A Survey on Key Techniques and Development Perspectives of Equivalent Consumption Minimisation Strategy for Hybrid Electric Vehicles

Chen, Z.[1], Liu, Y.[1*], Ye, M.[2], Zhang, Y.[3], Chen, Z.[4, 5*] and Li, G.[5]
1 = State Key Laboratory of Mechanical Transmissions & School of Automotive Engineering, Chongqing University, Chongqing 400044, China
2 = Key Laboratory of Advanced Manufacture Technology for Automobile Parts, Ministry of Education, Chongqing University of Technology, Chongqing 400054, China
3 = Sir William Wright Technology Center, Queen's University Belfast, Belfast, BT9 5BS, United Kingdom
4 = Faculty of Transportation Engineering, Kunming University of Science and Technology, Kunming 650500, China
5 = School of Engineering and Materials Science, Queen Mary University of London, London, E1 4NS, UK
* = Corresponding author details, andylyg@umich.edu (Liu, Y.) and chen@kust.edu.cn (Chen, Z.)

Abstract: Hybrid electric vehicles (HEVs), as a promising solution to mitigate environmental pollution and reduce fuel consumption, employ a combination of fuel and electric power as power supply for boosting the vehicle's fuel economy. Comparing to conventional internal combustion engine (ICE) driven vehicles, the additional propulsion power source in electrified powertrain systems of HEVs leads to the extra control degree of freedom. Thus, a well-designed energy management strategy (EMS) is indispensable to cope with the complexity of the power distribution existing in multiple power source system. Equivalent consumption minimisation strategy (ECMS) is one of the most promising EMS techniques due to its capability of achieving the real-time local optimal control. In ECMS, a key parameter – equivalent factor (EF) is usually employed to unify the ICE fuel consumption and the electric energy consumption into a single variable representing the equivalent fuel economy, thereby achieving the instantaneous fuel economy optimisation. This paper comprehensively surveys the state-of-the-art in ECMSs for PHEVs and HEVs. Firstly, the basic operation mechanism of ECMSs is discussed. Then, ECMSs are classified based on their dependence on either online computation or offline pre-computation. Moreover, the core technique of ECMSs – EF adaptation is elaborated in terms of their principles, key characteristics, advantages, and disadvantages. In addition, the key factors for the EF adaptation as well as the corresponding factor integration methods are analysed and summarised. Finally, future research trends and the gaps for the development of ECMSs are discussed.

Highlights:

- A comprehensive review of ECMS for (P)HEVs is presented.
- A novel classification of EF adaptation methods in ECMS is proposed.
- Insights into key factors for the EF adaptation are discussed.
- The most important trends in ECMS development are highlighted and discussed.

Key words: Hybrid electric vehicle (HEV), Plug-in hybrid electric vehicle (PHEV), energy management strategy (EMS), optimal control strategy, equivalent consumption minimisation strategy (ECMS), equivalent factor (EF).

Word Count: 13796

Nomenclature:

Greek Letters

λ	constant ratio of energy delivered to wheels and recuperated energy
β	scaling factor
μ	calibratable variable
α	ratio of nominal AER to the total trip
γ	sale price ratio of electric power to fuel

Abbreviations

HEV	hybrid electric vehicle
PHEV	plug-in hybrid electric vehicle
ICE	internal combustion engine
ECM	energy management strategy
RB	rule-based
OB	optimisation-based
LB	learning-based
DP	dynamic programming
ECMS	equivalent consumption minimisation strategy
EF	equivalent factor
PMP	Pontryagin's minimum principle
GA	genetic algorithm
PSO	particle swarm optimisation
A-ECMS	adaptive equivalent consumption minimisation strategy
SOC	state of charge
PID	proportional-integral-derivative
SVM	support vector machine
GIS	geographic information system
LVQ	learning vector quantisation
P-ECMS	predictive equivalent consumption minimisation strategy
DOE	design of experiments
PI	proportional integral
NN	neural networks
ANFIS	adaptive neuro-fuzzy inference system
HiL	hardware-in-the-loop
NARX	nonlinear autoregressive with exogenous inputs
RNN	recurrent neural network
CD	charging-depleting
CS	charge-sustaining
SPM	single particle model
SOH	battery state of health
MPC	model predictive control
NN-based	artificial-neural-networks-based
CNN	chaining neural network
RBF	radial basis function
RNN	recurrent neural network
GPS	global positioning system
ITS	intelligent transportation system
SPAT	signal phase and timing
PSD	participatory sensing data
PCA	principal component analysis
AER	all-electric range
ELM	extreme learning machine

Symbols

S_{dis}	discharging equivalent factor
S_{chg}	charging equivalent factor
S	equivalent factor
P_e	net power charged to battery (kW)
t	time (s)
u	control variable
$\bar{\eta}_e^{(d)}$	average electric circuit efficiencies for discharge
$\bar{\eta}_e^{(c)}$	average electric circuit efficiencies for charge
$\bar{\eta}_f$	average efficiency for combustion engine
W	weighting factor
SOC_0	desired SOC value
$SOC_{\max}$	prescribed battery SOC upper limits
$SOC_{\min}$	prescribed lower battery SOC limits
S_0	square root of product of discharging and charging equivalent factor
p	probability of electric energy consumption
E_r	expected remaining mechanical energy demand (kW)
E_e	consumed electrical energy (kW)
ΔSOC	SOC deviation
E_{ref}	reference of consumed electrical energy (kW)
SOC_C	SOC centre
S_C	equivalent factor centre
l_r	SOC range scaling factor
l_s	Slope at the SOC centre of tangent curve
SOC_{ref}	SOC reference trajectory for PHEVs
K_P	proportional gain
K_I	integral gain
v_{std}	standard deviation of vehicle speed (m/s)
v_{ave}	average speed (m/s)
E_{re}	required tractive energy (kW)
E_b	recycled braking energy of future travel (kW)
X_e	nominal all-electric range (m)
X_t	total trip distance (m)
x_e	real-time all-electric range (m)

1. INTRODUCTION

Nowadays, due to widespread application of hydrocarbon-based transportation, the resulting issues such as environmental pollution, climate change and energy crises have become major concerns for automobile industry. As such, investigating high-efficient and environment-friendly alternative powertrain technologies draw massive attention from researchers in transportation sector. Among all exiting promising powertrain technologies, (plug-in) hybrid electric vehicle ((P)HEV) have been widely employed all over the world, due to their capacity to recover braking energy and the fact that an additional control degree of freedom in the powertrain raised by electrification is able to potentially increase the efficiency of powertrain system. (P)HEVs refer to vehicles that introduce the electric propulsion systems as the secondary energy sources into the conventional internal combustion engines (ICEs) based vehicles; in other words, multiple power sources are existed in (P)HEVs powertrain system. It is commonly acknowledged that the reduction of fuel consumption and tailpipe emission levels of (P)HEVs crucially depend on the control of power distribution among the multiple power sources, referred to as energy management strategy (EMS) [1].

The main function of EMS is to control and coordinate the power generation, energy storage and power flow within subsystems, with intention to fully exploit energy saving potential as well as to optimising a metric such as fuel/electricity consumption, emission, or some careful combination thereof [2]. To be specific, EMSs aim to not only split the supply power between multiple propulsion sources to satisfy all sorts of power demands such as the on-board electric power requirement and propulsion load, but maximise the vehicle overall efficiency and minimise emission levels without compromising the important aspects of the vehicular performance, such as driving range, acceleration, comfort, and convenience [3]. However, it has been proven that the fuel economy improvement and pollutant emission reduction are conflicting objectives [4, 5]. Thus, the EMS also should be sophistically tuned to satisfy a trade-off between them.

In conclusion, EMS is the supervisory control to generate the setpoint for the component-level controllers. The ultimate aim of EMS is to achieve lower both fuel consumption and engine emissions while delivering all energy requirements. Note that characteristic of hybrid drive train is considered as discrete dynamic system, which has time-varying plant, multi-domain variables, and nonlinear variable [6]. Therefore, EMSs in hybrid vehicles should be intelligent enough to promote the coordination of the component level operation. However, the complex configuration and behaviour of multi-source hybrid energy systems, as well as the complexity and uncertainty of real-world driving conditions, raise massive challenges to develop a robust and adaptive

EMS. Furthermore, to be applicable for real-time control, the EMS should be computationally efficient enough to satisfy the memory constraint of on-board microprocessor.

Generally, EMSs can be divided into three major categories: rule-based (RB), optimisation-based (OB), and learning-based (LB) [7]. Since this work will focus on elaborating the existing ECMS techniques in literature, only brief discussion about each category of EMSs will be presented in follows. A detailed classification of EMSs is plotted in Figure 1, and the corresponding comprehensive review can be found in Refs. [7] and [8].

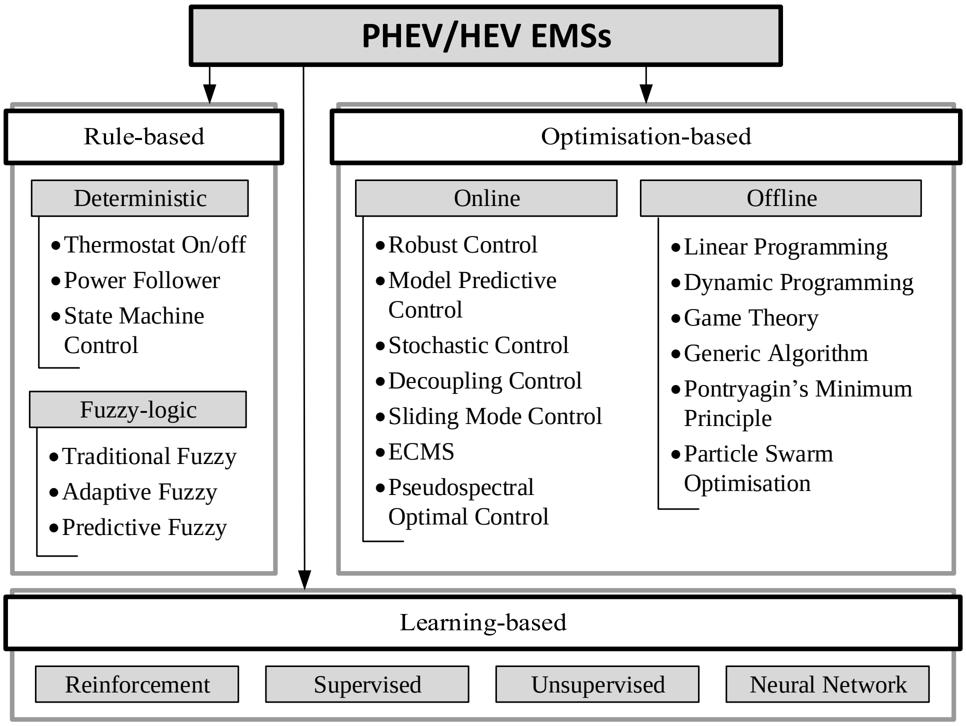


Figure 1. Classification of HEV energy management strategies

Rule-based (RB) EMSs are considered as the online method, owing to the real-time feasible implementation. Generally, the logical control rules of RB-EMSs are predefined based on human expertise, heuristics, or intuition without the consideration of any upcoming driving conditions. The main advantages of RB-EMSs lie in their simplicity and robustness, owing to the real-time feasible implementation when locating the rules in a look-up table, state machine or fuzzy logic table. Nonetheless, it relies deeply on experiences from experts and cannot guarantee the optimality due to the lack of adaptiveness to deal with time-varying scenarios. The RB-EMSs can be sub-classified into deterministic and fuzzy rule-based EMSs.

