Review of Energy Management Strategies in Plug-in Hybrid-Electric Vehicles

J. Rohith and G. T. Mahesha

Abstract As a step toward a pollution-free environment, governments and regulatory bodies worldwide are moving toward cleaner means of transportation. A lot of tailpipe emissions occur in a conventional internal combustion engine. One solution to these hazardous emissions is the use of hybrid-electric vehicles (HEVs) or fully electric vehicles (EVs). The HEVs, especially plug-in HEVs (PHEVs), are soon expected to have more significant commercial applications, as the EVs may take more time for their larger part of the share. A hybrid-electric vehicle employs an IC engine combined with a smaller battery and an electric motor. On the other hand, a PHEV consists of a much larger capacity battery storage known as a rechargeable energy storage system (RESS). It is equally important to apply a stable drivetrain topology for greater efficiency. PHEV blends power from battery and engine using an energy management system, which always tries to impart the best driving conditions, least emissions, and maximum mileage and range. In the paper, an overview of all the control strategies is reviewed with few simulation results.

Keywords Energy management · Control strategies · PHEV · SOC · Vehicle to the grid

1 Introduction

The transportation sector consumes 49% of the world's oil resources worldwide and is one of the most rapidly growing consumers of available global energy. It is predicted that, at this rate of consumption, total oil reserves will be depleted by 2038 [1]. Researchers are developing various alternative power trains, which are gaining much attention lately. A hybrid-electric vehicle (HEV) is one among them and can reduce exhaust gases, saves fuel, and paves the way for a greener environment. An HEV can reduce the consumption of fossil fuels by 70% [2, 3].

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A hybrid vehicle consists of an IC engine combined with a battery storage system that supplies energy to an electric motor. For HEV, there are two types of propulsion systems, mainly an ICE and battery supply with a rechargeable energy storage system (RESS). Superior range and versatility in the modules' scale are the most important benefits that an HEV has over a pure EV.

An efficient drivetrain design is essential for an HEV as it impacts mechanical efficiency, fuel consumption, and price. A drivetrain is the collection of parts that supply power to the vehicle's wheels from the engine or motor. The drivetrain's configuration defines how the electric motor functions combined with the traditional engine in hybrid-electric vehicles. Series, parallel, and series–parallel hybrids are the necessary powertrains available in an HEV.

Series Hybrid: Only the engine, which in turn charges the batteries, can drive the motor. The transmission operates by an electric motor, which is entirely battery powered. It is an effortless but not the most powerful method.

Parallel Hybrid: The engine and the battery run the motor, which in turn powers the transmission. Only the engine spins the rotor when the battery is exhausted.

Series–Parallel Hybrid: It is a blend of series and parallel systems. With a power-split unit, the engine may selectively drive the wheels or the generator, or both based on driving conditions. This arrangement is deemed the most successful and was assimilated by Toyota.

Figure 1 shows a pictorial view of all the drivetrains, the red line indicating the engine line and the blue being the electrical supply.

Enormous versatility is available in choosing the structures for power splitting. Based on the hybridization, i.e., the engine's size and the battery source, an HEV classification is done. Figure 2 illustrates the different types of HEV's based on the size of the battery and IC engine.

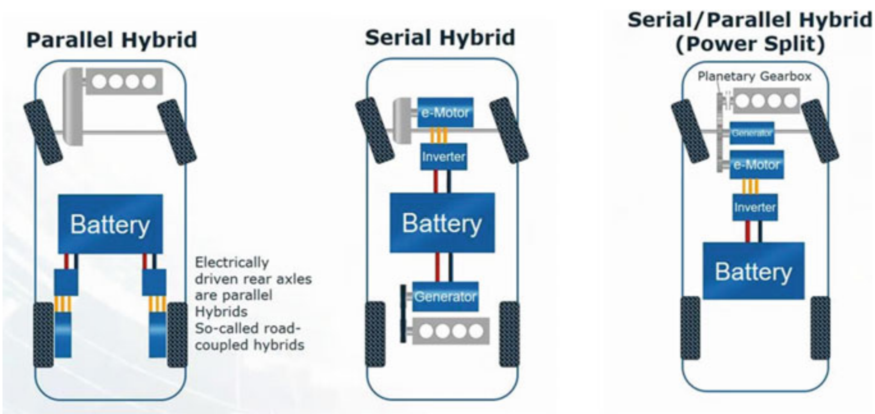

Fig. 1 Classification of drivetrain designs [4]

