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# Thorough state-of-the-art analysis of electric and hybrid vehicle powertrains: Topologies and integrated energy management strategies

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ABSTRACT

Hybrid and electric vehicles have been demonstrated as auspicious solutions for ensuring improvements in fuel saving and emission reductions. From the system design perspective, there are numerous indicators affecting the performance of such vehicles, in which the powertrain type, component configuration, and energy management strategy (EMS) play a key role. Achieving an energy-efficient powertrain requires tackling several conflicting control objectives such as the drivability, fuel economy, reduced emissions, and battery state of charge preservation, which make the EMS the most crucial aspect of powertrain system design. Accordingly, in the present study, various powertrain systems and topologies of (plug-in) hybrid electric vehicles and full-electric vehicles are assessed. In addition, EMSs as applied in the literature are systematically surveyed for a qualitative investigation, classification, and comparison of existing approaches in terms of the principles, advantages, and drawbacks through a comprehensive review. Furthermore, potential challenges considering the gaps in research are addressed, and directives paving the way toward further development of powertrains and EMSs in all respects are thoroughly provided.

## 1. Introduction

The widespread application of hydrocarbon-based transportation has been raising global issues such as an increase in the demand for petroleum production, high gasoline prices, and climate change. Hence, searching for highly efficient, safe, and clean alternative solutions to these issues have been among the most emphasised challenges attracting the attention of researchers in both the environment and transportation sectors [1]. Accordingly, the development of innovative technologies for the utilisation of (plug-in) hybrid electric vehicles ((P)HEVs) and full-electric vehicles (FEVs) is a potential environmentally friendly and cost-effective solution. To achieve a seamless transition from traditional internal combustion engine (ICE)-based vehicles to fully electric vehicles, (P)HEV technologies have recently been employed not only in passenger cars, but also in heavy-duty vehicles [2]. By contrast, FEVs have recently received significant interest owing to recent revolutions in charging infrastructures [3] and the viability of controllable loads supporting the grid in vehicle-to-grid (V2G), vehicle-to-building (V2B), vehicle-to-home (V2H), and vehicle-to-infrastructure (V2I) applications [4–6].

The powertrain design procedure of hybrid and electric vehicles includes different levels, whereas the present study focuses on a powertrain topology and an EMS design. In this regard, Fig. 1 illustrates a system-level design process to achieve an energy-efficient powertrain [7]. First, a powertrain topology should be selected based on the intended transport assignment of a vehicle and the trade-off between cost and performance. A variety of powertrain topologies and component layouts for electric vehicles found in the literature are reported in Ref. [8]. Based on the selected topology, the second stage is to determine the required technology and dimensions for the respective hybrid components, including the energy storage system (i.e. the battery, supercapacitor, and fuel cell) [9], electric motors [10], and dc-dc/dc-ac converters [10]. The objective function of the EMS optimisation problem is normally coupled with powertrain topology selection, whereas technology and component sizing are treated as optimisation constraints.

EMSs will play a crucial role in the development of new generations of clean vehicles. The main objective of an EMS is to split the supply power by considering optimal multi-motive-sources to satisfy driving

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**Abbreviations**

| *Abbreviation* | *Description* |
|---|---|
| CAV | Connected and Automated Vehicle |
| CD | Charge Depleting |
| CFNN | Compensation Fuzzy Neural Network |
| CO | Carbon Monoxide |
| CP | Convex Programming |
| CS | Charge Sustaining |
| CVT | Continuously Variable Transmission |
| DACS | Decentralised Adaptive Control System |
| DFA | Derivative-Free Algorithms |
| DP | Dynamic Programming |
| DRL | Deep Reinforcement Learning |
| ECMS | Equivalent Consumption Minimisation Strategy |
| EF | Equivalence Factor |
| EGR | Exhaust Gas Recirculation |
| EM | Electric Motor |
| EMS | Energy Management Strategy |
| ENN | Elman Neural Network |
| ES | Extremum Seeking |
| ESS | Energy Storage System |
| EVT | Electric Variable Transmission |
| FC | Fuel Cell |
| FC-FEV | Fuel Cell Full-Electric Vehicle |
| FEV | Full-Electric Vehicle |
| FL | Fuzzy Logic |
| GA | Genetic Algorithm |
| GIS | Geographical Information System |
| GPS | Global Positioning System |
| GT | Game Theory |
| HC | Hydrocarbon |
| HESS | Hybrid Energy Storage System |
| HMM | Hidden Markov Model |
| ITS | Intelligent Transportation System |
| ICE | Internal Combustion Engine |
| LB | Learning-based |
| LMI | Linear Matrix Inequality |
| LP | Linear Programming |
| LPF | Low Pass Filter |
| MOGA | Multi-Objective Genetic Algorithm |
| MPC | Model Predictive Control |
| NNL | Neural Network Learning |
| NOx | Nitrogen Oxide |
| OB | Optimisation-based |
| P-HEV | Parallel Hybrid Electric Vehicle |
| PI | Proportional Integral |
| PID | Proportional Integral Derivative |
| PMP | Pontryagin's Minimisation Principle |
| LOPPS | Learning Optimal Power Source |
| PSAT | Powertrain System Analysis Toolkit |
| PSO | Particle Swarm Optimisation |
| PSOC | Pseudospectral Optimal Control |
| QP | Quadratic Programming |
| RB | Rule-based |
| RC | Robust Control |
| RL | Reinforcement Learning |
| RMS | Root Mean Square |
| SA | Simulated Annealing |
| SC | Supercapacitor |
| S-HEV | Series Hybrid Electric Vehicle |
| SCR | Selective Catalytic Reduction |
| SMC | Sliding Mode Control |
| SMS | State Machine Strategy |
| SoC | State of Charge |
| SP-HEV | Series-Parallel Hybrid Electric Vehicle |
| SQP | Sequential Quadratic Programming |
| UC | Ultra-Capacitor |
| V2B | Vehicle-to-Building |
| V2G | Vehicle-to-Grid |
| V2H | Vehicle-to-Home |
| V2I | Vehicle-to-Infrastructure |
| WHR | Waste Heat Recovery |

demands. Thus, an efficient EMS can help reduce the fuel consumption when considering the battery performance (i.e. the current rate and lifetime) and the tailpipe emissions level. However, the design of a highly efficient and adaptive EMS is a challenging task owing to the complex structure of powertrain systems and uncertain driving conditions. Furthermore, the EMS should have a sufficiently simple and fast real-time controller with a desired computational speed for the implementation of a global optimisation algorithm.

A remarkable amount of research into EMSs has been conducted over the last decade, not only for (P)HEVs [11], but also for FEVs [12,13]. The present study intends to foster a better understanding of powertrain topologies and EMSs through a review of the existing literature and by identifying the key research needs. The contributions of this study are as follows. First, an overview of various (P)HEV and FEV topologies and their component configuration is provided alongside different vehicle modelling approaches. Second, this study provides a comprehensive and current review of the concepts recently published on EMSs, reflecting a broad spectrum of optimisation algorithms and objective functions.

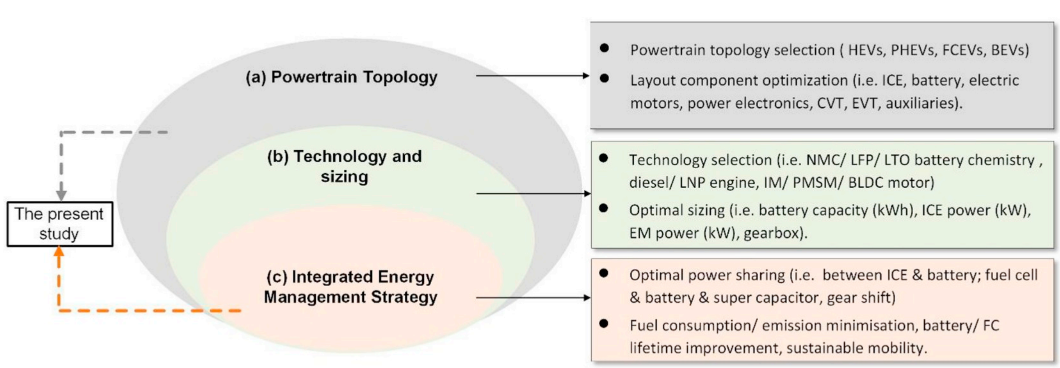


**Fig. 1.** System-level design used to achieve an energy-efficient powertrain.

Based on historical perspectives and the main concepts of each control strategy from earlier periods of the EMS design, development and state-of-the-art technologies are devised for an integrated EMS (iEMS). The aspects within the research field of optimisation for powertrain and EMS control are widespread. This article describes the important keys to achieving optimal control strategies, identifying knowledge gaps, and offering recommendations for future research.

The remainder of the present study is organised as follows. Section 2 presents a broad variety of powertrain systems for HEVs, and investigates the electrical configuration of HESS in FEVs, which have been most widely used for EMS development in previous studies. Section 3 classifies the control algorithms for both (P)HEVs and FEVs, whereas Section 4 discusses the advantages/disadvantages of EMSs and reveals the prospective opportunities for future research trends. Finally, some concluding remarks are given in Section 5.

## 2. Vehicle powertrain topologies

This section focuses on the main powertrain topologies for (P)HEVs/FEVs and their key characteristics. To formulate an EMS optimisation problem, first it is necessary to understand the operation modes of a powertrain topology. A powertrain modelling approach and the complexity level suitable for EMS development are also briefly discussed. Various powertrain topologies with different capabilities can be designed by modifying the connection of the power sources. A connection can be either a mechanical or electrical coupling. In general, the HEV powertrain has three main configurations, namely series, parallel, and series-parallel, whereas the FEV powertrain consists of two types according to the main onboard energy source, either battery- or fuel-cell-based. Fig. 2 shows the predominantly used powertrain topologies of (P)HEVs and FEVs.

### 2.1. Hybrid electric vehicles

#### 2.1.1. Series HEVs

In a series-HEV (S-HEV) topology, the ICE drives a generator whose electrical power output is combined with the power coming from the electrical storage and that transmitted through an electric dc-bus to an electric motor (EM) driving the wheels (see Fig. 3). Because the ICE is freely decoupled from the wheels, it can operate at optimal efficiency by selecting the ICE speed according to the load profiles. Achieving a high performance in stop-and-go driving, S-HEV topologies are primarily being considered for buses and urban vehicles, but are not suitable for highway or inter-urban driving owing to higher conversion losses and the need for a large EM at high speeds [14].

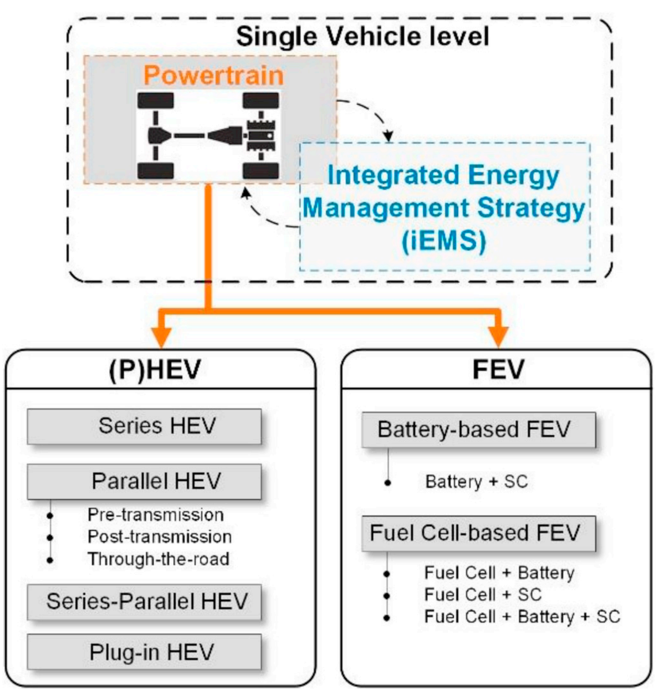


**Fig. 2.** Classification of powertrain topologies for (P)HEVs and FEVs.

#### 2.1.2. Parallel HEVs

In parallel-HEV (P-HEV) topology, the combined power is mechanical rather than electrical, in which the ICE and the EM are connected to a torque coupling such that their torque is combined and then transmitted to the wheels using a conventional driveshaft and possibly a differential gear (see Fig. 4). P-HEV powertrain systems can be roughly categorised into post- and pre-transmission configurations [15]. Another modification of a P-HEV is a through-the-road (TtR) HEV [13], which combines two sources of traction forces 'through the road' by applying ICE for the front wheels and EMs (typically in-wheel motors) for the rear wheels [14]. The energy losses of the P-HEV are smaller than those of the S-HEV owing to the mechanical connection. However, the ICE used in a P-HEV is normally larger, whereas the EM is comparatively smaller and less powerful than the corresponding EM used in an S-HEV. P-HEVs are also less suited for frequent stop-and-go traffic occurring under typical urban driving conditions.

#### 2.1.3. Series-parallel HEVs

A series-parallel HEV (SP-HEV), also known as a power-split HEV (see Fig. 5), combines the complementary advantages of series and parallel HEVs. First, SP-HEV topology can reduce the size of the energy storage system (ESS) and EM compared to those of an S-HEV [18], and can reduce the ICE sizing compared to that of a P-HEV. Second, because S-HEVs are more efficient at lower vehicle speeds whereas P-HEVs are more efficient at high speeds, SP-HEVs can obtain a speed advantage. However, SP-HEV powertrains are complex structures requiring two EMs acting as a generator and a drive motor connected to a planetary gear set that replaces the traditional gearbox and acts as a continuously variable transmission (CVT). Thus, the power flow control of a power-split system is one of the key challenges for an SP-HEV because it includes the normal/standard operating modes of both series and parallel HEVs in addition to other modes such as engine-heavy and electric-heavy modes [19].

Table 1 summarises the main advantages and disadvantages of the three HEV powertrains in more detail.

#### 2.1.4. Plug-in HEVs

As shown in Fig. 6, a plug-in hybrid electric vehicle (PHEV) essentially possesses the same configuration as an HEV but with an external electric charging plug, bigger electrical components (i.e. electric motor and battery), and a downsized engine. Owing to the high capacity of the electrical components, PHEVs can run on full-electric mode for long periods.

In a (P)HEV, there are several operation modes, including battery alone mode (only the battery provides power), engine alone mode (only the ICE propels the vehicle), combined mode (both the ICE and battery provide the required power), and power split mode (the ICE power is split to drive the vehicle and charge the battery). The possible operation modes in (P)HEVs directly depend on the components used, the application, and the vehicle topology. Table 2 provides a breakdown of various possible operation modes considering the (P)HEV topologies.