By contrast, the concept of optimisation-based (OB) EMSs is to utilise various optimisation methodologies to minimise specific cost functions with the constraints of the dynamic state, thereby finding the optimal controlling sequence. OB-EMSs can generally be classified into online and offline strategies. The offline OB-EMSs are the non-causal and global optimisation strategy that requires a priori knowledge of future driving conditions such as future driving speed, while the online strategies are the causal and local optimisation strategies that neither requires a prior knowledge of driving cycles nor ensures the optimal solution in the real-time applications [7, 8]. Regarding the offline OB-EMSs, the global optimisation techniques are deployed to find the absolute optimal control policy under given driving cycles. The global optimisation algorithms such as dynamic programming (DP) may result in high computational burden. Besides, the knowledge of the entire driving information needs to be acquired *a priori*. Obviously, it is difficult to apply the global optimisation methods in real-time controllers. However, the global optimal solution can be served as a benchmark for development of other EMSs techniques, this is, it is exploited to evaluate the controlling performance, extract the optimal control rules, and adjust the control parameters for the other EMS techniques. While, the online OB-EMSs convert the global optimisation problem of offline EMSs into an instantaneous optimisation problem, and attempt to obtain local optimal control decision without a prior knowledge of the entire driving cycle. Due to the resulting low computational effort, it yields the potential of being implemented in real-time control problems. Note that a typical instantaneous optimisation algorithm is the equivalent consumption minimisation strategy (ECMS), which is the most well-known real-time EMS and has been extensively employed in practice.

Learning-based (LB) EMSs have been rapidly developed in the last few years and shown promising potential because of its high adaptiveness to different driving conditions. LB-EMSs employ advanced data mining schemes for massive historical and real-time driving-related data to derive the optimal control decisions. For this method, the precise powertrain model is not imperative for the high-quality control. However, similar to other data-driven methods, the controlling performance of LB-EMSs strongly depends on the quality of training datasets. In addition, it is quite time-consuming to establish and structure a correct database. According to the learning type, LB-EMSs can be sub-grouped as reinforcement learning, supervised/unsupervised learning, neural network learning, and classification learning approaches [7].

In the existing literature, a number of reviews on different EMSs of HEVs and PHEVs have been conducted over the last decade [6-10]. However, to the authors' knowledge, there is still a lack of a comprehensive review of ECMS which is one of the most promising EMS techniques. The basic concept of ECMSs is to unify the ICE fuel consumption and the battery electric energy consumption into a single variable representing the fuel economy of vehicles. To achieve the required energy conversion, the equivalent factor (EF) is introduced in ECMS to weigh the electricity consumption, consequently transforming electric energy expenditure into an equivalent quantity of fuel consumption. As a result, the total fuel consumption is the sum of real fuel consumption by ICE and equivalent fuel consumption of electric motors. By doing so, ECMSs are able to instantaneously optimise the fuel economy by minimising the total fuel consumption at each instant. Note that the EF is an important dynamic variable determining the improvement of the fuel economy. Hence, EF adaptation methods must be properly developed to achieve the optimal fuel economy over different driving cycles.

Thus, this work intends to foster a better understanding of ECMSs, especially EF online adaptation methodologies, through a comprehensive review of the state-of-the-art ECMS techniques including the principles, key characteristics, advantages, disadvantages, and key factors for EF adaptation. The remainder of this study is organised as follows. The theory of ECMS is explained in Section 2. In Section 3, the overall classification for ECMSs of HEVs is elaborated. Section 4 provides detailed insight of various EF adaptation methods. Section 5 discusses the key factors that significantly affect the performance of the EF online adaptation. Finally, the future trends, as well as research directions in ECMSs of HEV/PHEVs, are highlighted in Section 6.

2. ECMS METHODOLOGY

ECMS is a well-known Pontryagin's minimum principle (PMP) inspired local optimisation method. This concept has been proposed firstly by Paganelli [11], on the basis of the following theory. For a long-distance trip, the battery power is negligible in comparison with fuel consumption. In this case, the energy consumed over a driving cycle is ultimately provided by the thermal energy released in ICE. Therefore, the battery can be considered as an auxiliary reversible fuel tank, this is, charged by consuming additional fuel in ICE and discharged to alleviate ICE load for fuel saving. To quantify the corresponding fuel consumption or saving, the EF is proposed to directly transform electrical energy into equivalent amount of fuel. As a result, the battery and fuel energy can be calculated and unified as the equivalent fuel consumption instantaneously, which enables EMS to optimise the vehicle energy consumption in real time. Therefore, the key characteristic of ECMSs is to convert the global optimisation into a local optimisation problem, thereby enabling the minimisation of the real-time equivalent fuel consumption at each instant [12]. Note that equivalent fuel calculation applies to not only the electrical energy, but also all sort of energy control objectives. For example, Paganelli et al. [13] introduced the EF to convert engine emission into equivalent fuel consumption penalty.

In conclusion, ECMS is a local-optimisation controller to calculate the equivalent fuel as a function of current system status and quantities measurable on board. The EF is utilised as the cost coefficient to weigh the selected on-board parameters. The outstanding advantage of ECMS is to provide the instantaneous optimal solution for power split strategy and, therefore, easily to be implemented in real-time energy management systems.

3. CLASSIFICATION OF ECMS

Since the key process of conducting ECMS is to properly design the EF, the ECMS methodologies can be classified according to EF adaptation techniques. Hence, Tran et al. [7] divides ECMS methodologies into two types: (i) offline design using global optimisation algorithms to find the optimal constant EF, and (ii) online adaptation adjusting EF in real-time.

The ECMSs with the offline EF design, called the basic ECMS, require the prior knowledge of the entire trip to realise the global optimality. The resulting optimal EF is fixed as a constant over the trip, due to the lack of the EF adaptation mechanism in the basic ECMS. Even worse, the EF has to be calibrated individually for each driving cycle. Note that various global optimisation algorithms are capable of performing the required EF optimisation, including DP [14], genetic algorithm (GA) [15], particle swarm optimisation (PSO) [16], ant colony optimisation [17], and PMP [18].

The ECMSs with online adaptation capability is referred as the adaptive ECMS (A-ECMS). The EF adaptation is typically realised based on the following factors: (i) battery state of charge (SOC) target and limits, (ii) the real-time value of battery SOC, and (iii) current and future driving conditions. Firstly, since ECMSs need to consider the battery SOC constraints such as battery charge sustainability and upper/lower boundary, the EF has to be adjusted based on the SOC-related parameters which are the aforementioned factor (i) and (ii). The required EF adjustment can be realised by different control methodologies, such as the weighting function, proportional-integral-derivative (PID) controller, map-based approach, neural network adaptation, and linear regression-based approach. These online EF adaptation methodologies will be elaborated in Section 4. Secondly, the EF adaptation can be further improved by considering the current and future driving conditions. The current driving condition refers to the powertrain efficiency and battery aging.

It is obvious that the powertrain efficiency directly influences the vehicle fuel consumption. Furthermore, the EF actually represents the chain of efficiencies entailed in transforming fuel into electric energy and vice-versa. Thus, the EF should change with the operating conditions of powertrain [19]. Similarly, battery aging will seriously affect the performance of the battery itself, thereby deteriorating the vehicle performance such as the reduction of maximum power and driving range. Hence, it should be taken into account during the EF adaptation as well. While, the future driving conditions can contribute to estimation of future power distribution over a certain horizon. As a consequence, ECMSs can take advantage of the prior knowledge of the power demand and, therefore, actively adjust the EF in advance, thereby enabling the local optimality to approach to the global optimality. In terms of future driving conditions, it has been proven that the future road information, speed prediction, and driver styles are critical to the control performance of the EF online adaptation. These key parameters are obtainable by different methods, such as the support vector machine (SVM) for the vehicle speed prediction [20], geographic information system (GIS) for the terrain preview [21], and learning vector quantisation (LVQ) neural network for the driving style recognition [22]. Note that the A-ECMS with prediction capabilities is called as the predictive ECMS (P-ECMS).

In comparison to the basic ECMS, it is more feasible to implement A- or P-ECMSs in real-time applications, owing to their capability of adapting to the complex real-world driving conditions. Hence, the increasing number of researches have been devoted to developing different forms of A- or P-ECMSs, and analyse their performance under different driving conditions. Given the development trends of ECMS techniques, this study is only dedicated to A- and P-ECMSs. Additionally, this comprehensive review is *NOT* presented according to categories of ECMSs, as there is no EF adaptation method that is exclusive for A- or P-ECMSs. Thus, it is worth discussing the state-of-the-art EF adaptation methods first, presented in Section 4. Then, the key factors that significantly affect the vehicle fuel economy will be analysed in Section 5.

4. EF ADAPTATION METHODS

It has been proven that the solution of PMP methods leads to a constant EF under the assumption that that the battery open-circuit voltage and internal resistance are independent on SOC [23]. The corresponding EF is called the optimal constant EF for the whole driving cycle. However, the amount of fuel required to recharge the battery strongly depends on two parameters which are the electrical power consumption for the torque assistance and the amount of energy available for braking regeneration. Obviously, these two parameters are highly correlated to the characteristics of the road conditions. Thus, the ECMS with the constant EF has to be properly tuned on the basis of prior knowledge of future driving information. Since it is extremely difficult to predict all aspects of the real-world driving conditions in advance, ECMS with the constant EF is likely to deliver sub-optimal fuel economy in practice. In addition, the optimal constant EF is highly correlated to the selected driving cycle used to refine the ECMS and may be inapplicable for the other driving cycles [24]. Therefore, the online adaptation or auto-regulation of EF is necessary to provide robustness and, ideally, to obtain results close to the optimum in real world driving.

It should be pointed out that the value of EF has a significant impact on battery SOC over whatever the driving cycle is [18, 25-27]. This is because that the battery SOC is changed by shifting the power distribution between ICE and motor to charge or discharge the battery, while the EF directly regulates the power distribution. Furthermore, due to concerns of battery aging and safety, the battery SOC constraints should be satisfied when the trajectory of EF value is optimised to improve the fuel economy. Therefore, all kinds of ECMSs consider introducing the SOC-related parameters as the feedback to the EF adaptation methods. Typically, the feedback is the battery SOC or the error between the target SOC and actual value. Additionally, in the design phase, the EF adaptation methods typically are sophisticated to regulate EF close to the global optimal EF under the selected driving cycles. Thus, when the designed EF adaptation methods are implemented in real time under unknown driving cycles, the resulting control actions attempt to stimulate the fuel economy to approach the global optimality.

In the following subsections, the state-of-the-art EF adaptation methods are reviewed and analysed in detail, including their mathematic principles, key characteristics, application scenarios, advantages, and disadvantages.

4.1. Weighting Function of S_{dis} and S_{chg}

This EF adaptation approach is to update the EF by the weighting function of two constant EFs which are corelated to battery charging and discharging scenarios, respectively. This approach is inspired by Guzzella's study [23], the basic concept of which is that the conversion efficiency between battery energy and fuel energy in any hybrid vehicle is only a function of the efficiencies of the electrical and fuel paths. Thus, Guzzella proposed to use the average charging and discharging efficiencies to calculate the EF, as:

$$S = \begin{cases} S_{dis} & P_e(t,u) < 0 \\ S_{chg} & P_e(t,u) > 0 \end{cases} \tag{1}$$

where

$$S_{dis} = \frac{1}{\overline{\eta}_e^{(d)} \overline{\eta}_f} \tag{2}$$

$$S_{chg} = \frac{\overline{\eta}_e^{(d)}}{\overline{\eta}_f} \tag{3}$$

where P_e is the net power charged to the battery including the power loss to the internal resistance. S_{dis} is applied when a positive amount of battery energy is used in the trip, this is, the storage system provides positive energy to the pulsation system. While, S_{chg} is for the negative battery energy, this is, the excessive energy is generated and stored in the storage system. $\overline{\eta}_e^{(d)}$ and $\overline{\eta}_e^{(c)}$ denote the average electric circuit efficiencies for discharge and charge, respectively. $\overline{\eta}_f$ is the average efficiency for combustion engine.

