

Article

An Enhanced Rule-Based Energy Management System with Integrated Route and Environmental Information for Battery–Supercapacitor Hybrid Electric Vehicles

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Abstract

In this paper, a route- and environment-aware rule-based energy management system (EMS) strategy for EVs equipped with HESSs consisting of a lithium-ion battery and a supercapacitor is proposed. The proposed rule-based EMS integrates driving mode classification, traffic conditions, road gradient, wind resistance, ambient temperature, and the supercapacitor (SOC) to determine the optimal power-sharing strategy between the battery and the supercapacitor under various driving conditions, including city, highway, and stop-and-go traffic. A mathematical model of the EV powertrain, battery, and supercapacitor is developed. The performance of the proposed rule-based EMS strategy is validated in MATLAB/SIMULINK under three representative driving cycles: the Urban Dynamometer Driving Schedule (UDDS), Artemis Motorway 130, and a Central Business District (CBD) driving cycle. It is shown that the proposed rule-based EMS strategy significantly reduces the battery current stress while increasing supercapacitor usage.

Keywords: electric vehicle (EV); hybrid energy storage system (HESS); battery–supercapacitor; energy management system (EMS); rule-based control; supercapacitor utilisation; battery current reduction; route-aware energy management

1. Introduction

The global transition toward sustainable transportation has accelerated the deployment of battery electric vehicles (EVs) as an effective means of reducing greenhouse gas emissions, improving energy efficiency, and decreasing dependence on fossil fuels [1]. Central to the performance of modern EVs is the energy storage system, which directly influences driving range, acceleration capability, energy efficiency, battery lifetime, and overall vehicle cost [2]. Lithium-ion batteries have become the preferred energy storage technology because of their high energy density, relatively long cycle life, and high charge–discharge efficiency [3]. However, despite these advantages, lithium-ion batteries remain susceptible to rapid degradation when subjected to repeated high-current charging and discharging events associated with aggressive acceleration and regenerative braking [4]. These operating conditions increase internal heat generation, accelerate electrochemical ageing, and reduce the usable lifetime of the battery pack [2,3].

To overcome these limitations, battery–supercapacitor hybrid energy storage systems (HESSs) have received considerable attention in both academia and industry [5]. A supercapacitor possesses significantly higher power density, faster charge–discharge capability, and



Academic Editor: JongHoon Kim

Received: 9 June 2026

Revised: 2 August 2026

Accepted: 6 August 2026

Published: 11 August 2026

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substantially longer cycle life than lithium-ion batteries, making it well suited for supplying short-duration high-power demands and absorbing regenerative braking energy [6]. By allowing the battery to provide the average propulsion energy while the supercapacitor manages transient power fluctuations, a properly designed HESS reduces battery current stress, increases regenerative energy recovery, improves overall energy efficiency, and contributes to improved battery durability [5–9].

The performance of a HESS depends not only on the hardware configuration but also on the effectiveness of its energy management system (EMS) [10]. The EMS determines the instantaneous power allocation between the battery and the supercapacitor while ensuring that the vehicle power demand is satisfied and both energy storage devices operate within their allowable limits [11]. Existing EMS strategies for battery–supercapacitor HESSs can generally be classified into three categories: rule-based control, optimisation-based control, and intelligent control [5,8,9,12,13].

Optimisation-based EMSs, including Dynamic Programming (DP) [14], Equivalent Consumption Minimisation Strategy (ECMS) [15], Pontryagin’s Minimum Principle (PMP) [16], Model Predictive Control (MPC) [17,18], Genetic Algorithms (GAs) [13], and Particle Swarm Optimisation (PSO) [13], have demonstrated excellent energy management performance by minimising predefined objective functions such as battery degradation, energy consumption, or equivalent fuel consumption [12,13]. However, many optimisation methods either require prior knowledge of the driving cycle or involve iterative computations that are computationally demanding for real-time implementation on embedded automotive controllers [19].

Recent advances in artificial intelligence have resulted in intelligent EMSs based on fuzzy logic [4,6,20], artificial neural networks [21], reinforcement learning (RL) [22], deep reinforcement learning (DRL) [22], and adaptive learning algorithms [23]. These approaches are capable of learning complex nonlinear relationships between vehicle operating conditions and optimal power allocation without relying on explicit mathematical models. Nevertheless, they generally require extensive training data, careful parameter tuning, and relatively high computational resources. Furthermore, their decision-making process is often difficult to interpret, which limits their adoption in safety-critical automotive applications where transparency and deterministic behaviour are essential.

Consequently, rule-based EMSs remain one of the most widely adopted approaches for practical battery–supercapacitor HESS implementation because of their simplicity, robustness, low computational complexity, and ease of implementation [16,24–26]. Conventional rule-based controllers typically determine the battery–supercapacitor power split using instantaneous measurements such as battery state of charge (SOC), supercapacitor SOC, and traction power demand [25,26]. While these approaches provide satisfactory real-time performance, their decision-making capability is generally limited to the current operating condition. As a result, they are unable to proactively prepare the HESS for upcoming driving events, frequently leading to conservative supercapacitor utilisation and unnecessary battery current stress.

Recent research has attempted to improve conventional rule-based EMSs by incorporating predictive information such as vehicle speed estimation, driving pattern recognition, or traffic information [18,23,27]. Although these studies have demonstrated improvements in energy management performance, many still rely on a limited set of predictive variables or require computationally intensive optimisation techniques. Furthermore, relatively few rule-based EMSs simultaneously consider multiple sources of readily available external information including road gradient, traffic density, wind speed, and ambient temperature to proactively adapt battery power allocation in real time.

This observation reveals an important research gap. Despite the widespread availability of navigation systems, digital elevation maps, weather services, and connected vehicle technologies, existing rule-based EMSs seldom integrate these external information sources into a unified supervisory control framework. Most published studies continue to rely primarily on instantaneous electrical measurements and therefore cannot anticipate future operating conditions that significantly influence vehicle power demand. Moreover, many published comparisons [28] only evaluate battery-only electric vehicles, making it difficult to distinguish improvements resulting from the HESS architecture itself from those arising from the EMS. Finally, battery lifetime improvements are frequently inferred from reduced battery current without evaluating additional battery stress indicators such as RMS current, energy throughput, and SOC variation.

To address these limitations, this paper proposes a route- and environment-aware rule-based energy management system for battery–supercapacitor hybrid electric vehicles. Unlike conventional rule-based controllers discussed in [24–26], the proposed EMS integrates battery SOC, supercapacitor SOC, traction power demand, driving mode, road gradient, traffic density, wind speed, and ambient temperature into a unified supervisory decision-making framework. These variables are used to dynamically adjust the allowable battery power, allocate transient power support to the supercapacitor, and maximise regenerative braking energy recovery while maintaining low computational complexity suitable for real-time embedded implementation.

The proposed controller is evaluated using a comprehensive MATLAB/Simulink model of a fully active battery–supercapacitor HESS under three representative driving cycles: the Urban Dynamometer Driving Schedule (UDDS), Artemis Motorway 130, and a Central Business District (CBD) driving cycle. To isolate the contribution of the proposed controller, its performance is compared with both a battery-only electric vehicle and a conventional rule-based HESS EMS. Performance is assessed using several quantitative battery stress and energy management indicators, including maximum battery current, RMS battery current, battery energy throughput, battery SOC variation, supercapacitor utilisation, regenerative braking energy recovery, and overall power-sharing characteristics.

The main contributions of this work are summarised as follows:

1. A route- and environment-aware rule-based EMS that integrates traffic density, road gradient, wind speed, ambient temperature, and driving mode classification into the supervisory power allocation process.
2. A dynamic battery power-limiting strategy that continuously adapts the allowable battery power according to both battery operating conditions and predicted external driving conditions.
3. A practical MATLAB/Simulink implementation incorporating detailed battery, supercapacitor, longitudinal vehicle dynamics, regenerative braking, and bidirectional DC/DC converter models.
4. A comprehensive comparative evaluation against both a battery-only EV and a conventional rule-based HESS EMS using multiple quantitative performance metrics to assess battery stress, supercapacitor utilisation, and regenerative braking performance.

The remainder of this paper is organised as follows. Section 2 presents the mathematical modelling of the electric vehicle and the hybrid energy storage system. Section 3 describes the HESS sizing methodology adopted for the simulation platform. Section 4 introduces the proposed route- and environment-aware EMS, including the supervisory control architecture and power allocation strategy. Section 5 presents the simulation setup and performance evaluation. Finally, Section 6 concludes this paper and outlines directions for future research.

2. Mathematical Modelling

The proposed route- and environment-aware energy management strategy (EMS) was developed and evaluated using a comprehensive mathematical model of a battery electric vehicle equipped with a battery–supercapacitor hybrid energy storage system (HESS). The mathematical model describes the vehicle longitudinal dynamics, battery, supercapacitor, bidirectional DC/DC converters, DC link, traction motor, and power balance relationships that govern the operation of the proposed supervisory controller. The model was implemented in MATLAB/Simulink using a discrete-time simulation framework.

To simplify the analysis while maintaining sufficient modelling accuracy for EMS evaluation, the following assumptions are adopted throughout this study:

- The vehicle travels on a rigid road surface without wheel slip.
- Tyre rolling radius remains constant.
- Drivetrain losses are represented by an equivalent efficiency.
- Battery and supercapacitor temperatures are assumed uniform.
- Converter switching dynamics are neglected and represented by average-value models.
- Electrical components operate within their specified voltage and current limits.

These assumptions are widely adopted in energy management studies because they preserve the dominant power flow characteristics while reducing computational complexity.

2.1. System Architecture

The electric vehicle considered in this study employs a fully active battery–supercapacitor hybrid energy storage system (HESS), as illustrated in Figure 1, while its corresponding legend is depicted in Figure 2. The architecture consists of a lithium-ion battery pack and a supercapacitor module connected to a common DC bus through independent bidirectional DC–DC converters. The DC bus supplies a three-phase voltage source inverter that drives the traction induction motor.

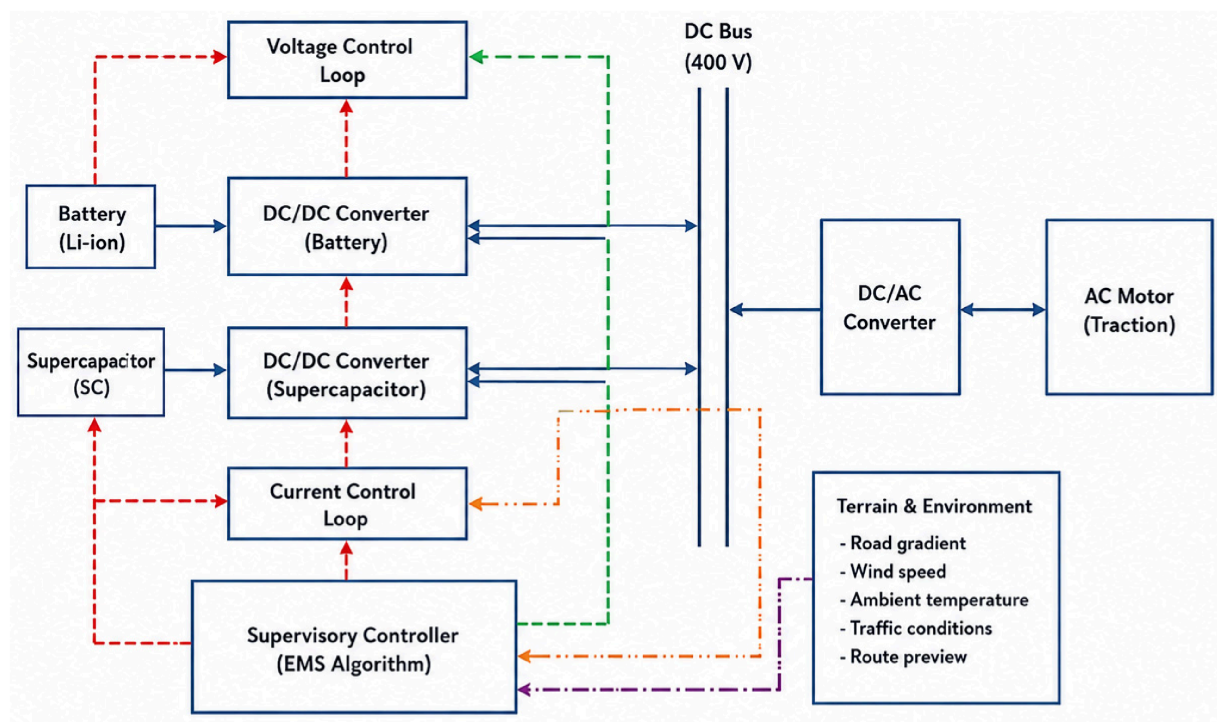


Figure 1. HESS-based EV system schematic diagram.

