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REVIEW PAPER

A comprehensive review on energy management strategies of hybrid energy storage systems for electric vehicles

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Abstract
The development of electric vehicles represents a significant breakthrough in the dispute over pollution and the inadequate supply of fuel. The reliability of the battery technology, the amount of driving range it can provide, and the amount of time it takes to charge an electric vehicle are all constraints. The eradication of these constraints is possible through the combination of energy storage systems. The hybrid energy storage system is potentially a significant development since it combines the advantages that are traditionally associated with batteries and supercapacitors. When compared to conventional energy storage systems for electric vehicles, hybrid energy storage systems offer improvements in terms of energy density, operating temperature, power density, and driving range. Thus, the review paper explores the different architectures of a hybrid energy storage system, which include passive, semi-active, or active controlled hybrid energy storage systems. Further, the effectiveness of hybrid energy storage systems based on the different architectures and operating modes was examined. Also, this work presents control modes of energy management strategies based on rules and optimization based strategies. Further, this review paper provides the effects of driving cycles and thermal behavior on the performance of hybrid energy storage systems. From this extensive review, based on simulation and experimental results, it is concluded that the battery parameters and energy management strategy for a hybrid energy storage system are the prime factors for the battery's charging and discharging time, state of charge, state of health, energy consumption, and safety of the electric vehicle.

Keywords Supercapacitor · Driving cycle · Battery · Electric vehicle

Abbreviations

A-ECMS	Adaptive equivalent consumption minimization strategy
AC	Alternating current
ANN	Artificial neural network
ARTEMIS	Artemis drive cycle
CATC	China automotive test cycle
CBDC	Chinese bus driving cycle
DC	Direct current
DNN	Deep neural network
DP	Dynamic programming
DPR	Driving pattern recognition
ECE 15	Urban driving cycle
EMS	Energy management strategy
ESS	Energy storage system
EV	Electric vehicle
EWMA	Exponential weighted moving average
FTP75	Federal test procedure
GA	Genetic algorithms
GHG	Greenhouse gas
HESS	Hybrid energy storage system
HIL	Hardware-in-the-loop
HWDC	Highway driving cycle
HWFET	The highway fuel economy test
IUDC	Indian urban driving cycle
Japan 10–15	Japanese 10–15 mode
LA92	"Unified" dynamometer driving schedule
Li-ion	Lithium-ion
LPF	Low-pass filter
LSTM	Long short-term memory
MANHATTAN	Manhattan drive cycle
MDP	Markov decision process

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MFB	Math function-based
MIC	Multi-input converter
MPC	Model predictive control
NEDC	New european driving cycle
Ni-MH	Nickel-metal hydride
NN	Neural network
NYCC	New York city cycle
PbA	Lead-acid
PD	Proportional derivative
PI	Proportional integrator
PID	Proportional integral derivative
PMP	Pontryagin's minimum principle
PSO	Particle swarm optimization
RCP	Rapid control prototype
RFOSMC	Robust fractional-order sliding mode control
RMS	Root mean square
RUL	Remaining useful life
SOC	State of charge
SOH	State of health
SOP	State of power
SRT	Single ratio transmission
SS-IFS	Squirrel search with improved food storage
Th strategy	Threshold strategy
UDDS	Urban dynamometer driving cycle
UDIT	Uninterrupted dual input transmission
US06	High-speed, steady-state driving cycle
VRLA	Valve-regulated lead acid battery
WLTC	Worldwide harmonized light-duty vehicles test cycles
WLTP	Worldwide harmonized light vehicles test procedure

1 Introduction

The use of fossil fuels for energy production has unpredictable consequences for greenhouse gas (GHG) emissions. The intensity of environmental changes resulting from GHG emissions has reached an uncertain level, leading to global warming. Nowadays, the automotive sector is highly focused on developing alternative fuel sources or clean energy technologies to reduce GHG emissions and increase vehicle performance. The commitment to reduce GHG emissions, the significant dependence on petroleum, the growing population, and availability are some critical variables that could accelerate the migration from gasoline-powered vehicles to electric vehicles (EVs) [1, 2]. EVs are more energy efficient than gasoline-powered vehicles, which can reduce GHG emissions and operational and maintenance costs [3]. The development of EVs is dependent on the advancement of their energy storage systems (ESS). The ESS or EV battery should satisfy basic requirements such as higher power density, energy density, operating temperature, and life cycle [4, 5]. The ESS of an EV has progressed from lead-acid (PbA) batteries to lithium-ion (Li-ion) batteries. The application of a PbA battery is preferable when cost is a major concern for the ESS of EVs. However, lower energy density, slow charging, insensitivity to the environment, poor cold temperature performance, regular maintenance, and a short lifecycle prevent their use in EVs. Nickel-metal hydride (Ni-MH) batteries have a reasonable power and energy density, a long lifecycle, are lightweight, and are environmentally friendly compared to PbA batteries. However, their self-discharge rate, cost, and charging time are higher compared to PbA batteries. Li-ion batteries are currently used in most of today's EVs because of their lightweight, high power and energy density, wide operating temperature, long lifecycle, and environmental friendliness [6, 7]. As a result of all the factors discussed above, the majority of EVs employ Li-ion battery technology for their ESS, as this technology exhibits the best performance across all the factors. Owing to the dynamic and steady-state conditions, design issues may arise regardless of the EV battery technology. To meet the peak power requirement of EVs, a larger battery is required, which results in increased weight, volume, and cost of the EV. It is possible to avoid using a large battery to supply a high peak current by using another ESS, such as a supercapacitor or fuel cell. Supercapacitors have a longer cycle life, minimal maintenance costs, superior power density, low-temperature performance, and a high rate capability for fast charging and discharging, compared with Li-ion batteries. Compared with Li-ion batteries, supercapacitors have a low energy density and high self-discharge rate, making them inefficient sources of energy for EVs. However, they can deliver a high amount of power in an abbreviated time [8–10]. Although they are not suitable for high usage periods, they are ideal for compensating for insufficient battery power during high peak power requirements due to their power delivering capability. As a result of all the factors discussed above, supercapacitors may also be useful as secondary ESS for EVs [11–13].

The combination of two or more energy sources is known as a "Hybrid energy storage system" (HESS), which aggregates the advantageous properties of each module. This system's initial objective is to increase the efficiency and capability of energy sources. The HESS is capable of being configured in a variety of diverse ways, as listed below.

- Fuel cell/battery [14, 15],
- Supercapacitor/battery [11, 16],
- Fuel cell/supercapacitor [17] and

- Battery/fuel cell/supercapacitor [18]

Compared to individual energy sources in EVs, HESS offers the potential for reliable energy storage, high power, improved energy efficiency, extended range and operating temperature, faster response, and long functional life. The combination of a supercapacitor and Li-ion battery is the optimal HESS for EVs. This is because the supercapacitor can deliver peak power very rapidly, which supports the battery meeting the peak power requirement of the EVs. The considerable EV power fluctuations that occur during acceleration and deceleration can be safely and effectively managed by a HESS. The involvement of HESS in EVs reduces charging and discharging rates, subsequently reducing the electrical and thermal stress on the battery, which increases the overall performance and lifecycle. However, the performance of HESS is based on their architecture, energy management strategy (EMS), sizing of battery and supercapacitor, parameters of supercapacitor and battery, types of direct current/direct current (DC/DC) converters, sizing of DC/DC converter, traction inverter, operating temperature, driving cycle, ambient temperature, vehicle, and motor parameters [8, 19–21].

This review article specifies an overview of the current research advancements in the emerging EMS of HESS for EVs. We have analyzed the latest developments in, HESS in terms of architecture and explored diverse emergent strategies of HESS for energy management between battery and supercapacitor. Furthermore, this work intends to examine the effect of temperature and driving cycle on HESS performance and the factors affecting the cost of HESS. The discoveries of this study contribute to the continuing research on EMS in HESS for future transportation and provide valuable insights for academicians and researchers. The brief information about the structure and flow of the present review article is as follows: The architecture, design, and performance of HESS are discussed in Sect. 2. Section 3 presents an overview of the energy management strategy for HESS performance. Sections 4, 5, and 6 discuss the effects of cost, driving cycle, and temperature on the performance of HESS and are followed by a conclusion, a summary and future scope in Sect. 7 and 8.

2 HESS's architecture, design, and performance

2.1 The architecture of HESS

The architecture of a HESS has a significant impact on the system's overall efficiency and effectiveness. As illustrated in Fig. 1, the architecture of HESS consists of supercapacitors, battery, converters, EMS, inverter, electric motor, transmission, and vehicle model. DC/DC converters or Boost/Buck converters are used to scale up or down the input voltage to the proper level and reduce voltage fluctuation. EMS is used to control the flow of energy between the battery and supercapacitor to supply the required power for the electric motor. The inverter converts the DC from the batteries to alternating current (AC) to deliver the power to the electric motor.

Based on its architecture, the HESS has been classified into passive controlled, semi-active controlled, and active controlled HESS. The passive controlled HESS is a parallel connection between a battery and a supercapacitor, as presented in Fig. 2. The battery and supercapacitor are linked directly to the direct current (DC) bus without the use of any added electronic components such as converters. As a result, this technology offers increased peak power, improved efficiency, and a longer battery life than traditional batteries. The benefit of this type of HESS is that it is easier to build and has fewer components. However, this system has no control over the system voltage or power distribution of ESS. Because of this, the supercapacitor is not exploited to its full potential in this passive controlled HESS [22–24].

The active controlled HESS has a built-in DC/DC converter for the battery and supercapacitor, as shown in

