Energy management techniques and topologies suitable for hybrid energy storage system powered electric vehicles: An overview

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Abstract
Energy management system (EMS) in an electric vehicle (EV) is the system involved for smooth energy transfer from power drive to the wheels of a vehicle. During acceleration and deceleration periods, batteries in EV undergo high peak power consumption. Therefore, battery lifecycle degrades and subsequently reduces the drive range of an EV. Thus, hybridization of different energy resources becomes essential and seen as one of the alternative solutions for afore said issues. Further, hybridization along with efficient EM strategies helps to: (i) optimally utilize the energy storage systems during discharging and charging, (ii) improve the performance which in turn improves efficiency, and (iii) extend the drive range (iv) reduce the battery size. Though, many articles have been reported so far in literature for hybrid energy storage system (HESS) related to EM techniques; comprehensive review on: the configurations related to HESS, various EM strategies used in EV, performance evaluation of EM strategies for HESS configurations is not yet published. Therefore, this paper intends to provide a comparative assessment on different types of HESS topologies, types of EM techniques. The performance indices based on battery peak current reduction; amount of power stored back during regenerative braking has been compared and discussed. Further, a comparative analysis has been made on the

List of Symbols and Abbreviations:
- $P_{\text{min}}$: minimum battery power
- $P_{\text{dem}}$: power demand
- $P_{\text{bat}}$: battery power
- $P_{\text{UC}}$: UC power
- $I_{\text{d}}(x(n))$: optimized objective function
- $g(x(n))$: cost function
- $k$: iteration or each step
- $V_{\text{e}, \text{min}}$: minimum UC voltage
- $V_{\text{e}, \text{max}}$: maximum UC voltage
- $V_{\text{rs}, \text{ref}}$: UC reference voltage
- $V_{\text{e}, \text{max}}$: maximum vehicle speed
- $V_{\text{ac}}$: voltage across UC
- $V_{\text{bat}}$: battery voltage
- $I_{\text{bat}, \text{rms}}$: battery RMS current
- $I_{\text{uc}, \text{conv}, \text{max}}$: maximum UC converter current
- $I_{\text{uc}, \text{conv}, \text{min}}$: minimum UC converter current
- $I_{\text{uc}, \text{conv}}$: UC current reference
- $H$: Hamiltonian function
- $\lambda(t)$: Co – state variable
- $r_k$: effective resistance of UC
- $C_{\text{bat}}$: battery capacity
- $C_{\text{uc}}$: UC capacity
- $x$: particle position
- $w$: weighting factor
- $v$: velocity of the particle
- $C_1$ & $C_2$: constant variables
- $r_1$ & $r_2$: random numbers
- $P_b$: local best value
- $G$: global best
- $E_{\text{bat}}$: charge
- $E_{\text{uc}}$: UC charge
- $I_{\text{uc}, \text{conv}, \text{min}}$: minimum state of charge across UC
- $I_{\text{uc}, \text{conv}, \text{max}}$: maximum state of charge across UC
- $I_{\text{uc}, \text{ref}}$: reference state of charge across battery
- $F$: input set matrix
- $G_{\text{bat}}$: disturbance matrix
- $P_{\text{batt}}$: battery powered electric vehicle
- $CBDC$: central business drive cycle
- $DCI$: driving cycle identification
- $DESS$: dual energy storage systems
- $DP$: dynamic programming
- $DPR$: driving pattern recognition
- $EM$: energy management
- $EMS$: energy management system
- $ESS$: energy storage system
- $ESSR$: equivalent series resistance
- $EV$: electric vehicle
- $FC$: fuel cell
- $PCIV$: fuel cell electric vehicle
- $FTP$: federal test procedure
- $SLC$: fuzzy logic controller
- $GBS$: gamma based strategy
- $HEV$: hybrid electric vehicle
- $HESS$: hybrid energy storage system
- $HIL$: hardware in loop
- $MPC$: model predictive control
- $NEDC$: new European drive cycle
- $NN$: neural network
- $NYCC$: New York city cycle
- $PEI$: power electronic interface
- $PHEV$: plug-in electric vehicle
- $PSS$: power split strategy
- $SA$: simulated annealing
- $SOH$: state of health
- $UDDS$: urban dynamometer driving schedule
- $WLTP$: worldwide harmonised light vehicle test procedure
- $WT$: wavelet transform
system design and voltage variations. Hence, this review may be a nonstop solution for researchers and engineers working in the field of EVs.

**KEYWORDS**

electric vehicles, energy management, hybrid energy storage systems

### 1 | INTRODUCTION

Engines driven by fossil fuel such as gasoline, petrol, diesel, etc., contribute 25% of world’s CO₂ emissions.¹⁻⁴ Not only being hazardous fossil fuel fed internal combustion engine (ICE) exhibits the poorest energy conversion efficiency of only 20%. Keeping various other factors in the background, research on EV driven partly/fully from electric power has received considerable interest in recent years. With formidable energy conversion efficiency of up to 60%; it is predicted that all passenger vehicles become 100% zero-emission vehicles by the year 2050.⁵

With favourable economic conditions prevail, electric vehicle (EV) manufacturer’s roll out many variants that include: plug-in hybrid electric vehicles (PHEVs), hybrid electric vehicles (HEVs), battery-powered electric vehicles (BEVs), fuel cell electric vehicles (FCEVs), and photovoltaic EVs. In recent times, BEV seems to be a promising technology leading the way towards decarbonization of environment. Due to a dawdling social acceptance BEV is expected to have a large market penetration in near future.⁷ Having bright prospects to become the future transport, its performance strongly relies on energy storage systems (ESS) preferred, control strategies adopted and energy management (EM) techniques applied.

Hence, the performance of different energy storage technologies, together with their formations, its characteristics, and features concerning EV applications have been assessed in References 6 and 7. It is been reported that to improve fuel economy, dynamic stability, reliability, and for efficient energy storage a power converter in EV plays a major role. Thus, review on various power electronics-based converters and its corresponding control strategies for BEVs is presented in Reference 8. Besides, a brief overview on various power converter topologies with different configurations adopted for FCEV’s is detailed in Reference 9. Both single, multistage power conversion arrangement for EV is discussed. Recently, a synoptic review on various energy sources, energy generation systems, types of existing BEV’s, and its EM strategies is deliberately discussed with its challenges faced and its latest solutions available in Reference 10. At the same time, different architectures and its operational characteristics suitable for HEV and FCEV are also discussed in Reference 11 and appropriate storage technologies and its characteristics are detailed in References 12 and 13.

Owing to become the future transport and to accomplish better performance, control; any BEV require energy management system (EMS). Its main function is to uphold the energy flow from ESS to vehicle wheels depending on the requirement. Further, an efficient EMS can aid in extending the EV drive range. Also, it restrains fast discharge that occur either during starting or sudden speed transition. To sustain such transitions ESS coupled with ultra capacitor (UC) is found to be the best alternative.¹⁴,¹⁵ Moreover, such type of EVs require an efficient EMS in handling issues related to hybridization of energy sources. Various forms of hybridization sources include combinations of high-power density (battery) with high energy density (UC), or fuel cell (FC).¹⁶ In literature, UC/battery combination is widely investigated since this combination supports: (a) high peak power consumption, (b) storage of excess energy while braking, and (c) extended battery lifetime. While, many EM techniques have been applied to manage this power split problem in UC/battery combination. The most prominent methods are grouped into rule-based and optimization-based techniques.¹⁷ These methods try to reduce peak battery current, optimize battery state of charge (SoC), and increase battery durability, thereby extending the drive range of an EV. Various architectures of HEV and its corresponding EM strategies are reported in Reference 18. Study on FC/ICE-based HEV in References 19 and 20 highlights the importance of optimization algorithms effecting the unknown parameters identification related to other EM strategies. In Reference 21, detailed battery/UC configurations are provided.

Though, few articles reported review of research works related to EM techniques but does not provide any in depth review on the EM strategies applied for sustainability of BEV. Moreover, a comprehensive study on configurations related to battery/UC HESS and a detailed review on EM methods applied for the abovementioned are yet to be arrived. Further, limitation on EM strategies applied for BEV is not covered in literature. Therefore, this article attempts to consolidate the works on different HESS configurations such as passive parallel, semi active, fully active, series reconfigurable topologies for battery/UC powered EV. Further, a detailed comparative analysis on
various topologies is also provided. Furthermore, implementation of EM strategies such as rule-based and optimization-based approaches applied for HESS at supervisory level is detailed. In addition, a comprehensive comparison is also presented for EM strategies applied for full active hybrid and semi-active type HESS arrangement based on performance evaluations such as efficiency, lifetime, range extension, and regenerative energy recovered. Based on the performance evaluations done some of limitations of EM strategies have been identified and thereby, a few suggestions and improvements have been recommended for betterment of battery system in HESS powered EV.

The following subsequent sections are detailed in the following way: Section 2 briefs on EV and its associated parts. The Section 3 elaborates the necessity of HESS and its classifications and Sections 4 and 5 describe the EM techniques and performance improvement achieved so far. Further, Section 6 provides some limitations and modification suggested to be implemented in near future.

