VFs. Relevant details can be referred to Paper F.

### 3.10 Event-Triggered Control Design

As mentioned in Section 1.3, almost all existing online EMSs adopt fixed execution periods owing to the conceptual simplicity and the convenient
implementation. In practice, the execution period should be carefully selected to balance the control performance and the computation efficiency according to the actual computing power of the target processor. As a result, all aforementioned EMSs in this chapter are designed with fixed periods. Among them, both the ADP-based EMS and the AC-based EMS can achieve excellent fuel economy in online applications with limited consumption of onboard computation resources. PIL simulation results exhibit that these two EMSs obtain more than 90% of the optimal equivalent fuel efficiency by offline DP at the expense of less than 150 Kbyte flash memory and less than 10% average CPU utilization on different driving cycles.

Nonetheless, it is also noteworthy that the maximum CPU utilization is always very high in these two EMSs, perhaps exceeding ten times the average CPU utilization. This huge gap indicates the computation loads are extremely uneven at different time steps and infers much longer end-to-end delays at those steps with larger loads. Such a consequence stems from the adoption of hierarchical control architecture with a fixed period for each module. Since the period of torque split control is 0.1 s, exactly one-tenth that of powertrain mode selection, the proposed EMSs have to run both modules at the start of every second. Even though the torque split problem is converted into a convex quadratic programming problem (3.26), its solving process is still more time-consuming than that of powertrain mode selection, which is a binary search process. Thus, the computation overhead obviously surges at this moment and then swiftly falls down.

After inspections, we found that applied ICE torque values always concentrate within a small range, shown in Figure 3.5. Such a result can be attributed to not only the specific ICE configuration but also the relatively slow variation of torque demand on the powertrain over many driving intervals. It implies that the high execution frequency of torque split control does not boost a better control performance but only aggravates the computation burden.

The above discussion motivates us to develop an event-triggered control mechanism by which the execution period of torque split control is not a fixed value anymore but can be flexibly adjusted according to the variation of torque demand on the powertrain. In this way, the newly proposed EMS is expected to maintain its numeric control performance but save much more onboard computation resources.

Similar to designed EMSs with fixed execution periods, this new strategy also follows the basic topology of the hierarchical architecture presented in Figure 3.2. More specially, it obtains the optimal speed profile \( v^o(t_k) \) from offline DP and exploits DP solutions to initialize the AVF coefficient matrix \( W \). Besides, it employs the same speed regulator, torque split control, and adaptive learning algorithm as the ADP-based EMS. Relevant details have
been described in Sections 3.1, 3.3, 3.7 and 3.8 and elaborated in Papers D and E. The essential difference lies in that there is an exquisite trigger module in the new strategy, which decides if a new ICE torque $T_{ce}^*$ needs to be calculated by the torque split control or the one used in the previous step can be simply inherited. For this target, a new control algorithm is designed for the powertrain mode selection by which it can not only determine the powertrain mode $u_{ce}^*$ but also provide an ICE torque reference $T_{ce}^*$ for the torque split control module in the hybrid mode.

The flowchart of powertrain mode selection is depicted in Figure 3.6. According to real-time state feedback, the equivalent fuel consumption for the electric mode and the hybrid mode, $\tilde{V}_0^W(\cdot)$ and $\tilde{V}_1^W(\cdot)$, are calculated and compared, wherein the ICE torque for the hybrid mode $T_{ce}^1$ is solved by the value-based PMP algorithm. If $\tilde{V}_0^W(\cdot)$ is less than $\tilde{V}_1^W(\cdot)$, the electric mode is selected and the ICE does not provide traction torque to the powertrain; otherwise, the hybrid mode is selected and $T_{ce}^1$ is assigned to $T_{ce}^*$. The sampling period of torque split control is one-tenth of that of powertrain mode selection, indicating in the hybrid mode, the torque split control can be executed at most ten times during the interval between two consecutive outputs from the powertrain mode selection. At the first of the ten steps, the torque split control can directly inherit the reference $T_{ce}^*$ as its output $u_{ce}^*$; at each of the following nine steps, an efficient trigger algorithm is executed to decide whether the current reference $T_{ce}^*$ is outdated.

