Real-time Power Management of Parallel Full Hybrid Electric Vehicles

by

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Abstract  

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Hybrid electric vehicles (HEVs) combine an electric motor/generator (EMG) and an energy storage system (ESS) with the internal combustion engine (ICE) to produce a fuel efficient (and low gaseous emissions) powertrain. The best fuel efficiency of an HEV is realizable only by a proper power management strategy (PMS), which distributes the vehicle power demand between the ICE and the ESS to achieve simultaneous objectives such as minimum overall fuel consumption, proper regulation of battery charge and frequency of engine stop/restart and maximum regeneration of braking energy. Performance of a PMS depends on the configuration of components (i.e., parallel or series), the degree of hybridization (i.e., relative driving capacities of the ICE and the ESS) and the preview length of future driving information. The main foci of this thesis are the PMSs that explore the best fuel saving capability of parallel full HEVs.

The research described starts with developing a parallel HEV model and an equal power conventional vehicle of a full size passenger car configured to what is a significant compromise to obtain excellent fuel consumption. The driving environment includes drive cycles such as Australian urban drive cycle (AUDC) to facilitate performance compatible with the Australian driving environment and road gradient to include more realistic and aggressive driving environments than standard fuel consumption test cycles.

The ultimate fuel saving capability of the HEV is firstly revealed. Such a solution is possible only with optimal or near-optimal PMSs with the knowledge of the
complete drive cycle, in other words, with “offline” PMSs. Two well-known offline strategies based on dynamic programming (DP) and equivalent consumption minimization strategy (ECMS) are implemented. This thesis introduces a new offline power management strategy (HCPMS) to solve the problem near-optimally within an acceptable computational time. Main features of the HCPMS are the iterative solution improvement procedure inspired by a hill-climbing heuristic, the feasible solution generation satisfying all component constraints and the objective function formulated to minimize the overall fuel consumption including ICE’s starting fuel and to meet the ideal final charge sustenance. HCPMS’s fuel saving is competitive to those of DP while it is 70 to 90 times faster than DP. HCPMS is always better in fuel optimality than ECMS and meeting the end-charge sustenance. Offline results of the HCPMS conclude that the HEV has 42.9 % of fuel saving potential over the AUDC compared to the conventional vehicle.

Secondly, the fuel saving capability of the HEV in real-time (online) driving is explored. In this thesis, a new design procedure for an online PMS based on the power-balancing strategy (PBS) is proposed and tested in a wide range of real driving. The PBS controller consists of rules that control the ICE within its “peak-efficiency region”, regulate the SOC properly and manage frequency of starting and stopping of the ICE. A new HEV architecture namely “ISG-assisted PHEV”, which consists of a downsized EMG supported by an integrated starter generator (ISG) to improve overall electrical efficiency, is also proposed. Results show that the HEV achieves 3.66 L/100km fuel consumption with the PBS controller over the AUDC leading to 41.3 % fuel saving compared to the conventional vehicle. This result is within 0.05 L/100km of the offline controller’s result, but without using complete driving information unrealistically. Interestingly, the ISG-assisted PHEV achieves fuel consumption of 3.32 L/100km saving fuel by 9.3% compared to the HEV (ISG-unassisted). This reflects the necessity of a high performing electrical system in online power balancing of HEVs. The result also means 47.5% overall fuel saving by the real world HEV compared to the conventional vehicle.

Thirdly, further fuel saving ability of the HEV with upcoming driving information is explored. A predictive framework that optimizes the management of instan-
taneous power demand with the look-ahead driving information is introduced. For this purpose, a computationally efficient PMS without sacrificing fuel optimality is necessary. A new PMS namely “ICE on/off PMS” is proposed for this application. The ICE on/off PMS is a combination of model-based and rule-based strategies. The steepest ascent hill-climbing algorithm optimizes the sequence of the ICE’s on or off status while a rule-based strategy splits the power demand between the ICE and the EMG according to the on or off status of the ICE. The results show the offline ICE on/off PMS is always more fuel efficient than the PBS controller, much faster (about 20 times) than the HCPMS and capable of handling all hard driving situations such as inclined roads. Furthermore, on level roads, it achieves offline fuel saving at about 80 s look-ahead period. With the presence of the road gradient, fuel saving of the HEV shows a heavy dependancy on the look-ahead information and requires a look-ahead time about 300 s to get the best HEV performance.

Lastly, the fuel saving capability of the HEV through intelligent driving was investigated. The intelligent vehicle velocity modification algorithm proposed by Manzie et al. is improved by 6.5% reduced fuel use. The intelligent HEV uses the look-ahead information from telematics to find an energy efficient speed trace and optimize the power management. Best results show up to 53.3% in ultimate fuel saving by the intelligent HEV on city cycles compared to the conventional vehicle.
Declaration

This is to certify that

(i) the thesis comprises only my original work towards the PhD,

(ii) due acknowledgment has been made in the text to all other material used,

(iii) the thesis is less than 100,000 words in length, exclusive of table, maps, bibliographies, appendices and footnotes.

Signature__________________________

Date______________________________
To my parents who dedicated their everything
to get me here
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Acronyms

\( \omega \) Speed demand at the output of the engine

\( \eta_{emg} \) Efficiency of the electric motor/generator

\( \eta_{ice} \) Efficiency of the internal combustion engine

\( \bar{\eta}_{chg} \) Average recharging efficiency of the electric system

\( \bar{\eta}_{dis} \) Average discharging efficiency of the electric system

\( \bar{\eta}_{ele} \) Average efficiency of the electric system

\( \eta_{opt} \) Highest efficiency of the internal combustion engine

\( \bar{\eta}_{ice} \) Average efficiency of the internal combustion engine

\( \omega_{emg} \) Output speed of the electric motor generator

\( \omega_{ice} \) Output speed of the engine

\( \lambda_{dis} \) Equivalent factor of discharged battery energy

\( \lambda_{chg} \) Equivalent factor of recharged battery energy

\( \rho \) Air density

\( a \) Acceleration of the vehicle

ADVISOR ADVanced VehIcle SimulatOR

ATHC Australian Truck Highway Cycle

AUDC Australian Urban Drive Cycles

\( C_{rr} \) Coefficient of rolling resistance
<table>
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<th>Abbreviation</th>
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<tr>
<td>$C_d$</td>
<td>Aerodynamic drag coefficient</td>
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<tr>
<td>CV</td>
<td>Conventional vehicle</td>
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<tr>
<td>CVT</td>
<td>Continuously variable transmissions</td>
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<tr>
<td>CARB</td>
<td>California Air Resources Board</td>
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<tr>
<td>DI</td>
<td>Direct injection</td>
</tr>
<tr>
<td>DoH</td>
<td>Degree of hybridization</td>
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<tr>
<td>DP</td>
<td>Dynamic programming</td>
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<tr>
<td>$E$</td>
<td>Energy</td>
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<tr>
<td>ECMS</td>
<td>Equivalent consumption minimization strategy</td>
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<tr>
<td>EISA</td>
<td>Energy Independence and Security Act</td>
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<tr>
<td>EMG</td>
<td>Electric motor/generator</td>
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<tr>
<td>EPA</td>
<td>Environmental Protection Agency</td>
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<tr>
<td>EPCA</td>
<td>Energy Policy Conservation Act</td>
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<tr>
<td>ESS</td>
<td>Energy storage system</td>
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<tr>
<td>$F$</td>
<td>Force</td>
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<tr>
<td>FCV</td>
<td>Fuel cell vehicle</td>
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<tr>
<td>FLC</td>
<td>Fuzzy logic controller</td>
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<tr>
<td>FTP-75</td>
<td>Federal Test Procedure</td>
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<tr>
<td>$g$</td>
<td>Gravitational acceleration</td>
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<tr>
<td>GPS</td>
<td>Global positioning system</td>
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<tr>
<td>HC</td>
<td>Hydro carbon</td>
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<td>HCPMS</td>
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HVAC  Heating ventilation and air conditioning
HWFET  Highway Fuel Economy Test
ICE  Internal combustion engine
ISG  Integrated starter generator
IV  Intelligent vehicle
IVVMA  Intelligent vehicle modification algorithm
LEV  Low emission vehicle
\( m \)  Vehicle mass
\( \dot{m}_f \)  Rate of fuel consumption of the engine
MPDC  Melbourne Peak Drive Cycle
mpg  Miles per gallon
NEDC  New European Drive Cycle
OECD  Organization for Economic Co-operation and Development
PBS  Power balancing strategy
\( p \)  Power
\( p_{dem} \)  Vehicle power demand
\( p_{ele} \)  Power contribution of the electric system to the total power demand
\( p_{Ice} \)  Power output of the engine
PHEV  Parallel hybrid electric vehicle
PnG  Pulse and glide
PNGV  Partnership for a New Generation of Vehicles
PMS  Power management strategy
PSAT  Powertrain System Analysis Toolkit
PSO  Particle swarm optimization
$Q_{HV}$  Lower heating value of the fuel
$Q_{max}$  Maximum energy storage capacity of the battery
QSS  Quasi-static simulation
$R_e$  Gear ratio between the electric driver’s output and engine’s output
$R_{gb}$  Gear ratio at the gear box
SDP  Stochastic dynamic programming
SOC  State of charge
$SOC_0$  Initial state of charge
$SOC_{max}$  Upper limit of the state of charge
$SOC_{min}$  Lower limit of the state of charge
$t$  Time
$T$  Torque
$T_{dem}$  Torque demand at the output of the engine
$T_{ele}$  Torque contribution of the electric system with respect to engine’s output shaft
$T_{emg}$  Torque of the electric motor generator
$T_{ice}$  Torque output of the engine
$T_{opt}$  Torque at the point of highest efficiency of the engine
$u$  Power split ratio
$v$  Vehicle speed
$v_{int}$  Speed of the intelligent vehicle
ZEV  Zero emission vehicle
1.1 Background to the Study

1.1.1 The Big Picture

The heavy consumption of fossil fuels to fulfill the world’s energy demand has eventually led to the global energy crisis and environmental issues such as global warming. The transportation sector, which consumes approximately 20% ($\sim 2 \times 10^{12}$ kWh) of the global energy demand to meet our needs for travel and goods transport and contributes 18% ($\sim 5.3$ Gt) of the total anthropogenic greenhouse gas emissions, is thus a major contributor to these problems [1]. Factors such as very slow growth...
rate of fuel resources and ever growing energy demand driven by development intensify the energy crisis. The number of cars and trucks of our planet is estimated to exceed 2.5 billion by 2050 whereas in 1992, these were about half a billion [2]. The future energy demand of transportation is further explained by Fig 1.1, in which liquid fuel consumption will increase by 45% from 2006 to 2030 [3]. Ever growing fuel demand of the transportation sector should be controlled before our world comes to a standstill. For every 1 L completely burnt petrol, an average of 2.32 kg of CO₂ is released [4]. Hence, parallel to the growth of the fuel demand, the CO₂ emission will also be increased. As shown in Fig. 1.2, world CO₂ emissions from the consumption of liquid fuels are projected to grow at an average annual rate of 0.9 percent from 2006 to 2030 [3]. All the growth in CO₂ emissions is projected to come from non-OECD countries. For instance, the highest projected rate of growth in petroleum-related CO₂ emissions is for China, at 3.2 percent per year. The connection of the CO₂ growth follows expected demand for vehicle usage and hence the fuel demand.
Until a viable technology replaces the internal combustion engine (ICE) based propulsion, intermediate control measures are required. With this aim, many government bodies with the cooperation of leading automakers, have been adopting new legislation for fuel economy and emissions from automobiles. For instance, the Partnership for a New Generation of Vehicles (PNGV) efforts to develop automobiles (family sedans) with three times 26.6 mpg of the current fleet-average fuel economy, or about 80 mpg without sacrificing desirable vehicle attributes [5]. In 1990, the California Air Resources Board (CARB) adopted a zero emission vehicle (ZEV) mandate as part of a comprehensive low emissions vehicle (LEV) program. This required that 2% of all new light-duty vehicles sold in 1998 and 10% sold in 2003 in the state by the largest auto manufacturers be zero emission vehicle [6]. This requirement was later postponed as automakers demonstrated other ways to meeting low HC, C and Nox gas emissions. Corporate Average Fuel Economy (CAFE) standards, which were originally enacted in the Energy Policy Conservation Act (EPCA) of 1975, was updated to a new goal of 35 mpg by 2020 by the EISA of 2007 [7]. To further reduce CO2 emissions from passenger vehicles, recently the Obama administration announced a goal of achieving 35.5 mpg by 2016 [8].

Meeting these standards requires transportation sector to search for new energy efficient and low emission vehicles and alternative energy sources. Some of such developments towards the energy efficient vehicles can be listed as

1. optimization of existing powertrain components (e.g., direct injection (DI) technology for internal combustion engines (ICEs), super charging and downsizing components, variable compression ratio and variable valve timing) [9];
2. reduction of curb weight [9];
3. development of new powertrain components (e.g., fuel cell technology, flywheels, ultra capacitors and continuously variable transmissions (CVT)) [10];
4. optimization of energy demand for operation of accessory system (42-volt electric system, integrated starter/generator) and low-energy lighting [11];
5. reducing losses such as aerodynamic drag, rolling resistance, and braking losses due to vehicle inertia [9];
6. integration of existing powertrains to produce improved powertrain technolo-
Hybrid Electric Vehicles (HEVs) is the technology generated from the last technique as a promising way to meet requirements for both vehicle performance and environment protection.

1.1.2 Hybrid Electric Vehicles (HEVs)

HEVs integrate a secondary power path that consists of electric motor/generators (EMGs) and an energy storage system (ESS) with their primary energy source i.e., the ICE. The properties such as energy reversibility and highly efficient performance of the secondary power components enable HEVs to consume less fuel energy and do less damage to the environment than conventional ICE only powered vehicles. The final fuel economy of this elegant powertrain architecture results in a combination of many strategies implemented during design and operational stages.

Proper configuration of components within the powertrain and their correct sizing are two major fuel saving strategies during design stage. The fuel economy depends on the interdependency of the components’ operation on each other; that is the configuration of the powertrain architecture. Based on the configuration, three main HEVs can be recognized; series, parallel and combined series-parallel [12]. In series HEVs, EMG, powered by the electric battery and/or the generator/ICE set, directly drives the vehicle. In parallel HEVs, both the ICE and the EMG drive the vehicle independently or cooperatively. Combined series-parallel HEVs can operate in either configuration or in combined configuration [13]. This study deals with a parallel HEV for its simplicity in comparison to combined series-parallel HEVs and its high fuel saving capability in comparison to series HEVs. For a selected HEV configuration, fuel efficiency can be further improved by the correct sizing of components. Proper match of the speed-torque characteristics of the ICE and the EMG enables them to meet driving loads at the operational constraints such as initial acceleration and cruising with minimum power rated components [14]. Compared to the conventional vehicle’s ICE, which is sized for peak power demand, HEV’s ICE can be downsized and used to supply only the average amount of the driver’s power.
1.1 Background to the Study

demand, while high power demands beyond its capacity, are shared with the electric motor [15].

Among the fuel saving strategies during the operation, regenerative braking is a key characteristic of HEVs as well as EVs [16]. Regenerative braking is defined as the recovery of energy during deceleration with the generator and energy storage set, instead of dissipating them in friction braking. Another strategy is the deceleration and idle stop strategy [17]. The unnecessary fuel consumption due to idling of the ICE during vehicle standstill and deceleration can be eliminated if a proper engine shut down and restart strategy is employed. The other main key strategy that determines the fuel economy of an HEV is how the positive energy demand is distributed within the power management strategy (PMS). This is the main focus of this thesis.

1.1.3 Power Management Strategy (PMS)

The PMS of an HEV refers to the algorithm, which splits the positive power demand between the ICE and the battery while allowing as much regenerative braking energy capture as possible so that the overall fuel consumption is reduced. It should also satisfy the other important simultaneous objectives such as meeting the instantaneous power demand of the vehicle (drivability), accounting for the operating limits of the ICE and the EMG (component reliability), maintaining proper state of charge (SOC) of the battery during driving and at the end of driving (charge sustenance) and employing the idle ICE start and stop if required. In other words, the power management controller should consider the energy conversion efficiency of the ICE, energy losses through electric power flow paths during discharging and recharging and torque and speed demands imposed by the driving style.

The difficulty of power management to meet these objectives depends on factors such as configuration of the powertrain, relative driving capacities of the ICE and the EMG and the level of future driving information accessible.
Chapter 1. Introduction

Configuration of the Powertrain

Power management strategy depends on the powertrain architecture i.e., series, parallel etc. and the type of the transmission i.e., fixed gear or continuously variable transmissions etc. These factors change the interaction of power sources as well as their speed and torque controllability with respect to the vehicle’s wheels. For a series HEV, fuel saving with the selection of the primary path or the secondary path is mainly decided by the electric battery whereas for parallel HEV, it is decided by round-trip efficiency of the combined electric battery and EMG. Thus, the fairly smooth and highly efficient secondary power flow path of the series HEV along with the controllability of ICE independently from the wheels speed enables a simpler PMS such as a rule-based controller for a series HEV. However, parallel HEVs require more sophisticated PMSs to properly use the secondary power path, which also has significant energy inefficiencies due to the combined EMG and battery set compared to the ICE, against the dependancy of traction components’ operation with wheel speed. This is further explained in Section 2.3.4.

Degree of the Hybridization

The degree of the hybridization is defined as the driving capacity of the electric system relative to that of the ICE. Accordingly, HEVs are mainly of two types; mild HEVs (mildly hybridized HEVs) and full HEVs (fully hybridized HEVs). Mild HEVs use the electric motor to assist the ICE in powering the drive wheels, partially capture regenerative braking and manage the ICE start/stop [18]. Since the effect of the inefficiencies of the small electrical system on the overall efficiency of the powertrain may be neglected, the power flow control strategy of the mild HEV can simply consider the performance improvement of the ICE. On the other hand, full HEVs are driven independently or cooperatively by an ICE and an EMG with driving capacity similar to the ICE. The larger electric system can also save more regenerative braking energy. Full HEVs have higher performance than mild HEVs. Minimizing the parallel full HEV’s fuel efficiency is a difficult task, though as the power flow controller requires handling the inefficiencies of both the EMG and the
ICE against other counteracting power management objectives.

**Preview Length of the Driving Information**

The performance of any power management controller strongly depends on the information available. A truly optimal fuel consumption can be achieved only if the entire driving cycle is perfectly known a priori [19]. It is recognized that HEVs can perform almost two times better than conventional vehicles when the complete future driving information is available to the power management system [20, 21]. Even though such algorithms are not realistic, they provide a benchmark for online PMSs. To achieve near-optimal fuel economy realistically in day-to-day driving, online PMSs need a great effort to optimize the HEV with instantaneous driving data such as speed, torque demands and battery charge available combined with immediate past and/or future predicted driving information.

### 1.2 Motivation

HEVs have been identified as vehicles having high fuel saving potential; therefore, they are recognized as one of the most promising solutions to burning issues of the global energy crisis and environmental concerns. However, the current HEV technology lags behind expected performance substantially due to reasons such as inabilities of subsystems to satisfy HEV requirements such as good energy storage with fast charging/discharging characteristics and high energy to weight ratio, and efficient energy converters. The other main reason is some deficiencies of power management systems, specifically in optimizing full hybrid systems [22], incorporating new telematic-based fuel saving strategies [23] and handling multiple auxiliary power sources such as integrated starter generators (ISGs) and super capacitors [24].

The ultimate performance of an HEV is given by optimal power management strategy over a predefined drive cycle. Even though this kind of strategy is unrealistic, it provides a benchmark for actual performance achievable by a newly designed PMS controller, reflects the fuel saving capability of the HEV powertrain and sometimes facilitates for designing online PMS controllers. However, finding the global
solution within an acceptable computational time is still a problem. Dynamic programming, which is an optimal optimization technique, has been widely applied. However, its high computational time and error due to state discretization needs an alternative technique to solve the global power management problem optimally within a reasonable computational time.

The actual fuel performance of an HEV is given by online PMSs simulating day-to-day driving, where predefined drive cycle of the journey is not available in advanced. Existing online PMSs are incapable of exploring the true fuel saving potential of parallel full HEVs because they cannot handle inefficiencies of both the ICE and the EMG. Fuzzy logic based controllers are widely applied in mild hybrids. Online PMSs based on the equivalent consumption minimization strategy are heavily sensitive to driving situations and unable to control SOC without finely tuned equivalent parameters to the drive cycle. To achieve optimal or near-optimal results using rule-based strategies requires knowledge base to cover all driving conditions, vehicle status and power split possibilities. Developing such a controller is cumbersome in terms of complexity of the controller, computational time and human knowledge of the powertrain behavior. This highlights the requirement of a robust and feasible online PMS controller that can optimize both power sources to achieve near-optimal fuel efficiency.

The fuel efficiency of the HEV can be further improved by a more intelligent PMS, which can predict the future power demand. Such a predictive PMS is possible with the current vehicle telematics technologies such as GPS combined with geographical information system (GIS) and wireless vehicle-to-vehicle and vehicle-to-infrastructure communication that can preview the future vehicle speed and road terrain for a limited distance, certainly beyond the driver’s vision. This situation is not addressed well enough in literature mainly because predictive PMS, which is robust and performing in real time, has not been developed. The reported algorithms are either unrealistic or based on simplified vehicle models. Therefore, innovation of such a predictive PMS will open opportunities for more fuel saving not only by predictive power management but also by intelligent driving styles such as speed modifications.
1.3 Aim and Scope

The main aim of this thesis is to investigate the fuel saving strategies of parallel full HEVs, which have the highest fuel saving potential of all HEV topologies compared to the simplicity. From this vast area of research that includes developing and improving new ICEs, electric drivers, energy storage and the transmission technologies and designing optimal HEV architectures with rightly sized components, etc., this thesis mainly considers developing new power management strategies and new HEV powertrain topologies.

1.3.1 Research Questions

By examining the existing research gaps presented in the previous section, the main research questions that will be dealt with this thesis can be listed as follows:

1. Can a computationally fast PMS be designed and validated to find this best fuel efficiency (or a solution comparable with existing best methods)?

2. What is the best fuel efficiency achievable by any PMS on the parallel HEV?

3. Can a robust and realistic online PMS be developed to fully optimize the parallel full HEVs?

4. What is the best fuel economy achievable by the HEV in real-time (online) driving?

5. What are the effects of the sub-system efficiencies on the fuel efficiency of the online PMSs and on the complexity of their architecture?

6. Can a real-time predictive power management strategy that uses upcoming driving information for optimizing the power management be developed?

7. How does the fuel saving of the HEV vary with the preview length of the upcoming driving information?

8. How much fuel can be saved by the speed modification for the HEV?
1.3.2 Assumptions

Following assumptions are made throughout this thesis.

1. Steady state operation of components is assumed.

2. Hot operation of the ICE is assumed all the time.

3. The frequency of the driving data available is 1 s. Therefore, any system dynamics higher than 1 Hz are neglected.

4. Auxiliary loads such as HVAC (heating ventilation and air conditioning), drive-by-wire devices and lighting loads are assumed to be neglected.

1.4 Contributions of the Thesis

Based on the research questions posed in the previous section the main contributions of this thesis are

1. Development of an iterative approach inspired by hill-climbing heuristics (HCPMS) to solve the offline power management problem near-optimally within a much faster than DP (just 3 to 4 times the drive cycle length).

2. A framework for satisfying all the component constraints and an objective function that can easily be adaptable to other optimization methods such as simulated annealing.

3. Design of a new powertrain architecture named parallel hybrid electric vehicle assisted by an integrated starter generator or ISG-assisted PHEV, which can improve the fuel efficiencies of online power management controllers.

4. A design procedure of an online PMS which can fully optimize parallel full HEVs irrespective of efficiency characteristics of the ICE and the EMG.

5. An analytical procedure to define a peak-efficiency region of the ICE as functions of the average efficiency of the supporting electrical system.
6. A method to regulate the SOC and the frequency of the ICE stops and restarts with respect to the output of the ICE.

7. A predictive PMS that can handle upcoming gradient and speed based driving information in real-time for optimizing the power management of HEVs.

8. Improvement of the intelligent vehicle velocity modification algorithm to save more fuel.

Some of the other secondary contributions are

1. A method to estimate immediate future regenerative braking.

2. A method that can refine sub solutions of other PMSs by taking them as initial solutions.

3. Applicability of all PMSs to the original vehicle model without any simplifications.

4. Combining model-based and rule-based strategies to produce a new PMS, which is computationally fast, near-optimal and robust.

1.5 Organization of the Thesis

This section summarizes the outline of the thesis.

Chapter 2 explains the important terminologies relevant to HEVs and reviews the existing literature. The performance measures of the PMS, model of the starting the ICE and starting fuel consumption and regenerative braking control are explained. Existing PMSs are identified as offline, online and predictive methods i.e. according to how the future driving information is used in the power management. Their advantages and disadvantages are presented to identify the research gaps.

Chapter 3 explains the parallel HEV model developed by the author, the models of each subsystem of the vehicle model and drive cycles that represents different driving environments including Australian roads and inclined roads. It also explains
the backward simulation technique. The model of the conventional vehicle, which is used as the benchmark vehicle is also presented.

Chapter 4 presents the model based PMS including dynamic programming, equivalent consumption minimization strategy, which will be used as benchmark controllers in the rest of the thesis. Particle swarm optimization used to optimize powertrain components is also briefly explained.

Chapter 5 describes the proposed iterative approach inspired by hill-climbing heuristics to find the global solution to the power management problem. The hill-climbing optimization techniques are introduced. Within the iterative technique, the generation of a new feasible solution to satisfy all the constraints of the problem is explained. The objective function is formulated to minimize the fuel consumption, achieve the perfect charge sustenance and control the frequency of the ICE stop and start by summing the actual fuel consumption and equivalent fuel consumption with the penalty fuel cost of starting and stopping the ICE. The quality of the solution is addressed with respect to the fuel consumption and the computational time. Finally, the ability of the method to refine the solutions of other methods by taking them as initial solutions.

In Chapter 6, a design procedure for an online power balancing strategy (PBS), whose underlying concept is to control the ICE within the peak-efficiency region by using the electric system, is proposed to achieve near-optimal fuel economy for parallel full HEVs. The peak-efficiency region of the ICE is identified as a function of the overall efficiency of the electric system. It will also be demonstrated how to meet objectives such as proper regulation of the SOC and maintenance of low number of starting and stopping of the ICE with respect to ICE’s output. A new vehicle architecture named ISG assisted PHEV is introduced to enhance the fuel saving capability of the PBS controller.

Chapter 7 investigates predictive fuel saving strategies of HEVs with the incorporation of upcoming driving information. A predictive framework that optimizes the distribution of the instantaneous power demand with the upcoming driving information is introduced. For this purpose, a computationally efficient PMS without sacrificing fuel optimality is necessary. A new PMS namely “ICE on/off PMS” is
proposed for this application. The ICE on/off PMS is a combination of model-based steepest-ascent hill-climbing algorithm that optimizes the best sequence of the ICE on/off status and a rule-based strategy that splits the power demand between the ICE and the EMG according to the on-off status of the ICE. The fuel saving capability of the HEV with the preview length of the upcoming driving information is investigated on level roads, inclined roads and intelligent driving with intelligent speed controlling.

Chapter 8 summarizes the main conclusions of the thesis.

### 1.6 Publications

#### Journal Publications


#### Conference Publications


2.1 Introduction

The history of hybridized vehicle technology dates back to late 1800 [25]. Since then, it has been advancing through numerous contributions [26]. Within the last 20-25 years, there has been substantial attention devoted to HEVs by researchers and auto makers mainly because of their potential to meet the ever-toughening fuel economy and emissions legislations. As noticed by Scierrata and Guzella this fact can be manifested in the increment of numbers of scientific publications published in each year related to hybrid vehicles in data bases like IEEEXplore [27]. An up-to-date review of the HEVs will explain that power management is still a handicap to realize the true fuel saving potential of HEVs and requires further developments.

The primary objective of this chapter is to review the past literature on various power management strategies of HEVs for understanding their merits and demerits. Secondarily, other fuel saving strategies such as powertrain topologies, correct sizing of components and performance improvement of sub systems, which are implemented during the design stage, are also explained here. Prior to focussing the main objectives, the background of HEVs is explained. Therefore, this chapter starts by overviewing important terminologies such as component configurations (series and parallel hybrids), degree of hybridization (full and mild hybrids), end-SOC controllability (charge sustaining and depleting hybrids), vehicle modes and regenerative braking. Then, with the sound knowledge of the field, power management strategies are reviewed under three categories according to how they apply future driving
information during power management to identify their limitations.

2.2 Hybrid Powertrain Technology

Hybrid powertrains refer to the powertrains produced by amalgamating distinct baseline powertrains. For instance, a fuel cell hybrid is a combination of a fuel cell and pure electric powertrains. Hybrids inherit good qualities, such as high energy efficiency, low emission, long driving range and secured drivability from individual powertrains while weakening the effect of their bad qualities on the new powertrain.

2.2.1 Baseline Vehicles

The candidate baseline powertrains whose performance can be improved by the hybridization are the conventional, pure electric and fuel cell powertains.

Conventional Vehicles (CVs)

Figure 2.1: Energy distribution of mid-size conventional vehicle in a typical urban drive cycle (highway cycle). Source: partnership for a new generation of vehicles (PNGV)

The conventional powertrains, which are powered by the internal combustion engines, are the dominant means for ground transportation. The long driving range, ease in refueling, lightweight energy source and low cost compared to other technologies are main reasons for their dominance [28]. Low energy efficiency is their main disadvantage. Reasons for the low efficiency can be grasped by seeing how the
energy is managed within the powertrain. As represented by U.S. Environmental Protection Agency (EPA) driving cycles, Fig. 2.1 shows the energy losses of main parts of a mid-sized passenger car over a typical urban drive cycle as a percentage of the fuel energy input to the ICE. The figures within brackets are for the highway driving as indicated by the low idle and braking losses. If the energy supply to accessories is considered useful and added to energy demand by the wheels, the overall ICE efficiency is just about 20-27%. Considerable amount of energy is lost due to idling when the vehicle is stationary and coasting especially during urban driving consisting of frequent stop and go pattern. The main cause of inefficiency of the powertrain is due to the huge energy loss within the engine itself. This is due to many reasons. The theoretical peak efficiency of a heat engine is limited by the air standard cycle, which usually employs the Otto cycle for reciprocating engines. Attaining even this limit practically is impossible because some heat is lost through cylinder walls before it is converted to useful work, and some fuel is burned at pressure lower than the ideal conditions. Part of the work produced inside the engine is dissipated to overcome many resistive forces before transmitting it to the output shaft. The inertial resistance of moving parts such as pistons, crankshaft, and valves; friction caused by pistons, bearings and lubricant (and other rubbing surfaces), pumping losses and aerodynamic drag are just a few of the resistive forces inside the ICE. It should be noted that the magnitude of these losses is different and depend on the speed and load of the ICE. The ultimate effect is that the ICE has part-load inefficiencies, which depend on the speed torque of the ICE. Furthermore, ICE of the conventional powertrain is sized to meet peak power demanding performance targets, such as acceleration and starting gradability. This size is such that it is roughly capable of meeting 10 times the power required to cruise at 60 mph [29]. Therefore, the ICE of the conventional powertrain amplifies the part load drawbacks by very frequently operating inefficiently compared to its peak efficiency when it meets such normal power demands, which are a small fraction of peak power. New engine technologies such as camless, fully flexible valve actuation [30], direct injection [31], lean burn engine concepts and downsizing with turbocharging, variable compression ratio, and variable intake valve lift will emerge to improve the fuel
efficiency. These advancements will be beneficial for any technology that uses ICE. Another main drawback of the conventional powertrain is the waste of fuel energy during braking, which can be reversible with a proper system. This is considerably higher in urban driving up to 5.8%. The other irreversible losses, i.e., aerodynamic and rolling resistance losses common to all types of powertains, are not considered here because their reduction is out of the scope for power management considerations.

Fuel Cell Vehicles (FCVs)

Fuel cells are another fuel propulsion technology, which has the strongest potential to replace ICE technology because of high efficiency and low or zero emissions [32]. Fuel cells use hydrogen as the fuel reacted by proton exchange air to produce electricity and release water and heat as the main by products [33]. The emission of the fuel cell depends on the source of hydrogen. Fuel cells that use hydrogen directly from an onboard storage (direct hydrogen fuel cell) release no emission, whereas fuel cells that use hydrogen-bearing fuels such as methanol to reform hydrogen onboard releases carbon dioxide. Therefore, FCVs are cleaner than CVs. The other advantages are the low operation noise, quick fueling and similar driving range as the conventional vehicles. Because of properties such as high power density (power per fuel cell active area) and low operating temperature of proton exchange membrane, fuel cells are attractive for automotive applications [34]. Fuel cells are not usually designed to be reversible in automotive applications. Therefore, hybridization with a reversible energy storage component such as an electric battery and super capacitor increase the fuel efficiency [32, 35, 36]. However, this technology may not be in the road for at least next two decades due to high production cost, the short life cycle of fuel cells, fuel generation and distribution and system complexity [2]. Therefore, HEVs should be the short term solution until this technology replaces them.