2 | SYSTEM DESCRIPTION

The schematic layout of EV is shown in Figure 1, it consists of a battery pack, power electronics interface (PEI), electric motor, and EMS. Several characteristics that decide appropriate battery selection are battery capacity, nominal voltage, C-rating, maintenance, reliability, cost and battery type. These batteries are either On-board or Off-board charged depending on type and availability. Moreover, battery pack should have the capacity to deliver peak power via PEI.

The PEI are the one in EV responsible for: (a) EV propulsion, (b) battery charging, (c) energy recovery during regenerative braking, and (d) powering the on-board appliances. Depending on the electric motor employed PEI configurations vary. In case of two-stage AC motor drive, DC-DC converter converts battery voltage to required high-voltage DC for propelling the motor drive; while, the inverter fed ac motor drive operates in two modes: propulsion mode and regenerative braking. During propulsion mode, the power is transferred to electric machine from the battery and vice-versa during regenerative braking. The reverse power flow is facilitated using bidirectional DC-DC converter at the front end. Whereas the DC motor drive that operates in similar manner is controlled by using front end two quadrant DC-DC converters.

The EMS unit that remains on top of the hierarchy perform the following functionalities: monitor continuously the battery status, generate control commands to PEI for suitable control action, and sustain battery charge for longer distance. Further, EMS also manages the power distribution from battery to various components such as auxiliary power supplies, air conditioning, etc.
3 Necessity of HESS and Its Configurations

In order to enhance ESS life cycle, limit surge discharge, improve energy availability, and system efficiency, it is customary to combine more than one energy storage either in parallel or series; this combination is called hybrid energy storage system (HESS). Various HESS combinations possible are battery/UC, UC/FC, battery/FC/UC, etc. Among many, the battery-UC combination offers several advantages such as peak power reduction, drive range extension, reduced battery degradation, improved lifetime, and State of Health (SoH). Meanwhile, this combination is appropriate for EV applications as it provide high-power density as well as high-energy density. Besides, batteries coupled with UC can store energy at the time of braking and assist for smooth energy transfer. In addition, UC can also sustain dynamic load profile of the vehicle and assist the vehicle for a longer drive range. Therefore, battery-UC combination support long-term EM and dynamic power regulation.

Evidently, coupling between HESS and the DC bus system is done through bidirectional DC-DC converters. Based on HESS and converter arrangement, four types of topologies are popular and they are passive parallel, semi-active topology, fully active hybrid, and series-parallel reconfigurable HESS configurations. Types of HESS and its possible configurations are depicted in Figures 2 and 3, respectively.

3.1 Passive parallel

In this topology, UC and battery are connected in parallel to DC-AC converter, that is, inverter as shown in Figure 3A. Absence of additional DC-DC converter made this topology lighter, smaller, and cheaper one. Additionally, fluctuations in DC-link voltages are comparatively less since the battery clamps the DC bus voltage constant. As the UC voltage is maintained constant due to battery pack it can be sized accordingly to match the characteristics of low-pass filter. Thus, large current peaks and low-voltage dips are avoided. Since the converter and ESS are connected in parallel its terminal voltage follows the discharge characteristics of a battery limiting the UC voltage. Therefore, wide output voltage variation cannot be arrived.

Further, as soon as the stored energy in UC is supplied to the load, its voltage drops drastically. At this instant, the battery has to balance both UC as well as the load leading to additional burden on the battery. This topology resembles a simple RC circuit wherein the discharge and charge current are dependent only on the battery/UC parameters. Although this topology is light, easy, and cheaper, it suffers from poor performance.

3.2 Semi-active hybrid

Previous configuration does not exhibit ideal constant current with reduced ripple characteristics; since it exhibits highly volatile drive cycles. Further, high dynamic current drawn cause battery degradation. Therefore, PEI is included between ESS to improve reliability. In most cases, a bidirectional converter is connected either to battery or UC is utilized to control the regenerative power making the system robust. Further it supports energy transfer into UC during...
deceleration and acceleration periods. At the same time, controlled charging and discharging improves battery performance. Hence, semi-active hybrid topologies have been widely investigated in recent literature. This topology is subdivided into four different types: (1) battery-UC active type - bidirectional DC-DC converter connected to UC (2) UC-battery active type - bidirectional DC-DC converter connected to battery (3) cascaded connection - bidirectional DC-DC converter between battery and UC with diode. (4) Cascade connection-unidirectional DC-DC converter instead of bidirectional one.

3.2.1 | Battery-UC active

In this type of configuration, a bidirectional DC/DC converter is placed in between UC bank and battery pack as depicted in Figure 3B. Due to which, the battery pack can be relieved from maintaining the DC bus voltage, allowing the battery pack to have a lower terminal voltage. At the same time, smaller battery voltage attribute to less weight and minimal expenses. Since UC is connected directly to the DC link it behaves like low-pass filter.\(^28\) Even though the UC acts as a low-pass filter, the whole range of UC’s voltage can be utilized as there is no direct clamping between UC and battery. In the regenerative mode, if the UC bank voltage is made low with respect to the battery voltage, then the energy flows back naturally into the UC improving the system efficiency.\(^26\) Moreover, the UC pack employed has lower equivalent series resistance (ESR) compared to the battery pack,\(^{27,29}\) thus, absorb the majority of current spikes.
occurred at the time of regenerative braking. Besides, charge and discharge rates of the UC and battery packs can then be controlled with the help of DC-DC converter.24 The rate at which the battery and UC can be charged and discharged can significantly improve the system efficiency and battery lifetime.30 However, the only difficulty that arises in this topology is its power converter control.24,31

3.2.2 UC-battery active

In another semi-active topology, the DC/DC converter is connected to battery instead of UC as found in Figure 3C. Decoupling battery from DC bus via converter is helpful in applications where smaller UC pack is preferred.28 Another benefit of this topology is that controlling DC-DC converter provides large variation in the UC voltage. Likewise, directly interfacing the battery to the DC bus keeps up a steady DC link voltage.32 At the downside, it is observed that there are situations like sudden consumption of peak power where battery cannot handle such power immediately. During such similar situation, it is desirable to directly connect the UC at the DC link so that it can handle large power fluctuations in a better way. However, an important disadvantage is the use of large current rated DC/DC converter that consequently increases the converter size compared to battery-UC active topology.33

3.2.3 Battery-UC topology with diode

A recent semi-active type that use battery/UC configuration along with bypass diode is shown in Figure 3D. Due to presence of diode, bidirectional converter can be bypassed during the power transfer from the battery to DC link. Further, the UC will be charged by the battery when its voltage is less than the battery voltage.31 In this way, the DC-DC converter can be designed for smaller power rating compared to active battery/UC configuration. However, the demerits of this topology are (1) operation of UC is limited by the battery voltage, (2) DC-link voltage varies widely, and (3) system becomes stable when UC voltage goes below battery voltage during acceleration mode. Hence, to further reduce the size and complexity in control bidirectional converter is replaced with a unidirectional converter as depicted in Figure 3E. As a result, the system efficiency improves and converter cost also reduces. Moreover, this modification makes the converter operation and control simple. During driving mode, the battery and UC reference voltages are inherently generated; hence, UC delivers the entire power to load when the battery voltage is less. Whereas in previous UC/battery with diode topology 2; the battery does not absorb any power since diode acts in reverse biased condition. The disadvantages of this topology are (1) during acceleration the system lacks degree of freedom to control and (2) wide variation in DC bus voltage. In Reference 34 a switch is added in series with the UC to existing topology to isolate the battery from direct charging. By operating the bidirectional DC-DC converter either in buck mode or boost mode owing to set of predefined rules manages the energy availability in batteries as well as UC. In Reference 35 by adding a switch in series and diode in parallel to existing topology leads to four different operations such as (a) battery boost mode, (b) battery buck mode, (c) UC buck mode, and (d) regenerative braking mode overcoming the abovementioned disadvantages.

3.3 Fully active hybrid

In this hybrid topology, multiple DC-DC converters are employed to overcome the disadvantages large DC bus voltage variations.32 Employing multiple bidirectional DC-DC converters achieves complete control over the UC and battery individually.36 By connecting more than one bidirectional DC-DC converters in parallel makes the DC-bus potential to be always constant. Also, the individual voltages of battery and UC are lower than the DC-bus potential minimizing the voltage balancing issues. Further, UC is fully utilized so that the UC voltage can be varied in wide ranges. Here, in this topology the UC bank and battery pack are separated from DC bus by integrating each other with DC-DC converter. The output terminals of each bidirectional DC-DC converter are connected in parallel as depicted in Figure 3F. Since the power flow from the battery and UC is decoupled from one another, this arrangement has autonomous control over ESS. One of the most important advantages of this topology is that it can allow lower DC link voltages hence, reduces the ESS size and its associated cost. Further, this topology maintains the DC link potential stable thereby maximizing
the utilization of UC operational voltage range.\footnote{37} One of the important limitations of this topology is the requirement of one or more full-sized converters that requires complex control systems and additional cost.