The flowchart of the trigger algorithm is exhibited in Figure 3.7. To distinguish from the index $k$ used by the powertrain mode selection, another index of $i$ with an increment of 0.1 is selected for the trigger within ten steps of 1 s. The trigger periodically receives a predicted SC voltage $\tilde{V}_{sc,k+1}$ from the powertrain mode selection, and computes the deviation to this value.
\[ \Delta V_{sc}^* \text{ based on the SC voltage at the first step } V_{sc,k} \]. After every 0.1 s, the trigger acquires a real-time SC voltage \( V_{sc,k+i} \) from the onboard sensor and checks if \( V_{sc,k+i} \) approaches to \( \tilde{V}_{sc,k+1} \) by applying \( T^*_{ce,k+i-1} \). If so, the trigger believes that the existing \( T^*_{ce,k} \) is still valid as the optimal ICE torque output at the current step \( T^*_{ce,k+i} \); otherwise, this \( T^*_{ce} \) is regarded as outdated, and thus the trigger will wake up the torque split control to calculate \( T^*_{ce,k+i} \) through the value-based PMP algorithm. After being sent out, the newly calculated \( T^*_{ce,k+i} \) will be used to update \( T^*_{ce,k} \). Nonetheless, in both cases, \( \Delta V_{sc}^* \) is always updated according to the gap between the newest SC voltage \( V_{sc,k+i} \) and the predicted reference \( \tilde{V}_{sc,k+1} \).

To wrap up, the complete EMS architecture with an event-triggered control mechanism is developed and illustrated in Figure 3.8. It consists of three parts, namely offline EMS, online EMS, and actuator control from top to bottom. By running DP, the offline EMS provides an optimal speed profile and initializes the AVF coefficient matrix for the online EMS. For reducing the computation complexity and saving the computation resources,
3.10. EVENT-TRIGGERED CONTROL DESIGN

Figure 3.7: Flowchart of Trigger Algorithm

the online EMS adopts a hierarchical architecture by which the powertrain mode and the torque allocation are separately optimized by various methods designed in this thesis. In addition, an event-trigger control mechanism is introduced for the torque split control aiming at eliminating the redundant computation overhead thus further improving the computation efficiency. The transient control decisions from an online EMS, including ICE on/off switch, ICE torque as well as EM torque, will be implemented on the corresponding powertrain components via the actuator control.
CHAPTER 3. EMS DESIGN

Figure 3.8: Complete EMS Architecture with Event-Triggered Control
Chapter 4

Contribution Summary

This chapter summarizes the research contributions of this thesis. The representative contributions of each appended paper are outlined and discussed in sequence, followed by a deep analysis concerning the significance of the event-triggered control mechanism.

4.1 Paper A

**Tong Liu, Lei Feng, Mikael Hellgren, and Jan Wikander**

Increasing Fuel Efficiency of a Hybrid Electric Competition Car by a Binary Equivalent Consumption Minimization Strategy

*IEEE International Conference on Automation Science and Engineering (CASE), 2018*

This paper presents a binary ECMS-based EMS for improving the equivalent fuel efficiency of a parallel HEV prototype. To preserve the ICE operation efficiency and reduce the energy management complexity, a special ICE configuration is adopted, where the ICE can only operate on the OOL or simply be switched off. In addition, a two-level hierarchical EMS architecture is designed to ensure that the proposed EMS can be executed by a low-cost microprocessor. The top-level control computes the real-time acceleration to regulate the HEV to follow the optimal velocity profile, which is provided by offline DP. The bottom-level control finds the best solution for splitting the total torque demand between the fuel and electric paths by a binary ECMS method, whose equivalence factor is easily calculated by a tangent-shape adaption function.

Simulation results on the driving cycle SEM16 show that this proposed
CHAPTER 4. CONTRIBUTION SUMMARY

EMS improves the equivalent fuel efficiency by around 50% over an RB-EMS, and reaches roughly 90% of the DP optimum after simple parameter calibration. Moreover, owing to the binary control variable and the one-step optimization horizon, this EMS consumes extremely less computation resources and can be executed in real-time on a portable microprocessor with a tiny end-to-end delay.