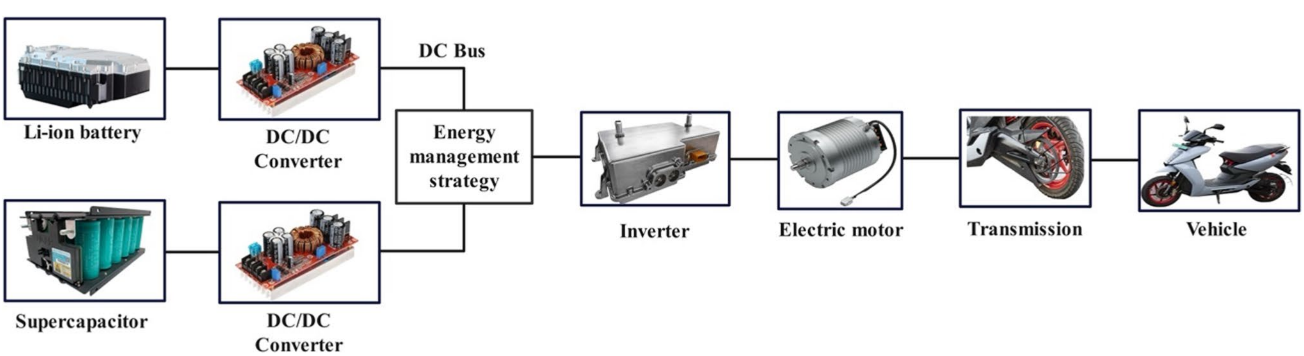


Fig. 1 Simple architecture of HESS

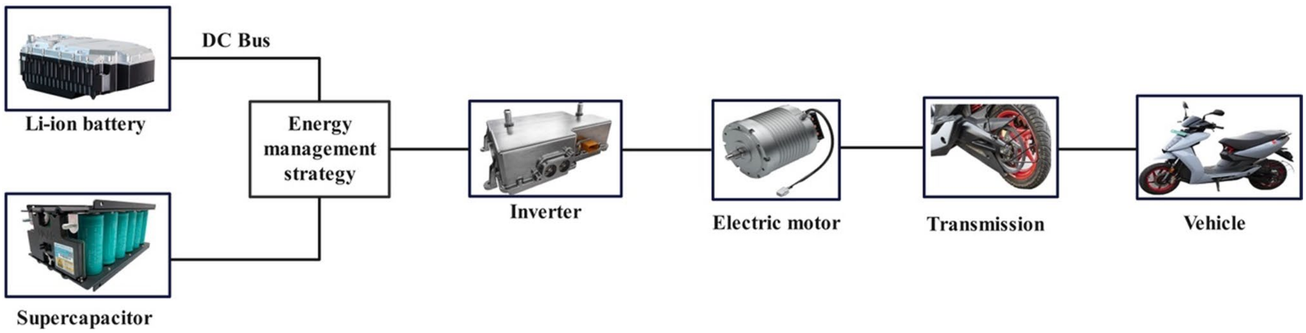


Fig. 2 The architecture of passive controlled HESS

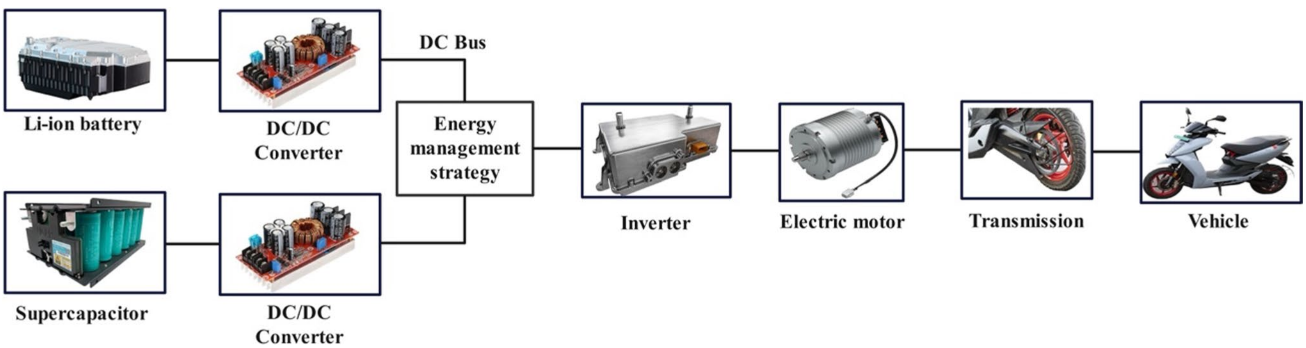


Fig. 3 The architecture of active controlled HESS

Fig. 3. Contrasted with passive and semi-active controlled HESS, they have the advantage of being more flexible and efficient in design. On the other hand, the disadvantages of the active controlled HESS include the excessive cost and the effectiveness of the configuration based on DC/DC Converters efficiency [25–27]. The advantages of an active controlled HESS are as follows:

- The supercapacitor and battery can have unique values in their voltage levels, allowing for more design flexibility in both ESS.
- It can achieve a higher power capability without exceeding the battery's current safety limit.
- It can maintain the terminal voltage because of the availability of individual DC/DC converters.

A bidirectional or unidirectional DC/DC converter connects two energy sources in a semi-active controlled HESS. In this case, one of the two ESS (a Li-ion battery or a supercapacitor) is connected directly to the DC bus, and the other one relates to the help of a DC/DC converter [28–30]. Semi-active controlled HESS is superior to passive controlled HESS in terms of both its responsiveness and its overall efficiency. Compared with active controlled HESS, semi-active controlled HESS has less complexity due to a reduced number of elements. Semi-active controlled HESS has been classified based on the position of the DC/DC converter: supercapacitor/battery, and battery/supercapacitor semi-active controlled HESS, as depicted in Figs. 4 and 5. Based on the review, the semi-active controlled HESS has been more adapted in recent research works [31–35]. Table 1 outlines the advantages and disadvantages of utilizing the different architectures of the HESS system.

2.2 General operating methods of HESS

The general operating methods of HESS have been divided into four modes based on the power sharing between the battery and supercapacitor [26]. Figure 6 presents the mode of operating methods with the primary energy source for the mode. Mode 1: during the starting, accelerating, and climbing load conditions, the electric motor requires peak power from the ESS of an e-scooter. In this condition, supercapacitors act as a primary energy source, and they can supply the peak power requirement of the electric motor. While the battery can act as a secondary energy source, it also supports the supercapacitor. Mode 2: during cruising speed conditions, the battery's power capability is adequate to supply the electric motor's power requirement. In this case, a supercapacitor can act as a secondary energy source to

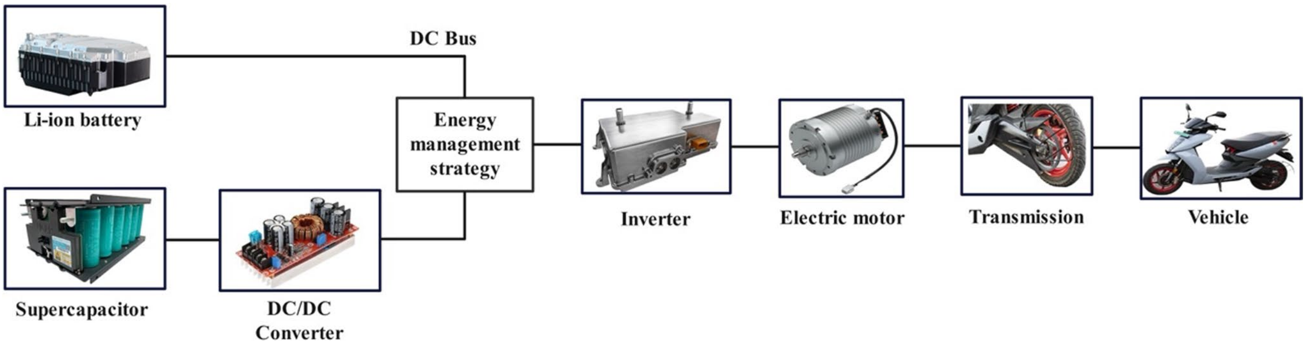


Fig. 4 The architecture of semi-active controlled supercapacitor/battery HESS

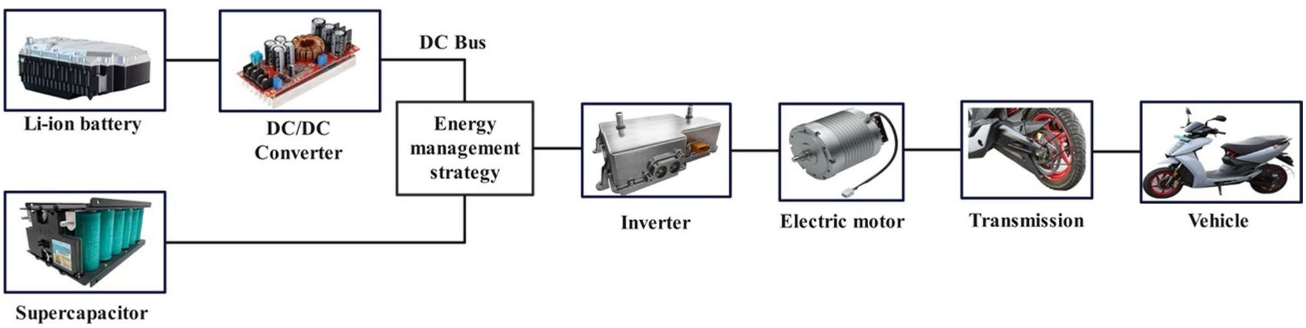


Fig. 5 The architecture of semi-active controlled battery/supercapacitor HESS

Table 1 Benefits and drawbacks of HESS configurations

HESS Structure	Advantages	Disadvantages
Passive	Inexpensive system due to fewer number of components. Simple in construction	No control over system voltage and power distribution
Semi-active	Configurable system. Ensure a good effort to balance cost and performance	The performance of the system is based on DC-DC converters have a greater need. System voltage stability requires monitoring
Active	High-level system adaptability. High-performance system. Flexible in design	The efficiency is affected by the DC-DC converter. Excessive cost

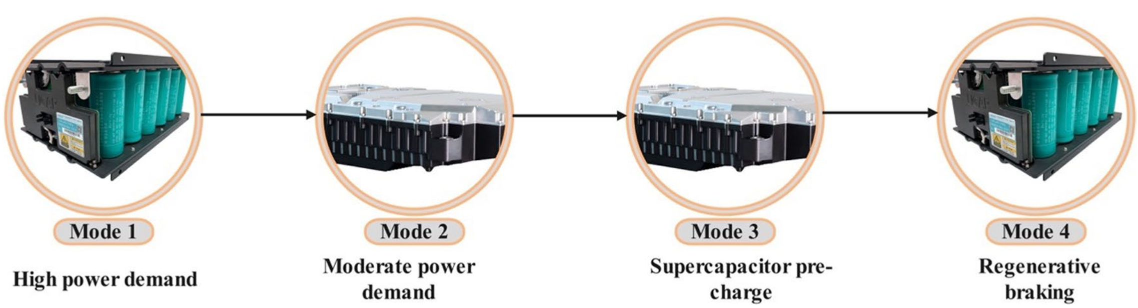


Fig. 6 The HESS's operating methods

support the power requirements of the electric motor. Mode 3: during the steady low speed, the battery's power capability is adequate to supply the electric motor without a secondary energy source. In this condition, the battery can charge the supercapacitor if its SOC is less than 100%. Mode 4: the developed kinetic energy during the deceleration of the e-scooter has been converted to electrical energy and stored in the supercapacitor.

2.3 Performance of HESS based on its architecture

For an electric motorcycle, Goussian et al. [24] designed a passive controlled HESS based on a lithium-ion capacitor. The set theory approach was used in this design to figure out the number of parallel and series cells in a Li-ion battery. Under this procedure, the final attributes of the Li-ion battery are its mass, minimum and maximum voltages, power, volume, energy, and maximum current per cell. The Li-ion battery specifications include the voltage, internal resistance, nominal power, capacity, size, weight, maximum power needed, C-rate, and cell spacing. Distinct options for size maps are available using the set theory technique, depending on the behavior and parameters of Li-ion battery cells. The final sizing map is determined by the Li-ion battery's thermodynamic characteristics and manufacturing viability. Finally, using a set theory approach, the size of the Li-ion battery and Li-ion capacitor is determined by a balanced combination. In this investigation, the addition of a Li-ion capacitor in a passive parallel connection lowered the standard deviation of the cell current by 42%, thereby reducing the stress on the Li-ion battery. In addition to this, it enhances the speed at which the motorcycle can accelerate as well as its range. To keep a supercapacitor voltage greater than the battery voltage, Cao et al. proposed a semi-active controlled HESS with a small DC/DC converter. In this system, the diode acts as a control switch to enable energy flow from the supercapacitor and battery to the DC bus, as shown in Fig. 7. When the supercapacitor voltage is subordinate to the battery voltage, the battery only supplies power directly. As a direct consequence of this, the load profile of the battery is stable. Furthermore, the battery isn't directly charged by regenerative braking; therefore, the battery will be protected from frequent charging, which extends its life.