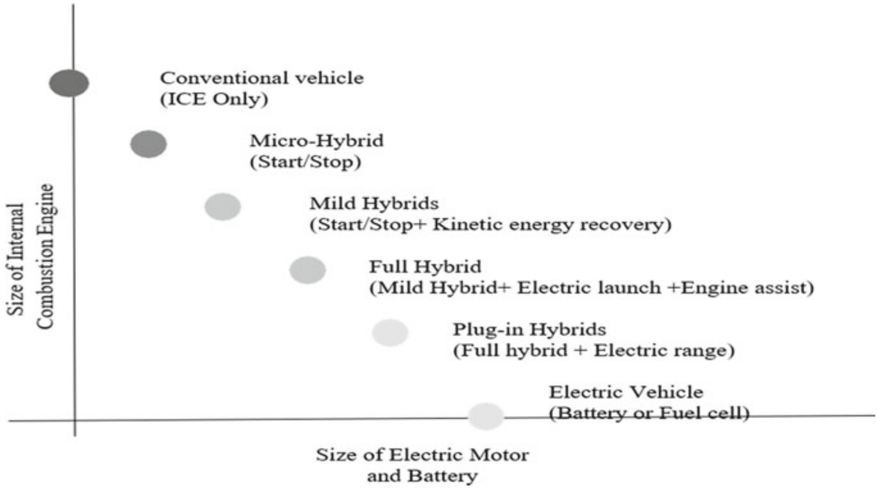

Fig. 2 Hybrid-electric vehicles based on the size of the IC engine and battery [5]

Much of the research is focused recently on plug-in hybrid-electric vehicles (PHEVs) that store and draw power from a renewable energy source. The concepts from a basic HEV can be implemented in developing a PHEV. Also, the primary source of power can be changed from fossil fuel to multiple sources like solar and wind to make the transportation sector even cleaner. PHEVs can all-electric mode, or pure engine mode or both combined based on the charge region. The main features of PHEVs are as follows.

(a) Recovering regenerative energy from brakes instead of dissipating as heat.
(b) Optimizing the splitting of power between various sources.
(c) Downsizing the engine while attaining the maximum requirement of the vehicle [6].

With their all-electric range in cities and an extensive cruising range and battery charging capabilities, PHEVs give a wide range and function as a range extender. Many pollutants are released when the engine runs in a transient mixture and is fixed by a PHEV. With its vehicle to grid technology (V2G), it can even power back the house if needed [7].

1.1 Terminology in Plug-In Hybrid Vehicle (PHEV)

State of Charge (SOC): It is relative to the initial charge of the battery to the current level of charge, also known as the remaining energy fraction present in the battery [8, 9].

Charge sustaining mode: Batteries state of charge (SOC) may increase or decrease in a driving profile, but by the end, it should come to an equivalent state.

Charge-depletion mode: The SOC of the battery on a driving profile shows a net drop in stowed energy.

All-electric range (AER): The vehicle's complete distance is in an electric mode until the engine turns ON [10].

The overall consumption advantages of today's HEVs are developed purely from developments in charge sustaining mode, as they have no charge-depleting mode. A PHEV that does not use petroleum (all-electric) in a charge-depletion mode and with a fuel economy in a charge-sustaining mode is equal to a traditional vehicle consuming 50% less petroleum as the first 40 miles will be electrically powered ex. PHEV40 [8]. A blended strategy is employed to maximize the charge-depletion time and even less fuel consumption in some cases.

1.2 Overview of Control Strategies in Plug-in Hybrid-Electric Vehicles

It is essential to maximize powertrain efficiency and increase the driving range. There are many challenges in employing the perfect control strategies in multi-source systems like plug-in HEV. The energy management system is an essential part in the control of HEVs. It plays a major role between the IC engine and the battery storage system is maintained and keeping the proper state of charge (SOC). Energy management can instantaneously identify and control the actuators in the system. By altering the input signals, various outputs can be formed, gaining maximum efficiency. A fixed control strategy cannot be adopted as there will be a change in the driving parameters and patterns, leading to poor fuel economy in HEV.