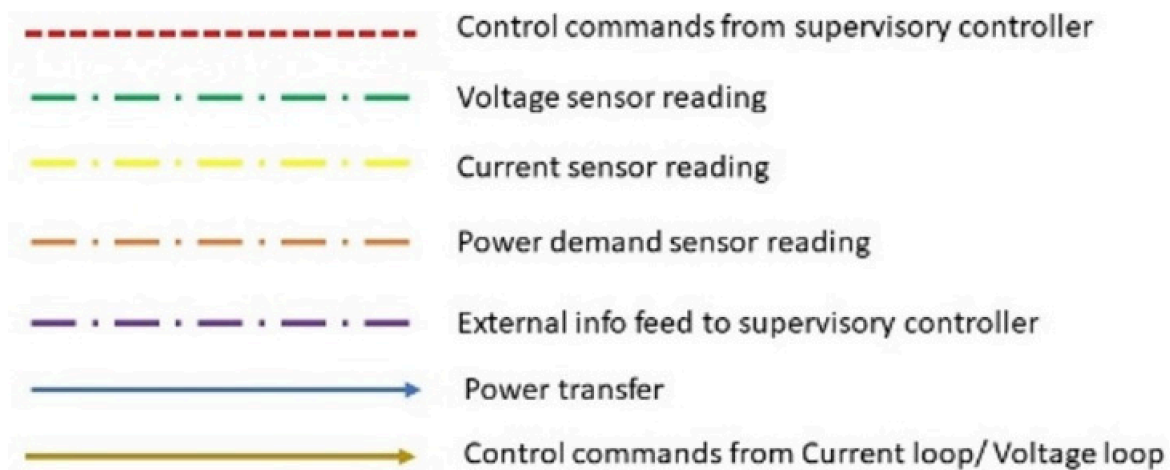


Figure 2. HESS-based EV diagram legend.

The supervisory energy management system (EMS)/controller determines the instantaneous power contribution of each energy storage device according to the vehicle operating conditions while satisfying the traction power demand. The battery is primarily responsible for supplying the average energy demand owing to its high energy density, whereas the supercapacitor supplies transient high-power demands and absorbs regenerative braking energy because of its high-power density. The objectives of the proposed EMS are the following:

- Minimise battery current fluctuations.
- Maximise supercapacitor utilisation.
- Improve regenerative energy recovery.
- Reduce battery electrical stress.

2.2. Electric Vehicle Dynamics

The dynamics of the motion of EVs can be described using Newton's second law of motion given by the following:

$$M \frac{dv}{dt} = F_t - F_r - F_a - F_g, \quad (1)$$

where F_t is the traction force (N), M is the vehicle mass (kg), v is the vehicle velocity (m/s), F_r is the rolling resistance force (N), F_a is the aerodynamic drag force (N), and F_g is the gravitational force caused by the road gradient (N).

From Equation (1), the total traction force required by the vehicle can be deduced as follows:

$$F_t = M \frac{dv}{dt} + F_r + F_a + F_g. \quad (2)$$

2.2.1. Rolling Resistance

The rolling resistance is given by the following:

$$F_r = C_r M g \cos \theta \quad (3)$$

where C_r is the rolling resistance coefficient, g is the gravitational acceleration, and θ is the road slope angle.

2.2.2. Aerodynamic Drag

The aerodynamic drag is given by the following:

$$F_a = \frac{1}{2} \rho C_d A v^2, \quad (4)$$

where F_a expresses the air density while C_d denotes the air drag coefficient. A is the vehicle frontal cross-section. Unlike conventional rule-based EMSs [29], the proposed controller updates the aerodynamic resistance using real-time wind speed information. The effective vehicle speed relative to the surrounding air is then given by the following:

$$v_{air} = v + v_w, \quad (5)$$

where v_w expresses the wind speed component opposing the vehicle motion.

2.2.3. Gradient Force

The gravitational force due to the road inclination is as follows:

$$F_g = Mg \sin \theta, \quad (6)$$

where the positive values of θ correspond to uphill driving, whereas negative values represent downhill driving where regenerative braking energy may become available.

2.3. Vehicle Power Requirement

The traction power required, P_{EV} , by the electric vehicle is given by the following:

$$P_{EV} = F_t v. \quad (7)$$

Substituting Equations (2)–(4) and (6) into (7) yields the vehicle dynamics as shown by the following

$$P_{EV} = \left(C_r Mg \cos \theta + \frac{1}{2} \rho C_d A v^2 + Mg \sin \theta + M \frac{dv}{dt} \right) v. \quad (8)$$

Equation (8) forms the basis for determining the instantaneous power demand supplied by the HESS.

2.4. Hybrid Energy Storage System

The HESS power balance is expressed by the following:

$$P_{EV} = \eta_b P_b + \eta_{sc} P_{sc}, \quad (9)$$

where P_b is battery power, P_{sc} is supercapacitor power, η_b is battery converter efficiency and η_{sc} is supercapacitor converter efficiency.

During regenerative braking, the required traction power is negative, as shown below:

$$P_{EV} < 0, \quad (10)$$

and the recovered energy is preferentially stored in the supercapacitor.

2.5. Battery Model

The lithium-ion battery is represented using a first-order equivalent circuit model consisting of an open-circuit voltage source, an ohmic resistance and a polarization branch. The battery terminal voltage, V_b , is given by the following:

$$V_b = V_{oc}(SOC_b) - I_b R_0 - V_p, \quad (11)$$

where V_{oc} is open-circuit voltage, R_0 is internal resistance, SOC_b is the battery SOC, V_p is polarization voltage and I_b is battery current.

2.5.1. Battery SOC Update Equation

The expression of the updated battery SOC at each discrete time step is given by the following:

$$SOC_b(k+1) = SOC_b(k) - \frac{\eta_b I_b \Delta t}{3600 Q_b}, \quad (12)$$

where $SOC_b(k)$ is the battery SOC at the current time step k , and $SOC_b(k+1)$ is the battery SOC at the next time step $k+1$. Q_b is battery capacity (Ah) and Δt is the simulation sampling period. The positive battery current corresponds to discharge while negative current denotes charging.

2.5.2. Battery SOC Constraints

The battery state of charge (SOC) is constrained within predefined minimum and maximum operating limits to ensure safe and reliable operation. In this way, the states of charge vary within an allowable range, as shown below:

$$SOC_{min} \leq SOC_b \leq SOC_{max}, \quad (13)$$

where SOC_{min} is the lower limit of 20% while SOC_{max} is the upper limit of 90%.

2.6. Supercapacitor Model

The supercapacitor is modelled using an equivalent series resistance (ESR) connected in series with an ideal capacitor. The terminal voltage, V_{sc} is given by the following:

$$V_{sc} = V_c - I_{sc} R_{ESR}, \quad (14)$$

where V_c is capacitor voltage, I_{sc} is the supercapacitor current and R_{ESR} is equivalent series resistance. The capacitor voltage evolves according to the following:

$$\frac{dV_c}{dt} = \frac{I_{sc}}{C}, \quad (15)$$

where C denotes the supercapacitor capacitance.

The expression of stored energy in a supercapacitor, E_{sc} , is given by the following:

$$E_{sc} = \frac{1}{2} C V_c^2. \quad (16)$$

Given that the supercapacitor capacitance remains constant and that the supercapacitor SOC is determined using the supercapacitor terminal voltage, one can determine the supercapacitor SOC, SOC_{sc} , by the expression below:

$$SOC_{sc} = \frac{V_c^2 - V_{min}^2}{V_{max}^2 - V_{min}^2} \times 100\% \quad (17)$$

where V_{min} and V_{max} are the minimum and maximum allowable terminal voltages, respectively. This definition reflects the quadratic relationship between stored energy and terminal voltage and provides a physically meaningful SOC for energy management purposes.

2.7. Battery and Supercapacitor Operating Constraints

During the operation of the EV, the proposed rule-based EMS enforces the operating limits on both the battery and the supercapacitor to ensure that both devices operate within their manufacturer-specified safe operating regions throughout the driving cycle. On the battery side, the following operating limits are enforced:

- Maximum discharge current.
- Maximum discharge current.
- SOC limits.
- Voltage limits.

On the other hand, the supercapacitor operating limits enforced by the proposed EMS are listed below:

- Maximum voltage.
- Minimum voltage.
- Maximum converter current.
- Converter power limit.

2.8. Integration with the Proposed EMS

The mathematical models described above provide the state variables required by the proposed supervisory controller. At every sampling instant, the EMS receives the following data:

- Battery SOC.
- Supercapacitor SOC.
- Vehicle speed.
- Traction power demand.
- Road slope.
- Traffic condition.
- Ambient temperature.
- Wind speed.

Using the above-mentioned inputs, the proposed EMS determines the optimal power allocation between the battery and the supercapacitor while satisfying system constraints and minimising battery electrical stress. The resulting power references are subsequently applied to the bidirectional DC–DC converters to regulate the energy flow within the HESS.

2.9. Discrete-Time Implementation

All mathematical models were implemented using a fixed-step discrete-time simulation in MATLAB/Simulink with sampling period Δt . At each sampling instant, the controller receives the battery SOC, supercapacitor SOC, vehicle speed, traction power demand, road gradient, traffic density, wind speed, and ambient temperature before computing the battery power limit and allocating power between the battery and supercapacitor. The resulting power references are applied to the bidirectional DC/DC converters, after which the battery and supercapacitor states are updated for the next control interval.

3. Hybrid Energy Storage System (HESS) Sizing

The performance of a battery–supercapacitor hybrid energy storage system (HESS) depends on both the sizing of its energy storage components and the effectiveness of

the supervisory energy management strategy (EMS). An appropriately sized HESS must simultaneously satisfy the vehicle's energy requirement, provide sufficient transient power support during rapid acceleration, and maximise regenerative braking energy recovery while operating within the electrical and thermal limits of the battery and supercapacitor. Inadequate sizing may lead to excessive battery current stress, poor utilisation of the supercapacitor, reduced regenerative energy recovery, or unnecessary increases in system cost and mass [28,30–32].

It should be emphasised that the primary contribution of this work is the development of the proposed route- and environment-aware rule-based EMS, rather than a novel HESS sizing methodology. Consequently, the battery and supercapacitor ratings adopted in this study were determined using established HESS sizing procedures reported in the literature [16,27,33]. These methodologies generally size the battery according to the vehicle's energy consumption and required driving range, while the supercapacitor is sized according to peak power demand, transient load characteristics, and the amount of recoverable regenerative braking energy [25,32,33]. Such an approach provides a practical compromise between energy capacity, power capability, system cost, battery lifetime, and overall vehicle efficiency [11,22].

The resulting HESS provides a realistic simulation platform for evaluating the proposed EMS under representative operating conditions. Since identical hardware parameters are maintained throughout all simulation cases, the improvements presented in this work are attributed solely to the proposed supervisory energy management strategy rather than differences in hardware sizing.

3.1. Vehicle Power Demand Analysis

First, the traction power demand is determined from the longitudinal vehicle dynamics presented in Section 2. Using the above-mentioned inputs in Section 2.8, the proposed EMS determines the optimal power allocation based on the expression in Equation (7). Hence, the total energy, E_{EV} , required during driving cycle is given by the following:

$$E_{EV} = \int_0^T P_{EV}(t) dt, \quad (18)$$

where T is the duration of a particular driving cycle. The selected driving cycles (UDDS, Artemis Motorway 130, and CBD) are used to determine the maximum power demand, average power demand, and regenerative braking energy available for storage in the supercapacitor.