The shortage of Guzzella's method is the deep dependence on the way of defining the average efficiencies. Typically, the accuracy of the average efficiency estimation over the whole driving cycle is low. As a consequence, this method often requires heuristic corrections to avoid excessive SOC deviation [23]. Hence, extensive studies have been performed to improve the battery SOC control of Guzzella's method. Zhang et al. [28] proposed to introduces an additional correction W as the weighting function into the EF expression, as:

$$S(t) = W(S_{dis}, S_{chg}, SOC(t)) \tag{4}$$

where $S(t)$ represents the EF factor translating battery energy into an equivalence fuel energy. W is defined as a piecewise constant function of battery $SOC(t)$, S_{dis}, and S_{chg}.

Figure 2 shows an example of modified EF curve with the correction W. In this plot, the value of S_{dis} and S_{chg} are calculated by Eq. (2) and (3) based on the assumed average efficiency. SOC_{rel} is the reference SOC, defined as $2(SOC - SOC_0)/(SOC_{\max} - SOC_{\min})$. SOC_0 is the desired SOC value, expressed as $S_0 = \sqrt{S_{dis} S_{chg}}$. $SOC_{\max}$ and $SOC_{\min}$ denote the prescribed upper and lower limits of the battery SOC. This improved approach restricts the EF to adjust only between S_{dis} and S_{chg} based on the SOC deviation from the reference. Therefore, better control over the battery SOC can be expected.

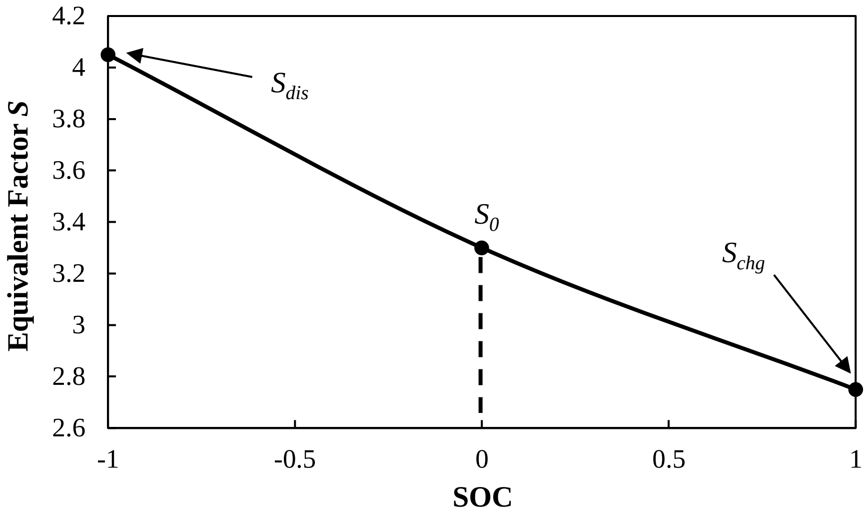


Figure 2. EF as function of relative SOC

Furthermore, the trip information can also be included as the additional correction factor in the function of S. In Refs. [29-36], the EF is restricted within S_{dis} and S_{chg} based on the probability of electric energy consumption $p(t)$, as:

$$S(t) = p(t)S_{dis} + (1 - p(t))S_{chg} \tag{5}$$

Sciarretta et al. [29] firstly proposed this energy-based method for HEV application. $p(t)$ is defined as:

$$p(t) = \frac{S_{dis}}{S_{dis} + S_{chg}} + \frac{E_e(t) + \lambda E_r(t)}{E_r(t)} \frac{\sqrt{S_{dis} S_{chg}}}{S_{dis} + S_{chg}} \tag{6}$$

where λ is assumed as a constant ratio of the energy delivered to the wheels and the energy recuperated by the electrical path. $E_r(t)$ is the expected remaining mechanical energy that still has to be delivered before the end of the trip. $E_e(t)$ refers to the battery energy that has been consumed in the trip.

Although this approach excludes the SOC deviation – ΔSOC, as a parameter of the EF adjustment, the charge sustaining can still be achieved. This is because that the proposed approach regulates battery SOC from the perspective of energy consumption and regeneration, instead of the SOC value itself. Thus, the performance of battery SOC control in this approach is highly dependent on the accuracy of the electrical and mechanical energy prediction, the key of which is the vehicle speed prediction. Note that the initial value of the EF is no longer required to be pre-set in this approach [30]. This energy-based approach was further developed for PHEV application by Larsson et al. [37]. The additional parameter $E_{ref}(t)$ is defined as the reference of the electrical energy consumption up to the time *t*, calculated by the battery SOC reference, and introduced in $p(t)$, as:

$$p(t) = \frac{S_{dis}}{S_{dis} + S_{chg}} + \frac{E_e(t) - E_{ref}(t) - \lambda E_r(t)}{E_r(t)} \frac{\sqrt{S_{dis} S_{chg}}}{S_{dis} + S_{chg}} \tag{7}$$

S_{dis} and S_{chg} can also be employed as the boundary condition of the EF online optimisation [12, 38]. By predetermining the EF boundary, the optimisation method is able to achieve fast search of the optimal EF in real time. Note that in Li's [12] research the predicted real-time operating efficiency of the electrical and fuel paths, instead of the average efficiency, are utilised to determinate the value of S_{dis} and S_{chg} in each time step.

4.2. PID Control

The proportional-integral-derivative controller, referred to as PID controller, is a popular closed-loop feedback mechanism to drive a system towards a target position. Due to the robustness, easy implementation, and low computational cost, PID controller has been widely used as the SOC-based feedback mechanism for the EF adjustment. It should be noted that the key difficulty of PID controllers is to tune the proportional, integral, and derivative gains to achieve the desired control response according to the characteristics of system behaviours.

4.2.1. Proportional Control

4.2.1.1. Proportional Linear Feedback

It has been proven that adding the contribution of integral gains on the basis of the linear proportional controller can improve the SOC convergence to the reference value [39]. Thus, only few studies utilised the linear proportional controllers to adjust the EF online [40-44].

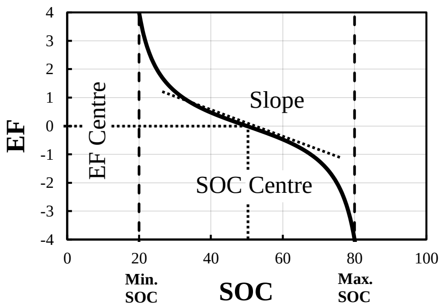
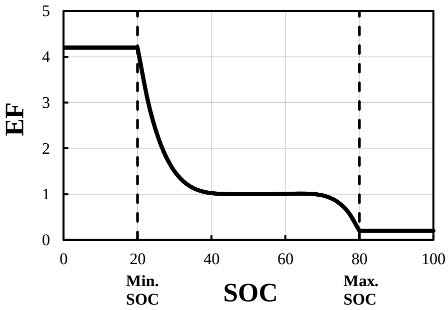
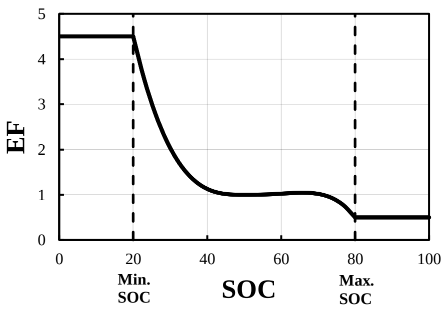
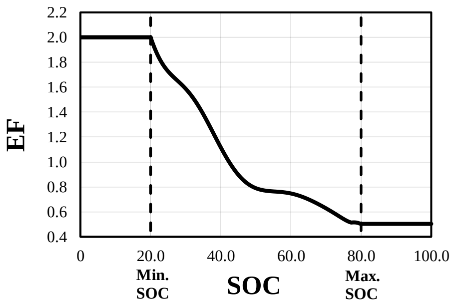
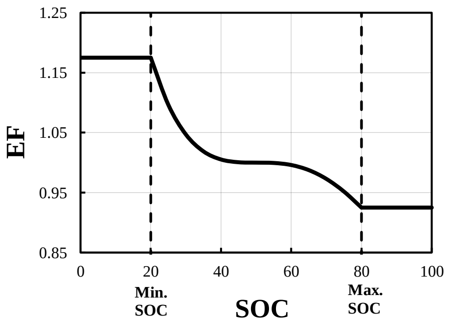
However, the linear proportional control method can be improved by tuning the combination of proportional gain, initial SOC, and initial EF [24]. This is because that all the three parameters significantly affect the SOC at the end of driving cycle. In Enang's study [24], a design of experiments (DOE) study of these three parameters has been performed over 11 typical driving cycles to investigate their influences on both the fuel saving and the final SOC. Then, the averaged fuel saving and final SOC over the selected driving cycles was represented as a function of aforementioned three parameters. Thus, if the initial SOC and expected final SOC are given, the proportional factor and initial EF can be optimised to deliver the minimum average fuel consumption, then applied as constants in ECMS. The novelty of this research is that 11 driving cycles were exploited in the DOE study, as the large amount of the driving scenarios in these cycles can contribute to better tuning of key parameters – proportional factor and initial EF.

4.2.1.2. Proportional Nonlinear Feedback – Tangent Shape

Under the assumption that the optimal EF can be constant for a given driving cycle, the controller should ideally find and apply the optimal value for the future driving mission. Thus, it is better that the adaptive EF approximately remain the optimal value around the SOC reference, to maximise the benefits of the hybridisation. On the other hand, when the SOC approaches to the upper or lower boundary of the prescribed SOC window, the electric energy should become completely free or extremely expensive, respectively. By doing so, the under- or over-charge of the battery can be avoided. Thus, the adaptive EF should be set to approach infinity at the SOC bounds [28]. All aforementioned desired characteristics of EF adaptation can be heuristically embodied by the tangent-shape function. Therefore, the various tangent-shape curves have been extensively employed as the nonlinear proportional gains, listed in Table 1.

The tangent-shape nonlinear proportional controller was proposed firstly by Paganelli et al. [13], which is Method 1 in Table 1. This method was embedded directly in the control system of a parallel hybrid truck in the field test. The corresponding road test shows that the charge-sustaining were achieved without any SOC violation. Thus, this method has been widely used to regulate the EF, and many alternative methods, such as Method 2 to 5 shown in Table 1, are derived from this method. It can be seen from Table 1 that all the presented methods are able to embody the desired characteristics of the EF adaptation. However, no researcher has performed the comparison of the control performance of these tangent-shape functions. In this review, Method 1 will be taken as an example and discussed in detail. The corresponding SOC-EF relation is plotted in Figure 3.