Compared with an HEV, the AER in a PHEV is helpful in refining mileage, efficiency, and emissions. Still, it may increase the intricacy by increasing the challenges for the control system design. Electric drive trains are more efficient and considerably cheaper. Most ICEs are very ineffective in transients as they consume a lot of energy, Hence, it is useful to run the vehicle in AER wherever feasible [11].

The energy is consumed significantly when the vehicle is idling. A PHEV control strategy is devised to turn off the engine when not in use, and the start-up efficiency is increased by converting to EV mode. The topology of the vehicles determines the engine turn-off and turn-on process. This is true for all parallel PHEVs. There is no necessity to operate the engine in an EV-start and propulsion until the traction battery is exhausted. Although the engine does not lead to acceleration, its load can be applied gradually and in a controlled manner, irrespective of the driver's requirement.

The engine logics are based on three criteria such as (1) threshold power required, (2) SOC of the battery, and (3) the capacity of the electric motor to provide the necessary power [11].

Several papers have been addressed based on the control strategies' overview in recent years [12–14].

The next section consists of the main control strategies such as rule-based and optimization-based and its subdivisions and the latest technological advancements in a plug-in HEV with some simulation results in real time.

2 General Classification of Control Strategies

Control strategies are mathematical models based on descriptive methods. They are broadly divided into two types, such as rule-based control strategy and optimization-based control strategy. These approaches are subdivided further on the way they are employed, which is shown in Fig. 3.

Control strategies focusing on rules help achieve fuel economy, productivity, optimal output, and lower pollution for a particular drive cycle. They are described by a series of parameters that are pre-programmed using specific mathematical models into the framework. Due to their simplicity, researchers have turned toward optimization-based strategies, involving an optimal method by minimizing the cost function.

Using the past as well as future information, regarding the trip controllers are designed. Most advanced control techniques involve a real-time data collection through sources such as on-board sensors and encoders.

2.1 Rule-Based Control Strategy

In a PHEV, the key goal of a rule-based strategy is to obtain optimum effectiveness. Moving the electric machine and the engine at its highest efficiency utilizing the

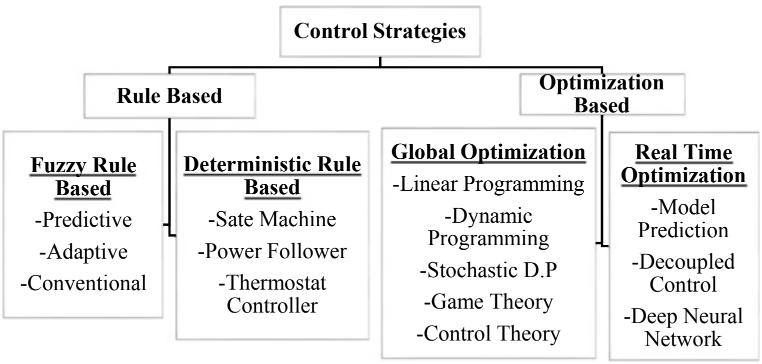

Fig. 3 PHEV control strategies [11]

all-electric range (AER) and maximum energy regeneration. There will not be any knowledge of the trip as the rules are predefined to get the desired output. It works on wide range of conditions without the knowledge of the trip beforehand. Changing of modes between one and the other depends on the acceleration and deceleration needed, engine and motor power demands, vehicle speed, and the SOC of batteries.

The following are the real-life rule-based strategies applied in Prius, a bend of both series and parallel topology (a) full EV mode of operation: If there is sufficient SOC in the battery, vehicle running at low speed and adequate coolant temperature. (b) Engine and motor sharing the power: When the engine is ON and the battery SOC is over the required SOC. (c) The engine only operation and charging of battery: When the battery's SOC dropped below the required SOC, (d) when the energy demanded is negative and the engine is OFF, the negative power needed is retained in the batteries utilizing the regenerative braking.