Owing to limited battery capacity, HEVs mostly utilise charge sustaining (CS) mode to charge/discharge their battery with a small number of cycles. By contrast, the PHEVs can operate in charge depleting (CD)–charge sustaining (CS) mode, in which the vehicle works in CD mode until the onboard rechargeable energy storage system depletes to a predefined lower state of charge (SoC), and then changes to CS mode. The CD-CS mode is widely used owing to its simplicity and ease of

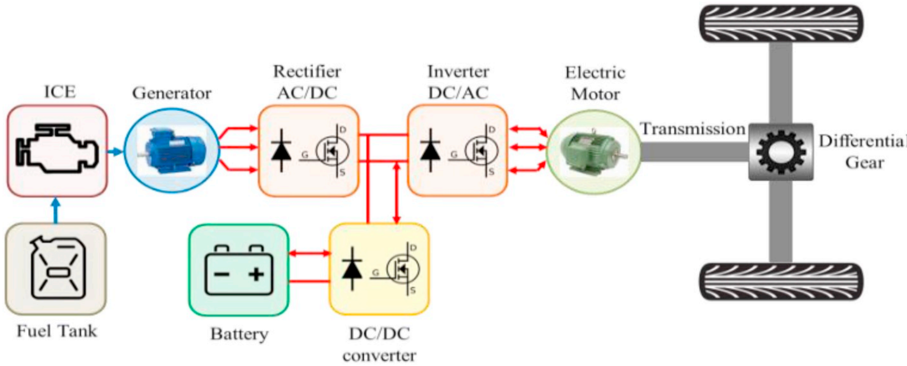


**Fig. 3.** ICE-based series-HEV configuration.

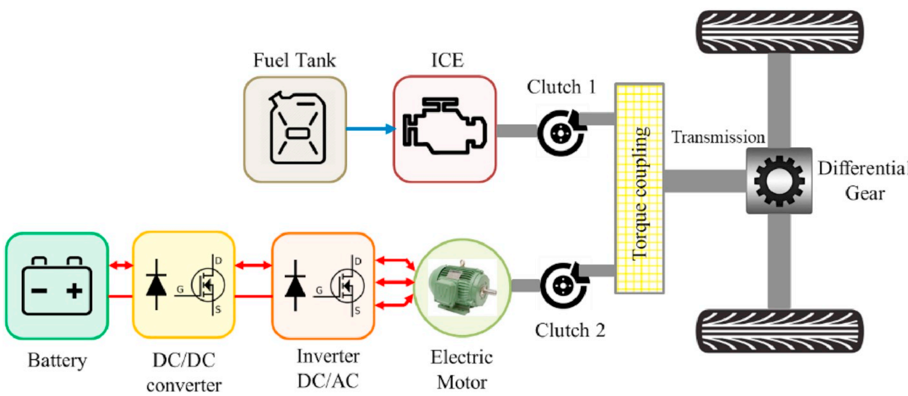


**Fig. 4.** ICE-based parallel-HEV configuration.

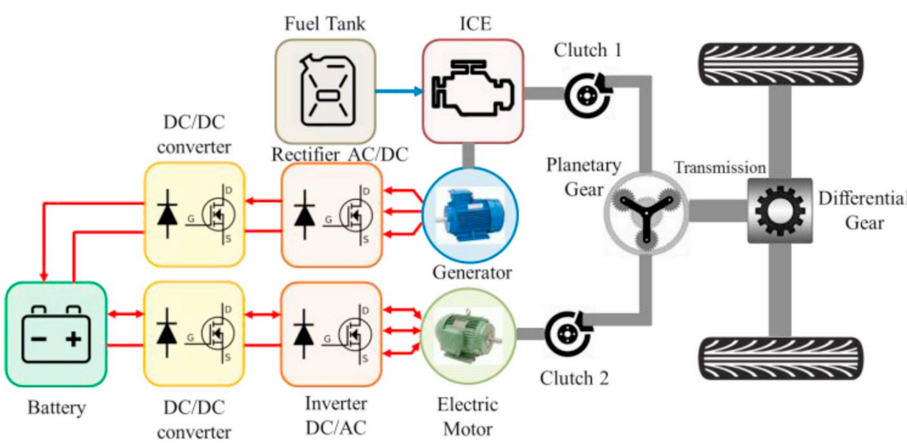


**Fig. 5.** ICE-based series-parallel HEV (complex type) configuration.

implementation, despite its lack of optimality. To improve the energy efficiency of a PHEV, numerous researchers have proposed the use of blended mode, in which the battery is gradually depleted along a previously known driving cycle [20]. However, this does not guarantee that optimal performance will be achieved over other driving cycles.

### 2.2. Full electric vehicles

#### 2.2.1. Battery-based FEVs

In battery-based configurations, the battery is the main source with a high-energy content. Thus, the battery can be combined with other high-power density devices such as a supercapacitor (SC) (also known as an ultra-capacitor (UC), or electric double-layer capacitor (EDLC)), high-power battery, or lithium-capacitor (LiC) to form a hybrid energy storage system (HESS). In general, batteries have a high energy density and low power density in contrast to an SC. Hence, an HESS can store sufficient energy and satisfy sudden power demands for the vehicle to achieve a required acceleration performance. Compared to a standalone battery-based FEV configuration, an HESS-based configuration exhibits numerous advantages such as a higher energy/power density, longer battery life span, faster dynamic response in acceleration mode, and the capability of absorbing more energy in regenerative braking mode [9]. HESS-based systems can vary when considering the converter type and their positions through a powertrain. An HESS can be classified into two main types: a semi-active configuration (see Fig. 7(a)–(c)) or a fully active configuration (see Fig. 8(a)–(c)). Specifically, the multiple-input

**Table 1**
Features of series, parallel, and series-parallel HEVs.

| Powertrain | Advantages | Disadvantages |
|---|---|---|
| Series | • Optimised efficient traction driveline (engine downsizing)<br>• Modular power plant possibilities (space packaging advantages)<br>• Long operational life<br>• Excellent transient response<br>• Zero emission operation possible | • Larger traction drive system<br>• Multiple energy conversions |
| | Application: Larger vehicles such as heavy-duty buses, trucks and locomotives. | |
| Parallel | • Economic gain at high cost<br>• Zero emission operation possible | • High voltages needed for efficiency<br>• Complex space packaging |
| | Application: urban passenger cars. | |
| Series-parallel | • Zero emission operation possible | • Very expensive system<br>• Control complexity<br>• Complex space packaging |
| | Application: passenger cars, light duty vehicles. | |

configuration shown in Fig. 8 (c) can be realised by different circuitry arrangements such as an averaging topology [21] (see Fig. 9(a)), coupled magnetic topology [22] (see Fig. 9(b)), Z-source topology [23] (see Fig. 9(c)), and cascoded topology [24] (see Fig. 9(d)).

### 2.2.2. Fuel cell-based FEVs

In fuel-cell (FC)-based FEVs, the FC is the main energy source used to generate electricity from hydrogen and air. The specific energy of an FC and its specific power are close to and much less than those of gasoline, respectively. Because FC systems have slow dynamics, fast power transients can lead to a gas starvation, resulting in permanent damage to the FC. Therefore, batteries, SCs, or battery-SCs can be integrated into a system to improve the dynamic performance and extend the FC lifespan. In this regard, the possible configurations and combinations FC-Bat, FC-SC, or FC-Bat-SC are illustrated in Fig. 10(a)–(c).

## 2.3. Powertrain modelling approaches suitable for EMS assessment

Once a vehicle topology is selected, modelling the powertrain is a fundamental step for devising an efficient EMS. The powertrain models should be sufficiently accurate to characterise the system and allow their validation using other high-fidelity models. Depending on the purpose of the research, different levels of complexity and accuracy are required to model a powertrain system (see Table 3).

From Table 3, to assess the EMS performance, the powertrain components can be modelled using steady-state and quasi-static models in which the experiment data are stored in look-up tables and their transient states are neglected. Depending on the direction of the calculation, modelling approaches for an EMS assessment can be classified as forward-facing (powertrain system analysis toolkit (PSAT) software and energetic macroscopic representation tools), backward-facing (ETH QSS-toolbox), and combined forward-backward facing (ADVISOR software) models [28]. A typical parallel HEV model based on the forward and backward approaches is illustrated in Fig. 11(a) and (b), respectively.

The forward modelling approach is based on the principle of integral causality (cause and effect) in which the output is always an integral function of the input, inducing a time delay from the input to the output. Hence, the forward modelling respects the physical limitations of the powertrain components. As can be seen in Fig. 11(a), the reference speed block generates the required speed, acceleration, and slope that a vehicle needs to follow. A driver block can employ a proportional integral controller to compute the set-point torque for the powertrain actuators. The heart of the control layer is the energy management strategy block, which generates the reference control signals (e.g. the requested torque for ICE and EM, or the requested currents for the battery and SC in HESS). The actual speed, which is an integration of the force applied, is then fed back to the driver and the EMS blocks.

Conversely, the backward modelling approach is based on a non-causal model, because the calculation process starts from the imposed reference speed used to calculate the required traction force at the wheel, and works 'backward' toward the ICE or primary energy source. In light of EMS development, a causal model of a forward approach is more appropriate than a non-causal model of a backward approach. A misunderstanding of the physical causality can lead to a nonphysical energy management that not only reduces the system efficiency but also increases the risk of damage [28]. However, the forward approach requires a longer computation time than the backward counterpart owing

**Table 2**
Possible operation modes of (P)HEVs.

| No | Operation modes | Powertrain topologies | | | |
|---|---|---|---|---|---|
| | | Series | Parallel | Series-Parallel | Plug-in |
| 1 | Battery alone mode | ✓ | ✓ | ✓ | ✓ |
| 2 | Engine alone mode | ✓ | ✓ | ✓ | ✓ |
| 3 | Combined mode | ✓ | ✓ | ✓ | ✓ |
| 4 | Power split mode | ✓ | ✓ | ✓ | ✓ |
| 5 | Stationary charging mode | ✓ | ✓ | ✓ | ✓ |
| 6 | Regenerative braking mode | ✓ | ✓ | ✓ | ✓ |
| 7 | Engine-heavy mode | – | – | ✓ | – |
| 8 | Electric-heavy mode | – | – | ✓ | – |
| 9 | Charging battery mode | – | – | – | ✓ |
| 10 | Extended driving mode | – | – | – | ✓ |

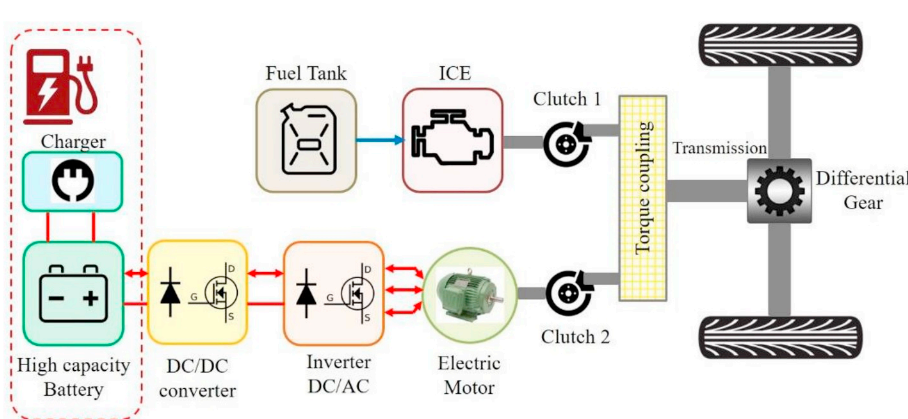


**Fig. 6.** ICE-based plug-in HEV configuration.

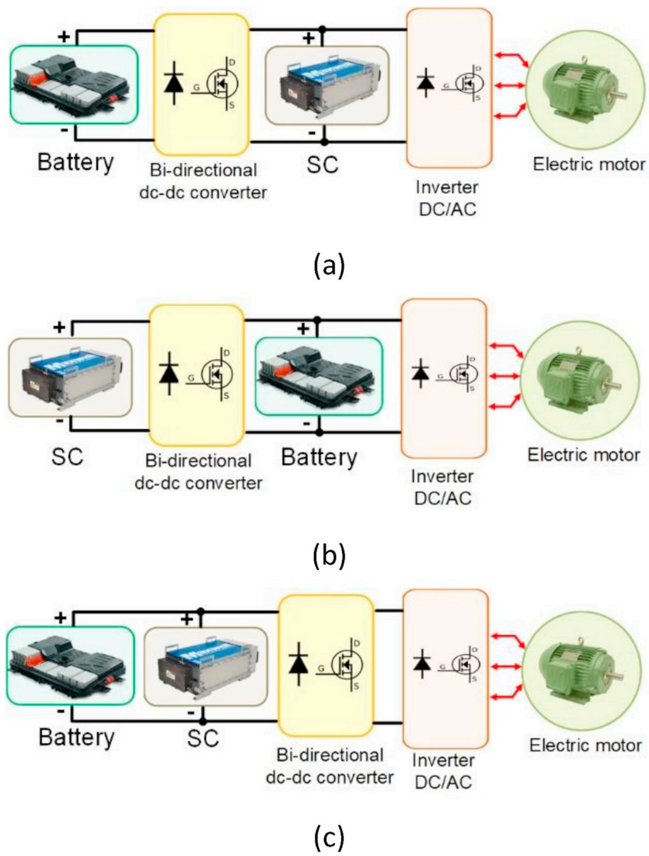


**Fig. 7.** Semi-active HESS configurations in battery-based FEVs: (a) battery-SC, (b) SC-battery, and (c) parallel configurations.

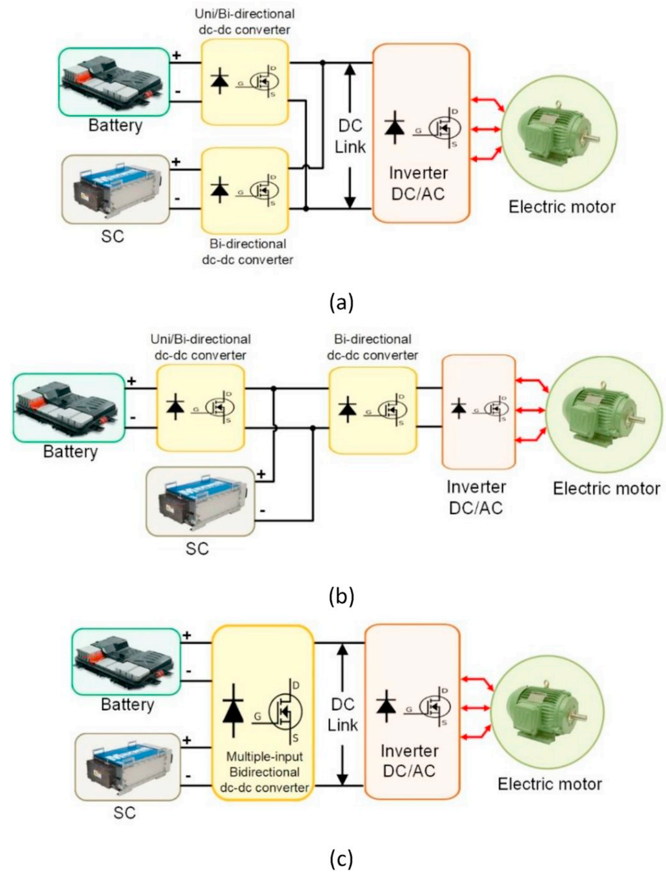


**Fig. 8.** Fully active HESS configurations in battery-based FEVs: (a) multi-port converter, (b) cascaded, and (c) multiple-input converter configurations.

to the inherit delay time of the causal principle. This makes backward approaches more suitable for optimisation in terms of the computational cost.

## 3. Energy management strategies for vehicles

### 3.1. Overview and classification of EMSs

(P)HEVs and FEVs are sophisticated electro-mechanical-chemical systems. The complex power flow, potential fuel economy improvement, and emission reduction rely on the selection of the topology and EMS. The main goal of an EMS is to share power through the components of the powertrain efficiently by selecting the appropriate operation modes. Such objectives include improving the fuel economy, reducing emissions, ensuring drivability, and maintaining the state of charge and lifetime of the energy storage system by considering the limitations. Fig. 12 provides a general overview of the EMS objectives for both (P)HEVs and FEVs.

During the past decade, a large variety of studies have been published on the use of an EMS for HEV, PHEV, and FEV applications. Although several alternative classifications can be found in the literature, the generally accepted arrangements agree with the existing EMSs, which includes three major types: rule-based (RB), optimisation-based (OB), and learning-based (LB). The RB-EMSs can be sub-classified into deterministic and fuzzy-logic EMSs working based on a set of predefined rules without prior knowledge of the trip. By contrast, OB-EMSs can be classified into offline and online optimisation based on the information level of driving conditions employed. In general, OB-EMSs have received more attention than RB-EMSs. Among the developed OB-EMSs, dynamic programming (DP), Pontryagin's minimisation principle (PMP), and metaheuristic search methods (i.e. the genetic algorithm (GA), particle swarm optimisation (PSO), and simulated annealing (SA)) are widely used offline for a global optimisation search. Meanwhile, equivalent consumption minimisation strategy (ECMS) and model predictive control (MPC) are extensively used as online OB-EMSs. The use of LB-EMS approaches has shown promising potential owing to the recent advances in machine learning and artificial intelligence techniques for online data-based network training approaches. LB-EMSs can learn from historical data or use previous driving data for online learning. Fig. 13 and Table 4 show the classification of the three main types and sub-types of EMSs for (P)HEV and FEV technologies. It can be seen that a versatile EMS can include a mixture of different techniques (RB, OB, and LB) forming an integrated EMS (iEMS) toward an improved fuel economy and performance. Thus, in this review article, when addressing a particular EMS categorisation, its combination with other techniques may be included.

As shown in Fig. 13, traffic information in a global positioning system (GPS) and a cloud database in an intelligent transportation system (ITS) can be integrated into an EMS to improve the vehicle performance. A massive amount of real-time data can be obtained through an intelligent infrastructure or connected vehicles [29]. There are numerous possibilities to improve an EMS by taking advantage of the surrounding information (e.g. driving conditions and driver styles). To recognise and predict future driving conditions, numerous researchers have proposed different predictive techniques, including GPS- or ITS-based techniques, statistic and clustering analysis techniques, and Markov chain-based techniques, which can be integrated into a variety of EMSs.