Table 1. Summary of tangent-shape nonlinear proportional controller

Methods	Function Expression	Example
Method 1 [13, 25, 40, 45-47]	$S = S_C + l_s \tan(\dfrac{l_r \pi}{2}(SOC - SOC_C)$	
Method 2 [17]	$S = a + b \times f(SOC)^4 + c \times f(SOC)^5$	
Method 3 [48]	$S = \begin{cases} a + b \times f(SOC)^3 & \Delta SOC < 0 \\ a + b \times f(SOC)^3 + e \times f(SOC)^4 & \Delta SOC > 0 \end{cases}$	
Method 4 [22]	Self-defined Function: $S = -0.948 \times SOC^{10} + 4.75 \times SOC^9 - 10.08 \times SOC^8 + 11.73 \times SOC^7 - 8.11 \times SOC^6 + 3.56 \times SOC^5 - 0.79 \times SOC^4 + 0.098 \times SOC^3 - 0.05 \times SOC^2$	
Method 5 [49-52]	$S = a + b \times f(SOC)^3 + c \times f(SOC)^4$	

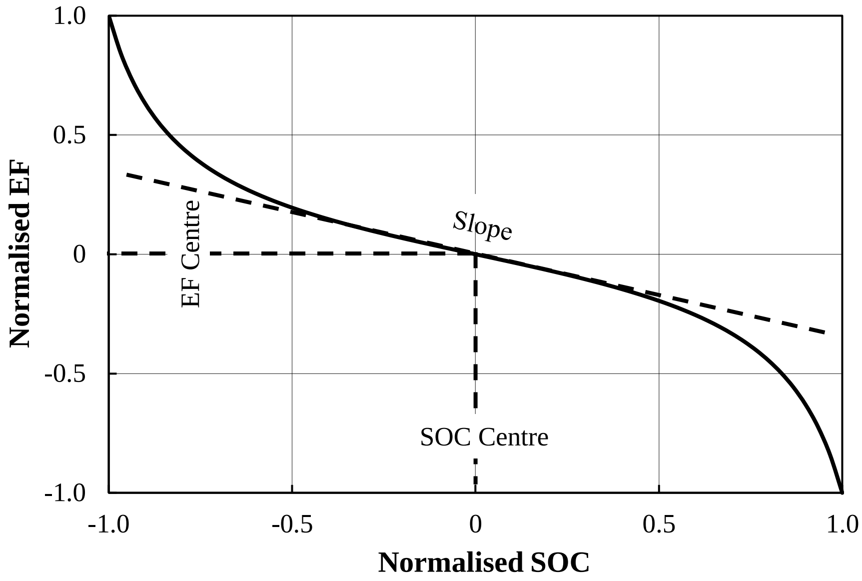


Figure 3. Typical SOC-EF tangent-shape curve

In Figure 3, the x-axle denotes the normalised battery SOC, with -1 representing the lower SOC limit, 0 being the SOC centre, and 1 expressing the upper SOC limit. The y-axle is the normalised SOC correction factor, this is, the EF. It can be clearly seen in Figure 3 that the EF is relatively flat when the battery SOC locates around the set point. This characteristic allows the optimal distribution to be maintained around the SOC reference. On the other hand, the absolute value of the SOC correction factor becomes larger when approaching the SOC limits, to prevent the battery from under- or over-charge regardless of the vehicle and driver demand.

In conclusion, the shape of this tangent curve satisfies all the desired changes of EF value and, therefore, can be utilised to adjust the EF in ECMS. However, it is still required to tune the shape of the tangent curve to reflect the battery charge and discharge characteristics in different powertrain configurations. For Method 1 shown in Table 1, the key tuning parameters of the tangent function are presented as follows.

a. SOC centre SOC_C: it should be fixed as the SOC reference. Note that the SOC reference can be varying along the trip for PHEVs.

b. EF centre S_C: ideally, the corresponding value should be optimised to achieve the maximum benefits from the hybridisation, or updated online based on the driving conditions such the battery SOC and the predicted speed profile.

c. SOC range scaling factor l_r: typically, the SOC bounds are prescribed in consideration of the battery aging and safety. Note that SOC range scaling factor is able to adjust the range of tangent curve, as well as the slope at the SOC centre of tangent curve.

d. Slope at the SOC centre of tangent curve: it controls the change rate of EF when the battery SOC is around the reference. The slope scaling factor l_s is able to change the slope at the SOC centre of tangent curve, while keeping the SOC range unchanged.

Sivertsson and Eriksson [25] performed a comprehensive study on key parameters of the tangent function in Method 1. The results show that the fixed tangent curve may cause the rapid change of the EF, so that the SOC occasionally violates the limit of the desired SOC window. In addition, the controller performance is too sensitive to the intuitive design of the initial EF. The promising fuel saving and charge sustaining only can be delivered with an accurate design of the initial EF. To overcome the aforementioned drawbacks, the EF centre of the tangent function S_C was forced to change with the trend of the current EF. In other words, both current battery SOC and EF value are regarded as the feedbacks to the EF adaptation. Regarding Method 2 to 5 in Table 1, although there exists a need to tune coefficients in corresponding EF functions, no tuning method can be found in the existing literature.

The tangent-shape feedback mechanism was originally designed for HEVs, which aims to maintain the SOC around a constant level. However, the desired SOC trajectory for PHEVs should be terminated at the lower bound of the allowable battery SOC. Thus, inspired by Ref. [25], Sivertsson [53] proposed to assign the SOC centre, called as SOC_C, with the predefined SOC trajectory. Furthermore, an additional parameter ΔSOC is introduced in the tangent-shape function, expressed as

$$S = S_C + l_s \tan(\frac{l_r \pi}{2\Delta SOC}(SOC - SOC_C)) \tag{8}$$

where ΔSOC is the allowed deviation from SOC_C.

In order to realise the decreased SOC window, ΔSOC is a monotonically increasing function of the travelled distance. By doing so, SOC control allows the large SOC tolerance at the early stage of the trip, while the narrow SOC tolerance band can ensure that the battery SOC can reach at the desired value at the end of trip. The example of reducing SOC tolerance is shown in Figure 4.

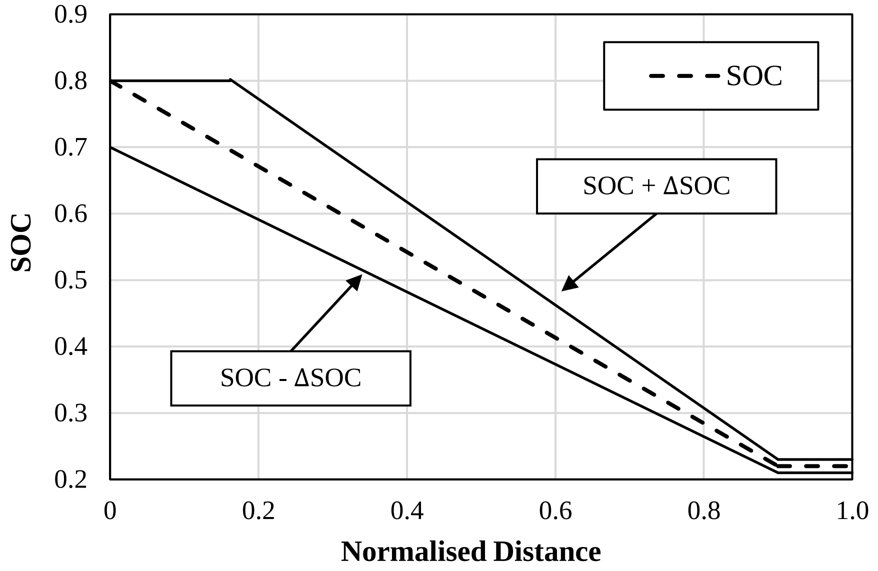


Figure 4. Example of decreasing SOC tolerance with the travelled distance

4.2.2. Proportional Integral (PI) Control

At present, PI controller is most widely adopted in industrial applications due to its simple structure, ease to design and low computational cost [54]. In order to compare with linear proportional controllers, a sensitivity study in terms of proportional and integral gains in linear proportional and PI controllers in HEVs has been performed by Onori and Serrao [39]. The results show that adding the contribution of integral gains can improve the SOC convergence to the reference value. Hence, many researchers employed a PI controller with the feedback of SOC-related parameter, to regulate EF for tracking the predetermined SOC reference of HEVs [33, 55-57] and PHEVs [58-62]. The corresponding EF adjustment rule can be formulated as

$$S(SOC,t) = S_0 + K_P(SOC_{ref} - SOC(t)) + K_I \int_0^t (SOC_{ref} - SOC(t))dt \tag{9}$$

where SOC_{ref} is the SOC reference trajectory for PHEVs, $SOC(t)$ is the real-time SOC value, K_P is a proportional gain, and K_I is an integral gain.

Although the proposed EF adaptation method has reasonable performance to regulate SOC, there is no any tuning process of the proportional and integral gains in these researches. Besides, Li et al. [12] claims that it is difficult to find a deterministic rule for regulating the parameters of PI controller. However, the robustness of PI controller was investigated by Feng et al. [58]. Within ±2 % deviation from the optimal EF initial value, the PI controller with the feedback of ΔSOC is still able to ensure that the actual SOC can track the reference and reach the desired terminal SOC. Simple tuning process has been demonstrated in Xie's research [63], which shows that the combination of the proportional and integral terms accounts for a small proportion of EF. Thus, with the known optimal constant EF, a few attempts can attain a satisfied combination of the proportional and integral terms.

4.3. Linear Regression-based Approach

Typically, the ECMS has to find both proper value of EF and local optimal control decision corresponding to the minimum value of the equivalent fuel consumption. If one of tasks can be devolved to a look-up table by linear regression methods, computational complexity will be dramatically reduced and, therefore, the corresponding ECMS is more applicable in practice.

In Lei's research [64], the initial EF and EF correction was predefined as look-up tables by genetic algorithm (GA) optimisation and fuzzy logic, respectively. Before the trip, the initial SOC and drive distance are required as inputs of the initial EF look-up table, shown in Figure 5. During the trip, the EF correction module dynamically regulates the EF based on the engine speed and the SOC deviation. The simulations conducted in a virtual traffic scene show that only around 5 percentage points reduction in fuel economy can be expected when comparing the proposed linear regression-based EF adjustment method with the global optimisation method.

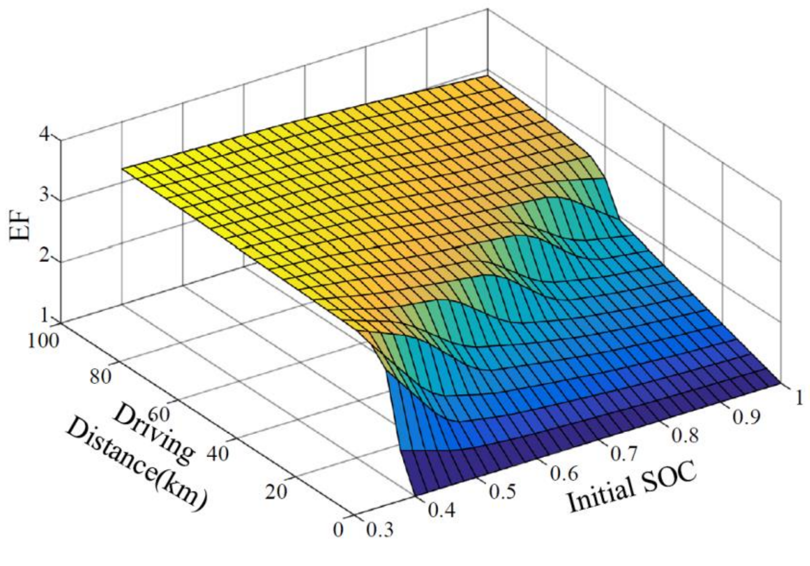


Figure 5. Relationship between driving distance, initial SOC and initial equivalent factor [64]

The optimal EF also can be directly tabulated as functions of vehicle driving and road conditions. In Refs. [59] and [65], PSO was employed to optimise the EF based on the historical traffic data offline and the optimal EF was tabulated with the inputs of drive distance and battery SOC. More complex linear regression approach was proposed by Lin et al. [22]. Three driving cycles were selected to generate the optimal EF look-up tables, respectively. The inputs were the battery SOC reference and the remaining trip distance. The driving pattern recognition was developed in this research to find the similarity of the upcoming trip to the selected representative driving cycles, to choose the corresponding optimal EF look-up tables. The schematic of the proposed strategy is shown in Figure 6.

Besides, the optimal control decision corresponding to different EF value can be obtained from fuel economy offline optimisation over different driving situations. Thus, it also can be tabulated in advance for the real-time applications. In Refs. [65] and [66], the optimal engine power demands were summarised in tabular form, the inputs of which are the tractive power demand and current battery SOC. In Sivertsson's research [25], the torque split and gear selection were optimised by DOE, and stored in look-up tables as functions of vehicle speed, torque demand, and EF.