4.2 Paper B

Tong Liu, Lei Feng, Mikael Hellgren, and Jan Wikander

A Binary Controller to Ensure Engine Peak Efficiency for a Parallel Hybrid Electric Car

IEEE Intelligent Transportation Systems Conference (ITSC), 2019

In this paper, two DP-based EMSs are designed to verify the superiority of a parallel HEV with a specially configured ICE that can only operate on its OOL, in contrast to the same HEV with a generally used ICE which can freely operate at any admissible point within its 2D efficiency map. To investigate optimal fuel economy in online applications, the energy management problems of the HEV with two different ICE configurations are formulated as two OCPs and then solved by offline DP, respectively. At last, optimized solutions are utilized to construct two online EMSs in the form of lookup tables.

Simulation results on the driving cycle SEM16 manifest that the HEV with the special ICE configuration has a 13% higher equivalent fuel efficiency than its counterpart without violating any system constraint. In addition, even though this binary-controlled ICE has to be restarted 4 times more than the generally used one, there is no rapid switch occurring during driving. Such a gratifying result should be attributed to the efficient ICE operation and thus reflects the advantage of this special ICE configuration.

4.3 Paper C

Tong Liu, Lei Feng, and Wenyao Zhu

Fuel Minimization of a Hybrid Electric Racing Car by Quasi-Pontryagin’s Minimum Principle

IEEE Transactions on Vehicular Technology (TVT), 2021

In this paper, a real-time implementable EMS is designed based on the special ICE configuration introduced in Papers A and B. Aiming
to achieve a near-optimal fuel economy with limited onboard computation resources, a quasi-PMP-based EMS that combines the advantages of both DP and PMP is designed to efficiently compute online torque split solutions. Unlike general PMP applications using either shooting methods or complex optimization methods to derive the optimal costate trajectory, this new method estimates the optimal costate through the HJBE with the aid of VF from offline DP. Moreover, targeting at the non-derivable state variable, i.e., the transient ICE on/off status, the difference method is adopted to effectively estimate its optimal costate.

PIL simulation results demonstrate that this proposed EMS contributes more than 96% equivalent fuel economy of the DP optimum but requires less than 1% onboard memory space. Furthermore, as an extension to investigate the superiority of the special ICE configuration, a similar methodology is manipulated to design an EMS for a generally used ICE. By contrast, the proposed EMS outperforms its counterpart with roughly 12% higher fuel economy as well as nearly 33% lower average CPU utilization.

4.4 Paper D

Tong Liu, Wenyao Zhu, Kaige Tan, Mingwei Liu, and Lei Feng

A Low-Complexity and High-Performance Energy Management Strategy of a Hybrid Electric Vehicle by Model Approximation

IEEE International Conference on Automation Science and Engineering (CASE), 2022

The most prominent contribution in this paper is to eliminate excessive ICE on/off switches by introducing a more robust ICE configuration, in which the ICE can flexibly operate within a narrow band around the OOL rather than strictly on the OOL. By means of optimized solutions from offline DP, the powertrain mode selection can be rapidly determined by a constrained MPC algorithm and the torque split problem is solved by a value-based PMP algorithm, respectively. Furthermore, two important methods are taken to further improve the online computation speed and reduce the memory space. By the model approximation on the fuel and electric paths, the complicated ICE and EM efficiency maps are replaced by parametric quadratic functions and thereby the complex nonlinear torque split problem is converted into a quadratic programming problem; by the surface fitting, the tabular VF of large size is estimated by carefully selected piecewise linear polynomials.

PIL simulation results on two driving cycles verify the superiority of the novel ICE configuration and the proposed EMS. In contrast to the special
ICE configuration adopted in **Papers A and C**, the new one enables a 60% decrease in the number of powertrain mode switches, implying less fuel consumption, more robust ICE operation, and longer ICE lifespan. Apart from this, the proposed EMS can attain almost the same control performance in terms of fuel economy, mode switch, and charge sustain, compared with the benchmark EMS without value fitting and model approximation. More significantly, benefiting from the efficient approximation on VF, the onboard memory occupation is further saved by 70%. Additionally, the simplified ICE and SC models contribute to an extra 30% decrease in average CPU utilization on both driving cycles.