A simple rule-based simulation run by bavait and anwar, proposed a rule-based controller compared with the simple rule-based model in ADVISOR software, using several drive cycles for Toyota Prius with a planetary gear train acting as a speed coupler. They proposed a set of new rule-based strategies. "(a) When the battery SOC falls below the aim level and the vehicle requires a positive power condition, the engine must be switched on. (b) When the battery's SOC reaches its intended capacity and the vehicle's power output is less than the full power that the engine will produce but is optimistic, the engine will be switched off. (c) When the battery SOC reaches its intended cap and the power needed by the vehicle exceeds the available power supplied by the engine but is optimistic, the engine shall be turned on. (d) When the vehicle's power requirement is negative and the battery's SOC is below its upper limit, the engine must be turned off" [15]. It is observed that Toyota Prius's basic rule strategy for a PHEV gave a 74.8 MPG mileage while PHEV's alternative or proposed rule-based control strategy produced an 87.6 MPG mileage for the 37.2-mile drive loop. The engine's function output improved 6 percent from 29 percent using the Prius approach to 35 percent using the RBS approach suggested.

Rule-based strategies are also known as a mode selector type system where a set of modes is shifted based on the battery's SOC characteristics. A simple mode selector energy consumption strategy is shown in the Fig. 4.

2.1.1 Deterministic Control Strategy

A deterministic strategy is based on certainty since there is no randomness. All the rules are based on certain predefined formulations. Rule-based controller operates on a bunch of rules set before the actual operation [17], and inputs are made instantaneously from the decision-making models. The undeveloped determined rule-based control strategy is the ON and OFF of ICE that is thermostat supervisor. It runs on the simple principle that the vehicle engine will be turned ON and OFF based on the ESS SOC values and the required torque.

A power follower system is used in this method, normally employed at minimum vehicle speeds. The motor is used to produce excess power when there is a greater

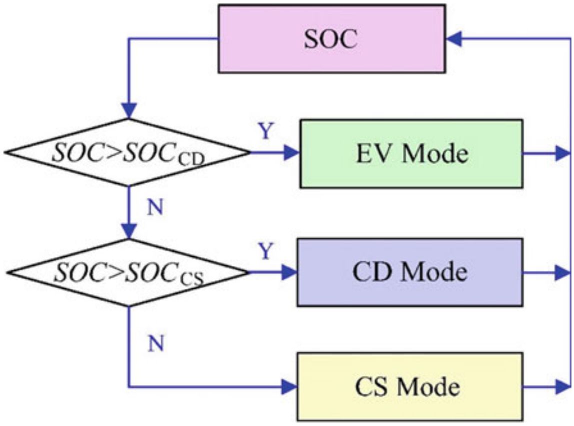

Fig. 4 Energy utilization mode switch control strategy [16]

demand of power. The motor charges the battery by regenerative braking. Hmidi, Salem et al. carried out a simulation [18] using a deterministic rule by the start/stop of the engine, electric assistance, i.e., boost function, regenerative braking with on-board charging at low speeds, is developed in an HEV. With 15–20 kmph speed and varying SOC values, it is observed that hybridization can significantly reduce fuel consumption by 10–15% on urban road and highway conditions. Applying it to a PHEV can increase efficiency even better.

Following these CS models, Toyota (Prius) and Honda (Insight) HEVs run on charging sustaining mode in ESS following a parallel topology of the drivetrain.

2.1.2 Fuzzy Logic Rule-Based Control Strategy

Fuzzy logic can be named as an extension of the deterministic rule-based approach. It is an ideal strategy for non-linear, time-varying systems as they are robust and adaptable to any situation. It gave a profound notion to the controller developed by Hmidi et al. [18] and gave a higher fuel economy. These are built on fixed rules that mainly run on CS rule-based model. These logics evaluate the driver's normal behavior, and they function accordingly. A controller that can pick the points of action by the lowest effect on fuel's economy, as instigated by Johnson [19], gave a better fuel economy compared to simple controls based on rules. It is impossible to optimize a system of more than two variables, which makes it a device constraint. The difficulty of the simulation makes it challenging to implement in real life. The system designed to use the depletion mode of charge instead of the maintaining mode of charge would have the highest fuel output [20]. Figure 5 shows the different modes AE mode, CS mode, CD mode based on SOC and time profile.