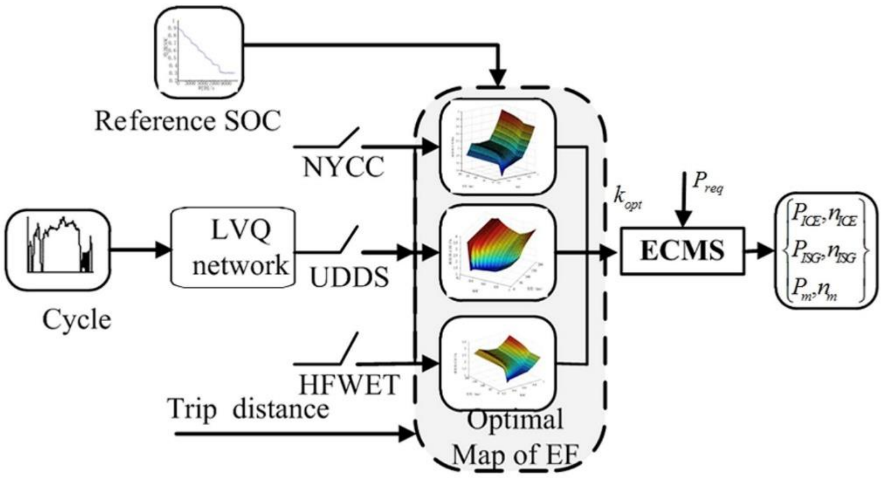


Figure 6. Schematic of the adaptive ECMS based on EF optimal maps combined with driving pattern recognition [22]

4.4. *Neural Network Adaptation*

The performance of linear regression-based ECMSs deteriorates dramatically when the driving conditions are completely different to any historical data used to construct the look-up tables. While, this issue can be efficiently resolved by neural networks (NNs), due to the corresponding strong generalisation and prediction capabilities. Additionally, NNs are capable of learning a complex and non-linear input/output relationship, which makes it applicable for vehicle-related applications. Furthermore, once the training datasets for NNs have been optimised, the well-trained neural networks are able to deliver the optimal EF value for ECMSs. Due to the aforementioned advantages, various NNs have been employed in ECMS for the energy management.

For ECMS application in hybrid electric buses, the adaptive neuro-fuzzy inference system (ANFIS) was exploited in Tian's research [67], to produce the optimal EF online. The corresponding inputs are the battery SOC and the power demand. To train the ANTIS, optimal trajectories of power distribution were firstly obtained by DP over two representative bus city drive cycles. Then, the optimal EFs were extracted from the achieved optimal trajectories by the rolling optimisation method and, therefore, utilised as the training samples for ANTIS. The hardware-in-the-loop (HiL) test results show that the combination of ANTIS and ECMS is able to achieve the preferable fuel economy which is fairly close to the global optimal solution delivered by DP.

Panagiotopoulos et al. [68] utilised nonlinear autoregressive with exogenous inputs (NARX) as the EF real-time predictor. The key characteristic of NARX method is to describe the modelled process based on a lagged input-output variable. As such, NARX is an efficient tool for modelling nonlinear systems [69]. In his research, DP was employed to optimise the EF offline with the consideration of the gear selection, engine on/off busyness, engine operating range constraints, and battery power regeneration speed constraints. Based on the optimised data, NARX was trained to predict EF in future domain based on the historical speed. The time series training inputs are vehicle speed, acceleration, engine speed, and battery SOC.

Computational time of EF neural network models have been discussed in Xie's study [70]. The basic neural network was utilised to adjust EF online with the inputs of the current requested power, battery SOC, and the ratio of the distance travelled to the total distance. This research shows that the time efficiency of NNs, defined as the computational time over the duration of entire trip, is verified sufficient to be applicable for online applications. The limitation of the neural network is that it is quite time-consuming to build a training database that contains sufficient samples and train the model on this basis [36, 71]. Thus, the NN-based EF adaptation method requires the numerous training samples to obtain a high-quality EF prediction. Furthermore, the selection of input variables for NN shows a significant impact on the network generalisation and performance [70]. However, to the authors' knowledge, the detailed study on the input selection for EF neural network model has not been performed yet.

4.5. Rule-Based Approach

In practice, due to the simplicity, ease to implement, and low computing burden, rule-based (RB) method has been widely applied in the hybrid vehicle industry [72-74]. However, the main disadvantage of RB method is that the optimality cannot be guaranteed due to the subjectivity of rule design. Therefore, the ECMS was proposed to integrate with the rule-based approach to combine the merits of rule-based and optimisation-based control strategies, this is, achieve both simplicity and optimality [51, 75-77]. Note that the same rule-based control methodology can be implemented to adjust the EF in ECMSs, or directly control the power split. In other words, the rule-based methodologies are common to both ECMSs and the rest of ESMs. For example, a fuzzy logic control method is utilised to regulate the EF variation at each instant in Wang's research [44], while Meng et al. [78] employ it to generate the torque demand of both engine and motor for a PHEVs.

Typically, the structure of this combined methods is that the rule-based control module is on the top layer of the control system to select hybrid operating modes [51, 66, 75, 79], calculate engine demand power [76], or determine the engine control action [77]. In contrast, the ECMS on the bottom layer is to deliver the optimal power distribution in the powertrain system. However, given the high-level randomness of the working conditions in real-world driving, the RB method is difficult to ensure that the engine and motor always works within high-efficiency operation envelops, as the boundary of mode switching is typically fixed and predefined by the experienced engineers [60]. To cope with it, Fan et al. [60] utilised DP to extract the optimal boundary of mode switching and shift schedule from collected historical driving data. Furthermore, Li's study [65] shows that RB with varying threshold delivered higher fuel saving than that with fixed one. The variable threshold was optimised by PSO and tabulated as a function of the battery SOC and power demand.

Due to the strong inference capability, the fuzzy logic can also be combined with the ECMS to adjust the EF. The fuzzy logic was exploited by Gupta et al. [80] to select operating modes in ECMS. In addition, the EF adaptation was determined by the fuzzy rule system in Wang's work [44]. The inputs of fuzzy-logic system were the SOC deviation and engine speed. The corresponding real driving cycle test shows that the fuzzy logic-based ECMS is able to improve the SOC charge sustainability and the fuel economy, comparing to the conventional SOC-based ECMS. While in Zhao's research [81], a scaling factor generated by the fuzzy rules was applied to the EF directly based on the deviation of battery SOC.

5. KEY FACTORS OF EF ADAPTATION

The optimal EF is significantly depended on the energy consumption along the entire trip. In addition, the energy consumption is, to a certain degree, correlated to vehicle driving conditions and road conditions.

Thus, to optimise the fuel economy further, the change of battery SOC should no longer be a single parameter to adjust EF. The vehicle-related and road-related parameters, such as drivetrain efficiency and terrain information, should also be considered as factors for EF adjustment. To identify the factors that conclusively determine the EF values, the correlation coefficients between EF and various factors were calculated over six different driving cycles by Zhang et al. [82] , shown in Figure 7.

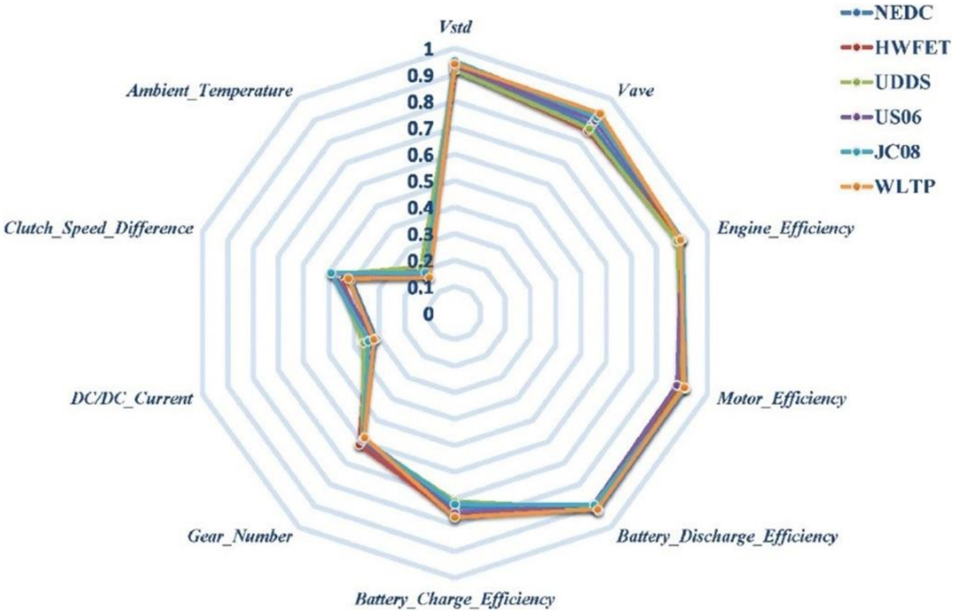


Figure 7. Correlation coefficients in various driving cycles [82]

Figure 7 shows the correlation coefficients of the chosen factors, which is on a scale of the highest correlation of 1 to the lowest value of 0. The results show that the strong correlation was expected in the velocity's standard deviation, the average velocity of the future travel route, engine efficiency, motor efficiency, battery discharge efficiency, and charge efficiency. Clearly, these high-correlation factors can be divided into two categories: the future driving conditions and current powertrain status. While, the future driving conditions can be grouped into road information, speed prediction, and driver styles. Additionally, the internal parameters of ECMSs, such as initial EF value, play a vital role in determining the control performance and, therefore, must be tuned properly. In conclusion, the comprehensive review of the key parameters of EF adaptation will be presented with respect to the ECMS internal parameters, current powertrain status, speed prediction, driver styles, road information, and driving pattern recognition.

5.1. *Internal Parameters*

5.1.1. *Initial EF Value*

Some EF adaption methods, such as PID control, regulate the EF by calculating EF variation at each instant. Thus, the current EF is strongly dependent on the previous EF value. In this manner, the EF is iterated and continuous at each control time step. Furthermore, the EF variation is typically determined by some selected vehicle state, while the vehicle state is significantly affected by the EF. Hence, for such closed-loop control system, different initial EFs can result in contrasting controlling sequences and, therefore, different energy consumptions. Refs. [38] and [42] prove that the sub-optimal initial EF values can contribute to the terminal SOC deviation and the increase of fuel consumption. Therefore. the initial value of the EF should be properly tuned for such EF adaption methods with continuous EF adjustment. A simple method to determinate the initial EF value is to assign it as the optimal determined EF for typical driving cycles [40], or as that for the upcoming trip if the corresponding prior knowledge is known [44]. While, the secant method can be used to quickly calculate the initial EF with a predetermined EF bounds [38].

More sophisticated approaches were utilised to calculate the initial EF in the following researches. In Zhang's research [29], the initial EF was optimised and tabulated as a function of the average speed and initial SOC. While, the initial EF is correlated with the driving distance by fitting the optimal EF over seven standard driving cycles [25, 83]. On top of the driving distance, Lei et al. [64] introduced initial SOC as the extra variable of initial EF expression. For hybrid buses, the driving condition of city buses is repetitive. As a consequence, the optimal initial EF obtained from the historical driving data is quite representative. In Xie's study [63], the shooting method was employed to find the optimal constant EF based on a speeding profile which was collected in the historical data for bus routes. Then, the optimal constant EF was validated over nine speeding profiles and considered as the initial EF for all tests. Note that three initial SOC levels were selected to investigate the influence of the initial SOC on the proposed ECMS. The results show that the deviation of the final SOC is negligible over all selected driving cycles, even with a fixed initial EF.

5.1.2. *SOC Reference*

Due to the charge-depleting nature of PHEVs, the SOC reference trajectory is required for ECMSs to ensure that the battery SOC gradually depletes along the trip. It is critical to design effective SOC trajectories for trips to achieve better fuel saving. The simplest expression of SOC reference trajectory is the linear function of the remaining trip distance. This method has been widely employed in ECMS researches [37, 84-86].