3.2. Battery Sizing

The battery is designed to provide the average propulsion energy required during vehicle operation while avoiding exposure to large transient current peaks. The minimum battery energy capacity is sized using the following expression:

$$E_b = \frac{E_{EV}}{\eta_b DOD}, \quad (19)$$

where E_b is the required battery energy, and DOD is the allowable depth of discharge. The battery capacitor is then determined using the expression below:

$$C_b = \frac{E_b}{V_{nom}}, \quad (20)$$

where V_{nom} is the nominal battery voltage. For this study, an 80 kWh lithium-ion battery pack was selected because it satisfies the vehicle energy requirement while maintaining adequate reserve capacity and limiting the battery operating range between 20% and

90% SOC, thereby reducing battery degradation. The maximum battery current is limited by the following:

$$I_{b,max} = \frac{P_{b,max}}{V_b}, \quad (21)$$

where $P_{b,max}$ is the allowable battery power determined by the proposed EMS.

Unlike conventional rule-based EMS in the literature, the proposed rule-based EMS intentionally limits the battery current so that high transient loads are supplied by the supercapacitor.

3.3. Supercapacitor Sizing

The supercapacitor is sized according to the maximum transient energy requirement and the regenerative braking energy available during the selected driving cycles [30,31]. The usable energy stored in a supercapacitor can be expressed by the following:

$$E_{SC} = \frac{1}{2}C(V_{max}^2 - V_{min}^2). \quad (22)$$

The required capacitance of the supercapacitor is therefore calculated as follows:

$$C = \frac{2E_{SC}}{V_{max}^2 - V_{min}^2}. \quad (23)$$

The required supercapacitor energy is determined from the regenerative braking energy, the acceleration energy and the allowable battery current reduction. Hence, the maximum regenerative braking energy is given by the following:

$$E_{regen} = \eta_r \int P_{regen}(t) dt, \quad (24)$$

where P_{regen} is the regenerative braking power and η_r is the regenerative braking efficiency. To maximise regenerative energy recovery, the proposed EMS maintains the supercapacitor SOC below its upper operating limit whenever possible.

3.4. Supercapacitor Operating Window

Unlike batteries, the energy stored in a supercapacitor is proportional to the square of its voltage. Consequently, operating the supercapacitor over its full voltage range significantly increases the available energy. The supercapacitor state of charge is defined by the following:

$$SOC_{SC} = \frac{V_{SC}^2 - V_{min}^2}{V_{max}^2 - V_{min}^2} \times 100. \quad (25)$$

For this study, the operating limits were selected as shown below:

$$20\% \leq SOC_{SC} \leq 95\%. \quad (26)$$

These limits ensure that there is sufficient reserve for generative braking, protection against over-voltage and that it improves the converter efficiency.

3.5. Bidirectional DC/DC Converter Sizing

Since both storage devices are interfaced through bidirectional converters, their ratings are selected according to the maximum instantaneous power delivered by the proposed EMS. The converter rating is given by the following:

$$P_{conv} = \max(P_b, P_{SC}). \quad (27)$$

The battery converter primarily regulates the DC bus voltage, whereas the supercapacitor converter controls the transient current supplied to the traction inverter. The current rating is calculated by the following:

$$I_{conv} = \frac{P_{conv}}{V_{DC}}, \quad (28)$$

where V_{DC} is the DC-link voltage.

A safety factor of approximately 20% is recommended to accommodate converter losses, component tolerances, and transient overload conditions.

3.6. Sizing Summary

Table 1 summarises the selected HESS parameters used throughout the simulation study. The proposed sizing methodology ensures that the battery supplies the average energy demand while the supercapacitor handles transient high-power events and regenerative braking energy. By allocating short-duration power peaks to the supercapacitor, the proposed EMS substantially reduces battery current fluctuations, thereby decreasing electrical stress on the battery. Furthermore, maintaining sufficient supercapacitor reserve capacity enables efficient recovery of braking energy under urban driving conditions, where frequent acceleration and deceleration occur.

Table 1. HESS parameters.

Parameter	Symbol	Value
Battery chemistry	-	Lithium-ion
Battery capacity	E_b	80 kWh
Battery nominal voltage	V_b	400 V
Battery SOC limits	-	20–90%
Supercapacitor operating voltage	V_{sc}	400 V
Supercapacitor SOC limits	-	20–95%
DC-link voltage	V_{DC}	400 V
Battery converter efficiency	η_b	98%
Supercapacitor converter efficiency	η_{sc}	98%
Transmission efficiency	η_t	98%

Unlike conventional battery-only electric vehicle architectures [28,31], the proposed HESS allows the battery to operate closer to its optimal operating region, while the supercapacitor compensates for rapid load variations. Consequently, the proposed sizing approach provides an effective compromise between system cost, energy efficiency, battery protection, and real-time implementation complexity.

The proposed electric vehicle adopts a 400 V DC bus architecture, which is representative of the voltage level employed by a large proportion of current production battery electric vehicles and research platforms [5]. A 400 V architecture provides a practical compromise between power capability, component cost, insulation requirements, and system complexity while enabling commercially available traction inverters, electric machines, battery packs, and bidirectional DC/DC converters to be readily integrated [24,25]. Compared with lower-voltage systems, a 400 V bus reduces the current required to deliver a given power level, thereby decreasing conductor size, copper losses, and thermal loading according to the power relationship $P = VI$ [24]. Although higher-voltage architectures (e.g., 800 V) further reduce current and improve high-power fast-charging capability, they

generally require more expensive power electronic devices, enhanced insulation, and additional safety measures [22]. Since the objective of this study is to evaluate the proposed route- and environment-aware energy management strategy rather than investigate the influence of the DC bus voltage, a 400 V architecture was selected as a representative industry-standard platform that provides realistic operating conditions for the developed battery–supercapacitor hybrid energy storage system [22,24].

4. Proposed Route- and Environment-Aware Energy Management System

The performance of a battery–supercapacitor hybrid energy storage system (HESS) is highly dependent on the strategy used to allocate power between the battery and the supercapacitor. Conventional rule-based controllers generally determine the power split using only the instantaneous vehicle power demand and the state of charge (SOC) of the energy storage devices [24,25]. Although this approach is computationally efficient, it does not fully exploit information regarding the upcoming driving conditions and therefore often results in conservative utilisation of the supercapacitor during normal vehicle operation.

To overcome these limitations, a route- and environment-aware supervisory energy management system (EMS) is proposed, as shown in Figure 3. Unlike conventional rule-based approaches [16,25], the proposed controller combines vehicle operating conditions with external environmental information to determine the appropriate power allocation between the battery and the supercapacitor. The controller continuously monitors the battery SOC, supercapacitor SOC, vehicle speed, traction power demand, road gradient, traffic conditions, wind resistance, and ambient temperature to achieve an adaptive yet computationally efficient power management strategy.

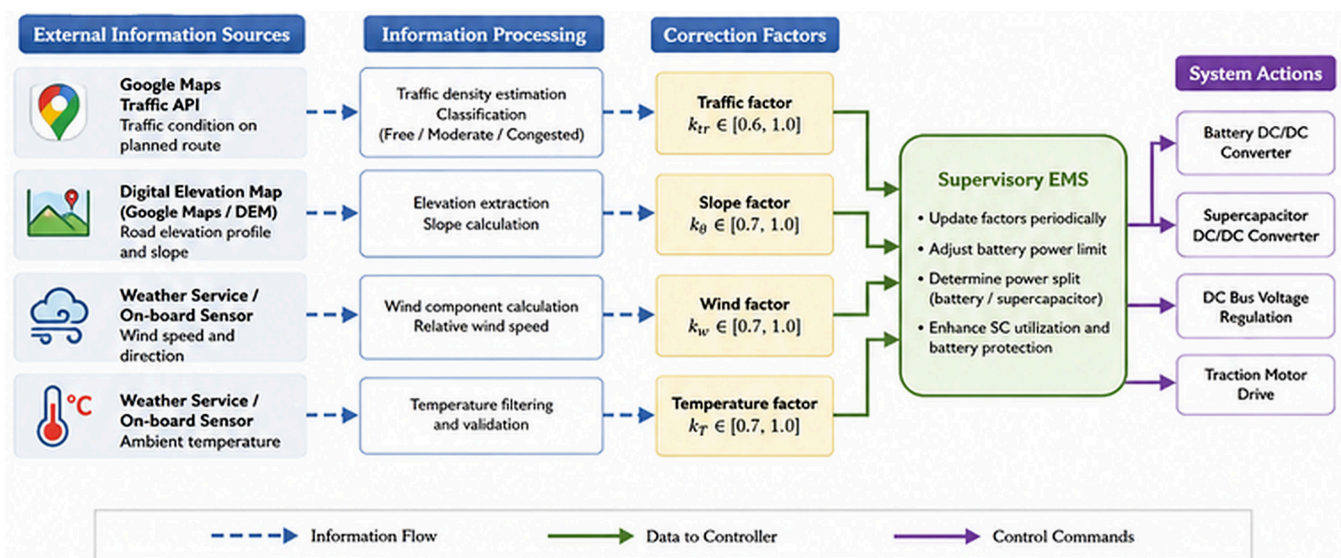


Figure 3. System flow diagram.

The proposed route- and environment aware rule-based EMS has three principal objectives:

- Minimise battery current stress and high-frequency current fluctuations.
- Maximise the utilisation of the supercapacitor for transient power support and regenerative braking energy recovery.
- Maintain all HESS components within their safe operating limits.

4.1. Supervisory Control Architecture

The proposed EMS follows a hierarchical supervisory control architecture consisting of four functional layers. The different layers are discussed in detail in the following lines.

4.1.1. Data Acquisition Layer

At this layer of the control strategy, the controller acquired measurement information about the battery SOC, the supercapacitor SOC, the battery current, the DC-link voltage, the vehicle speed, the traction power demand, the road slope, the traffic density, the wind speed and the ambient temperature. On the other hand, the battery and supercapacitor electrical quantities are measured directly by onboard sensors, whereas the environmental variables are obtained from the vehicle navigation system, the road characteristics, weather information, and vehicle-mounted sensors. In the following lines, the different expressions of the above-mentioned measurements are discussed.

Characterisation of Traffic Information

Traffic congestion significantly influences the power demand characteristics of an electric vehicle. Dense urban traffic results in frequent acceleration and braking events, whereas free-flow traffic is generally characterised by smoother power demand.

The proposed EMS obtains traffic information from the vehicle navigation system or an online traffic service (e.g., Google Maps, HERE Maps, or TomTom Traffic API). The traffic conditions along the selected route are classified into three operating levels:

- Highway traffic conditions.
- City traffic conditions.
- Stop-and-go traffic conditions.

The traffic state is represented by a traffic correction factor [29], $k_{tr} \in [0.6, 1.0]$ where $k_{tr} = 1.0$ corresponds to free-flow traffic, $k_{tr} = 0.8$ represents moderate traffic, and $k_{tr} = 0.6$ represents heavy congestion. The correction factors were determined empirically through repeated MATLAB/Simulink simulations to balance battery current reduction and vehicle performance. Values that were smaller than 0.8 excessively restricted battery power, whereas values above 0.9 produced little improvement in battery current reduction. Therefore, 0.8 represented an appropriate engineering compromise. When congestion is detected, the supervisory controller reserves more supercapacitor energy for repeated acceleration events by reducing the allowable battery power limit.

Characterisation of the Road Characteristic Information

The road gradient has a significant influence on the traction power required by an electric vehicle. Uphill driving increases the propulsion power demand, whereas downhill driving creates opportunities for regenerative braking. The road elevation profile is obtained from a Digital Elevation Model (DEM) or navigation system [15,34]. The road slope is calculated as $\theta = \tan^{-1}\left(\frac{h_2 - h_1}{d}\right)$ where h_1 and h_2 denote the elevations at two consecutive route points and d is the horizontal distance between the two points. The calculated slope is incorporated into the vehicle dynamics described in Section 2 and simultaneously used by the supervisory controller, where θ_{th} is a predefined threshold (typically 2°) [29,34] and where $0.7 \leq k_\theta \leq 1.0$ [15,35]. The selection of k_θ is determined in Section 4.2.3.

Characterisation of the Wind Speed Resistance Information

Aerodynamic drag becomes increasingly important at medium and high vehicle speeds. A wind correction factor $k_w \in [0.7, 1.0]$ [34] is calculated to reduce the allowable battery power whenever strong headwinds are encountered [34].

Characterisation of the Battery Temperature

Battery performance strongly depends on operating temperature. Low temperatures increase internal resistance and reduce available power, while high temperatures accelerate battery degradation $k_w \in [0.8, 1.0]$ [36]. This is done to ensure that the excessive battery current is avoided under adverse thermal conditions.