Logical relations AND and NOT (even OR) are used in the fuzzy laws of Table 1. The Boolean logic which is a traditional one was generalized to fuzzy alternatives for this purpose. These fuzzy equivalents can be implemented in many ways but in

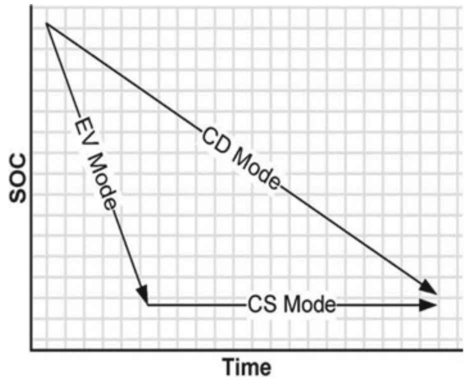

Fig. 5 SOC profile with time [11]

Table 1 Sample rules for fuzzy logic control of a PHEV [21]

Rule base of the fuzzy logic controller
1. **If** SOC is too high, **then** P_{gen} is 0 kW
2. **If** SOC is normal **and** P_{driver} is normal **and** ω_{em} is optimal, **then** P_{gen} 10 kW
3. **If** SOC is normal **and** $\omega_{\underline{em}}$ is **not** optimal, **then** P_{gen} is 0 kW
4. **If** SOC is low **and** P_{driver} is normal **and** ω_{em} is low, **then** P_{gen} is 5 kW
5. **If** SOC is low **and** P_{driver} is normal **and** ω_{em} is **not** low, **then** P_{gen} is 15 kW
6. **If** SOC is too low, **then** p gen is P_{gen}, max
7. **If** SOC is too low, **then** scale factor is 0
8. **If** SOC is **not** too **and** P_{driver} is high, **then** P_{gen} is 0 kW
9. **If** SOC is **not** too low, **then** scale factor is 1

general, AND is the minimum operator used, NOT is for simple compliment, and OR is the maximum operator. Using these fuzzy set, a fuzzy controller can be built.

The perceptive mechanism used in fuzzy logic can be explained in four key steps [21]

- Fuzzification: Using the membership functions, the three input values of the degree membership of a fuzzy logic controller are computed.
- Degree of Fulfillment: This is the degree to which the rules are valid, when the precursor of every rule from Table 1 is figured using fuzzy logic operator.
- Inference: If–then the operation constitutes implication. The degree of the enforcement standard is used to alter the rules accordingly. It is done by multiplying the amount of fulfillment of the precedent by the resulting rule. Table 1, rule 2 is an example.
- Aggregation: For every output of a controller, the outcomes are combined into a specific value from the inference step. By taking the average of the inference results, this is done.

For the default controller, all components' performance is lower, except for the ICE where the default controller's optimization is more efficient. There is no trade-off between the performance of the other PHEV modules and the ICE engines' performance. Therefore, the ICE's operating points are closer to the default controller's optimum curve than for the FLC [21].

Results of simulation applying the different drive cycles suggest possible changes utilizing the fuzzy reasoning defined in the SAE J1711 standard compared to other techniques that only maximize ICE efficiency [22].

2.2 Optimization-Based Control Strategy

Local optimization is the significant limitation of a rule-based CS as we cannot optimize the PHEV as a unit. Two primary standards are present for a global strategy, one focused on past evidence, and the other focused on the compilation of real-time data. In a set of rules, optimization takes place with the learning system while responding to the situation. They were considering maximum performance requirements from the powertrain configuration. It also allows two factors, i.e., mileage levels and pollution expectations, to be combined into a minimized cost function. The fuel efficiency depends mainly on the controller's capacity to maximize, and the controller can forecast the potential condition of the trip correctly. A lot of effort to enhance the performance is noticed, but the right balance of application is difficult in optimization.