Pure Electric Vehicles

Pure electric vehicles, which are also known as battery electric vehicles, are characterized by the use of only electric energy for the propulsion through an electric
motor (the prime mover) and electric battery (energy storage). Simplified transmission system, low operating noise, high efficiency and regenerative braking are the main advantages of pure electric vehicles. Furthermore, these vehicles have zero ‘tail pipe’ emission; therefore, suitable for cities where vehicle emissions have caused environmental pollution. However, marketing as zero emission vehicles depends on how clean is the electricity that is used to charge the batteries. Furthermore, the high initial cost, short driving range, long charging (refueling) time, grid-dependancy, and reduced passenger and cargo space have proven to be limitations of pure electric vehicles [37].

2.2.2 Hybrid Electric Vehicles

Hybrid electric vehicles combine pure electric and conventional powertrains and have better overall performance than either individual powertrain. Most of the HEVs are of parallel type in which the integration of the two powertrains is distinct. The HEV has improved fuel economy and lower tail pipe emissions than the ICE-powered vehicle while it has a large driving range and grid independency compared to battery-powered vehicle. The high fuel economy is the result of reducing energy losses indicated by highlighted boxes in Fig. 2.1, therefore, the main fuel saving strategies are regenerative braking, idle stop and start, component downsizing and proper power management of the powertrain.

Regenerative Braking Energy

Regenerative braking is the concept of converting the kinetic (and potential) energy, which is usually dissipated as heat energy in conventional friction braking, to electrical energy that can be used as motive energy in future driving. During the regenerative braking, the electric machine is engaged with wheels as a generator producing electricity. The resistive torque exerted by the generator through the mechanical drive to the wheels decelerates the vehicle. This regeneration is possible because of the energy-flow reversibility of the electrical components.

Torque and efficiency of regenerative braking system depend on factors such as
vehicle speed, deceleration, vehicle mass and the size of the generator. Only a small portion of the kinetic energy is dissipated as irreversible losses due to aero drag and rolling resistance. The vehicle’s combined linear rotating inertia energy is available for the regenerative braking system. However, some part of this energy may again be lost as friction braking, which is applied when the intensity (power and torque) of the required resistance exceeds the maximum regenerative braking capacity. Friction braking also ensures the safety of the vehicle in the event of failure of the regenerative braking system. Because of this cooperation of regenerative and friction braking, the braking system of an HEV has advantages over a conventional friction braking; high braking capacity, longer lasting friction brakes [16,38].

Referring to Fig. 2.1, the fuel saving from regenerative braking can be approximately calculated. Assuming no energy dissipation in friction braking, 0.95% of transmission efficiency, 0.86% of discharging efficiency and 0.88% of recharging efficiency, the amount of fuel saving equivalent to 5.8% of kinetic energy can be calculated by multiplying the round trip electrical efficiency (0.95^2 × 0.88 × 0.86 = 0.683) and dividing efficiency of the thermal path (0.27 × 0.95 = 0.257) as 5.8%×0.683/0.257 = 15.4%. The actual amount should be slightly smaller because of irreversible losses and limited regenerative capacity. In general, regenerative braking may yield 10%-15% fuel savings [39].

**Idle ICE Stop-Start Strategy**

Whenever the vehicle does not demand any power from the engine for a considerable period such as stopping at a traffic light, costing or braking (or electric driving in HEVs), the ICE can be shut off otherwise idled. In a conventional vehicle, the ICE idles and consumes fuel to overcome internal friction, etc. at its idle speed, which is necessary to be ready for the next acceleration. This is really uneconomical and consumes considerable amount of fuel in urban driving as much as 17% indicated by Fig. 2.1.

In HEVs, a stop-strategy can be employed to save some amount of fuel from idle losses by cutting off the fuel supply to the ICE. Unlike the ICE, the electric motor has high initial torque; therefore, can start the vehicle from zero speed and
2.2 Hybrid Powertrain Technology

accelerate it [40]. Meantime, the ICE can be started with no load such that starting energy consumption and emissions are minimized.

**Engine Downsizing**

Besides the engine technologies that reduce part-load inefficiencies discussed in Section 2.2.1, the ICE downsized in its capacity can save fuel compared to an oversized ICE. An engine downsized with maintained vehicle performance reduces part load inefficiencies, pumping work and inertial losses [41]. In the case of HEVs, the ICE could be downsized with the assistance of the electric battery (and electric motor) in meeting peak power demands such as acceleration and gradeability, to shift the cruising point towards the point of highest efficiency thus increasing the overall efficiency [14, 42]. Hence, the energy losses of the ICE in Fig. 2.1 can be partially eliminated as a result of engine downsizing during hybridization process.

**Power Management Strategy**

With the secondary power source capable of delivering or storing energy, inefficient engine operation can be eliminated by operating it around the peak-efficient point or stopping its operation through proper power splitting. The power management strategy of an HEV coordinates the power split, stop/start of the ICE and regenerative braking to maximize the fuel saving. Without a proper power management strategy, the above strategies will not be effective and may result in a fuel economy worse than that of the conventional vehicle. Therefore, this is the key component of any hybrid system.

As discussed in Chapter I, the objective of the power management is to minimize the fuel consumption while meeting other simultaneous objectives such as maintaining proper SOC, satisfying vehicle power demand consistently, etc. The difficulty of power management and its fuel savings depend on the topology of the HEV, its degree of hybridization and the preview length of future driving information. Different power management strategies will be discussed under these contexts in the remaining of the chapter.
2.3 Hybrid Configurations

An HEV has many energy transformations; chemical to mechanical at the engine, chemical to electrical (or vise versa) in battery and electrical to mechanical at the motor and mechanical to electrical at the generator. Before coming to the wheels, chemical energies of the fuel tank and the battery can be combined as mechanical form or electrical form. Depending on which form of energy is hybridized, the configuration of power sources of an HEV is determined. There are many ways to configure power sources of an HEV. Three such configurations are series, parallel and combined series-parallel [12,43].

2.3.1 Series HEV

![Diagram of Series HEV]

Figure 2.2: Topology of a series HEV

Fig. 2.2 shows the component configuration of a series HEV, in which the two power sources are combined electrically. The ICE/generator set converts the chemical energy of the fuel into electrical energy. Wheels are driven by the EM with electric energy from the electric battery and/or the generator/ICE set. The absence of the direct mechanical connection between wheels and the ICE allows the ICE to operate independently from the vehicle speed. Therefore, the ICE of a series HEV can be controlled close to its peak-efficiency region, which is the main advantage of the series configuration. The transmission can be simplified because electric motors have higher torque at low speeds than the ICE. By fitting a pair of motors directly to wheels, the final drive may also be eliminated. Furthermore, the large EMG can
capture more regenerative braking if the battery is capable of doing so.

The main disadvantage is the high energy loss within each of the long sequences of energy conversions that reduces the overall efficiency of the powertrain. The series HEV is definitely heavier than the equally powered conventional vehicle because the battery has lower power to weight ratio than the ICE and the sum of the power capacities of the motor and the ICE is always larger than the power of the conventional ICE. Therefore, there is a less opportunity to gain fuel saving by component sizing.

2.3.2 Parallel HEV

![Figure 2.3: Topology of a parallel HEV](image)

Fig. 2.3 shows a schematic diagram of a typical parallel HEV. The ICE is directly coupled to wheels and mechanical energy from battery/EMG set is combined just before the gear box. Therefore, in a parallel HEV, both the ICE and the EMG can drive the vehicle independently or cooperatively. The possibility for direct energy flow from the ICE to wheels enables the parallel HEV switching to the most efficient driving using the ICE whenever the ICE can operate around the peak-efficiency region. Because of the parallel connection, capacities of the ICE and EMG can be varied while unchanging the total driving capacity of the vehicle. Therefore, components of the parallel HEVs can be optimized to achieve a good fuel economy within the required drivability. One disadvantage of the parallel topology is the reduced speed controllability of the ICE due to its mechanical connection with the
wheels. The use of a single electric machine to serve as a motor and a generator is another disadvantage of the parallel configuration [22]. However, these drawbacks can be overcome with a good power management strategy leading to a greater fuel saving than possible with series HEVs.

2.3.3 Combined Series-Parallel HEV

Combined series-parallel HEVs can operate in either configuration or in combined configuration [13]. As shown in Fig. 2.4, the ICE, EMG and electric generator (EG) are combined with a planetary gear (power split device) to take advantage of both parallel and series HEVs. The Toyota hybrid system is an example for this type of HEVs. By operating the powertrain in the series/parallel configuration, the ICE may be operated close to its peak-efficiency region due to the flexibility in both torque and speed changeability at the ICE output. However, the energy losses in the energy flow path consisting of the EMG and EM may counteract the gain from efficiency improvement of the ICE.

2.3.4 HEV’s Configuration and the Control Strategy

The process of hybridization can also be seen as adding a secondary power flow path to the direct power flow path between the ICE and wheels via the battery. The
battery works as an energy buffer by storing the energy from ICE temporarily and releasing on demand. The performance of the power management depends on how effectively it uses this secondary power path to save energy losses, which varies with the configuration of the powertrain. Therefore, the difficulty of powertrain control for the best fuel economy depends on the configuration of the powertrain.

Figure 2.5: Two main energy flow paths from ICE to wheels in series and parallel HEVs

Fig. 2.5 depicts the two power-flow paths of series and parallel powertrains. Label (1) indicates the direct power flow path while label (2) represents the secondary power flow path via the battery. For the series HEV, battery is the only component of path (2) additional to the path (1). Therefore, efficiency characteristic of the battery is the critical variable determining the choice of path (1) or path (2). Battery has a fairly smooth efficiency surface in the power domain as well as highly efficient behavior. Therefore, selection of path (2) over path (1) can be made easily and
independently from the vehicle driving pattern (power demand). This is the insight into the possibility of controlling series HEVs with simple control procedures. An ICE on/off controller, in which the ICE/generator set supplies the average demanded power while battery supplies ripple power, perform well for series HEV [44]. Because the little dependency of efficiency of the battery with its power, the power split ratio can be changed very roughly just to optimize the ICE/generator set. This explanation is supported by the fact that in the implementation of dynamic programming for the optimal energy management of series HEV, Brahma et al. [45] changed the split ratio coarsely at intervals of 5 kW to get the optimal results. However, for parallel HEVs, a very fine grid of state variable is required to get the optimal results, and this increases the computational complexity exponentially. The reason can be understood by analyzing its configuration as follows.

In case of parallel HEVs, the selection of path (2) is affected not only by the battery but also by the EMG. The efficiency characteristic of EMG is heavily nonlinear compared to that of the battery. Since the net effect is square of the multiplied efficiencies, the effects of inefficiencies of additional component in path (2) is really important. The selection of path (2) is also affected by the driving demand. Therefore, the power management of a parallel HEV towards its optimal fuel economy is more difficult than a series HEV. However, the reader is reminded that parallel HEVs have more fuel saving potential than series HEVs.

Parallel HEVs are selected in this work for their simplicity in comparison to combined series-parallel HEVs and high fuel saving capability in comparison to series HEVs. Therefore, this study only focuses on the parallel HEVs in what follows.

2.4 Component Sizing

The design of any vehicle must meet the customer expected performance because the customer satisfaction is prime importance. Any design based only on minimizing fuel consumption will result in a small power plant; therefore, poor driving performance. Thus, any HEV design should also meet established performance requirements of passenger vehicles.
2.4 Component Sizing

2.4.1 Vehicle Performance Requirements

PNGV’s performance requirements for a passenger vehicle can be listed as [5, 46].

- Acceleration time: time for 0-97 km/h ≤ 12 s; time for 0-137 km/h ≤ 23.4 s; time for 64-97 km/h ≤ 5.3 s;
- Maximum speed: over 137 km/h;
- Gradeability: 6.5% grade at 88.5 km/h with 272 kg additional weight for 1200 s;
- Distance: 42.7m in 5 s.

These requirements mainly size total power capacity of the vehicle and gear ratios, etc. to suit the vehicle mass [47]. Sizing of the single power source (in case of CVs) to meet these requirements is very straightforward. Because of dual power sources, a wide feasible range for each of the power capacities of the ICE and EMG exits. Selection of the best configuration should therefore, consider minimizing the fuel consumption (or emission) while satisfying performance requirements under a good optimization method such as genetic algorithm [46, 48, 49], particle swarm optimization [50], direct algorithm [51] and multi-objective optimization [52].

2.4.2 Degree of Hybridization

It should be noted that the electric power can be varied within the total power capacity of the powertrain such that the HEV holds the above performance requirements. According to the level of electric power, the function of the electric system is also varied. Therefore, to distinguish the difference amongst HEVs especially in the same topology, a parameter namely the “degree of hybridization” (DoH) is introduced and defined as the ratio of driving capacity of the electric system to the total capacity [47]:

\[
DoH = \frac{P_{ele,\text{max}}}{P_{\text{ice,\text{max}}} + P_{ele,\text{max}}} \tag{2.1}
\]

For a conventional vehicle, \(DoH = 0\) and for an electric vehicle, \(DoH = 1\). Depending on the degree of hybridization, HEVs can be mainly categorized as mild hybrids...
and full hybrids.

Mild Hybrids

The electric system of the mild hybrids has much smaller driving capacity than the ICE (about 10-20 kW) [37]. Therefore, it can only assist the ICE partially. The typical energy saving capacity of mild hybrids is about 20%-30% in city driving. Examples for the commercial models are the Honda Civic and Honda Insight.

Full Hybrids

The electric system of a full hybrid shares driving responsibilities equally with the ICE while saving more regenerative braking energy than mild hybrids. Therefore, full hybrids have a greater potential fuel saving capacity (about 30%-50%) than mild hybrids, provided that the power flow of the powertrain is properly controlled.

2.4.3 Degree of Hybridization and Control Strategy

The overall efficiency of the powertrain is governed by the efficiency characteristics of the power component that contributes most to driving. The PMS of such a hybrid system should optimize the dominant power source. The ICE is the dominant power source of the mild hybrid; therefore, PMS of the mild hybrid needs to optimize the ICE power delivery. On the other hand, both ICE and EMG are equally dominant on a full hybrid; therefore, PMS of the full hybrid needs to optimize both power sources. When it comes to maintaining proper SOC, maintenance of the SOC of a small electric system with a large recharging source is relatively easier than a large electrical system with small recharging source. Therefore, maintaining SOC during power management for full hybrids is more curial than mild hybrid, because recharging a discharged battery is slow and any large driver demand exceeding the capacity of the smaller ICE will deteriorate overall fuel economy. Because of these reasons, optimizing a full hybrid towards the best fuel economy is harder and needs more effort than optimizing a mild hybrid.
2.5 Power Management Strategy

As explained initially, the power management strategy of an HEV is the high level algorithm that coordinates energy saving by the proper engine management, battery management and regenerative braking capture. Engine management involves use of electric motor to control the ICE close to its peak-efficiency region or stop its inefficient operation. Battery management implies control of the battery SOC within its safe limits throughout driving and finish the journey with sufficient SOC left. The safe limits are the upper limit that prevents battery from over-charging and lower SOC limit that prevents from over-discharging.

2.5.1 Definition of Vehicle Modes

In response to the positive power demand, many power flow paths can be created within the parallel HEV powertrain. Each of these power flow paths can be identified schematically by vehicle modes as in Fig. 2.6 and numerically by the power split ratio $u$, which is defined as ratio of the power contribution of the electric system $p_{ele}$ to the total power demand $p_{dem}$ as

$$u(t) = \frac{p_{ele}(t)}{p_{dem}(t)} \quad (2.2)$$

Each mode can be defined as follows:

- $u(t) = 0$ - pure thermal mode
- $u(t) = 1$ - pure electric mode
- $0 < u(t) < 1$ - hybrid mode
- $u(t) < 0$ - recharging mode

The pure thermal mode is preferred when the ICE operates in its peak-efficient region. Pure electric mode is selected when the ICE operation is very inefficient in situations such as low vehicle speed. In the hybrid mode, both the ICE and EMG
are used. This mode is activated either to meet high power demands exceeding the ICE’s power capacity or to avoid low efficiency of the ICE operation at high torques. When the SOC is low, the ICE produces excess energy to recharge the battery efficiently. Determination of the best $u$ for hybrid and recharging modes reflects the intelligence of the power management strategy.

### 2.5.2 End-Charge Controlling

According to how the SOC is managed, HEVs are of two types: charge depleting and charge sustaining HEVs. Charge depleting HEVs consume battery energy continuously during driving such that the final SOC drops to a low threshold at the end of the journey [53]. Since the vehicle cannot maintain the energy level on its own, its driving range is limited and requires charging from an external power source between journeys. Plug-in hybrids are charge depleting hybrids. The disadvantages
are the limited driving range and the large battery pack.

Contrastingly, charge sustaining HEVs can maintain its SOC in a satisfactory level continuously; therefore, its driving range is not affected by the battery capacity. This type of HEV requires a smaller battery pack and no charging between journeys compared to charge depleting hybrids. However, maintaining the SOC against contradictory objectives such as reducing fuel is a hard task.

The difficulty of power management in two types can be understood by their power management problems (formulated in Section 5.2). The power management problem of the charge depleting hybrids is similar to that of charge sustaining HEVs but with relaxed end-charge constraint. Larger battery pack of charge depleting HEVs than charge sustaining HEVs provide the controller enough decision time with long charging discharging cycles [54]. Therefore, controlling charge sustaining hybrids are more complex than charge depleting hybrids. Furthermore, charge sustaining hybrids offer an attractive means of significantly improving the fuel economy of all types (sizes) of vehicles using both gasoline and diesel engines [55].

2.5.3 Performance Measures

Performance measures are the criterion used to evaluate different PMSs. The following are the main performance measures:

1. optimality of the fuel consumption results: the proper use of electric system in power distribution requires to deliver a good overall fuel efficiency,
2. the ability to control the SOC during and at the end of driving: finishing the journey with minimal change of battery energy or final charge sustenance requires more control effort and sacrifice of fuel efficiency. When the final energy level differs from that of the initial level, the fuel consumption should be corrected,
3. computational speed,
4. regulating number of starts and stops of the ICE.
2.6 Power Management with Different Levels of Driving Information

The dynamics of an HEV are such that any control decision of the PMS affects the future decisions. Future driving distance (or time) that the effect of a control decision remains for depends on the HEV model, drive cycle, etc. Sometimes this distance is identified as a mission within long drive cycles [56]. Therefore, the fuel saving capability of HEV power management depends on the preview length of driving information used [19,57]. According to the level of driving information used, the power management strategies are classified into three broad categories; offline, online and predictive strategies.

2.6.1 Offline Power Management Strategies

Offline strategies use prior knowledge of the complete future driving information, either directly or indirectly. Hence, they are of two types.

Offline strategies using the driving information directly require the exact speed variation of the vehicle at each time instant. The power management problem is formulated as an optimization problem with a global objective such as minimizing the overall fuel consumption, subject to the operating limits of the ICE, EMG and ESS. Many strategies have been adopted to solve this problem such as linear programming [20], mixed integer programming [58], quadratic programming [59] and sequential quadratic programming [60]. Among them, dynamic programming (DP), which can solve this problem optimally, is the widely applied method [61,62].

Lin et al. [61] used DP to solve the problem for a hybrid electric truck. Control actions were the power split between the power sources and gear manoeuvre. The DP finds the sequence of control actions that minimize the combined overall fuel consumption and emissions. DP of this problem requires much computational time. As it also depends on the trajectory of the full drive cycle, DP is non-causal [63]. However, the usefulness of these results is shown by applying them to tune design parameters of a rule-based real-time controller. The real-time strategy with tuned
parameters can achieve significant improvements in fuel economy and emissions reduction over the baseline rule-based controller over particular drive cycles. This study shows the capability of DP to optimize multi-objectives and design of causable controllers using non-causable control techniques. However, the fuel optimality and charge sustenance of the tuned rule-based controller may be limited only to the considered drive cycles, since the design outcome is heavily cycle dependent.

As an alternative, to reduce the drive cycle dependency of DP, Lin et al. [64] proposed stochastic dynamic programming (SDP). The underlying assumption is that the driver behavior can be approximated with a Markovian process. Instead of being optimized on a given drive cycle, the power management strategy is optimized over many drive cycles in an average sense. This design technique yielded better performance than previously explained rule-based controllers designed with DP results. The primary advantage of this approach is that the control law is designed from an optimization criterion, a model of the plant dynamics and a model of the driving pattern statistics. A weakness in this approach is that the optimization criterion discounts future costs and assigns a penalty to state of charge (SOC) deviation from a set point at every instant in time leading to tuning two parameters, the discount factor and the penalty for SOC deviation. To overcome the multiple tuning parameters arising from the discounted, infinite-horizon formulation, Tate et al. [65] proposed a shortest path SDP method with a better SOC control and fewer parameters (just one) to tune. It should be noted that the common assumption of approximating the driving with a Markovian process, to represent the power demand from the driver, but it may not necessarily be valid for real driving because there are many outside factors such as traffic flow dynamics and traffic lights that may not be captured with the proposed Markov driver.

The linear programming based power management strategy proposed by Tate and Boyd [20] for series hybrid is worth reviewing here because of applicability to parallel HEV as in work by Koot et al. [58]. They formulated the problem as a nonlinear convex optimization problem. This convex problem was then accurately approximated as a large linear programming problem and then solved to find the global minimum fuel consumption. The convex behavior of the models of the en-
gine/generator set and the battery, neglects the speed and torque characteristics of the engine and effect of SOC on the battery efficiency. Therefore, the power management solution based on the simplified model may not be optimal on the real world HEV. As mentioned before, Koot et al. [58] extend this work to a parallel HEV. The power management problem was posed as a mixed integer linear programming problem consisting of a binary integer variable that determines the ICE on/off status. Because finding global solution to the problem within a reasonable time over a long driving cycle is difficult, it may be solved using receding horizon approach. Unlike for the series HEV, operating the components at their best efficiency point is not possible at each power output for parallel HEVs. Therefore, neglecting the dependency of the efficiency on speed, torque or SOC causes more error than for series HEVs.

The power management strategy proposed by Koot et al. [59] for maximizing the fuel efficiency of the conventional ICE powering the electric power-net is similar to the HEV power management problem and applicable to a mild hybrid with an integrated starter generator (ISG). They showed that up to 2% fuel can be saved by powering the electric power net by generating electricity and storing it when the ICE is most efficient with the additional electrical load from the alternator. In addition to DP, the problem is solved optimally by quadratic programing. However, the simplified quadratic models of components may lead to errors in applying real vehicle. Application to a larger electric machine, which has a larger capacity than the alternator, may also consume huge computational time.

In offline methods using the complete future information indirectly, detailed driving information may not be necessary at the beginning. The good example is the PMS based on the equivalent consumption minimization strategy (ECMS). It replaces the global objective of the offline PMS (previously addressed) with an instantaneous objective. Instead of minimizing the overall fuel consumption, the ECMS minimizes the instantaneous actual fuel consumption of the ICE and the fuel equivalent to the electrical power flow of the electrical system. As far as charge sustainability of the HEVs is concerned, any chemical change of the battery due to electrical power flow of the forward path needs to be rectified by a backward path
in the future. The equivalent fuel of the instantaneous usage of the electric system is the fuel used or saved by this future rectifying process. The calculation of the true amount of equivalent fuel requires the exact efficiencies of the future rectifying energy flow paths. Since they are not known in advance, the equivalent factors are calculated based on average efficiencies of energy flow paths. Sciarretta et al. [21] used complete driving information to tune the equivalent parameters and to extract some other statistical parameters. Once these parameters are known, the algorithm proceeds, with the distributing the power demand between the ICE and EMG by minimizing the sum of instantaneous fuel and the equivalent fuel such that the best overall fuel consumption is achieved, and the SOC is properly controlled. This will be thoroughly explained in the chapter IV. This method finds the near-optimal solution to the problem within a very short period of time compared to the DP. However, it suffers from the high sensitivity to statistical parameters; therefore, the strategy requires accurate fine tuning of parameters for drive cycles separately.

The sub-optimal strategy proposed by Delprat et al. [66] based on the optimal control method minimizes an objective function combining instantaneous fuel consumption and the change of battery energy over the whole drive cycle. The evaluation of the Lagrange parameter that results in the minimum fuel consumption is the core of this strategy. The piecewise linear approximation of the ICE fuel map may not be generalized to all ICEs.

Choi and Kim [67] optimized an HEV equipped with CVT, by using a similar approach to the ECMS combined with a rule based strategy. In their approach, minimizing the operational cost, which is the sum of costs of fuel and electricity at a unit time, is the objective. Again, the cost of fuel and electricity within the powertain is not comparable without a proper conversion factor. Two conversion factors for recharging and discharging situations are derived based on the average ICE efficiency and average electrical discharging and recharging efficiencies. The implemented rules are such that at known low efficiency and high efficiency operations of the ICE, only the electric system and ICE works respectively. Thereby, pure electric mode is selected at vehicle speed approximately below 30 km/h; pure thermal mode is operated at vehicle speed approximately between 30 km/h and 55
km/h and the best ICE operating region is achieved with the CVT. At high speeds, there are many options for vehicle modes. Therefore, above 55 km/h, the fuel minimization algorithm described above is executed. The final charge sustenance is achieved by adjusting the high speed margin for a user-defined low speed margin. The method achieves up to 45% improvement on fuel consumption compared to the conventional vehicle. Fuel economy improvement of 17% is accounted for by the power split strategy while the rest of the improvement is by the regenerative braking and stop/start strategy. This algorithm suffers from some issues; maintenance of the SOC within limits is not possible for long driving because of missing way to control online SOC and tuning the upper speed limit to achieve final charge sustenance may be cumbersome.

Overall, the requirement of the complete schedule of the journey in advance hinders offline methods applying in real time HEV power control. However, they have the advantages such as design of powertrains, design of online controllers [60] and usability as a base line for evaluating online controllers.

2.6.2 Online Power Management Strategies

Assumption of prior knowledge of complete drive cycle for common day-to-day (online) driving may be unrealistic. Therefore, online strategies address the problem when the prior knowledge of the complete future driving information is not available. The best fuel saving with HEVs’ online power management may reflect the actual fuel saving capability in real world HEVs. Generally, these strategies use the knowledge of the physical behavior of components of the powertrain. The majority of online strategies are based on the concept of “power balancing”, which refers to the distribution of the vehicle’s instantaneous power demand among power sources so that the overall efficiency is maximized or the best rate of fuel use is maintained [10].

Online power balancing strategies have been implemented by using fuzzy logic [68], neuro-fuzzy networks [69–71], rule-based control techniques [63] and power follower control strategies [72].

The ICE on/off (thermostat) strategy is one of the basic rule-based controllers to control the HEV powertrain [73,74]. In this strategy, the ICE is mostly operated
2.6 Power Management with Different Levels of Driving Information

at its optimal torque curve when it is on. The upper and lower SOC limits are the
references used to control on/off status of the ICE. When the SOC reaches the upper
SOC limit, the ICE is switched off and the vehicle is only propelled by the electric
motor. When the SOC hits the lower limit, ICE is switched on. In a thermostat
strategy, SOC follows a saw-tooth path. This control strategy is possible with a
large EMG that can meet the vehicle peak power alone during the ICE off time.
The fuel saved by optimizing the ICE may be heavily affected by the large electrical
losses. Moreover, the ICE may be also switched off during its preferable driving
conditions.

In the power follower control explained in [47, 75, 76], the ICE is the primary
source of power, and battery is used to avoid known ICE inefficient operations at
very low speed and low power demands, and to assist the ICE at power demands
higher than ICE capacity. When the SOC is very low, the ICE provides additional
power to recharge the battery. This electric-assist control strategy is a commonly
found approach to many practical parallel HEV applications, such as the Toyota
Prius and Honda Insight [72].

Previously discussed deterministic rule-based controllers do not consider much
about variation of the driving situation, and they are less robust and adaptive to
highly varying driving situations. Therefore, fuzzy rule-based controllers may be
superior to deterministic rule-based controllers on HEV power management.

A fuzzy logic controller (FLC) proposed by Baumann et al. [10] changes both the
torque and speed of the ICE to shift its operation towards the point of the highest
efficiency from four low efficient operations of the ICE at low and/or high speed and
torque. The torque of the ICE is varied by torque split with the electric motor, and
the speed is varied by changing the gear position. Therefore, the fuzzy controller has
two control variables i.e., gear position and EMG’s torque and uses three inputs i.e.,
speed demand, torque demand and the SOC. The strategy focuses on optimizing
only the ICE; therefore, this is preferable for mild PHEVs. It is also not necessarily
charge sustaining. A similar work is done by He et. al [77].

In the work done by Salman et al. [78] and the similar work of Schouten et
al. [68,79], FLCs developed for parallel HEVs optimize both the EMG and the ICE.
They adopt the average round-trip efficiency of the electric power flow paths in a systematic way to find the low power limit below which electric system is favored for fuel minimization. The simulation result over standard driving cycles shows significant improvement over the fuzzy controllers that optimize only the engine efficiency. However, the heavy dependency of the rules on the SOC may reduce ability to optimize the overall fuel consumption of the controller. On the other hand, the end SOC condition is neglected because of the difficulty of implementing such constraints with FLCs. The same control scheme is used by Kheir et al. [80] to combine both the emissions reduction and fuel economy improvement.

The design of fuzzy logic controllers involves many parameters, which determine the overall performance of the controller. Therefore, the parameters require proper tuning for best results. Due to the large number of rules and inter-dependency, human intuition fails to properly tune them. This problem may be solved with an external optimization algorithm combined with the FLC. Poursamad and Montazeri [81] used genetic algorithm to tune the parameters defining the fuzzy rules and membership functions towards improved fuel economy and reduced emission performance over predefined drive cycles (offline). However, the tuning procedure depends on the driving style; the offline tuned set of control parameters may fail in another driving situation.

The tuning of the parameters over the whole drive cycle may not be optimal. Therefore, the parameters should be tuned according to driving style. Langari and Won [82, 83] proposed a fuzzy torque distributor based intelligent energy management agent that incorporates a subagent-driving information extractor, driving situation identifier, and SOC compensator to determine the effective distribution of torque between the motor and the engine. Several characteristic parameters which affect the fuel consumption and vehicle emissions as indicated by Ericsson [84] are identified by the driving information extractor. These parameters are then used by a driving situation identifier, which consists of the roadway type, driving style of the driver, driving trend, and the driving situation identifiers, to identify the long term, short term and instantaneous driving characteristics. In overall, the study attempts to relate fuel consumption related factors determined by the driver, road type etc
to the energy management of the hybrid drivetrain. However, a main drawback is neglecting the effect of driveline efficiencies.

The rule-based intelligent approaches are intuitive, relatively simple to design, and easily implemented in modern digital real time controllers. They are also fast and robust [77]. However, they do not gain the true benefits of the HEVs because they usually fail to fully optimize HEVs especially full hybrids because of their inability to handle inefficiencies of both the engine and electric system while meeting other requirements such as maintaining proper SOC [22, 59]. Additionally, most of them concentrate on the instantaneous optimization of the operation, so the SOC may be out of control with the presence of heavy future demands such as at upgrading a steep and long hill or downgrading. These controllers also suffer from the requirement of much tuning effort, and they are not transferable to other powertrains easily [19].

The final category of online PMS is model-based online PMSs. The equivalent consumtpin minimization stratergy has been the widely applied concept behind these strategies [19, 21, 27, 85–88]. Proper control of the SOC is the toughest task, which gets the total attention of the ECMS-based online PMS.

2.6.3 Predictive Power Management Strategies

Even though the requirement for complete future driving information is unrealistic, a partial information for some distance beyond the driver’s vision is possible with new on-board telematics technologies such as GPS and traffic-flow information systems [89]. GPS combined with geographical information systems (GIS) can be used to get static information such as the road gradient [90]. Simple telematics devices that can communicate to other vehicles or road infrastructures, can provide dynamic information such as traffic speed ahead [54]. Integration of these devices with the power management controller enables HEVs to further save fuel with preview of the driving pattern and terrain information. The fuel saving from such information entirely depends on the performance of the predictive power management controller. This subsection is devoted to review the existing predictive PMSs.

Johannesson et el. [91] presented the fuel saving ability with different level of
driving information. In the lower level of previewing method, driving information about abstract knowledge of driving pattern i.e., urban or highway driving is modeled with a homogeneous Markovian driver having power demand and velocity as states. The PMS based on infinite horizon SDP is used for this case. In the higher level of previewing method, driving information about road gradient and vehicle velocity is modeled with non-homogeneous Markovian driver that transits from one position to another with velocity and acceleration states. In this case, PMS based on finite horizon SDP is used. Important results are that a position-dependent controller can achieve offline results and position-dependent strategy is more crucial for full hybrids than mild hybrids. Major drawback is that the PMS studied here deviate from real-time implementation.

Back et al. [23] shows the use of DP in predictive power management of HEVs. The main focus is to demonstrate the methods to overcome the challenges of adopting DP as the power management algorithm. Therefore, a simplified journey, in which the vehicle moves at a constant speed over a known terrain (because of the GPS) is considered. DP is applied to solve the optimization problem at each time step by proceeding with the receding horizon technique. Generally, application of DP to solve the power management problem consumes large computational time because of the discretization of the state space. This work explains the means of reducing the computational time by methods such as constraining the SOC search space and varying the size of the SOC grid with the distance. However, the time consumption for the complete journey will still be very large.