Liu et al. [62] claim that the relation between SOC and trip distance is not completely linear. To be specific, arc-shaped curve of SOC reference is employed when the initial SOC is higher than the maximum SOC of 85%. When the battery SOC is below 85%, the SOC reference is still a SOC-distance linear curve. On top of the trip distance, Tian et al. [87] introduced the future average speed, which can be provided by intelligent transportation system (ITS), as the extra variable to define the SOC reference. Besides, the vehicle speed-related parameters used to calculate SOC reference can be replaced by the predicted vehicle's power demand [58]. The fundamental concept is that ΔSOC should be proportional to both the trip distance and the power demand. However, all SOC-distance approaches are only applicable when the topography is assumed flat [88, 89].

More complex methods, combining DP with simplified efficiency models of engine and motor, can be implemented to generate the SOC reference trajectory in each step of prediction horizon [20, 64]. The proposed method can provide a SOC reference trajectory that highly correlates to the one generated by global optimal strategy. However, the short-term speed prediction has to be known in advance. Neural network (NN) and the corresponding derivatives, such as the basic neural network [87], recurrent neural network (RNN) [59], and neuro-fuzzy system [90], have also been widely used to generate the SOC reference trajectory. In Tian's research [87], the simulation results show that the well-trained neural network is able to generate a SOC reference close to the global optimality over the untrained driving cycles.

5.2. Current Powertrain Status

5.2.1. Drive Train Efficiency

Theta It has been widely proven that the value of EF should represent the chain of efficiencies through which the fuel is transformed into electrical power or in a reverse manner [82]. Thus, the EF adjustment should consider the efficiency of various components in powertrain, such as engine, motor, battery, etc. Typically, the reasonable evaluation of the component average efficiency are exploited to adjust the EF directly or indirectly. For example, Feng et al. [58] fixed the initial EF value as the ratio of motor and engine average efficiencies. While, Chen et al. [21] utilised the average engine efficiency to calculate the S_{dis} and S_{chg}, referring to Section 4.1. In addition, the EF boundary for ECMSs in a parallel HEV was determined by the average efficiencies of motor, battery, inventor, and engine [91]. Different basic EFs were proposed in Refs. [82] and [35] for four driving modes: 1) discharging in Charging-Depleting (CD) stage, 2) discharging in Charge-Sustaining (CS), 3) charging in CD stage, 4) charging in CS stage. All the proposed EFs were functions of motor, battery, and engine efficiencies, thereby considering as the baseline for online EF adaptation. Kommuri et al. [19] claim that the penalty of the sub-optimal engine efficiency should also be introduced directly into the EF adaptation law. This is because although the EF is considered as an optimisation variable for the optimal fuel consumption, it does not adopt the EF for exploiting the engine to operate in the optimum region in most of its operational time throughout the drive cycle. Thus, in their research, the engine optimal performance deviation was considered as a penalty in the cost function. The simulation results show that the ECMS with the penalty of the sub-optimal engine efficiency can promote the engine to operate in high-efficiency region, as shown in Figure 8, thereby contributing to significant improvement of fuel consumption in all selected vehicles over two drive cycles. It can be clearly seen in Figure 8 that the ECMS with the penalty of the sub-optimal engine efficiency forces the engine to operate more frequently around the optimum operating region between the two blue lines.

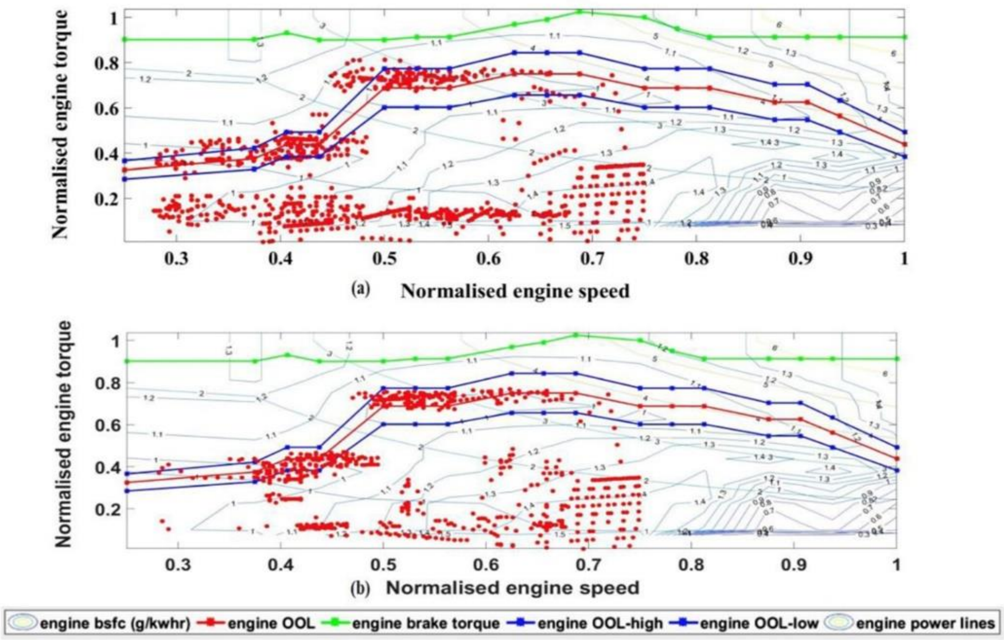


Figure 8. Engine operating points comparison [19]. The OOL stands for the engine optimum operating line. The top plot shows the engine operating points with a basic ECMS, while the bottom plot represents that with the proposed ECMS.

Besides, Mayer et al. [92] leveraged a fixed cost of the engine on/off frequency to represent the penalty of the sub-optimal engine efficiency. In Fridén’s study [40], the speed-dependent engine on/off cost was introduced in the EF adaptation low, as the engine efficiency is higher when the engine switches on at high speed, and vice versa.

5.2.2. Battery Aging

For HEVs and PHEVs, battery aging significantly deteriorates the whole efficiency of vehicles as the battery performance degrades with aging. The reduction of both capacity and discharge capability are the main consequences of battery aging. From the perspective of the fuel economy optimisation, the optimal battery usage is to utilise the electrical energy to minimise the fuel consumption as much as possible. Aa a result, to meet the driver's power demand, the control strategy may charge or discharge the battery quickly and deeply, thus accelerating the battery aging [93]. Therefore, minimising battery health degradation and maximising fuel economy are the two competing objectives in EMSs, which has been proven in Refs. [19, 94, 95].The main approaches to modelling battery aging are the empirical modelling [96], the electrochemical methods [97, 98], and the performance-based methods [99]. The empirical model requires low computational efforts and, therefore, is applicable to online EMSs. However, it is non-predictive and heavily relied on test data [100]. On the contrary, the electrochemical methods are capable of capturing the fundamental physical phenomenon affecting battery behaviours and aging, while requiring high computational power. The performance-based methods intend to establish simple correlations between stress factors and capacity fade, and only require the battery SOC as the model input. These correlations typically are induced from aging tests conducted under several conditions [101].

Undoubtedly, the battery aging results in overall systematic performance degradation. Therefore, many researches advance the EF adaptation law to find the optimal trade-off between the fuel economy and battery lifetime [59, 102]. Chen et al. [102] exploited the quantified battery aging as a feedback of EF adjustment to improve the fuel economy. Han et al. [59] proposed a weighting factor to balance the energy consumption and battery aging, which was optimised offline by PSO with the historical traffic data. Liang and Makam [100] proposed an electrochemical method, called as the simplified single particle model (SPM) aging model, to evaluate the battery state of health (SOH) which is considered as an aging factor in ECMS. To be specific, the detailed SPM model is used to generate steady-state map of the capacity fade rates at different battery running conditions. Then, the supervisory control algorithm receives periodic updates of the battery capacity and internal resistance as the battery ages.

5.3. *Speed Prediction*

The future vehicle speed is the key parameter to represent the future driving condition. Thus, one of main challenges for P-ECMSs is to establish a proper methodology to predict vehicle speed with a minor deviation from the actual speed. Refs. [33] and [42] highlight that the priori information of vehicle speed can contribute moderate improvement of the fuel economy.

The simplest velocity prediction method, employed in Refs. [43] and [88], is that the vehicle is expected to run with speed limits along the entire road. The acceleration and deceleration rates were assumed as constants, either predefined by experienced engineers [88] or calculated by the maximum propulsion power and maximum brake force with the vehicle weight [43]. The proposed velocity estimation method can work with the pre-load map containing the information of speed limits and, therefore, no intelligent transportation system is required. Despite the aforementioned advantage of the simplified velocity prediction method, Gong’s study [103] shows that around 18% deterioration of fuel saving can be expected when the simplified speed estimation is employed to compare with the high-accuracy speed prediction method. Actually, different vehicle speed predictors are investigated and developed for the model predictive control (MPC), as the performance of MPC strongly depends on the quality of the speed prediction. Currently, the exponential prediction [104-106], Markov-chain prediction [107-109], and artificial-neural-networks-based (NN-based) prediction [110-112] are commonly employed in MPC related researches. These speed predictors also can be employed in ECMSs [12].

The advantage of these predictors is that only several key statistical parameters, instead of the entire traffic data, are required for the speed prediction, which contributes to ease the prediction process. The exponential prediction is a simple method to provide an intuitive understanding of how the velocity prediction affects fuel economy. Markov-chain velocity predictor is able to provide high-quality speed prediction. However, it relies on not only the present vehicle states, but also the historical values [113]. While, the NN-based prediction, such as chaining neural network (CNN) [30], BP neural network [31], radial basis function (RBF) neural network [42, 114], and recurrent neural network (RNN) [115] only requires the historical velocity sequences without compromising the accuracy of speed prediction. For ECMS applications, Li et al. [12] presented comprehensive comparisons among aforementioned speed predictors. The simulation results, shown in Figure 9, show that the predicted velocity sequences of NN-based speed predictor can capture the trend of the actual vehicle speed better than the others, thereby achieving the better fuel economy improvement. Lei et al. [20] improved the performance of exponential prediction by using the support vector machine (SVM) according to the road type. It can dynamically regulate the key factor of the exponential prediction, referred to as the decay coefficient, to improve the prediction precision of the future speed.

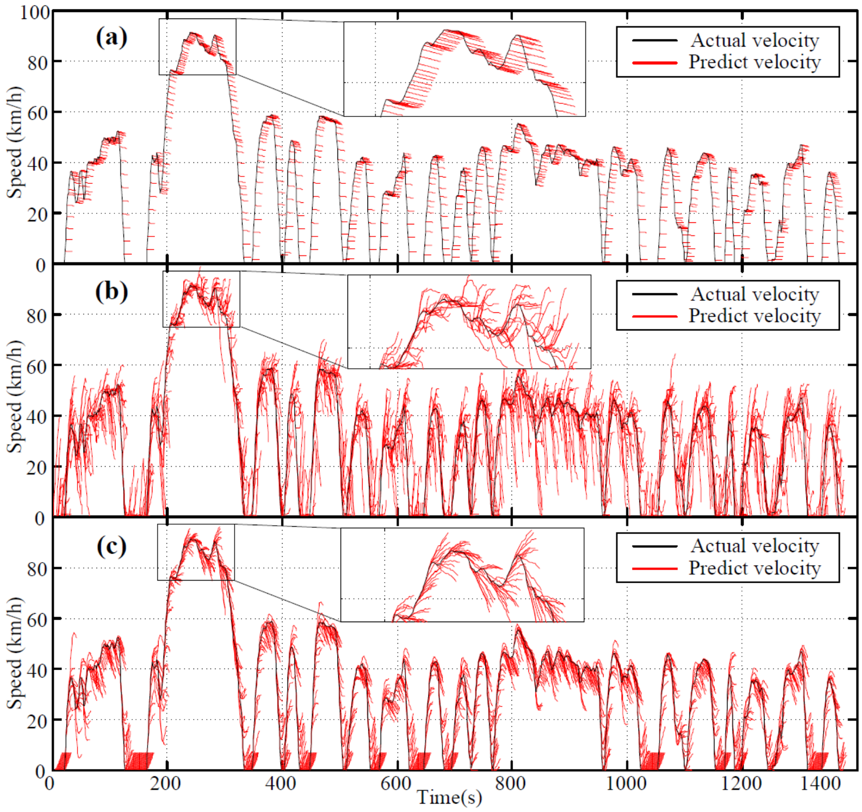


Figure 9. Predicted velocity sequences of UDDS [12]. (a) Exponentially varying predictor; (b) Markov-chain predictor; (c) GA-BPNN predictor. The black curve presents the actual speed of UDDS, and the red curve denotes the predicted velocity sequences across the prediction horizon at each time step.