4.1.2. Driving Mode Classification Layer

The driving mode classification is determined based on the data collected on the first layer about the traffic density, the average vehicle speed and the road characteristics. The controller classifies the current driving mode of the EV as either the urban driving mode, the stop-and-go traffic driving mode, or the highway driving mode. Table 2 provides different thresholds on the average vehicle speed. The classification allows for the rule sets to be activated according to the expected power demand characteristics.

Table 2. Driving conditions vs. speed.

Driving Mode	Average Speed
Traffic	<20 km/h
City	20–70 km/h
Highway	>70 km/h

4.1.3. Power Allocation Layer

The power allocation layer constitutes the core of the proposed route- and environment-aware energy management system. Its primary function is to determine, at each control interval, the proportion of the traction power demand supplied by the lithium-ion battery and the supercapacitor while ensuring that both energy storage devices operate within their allowable electrical and state-of-charge (SOC) limits. The power allocation strategy seeks to minimise battery current stress, maximise supercapacitor utilisation during transient operating conditions, and improve regenerative braking energy recovery. Similar objectives have been reported for battery–supercapacitor hybrid energy storage systems in the literature; however, conventional rule-based controllers generally determine the power split using only instantaneous battery SOC, supercapacitor SOC, and traction power demand without considering anticipated driving conditions or environmental influences [20,23,26,37,38].

The total traction power required by the electric vehicle is supplied jointly by the battery and the supercapacitor through their respective bidirectional DC/DC converters. The power balance of the hybrid energy storage system is expressed as follows:

$$P_{req} = \eta_b P_b + \eta_{sc} P_{SC}, \quad (29)$$

where P_{req} is the instantaneous traction power demand, and P_b and P_{sc} are the battery and supercapacitor powers, respectively, while η_b and η_{sc} represent the efficiencies of the battery and supercapacitor power conversion paths. Equation (29) defines the overall power balance of the hybrid energy storage system; however, the proposed EMS determines the individual battery and supercapacitor power references using the supervisory control strategy described below.

During propulsion ($P_{req} > 0$), the EMS first computes the maximum allowable battery power according to the operating conditions:

$$P_{b,lim} = K_{ext} P_{b,max}, \quad (30)$$

where $P_{b,max}$ is the rated battery power, and K_{ext} is the external correction factor obtained from the combined influence of road gradient, traffic density, wind speed, and ambient temperature. The correction factor continuously adjusts the battery power limit so that the battery is protected during demanding operating conditions while allowing greater battery utilisation under favourable conditions.

The battery reference power is then determined as follows:

$$P_b = \min(P_{req}, P_{b,lim}), \quad (31)$$

ensuring that the battery never exceeds the dynamically calculated allowable power limit. The remaining propulsion power is supplied by the supercapacitor:

$$P_{sc} = P_{req} - P_b. \quad (32)$$

Consequently, when the vehicle operates under low or moderate power demand, the battery supplies the entire traction load because $P_{req} \leq P_{b,lim}$. Conversely, during rapid acceleration or other high-power transient events where $P_{req} > P_{b,lim}$, the battery output is limited to $P_{b,lim}$, while the supercapacitor supplies the remaining power demand. This strategy significantly reduces battery peak current, decreases battery energy throughput, and allows the supercapacitor to exploit its high-power density for transient load support [23,26,37,38].

During regenerative braking ($P_{req} < 0$), the proposed EMS reverses the power flow and prioritises charging of the supercapacitor because of its superior charge acceptance capability and ability to absorb high-power transients without significant degradation [22,25,36]. The regenerative braking power allocated to the supercapacitor is calculated as follows:

$$P_{sc} = \min(|P_{regen}|, P_{sc,max}), \quad (33)$$

where P_{regen} is the available regenerative braking power, and $P_{sc,max}$ is the maximum allowable charging power of the supercapacitor.

The remaining regenerative energy is directed to the battery:

$$P_b = P_{regen} + P_{sc}, \quad (34)$$

provided that

$$SOC_b < SOC_{b,max}, \quad (35)$$

and

$$|I_b| < I_{b,max}, \quad (36)$$

If either the battery or the supercapacitor reaches its charging limits, any excess regenerative energy is dissipated through the conventional mechanical braking system. Prioritising the supercapacitor during regenerative braking increases energy recovery efficiency while reducing battery charging stress, thereby contributing to improved battery lifetime [25,26,36].

The proposed power allocation strategy differs from conventional rule-based EMSs in that the battery power limit is not fixed. Instead, it is continuously adjusted according to external environmental information and predicted driving conditions before the power split is performed. This enables the controller to proactively reduce battery loading during demanding operating conditions while maintaining sufficient supercapacitor energy to support future acceleration and regenerative braking events.

4.1.4. Converter Control

The power references determined by the supervisory energy management system are converted into current reference signals for the bidirectional DC/DC converters interfacing the battery and supercapacitor with the common DC link. The primary objective of the converter control layer is to accurately regulate power flow while maintaining a stable DC-link voltage and ensuring that both energy storage devices operate within their specified current, voltage, and state-of-charge (SOC) limits. Similar hierarchical control architectures have been widely adopted for battery–supercapacitor hybrid energy storage systems because they decouple the high-level energy management strategy from the low-level converter dynamics [38].

The battery is connected to the DC bus through a bidirectional DC/DC converter operating in voltage-control mode. Since the battery serves as the primary energy source, its converter regulates the DC-link voltage by controlling the battery current according to the reference generated by the supervisory EMS. The battery current reference is obtained from the calculated battery power reference:

$$I_{b,ref} = \frac{P_b}{V_b}, \quad (37)$$

where P_b is the battery power reference determined by the supervisory controller, and V_b is the instantaneous battery terminal voltage.

The supercapacitor is interfaced through a second bidirectional DC/DC converter operating in current-control mode. Owing to its high-power density and rapid dynamic response, the supercapacitor is responsible for supplying transient propulsion power and absorbing high-power regenerative braking energy. The corresponding reference current is calculated as follows:

$$I_{sc,ref} = \frac{P_{sc}}{V_{sc}}, \quad (38)$$

where P_{sc} is the supercapacitor power reference, and V_{sc} is the instantaneous supercapacitor voltage.

Both converters employ conventional cascaded control structures consisting of an outer voltage (or power) regulation loop and an inner current regulation loop. The outer loop generates the required current reference, while the inner loop regulates the converter duty cycle using pulse-width modulation (PWM) to ensure accurate tracking of the commanded current. Proportional–integral (PI) controllers are adopted for both regulation loops because of their simplicity, robustness, and widespread application in bidirectional DC/DC converter control for electric vehicle hybrid energy storage systems [20,23,26,37,39].

To guarantee safe operation, the converter controllers continuously monitor battery current, supercapacitor current, terminal voltages, and state of charge. If the commanded current exceeds the allowable operating limits, the reference is automatically saturated before being applied to the PWM controller. Consequently, the supervisory EMS determines the desired power allocation, while the converter control layer ensures that the commanded battery and supercapacitor powers are accurately delivered to the DC bus without violating the electrical constraints of either energy storage device.

It should be noted that the novelty of this work lies in the proposed route- and environment-aware supervisory energy management strategy rather than the converter control algorithms themselves. Therefore, conventional PI-based converter controllers, which have been extensively validated in the literature for bidirectional DC/DC converters in battery–supercapacitor hybrid energy storage systems, are adopted in this study [16,20,23,26,37,39].

4.2. Battery Power Limitation

To reduce battery degradation, the proposed EMS limits the battery output power to the following:

$$P_{b,max} = \eta_b P_{rated} k_{SOC} k_{tr} k_{\theta} k_w k_T, \quad (39)$$

where P_{rated} is the rated battery power, η_b is the converter efficiency, and k_{SOC} is the SOC correction factor. The correction factors reduce the allowable battery loading whenever the battery operates under unfavourable conditions. The determination of the different correction factors in Equation (39) is discussed in the next subsections. This battery power output shown in Equation (39) enables the proposed EMS to respond continuously to changing environmental conditions while preserving battery health.

4.2.1. SOC Correction Factor

The battery correction factor is mainly determined based on the battery SOC as follows:

$$k_{SOC} = \begin{cases} 1, & 30\% \leq SOC_b \leq 90\% \\ 0.8, & 20\% \leq SOC_b < 30\% \\ 0, & SOC_b < 20\% \end{cases} \quad (40)$$

4.2.2. Temperature Correction Factor

The battery capability decreases at low and high temperatures. In this way, the temperature correction factor is selected as shown below [36,40]:

$$k_T = \begin{cases} 1, & 15^\circ\text{C} \leq T \leq 35^\circ\text{C} \\ 0.9, & 5^\circ\text{C} \leq T < 15^\circ\text{C} \\ 0.8, & T < 5^\circ\text{C} \\ 0.85, & T > 35^\circ\text{C} \end{cases} \quad (41)$$

4.2.3. Road Gradient Correction

Road gradient directly affects the traction power required by the vehicle through the gravitational force component:

$$F_{\theta} = mgsin\theta, \quad (42)$$

where m is the vehicle mass, g is gravitational acceleration, and θ is the road-gradient angle. During uphill driving ($\theta > 0$), the gravitational force opposes vehicle motion, increasing the traction torque and power required to maintain the desired speed. The effect becomes more pronounced as the gradient increases. Conversely, during downhill driving ($\theta < 0$), gravity assists vehicle motion and may create an opportunity for regenerative braking. Road-gradient information is therefore commonly included in predictive and adaptive vehicle energy management strategies because it significantly influences future power demand and the optimal power split between onboard energy sources [15,34,35].

In the proposed EMS, the road-gradient correction factor reduces the allowable battery power as the uphill gradient increases. It is defined as follows:

$$k_{\theta} = \begin{cases} 1 - \frac{\theta}{\theta_{max}}(1 - k_{\theta,min}), & 0 < \theta < \theta_{max} \\ k_{\theta,min}, & \theta \geq \theta_{max}, \\ 1, & \theta \leq 0, \end{cases} \quad (43)$$

where θ_{max} is the maximum uphill gradient considered by the controller, and $k_{\theta,min}$ is the minimum permissible road-gradient correction factor. The saturation at $k_{\theta,min}$ prevents

the allowable battery power from becoming zero or negative when the measured gradient approaches or exceeds $\theta_{\max}$.

For uphill operation, the corrected battery power limit is calculated as follows:

$$P_{b,lim,\theta} = k_{\theta} P_{b,max}, \quad (44)$$

where $P_{b,max}$ is the nominal maximum battery power. Equation (43) establishes an inverse relationship between the uphill gradient and k_{θ} : as θ increases, k_{θ} decreases. Consequently, the battery power limit is reduced, and a greater proportion of the additional traction-power demand is assigned to the supercapacitor, subject to its voltage, SOC and power limits. For example, assuming $k_{\theta,min} = 0.5$ and $\theta_{\max} = 10^{\circ}$, an uphill gradient of 2° gives $k_{\theta} = 0.90$, whereas an uphill gradient of 8° gives $k_{\theta} = 0.60$. Thus, a steeper climb produces a lower—not higher—correction factor.

The resulting propulsion-power references are determined from the following:

$$P_b^* = \min(P_{req}, P_{b,lim,\theta}), \quad (45)$$

and

$$P_{sc}^* = P_{req} - P_b^*. \quad (46)$$

This allocation limits battery peak current during the increased power demand associated with climbing and transfers the excess transient load to the supercapacitor. Such use of route-gradient information is consistent with grade-aware energy management studies showing that road slope can be used to adapt power allocation and improve supervisory-control performance [15,29,35].

The supercapacitor is not intended to sustain the complete climbing load indefinitely. Its contribution is restricted by its minimum SOC or voltage and maximum discharge-power limits. If the climb persists and the supercapacitor reaches its lower operating limit, the battery supplies the remaining demand within its safe electrical limits. Therefore, the road-gradient correction factor principally reduces short-duration battery power peaks and prepares the HESS for anticipated climbing conditions rather than permanently withholding battery energy throughout a prolonged ascent.

For level or downhill roads, ($\theta \leq 0$), $k_{\theta} = 1$ is used in the propulsion allocation layer. Downhill regenerative power is managed separately by the regenerative-braking logic, which prioritises charging the supercapacitor before allocating the remaining recoverable power to the battery.

4.2.4. Supercapacitor Power Limitation

The maximum supercapacitor power is determined using the expression below:

$$P_{SC,max} = \eta_{SC} P_{SC, rated} k_{SOC, SC}, \quad (47)$$

where the SC correction factor is given by the following:

$$k_{SOC, SC} = \frac{SOC_{SC}}{100} \quad (48)$$

Consequently, higher SOC implies larger transient power capability.