Fuzzy logic based predictive PMSs are considered because of their fast computation and robustness to varying driving situations. Adaptive fuzzy logic controller developed by Rajagopalan et al. [92] uses GPS data of the traffic information in the form of speed and elevation information along a look-ahead window to prepare the electric system for future conditions such as heavy traffic, steep grade, etc. This controller considers not only fuel economy but also emission reduction, and the simulation results show a good compromise between them.

Among all techniques, the ECMS is the widely applied concept to develop predictive PMSs because of its fast computation and near-optimal performance when
designed well. The global equivalent parameters that achieve minimum fuel consumption and guarantee the final charge sustenance cannot be defined for a journey with heavily mixed driving situations, such as a succession of an urban and a highway cycles. Therefore, the equivalent parameters need to be tuned on-the-go. In the predictive PMS of Musardo et al. [56], they tuned the equivalent factors for the current driving style defined by the current mission which is the driving length consisting of the immediate past and predicted driving data. The tuning phase identifies the best equivalent factors, which results in the minimum fuel consumption for the ECMS over the mission, through a generic nonlinear optimizer. However, the performance of the algorithm is indirectly affected by the external factors such as probability constructor and performance of the nonlinear optimizer. Ambuhl and Guzzella [19] derived the equivalent factor as a function of the deviation of the SOC from a reference level. Therefore, this method is mainly about how to generate the reference SOC trajectory for any journey. An approximate drive cycle is constructed with road terrain given by the GPS and vehicle velocity at each road segment of the route. Using this drive cycle, the variation of the positive and negative power over the journey demand is calculated. Using this information, a reference SOC trajectory is constructed with the help of quadratic optimization strategy such that the regenerative energy capture is maximized and the least variation of SOC is maintained. For drive cycles, in which driver demand is more dominant by the driving style than the road terrain, the reference SOC trajectory should be updated on-the-go to achieve proper final charge sustenance. In similar work, Zhang et al. [88] developed a rule-based ECMS which uses future driver demand predicted through the knowledge about road terrain given by GPS. The key contribution of the study is the development of the PMS that can handle the driving scenarios, which largely fluctuate the SOC. The effect due to variation of velocity is neglected.
In the previous chapter, a range of power-flow controlling techniques of HEVs were revised. This chapter provides a review of modeling vehicles and their different simulation approaches. It then provides a detail explanation about the parallel HEV model developed by the author along with selected family of drive cycles to simulate ranges of driving environments. The model of the conventional vehicle, which is used as the benchmark vehicle is also presented.

3.1 Simulation Methods

According to the direction of power flow calculations, vehicle simulation approaches can be mainly categorized into two; forward-facing approach and backward-facing approach.

3.1.1 Forward-facing Simulation

In forward-facing approach, the power flow calculations are conducted in the direction of tractive energy flow. Therefore, this approach simulates the real driving process, in which the vehicle is accelerated according to the driver’s acceleration (or throttle) and braking commands. Fig. 3.1 illustrates schematic representation of the forward-facing simulation. The driver model determines throttle and brake commands to meet the targeted speed at the next time instance of the drive cycle.
from the present speed. The throttle command is then translated into a driver’s torque (or power) demand. The power management controller splits the demanded torque between the engine and the motor, which provide the torque to the transmission model accordingly. Tractive torques are translated to the vehicle speed by the transmission and vehicle dynamics. The Powertrain System Analysis Toolkit (PSAT) developed by Argonne National Laboratory, US is an example of forward type simulation software.

Forward-facing approaches simulate the actual driving process, deal with quantities measurable in a physical drivetrain such as control signals and true torques, and handle vehicle systems including dynamic models. Therefore, vehicle controllers can be developed and tested effectively in this type of simulation method [93]. Therefore, power management strategies based on forward-facing approaches can be directly transferred to hardware [94]. The major weakness of the forward-facing approach is its slow simulation speed due to higher order integration schemes using relatively small time steps and multiple iterations required in attempting to match the velocity demanded by the drive cycle.

3.1.2 Backward-facing Simulation

In backward-facing simulation, power flow calculations are conducted backwards relative to the flow of tractive power simulating. This simulates opposite of what exactly happens in real driving process. A schematic representation of backward-facing approach is shown in Fig. 3.2. It is based on the hypothesis of how each component should perform if the vehicle exactly follows the speed trace of the drive cycle. Therefore, they do not require a driver model like forward-facing simulations.
The speed profile of the drive cycle is translated to profiles of tractive torque and speed of wheels through vehicle dynamics. Quantities at the wheels are translated to the corresponding quantities at the output of the power sources. The PM controller distributes the torque (power) demand between the ICE and the EMG according to its PMS. Quasi-static simulation tool box (QSS-TB) developed by the measurement and control laboratory of the Swiss federal institute of technology Zurich is an example of a backward simulator [95,96].

The backward-facing approach is enabled by the availability of the component performance maps that detail efficiency or loss vs. output speed/torque/power, but these are normally produced through steady-state testing of components and therefore, do not model dynamic effects [97]. The inputs and outputs of each component of the model are not measurable in the physical powertrain. Thus, backward simulation is not suitable for detailed design and testing of real world controllers [93]. The backward-facing approaches are beneficial in simplicity [98]. They also provide fast computation because of features, such as fast interpolation within steady state maps and computation within large time steps (in the order of 1s). Therefore, backward simulation is the widely applied technique in HEV simulations [99].

3.1.3 Combined Backward/Forward-facing Simulation: ADVISOR

The underlying assumption of always meeting the speed trace of the drive cycle may not hold for extreme driving conditions such as hard acceleration, steep hill
climbing due to the limited speed, torque or power capabilities of power sources and other components. ADVISOR (ADVanced VehIcle SimulatOR) deals with this problem by combining the backward-facing simulation with the forward-facing approach. Fig. 3.3 illustrates the calculation procedure of the hybrid backward/forward facing approach. The backward-facing is the main approach while the forward-facing approach assures that computed vehicle speed never exceeds the speed that can be achieved to the corresponding components limitation [98]. Whenever the simulation finds any variable exceeding its performance limit during the backward simulation phase, the speed profile is changed accordingly by the forward approach. The main component performance limits that enforce the forward phase are tyre slip, torque, speed and power limits of the engine and motor and SOC of the battery, etc.

ADVISOR contains a large library of different vehicle types including HEVs (series, parallel and Toyota hybrid system), pure electric, fuel cell and conventional vehicles. Because of ADVISOR’s comprehensive modeling of energy losses through powertrains and recognition as a well validated simulation tool, it is widely used as an analysis tool for vehicle performance, fuel economy and tail pipe emissions etc. It is also flexible, easy to use, replicable and open, such that new technologies, unique energy management strategies, and alternative vehicle configurations could be easily incorporated into and evaluated within a system architecture [100].

ADVISOR’s power management strategy is a rule-based one that includes activities such as “when the engine torque output is low and the battery SOC is high, turn off the engine”. It supports well to evaluate and design similar controllers because they require few numbers of simulation runs. Therefore, its ability to explore the
fuel saving capability of the HEVs may be within rule-based strategies. To design PMS beyond rule-based strategies, ADVISOR’s capability is limited due to many reasons; The limited user customizability (only predefined system structures are usually accessible to the user [95]) and large computational burden when plugged with energy management algorithms requiring many iterations.

Therefore, here, a parallel HEV model was implemented using Matlab programming codes with data extracted from ADVISOR. The main features are sufficient depth of modeling energy losses, law memory in loading the vehicle model and customizability of configuration of components beyond conventional parallel configuration.

### 3.2 The Parallel HEV Model

A detailed description of the parallel HEV model is presented in this section. Main components of interest are vehicle dynamics, transmission dynamics, the ICE, the EMG and the battery. Some basic concepts behind the model are summarized here. The model is developed based on the backward-facing simulation with simplified vehicle dynamics. Linear scaling of components is used to produce components with different sizes with the assumption that efficiency variation with capacity is insignificant from the original component. Change of gross vehicle weight due to the changes of component sizes is approximately modeled. This modeling may be acceptable for HEVs since the fuel consumption of HEVs is less sensitive than that of CVs. For instance, the study by Reynolds and Kandlikar shows that a 100 kg change in vehicle weight increases fuel consumption by only 0.4 L/100 km in HEVs, compared with 0.7 L/100 km in CVs [101]. Non-traction auxiliary loads such as HVAC, drive-by-wire devices and lighting loads are neglected. Thus, there is no power demand from the power sources when the vehicle is at standstill. Inclusion of these loads modeled properly may account for about 2.0% extra fuel consumption as in Fig. 2.1 and as high as 7.0% in case of heavy vehicles [102]. All the data are extracted from the ADVISOR.

The first building block of the backward-facing simulation procedure is the vehicle
dynamics that converts the speed profile of the drive cycle into a profile of resistive force at the wheels.

3.2.1 Vehicle Dynamics

Tractive force from the power sources propelling the vehicle, overcomes the total resistive force at the wheel. The total resistive force is the sum of the resistive forces, which can be obtained by the longitudinal vehicle dynamics. Fig. 3.2.1 shows the resistive forces acting on the vehicle of mass $m$ moving at speed $v$ on a road with a slope of angle $\theta$. The main component of the total resistive force are:

1. aerodynamic drag
2. rolling resistance
3. grading resistance
4. inertial resistance

Aerodynamic Drag: The aerodynamic drag is referred to as the resistive force exerted by the surrounding air on the body of the vehicle what in motion. It consists of two components: shape drag and skin friction. Shape drag is the resultant resistive pressure force from the high pressure zone due to the contraction of the air at the front of the vehicle and the low pressure zone due to vortices at the tail of the vehicle body. Skin friction force is caused by the viscous friction of the relative movement of the air particles closed the skin of the vehicle body. Thus, the aerodynamic drag depends on the factors such as the vehicle speed $v$, frontal area of the vehicle $A$, shape and smoothness of the protrusions of the vehicle shell design, air density $\rho$:

$$F_{air} = \frac{1}{2} AC_d \rho (v + v_w)^2$$

(3.1)

where $C_d$ is the aerodynamic drag coefficient that characterizes the shape of the vehicle and $v_w$ is the component of wind speed resisting the forward movement of the vehicle [73].
Rolling Resistance: The loaded vehicle wheels rolling over the road surface experiences a rolling resistance as a result of the deformation of the tyre material and the road surface. On a hard surface, the hysteresis due to the deformation of the tyre material produces an uneven pressure distribution at the contact surface with the roadway such that the ground reaction force is shifted towards the direction of vehicle movement from the wheel axle [103]. The weight acting on the wheel and the road normal forces are misaligned and thus exert a retarding torque. By representing it as a force opposing the rotation of the wheel, the rolling resistance on an inclined road can be expressed as

$$F_{rolling} = mgC_{rr}\cos(\theta)$$

where $C_{rr}$ is the coefficient of rolling resistance, which depends on factors such as tyre material, tyre inflation pressure, road roughness and road material.

![Diagram of resistive forces acting on a vehicle in motion and a quarter car model](image)

(a) Resistive forces acting on a vehicle in motion  
(b) Quarter car model

Figure 3.4: Vehicle dynamics

Inertial Resistance: The acceleration of the vehicle and other spinning components such as ICE creates rotational inertia resistance. From the Newton’s second law of motion, the inertia resistance can be expressed as,

$$F_{inert}(t) = (m + m_{eq}) \frac{dv(t)}{dt}$$

(3.3)
where $m_{eq}$ is the equivalent powertrain spinning mass with respect to wheels.

**Grade Resistance**: The road inclination produces a weight component, which is always directed in the downward direction. Therefore, in the uphill motion, the grade resistance opposes the motion whereas in downhill motion, the resistance supports the motion. The grade resistance is given by,

$$F_{grad} = mgsin(\theta)$$  \hspace{1cm} (3.4)

Therefore, by referring to the quarter car model in Fig. 3.2.1, total instantaneous resistive force on a vehicle moving in an inclined road can be expressed as

$$F_{wheels}(t) = F_{air}(t) + F_{rolling}(t) + F_{iner}(t) + F_{grad}(t)$$ \hspace{1cm} (3.5)

$$= \frac{1}{2}A C_d \rho v(t)^2 + mgC_{rr}cos(\theta) + m \frac{dv(t)}{dt} + mgsin(\theta)$$ \hspace{1cm} (3.6)

The tractive force required to follow the speed profile is equal to the resistive force $F_{wheels}$. The tractive torque $T_{wh}$ at wheels will be $F_{wheels}r_{wh}$ and rotational speed $\omega_{wh}$ will be $v/r_{wh}$ where $r_{wh}$ is the rolling radius of wheels, which is usually 2-3% less than the tyre radius.

### 3.2.2 Transmission Dynamics

The transmission system consists of a gearbox and a final drive (and clutches). It converts the torque and rotational speed of the wheels to the torque demand $T_{dem}$ and speed demand $\omega$ respectively, at the ICE output as

$$T_{dem}(t) = T_{wh}(t)/(R_{fd}R_{gb}(t)\eta^k_{gb}(t)), \hspace{1cm} (3.7)$$

$$\omega(t) = \omega_{wh}(t)R_{fd}R_{gb}(t), \hspace{1cm} (3.8)$$

where $r_{wh}$ is the wheel rolling radius, $R_{fd}$ is the gear ratio of the final drive, $R_{gb}(t)$ is the gear ratio of the selected gear at time $t$ and $\eta_{gb}$ is the efficiency of the selected gear. The index $k$ takes 1 for positive power demands and -1 for negative power demands. Here, negative power is assumed to be regenerated through the
transmission.

A speed-dependent gear shifting logic is employed as in [93] and [104]. Speed limits of the shifting logic is as follows:

\[1 \rightarrow 2 \text{ and } 2 \rightarrow 1 \text{ at } 24 \text{ km/h}\]
\[2 \rightarrow 3 \text{ and } 3 \rightarrow 2 \text{ at } 40 \text{ km/h}\]
\[3 \rightarrow 4 \text{ and } 4 \rightarrow 3 \text{ at } 64 \text{ km/h}\]
\[4 \rightarrow 5 \text{ and } 5 \rightarrow 4 \text{ at } 75 \text{ km/h}\]

It should be noted that the upshift and downshift speeds are the same. The efficiency of the transmission is modeled to be dependent on gear position and assumed to be constant for each position. The efficiency values of gear positions 1 to 5 are

\[\eta_{gb} \in [0.93, 0.95, 0.97, 0.98, 0.97].\]

Inefficiencies of the final drive is neglected.

The transmission ratios and final driver ratio greatly influence fuel economy and emissions because they determine operating speeds and loads on the ICE. Therefore, all five gear ratios should be optimized so that the engine will operate close to its fuel optimum region. The best set of gear ratios can be obtained by solving a generic optimization problem formulated with gear ratios as the elements of the design variable and overall fuel consumption of the powertrain over the simulated drive cycle as the cost function. Particle swarm optimization (PSO) [105], which is a good candidate to solve nonlinear, constrained problems [106], was used to find the set of best gear ratios

\[R_{gb} = [2.697, 1.839, 1.354, 1.151, 0.776].\]

Detailed information about formulation of the optimization problem is provided in Appendix A.1.

### 3.2.3 Model for the Engine

In the backward-facing simulation, the engine model calculates the fuel consumption (or emissions) for its power output at any operating point defined by two variables
out of speed, torque and power. At any operating point, the efficiency of the ICE (fuel conversion efficiency) is defined as the ratio of the power output to the fuel energy input:

$$\eta_{\text{ice}}(\omega_{\text{ice}}, T_{\text{ice}}) = \frac{T_{\text{ice}}\omega_{\text{ice}}}{\dot{m}_f Q_{HV}}$$

where $T_{\text{ice}}$ is the torque output, $\omega_{\text{ice}}$ is the output speed, $\dot{m}_f$ is the rate of fuel consumption and $Q_{HV}$ is the lower heating value of the fuel. This parameter captures all the losses of the ICE including the combustion losses, friction losses, heat energy losses, inertia losses, etc. The function $\eta_{\text{ice}}(.)$ is heavily nonlinear and exact analytical function is difficult to translate. Some efforts towards this approach are Willans line method [63,96] and smoothened maps [59,85]. However, these approximations cannot be generalized to all ICES due to high nonlinearity and PMS based on these approximations may not perform well in real world vehicles. The other common, easy and popular way is the use of look-up table of $\eta_{\text{ice}}(.)$ in other words, an engine map generated from steady-state engine bench tests. In the real operation, there are other effects such as the influence of ambient temperature. By neglecting them, the steady state map is a good approximation when there is no accurate model.

![Figure 3.5: The steady state efficiency map of the ICE](image-url)
3.2 The Parallel HEV Model

Complex models based on combustion models, and mechanical losses will increase the computing time during the power management.

Figure 3.6: The steady state fuel map of the ICE

Figure 3.5 shows the efficiency map of Honda Insight ICE, which is the baseline ICE considered in this work, on the speed-torque plane. It is essential to understand the characteristics of the efficiency behavior of the ICE upon developing the PMS controller. The maximum torque curve represents the highest ICE torque achievable for any speed. Dashed lines show constant efficiency contours, where their values increase towards the inner contours. The convergent point of the efficiency contours is the operating point with the highest efficiency $\eta_{\text{ice}}^{\text{opt}}(\omega, T_{\text{ice}}^{\text{opt}})$ achievable from the ICE. The efficiency on the optimal torque path ($T_{\text{ice}}^{*}(\omega)$) (dot-dash line) is the maximum efficiency achievable at a particular speed $\omega$ within the maximum torque envelop. The optimal ICE torque that results in maximum ICE efficiency at $\omega$, ($T_{\text{ice}}^{*}(\omega)$) can be found by

$$T_{\text{ice}}^{*}(\omega) = \arg \max_{T \in \mathcal{T}} \{\eta_{\text{ice}}(\omega, T)\}, \quad (3.10)$$
with \( T_{\min}(\omega) \leq \mathcal{T} \leq T_{\max}(\omega) \). The Insight ICE has improved efficiency characteristics (peak efficiency of about 0.4 and at part-load too) because of the utilization of many advancements such as variable valve timing and electronic lift control (VTEC), lean burn technology, use of light weight and high strength materials (lighter connecting rods, oil pan, etc.) and friction reducing techniques (piston skirt with micro-dimples) [107, 108].

With the known efficiency map, the corresponding fuel map can be generated according to (3.9). The fuel map of the Honda Insight ICE is shown in Fig. 3.6.

3.2.4 Model for the Electric Motor/Generator

![Figure 3.7: The steady state efficiency map of the EMG](image)

The EMG simulates the electromechanical energy conversion of the physical electric machine in both directions, i.e., motor mode and generator mode. The mechanical end of the EMG is characterized by shaft speed and torque and electrical end is characterized by the electrical power (or terminal voltage and current). During this conversion, energy is lost due to copper losses caused by electrical resistance of the wires (and brushes), iron losses caused by hysteresis and eddy currents in
the rotor, friction and windage losses [109]. The energy conversion efficiency of the
EMG $\eta_{emg}(\omega_{emg}, T_{emg})$ defined as the ratio of the power output to the power input
represents all the losses at any operating point defined by speed $\omega_{emg}$ and $T_{emg}$:

$$\eta_{emg}(\omega_{emg}, T_{emg}) = \left( \frac{T_{emg}\omega_{emg}}{p_{emg}} \right)^k$$

(3.11)

where, index $k = 1$ for motor mode and $k = -1$ for generator mode. The analytical expression for $\eta_{emg}(.)$ requires approximations for variables that define various
losses and may lead to errors in some operating regions. Therefore, a look-up table
(efficiency map) of $\eta_{emg}(.)$ generated from steady-state tests on the motor is used in
the model.

Unlike other industrial applications, electric motors used in EVs and HEVs usu-
ally require frequent starts and stops; high rates of acceleration/deceleration; high
torque and low-speed when hill climbing; low torque and high-speed when cruising,
and a very wide speed range of operation [73]. Continuous operation at high ef-
iciency is another important requirement [110]. Also, the motor drive needs high
controllability, steady state accuracy, and good transient performance. In addition
to the above requirements of traction motors, the electric drives of HEVs must meet
the requirements for the regenerative braking. The design of electric drives to meet
all these requirements is a challenge. DC motor drives have the proper characteristics
for traction application and were popularly used a couple of decades ago. However,
their disadvantages such as bulky construction, low efficiency, the need of mainte-
nance, and low reliability, mainly due to the presence of the mechanical commutator
(brush) led to the quest for advanced candidates [111]. Among the candidate electric
drives such as induction motors, and switched reluctance motors, permanent
magnet (synchronous) electric motor/generator (Honda) is selected as the base elec-
tric machine due to many reasons: high torque density, therefore, less weight, high
efficiency due to the absence of rotor winding and rotor copper losses [112–114].

Fig. 3.7 shows the efficiency map of the Honda EMG having 30 kW capacity,
300 Nm peak torque and 0.91 peak efficiency. The choice of this EMG is also made
because it has been frequently used in HEV modeling developments. Although
more recent motors [115] may have some (4%) improvement in peak efficiency, the efficiencies of the part-load region tend not to have improved. Generally, the motor torque speed characteristics are such that at low speeds, the motor has a constant torque and at high speeds, the motor has a constant power. The high torque at low speeds is preferred for acceleration and hill climbing. This high torque at low speed also enables meeting a good acceleration performance with a small motor with low power rating. This torque speed characteristic is determined by the ratio of the maximum motor speed to the base speed defined as the speed at which constant torque and power regions are separated. It is said that two motors have the same speed-torque characteristics only when they have the same speed ratio [116]. According to the previous explanation, traction motors with high speed ratios are preferred for HEVs because they can effectively reduce the required motor power rating, thus reducing battery power rating. For the motor considered here, the speed ratio is about 5, which is a good selection.

3.2.5 Model for the Battery

The battery model in the vehicle simulation represents the electrochemical energy conversion and associated energy losses of the physical energy storage system of the HEV including the controller losses. Before presenting the battery model, important terminologies and selected battery type is introduced first.

Key attributes of a battery in the application of vehicle propulsion are the cycle life (or the calendar life), specific energy density, specific power, and cost of manufacturing (and repairing). The cycle life represents the number of charging and discharging cycles possible before it loses its ability to hold a useful charge. Life cycle typically depends on the depth of discharge. The specific energy and power describe, respectively, the energy content (determining the vehicle range) and the maximum power (determining the vehicle acceleration performance) as a function of the weight of the battery [117,118].

Parallel full HEVs require a battery with a specific power high enough to supply the peak power of the large motor and to handle high instantaneous powers for short time periods [15]. Due to the dependability on the electric system being similar to
that on the ICE, the battery should also have an energy storage capacity greater than that needed to permit the vehicle to meet appropriate driving cycles. However, the additional energy stored permits the battery to operate over a relatively narrow state-of-charge range (often 5%-10% at most), which greatly extends the battery cycle and calendar life [55].

Three major battery chemistries can be seen as the options to meet above requirements: lead acid, nickel metal hydride and lithium-ion. Lead acid batteries have a relative low energy density therefore, their adoption as HEV’s energy storage is limited [119]. Today, all the hybrids of this type being marketed by the auto companies utilize nickel metal hydride batteries. Just emerging vehicles using lithium-ion batteries are being marketed following extensive prototype testing [120]. Lithium-ion is selected as the base battery technology since they have superior characteristics in terms of energy density over 100Wh/kg and high power density and have been widely accepted in applications when size, weight, and performance are critical [55,119,121].

Upon deciding the battery type and the capacities, proper modeling is required to capture energy losses and to define energy efficiency in both discharging and recharging. Depending on the depth energy loss modeling, many battery models can be found [122]. In this work, an internal resistance model (Rint model) is used. The equivalent circuit of the battery model is shown in Fig. 3.8.

![Equivalent circuit of the internal resistance battery model](image)

Figure 3.8: The equivalent circuit of the internal resistance battery model

It consists of a voltage source with $V_{oc}$ voltage and $R_{int}$ internal resistance. For a battery with a $C$ Ampere hour capacity and $V_{oc}$ rated voltage, its capacity is
\[ Q_{\text{max}} = V_{oc} \times C \times 3600. \]  
\[ C \] is a function of the charging or discharging current. Nonetheless, this fact is neglected in this model for the simplicity. It is important to note that \( V_{oc} \) and \( R_{int} \) heavily depend on the SOC which is defined as the ratio of remaining charge capacity to \( Q_{\text{max}} \) as

\[
SOC = \frac{E_{\text{ess}}}{Q_{\text{max}}}
\]  

(3.12)

where \( E_{\text{ess}} \) is the remaining energy level of the battery. These quantities are also affected by the temperature and it is neglected here. \( R_{int} \) also varies with discharge and recharge status of the battery. Let \( R_{dis} \) be the resistance at discharge and \( R_{chg} \) be the resistance at charge. Fig. 3.9 shows the variation of \( V_{oc}, R_{dis} \) and \( R_{chg} \) with \( SOC \). The preferred SOC range that maintains high \( V_{oc} \) and low \( R_{int} \) can be seen as 0.4-0.8. The lower SOC limit also prevents the battery from being over discharged and upper SOC limit ensures that battery is not over charged.

From Ohm’s law, current flowing through the battery \( I \) can be calculated as

\[
I = \frac{V_{oc} - \sqrt{V_{oc}^2 - 4 \times R_{int} \times P_{ess}}}{2 \times R_{int}}
\]  

(3.13)
3.2 The Parallel HEV Model

$P_{\text{ess}}$ is the power at the battery terminal. Then, the efficiency of the battery can be defined as,

$$\eta_{\text{ess}}(\text{SOC}, P_{\text{ess}}) = \left\{ \frac{V_{oc}I}{P_{\text{ess}}} \right\}^k \quad (3.14)$$

The map of $\eta_{\text{ess}}(.)$ for the considered lithium-ion battery is shown in 3.10. The efficiency map represents the basic forms of voltage losses due to ohmic losses, electrolyte concentration, reaction activity. High efficiency of the selected lithium-ion reflects its resistance [55].

![Figure 3.10: The efficiency map of the battery](image)

3.2.6 The Overall Configuration

Table A.2 in Appendix A.1 summarizes the numerical parameters of each sub-system of the vehicle model. The vehicle is sized as a typical Australian full sized sedan (upper medium class using Australian practice) and power plant sizing close to that for optimum efficiency resulting in a degraded acceleration time [123]. Thus, whereas the market presently demands a 0-100 km/h time of around 7 seconds, the vehicle modeled here has an acceleration time of about 12 seconds, which would not be acceptable, but it does serve to guide the enumeration of close to the best possible
fuel consumption for this size of the vehicle. Reader may refer to A.4.1 for more information on the validation of the vehicle model.

3.2.7 Fuel Consumption Calculations

Once $T_{dem}$ and $\omega$ is calculated, power management controller distributes $T_{dem}$ between the ICE and EMG according to its PMS such that the energy balance is held as

$$T_{dem} = T_{ice} + T_{ele}$$  \hspace{1cm} (3.15)

where $T_{ele}$ is the torque contribution of the EMG with respect to ICE output shaft. Equ. 3.15 assumes that no energy losses due to braking. After the speed coupler (having gear ratio $R_e$) between the EMG output and ICE output, the torque of the EMG becomes $T_{emg} = T_{ele}R_e$ and speed becomes $\omega_{emg} = \omega/R_e$.

The clutch actions of the power sources are removed. Therefore, whenever the torque (or speed) of power sources is zero, they are stopped. This applies to the EMG when the vehicle is stationary because the EMG operates most of the positive and negative power demands. Clutch engagement on the EMG operation has not much effect because it can start from zero speed and operate all the way to its maximum speed without many problems. However, this strategy forces ICE to stop during deceleration, idling and inefficient ICE operations. This is also equivalent to idle-stop strategy in which HEVs are capable of saving fuel.

It is well known that starting fuel consumption is higher than idle fuel consumption due to transient effects and ICE cold operation effects. Even if electric launch is used, battery energy used involves a fuel consumption penalty later. Therefore, a stating fuel consumption is included in the model. To be realistic, the idle stop strategy should consider starting fuel consumption of the engine even when the engine is hot.
3.2 The Parallel HEV Model

Starting fuel cost

The starting fuel consumption heavily depends on the initial temperature of the ICE. For instance, cold start fuel consumption is up to 10 times larger than a warm start fuel consumption [124]. Even so, it is assumed that the start process for the warm ICE and a very simplified process is assumed.

The conventional engine start process consists of three phases: the cranking, the startup process, and the steady at idle [125]. The ICE is cranked by the starter motor to give initial momentum to assist the compression and firing in the first fuel injection cycle. As the combustion starts, the ICE accelerates until it reaches a higher speed (than the idle speed) which is required to obtain a robust start. During steady idle, the ICE decelerates to a steady idle speed.

The electric start process of the HEV may be different and quicker than the conventional start. This high-speed motoring of the ICE restart also improves the cylinder conditions for combustion because the cylinder pressure and temperature increase as well [126]. An approximate starting fuel consumption is calculated with assumed starting process that cranks the ICE to a speed significantly higher than idle speed by the electric system. The electric motor cranks the ICE from zero speed to $\omega_{ss}$ within time $t_{ss}$. The motor overcomes the total resistive load $T_{res}$, which is the sum of inertia load $T_{iner}$ and friction loads $T_{fric}$, i.e., $T_{res}(t) = T_{fric}(t) + T_{iner}(t)$. The friction torque, which is a function of the engine speed, can be calculated using Heywood’s friction model [127]

$$T_{fric}(t) = \frac{C_{ice}}{\omega(t)} \left\{ 0.97 + 0.15 \left[ \frac{60}{2\pi} \omega(t) \right] + 0.05 \left[ \frac{60}{2\pi} \omega(t) \right]^2 \right\}$$

where $C_{ice}$ is the capacity of the ICE in liters. The inertial torque can be calculated from Newton’s second law of motion as

$$T_{iner}(t) = \frac{1}{2} I_{ice} \dot{\omega}(t)$$

where $I_{ice}$ is the inertial of the ICE and $\dot{\omega}$ is the angular acceleration of the ICE. The electrical energy required from the battery to crank the ICE can simply be
calculated by integrating over the stating time. The estimated fuel consumption involved in this process is given by the fuel required to replace this battery energy. Accordingly, the starting fuel consumption is

$$M_{sf} = \frac{1}{\eta_{ice,s} \eta_{dis,s} Q_{HV}} \sum_{t=0}^{t_{res}} \frac{T_{res}(t) \omega(t)}{\eta_{dis}(t)} \Delta t$$  \hspace{1cm} (3.18)$$

where $\eta_{ice,s}$ is the efficiency of the engine at energy replacement, and $\eta_{dis,s}$ is the electric system’s recharging efficiency. In reality, this is likely to be an optimistic (low) fuel quantity since it is assumed that the engine is full warmed and there are no starting losses in clutch engagement.

**SOC correction**

For HEVs, the fuel consumption for a complete journey can be accepted as the final one only if the final SOC is equal to the initial value, i.e., balanced final SOC. For journeys with unbalanced final SOC, an SOC correction procedure is required to extract the fuel hidden (net saving/use) inside the battery also known as equivalent fuel. For instance, the fuel consumption for a journey with discharged battery is less than the actual value. However, more fuel should be spent to balance the final SOC. On the other hand, the fuel consumption for a journey with an over charged battery includes excess fuel that is saved as electric energy inside the battery.

The fuel equivalent to the final SOC difference depends on the efficiencies of the energy flow paths of the power train [21]; therefore, depends on the drive cycle, vehicle model, final SOC and the actual method of correction, etc. By using the average component efficiencies and the frequency of the regenerative braking path used, two equivalent factors can be defined to convert final SOC difference to equivalent fuel [86]. These methods involve detailed calculation of equivalent factors because the equivalent factors are used in objective functions in online driving. However, less complex calculation of equivalent factors can be employed for offline corrections as long as the PMS leads to small SOC differences. The final SOC difference is multiplied by an equivalent factor, $\lambda_{dis}$ if the final battery status is discharged or
\( \lambda_{chg} \) if the final battery status is recharged, to calculate the equivalent fuel as

\[
m_{eq} = \frac{\lambda}{\rho f Q_{HV}} (SOC(1) - SOC(n))
\] (3.19)

and

\[
\lambda = \begin{cases} 
\lambda_{dis} = 1/(\eta_{ice}^{opt} \bar{\eta}_{ele}) & \text{if } SOC(1) > SOC(n) \\
\lambda_{chg} = \bar{\eta}_{ele} / \eta_{ice}^{opt} & \text{else.}
\end{cases}
\]

where \( \eta_{ice}^{opt} \) is the average efficiency of the engine and \( \bar{\eta}_{ele} \) is the average efficiency of the electrical system. These two equivalent factors correspond to zero-speed recharging, with the ICE operating at the point of the highest efficiency.

### 3.3 Model for the Conventional Vehicle

The conventional vehicle is used as the baseline vehicle to demonstrate the fuel saving capability of the HEV and different PMSs. Therefore, the conventional vehicle should be comparable with the HEV. Accordingly, the kerb weight, vehicle chassis model are the same. The gross vehicle weight may change due to the different component configurations resulting in change of fuel consumptions. This is overcome in modeling since the weights of components are considered in the model. The most important fact to note is that the conventional vehicle is equally powered as the HEV. Thus, the conventional vehicle has an 80 kW Honda Insight engine. The same transmission as the HEV is used. The important parameters of the vehicle model are given by Table A.2 in Appendix A.2.