Obviously, the prior knowledge of driving conditions like traffic flow and traffic light status is crucial to predict future driving profile. While, the driving conditions can be easily obtained through the intelligent traffic and wireless communication systems such as global positioning system (GPS) and intelligent transportation system (ITS). Thus, many speed prediction methods take advantages over the acquired global driving conditions to improve the reliability of predicted speed [57, 116-118]

In terms of speed predictors in ECMSs, Qiu et al. [41] employed the vehicle speed target directly as the predicted vehicle speed for ECMS controller. In their research, MPC was utilised to calculate the optimal target velocity profiles based on signal phase and timing (SPAT) information. The aim of target velocity optimisation is to reduce the idling time and minimise the vehicle’s acceleration. Refs. [35] and [36] applied the GPS data collected by the mobile crowed sensors mounted on floating cars to estimate the traffic flow and future travel time, thereby calculating the future speed profile. Participatory sensing data (PSD) also can be used to collect the traffic data [82]. PSD is the GPS data uploaded to a cloud server instantly by the volunteered floating cars on the road. Thus, the advantage of this method is that the velocity prediction is performed based on the real-time data without imposing any computation load on vehicle hardware. Furthermore, the high accuracy of the speed prediction can be achieved, as the database is created by the vehicles along the route and various driving styles.

Many studies have been performed to investigate the method of merging the future driving conditions into ECMSs. Tian et al. [87] utilised the predicted average speed as an input of NN to generate the optimal SOC reference. Li et al. [12] calculated the EF optimisation boundary by the speed information in a short-term future time domain. In addition, the regenerative energy can be calculated by the predicted speed and introduced into the EF adaptation as the correction factor [33]. Moreover, the EF adjustment can be regulated by a speed-related variable, called the probability of electric energy consumption [29-36]. This EF adaptation method has been discussed in detail in Section 4.1 in this study. The predicted vehicle speed also can be utilised to calculate the required tractive energy and the recycled braking energy, then directly introduced as a scaling factor β in EF adaptation law [82]. The scaling factor β is expressed as

$$\beta(t) = \frac{v_{std}(t)}{v_{ave}(t)} \frac{\mu(E_{re}(t) - E_b(t))}{E_{re}(t)} \tag{10}$$

where v_{std} is the standard deviation of the vehicle speed, v_{ave} is the average speed, E_{re} and E_b are required tractive energy and the recycled braking energy of future travel, and μ is the calibratable variable.

5.4. *Driver Style*

Driving styles are defined as the habits how drivers operate vehicles according to various driving scenarios. It has been proven to play a critical role in vehicle performance optimisation [119]. The studies in Refs. [120] and [121] show that comparing with the moderate drivers, up to 90% extra energy can be consumed by aggressive. For ECMS applications, Tian et al. [47] claim that the power consumption and terminal SOC are different for conservative and aggressive drivers. Hence, it is necessary to take into account the driving style in the EF adaptation.

Typically, the development of the driving style identification can be divided into offline and online stage. The offline stage contains driving information acquisition, driving information analysis, and creation of decision-maker. The driving information acquisition can be achieved by establishing the driving style-related database by means of self-report questionnaire [36] or driving data collection [47]. Then, the feature selection can be performed to obtain characteristic parameters that can determine driving styles, by different methods such as the forward selection method [122, 123] and the conditional likelihood maximisation method [124]. Typically, vehicle speed, throttle opening and acceleration are adopted to characterise the driving styles, due to their capability of capturing the relationship between fuel economy and driving styles [125, 126]. Based on the selected features, the classification of driving styles can be performed, typically by the *K*-means clustering algorithm [36, 127, 128] and principal component analysis (PCA) [129]. After completing the driving information analysis, the final task in the offline stage is to establish the driver style identification algorithm, usually by adopting Markov chain [128], kernel density estimation and entropy theory [126], fuzzy logic rules [113, 130], *K*-means neighbour [47], or machine learning methods [131, 132]. In the online stage, the corresponding features are collected simultaneously during driving and fed into the trained driver style identification algorithm to recognise the current diving style, thereby realising driving style-related EF adaptation in real time.

In Zhang's research [36], BP NN was utilised to realise the instantaneous online driving style identification and, therefore, predict the change rate of accelerator pedal position. Then, the aggressiveness of the pedal position variation was converted into a scaling factor to adjust the EF. The simulation results show that around the fuel economy improvement of around 7% was expected by considering the driving style. The driving styles can also be converted directly into a penalty in EF adjustment [47]. It should be noted that the conversion from driving styles to the EF penalty should be tuned properly for each driving style, in order to fully utilise the resulting possible improvement of fuel economy. Qin et al. [133] optimised the relationship between EF and fuel consumption, but only for three driving styles. Guo et al. [134] claim that the driving style recognition should be established in consideration of driving cycles. Thus, fuzzy logic identifier was employed to recognise both driving cycles and driving styles simultaneously. With the EF optimisation for each driving styles, the vehicle dyno tests show that the driving-style-adaptive optimal control strategy delivered approximately 4% fuel saving, compared with the conventional ECMS.

5.5. Road Information

5.5.1. Travel Distance

The decision to operate PHEV in Charging-Depleting/Charge-Sustaining (CD/CS) or blended mode is crucial to maximise the powertrain energy efficiency [135]. Thus, the ideal scenario is that the power demand for the entire trip is known in advance to compare the resulting all-electric range (AER) with the distance of the upcoming trip and, therefore, select the proper operating mode. Nevertheless, the power demand for the entire trip is difficult to evaluate before the trip. For simplicity, some researchers proposed to harness the priori information of travel distance and nominal AER instead [84, 88]. The trip distance estimation can be performed easily and accurately by means of GPS and GIS.

Zhang et al. [84] applied the ratio α between nominal AER and the total trip to switch on/off of the EF adjustment. Additionally, they claim that it is unfair to minimise the fuel consumption without considering the price of grid energy, and the expenditure of electric energy consumed over the trip should be taken account into the EF adjustment. Thus, the sale price ratio γ between electric power and fuel was introduced as a variable of the EF function, expressed as

$$S(t) = S_0/\gamma + \sqrt{1-\alpha^2}(S_0 - S_0/\gamma) \tag{11}$$

where $\alpha = \max(\frac{X_e}{X_t},1)$, X_e is the nominal AER, and X_t is the total trip distance. When the nominal AER is higher than the total trip, then $\alpha = 1$. Thus, $S = S_0/\gamma$ reflects the fact that all propulsion power will be provided by the electric sources. In contrast, when the nominal AER is much smaller than the total trip, then $\alpha \approx 0$. In this case, $S = S_0$ indicates that the available electric energy in the on-board battery is negligible, compared to the required energy to complete the trip. When $0 < \alpha < 1$, the EF will be adjusted according to the remaining distance of the trip.

Similar EF adjustment method was applied to investigate the effect of trip distance information in EF adaptation [88]. The simulation results show that the knowledge of trip distance is a significant factor for energy cost saving of PHEVs, and the achieved fuel improvement is quite close to the optimal benchmark. Different from the approach proposed by Zhang et al. [84], the AER is calculated in real time, expressed as

$$x_e(t) = \frac{SOC(t) - SOC_{\min}}{SOC_{\max} - SOC_{\min}} X_e \tag{12}$$

where $SOC(t)$ is the current SOC.

In addition to the PHEV mode selection, the trip distance is massively utilised to generate the SOC reference trajectory [37, 84-86], which has been elaborated in Section 5.1.2.

5.5.2. Terrain Preview

Preview terrain information will facilitate the control system to utilise the electric power more effectively [37]. This is because, with the knowledge of the upcoming steep hill, the energy management system is able to actively charge the battery up in advance of the hill. Thus, there is enough electric power for large power demand during the uphill ascent. While, the battery can be deliberately heavily discharged before a downhill descent, as the high regenerative power is available during the downhill. Typically, the future road terrain can be easily obtained by GIS.

A sensitivity study was performed to investigate the effect of terrain information in fuel saving [136]. Ten levels of road grades were employed in this study. The simulation results show that the highest fuel economy improvement of 48.7% was observed with the maximum grade. In view of the real-world driving cycles, the moderate improvement in fuel economy can be expected due to the preview terrain information [21, 28, 37, 137]. Moreover, the terrain preview can contribute to the reduction of the average energy flow to and from battery, thereby extending the battery lifetime. However, only cruise mode was selected to demonstrate the benefits of the terrain preview. In addition, the future power demand was assumed to be known in these researches, due to the availability of the terrain information, without concerning any actual traffic condition.

Chen and Vahidi [88] analysed the impacts of different levels of previewed knowledge on the performance of ECMSs in PHEVs. Three levels of previewed knowledge were defined, including level 1: the knowledge of terrain, trip length and estimated velocity, level 2: hilly terrain and distance to next charging station, and level 3: without any preview. The simulation results indicate that the knowledge of distance to the next charging station can significantly improve the fuel economy of PHEVs, as the electric energy in battery can be fully exploited in this case. Additionally, terrain preview can boost the fuel saving if there are large elevation changes in the coming trip.

5.5.3. Route Recognition

There are several ECMS applications which are developed with the assumption that the trip distance and terrain preview information are known *a prior* [138, 139]. Although the required information can be achieved through the navigation system with the pre-set route, it might be considered unrealistic for every day usage that the driver explicitly informs the vehicle of the coming route [37]. Hence, it is better to autonomously recognise the upcoming trip by the vehicle control system. However, there exists only few studies investigating the integration between the ECMSs and route recognition methods.

A 2-dimensional cross-correlation method was developed to recognise the current trip based on the historical driving data, thereby determining the operating mode in PHEVs [37]. This heuristic route recognition algorithm is based on the trip GPS-trajectory and starting time. Its main advantage lies in the low complexity and ease of implementation. In the research of Zeng and Wang [140], the road-segment-based model training by the historical driving data was leveraged to estimate the probability of running a route stored in historical data, thereby regulating the control parameters. The concept of the proposed route recognition method is described as follows. The current vehicle position and travelling direction can be easily accessed by GPS. Hence, all possible routes within a short-term preview horizon are possibly enumerated. While, the possibility of vehicles driving into each road can be estimated by the historical driving data.

5.6. Driving Pattern Recognition

Driving patterns are defined as the description of the combination of road environment and state of vehicles [141]. Since the optimal EF should be adjusted with the road conditions, several studies investigated the driving pattern recognition with the intention of regulating the EF periodically and, therefore, improving the fuel economy. It needs to be noted that the route recognition is to predict the specific route for the upcoming trip, while the driving pattern recognition is to identify the current trip as a certain type of representative driving patterns, such as suburban, highway, or existing driving cycles. Due to the complexity and strong uncertainty of the real driving environment, it is quite difficult to exactly predict the upcoming route of the current trip. Thus, compared with the route recognition, it is more feasible to obtain the future driving pattern under the assumption that it remains unchanged within a certain period of time.