3.4 | Series reconfigurable configuration

In recent literature, a new HESS configuration has been suggested and implemented for EVs. This topology as presented in Figure 3G uses several bidirectional switches to rearrange the HESS configuration from series to parallel connection. Whenever the DC bus voltage falls low, UC bank is charged by the battery pack. This functionality is suitable for the vehicle under standstill condition. Besides, this topology is advantageous during peak power demand, which occurs typically during periods of acceleration and deceleration of EV. When the switch T2 is closed, battery pack and UC bank are connected in series that makes DC bus potential to be greater than or equal to the UC voltage allowing propulsion motors to withstand maximum torque at high operation speeds. Additional DC-DC converter makes energy sources decoupled from DC link. Further, this configuration shares the similar advantages as the active UC/battery topology and battery/UC topology.\footnote{38} But the main disadvantage is the complex control strategies required to manage the energy balance between two sources. Another probable drawback is risks related to failure of switches T1, T2 and T3. Moreover, recent study conducted does not mention about the nature of power electronic switches to be used along with DC link of the system. Use of electromagnetic contractors compromises the system performance at the risk of contact failure. At the same time, solid-state switches for this type of application adds the complexity and reduces the risk of welding the contact.

A comparative assessment on different HESS topologies is provided in Table 1 based on various parameters such as converter type, number of converters required, number of switches used, maintaining the constant DC bus voltage or not, conversion stages, efficiency, complexity, and also stating its advantages and disadvantages.

4 | EMS AND ITS REVIEW ON EM STRATEGIES APPLIED FOR HESS POWERED EV

Energy Management System (EMS) in EV is essentially an Electronic Control Unit (ECU) that helps utilize the available energy resources sensibly. Controlled via advanced microprocessor unit it receives various sensory inputs, internal system and driver commands to calculate the required power demand. Upon which appropriate control signals to PEI initiates for smooth energy transfer from the battery to wheels and vice-versa. EMS not only interpret and record the data, but also observes the data from the sensor inputs and tries to improve the drive range by applying appropriate control algorithms (Figure 4).

One of the important functionality of EMS in EV is effective power splitting between ESS. To optimally divide the power demand between ESS, many deterministic control equation or strategy in EMS is applied. However, factors like: such as driver command, trip length, electric motor/generator speed, and the SoC of battery, etc., are involved in EMS selection. Further, without these data or information, one may have a limited control over the power split problem. To summarize, EMS in HESS are meet the load demand, sustain the battery voltage and UC charge, improve the overall efficiency of the system, and extend the battery lifetime.

Various techniques that have been suggested so far in the recent literature for EM implementation in HEVs, PHEVs, or HESS in EVs are (i) rule-based strategy and (ii) optimization-based technique. Most of the previous proposed methods are suggested for battery/UC combination, FC/battery/UC combination. This section exclusively elucidates various EM control strategies discussed in the literature for battery/UC combination with advantages and disadvantages of each method explained. Moreover, a comparison table based on the mode of application is arrived and presented in Table 2. Classification of different EM techniques available for HESS is portrayed in Figure 5.

4.1 | Rule-based control strategy

Rule-based control techniques are framework that creates deterministic design rules based on empiric or heuristics, human expertise, for predefined drive cycles of the vehicle. These rules are generally implemented using a lookup table or if-then rule expressions. The rule-based strategies are classified into (a) deterministic rule-based, (b) frequency based, (c) fuzzy logic-based, and (d) neural network-based control.
### TABLE 1  Comparative assessment of hybrid energy storage system topologies

| Parameters                              | Passive parallel | Battery-UC active         | UC-battery active            | Battery UC with diode topology 1 | Battery UC with diode topology 2 | Fully active | Series reconfigureable |
|-----------------------------------------|------------------|---------------------------|------------------------------|---------------------------------|---------------------------------|--------------|------------------------|
| Type of DC-DC converter                | NA               | Bidirectional DC-DC       | Bidirectional DC-DC          | Unidirectional DC-DC            | Bidirectional DC-DC             | NA           | NA                     |
| Number of DC-DC converter              | 0                | 1                         | 1                            | 1                               | 1                               | 2            | NA                     |
| Number of switches used                 | 0                | 2                         | 2                            | 1                               | 1                               | 4            | 3                      |
| Constant DC bus                        | No               | No                        | No                           | No                              | No                              | Yes          | Yes                    |
| Voltage variation on $V_{ac}$           | Less             | Medium                    | Medium                       | High                            | High                            | Less         | Medium                 |
| DC-DC conversion stages from $V_{batt}$| 0                | 1                         | 1                            | 1                               | 1                               | 2            | 1                      |
| Efficiency                              | High             | Average                   | Average                      | Average                         | High                            | Less         | Average                |
| DC-DC converter efficiency              | Not Applicable   | Average                   | Average                      | Average                         | High                            | High         | NA                     |
| Complexity                              | Less             | Average                   | Average                      | Average                         | Average                         | High         | High                   |
| Cost                                    | Less             | Average                   | Average                      | Average                         | Average                         | High         | Average                |
| Advantages                              | Simple, reliable, lower cost | Easily stores the regenerative energy, improves lifetime, high power rated converter is enough | Full control over battery current under traction mode | Low power rated DC-DC converter is required | Simple to control, reliable, cost effective | Highly reliable, independent control, operates at lower DC-bus voltages | Ease to provide power under peak load condition |
| Disadvantages                           | System cannot be controlled, no effective utilization of storage elements | Voltage control of UC is difficult | Voltage of UC is not controlled, high power rated converter is required | Operation of UC is limited by the battery voltage, wide DC bus variation, system is uncontrollable when $V_{ac} < V_{batt}$ | Control lacks the degree of freedom, wide variation in DC bus voltage | Highly complex to control, large-sized power converters are required, high cost | Complex to control and to manage the energy sources, high risks of switch failure |
4.1.1 Deterministic rule-based control strategy

A deterministic rule-based approach for a battery-UC HESS arrangement with focus on power split is discussed in References 37, 39, 48-51. In this kind of control strategy, a preselected reference battery power \( P_{\text{min}} \) is calculated. Based on \( P_{\text{min}} \) value, three rules are framed: (1) If load demand power \( P_{\text{dem}} \) is below 0, UC consumes all the regenerative braking power within its charging limit; (2) If \( P_{\text{dem}} \) is greater than \( P_{\text{min}} \), UC delivers \( (P_{\text{dem}} - P_{\text{min}}) \) maximum discharging power in that state while battery provides \( P_{\text{min}} \); (3) Otherwise, battery supplies power within the battery discharging limits. Using this rule-based control strategy, the authors have shown that the hybridized battery-UC system can effectively minimize the peak current of the battery, and also extend the battery lifespan. The flow chart of control strategy implemented is presented in Figure 6. With slight modifications in Reference 52 a voltage control for UC side converter is incorporated. The control technique followed depends upon the power demand \( P_{\text{dem}} \), threshold battery power \( P_{\text{min}} \) and the charging power coming from the battery to UC \( P_{\text{UC}} \). Therefore, these parameters should carefully be chosen depending upon type, size, and drive cycle of the vehicle.

4.1.2 Frequency-based control strategy

Another representative rule-based control strategy is the frequency-based power decomposition strategy employed in References 40, 53-60 for battery-UC HESS power split problem. In this method, the power demand of the HESS is handled using high and low frequency signals. According to the power demand, UC deliver high frequency component and batteries deliver low-frequency components of the power consumption respectively. The combination of UC along with battery filter out the peak current and reduce battery degradation losses. However, this type of filter-based strategy has several disadvantages: (1) it provides a very large phase shift. (2) The cutoff frequency of the filter needs to be adjusted in the design in accordance with load demands.

4.1.3 Fuzzy logic based control strategy

Fuzzy logic-based control strategies are good at dealing with complex decisions and model uncertainty. The basic idea of fuzzy logic-based control strategy is to use the available knowledge or expertise about the problem to construct a number of fuzzy rules to mimic human thinking and reasoning, which are finally represented as a collection of if-then rules. Having been proposed for EM strategies in References 41, 61-67, an adaptive fuzzy controller for EM of battery/UC HESS is proposed in Reference 67 and depicted in Figure 7. Generally fuzzy logic focuses three steps: (a) fuzzification, (b) inference, and (c) defuzzification. Based on the input, a membership is utilized to convert input into fuzzified inputs. Further, an inference mechanism is framed based on the rule base to arrive at conclusions. These conclusions have to undergo the process of defuzzification to generate control input to the system. The main advantages of fuzzy logic approach are (1) tolerant and robust to component variations and imprecise measurements, (2) flexibility and adaptation, as the fuzzy logic rules can be simply framed. However, the fuzzy logic control strategy cannot be an effective control or the optimal control under different driving situations as it still depends on rules and experiences. Another disadvantage of the fuzzy logic approach method is that the defuzzification process takes significant time and memory.
TABLE 2  A comparative analysis of EM strategies

| Ref | EM strategy              | Advantages                                           | Disadvantages                                                                 | Application mode |
|-----|--------------------------|------------------------------------------------------|-------------------------------------------------------------------------------|------------------|
| 39  | Deterministic rule-based | Simple, reliable and robust, low computation complexity, easy to implement | Not adaptive and poor parametric calibration                                  | Online mode      |
| 40  | Frequency separation     | Simple and easy implementation                       | Not robust, filter design is difficult                                         | Online mode      |
| 41  | Fuzzy logic based        | Robust and good with model uncertainties and state variations, real time implementable | Dependent on membership functions, optimal control is not guaranteed         | Online mode      |
| 42  | Neural network           | It is more robust to new information, real time implementable. | Large amount of training data is required; stability is not guaranteed.        | Online mode      |
| 43  | Dynamic programming      | Global optimal solution is found, optimal control, easy to solve nonlinear optimization problems | Not real time implementable, requires heavy computational burden              | Offline mode     |
| 44  | Pontryagin’s principle   | Easy to adapt and simple to implement, no additional controllers required | Computation burden is heavy.                                                | Online mode      |
| 45  | Instantaneous optimization| Optimal value is found at each instant               | Not guaranteed to be optimal,                                               | Online mode      |
| 46  | Particle swarm optimization| Minimal computation time, best optimal solution can be found, easy to implement | High-speed controller is required to implement in real time with large memory | Offline/Online mode |
| 47  | Simulated annealing      | It can also search best optimal point after the local optimum | Larger search space is required                                              | Offline/Online mode |
| 48  | Model predictive control | Has potential for real-time implementations; Easy to handle constraints directly in the design procedure. | May compromise with model accuracy by using linearized model. May need large memory for heavy computations | Online mode      |