In general, GPS or ITS information is used to update the control rules or parameters of an EMS, which is called an adaptive-EMS, and includes an adaptive FL [30], adaptive ECMS [31], or telematics-MPC [32]. In addition, statistic and clustering analysis methods are widely used for

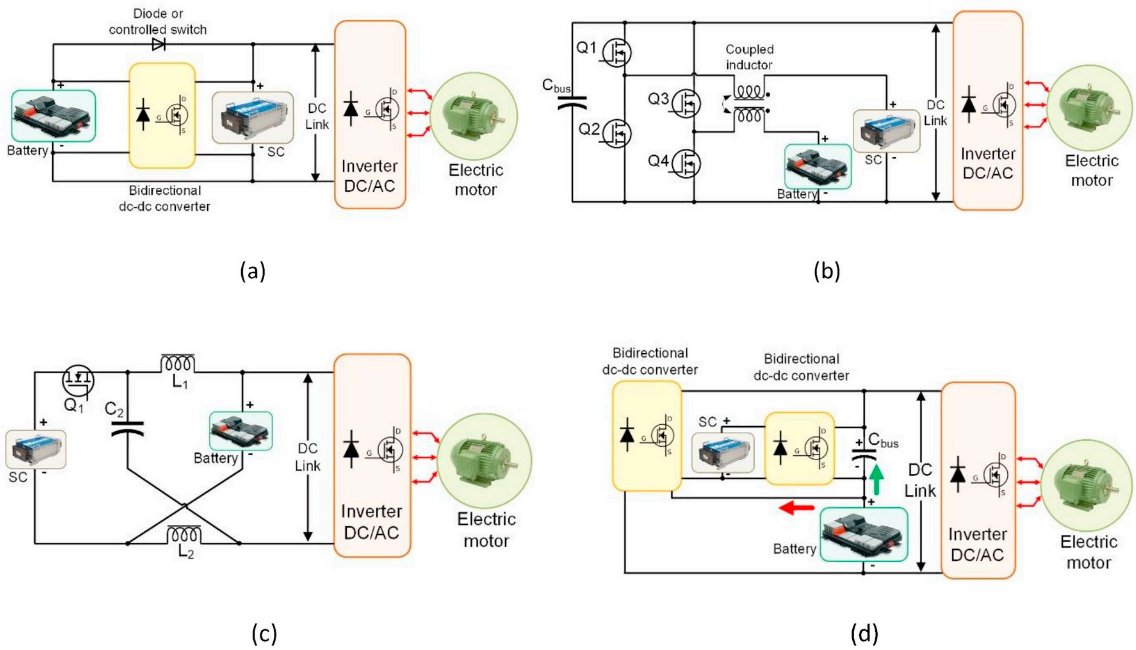


**Fig. 9.** Different circuitry arrangements for multiple-input converter configuration for battery-based FEVs: (a) averaging [21], (b) coupled magnetic [22], (c) Z-source [23], and (d) cascoded topologies [24].

driving cycle recognition in a predictive EMS, including a predictive FL and predictive ECMS. To analyse the set of driving pattern parameters characterised in certain driving cycles, several threads of parameters are collected in each time window (e.g. 150–200 s). The set of collected parameters mainly consists of the average speed, acceleration/deceleration, maximum acceleration, and maximum speed, and are collectively gathered in sub-groups to train the classification model. Corresponding algorithms, as reported in Ref. [33], include a Bayesian algorithm, decision tree, rough set theory, fuzzy clustering, learning vector quantisation neural network [34] and support vector machine [35]. In the third prediction method, the stochastic process such as power demand from the driver, the vehicle velocity, and engine torque can be treated as a stochastic Markov chain represented by a state vector. This technique can be realised using several different EMSs including a stochastic DP [36] and stochastic MPC [37]. To compensate the impact of a deficient driving style on the fuel economy, numerous researchers have proposed different methods to recognise the driving styles and integrate them into an EMS. The recognition methods [34] used for an EMS include a statistical analysis, jerk analysis, Gaussian mixture models, and fuzzy classification.

### 3.2. Rule-based EMSs

Rule-based (RB) EMSs are based on heuristics, intuition, or human expertise without *a priori* knowledge of a predefined driving cycle. The main advantage of an RB-EMS is its simplicity, owing to the real-time feasible implementation when using a look-up table or state machine logic on a vehicle powertrain. However, an RB control strategy has several disadvantages. The first is its lack of optimality while requiring information regarding the driving cycle in advance. In addition, a significant calibration effort is required to guarantee the performance within a satisfactory range for any driving cycle. The setting rules are not scalable to different powertrain architectures or different component sizes. Other optimisation and recognition techniques can be integrated into an RB-EMS to enhance their performance. Such strategies include a multi-mode strategy combined with an ECMS [46], state machine control based on an ECMS [50], a thermostat combined with driving recognition [40], and a multi-mode EMS based on driving pattern identification using learning vector quantisation and a neural network [48]. Although a rule-based EMS may not obtain the optimal solution, it has still received attention owing to its simplicity in terms of a real-time implementation. RB-EMSs can be further sub-classified into deterministic and fuzzy-logic EMSs.

#### 3.2.1. Deterministic strategies

In a deterministic RB-EMS, the rules can be extracted from experience, in which the main energy sources (i.e. ICE and fuel cell) are controlled to perform mostly under optimal working conditions or in a high efficiency region (see Fig. 14) to enhance the fuel economy and minimise the energy transmission loss. The optimal working conditions can be referred to as the optimal working point [39], optimal operation line [44], or optimal efficiency region [45]. For example, in a series-parallel HEV with a planetary gear set and continuously variable transmission, the ICE can be freely adjusted to the optimal operating point. Another deterministic rule for power splitting is frequency-decoupling control, in which the energy sources with slow dynamics (e.g. the ICE in an HEV or the FC in an FEV) provide low-frequency power, whereas other energy sources with faster dynamics can compensate the required power by providing the peak and/or high-frequency power.

##### 3.2.1.1. Optimal working condition based strategies

*3.2.1.1.1. Thermostat (on/off) strategy.* In a thermostat strategy (known as an on/off strategy), the ICE can operate at its optimal efficiency point of the engine's efficiency map providing a constant torque and speed to maintain the battery SoC between the predefined upper and lower limits. This can be achieved by turning the ICE on/off when required. The difference between the power delivered by the sweet point and the demand will either be supplied to charge the battery (engine traction and battery charging mode) or support the battery for supplying the required load in assistant (hybrid traction) mode. The thermostat (on/off) strategy offers the best efficiency for an engine-generator set; however, the overall system efficiency of the HEV will be low. This strategy can be found mostly in a series HEV and for stop-and-go city driving applications.

Similarly, the thermostat strategy can be applied in an FC-battery-SC

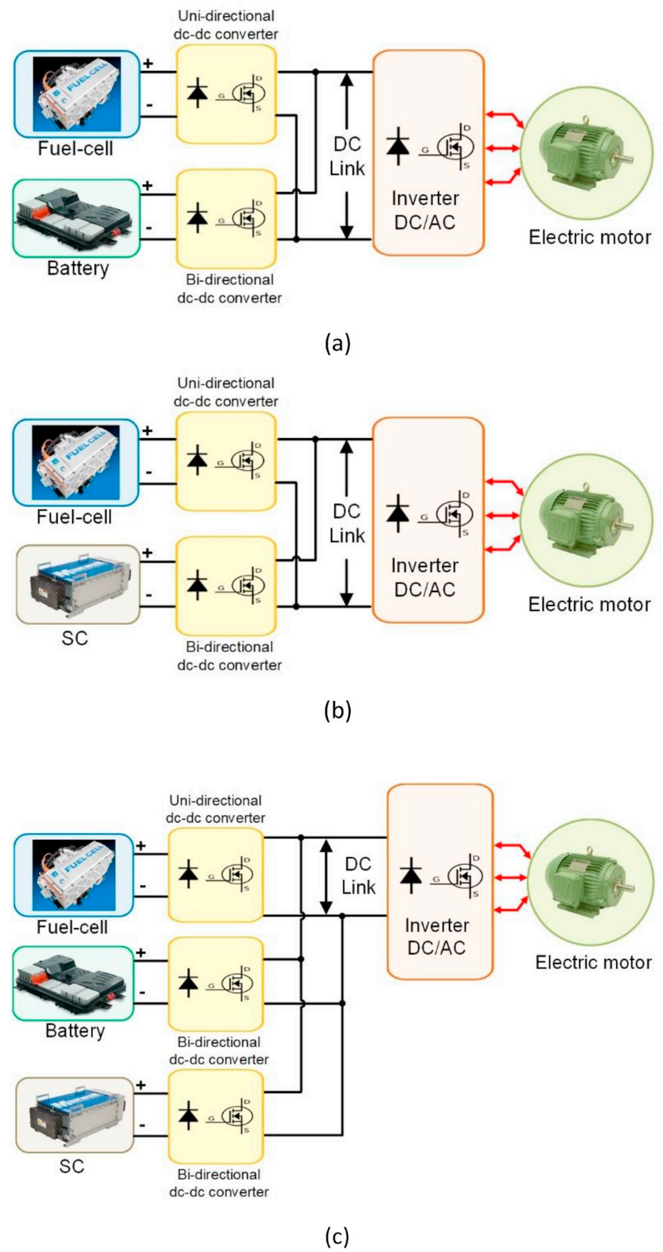


**Fig. 10.** Fuel-cell-based FEVs: (a) battery [25], (b) SC [26], and (c) battery-SC [27] hybrid fuel cell topologies.

system [41]. In this case, the FC operates at the most efficient power level and turns on/off when the battery SoC reaches the low/high limit, respectively.

*3.2.1.1.2. Power follower (baseline) strategy.* The power follower strategy (known as a baseline control) appoints the engine/generator unit as the main power source, and the controller adjusts the output power to follow the power requirement of the vehicle. The rules of the power follower strategy are based on some heuristics and human reasoning. For example, the EM only works if the vehicle speed is below a certain minimum value, the EM supports the engine if the power demanded is greater than the maximum engine power, the EM charges the batteries through regenerative braking, and the engine charges the battery through an EM-generator if the battery SoC is lower than its predefined minimum value. The power follower strategy can offer the benefits of overall system efficiency and an improved durability of the batteries when compared to a thermostat strategy. A power follower control strategy also provides a sustainable SoC with a stable bus voltage

**Table 3**
Levels of complexity for modelling HEV components.

| | Simplified model | Medium/High-fidelity model |
|---|---|---|
| Research purpose | Energy management, performance, and emission | Drivability, stability and handling<br>Noise, vibration and harshness |
| Modelling approach | Forward/Backward | Forward |
| Vehicle dynamics | Lumped vehicle and powertrain inertia; Longitudinal model | Longitudinal-lateral model |
| Type of model | Static/Quasi-static model | Low-frequency/High-frequency dynamic model |
| Engine | Stationary fuel consumption map | First-order dynamics and fuel consumption map |
| Engine starter | Instantaneous power on | Electrical cranking |
| Clutch/Torque converter dynamics | Instantaneous engagement | Slip dynamic |
| Electric motor/Generator | Efficiency map | d-q model |
| Converter/Inverter | Constant efficiency or efficiency map | Average/small-signal model |
| Battery/SC | Electrical model with SoC and SoH model | First- or second-order model |
| Fuel Cell | Stationary hydrogen consumption map or efficiency map | First-order dynamics and hydrogen consumption map |

[209]. Combining the advantages of both strategies above, a hybrid thermostat and power follower can further improve the fuel economy of a series HEV [42] and a parallel HEV [43].

*3.2.1.1.3. State machine strategy (multi-mode strategy).* A state machine strategy (SMS), also known as a multi-mode strategy, works on a specific operation or state of the vehicle using a flow chart or decision tree of the stable conditions related to the previous conditions and present input values. In an HEV application, the state machine [47] dictates the operating modes, for example, the engine mode (ICE propelling the vehicle), boosting mode (both ICE and EM propelling the vehicle), and charging mode (ICE propelling the vehicle and charging the battery). The transition between the operating modes is decided based on the change in driver demand, a change in the vehicle operating conditions, and system/subsystem faults. Implementation of a vehicle controller through a state machine facilitates a fault-resilient supervisory control of the entire system.

For use in an FC FEV, Xu et al. [49] developed a multi-mode real-time control strategy based on three typical processes of the FC system, taking the fuel economy and system durability into consideration. In Ref. [51], SMS based on a droop control is proposed to distribute the demand when considering the state change. The transient-free safe operating conditions for a polymer electrolyte membrane FC (PEMFC) are guaranteed to achieve a better energy efficiency of the overall hybrid system.

*3.2.1.2. Frequency-decoupling strategies.* This strategy relies on a decoupling of the low- and high-frequency components of the load demand signal and applying low-frequency content to the high-energy source in the system, whereas the high-frequency is compensated using an auxiliary fast-responding source. Frequency-decoupling can be realised through a simple low-pass filter (LPF), a gliding average strategy [58] (known as a Phlegmatising strategy), or a time-frequency representation tool such as a wavelet-transform (WT).

For use in a series HEV, Kim et al. [52] controlled the power sources based on the frequency content to mitigate aggressive engine transients when driving under an aggressive drive cycle, increasing the fuel economy by 5.9%, improving the battery life, and decreasing the emissions by 62.7%. For an FEV, an LPF has been applied in an HESS [53] and FC-battery systems [54] to soften the battery and FC peak

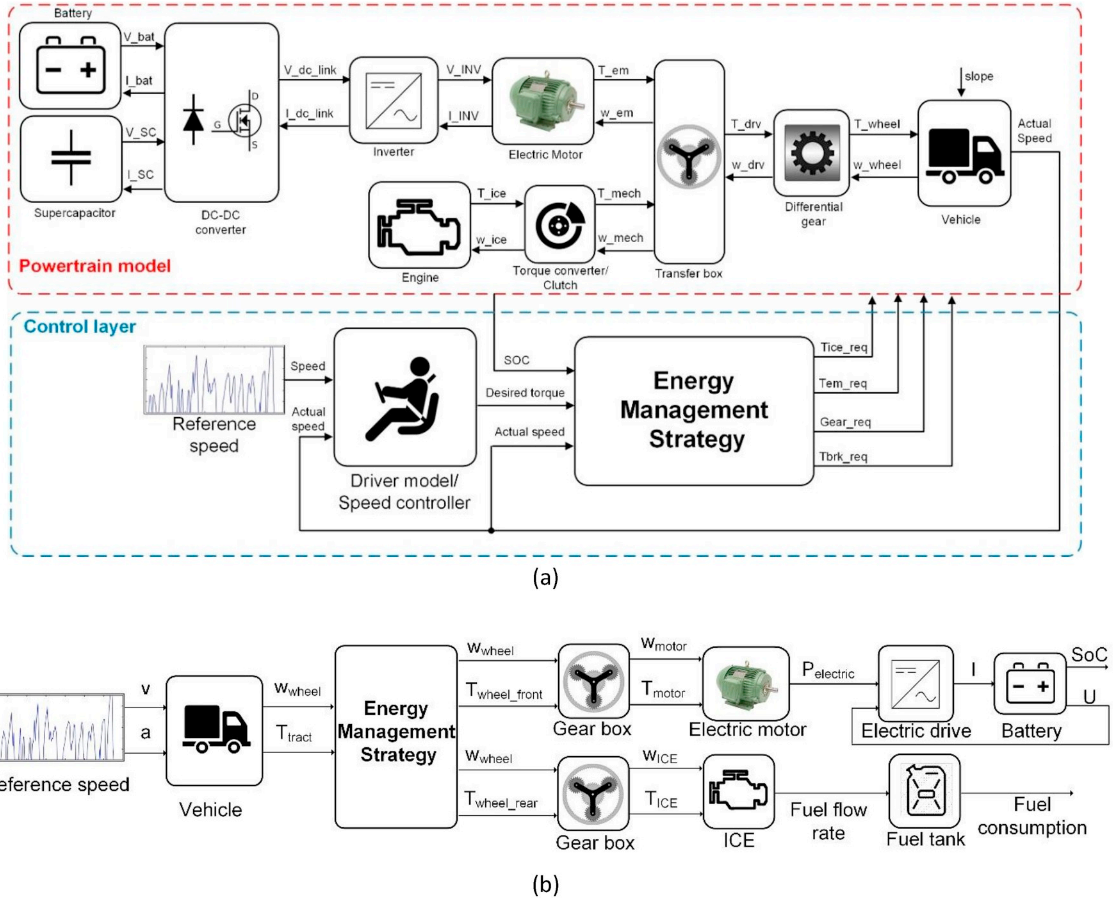


**Fig. 11.** Modelling approach of a parallel HEV: (a) forward- and (b) backward-facing models.

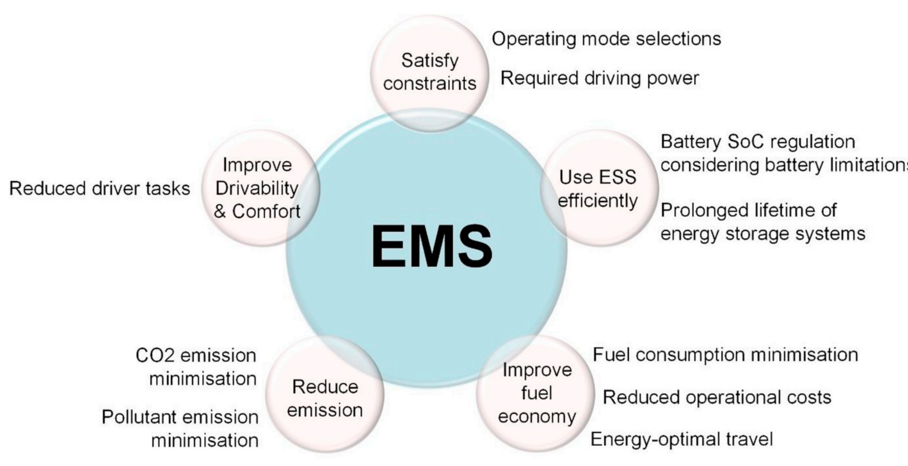


**Fig. 12.** General overview of EMS objectives.

current demand, respectively. However, the decision regarding the decomposition depth of the LPF and the gliding average strategies applied are arbitrary and are unable to constrain the SoC boundary and the final SoC value, which requires a combination with other control strategies to overcome existing drawbacks.