Song et al. [31] developed a semi-active controlled HESS with a unidirectional DC/DC converter to reduce battery capacity loss and improve the system efficiency, as shown in Fig. 8. The primary purpose of the unidirectional DC/DC converter in this configuration is to store the regenerative braking energy in the battery once the supercapacitor has been fully charged. The China Bus Driving Cycle (CBDC) was utilized to estimate the efficacy of the design. Driving and braking modes are the two modes of operation that can be used with these systems. The supercapacitor can provide all the essential power for the electric motor if the voltage of the supercapacitor in the driving mode is greater than the voltage of the battery. If the supercapacitor voltage is less than or equal to the battery voltage, the battery, and supercapacitor both power the electric motor concurrently when in driving mode. When the vehicle is in brake mode, the supercapacitor stores all the regenerative braking energy if it is not fully charged. If the supercapacitor is fully charged, the entire amount of regenerative braking energy is stored

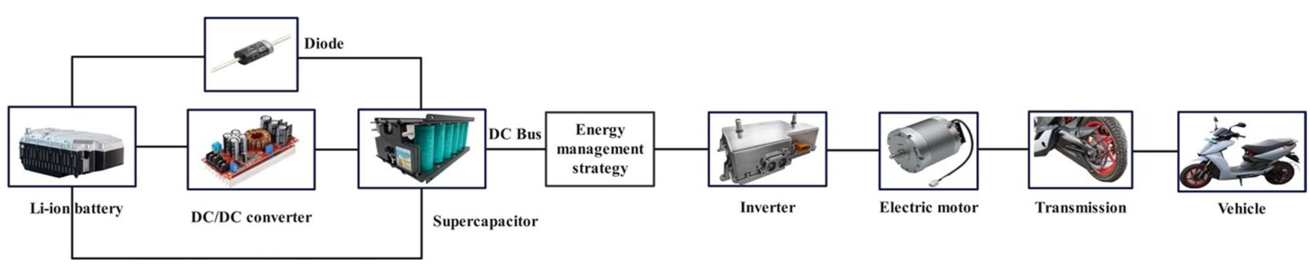


Fig. 7 Semi-active controlled HESS with diode

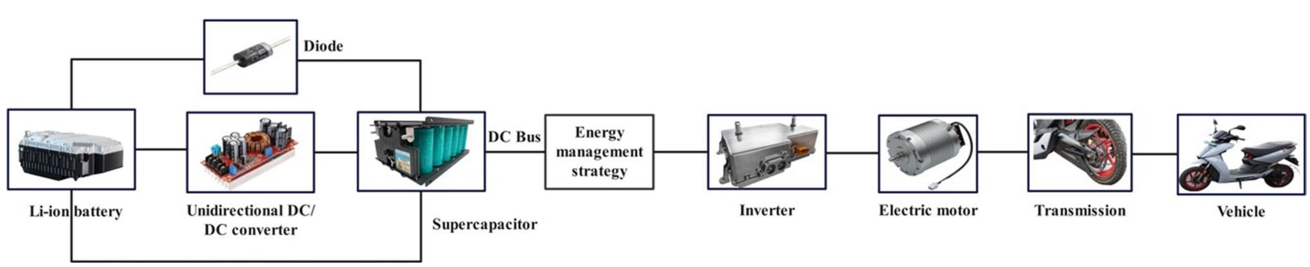


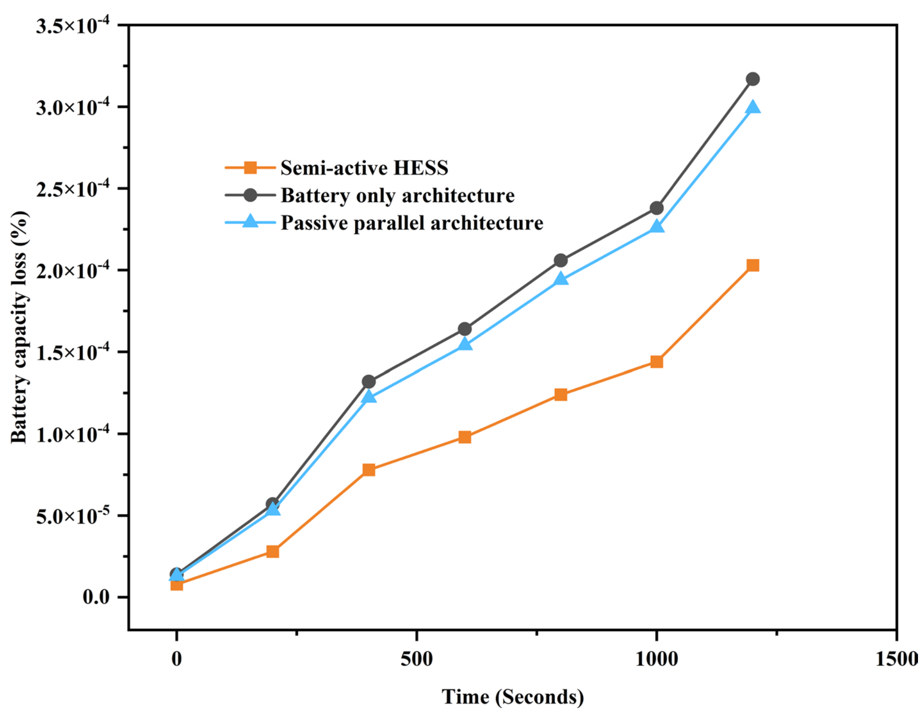
Fig. 8 Semi-active controlled HESS with unidirectional DC/DC converter

in the battery. The amount of strain placed on the battery is decreased due to this configuration. In this study, the author contrasted passive controlled and semi-active controlled HESS with the battery-only configuration. To power the electric motor in passive mode, the battery was directly connected to the supercapacitor through the DC bus. In a battery-only configuration, the electric motor receives all the power it needs from the battery. The results assure that capacity fading for semi-active managed HESS is 40% lower than the other two configurations, as shown in Fig. 9.

Walvekar et al. [25] investigated the performance of active controlled HESS for electric two-wheelers using MATLAB Simulink. In this study, MATLAB Simulink was used to model the vehicle, driving cycle, electric powertrain, and HESS of an electric two-wheeler. The key objectives of this paper are to extend the battery's life by lowering current transients and enhancing the system's peak power capacity. This study analyzes three different configurations of HESS with distinct levels of hybridization. According to this analysis, as the degree of hybridization (%) increases, the peak current consumption and voltage fluctuation of the battery decrease. However, beyond a 20% degree of hybridization, there was no appreciable improvement in the battery characteristics, as shown in Fig. 10. The results show that active/semi-active controlled HESS performs better than passive controlled HESS, and the design of HESS and the % of hybridization have an impact on the system's efficiency and battery life.

For EVs, Porru et al. [36] designed a HESS that protects the battery pack from power fluctuations. A neutral point-clamped converter is used in this system to link the battery pack and a supercapacitor module. This study integrates a supercapacitor into a DC bus, which adjusts the voltage over an extensive range, and it can be used to its maximum potential. By making efficient use of the supercapacitor, the HESS can prevent the battery pack from supplying high peak currents during the acceleration and deceleration of an EV. Proper management of the HESS energy flows, which was made possible using a suitable neutral point clamped converter system, made it possible to provide a high peak current. From the simulation results, it was concluded that the addition of a supercapacitor to an ESS enhances the performance of the EV based on different configurations of the system. The simulation, design, and experimental validation of power electronic interfaces for HESS EVs were developed by Kumar et al. [37] in their research. The primary objective of the author is to offer the required acceleration and deceleration while imposing as little stress as possible on the battery pack. In this research, the battery and supercapacitor pack are coupled using buck converters and buck-boost converters. The battery pack's primary job in this architecture is to supply the nominal current required by the motor. The supercapacitor and battery pack both provide the necessary power when the motor is accelerating because a high current is needed. When the speed is stable, less current is needed; therefore, the battery pack is the only source of power. The battery pack does not receive the regenerative impulsive current created by the motor during braking; instead, a supercapacitor pack is used to store it. Based on the simulation and experimental

Fig. 9 Battery capacity loss versus Time



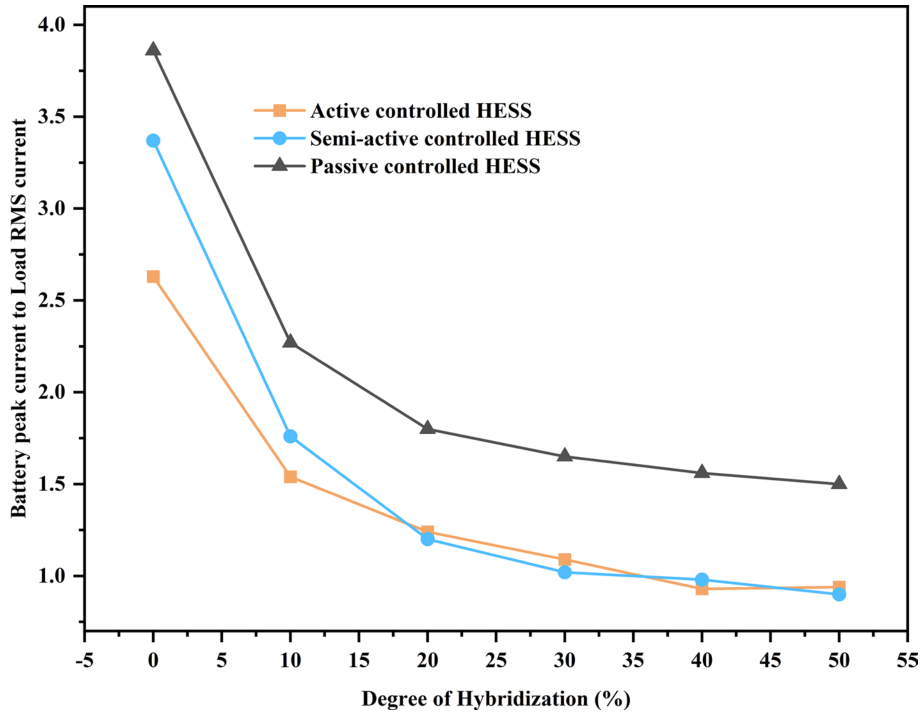


Fig. 10 Degree of hybridization versus Battery current

outcomes, the reduction of battery current will reduce battery stress. Chuan et al. [23] compared the battery-only configuration with passive controlled HESS for EVs in simulation, mathematical modeling, and experimental studies. From the results, compared with the battery-only configuration, passive controlled HESS has 2.6 times the power capability, an increase of 30% in discharge time, and a 6% increase in energy efficiency. This is because the supercapacitor pack provides a large amount of power during pulse power demands. The four different semi-active controlled HESS configurations for an EV with a battery-only configuration are compared by Song et al. The author's primary goal is to validate the HESS's efficiency while also lowering its total cost. The author uses dynamic programming (DP) to optimize the four HESS configurations. A bidirectional DC/DC converter connects the supercapacitor to the battery and DC bus in the first configuration, as depicted in Fig. 3. This configuration supplies unique voltage for the supercapacitor and battery. Its frequent operation under pulsed and peak power circumstances, which lower system efficiency, and make it costly. As seen in Fig. 4, the second configuration uses a DC/DC converter to link the battery to the supercapacitor and DC bus. In comparison to configuration 1, this arrangement reduces the DC/DC converter's power output. The third configuration is shown in Fig. 5 and isolates the battery from the supercapacitor/DC bus using a small DC/DC converter and a diode. With this configuration, the DC/DC converter's power output can be further reduced. When the supercapacitor voltage drops below the battery voltage, the system's working range is restricted, and the DC bus voltage changes. In configuration four, as depicted in Fig. 7, when the supercapacitor has been fully charged during regenerative braking, a small unidirectional DC/DC converter is needed to regulate the energy flow to charge the battery. This configuration lowers converter costs while improving system efficiency. The results of the sizing validate that:

- Configuration four has a high operation cost because its control strategy lacks the degree of freedom;
- Configurations two and three have comparable results; and
- When the supercapacitor cost is low, configuration one achieves a lower cost than configuration two, and when the supercapacitor cost rises, the cost is higher than that of configuration two.

According to simulation studies, the semi-active regulated HESS's overall running costs have been reduced by 50% when compared to a battery-only architecture as shown in Fig. 11 [32]. Wasim et al. proposed an active parallel HESS to reduce the pulsed load on the EV. In this research, the author utilizes the supercapacitor to supply the pulsed load requirement of EV. The capacity of the battery is reduced by 50% because of the proposed HESS [38].