FIGURE 5  Classification of EM strategies of HESS

4.1.4  | Neural network-based control strategy

Neural Network (NN) resembles the characteristics of human brain that tries to take intelligent decisions through thinking, computing, and mimicking neuronal activities of the human behavior. Further, NN method train itself from the repeated learning process through a large number of training data instances and updates the weights of hidden layer through weight adaption function as depicted in Figure 8.68. Recently, NN-based control strategy for EV battery/UC HESS has been proposed in References 69-71. Despite, NN for HESS powered EV require large amount of training
data sets from the past information to minimize the battery peak currents and obtain ideal UC current. This technique to ascertain best power split between battery and UC. Moreover, power demand, different drive cycle sets are taken as input data and UC current as the output data to NN. This method offers following advantages: (a) high degree of freedom, (b) strong thinking and adaptive capability (c) can solve nonlinear control problems, and (d) fault tolerant. Accuracy of this method depends on the amount of training data set used.

4.2 | Optimization based control strategy

Unlike rule-based control methods for EM, optimization-based control utilizes either optimal control theory or soft computing algorithms. EM using optimal control do not require prior information to solve the control problem. The following section discusses and analyzes optimization-based control methods applied for EM in HESS powered EV. There are classified as (1) Dynamic Programming (2) Pontryagan’s Principle, (3) Instantaneous optimization, (4) metaheuristic optimization methods and (5) Model predictive control.

4.2.1 | Dynamic programming

Unlike the rule-based methods, the dynamic programming (DP), one of the most prevailing mathematical tools obtained from Bellman’s optimality principle, generally depends up on system model to compute the best control
strategy. This model can be either numerical or analytical. Based on the model, the best power split control strategy can be obtained by applying DP. Prior it requires accurate terrain information to predict the future power demand of HESS. A detailed energy optimization in HESS using DP is detailed in Reference 73. DP is applied to optimize the size of UC which influences the battery degradation and cost in an EV. The objective function treated as cost function for DP is described as:

\[ J_d(x(n)) = g_d(x(n)). \]  

(1)

The objective function for \( n \)th step is

\[ J_k(x(n)) = \min\{g_k(x(n), u(m)) + (J_{k+1}(f_{k+1})\}, \]  

(2)

where \( g_d(x(n)) \) represents the cost of the end step, \( g_k(x(n), u(m)) \) represents cost of step \( k \), \( f_{k+1} \) signifies the step variable at \( k + 1 \), \( (J_{k+1}(f_{k+1}) \) is the optimized objective function with best result at step \( k + 1 \). In case of multiple input and multipleo (MIMO) systems DP uses large amount of data leading to heavy computational burden.

### Instantaneous optimization

For EM in HESS, it is necessary to have accurate information on the drive cycle to predict the future power demand. On the other hand, it is not so simple to obtain the accurate power demand data since the vehicle movement depends on various factors such as driving patterns and traffic on the road. To solve an EM problem with no future operating information available, formulates an instantaneous optimization problem for a battery-UC HESS power split problem. In order to utilize the UC efficiently, the UC should be discharged or charged properly. Since, prediction of a future power demand profile is difficult, a simple strategy based on vehicle speed \( (V_s) \) can be used to adjust the UC SoC: Whenever \( V_s \) is low, UC should be operated in a high SoC range, so that UC can deliver stored energy that is capable to meet peak power during accelerations. On the contrary, the UC SoC needs to be low if there \( V_s \) is high because of regenerative power during decelerations. In particular, the electric machine usually requires a large power whenever the \( V_s \) increases from zero. Thus, a reference voltage of UC \( V_{uc,ref} \) is adjusted using the following equation.

\[ V_{uc,ref} = V_{uc,min} - V_{uc,max} \frac{V_s}{V_{s,max}} + V_{uc,max}, \]  

(3)

where \( V_{uc,min} \) and \( V_{uc,max} \) are the boundary of the UC voltages and \( V_{s,max} \) is the maximum vehicle speed. The UC reference voltage is repeatedly computed and updated according to real-time vehicle speed. This UC reference voltage value is used in the instantaneous optimization method to minimize the battery current fluctuations, the battery current magnitude, and the difference between the actual UC voltage and its corresponding reference value. The convex
optimization problem is formulated, which is repeatedly solved by general solvers in polynomial time. The optimal power split between the battery and UC is computed at each instant. The advantage of this instantaneous optimization-based control strategy is that it does not depend on the future vehicle operating profile. Besides, to confirm that UC can supply or consume adequate power at each interval of time, the UC reference value is updated deterministically.

4.2.3 | Pontryagin’s principle

To solve optimal control problems another method proposed in Reference 78 is based on Pontryagin’s principle. This method gives the optimal control over dynamical system that moves from one state to another in presence of constraints. Taking state or control inputs by treating the system as Hamiltonian system (HS) EM for HESS is designed. In case of EM in HESS-based EV, it is a two-point boundary value problem where the battery RMS current must be minimum for conditions of Hamiltonian. Further, to solve this problem for EM in EV three things are to be defined, they are (a) systems dynamical model (b) cost function, and (c) constraints. In References 44 and 79 for EM, the dynamics of UC are considered and taken as state variable, the battery RMS current \(i_{\text{bat\_rms}}\) is taken as cost function to minimize under peak load demands, and the constraints is to regulate the UC voltage \(V_{uc}\) and the current \(I_{uc\_conv}\) flowing out the converter. The corresponding equations are mentioned in Equations (3) to (6).

\[
\text{Dynamical Model:} \quad \frac{d}{dt} V_{uc} = -V_{bat} \eta_{\text{conv}} \frac{i_{\text{uc\_conv}}}{C_{uc} V_{uc}}. \tag{4}
\]

\[
\text{Cost Function:} \quad I_{\text{bat\_rms}} = \frac{1}{t_f - t_0} \int_{t_0}^{t_f} i_{\text{bat}}^2 dt. \tag{5}
\]

\[
\text{Constraints:} \quad V_{uc\_min} \leq V_{uc} \leq V_{uc\_max}, \quad -I_{uc\_conv\_max} \leq I_{uc\_conv\_ref} \leq I_{uc\_conv\_max}. \tag{6}
\]

From the system model in Equation (3) this strategy needs to arrive an optimal control equation such that it can track the trajectory of traction current by generating suitable battery reference current. The Equation (4) as Hamiltonian function described in Equation (7)

\[
H = i_{\text{bat}}^2 - \frac{V_{bat}}{V_{uc}} \eta_{\text{conv}} I_{uc\_conv\_ref}. \tag{8}
\]

where \(\lambda(t)\) is a co-state variable which is the product of current and capacitance. The Equation (8) has satisfy necessary conditions for minimization of Hamiltonian under Equation (8).

\[
\frac{\partial H}{\partial I_{\text{bat\_ref}}} = 0. \tag{9}
\]

Further, the optimal control law can be derived as by solving the Equations (8) and (9) by satisfying the constraints. Finally, the control law is the battery reference current \(i_{\text{bat\_ref}}\) obtained is given as\(^{44}\) in Equation (9) and implementation is depicted in Figure 9.
\[ i_{\text{bat ref}} = \frac{\lambda V_{\text{bat}}}{2V_{uc}} \left( V_{uc} - \frac{V_{uc}^2 - 4R_{uc}V_{uc}I_{uc}}{V_{uc}^2 - 4R_{uc}V_{uc}I_{uc} - V_{uc}I_{uc}} \right), \] (10)

where \( R_{uc} \) is the effective resistance of UC.