4.3. Power Allocation Strategy

The power allocation is conducted based on four cases based on the required tractions and the available battery power and super capacitor power. The four cases are discussed in the following subsections.

4.3.1. Case 1

The first case occurs when the traction power demand is lesser or equal to the maximum battery power that is available, as shown below:

$$P_{req} \leq P_{b,max} \quad (49)$$

In this case, the battery supplies the maximum power while the supercapacitor is not expected to supply anything, resulting in the following:

$$\begin{aligned} P_b &= P_{req}, \\ P_{SC} &= 0. \end{aligned} \quad (50)$$

4.3.2. Case 2

The second case occurs when the traction power demand is higher than the available maximum power of the battery:

$$P_{req} > P_{b,max} \quad (51)$$

The battery is allowed to supply up to its maximum, as shown below:

$$P_b = P_{b,max} \quad (52)$$

The remaining required power is provided by the supercapacitor, as shown below:

$$P_{SC} = P_{req} - P_b \quad (53)$$

4.3.3. Case 3

The third operating case occurs during regenerative braking when the traction power demand becomes negative:

$$P_{req} < 0 \quad (54)$$

During regenerative braking, the proposed EMS prioritises charging the supercapacitor because of its high charge acceptance capability, high-power density, and ability to absorb large transient currents with minimal degradation [26,36,38]. Consequently, the recovered braking energy is first directed at the supercapacitor, provided that its state of charge remains below the upper operating limit:

$$SOC_{SC} < SOC_{SC,} \quad (55)$$

In this case, the charging powers are determined as follows:

$$P_{sc} < \min(|P_{regen}|, P_{sc,max}), \quad (56)$$

and

$$P_b = P_{regen} - P_{sc}, \quad (57)$$

where P_{regen} is the available regenerative braking power.

To ensure that the supercapacitor remains capable of supporting both future acceleration events and subsequent regenerative braking, the proposed controller maintains the supercapacitor SOC within three operating regions:

- SOC < 30%: low-energy region.
- 30% ≤ SOC ≤ 70%: normal operating region.
- SOC > 70%: high-energy region.

A target operating point of approximately 50% SOC is adopted because it provides an effective compromise between energy availability for propulsion assistance and reserve capacity for regenerative braking. At approximately 50% SOC, the supercapacitor has sufficient stored energy to support high-power acceleration while simultaneously retaining adequate capacity to absorb braking energy without reaching its maximum voltage limit. Similar midpoint operating strategies have been widely adopted in battery–supercapacitor hybrid energy storage systems to maximise bidirectional power capability and improve overall energy utilisation [26,38].

When the supercapacitor SOC exceeds 70%, the controller gradually reduces the charging power allocated to the supercapacitor and diverts the remaining recoverable energy to the battery, provided that the battery charging constraints are satisfied. Conversely, when the supercapacitor SOC falls below 30%, the controller limits further discharge of the supercapacitor during propulsion so that sufficient energy is retained for future transient power demands.

This adaptive SOC management enables the supercapacitor to operate around its preferred mid-SOC region, thereby improving regenerative energy recovery, reducing battery current stress, and maintaining sufficient power reserve for both acceleration and braking events.

4.3.4. Case 4

The fourth operating case occurs when the supercapacitor reaches its allowable operating limits and is unable to either supply or absorb additional power. This situation may arise during prolonged acceleration, where the supercapacitor state of charge (SOC) decreases to its minimum allowable value, or during sustained regenerative braking when the supercapacitor becomes fully charged. Under these conditions, the EMS modifies the power allocation to ensure safe operation of the hybrid energy storage system while maintaining vehicle propulsion whenever possible.

During propulsion, the supercapacitor is prevented from further discharging under the following condition:

$$SOC_{SC} < SOC_{SC,min}, \quad (58)$$

where $SOC_{SC,min}$ is the minimum allowable state of charge of the supercapacitor.

Consequently,

$$P_{SC} = 0, \quad (59)$$

and the battery supplies the required traction power subject to its allowable operating limit, as follows:

$$P_b = \min(P_{req}, P_{b,lim}). \quad (60)$$

If the required traction power exceeds the allowable battery power, the following is the result:

$$P_{req} > P_{b,lim}. \quad (61)$$

The delivered propulsion power is then given by the following:

$$P_{EV} = P_{b,lim}, \quad (62)$$

thereby preventing excessive battery current and ensuring that the battery operates within its safe electrical limits.

Similarly, during regenerative braking, if the supercapacitor reaches its upper state-of-charge limit, the following is the result:

$$SOC_{SC} < SOC_{SC,max}, \quad (63)$$

where the remaining regenerative energy is directed to the battery, provided that the battery can safely accept the charging current. If both the battery and the supercapacitor reach their charging limits, any excess regenerative energy is dissipated through the conventional mechanical braking system.

This operating case prevents over-discharge and over-charge of the supercapacitor while maintaining safe operation of the battery. Similar operating constraints have been widely adopted in battery–supercapacitor hybrid energy storage systems to preserve the lifetime of both storage devices and ensure reliable vehicle operation [19,25,26].

5. Simulation Results

To evaluate the effectiveness of the proposed route- and environment-aware rule-based energy management system (EMS), comprehensive simulations were performed. The simulations were carried out in MATLAB/Simulink R2024b on a computer equipped with an Intel Core i7 processor, 16 GB RAM, running Windows 11. The performance of the proposed rule-based EMS for EVs was tested under three representative driving cycles: the Urban Dynamometer Driving Schedule (UDDS), Artemis Motorway 130, and a Central Business District (CBD) driving cycle. The complete electric vehicle (EV) model consisted of the vehicle longitudinal dynamics, traction motor, inverter, battery, supercapacitor, bidirectional DC/DC converters, and the proposed supervisory controller, which are depicted in Figure 4. The simulations were carried out under representative urban and highway driving conditions to assess the controller’s ability to allocate power between the battery and the supercapacitor while reducing battery current stress. The data used for the simulation are displayed in Tables 3 and 4. These driving cycles were selected to represent urban, highway, and congested traffic conditions, respectively. The effectiveness of the proposed controller was assessed by comparing its performance with two baseline configurations.

Table 3. Electric vehicle parameters.

Parameter	Symbol	Value
Vehicle mass	M	2180 kg
Motor rated power	P_m	156.6 kW
Battery capacity	E_b	80 kWh
Vehicle frontal area	A	2.35 m ²
Air density	ρ	1.02 kg/m ³
Transmission efficiency	η_t	98%
Air drag coefficient	C_d	0.30
Rolling resistance coefficient	C_r	0.01
Gravity	g	9.81 m/s ²

1. Battery-only EV equipped with a conventional rule-based EMS.
2. Battery–supercapacitor HESS equipped with a conventional rule-based EMS.
3. Battery–supercapacitor HESS equipped with the proposed route- and environment-aware EMS.

Overall Simulation Framework Implemented in MATLAB/Simulink

Route-Aware Energy Management for Battery–Supercapacitor Hybrid Electric Vehicle

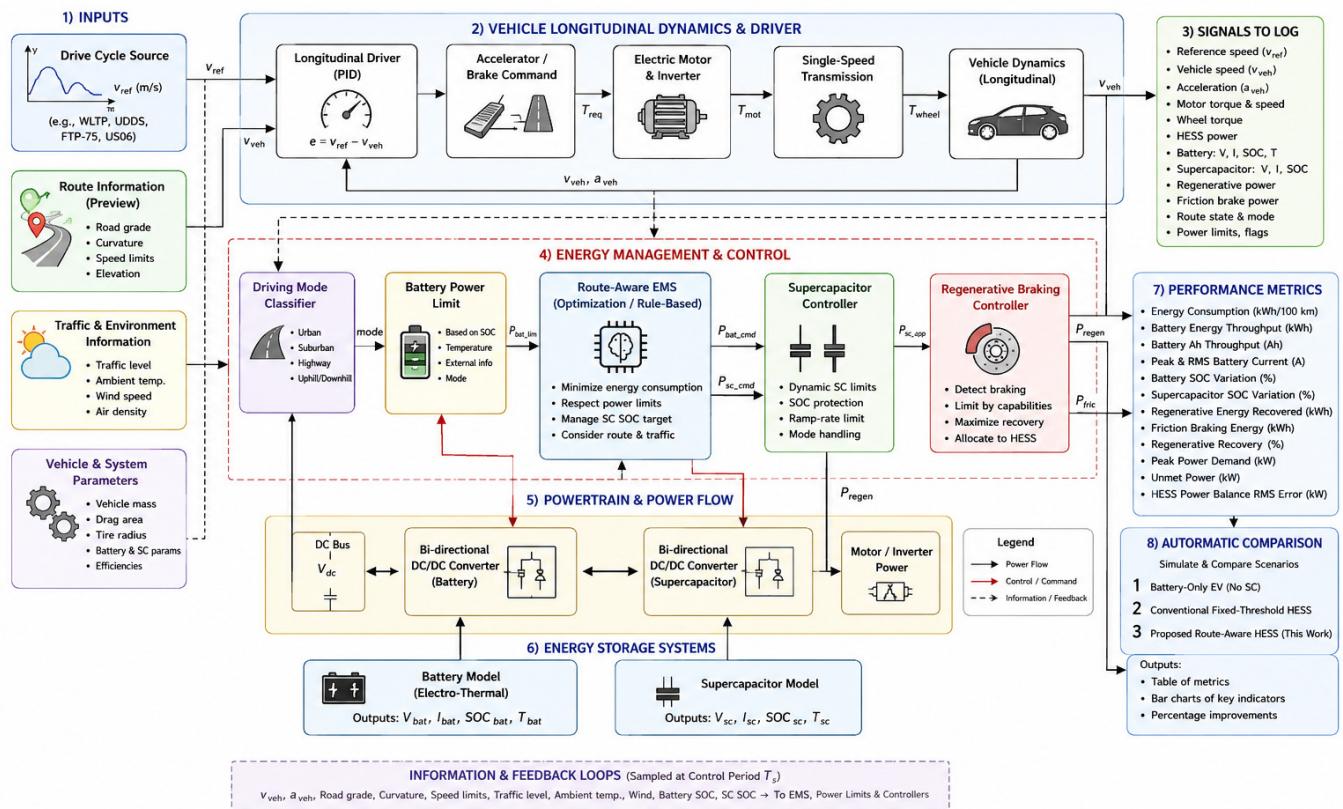


Figure 4. Simulation framework.

Table 4. HESS parameters.

Parameter	Value
Battery chemistry	Lithium-ion
Battery nominal voltage	400 V
Battery SOC operating range	20–90%
Initial battery SOC	80%
Supercapacitor initial SOC	80%
Supercapacitor operating range	20–95%
Battery converter efficiency	98%
Supercapacitor converter efficiency	98%
DC-link voltage	400 V

The inclusion of the conventional HESS controller isolates the benefits of the proposed control strategy from those resulting solely from the addition of the supercapacitor hardware, thereby providing a fair and rigorous comparison. The controller performance was evaluated using the following quantitative performance metrics:

- Maximum battery current.
- RMS battery current.
- Battery energy throughput.
- Battery SOC variation.
- Supercapacitor SOC variation.
- Supercapacitor utilisation ratio.

- Regenerative braking energy recovery.
- Power-sharing characteristics.
- Computational execution time.

5.1. Performance Under the UDDS Driving Cycle

The UDDS driving cycle is characterised by frequent acceleration and deceleration events that produce substantial transient power demands and numerous opportunities for regenerative braking. These operating conditions provide an effective benchmark for evaluating the proposed controller. The main key points of the performance comparison under the UDDS driving cycle are displayed in Table 5. The battery-only configuration experiences repeated current peaks exceeding 318.85 A, indicating that the battery alone is responsible for supplying both the average and transient vehicle power demand. When the conventional HESS controller is introduced, the maximum battery current is reduced because the supercapacitor contributes during high-power events. However, the proposed EMS further decreases battery current by incorporating route and environmental information into the supervisory control process, thereby anticipating upcoming transient events and improving supercapacitor utilisation. The maximum battery current is reduced to approximately 154.11 A, corresponding to an approximate 51.67% reduction compared with the battery-only configuration. In addition, the RMS battery current decreases significantly, indicating that the proposed EMS not only limits current peaks but also reduces the overall electrical stress experienced by the battery throughout the driving cycle.