Table 2. Characteristic parameters for different driving pattern recognitions

Method		Recurrent Neural Network	LVQ Network			Fuzzy Recognition Algorithm		Minimum Distance Classifier	Extreme Learning Machine
Reference		[142]	[143]	[22, 144]	[145]	[146]	[17]	[147]	[148]
Speed	average	✓	✓	✓	✓	✓	✓	-	✓
	minimum	✓	-	-	-	-	-	-	
	maximum	✓	✓	✓	-	-	-	-	✓
Acceleration	average	✓	✓	✓	✓	-	✓	✓	✓
	minimum	✓	-	-	-	-	-	-	-
	maximum	✓	✓	✓	-	-	-	-	✓
Deceleration	average	-	✓	✓	✓	-	✓	-	✓
	maximum	-	✓	✓	-	-	-	-	✓
Average Driving Speed (except stop)		-	-	-	✓	-	✓	✓	-
Speed Standard Deviation		-	-	-	✓	-	-	✓	-
Acceleration Standard Deviation		-	-	-	✓	-	-	✓	-
Deceleration Standard Deviation		-	-	-	✓	-	-	-	-
Idle Time		-	-	✓	-	-	-	-	✓
Idle Time Factor (idle time/total time)		✓	✓	✓	✓	-	✓	✓	✓
High Speed Factor (high speed time/total time)		-	✓	-	-	-	-	-	-
Mid Speed Factor (mid speed time/total time)		-	✓	-	-	-	-	-	-
Low Speed Factor (low speed time/total time)		-	✓	-	-	-	-	-	-
Acceleration Time Ratio (accelerating time/total time)		-	-	✓	-	-	-	-	✓
Deceleration Time Ratio (decelerating time/total time)		-	-	✓	-	-	-	-	✓
Constant Speed Time Ratio (contend speed time/total time)		-	-	✓	-	-	-	-	✓
Cruise time ratio (cruise time/total time)		-	-	-	-	✓	-	-	-

The basic principle of driving pattern recognition is to firstly sample and extract feature parameters from the historical driving data. Then, the NN and the fuzzy recognition method are commonly adopted to establish the driving pattern recognition [8]. Regarding the representative feature parameters, there is no consensus on the precise definition of which cycle characteristic parameters should be selected to describe a driving pattern. The Ericsson's research [149] shows that up to 62 characteristic parameters can be extracted from a given driving cycle. Given the possible correlation among these parameters, a set of independent parameters should be extracted from the original 62 cycle characteristic parameters. Additionally, less characteristic parameters are able to contribute the reduction of computation burden. Thus, the reduced cycle characteristic parameters are typically introduced in the driving pattern recognition method. The corresponding examples are listed in Table 2.

As can be seen in Table 2, there is no standard set of cycle characteristic parameters for the driving pattern recognition, even for the same recognition methodology. Hence, further research on the key characteristic parameters needs to be performed. Once the cycle characteristic parameters are determined, learning vector quantisation (LVQ) neural network [22, 143-145, 150], Hamming neural network [151], extreme learning machine (ELM) [148], recurrent neural network (RNN) [142, 152], fuzzy driving cycle recognition algorithm [17, 146], and minimum distance classifier [147, 153] can be introduced to establish the driving pattern recogniser. It should be pointed out that the LVQ neural network is the most popular methodology for driving pattern recognition, as it is considered as an efficient method to recognise a complex and non-liner object [154]. Typically, the EF will be optimised offline over each selected driving pattern and tabulated for the online application. Therefore, the driving pattern recognition can select the optimised EF value or tables by analysing the similarity of the current trip to the representative driving patterns, thereby periodically updating the EF in ECMSs to achieve better fuel economy.

6. CONCLUSION AND FUTURE WORK

Throughout the literature, various ECMSs for HEVs have been extensively attracted the attention of many researchers in vehicle industry, due to their reliability and promising performance in delivering optimal energy management in real time. It should be noted that ECMSs with the online adjustment capability are able to adjust the EF in real time based on the selected effective pr, thereby fully exploiting the energy-saving potential of hybridisation. Thus, many EF online adaptation methods have been proposed and implemented with the intention of improving the adaptability and optimality of ECMSs. Given the advantages of ECMSs, this paper presents a comprehensive review for the state-of-the-art ECMSs and the corresponding key factors.

PID controllers and weighting function of S_{dis} and S_{chg} are the simplest methods to adjust EF online. However, there is the lack of researches on developing proper tuning process for the internal parameters of both adaptation methods. While, given that the linear regression-based ECMSs utilise the predefined look-up tables generated by the global optimisation over several typical driving cycles, it is able to guarantee the optimality as well as being applicable for the real-time applications. Nevertheless, the performance of linear regression-based ECMSs deteriorates dramatically when the driving conditions are completely different to the driving cycles used to generate the look-up tables. This issue can be resolved by adopting neural networks. Thus, various neural network-based EF adaptation methods were proposed and has capability of delivering the considerable fuel saving. Although the selection process for inputs of EF neural network models is still immature, EF neural network adaptations are the most promising EF adaptation methods for ECMSs due to its generalisation and prediction capabilities. Regarding the rule-based EF adaptations, it is able to deliver decent energy-saving with the sophisticated rules predefined and calibrated by experienced engineers, while the corresponding design process is typically quite time-consuming and the resultant energy-saving may be quite far from the optimality. Essentially, the presented EF adaptation are controllers that adjust the EF online based on feedbacks. Hence, some control methodologies, such as NN and rule-based approach, are common to both ECMSs and the remaining EMSs. The merely difference is that the control variable of EF adaptation method in ECMSs, which is the EF, is dissimilar to that of the rest of EMSs.

According to the existing literature, internal parameters, current powertrain status, speed prediction, driver styles, road information, and driving pattern recognition play vital role of achieving the optimal energy-saving. The internal parameters refer to variables inside the EF adaptation methods which should be tuned properly to deliver the desired EF adaptation over driving cycles, such as the proportional gains in EF proportional controlling and the initial EF value at the beginning of the trip. Besides, a SOC trajectory is required as the reference for the SOC regulation in PHEVs' ECMSs, due to the charge-depleting nature of PHEVs. It is critical to design effective SOC reference trajectories for trips in order to achieve high fuel saving. Regarding the current powertrain status, the drive train efficiency and the battery aging should be considered in the EF adaptation, as the control mechanism of ECMSs indicates that that value of EF should represent the chain of efficiencies of the energy paths from fuel to battery and vice versa. Moreover, the prior knowledge of the power demand distribution in a finite horizon is beneficial for ECMSs to further improve fuel economy, as ECMSs can actively adjust the EF in advance rather than the passive adjustment, thereby achieving the optimal energy distribution in that finite horizon. For example, the battery can be deliberately heavily discharged before a downhill descent if the terrain information is known prior. This active control could make full use of the potential power regeneration. Thus, aiming to improve the ECMSs' control performance, various future driving conditions are exploited in the EF adaptation by predicting the future vehicle speed, recognising the driving styles and patterns, previewing the terrain information, identifying the upcoming route information.

According to the analysis above, significant efforts have been made in the field of ECMS techniques, offering promising solution. However, the rapid development of intelligent transportation system (ITS), connected vehicle technologies, and artificial intelligence technologies offer unprecedented opportunities to improve the performance of ECMSs. Thus, how to excavate the promising potentials to further improve the ECMS performance is one of the key challenges. Furthermore, the advanced ITS and connected vehicle technologies can provide numerous traffic and vehicle information for the ECMS design. It is no doubt a challenging task to evaluate the available information and select proper factors that conclusively determine the vehicle energy consumption. In addition, how to make full use of the selected factors to improve the fuel saving of ECMS techniques needs to be investigated. Hence, based on the aforementioned challenges, the following part will present a brief analysis about the outlook of the ECMS development.

6.1. Integration of ECMSs and ITS

The main challenge of current ECMSs is that the majority of ECMSs are developed over specific driving cycles, which results in low adaptiveness to real diving conditions. To overcome this challenge, the current and future driving conditions in real world ideally should be considered in the ECMS design, then collected and fed into ECMS application. The current driving conditions can be easily accessed through on-board sensors. While, with the development of ITS, the access of future driving conditions, such as the future traffic flow and traffic light information, can be easily accessed. Thus, the integration of ECMSs and ITS can be further beneficial to fuel saving of HEVs. There already exists global optimisation methods that are capable of delivering an optimal EF trajectory for the global fuel-saving optimality if the future driving conditions could be provided by ITS. Whereas, the global optimisation based ECMSs are still inapplicable for the real-time energy control in practice due to the high computational complexity.

The dynamic driving conditions provided by ITS can contribute to high-accuracy driving condition predictions, such as the upcoming vehicle speed and driving patterns. In this scenario, the performance of ECMSs can be improved dramatically. Therefore, the ECMSs incorporating ITS are possible future trends. To be specific, the driving style recognition, speed prediction, and driving pattern recognition can be further developed with the support of ITS. The corresponding key technical challenges are the selection method of influential driving conditions for ECMS and the integration method for ECMS and ITS.

6.2. Learning-Based ECMSs

Machine learning has been widely harnessed to solve complex problems in engineering applications and scientific field. Regarding the energy management for PHEVs/HEVs, learning-based (LB) EMSs are capable of making the optimal control decisions with the support of embedded advanced data mining schemes for numerous historical and real-time driving-related data. However, the control performance of LB-EMSs is significantly dependent on the quality, structure, and size of the training datasets.

Currently, only NNs have been extensively incorporated with ECMSs, mainly accounting for the route and driving pattern recognition. There are merely few researches on utilising neural networks to adjust the EF over the trip. However, the excellent capabilities of the generalisation and prediction of NNs are desirable for the online EF adaptation. Additionally, all the existing researches on NN-based EF adaptations demonstrated the promising fuel saving for HEVs. Thus, significant efforts should be placed to develop NNs for the EF adaptation. Besides, other types of machine learning methods, such as reinforcement learning, also should be investigated to improve the EF adaptation as well.

6.3. Components and Vehicle Model Improvement

Currently, the majority of the ECMS research are performed with the simplified vehicle-level dynamic models due to the resulting low computational cost. The simplified vehicle models are able to dramatically reduce the ECMS development cycle, especially when the numerous virtual simulations are required in the research. However, the parasitic drawback of the simplified model is low fidelity. Thus, although the promising solutions are demonstrated based on the simplified vehicle models, the fuel economy degradation is always expected when the proposed ECMSs are tested in real vehicles. The main issue is that the simplified vehicle models lack the details of component modelling, which cannot capture the key vehicular transient response and deteriorate the simulation fidelity. The ECMSs developed with the low-quality modelling will be less reliable for actual applications. In addition, only when the vehicle model fully represents the dynamic characteristics of the real vehicles, the designed ECMSs can then guarantee the optimality demonstrated in the development phase. Whereas, the computational cost is still required to be considered for efficient researches. Hence, how to attain the optimal trade-off between the model complexity and computational cost in the ECMS development should also be investigated in the future.

6.4. ECMSs of Multiple Connected Vehicles

The connected vehicle technologies also are able to increase the prediction accuracy of vehicle state in a future time domain, thereby providing great potentials for improvement of fuel economy. Currently, the single-vehicle scenario is the main research object for the ECMS develop. However, many researches [41, 155] have demonstrated the benefits of cooperative energy management of the connected multi-vehicle on overall energy consumption minimisation. This is because that connected vehicles can take advantage of the driving information shared by the surrounding vehicles to actively adjust the energy management strategy, which increase the adaptiveness of EMSs. To the best of authors' knowledge, there is no research on developing ECMSs for the connected vehicles. Hence, how to extend the single-vehicle ECMSs techniques to the multi-vehicle co-optimisation strategies is critical for future development of ECMS.

In addition, the major characteristic of the connected multiple vehicles is the heterogeneous dynamic features, such as the powertrain topology. The resulting diversity of EMS is another challenge for the establishment of coupling mechanism in ECMSs. Even worse, the requirements of safety, system mobility and systematic efficiency for different vehicles will be heterogeneous as well. Definitely, a high-level cooperative energy management system should be developed to determine the trade-off between various requirements of connected cars in the same platoon. Regarding ECMSs, how to adapt to the high-level control system is the challenge that should be tackled in the future.

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