2.2.1 Global Optimization System

Optimization-based management methods, as they refer to HEVs and PHEVs, are typically divided into two groups. Technical developments such as the global positioning system (GPS), global information system (GIS), traffic data collection in real-time, and Internet maps have rendered it simpler to schedule a trip [23, 24]. Linear programming is one of the commonly used optimization methods. When a PHEV is designed and a controller is installed, it should match the global optimization model. "Together, an engine and an electrical machine power a PHEV, and parallel topologies directly relate to the two elements torques and speeds. The control theory method exploits this relationship to define a cost function using only two decision variables" [25]. The Bellman principle [26] taking the engine torque as the criteria of command, a real-time control strategy using MATLAB Simulink is developed. During the cycle, the energy loss is minimized. A generic algorithm is also one of the non-linear optimization methods [27]. Such strategies rely on the direction, road profile, congestion level, atmospheric conditions, and further details taken from the global position system (GPS), intelligent transport systems (ITSs), geographic information systems (GIS), and traffic modeling [28, 29].

2.2.2 Real-Time Optimization

Real-time optimization majorly uses past data in analyzing and optimizing a trip. Various techniques have been used for programming the techniques, and dynamic programming (DP) is one among them [28]. A DP is a closed-loop form of optimization strategy. In general control questions, DP is an algorithm capable of evaluating the best possible global solutions. Taking into consideration the current and potential consequences of management choices, the desired approach is accomplished by reducing undesirable outcomes [29–31]. It is used in any problem to which the findings are to be made in steps to find a minimal decision pathway [32–34]. A dynamic programming algorithm consists of the engine's battery level and speed, which influences the rate of fuel and is regarded as regulated or controlled variables are induced. This gives very high-computational cost—however, two degrees of freedom of optimization. The flowchart shows steps involved in DP in Fig. 6.

The motor constraints, the battery, and the engine, should be considered correct, and the engine fuel rate should be calculated using different battery currents. Simultaneously, it is possible to build up the cost to go matrix, then an optimal SOC curve and maximum battery current with various starting SOC can be determined.

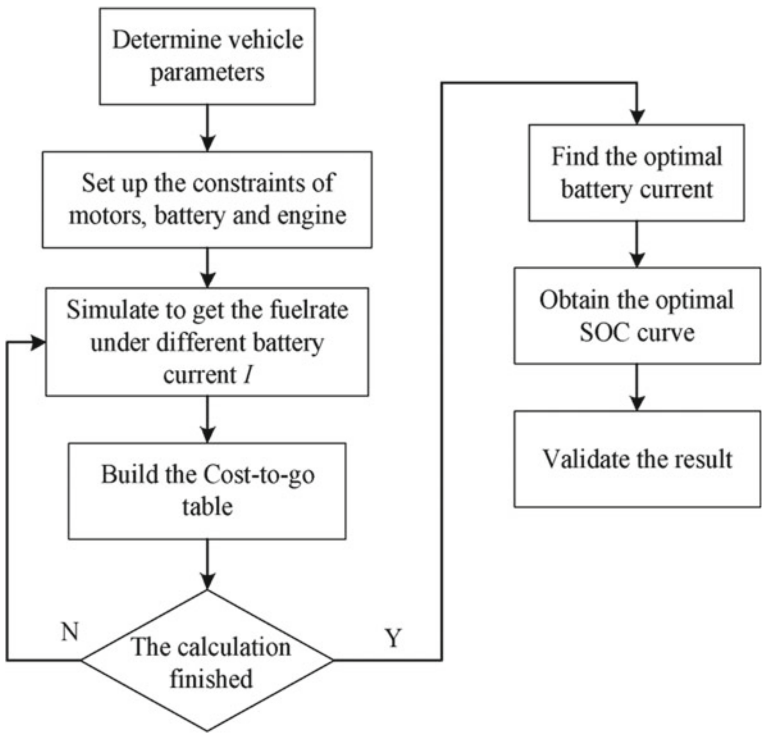

Fig. 6 Procedure of dynamic programming method [35]

Table 2 Vehicle parameters [35]

Vehicle type	Plug-in split HEV
Vehicle mass	1641.3 kg
Engine power	57 kW
Motor power	25 kW, peak power 50 kW
Generator power	15 kW, peak power 30 kW
Planetary gear set	Sun gear 30 teeth Ring gear 78 teeth
Battery	Lithium-ion battery Rated capacity 20 Ah Rated voltage 356 V

With the number of drive cycles simulated by Chen and Xu using dynamic programming taking Table 2 of the vehicle parameters, it is observed that the default algorithm discharges the battery quicker than the DP method. The level of engine efficiency based on various algorithms are being compared. The average engine efficiency is observed to be higher when the DP method is applied compared with the default algorithm. The contrasts will illustrate to some degree how the DP system will minimize fuel consumption.