A WT-based EMS was developed for use in a PHEV [55] to reduce the damage caused by the transient and peak power demands placed on the battery. In an FEV, three-level wavelet-transform decomposition [56] based on the mother wavelet is used to decompose the high- and low-frequency components in the power demand of an electric vehicle. Thus, the base power can be supplied by the primary battery pack, whereas the transients can be compensated by the UC bank.

#### 3.2.2. *Fuzzy logic strategies*

An FL strategy converts human experience and reasoning into a set of IF-THEN rules. This conversion process consists of five stages: input quantisation, fuzziness, fuzzy reasoning, inverse fuzziness, and output quantisation. The performance of an FL strategy is determined by the membership function and fuzzy rules at the fuzzy reasoning stage. Because the fuzzy rules can be easily tuned, the advantage of this method is its robustness owing to its independence from the mathematical model of the controlled system and its adaptation. This enables

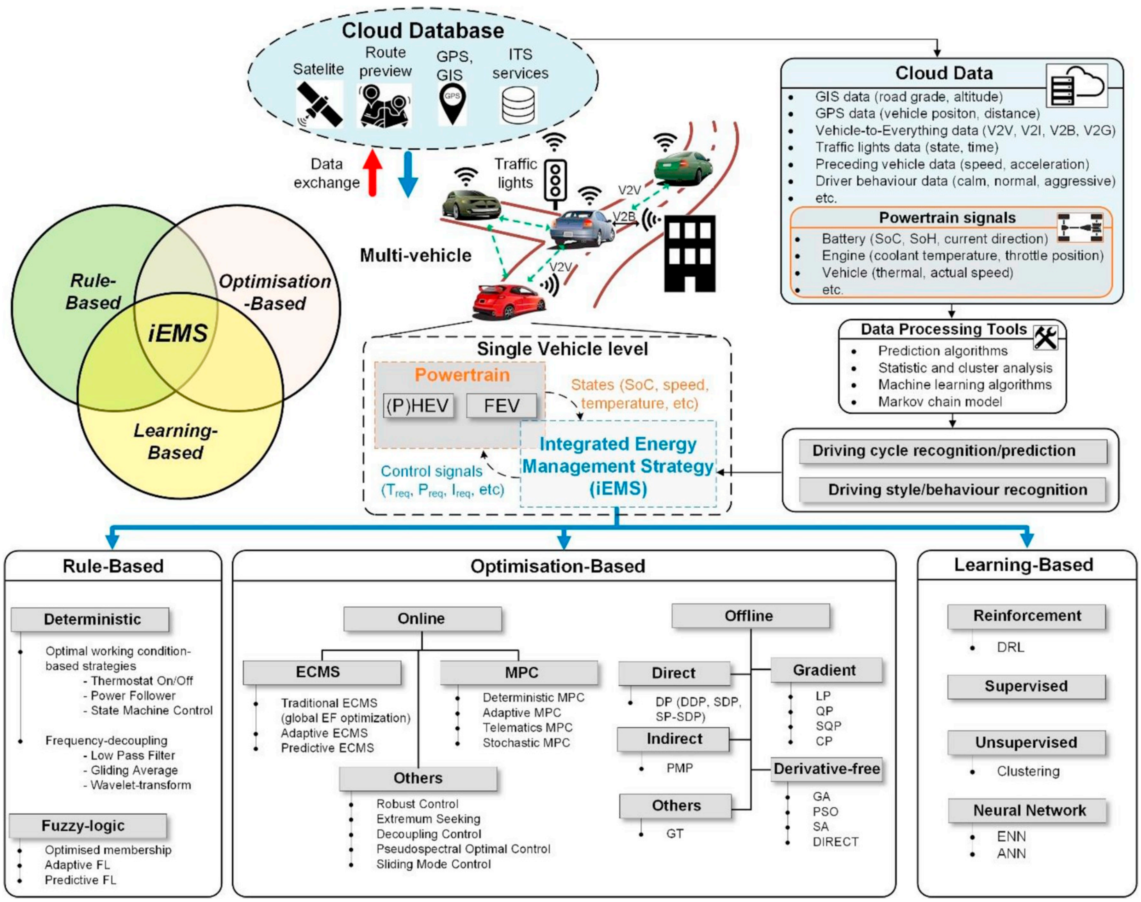


**Fig. 13.** Classification of energy management strategies and the iEMS concept.

the FL strategy to handle the multi-domain, time-varying, and nonlinear problems found in the EMS of the vehicle system. For example, Baumann et al. [59] and Salman et al. [60] developed a fuzzy logic control to coordinate the operation of parallel HEV subsystems. He et al. [61] worked on a fuzzy logic controller to efficiently control the engine operation. Schouten et al. [76] presented a fuzzy logic controller to determine the power split between the engine and motor using a forward-facing model built in PSAT. However, FL strategies cannot guarantee an optimal performance.

*3.2.2.1. Optimised-fuzzy-rules control.* An optimised FL controller is used to tune the controller through an optimisation algorithm to achieve the control objectives, such as a minimisation of the fuel consumption, a minimisation of the emissions, and SoC maintenance, and enhance the driving performance. To improve the fuzzy RB strategy applied, the membership function and fuzzy rules can be optimised by utilising evolutionary optimisation algorithms such as the proportional factor algorithm [62], PSO [63], GA [64], and Bee algorithm [65] for an HEV, or the DIRECT algorithm [67] for a fuel-cell HEV.

*3.2.2.2. Adaptive fuzzy logic control.* Adaptive algorithms are integrated in an FL-RB strategy to improve its self-adaption. Regarding the (P)HEV, Saeks et al. [70] proposed a decentralised adaptive control system (DACS) for a four-wheel-drive HEV powertrain for adaptation with unknown tire dynamics, changing road surfaces, and vehicle loading. Mohebbi et al. [71] developed the adaptive neural fuzzy interference system to maximise the vehicle torque and minimise the fuel consumption. Wang et al. [72] proposed two neural-network-based adaptive estimators for the torque and speed of both the EM and engine, namely a compensation fuzzy neural network (CFNN), to obtain a better acceleration and deceleration performance of an HEV. The CFNN is a hybrid control system that merges the features of both a fuzzy neural network controller and an adaptive compensated controller. Chen et al. [210] presented an intelligent power management strategy using a machine learning algorithm (learning optimal power sources (LOPPS)) and a fuzzy power controller for an HEV powertrain based on multiple sources. The LOPPS algorithm learns from simulation data on the possible requested power with SoC constraints, and then generates the optimal power sharing between the power sources for an online EMS application.

*3.2.2.3. Predictive fuzzy logic control.* Predictive FL control works based on the predicted future state of the vehicle, performing real-time control tasks and generating control power sharing signals. In Ref. [75], a predictive FL-RB is designed to determine how a vehicle reacts to the future states of a traffic flow and steep grade gathered from a GPS.

### 3.3. Optimisation-based EMSs

The objective of optimisation-based (OB) EMS is to find the optimal control sequence (i.e. reference power demand) that minimises a cost function while meeting the dynamic state constraints such as the global state constraints (e.g. battery SoC) and local state constraints (e.g. power limit, speed limit, and torque limit). The cost functions can be different representations such as the fuel consumption, the hybridisation costs, the payload weight of the vehicle, the exhaustive gases emissions (i.e. NOx, HC, and CO), the power efficiency of the electric generation path in a series HEV, the hydrogen consumption in an FC-FEV, and the root mean square (RMS) of the battery current in an FEV. The OB strategies can generally be grouped into two types, offline and online strategies,

**Table 4**
Taxonomy of EMSs for (P)HEV and FEV technologies.

| EMS classifications | | | | (P)HEV | | | | FEV | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Series | Parallel | Series-Parallel | Plug-in | Bat/SC | FC-Bat or FC-SC | FC-Bat-SC |
| Rule-based | Deterministic | Optimal working condition | Thermostat (on/off) | [38] | – | [39] | – | – | [40] | [41] |
| | | | Power follower (baseline) | [42] | [43] | [44,45] | – | – | [46] | – |
| | | | State machine control (multi-mode strategy) | – | [47] | – | – | – | [48–50] | [51] |
| | | Frequency-decoupling | Low-pass filter | [52] | – | – | – | [53] | [54] | – |
| | | | Wavelet-transform | – | – | – | [55] | [56] | – | – |
| | | | Gliding average strategy (Phlegmatising control) | – | [57] | – | – | – | [58] | – |
| | Fuzzy logic | Conventional | | – | [59–61] | – | – | – | – | – |
| | | Optimised membership | | – | [62–65] | – | – | [66] | [67,68] | [69] |
| | | Adaptive | | – | [70–72] | – | – | [73] | [74] | – |
| | | Predictive | | [75] | [76] | – | – | [77] | – | – |
| Optimisation-based | Offline | Direct | Dynamic Programming | [78,79] | [80] | [81] | [82,83] | [84] | [85] | – |
| | | Indirect | Pontryagin's Minimum Principle | [86] | [87–89] | [90] | | [91] | [92] | [93] |
| | | Gradient | Linear Programming | [94] | [95] | – | – | – | [96] | – |
| | | | Quadratic Programming | [97] | [98] | – | – | – | – | – |
| | | | Sequential Quadratic Programming | – | [99,100] | – | – | – | – | – |
| | | | Convex Programming | [101,102] | – | – | [103] | [104] | [105] | – |
| | | Derivative-free | Simulated Annealing | [106] | [107] | [90] | [108] | [108] | – | – |
| | | | Genetic Algorithm/Multi-Objective GA | [109] | [110–113] | [114,115] | | [116] | – | [117] |
| | | | Particle Swarm Optimisation | – | [118] | [119] | [120] | – | [121] | – |
| | | | Divided Rectangular | – | [122,123] | [124] | – | – | [67,125] | – |
| | | Others | Game Theory | – | [126] | – | – | – | [127] | – |
| | Online | Equivalent Consumption Minimisation Strategy | Traditional ECMS (Constant equivalence factor over driving cycle) | – | [128–132] | [133] | – | – | – | [134] |
| | | | A-ECMS (SoC feedback) | [135] | [136–138] | [139] | – | – | [140] | [141] |
| | | | A-ECMS (Current direction consideration) | [142] | [143] | – | – | – | [144] | [145] |
| | | | T-ECMS (Driving cycle prediction) | [146] | [31,147–149] | – | [150,151] | – | [152] | – |
| | | | T-ECMS (Driving cycle pattern recognition) | – | [153–155] | – | – | – | – | – |
| | | Model Predictive Control | Deterministic MPC | [156] | – | [157] | | [158,159] | – | – |
| | | | Stochastic MPC | [156,160] | [37,161,162] | [163,164] | [164–167] | – | [168] | – |
| | | | Telematics MPC | – | – | [169,170] | – | – | [171] | – |
| | | | Adaptive prediction horizon length | – | [172,173] | [174] | – | – | [175] | – |
| | | Others | Robust control | – | [95,176] | [177] | – | – | [178] | – |
| | | | Extremum seeking | – | [179] | [180] | – | – | [181] | – |
| | | | Decoupling control | – | [182] | [183] | – | – | [184,185] | – |
| | | | Pseudospectral Optimal Control | [186,187] | [188] | – | – | [189,190] | – | – |
| | | | Sliding mode control | [191] | – | – | – | – | [192] | [193] |
| Learning-based | Reinforcement Learning/Deep Reinforcement Learning | | | [194,195] | [196] | – | [197–200] | [204] | – | – |
| | Supervised Learning | | | – | [202] | – | – | – | – | – |
| | Unsupervised Learning | | Clustering | – | [203,204] | – | [115] | – | – | – |
| | Neural Network Learning | | Elman Neural Network | – | [205] | – | – | – | – | – |
| | | | Artificial Neural Network | [206] | – | [207] | – | – | – | [208] |

according to their dependency on *a priori* knowledge and information of the driving conditions.

*3.3.1. Offline strategies*

An offline OB strategy is a non-causal and global optimisation strategy because it requires *a priori* knowledge from typical driving cycles. The importance of finding non-causal optimal solutions of offline strategies is in providing a benchmark solution (global optimum) that other causal strategies can be compared against, and providing modified online strategies. Therefore, offline strategies are still gaining attention from researchers.

Because power flow paths are different between powertrain topologies, the problem formulation is also different. For example, an optimisation problem in a series HEV can be a minimisation of the energy consumed along the generation path. In a parallel HEV, the optimisation problem can be a minimisation of the fuel consumption and the selected

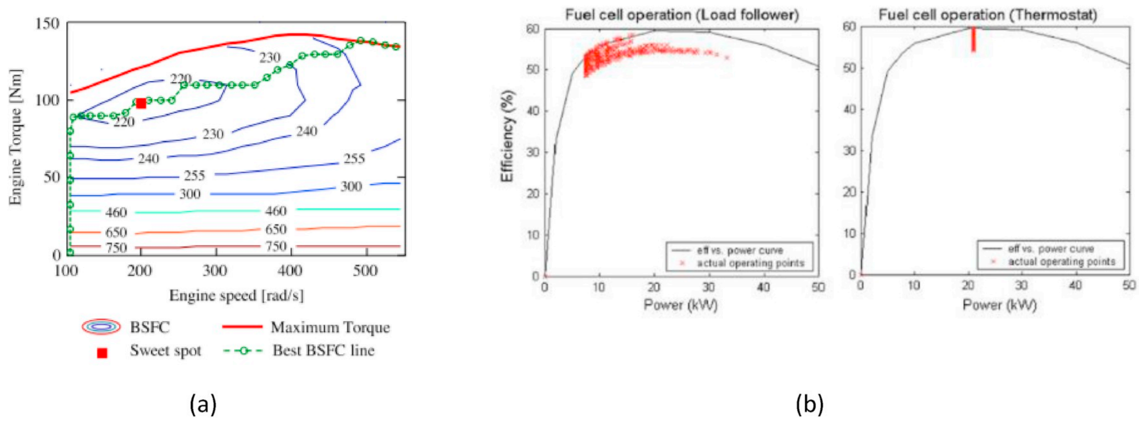


**Fig. 14.** Efficiency maps and operating points: (a) ICE-based HEV; (b) FC-based FEV [20].

emission species over the driving cycle. The constraints are normally the power demand for the vehicle, the boundary of the battery SoC, or the drivability. After defining the problem and constraints, an algorithm needs to be employed to find a solution, such as in a gear-shifting sequence, or a power-split between the ICE and the EM. Regarding the problem-solving approaches used for the EMS problem, offline OB strategies can generally be sub-divided into four types: direct, indirect, gradient, and derivative-free types. Direct algorithms approximate an optimal control problem as a static optimisation through a discretisation, whereas indirect algorithms are based on the optimal control theory and a calculus of the variations. By contrast, gradient algorithms use the derivative information of the objective function, which is under mathematic conditions such as the continuity, differentiability, or satisfying the Lipschitz condition, to solve the optimisation problem. To avoid a dependency on the derivatives, derivative-free algorithms use a stochastic search iteratively over the entire design space to find the global optimum. A classification of offline OB EMS strategies according to the problem-solving approach is shown in Fig. 15.

*3.3.1.1. Direct algorithms.* The most widely used algorithm for solving the EMS optimisation problem directly in an offline application is dynamic programming (DP), which was pioneered by Bellman during the 1950s to find numerical solutions. Because DP requires *a priori* knowledge of the driving cycle, it is also known as deterministic DP (DDP). The basic ideas behind DDP is that the nonlinear dynamic optimisation problem is subdivided into sub-problems in a discrete time. A cost-to-go function is then formulated at each sample time. The same optimal control policy can be achieved by using a backward recursive method or a forward dynamic programming technique to solve the sub-problems.