### 4.5 Paper E

**Tong Liu**, Kaige Tan, Wenyao Zhu, and Lei Feng

*Computationally Efficient Energy Management for a Parallel Hybrid Electric Vehicle Using Adaptive Dynamic Programming*

*IEEE Transactions on Intelligent Vehicles (T-IV), 2023*

This paper presents a computationally efficient ADP-based EMS for HEV energy management. During online control, this EMS can not only rapidly compute the optimal powertrain mode and torque allocation, but also efficiently update the AVF according to actual fuel and electricity consumption. More specially, the optimal control for powertrain mode and torque split relies on the AVF, which is initialized based on the tabular VF from offline DP and approximated by piecewise cubic polynomials rather than complicated NNs so as to reduce the computation complexity and the memory occupation without obviously compromising the numeric accuracy. By introducing a constraint on ICE operation, the complex MINLP problem for mode selection is converted into a binary search problem and thus can be easily solved by one-step lookahead with the AVF. Identical to that in **Paper D**, the torque split problem in the hybrid mode is solved by a value-based PMP algorithm with the Hamiltonian formulated as a constraint quadratic programming problem.

The superiority of this proposed EMS is reflected in three aspects and verified by PIL Monte Carlo simulations. First, in contrast to an adaptive PMP-based EMS with tediously calibrated parameters, the proposed EMS achieves at least 5% higher equivalent fuel economy after sufficient training, shortening the gap with the DP optimum to less than 3%. Second, even if actual driving conditions become unfavorable, this ADP-based EMS can quickly adapt to them within merely several episodes and generate obviously higher fuel efficiency than a non-adaptive DP-based EMS. Third, regarding
the memory overhead, the AVF saves at least 70% onboard flash memory by employing piecewise polynomials to replace the tabular VF. In summary, benefiting from efficient computing and learning, the proposed ADP-based EMS can rapidly adapt to its driving scenarios and thereby adjust its AVF coefficients. By this means, it can contribute to more than 97% of the optimal fuel economy with less than 3% average CPU utilization on a portable microprocessor.

4.6 Paper F

Tong Liu, Kaige Tan, Wenyao Zhu, and Lei Feng

Optimal and Adaptive Engine Switch Control for a Parallel Hybrid Electric Vehicle Using a Computationally Efficient Actor-Critic Method

2023 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM), 2023

This paper presents a novel EMS that contains an efficient AC method to regulate the powertrain mode of a parallel HEV. General AC methods represent their actors and critics as NNs with arbitrary initialization and thus usually suffer several drawbacks, such as lengthy training time, risk of divergence, and enormous computation overheads. On account of this, the proposed AC method employs piecewise cubic polynomials to formulate the actor and the critic and exploits DP solutions to initialize their parameters before online training. In this way, the AC agent can avoid the adverse effects of “cold start”.

PIL simulation results verify the advantages of this AC-based EMS by comparing its performance with an RB-EMS, which is derived from offline DP and has a tabular VF. After a small number of learning iterations, the proposed EMS can effectively eliminate improper mode switches and reduce the energy consumption caused by these mode switches. Therefore, it upgrades the robustness of ICE operation and improves the equivalent fuel efficiency to nearly 95% of the DP optimum, obviously outperforming its benchmark, an RB-EMS. Taking the online computation efficiency into consideration, this proposed EMS saves more than 50% of the memory space and consumes only 1.3% more of the average CPU utilization compared with the RB-EMS, owing to the concise structure of piecewise polynomials and the efficient computation.
4.7 Event-Triggered Control

In view of the challenge posed in Section 1.3, an event-triggered control mechanism is introduced to improve the computation efficiency of the EMS with a hierarchical architecture by eliminating unnecessary computation overhead. To this end, an efficient trigger algorithm is designed for rapidly deciding if the ICE torque at the current step can inherit the previous value instead of being calculated by the complex optimization algorithm. The advantage of the new EMS with an event-triggered control mechanism is verified by comparing it with a benchmark EMS, the ADP-based EMS with a fixed period for the torque split control, on two driving cycles SEM16 and STHLM. The relevant results concerning fuel economy and the online computation efficiency are demonstrated in Tables 4.1 and 4.2, respectively.