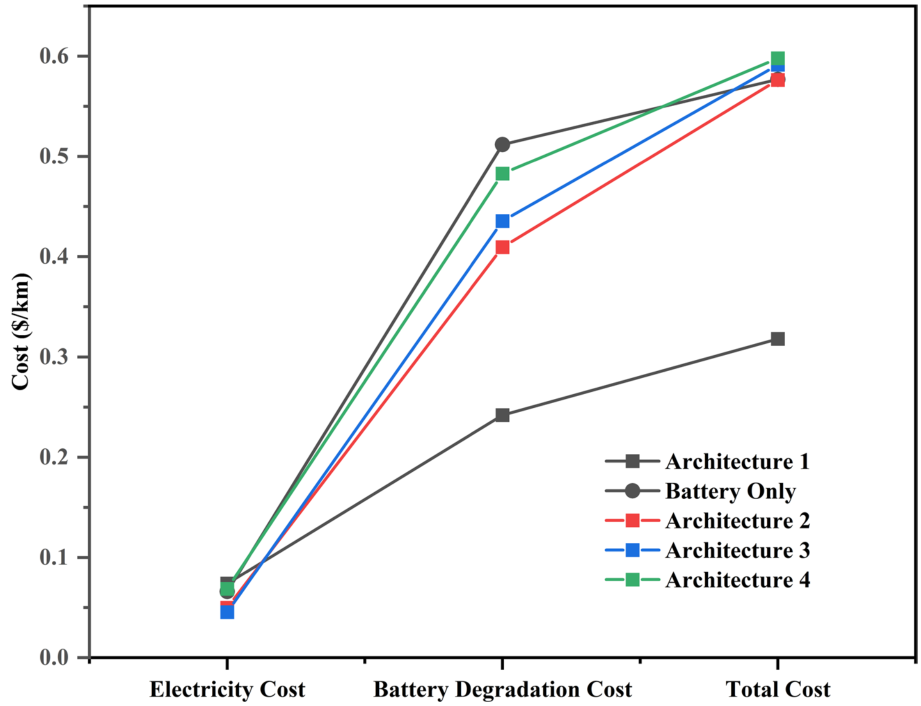


Fig. 11 Overall running cost of HESS

3 Energy management strategies for HESS

Energy management strategy enhances the benefits of the HESS for EVs, through continuous monitoring and power-flow splitting. As part of the EMS design, the following are considered: the vehicle's speed, acceleration, state of health (SOH), load voltage, current demand, and state of charge (SOC) of the battery and supercapacitor. EMS for HESS is classified into two types: Rule-based and Optimization-based strategies as depicted in Fig. 12.

A mathematical model creates the rules of the rule-based EMS, and the rules are based on deterministic and fuzzy modes. Global and real-time algorithms are two types of optimization-based methods. Rule-based strategies depend on pre-established control principles and can't be adjusted to changing load situations. Zheng et al. [39] validated the effectiveness of HESS in simulation and experiments in the semi-physical rapid control prototype (RCP). To improve the performance of HESS, this study develops an adaptive rule-based strategy. The EMS's control parameters were developed using the established driving circumstances in this study. Electrical loading equipment is used for the validation of the RCP test to improve precision and reduce validation risk. Based on experimental and simulation validation, the HESS achieves a 76.5% decrease in average output power variation rate and a 2.8% battery energy savings. It improves the battery's lifetime and reduces the capacity loss of the battery compared to a battery-alone configuration. Zhang et al. [40] proposed a rule-based and power-balancing strategy to keep the battery under the peak current requirement without overcharging or overdischarging the supercapacitor to improve the performance and lifetime of the battery. Experimental validation shows that the HESS increases the battery lifetime by sharing the low-frequency current demand and distributing the high-frequency current demand to the supercapacitor pack. Nguyen et al. [41] implemented a combination of rule-based strategy and predictive energy management in HESS. Rule-based current distribution in a supercapacitor depends on battery control current, charging current, and regeneration currents. The battery control current, regeneration current, and reference voltage for the supercapacitor are all determined by predictive energy management. The supercapacitor's reference voltage is calculated continuously to determine whether to charge it or discharge it. For the battery's entire trip, global optimization determines the ideal control and regeneration current values. Battery usage can be decreased by up to 13%, and battery energy deficiencies can even be decreased by up to 63%, both of which will increase battery lifetime based on simulation. To ensure that the supercapacitor pack can supply the high current demand during acceleration and deceleration, ElGhanam et al. [42] developed a rule-based strategy with an ideal supercapacitor sizing model. The depleted supercapacitors will receive a charge from the battery so that they can provide high current demand. According to the simulation results, HESS improves the battery capacity deficiency assessed in the battery-only configuration and lowers the peak current to 55.7%. Bai et al. [43] developed a 2nd-order controller (H_∞ controller) to control the output and input charging current of the supercapacitors. In this research, the

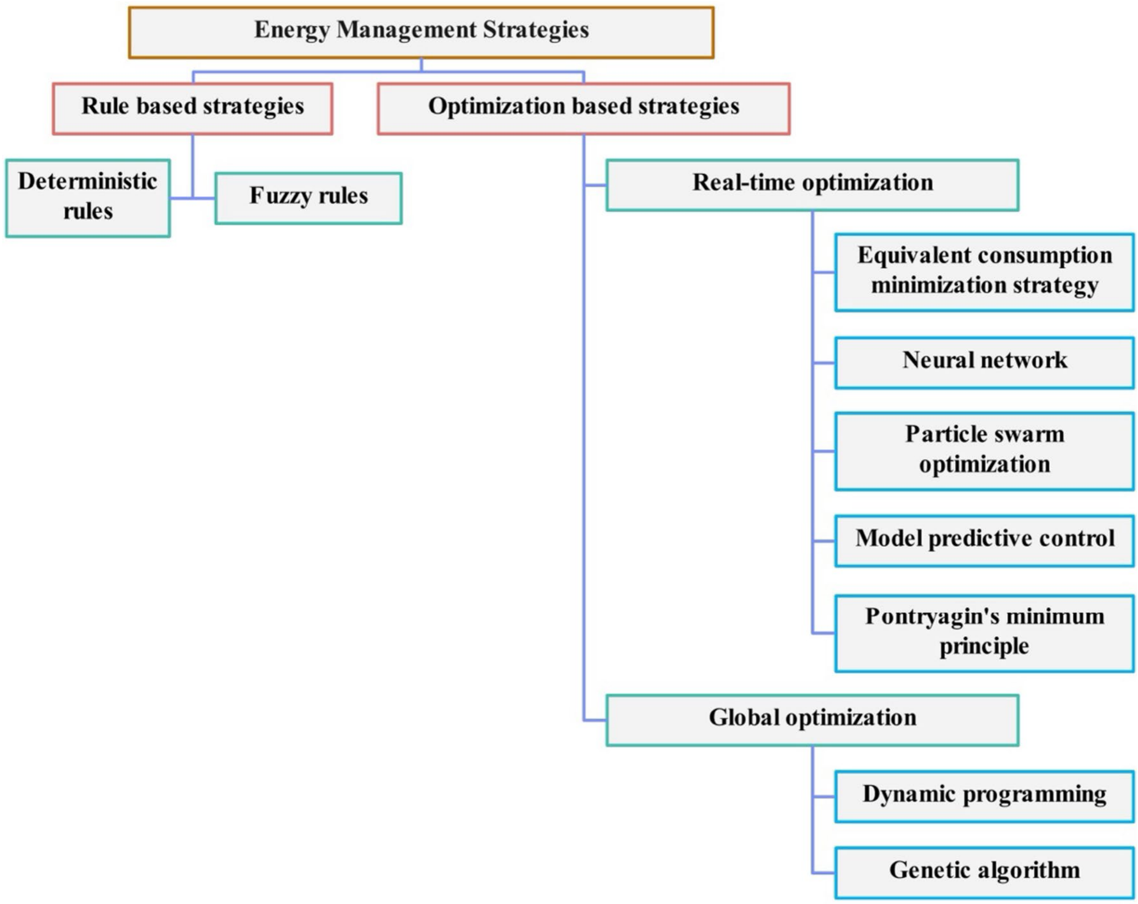


Fig. 12 Types of energy management strategy for HESS

author utilizes a rule-based strategy to identify the supercapacitor current, which is regulated by the H_∞ controller, to improve the effectiveness of the EMS. Zhang et al. developed a unidirectional semi-active HESS with two switches to replace the bidirectional DC/DC converter. The main objective is to reduce battery degradation while increasing braking energy regeneration. When it comes to distributing power between the battery and the supercapacitor pack, a rule-based strategy is applied. A control strategy based on different driving cycles with seven operating modes. The selection of the operating mode is determined by the demand power and SOC of the ESS. Simulated results indicate that this HESS reduces battery degradation by 30% when compared to other HESS. According to Shende et al. [44], battery parameters can be improved by implementing a rule-based strategy. The supercapacitor serves as a secondary source of income in this, with the battery serving as the primary source. Supercapacitors are employed in this research to provide for and absorb the high peak power demands. The strategy that is being suggested reduces the amount of variation in the current that is being input and output by the battery. Hussain et al. [45] proposed a real-time EMS consisting of a fuzzy logic controller-based low-pass filter (LPF) and an adaptive proportional integrator (PI)-based charge controller. The key objective of the suggested EMS is to lessen the battery's stress, temperature, and power losses. The adaptive LPF continuously updates the load current and SOC of the supercapacitor to the fuzzy logic control as an input, and the output is the frequency. The adaptive PI-based charge controller is used to protect the supercapacitor from over-discharging and undercharging. According to the findings, the EMS lowers the stress on the battery as well as the temperature and the amount of power that is lost. A HESS EMS with a bidirectional multi-input converter (MIC) for EVs was presented by Akar et al. There are three distinct modes of operation that the MIC can execute: charging or discharging, regenerative, and discharging. The mode of operation is identified with the fuzzy logic-based EMS through the examination of the output voltage. The reference battery power is decided by a fuzzy logic control, considering the output voltage and SOC supercapacitors, to determine if the output needs to be energized. The battery is then ensured to meet the necessary load demand and utilize all the braking energy by regulating the SOC of the supercapacitor at a reference value using the reference power. A rate limiter regulates the slew rate of the battery power reference while a PI controller modulates the battery current to reach the desired battery power. To choose between charging and discharging modes, the suggested control method compares the battery and output power levels [46]. Jaarsveld et al. [26] developed an active controlled HESS to reduce the peak power drawn from the battery. In this research, the author uses fuzzy logic to control DC/DC converters and a rule-based control strategy to regulate the operating modes of the HESS, as shown in Fig. 13. Based on the experimental implementation, active controlled HESS effectively reduced the peak power requirement of the battery. Zhang et al. [47] predicted the future load power requirements using the Markov chain model. The predicted results are used by an LPF and a fuzzy logic controller to reduce the battery peak current. In this, the author validates the effectiveness of EMS in both simulation and experiments. Based on the results, compared with conventional control strategies, the EMS reduces the peak current requirement of the battery.

Bo et al. [48] proposed a robust fractional-order sliding mode control (RFOSMC) for an active controlled HESS. This study tries to develop an RFOSMC strategy from four distinct aspects, as shown in Fig. 14. In stage 1, a rule-based strategy is developed to determine the optimal power demand and the current reference of the battery. The rule-based strategy considers factors such as traction condition, voltage of the supercapacitor, regenerative braking condition, and SOC of the supercapacitor and battery. In stage 2, a sliding-mode state and perturbation observer are used to approximate real-time values of nonlinearities, uncertainties, and disturbances. In stage 3, a fractional order proportional derivative (PD) is used to improve reference tracking performance and meet the requirement of only battery current and DC bus voltage measurements for easier implementation. In stage 4, the RFOSMC implementation is verified using a dSPACE-based hardware-in-the-loop (HIL) test system.