The utilisation of DDP can be found in various types of HEVs [80,81] and PHEV [83]. For a fuel cell-battery FEV, Sundstrom et al. [85] used DDP to minimise the cost function formulated from a serial multiplication function of a SoC deviation, the hydrogen consumption, and the excess oxygen ratio. Santucci et al. [84] proposed a DP formulation for estimating an ideally achievable increase in battery life duration through the HESS. The major issues DDP are (i) a heavy computation owing to the quantisation of the states and control variables, (ii) an inherent 'curse of dimensionality', and (iii) dependency of the driving cycle. The drawbacks make DDP infeasible for real-time implementation. Although DDP can be only used offline, it has been still useful as an optimal benchmark for other controllers or as a method to extract the control parameters for the RB EMSs.

However, the control law derived from DDP can only work with a specific driving cycle, and it might not guarantee a level of optimality or a sustained charge under other driving cycles. Furthermore, the feedback solution to DDP is not directly implementable and the rule extraction is time-consuming. To overcome these issues, Lin et al. [36] first proposed a stochastic DP (SDP) in which the model of the driver

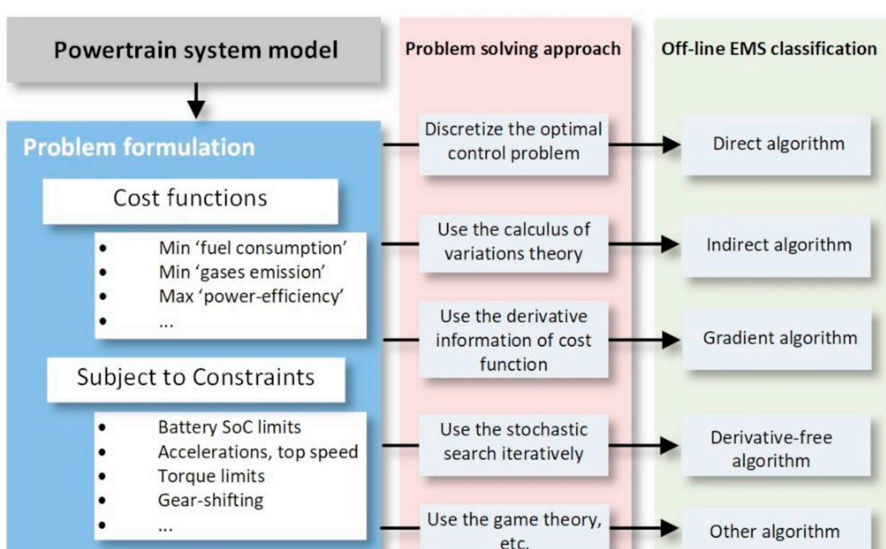


**Fig. 15.** Classification of offline OB-EMSs based on problem solving approach.

demand is treated as a Markov chain with transition probabilities. The EMS is then optimised over a family of random driving cycles in an average sense. However, SDP still has certain drawbacks. First, the optimal solution of SDP can only be obtained under a given Markov chain model. Second, the computation process for solving the SDP problem requires a significant amount of time owing to the value/policy iterations. Finally, the future discounted costs are selected based on the mathematical expediency, leading to difficulties in justification on engineering grounds. To tuning parameters have been introduced as a discount factor and SoC deviation penalty of an ESS. To handle the previously mentioned issues of SDP, Tate et al. [211] developed a shortest path SDP (SP-SDP), which is known to be a variation on an infinite horizon SDP. The SP-SDP technique achieves a better SoC control and has fewer parameters to tune owing to a minimisation of the total undiscounted costs. However, to generate the control law, the SP-SDP problem is solved through a collection of techniques including linear programming, a barycentric interpretation, and a constraint generation.

*3.3.1.2. Indirect algorithms.* The most well-known algorithm for solving the optimal control problem indirectly is Pontryagin's minimum principle (PMP), which is an extension of the calculus of variations, particularly the Euler–Lagrange equation [212]. This was derived in 1956 by the Russian mathematician Lev Pontryagin to solve the constrained global optimisation problem. For an optimum solution, the PMP provides only the necessary conditions while the sufficient conditions are satisfied using the Hamilton–Jacobi–Bellman equation.

The key idea of the PMP is that the constrained global optimisation problem is reduced to the local Hamiltonian minimisation problem. The Hamiltonian is characterised by a costate, which is interpreted as a weighting factor for the electrical usage [213]. The optimal value of the initial costate can be found through an iterative process if full knowledge of driving cycle is pre-determined. With different driving cycles, the initial costate may have different values. The PMP has a heavy computation load, because the size of the look-up table will increase exponentially with the number of dimensions. This means the storage capacity and computational power of the controllers also need to be increased, leading the PMP to be inapplicable for direct use in real-time applications.

Delprat et at [87]. introduced an application of PMP for achieving an optimised EMS of a parallel HEV in 2001. Later, Serrao et al. [86] applied the same concept to find the optimal power split strategy for a hybrid electric refuse truck. Regarding the FEV, Bernard et al. [93] used the PMP as a global optimisation method to determine an efficient power splitting between the FC and ESS (battery, SCs) to minimise the hydrogen consumption for a given driving cycle. In another study, Hemi et al. [92] combined an optimal control solved using the PMP and Markov chain for an FC-SC vehicle.

Although the PMP offers optimal solutions close to the DP results, the initial costate has a considerable effect on the SoC variation [88]. Therefore, a number of solutions have been proposed to estimate the initial costate. To correct the initial costate, the first approach is based on the use of feedback controller(s) (i.e. proportional (P) [214], proportional integral (PI) [215], proportional integral derivative (PID) [216] and nonlinear control [217]) on the error signal between the actual battery SoC/SoE states and the respective reference states, which can be derived from past, present, and future information. In this regard, Pham et al. [214] used two P feedback controllers (the dynamics of the battery energy and the battery temperature). Kessels et al. [215] applied a PI feedback controller to examine an adaptive strategy. Yu et al. [216] employed a PID feedback controller to manage the fuel consumption-to-electricity depletion ratio and achieve a preplanned energy consumption process by following the SoC profile. Ambühl et al. [217] utilised a nonlinear controller with an anti-windup scheme to estimate the initial costate. The limit of this approach is that the optimal costate value can be computed only if the future driving cycle is known in advance. Therefore, the driving cycle prediction or driving pattern recognition based on the GPS or ITS have been incorporated with the PMP to handle the dependence of the costate on the battery SoC. Kim et al. [218] introduced two parameters, namely the effective SoC drop rate and the effective mean power of driving cycles, which are gathered from both the GPS and traffic information system, to approximate the optimal costate. Boehme et al. [219] also built a future driving profile from the information provided by the modern navigation systems, which is later transferred to the formulation of PMP to update the costate.

To ease the massive computational load required by the instantaneous Hamiltonian optimisation, researchers have tried to simplify the constrained optimisation problem by using a dampened Newton-method [219], indirect variation of the extremals, or the shooting method based on the Newton–Raphson method to handle the multiple initial conditions [213]. Another way to reduce the computation time of the PMP is an approximate-PMP (A-PMP) proposed by Hou et al. [220] based on the observation of some regular patterns in the numeric PMP results. In this technique, the turning point of the engine fuel rate is specified by a piecewise linear approximation strategy. By introducing a simple convex approximation to the local Hamiltonian, the A-PMP law needs to calculate and evaluate five candidate Hamiltonians to find the optimal control for the PHEV powertrain.

*3.3.1.3. Gradient algorithms.* Vehicle powertrains have become more sophisticated with nonlinear models of the ICE, EM, battery, and complex constraints. To reduce the calculation time and increase the robustness of the optimisation solution, the powertrain systems or objective functions need to be efficiently simplified as analytical equations for use in the gradient algorithms. Such algorithms use the derivative information of an objective function, which is under mathematic conditions, such as the continuity or differentiability, or satisfy the Lipschitz condition to solve the optimisation problem. Gradient-algorithm-based EMSs are mainly classified into linear programming (LP), quadratic programming (QP), sequential quadratic programming (SQP), and convex programming (CP). The LP frames the algorithms for a solution to the optimisation problems with linear objectives and constraints, the QP frames the algorithms for a solution to the optimisation problems using quadratic objective and linear constraints, and CP frames the algorithms for a solution to the optimisation problems using convex objective and concave inequality constraints.

In an LP-based EMS, the fuel economy optimisation of a series HEV is considered as a convex nonlinear optimisation problem, which is approximated using piecewise-linear approximations [94], or bound constraints are derived by means of a set of linear matrix inequalities [95]. In a QP-based EMS, the powertrain model is also approximated to achieve a QP structure given by a quadratic cost criterion subject to linear constraints. A QP-based EMS can be found in a mixed-integer quadratically constrained linear program studied by Beck et al. [97] and Koot et al. [98]. With the CP technique, the vehicle models are simplified to comply with the convexity requirements. For example, the engine on/off is eliminated, the equality constraints are relaxed, and the battery energy is used instead of a battery SoC to preserve the convexity. Therefore, an optimisation problem consisting of a cost function and inequality constraints can be expressed in a convex form and affine equality constraints. Normally, a vehicle can be modelled using quadratic equations (Zhang et al. [103], Egardt et al. [101], Hu et al. [102]) in which the EM losses and the fuel power at each engine speed are approximated well using a second-order polynomial, and the battery power is modelled through a quadratic-over-linear expression. Similarly, in a fuel-cell HEV, the hydrogen consumption is also approximated using a quadratic function [104,105]. After the optimisation problem is formulated as a standard convex problem, the non-affine equality constraints can be transformed into convex inequalities. Thus, the optimisation problem can be solved using solvers such as SeDuMi, SDPT3, and

MATLAB-based packages (e.g. CVX and YALMIP) which can automatically transform the problem into a sparse matrix form before passing the problem to the solver. However, because the fidelity of the vehicle model is decreased for simplification, the stand-alone gradient algorithms can only attain near-optimal solutions.

*3.3.1.4. Derivative-free algorithms.* The use of derivative-free algorithms (DFAs) in an EMS control application is among the potential techniques to solve problems in which derivative information is unavailable, unreliable, or impractical to obtain. Compared with gradient algorithms, DFAs are able to converge at a global solution. The DFAs for EMS control found in the literature mainly consists mainly of metaheuristic algorithms such as simulated annealing (SA), the genetic algorithm (GA), multi-objective genetic algorithm (MOGA), particle swarm optimisation (PSO), and divided rectangular (DIRECT) algorithm.

SA was originated by Kirkpatrick [221] in 1983, inspired from the metal annealing process [222]. The algorithm searches for a solution through a stochastic technique, taking the solution candidates and considering improvements with respect to the objective function. However, the SA method cannot guarantee that a global optimal solution has been reached. In addition, repeated annealing is extremely slow, particularly in the case of dealing with computationally expensive objective functions. To overcome these disadvantages, researchers have used the SA in conjunction with other complementary algorithms such as the RB, PMP, and GA. In 2007, Wang et al. [106] first utilised the SA to optimise the short-term power management and the RB to reduce the search space of the long-term energy management for a series HEV. Hui et al. [223] implemented the GA method at an earlier stage owing to its capability of achieving a robust global convergence, and used the SA in a later stage of the optimisation process for a hydraulic hybrid vehicle case. Likewise, in Ref. [107], the SA is hybridised with the PSO to upgrade the convergence capabilities of the SA. Chen et al. [90] took advantage of the SA for searching the optimal engine-on power and maximum current coefficient, and used the PMP to find the battery current commands. This method can ease the computation time for random driving conditions. For the application of HESS in an FEV, Trovao et al. [224] also exploited the SA to seek an optimised energy share between the battery and SC for short-term power management (tactical level), and used the RB method for long-term energy management (strategic level).

The GA is another stochastic search method inspired from natural selection and genetic evolution originated by Holland [225] in 1975. The GA principle consists of three main phases: reproduction, crossover information, and mutation. The GA can solve the nonlinear, non-convex, multimodal, and discontinuous-time optimisation problems to search the global optima by removing the local optima traps. Piccolo et al. [226] first realised the GA for optimisation of the energy flow management of HEVs in 2001. To minimise the fuel consumption of a power-split PHEV, Chen et al. [114] used the GA to find the optimal engine-on power threshold and QP to obtain the optimal battery current with a fast speed. The capability of parallelism detection between separated agents also makes the GA beneficial to multi-objective optimisation problems such as the energy cost and battery health [227], the fuel consumption, and the emission terms [113,226]. The GA with a Pareto-optimal solution, i.e. MOGA, can be exploited to solve the multi-objective optimisation problems. The MOGA technique was utilised to optimise the powertrain component sizing and the fuel consumption, and minimise the emissions [112,228].

PSO was originated by Kennedy and Eberhart [229] in 1995, and is based on the behaviour of social organisms moving in groups, such as ant colonies and birds flocking in nature. Members within a group will share information and locally interact with each other and update their last best position and the group's best solution toward reaching an optimal solution. If the improved position is discovered, the swarm particles will move to the identified location. This process is iterated to find the optimal solution. The PSO algorithm was first introduced in 2006 by Wang et al. to optimise the strategy parameters for a greater fuel economy and lower emissions for a series HEV [230]. Researchers have also used PSO to obtain optimisation results for training a neural network (NN) [119] or tuning the control parameter of an FL controller [120] and operational parameters [230]. In addition to the energy control, PSO algorithms have been widely used for the optimised design of the electromechanical systems [231,232], SC and fuel cell sizing [233].

DIRECT was proposed by Jones [234] in 2001, and is a modification of the standard Lipschitzian approach in which the use of a Lipschitz constant is eliminated by searching all possible values for the constant, thus placing a balanced emphasis on both global and local searches [122]. DIRECT has been mostly used offline to optimise the most influencing control parameters of RB strategies for a set of drive cycles (e.g. Rousseau et al. [123], Whitefoot et al. [124], and Gao et al. [122]). In a fuel-cell HEV, Markel et al. [88. ] and Li et al. [67] also used DIRECT to optimise the membership function of an FL controller. Compared to other metaheuristic optimisation algorithms, DIRECT is relatively simpler because it does not require tuning parameters and can handle both equality and inequality constraints.

A general categorisation of the discussed gradient-based and derivative-free approaches is summarised in Fig. 16.

*3.3.1.5. Other algorithms.* Dextreit et al. [126] applied game theory (GT) to develop an EMS for a Jaguar Land Rover Freelander 2 HEV. Driver intention regarding the desired vehicle performance (called the leader) and the fuel economy (called the follower) were considered as two non-cooperative players who have conflicting objectives in a competitive game. In non-cooperative GT, most of the drivers do not think or explicitly try to optimise their driving behaviour for a better fuel economy and emissions while driving. Gielniak et al. [127] also applied GT to an FC HEV in which the powertrain efficiency and vehicle performance are conflicting interests. Although GT uses simpler equations than DP and a similar receding horizon as MPC [126], the computation burden of GT can be comparable to that of DP, making its application difficult for online implementation. In addition, the dependency of GT to certain component models makes the extension of its applicability limited to the use in a broad range of powertrain systems [127].

### 3.3.2. *Online strategies*

An online strategy is a causal and local optimisation strategy because it neither requires *a priori* knowledge of the driving cycle nor ensures the optimal solution in a real-time implementation. Conceptually, the global optimisation problem of an offline EMS is formulated in an instantaneous optimisation problem for implementation with a limited computational time and memory resources in real-time, as shown in Fig. 17. An equivalent consumption minimisation strategy (ECMS) and model

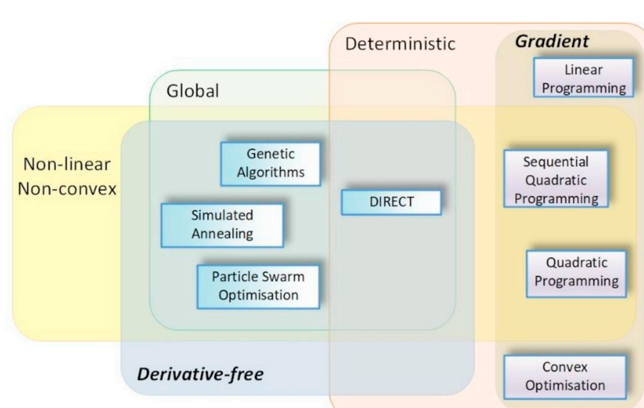


**Fig. 16.** Categorisation of gradient-based and derivative-free algorithms.

predictive control (MPC) are the most well-known real-time EMSs and have been extensively used in different applications.

*3.3.2.1. Equivalent consumption minimisation strategies.* The ECMS, as a realisation of offline PMP, as shown in Fig. 17, was originated by Paganelli et al. [128] for parallel HEVs that operate under a charge-sustaining condition. The global optimisation problem of PMP is reformulated into a local optimisation problem by minimising the equivalent fuel consumption. The ECMS calculates the equivalent fuel factor, which accounts for the actual fuel consumption required to recharge the batteries and to recuperate the regenerating braking energy. The equivalence factor (EF) of the ECMS has the same role as the costate of the PMP.