### 4.2.4 Meta-Heuristic-based EM strategies

In hybrid energy storage-based EV, the foremost problems of EM due to load demand result in unpredictable drive range and wide variations in power request. The key goal of the EM is to minimize the absolute difference between power supplied and the power demand by HESS, that is, battery and ultracapacitor. At any instant, the whole power supplied by HESS is the linear combination of instantaneous power delivered by these sources. The optimization problem formulated is given in Equation (11) can be solved for each time interval \( k = 1, 2 \ldots n \), as in Reference 66:

\[ f = \min_{C_{\text{bat}},C_{\text{SC}}} \left[ P_{\text{dem}}(k) - \left[ C_{\text{bat}}(k)P_{\text{bat}}^{\text{max}}(k) \right] + \left[ C_{\text{SC}}(k)P_{\text{SC}}^{\text{max}}(k) \right] \right]. \] (11)

Subjected to the following constraints:

\[ P_{j}^{\text{min}}(k) \leq P_{j}(k) \leq P_{j}^{\text{max}}(k), \] (12)

\[ V_{j}^{\text{oc}}(k) = V_{j}^{\text{oc, min}} + \delta_j \cdot \text{SoC}_j(k), \] (13)

\[ I_j(k) = P_j(k) / V_{j}^{\text{oc}}(k), \] (14)

\[ P_{j}^{\text{max}}(k+1) = V_{j}^{\text{oc}}(k) \cdot I_{j, \text{ref}} \] (15)

With \( j \in \{\text{bat}, SC\} \)

where \( C_{\text{bat}}, C_{\text{SC}} \) are control variables to define power variation between the sources. At each interval of time, the model calculates the open circuit voltage \( (V_{j}^{\text{oc}}(k)) \) as a function of source’s SoC \( (\text{SoC}_j(k)) \), the minimum open-circuit voltages \( (V_{j}^{\text{oc, min}}(k)) \) and the no-load voltage drops \( (\delta_j) \). From these constraints given in above, the reference currents and voltages can be generated by solving the objective function using any one of meta-heuristic algorithms. In this section, a detailed description of particle swarm optimization (PSO) and simulated annealing (SA) algorithm have been discussed.

**Particle swarm optimization (PSO)**

PSO is a popular meta-heuristic optimization algorithm evolved based on the phenomenon of bird flocking.\(^{80,81}\) In this technique, the search space is defined as target vectors chosen as swarm particles. These swarm particles accelerate...
along the predefined search space with a velocity \( v \) to attain the global best position. Generally, PSO algorithm has three phases of implementation. They are initialization phase, exploration phase, and evaluation phase.

- **Initialization Phase:** Initialize the population size and random search space.
- **Exploration Phase:** The swarm particle current position is updated \( (x_i) \) as they accelerate along \( w \) the defined search space with a velocity \( v_i \). Throughout the exploration phase, the particle current best position is updated as \( P_{\text{best}} \) and the global best position is treated as \( G_{\text{best}} \). Each particle’s position is updated using following Equations (16) and (17)

\[
x_i^{k+1} = x_i^k + v_i^{k+1},
\]

\[
v_i^{k+1} = w.v_i^k + [r_1 C_1(P_{\text{best}} - x_i^k)] + [r_2 C_2(G_{\text{best}} - x_i^k)],
\]

where the \( x_i^{k+1} \) denotes the updated position of the \( i \)th particle, \( x_i^k \) is the initial position of the \( i \)th particle, the \( v_i^k \) is the initial velocity, and \( v_i^{k+1} \) is the updated velocity. \( w \) is the inertia factor that impacts the velocity of the particle. \( C_1 \) and \( C_2 \) are constant variables that controls individual behavior and social behavior of each particle. \( r_1 \) and \( r_2 \)

- **Evaluation Phase:** The evaluated fitness value of the particles is updated and also data is recorded as \( P_{\text{best}} \) and \( G_{\text{best}} \).

\[ P_{\text{best}} = x_i^k \text{ if } f(x_i^k) \geq f(P_i), \]

\[ G_{\text{best}} = P_{\text{best}} \text{ if } f(P_{\text{best}}) \geq f(G_{\text{best}}). \]

For better understanding, the flow chart shown in Figure 10 is provided. PSO method is a continuous process of finding the global best solution in minimal computation time which makes suitable for real-time applications like EM for EVs powered by HESS, optimal sizing of battery/UC systems.

**Simulated annealing algorithm**

Recently, a stochastic optimization method known as simulated annealing (SA) is being used to find the global extremums for solving large optimization problems.\(^{82}\) It is based on physical annealing analogy involving the process of solidification of fluids and random distribution of particles in the liquid. SA algorithm has two main stages. They are one is shift over between the states and the other one is to control the temperature to acquire the minimal energy state. This optimization method starts with initialization of solid state \( x_0 \) which has an initial energy level of \( E_1 \). The forthcoming state \( x_2 \) with an energy level of \( E_2 \) will be accepted if the following Equation (20) is satisfied.

\[ E_1 - E_2 \leq 0. \]

And if \( E_1 - E_2 > 0 \), is satisfied then probability function in terms of energy and temperature can be written as in Equation (21)

\[ P(E, T_c) = e^{\frac{E_1 - E_2}{kT_c}}, \]

where \( T_c \) denotes the control parameter, it can be varied in the entire search space of the algorithm until the lowest energy state is achieved. The merit of this algorithm is having highest probability to find the best optimal point after getting the local optimum point. Further, it keeps on searching the solutions until the objective function provides a
better solution than the current candidate solution. Furthermore, for better understanding a flow chart describing the process of SA is depicted in Figure 11.

### 4.2.5 Model predictive control

Commonly called as receding horizon control, model predictive control (MPC) predicts the future inputs from the past information by minimizing the cost function with real time optimization and feedback correction from the predictive models. The schematic diagram of MPC is depicted in Figure 12. Due to inherent optimization and feedback correction in MPC are used to solve HESS-based EM problems in EVs. In this type of control, a state space model of system can be used to predict the future value of output variables. The model outputs and process outputs are compared and processed through the prediction block to predict the future outputs of the process. At each sampling instant, the set point calculation has been done to fix the targets or set points to the controller. Further, feedback error is corrected based on the optimization problem defined over the finite horizon time. The performance of MPC mainly depends upon two aspects: (1) one is prediction accuracy and (2) control strategy optimization. Here in the case of HESS-based EM, the objective function formulated to minimize the power demand of the battery by efficiently utilizing UC under acceleration and deceleration conditions. Further, depending on the HESS arrangement, the control problem is treated to optimize the cost function compromising the conflicts between battery and UC as mentioned in Reference 47 is given as

\[ \sum_{k=0}^{N-1} \left[ \omega_1 P_{\text{batt}}(k)^2 + \omega_2 (P_{\text{batt}}(k) - P_{\text{batt}}(k+1))^2 \right] + \sum_{k=0}^{N-1} \left[ \omega_3 (\text{SoC}_{\text{uc}} - \text{SoC}_{\text{ubatt}}^\text{ref})^2 + \omega_4 (\text{SoC}_{\text{batt}} - \text{SoC}_{\text{ubatt}}^\text{ref})^2 \right]. \]

Subjected to constraints:

\[ x(k+1) = Fx(k) + G_u(k)u(k) + G_w(k)w(k) \]  \hspace{1cm} (23)

\[ k \in \{0,...,N-1\} \]
where $\omega_1$, $\omega_2$, $\omega_3$, $\omega_4$ are the weights of the cost function for battery power and power variation in batteries and SoC for reference tracking. $x$ is denoted as the state variable, $F$, $G_u$, $G_w$ are the state input and disturbance matrices; $\text{SoC}_{\text{uc}}^{\text{min}}$, $\text{SoC}_{\text{uc}}^{\text{max}}$, $\text{SoC}_{\text{batt}}^{\text{min}}$, $\text{SoC}_{\text{batt}}^{\text{max}}$ are the respective minimum and maximum charge levels of battery and UC. $P_{\text{batt}}^{\text{max}}$, $P_{\text{batt}}^{\text{min}}$ are the
limits of the battery. By solving this cost function, an optimal power references for battery SoC, UC SoC are obtained for EM between these two sources.

5 | PERFORMANCE EVALUATION OF EM STRATEGIES APPLIED FOR EM IN HESS CONFIGURATIONS

With various approaches on EM strategies have been detailed in previous sections; adoption of these strategies semi-active and fully active hybrid topologies is reviewed. While many techniques have been derived and tested with different drive cycles such as UDDS, NEDC, ECE-15, ECE45, ARTEMIS, LA92, US06, FTP75, CBDC, WJC, JC08, HWFET; its assessment on a common platform is quite difficult. Therefore, the following section critically reviews the works done on EM strategies applied for semi-active and fully active topologies only. In addition, a comparative study is also carried out for above said topologies based on battery power, UC power, drive cycle used for testing, peak power demand, and regenerative power recovered during deceleration. Further, the performance evaluation is also made to know the improvements on the battery lifetime, battery RMS current reduction, and drive range extension.

5.1 | Performance evaluation of EM strategies applied for semi-active configuration

Most of the works reviewed so far use semi-active topology with any one of the following: (1) Rule-based approach, (2) Fuzzy logic, (3) Frequency separation, (4) Dynamic programming, (5) Instantaneous optimization, (6) SA, (7) PSO optimization, and (8) Model predictive control (MPC) strategy. The block detailed diagram of semi-active HESS-based EMS is shown in Figure 13. Commonly two quadrant bidirectional converters are used at the power stage at the battery side while UC is connected directly to the DC bus. Any one of the abovementioned EM strategies is employed at high or top level providing suitable inputs to the power controller at the bottom level thus, controls the current flow from the battery depending on the power demand.

A simple deterministic rule-based control strategy is proposed in Reference 84 to meet the adequate power demand as well as to utilize the energy available during regenerative braking. The strategy proposed has three different modes of operation acceleration mode, constant speed mode, and braking mode. The mode is selection automatic based on the drive cycle. From the results, it is seen that the energy consumed by battery is reduced up to 47.99% for City II and drive range is extended by 27.17%, and 13.47% for ECE-15, and NEDC drive cycles, respectively.