At first glance, the equivalent fuel efficiency of the new EMS is slightly worse than that of ADP-based EMS on both driving cycles, with a gap of less than 1%. In addition to this, the new EMS occupies nearly 10 Kbyte larger flash memory space for accommodating the complete algorithm and requires around 10 Kbyte larger RAM size during execution than its counterpart. The reasons for such results are twofold. Since the ADP-based EMS updates the ICE torque output in the hybrid mode with a fixed period of 0.1 s which cannot be less than the actual period of that in the new EMS, it definitely enables a control performance no worse than the new EMS. Besides, in online implementation, the ADP-based EMS with a time-triggered control mechanism only relies on the built-in timer to periodically call for the torque split control algorithm, whereas the new EMS contains an extra trigger algorithm and thereby generates more memory overhead.

Table 4.1: PIL Simulation Results on Driving Cycle SEM16

<table>
<thead>
<tr>
<th>Control Strategy</th>
<th>New EMS</th>
<th>ADP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equivalent Fuel Efficiency (km/L)</td>
<td>190.9</td>
<td>192.7</td>
</tr>
<tr>
<td>Flash Memory Occupation (Kbyte)</td>
<td>95.81</td>
<td>90.63</td>
</tr>
<tr>
<td>RAM Occupation (Kbyte)</td>
<td>43.09</td>
<td>39.68</td>
</tr>
<tr>
<td>Max. CPU Utilization (%)</td>
<td>12.58</td>
<td>23.96</td>
</tr>
<tr>
<td>Avg. CPU Utilization (%)</td>
<td>1.60</td>
<td>2.82</td>
</tr>
</tbody>
</table>

Apart from these aforementioned minimal gaps, the most significant differences between the two EMSs are reflected in the online computation overhead. In contrast to the ADP-based EMS, the new one enjoys a roughly 50% less maximum CPU utilization and a more than 33% reduction in average CPU utilization, implying a much less risk to miss the deadline in a real-time embedded system and an obviously shorter end-to-end delay in a closed-loop feedback control system. The decreased maximum value bene-
4.7. EVENT-TRIGGERED CONTROL

Table 4.2: PIL Simulation Results on Driving Cycle STHLM

<table>
<thead>
<tr>
<th>Control Strategy</th>
<th>New EMS</th>
<th>ADP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equivalent Fuel Efficiency (km/L)</td>
<td>180.5</td>
<td>182.1</td>
</tr>
<tr>
<td>Flash Memory Occupation (Kbyte)</td>
<td>154.40</td>
<td>145.60</td>
</tr>
<tr>
<td>RAM Occupation (Kbyte)</td>
<td>44.29</td>
<td>40.93</td>
</tr>
<tr>
<td>Max. CPU Utilization (%)</td>
<td>12.93</td>
<td>27.08</td>
</tr>
<tr>
<td>Avg. CPU Utilization (%)</td>
<td>2.00</td>
<td>2.95</td>
</tr>
</tbody>
</table>

fits from the “off-peak execution”, by which the torque split control module cannot be executed at the same step as the powertrain mode selection module, and thus the computation load at the beginning step of each second is extremely reduced. More importantly, thanks to the trigger algorithm in the new strategy, in most of the steps during the hybrid mode, the existing ICE torque reference is continuously used as the optimal control action from the EMS and thus the computation overhead for executing the optimization algorithm is saved. For instance, on the driving cycle SEM16, the hybrid mode totally lasts 121 s, corresponding to 1210 torque split decisions calculated by the optimization algorithm if an EMS with fixed control periods is employed. With the trigger algorithm, the optimization algorithm is called for in only 451 steps, while in other 759 steps, accounting for 62.7% of all, the reference value is directly assigned to the transient torque output without any complex calculation, referring to the 1.22% drop of average CPU utilization in Table 4.1. Relevant details are demonstrated in Figure 4.1. A similar result emerges on the driving cycle STHLM as well, i.e., in more than 60% steps in the hybrid mode, the computation load for executing value-based PMP algorithm is omitted, leading to the descent in CPU utilization displaced in Table 4.2.
Figure 4.1: ICE Torque on Driving Cycle SEM16 by EMS with Event-Triggered Control (a) Distribution of ICE Operation Points (b) Profile of ICE Torque Value (c) A Segment of Trigger Decision: Ref. means the transient ICE torque value is assigned by the reference, whereas Calc. means this value is calculated by the optimization algorithm.
Chapter 5