Researchers have focused on a proper estimation of the EF, which is generally dependent on three unpredictable factors: the battery SoC limits, the direction of the electric current, and the driving cycle information. Estimation techniques can be classified into two types, as illustrated in Fig. 18: (i) offline estimation using global optimisation algorithms to find the optimal EF, which is constant over the driving cycle, and (ii) online estimation updating the EF in real-time.

In an offline EF estimation, full knowledge of the given driving cycle must be known to find the optimal constant EF, which can be extracted from the DP [129], GA [129], DP-based marginal cost method [130], average energy conversion efficiency [131], shooting algorithm required drivability constraints [132], and adaptive ant colony optimisation [148]. However, there is a need for a re-calibration of the EF for an individual driving cycle.

In an online EF estimation, the EF is updated based on the consideration of uncertain factors such as (i) the battery SoC limits, (ii) the direction of the electrical current (i.e. charging and discharging of the ESS), and (iii) the driving cycle information. Firstly, because the battery SoC varies unpredictably, a correction term for the SoC or SoE deviation is added into a constant optimal EF obtained from the offline estimation. The correction term can be realised by different controllers such as P [136], PI [137,138], and nonlinear feedback control [130]. However, the EF is sensitive to driving cycles. Secondly, in addition to the battery SoC considered, the direction of the electrical current needs to be considered to improve the robustness of the EF estimation. In Ref. [142], a two-argument ECMS that operates based on two current directions is used by employing functions based on the SoC limits and its derivations. The penalties are considered for electric energy usage if the changing rate of the battery SoC is rapidly deceasing/increasing. By contrast, if the battery SoC changes smoothly, no penalty is considered. Thirdly, the EF estimation can be further improved by taking into account the preview information of the driving cycle such as the vehicle position [146, 150], elevation profile and average speed [149], trip length and change in elevation [151], past and predicted vehicle speeds, and GPS data [31]. The preview information of the driving cycle can be provided from the prediction and pattern recognition techniques.

In the driving cycle prediction, the best value of EF is identified based on the receding-horizon optimisation with the help of the speed predictor, which can employ the past, current, and future information from in-vehicle 3D maps, a GPS-based navigation system, and a telemetry system. This technique, called telemetric-ECMS (T-ECMS) [235] is dependent on the optimisation window sizes and the prediction error, driving profiles, and level of the preview information. By contrast, the driving cycle pattern recognition [155] is used to identify which type of driving conditions the vehicle is undergoing to select the most appropriate EFs from a predefined set.

Regarding the fuel-cell FEV, the ECMS is employed to minimise the hydrogen consumption. The electric energy of the battery and SC can be transformed into an equivalent hydrogen consumption thanks to the freedom of adding a battery as a long-term energy buffer and the SC as a peak power buffer. For the fuel cell–SC HEV, Rodatz et al. [144] introduced the estimated probability into two equivalent factors regarding the charging and discharging to avoid the deviation of the SC SoC beyond the limitations with a short time horizon of the probability evaluation. For the fuel cell–battery-SC HEV [145], a fuel-cell efficiency penalty coefficient, a battery SoC coefficient, and an SC SoE coefficient are designed for the ECMS to operate the fuel cell system at its best efficiency. Garcia et al. [236] compared the ECMS with different control strategies such as state machine control, rule-based, fuzzy logic, classical PI control, and frequency decoupling and gliding average strategies. The results show that the ECMS can provide the best performance in the hydrogen consumption reduction and minimum stress on the fuel-cell system.

*3.3.2.2. Model predictive control based strategies.* The MPC was introduced to tackle the issue of the DP algorithm, as shown in Fig. 17. In the DP, the global optimal control can be achieved when all future information including the road shape, state of the vehicle, and the road loads are known in advance. Such conditions are impractical to obtain in advance for real-time applications. Therefore, the MPC operates based on a receding-horizon control strategy with a predictive scheme using three main steps [237]: (i) calculating the optimal inputs over a prediction horizon to minimise the objective function subject to the constraints, (ii) implementing the first element of the derived optimal inputs to the physical plant, and (iii) moving the entire prediction horizon forward and repeating from step (i). The optimal control problem in the finite domain is solved at each sampling instant, and control actions are obtained based on an online rolling optimisation. However, the performance of the MPC is sensitive to the model quality. The mismatch of the models is represented in the models of the wheels, weather, road conditions, and sensor accuracy. To minimise this mismatch and disturbances, the horizon length has to be tuned, or GPS information is used with the MPC to improve the prediction results. Fig. 19 shows a diagram of a typical MPC consisting of a predictor employing a prediction algorithm, an optimal control problem, and a numerical optimisation algorithm used to solve this problem.

From a prediction algorithm perspective, the MPC can be classified

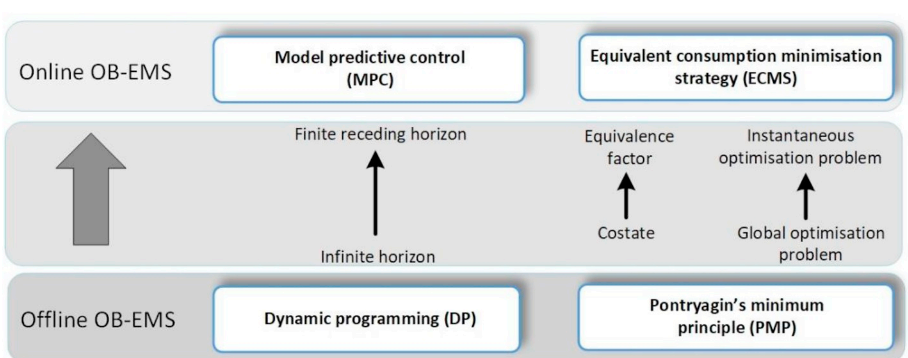


**Fig. 17.** Online OB-EMSs conducted from offline OB-EMSs.

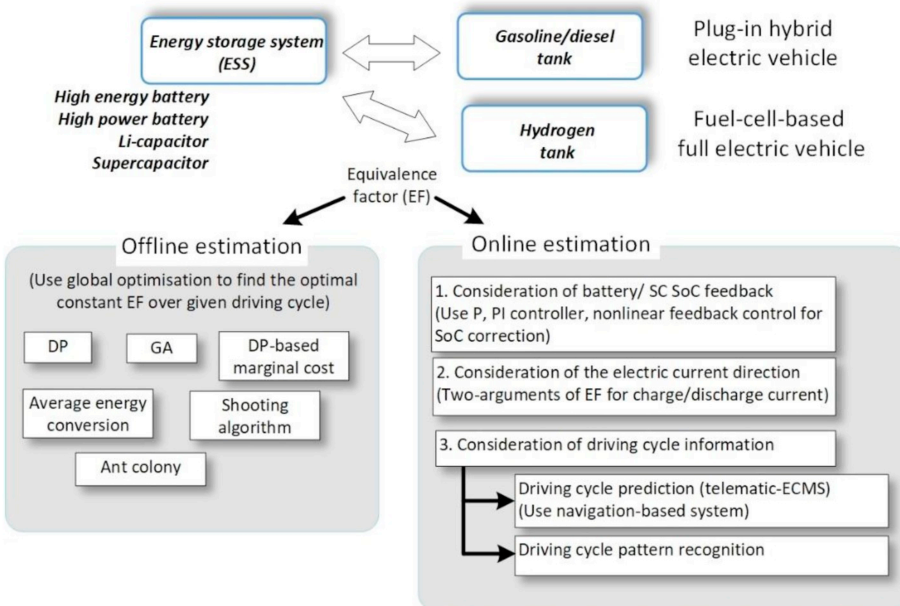


**Fig. 18.** Estimation techniques for the EF of ECMS.

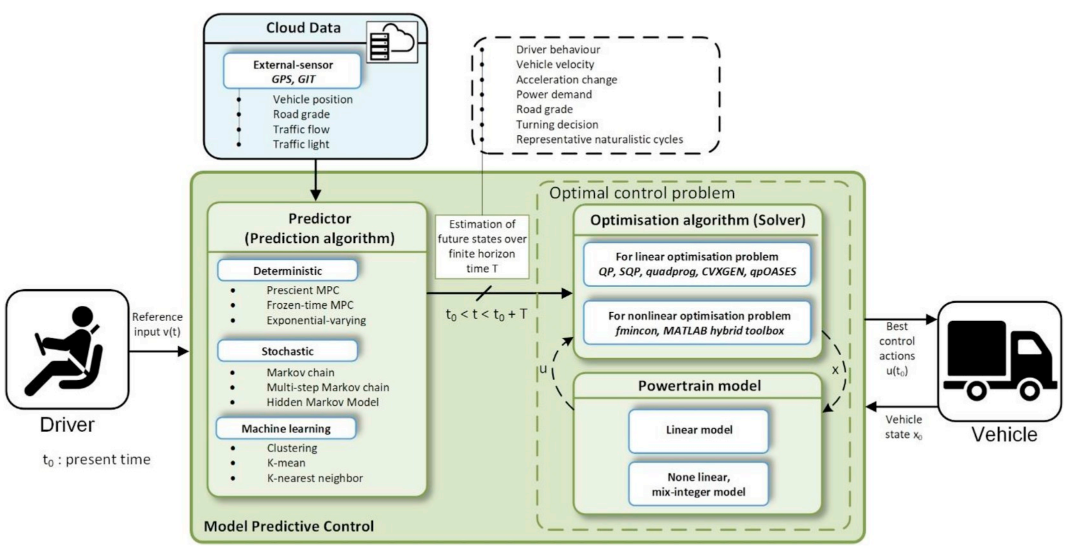


**Fig. 19.** Diagram of MPC based EMS.

into subclasses: deterministic and stochastic. In Ref. [157], Banvait et al. implemented different types of deterministic MPC. In their research, a prescient-MPC (P-MPC) exploits *a priori* knowledge of the requested power demand for a given future horizon window, and it was reported that P-MPC can achieve 96% of the optimality of the DP. A frozen-time MPC (FT-MPC) assumes the actual power demand as a constant along the entire prediction horizon. An exponential-varying-MPC (ExpVar-MPC) considers the unknown driver demand torque to be exponentially decreasing over the prediction horizon. Owing to unrealistic assumptions, the deterministic-MPC has been used as a benchmark to evaluate other MPC-based EMSs.

Stochastic-MPC (S-MPC) is a special case of the stochastic DP (S-DP) (Lin et al. [36]) and shortest path SDP (Tate et al. [211], Opila et al. [163]). Compared to S-DP, S-MPC can easily adapt itself to changes in the stochastic parameters and high-order models. To design the S-MPC, Markov chains are used to predict unknown future information or arbitrary processes (e.g. driver behaviour [167], vehicle velocity [37], acceleration change, power demand [156], road grade [166], turning decision [162] and representative naturalistic cycles). Johannesson et al. [37] applied the Markov-chain model for the velocity and power demand to develop two controllers: a position-invariant controller using a homogeneous Markov-chain model and a position-dependent controller using stochastic a Markov-chain model. After integrating the Markov-chains into the DP algorithm, it was found that the stochastic-MPC based on a navigation system and a traffic-flow information system can obtain close to the minimal attainable fuel consumption results. Ripaccioli et al. [156] modelled the driver's future power demand as a Markov chain and designed the S-MPC for a series HEV. The performance of S-MPC was compared with that of P-MPC and FT-MPC, and it was reported that the proposed S-MPC has a fuel economy similar to that of the P-MPC. Josevski et al. [161] used multiple horizons for a stationary Markov chain to generate the driver torque demand. Wang et al. [166] used the hidden Markov model (HMM) to reconstruct the drive cycle. The process of driving pattern prediction was abstracted as the HMM, driving trips were regarded as the state in the HMM, and driving snippets were regarded as the emissions of the HMM. Jang et al. [162] considered the road grade of the future route, speed change, and turning information as a Markov chain. In their study, the performance of S-MPC was reported to be close to the optimal DP results, whereas an ECMS without a road grade preview performed less desirably in hilly regions. Li et al. [167] designed a driving-behaviour-aware S-MPC by using the Markov chains to model eight different driving behaviours, which were classified using the k-means algorithm or k-nearest neighbour algorithm [238]. Jieli et al. [164] treated the acceleration change process as a multi-step Markov chain, in which the vehicle acceleration in the future was only related to the current velocity instead of historical information.

Payri et al. [160] estimated the future driving power requirements in a stochastic fashion based on past information of the vehicle power demands (by clustering and an adaptive approach) to find the equivalence factor of the ECMS. Because the S-MPC depends on the quality of the predictors, telemetry technologies such as an ITS, onboard GPS, geographical information system (GIS), and an advanced traffic flow modelling technique have been employed to improve the prediction accuracy, which is called telematics-MPC [32]. This technology is more attractive in buses and other service vehicle applications because the route is predefined or fixed, leading to an accurate prediction of the propulsion load. In this regard, Johannesson et al. [169] chose the clutch/lock switching through a receding horizon optimisation over several possible future load profiles identified from GPS data record along a bus route. Sun et al. [170] integrated the traffic velocity data into a two-layer MPC framework to generate the global SoC trajectory.

As can be seen in Fig. 19, an MPC formulation is dependent on the powertrain models including a linear model and nonlinear mix-integer model. Because the model of a powertrain system is nonlinear and dynamic with some inequality and equality constraints, the MPC power management problem can be reformulated into a nonlinear and constrained optimisation problem. Therefore, a nonlinear MPC requires nonlinear solvers such as the command '*fmincon*' in MATLAB/Simulink. However, because a nonconvex objective function is held, the solution achieved may only reach the local optima. To overcome this issue, the model of the powertrain and constraints need to be linearised and discretised, and the MPC can thus be converted into a quadratic problem, which can be solved using numerous well-established toolboxes such as '*quadprog*', CVXGEN, and qpOASES. To make the quadratic problem solvers sufficiently fast for a real-time implementation, a linear constrained MPC can employ numerical algorithms such as an active set, interior point, or trust region. In reality, the powertrain system operates under discrete states such as the gear-shifting ratios, engine or clutch on/off states, or different modes. Therefore, the MPC becomes a mixed-integer MPC that can be developed using the hybrid toolbox in MATLAB.

It should be noted that the prediction horizon length of the MPC should be adapted to the varying working conditions to obtain a better solution. For example, Rezaei et al. [172] found that the predictive horizon length is 10 and 20 s for highway and city driving, respectively. Borhan et al. [174] tuned the adjustable parameters such as penalty weights, prediction horizon, and time constants using a rule-based method to adapt to driver torque demands. In heavy-duty HEVs such as city buses, delivery trucks, and refuse collection trucks, the mass can vary up to 500% from fully loaded to unloaded conditions. Therefore, it is necessary to consider the mass in the MPC controller. Caihao et al. [173] selected the predictive horizon from 10 to 100 s, and incorporated an on-board parameter estimator to update the total vehicle mass in real-time, leading to a 6% reduction in the fuel consumption.

#### *3.3.2.3. Other algorithms*

*3.3.2.3.1. Robust control.* The objective of robust control (RC) is to determine an output feedback controller that minimises the fuel consumption. To construct the output feedback control, Pisu et al. [95] used the linear matrix inequality (LMI) constraints, whereas Reyss et al. [177] used H-infinity control and Fekri et al. [176] utilised a mixed-μ synthesis. RC can tackle the parametric uncertainties, sensor noises, and estimation errors, guaranteeing the stability and robustness. However, owing to a simplification of a nonlinear time-varying system into a linear time-invariant system (using the Willans line model for the ICE and EM), RC only reaches a sub-optimal solution.

The effectiveness of RC can be used for the EMS of an FC-SC hybrid system of an FEV as reported in Ref. [178]. In this study, in the feedback path of a control loop, a structure including of an adaptive predictive controller and a robustness filter were utilised. The feedforward action was used to improve the regulation behaviour when the disturbances are produced from three different driving cycles. It was reported that an RC-based EMS can operate the FC preferably at maximum efficiency to improve the hydrogen economy.

*3.3.2.3.2. Extremum seeking.* As an online adaptive optimisation algorithm, the extremum seeking (ES) method can be effectively employed to find an extremum (maximum or minimum) value of a static nonlinear system in real-time. ES is a derivative-free search algorithm used to find the optimum operating point of a performance function. The ES algorithm formulates a sliding surface where the objective function is forced to follow a time increasing function, and a discontinuous switching function is selected for the optimisation parameter. Based on this principle, Dincmen et al. [179] first proposed the use of ES to search the optimum torque distribution between an ICE and an EM for maximum powertrain efficiency. To compensate the inherent deficiencies of the SDP algorithm, Wang et al. [180] proposed a SDP-ES in which ES was used as an output-feedback based optimisation tool to locally compensate the optimal SDP control.

A variation of the ES control method is a fractional-order ES applied in the EMS for an FC-HEV [181]. Fractional-order calculus was used to achieve a faster convergence speed and higher robustness. The fractional-order ES method can maintain the battery SoC in a defined zone to operate the fuel cell system in its high efficiency range with higher power stability.