Similar to the HEV, backward simulation model is developed. Any positive torque demand is supplied by the ICE while the mechanical brake is applied during negative power demand. During idling and decelerating, the ICE is operated at its idle operating point. Therefore, the engine consumes idle fuel to maintain the idle speed.
3.4 Drive Cycles

A drive cycle represents the time-speed trace of the vehicle moving over typical driving conditions. The primary intention of the drive cycles is to provide a realistic and practical test for the emission of vehicles. This facility is now extended to investigate the effect of driving style on fuel consumption and to test power management controllers of HEVs, etc. The driving patterns with heavy acceleration, power demand and high engine speeds consumes more fuel [84]. In addition, there are many other factors that influence the fuel consumption (and emissions) and should be considered in developing driving patterns. The driving patterns are interrelated with the driver and vehicle as summarized by Fig. 3.11 [128]. The simple driving patterns represented by most of the existing drive cycles may fail to represent the real world driving patterns [129]. Furthermore, these cycles are developed for conventional vehicles; therefore, they may not be capable of fully testing the power management strategies of HEVs that use different types of power sources to propel or brake. For

![Figure 3.11: Representation of information influencing the drive cycle. Source: [128]](image_url)
instance, HEV control strategies are more sensitive to driving patterns than conventional vehicle controls. If the HEV is not controlled properly for the driving pattern, the SOC may violate the recommended limits leading to deteriorated fuel economy. Thus, these standard driving cycles may be modified to facilitate these modern requirements.

Fig. 3.12 shows selected six drive cycles: New European Drive Cycle (NEDC), Federal Test Procedure (FTP-75), Australian Urban Drive Cycles (AUDC), Melbourne Peak Drive Cycle (MPDC), Highway Fuel Economy Test (HWFET) cycle, and Australian Truck Highway Cycle (ATHC). These cycles are chosen to reflect different driving characteristics. The first four cycles represent urban driving while last two cycles represent highway cycles. Table 3.1 summarizes some important statistical data of the selected drive cycles.

<table>
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<tr>
<th>Table 3.1: Drive cycle stastics</th>
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NEDC consists of repeated constant acceleration and cruising phases. Therefore, they have limited operating points of the power components. It shows a quite unrealistic driving pattern. However, the heavy driving load of the high speed driving segment following the urban driving may be critical for proper SOC control during HEV power management. The FTP-75 is a real-world cycle but the acceleration rate is intentionally bounded; therefore, it may not be aggressive enough to test power management controller. On the other hand, AUDC is closer to real driving over a 24 hour period than FTP-75 because it reflects accelerations achievable in real driving. MPDC from peak hour traffic driving has a higher peak speed, acceleration
and deceleration than both these cycles. Therefore, it could be a good test cycle for PM controllers. From the highway cycles, HWFET represents highway driving conditions under 96 km/h and is used to determine the US composite fuel economy. The ATHC has the maximum speed up to 120 km/h and longer journey distance compared to the HWFET.
4.1 Introduction

Model-based PMSs are referred here to the strategies based on mathematically-defined dynamics of the HEV rather than relying on the approximated linguistic if-then rules developed by the general knowledge of dynamics as in rule based strategies. As mentioned before, dynamics of the HEV considered within the scope of this thesis includes only the steady state behavior. Since the mathematical model of one HEV can fit into any HEV with the same configuration, model based strategies have the advantages of easy transferability with less tuning effort compared to rule based strategies. Upon a good design, they can also produce optimal or near-optimal results. Some examples for model-based PMSs are the optimal control [66, 130, 131], model predictive control [132, 133], dynamic programming, quadratic programming, linear programming and equivalent consumption minimization strategy. The dynamic programming and the equivalent consumption minimization strategy, which are widely applied in the context of power management of parallel HEVs, are discussed in detail and will be used as benchmark algorithms for evaluating new algorithms later in the thesis.
4.2 Dynamic Programming (DP)

4.2.1 Problem Definition

Determining the fuel-optimal power split at positive power demands, as well as regenerating as much as energy at negative power demands, is a primary task of the power management. For randomly varying power demands caused by continuous driving, the fuel optimal power split determines the sequence of power split ratios that minimizes the overall fuel consumption. The proper split of power demand at any driving instance is determined by the current status of the HEV (i.e. charge level etc). It also changes the vehicle status of the next driving instance. Consequently, any decision of power split ratio affects the future decisions. Because of the interdependency of decisions, a proper construction of the PMS is required beyond simple methods like greedy algorithms.

The problem of power management over a known drive cycle is how to find the optimal sequence of the power split ratio between the motor and engine that minimizes the overall fuel consumption within the constraints imposed by the motor, engine, and the battery. This can be described by the following optimization problem:

\[
M_f = \min_{u_{\text{min}} \leq u \leq u_{\text{max}}} \left\{ \int_0^n \dot{m}_f(t, u(t)) dt \right\} \quad (4.1)
\]

\[
\begin{align*}
p_{\text{ice}}(t) + p_{\text{ele}}(t) &= p_{\text{dem}}(t) \\
p_{\text{ice}}(t) &\leq p_{\text{ice, max}}(\omega_{\text{ice}}(t)) \\
p_{\text{ele, min}}(\omega_{\text{ele}}(t)) &\leq p_{\text{ele}}(t) \leq p_{\text{ele, max}}(\omega_{\text{ele}}(t)) \\
SOC_{\text{min}} &\leq SOC_t \leq SOC_{\text{max}} \\
SOC_0 &= SOC_n
\end{align*}
\quad (4.2)
\]

where, \(\dot{m}_f\) is the instantaneous rate of fuel consumption, \(u\) is the power split ratio, \(u_{\text{max}}\) is the highest split ratio, \(u_{\text{min}}\) is the lowest split ratio, \(n\) is the length of the drive cycle, \(p_{\text{ice}}\) is the mechanical power output of the ICE, \(p_{\text{ele}}\) is the mechanical power of the electrical system, \(p_{\text{dem}}\) is the power demand of the vehicle, \(p_{\text{ice, max}}(\omega_{\text{ice}})\)
4.2 Dynamic Programming (DP)

is the maximum power of the ICE at the output speed $\omega_{\text{ice}}$, $p_{\text{ele, max}}(\omega_{\text{ele}})$ is the maximum power of the electric machine (motor mode) at the output speed $\omega_{\text{ele}}$, $p_{\text{ele, min}}(\omega_{\text{ele}})$ minimum power of the electric machine, $SOC_t$ is the SOC at the time, $SOC_{\min}$ is the lower SOC limit, $SOC_{\max}$ is the upper SOC limit, $SOC_0$ is the initial SOC and $SOC_n$ is the final SOC.

The number of split ratios to be determined is equal to the number of time points of the drive cycle; therefore, it is in the order of thousands. Each time split ratio has a continuous feasible range. Therefore, finding the global solution to the power management problem is a difficult task. Because of the existence of a huge number of sequences of split ratios, solving the problem with methods like brute force enumeration within a reasonable time is impossible. As mentioned before, control action taken at each instant affects the following. Dynamic programming is a well-suited optimal technique that can solve the power management problem more efficiently than brute force methods.

4.2.2 Dynamic Programming Basics

DP is a multistage decision making method applicable for discrete optimization problems. It is based on the recursive procedure that starts with a small sub problem of the same kind as the original problem and subsequently develops the solution to the original problem. This solution construction is possible only for problems that obey Bellman’s principle of optimality. The idea can be understood by analyzing the nature of the dynamic system. A dynamic system can be represented by

$$x_{t+1} = f(x_t, u_k, w_t) \quad \text{for } t = 0, 1, 2, ..., N - 1$$  \hspace{1cm} (4.3)

where, $x$ is the state variable (the dependent variable), $u$ is the control variable (independent variable), $t$ is the stage variable, $w$ is the disturbance to the system and $N$ is the control horizon. It is assumed that all variables are known certainly. The state transition function (4.3) also explains how the control at one stage transforms
one state into a state in the next stage. Let any feasible state trajectory be

$$\Omega = \{x_0, x_1, x_2, ..., x_{N-1}, x_N\}, \quad (4.4)$$

and the corresponding control policy be

$$\pi = \{u_0, u_1, u_2, ..., u_{N-1}\}. \quad (4.5)$$

In most of the control problems represented by (4.3), the cost of control policies is determined by the costs of each state transition, which are additive over the stages and terminal costs. Thus, the cost of the control policy $\pi$ starting at state $x_0$ can be represented as,

$$J_\pi(x_0) = g(x_N) + \sum_{t=0}^{N-1} g(x_t, u_t) \quad (4.6)$$

where, $g(x_t, u_t)$ is the transition cost at the state $x_t$ with the control action $u_t$ and $g(x_N)$ is the terminal cost that represents the penalty cost for deviating from the targeted state.

The optimal cost for the optimization problem is then given by

$$J^*_\pi(x_0) = \min_\pi J_\pi(x_0) \quad (4.7)$$

and the optimal control policy $\pi^*$ is the one that satisfies $J^*_\pi(x_0) = J^*_\pi(x_0)$. The approach of the DP to find these optimal quantities is based on a simple property of the multistage decision processes known as the principle of optimality.

### 4.2.3 The Principle of Optimality

According to Bellman’s principle of optimality for multistage decision processes [134]:

“An optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision”
4.2 Dynamic Programming (DP)

The theory can be proven by the simple induction method as in [135]. In another way, the principle of optimality explains that if a solution to a subproblem is available, it can be used to solve a bigger problem, which consists of the subproblem, much more easily. In this way, the optimization problem of (4.7) can be solved recursively starting from a smaller sub-problem as

\[
J^*_{\pi_k}(x_k) = \min_{u_k \in U_k(x_k)} \left\{ g(x_k, u_k) + J^*_{\pi_{k+1}}(x_{k+1}) \right\}
\]  

(4.8)

where \( J^*_{\pi_{k+1}}(x_{k+1}) = \min_{\pi_{k+1}} J_{\pi_{k+1}}(x_{k+1}) \), which corresponds to the optimal policy \( \pi_{k+1} = \{ u_{k+1}, u_{k+2}, u_{k+3}, ..., u_N \} \). The optimal policy for the new sub-tail problem starting from \( k^{th} \) stage will consequently be \( \pi_k^* = \{ u_k, \pi_{k+1}^* \} \).

4.2.4 Backward DP algorithm

DP can be implemented starting from the last stage or the first stage. The backward DP starts from the last stage at the intended final state \( x_N \). The optimal cost for the sub-problem is simply given by

\[
J^*_{\pi_N}(x_N) = g(x_N)
\]  

(4.9)

It then proceeds backwards with respect to the stage variable calculating the optimal costs for each sub-problem starting from all feasible states as indicated by (4.7). The cost generated at the last step \( J^*_{\pi_k}(x_0) \) is the optimal cost of the problem. The corresponding optimal path can be revealed by back tracking.

4.2.5 Power Management of HEVs with DP

The power management problem presented above is to find the sequence of control actions that result in the minimum fuel consumption for a known journey starting with \( SOC_0 \) initial energy level and finishing with \( SOC_T \), final energy level, against other component constraints. The selection of a proper variable for defining the DP based PMS, will make the constraint satisfaction easy. Time is the stage variable whose range is decided by the drive cycle and varied in the interval of 1s. The state
Chapter 4. Model-Based Power Management Strategies for Parallel Hybrids

of charge \( SOC \) is selected as the state variable while either the mechanical power of the EMG \( p_{ele} \) or the power split ratio is selected as the control variable. The selection of SOC as the state variable enables satisfying all the constraints clearly. The state space of the DP is prepared by discretizing the SOC into a fine grid of size \( \Delta SOC \) within the range \( SOC_{\text{min}} (=0.4) \leq SOC \leq SOC_{\text{max}} (=0.8) \). Due to the end-SOC constrain, the feasible region of the SOC closed to the starting and end of the journey is governed by the maximum recharging and discharging capability of the electrical system. Fig. 4.1 shows the feasible area of the SOC, which is bounded by the upper SOC boundary \( SOC_{up} \) and the lower SOC boundary \( SOC_{lw} \). Two boundaries are given by,

\[
SOC_{up} = \min(SOC_{up}^1, SOC_{max}, SOC_{up}^2) \quad (4.10)
\]

\[
SOC_{lw} = \min(SOC_{lw}^1, SOC_{min}, SOC_{lw}^2) \quad (4.11)
\]

with,

\[
SOC_{up}^1(k) = SOC_0 + p_{chg,max}/\eta_{chg}(k),
\]

\[
SOC_{up}^2(k) = SOC_0 + p_{dis,max} \ast \eta_{dis}(n-k),
\]

\[
SOC_{lw}^1(k) = SOC_0 - p_{chg,max}/\eta_{chg}k,
\]

\[
SOC_{lw}^2(k) = SOC_0 - p_{dis,max} \ast \eta_{dis}(n-k)
\]

where, \( p_{chg,max} \) is the maximum charging power, \( p_{dis,max} \) is the maximum discharging power, \( \eta_{chg} \) is the charging efficiency and \( \eta_{dis} \) is the discharging efficiency of the electrical system. It should also be noted that reducing the search space in this way will considerably reduce the computational time of the DP.

The state-transition function of the HEV model can be represented as

\[
SOC_{k+1} = SOC_k - \Delta SOC_k \quad (4.12)
\]
4.2 Dynamic Programming (DP)

\[ \Delta SOC_k = \begin{cases} 
\frac{p_{ele}(k)/[\eta_{mot}(k)\eta_{bat}(k)Q_{max}]}{\eta_{gen}(k)\eta_{bat}(k)/Q_{max}} & \text{if } p_{ele}(k) > 0 \text{ (discharge)} \\
p_{ele}(k)/\eta_{gen}(k)\eta_{bat}(k)/Q_{max} & \text{if } p_{ele}(k) < 0 \text{ (recharge)} 
\end{cases} \] (4.13)

From the power balancing relationship, the power output of the ICE is \( p_{ice} = (p_{dem} - p_{ele}) \). It should be noted that the ICE consumes fuel only for positive power delivery. Therefore, the fuel consumption of state transitions \( m_{fc} \) is positive only
Chapter 4. Model-Based Power Management Strategies for Parallel Hybrids

at positive ICE power output (or at positive torque). The fuel consumption of the ICE has two components; fuel for the power delivery \( m_{pd} \) and the starting fuel consumption \( m_{s/s} \). Hence, the state transition cost function becomes

\[
m_{fc}(k) = \begin{cases} 
m_{fc,act} + m_{s/s} & \text{if } T_{\text{ice}}(k) > 0 \\
0 & \text{if } T_{\text{ice}}(k) \leq 0 
\end{cases}
\] (4.14)

The fuel for the power delivery is simply \( m_{fc,act} = (p_{dem} - p_{ele})/\eta_{\text{ice}}(k)/Q_{LHV} \). The starting fuel cost is modeled as a function of torque difference of the two states to reduce the unnecessary torque fluctuations as

\[
m_{s/s}(k) = \frac{q_{ss}}{2 \times T_{\text{ice, opt}}} |T_{\text{ice}}(k) - T_{\text{ice}}(k + 1)|
\] (4.15)

In eqn. 4.15, it is approximated that the ICE consumes \( q_{ss} \) fuel to reach the torque at the point of highest efficiency \( T_{\text{ice, opt}} \) in a single ICE start. Any torque variation (either positive or negative) is assumed to consume fuel proportional to \( q_{ss}/(2 \times T_{\text{ice, opt}}) \). The factor 0.5 is to compensate the torque cumulation in both deceleration and acceleration phase of the ICE during the backward DP.

The backward DP starts from a known final SOC, which is targeted to be equal to the initial SOC at the end of driving and proceeds backward checking all possible state transitions within the feasible region. Starting at an intermediate state \( SOC_k \) at time (or stage) \( k \), the optimal fuel cost for completing the rest of the drive cycle does not depend on the previous driving. Therefore, this problem obeys the principle of optimality.

Therefore, the recursive rule of the backward DP based PMS with \( J_{\pi_k}(SOC_k) \) as the minimum fuel cost starting from \( SOC_k \) at time \( k \) can be formulated as

\[
J_{\pi_k}(SOC_k) = \min_{p_{chg,\max}(k) \leq p_{ele}(k) \leq p_{dis,\max}(k)} \left\{ m_{fc}(SOC_k, p_{ele}(k)) + J_{\pi_{k+1}}(SOC_{k+1}) \right\}
\] (4.16)

where \( \pi_k \) is the corresponding optimal control policy \( \pi_k = \{p_{ele}(k), p_{ele}(k+1), p_{ele}(k+2), ..., p_{ele}(n-1)\} \). The optimal cost at the last stage \( J_{\pi_{k-1}}(SOC_0) \) is the minimum
fuel for the complete drive cycle with starting battery energy at $SOC_0$.

4.3 Equivalent Consumption Minimization Strategy (ECMS)

Power management strategy using an objective function of “minimizing the overall fuel consumption” similar to the DP requires the knowledge of the driving data within the control horizon explicitly. Handling such a global objective may be computationally hard. The equivalent consumption minimization strategy introduces an instantaneous objective function, which can promisingly be used to optimize HEVs efficiently and near-optimally [136, 137].

4.3.1 Problem Definition

As far as the charge sustaining HEV is concerned, any chemical energy disturbance in the battery caused by the power management with the electrical system needs to be rectified in the future. A current battery discharge should be rectified by a recharge consuming fuel energy while a current recharge should be rectified by a future discharge saving fuel. The fuel consumed or saved in the rectifying process is the equivalent fuel of the instantaneous electrical energy. The underlying concept of the ECMS is to minimize the sum of the instantaneous actual fuel consumed by the ICE and the equivalent fuel of the instantaneous electrical energy. The equivalent fuel is path dependent. This point is elaborated by power flow diagrams in Fig. (4.3), which shows the forward path and backward path (highlighted) involving in the battery discharging (left) and recharging (right) instances.

Production of $E_{ele}$ mechanical energy at the motor output during a forward discharging process consumes $E_{ele} / \eta_{dis}$ amount of chemical energy, where $\eta_{dis}$ is the discharging efficiency of the electrical system. During the backward rectifying path, the fuel energy flows from fuel tank to the battery via the engine and the generator replacing drained battery energy. Exact power flow calculation is impossible because the true efficiencies of components of this path are unknown. However, approximate
(a) Power flow of the HEV powertrain for an electrical discharge  
(b) Power flow of the HEV powertrain for an electrical recharge

Figure 4.3: Graphical explanation of the ECMS with the backward power flow paths corresponding to forward discharge and recharge
calculations are possible with average efficiencies. Therefore, by using the average engine efficiency $\bar{\eta}_{ice}$ and average recharging efficiency $\bar{\eta}_{chg}$, the equivalent fuel energy of the discharged electrical energy in the forward path is calculated as $E_{ele}/(\eta_{dis} \ast \bar{\eta}_{chg}\bar{\eta}_{ice})$.

During a forward recharging process, $E_{ele}$ electrical energy flow will increase the chemical energy of the battery by $\eta_{chg} E_{ele}$, where $\eta_{chg}$ is the recharging efficiency of the electrical system. The stored battery energy will save fuel in future. Therefore, during the backward rectifying path, $\bar{\eta}_{dis}\eta_{chg}E_{ele}$ amount of energy will be available at the power transmission saving $\bar{\eta}_{dis}\eta_{chg}E_{ele}/\bar{\eta}_{ice}$ amount of fuel energy.

Therefore, The ECMS replaces the global objective function with a local one as follows:

$$M_f = \sum_{0}^{n} \min_{u_{min}(t) \leq u \leq u_{max}(t)} \left\{ \dot{m}_f(t, u(t)) + \lambda(t) \frac{E_{ele}(t, u(t))}{Q_{LHV}} \right\}$$

(4.17)

where, $\lambda$ is the equivalent factor that converts the instantaneous electrical energy change to equivalent fuel.

### 4.3.2 Equivalent Factors

The control of the equivalent factor $\lambda$ to maintain the optimality of the results as well as satisfying the constraints is the key part of the ECMS-based PMSs. According to the above explanations, $\lambda$ depends on the discharge or recharge status of the battery and can be defined with known average efficiencies as follows:

$$\lambda = \begin{cases} \lambda_{dis} = 1/(\eta_{chg}\bar{\eta}_{ice}) & \text{if } E_{ele} > 0 \text{ (discharge)} \\ \lambda_{chg} = \bar{\eta}_{dis}/\bar{\eta}_{ice} & \text{if } E_{ele} < 0 \text{ (recharge)} \end{cases}$$

However, for online driving, the driving style changes randomly; therefore, component efficiencies change. Therefore, an equivalent factor should be changed in an on-the-go manner.
4.3.3 Offline ECMS

The offline ECMS, developed by Scierrata et al. [21], which will be presented here and used as a benchmark PMS in this thesis.

When the average efficiencies are unknown, another way to calculate equivalent factors is to send known energy quantities through the discharging and recharging paths at as many different operating points as possible and measure the resulting quantity from the other end. This can be done by running the vehicle over the drive cycle intended to be simulated with a constant power split ratio, calculating the cumulative fuel energy and battery energy, and performing similar multiple runs for different power split ratios. For a power split ratio $u^i$ at the $i^{th}$ run, the cumulative fuel energy is calculated as

$$E_{fuel}(u^i) = \int_n (1 - u^i)p_{dem}(t)\eta_{ice}(t)dt,$$  (4.18)

while cumulative electrical energy is calculated as

$$E_{ele}(u^i) = \int_n u^i p_{dem}(t)\eta_{ele}(t)\text{sign}(u^i)dt$$ (4.19)

The variation of $E_{fuel}$ as a function $E_{ele}$ takes the form of two piecewise linear relationships. Fig. 4.4 illustrates this relationship between $E_{fuel}$ and $E_{ele}$ for the author’s parallel HEV model over FTP-75. The slope of the straight lines for $u < 0$ is equal to $\lambda_{dis}$ and slope of the straight line for $u > 0$ is equal to $\lambda_{chg}$.

According to (4.17), the value of electrical energy relative to fuel energy can be varied with $\lambda$. For instance, when the SOC is low, a large $\lambda$ reduces the use of electrical energy and forces to recharge, whereas when the SOC is high, a small $\lambda$ makes electrical energy cheaper than fuel energy and forces to discharge. Furthermore, if the final status of the battery is going to be discharged, a large $\lambda$ is preferred, whereas for a final recharged battery status, a small $\lambda$ is preferred. To suit both objectives, the instantaneous equivalent factor can be expressed as a function of $\lambda_{dis}$.
4.3 Equivalent Consumption Minimization Strategy (ECMS)

Figure 4.4: Variation of $E_{fuel}$ with $E_{ele}$ for FPT-75

and $\lambda_{chg}$ as

$$
\lambda = p * \lambda_{dis} + (1 - p) * \lambda_{chg}
$$

(4.20)

where $p \in [0, 1]$ is the probability of battery being discharged at the end of driving upon pursuing the current split ratio for the rest of the driving and proven to be expressed as follows:

$$
p(t) = \frac{u_r/\bar{\eta}_{ele} - \rho}{u_r/\bar{\eta}_{ele} + \bar{\eta}_{ele}u_l} + \frac{E_{bat}(t)}{(u_r/\bar{\eta}_{ele} + \bar{\eta}_{ele}u_l)(E_m - E_m(t))}
$$

(4.21)

where, $u_r$ is the upper split ratio, $u_l$ is the lower split ratio, $\bar{\eta}_{ele}$ is the average electrical efficiency, $E_{bat}$ is the current battery energy, $E_m$ is the total mechanical energy demand of the complete drive cycle, $E_m(t)$ is the total mechanical energy for the rest of the drive cycle and $\rho$ is the ratio of the total negative mechanical energy demand to the total positive mechanical energy demand.

Thus, at each time instance $p$ is calculated from (4.20). The instantaneous $\lambda$ is known with (4.20). Then, the best instantaneous power split ratio is calculated from (4.17).
4.4 Other Optimization Methods

4.4.1 Particle Swarm Optimization (PSO)

PSO is a population based (gradient free) stochastic optimization technique proposed by Eberhart and Kennedy [138,139]. It is a popular optimization technique because of its ability to solve heavily nonlinear multi-dimensional problems successfully, with fast convergence and its simplicity in implementation. It is based on the foraging behavior of swarms like a flock of birds or a school of fish. During foraging, individual member of the swarm search for food randomly within its environment and use its own sensing ability and others’ information to find the best food source. In PSO, the individual is the particle that represents one feasible solution. The food sources are local or global solutions of the optimization problem.

In a ‘d’ dimensional search space, the position and the velocity of a particle labeled ‘i’ can be represented by $X_i = (x_{i1}, x_{i2}, ..., x_{id})$ and $V_i = (v_{i1}, v_{i2}, ..., v_{id})$. Let the $P_i$ and $P_g$ represent the best position found by the $i^{th}$ particle and global best position found so far by any particle in the population. The velocity and position of a particle are updated according to

$$v_{id} = \omega \times v_{id} + c_1 \times rand(\cdot) \times (p_{id} - x_{id}) + c_2 \times Rand(\cdot) \times (p_{gd} - x_{id}) \quad (4.22)$$

$$x_{id} = x_{id} + v_{id} \quad (4.23)$$

where, $c_1$ and $c_2$ are the acceleration coefficients varying with iteration as proposed by Ratnaweera et al. [105], $rand(\cdot)$ and $Rand(\cdot)$ are the random numbers generated from a uniform distribution in the range [0,1], and $\omega$ is the inertia weight, which is suggested by Shi and Eberhart [140]. $c_1$, $c_2$ and $\omega$ are varied with the iteration number as follows:

$$c_1 = (c_{1f} - c_{1i}) \frac{iter}{MAXITER} + c_{1i} \quad (4.24)$$

$$c_2 = (c_{2f} - c_{2i}) \frac{iter}{MAXITER} + c_{2i} \quad (4.25)$$
4.5 Simulation Results

Performance of the DP and the ECMS based PMSs on the HEV is tested for selected drive cycles and simulation results are compared in Table 4.1. The DP is always more fuel optimal than the ECMS by saving up to 0.04 L/100km for both city and highway driving cycles. However, the DP consumes huge computational time. By analyzing the search space in Fig. 4.2, the number of functional evaluations of the DP can be approximately calculated as

\[
N_{DP} = \left( \frac{SOC_{max} - SOC_{min}}{\Delta SOC} \right) \times \frac{p_{ess,max}}{Q_{max} \Delta SOC} \times n
\]  

(4.27)

where, \( p_{ess,max} \) is the maximum battery power. Therefore, the computational time of the DP increases exponentially with \( \Delta SOC \) meanwhile the quality of the solution is improved. Table 4.2 illustrates how the fuel consumption results and computational time vary for discretization size of 750 J, 650 J and 500 J.

High computational efficiency of the ECMS is its main advantages. The computational complexity of the ECMS is approximately equal to

\[
N_{ECMS} = 2 \left( \frac{u_r - u_i}{\Delta u} \right) \times n
\]  

(4.28)

where \( \Delta u(= 0.1) \) is the size of the discretization of split ratio. A factor of 2 is
Table 4.2: Variation of the fuel consumption (L/100km) and computational time (s) of the DP for varying size of the state discretization

<table>
<thead>
<tr>
<th>Drive Cycle</th>
<th>$\Delta SOC = 750$ J</th>
<th>$\Delta SOC = 650$ J</th>
<th>$\Delta SOC = 500$ J</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Fuel con.</td>
<td>Time</td>
<td>Fuel con.</td>
</tr>
<tr>
<td>NEDC</td>
<td>3.98</td>
<td>70353</td>
<td>3.94</td>
</tr>
<tr>
<td>FTP-75</td>
<td>3.76</td>
<td>113851</td>
<td>3.71</td>
</tr>
<tr>
<td>AUDC</td>
<td>3.75</td>
<td>81213</td>
<td>3.70</td>
</tr>
<tr>
<td>HWFET</td>
<td>3.99</td>
<td>82303</td>
<td>3.99</td>
</tr>
</tbody>
</table>

due to the same computational time for preprocessing stage of equivalent factors. Comparsion of (4.27) and (4.28) explains the reason for the huge computational time difference between the DP and the ECMS. Because of the fast computation, the ECMS is well-suited for real-time power management.

Figure 4.5: Variation of SOC over FTP-75 for power management with DP (continuous) and ECMS (dashed)

In comparison of the SOC controllability, the DP also can meet the end charge sustenance perfectly since it has the control of starting and final SOCs. The ECMS meets the end charge sustenance satisfactorily when it is at its best fuel performance. Fig. 4.5 shows the variation of the SOC for the DP and ECMS over FTP-75.
5.1 Introduction

In this chapter, an iterative method is newly proposed to solve of the offline power management problem near-optimally within a reasonable time. As stated in previous chapter, the problem is defined as finding the best sequence of power split ratios that result in minimum overall fuel consumption for a known drive cycle. It is reminded here that solving the power management problem optimally against hard constraints such as meeting the expected level of the battery energy at the end of the journey (end-charge sustenance) is a challenging task.

Past techniques such as linear programming [20], mixed integer programming [58], quadratic programming [59] and optimal control techniques [66] require a simplified vehicle model. Another two popular strategies are the dynamic programming [61] and the equivalent consumption minimization strategy [21]. As explained in the previous chapter, DP needs a huge computational time to find the optimal solution due to either fine descritization of the state variable or the interpolation between grid points of the state space. On the other hand, ECMS suffers from the high
sensitivity to strategy parameters specific to each drive cycle; therefore, requires a large tuning effort. Moreover, achieving the end-charge sustenance with the ECMS is not necessarily guaranteed always.

In this work, a new strategy inspired by a hill-climbing heuristic is proposed to solve the global energy management problem with less computational cost than the DP and more optimally than the ECMS. The main contributions are the properly formulated objective function and a feasible solution evolvement method. The proposed hill-climbing power management strategy (HCPMS) starts with a feasible initial solution, which is evolved towards the final solution always in the direction of solution improvement. The objective function consists of the actual fuel consumption, a penalty to reduce the final deviation of the battery energy and a penalty to reduce frequent stopping and starting of the engine. Results also show that HCPMS can improve poor solutions of other methods by taking them as initial solutions.

### 5.2 Offline Power Management Problem

The power management strategy of the HEV splits the positive power demand between the ICE and the battery while capturing as much energy as possible from regenerative braking energy, such that the overall fuel consumption is minimized. Thus, the fuel efficiency of an HEV strongly depends on its PMS. The PMS should also handle counteracting objectives such as maintaining the proper energy level of the battery, torque and speed variable limitations of the ICE and the EMG against nonlinearly varying efficiency of the ICE and EMG with their speeds and torques, and the rapidly varying power demand throughout driving. The latter also means that the fuel efficiency of the PMS depends on the level of driving information used [82, 91]. The full potential for fuel saving of an HEV can be obtained by the global solution to the power management problem formulated with the complete prior knowledge of the future driving information. Even though this kind of strategy may be unrealistic, it can be used as a benchmark for the other control strategies and as a guidance to design real time PMSs as in [61].

For a known driving cycle, the energy management problem of HEVs can be
defined as finding the minimum overall fuel consumption (5.1) subject to constraints on mechanical components (i.e., ICE and EMG) (5.3) and (5.4) and SOC constraints on the battery (5.5) and (5.6) and re-represented as

\[ M_f = \min \sum_{t=1}^{n} m_f(t) \]  \hspace{1cm} (5.1)

subject to

\[ p_{ice}(t) + p_{ele}(t) = p_{dem}(t) \]  \hspace{1cm} (5.2)

\[ p_{ice}(t) \leq p_{ice,max}(\omega_{ice}(t)) \]  \hspace{1cm} (5.3)

\[ p_{ele,min}(\omega_{ele}(t)) \leq p_{ele}(t) \leq p_{ele,max}(\omega_{ele}(t)) \]  \hspace{1cm} (5.4)

\[ SOC_{min} \leq SOC_t \leq SOC_{max} \]  \hspace{1cm} (5.5)

\[ |SOC_0 - SOC_n| \leq SOC_{th} \]  \hspace{1cm} (5.6)

where, \( m_f \) is the instantaneous fuel consumption, \( p_{ice,max}(\omega_{ice}) \) is the maximum power of the ICE at the output speed \( \omega_{ice} \), \( p_{ele,max}(\omega_{ele}) \) is the maximum power of the electric machine (motor mode) at the output speed \( \omega_{ele} \), \( p_{ele,min}(\omega_{ele}) \) minimum power of the electric machine, \( p_{dem} \) is the power demand of the vehicle, \( n \) is the length of the drive cycle, \( SOC_t \) is the SOC at the time, \( SOC_{min} \) is the lower SOC limit, \( SOC_{max} \) is the upper SOC limit and \( SOC_{th} \) is the allowable threshold for the deviation of end SOC from the initial SOC. Charge-sustaining constraint (5.6) ensures that the vehicle finishes the journey with sufficient battery energy for the next journey. Moreover, when \( SOC_{th} = 0 \), the problem becomes the hardest to be solved and satisfies ideal charge sustenance.
Chapter 5. An Iterative Approach Inspired by Hill-Climbing Heuristics for the Offline Power Management of Hybrid Electric Vehicles

5.3 Hill-Climbing Heuristics

Hill-climbing is a gradient free, random search optimization technique, which was first proposed for maximization problems as the name indicates. It starts with a feasible low quality solution (i.e. from the bottom of the hill) and evolves its solution by perturbing its current solution always in the direction of solution improvement (i.e., climbing the hill) until the best possible result is achieved (i.e., reaching the hilltop). Therefore, main steps of a hill-climbing algorithm can be summarized as,

**Step 1**: Initialization - generate a random solution initially and set it as the current solution

**Step 2**: Generation - generate new solution(s) by perturbing the current solution

**Step 3**: Evaluation - evaluate the current solution, update the current solution with the new solution if the new solution is better than the current solution otherwise stop.