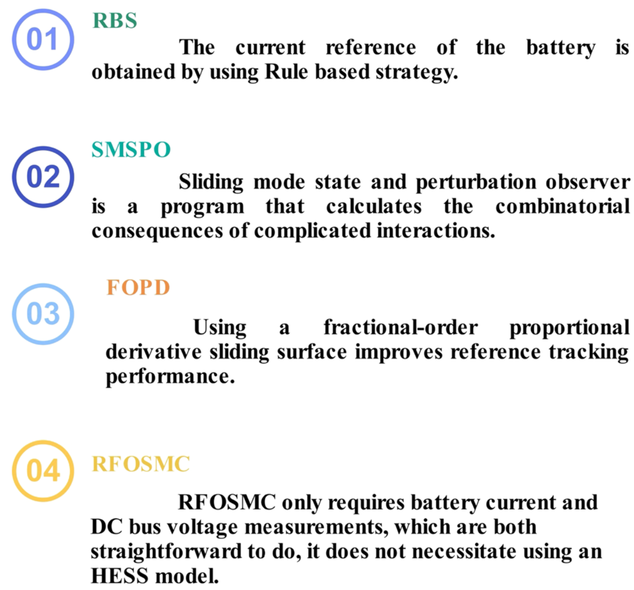


Fig. 14 Distinct aspects of RFOSMC strategy

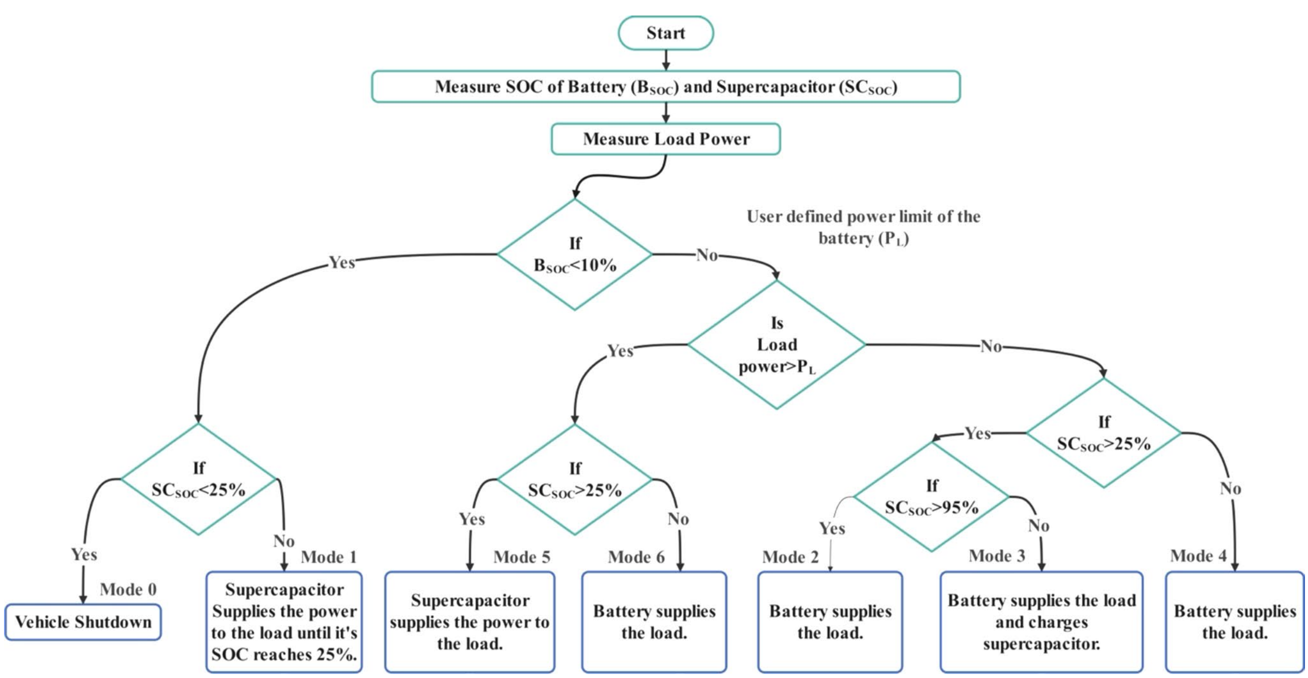


Fig. 13 Flowchart of the Flow of operations for Rule-based EMS in HESS

In comparison to previous strategies, RFOSMC enhances tracking performance.

For EVs operating under real-time constraints, Castaings et al. [49] compared and examined the effects of supercapacitor voltage on optimization-based (λ-control) and rule-based (filtering) strategies. In the filtering-based strategy, the battery current reference is carried out by applying the battery with a low-frequency current while the supercapacitors provide a high-frequency current. The LPF's output is the battery current reference, and the relationship between its value and the LPF's cut-off frequency is direct. The frequency value will be selected to reduce the battery current's root mean square (RMS) value. When the supercapacitor voltage manages to reach its maximum or minimum value, the battery current reference is modified to gradually revoke the supercapacitor current. The optimal control level is reached at the first level of the optimization-based EMS, known as the λ -control strategy. In the second level, the necessary battery current reference complies with the demands of optimal control. The results of the experiments show that the two strategies behave similarly in unpredictable real-world driving cycles. The battery current's RMS value varied by 2% between the two optimization and rule-based strategies. According to the results, the optimization-based strategy is better for a varied range of supercapacitor voltages. Rule-based EMS are efficient as they do not require any complex calculations. However, it has limitations as follows: Due to their rigid predefined rules, which could not cover all possible responses, rule-based strategies are difficult to adapt to new conditions. Due to the requirement of periodic rule changes when input data or the environment changes, maintaining rule-based strategies can be difficult. Due to human design and decision-making influence, rule-based strategies may prefer some inputs or outputs over others, which can lead to bias.

Optimal control modes in HESS are determined as quickly as possible by optimization-based strategies. Most of the optimization-based strategies are based on model predictive control (MPC), genetic algorithms (GA), particle swarm optimization (PSO), and DP. Liu et al. [10] developed a load-adaptive real-time energy management strategy for HESS using DP optimization to optimize energy savings and extend battery lifetime. Control rules for the strategy are developed based on the four different driving cycles. Load-adaptive real-time EMS outperforms the rule-based strategy in terms of low computational cost, battery energy savings, and reduced battery capacity. Zhu et al. [50] observed a three-dimensional DP approach to find the optimal size and sensitivity analysis of a HESS for EVs to lower the financial cost over the life of the vehicle. In this study, the optimization of sizing has six steps.

- In step 1, vehicle parameters (driving range, driving cycle), HESS configuration (passive, semi-active, or active-controlled HESS), and HESS parameters (Cost of the supercapacitor, battery, and DC/DC converter) are taken as inputs.
- The optimization algorithm iterates through the viable set of HESS sizes in step 2, which is bound by the energy and power necessities of the vehicle propulsion.
- In step 3, the process of optimization travels through the EMS in conjunction with the timeline.
- In step 4, the optimization process calculates the electrical level of the HESS parameters (SOC, SOH, voltage, and current).
- Based on the analysis, the objective function estimates the financial cost of the vehicle during its lifetime in step 5.
- The DP strategy can determine the optimal scenario for the size and EMS of the HESS in step 6 based on the preceding phases.

The system's sensitivity analysis takes a one-at-a-time approach, assessing one element at a time while maintaining the performance of the other factors. The sensitivity elements include the cost of the supercapacitor, battery, and DC/DC converter, driving cycle, driving range, HESS configuration, nominal bus voltage, and efficiency of the DC/DC conversion. According to the investigation, reducing the size of the HESS configuration will lower the cost of the HESS. Battery deprivation accounts for the majority (more than 75%) of the HESS's cost. About 11% of the HESS cost is allocated to supercapacitor packs and DC/DC converters. The vehicle driving cycle is the most dominant factor in the cost of the HESS because it determines the power requirement from the battery and supercapacitor pack. Wang et al. [51] proposed a two-layer adaptive DP optimization EMS to provide real-time power distribution to the ESS. The driving level is determined by the higher layer's driving pattern recognition (DPR) using learning vector quantization. Based on the findings of the recognition, the lower layer modifies the power allocation between the battery and supercapacitor pack. The purpose of DP is to define a cost function that reduces energy loss and maximizes battery life. According to the simulation results, the suggested EMS increases system efficiency when compared to a rule-based strategy. Based on flexible perception and neural network (NN) fitting, Zhu et al. [52] developed adaptive energy management of a HESS for EVs. The primary objective of the research is to increase system efficiency while simultaneously reducing the overall system cost. Using a DP approach, the finest offline EMS is created, distributing the HESS power to the supercapacitor and battery pack as efficiently as possible. The best EMS that DP can solve can only be used on an offline scale and cannot be implemented online because DP needs knowledge of the full driving cycle before initiating optimization. The following tasks can be accomplished via adaptive online EMS with variable perceptual horizon and NN:

- Record each microtrip's driving behavior;
- Real-time prediction and updating of the power boundary; and
- Recreate the "*N*-shape" link between supercapacitor operating power and HESS power requirements.

The 200-s micro-trips that make up the real-time driving circumstances are divided by the variable perception horizon. The current horizon's driving behavior will be extracted as each horizon concludes to enforce the power prediction made by HESS. The NN used in this study predicts just one outcome from three driving states as input. The rule-based approach predicts the direction of HESS's power, either positively or negatively. If the result is negative, the supercapacitor pack is probably capable of recovering its charge. The supercapacitor is anticipated to execute power peaking and collaborate with the battery if the test is positive. As a direct result of this, the EMS now features significantly less complexity, flexibility, and perceptive decision-making. Santucci et al. [53] validated the MPC and DP strategies in simulation with a rule-based strategy to reduce battery aging for different driving cycles. The power is divided using a rule-based strategy, matching the needs and SOC of the supercapacitor pack. MPC strategy involves the prediction of future output, evaluation of the cost function, and adaptation of control policy with high accuracy and low computational cost. The MPC strategy has a low hierarchical level, which makes it more practical for real-world implementation. A DP strategy was developed to understand the potential benefits of global optimization through a driving cycle. From the simulation results, the MPC strategy reduces the RMS value by 6% and the peak value by 17%, and the DP strategy further reduces the RMS value by 10% and the peak value by 45%. According to Zheng et al. [54], based on Pontryagin's Minimum Principle (PMP), it can reduce battery capacity loss and energy consumption. PMP instantaneously calculates and allocates the required power and regenerative braking energy to the ESSs. The PMP minimizes energy consumption and capacity loss, according to the simulation results. Pravin et al. [55] developed an optimal control algorithm for energy management in HESS using a deep neural network (DNN). It employs DNN to help the proportional integral derivative (PID) controller learn and forecast the control parameters to achieve optimal energy management. Squirrel search with improved food storage (SS-IFS), a model meta-heuristic technique, is suggested for creating the ideal controller parameters. The fusion of DNN and SS-IFS improves the accuracy and performance of the HESS. Sharma et al. [56] proposed an NN-based PI controller for HESS for EVs in MATLAB Simulink. The proposed controller will cut down the ripple current, which will result in an increase in the battery's life and the amount of energy it can recover. Zhang et al. [57] developed an NN-based strategy for the prediction of power requirements and a power distribution strategy for HESS. For the efficient prediction model, it groups the driving cycles into three distinct driving patterns. To train the NN and distribute predictive information, characteristic parameter data were extracted from the driving pattern. PSO is used to allocate the power-sharing among the battery and supercapacitor based on an NN-based strategy. This strategy reduces the battery voltage, energy consumption, battery temperature, and cost of the system. Jiang et al. [58] proposed a power distribution strategy combining offline optimization and online DPR. The PSO algorithm is used offline to perform optimization on the power distribution parameters. To achieve online application and adaptability, a DPR that is based on NN is utilized in the Worldwide harmonized Light-duty vehicles Test Cycles (WLTC). Battery power fluctuations are mitigated, and the overall lifespan of the batteries is extended because of the strategy that was proposed. Powade et al. [59] developed a semi-active controlled HESS with PSO to improve the battery cycle life. PSO is utilized to achieve an optimal HESS for a given drive cycle. The results of a battery-alone configuration are compared to the results of an optimized HESS for both its size and its battery cycle life. The findings show that using HESS results in an increase of 8.927% in battery cycle life. Liu et al. [60] projected an improved Li-ion battery depletion model based on the electrochemical process of capacity fading and the effect of cycle current. A GA-based parameter identification approach was used to find the preliminary parameters of this system. To monitor model parameters and states throughout the cycle process, a particle filter-based architecture is intended. Remaining useful life (RUL) can be estimated by specifying the procedures for assessing short- and long-term degradation. Battery cycling test datasets with constant and variable cycling currents are used to validate the recommended prediction approach. The preliminary findings provided empirical support for the accuracy, precision, and practicality of the proposed strategy for HESS management. Chen et al. [61] analyzed the interface circuit and nonlinear control strategy for HESS using MATLAB Simulink. Three nonlinear control EMSs were used in this study to allocate power between the supercapacitor pack and the battery. Six different driving cycles were used to test the wavelet transform, moving average filter, and LPF EMSs. The wavelet transform outperforms the LPF and the moving average filter in terms of system effectiveness, according to the simulation results.