Table 5. Performance comparison under the UDDS driving cycle.

Performance Indicator	Battery-Only ESS	Conventional HESS EMS	Proposed HESS EMS	Improvement
Maximum battery current (A)	318.85	154.78	154.11	51.67%
RMS battery current (A)	120.85	94.833	58.486	51.60%
Battery SOC variation (%)	10.938	12.964	7.9159	27.70%
Supercapacitor utilisation (%)	0	68.591	75.483	10%

5.2. Performance Under the Artemis Motorway 130 Driving Cycle

The Artemis Motorway 130 driving cycle represents sustained highway operation characterised by relatively constant vehicle speeds and prolonged high-power demand. Under these conditions, the battery supplies most of the average propulsion energy, while the supercapacitor primarily mitigates transient power fluctuations. The main key points of the performance comparison under the Artemis Motorway 130 driving cycle are displayed in Table 6. The conventional battery-only configuration exhibits current peaks approaching 320.97 A, together with repeated charging and discharging cycles. The conventional HESS controller reduces these current peaks by allocating transient power to the supercapacitor; however, the proposed EMS further improves battery protection by dynamically adjusting the battery power limit according to road gradient, traffic conditions, wind resistance, and ambient temperature. As a result, the maximum battery current decreases to approximately 154.63 A, while the battery operates predominantly in the discharge mode. This behaviour is consistent with the proposed control philosophy, which prioritises charging of the supercapacitor during regenerative braking events.

Table 6. Performance comparison under the Artemis Motorway 130 driving cycle.

Performance Indicator	Battery-Only ESS	Conventional HESS EMS	Proposed HESS EMS	Improvement
Maximum battery current (A)	320.97	155.37	154.63	51.82%
RMS battery current (A)	155.81	129.78	112.28	27.93%
Battery SOC variation (%)	18.135	17.647	14.885	17.92%
Supercapacitor utilisation (%)	0	96.552	96.121	0.44%

5.3. Performance Under the CBD Driving Cycle

The CBD driving cycle represents highly congested urban traffic with numerous stop-and-go events. These operating conditions maximise the utilisation of the supercapacitor owing to the high frequency of acceleration and regenerative braking events. The main key points of the performance comparison under the CBD driving cycle are displayed in Table 7. Compared with the conventional controllers, the proposed EMS demonstrates the largest performance improvement under this driving cycle. The traffic-aware supervisory algorithm reserves sufficient supercapacitor energy for repeated acceleration events while maintaining adequate storage capacity for regenerative braking. Consequently, battery current fluctuations are substantially reduced, and regenerative braking energy recovery is increased.

Table 7. Performance comparison under the CBD driving cycle.

Performance Indicator	Battery-Only ESS	Conventional HESS EMS	Proposed HESS EMS	Improvement
Maximum battery current (A)	313.77	154.09	152.9	51.27%
RMS battery current (A)	96.536	78.391	57.879	40.05%
Battery SOC variation (%)	4.0373	4.4906	3.4925	13.40%
Supercapacitor utilisation (%)	0	36.065	42.801	18.68%

5.4. Battery State of Charge Analysis

Figure 5a,b and Figure 6 present the battery SOC evolution for the three controller configurations under the UDDS, Artemis 130 and CBD driving cycles. The battery-only configuration exhibits the largest SOC fluctuations owing to repeated high-current charge and discharge events. The conventional HESS controller partially mitigates these fluctuations by transferring transient power demand to the supercapacitor. The proposed EMS further smooths the battery SOC trajectory by proactively allocating transient power according to anticipated route and environmental conditions. Consequently, the battery operates within a narrower SOC window throughout the driving cycle. The reduced SOC fluctuation is expected to decrease battery degradation associated with a repeated high-rate driving cycle.

5.5. Supercapacitor State of Charge Analysis

Figure 7a,b and Figure 8 illustrate supercapacitor SOC evolution for the three controller configurations under the UDDS, Artemis 130 and CBD driving cycles. The proposed controller maintains the supercapacitor within its predefined operating range while ensuring that sufficient reserve capacity remains available for regenerative braking. Unlike the conventional controller, which often maintains the supercapacitor near full charge, the proposed EMS actively regulates the supercapacitor SOC around its optimal operating

region. This strategy maximises both transient power support and regenerative braking energy recovery.

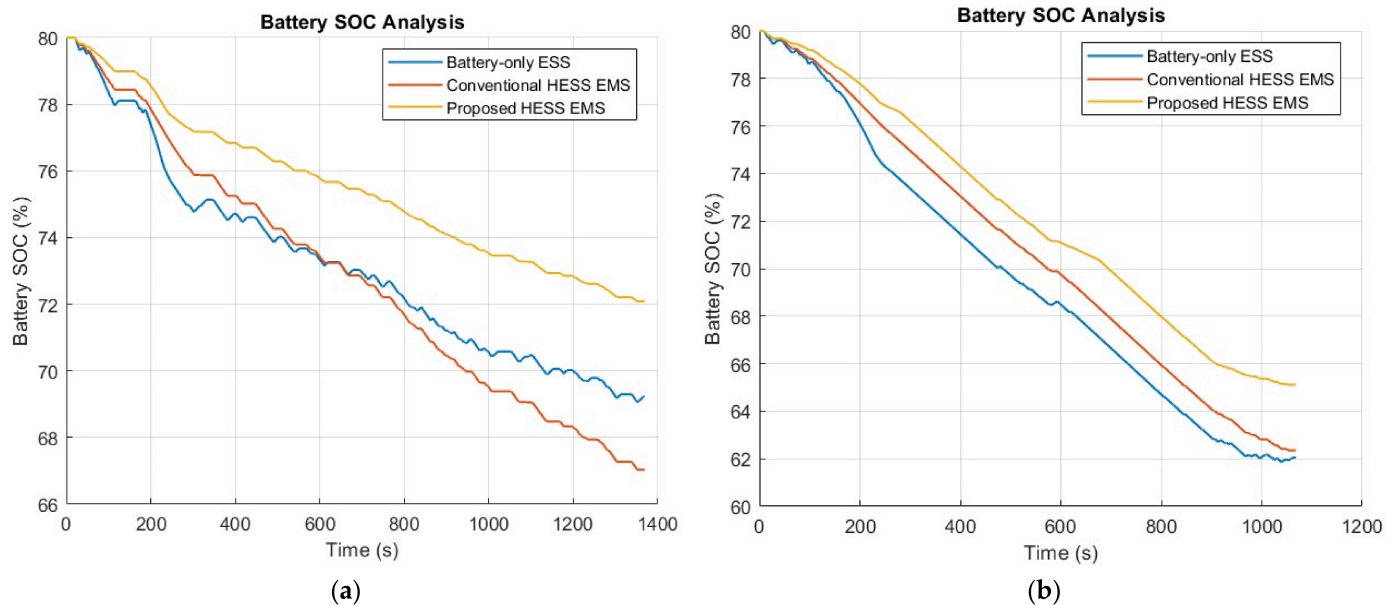


Figure 5. Battery SOC performance analysis. (a) Performance of the proposed HESS recorded under UDDS driving cycle; (b) performance of the proposed HESS recorded under Artemis 130 driving cycle.

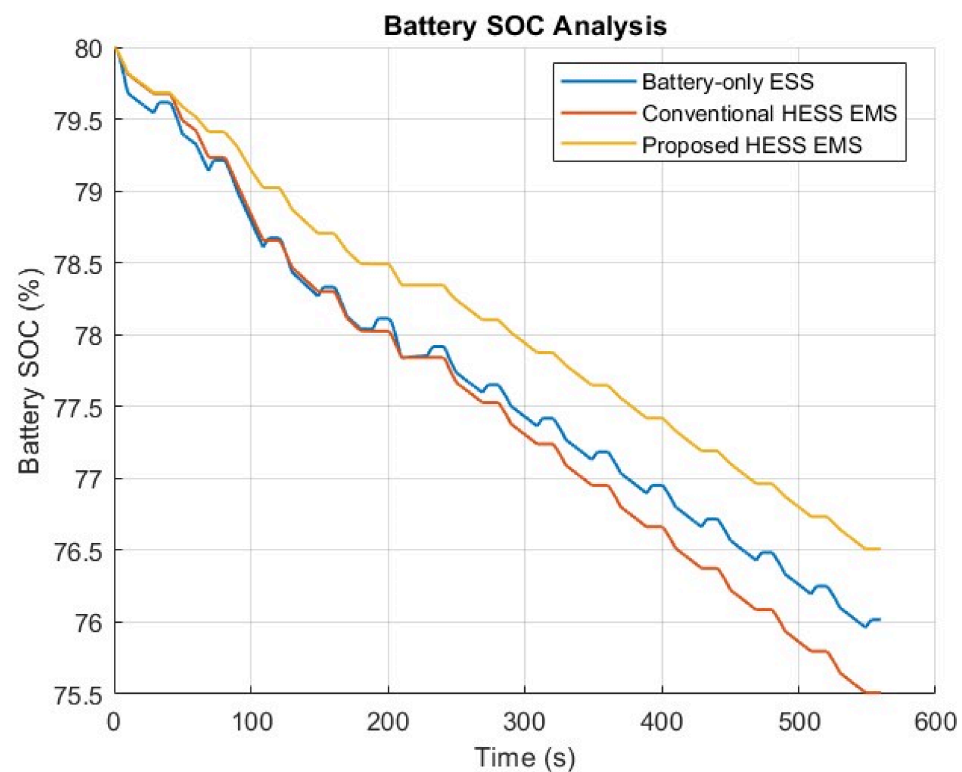


Figure 6. Performance Analysis of the HESS battery SOC CBD driving cycle.

5.6. Battery Energy Throughput Analysis

Battery energy throughput is an important indicator of battery degradation because it represents the cumulative electrical energy processed by the battery. Figures 9–11 compares the battery energy throughput for the three controller configurations. The proposed EMS achieves the lowest battery energy throughput by allowing the supercapacitor to absorb

high-power transients. Consequently, the battery supplies primarily the average propulsion power, thereby reducing cumulative electrochemical stress.

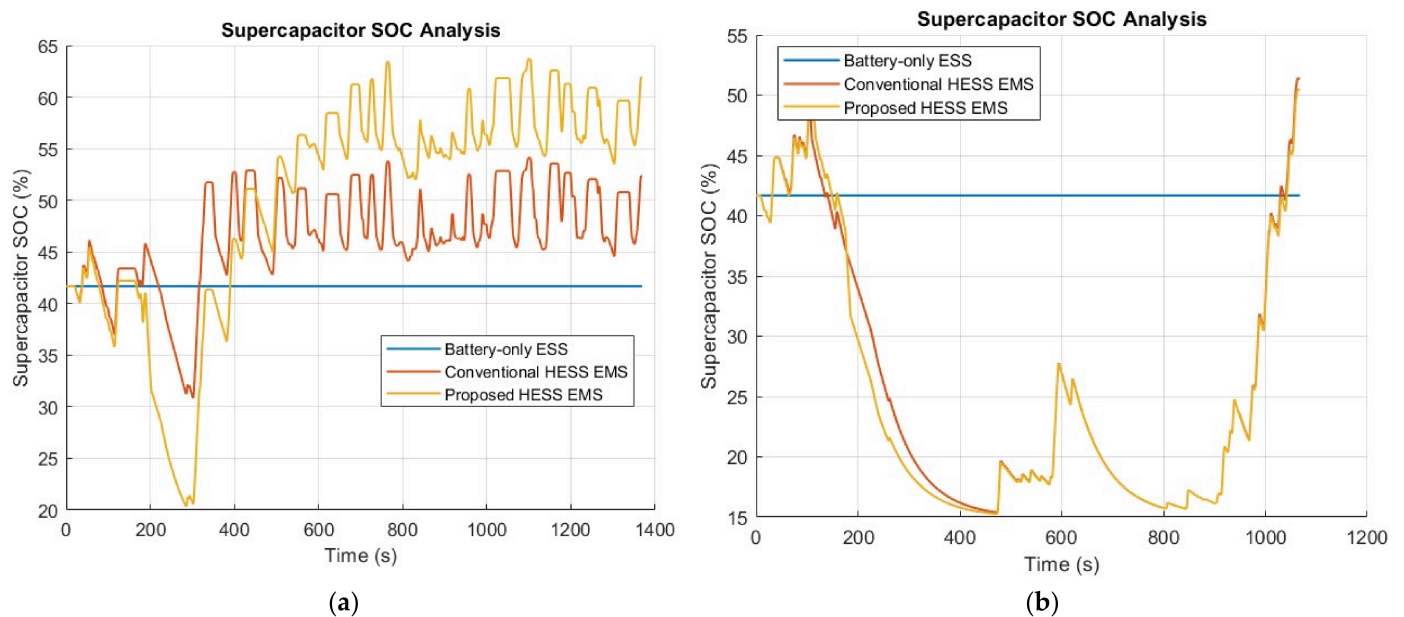


Figure 7. Supercapacitor SOC performance analysis. (a) Performance of the proposed HESS SC recorded under UDDS driving cycle; (b) performance of the proposed HESS SC recorded under Artemis 130 driving cycle.