According to the perturbation and solution updating mechanism, there are many variants of hill-climbing heuristics. These algorithms are popular due to their simple, efficient and straightforward implementation and they may sometimes yield competitive results [141]. However, due to the lack of capability to escape from local stagnation, hill-climbing heuristics are easily susceptible to trap in local optima. Therefore, they are combined with global optimization methods as local search algorithms [142, 143]. For instances, Al-kazemi and Mohan [144] combine hill-climbing with normal PSO to produce a highly robust PSO algorithm and the genetic algorithm is combined with hill climbing to produce memetic algorithm [145]. Here, I demonstrate successful use of hill-climbing heuristics as a global optimization method to solve the energy management problem of HEVs.
5.4 Hill-Climbing Power Management Strategy (HCPMS)

Any use of the battery during the power management of the HEV changes the SOC according to

\[ SOC_{k+1} = SOC_k + \Delta SOC_k. \]  

(5.7)

Here, \( \Delta SOC_k \) is the change of SOC during time interval (1s) at any \( k \in [1, n] \) and given by \( \Delta SOC_k = -p_{ele}(k)/[\eta_{ele}(k)\eta_{bat}(k)Q_{max}] \) if discharging i.e., \( p_{ele}(k) > 0 \) or \( \Delta SOC_k = -p_{ele}(k)\eta_{ele}(k)\eta_{bat}(k)/Q_{max} \) if recharging i.e. \( p_{ele}(k) < 0 \), where \( \eta_{ele} \) is the efficiency of the EMG and \( \eta_{bat} \) is the efficiency of the battery. The fuel consumption corresponding to the SOC change in (5.7) will be

\[ \dot{m}_f(k) = \frac{p_{dem}(k) - p_{ele}(k)}{\eta_{iec}(k)}. \]  

(5.8)

Let \( SOC = [SOC_1, SOC_2, ..., SOC_{n+1}] \) be the decision variable and \( M_f = [\dot{m}_f(1), \dot{m}_f(2), ..., \dot{m}_f(n)] \) be the output variable of the optimization problem. Clearly, by rewriting (5.2) and (5.4) as a function of \( SOC \), the power management problem can be represented in terms of \( SOC \). Finally, the optimum solution \( SOC^* \) for the power management problem is the \( SOC \) that satisfies all constraints and the following equation

\[ SOC^* = \arg \min_{[\Delta SOC_1, \Delta SOC_2, ..., \Delta SOC_{n+1}]} \left\{ \sum_{k=1}^{n} \dot{m}_f(k) \right\}. \]  

(5.9)

The calculation of the total fuel cost for an \( SOC \) with unbalanced final energy level i.e., \( SOC_1 \neq SOC_{n+1} \) requires a proper method to convert unbalanced final battery energy into equivalent fuel. With the presence of such a method, the fuel economy of a low quality \( SOC \) can be improved by searching for a better power split ratio by varying \( \Delta SOC_k \). This is the underlying concept of the HCPMS.

HCPMS starts with an initial feasible \( SOC \), which is then evolved towards the final solution according to the following procedure: a new feasible \( SOC \) is produced
Begin
  Initialize SOC vector
  Evaluate the initial SOC
Repeat
  Select a random dimension $k$ of the SOC
  Generate a new SOC:
    offset $SOC_{k+1}$, $SOC_{k+2}$... $SOC_n$ with respect to $SOC_k$
    by $\Delta$SOC satisfying constraints (2), (3) and (4)
  Evaluate the new SOC
  If the new SOC is better than the current SOC
    replace the current SOC
Until stopping condition satisfied
End

Figure 5.1: Hill-climbing power management strategy

from the current by perturbing $\Delta SOC_k$ at a randomly selected time $k$. The current SOC is replaced by the new SOC if the new SOC is better than the current one. Accordingly, the proposed HCPMS can be outlined as in Fig. 5.1. Three main components of the HCPMS can be identified as initialization, generation and evaluation.

5.4.1 Initialization

Variables $SOC$ and $M_f$ are initialized by running the vehicle with the ICE. Whenever the power demand exceeds the ICE’s maximum capacity (i.e. $p_{\text{ice}}(k) \leq p_{\text{ice, max}}(\omega_{\text{ice}}(k)))$, the ICE is operated at its maximum capacity while the balance of the power demand is supplied by the electric system. Therefore, the control rule for generating initial SOC is

$$
\begin{cases}
  p_{\text{ice}}(k) = p_{\text{dem}}(k), p_{\text{ele}}(k) = 0 & \text{if } p_{\text{dem}}(k) \leq p_{\text{ice, max}}(\omega_{\text{ice}}(k)) \\
  p_{\text{ice}}(k) = p_{\text{ice, max}}(\omega_{\text{ice}}(k)), p_{\text{ele}}(k) = p_{\text{dem}}(k) - p_{\text{ice}}(k) & \text{if } p_{\text{dem}}(k) > p_{\text{ice, max}}(\omega_{\text{ice}}(k))
\end{cases}
$$

(5.10)

5.4.2 Generation

A dimension $k$ of the current SOC is randomly selected. A new SOC is generated from the current SOC by offsetting all its dimensions after $k^{th}$ dimension (i.e.,
5.4 Hill-Climbing Power Management Strategy
(HCPMS)

$SOC_{k+1},SOC_{k+2},\ldots,SOC_{n+1}$ by $\Delta SOC_{k,new}$ generated stochastically. According to the SOC update Eq. (5.7), this perturbation method of HCPMS is equivalent to the change of energy split between the ICE and the battery at time $k$.

To secure the feasibility of the SOC, $\Delta SOC_{k,new}$ needs to be varied within the feasible region determined by constraints (5.3)-(5.5). As illustrated by Fig. 5.2, the feasible range of $\Delta SOC_{k,new}$ can be found with two limits, the feasible recharging capacity $\Delta SOC_{kchg}^*$ and the feasible discharging capacity $\Delta SOC_{kdis}^*$. These two quantities are determined by both instantaneous and future operational limits of components.

![Figure 5.2: Graphical representation of the generation of the new SOC from the current SOC](image)

As stated previously, Equs. (5.3) and (5.4) can be rewritten with respect to battery energy as follows;

$$0 < \Delta SOC_{k,new} \leq \Delta SOC_{kchg,max}$$  \hspace{1cm} (5.11)

$$\Delta SOC_{kdis,max} \leq \Delta SOC_{k,new} < 0$$  \hspace{1cm} (5.12)

where $\Delta SOC_{kchg,max}$ is the maximum instantaneous recharging capacity and $\Delta SOC_{kdis,max}$ is the maximum instantaneous discharging capacity. They can be
expressed as follows:

\[ \Delta SOC_{k,chg,max} = \min\left( p_{ice,max}(k) - p_{dem}(k), p_{gen,max}(k) \right) \eta_{gen} \eta_{bat} / Q_{max}. \] (5.13)

\[ \Delta SOC_{k,dis,max} = \left[ \min\left( p_{dem}, p_{mot,max}(k) \right) \right] / (\eta_{mot} \eta_{bat} Q_{max}). \] (5.14)

Here, \( p_{mot,max} \) is the maximum power of the electric driver in motor mode and \( p_{gen,max} \) is the maximum power in the generator mode. From (5.5), the future recharging capacity \( \Delta SOC'_{k,chg,max} \) is determined by the smallest gap between the upper limit of the battery energy, \( SOC_{max} \) and the highest level of the future trace. Therefore,

\[ \Delta SOC'_{k,chg,max} = \min [SOC_{max} - SOC(t)] \quad \text{for } \forall t \in [k, n + 1] \] (5.15)

Similarly, the future discharging capacity is the smallest gap between the lower safe charge level of the battery and the lowest level of future trace and given by

\[ \Delta SOC'_{k,dis,max} = \min [SOC(t) - SOC_{min}] \quad \text{for } \forall t \in [k, n + 1] \] (5.16)

The feasible recharging capacity is the smallest value of the instantaneous and future recharging capacities. Therefore,

\[ \Delta SOC^*_{k,chg,max} = \min(\Delta SOC_{k,chg,max}, \Delta SOC'_{k,chg,max}) \] (5.17)

Similarly, the feasible discharging capacity is the smallest value of the instantaneous and future discharging capacities. Thus,

\[ \Delta SOC^*_{k,dis,max} = \min(\Delta SOC_{k,dis,max}, \Delta SOC'_{k,dis,max}) \] (5.18)

Finally, with the known feasible range of \( \Delta SOC_{k,new} \), the current \( SOC \) is perturbed stochastically according to

\[ \Delta SOC_{k,new} = c \Delta SOC^*_{k,chg,max} + (1 - c) \Delta SOC^*_{k,dis,max} \] (5.19)
where, \( c \) is a random number generated under beta distribution \( \text{Beta}(0.4, 1) \). The selection of beta distribution is argued by the fact that \( \Delta SOC^*_{k,chg,max} \gg \Delta SOC^*_{k,dis,max} \) at frequent small power demands compared to the full capacity of the ICE. Alternatively, the uniform distribution can be used with increased discharged range by multiplying \( \Delta SOC^*_{k,dis,max} \) with a factor like 1.2 and accepting only feasible \( \Delta SOC_{k,new} \). Both methods are compared in Section 5.5. Then a new \( SOC \) is generated from \( \Delta SOC_{k,new} \) by updating the current \( SOC \) according to (5.7). Since the generation process changes the energy split only at one dimension, the current \( M_f \) is changed only at that dimension to generate new \( M_f \).

### 5.4.3 Evaluation

Here, an objective function for evaluating the \( SOC \) is developed. The overall fuel consumption is the sum of all elements of \( M_f \). The charge sustenance in constraint (6) may be achieved by adding a proper penalty function to the objective function. In order to penalize the deviation of the initial charge level from the initial level, a penalty cost function can be defined as,

\[
m_{f,\text{equ}} = \lambda [SOC(1) - SOC(n + 1)]
\]  

where, \( m_{f,\text{equ}} \) can be interpreted as the equivalent fuel required to compensate the drained battery energy or saved in the charged battery. As explained in Section 4.3.2, the equivalent factor \( \lambda \) depends on the energy flow path of the future energy compensation. By referring to Section 4.3.2, \( \lambda \) is approximated to different values depending on the final status of the battery by

\[
\lambda = \begin{cases} 
\lambda_{\text{dis}} = 1/(\bar{\eta}_{\text{ice}}\bar{\eta}_{\text{ele}}) & \text{SOC}_1 < \text{SOC}_{n+1} \\
\lambda_{\text{chg}} = \bar{\eta}_{\text{ele}}/\bar{\eta}_{\text{ice}} & \text{else}
\end{cases}
\]

where \( \bar{\eta}_{\text{ice}} \) is the average efficiency of the ICE and \( \bar{\eta}_{\text{ele}} \) is the average efficiency of the electrical system.

Moreover, the stochastic evolving process described above causes the ICE to
stop and start frequently. Physically, frequent starting and stopping of the ICE has negative effects on both fuel consumption and emissions. Therefore, a penalty fuel cost $\dot{m}_{f,\text{st}}$ is added to the objective function to reduce the frequent starting and stopping of the ICE as

$$\dot{m}_{f,\text{st}}(k) = \alpha [T_{\text{ice}}(k) - T_{\text{ice}}(k - 1)] + |T_{\text{ice}}(k + 1) - T_{\text{ice}}(k)|$$ (5.22)

where $T_{\text{ice}}$ is the torque of the ICE.

The addition of all fuel costs together makes the objective function of HCPMS as

$$M_{\text{SOC}} = \sum_{t=1}^{n} \dot{m}_{f}(t) + \sum_{t=1}^{n} \dot{m}_{f,\text{st}}(t) + m_{f,\text{equ}}$$ (5.23)

During the solution update, the current $\text{SOC}$ is replaced with the new $\text{SOC}$ if the objective value of the new $\text{SOC}$ is smaller than that of the current $\text{SOC}$.

## 5.5 Results

### 5.5.1 Parameter Selection

![Figure 5.3: Variation of the fuel consumption of the HEV for different $\lambda_{\text{dis}}$ and $\lambda_{\text{chg}}$ over FTP-75](chart)

Figure 5.3: Variation of the fuel consumption of the HEV for different $\lambda_{\text{dis}}$ and $\lambda_{\text{chg}}$ over FTP-75
5.5 Results

Before generating main results, numerical values for strategy parameters are selected. Value of $\lambda_{\text{dis}}$, $\lambda_{\text{chg}}$ and $\alpha$ needs to be precisely defined for the best performance of the HCPMS. Fig. 5.3 shows the fuel consumption of the HEV for different $\lambda_{\text{dis}}$, $\lambda_{\text{chg}}$. It can be seen that best values for $\lambda_{\text{dis}}$ and $\lambda_{\text{chg}}$ are respectively 3.0 and 2.5. Best $\alpha$ for maintaining the low frequent ICE stops and starts is 0.003.

![Figure 5.4: Fuel convergence curves for perturbations based on the beta (solid line) and uniform (dotted line) distributions on FTP-75. Corresponding minimum fuel consumptions achieved by each method is shown.](image)

Moreover, selection of beta and uniform distributions depends on the required rate of convergence and quality of the results. Fig. 5.4 shows the convergence curves of the HCPMS when the solution is perturbed by the beta distribution and uniform distribution for FTP-75. It can be seen that the uniform distribution has a fast convergence rate; however, beta distribution achieves a slightly better fuel saving over the uniform distribution.

5.5.2 Main Results

The HCPMS was simulated on the parallel HEV model for different drive cycles. The results are compared with respect to DP and ECMS over the different drive cycles in Tables 5.1 and 5.2. Fuel consumption, the percentage deviation of the final and initial
energy of the battery and the computational time are the considered performance measures. The SOC grid of size 500 J is used for DP. Fuel consumptions of all EMSs are corrected equally by the correction procedure in Chapter 3.2.7 when the final and initial energy levels are different. For the battery, the following variable setup was used. $SOC_{min} = 0.40$, $SOC_{max} = 0.80$ and the initial $SOC = 0.60$. Furthermore, the fuel consumptions of the HEV are compared with those of a conventional vehicle with power equal to the HEV.

Table 5.1: Comparison of the fuel consumptions ($L/100km$) of the HCPMS, the DP and the ECMS for different driving cycles

<table>
<thead>
<tr>
<th>Drive Cycle</th>
<th>Fuel (L/100km)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DP</td>
</tr>
<tr>
<td>NEDC</td>
<td>3.90</td>
</tr>
<tr>
<td>FTP-75</td>
<td>3.65</td>
</tr>
<tr>
<td>AUDC</td>
<td>3.64</td>
</tr>
<tr>
<td>HWFET</td>
<td><strong>3.98</strong></td>
</tr>
</tbody>
</table>

Table 5.2: Comparison of the percentage deviation of the final state of charge from the initial level (0.6) (%) and the computational time (s) of HCPMS, DP and ECMS for different driving cycles.

<table>
<thead>
<tr>
<th>Drive Cycle</th>
<th>Percentage of final SOC deviation (%)</th>
<th>Computational time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DP</td>
<td>ECMS</td>
</tr>
<tr>
<td>NEDC</td>
<td>0</td>
<td>+1.0</td>
</tr>
<tr>
<td>FTP-75</td>
<td>0</td>
<td>-1.8</td>
</tr>
<tr>
<td>AUDC</td>
<td>0</td>
<td>-4.5</td>
</tr>
<tr>
<td>HWFET</td>
<td>0</td>
<td>-3.8</td>
</tr>
</tbody>
</table>

Results show that HCPMS performs better than DP over city cycles and the same as the DP over highway cycles. Due to the descritization errors, DP has less control over the ICE stop starts. Therefore, DP’s fuel economy is slightly poorer than the HCPMS for city driving. Furthermore, this fuel performance HCPMS is further strengthened by the much lower computational time compared to the DP. Similar to the DP, the HCPMS also satisfies the end-charge sustenance perfectly. In comparison to the ECMS, the HCPMS outperforms the ECMS in fuel consumption and the final charge sustenance. Despite the higher computational time compared
5.5 Results

Figure 5.5: Output result of the SOC of DP, ECMS and HCPMS over FTP-75

to the ECMS, the HCPMS avoids the requirement of parameters tuned separately to each drive cycle like the ECMS.

The SOC controlling results of the three strategies for FTP-75 is shown in Fig. 5.5. HCPMS controls the SOC during driving properly similar to benchmark controllers. It also achieves the end-charge sustenance perfectly similar to the DP whereas the ECMS fails to do so.

Figure 5.6: Comparison of the torque output of the ICE for the DP and the HCPMS over FTP-75
Chapter 5. An Iterative Approach Inspired by Hill-Climbing Heuristics for the Offline Power Management of Hybrid Electric Vehicles

Fig. 5.6 shows the speed-torque profile of the engine of the DP and the HCPMS over FTP-75. It can be seen that both methods control the ICE in a similar way to achieve their best results. Due to the discretization errors, very small torque can be seen for the DP representing less controllability of the ICE stops and starts. This behavior is neglected in calculating the starting fuel costs for the DP. The similarly of the control of the ICE by the HCPMS and the DP is further seen by Fig. 5.7 in which the operating points of the ICE are compared for both strategy on the speed-torque plane.

Another advantage of the HCPMS is that it can refine solutions of the other methods given their results as initial solutions. Table 5.3 shows the results of DP and ECMS improved by HCPMS. It can be seen that HCPMS improves solutions up to 1.5% for both DP and ECMS. The results of the DP may be improved because of discretization errors while those of the ECMS may be due to poor optimality.

This can be further observed by the SOC trajectory of DP and ECMS after refining with HCPMS as shown in Fig. 5.8. It shows the considerable deviation of ECMS’s SOC curve after refinement with the adjustment of final charge sustenance.
Figure 5.8: Comparison of the SOC results of the DP and ECMS after refining of
with the HCPMS over the FTP-75

(a) DP results improved by the HCPMS

(b) ECMS's results improved by the HCPMS
Table 5.3: Improvement of DP’s and ECMS’s fuel performance by using HCPMS

<table>
<thead>
<tr>
<th>Drive Cycle</th>
<th>Fuel Consumption (L/100km)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HCPMS$_{DP}$</td>
</tr>
<tr>
<td>NEDC</td>
<td>3.84</td>
</tr>
<tr>
<td>FTP-75</td>
<td>3.61</td>
</tr>
<tr>
<td>AUDC</td>
<td>3.60</td>
</tr>
<tr>
<td>HWFET</td>
<td>3.98</td>
</tr>
</tbody>
</table>

As revealed by offline PMSs, the parallel HEV consumes only 3.61 L/100km fuel over AUDC compared to 6.32 L/100km of fuel consumption of the conventional vehicle, demonstrating up to 42.9 % of fuel saving potential of HEVs on city driving compared to the conventional vehicle. Fuel saving of the HEV in highway driving is 18.8%, which is entirely due to the proper management of positive power between the ICE and the EMG because there is not much energy wasted due to braking and idling.
6.1 Introduction

In this chapter, a new online power management strategy for parallel full HEVs is introduced. Previously discussed offline strategies such as DP [61] and HCPMS [146] can successfully optimize parallel full HEVs and produce optimal or near-optimal results. However, the requirement of the complete journey information in advance hinders them applying in real-world HEV power management.

In contrast, online strategies consider day-to-day driving situations, where the complete journey information is not available in advance. Online power flow control of parallel full HEVs to achieve their full fuel saving capability is a difficult task since the power flow controller requires handling inefficiencies of both the EMG and the ICE equally against counteracting power management objectives. Without knowing the future driving conditions, achieving these objectives against randomly varying power demand is more tough. Most of the existing online PMSs use the general knowledge of the overall physical behavior of the powertrain for the power management. They are based on the concept of “power balancing”, which refers to
the distribution of the vehicle’s instantaneous power demand among power sources so that the overall efficiency is maximized or the best rate of fuel use is maintained [10]. Online power balancing strategies implemented by using fuzzy logic [68], neuro-fuzzy networks [69–71], rule-based control techniques [63] and power follower control strategies [72] are capable of well optimizing mildly hybridized parallel HEVs. However, they may not achieve a good fuel efficiency when compared with offline solutions in full hybrid applications because of their inability to handle inefficiencies of both the engine and electric system while achieving other power flow control objectives [22].

The proposed online power balancing strategy (PBS) for achieving near-optimal fuel efficiency on parallel full HEVs relies on the concept of using the electric system to control the ICE within the operating region around the point of the highest efficiency (peak-efficiency region). This work also shows how to identify the peak-efficiency region of the ICE as a function of the overall efficiency of the electric system. It will be demonstrated how to meet objectives such as proper regulation of the SOC and maintenance of low number of starting and stopping of the ICE events by directly controlling ICE energy output. The role of electrical system in power management will also be investigated by proposing a new HEV consisting of an electrical system with improved overall efficiency.

6.2 Online Power-Balancing problem of the HEV

In this Section, an analytical expression is derived for the energy demand of the ICE for a driving segment and the power balancing problem of the HEV is analyzed based on the electric system’s counteracting effects on the energy demand on the ICE and its efficiency (fuel conversion). Power flow from power sources to the wheels is called positive, and the reverse is called negative.

The total fuel consumed by an ICE to propel a vehicle over a certain driving segment depends on the energy demand on the ICE and its efficiency. For a conventional vehicle, the total energy demand on the ICE is the sum of the positive energy demand and the total energy losses through the power transmission system. For an
Figure 6.1: Variation of HEV’s power demand along the represented driving segment. Area under the positive power demand curve is the positive energy demand. Kinetic energy of the vehicle is partially dissipated due to irreversible resistances and the limited capacity of regenerative braking system

HEV, it depends on the energy losses in different energy flow paths, regenerative braking energy captured and the energy contribution of the battery to the total power demand.

Figure 6.2: Power flow of the HEV powertrain during discharge and recharge modes

When meeting positive power demand, the battery can be either in recharge or discharge. The power flow diagrams for these two cases are shown in Fig. 6.2. In both modes, the sum of thermal and electric power flows should be equal to the
power demand if the braking energy losses are neglected. Therefore, the energy balance of the system in discharge mode is given by

\[ p_{\text{ice,dis}},m(t) + p_{\text{dis}}(t) = p_{\text{dem,dis}},m(t), \]  

(6.1)

where \( p_{\text{ice,dis}},m \) is the ICE power output, \( p_{\text{dem,dis}},m \) is the vehicle power demand and \( p_{\text{dis}} \) is the power output from the electric system in discharge mode. Similarly, the energy balance for the recharge mode can be written as

\[ p_{\text{ice,chg}},m(t) - p_{\text{chg}}(t) = p_{\text{dem,chg}},m(t), \]  

(6.2)

where \( p_{\text{ice,chg}},m \) is the ICE power output, \( p_{\text{dem,chg}},m \) is the power demand and \( p_{\text{chg}} \) is the power flow into the electric system in recharge mode. By integrating (6.1) and (6.2) for the complete driving schedule and adding them together, By neglecting the braking energy losses, the relationship between the energy contributions of power sources, and the energy demand for the complete driving segment can be obtained as

\[ E_{\text{ice}} + E_{\text{dis}} - E_{\text{chg}} = E_{\text{dem}}^+, \]  

(6.3)

where \( E_{\text{ice}} \) is the ICE energy output, \( E_{\text{dem}}^+ \) is the total positive energy demand and \( E_{\text{dis}} \) is the energy output of the electric system in discharging and \( E_{\text{chg}} \) is the energy input to the electric system in recharging.

The net change of the internal battery energy over \( t_p \) driving period \( E_{\Delta \text{ess}} \) is equal to the sum of the total energy during discharging, recharging and regenerative braking, thus

\[ \Delta E_{\text{ess}} = \int_{t_p} p_{\text{dis}}(t)\eta_{\text{dis}}(t)dt - \int_{t_p} p_{\text{chg}}(t)\eta_{\text{chg}}(t)dt - \int_{t_p} p_{\text{reg}}(t)\eta_{\text{chg}}(t)dt, \]  

(6.4)

where \( t_p \) is the driving period, \( p_{\text{reg}} \) is the mechanical power input to the generator during regenerative braking and \( \eta_{\text{dis}} \) and \( \eta_{\text{chg}} \) are the instantaneous efficiencies of the electrical system during discharging and recharging respectively.
Let us assume that the variation of the discharging and recharging efficiencies of the electric system with its operating conditions is negligible. This is a reasonable assumption for the new vehicle model presented in Section III. Therefore, (6.4) may be approximated as

$$\Delta E_{ess} = \frac{E_{dis}}{\bar{\eta}_{dis}} - \bar{\eta}_{chg} E_{chg} - \bar{\eta}_{chg} E_{reg}$$

where $\bar{\eta}_{dis}$ and $\bar{\eta}_{chg}$ are the average efficiencies of discharge and recharge electrical paths respectively. By combining (6.3) and (6.5), energy balance of the powertrain can be expressed as

$$E_{ice} + E_{\Delta soc} = E_{dem}^+ - E_{reg} + E_{ele,loss},$$

where $E_{ele,loss} = \left[\frac{1}{\bar{\eta}_{dis} \bar{\eta}_{chg}} \right] - 1$ is the electrical energy losses and $E_{\Delta soc} = \Delta E_{ess} / \bar{\eta}_{chg}$ is the energy contribution from the battery. Equation (6.6) may be extended to estimate the actual driving energy demand on the ICE. In this case, the charge sustenance should be satisfied by correcting the change of the final battery energy. For instance, the ideal charge sustenance is achieved when $E_{\Delta ess} = 0$. By using (6.6) and neglecting the additional electrical energy losses in achieving the charge sustenance, actual driving energy demanded at the ICE output of the HEV can be approximated as

$$E_{ice,cs} = E_{dem}^+ - E_{reg} + E_{ele,loss} + E_{\Delta soc}.$$  

Equation (6.7) will be further extended in section 6.4 to estimate energy demand on the ICE in online driving. Total fuel energy consumption of the ICE ($E_{fuel}$) to produce $E_{ice,cs}$ can be calculated as follows:

$$E_{fuel} = \int_{t_p} p_{ice}(t) / \eta_{ice}(t) dt \approx \frac{E_{ice,cs}}{\bar{\eta}_{ice}},$$

where, $\eta_{ice}$ is the instantaneous efficiency, $P_{ice}$ is the power output and $\bar{\eta}_{ice}$ is the average efficiency of the ICE.
Equations (6.7) and (6.8) reflect the efficiency improvement version of the power-balance problem. Improving the overall ICE efficiency \( \bar{\eta}_{\text{ice}} \) by using the electrical system in power balancing will reduce fuel consumption, but (6.7) shows that the additional ICE load due to electrical losses will counteract the fuel saved from power balancing. Improving the regenerative energy capture will reduce the fuel consumption. It follows that HEV power balancing needs to use the electrical system effectively to improve ICE efficiency and regenerative energy capture.

### 6.3 Integrated Starter Generator-assisted Parallel Hybrid Electric Vehicle

Inefficiencies of the EMG in useful operating conditions on both motoring and generating modes is a disadvantage for the parallel HEV [22]. As stated earlier, this may also increase the complexity of the power-flow controller. To reduce inefficiencies due to load incompatibility, we downsize the EMG and integrate it with an integrated starter generator (ISG) while maintaining the same driving capacity for the electrical system. We call this new vehicle a parallel hybrid electric vehicle assisted by an integrated starter generator (ISG-assisted PHEV). The new vehicle will increase the fuel-saving capacity of the PBS controller because of the widened peak-efficiency region of the electrical system. Improved efficiency of the electrical system also means more energy recovery from regenerative braking [147]. The architecture of the ISG-assisted PHEV and the control of the EMG and ISG are explained here.

#### 6.3.1 ISG

The ISG is emerging as a low-cost fuel-saving technology in vehicles [148]. In addition to its conventional alternator functions, it fulfills some functional requirements of mild hybrid systems including starting the stopped ICE, driving the vehicle when starting, driving the auxiliaries when the ICE is stopped, and regenerative braking [11]. Supporting the ICE during acceleration is also possible with ISG technology [149]. The power-flow control of fully hybridized parallel HEVs in this work will
become a new application of ISGs.

### 6.3.2 Architecture of the ISG-assisted PHEV

Fig. 6.3 shows the schematic diagram of the ISG-assisted PHEV. The EMG and ISG powered by the battery are connected parallel to the electric power splitter. The ISG also connects with the ICE and serves as the starter. The central power splitter splits driving demand between the ICE and electrical system, as commanded by the PBS controller. The electric power splitter distributes the electrical load between the EMG and the ISG according to the strategy described in Section 6.3.3.

#### 6.3.3 The Electric Power Splitter

The EMG and ISG are controlled to achieve the highest efficiency of the electrical system when responding to any power demand (positive or negative). Power flow through electric components is illustrated by Fig. 6.4. Let the electric power-split ratio $u_e$ be the controlling variable, defined by

$$u_e(t) = \frac{p_{isg}(t)}{p_{ele}(t)},$$  \hspace{1cm} (6.9)
where $p_{\text{isg}}$ is the contribution of the ISG to the electrical power demand $p_{\text{ele}}$. The power contribution from the EMG $p_{\text{emg}} = (1 - u_e)p_{\text{ele}}$. $u_e = 0$ means that the total contribution is from the EMG, while $u_e = 1$ indicates that the total contribution is from the ISG. For any $p_{\text{ele}}$, $u_e$ is varied between lower limit $u_{\text{e,min}}$ and upper limit $u_{\text{e,max}}$. These limits are imposed by operational capacities of the EMG and ISG.

The optimal split ratio $u_e^*$ is the $u_e$ that maximizes the overall electrical efficiency, given by:

$$u_e^*(t) = \arg\max_{u_e \in [u_{\text{e,min}}, u_{\text{e,max}}]} \left\{ \frac{p_{\text{ess}}(u_e,t)\eta_{\text{ess}}^k(p_{\text{ess}})}{p_{\text{ele}}(t)} \right\}^k$$

(6.10)

where $p_{\text{ess}}(u_e,t) = (p_{\text{isg}}(u_e,t)\eta_{\text{isg}}^k + p_{\text{emg}}(u_e,t)\eta_{\text{emg}}^k)$, $\eta_{\text{ess}}$ is the efficiency of the battery, $\eta_{\text{emg}}$ is the efficiency of the EMG and $\eta_{\text{isg}}$ is the efficiency of the ISG. $k = -1$ in discharge and $k = 1$ in recharge.

### 6.4 Online Power Balancing Strategy

In this Section, we present the proposed online power balancing strategy.

By following the power-balancing problem formulated in Section 6.2, the main concept of the PBS is to shift the inefficient operating points of the ICE toward its point of the highest efficiency by effectively using the electrical system. The use of
the electrical system in power balancing causes fluctuation of the SOC. To prevent the battery from overcharging and overdischarging, the SOC should be regulated within prescribed safe limits, which is also necessary to maintain the driveability of the vehicle. To avoid charging the battery between journeys, the PBS controller should also be capable of managing the SOC at the end of the journey close to the target SOC (i.e., final charge sustenance). Additionally, during the power-balancing process, infrequent ICE stopping and restarting is advisable to avoid unnecessary energy losses.

Thus, the underlying tasks of the PBS controller can be summarized as here.

- Vehicle power demand is always satisfied.
- Power demand is distributed between the ICE and the electric system so that the ICE operates in its best operating region.
- SOC is maintained within ESS limits and the final charge sustenance is achieved.
- The minimum possible ICE stops and restarts is maintained.

Figure 6.5 shows the architecture of the overall power splitting system of the ISG-assisted PHEV powertrain including all inputs and outputs of PBS controller, central power splitter and the electric power splitter. The PBS controller is the main controller, which coordinates sub-level component controllers according to its power

![PBS controller diagram](image-url)

Figure 6.5: Architecture of the overall power split system of the ISG-assisted PHEV powertrain

- $T_{dem}$ - torque demand
- $\omega$ - speed demand
- $SOC$ - state of charge
- $e$ - ICE on-off status
- $\Delta T$ - torque split
- $u_e$ - electric power split ratio
- $T_{ele}$ - torque contribution from electric system
- $T_{ice}$ - ICE torque
- $T_{emg}$ - EMG torque
- $T_{isg}$ - ISG torque
splitting strategy. At each time instant, the PBS controller determines the torque split $\Delta T$ and electric power split ratio $u_e$ by using inputs of torque demand $T_{dem}$, speed demand $\omega$, SOC and current ICE on/off status $e$. $T_{dem}$, $\omega$ are calculated from the drive cycle by using the backward simulation with assumed quasi-static motion. It should be noted that the speeds of prime movers are not changeable because of their direct connection to wheels through the transmission system. Therefore, the power split is achieved by changing the torque outputs of prime movers without changing their speeds. The signal $\Delta T$ is sent to the central power splitter, which splits $T_{dem}$ into the ICE torque $T_{ice}$ and the torque contribution to the $T_{dem}$ by the electric system $T_{ele}$. The electric power splitter splits $T_{ele}$ between the EMG and the ISG as determined by the PBS controller with $u_e$.