Discussion and Conclusion

This chapter contains three sections. The first section answers each posed RQ by exemplifying adopted methods with relevant results. Then, the second section concludes this thesis by highlighting motivations and contributions. Finally, the third section points out some limitations of this thesis and puts forward corresponding suggestions for future research.

5.1 Answers to Research Questions

**RQ.1:** How to design an online EMS that can improve the fuel economy of a parallel HEV and satisfy the real-time requirement?

**Answer:** Three methods are developed to achieve a balance between the control performance and the computation overhead.

The first method is the smart utilization of optimized results by offline DP. Although the DP method cannot be directly implemented in online applications, its solutions, including optimal profiles of state variables and the VF, can be effectively exploited by online optimization methods, such as ECMS, PMP, and MPC, to search for optimal real-time control actions that minimize the total cost in the remaining driving process.

The second method is the limited ICE operation space. Two different ICE configurations are adopted in this thesis by which the ICE can operate either strictly at the OOL or within a narrow band around the OOL. As a result, the ICE is ensured to operate with close-to-peak efficiency after ignition, but computation loads for both online and offline computation are extremely relieved owing to the limited searching space.

The last method is the hierarchical control architecture. Since the formulated OCP concerning HEV energy management is an MINLP problem
that contains a binary control on the mode switch and a continuous control on the torque split, it is time- and resource-consuming to solve the two control variables in online execution simultaneously. Thus, a hierarchical architecture is introduced to decompose the complicated OCP into sequentially correlated sub-problems to reduce the overall complexity. At first, the powertrain mode is rapidly determined with the aid of some proper assumptions. If the powertrain is in the hybrid mode, the torque split result will be calculated by an efficient optimization algorithm.

**RQ.2:** How to obtain close-to-optimal fuel economy with robust operations on ICE on/off switches?

**Answer:** ICE on/off switches refer to powertrain mode switches. For robust operations on the ICE, the ICE is expected to maintain its current on/off status for at least 10 s after one switch. To avoid unnecessary switches, an equivalent fuel consumption, with respect to the average energy consumption on ICE ignition/flame-out and clutch dis/engagement, is added to the instant cost of the formulated OCP if one mode switch is conducted at the current step. In the meantime, to find out the right moments to switch the mode for (close-to-)optimal fuel economy, the influence of future driving information, in the form of control policy and/or VF obtained from offline DP, is fully assessed at each step of the online optimization process. Moreover, to further decrease the mode switching times, the initially proposed special ICE configuration is replaced by a more robust one, by which the ICE torque can flexibly vary around the OOL rather than being strictly located on this line.

**RQ.3:** How to design an implementable EMS for a target processor with limited computation resources, given the requirements in RQ.2?

**Answer:** A hierarchical control architecture, shown in Figure 3.2 is designed to effectively reduce the OCP complexity in online execution. The original OCP (3.2) is a co-optimization problem that contains not only energy management but also speed planning. In this hierarchical architecture, the optimal speed is computed offline, and based on this, the online EMS iteratively determines the optimal powertrain mode and calculates the optimal torque allocation in sequence. By this means, the dimension of tabular policy and/or VF for online utilization is radically reduced so as to save the onboard memory occupation. Especially to the torque split control by a value-based PMP, only half of the VF related to the hybrid mode is required.