*3.3.2.3.3. Decoupling control.* Decoupling control (DC) is a model-based strategy used to handle conflicting performance objectives, such as the fuel economy, SoC regulation, and drivability. By exploiting the structure of the powertrain dynamic model, decoupling means that the battery control and drivability control are decoupled using the power request constraint and vice versa. To do so, Pisu et al. [182] and Barbarisi et al. [183] separated the control signal into three components. The first component was dedicated to the satisfaction of the driver power request and was designed by applying an ECMS. The second component was devoted to the control of the battery SoC, whereas the third component was used to ensure the drivability.

The concept of DC has also been effectively applied in an FC FEV application. As reported in Ref. [184], the DC strategy was used to balance the power flow between the stack and battery to avoid electrochemical damage owing to a low oxygen concentration in the FC cathode. In this study, the duty cycle of a dc-dc converter as the input of the controller was decoupled by two controllers. The first one regulates the compressor using a classic PI controller, and consequently, oxygen is supplied to the cathode. The second one optimally manages the current demanded by the fuel cell and battery using a linear-quadratic control strategy acting on the converter. In Ref. [185], a decoupling diffeomorphism method was used to decouple the inherent coupling owing to the connection of the FC and SC to a common dc-bus. The control actions for the DC strategy were decoupled by two sliding mode controllers. The first-order sliding mode accurately manages to regulate the dc-bus voltage with a low-voltage drop due to abrupt load variations, and the second-order sliding mode has minimum chattering and a faster recovery from voltage drops.

*3.3.2.3.4. Pseudospectral optimal control.* Another recent variation of an optimisation-based mathematical method extended to an EMS is pseudospectral optimal control (PSOC) which is a direct method for solving optimal control problems. PSOC transcribes an optimal control problem into a nonlinear programming (NLP) problem by parameterising the state and control variables using global polynomials at a set of collocation nodes [187]. Therefore, it is necessary to model the powertrain components using analytic expressions rather than look-up tables. Based on the discretisation scheme adopted, a commonly used PSOC method can be generally classified into three categories, namely Legendre PSOC [188], Gauss PSOC, and Radau PSOC [186,187]. In Ref. [187], an upper-level controller employs a Radau PSOC to periodically update the initial costate of the PMP, which was used for a lower power split controller in a series HEV. PSOC power management is particularly attractive for vehicles driving on known fixed routes (e.g. city buses) because it can incorporate future driving information systematically. However, in Ref. [188], owing to the nonconvex and nonlinear nature of a parallel HEV powertrain model, the Legendre PSOC was utilised to convert the discontinuous nonlinear optimal control problem of three cruising strategies into an NLP problem for a more accurate numerical computation.

In an HESS, including the battery and SC, where minimum electrical energy loss is considered as an optimal control problem, the PSOC was employed to find the global optimal solutions incorporated into a logic threshold control strategy [189,190].

*3.3.2.3.5. Sliding mode control.* Sliding mode control (SMC) has gained popularity in automotive application thanks to its robustness against time-varying parameters and the highly nonlinear nature of a vehicle system. Concerning a series HEV application, Gokasan et al. [191] proposed two chattering-free SMCs to restrict the engine operation to its region of optimal efficiency. One of the designed SMCs applies engine speed control whereas the other SMC controls the engine/generator torque, and together they maintain the engine to within the optimal efficiency region of the torque-speed curve.

In a hybrid system of an FC, battery, and SC, Kraa et al. [192] and Ayad et al. [193] used an SMC for three operational modes (i.e. normal, discharging, and charging) to keep the FC operating in only nearly steady state conditions. The SMC ensures a high safety and fast dynamics of the FC current. However, a fast sliding mode current loop for the SC converter is used to satisfy the power demand by the load and to share the current load demand between the FC and the SC.

### 3.4. Learning-based EMSs

Learning-based EMS (LB-EMS) employs advanced data mining schemes for massive historical and real-time information to derive the optimal control law. In the LB-EMS, the precise model information is no longer required to make the control decision. However, it is difficult and time-consuming to establish a correct database the structure and size of which have a direct effect on the controller performance. Data-driven methods and machine learning are adaptive and are able to manage large datasets efficiently under different external driving conditions and drivers. LB algorithms can be incorporated into model-based approaches to tune the control parameters optimised for different driving cycle types (e.g. urban or highway), derive the thresholds for rule-based EMSs, or recognise the driver's driving style (e.g. calm or aggressive). By grouping the algorithms based on their learning type, an LB-based EMS can be sub-categorised into reinforcement learning, supervised/unsupervised learning, neural network learning, and classification learning approaches.

#### 3.4.1. Reinforcement learning

A reinforcement learning (RL) system consists of two components: a learning agent and an environment where the learning agent interacts continuously with the environment. At each time step, the learning agent receives an observation of the state of the environment. The learning agent then chooses an action, which is subsequently input to the environment. The environment then moves to a new state owing to the action, and the reward associated with the transition is calculated and fed back to the learning agent. Along with each state transition, the agent receives an immediate reward, which is used to form a control policy that maps the current state to the best control action upon that state. At each time step, the agent makes the decision based on its control policy. Ultimately, the optimal policy can guide the learning agent to take the best series of actions to maximise the cumulated reward over time, which can be learned after sufficient training. A graphical illustration of the learning system is given in Fig. 20. The RL-EMS can autonomously learn the optimal policy based on the data inputs, without any prediction or predefined rules.

Several RL-based EMSs have recently been reported. Zou et al. [194] and Teng Liu et al. [195] proposed an RL-EMS for a series HEV. A recursive updating algorithm representing the real-time power-request transition probability was proposed, leveraging the power-request transition probability in the near past and previous history. The Kullback–Leibler (KL) divergence rate was applied to measure the difference in the power-request transition probability. The RL algorithm was triggered to update the EMS online when the power-request transition probability differs significantly according to the KL divergence rate. Xuewei et al. [197] adopted a temporal-difference-learning strategy for the RL problem in a plug-in HEV. Li et al. [198] used the RL method with a continuous state and action spaces, called an Actor-Critic method, to derive the optimal control strategy for a PHEV. Lin et al. [196] presented a nested RL framework for a parallel HEV, in which the inner-loop RL minimises the operating cost and the outer-loop modulates the battery SoH degradation globally.

Deep reinforcement learning (DRL)-based EMS combines a deep neural network, called a deep Q-network, with a conventional RL. Hu et al. [199] designed a DRL-based EMS for a PHEV using a fixed target Q network that can obtain the action directly from the driving state. However, the critical issue of the RL and DRL is how to output the continuous actions; otherwise, the ICE output torque will suffer from violent oscillations owing to the discretised output action.

#### 3.4.2. Supervised learning

In supervised learning, a model is prepared through a training process in which it is necessary to make predictions and corrections based on the prediction errors. The training process continues until the model achieves the desired level of accuracy of the training data. In supervised learning, the training data requires corresponding labels for the sake of a problem classification. Supervised learning has been considered for an EMS based on an error-correction learning approach. This assumption implies that the training data are labelled, and the desired output of the training input set is known to feed the training algorithm for a computation of the parameters and an emulation of the desired behaviour.

In this regard, Chin et al. [202] used the root mean square error to assess the performance of the selection algorithm, which is precompiled from all possible conditions in the knowledge database storing the sensor data of the EM and gas engine, such as the fuel system status, engine coolant temperature, and throttle position.

#### 3.4.3. Unsupervised learning

In unsupervised learning, a model is prepared by deducing structures presented in the input data. The deduction procedure can (i) extract general rules, (ii) apply a mathematical process to systematically reduce the redundancy, or (iii) organise the data based on the similarity. The input data may come with an associated cost function for minimisation.

Grelle et al. [203] used the c-means clustering to group the elements of the database that contain the optimal hybridisation degree over standard driving cycles along with the corresponding state-vector of the vehicle, such as the vehicle speed, the battery SoC, the catalyst temperature, and the ICE temperature. A knowledge-based control strategy based on a fuzzy c-means clustering algorithm will be trained throughout all the driving cycles. Based on the same concept, to extract the RB control strategies for a parallel HEV, Mattia et al. [204] used a clustering algorithm that is preliminarily run to generate the set of

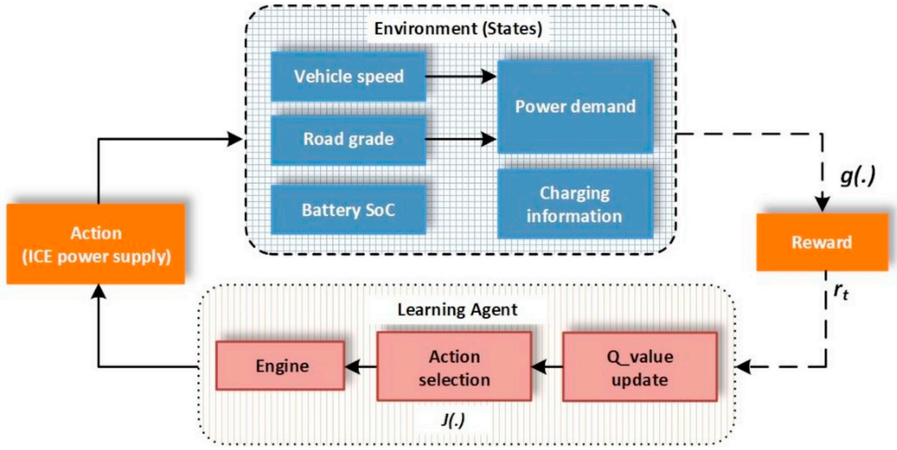


**Fig. 20.** Graphical illustration of a reinforcement learning system.

clusters.

### 3.4.4. Neural network learning

Neural network learning (NNL) is modelled based on neurons in the human brain. Like a real neuron, which has multiple connections (i.e. synapses), nodes are objects in a neural network that have multiple inputs and outputs. By connecting many of these neurons into layers forming a network, different types of behaviours can be modelled. Murphey et al. [207] introduced a machine learning framework that includes an artificial neural network for the roadway types and traffic congestion level prediction and another learning optimal energy control (i.e. the DP algorithm). Another type of NNL-based EMS for a vehicle is an Elman neural network (ENN), which can gradually learn by imitating the human brain. In essence, it improves the learned knowledge and the neuron weight. Ruijun et al. [205] used the instantaneous optimal control rules based on an ECMS to train the ENN and to maintain the SoC value within a high efficiency range and reduce the computational time by 60%. Other types of NNL such as neural dynamic programming [239], and a back propagation neural network [240] can be used for an EMS in an HEV.

## 4. Discussion and outlook

Regarding the previous sections, significant efforts have been made by researchers in the field of EMS for P(HEV) and FEV powertrains, leading to remarkable results. However, the recent rapid trends in the application of smart transportation systems, emerging technologies in powertrain components, and computational techniques are bringing about significant opportunities to enhance the performance of EMSs. With the ongoing evolution of new communicative concepts such as vehicle-to-infrastructure (V2I), vehicle-to-vehicle (V2V), and connected and automated vehicles (CAV), promising potential needs to be unleashed for further improvements in driving performance and fuel economy. Hence, this section discusses viewpoints that have not been previously considered, or have been given little attention, and will potentially be expected as future research directions in this field.

To this end, first a summary on the capabilities of the main studied EMSs described in the present article is provided to identify the exploitable gaps in the present level of research. The key characteristics of the EMSs described herein are recapped in Fig. 21 from the perspectives of a real-time implementation and optimal prediction capabilities.

RB-EMSs have exhibited successful functionalities in terms of implementation for real-time applications, whereas offline OB-EMSs are being challenged in terms of their application in online use-cases owing to existing computational burden. An RB-EMS by its nature suffers from sub-optimality issues and is unable to guarantee the satisfaction of

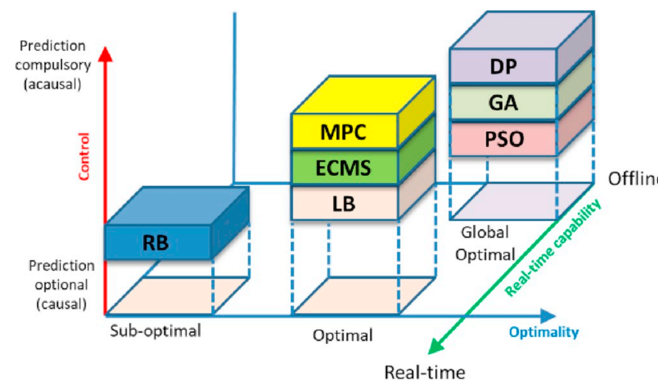


**Fig. 21.** General comparison of studied EMSs.

integral constraints such as a sustained charge. It requires a tremendous amount of time to tune the control parameters of an RB-EMS for a specific transport assignment. Therefore, the robustness of the controller will be profoundly affected in the absence of route preview information. However, although known to yield a global optimal solution, the DP, GA, and PSO approaches might present non-causal results that are non-implementable in real-time. From the same perspectives, Table 5 provides the advantages and disadvantages of the main EMSs being studied.

The performance comparison of various EMSs in term of fuel efficiency, emission, vehicle performance is described in Table 6. It should be noticed that none of them can solely address all requirements of the control objectives in a simultaneous manner. Therefore, many researchers have mixed different optimisation algorithms to combine their complementary characteristics, enhancing the EMSs performance. For example, Elbert et al. [241] combined the CP with the PMP to optimise both the ICE on/off signal and power split in a series hybrid transit bus. In their research, the PMP analytically obtains the ICE on/off strategy, which is then used along with a convex optimisation to compute the optimal solution. This combination allows for the introduction of integer variable optimisation within the convex framework. Nuesch et al. [242] combined the DP with the CP to resolve mixed integer EMS optimisation problems, which allows integrating an engine on/off mechanism and gearshift into a convex optimisation. Panday et al. [243] developed a synergy between the GA and the PMP in which the optimal results of the GA is the input of the PMP.

From the optimisation aspect, it turns out that most of the considered studies have focused on the use of older algorithms (e.g. GA, PSO, and SA) for OB-based EMS control. However, in total, more than 40 different natural-inspired algorithms exists in the literature [253]. Among them, there is a plethora of new algorithms that have not been utilised in the

**Table 5**
Summary of advantages/disadvantage of main EMSs.

| Algorithm type | Strategy | Main Advantages | Main Challenges |
|---|---|---|---|
| Rule-based | Deterministic | • Simplicity (If-then rules) | • Low fuel economy |
| | Fuzzy-Logic | • Robustness, adaptive and predictive capabilities | • Required calibration for control parameters regarding different driving cycles |
| Offline Optimisation-based | DP | • Global optimality<br>• Benchmark for other EMSs | • Curse of dimensionality<br>• Driving cycle information needed in advance<br>• High computational cost |
| | PMP | • Global trajectory optimal control | • Complex mathematics<br>• Required approximation of modelling to reduce computation effort |
| | Gradient | • Fast computation | • Strong model simplification<br>• Derivative information of objective function needed<br>• Complex mathematics |
| | Derivative-Free | • Capability of getting rid of local optima by stochastic solution search | • Optimality not guaranteed in limited number of iterations |
| | Game Theory | • Comprehensive trade-off of conflicting objectives<br>• Consider driver behaviour in EMS | • Curse of dimensionality<br>• Burden of computation |
| Online Optimisation-based | ECMS | • Online implementation<br>• Engineering interpretation of one cost function | • Driving cycle sensitivity for equivalence factor<br>• Local optima |
| | MPC | • Adaptive and predictive capability<br>• Solutions close to global optima with less computational effort online | • Requirement of preview driving pattern, terrain/future driving information<br>• Prediction horizon sensitivity |
| | Robust Control | • Robustness with parametric uncertainties and sensor noises | • Mathematical complexity due to a nonlinear time-invariant system |
| | Sliding Mode | • Robust to uncertainties and parameters change | • Complex mathematic formulation |
| Learning-based | Reinforcement Learning | • Model-free control | • Time consuming for preparing database |
| | Neural Network | • Learning and adaptive capability | • Quality and quantity of training data needed to be qualified<br>• Uncertain behaviour out of the training space |

EMS optimisation area. From the optimisation perspective, the incorporation of more newly emerged algorithms to EMS applications would be a prosperous area of research, specifically for online applications. In this regard, examining these new algorithms may contribute to the field in terms of computational cost, superiority in handling complex multi-objective cases, and the potential hybridisation with other EMS control techniques for satisfying the control objectives more efficiently. These new algorithms can include the newly emerged swarm-based, bio-inspired, physics- and chemistry-based, and social-based approaches proposed during the last decade. Table 7 lists some of these algorithms that merit examination regarding the OB-based EMS control of in a vehicle.