Before developing the PBS controller, important operating characteristics of the ICE, EMG and ESS should be identified. From the efficiency map of the battery in Fig. 3.10, it can be seen that overall the discharging and charging efficiencies of the battery is high. The efficiency map of the hybridized two electric drivers resulting from (6.10) also shows that the hybridization of drivers has significantly improved the efficiency characteristics over the individual drivers. Therefore, we neglect the efficiency variation of the electrical system with its load in designing the PBS controller.

### 6.4.1 Peak-Efficiency Region of the ICE

Figure 6.6 shows a typical efficiency map of an ICE on speed-torque plane. The maximum torque curve represents the highest ICE torque achievable for any speed. Let $\eta_{ice}(\omega, T_{ice})$ represent the efficiency at any ICE operating point $(\omega, T_{ice})$. Dashed lines show constant efficiency contours, where their values increasing towards inner contours. The convergent point of efficiency contours is the operating point with the highest efficiency $\eta_{ice}^{opt}(\omega, T_{ice}^{opt})$ achievable from the ICE. The efficiency on the optimal torque curve $(T_{ice}^{opt}(\omega))$ is the maximum efficiency achievable at a particular speed $\omega$ within the maximum torque envelope.

Any operating point of the ICE may be shifted toward the point of highest efficiency with power balancing. The amount of fuel thus saved depends on electrical
6.4 Online Power Balancing Strategy

Figure 6.6: Important operating regions and characteristic curves of the ICE. Peak-efficiency region is bounded by two speed limits $\omega_L$ and $\omega_H$ and two torque limits $T_L(\omega)$ and $T_H(\omega)$.

Energy loss. As stated in (6.6), electrical energy loss has two parts: loss of the forward path during the shifting process and the loss of the reverse path, through which the unbalanced energy of the battery due to the shifting process will be rectified in future. The efficiency improvement of the ICE will be fuel beneficial only if the energy saved on the ICE is greater than the total electrical energy loss. Therefore, ICE-alone operation is fuel efficient within an operating region around the point of the highest efficiency. We identify this operating region as the peak-efficiency region indicated by the shaded area of the ICE map in Fig. 6.6. It can be defined by the operating region $T_L(\omega) \leq T_{ice}(\omega) \leq T_H(\omega)$ and $\omega_L \leq \omega \leq \omega_H$, where $T_L(\omega)$ is the lower torque boundary, $T_H(\omega)$ is the upper torque boundary, $\omega_L$ is the lower speed limit and $\omega_H$ is the upper speed limit of the peak-efficiency region. The two torque boundaries and speed limits are given by the operating points that satisfy the following equations:

$$T_L(\omega) := \eta_{ice}(\omega, T_L(\omega)) = \frac{\eta_{ice}^*(\omega)}{T_{ice}^*(\omega)} \left[ T_L(\omega) + (T_{ice}^*(\omega) - T_L(\omega))\eta_{dis}\eta_{chg} \right]$$

$$T_H(\omega) := \eta_{ice}(\omega, T_H(\omega)) = \frac{T_{ice}^*(\omega)\eta_{ice}^*(\omega)\eta_{dis}\eta_{chg}}{[\eta_{opt}(T_{ice}(\omega) - T_{ice}^*(\omega)) + T_{ice}^*(\omega)\eta_{dis}\eta_{chg}]}$$

$$\omega_L := \eta_{ice}(\omega_L, T_{ice}^*(\omega_L)) = \frac{\eta_{ice}^*(\omega_L)}{p_{ice}^*(\omega_L)} \left[ \eta_{opt}(p_{ice} - p_{ice}^*(\omega_L))\eta_{dis}\eta_{chg} + p_{ice}^*(\omega_L) \right]$$
\[ \omega_H := \eta_{\text{ice}}(\omega_H, T_{\text{ice}}^*(\omega_H)) = \frac{p_{\text{ice}}^*(\omega_H)\eta_{\text{ice}}^{\text{opt}}\eta_{\text{dis}}\bar{\eta}_{\text{chg}}}{p_{\text{ice}}^*(\omega_H) - p_{\text{opt}}^{\text{ice}} + p_{\text{ice}}^{\text{opt}}\eta_{\text{dis}}\bar{\eta}_{\text{chg}}} \] \tag{6.14}

where \( p_{\text{ice}}^{\text{opt}} \) and \( \eta_{\text{ice}}^{\text{opt}} \) are respectively power and the efficiency at highest ICE efficiency point. The concept behind the formulations of (6.11)-(6.14) is explained in Appendix A.3. Shifting the ICE operation into the peak-efficiency region through power balancing will save fuel, only when it operates outside the peak-efficiency region. The best targeted operating point in this case is the point on the optimal torque curve corresponding to the speed demand. Therefore, we argue that the peak-efficiency region of the ICE powering the PHEV is determined by the performance of the electric system. For example, with a highly efficient electric system, the ICE can be controlled closer to the operating point of highest efficiency, leading to a smaller peak-efficiency region.

### 6.4.2 Power Balancing Rules

With the knowledge of important operating characteristics of the ICE and other components, derivation of power balancing rules is now possible. At any speed, operating torque of the ICE is determined by

\[ T_{\text{ice}} = T_{\text{dem}} + \Delta T, \] \tag{6.15}

where \( \Delta T \) is the change of torque at the ICE output from the torque demand \( T_{\text{dem}} \). From the energy balancing relationship of the powertrain, output torque of the electric system \( T_{\text{ele}} \) relative to the ICE output shaft is

\[ T_{\text{ele}} = -\Delta T. \] \tag{6.16}

Modes of the vehicle can be described from the value of \( \Delta T \) here.

- \( \Delta T = T_{\text{dem}} \) - pure electric mode
- \( 0 < \Delta T < T_{\text{dem}} \) - hybrid mode
- \( \Delta T = 0 \) - pure thermal mode
6.4 Online Power Balancing Strategy

- $\Delta T < 0$ - recharge mode

As described earlier, the PBS controller aims to operate the ICE within its peak-efficiency region. Two instances that hinder from operating the ICE within its peak-efficiency region are high torque demand and low SOC.

At high torque demands: When $T_{dem}$ exceeds the sum of the maximum electric torque capacity $T_{ele, max}$ and optimum ICE torque (i.e., $T_{dem} > T_{ice}^*(\omega) + T_{ele, max}$), the electric system is operated at maximum capacity while balance of energy is assigned to the ICE, i.e., $\Delta T = -T_{ele, max}$. If $T_{dem}$ exceeds the sum of the maximum torque capacities of the ICE, the EMG and the ISG, then gear downshifting is pursued to the points where all systems are close to or at their maximum power.

At low SOC conditions: Low battery energy is identified by the reference level $SOC_{Low}$. When the SOC falls below $SOC_{Low}$, the battery should be quickly recharged to its normal level. Therefore, the battery is recharged by the ICE with the maximum possible recharging capacity. Thus, the power balancing rule when $SOC(t) < SOC_{Low}$ is $\Delta T = T_{ice, max} - T_{dem}$. The resulting recharging at high ICE torque may deteriorate the overall fuel economy. However, the negative effect of this inefficient recharging may be reduced by setting the $SOC_{Low}$ such that the occurrence of low SOCs and the recharging duration are minimal. We find the best value of $SOC_{Low}$ for our vehicle model is 0.42.

Outside the above two cases, the following rules are designed to minimize fuel consumption.

Outside the optimal speed range ($\omega < \omega_L$, $\omega > \omega_H$): At low speeds ($\omega < \omega_L$) and high speeds ($\omega > \omega_H$), operating the ICE is uneconomical. The latter event is unlikely to occur because such high speed during only way occur if there is no road speed limit. Therefore, the pure electric mode is activated by assigning the total power demand to the electrical power sources while the ICE is stopped, i.e., $\Delta T = -T_{dem}$.

Within the optimal speed range ($\omega_L \leq \omega \leq \omega_H$): When the ICE operates within the optimal speed range, it can be controlled within its peak-efficiency region by a proper $\Delta T$. The value of $\Delta T$, and therefore the vehicle mode, is determined by comparing $T_{dem}$ with $T_L$ and $T_H$. 
1. When $T_{dem}(\omega) > T_H(\omega)$: The ICE is operated at the point of optimal torque by activating the hybrid mode. Thus, $\Delta T = T_{icem}(\omega) - T_{dem}(\omega)$

2. When $T_L(\omega) \leq T_{dem} \leq T_H(\omega)$: Since operating the ICE alone within the peak-efficiency region is economical, the pure thermal mode is activated. Thus, $\Delta T = 0$

3. When $T_{dem}(t) < T_L(\omega)$: Operating the ICE within the low torque region is uneconomical. It is avoidable either by activating the pure electric mode or the recharging mode so that the ICE can operate in its peak-efficiency region.

Pure electric and recharging modes affects the battery energy and fuel consumption completely oppositely. The recharge mode consumes fuel; however, improvement of the SOC will secure drivability of the electric system. Moreover, an overcharged battery may waste energy from future regenerative braking. On the other hand, the pure electric mode consumes only battery energy; therefore, zero fuel. Besides, the reduction of the SOC below $SOC_{Low}$ may cause drivability issues in future driving.

Accordingly, power balancing at low torque demands within the optimal speed range requires a switching strategy to select the vehicle mode between the pure electric mode and the recharge mode. This strategy should maintain expected goals such as optimality of fuel consumption results, satisfying SOC constraints and avoiding frequent stopping and restarting of the ICE. In the following sub section, we define a reference variable which is used to directly control the energy production of the ICE to meet all these requirements.

### 6.4.3 Driving Style Based Battery Recharge

The energy demand on the ICE for an incomplete driving segment $E'_{icem}$ can be expressed by rewriting (6.7) as follows:

$$E'_{icem}(t) = E'_{dem}(t) - E_{reg}(t) + E_{ele,loss}(t) + E_{\Delta SOC}(t). \quad (6.17)$$
All ‘E’ terms in (6.17) represent the cumulative energy quantities from the start of the journey to the current time instant ‘t’.

As stated in (6.6), by controlling the ICE’s energy output with reference to the ICE energy demand calculated in (6.17), SOC can indirectly be controlled around its reference level. However, (6.17) does not consider the reduction of the energy demand on the ICE due to the energy recovery from the future regenerative braking energy. Therefore, (6.17) may not satisfy the end SOC constraint (or charge sustainability). To achieve the charge sustainability of (6.17), reduction of the ICE demand due to the energy recovered from immediate future regenerative braking should be considered. Let $\Delta E_{\Delta \text{soc}}$ be the reduction of the ICE’s energy demand due to the change of SOC from the immediate future regenerative braking. For a braking event with constant deceleration, $\Delta E_{\Delta \text{soc}}$ is a function of the following parameters:

- speed of the vehicle ($v_{rb,s}$) just before brake is applied, which determines the stored kinetic energy of the vehicle;
- deceleration ($d$) during braking, which characterizes the irreversible losses during braking and the energy losses due to the maximum capacity of regenerative braking system,
- charging efficiency of generators
- charge acceptance and charging efficiency of the ESS

From the simplified dynamics of the braking event with zero final speed of the vehicle, $\Delta E_{\Delta \text{soc}}$ can be approximated by,

$$\Delta E_{\Delta \text{soc}}(t) \approx \lambda(v_{rb,s}, d)\bar{\eta}_{\text{ess,chg}} m v_{rb,s}^2(t)/(2\bar{\eta}_{\text{chg}}),$$

(6.18)

where $m$ is the vehicle mass, $\bar{\eta}_{\text{ess,chg}}$ is the average recharging efficiency of the battery calculated by using immediate past information and $\lambda$ is the fraction of electrical energy generated from the total kinetic energy of the vehicle.

To find the actual $\lambda$ for a regeneration event, the speed variation during deceleration should exactly be known, but knowing this beforehand is impracticable. We
approximate it to a braking event with a constant deceleration. With the assumption that the driving style does not suddenly change, we approximate the braking style of the immediate future to be the same as the immediate past. Accordingly, the deceleration of the immediate-future braking is assumed to be equal to the mean deceleration during the last stop of the vehicle. The value of $\lambda$ is calculated for the approximated immediate future braking event characterized by the current vehicle speed and the predicted constant deceleration. To reduce the unnecessary computational cost for processing the vehicle dynamics in each calculation of $\lambda$, we precompute a 2-D look-up table of $\lambda$ as a function of feasible combinations of vehicle speed and deceleration as shown in Fig. 6.7 by using vehicle dynamics and energy losses through the transmission and generator during regenerative braking.

To prevent the ICE from frequent stopping and restarting, $E_{\text{ice}}'$ should be penalized with a suitable cost function. A possible expression for such a cost function $E_{\text{ice,s/s}}$ is

$$E_{\text{ice,s/s}}(t) = (e(t - 1) - e(t))E_{\text{start}},$$

(6.19)

where $e$ is a binary variable to indicate on-off status of ICE. Finally, The total ICE
energy demand for online driving of the HEV is thus estimated as:

\[ E_{\text{ice,est}}(t) = E_{\text{dem}}^+(t) - E_{\text{reg}}(t) + E_{\text{ele,loss}}(t) + E_{\Delta \text{soc}}(t) - \Delta E_{\Delta \text{soc}}(t) + E_{\text{ice,s/s}}(t) \]  

(6.20)

Thus, the activation of the electric mode or recharge mode in the low torque region is decided by comparing the actual energy supplied by the ICE \( E_{\text{ice,act}} \) with \( E_{\text{ice,est}} \) as follows:

\[
\begin{align*}
\text{when } e(t-1) = 0, & \quad e(t) = \begin{cases} 
1 & E_{\text{ice,act}} < E_{\text{ice,est}} \\
0 & \text{else}
\end{cases} \\
\text{when } e(t-1) = 1, & \quad e(t) = \begin{cases} 
0 & E_{\text{ice,act}} \geq E_{\text{ice,est}} \\
1 & \text{else}
\end{cases}
\end{align*}
\]

(6.21) \hspace{1cm} (6.22)

Here, \( e(t) = 1 \) indicates that the recharge mode is activated. Therefore, \( \Delta T = T_{\text{eng, opt}}(\omega) - T_{\text{dem}} \) while \( e(t) = 0 \) means pure electric mode is activated, and hence, \( \Delta T = -T_{\text{dem}} \).

### 6.5 Simulation Setup

#### 6.5.1 Vehicle Models

The new vehicle i.e., the ISG-assisted PHEV is also modeled in the same way as the parallel HEV, which will be known as the ISG-unassisted PHEV in this chapter. The important parameters of the two models are listed in Table A.2 in Appendix A.2. The ISG-unassisted PHEV provides a basis for the performance improvement of the ISG-assisted PHEV while the conventional vehicle provides a baseline to compare fuel performance of HEVs.
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6.5.2 Benchmark Controller: ECMS

The offline ECMS controller proposed by Sciarretta et al. in [21] was used as the benchmark for evaluating the fuel performance of the PBS controller. The ECMS to control the frequency of the ICE stop and starts can be re-presented with the terms used in the PBS controller as:

$$\Delta T_{opt}(t) = \arg \min_{\Delta T} \left\{ \frac{T_{\text{ice}} \omega}{\eta_{\text{ice}}(\omega, T_{\text{ice}})} - s \Delta T \omega + E_{\text{stop/start}} \right\},$$  \hspace{1cm} (6.23)

Similar to the PBS controller, $E_{\text{stop/start}}$ is modeled as in (6.19). In this case, $E_{\text{start}}$ is tuned for each drive cycle to get the best results. An approximate value for $E_{\text{start}}$ is the energy required by the ISG to overcome the inertia of the ICE when accelerating it from zero speed to idle speed.

6.6 Results

This section presents the simulation results of the proposed PBS controller on the ISG-assisted PHEV. Simulation factors that affect the performance of the PBS controller are discussed first.

6.6.1 Performance Parameters of the PBS controller

Effectiveness of the Proposed Predicting Strategy of Immediate-future Regenerative Braking Energy

Fig. 6.8 shows the variation of the SOC over FTP_75 for the PBS controller with predicted (predicted $\Delta E_{\Delta \text{soc}}$), actual (actual $\Delta E_{\Delta \text{soc}}$) and neglected ($\Delta E_{\Delta \text{soc}} = 0$) immediate-future regenerative braking energy. The PBS controller with actual $\Delta E_{\Delta \text{soc}}$ knows the exact future regenerative braking power recoverable during the next stop. The effectiveness of the proposed predicting strategy can be identified through the SOC controllability of the PBS controller during driving and at the end of driving.

It can be seen that the SOC of the proposed PBS controller (with predicted
6.6 Results

Figure 6.8: Comparison of the SOC controllability of the proposed PBS controller that uses predicted $\Delta E_{\Delta soc}$ with another two controllers: PBS controller that uses actual $\Delta E_{\Delta soc}$ and PBS controller that neglects the immediate future regenerative braking energy (i.e. PBS with $\Delta E_{\Delta soc} = 0$), over the FTP-75

$\Delta E_{\Delta soc}$ follows the SOC of the PBS controller with actual $\Delta E_{\Delta soc}$ more closely than the PBS controller with $\Delta E_{\Delta soc} = 0$, and therefore, reduces unnecessary recharging as in the case of neglected immediate-future regenerative braking energy. Moreover, the proposed PBS controller also achieves the final charge sustenance very close to the PBS with actual $\Delta E_{\Delta soc}$ and far better than the PBS controller with $\Delta E_{\Delta soc} = 0$. The proposed PBS controller is thus shown closely predicting the immediate-future of the actual regenerative braking energy recoverable, in the absence of exact future information of the vehicle speed.

Effect of Average Discharging and Recharging Efficiencies of the electric system

The performance of the PBS controller depends on $\bar{\eta}_{dis}$ and $\bar{\eta}_{chg}$ because they determine the peak-efficiency region of the ICE. As the difference between $\bar{\eta}_{dis}$ and $\bar{\eta}_{chg}$ is small, we examine effects of these two parameters together by defining another parameter $\bar{\eta}_{ele} = \sqrt{\bar{\eta}_{dis}\bar{\eta}_{chg}}$. Since $\bar{\eta}_{dis}$ and $\bar{\eta}_{chg}$ always appear as their product in all boundary equations, $\bar{\eta}_{ele}$ can also replace them easily.

Fig. 6.9 shows the variation of fuel consumptions of the PBS controller on the ISG-assisted PHEV with varying $\bar{\eta}_{ele}$ for each of the selected drive cycles. For a clear
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Figure 6.9: Variation of the normalized fuel consumption with the average electrical efficiency $\bar{\eta}_{ele}$ for different drive cycles. The ISG-assisted PHEV with the PBS controller is used for the test.

Figure 6.10: Operating points of the ICE for different $\bar{\eta}_{ele}$ for FTP._75. Operating points of the ICE spread to inefficient regions as $\bar{\eta}_{ele}$ is lowered.
comparison, the fuel consumption of each drive cycle is normalized with respect to the minimum fuel consumption of that cycle. The variation in fuel consumption with $\bar{\eta}_{ele}$ has similar trends for all drive cycles: at low $\bar{\eta}_{ele}$, fuel consumption is high. This is because the peak-efficiency region defined by $\bar{\eta}_{ele}$ lower than the actual efficiency results in inefficient ICE operations, which can be further improved by using the electrical system through power balancing. This can be seen in Fig. 6.10, which illustrates how the operating points of the ICE spread to inefficient regions as $\bar{\eta}_{ele}$ is lowered, for the NEDC.

Furthermore, Fig. 6.9 shows that the fuel consumption for $\bar{\eta}_{ele}$ between 0.86-0.94 becomes the lowest for most of the drive cycles irrespective of city or highway driving. Therefore, a value for $\bar{\eta}_{ele}$ can easily be defined so that the best performance of the PBS controller is achieved for any driving situation. This explains the high robustness of the PBS controller to $\bar{\eta}_{ele}$ and also the effortless tuning of $\bar{\eta}_{ele}$.

For a very small peak-efficiency region of the ICE, the transmission system with discrete gear shifting may fail to match the speed demand at the ICE output to the optimal speed range of the ICE selected by the PBS controller. Consequently, the PBS controller fails to operate the ICE for a sufficient period of time to maintain the proper SOC. Thus, the performance of the PBS controller may deteriorate for unnecessarily high $\bar{\eta}_{ele}$ as indicated by the increment of the fuel consumption for NEDC and ATHC in Fig. 6.9, when $\bar{\eta}_{ele}$ exceeds 0.94.

The PBS controller requires initial definition of few other parameters. It uses $\bar{\eta}_{ele} = 0.94$ for the ISG-assisted PHEV and $\bar{\eta}_{ele} = 0.84$ for the ISG-unassisted PHEV. $E_{start}$ is set to 8 times that of the idle fuel consumption. The initial value for $d$ is guessed because no past driving information is available at the beginning. The initial value of deceleration is set to $1 \text{ m/s}^2$ considering the highway cycles, in which the value of deceleration may not update on-the-go because of no vehicle stopping. Results presented in the next sub section are for the same set of parameters for all the drive cycles.
6.6.2 Fuel Efficiency of the PBS Controller with the ISG-assisted PHEV

Fuel consumption results of the conventional vehicle, the ISG-assisted PHEV and ISG-unassisted PHEV for both PBS and ECMS controllers are presented in Table 6.1. The reported results for HEVs have been equally subjected to a SOC correction procedure in chapter 3.2.7 when the final and initial energy levels are different.

Table 6.1: Fuel performance ($L/100km$) of the ISG-assisted PHEV, the ISG-unassisted PHEV on both PBS and ECMS controllers and the conventional vehicle over different drive cycles

<table>
<thead>
<tr>
<th>Drive Cycle</th>
<th>ISG-unassisted PHEV</th>
<th>ISG-assisted PHEV</th>
<th>Conventional Vehicle</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ECMS cont.</td>
<td>PBS cont.</td>
<td>ECMS cont.</td>
</tr>
<tr>
<td>NEDC</td>
<td>3.93</td>
<td>3.88</td>
<td>3.58</td>
</tr>
<tr>
<td>FTP-75</td>
<td>3.69</td>
<td>3.65</td>
<td>3.34</td>
</tr>
<tr>
<td>MPDC</td>
<td>4.10</td>
<td>4.09</td>
<td>3.79</td>
</tr>
<tr>
<td>AUDC</td>
<td>3.68</td>
<td>3.66</td>
<td>3.33</td>
</tr>
<tr>
<td>HWFET</td>
<td>4.02</td>
<td>3.99</td>
<td>3.84</td>
</tr>
<tr>
<td>ATHC</td>
<td>4.77</td>
<td>4.73</td>
<td>4.67</td>
</tr>
</tbody>
</table>

Results show that the ISG-assisted PHEV significantly improves fuel efficiency compared to the ISG-unassisted PHEV for both controllers. For the PBS controller, the ISG-assisted PHEV improves fuel efficiency relative to the ISG-unassisted PHEV up to 9.3% (AUDC) for city driving and up to 3.5% (HWFET) for high-way driving. A similar improvement is also demonstrated for the ECMS controller. The observed improvements are clearly due to the reduction of inefficiencies of the ISG-assisted electrical system. Thus, these results demonstrate the necessity of an efficient electrical system for effective power flow control of HEVs and prove the capability of the proposed ISG-assisted PHEV as such.

On the other hand, results for the PBS controller show that its performance is very competitive with that of the ECMS controller. For the ISG-unassisted PHEV, the PBS controller performs better than the ECMS controller for all drive cycles considered. For the ISG-assisted PHEV, the PBS controller performs as well as,
or sometimes better than the ECMS controller. This performance also has other advantages, such as effortless (one-off) parameter tuning and not needing any future driving information. Such efficiency may thus be achievable in a physical HEV, because no unrealistic assumptions are behind the PBS controller. Therefore, results are (achievable in a real implementation) believable, e.g., compared to the conventional vehicle, the HEV can improve fuel use up to 47.9% (MPDC).

Fig. 6.11(a) represents the other output results of the PBS controller for the NEDC. The SOC is well controlled within the desired limits during driving, and the final SOC is achieved with +1.2% deviation from the initial SOC. It is also interesting to notice that the PBS controller can maintain very few ICE starts and stops. The torque outputs of the ISG and the EMG reflect that the ISG heavily supports the EMG to meet small torque demands, while the EMG responds to high positive torque demands and regenerative braking. Figures 6.11(b), 6.11(c) and 6.11(d) show the operating points of the ESS, EMG and ISG respectively. The operating points of the ICE are illustrated on its efficiency map in Fig. 6.11(e). It clearly shows the ability of the PBS controller to control the ICE within a very small peak-efficiency region with the help of ISG-assisted PHEV configuration.

It is also important to test the PBS controller in a long and changing driving environment, because short drive cycles modeled on monotonic driving environments may not be strong enough to fully test an energy management controller. Such a driving environment may be modeled by combining different standard drive cycles. To compare the fuel efficiency of the PBS controller over combined drive cycles, we define the theoretical fuel consumption of the combined cycle ($Combined_{FC}$) as the distance-weighted average fuel consumption of the combining cycles by

$$Combined_{FC} = \frac{\sum_{i=1}^{k} (FC_i Dist_i)}{\sum_{i=1}^{k} Dist_i}$$

(6.24)

where $FC_i$ is the minimum fuel consumption for the $i^{th}$ drive cycle, $Dist_i$ is the distance covered by the $i^{th}$ drive cycle and $k$ is the number of individual drive cycles containing in the combined cycle.

To prove its efficiency over long journeys, the fuel performance of the PBS con-
Figure 6.11: Results of the PBS controller over the NEDC
Table 6.2: fuel performance (L/100km) of the PBS controller over combined drive cycles

<table>
<thead>
<tr>
<th>Combined Drive Cycle</th>
<th>Fuel Consumption/(L/100km)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PBS controller</td>
</tr>
<tr>
<td>FTP-75+HWFET</td>
<td>3.59</td>
</tr>
<tr>
<td>HWFET+ FTP-75+HWFET</td>
<td>3.67</td>
</tr>
<tr>
<td>NEDC + HWFET + FTP-75</td>
<td>3.60</td>
</tr>
</tbody>
</table>

troller should be at least better than the distance-weighted fuel consumption of the combined cycle. NEDC, FTP-75 and HWFET are used to form combined cycles. Table 6.2 summarizes the fuel consumption for different combined cycles.

Results show that PBS controller achieves equal or improved (0.01L/100km) fuel efficiency compared to _Combined.FC_ over the tested combined drive cycles. Figure 6.12 shows the change in SOC for NEDC+HWFET+FTP-75 combined cycles. Considering these results, it can be concluded that the PBS controller is capable of maintaining the same performance as standard drive cycles without any drivability problems arising from long distance driving with changing driving environments. This also confirms the high robustness of the PBS controller to change of driving environments.

Furthermore, PBS controller can easily be adaptable to other parallel full HEVs with different components and demonstrates similar performance consistently. This
is illustrated in Appendix A.4.2.
Chapter Seven

Predictive Power Management of Hybrid Electric Vehicles

7.1 Introduction

This chapter explores fuel saving capabilities of HEVs through real-time predictive strategies that use the upcoming driving information. The main focus is to develop a predictive PMS that can optimize the HEV with such information handling in real-time driving. The future driving conditions (i.e., road grade and traffic flow) considerably affect the performance of the HEV’s power management [150]. It was seen in Chapter 5 that the optimal power management is possible only when the drive cycle of the complete journey is known beforehand. This assumption is quite unrealistic for day-to-day driving schedules.

However, prediction of the power demand for a limited previewing distance, certainly beyond the driver’s vision capability, is realistically achievable with the up-to-date navigation technologies as shown in Fig. 7.1. Currently available GPS-based vehicle navigation devices can track the position of a vehicle accurately. They also have extended features to provide the other information such as upcoming traffic density, tracking fellow vehicles, estimated travel time and route tracking. Integration of GISs enables it to extract static information such as road slopes, segment lengths, speed limits, and traffic stops ahead [90]. The wireless technologies used in intelligent transportation systems (ITSs) to communicate other vehicles (i.e., vehicle-to-vehicle), road infrastructure (i.e., vehicle-to-infrastructure) and mo-
bile stations can predict dynamic information such as traffic flow speed ahead [54]. Ultimately, a telematic device can be built onboard the HEV to preview speed and terrain information within the previewing window.

On the other hand, online PMSs without any previewing capability may fail to control SOC properly against unexpected heavy driving events such as steep grades. Therefore, the fuel performance of the PMS in this case will deteriorate; otherwise the HEV needs a large battery pack. The optimization of the power split with the look-ahead driving information will save more fuel than online PMS. The development of such a predictive PMS will enable to investigate the fuel performance of hybrids on level roads, inclined roads and intelligent driving with speed modification as illustrated in this chapter.

The power management with look-ahead information essentially requires receding horizon controlling approach as shown in Fig. 7.2. The instantaneous torque demand $T_{dem}(t)$ and speed demand $\omega(t)$ are exactly known from the driver’s accelerating and braking commands. Predicted sequence of torque demand $\hat{T}_{dem}(t+1), \hat{T}_{dem}(t+2), ..., \hat{T}_{dem}(t+t_p)$ and speed demand $\hat{\omega}(t+1), \hat{\omega}(t+2), ..., \hat{\omega}(t+t_p)$ are calculated from look-ahead speed and gradient information and longitudinal vehicle dynamics.
7.2 Problem Statement

Figure 7.2: The architecture of the predictive power management strategy

The PMS calculates the best sequence of torque split ratios that minimizes the fuel consumption over the look-ahead horizon. Only the current split ratio that determines the best torque of the ICE $T_{ice}^*$, torque of the electrical system $T_{ele}^*$ are applied. The same procedure is repeated in the next time step with updated states. Besides the accuracy of the prediction, performance of the PMS mainly determines the amount of fuel saving from the incorporation of look-ahead information into the HEV power management. The computationally fast, fuel optimal and highly robust PMS is the requirement for such an application. Only a few studies have attempted to develop a predictive PMS in the literature [19,23,57,88]. The HCPMS developed in Chapter 5 still consumes computational time beyond the requirement for real-time application; therefore, it cannot be applied in predictive power management. On the other hand, the online PBS controller [151] developed in Chapter 6 neglects the road gradient; therefore, it may not be successful on uneven roads. Therefore, a new PMS much faster than HCPMS and more fuel optimal than the online PBS is developed here for predictive power management.

7.2 Problem Statement

It was shown by validating against the ECMS that the power balancing rules developed in Chapter 6 can split an instantaneous power demand near-optmally between
power sources. The set of rules can be rearranged such that it can split instantaneous power demand for a given ICE status and state of charge. Let $\dot{m}_f(e_t, SOC_t)$ denote the function of rules that determines the fuel consumption for a given ICE status $e$ and $SOC$. $e \in \{0, 1\}$ is a binary variable that represents ICE on for $e = 1$ and ICE off for $e = 0$. Therefore, the power management problem is to find the best sequence of the ICE status i.e. $[e_1, e_2, e_3, \ldots, e_{tp}]$ that gives the minimum overall fuel consumption $M_f^*$ for the look ahead period $t_p$ starting from $k^{th}$ time and can be described as

$$M_f^*(t_p|k) = \min_{[e_1, e_2, e_3, \ldots, e_{tp}]} \left\{ \sum_{t=1}^{t_p} \dot{m}_f(e_t, SOC_t) \right\}$$

subject to

$$SOC_{min} \leq SOC_t \leq SOC_{max}$$

$$SOC_t - SOC_{t+t_p} \leq \Delta SOC_{t+t_p}$$

where $SOC_t$ is the SOC at time $t$, $SOC_{min}$ is the lower SOC limit, $SOC_{max}$ is the upper SOC limit, $SOC_0$ is the initial SOC and $SOC_{t+t_p}$ is the SOC at the end of the look ahead period, $\Delta SOC_{t+t_p}$ is the allowable SOC deviation at the end of the look ahead period.

It should be noted that power balance equation and mechanical constraints of the ICE and EMG are removed from the problem because these constraints are addressed within the rule-based power split strategy. Therefore, the computational overhead on the optimization algorithm is reduced.
7.3 Predictive power management with ICE on/off PMS

The power management problem described in the last section is a binary integer optimization problem, which is N-P hard. For example, in using a brute force enumeration, there are $2^n$ solutions for an $n$-dimensional problem. Here, $n$, which is equal to the preview length, is of order 100. Therefore, methods like brute force enumeration consume huge computational time for one solution. The adopted strategy also requires to solve the problem repeatedly whenever the future driving information is updated. Therefore, it should also be computationally fast enough for real-time application. To satisfy these requirements, a new PMS based on steepest-ascent hill-climbing heuristics is proposed here.

The sequence of SOC change $SOC = [SOC_1, SOC_2, SOC_3, ..., SOC_{tp}]$ and sequence of the status of the ICE $e = [e_1, e_2, e_3, ..., e_{tp}]$ are respectively selected as the state variable and the control variable, where $SOC_i$ is the state of charge and $e_i$ is the ICE’s on or off status at the $i^{th}$ time. The outline of the ICE on/off PMS can be represented as follows:

**Algorithm 1 ICE on/off Power Management Strategy Based on Steepest-Ascent Hill-Climbing**

- Generate initial $e$, $SOC$ and calculate initial $M_f$
- Set the initial solution to the current solution
- **while** a new improvement found **do**
  - Generate a new $e$ from the current $e$ as follows:
    - Set the current $e$ to the best $e$ and highest fuel saving $FS_h = 0$
    - **for** $i = 1$ to $tp$ **do**
      - Generate a new $e^i$ by inverting the element at $i$, i.e., $e_i = \bar{e}_i$
      - Evaluate the new $e^i$ to find the objective value $M_f^i$. Record the new fuel saving $FS_i = M_f - M_f^i$
      - Update the best $e$ with new $e^i$ and $FS_h = FS_i$ if $FS_i > FS_h$
    - **end for**
    - Update current $e$ with the best $e$ and $M_f$
- **end while**

Main steps of the ICE on/off PMS are described here.
Chapter 7. Predictive Power Management of Hybrid Electric Vehicles

7.3.1 Initialization

A feasible initial solution to $e$ is generated according to Algorithm 2. The HEV is powered with the ICE in most of the time. The basic rule is that the ICE is on during positive power demands; otherwise, it is off. This rule may not necessarily maintain SOC within safety limits. For instance, the ICE operation at low torques activates recharging mode and SOC curve will fluctuate closed to the upper SOC boundary. Rules in Lines (4)-(10) will adjust $e$ to control the initial $SOC$ between 0.55 and 0.65.