**RQ.4:** How to effectively reduce both the computation overhead and the memory occupation of an EMS without obviously degrading its control performance?
Answer: The two targets are concurrently achieved by the value fitting and the model approximation. To eliminate the “curse of dimensionality”, the tabular VF of explicit values is converted into parametric functions. Unlike common methods that approximate the VF as complicated NNs, an efficient value fitting method is employed to separate the complete tabular VF into several segments and then approximate them by piecewise polynomials. As the tabular VF of over ten thousand elements is replaced by a coefficient matrix of only several tens of coefficients, the onboard memory occupation significantly plunges. The torque split problem is a complex nonlinear programming problem that requires explicit information from the 2D ICE and EM efficiency maps. Through an efficient model approximation, transient power flows on both fuel and electric paths are expressed as parametric quadratic functions. And then, the torque split problem is reformulated as a constrained quadratic programming problem that can be rapidly solved in online control.

RQ.5: How to rapidly adapt an EMS to uncertain driving conditions?

Answer: Uncertain driving conditions are reflected as inaccurate prior knowledge of the road slope angle and suddenly increased aerodynamic and rolling resistances. The rapid adaption is realized by introducing a computationally efficient online learning algorithm for updating the AVF coefficient matrix. The AVF accuracy dominates control performances of the ADP-based and AC-based EMSs since the former relies on the AVF to generate optimal control actions and the latter selects the AVF as the critic to evaluate control actions from the actor. As aforementioned, the AVF is initialized by the optimized VF from offline DP in the form of piecewise polynomials. For a balance between the learning speed and the system robustness, batch gradient descent is adopted to update the coefficient matrix during online control. At each step, if the batch is not full and the powertrain mode maintains, the EMS will not update anything but only append the new sample into the batch; otherwise, the EMS will employ the gradient descent rule to update the coefficient matrix according to all saved samples and then reset the batch.

RQ.6: How can a flexible control period further improve the EMS computation efficiency?

Answer: An event-triggered control mechanism is applied on the torque split control for avoiding the unnecessary execution of the complex optimization algorithm at some steps in the hybrid mode. This functionality is realized through an efficient trigger algorithm. At each step in the hybrid mode, the trigger algorithm receives the real-time SC voltage and decides whether the reference ICE torque value is still valid or not. If so, the EMS
CHAPTER 5. DISCUSSION AND CONCLUSION

will directly use this reference value as the optimal ICE torque output; otherwise, the EMS calls for the value-based PMP algorithm to calculate a new solution as the output and uses it to update the reference value. PIL simulation results on two driving cycles show that, with the aid of this event-triggered control mechanism, the execution of the value-based PMP algorithm is skipped at more than 60% of all steps in the hybrid mode without visible compromise on fuel economy, contributing to significant decreases on both maximum and average CPU utilization at the cost of a slight rise on the memory occupation.

5.2 Conclusion

The advantages of HEVs in terms of energy conservation and emission reduction highly rely on the performances of onboard EMSs, whereas the current EMS research encounters several considerable challenges. On account of this, this thesis concentrates on designing computationally efficient and adaptive EMSs for parallel HEVs, in which ICE spinning speeds are closely associated with vehicle speeds.

Since the control target for the HEV under investigation is to minimize the equivalent fuel consumption over a specific driving cycle with a fixed distance and constrained driving time, the original OCP is formulated as a co-optimization problem, including energy management and speed planning. In addition, due to the complex powertrain dynamics, this OCP is also an MINLP problem, containing both discrete and continuous variables.

To reduce the OCP complexity and ensure the ICE operates with close-to-peak efficiency, two types of special ICE configurations are adopted, by which the ICE can operate either strictly at the OOL or within a narrow range around the OOL. After careful consideration and comparisons, the latter one is finally selected owing to its excellent balance between computation complexity and system robustness.

To lessen the computation burden in online control, the original OCP is decomposed into three sub-problems, and the hierarchical control architecture illustrated in Figure. 3.2 is established. At first, offline DP tackles the speed planning problem and provides an optimal speed profile to online control as a reference. Then, the energy management problem is iteratively solved through an online EMS of two layers, in which the powertrain mode is determined in the upper layer and the torque allocation is optimized in the lower layer.