(a) *Deep Neural Networking*

Neural networks offer brain-like activity inspired by biological brain behavior. Depending on the input characteristics, the signals are sent to other neurons like in the brain as it sends to other neurons through dendrite. These processes are usually expressed with transfer functions [36]. Layers are built combining the neuron network. Based on complexity, desired fidelity, and model nonlinearity, the density of neurons may change. Training data are required to determine the neuron parameter calculation [37].

The error backpropagation is used for enhancing error convergence in NN, which optimizes the training data error. A least-squares regression process is used in training, where the initial values of dendrites weights are assigned randomly [36, 38]. The NN performance is influenced directly by the quality of training, e.g., overfitting risk. However, an optimal amount of training data exists, and therefore, there will not be any improvement in performance with excess training data. The construction of a typical neural network is shown in Fig. 7.

A power-split hybrid-EV EM system cantered on machine learning by Murphey, which is trained by dynamic programming that combines terrain knowledge with the jamming level forecast, and applied NNs concept to enhance battery performance and speed of the engine [39].

Khayyam and Bab-Hadiashar [40] projected a neural network application in hybrid multilayer adaptive fuzzy neuron interpretation, to increase and adapt the application range, the fuzzy logic controller is given learning characteristics with the help of NN. They have designed a controller that can spontaneously tune the values

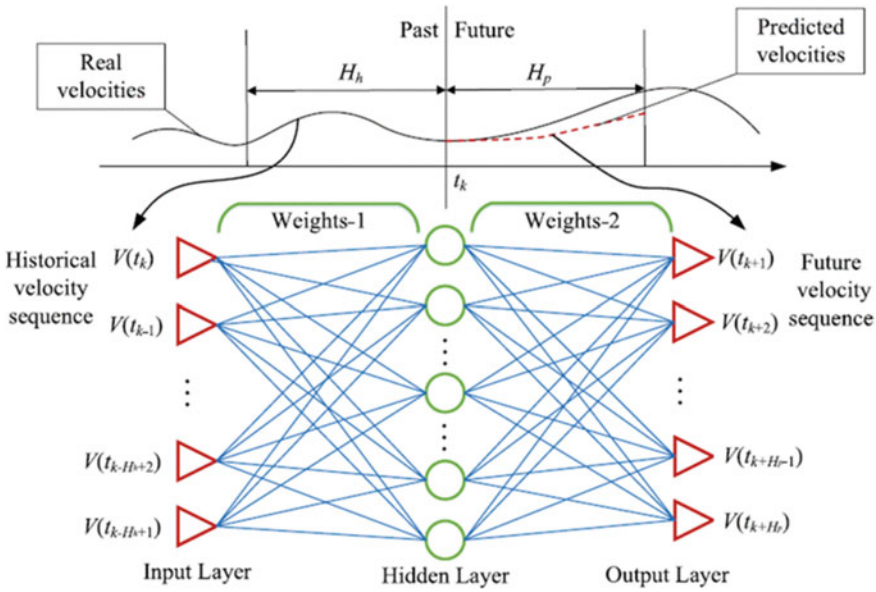

Fig. 7 Neural network strategy in real versus predicted velocities [36]

themselves, according to the influence of roads, driver's behavior, and environmental conditions.

Chen et al. [35] give intelligent controllers the need for a wide range of use and follow a good trade-off between computational effort and algorithm robustness. To lessen the fuel consumption of a PHEV, the author employs NN, which takes training data from wide-ranging driving conditions. Working with different levels of trip information, the NN consists of modules N1 and N2.

Incorporating neural network into a model predictive control in the short term by Sun et al. also presented a machine learning-based NN algorithm and claimed to have a 92% fuel optimality compared to a DP algorithm [41, 42].