A new power management strategy to improve accuracy and overcome uncertainties of terrain information is studied in References 66 and 67. With the aim of improving the battery life, the overall system performance estimation is made. Further, the EM strategy has the advantage of adaptation to select the appropriate membership function according to previous drive cycle patterns. Through this adaptability of the strategy is able to suppress battery charging/discharging current variation by less than 4% achieving efficiency of 86.20%.

As an alternative, power split strategy has been proposed in Reference 40 where power demand of the vehicle is subdivided into low and high frequency components. The low frequency component is allowing to supply by battery while the high frequency component of power demand gets bypassed through UC pack. In Reference 63 a wavelet transform-based (WT) frequency decoupling EM scheme is proposed at the bottom level to split the power demand between battery and UC. Whereas this EM scheme is supervised by fuzzy logic controller (FLC) at the top level to generate suitable power references to parallel active HESS arrangement. This modification enables the control strategy to optimally utilize the energy from UC and makes the system robust in any unpredictable driving conditions. Furthermore, this EM technique extends the battery life time and reduce stress on the battery. In addition to WT-fuzzy at supervisory level an adaptive WT-fuzzy logic-based EM has been proposed in Reference 58 by integrating driving pattern recognition (DPR) for UC in EV applications. Cluster analysis is utilized by DPR and adaptive wavelet transform extracts and allocate the respective frequency components to UC and battery during power demand conditions. Further, the proposed technique reduces the charging and discharging battery current to 58.2% and enhances the battery life and vehicle endurance limit by 6.16% and 11.06%, respectively.

Recently, pontryagin’s minimum principle applied for EM in HESS for EV applications for EM has been proposed in References 44 and 79. The derived control law helps in a feedback control eliminating the usage of additional controllers. Tazzari zero and NEDC models are used for reference and validation purpose. The simulation results prove that the proposed strategy provides a longer battery life and dominates existing pure battery-based EV in terms of RMS current reduction.
of battery by 50%. In another approach, a new EM is formulated to minimize the battery current variations and power loss using instantaneous optimization problem. Further, this EM approach contains two parts: one part for calculating the UC voltage reference depending on the load dynamics and the other part is for optimizing the current sharing between energy storage devices. Furthermore, a technique to compute the voltage reference for UC under real-time operating conditions considering regenerative braking is also proposed. As a result, concurrent reduction in dynamic battery power up to 45% is achieved compared to rule-based approach. Another method was proposed to adaptively switch between the: buck/boost mode, battery/UC mode optimizing the energy distribution by SA for semi-active type arrangement achieving the improvement of 2.2% for UDDS and 0.7% for NEDC in comparison with rule-based strategy.

Alternatively, a convex optimization-based power sharing strategy for two propulsion machines fed by semi-active type HESS is proposed. From the results, it is found that (1) 10% improvement in power train efficiency, (2) 82% reduction in battery lifetime cost, and (3) 27% of driving range extension are achieved. In addition, an optimization problem is framed to minimize the error between UC reference, actual currents, and the battery current. The proposed problem is solved applying Kuhn-Tucker conditions; hence, battery performance is evaluated based on the battery's State of Health (SoH). To optimally derive the best HESS configuration, a dynamic programming approach is considered in Reference 74 for an electric bus. After obtaining the best configuration and size of HESS, a supervisory control made of rule-based strategy has been implemented to reduce the battery lifetime cost significantly.

A nonlinear MPC method is studied in detail in Reference 47 by considering nonuniform sample time at supervisory level. For predicting the future inputs, the control problem is defined over a short and long prediction horizon with two different sample times. At start, the prediction horizon time is taken as smaller sample time to reduce the battery peak current. Later, the longer sample time at the high-level prediction is made to fully utilize the UC’s to decrease the rapid change in power by maintaining a constant voltage at the battery. Thereby, it also reduces the peak power consumption, which in turn improves the driving range, lifespan of a battery, and vehicle performance. Additionally, the reference for the UCs and battery is updated more often, it allows further improvements in battery power variations. A detailed comparative study in Reference 52 has been done using deterministic rule-based, frequency-based, fuzzy logic, MPC methods for a HESS-based EV. From the results, it can be understood that the life cycle cost of HESS is reduced by 23% compared to battery-operated EV. A comparative study is also performed between optimization-based and rule-based EM strategies in Reference 50. As far as the practical application is concerned, a deterministic rule-based and fuzzy logic is regarded as the best choices because of their notable performance and easy implementation.

Further, in case of a semi-active topology the performance evaluation is also critically evaluated based on voltage variation and system design is presented in Table 3.

### 5.2 Performance evaluation of EM strategies applied for fully active configuration

Compared to the semi-active topology, fully active hybrid topology is adopted for the reason that the battery power flow is regulated via additional bidirectional converter. The EMS of fully active HESS configuration is shown in Figure 14.
As mentioned in earlier sections, this topology has full control over battery current as well as the UC voltage. It is imperative that the control techniques play a major role in enhancing the durability of the battery, extending the drive range, and maintaining stiff DC-bus voltage; a comparative analysis on voltage variations and system design is performed for EM techniques applied in fully active topology (Table 4).

Using rule-based control strategy, the authors in Reference 39 have shown that the hybridized battery-UC system is capable of reducing the peak current of battery along with improved lifespan of battery. A novel rule-based EM strategy for light EVs with multienergy sources connected next-generation transportation is explained in Reference 37. The proposed system focuses on the efficacy enhancement by combining multiple renewable source models and control algorithms with multiple switches for maximum energy harvest. The performance of proposed system establishes a benchmark with standard ECE-47 drive cycle under standard and abnormal constraints. The results show that with proper control algorithm the energy between multiple sources can be effectively managed. An EM strategy incorporating rule-based meta-heuristic technique is presented in Reference 48 for multiple sources fed EVs. First, a long-term management with dynamical solution space with a set of possible rules is evolved to monitor the energy level of the battery. Second, a simulated annealing technique is utilized to optimally share the power. The generated references to lower-level controllers of DC-DC converters meet the power demand irrespective of future power requirements. This EM method achieves good control and provides feasible possibilities to share available energy via online among various sources with better range and reliability.

A hybrid active parallel topology with two separate DC-DC converters one for NiMH battery and another one for UC’s that operates in bidirectional mode, is proposed in Reference 49. A cascaded control scheme is deduced through current and voltage controllers for battery voltage regulation. Subsequently, an EM approach incorporating a power follower with efficiency map to generate reference current for a UC fed DC-DC converter depending on the power demand is developed. Advantages of this EM strategy are (1) improvement in the DC link voltage stability, (2) UC is also recharged through recovered energy during braking conditions. Hardware in Loop (HIL) testing in real time following a similar strategy using particle swarm optimization to share power optimally is explained in Reference 49. A comparative study is also performed on optimization based and rule-based EM strategies in Reference 50. By controlling the required UC voltage range, the lambda control can be employed for high UC voltage ranges; wherein the rule-based or filtering techniques could be used for narrow voltage ranges. Only 2% improvement is obtained in the RMS current of the battery. But the efficiency aspects of the entire model are not taken into account in this study. In Reference 51 a control strategy incorporating deterministic rules for a power follower approach in power management of dual energy storage system (DESS) has been proposed. Here, the EM is decomposed into two layers such as strategy and control. A cascaded or decoupled EM method is used to control the battery side converter and the current control strategy based on the power follower approach is used for UC side converters.

An adaptive frequency splitter is utilized in Reference 55 for channelizing the low-frequency and high-frequency content to the battery and UC by considering UC as the peak power unit. The outcome of the work recommends that it is suitable only for off-loading applications owing to its simplicity, flexibility, and robustness. Novel frequency adaptive based Power Split Strategy (PSS) for HESS is detailed in References 56 and 57. The developed PSS produces uninterrupted outputs; hence, variations in the driving conditions can be identified in real time even for small transitions by observing the working conditions of every source. Further, in References 59 and 85 Driving Cycle Identification (DCI) incorporating Learning Vector Quantization (LVQ) NN to forecast the power demand during the power-sharing between the battery and UC is outlined. A multilevel Haar wavelet transform (Haar-WT) is incorporated for assigning frequency components required for UC during power demand circumstances. Further, the proposed technique reduced the overcharging of a UC, thereby increasing the system efficacy and lifetime of the battery.

An artificial potential field is developed in Reference 60 to allocate power for HESS by estimating the power allocation ratio and cutoff frequency with the aid of existing virtual attractive force. Employment of artificial potential field allows the battery to operate in normal operating limits with reduced stress. It is found that the proposed system reduces 15% of battery capacity loss thereby enhancing the lifetime of the battery.