Algorithm 2 Initialization of the ICE on/off PMS

1: for $i = 1$ to $t_p$ do
2: if $T_{dem}(i) > 0$ then
3:   $e_i = 1$
4:   if $SOC_i > 0.65$ then
5:     $e_i = 0$
6:     else if $\omega_i > \omega_L$ & $\omega_i < \omega_H$ then
7:       if $SOC_i > 0.55$ & $T_{dem}(i) < 20$ then
8:         $e_i = 0$
9:     end if
10:   end if
11: else
12:   $e_i = 0$
13: end if
14: end for

The regenerative braking during initialization is switched off because it needs to be done in parallel to power split to escape from local optima.

7.3.2 Solution Evolving Mechanism

The solution evolving mechanism has two components: a rule-based power balancing procedure and the steepest-ascent hill-climbing method.

Power-Balancing Rules

Power-balancing rules are shown in Algorithm (3). Line (1) represents the power balancing equation. When $T_{dem}$ exceeds the sum of the maximum electric torque capacity $T_{ele,max}$ and optimum ICE torque $T_{ice}^*$, the electrical system is operated at
maximum capacity while the balance of energy is assigned to the ICE as shown by Lines (2)-(6). With the ICE on, rules are designed to operate it within the peak efficiency region (Lines (7)-(21)). With the ICE switched off, total power demand is supplied by the electrical system as in line (22).

**Algorithm 3** $\dot{m}_f(e_i, SOC_i)$: Power Balancing Rules

1: $T_{ice} = T_{dem} + \Delta T$, $T_{ele} = -\Delta T$
2: if $T_{dem} > T^*_{ice}(\omega) + T_{ele,max}$ then
3: $\Delta T = -T_{ele,max}$.
4: Calculate $\dot{m}_f$, $\Delta SOC_i$
5: return $\dot{m}_f$, $\Delta SOC_i$, $e_o = 1$
6: end if
7: if $e = 1$ then
8: $e_0 = 1$
9: if $\omega_L \leq \omega \leq \omega_H$ then
10: if $T_{dem}(\omega) > T_H$ then
11: $\Delta T = T^*_{ice}(\omega) - T_{dem}(\omega)$
12: else if $T_L(\omega) \leq T_{dem} \leq T_H(\omega)$ then
13: $\Delta T = 0$
14: else
15: $\Delta T = T^*_{ice}(\omega) - T_{dem}(\omega)$
16: end if
17: else
18: $\Delta T = -T_{dem}$
19: $e_0 = 0$
20: end if
21: else
22: $\Delta T = -T_{dem}$
23: $e_0 = 0$
24: end if
25: Calculate $\dot{m}_f$, $\Delta SOC_i$
26: return $\dot{m}_f$, $\Delta SOC_i$, $e_o$

**Steepest-Ascent Hill-Climbing Optimizer**

The steepest-ascent hill climbing is the optimization algorithm selected to optimize the sequence of the ICE status along the previewed distance because it is well capable of optimizing $e$ with a proper objective function. Perturbation to $e$ can simply be done by flipping binary elements at the non zero power demands in the sequence. From the current $e$, generation of the new $e$ is as follows:
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1. Starting from left, generate a new $e^i$ for each position $i$ by flipping the element at that position where the power demand is positive.

2. Find new $SOC^i$ for each feasible new $e^i$.

3. Evaluate each new $e^i$ and record the objective value.

4. After finishing the procedure for all dimensions, the new $e^i$ with the highest quality and its state variable $SOC^i$ is selected as the candidate solution for the next iteration.

For the generation process to be feasible, it should satisfy (7.2); therefore, a new $e^i$ will be feasible if $\Delta SOC^i$ satisfies

\[
\begin{cases}
\Delta SOC^i < \min(SOC_{max} - SOC_t), \quad \forall t \in [i, T_p] \quad \text{if } \Delta SOC^i > 0 \\
\Delta SOC^i < \min(SOC_{min} - SOC_t), \quad \forall t \in [i, T_p] \quad \text{if } \Delta SOC^i < 0
\end{cases}
\]

(7.4)

### 7.3.3 Evaluation

Each $e_i$ is evaluated with a proper objective, which considers the actual fuel cost for driving, starting fuel cost of the ICE and equivalent fuel of the final SOC deviation. Therefore, the objective function of the ICE on/off PMS is

\[
M_{SOC_i} = \sum_{t=1}^{T_p} [\dot{m}_f(t) + \dot{m}_{f, st}(t)] + m_{f, equ}
\]

(7.5)

and, $m_{f, equ} = \lambda [SOC_1 - SOC_{t_p}]$ and $\dot{m}_{f, st}(k) = \max(0, m_{s/s}[e_k - e_{k-1}])$, where $\lambda$ is the equivalent factor and $m_{s/s}$ is the starting fuel consumption of the ICE.

### 7.4 Fuel Saving by Vehicle Speed Control

The speed control of ICE only powered conventional vehicles with the look-ahead information is an emerging approach to save fuel and reduce emissions in the field of intelligent vehicle systems (IVS) [152]. The road gradient, speed transients and irreversible energy losses such as aero drag are the main components of the power
demand that determine the fuel consumption of a vehicle. It has been shown that predictive control of speed and gear shifting of heavy trucks over a road terrain can reduce fuel consumption up to 2.5% [153, 154]. Acceleration of a vehicle along a fuel-optimal speed trajectory can save fuel because of reduction in unnecessary transients of the ICE and improvement of ICE’s efficiency of operation [155]. High energy losses from braking and engine idling is another concern in frequent stop-and-go driving under heavy traffic flow. As discussed in Section 2.2.1, these losses account for up to 22.8% of the total fuel consumption. Besides the hybridization of the powertrain, an intelligent speed control in a way that minimizes braking, idling and some irreversible energy losses is another promising fuel saving technique under this congested traffic scenario. The intelligent velocity modification algorithm (IVVMA) proposed by Manzie et al. [104] to control the speed of a vehicle with look-ahead information is of great interest in this context and used here to explore the fuel saving of HEVs facilitated with such an intelligent speed controller.

### 7.4.1 Intelligent Vehicle Velocity Modification Algorithm (IVVMA)

IVVMA is developed for an intelligent vehicle (IV), which is a conventional vehicle with inbuilt telematic devices, on a level road. The telematic system is capable of analyzing the traffic flow pattern ahead and predicting the speed trajectory of any vehicle within the look-ahead time. It is obvious that the speed control of a vehicle in a traffic flow is mainly constrained by the driving style of the leading vehicle i.e., the vehicle just in front. The objective of IVVMA is to control the IV on a path that consumes the least amount of fuel for traveling the same distance as other vehicles. It should be also noted that speed control for minimum fuel may force the IV to overtake the leading vehicle. Here, overtaking is disallowed for not disturbing the ongoing traffic. Therefore, the underlying concept of the IVVMA is to travel the same distance as the leading vehicle spending the same travel time without overtaking it. Algorithm (4) illustrates the IVVMA when the overtaking is disallowed.
Algorithm 4 Intelligent Vehicle Velocity Modification Algorithms (IVVMA)

1: for $t = 1$ to $n/\Delta$ do
2:   for $i = 1$ to $t_p/\Delta$ do
3:     $\hat{x}_{\text{lead}}(t + i\Delta) = x_{\text{lead}}(t) + \alpha \sum_{k=0}^{i} v_{\text{lead}}(t + i\Delta)\Delta$
4:   end for
5:   $j = 0$
6:   while $j < t_p$ do
7:     $\tilde{v}^j = [\hat{x}_{\text{lead}}(t + t_p - j\Delta) - x_{\text{int}}(t)]/\alpha(t_p - j)$
8:     for $i = 1$ to $t_p - j$ do
9:       $\hat{x}_{\text{int}}(t + i\Delta) = x_{\text{int}}(t) + i\Delta \tilde{v}^j$
10:      end for
11:     if $\hat{x}_{\text{lead}}(t + i\Delta) > \hat{x}_{\text{int}}(t + i\Delta) \quad \forall i \in [1, t_p - j]$ then
12:       $v_{\text{int}}(t) = \tilde{v}^j$
13:       $j = t_p$ : (to leave for the next time step)
14:     else
15:       $j = j + 1$
16:     end if
17:   end while
18: end for

where,

$\alpha$ - the unit conversion factor

$\Delta$ - the sampling rate (usually 1s).

$n$ - length of the drive cycle

$t_p$ - look-ahead time of the telematic device

$\hat{x}_{\text{int}}$ - the predicted position of the leading vehicle

$x_{\text{int}}$ - the actual position of the leading vehicle

$\hat{x}_{\text{lead}}$ - the predicted position of the leading vehicle

$x_{\text{lead}}$ - the actual position of the leading vehicle

$v_{\text{int}}$ - the speed of the intelligent vehicle

$v_{\text{lead}}$ - the speed of the leading vehicle

The description of the IVVMA is as follows:

**step 1:** Find the position trajectory of the leading vehicle over the preview window starting from current time $t$ as in Line (3).

**step 2:** Find the speed that allows the intelligent vehicle to travel the maximum distance within the previewed distance without overtaking the leading vehicle.
while spending the same time as the leading vehicle and set that speed as the intelligent vehicle’s current speed (Lines (5)-(17)).

### 7.4.2 Extended Intelligent Vehicle Velocity Modification Algorithm (extended IVVMA)

The acceleration of the intelligent vehicle $a_{int}$ with the instantaneous preview length of $t_p' = t_p - j$ can be derived (see Appendix A.5.1 for the derivation) as

$$a_{int}(t) = \frac{1}{t_p'} [v_{lead}(t + t_p' + 1) - v_{lead}(t)]. \quad (7.6)$$

where $j$ is the reduction of the preview time as indicated in algorithm 4. Assumption of $j$ to be unchanged between the two consecutive time instances is made in deriving equ (7.6) and valid because the driving style does not change drastically within two time instances.

Clearly, $a_{int}$ depends on the length of the preview window and difference between the starting and end speed of the previewed speed trace. It can be observed that $t_p' \approx 1$ when leading vehicle accelerates; therefore intelligent vehicle follows the leading vehicle closely during acceleration. However, deceleration events of the leading vehicle at future stops that create $v_{lead}(t + t_p' + 1) << v_{lead}(t)$ lead to use of braking in the intelligent vehicle unnecessarily even if there is an enough gap between intelligent vehicle and leading vehicle to coasting. Therefore, the IVVMA is extended as in algorithm (5) save more fuel by proper control of deceleration.

Coasting is the driving process in which the vehicle is decelerated by external resistive forces. The ideal coasting deceleration at any speed can be found by the vehicle dynamics as in Appendix A.5.2. The idle operation of the engine in this coasting process consumes fuel. Therefore, a fuel efficient coasting deceleration for any vehicle speed can be found by studying the vehicle model as in Appendix A.5.2. Fig. 7.6 shows the ideal coasting deceleration and fuel optimal deceleration of the considered conventional vehicle model.

Let $d_{est}$ be the fuel efficient coasting deceleration at a particular speed. Sometimes, the gap between the leading and intelligent vehicles is so small that decelera-
Chapter 7. Predictive Power Management of Hybrid Electric Vehicles

Figure 7.3: Comparison of theoretical coasting deceleration and fuel efficient deceleration of the conventional car

7.5 Preliminary Results

The fuel efficiency and computational complexity of the proposed PMS are investigated with offline power management. Additionally, results of the extended IVVMA are assessed over IVVMA before applying it in the intelligent HEV.

7.5.1 Validation of the ICE on/off PMS

Before adopting the newly proposed PMS in the predictive framework, its fuel efficiency and computational time should be assessed for its suitability to predictive
Algorithm 5 Extended Intelligent Vehicle Velocity Modification Algorithms (extended IVVMA)

1: for $t = 1$ to $n/\Delta$ do
2:     for $i = 1$ to $T_p/\Delta$ do
3:         $\hat{x}_{\text{lead}}(t + i\Delta) = x_{\text{lead}}(t) + \alpha \sum_{k=0}^{i} v_{\text{lead}}(t + k\Delta)\Delta$
4:     end for
5:     $j = 0$
6:     while $j < T_p$ do
7:         $\bar{v}^j = [\hat{x}_{\text{lead}}(t + T_p - j\Delta) - x_{\text{int}}(t)]/\alpha(T_p - j)$
8:             for $i = 1$ to $T_p - j$ do
9:                 $\hat{x}_{\text{int}}(t + i\Delta) = x_{\text{int}}(t) + i\Delta \bar{v}^j$
10:            end for
11:            if $\hat{x}_{\text{lead}}(t + i\Delta) > \hat{x}_{\text{int}}(t + i\Delta)$ $\forall i \in [1, T_p - j]$ then
12:                $v_{\text{int}}(t) = \bar{v}^j$
13:        a$_{\text{dem}}(t) = v_{\text{int}}(t) - v_{\text{int}}(t - 1)$
14:        if $a_{\text{dem}}(t) < 0$ then
15:            calculate $d_{\text{cst}}$ and $d_{\text{pos}}$
16:            if $d_{\text{cst}} < d_{\text{pos}}$ then
17:                $a_{\text{int}}(t) = \max(d_{\text{cst}}, a_{\text{dem}}(t))$
18:            else
19:                $a_{\text{int}}(t) = d_{\text{pos}}$
20:            end if
21:            $v_{\text{int}}(t) = v_{\text{int}}(t - 1) + a_{\text{int}}(t)$
22:        end if
23:        $j = T_p$
24:    else
25:        $j = j + 1$
26:    end if
27: end while
28: end for
Chapter 7. Predictive Power Management of Hybrid Electric Vehicles

The newly proposed PMS is named as “ICE on/off PMS” afterwards to distinguish from other algorithms.

Table 7.1: Comparison of fuel consumptions \((L/100km)\) and computational time \((s)\) of the offline ICE on/off PMS with the HCPMS and the PBS controllers for different driving cycles.

<table>
<thead>
<tr>
<th>Drive Cycle</th>
<th>Fuel Consumption ((L/100km))</th>
<th>Computational Time ((s))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HCPMS</td>
<td>PBS</td>
</tr>
<tr>
<td>NEDC</td>
<td>3.85</td>
<td>3.88</td>
</tr>
<tr>
<td>FTP-75</td>
<td>3.62</td>
<td>3.65</td>
</tr>
<tr>
<td>AUDC</td>
<td>3.61</td>
<td>3.66</td>
</tr>
<tr>
<td>HWFET</td>
<td>3.98</td>
<td>4.02</td>
</tr>
</tbody>
</table>

Table 7.1 compares fuel consumptions and computational times of the offline ICE on/off PMS with those of the PBS and the HCPMS. As expected, the ICE on/off PMS always performs better than the PBS controller, which doesn’t have look-ahead capability. The ICE on/off PMS demonstrates fuel performance very close to the HCPMS achieving its fuel efficiencies always within the boundary of 0.02 L/100km from HCPMS. It also reveals the considerably high fuel efficiency of the power balancing rules. Therefore, irrespective of the rule-based power balancing,

![Figure 7.4: Initial and final ICE on-off sequence for FTP-75](image)

the fuel efficiency of the proposed ICE on/off is satisfactory compared to HCPMS that directly optimizes the power split ratio. This result is further strengthened by the lower computational time compared to HCPMS. It is up to 20 times faster than HCPMS (results for HWFET). In overall, it can execute results for all the
drive cycles, which are generally more than 1000 s long, in a time period of half the duration of the drive cycle or better. The actual proportions are in Table 7.1.

Fig. 7.4 shows the initial and the final sequence of the ICE on-off status for FTP-75. Since the torque demand of the FTP-75 fluctuates heavily, initial sequence of the ICE on-off status stops and restarts the ICE very frequently (about 100 times). The final solution reduces the number ICE restarts to 50 times. Fig. 7.5 illustrates the corresponding initial and final sequence of the SOC variation. It is worth noticing that the proposed initialization algorithm generates successful feasible initial solutions, which can be improved towards the final solutions in Table 7.1. Especially, generating such an initial solution to NEDC is challenging. Furthermore, the final charge sustenance is also achieved perfectly similar to the HCPMS. Fig. 7.5 also shows how deviation of SOC is balanced around the targeted SOC with the ICE on/off PMS.

### 7.5.2 Extended IVVMA

The extended IVVMA controls mainly the deceleration of the vehicle in a fuel beneficial way. Fig. 7.6 illustrates the modification of the FTP-75 drive cycle by extended IVVMA for a preview length of 50 s. It can be seen that the extended IVVMA decelerates the intelligent vehicle more gradually than the IVVMA does. Rather than
braking and cruising at constant speeds, it finds that coasting (i.e., less braking) and acceleration is more fuel saving.

![Graph showing speed vs time for different drive cycles](image)

Figure 7.6: FTP-75 modified by the extended IVVMA (solid) and IVVMA (dashed) with 50 s look-ahead time

Fig. 7.7 shows the distance separation between the intelligent vehicle with 50 s preview time and the leading vehicle over FTP-75. It can be seen that the extended IVVMA follows the leading vehicle more closely than the IVVMA. The maximum separation of about 300 m of IVVMA is reduced to 230 m by the extended IVVMA leading to a reduction of maximum separation by about 23%. This may indicate that the extended IVVMA requires telematics devices with reduced previewing capability.

Fig. 7.8 shows the variation of fuel consumption with the look-ahead time for extended IVVMA and IVVMA over FTP-75. IVVMA reduces fuel consumption gradually for its look-ahead time up to 70 s, beyond which the increment of look-ahead starts deteriorating the fuel saving. It can reduce fuel consumption of the conventional vehicle (6.23 L/100km) to 3.98 L/100km with 70 s look-ahead time demonstrating 36% fuel saving. On the other hand, extended IVVMA reduces fuel consumption to 3.71 L/100km with just 50 s look-ahead time demonstrating 40.4% overall fuel saving. Similar fuel saving trends can be observed for all city cycles and best fuel consumption achieved for each drive cycle is reported in Table 7.2.
7.5 Preliminary Results

Figure 7.7: Distance separation between the leading vehicle and intelligent vehicle for IVVMA and extended IVVMA with 50 s preview time over FTP-75.

Figure 7.8: Variation of fuel consumption for extended IVVMA (solid) and IVVMA (dashed) with preview time over FTP-75.
In overall, the extended IVVMA can save further 6.5% fuel compared to IVVMA with reduced preview time for all the drive cycles. Furthermore, the HEV’s fuel performance for the same drive cycle is also represented in Fig. 7.8. For a fair comparison, ISG-assisted PHEV using the online PBS is chosen for the hybrid fuel consumption. This is a fair comparison since both the powertrain architecture and power management strategy are realistic.

It has been noted that smoothing the drive cycle after a particular look-ahead time does not reduce fuel consumption. This is because the advantage of efficient ICE operation caused by moderate acceleration diminishes as the drive cycle is over-smoothed to a constant low, speed driving cycle. This idea can be further investigated by comparing the ICE operating points of drive cycle modified by different look-head time as shown in Fig. 7.9. Some of the efficient operating points of the ICE for 50 s preview is shifted to inefficient regions for 100 s preview. Therefore, the results can be useful in choosing a fuel beneficial as well as cost effective, telematics systems for look-ahead control of conventional vehicles.

### 7.6 Simulation Results of Predictive Power Management

With the validation of the performance of the ICE on/off PMS on level roads, it is applied in the predictive power management. Fuel performance of the HEV with the length of the look-ahead preview is investigated on level roads, inclined roads and intelligent driving with speed modification.
7.6 Simulation Results of Predictive Power Management

7.6.1 Predictive Power Management on Level Roads

Only speed information is considered first while neglecting gradient information with the assumption of level roads. The speed profile of the HEV over the preview length is assumed to be exactly known. The HEV was simulated for varying preview time over different drive cycles and the fuel consumption for each run was observed. Fig. 7.10 shows the variation of the fuel consumption with the increasing preview time for NEDC, FTP-75 and AUDC. It can be seen that the HEV requires only about 60-80 s to achieve the best demonstrated fuel saving range for FTP-75 and AUDC whereas it requires about 150 s preview for the NEDC. The longer preview of NEDC may be due to the last driving segment, after a sequence of four repeated segments, representing high speed and acceleration for highway driving, which is unrealistically high for real world driving in most part of the world. Otherwise, a preview length about 80 s is sufficient to optimize the HEV on level roads.
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Figure 7.10: Variation of the fuel consumption of the HEV with the look-ahead time for NEDC, AUDC and FTP-75 (on level roads)
7.6 Simulation Results of Predictive Power Management

7.6.2 Predictive Power Management on Inclined Roads

Road gradient has a significant effect on the fuel consumption and emissions of vehicles. Compared to a level road, driving on inclined roads causes the powertrain to operate harder on positive grades and may loss much of this energy on long negative grades. An HEV on inclined roads may consume battery energy continuously on positive grades and recharge the battery on subsequent negative grades, leading to deep energy fluctuation of the battery. If the battery is downsized for only level road use, good practice, power management of the HEV toward the best fuel efficiency may require a fully charged battery at the bottom of a hill and may empty it just before arriving at the downgrade. This illustrates the requirement of forecasting the upcoming road gradient for proper power management of HEVs on inclined roads.

To investigate the effect of road gradient on fuel consumption, the HEV was
tested for look-ahead with combined speed-gradient information. The speed and
gradient information over the preview distance is assumed to be exactly known.

Table 7.3: Fuel consumptions (L/100km) and computational time (s) for HCPMS
and ICE on/off PMS over drive cycles including road gradient

<table>
<thead>
<tr>
<th>Drive Cycle</th>
<th>Fuel consumption (L/100km)</th>
<th>Computational time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HCPMS</td>
<td>ICE on/off PMS</td>
</tr>
<tr>
<td>NEDC&lt;sub&gt;elv&lt;/sub&gt;</td>
<td>3.75</td>
<td>3.77</td>
</tr>
<tr>
<td>FTP-75&lt;sub&gt;elv&lt;/sub&gt;</td>
<td>3.37</td>
<td>3.24</td>
</tr>
<tr>
<td>AUDC&lt;sub&gt;elv&lt;/sub&gt;</td>
<td>4.36</td>
<td>4.37</td>
</tr>
</tbody>
</table>

Three drive cycles i.e., NEDC<sub>elv</sub>, FTP-75<sub>elv</sub> and AUDC<sub>elv</sub>, were constructed by
adding gradient profiles to the standard drive cycles NEDC, FTP-75 and AUDC
respectively as shown in Fig. 7.11. A sinusoidal profile of gradient with a maximum
5% grade was added to NEDC so that the net elevation at the destination becomes
zero. For the FTP-75 and AUDC, the gradient profile is obtained from a database
in ADVISOR namely “NREL2VAIL”. Gradient profiles for both drive cycles are
added starting from the 14<sup>th</sup> km in this file. Consequently, FTP-75<sub>elv</sub> has a elevation
reduction while AUDC<sub>elv</sub> has a small increase in elevation by the destination.

Firstly, the ICE on/off PMS is tested for offline power management with full
preview of the route information. Results are compared with those of the HCPMS
in Table 7.3. The same equivalent parameters that were used for the offline power
management on level roads are used here. These results show that the ability of the
ICE on/off PMS to maintain its performance in extreme driving instances whereas
HCPMS sometimes fails to do so. For instance, HCPMS gets stuck in local stagna-
tion on FTP-75<sub>elv</sub>. Considering the fast computational time and secured optimality,
the overall performance of the ICE on/off PMS is as good as the HCPMS over the
illustrated driving instances on non-level roads.

Fig. 7.12 shows the variation of the fuel consumption with the increment in
look-ahead period for NEDC<sub>elv</sub>, FTP-75<sub>elv</sub> and AUDC<sub>elv</sub>. It can be seen that the
fuel consumption strongly reduces with the increment of preview length on uneven
roads. The overall fuel consumption can be reduced by preview information up to
about 300 s for all considered drive cycles; after that, the improvement in fuel use
is insignificant. Therefore, a preview time of about 300 s is a good look-ahead time.
Figure 7.12: Variation of fuel consumption of the HEV with look–ahead time for NEDC\textsubscript{elv}, FTP-75\textsubscript{elv} and AUDC\textsubscript{elv}
for achieving the illustrated best possible results on inclined roads. It can also be
concluded that road gradient is a dominant factor in HEV control on inclined roads
and the HEV performance is improved by a longer look-ahead distance on inclined
roads than needed for level roads. The required look-ahead time may be realistically
achieved because of the static nature of gradient data.

7.6.3 Predictive Power Management with Speed Modifica-
tion

Figure 7.13: Variation of fuel consumption with the look-ahead time of the intelligent
HEV for NEDC, FTP-75 and AUDC
Next, for level roads, the power management strategy is combined with the extended IVVMA to investigate the gain in fuel saving through both hybridization and speed modification. The vehicle of this type can be introduced as an “intelligent HEV” which uses in-built telematics to forecast its immediate future driving information, thus allowing a more fuel beneficial driving profile to be planned and used for the power management. Of course, the driver of the vehicle no longer manages its driving speed.

Fig. 7.13 shows the variation of the fuel consumption with the look-ahead time for the intelligent HEV, demonstrating a significant reduction in fuel consumption with the increasing look-ahead time for all city cycles. The fuel consumption of the intelligent HEV is strictly related to the look-ahead time despite the low mean speed at long look-ahead distances unlike the conventional intelligent vehicle. This is because of the capability of PMS to optimize the HEV even at low speeds. A 100 s preview seems to be sufficient to achieve the possible fuel saving on intelligent HEV.

Table 7.4: Energy balance table of the HEV and intelligent HEV powertrains for the FTP-75 cycle

<table>
<thead>
<tr>
<th>Component</th>
<th>Energy loss/ Input (MJ)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Hybrid PMS</td>
</tr>
<tr>
<td></td>
<td>Predictive PMS</td>
</tr>
<tr>
<td></td>
<td>Intelligent hybrid PMS</td>
</tr>
<tr>
<td></td>
<td>(Predictive PMS + IVVMA)</td>
</tr>
<tr>
<td>Engine</td>
<td>12.728</td>
</tr>
<tr>
<td></td>
<td>10.216</td>
</tr>
<tr>
<td>Motor/Generator</td>
<td>1.128</td>
</tr>
<tr>
<td></td>
<td>1.329</td>
</tr>
<tr>
<td>Battery</td>
<td>0.150</td>
</tr>
<tr>
<td></td>
<td>0.138</td>
</tr>
<tr>
<td>Transmission</td>
<td>0.393</td>
</tr>
<tr>
<td></td>
<td>0.229</td>
</tr>
<tr>
<td>Mechanical Braking</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>0.114</td>
</tr>
<tr>
<td>Fuel energy input</td>
<td>20.598</td>
</tr>
<tr>
<td></td>
<td>16.608</td>
</tr>
<tr>
<td>Regenerative Braking</td>
<td>3.096</td>
</tr>
<tr>
<td></td>
<td>0.003</td>
</tr>
<tr>
<td>Positive Energy demand</td>
<td>9.298</td>
</tr>
<tr>
<td></td>
<td>5.383</td>
</tr>
</tbody>
</table>

Table 7.4 shows how the intelligent HEV saves more fuel over the normal HEV. The intelligent HEV demands less positive energy and generates insignificant negative energy at wheels whereas normal HEV demands high positive energy and generates a significant amount of negative energy at wheels leading to a reduction of net power demand by intelligent HEV over normal HEV. Energy losses of the in-
Chapter 7. Predictive Power Management of Hybrid Electric Vehicles

Intelligent HEV’s engine are reduced. Higher electrical energy losses of the intelligent HEV show the extended use of the electrical system to optimize the HEV in low speed driving.

Table 7.5: Summary of fuel consumption (L/100km) of different predictive fuel saving strategies compared with the baseline conventional vehicle

<table>
<thead>
<tr>
<th>Drive Cycle</th>
<th>Fuel consumption (L/100km)</th>
<th>Conventional vehicle</th>
<th>Intelligent conv. vehicle</th>
<th>HEV + Predictive PMS</th>
<th>Intelligent HEV</th>
</tr>
</thead>
<tbody>
<tr>
<td>NEDC</td>
<td>6.36</td>
<td>3.96 (37.7)</td>
<td>3.86 (39.3)</td>
<td>3.17 (50.2)</td>
<td></td>
</tr>
<tr>
<td>FTP-75</td>
<td>6.23</td>
<td>3.71 (40.4)</td>
<td>3.62 (41.9)</td>
<td>2.91 (53.3)</td>
<td></td>
</tr>
<tr>
<td>AUDC</td>
<td>6.32</td>
<td>3.57 (43.5)</td>
<td>3.62 (42.7)</td>
<td>3.00 (52.5)</td>
<td></td>
</tr>
<tr>
<td>HWFET</td>
<td>4.90</td>
<td>4.73 (3.5)</td>
<td>3.98 (18.8)</td>
<td>3.93 (19.8)</td>
<td></td>
</tr>
</tbody>
</table>

Table 7.5 summarizes the fuel saving capabilities of different predictive strategies with respect to conventional fuel consumption. All vehicles have equal maximum power, gear box (transmission) and vehicle design (except that the conventional vehicle is lighter). Fuel saving of the conventional powertrain through hybridization and intelligent driving show reduction of the order of 41% and 52% respectively for city driving. For the best strategy, an ultimate fuel saving up to 53.3% (FTP-75) is possible with the HEV. When the conventional vehicle is made intelligent, its fuel savings are comparable to those of the HEV with predictive PMS. The ultimate gain of the intelligent HEV is only about 10% by the HEV addition, but the contrast in highway driving, the gain is higher about 15%.
This thesis focused on designing and evaluating power management strategies for exploring the best fuel saving capability of parallel full HEVs. Parallel full HEVs were selected due to their high fuel saving potential. However, optimal or near-optimal power management was challenging and suffered from lack of robust and computationally fast strategies. Fulfilling these research gaps, a new, computationally fast, near optimal offline PMS was proposed. Moreover, a new design procedure for an online PMS based on a rule-based strategy to control the ICE within its “peak-efficiency region” was proposed. The literature review reveals that there has been little previous research into predictive PMS that can manage the power demand in real-time according to the upcoming speed and gradient information over the predicting horizon. Therefore, a new PMS was designed by combining a model-based strategy to control the ICE on or off status and a rule-based strategy to split the power demand between power sources according to the ICE status and used in the model predictive framework to deal with upcoming speed and gradient based driving information. The performance of the new strategies was evaluated with respect to established power management strategies such as DP, ECMS and predictive fuel saving strategies such as IVVMA.

8.1 Summary of Conclusions

For a known drive cycle, the power management problem of HEVs is to find the best sequence of power split ratios that achieve the minimum fuel consumption with
no or small change in state of charge at the end of driving while satisfying other performance limitations of the ICE, EMG and ESS. Irrespective of non-casuality, the optimal solution to this problem is of great interests since it provides benchmark performance for other causal controllers, defines the fuel saving potential of HEVs and sometimes bases for designing casual controllers. However, finding the optimal solution to this problem is challenging due to many reasons such as the integral nature of the objective function and some constraints; hard constraints like final charge sustenance and the large problem dimension, which is equal to the length of the drive cycle, usually of the order of thousands and having infinite solutions within the continuous feasible range for most of the dimensions. DP and ECMS are two well-known strategies applied to solve this problem. The DP, which is an optimal method, suffers from heavy computational complexity while the ECMS, which is a sub-optimal method, has a drawback of high sensitivity to its strategy parameters and requires great effort to fine tune them. Therefore, the main research questions arising from the gaps of this part of research were,

Q1. Can a computationally fast PMS be designed and validated to find this best fuel efficiency (or a solution comparable with existing best methods)?

An iterative power management strategy inspired by a hill-climbing heuristic (HCPMS) was proposed to solve the power management problem near-optimally with a relatively fast computational time. The performance of HCPMS was compared with DP and the offline ECMS. The HCPMS outperformed the DP with its comparatively very fast computation while achieving a fuel saving competitive with the DP. For all drive cycles studied, DP consumes more than 43 hours of computing time whereas HCPMS requires only less than 1 hour, that is about 70 to 90 times faster than DP. HCPMS achieves the same fuel consumption as DP on highway cycles and a slightly better fuel consumption on the city cycles because HCPMS has the full control over the ICE start and stop frequency whereas DP fails to do so because of discretization errors in the SOC. Furthermore, HCPMS is always better in fuel optimality than the ECMS and always meets the end-charge sustenance identical to the DP. Unlike the ECMS, the HCPMS does not require tuning its parameters separately to each drive
cycle due to their high robustness and maintains a low number of stops and starts of the ICE. Moreover, HCPMS can also refine poor solutions of the other methods including DP and ECMS by taking them as initial solutions.