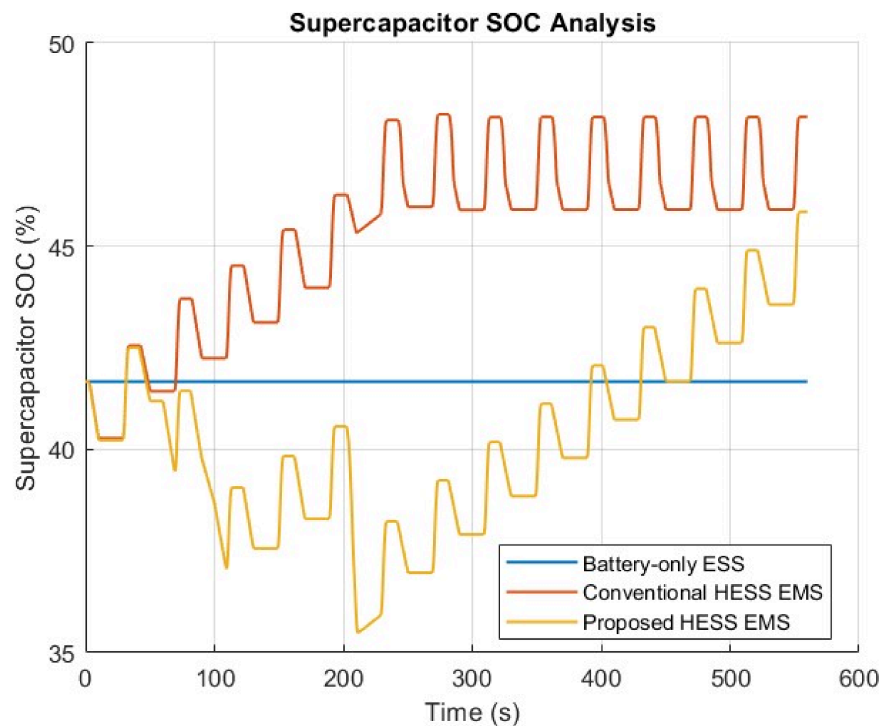


Figure 8. Supercapacitor SOC performance analysis under CBD driving cycle.

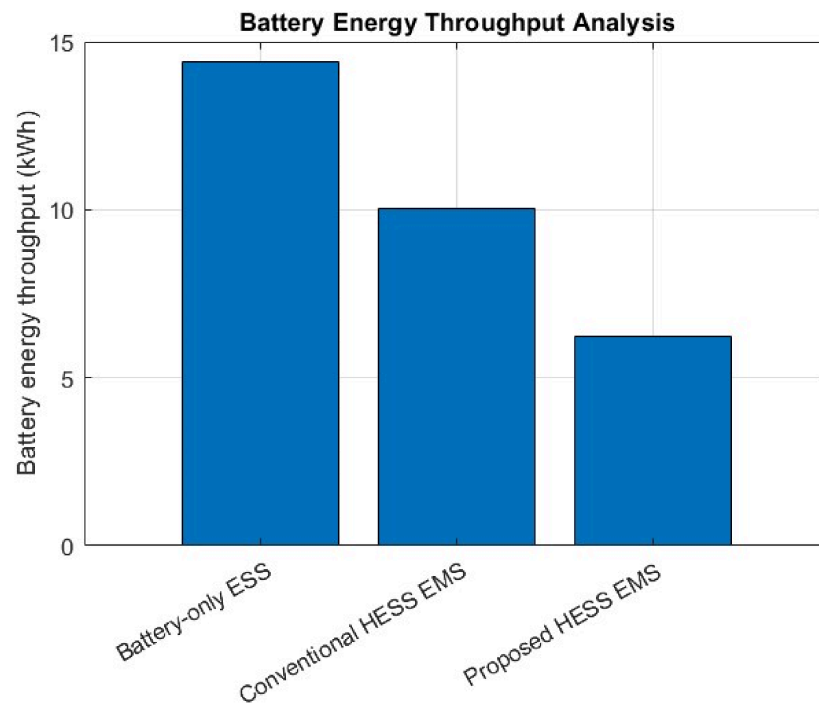


Figure 9. Battery energy throughput analysis under the UDDS driving cycle.

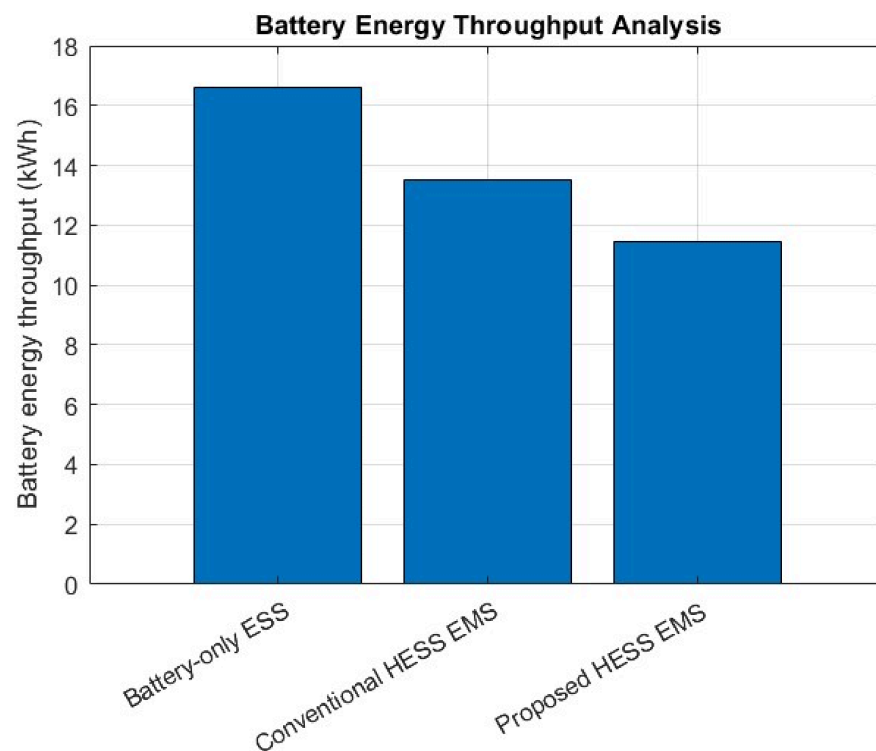


Figure 10. Battery energy throughput analysis under Artemis 130 driving cycle.

5.7. Regenerative Braking Analysis

Figures 12–14 compare the regenerative braking energy recovered under the three driving cycles. The proposed EMS consistently recovers more braking energy than both baseline controllers because the supervisory controller reserves sufficient supercapacitor capacity before entering sections of the route where repeated braking events are anticipated. The greatest improvement is observed during the CBD driving cycle, where frequent braking events provide significant opportunities for energy recovery.

5.8. Supercapacitor SOC Threshold Sensitivity Analysis

To justify the selection of the 50% supercapacitor SOC threshold, a sensitivity analysis was performed using threshold values of 30%, 50%, and 70%. The results from the sensitivity analysis of the supercapacitor SOC are displayed in Table 8.

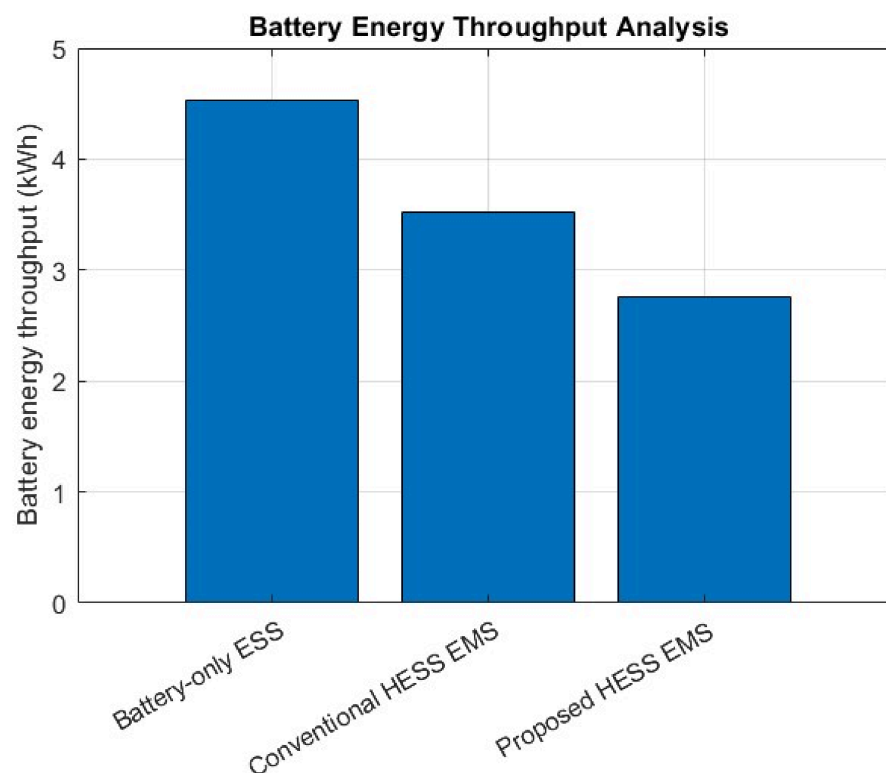


Figure 11. Battery energy throughput analysis under CBD driving cycle.

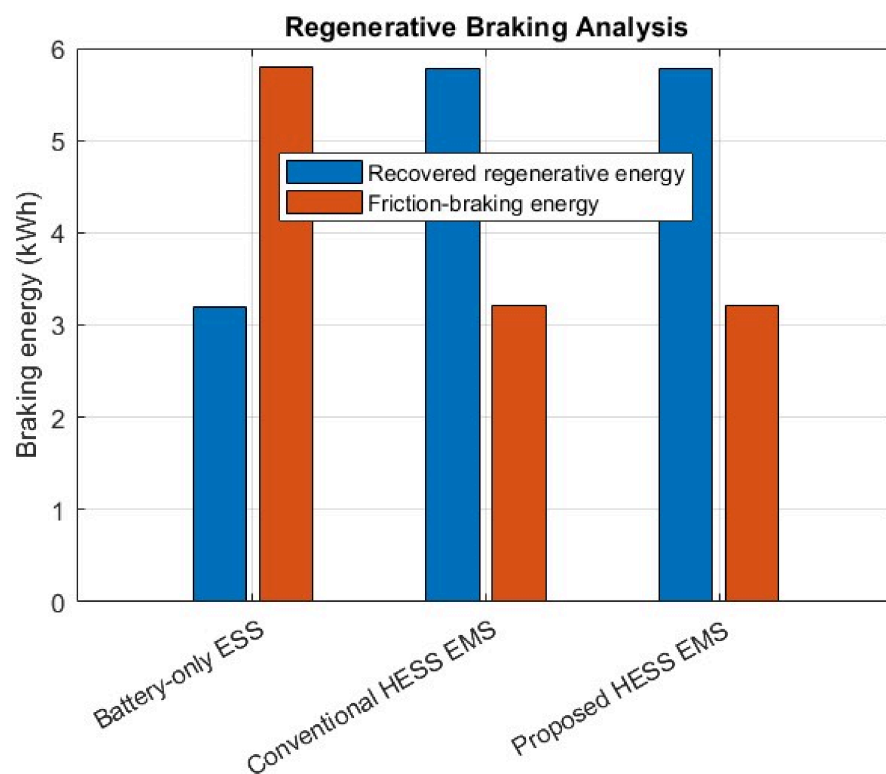


Figure 12. Regenerative braking analysis under UDDS driving cycle.