Wavelet-based power management for HESS was proposed by Masoud et al. to improve the battery lifetime [62]. Based on the frequency of the demand current, a wavelet-based EMS is created to reduce the fluctuations of the battery current. A wavelet filter is utilized in this work to facilitate the distribution of power between the supercapacitor and the battery. The high-frequency component is provided by the supercapacitor even though the demand power is less than the battery's maximum power. The battery satisfies the requirement for the low-frequency component of the energy demand. To show how effective wavelet-based power management is, it is compared to state of power (SOP) management and supercapacitor-based power management. The findings lead to the conclusion that wavelet-based power management has a battery lifetime improvement of 115% and 3%, respectively, over conventional energy storage systems and SOP management strategies. Nguyen et al. [63] proposed three adaptive schemes based on the supercapacitor's ability for the adaptive filtering-based strategy to improve the vehicle's performance and battery lifetime. Adaptive schemes based on SOC-based, energy-based, and voltage-based schemes have shown a significant reduction in the RMS value of the battery current. Based on the offline simulation and experimental validation, using HIL can reduce the battery's RMS current. Additionally, compared to a battery-only configuration, an adaptive filtering-based strategy lowers the battery current's standard deviation value by 83%. Ren et al. [64] suggested an adaptive power distribution strategy for HESS to reduce the battery energy in the electric vehicle. To increase energy efficiency, an LPF developed with an adaptive strategy was utilized to determine the cut-off frequency and distribute the power demand among the battery and supercapacitor. The adaptive LPF strategy increases the use of the supercapacitor and increases the flexibility of the system. Utilizing this strategy can result in a 20–40% reduction in the amount of battery energy used based on simulation results. Hredzak et al. [65] proposed an MPC strategy to control the SOC of the battery, battery supercapacitor current, and voltage within the predefined limits. In this research, the author increased the MPC's objective function to reduce ultracapacitor voltage fluctuations. Based on the experimental research, supercapacitors responded to fast current changes, while batteries responded to slow current changes. Akhil et al. [66] simulated the proposed MPC strategy in MATLAB Simulink and validated it on the dSPACE platform for HESS. For DC-link voltage control, HESS provides a dynamic reference current computation. A power management algorithm lowers the battery discharge rate and balances the load and the sources. It predicts the battery and supercapacitor currents and efficiently produces them by modulating signals. Chen et al. [67] proposed a long short-term memory (LSTM) based speed detector method to predict the driving cycles for an MPC strategy to reduce the energy dissipation from the battery. The author uses simulation and a HIL platform to validate the efficiency of the EMS. Based on the results, evaluated with the fuzzy logic control strategy, the MPC strategy reduces the energy dissipation from the battery by 15.3%.

Optimization-based strategies can handle complex problems and adapt to environmental changes. However, it has the following disadvantages such as the iterative process through which optimization-based strategies evaluate the objective function and constraints repeatedly until a solution is discovered makes them computationally expensive. The solutions of optimization-based strategies vary depending on the initial conditions, which may result in slow convergence or perhaps even non-convergence. The need for specialized algorithms and a full understanding of the problem might make it difficult to implement optimization-based strategies, especially for complex problems. Xu et al. [68] recommended a hierarchical Q-learning network for the optimization of energy effectiveness and battery lifetime. The Q two levels of the hierarchical Q-learning network are $Q1$ and $Q2$, respectively. It also features a power distribution layer that uses the data saved in the upper layer to calculate the power distribution between the battery and the supercapacitor. As a trigger, the $Q1$ and $Q2$ layers are utilized in the activation of the supercapacitor. To increase energy efficiency and the battery's lifespan, the $Q2$ layer gives the supercapacitor additional control and flexibility. The proposed hierarchical Q-learning network is contrasted with rule-based and single-layer Q-learning methods. According to the findings, the proposed strategy enhances range by 1.5% and reduces battery capacity loss by 20% when compared to a rule-based strategy without a supercapacitor. The suggested hierarchical Q-learning system reduces battery capacity fade by 13% and substantially extends the battery lifetime when compared to a single-layer Q-learning approach. Sarvaiya et al. [69] explored the four EMS for extending battery life and improving fuel efficiency. Fuzzy logic control, adaptive equivalent consumption minimization strategy (A-ECMS), thermostat, and Q-learning are four control methods that are investigated concerning battery aging. The outcomes of the four control strategies are contrasted in terms of battery lifetime. Based on that analysis, the A-ECMS statistics validate an improvement in battery lifetime over the rule-based strategy. Xiong et al. [70] compared the rule-based, reinforcement learning, and DP strategies to verify the power distribution of HESS in HIL. Based on experimental and simulation validation, real-time reinforcement and DP strategies are more effective at lowering the battery's discharge current and improving battery lifetime than a rule-based strategy. Wu et al. [71] suggested an adaptive power allocation technique based on an artificial potential field with a compensator. To secure the SOC limitation of the supercapacitor, a potential field is composed at the level of power allocation. The load power allocation ratio serves as a mapping for the simulated forces that are present in this field. The cut-off frequency is calculated by taking the load spectrum and dividing it by the allocation ratio. A feed-forward compensator is employed at the control level to predict load fluctuations and avoid DC-link fluctuations. The authors investigated battery capacity loss in various driving cycles using the supercapacitor's SOC at distinct levels. According to the author, the supercapacitor's SOC is found to play a role in the battery's life extension and capacity loss. The suggested adaptive power allocation strategy reduces battery capacity loss in the urban driving cycle by more than 15%. Pan et al. [72] proposed a hysteresis current control strategy to improve the operating range of the EVs. In MATLAB Simulink, the HESS and EMS were developed, and the drive cycle test was performed. The operating modes of this EMS are determined by the battery discharge and the DC bus current. In stage 1, the currents flowing through the DC bus and the battery discharge are equal. In this scenario, the battery is the only source of power that can be drawn from. In stage 2, the required current through the DC bus is greater than the required current through the battery discharge. In this situation, the power demand that must be met can be satisfied by either battery or supercapacitor. The DC bus current that is required in stage 3 is less than the current that is being drawn from the battery. Under these conditions, the battery will be able to satisfy the required levels of power while simultaneously recharging the supercapacitor. The supercapacitor will recuperate the kinetic energy generated during the braking in stage 4 once the vehicle is in braking mode. According to the simulation results, a dual ESS system increases the operational range of EVs while lowering the peak current discharge of the battery as compared to a battery-only configuration. Zhang et al. [73] developed an EMS for a HESS in MATLAB Simulink and used an NN, wavelet transform, and fuzzy logic to make the system more efficient and extend the battery's life as shown in Fig. 15. Nine typical driving cycles serve as the datasets for the Haar wavelet in this research. Four separate operational cycles are used to evaluate the effectiveness of the strategy. The power demand is divided into low and high frequency components using frequency decomposition. The low-frequency component is used by the NN after decomposition. In this work, the frequency decomposition algorithm and load power requirement serve as the NN's inputs. Datasets are utilized to train the NN model (80% of training samples) in the lower frequency portion of the driving cycle, with the remaining 20% created based on performance validation. The fuzzy logic controller has two input variables: slow variation power demand and supercapacitor voltage. The results of this study were validated on a real-time hardware platform. From the results, it is identified that supercapacitor and battery current are reduced, voltage fluctuations are reduced, the battery cost is lowered by 18%, and it recovers 44% more regenerative braking energy when compared to conventional algorithms.

Yang et al. [74] proposed uninterrupted dual input transmission (UDIT) and HESS to advance energy efficiency and battery life compared to single ratio transmission (SRT) and battery electric vehicles. An optimal control strategy was created to assess the integrated system's battery power and capacity degradation based on various driving cycles. Instead of SRT, UDIT uses two traction motors and three modes of operation (Motor 1 drives, Motor 2 drives, and Motor 1 and 2 drives) based on the required power. To improve HESS's parameters, a mixed-integer, multi-objective genetic algorithm is created. The objective of the algorithm is to achieve a balance among energy consumption, battery degradation, and acquisition costs. The algorithm generates Pareto-optimal solutions by balancing cost, energy loss, and battery life. According to the simulation results, the suggested UDIT has a 19% higher energy efficiency than SRT and a 30% lower rate of battery capacity loss. Wang et al. [35] suggested an average power method for power-splitting of the semi-active controlled HESS. The supercapacitor can function as a power filter modification due to the average power approach used in the suggested solution. As a result, the battery must deliver stable, compensatory power to the motor. The reference power ought to be greater than the final average power based on the average power demand. The power distribution and mode selection are as follows: The pure supercapacitor operating mode will be started in the driving mode if the supercapacitor voltage is greater than 95%. The battery operation mode is started if the supercapacitor voltage is between 71 and 95% and the power

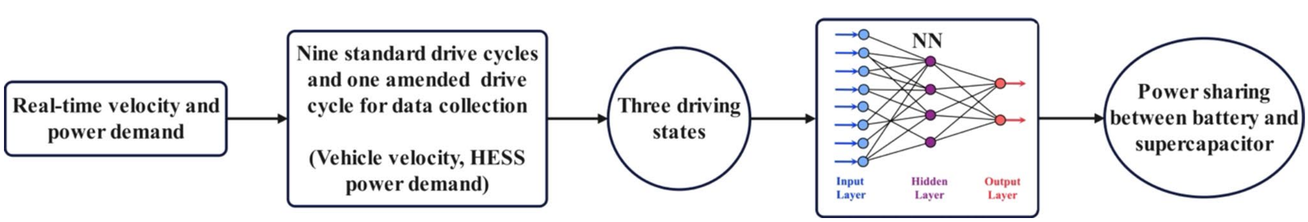


Fig. 15 The structure of an optimization-based EMS for the HESS

consumption is lower than usual. Both the supercapacitor and the battery must provide the necessary power if the power demand is equal to or more than the average power. In the braking mode, if the supercapacitor voltage is less than 95%, energy recovery mode is activated during the braking to charge the supercapacitor. The proposed power-split approach is verified using the Simulink model in the Urban Dynamometer Driving Cycle (UDDS). From the results, it is identified that a reduction in high-frequency power consumption from the battery will increase battery life and reduce battery stress. Zhao et al. [75] investigated HESS's energy transfer and distribution technique to improve regenerative braking energy recovery and utilization efficiency. An approach to power distribution was suggested by the author to improve energy recovery and efficiency. For HESS, quantitative formulas are developed specifically to evaluate the rate of regenerative braking energy recovery. Comparing the proposed allocation approach to various power distributions, it has been found that the suggested allocation strategy can increase HESS's efficiency. Hu et al. [76] proposed an intelligent EMS for HESS for EVs based on DPR. A wavelet transform module, a DPR module, and a fuzzy control module compensate for this EMS. The DPR categorizes driving cycles into different patterns based on characteristics acquired from prior driving data sampling windows using cluster analysis and pattern recognition. DPR is used to differentiate between different driving patterns in real-time. To transfer the high-frequency components of the power demand to the supercapacitor, an adaptive wavelet transform is utilized. These impulsive shifts in power levels, as well as their inconsistency, are a direct consequence of the recognition discoveries. On the other hand, the battery is subject to receiving low-frequency components. Using the fuzzy logic module, the SOC of the supercapacitor can be maintained at the level that is desired. The results of the simulation show an increase in both the lifetime of the battery as well as the effectiveness of the system. Capasso et al. [77] suggested a revolutionary energy management strategy for HESS to improve battery lifetime. The current battery profile is optimized for specific operating cycles using a nonlinear programming prototype offline technique. This has led to the development of a real-time control technique based on a limited minimization problem. This control method decreases the peak charging and discharging currents to enhance battery lifetime. Armenta et al. [78] developed an advanced EMS for controlling the supercapacitor discharge and increasing the range of the EVs. This research suggests an adequate discharge of energy from the supercapacitor to use all the energy produced by regenerative braking. For the validation of EMS, the author uses the MATLAB Simulink model of the electric vehicle. Results show that effective utilization of regenerative braking energy reduces the energy consumption of EVs and increases their operating range. Veneri et al. [79] investigated the effectiveness of HESS for urban commercial vehicles with three different EMSs. The first EMS is the threshold strategy (Th strategy), in which the battery pack supplies the motor drive with current up until the threshold value, which is already defined. Then, based on the variation between the battery and the electric drive current value at the threshold level, the supercapacitor pack supplies the required current. The second EMS is Exponential Weighted Moving Average (EWMA); in this method, the battery and supercapacitor pack combine to supply the motor drive with the necessary current. The voltage of the supercapacitor pack optimizes the charging and discharging operations in the third EMS, which is the Ke strategy. From the experimental observations, HESS provides high peak power demands, reduces the effects of high charging and discharging, and increases the lifetime of the battery pack. Zhang et al. [80] validated the EMS established by a combination of the Haar wavelet transform and MPC. While the battery responds to low-frequency components in the HESS, the supercapacitor pack handles the high-frequency power components. A filtering module is necessary since the distributed MPC is unable to automatically divide the load power demand into frequent components. Each power source has physical constraints that affect the received power; thus, the controller reference power must be established within those constraints. This research combines a filtering based MPC strategy with a distributed MPC strategy to achieve better control. The supercapacitor receives the high frequency of the power demand, which is split up into frequency components by the wavelet transform function, and the battery receives the low frequency. Relative management of power demand within the widest possible range is made possible by the MPC controller's performance being transmitted back to the wavelet transform for coefficient regulation. Liu et al. [81] investigated a parameter-matching strategy to optimize the HESS to ensure the power performance of EVs. There are three stages involved in implementing this strategy.