**Q2. What is the best fuel efficiency achievable by any power management strategy on the parallel HEV?**

According to HCPMS’s results, the modeled parallel HEV consumes only 3.61 \( L/100km \) fuel over AUDC, whereas the equally powered conventional vehicle consumes 6.32 \( L/100km \), demonstrating 42.9 % of fuel saving potential compared to the conventional vehicle.

Assumption of prior knowledge of complete future driving on a journey (i.e., drive cycle) for common day-to-day driving may be unrealistic. Therefore, the best fuel saving with HEVs’ online power management in which no prior knowledge of driving is needed, reflect the actual fuel saving capability of real world HEVs. Online power management of parallel full HEVs that achieve a fuel efficiency comparable with those of offline power management is challenging, due to difficulty of equally optimizing the performance of both the ICE and electric system and meeting the component constraints against randomly varying driver demand. Many of the existing heuristic controllers fail to do so. Thus, the online power management of HEVs in this research answers the following questions:

**Q3. Can a robust and realistic online PMS be developed to fully optimize the parallel full HEVs?**

A design procedure of an online power management controller namely the “PBS controller” was proposed to optimize parallel full HEVs. It was argued that the peak-efficiency region of the ICE depends on the performance of the supporting electric system, thus the equations for the speed-torque boundaries of the peak-efficiency region as functions of the discharging and recharging efficiencies were derived. Key components of the proposed controller are the rule-based strategy to control the ICE in its peak-efficiency region and to control the energy production of the ICE so that the SOC is properly regulated and the frequency of starting and stopping of the ICE is managed. To achieve further fuel saving, an additional HEV hardware architecture namely “ISG-assisted PHEV” was also proposed. The main feature
of this new vehicle architecture is the support for the ICE by an electrical system improvement, which consists of a downsized EMG and an ISG that can be coupled with the EMG. It was shown that the ISG-assisted PHEV enabled the PBS controller to control the ICE within its peak-efficiency region in a very similar way to having a continuously variable transmission, although employing a likely lower cost DSG.

Q4. What is the best fuel economy achievable by the HEV in real-time driving (online driving)?

The online PBS controller demonstrated a fuel consumption of 3.66 L/100km on ISG-unassisted PHEV over AUDC leading to 41.3% fuel saving with respect to the conventional vehicle. This fuel consumption was within 0.05 L/100km of the best HCPMS (offline controller) performance but without any look-ahead capability. For the same drive cycle, ISG-assisted PHEV consumes only 3.32 L/100km of fuel with online PBS controller leading 47.5% overall fuel saving compared to the conventional vehicle. The above performance of HEVs with the PBS controller on short drive cycles was confirmed by achieving the same fuel performance over long and changing driving patterns.

Q5. What are the effects of the sub-system efficiencies on the fuel efficiency of the online PMSs and on the complexity of their architecture?

ISG-assisted PHEV has an electrical system with improved overall efficiency. Results have shown that the ISG-assisted PHEV reduces fuel consumption further up to 9.3% for both PBS and ECMS controllers compared to the ISG-unassisted PHEV. Because of the improved overall electrical efficiency, the ISG-assisted PHEV can define a ICE’s peak-efficiency region with $\bar{\eta}_{ele} = 0.94$ compared to 0.84 of the ISG-unassisted PHEV leading to the improvement of overall efficiency of the ICE. This reflects the necessity of a high performing electrical system in online power balancing of HEVs. Despite the simple architecture of the PBS controller, it performs near-optimally with fast computational time, which is less than 5 s for all standard drive cycles.

Online controllers such as the PBS and the ECMS, which do not consider road gradient, may not necessarily be fuel optimal or charge sustaining in these drive cycles. The inclusion of the upcoming driving information from on-board telematics
devices, readily available for automotive applications, to the power management of HEVs will be more fuel beneficial than strategies without using any information. Predictive power management strategies that can fulfill requirements of these applications are not sufficiently addressed in current research. Here, answers to the research questions related to predicted fuel saving strategies of HEVs are presented.

**Q6. Can a real-time predictive power management strategy that uses upcoming driving information for optimizing the power management be developed?**

A new PMS namely “ICE on/off PMS”, was proposed as the power management algorithm in a predictive framework because of its improved computational efficiency and sufficiently high fuel saving capability. The ICE on/off PMS can also be viewed as the combination of a model-based optimization strategy to control the ICE on/off status and rule-based strategy to split power demand according to the ICE status and the battery SOC. A steepest ascent hill-climbing algorithm optimizes the sequence of the ICE on/off status represented as a binary variable, while a rule based strategy splits the power demand between the ICE and the EMG such that ICE is operated within its peak efficiency region if its status is ‘on’. Unlike other existing PMSs, which control the power split ratio directly, the optimization of ICE’s on/off sequence makes the ICE on/off PMS computationally fast and robust to predicted driving information of the journey. Results here showed that the offline ICE on/off PMS is always better than the PBS controller in terms of fuel efficiency and capable of executing results in about 100 s for 1000 s long drive cycles (HWFET) demonstrating about 20 times computationally faster than the HCPMS.

**Q7. How does the fuel saving of the HEV vary with the preview length of upcoming driving information?**

A predictive PMS based on the ICE on/off PMS was proposed to investigate the fuel saving capability of the parallel HEV with upcoming driving information. When only the speed information is considered, about 80 s look-ahead period was sufficient to achieve equal results to the offline strategy. The proposed predictive PMS showed well its capability for power management of the HEV even with the presence of road gradient. With the combined speed and gradient based look-ahead information, the
reduction of fuel consumption with the increment of look-ahead period showed heavy dependency of the HEV performance on road gradient. It was found here that a look-ahead time should be about 300 s to get the best HEV performance on the inclined roads.

Q8. How much fuel can be saved by the speed modification of the HEV when the upcoming information is known?

Furthermore, the fuel saving capability of HEVs through speed modification that simulates an intelligent HEV was investigated. The intelligent vehicle velocity modification algorithm (IVVMA) proposed by Manzie et al. was improved by better controlling the vehicle deceleration. The improved IVVMA demonstrated about 6.5% improvement over the IVVMA. The intelligent HEV modifies the speed by the improved IVVMA and manages the power demand on the modified speed trace according to the predictive PMS proposed. The results showed that up to 53.3%

Figure 8.1: Overall summary of fuel savings with all the strategies addressed in this thesis compared to the conventional vehicle on the AUDC
overall fuel saving was possible by the intelligent HEV on city cycles compared to the conventional vehicle.

Finally, the fuel consumptions of all the fuel saving strategies addressed in this thesis can be compared with respect to that of the conventional vehicle as in Fig. 8.1 on AUDC. It clearly shows the fuel savings with the combination of different powertrain architectures, PMSs and driving style controlling and may become a guideline to select the best strategy by comparing the fuel saving, cost of implementation and practicability of implementation.

8.2 Future Research

In future work, the existing speed prediction method that assumes the exact speed information, a more realistic model that constructs a speed trace using the traffic information, speed limitations and length of road segments of future driving can be used for the predictive power management. This model may provide a platform to check the robustness of the PMS to the upcoming speed profile (or the drive demand). The HCPMS, which searches for the best power split ratio, can be applied in the model predictive framework and used as a benchmark for the above testing.

Besides the fuel consumption, the vehicle emission is also an important factor to manage. In this dissertation, only the fuel saving was the main objective and emission of the HEV was neglected. The vehicle model can be included the emission and power management strategies can be updated to include the vehicle emission.

The fuel saving by the speed modification may depend on the powertrain. Therefore, the IVVMA developed for the conventional vehicle may not be fuel optimal for hybrid vehicles. Furthermore, an optimization method that can handle both speed modification and the power management together will give the best fuel saving results from the hybridization of two methods. To this end, a speed modification algorithm that considers the ICE efficiency characteristics and road gradient, which are neglected in developing the IVVMA, may be required in the future.

All the power management strategies developed in this work is based on the feed-backward vehicle simulation model with quasi-static assumption. Therefore,
the reported performance on the simple vehicle model may not be valid on the real world HEV model. These PMSs may be improved further for real world application by testing on feed forward vehicle model with detailed vehicle dynamics.
Bibliography


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A.1 Optimization of Transmission Gear Ratios with the PSO

Design of the gear ratios of the transmission system with the PSO is explained here. The overall fuel consumption of a powertrain is the set of the gear ratios of the transmission because they determine the operating regions of the ICE. Moreover, when the torque (or speed) demand exceeds the torque (or speed) limits of the ICE, downshift (or upshift) of the gear position should bring it to feasible operating area. A good transmission system operates the ICE in the vicinity of the point of the highest efficiency while always meeting the torque and speed demands of the vehicle. This is essentially an optimization problem, which can be presented as

$$ TotalFuel^* = \min_{R=[r_1, r_2, r_3, r_4, r_5]} \left\{ \sum_{k=1}^n m_f[R(\xi(t))] \right\}. \quad (A.1) $$

s.t.

$$ R_k > R_{k+1} \quad \text{for} \ k = 1, 2, 3, 4 \quad (A.2) $$

The objective function in Equ. (A.1) minimizes the overall fuel consumption of the vehicle for the considered drive cycle by varying the set of gear ratios $R$. The function $\xi(.) \in \{1, 2, 3, 4, 5\}$ represents the employed speed-dependent gear shifting
procedure that shifts the gear position according to the output speed demand of the gear box. Fig. A.1 illustrates the searching behavior of the PSO for each gear ratio with the resulting fuel consumption.

![Figure A.1: Searching behavior of the PSO for the gear box optimization problem](image)

The PSO can solve this non-linear optimization problem easily with the definition of a particle with $R = [r_1, r_2, r_3, r_4, r_5]$ a function that releases the overall fuel consumption for any feasible $R$. PSO for optimizing the gear ratios was implemented in MATLAB. The set of parameters used for the PSO are listed in Table A.1.

Table A.1: Set of parameters used by the PSO for optimizing the gear ratios of the transmission

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c_{1i}$</td>
<td>2.5</td>
</tr>
<tr>
<td>$c_{1f}$</td>
<td>0.5</td>
</tr>
<tr>
<td>$c_{2i}$</td>
<td>0.5</td>
</tr>
<tr>
<td>$\omega_1$</td>
<td>0.9</td>
</tr>
<tr>
<td>$\omega_2$</td>
<td>0.7</td>
</tr>
<tr>
<td>MAXITER</td>
<td>300</td>
</tr>
<tr>
<td>No. of particles</td>
<td>25</td>
</tr>
<tr>
<td>Initial $R$</td>
<td>[3.8, 2.2, 1.6, 1.05, 0.6]</td>
</tr>
</tbody>
</table>
A.2 Important Data of the ISG-Unassisted PHEV, the ISG-Assisted Parallel HEV and the Conventional Vehicle

All these vehicles model a typical Australian full sized sedan. Even though slight variations of vehicle masses because of different component sizes are not mentioned here, vehicle models consider the mass variation with component sizing. The ISG-unassisted PHEV consisting only the EMG as the electrical driver also refers to the normal parallel HEV, where not mentioned.
Table A.2: Numerical values of important data of ISG-assisted parallel HEV, ISG-unassisted PHEV and the conventional vehicle

<table>
<thead>
<tr>
<th>Component</th>
<th>Parameter</th>
<th>Symbol</th>
<th>ISG-assisted PHEV</th>
<th>ISG-unassisted PHEV</th>
<th>Conventional Vehicle</th>
</tr>
</thead>
<tbody>
<tr>
<td>ICE (Honda Insight, VTEC-E SI engine)</td>
<td>peak power</td>
<td>$P_{icemx}$</td>
<td>50 kW</td>
<td>50 kW</td>
<td>80 kW</td>
</tr>
<tr>
<td></td>
<td>peak torque</td>
<td>$T_{icemx}$</td>
<td>90 Nm</td>
<td>90 Nm</td>
<td>145 Nm</td>
</tr>
<tr>
<td></td>
<td>at 480 rad/sec</td>
<td></td>
<td>0.4</td>
<td>0.4</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>peak efficiency</td>
<td>$\eta_{opt}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EMG (Honda permanent magnet motor)</td>
<td>peak power</td>
<td>-</td>
<td>20 kW</td>
<td>30 kW</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>peak torque</td>
<td>-</td>
<td>200 Nm</td>
<td>300 Nm</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>peak efficiency</td>
<td>-</td>
<td>0.91</td>
<td>0.91</td>
<td>-</td>
</tr>
<tr>
<td>ISG (Honda permanent magnet motor)</td>
<td>peak power</td>
<td>-</td>
<td>10 kW</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>peak torque</td>
<td>-</td>
<td>45 Nm</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>peak efficiency</td>
<td>-</td>
<td>0.96</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>ESS (Li-Ion battery)</td>
<td>voltage</td>
<td>$V$</td>
<td>300 V</td>
<td>300 V</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>capacity</td>
<td>$C$</td>
<td>3.2 Ah</td>
<td>3.2 Ah</td>
<td>-</td>
</tr>
<tr>
<td>Transmission system</td>
<td>gear ratio</td>
<td>$R_{gb}$</td>
<td>[2.697 1.839 1.354 1.151 0.776]</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>gear efficiency</td>
<td>$\eta_{gb}$</td>
<td>[0.93 0.95 0.97 0.98 0.97]</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>final drive ratio</td>
<td>$R_{fd}$</td>
<td>3.98</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>EMG/ICE gear ratio</td>
<td>$R_c$</td>
<td>0.83</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>ISG/ICE gear ratio</td>
<td>-</td>
<td>0.57</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>gear shifting procedure</td>
<td>-</td>
<td>1-2-3-4-5 shifts</td>
<td>at 24, 40, 64, 75 km/h</td>
<td></td>
</tr>
<tr>
<td>Vehicle data</td>
<td>rolling radius of wheel</td>
<td>$r_{wh}$</td>
<td>0.29 m</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>frontal area</td>
<td>$A$</td>
<td>1.92 m²</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>drag coefficient</td>
<td>$C_d$</td>
<td>0.32</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>coefficient of rolling resistance</td>
<td>$C_{rr}$</td>
<td>0.015</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>total mass</td>
<td>$m$</td>
<td>1665 kg</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
A.3 ICE’s Peak-efficiency Region

The derivation of $T_L(\omega)$, $T_H(\omega)$, $\omega_L$ and $\omega_H$ is explained here. Improvements of four inefficient ICE operations are analyzed. $T_L(\omega)$ and $T_H(\omega)$ are obtained by shifting the ICE operation onto the optimal torque curve from low torque and high torque regions respectively. $\omega_L$ and $\omega_H$ are obtained by shifting the ICE operation onto the point of the highest efficiency from low speed and high speed ends of the optimal torque curve respectively. It is assumed in this case that the required speed change to shift the ICE operation is allowed by the transmission system. The corresponding change of operating points of the ICE and the power flow of the ICE and the electric system are shown in A.2. For all these cases, the energy balance and energy loss should be considered.

A.3.1 Lower Torque Boundary of the ICE’s Peak-Efficiency Region

Consider improving the low efficient ICE operation at low torque $T_{\text{ice}}(\omega)$ by shifting it to $T_{\text{ice}}^*(\omega)$ while supplying $E (= pt_1)$ amount of energy at a $p$ power demand. The efficiency of the ICE is improved from $\eta_{\text{ice}}(\omega, T_{\text{ice}})$ to $\eta_{\text{ice}}^*(\omega)$. Fig. A.2(a) shows the change of operating points of the ICE and the power output (or input) of the ICE and the electric system.

In case of hybrid operation of the ICE with the electric system, the ICE should charge the battery for $t_2$ time long so that electric system can meet the demand when the ICE’s power is cut off. Thus,

$$ (p_{\text{ice}}^* - p)t_2 = \frac{p}{\eta_{\text{dis}}\eta_{\text{chg}}}(t_1 - t_2). \quad (A.3) $$

Energy loss during the ICE-alone operation is equal to

$$ pt_1 \left( \frac{1}{\eta_{\text{ice}}(\omega, T_{\text{ice}})} - 1 \right). \quad (A.4) $$

Energy loss during the hybrid operation of the ICE with the electric system is
(a) Shifting of the ICE operating point at low torque to the optimal torque curve

(b) Shifting of the ICE operating point at high torque to the optimal torque curve

(c) Shifting of the ICE operating point at a low-speed end of the optimal torque curve towards the highest ICE efficiency point

(d) Shifting of the ICE operating point at a high-speed end of the optimal torque curve towards the highest ICE efficiency point

Figure A.2: Improving the efficiency of the ICE operation by using the electric system
calculated to
\[ p^*_\text{ice} t_2 \left( \frac{1}{\eta^*_\text{ice}(\omega)} - 1 \right) + (p t_1 - p t_2) \left( \frac{1}{\bar{\eta}_\text{dis}\bar{\eta}_\text{chg}} - 1 \right). \] (A.5)

In order for the use of electric system to be fuel efficient, energy loss of the hybrid operation should be less than that of the ICE-alone operation. Thus,
\[ p^*_\text{ice} t_2 \left( \frac{1}{\eta^*_\text{ice}(\omega)} - 1 \right) + (p t_1 - p t_2) \left( \frac{1}{\bar{\eta}_\text{dis}\bar{\eta}_\text{chg}} - 1 \right) \leq p t_1 \left( \frac{1}{\eta_{\text{ice}}(\omega, T_{\text{ice}})} - 1 \right) \] (A.6)

By removing \( t_1 \) and \( t_2 \) from (A.3) and (A.6) and simplifying, the following condition is derived.
\[ \eta_{\text{ice}}(\omega, T_{\text{ice}}) \leq \frac{\eta^*(\omega)}{p^*_\text{ice}(\omega)} (p + (p^*_\text{ice}(\omega) - p)\bar{\eta}_\text{chg}\bar{\eta}_\text{dis}) \] (A.7)

The equality condition in (A.7) gives the set of ICE operating points, at which the use of the electric system to improve ICE’s efficiency results no gain. Therefore, the lower torque boundary of the peak-efficiency region of the ICE, \( T_L(\omega) \) can be obtained from the equality condition in (A.7) as,
\[ \eta_{\text{ice}}(\omega, T_L(\omega)) = \frac{\eta^*(\omega)}{T^*_\text{ice}(\omega)} [T_L(\omega) + (T^*_\text{ice}(\omega) - T_L(\omega))\bar{\eta}_\text{dis}\bar{\eta}_\text{chg}] \] (A.8)

### A.3.2 Upper Torque Boundary of the ICE’s Peak-Efficiency Region

Consider improving the low efficient ICE operation at torque \( T_{\text{ice}}(\omega) (> T^*_\text{ice}(\omega)) \) by shifting it to \( T^*_\text{ice}(\omega) \) while supplying \( E (= p t_1) \) amount of energy at a \( p \) power demand. The efficiency of the ICE is improved from \( \eta_{\text{ice}}(\omega, T_{\text{ice}}) \) to \( \eta^*_\text{ice}(\omega) \). Fig. A.2(b) illustrates the change of operating points and the variation power output (or input) of the ICE and the electric system.

The ICE should operate for a \( t_2 (> t_1) \) time long so that it can replace the
drained battery energy completely. Therefore, from energy balance,

\[ p_{\text{ice}}^* t_2 = p t_1 + (p - p_{\text{ice}}^*) t_1 \left( \frac{1}{\eta_{\text{dis}} \eta_{\text{chg}}} - 1 \right). \]  

(A.9)

Energy loss in ICE-alone operation is given by

\[ p t_1 \left( \frac{1}{\eta_{\text{ice}}(\omega, T_{\text{ice}})} - 1 \right). \]  

(A.10)

Energy loss during the hybrid operation of the ICE with the electric system is calculated to

\[ (p - p_{\text{ice}}^*) t_1 \left( \frac{1}{\eta_{\text{dis}} \eta_{\text{chg}}} - 1 \right) \]  

(A.11)

Improvement of the ICE’s efficiency to be fuel efficient, energy losses of the hybrid operation of the ICE and the electric system should be less than that of the ICE-alone configuration. Thus,

\[ p_{\text{ice}}^* t_2 \left( \frac{1}{\eta_{\text{ice}}^*(\omega)} - 1 \right) + (p - p_{\text{ice}}^*) t_1 \left( \frac{1}{\eta_{\text{dis}} \eta_{\text{chg}}} - 1 \right) \leq p t_1 \left( \frac{1}{\eta_{\text{ice}}(\omega, T_{\text{ice}})} - 1 \right). \]  

(A.12)

By removing \( t_1 \) and \( t_2 \) from (A.9) and (A.12) and simplifying, the condition for the shifting of operating points to be effective, can be derived as

\[ \eta_{\text{ice}}(\omega, T_{\text{ice}}) \leq \frac{p \eta_{\text{ice}}(\omega) \eta_{\text{chg}} \eta_{\text{dis}}}{(p - p_{\text{ice}}^*(\omega)) + p_{\text{ice}}^*(\omega) \eta_{\text{chg}} \eta_{\text{dis}}}. \]  

(A.13)

The equality relationship of (A.13) gives the ICE operating point, at which energy losses of both configurations are equal. Accordingly, the upper toque boundary of the peak-efficiency region of the ICE \( T_H \) is given by the operating points that satisfy

\[ \eta_{\text{ice}}(\omega, T_H(\omega)) = \frac{T_{\text{ice}}^*(\omega) \eta_{\text{ice}}^*(\omega) \eta_{\text{dis}} \eta_{\text{chg}}}{[T_H(\omega) - T_{\text{ice}}^*(\omega) + T_{\text{ice}}^*(\omega) \eta_{\text{dis}} \eta_{\text{chg}}]} \]  

(A.14)
A.3.3 Lower Speed Limit of the ICE’s Peak-Efficiency Region

Consider improving the efficiency of ICE operation at low-speed end of the optimal torque curve by shifting towards the point of the highest efficiency when meeting a power demand $p_{\text{ice}}^*(\omega)$. Figure A.2(c) shows the change of operating points and the variation of the power flows through the ICE and the electric system. It is assumed that the required speed change to shift the ICE operation is allowed by the transmission system. The energy balance and energy loss for this case similar to A.3.1; therefore takes the form of equations (A.3) and (A.6). By substituting $p$ with $p_{\text{ice}}^*(\omega)$ and $p_{\text{ice}}^*(\omega)$ with $p_{\text{ice}}^{opt}$ in (A.6), the condition that the improvement of the efficiency of the ICE is fuel-efficient is given by,

$$\eta_{\text{ice}}(\omega, T_{\text{ice}}^*) \leq \frac{\eta_{\text{opt}}}{\eta_{\text{ice}}} \left( p_{\text{ice}}^{opt} + (p_{\text{ice}}^{opt} - p_{\text{ice}}^*) \bar{\eta}_{\text{chg}} \bar{\eta}_{\text{dis}} \right)$$  (A.15)

Therefore, the lower speed boundary of the best ICE operating region $\omega_L$ is given by the $\omega$ that satisfies the equality condition in (A.15) as

$$\eta_{\text{ice}}(\omega_L, T_{\text{ice}}^*(\omega_L)) = \frac{\eta_{\text{opt}}}{\eta_{\text{ice}}} \left[ (p_{\text{ice}}^{opt} - p_{\text{ice}}^*(\omega_L)) \bar{\eta}_{\text{dis}} \bar{\eta}_{\text{chg}} + p_{\text{ice}}^*(\omega_L) \right]$$  (A.16)

A.3.4 Upper Speed Limit of the ICE’s Peak-Efficiency Region

The efficiency of the ICE operated at high-speed end of the optimal torque curve can be improved by shifting towards the point of the highest efficiency, using the electric system. Figure A.2(d) shows the change of ICE operating points and the power flows through the ICE and electric system. Power demand $p_{\text{ice}}^*(\omega)$ is met for $t_1$ time period. It is assumed that the required speed change to shift the ICE operation is allowed by the transmission system. This is similar to the case in A.3.2. Thus, by substituting $p$ by $p_{\text{ice}}^*(\omega)$ and $p_{\text{ice}}^*(\omega)$ by $p_{\text{ice}}^{opt}$ in (A.13), the condition that
the improvement of the efficiency of the ICE to be fuel efficient, becomes

\[ \eta_{\text{ice}}(\omega, T_{\text{ice}}^*) \leq \frac{p_{\text{ice}}^*(\omega) \eta_{\text{chg}} \eta_{\text{dis}}}{p_{\text{ice}}^*(\omega) - p_{\text{opt}}^* + p_{\text{ice}} \eta_{\text{chg}} \eta_{\text{dis}}} \]  

(A.17)

Therefore, the upper speed boundary of the best ICE operating region \( \omega_H \) is given by the \( \omega \) that satisfies the equality condition in (A.17) as

\[ \eta_{\text{ice}}(\omega_H, T_{\text{ice}}^*(\omega_H)) = \frac{p_{\text{ice}}^*(\omega_H) \eta_{\text{chg}} \eta_{\text{dis}}}{p_{\text{ice}}^*(\omega_H) - p_{\text{opt}}^* + p_{\text{ice}} \eta_{\text{chg}} \eta_{\text{dis}}} \]  

(A.18)

### A.4 Validation of the Vehicle Model and the PBS controller

This section of the appendix is dedicated to give more information to the reader about the vehicle model and the PBS controller. Two main objectives here are to validate the vehicle model for its low fuel consumption with Honda Insight ICE and to ensure the demonstrated performance of the PBS controller on different parallel full hybrid configurations.

#### A.4.1 Validation of the Vehicle Model

The fuel consumption results of vehicle models used in this thesis demonstrates small figures compared to real world data. This is mainly due to two reasons: improved peak efficiency of Honda Insight ICE and optimization of models focusing on best fuel performance. Fuel performance of the conventional vehicle is compared to explain the effects of these two cases. A Ford Falcon ICE with peak efficiency of 0.325 is compared with the Honda Insight ICE. Results are given in Table A.3, which shows about 1.8 L/100 km for 0.75 peak (and also part-load efficiency) improvement of the ICE efficiency.

The real world fuel consumptions demonstrates higher fuel consumption because they are design to meet the peak power demand and vehicle performance. Next, a conventional vehicle with 180 kW Ford Falcon ICE sized to meet the vehicle performance is tested with the developed vehicle model. Results are shown in Table A.4,
Table A.3: Comparison of fuel consumption of Ford Falcon ICE (0.325 peak efficiency) and Honda Insight ICE (0.40 peak efficiency) sized to meet the best fuel performance on the conventional vehicle

<table>
<thead>
<tr>
<th>Drive cycle</th>
<th>Fuel consumption (L/100km)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Ford Falcon</td>
</tr>
<tr>
<td>NEDC</td>
<td>8.19</td>
</tr>
<tr>
<td>FTP-75</td>
<td>8.02</td>
</tr>
<tr>
<td>HWFET</td>
<td>6.30</td>
</tr>
</tbody>
</table>

which also includes the corresponding ADVISOR’s fuel consumption data obtained directly from Lim’s thesis [156]. It should be noted that these results are heavily dependent on the transmission and idle fuel consumption of vehicle models etc. Results, which also agree with those of ADVISOR model, show that fuel performance of the vehicle deteriorates by about 1.8 L/100km from its best fuel performance when the ICE is oversized to meet the vehicle performance requirements. The overall improvement of the fuel saving (about 3.5 L/100km) due to combined effects of high engine efficiency and optimised engine size demonstrates reasons for low fuel consumption figures in this thesis.

Table A.4: Fuel consumption of conventional Ford Falcon vehicle sized to meet standard vehicle performance

<table>
<thead>
<tr>
<th>Drive cycle</th>
<th>Fuel consumption (L/100km)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Author’s Model</td>
</tr>
<tr>
<td>NEDC</td>
<td>10.20</td>
</tr>
<tr>
<td>FTP-75</td>
<td>9.86</td>
</tr>
<tr>
<td>HWFET</td>
<td>7.80</td>
</tr>
</tbody>
</table>

A.4.2 Validation of the PBS controller

PBS controller can be adapted to different configurations with different components much easier (one-off parameter tuning) than other rule-based controllers which require extensive tuning effort. In addition to demonstrated performance on the Honda Insight, the PBS controller is also tested on two more parallel full HEVs that use Ford Falcon ICE (Fig. A.3(b)) and Toyota Prius ICE (Fig. A.3(c)). Results are

\(^2\text{With optimized transmission}\)
(a) Efficiency map of Honda Insight ICE

(b) Efficiency map of Ford Falcon ICE

(c) Efficiency map of Toyota Prius ICE

Figure A.3: Efficiency maps of Honda Insight, Ford Falcon and Toyota Prius ICEs
shown in Table A.5. Offline fuel consumption results are included within brackets for the comparison.

Table A.5: Performance of the PBS controller with Ford Falcon, Toyota Prius and Honda Insight ICES

<table>
<thead>
<tr>
<th>Drive cycle</th>
<th>Fuel consumption (L/100km)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Ford Falcon</td>
</tr>
<tr>
<td>NEDC</td>
<td>4.89 (4.84)</td>
</tr>
<tr>
<td>FTP-75</td>
<td>4.48 (4.45)</td>
</tr>
<tr>
<td>MPDC</td>
<td>4.99 (4.91)</td>
</tr>
<tr>
<td>AUDC</td>
<td>4.47 (4.44)</td>
</tr>
<tr>
<td>HWFET</td>
<td>4.99 (4.96)</td>
</tr>
</tbody>
</table>

It can be seen that the performance of the PBS controller is consistent on the Ford Falcon and Toyota Prius ICES, which has very different efficiency characteristics. In adopting to vehicle models, the PBS controller does not require much tuning effort except $\bar{\eta}_{ele}$, which can easily be tuned. Therefore, PBS controller has the advantage of transferability which is a characteristic of model-based power management controllers.

A.5 Intelligent Vehicle

A.5.1 Acceleration of the Intelligent Vehicle

Instantaneous acceleration of the intelligent vehicle $a_{int}$ at time $k$ is given by the difference equation

$$a_{int}(k) = \frac{[v_{int}(k+1) - v_{int}(k)]}{\Delta t}$$  \hspace{1cm} (A.19)

where, $\Delta t$ is the sampling period, which is equal to 1s, and $v_{int}(k)$ and $v_{int}(k+1)$ are respectively the speed of the intelligent vehicle at time $k$ and $k + 1$, which are given by (A.20) and (A.21).

$$v_{int}(k) = \frac{1}{T_p} \sum_{i=k}^{k+T_p} v_{lead}(i)$$  \hspace{1cm} (A.20)
\[ v_{int}(k + 1) = \frac{1}{T_p} \sum_{i=k+1}^{k+T_p+1} v_{lead}(i) \] (A.21)

\( T_p \) is the look-ahead time. Therefore, the acceleration of the intelligent vehicle is given by

\[ a_{int}(k) = \frac{1}{T_p} [v_{lead}(k + T_p + 1) - v_{lead}(k)] \] (A.22)

### A.5.2 Coasting Deceleration of the Intelligent Vehicle

The ideal coasting deceleration of the vehicle \( d_{cst,th} \) traveling at speed \( v(t) \) is given by equ. 3.7 with zero motive power as

\[ d_{cst,th} = -\frac{1}{m} \left[ \frac{1}{2} AC_d \rho v(t)^2 + mg \cos(\theta) \right] \] (A.23)

To find the fuel efficient deceleration (or acceleration) for a particular speed, the vehicle can be decelerated at different rates of decelerations in that speed and fuel consumption can be calculated. The best deceleration needs to be found with a proper objective function.

Fig. A.4 illustrates the variation of speed and distance for constant speed and declarations followed by the coasting driving. Total distance for the deceleration driving action can be calculated with following steps:

from equations of motions,

\[ d_1 = v + \frac{d}{2} \] (A.24)

\[ d_2 = \int_{(v+d)}^{0} -\frac{m\dot{v}}{0.5AC_d \rho \dot{v}^2 + mg \cos(\theta)} d\dot{v} \] (A.25)

\[ d_d = d_1 + d_2 \]
Figure A.4: Variation of speed with distance for a constant deceleration followed by coasting of the vehicle moving at speed $v$

\[
= v + \frac{d}{2} + \int_{(v+d)}^{0} \frac{-m\dot{v}}{0.5AC_d\rho\dot{v}^2 + mgC_{rr}\cos(\theta)} d\dot{v}
\]

Similarly, for the constant speed,

\[
d_0 = v + \int_{(v)}^{0} \frac{-m\dot{v}}{0.5AC_d\rho\dot{v}^2 + mgC_{rr}\cos(\theta)} d\dot{v}
\]

Let $\dot{m}_{f,v}$ be the rate of fuel consumption at speed $v$ and $M_{d_d}$ be the total fuel consumption involved in traveling $d_d$ distance with the deceleration. Since the fuel consumptions for different decelerations are not comparable due to different distance traveled, fuel consumptions need to be corrected for traveling a equal distance. Therefore, fuel consumption to travel $d_0$ distance in the case of deceleration is corrected as,

\[
\xi(v, d) = M_{d_d} + \frac{d_0 - d_d}{v} \dot{m}_{f,v}
\]  

(A.26)

Finally, fuel efficient coasting deceleration at the vehicle speed $v$ ($d_{cst,v}$) can be
obtained by minimizing $\xi(v, d)$ in (A.27) as

$$d_{\text{cat}0v} = \arg \min_{d_{\text{min}} \leq d \leq 0} \{\xi(v, d)\} \quad (A.27)$$
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2010

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