Designed EMSs leverage the VF to calculate and/or evaluate optimal control actions but the tabular VF with explicit values suffers the “curse of dimensionality”. Common methods usually utilize complicated NNs to approximate VF, leading to enormous computation overheads when updating
the NN coefficients. To overcome this issue, an efficient parametric approximation method is designed, by which the complete tabular VF is separated into several time-dependent segments with the aid of DP solutions, and then approximated by piecewise polynomials with concise structures.

Two methods are applied to the torque split control to improve the computation efficiency for the optimal torque split solution in hybrid mode. The first one is the model approximation, by which transient power flows on both fuel and electric paths are modeled as second-order polynomials and thus the OCP for torque split is converted into a constrained quadratic programming problem that can be rapidly solved. The second one is the event-triggered control mechanism, by which the optimal ICE torque can directly inherit the reference value when the powertrain torque demand levels off, and thereby the computation overhead resulting from the frequent execution of optimization algorithm can reduce to a large extent.

To sum up, several creative methods are proposed in this thesis to design real-time implementable EMSs that remedy deficiencies and limitations of existing EMSs. The performances of developed EMSs in online applications are tested on different driving cycles through PIL simulations based on a portable microprocessor. PIL simulation results adequately manifest the advantages of proposed EMSs in terms of fuel economy, computation efficiency as well as adaptivity and reveal the contribution of this thesis to future EMS development.

5.3 Future Work

To further improve the comprehensive performances of online EMSs and obtain more reliable testing results, several avenues for future research are listed follows.

Adaptive Learning Algorithm

Although this thesis decreases the complexity of LB-EMSs through polynomial approximation of the VF, the value overestimation problem for LB-EMSs is not properly addressed. Many state-of-the-art LB-EMSs utilize extra target DNNs to mitigate this issue. The same approach can be adopted by introducing an extra target AVF into the adaptive learning algorithm. Apart from this, another critical issue, hyperparameter sensitivity, should be carefully accommodated in future research for rapid and reliable learning.

Event-Triggered Control Mechanism

In this thesis, an event-triggered control mechanism is successfully applied to the online EMS and contributes to a remarkable reduction in CPU
utilization without obvious compromise in control performance. Confined to the limited time and scope of this thesis, this method is only adopted by the torque split control, and its effectiveness is only verified by the EMSs for a specific parallel HEV. Further improved computation efficiency can be anticipated if this method is also utilized in the powertrain mode selection. More profoundly, this method can be flexibly manipulated to develop computationally efficient EMSs for diverse types of electrified vehicles, including battery-SC EVs, plug-in HEVs, fuel cell HEVs, and so on.

More Realistic Verification Methods

PIL simulations applied in this thesis verify the superiority of proposed EMSs in terms of computation efficiency and fuel economy. However, since the HEV model cannot reflect the exact dynamics of the actual vehicular system and the selected STM32 microprocessor is not a real system-on-chip, numeric results from PIL simulations, including fuel consumption and SOC variation, are different from truths in the real world. To obtain more realistic results, more physical verification methods, ranging from HIL simulation to system integration testing until field testing, should be progressively adopted in future research to evaluate the robustness of designed EMSs in practical usage. Additionally, various driving cycles containing different terrain information and speed profiles should be manipulated to test the general effectiveness of designed EMSs.

Co-optimization of Energy Management and Component Sizing

Fuel economy of an HEV can be improved by not only the appropriate EMS but also the reasonable powertrain configuration and dimensions. Previous research has revealed that the size of each powertrain component, such as the battery pack, the SC, the gearbox, the ICE, the EM, and so forth, can considerably affect the overall control performance of a designated EMS, while the optimal result dramatically changes under various driving scenarios and different system constraints [9], [29]–[31]. Therefore, the demand for both the optimal powertrain structure design and the real-time implementable energy management motivates efficient co-optimization approaches. In spite of many published achievements in recent years, almost all of them only concentrate on the optimal sizing of a single component, which fails to explore the greatest potential of improving HEV performances. In view of this, more studies should be dedicated to computationally efficient methods for multi-object co-optimization.
References


CHAPTER 5. DISCUSSION AND CONCLUSION


5.3. FUTURE WORK


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Appended Papers