In Reference 62 a detailed modeling, analysis, and sizing of multiple ESS with fuel cell, battery, UC are investigated. A fuzzy-rule-based supervisory EM algorithm is proposed in monitoring and control. The energy flow in UC is tested for simple ECE-15 urban drive cycle. The results suggest that voltage fluctuations caused by load characteristics are smoothened by UC, and battery voltage is maintained constant most of time with the help of fuel cell. A position-based power management is proposed in Reference 41 using T-S fuzzy logic for HESS in practical implementation of electric tram. Here, the global positioning systems (GPS) are used to predict the future power flow and energy demands for preparation of UC control. And also, a heuristic optimization algorithm called differential evolution (DE) is used to
Table 3: A Comparison table for EM techniques applied to the semi-active topology.

| Ref | EM approach                      | System specifications | Battery specifications       | UC specifications  | Nominal motor/Converter Power (KW) | Voltage variations | Power demand | Drive cycles tested | UC voltage variations (V) | DC Bus voltage (V) | Regenerative peak power demand (KW) | Peak power demand (KW) | Experimental/Simulation validation |
|-----|----------------------------------|------------------------|------------------------------|---------------------|------------------------------------|--------------------|--------------|---------------------|-------------------------------|----------------|---------------------------|------------------------|-------------------------------------|
| 84  | Deterministic rule-based approach | Li-NMC, 4.2 V, 10 Ah, 109 in series, 15 in parallel | BACP300, 2.85 V, 2000F; 107 in series | 30                  | 114.04 to 316.77                   | Between 400 V and 450 | CITY II, ECE-15, NEDC | 30                  | 20                            | Simulation                |                                      |
| 50  | Frequency-based approach         | LiFePO4-12.8 kWh       | 45 V, $C_{uc} = 290 F$       | 15                  | 29.25 to 40.5                      | 80                 | WLTC         | -                   | -                            | Both                      |                                      |
| 40  | Frequency-based approach         | LiFeMnPO4-14.4 kWh     | BMOD0165P048B01-48 V, 165 F | 12                  | 48 to 80 V                         | 96                 | NEDC, UDDS, US06, LA92 | 35.32, 32.35, 70.83, 43.57 | 25.25, 22.67, 43.67, 73.73 | Both                      |                                      |
| 58  | Adaptive wavelet transform-based approach | NiMH, 29.16 kWh | Maxwell PC2500 | -                   | -                                 | Between 307 V and 330 | NYCC         | -                   | -                            | Simulation                |                                      |
| 63  | Fuzzy logic based approach       | LiFePO4-24 kWh, BCAP0150, 600 V, 1.35F | 129 for motor 1, 49 for motor 2 | 30 to 600            | 300 to 600                         | UDDS               | 57           | 57                  | 20.5                          | Simulation                |                                      |
| 66  | Fuzzy logic-based approach       | Li-ion-66.3 kWh        | BMOD0165 P048, 48 V, $C_{uc} = 110 F$ | 90                  | 680 to 1200                        | 545 to 570         | Heavy duty driving condition | 141.27, 150                    | Both                      |                                      |
| 73  | Convex optimization              | Li-ion-15 kWh          | 56 V, $C_{uc} = 3400 F$      | 50                  | 70 to 150                          | 350 to 320         | FTP75        | 50                  | 20                            | Simulation                |                                      |
| 74  | Dynamic programming              | LiFePO4, 115 kWh       | 600 V, $C_{ac} = 11.2 F$     | -                   | 325 to 675 for CBDC, 320 to 610 for UDDS | 300 to 600         | CBDS, UDDS   | 173, 338            | 131, 192                     | Simulation                |                                      |
| 4479| Pontrygins minimum principle (PMP)| TS-LFP160AHA, 12.48 kWh | BMOD0165 P048, 48 V, $C_{uc} = 165 F$ | 15                  | 44 to 48                           | 76 to 79           | NEDC         | -                   | -                            | Both                      |                                      |
| 75  | Convex optimization              | LiFePO4, 28.2 kWh      | 600 V, $C_{uc} = 6.75 F$     | -                   | -                                 | 300 to 600         | UDDS         | 50                  | 20                            | Simulation                |                                      |
| 52  | LiFePO4, 115 kWh                | 600 V, $C_{ac} = 11.2 F$ | -                   | -                                 | -                                 | 173, 200         | 131, 300      | Simulation            |                                       |                                      |

(Continues)
| Ref | EM approach | Battery specifications | UC specifications | Nominal motor/Converter Power (KW) | Voltage variations | Power demand |
|-----|-------------|------------------------|-------------------|-----------------------------------|-------------------|--------------|
|     | Model predictive control (MPC) | | | | | |
|     | Fuzzy logic control (FLC) | | | | | |
|     | Frequency-based control | | | | | |
|     | Dynamic programming (DP) | | | | | |
| 47  | Model predictive control | LiFePO4, 36.8 kWh BMOD250, $C_{uc} = 250$ F, 130 V | 30 | 64.8 to 129.6 | 325 | VWU-city cycle | 28 | 7 | Simulation |
optimize the output membership functions of T-S-based FLC. Another FLC-based EM scheme is presented in Reference 64 for three-wheeled EVs using a fully active hybrid topology. In this article, an inner loop control is proposed for intelligent power sharing between UC and battery. Further, results suggest that UC’s are able to smoothen and reduce the RMS current of battery with significant improvement in a lifetime and minimizing the battery cost. An adaptive fuzzy logic controller for EM in parallel active topology is proposed in Reference 67 and tested for various drive cycles based on simulation studies. A nonisolated multi-input bidirectional DC-DC converter is used for HESS EM problems solved by FLC scheme in EVs. The results suggest that there is an achievement of 55% improvement in battery lifetime.

To outperform the rule-based EM strategies, a supervisory EM strategy has been proposed in Reference 70 by formulating the power sharing problem as multiobjective optimization. This is solved by applying DP method for various data sets of drive cycles. The results obtained are utilized to train the neural networks. This intelligent EM controller at supervisory level improves the battery life by 60% and achieves higher efficiency. A SA coupled with dynamically restricted search space used global optimization to solve the EM problem in fully active HESS-based EV. A supervisory architecture based on short-term and long-term management is detailed to accomplish the overall EM. Also, a comparative study has been done using PSO and SA for similar optimization problems. Both SA and PSO EM approaches obtain consistently good results. There is slighter advantage of using PSO as it takes less computational burden than SA. The outcome shows that PSO provides a good solution for online energy distribution among two energy sources by reducing power losses occurring in the battery by reducing the rapid battery usage. In Reference 45 proposes a mathematical representation of an EM for HESS in EV by using gamma functions. First gamma-based strategy (GBS) used to solve EM problem and the genetic algorithm is used to optimally choose the value of gamma (γ) to improve the performance of GBS strategy. The parameters considered are RMS current and peak current of battery, life cycle cost for a HESS powered EV. The obtained results are compared with the rule-based strategy. These methods capable are minimizing battery RMS current by 40% in NEDC. It is observed that EV with HESS consumes higher energy. The difference is about 0.5% against RBS and GBS. It also causes increase in weight and losses in DC-DC converters.

The study in Reference 70 deals with a novel predictive algorithm, which utilizes a state-based technique to forecast load demands. Decisions made on power distribution are in real time-based forecasts and possibilities of state trajectories related to system losses. Thus, fully active HESS is implemented and validated experimentally with a programmable drive cycle with well-built regenerative power component. It is practically proved that the HESS is more capable, efficient, and captures the excessive regenerative energy wasted under braking because of battery’s inadequate consumption of charge current potential.

For fully active hybrid topology polynomial correctors have been used for current and voltage control of UC and batteries. The EM is achieved by controlling the current sharing between loads and DC-bus voltage. Here two different methods have been proposed. One is to control the current of UC and DC-bus voltage control by taking the battery current as the inner loop. Second, by keeping the battery voltage fixed to control the current for both UC and battery are proposed via polynomial corrector method. A control scheme in Reference 87 proposed for parallel hybrid topology says that any supervisory EM methods can be applied to get an efficient operation of HESS-based EV.
| Ref  | EM approach                      | Battery specifications | UC specifications | Nominal power rating of motor/Converter (kW) | UC voltage (V) | DC bus voltage (V) | Drive cycles tested                                                                 | Peak power demand (kW) | Regenerative peak power (kW) | Validation Type                      |
|------|----------------------------------|------------------------|-------------------|---------------------------------------------|----------------|-------------------|--------------------------------------------------------------------------------------|------------------------|-----------------------------|-----------------------------------|
| 484951 | Rule-based approach, PSO        | NiMH-1 kWh             | Nesscap-130 V, $C_{uc} = 11.1$ F | 500                                         | 25 to 35 V     | 110 V             | ARTEMIS, ECE-15, NYCC, US06                                                             | 0.6                    | 0.2                         | Experimentation at reduced scale |
| 56,57 | Frequency separation-based approach, LQG | Li-ion 0.6 kWh          | 48 V, $C_{uc} = 165$ F | 3                                           | 32 to 42 V     | 150 V             | ECE-15, IFSTTAR                                                                   | 0.6                    | 0.2                         | Experimentation at reduced scale |
| 59    | Haar WT-based approach           | Li-ion 403 kWh          | BMOS000, 140 V, 55F | -                                           | 65 V to 145 V  | 255 to 296 V       | WVUSUB, UDDS, UKBUS6, INDIA_HWY_SAMPLE, INDIA_URBAN_SAMPLE                         | 19                     | 26                          | Experimentation at reduced scale |
| 60    | Adaptive power allocation        | LiFePO$_4$ 16 V, 52 Ah | MAXWELL 100F, 2.7 V | -                                           | -              | 24 V              | US06, NYCC                                                                     | 0.6                    | 0.2                         | Experimentation at reduced scale |
| 64    | Fuzzy logic-based approach       | Li-ion, 96 V, 12.4 kWh  | BCA0350, 85.5 V, $C_{uc} = 175$ F | 28                                         | 42.8 to 85.5 V | 108 V             | Real Drive Cycle                                                                 | 24.2                   | 11.2                        | Experimental                      |
| 65    | Fuzzy logic-based approach       | Li-ion 70 V, 1.4 kWh    | 125 V, $C_{uc} = 63$ F | 3                                           | 30 to 120 V    | 75                | UDDS, ECE-15                                                                    | 57, 47.8               | 20.5, 5.8                   | Both, experimentation at reduced scale |
| 70    | DP with neural network based approach | LiFePO$_4$, 34 kWh    | BACP2000, 203 Wh    | 36                                         | 135 to 270 V   | 360               | UDDS, NYCC, ARTEMIS, WVU                                                            | 57                     | 20.5                        | Simulation                      |
| 72    | Simulated annealing              | NiMH, 96 V             | BMOD0330, 86 V, $C_{uc} = 52.8$ F | 0.5                                         | 37 to 42.5 V   | 108               | ECE-15                                                                            | 47.8                   | 5.8                         | Both, experimentation at reduced scale |
| 46    | SA and PSO                       | NiMH, 96 V             | BMOD0330, 86 V, $C_{uc} = 52.8$ F | -                                           | -              | -                 | ARTEMIS                                                                          | 38                     | 16                          | Simulation                      |
| 45    | Genetic algorithm                | LiFePO$_4$, 320 V, 22.1 kWh | 390 V, $C_{uc} = 27.5$ F | 67.2                                         | 200 to 391.5 V | 400               | NEDC, ECE-15                                                                    | 18                     | 12                          | Simulation                      |
| 77    | Predictive power optimization    | Li-ion, 27 V, 0.229 kWh | 27 V, $C_{uc} = 37.24$ F | 0.5                                         | -              | 50                | Light and heavy drive cycles                                                          | -                      | -                           | Both, experimentation at reduced scale |
TABLE 5  A comparative assessment on improvements obtained by EM technique applied to HESS-based EV