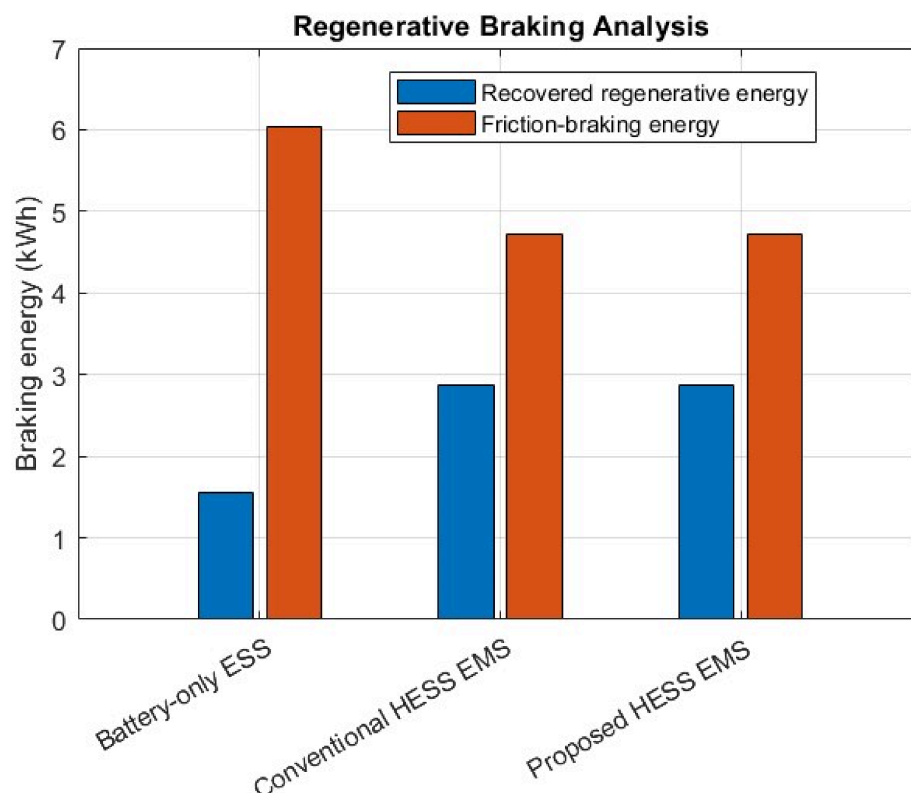


Figure 13. Regenerative braking analysis under Artemis 130 driving cycle.

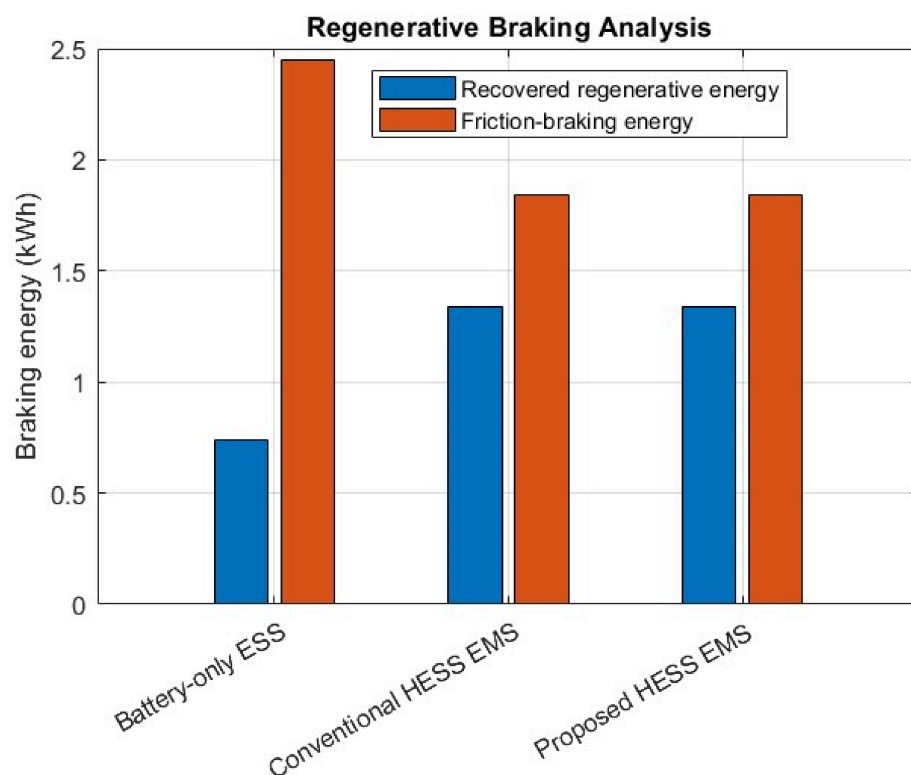


Figure 14. Regenerative braking analysis under CBD driving cycle.

When the threshold was reduced to 30%, insufficient energy remained in the supercapacitor during rapid acceleration events, resulting in increased battery current. Conversely, maintaining the supercapacitor above 70% reduced the available storage capacity for re-

generative braking. A threshold of 50% therefore provides the best compromise between transient power support and regenerative energy recovery.

Table 8. Sensitivity analysis of the supercapacitor SOC threshold.

SC Threshold	Peak Battery Current	Regenerative Energy	SC Utilisation	Overall Performance
30%	Higher	Low	High	Moderate
50%	Lowest	Highest	Highest	Best
70%	Moderate	Reduced	Lower	Moderate

5.9. Controller Computational Complexity

One of the principal advantages of the proposed EMS is its low computational complexity compared with optimisation-based controllers. Unlike Model Predictive Control (MPC) [17], Dynamic Programming (DP) [37], or Reinforcement Learning (RL) [12,21,22], the proposed controller relies exclusively on algebraic calculations and logical decision rules. The average execution time per control cycle is significantly lower than that of optimisation-based EMS techniques, making the proposed controller suitable for real-time implementation on embedded automotive electronic control units (ECUs).

5.10. Overall Qualitative Comparison

Table 9 provides an overall qualitative comparison between the proposed route- and environment-aware rule-based energy management system and representative energy management strategies reported in the literature. It can be observed that conventional rule-based controllers generally rely on instantaneous variables, such as battery state of charge (SOC), supercapacitor SOC, and traction power demand, resulting in simple implementation and low computational complexity. However, these approaches are inherently reactive and cannot adapt their power allocation to anticipated changes in driving conditions. In contrast, optimisation-based methods, including Dynamic Programming (DP) [9], Model Predictive Control (MPC) [17], and Equivalent Consumption Minimisation Strategy (ECMS) [15], typically achieve improved energy efficiency by exploiting predictive information, but their computational requirements and dependence on accurate system models limit their suitability for real-time embedded implementation. Similarly, intelligent approaches based on fuzzy logic, neural networks, or reinforcement learning offer adaptive decision-making capabilities but require extensive training, calibration, or computational resources.

Table 9. Overall controller performance summary.

Performance Metric	Battery-Only	Conventional HESS	Proposed EMS	Improvement [%]
Peak battery current	317.86	154.75	153.88	51.58
RMS battery current	124.40	101	76.21	38.73
SOC variation	11.04	11.7	8.77	20.56
Supercapacitor utilisation	0	67.07	71.47	6.56
Computational complexity	Low	Low	Low	-

The proposed EMS aims to bridge the gap between these approaches by retaining the simplicity, transparency, and real-time feasibility of a conventional rule-based controller while incorporating route and environmental information—including road gradient, traffic conditions, wind speed, and ambient temperature—to proactively adapt battery power allocation. Consequently, the controller can reduce battery current stress, improve superca-

pacitor utilisation, and increase regenerative energy recovery without introducing iterative optimisation or machine-learning algorithms. As summarised in Table 9, the proposed method therefore provides a practical compromise between control performance and implementation complexity, making it well suited for real-time electric vehicle applications where computational efficiency, robustness, and ease of implementation are important design considerations.

6. Conclusions

This paper presented a route- and environment-aware rule-based energy management system (EMS) for battery–supercapacitor hybrid energy storage systems (HESSs) in electric vehicles. Unlike conventional rule-based controllers that primarily rely on battery state of charge (SOC), supercapacitor SOC, and instantaneous power demand, the proposed supervisory controller integrates additional real-time information, including traffic conditions, road slope, wind resistance, and ambient temperature, to improve the power allocation between the battery and the supercapacitor. By incorporating these external variables into the decision-making process, the controller enhances supercapacitor utilisation while maintaining the low computational complexity required for real-time implementation. A comprehensive mathematical model of the electric vehicle, battery, supercapacitor, and HESS was developed in MATLAB/Simulink to evaluate the proposed controller. The performance of the EMS was assessed under three representative driving cycles, namely the Urban Dynamometer Driving Schedule (UDDS), Artemis Motorway 130, and a Central Business District (CBD) driving cycle. The proposed controller was compared with both a conventional battery-only energy storage system and a conventional rule-based HESS controller to isolate the benefits of the proposed supervisory strategy.

The simulation results demonstrate that the proposed EMS effectively reduces battery electrical stress while increasing the utilisation of the supercapacitor across a wide range of operating conditions. Under the UDDS driving cycle, the maximum battery current was reduced by approximately 51.67%, decreasing from values exceeding 300 A in the battery-only configuration to less than 160 A when the proposed HESS controller was employed. Similar improvements were observed under the Artemis Motorway 130 and CBD driving cycles, where the controller consistently reduced battery current peaks, smoothed battery SOC variations, increased regenerative braking energy recovery, and improved supercapacitor utilisation. Furthermore, the proposed EMS maintained the battery predominantly within its desired operating region by allocating transient power demands and regenerative braking energy to the supercapacitor whenever appropriate.

Compared with optimisation-based energy management strategies, such as Model Predictive Control (MPC), Dynamic Programming (DP), and reinforcement learning (RL), the proposed controller offers several practical advantages. Its decision-making process relies on simple logical rules and algebraic calculations, resulting in low computational complexity and making it suitable for implementation on production automotive electronic control units without requiring high-performance processors or extensive online optimisation. Consequently, the proposed approach provides an attractive compromise between control performance, implementation simplicity, and real-time applicability.

The results also demonstrate the value of incorporating route and environmental information into rule-based energy management. By anticipating changes in traffic density, road gradient, wind resistance, and ambient temperature, the supervisory controller proactively adjusts the allowable battery power and allocates additional power support to the supercapacitor before significant load transients occur. This predictive capability enables more effective utilisation of the supercapacitor than conventional rule-based strategies that respond only to instantaneous operating conditions.

Although the proposed controller significantly reduced battery current peaks, RMS current, and battery energy throughput, it should be noted that this study did not include a detailed electrochemical battery degradation model. Consequently, the reported improvements should be interpreted as demonstrating a reduction in battery electrical stress rather than direct proof of increased battery lifetime. Overall, the proposed route- and environment-aware rule-based EMS provides an effective and computationally efficient solution for battery–supercapacitor hybrid energy storage systems. By integrating readily available route and environmental information into a transparent supervisory control framework, the proposed strategy improves battery operating conditions, enhances supercapacitor utilisation, and increases regenerative braking effectiveness while maintaining the simplicity and robustness that make rule-based energy management attractive for practical electric vehicle applications.

Author Contributions: Conceptualization, N.M.K.; methodology, N.M.K.; software, N.M.K.; validation, N.M.K.; formal analysis, N.M.K.; investigation, N.M.K.; resources, N.M.K.; data curation, N.M.K.; writing—original draft preparation, N.M.K. and M.W.K.M.; writing—review and editing, M.W.K.M.; visualization, M.W.K.M. and N.M.K.; supervision, M.W.K.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data presented in this study are available from the corresponding author upon request.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

API	Application Programming Interface
CBD	Central Business District
DEM	Digital Elevation Model
DP	Dynamic Programming
DRL	Deep Reinforcement Learning
ECMS	Equivalent Consumption Minimisation Strategy
EMS	Energy Management System
ESR	Equivalent Series Resistance
EV	Electric Vehicle
GA	Genetic Algorithm
HESS	Hybrid Energy Storage System
MATLAB	Matrix Laboratory
MPC	Model Predictive Control
PMP	Pontryagin's Minimum Principle
PSO	Particle Swarm Optimisation
RL	Reinforcement Learning
SOC	State Of Charge
UDDS	Random Forest

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