Game theory, sliding mode controller, convex programming, and analytical solution are some of the futuristic control strategies.

(b) *Energy management using a vehicle-to-vehicle interaction with intelligent transport.*

The increase in the advance driving assistance system and intelligent EMS makes possible shifts toward predictive EMS. Optimum productivity needs to take the most useful trip data, mainly from Google services. Such data gathered were used in combination with predictive model control by Sun et al., he also built a two-stage EMS controller for a power-split PHEV. For an optimized SOC reference path, real-time traffic information is collected for running a long term with the supervised control system. Over the last few years, connected and intelligent vehicle technology has surfaced to catalyze the optimal fuel economy in an eco-driving system developed by

Ko et al. considering traffic signals and leading vehicles the power demand assumed [43–45].

Vehicles run mostly on random and transients and majorly depend on traffic, road type, weather, driver style. Thus, random and biased errors are observed in vehicles [46].

3 Moderns Control Strategies for HEVs

In providing an efficient power system, the current power demand and the future power requirement have to be determined. This gives a real-time distribution of the total decision variable. In an **extreme learning machine algorithm (ELM)** developed by Zhang et al. [47] considering traffic and urban driving conditions, with vehicle-to-vehicle (V2V), a one-step model is designed. A multi-step optimal algorithm with many single steps is built for driver torque demand prediction.

Consumption of fuel and environmental pollution is drastically reduced with the application of advanced control strategies. Based on the driving conditions like urban environment and traffic conditions, the SOC values' variation plays a major role in planning a CS. In a study by Erfan et al. [48], a new rule-based CS with SOC parameters and teaching learning-based optimal CS is employed. It is observed that an **optimal charge-depletion strategy (OCDS)** can significantly improve fuel consumption than an AER-focused CS. An OCDS is used in a long trip, whereas an AER is more efficient for a shorter trip.

Sometimes, there may be a condition where prior knowledge of the trip is not present, and a **deep-reinforced learning (DRL)** can be used. "It observed that original DRL-based EMS achieves an average 3.5% gap from benchmark compared to model predictive EMS" [49].

Table 3 illustrates the pros and cons of various energy management strategies that are used in PHEVs.

4 Conclusions

The following inferences are drawn from the review of the technical papers published on hybrid-electric vehicle energy management strategies.

Plug-in hybrid-electric vehicle (PHEV) configuration is a promising transportation mode because of its range extender ability. Energy management strategies adapted in PHEVs can be broadly categorized as rule-based (RB), optimization-based (OB), and learning-based (LB) strategies. Rule-based strategies are easy to program and cost-effective. However, no on-board prediction capabilities make them insignificant.

Adaptive control algorithms like fuzzy logic, dynamic programming, and deep neural networks increase the fuel economy and reduce emissions. Most of these

Table 3 Main EMS strategies and their application summary

Strategy	Main advantage	Main disadvantage	Simulation result (if any)	References
General rule-based	Balanced SOC	Not optimal	NA	[14, 15, 17, 50]
Predicted rule or new rule-based (anwar and bavait)	Increased SOC	Lacks real-time data	The mileage of the PHEV increased by 16%	[15, 17]
Deterministic	Computational simplicity	Only applicable for series hybrid powertrain	NA	[17, 50]
Fuzzy logic	Can be Easily tuned	Very complex	The drive cycle by SAE J1711 gives optimal efficiency	[8, 19–21, 23]
Global optimization system	Optimal solution	Cannot be implemented in real-time system	NA	[24–29]
Real-time optimization	Instantaneous minimization of the cost function, does not need proper knowledge of the drive cycle	Values of equivalence factor are difficult to obtain for different DC	The average efficiency of the engine is higher	[30–33]
Deep neural network	Very adaptive	Difficult to program	NA	[35–40]
Vehicle-to-vehicle interaction/intelligent transport	Trip-based online system	Random and biased errors	NA	[44–46]

algorithms require the drive cycle information beforehand, or a training system is necessary in neural networks. Versatile energy management strategies in hybrid-electric vehicles can include a blend of various techniques (RB, OB, and LB), forming an integrated EMS (iEMS) toward improved fuel economy and performance.

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