- In step 1, six driving cycles were analyzed to identify power demand and develop a kinetic equation for the vehicle model.
- Step 2 involved the calculation of the necessary amounts of energy and power.
- In step 3, the considerations for the combined power source are optimally matched based on cost, and weight.

So et al. [82] proposed an EMS and power management strategy to improve the battery's lifetime. The EMS ensures the SOC level of the supercapacitor for forthcoming accelerations while minimizing the SOC of the supercapacitor for storing regenerative braking energy. This is carried out through the utilization of a target supercapacitor energy band that consists of speed-dependent variables. The power management strategy has a speed-dependent battery power limit that ensures constant speed power and supercapacitor usage during low power requirements. Li et al. [83] adopted the Markov decision process (MDP)-based strategy with bilinear interpolation to compare it to the discrete power management strategy. The MDP-based strategy is used to distribute the power between the battery and the supercapacitor. Utilizes bilinear interpolation to smooth the power distribution and determine the required supercapacitor size and energy reserve for the supercapacitor. From the results, it is concluded that, compared with the discrete power allocation strategy, the proposed strategy reduces the energy loss by up to 10% and improves battery lifetime. Zhang et al. [84] used a wavelet-transform-based EMS to study the optimal size of HESS, considering battery health management, especially SOH, HESS weight, and manufacturing cost. A wavelet-transform-based EMS is used to distribute the power between the battery and supercapacitor, while UDDS represents real power demands. Katuri et al. [85] proposed a math function based (MFB) controller to achieve a smooth conversion between the battery and supercapacitor. The MFB controller was integrated with PI, PID, fuzzy, and artificial neural networks (ANN). The load that is placed on the motor determines how the MFB controller is operated. The controller's operational mode can be subdivided into one of four distinct sub-modes. A change in the power state will take place at some point, but it will depend on the operating mode. According to the findings of the simulation, the MFP controller ANN allows for a more seamless transition than the other combinations. Zhang et al. [86] proposed a combination of EMS based on fuzzy rules and real-time vehicle speed data. In this research, fuzzy rules are based on the SOC of the battery and supercapacitor to reallocate the required power, which is optimized by the real-time vehicle speed data. The author constructs the vehicle model with the help of an advanced simulation of a vehicle. From the simulation results, it is verified that the proposed EMS reduces the total energy consumption of the EV. Table 2 compares the configuration, EMS, simulation, experiment method, and driving cycles used for verifying HESS. Based on the study, several researchers have not focused on the real-time implementation of EMS due to the computationally expensive, complex strategy, and processing time. To overcome the drawbacks of rule-based and optimization-based EMS, several researchers utilized hybrid strategies (combinations of different strategies). However, in comparison to traditional strategies, hybrid ones are both more difficult to implement and more expensive.

4 Factors affecting the cost of HESS

Size, capacity, battery type, installation, maintenance, and operation costs are just a few of the variables that affect the cost of HESS. These factors can offset the higher upfront cost, making them a cost-effective preference for certain applications. The cost of HESS systems depends on the specific application and requirements, but they can be a cost-effective option for grid stabilization and renewable energy integration.

Lahyani et al. [87] studied the degradation of a valve-regulated lead acid battery (VRLA) combined with supercapacitors under pulsated load power. In this study, the VRLA battery underwent two aging cycles at 40 °C, with the first providing full pulsated load power and the second providing filtered power. An LPF in a HESS is used to filter the power for the battery. When the HESS battery is in its idle state, the supercapacitors are allowed to be recharged. From the results, it is identified that the smoothing power extracted from the battery increases the lifecycle of the battery. In this analysis, the battery-only system can perform for 150 cycles before it loses an initial capacity of 20%, while the HESS expects 255 cycles. Because the hybridized system decreases battery stress and energy consumption. Based on the increase in HESS cycles, the depreciated cost of the system was reduced to 17.6% compared to the battery-only system. Huang et al. [88] propose an optimization method based on DP that combines the influence of mass and driving behavior to optimize the EV load power and operation costs. This method considers load power variations, mass increases, and driving conditions, focusing on the mass of the supercapacitor. The optimal sizing of supercapacitors reduces operation costs by 3.96–6.54% compared to no mass influence. By slightly increasing supercapacitor packs, high-performance versions can obtain lower operation costs. The effects of various temperatures and battery costs on the integrated optimization of HESS are examined by Song et al. in their study [89]. Using the DP technique, the HESS operating cost of each supercapacitor size is reduced, and the best supercapacitor size is identified. The findings of the supercapacitor sizing indicate a considerable disparity in the capital cost of supercapacitors and HESS running costs. The ideal supercapacitor size is stable at a range of battery prices and temperatures, but the operating cost rises as supercapacitor capital costs rise. Based on DP results, which indicate a linear relationship between total power demand and supercapacitors, the best EMS for online applications can be identified. For the EMS to be reliable and work at its best in a variety of settings, it should be designed for variable battery costs and temperatures. Li et al. [90] proposed an incentive learning-based EMS for HESS to reduce battery depreciation and power loss costs. In this research, the

Table 2 A comparative analysis of different EMS for HESS

Ref	HESS config.	Energy management strategy	Simulation	Experiment method	Driving cycles
Zhu et al. [52]	Supercapacitor/battery semi-active	Combination of flexible perception and NN	MATLAB simulink	Real-time	"Unified" dynamometer driving schedule (LA92) representative drive cycle
Bo et al. [48]	Active	RFOSMC	MATLAB simulink	dSPACE	Based on operating condition
Santucci et al. [53]	Supercapacitor/battery semi-active	Combination of MPC and DP	Vehicle simulator	–	Federal test procedure (FTP75) Artemis drive cycle (ARTEMIS) new european driving cycle (NEDC) high-speed, steady-state driving cycle (US06)
Xu et al. [68]	Battery/supercapacitor semi-active	*Q*-learning	MATLAB simulink	–	UDDS worldwide harmonized light vehicles test procedure (WLTP)
Zheng et al. [39]	Supercapacitor/battery semi-active	Adaptive rule-based	Computer simulation	dSPACE	China automotive test cycle (CATC) NEDC UDDS
Zhang et al. [40]	Supercapacitor/battery semi-active	Rule-based	–	dSPACE	UDDS NEDC
Castaings et al. [49]	Supercapacitor/battery semi-active	Optimization and rule-based	Energetic macroscopic representation	dSPACE	WLTP real driving cycles
Xiong et al. [70]	Battery/supercapacitor semi-active	Rule-based, DP, and reinforcement learning	–	HIL	CBDC
Wang et al. [51]	Battery/supercapacitor semi-active	Two-layer adaptive DP	Monte carlo simulation	–	New York city cycle (NYCC) UDDS US06 LA92 The highway fuel economy test (HWFET)
ElGhanam et al. [42]	Battery/supercapacitor semi-active	Rule-based	MATLAB simulink	–	NYCC
Shende et al. [44]	Active	Rule-based	MATLAB Simulink	HIL	Indian driving cycle
Bai et al. [43]	Supercapacitor/battery semi-active	Rule-based	–	Real-time	Based on load demand
Zheng et al. [54]	Supercapacitor/battery semi-active	PMP	Simulation	–	UDDS NEDC Japanese 10–15 mode (Japan 1015)
Zhang et al. [73]	Supercapacitor/battery semi-active	Combination of NN, wavelet transform, and fuzzy logic	MATLAB simulink	Real-time hardware	Manhattan drive cycle (MANHATTAN) UDDS HWFET
Yang et al. [74]	Supercapacitor/battery semi-active	Real-time	Simulation	–	NEDC FTP75 LA92 HWFET UDDS WLTP
Masoud et al. [62]	Active	Wavelet-based	Simulation	–	FTP75
Hussain et al. [45]	Supercapacitor/battery semi-active	Real-time	MATLAB simulink	–	US06 ARTEMIS
Wang et al. [35]	Battery/supercapacitor semi-active	Power-split	MATLAB simulink	–	UDDS
Zhao et al. [75]	Supercapacitor/battery semi-active	Power-allocation	MATLAB simulink	–	NEDC UDDS

Table 2 (continued)

Ref	HESS config.	Energy management strategy	Simulation	Experiment method	Driving cycles
Hu et al. [76]	Supercapacitor/battery semi-active	Combination of wavelet-transform and fuzzy logic	MATLAB simulink	–	Based on operating condition
Armenta et al. [78]	Supercapacitor/battery semi-active	Adaptive rule-based	MATLAB simulink	–	City II urban driving cycle (ECE 15) NEDC
Pravin et al. [55]	Active	DNN and SS-IFS	MATLAB simulink	–	Based on operating condition
Nguyen et al. [63]	Supercapacitor/battery semi-active	Adaptive filtering	MATLAB simulink	HIL	ARTEMIS NEDC
Jiang et al. [58]	Supercapacitor/battery semi-active	PSO	simulation	–	UDDS WLTC NEDC US06
Powade et al. [59]	Supercapacitor/battery semi-active	PSO	MATLAB simulink	–	UDDS
Chen et al. [61]	Battery/supercapacitor semi-active	Fuzzy logic MPC DP	–	HIL	Speed predictor
Zhang et al. [80]	Active	Wavelet transform and MPC	MATLAB simulink	–	NYCC UDDS nurembergR36
Li et al. [83]	Active	MPC	–	Down-scaled platform	UDDS CBDC
Zhang et al. [57]	Active	NN	MATLAB simulink	–	India_Hwy_Sample NYCC UDDS India_Urban_Sample NurembergR36

Table 3 Life cycle cost for different driving cycles with SRT & BEV, UDIT & HESS

Driving cycle	System	Acquisition cost	Operating cost	Replacement cost	Manufacturing cost	Life-cycle cost	Enhance
NEDC	SRT & BEV	4669.83	503.71	4897.759	–	10,071.3	
	UDIT & HESS	4876.83	398.86	2454.926	60.84	7791.45	22.64%
FTP75	SRT & BEV	4669.83	486.75	4897.759	–	10,054.34	
	UDIT & HESS	4876.83	390.54	2454.926	60.84	7783.13	22.59%
LA92	SRT & BEV	4669.83	652.27	9747.38	–	15,069.48	
	UDIT & HESS	4876.83	545.84	4897.759	60.84	10,381.27	31.11%
HWFET	SRT & BEV	4669.83	1272.97	12,154.29	–	18,097.09	
	UDIT & HESS	4876.83	1028.83	7328.557	60.84	13,295.06	26.53%
UDDS	SRT & BEV	4669.83	436.01	4897.759	–	10,003.6	
	UDIT & HESS	4876.83	348.88	2454.926	60.84	7741.47	22.61%
WLTP	SRT & BEV	4669.83	792.38	14,549.34	–	20,011.55	
	UDIT & HESS	4876.83	666.74	9747.38	60.84	15,351.8	23.28%

author utilizes the MDP model to develop EMS based on the SOC of the supercapacitor and battery, and load demand. From the simulation results, the proposed EMS reduces the battery cost of capacity loss and power loss. Yang et al. [74] proposed a UDIT and HESS with a real-time control approach and compared the results to SRT with a battery-only configuration in EVs to lower the system's life cycle cost. Because of the supercapacitor, the UDIT and HESS have a higher initial acquisition cost than the SRT. However, the operating cost and replacement cost of the battery are significantly lower, which offers a better life cycle cost. The following Table 3 compares the life-cycle cost and enhancement of the different driving cycles with SRT, and BEV, UDIT, and HESS. The following expression has been used to express the life cycle cost:

Life cycle cost = Operating cost + Replacement cost + Manufacturing cost + Acquisition cost.