| Rule-based EM technique | Semi-active-type HESS | Full active-type HESS | Limitations/Challenges |
|-------------------------|-----------------------|-----------------------|------------------------|
| EM techniques           | a) b) c) d)           | a) b) c) d)           |                        |
| Deterministic rule-based| High Medium Low Low   | Low Medium Medium Low | Not suitable for all the drive cycles, |
| Frequency separation    | Medium Low Low Low    | Low Low Low Low Low   | Prior info on frequency is needed |
| Fuzzy Logic-based       | Medium Medium Medium Low | Low Medium Medium Low | Fast variation cannot be tracked |
| Neural network          | NA NA NA NA          | Medium High High Medium | Prior data and requires high computation |

| Optimization-based EM technique | Semi-active-type HESS | Full active-type HESS | Limitations/Challenges |
|---------------------------------|-----------------------|-----------------------|------------------------|
| Dynamic programming             | High Medium Low High  | Medium Medium Low Low | Optimality not guaranteed, Complex programming. |
| Pontryagin’s principle          | Medium Low Low NA NA  | NA NA NA NA NA       | To be investigated to understand its performance. |
| Instantaneous optimization      | Medium Low High Low   | NA NA NA NA NA       | Optimality not guaranteed. |
| Particle swarm optimization     | NA NA NA NA High     | High High Medium Low | Longer convergence time. |
| Simulated annealing             | NA NA NA NA High    | High High Medium Low | High computation time, complex programming. |
| Model predictive control        | Low Medium Low Low   | NA NA NA NA NA       | Nonuniform sample times. |

Note: NA – Not applied, High>70%, 30% < Medium <70%, Low <30%.

6 | SUGGESTIONS FOR IMPROVEMENTS IN EM FOR HESS BASED EV

The EM strategies in this review focus on efficient and flexible use of UC with battery present in EV for various drive cycles. The challenge that still persists in EM is due to improper sizing of UC and influence of EM strategy on battery aging. Therefore, suitability study on different EM techniques applied for semi and fully active BESS is conducted based on the following parameters: (a) reduction of battery peak current, (b) drive cycle extension, (c) lifetime maximization, and (d) capacity loss minimization and are tabulated in Table 5. To define the method suitability parameter, index such low, medium, and high are used. For instance, high indicates an acceptance percentage of greater than 70%, medium acceptance is between 30% and 70%, and lowest suitability with less than 30% is taken as low. From Table 5, the following lists the limitations that are been observed from EM techniques applied for both semi-active and fully active configurations.

- The deterministic rule-based and fuzzy logic-based strategies can be implemented in real time with less computational burden. Being robust and wise to parameter variations these methods failed to tackle the fast variations in power demand for the battery.
- Filtration or frequency-based EM technique can decouple load power into different frequency components effectively but requires efficient estimation of frequencies that needed to be separated.
- DP, instantaneous and convex optimization, techniques can minimize the power demand from battery, but these methods are sensitive to model uncertainties, change in drive pattern, and excessive computational burden in obtaining optimal solution.
- Meta-heuristic techniques such as GA, PSO, and SA applied for EM in battery/UC powered EV imposes challenges in the real-time implementation in the form of control parameters selection and tuning.
Based on the abovementioned limitations and literature review performed so far, the following are some of the suggestions that are possible to be investigated in near future to enhance the performance of HESS-fed EV.

- Rule-based strategy for semi-active and fully active hybrid topologies achieves reduction up to 81% and less than 30% in battery peak current.\textsuperscript{48,84} But to clearly investigate the performance improvements, its advantages and disadvantages a comparative study need to be performed between the same under similar power ratings.
- MPC-based EM strategy showcase better performance among methods therefore can be implemented at supervisory level for parallel active hybrid topology under different sample times to achieve battery peak current reduction >40% as in Reference 45.
- A comparative study between different EM strategies applied for fully active topology can be done to evaluate the effectiveness of each strategy under NEDC, UDDS, NYCC, US06, ECE-15, ECE-45, ARTEMIS, WYC, and WVU drive cycles.
- An extended suitability study can be performed for various DC-DC converters such as cuk, sepic, Luo, Full bridge converter, etc., to study its system efficiency under dynamic braking conditions, stability, and its cost for EV applications.
- In case of a battery/UC with diode topology, a supervisory level controller based on MPC can be applied to evaluate the performance indices such as efficiency, lifetime, degradation, SoH, and drive range extension.
- Impact of EM strategies on battery aging can be explored using optimization-based technique in order to minimize the battery aging and capacity loss more than 10%.
- Multiple objective functions can be formulated based on battery SOH, configuration, cost, weight and can be solved using various optimization methods for optimal UC sizing for HESS to lessen the size of the battery.

7 CONCLUSIONS AND RECOMMENDATIONS

Due to varied drive cycles of EV, the battery combined with UC has a huge potential to improve performance and efficiency of the EV system. This article presents a brief overview on (1) classification of HESS topologies such as passive parallel, semi-active, fully active, and series reconfigurable topologies, (2) EM strategies such as a rule-based and optimization-based techniques, and (3) application of EM strategies for these HESS topologies. A detailed comparative study is presented to analyze the performance of EM strategies applied to these HESS topologies. The different topologies of hybridizing the battery and UC are also studied to understand its own advantages and disadvantages. Based on the study performed in previous sections, the following conclusions are derived:

- Many available EM methods are applied only for semi-active and parallely active hybrid topologies.
- Choosing an appropriate EM strategy at the supervisory level can significantly reduce the battery peak current, lifetime cost, degradation, and extends the driving range.
- A predefined rule-based EM strategy for semi-active type HESS arrangement provides significant improvements in drive range extension for City II, ECE-15, and NEDC drive cycles.
- Selection of optimal UC size and application of DP improves the life cycle cost and reduces the size of battery.
- Based on the analysis, it is noted that MPC-based EM strategy at the supervisory level functioning at nonuniform sample time for semi-active arrangement has shown significant reduction of stress on the battery, thus increasing the lifetime.
- For the predefined set of drive cycles optimization-based EM strategies provide better results simultaneously. These techniques work well in offline than online.
- For fully active HESS arrangement stability of the entire system is improved with usage of efficiency maps along with rule-based strategy.
- Fuzzy logic controller at the supervisory level for fully active HESS arrangement with frequency-based control has noteworthy improvements in reducing capacity loss and extends the life of the battery up to 55%.
- Application of metaheuristic algorithms such as PSO and SA at short-term level supported by well-tuned rule-based strategy exhibit better results with lesser computation time for various drive cycles.
- Dynamically restricting search space of SA technique at supervisory level maximizes the usage of UC for fully active type HESS arrangement under regenerative braking conditions.
From the above derived conclusions, the following are the few recommendations suggested for the upcoming researchers in the field of energy management for EVs powered by battery/UC:

- The performance parameters such as battery peak current reduction, efficiency of the system, lifetime improvement, drive range extension for a single EM strategy can be investigated.
- Some of the meta-heuristic algorithms such as firefly, dragon fly, whale optimizations methods can be used for obtaining the better battery energy efficiency and optimal sizing of UC.
- For fully active and semi active-type hybrid configurations, a nonlinear controller such as backstepping approach can be applied to have better performance and efficiency under dynamic operating conditions.
- Hybridizing the nonlinear controllers such as backstepping and MPC can also be accomplished for the HESS powered EV systems to enhance the performance and efficacy.

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CONFLICTS OF INTEREST
Authors declare that there are no conflicts of interest.

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