From a topological standpoint, the emerging powertrain components can be alternatives to conventional versions, contributing to the formation of innovative configurations and consequently the corresponding EMS control. An electric variable transmission (EVT) can be considered one such technology. EVT is an electromechanical conversion device that consists of a stator and two concentric rotors. An EVT, also known as a dual mechanical port electric machine, is a competitive alternative power split device that combines the functionalities of both electrical machines and a mechanical gear set into a single machine. The EVT can provide a variable transmission during moments of positive and negative loading. Therefore, it can be a promising alternative to a CVT in a hybrid vehicle topology, providing significant improvements in the overall system efficiency.

To integrate the EVT into a powertrain system, the inner rotor is connected to the ICE, whereas the outer rotor is connected to the wheels, as illustrated in Fig. 22. By means of an electromagnetic torque interaction between both rotors, part of the ICE power is transmitted in an electromagnetic manner to the wheels. The remaining part of the power is exchanged electrically through a bidirectional electric drive. The battery can provide power through a second electric drive to the stator winding, and thus the torque on the outer rotor can be increased or decreased by means of the stator-outer rotor torque interaction. The EVT system can provide the possibility of decoupling the wheel and the engine speed to help enhance the vehicle performance by having the engine operate at its maximum point of efficiency. In addition, it can reduce maintenance costs and prevent losses in the mechanical involvement of the gears as the power can be split in an electromagnetic manner.

The control strategy of an EVT-based powertrain is in the theoretical research stage with limited lab validation. Researchers have mainly focused on a magnetic flux coupling analysis [284], torque analysis [285], and operation mode analysis [286]. Johannesson et al. [169] used a predictive control scheme for an EVT system to access to a data record of previous driving along a bus route to use the clutch/lock more efficiently. There have also been few studies focusing on the EMS of passenger vehicles equipped with an EVT-based topology employing an on/off mechanism, ECMS, and low-pass filter techniques toward improving the fuel economy [287–289]. However, improvements in the energy management optimisation and an integrated design for such systems are still under the development stage considering the potential under such a configuration. By contrast, the current EVT models featuring a complex approximation of the magnetic fields might overestimate the potential for energy savings and do not cover the full working range of the considered components. Furthermore, EVT-based technologies are associated with the utilisation of multiport converters and multiple energy sources, increasing the complexity of the control and the EMSs. There is hence a need for developing innovative integrated-design methodologies as well as energy management algorithms at the local and global control levels. This must comply with the limitations of the operating conditions and a minimisation of the total cost of ownership of the powertrain systems.

Considering the perspective of information technology, raw

**Table 6**
Summary of EMS control methods and performance comparisons.

| Control Methods | Reference | Main results |
|---|---|---|
| Power split and Torque split | [244] | • High-speed drive cycle benefits from power split strategy.<br>• The low-speed drive cycle could gain from the torque split strategy |
| Rule-based and Global Optimisation-Based | [245, 246] | • Compared to the DP strategy, the fuel consumption of the RB strategy is higher in urban cycles.<br>• In highway cycles, RB control can reduce the fuel consumption that is close to the optimal results of DP control. |
| Rule-based (Thermostat, Power Follower), Equivalent Fuel Consumption Control (EFCC) | [247, 248] | • Thermostat control strategy makes the ICE operate at its most efficient condition.<br>• Power follower control strategy provides sustainable SoC with stable bus voltage.<br>• EFCC offers the best overall fuel economy. |
| Stochastic DP, ECMS | [249] | • Both control strategies were found to be near-optimum.<br>• The engine power commanded by the ECMS oscillates continuously.<br>• The engine power generated by the SDP algorithm is much smoother |
| Deterministic logic, Fuzzy logic | [250, 251] | • The fuzzy logic control strategy shows better fuel efficiency, emissions, and battery performance. |
| A-EMS, Fuzzy Logic, Parallel Electric Assistant (PAE) | [252] | • A-EMS has a higher fuel economy, lower emissions output, but relatively poor drivability.<br>• The PEA attempts to minimise engine energy usage but has a higher emissions output. |
| Derivative-free algorithms (SA, GA, PSO, DIRECT) | [122] | • The PSO and the GA are superior approaches compared to the SA and the DIRECT in term of fuel economy, vehicle performance, computation time, for a fixed number of iterations. |

**Table 7**
Recently proposed natural-inspired algorithms in pure-computational field, with potential use in future EMS applications.

| Algorithm name | Author | Ref. | Class |
|---|---|---|---|
| Accelerated PSO | Yang et al. | [254] | Swarm-based |
| Consultant-guided search | Iordache | [255] | Swarm-based |
| Wolf search | Tang et al. | [256] | Swarm-based |
| Bumblebees | Comellas and Martinez | [257] | Swarm-based |
| Bat algorithm | Yang | [258] | Swarm-based |
| Krill herd | Gandomi and Alavi | [259] | Swarm-based |
| Eagle strategy | Yang and Deb | [260] | Swarm-based |
| Cuckoo search | Yang and Deb | [261] | Swarm-based |
| Hierarchical swarm model | Chen et al. | [262] | Swarm-based |
| Firefly algorithm | Yang | [263] | Swarm-based |
| Dolphin echolocation | Kaveh and Farhoudi | [264] | Bio-inspired |
| Brain storm optimisation | Shi | [265] | Bio-inspired |
| Atmosphere clouds model | Yan and Hao | [266] | Bio-inspired |
| Eco-inspired evolutionary algorithm | Parpinelli and Lopes | [267] | Bio-inspired |
| Flower pollination algorithm | Yang | [268] | Bio-inspired |
| Group search optimiser | He et al. | [269] | Bio-inspired |
| Human-inspired algorithm | Zhang et al. | [270] | Bio-inspired |
| Paddy field algorithm | Premaratne et al. | [271] | Bio-inspired |
| Big bang-big crunch | Zandi et al. | [272] | Physics/ Chemistry-based |
| Black hole | Hatamlou | [273] | Physics/ Chemistry-based |
| Electro-magnetism optimisation | Cuevas et al. | [274] | Physics/ Chemistry-based |
| Gravitational search | Rashedi et al. | [275] | Physics/ Chemistry-based |
| Spiral optimisation | Tamura and Yasuda | [276] | Physics/ Chemistry-based |
| Water cycle algorithm | Eskandar et al. | [277] | Physics/ Chemistry-based |
| Anarchic society optimisation | Shayeghi and Dadashpour | [278] | Social-based |
| Artificial cooperative search | Civicioglu | [279] | Social-based |
| Backtracking optimisation search | Civicioglu | [280] | Other |
| Differential search algorithm | Civicioglu | [281] | Other |
| League championship algorithm | Kashan | [282] | Social-based |
| Social emotional optimisation | Xu et al. | [283] | Social-based |

quantitative and qualitative data are an indispensable input of any intelligent EMS. Connected and automated vehicles (CAVs) [290] coinciding with the growing cloud computing and ITS are trending as a vital viewpoint for an EMS design. In addition, the development of infrastructures that can simultaneously sense, save, and integrate datasets of traffic, routes, weather, vehicles, road signs, speed, preceding cars, and other factors and use them for prediction purposes can be considered. For employing such techniques to reach the optimal power splitting, detailed studies at the component and system levels need to be conducted on communication devices, sensors, and their interaction [291]. In addition, there will be opportunities for looking into EMS design concepts exclusively for CAV applications when considering their unique features. For instance, in contrast with non-automated vehicles, automated vehicles equipped with Advanced Driver Assistance Interface Specification (ADASIS) [292] are not necessarily forced to follow the driver behaviours. This brings a degree of freedom for designers to more efficiently search for new fuel saving outlooks. However, the conflicting trade-off between the driver preferences in a comfort level context, the fuel economy, and the vehicle performance merits investigations into the EMSs of the V2V and V2I frameworks. Driver behaviour has been neglected in many of the previous EMS studies [293]. Searching for approaches to incorporate stochastic human driving behaviours into the

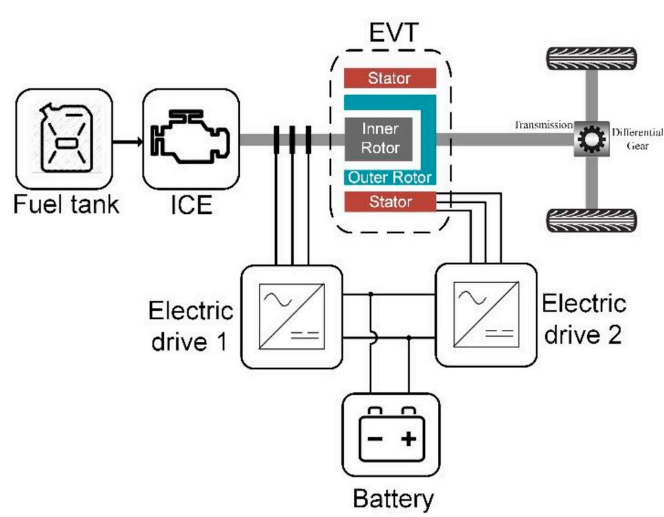


**Fig. 22.** HEV powertrain system based on an extended EVT.

EMS will be an attractive topic, which can greatly contribute to real-world applications.

Finally, EMSs can be extended to multi-time scales, multi-vehicle interaction, and multi-information levels. The combination of OB algorithms with machine-learning techniques can pave the way toward an evaluation of larger spaced EMS types. In this regard, the EMS considers a fleet of vehicles instead of a single vehicle in interaction with a smart grid, as well as smart charging rate optimisation concepts, thanks to the emerging smart devices. The final purpose of such approaches is to increase the road capacity and overall efficiency in all respects. These techniques are mostly employed in heavy-duty applications such as fleets of city buses, whereas their application to groups of passenger vehicles is expected to be a thriving research topic in the future. This can include designing EMSs in frameworks that consider the smart and sustainable city concepts. Focusing on approaches that can provide accurate predictions for long time frames can help achieve an optimal situation awareness using ITS incorporated into big data. In addition, this can merge the autonomy concepts with fuel consumption saving and emissions minimisation objectives through the proposal of fully adaptive and intelligent EMS control approaches in the future. The discussed items can be summarised in an integrated EMS (iEMS) concept, which can intelligently consider various situations as space and uncertainties increase. In this regard, Fig. 23 illustrates such an iEMS and the increasing levels of information, time horizon, and number of vehicles.

From an integrated EMS perspective, as illustrated in Fig. 23, various integration possibilities can be considered for future research trends. At a single powertrain level, the EMS can be incorporated into other subsystems, for instance, aftertreatment [292], a waste heat recovery (WHR) system [294], or thermal loads [295] (e.g. heating ventilation and air conditioning [296] and battery cooling [297]). This can lead to improvements in fuel economy while considering the tailpipe emissions of hydrocarbons, carbon monoxide, and nitrogen oxide (NOx). The diesel engine-aftertreatment-WHR system seems to be a promising energy recovery technology, especially for heavy-duty vehicles targeting legislation goals such as those in Euro-VI [292].

A WHR system is usually equipped with a turbocharger with a variable turbine geometry and a high-pressure exhaust gas recirculation (EGR) system with the corresponding EGR valve and EGR cooler [294]. The WHR system recovers the heat energy from the engine and converts it into useful mechanical energy for propulsion, resulting in up to a 6% fuel consumption reduction [292]. An exhaust gas aftertreatment consists of a diesel oxidation catalyst, a diesel particulate filter, an ammonia oxidation catalyst, and the most important sub-system, which is known as a urea-based selective catalytic reduction (SCR) deNOx system. In SCR systems, researchers have recently placed major efforts into proposing efficient ammonia dosing strategies for removing NOx without generating an excessive ammonia slip at the tailpipe [294].

The trade-off between fuel consumption and tailpipe emissions in an aftertreatment-WHR system can be effected by several dynamic behaviours such as the battery temperature [298], engine-out temperature [299], catalyst temperature [300], and engine cold-start conditions [301]. The suggested ways for incorporating the considered factors into an optimal power control problem are extending the Hamiltonian function of the PMP technique [300] or extending the cost function of the MPC technique [298] combined with other additional strategies. In this regard, these previously used effective strategies include an engine on/off filter [300], precision cooling strategy [302], road grade preview [298], and traffic information prediction [295]. The challenges of employing such approaches are their need to develop high-fidelity models including the dynamic transient behaviours of the engine and battery. Consequently, they come with time and cost consumptions for the powertrain control development. In the near future, self-learning and model-based control systems that can automatically determine the optimal control settings on the road will be a remedy to overcome the limitations of a traditional EMS based on quasi-static and map-based models [292].

It is inevitable that powertrain topologies and power control problems will grow increasingly more complex. This calls for the development of a complete hierarchical EMS system to coordinate efficiently the multi-scale time horizons, guaranteeing an optimal solution and driver safety. A future research trend will be a synthesis of different control layers into a concrete holistic EMS framework, for example, an integrated powertrain control with a sensor-based emission measurement system [292], an integrated optimal EMS framework [29], and a

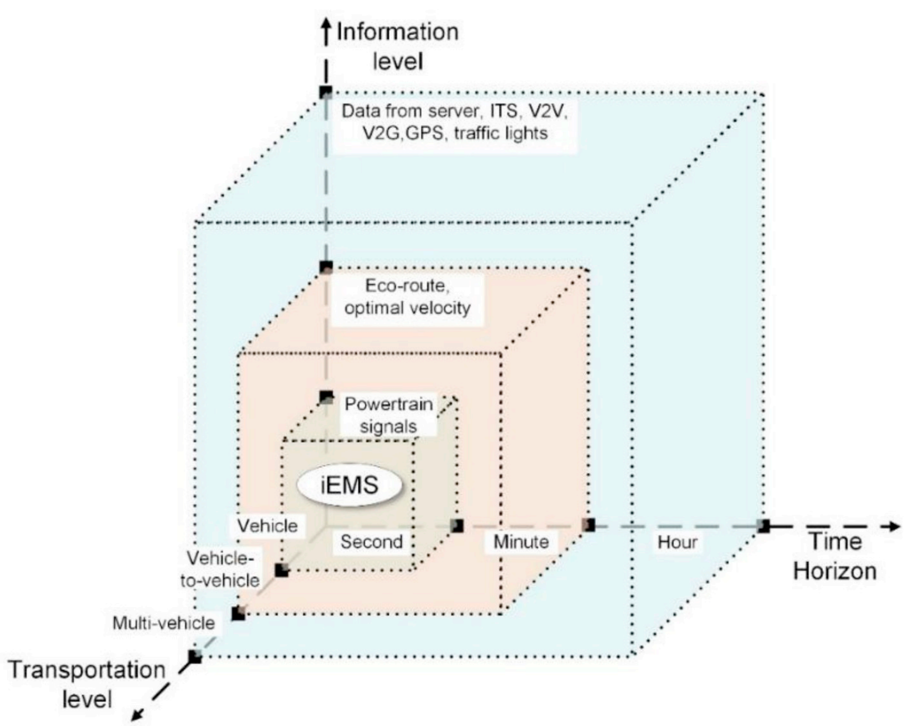


**Fig. 23.** Increasing EMS design space toward achieving integrated EMS.

multi-level EMS [303,304]. A complete multi-level EMS structure typically consists of two [29] or three [303] levels, which applies different optimisation tasks depending on the response time of the control variables (e.g. vehicle speed and battery energy). In such a structure, the higher level (vehicle level) can be used to consider the traffic information (e.g. traffic signal phases, timing information, and surrounding vehicle information). Alongside this, the road conditions (e.g. altitude, road grade, and speed limits) can be simultaneously considered to optimise the vehicle's speed trajectories. An optimised speed trajectory over a specific route can be integrated into an EMS embedded at a lower level (powertrain level) to further enhance the fuel economy, which is called an eco-driving based EMS [29]. With the aid of cyber-physical systems [305], the integration of eco-driving into an EMS at the double-vehicle level through an adaptive/predictive cruise control concept [306], or at multiple-vehicle platooning level [307], merits consideration as a promising topic in the near future.

## 5. Conclusion

Throughout the literature, the design aspects of powertrains and the EMSs of hybrid and electric vehicles have increasingly attracted the attention of many researchers. With this regard and considering their applications, several powertrain topologies and corresponding EMSs have been proposed to address such control objectives as reducing fuel consumption and emissions, ESS charge maintenance, and enhancing the drivability and vehicle performance. In the present study, various (P) HEV and FEV configurations were initially reviewed followed by vehicle modelling approaches. Comprehensive classifications and comparisons of existing EMS techniques, their controllability contributions, fundamental principles, and advantages and disadvantages were provided. Consequently, the research gaps were identified, and corresponding future research directions toward improving the adaptability and efficiency of EMS approaches were provided. Considering the recent advances in intelligent- and information-based approaches, the potential incorporation of new frameworks/algorithms, communicative concepts, technologies, and infrastructures in the design of an EMS to address the existing uncertainties toward achieving a real-time robustness was proposed.

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