5 Effect of driving cycle on HESS performances

The driving behavior of the electric vehicle plays a significant role in the battery stress, battery peak current requirement, battery temperature, energy utilization, sizing of the system, and lifecycle of the battery in the HESS of an EV. Based on the driving behavior, it will have different energy demands, power demands, battery temperatures, and lifecycles of the battery. This section discusses the effect of the driving cycle on the performance of a HESS.

A fuzzy logic control strategy was used to create an active-controlled HESS by Jaarsveld et al. A fuzzy logic control strategy is utilized for the management of the DC/DC converters. Error and its derivatives are used in the fuzzy logic controller to decide what control action should be taken. A rule-based control method is utilized to maintain control over the HESS's operational modes. Depending on the amount of power the load draws, this system uses various operating approaches to govern the energy flow through the system. Based on experimental validation, this control strategy lowers the needed power rating from the battery and limits the maximum current dragged from it. The technology decreased the battery's required peak power for the WLTC class 2 driving cycle by 79%, the ECE 15 driving cycle by 84%, and the NYCC driving cycle by 90% [26]. Wu et al. [71] studied the capacity loss of different batteries with different driving cycles (LiCoO2 and Li ($NiMnCoO_2$)) and compared the results. In the US06 driving cycle, a LiCoO2 battery has a capacity loss of 0.0134 and a life extension of 1.5% with an initial SOC of 42% supercapacitor. The same battery has reduced half of the battery capacity loss and 13 times the life extension in the NYCC driving cycle, with an initial SOC of 84% of the supercapacitor when compared to the US06 Driving Cycle. On the other hand, the Li ($NiMnCoO_2$) battery has a capacity loss of 0.0450 in the US06 driving cycle under an initial SOC of 42% supercapacitor and a life extension of 0.889%. The same battery has been reduced to 0.0175 of the battery capacity fade and 23 times the life extension in the NYCC driving cycle, with an initial SOC of 84% of the supercapacitor compared to the US06 Driving Cycle. Saw et al. [91] developed a HESS to test the electrical and thermal performance under various driving conditions. The main goal of this study is to improve battery life by improving their safety and reliability. The functioning of the HESS is evaluated using the Simulink model with various driving cycles. In this configuration, the battery and the supercapacitor each contribute an equal amount of power to the overall system. From the results, compared to a battery-only configuration, UDDS and US06 driving cycles have lowered peak current demands on the battery by 63% and 72%, respectively. According to the findings of this research, the battery's dynamic stress, and peak current demand are reduced in the HESS. To improve the battery life of an EV's HESS, Hsieh et al. [92] simulated and tested the C-rate control technique. The suggested HESS delivers enough power for EV dynamic motions, keeping the battery current within an acceptable range to prevent battery deprivation. In conjunction with a lower current-sensing technology, a pulse-width modulation control mechanism is also developed. The current transformer supplies feedback to the DC-DC converter controller, which manages and monitors battery current variations. The suggested HESS can decrease the battery life fade by 2.4% per year, with an added 1.5 years of battery life. Zhang et al. suggested a real-time HESS EMS that includes filtering and fuzzy logic control [33]. The battery size of the battery-alone system and HESS is investigated for various driving cycles, as shown in Table 4. It reveals that the decrease rate for the Indian Urban Driving Cycle (IUDC) is higher, but the battery size is more significant than for the NEDC compared to the Highway Driving Cycle (HWDC). The primary factor that figures out the size of the battery is the peak current consumption of the system.

Xu et al. [93] validated the hierarchical Q-learning network with two baseline strategies for two driving cycles (UDDS and WLTP). The inclusion of a supercapacitor enhances the range by a small amount. The results show that including a supercapacitor in this system increases the operating range and reduces the capacity fading of the system. Chau et al. demonstrated the HESS in three different driving approaches: normal driving, acceleration/hill-climbing, and the braking/down-hill approach. The HESS was designed with a regulating attitude, allowing the batteries to always function at their graded output power level, with supercapacitors delivering and receiving the power differential during acceleration and hill climbing, respectively. Barcellona et al. [22] experimented with a passive-controlled HESS for EVs. In this research, the author compares two different driving cycles for three different EVs at three different operating temperatures. From the results, it is concluded that the driving behavior of the EV will affect its operating range.

Table 4 Comparison of reduction rate for driving cycles

Driving cycle	Battery only system (Wh)	HESS (Wh)	Reduction (%)
NEDC	1180	405.3	65.65
HWDC	1191	612.1	48.61
IUDC	2390	510.9	78.62

6 Impact of ambient and cell temperature on the performance of HESS

The ambient temperature and cell temperature of the electric vehicle play a significant role in the battery temperature, capacity fading, and lifecycle of the HESS of an electric vehicle. HESS has a significant impact on the thermal behavior of EVs. It is used to decrease the thermal stress on the battery, improve the efficiency of the climate control system, and improve the comfort of the passengers. This can help improve the range, efficiency, and overall driving experience of electric vehicles. The influence of HESS on the thermal characteristics of EVs is the topic of discussion in this section.

Barcellona et al. [22] experimented with a passive HESS for an EV at a low temperature. The main intention of this study is to verify the effect of adding a supercapacitor to the Li-ion battery pack on the operating range and starting possibilities of the EVs at low temperatures. For verification, passive-controlled HESS was compared with a Li-ion battery-only configuration at different operating temperatures. Based on the experimental results, the addition of supercapacitors supplies the possibility to start the EVs at low operating temperatures (− 20 °C) and extends the operating range. From the experiments, when the operating temperature is − 20 °C, the passive controlled HESS EV will start without trouble, with an average of 3.33 km of range extension. On the other hand, at an operating temperature of − 10 °C, the passive hybrid energy system has an average range extension of 37.2 km. According to Zhang et al. [73], environmental temperature and driving cycle selection affect battery capacity fading. In this, the author utilizes filtering and fuzzy logic control to reduce the requirement for battery energy capacity. Because the battery's peak current consumption is reduced, the battery's capacity fading cost is also reduced. In addition, the vehicle's operating temperature influences the cost of battery fading. For example, the capacity-fading cost of the IUDC is lower than that of the NEDC and Highway Drive Cycles. Therefore, the operating parameters are what determine the cost of the battery's capacity, which gradually diminishes over time. Song et al. [31] optimized the sizing of the HESS with three parameters under two operating temperatures. Parameter 1: low supercapacitor cost; Parameter 2: least battery capacity loss; and Parameter 3: trade-off between low supercapacitor cost and least battery capacity loss. From Table 5, the battery has an extended lifecycle of 67% in parameter 2 compared with the battery-only system. The author concluded that the battery capacity fades rapidly by increasing the supercapacitor's ability.

Table 5 Comparison of battery lifecycle in km for different parameters

Parameter	Battery lifecycle L_{Cycle} (10^5 km)
Battery	3.65
Parameter 1	3.93
Parameter 2	6.08
Parameter 3	6.75

Wight et al. [94] investigated the HESS's performance throughout a wide temperature range (between − 20 and 20 °C) and in rapid drive tests. According to the authors, the driving cycle has substantially influenced the efficiency of DC/DC-regulated supercapacitors in EVs. The peak current of the batteries was carefully managed, reducing the load on the batteries. The supercapacitors made it possible to harvest added energy from the batteries. However, the capacitor's ability to absorb regenerative braking energy quickly and increase EV efficiency was severely limited. According to the authors, the supercapacitor could be suited for urban bus applications. The effectiveness of the GA-optimized fuzzy control EMS of HESS for EVs was examined by Wang et al.[95]. The main idea of the GA is to increase the DC/DC converter's effectiveness. By refining the fuzzy membership function formulation to minimize energy loss, this strategy enhances the performance of the conventional fuzzy control strategy. Four steps make up the fuzzy control optimization process. To simulate the driving conditions, the UDDS is chosen in step 1. Step 2 involves conducting characteristic experiments with batteries and ultracapacitors at various outside temperatures. Thevenin model is selected to construct a battery and a supercapacitor model in step 3, and the accuracy is further assessed. Finally, GA is used to enhance the fuzzy membership function. Results prove that GA-optimized fuzzy control strategies reduce energy consumption with an improved energy economy when compared to non-optimized EMSs.

7 Conclusion

Electric vehicles that use Li-ion batteries reduce GHG emissions, which helps conserve the environment and reduce the carbon footprint of transportation. However, due to losses in performance and capacity, the battery's power capabilities are significantly limited. Limited range anxiety and Li-ion battery power can hinder an EV owner's ability to travel long distances and climb steep hills. Supercapacitors have a low energy density, making them inefficient for EVs, but suitable for compensating for insufficient battery power during peak demands. HESS provides reliable energy storage, high power, improved efficiency, extended range, and long functional life for EV batteries. The preferred HESS for EVs is a coupled supercapacitor and Li-ion battery, as it provides quick power and manages power fluctuation safely.

Slowing charging and discharging rates reduces stress on batteries, improving their performance and lifecycle. The benefits of integrating supercapacitors with batteries in EVs to enhance their power delivery, operating temperature, cost, lifecycle of the battery, and operating range. The importance of a HESS in managing power fluctuation during acceleration and deceleration in EVs. From the literature, it is identified that if cost is the important factor for HESS, passive-controlled HESS is a good option because it has the simplest control system, is the least expensive, and is the least complex. Semi-active controlled HESS has a good compromise between performance, efficiency, cost, and complexity. Active-controlled HESS has the top priority for performance and efficiency, neglecting the cost of the system. The EMS of HESS is used to safeguard the reliable and efficient operation of the EVs. EMSs are designed to take advantage of both ESSs. However, EMS must address energy efficiency, reduce costs, and ensure reliability. Rule-based EMSs are based on a set of rules that are pre-defined by the user and are simple to implement and effective in some cases, but not able to be adopted under variable conditions. Optimization-based strategies use mathematical optimization techniques to find the optimal way for energy management, but they are more complex to implement. The development of effective energy management strategies for HESSs is essential for the widespread adoption of these systems. Based on experimental validation, this fuzzy control logic strategy lowers the needed power rating from the battery and limits the maximum current dragged from it. The technology decreased the battery's required peak power for the WLTC class 2 driving cycle by 79%, the ECE 15 driving cycle by 84%, and the NYCC driving cycle by 90%.

8 Summary and futurescope

This review article presents an overview of the ESS of an EV consisting of a battery and supercapacitor. In addition, various types of architecture, performance, and operating modes of an HESS are considered in this study. The various technical aspects of EMS, including its architecture, control methods, and approach, are studied. It also emphasizes the impact of vehicle speed, acceleration, temperature, SOC, SOH, load voltage, and current demand on the performance of HESS. Further, this study discussed the variables affecting the cost of the HESS. Also, a brief discussion has been done on the effect of the driving cycle, and thermal behavior on the performance of HESS. Thereby, the author suggests a few noteworthy points for the future possibilities of HESS, which are highlighted below:

- The main issue in the HESS is the optimization of energy flow between the battery and supercapacitor. Further research should be concentrated on the EMS based on machine learning or artificial intelligence based EMS to accurately predict future energy demand.
- Generally, the current EMSs are focused on energy optimization, battery capacity loss, energy consumption, cell temperature, and lifetime. Further, the research is to be focused on the real-time implementation, charging and discharging time of ESS, cost, and depth of discharge of the battery.
- The influence of different parameters on the performance of HESS is analyzed with the results of simulation and experimental studies for different architectures. In addition, the research should be focused on the motor parameters and their effectiveness.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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