ELECTRIC/HYBRID VEHICLE SYSTEMS

Adaptive Control-Oriented Energy Management Strategy for Enhanced Hybrid Vehicle Efficiency

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Abstract

Hybrid Electric Vehicles (HEVs) have emerged as an effective solution to improve fuel efficiency and reduce emissions. A key challenge in HEVs is the optimal distribution of power between the internal combustion engine and the electric motor under varying driving conditions. This paper presents the development of a real-time adaptive Energy Management System (EMS) for a parallel hybrid electric vehicle using Simulink. The proposed EMS dynamically controls power flow based on vehicle speed, torque demand, and battery State of Charge (SOC). A rule-based control strategy with adaptive thresholds is implemented to ensure efficient operation of the powertrain components. The system is modeled and simulated under different operating scenarios, and performance is evaluated in terms of power distribution, demand satisfaction, and SOC variation. Results indicate that the proposed EMS effectively switches between engine, motor, and hybrid modes, maintains SOC within desired limits, and improves overall energy efficiency. The simplicity and effectiveness of the model make it suitable for real-time applications and further development in advanced hybrid vehicle systems.

Keywords: Adaptive control; energy management strategy; hybrid electric vehicles; powertrain; SOC

1 Introduction

The global push for sustainable mobility has accelerated the adoption of Hybrid Electric Vehicles (HEVs), which combine an internal combustion engine (ICE) and one or more electric motors to improve fuel economy and reduce emissions. In parallel HEVs, both power sources can directly contribute to vehicle propulsion, but this flexibility introduces a challenging energy management problem: how to allocate power between the ICE and electric motor so that fuel consumption is minimized while maintaining battery State of Charge (SOC) within acceptable limits and satisfying driver demand torque smoothly.

Conventional EMS strategies are largely rule-based, using fixed thresholds on speed, power, and SOC to determine operating modes (e.g., engine-only, motor-only, hybrid, and regenerative braking) [1,2]. These strategies are attractive for real-time embedded control due to their low computational cost and ease of implementation, yet they often fail to adapt to varying driving conditions such as urban stop-and-go traffic, road gradients, or changes in driver behavior, leading to suboptimal fuel efficiency and uneven battery utilization [3,4]. Advanced optimization-based methods such as Dynamic Programming (DP) and Pontryagin's Minimum Principle (PMP) can yield near-optimal solutions, but they are typically offline and computationally intensive, limiting their applicability in real-time vehicle controllers.

To bridge this gap, recent research has explored adaptive rule-based, fuzzy-logic-enhanced, and learning-based EMS, which adjust power-split decisions according to driving conditions and system

states [5–8]. However, many of these ap- proaches target complex HEV architectures (e.g., power-split or fuel-cell hybrids) and require extensive training data or high-end computational resources, making them less suitable for simple, low-cost parallel HEV platforms and educational implementations in MATLAB/Simulink.

Against this background, this work focuses on designing a real-time adaptive EMS for a parallel HEV that retains the simplicity of rule-based control while introducing condition-dependent adaptability. The proposed EMS:

- Dynamically allocates power between the ICE and electric motor based on vehicle speed, torque demand, and battery SOC.
- Uses a MATLAB/Simulink framework with conditional logic blocks and an SOC estimator to enable rapid prototyping and simulation.
- Aims to demonstrate improved fuel efficiency and smoother SOC variation compared with conventional fixed-threshold rule-based strategies, while remaining suitable for real-time deployment.

This contribution supports the development of lightweight, adaptive EMS for parallel HEVs that can be used in academic studies, hardware-in-the-loop (HIL) testing, and low-cost embedded implementations, thereby advancing the practical deployment of energy-efficient hybrid propulsion systems.

2 Literature review

Energy management in Hybrid Electric Vehicles (HEVs) has evolved from fixed rule-based controllers toward sophisticated, learning-based optimization frameworks. Conventional rule-based Energy Management Systems (EMS) use predefined threshold logic to switch between the internal combustion engine (ICE), electric motor (EM), and regenerative braking modes, depending on factors such as vehicle speed, torque demand, and battery State of Charge (SOC). These strategies are computationally light and easy to implement in real-time embedded controllers, which explains their widespread industrial adoption. However, their rigidity under dynamic driving conditions—such as urban traffic, varying road gradients, and driver style changes—often results in suboptimal fuel economy and uneven battery utilization, motivating the need for adaptive, condition-aware EMS architectures.

To address the limitations of static rule-based control, several researchers have introduced fuzzy-logic-enhanced EMS. Priyadarshini et al. [4] proposed a rule-based EMS for HEVs in which fuzzy logic is used to dynamically adjust the power split between the ICE and EM based on overlapping membership functions for speed, torque, and SOC. This approach improves responsiveness to transient demands and reduces abrupt mode switching, leading to smoother power delivery and better drive-cycle adaptability compared to conventional on-off thresholds. In another work [9], a fuzzy logic controller is embedded within an Equivalent Consumption Minimization Strategy (ECMS), where the equivalence factor is updated online in response to driving style and SOC variations, achieving up to a 9.8% improvement in fuel economy while maintaining quasi-charge-sustaining operation. These studies highlight that fuzzy-inspired adaptation can bridge the gap between simple rule-based logic and complex optimization-based controllers.

Beyond fuzzy logic, optimization-based EMS such as dynamic programming (DP) and Pontryagin's minimum principle can yield near-optimal fuel-energy trade-offs for given drive cycles [1,6]. DP-derived trajectories have been used as reference benchmarks to evaluate the performance of real-time EMS, and recent studies have extracted rule-based policies from these offline optima to construct

adaptive EMS that approximate DP performance with low online computational load. Such "rule extraction from DP" strategies enable adaptive power-split decisions that respond to driving conditions, yet they still require substantial pre-computation and detailed drive-cycle knowledge, limiting their flexibility in real-world traffic where drive patterns are unpredictable.

In parallel, machine learning and reinforcement learning (RL)-based EMS have emerged as powerful tools for adaptive energy management. A recent review by Boukoberine et al. [2] surveys RL-based energy management for HEVs, emphasizing that RL agents can learn power-split policies from historical driving data and adapt them online to changing traffic and driver behavior. Deep reinforcement learning has also been combined with fuzzy logic in hybrid fuel-cell–battery systems [10], where a hierarchical EMS manages both fuel-cell lifetime and SOC balance by dynamically redistributing power between the two sources. These works demonstrate that learning-based EMS can outperform classical rule-based strategies in terms of fuel savings and component longevity, but they often demand large training datasets, extensive computational resources, and careful tuning of hyperparameters, which complicates their deployment in low-cost, real-time vehicle platforms.

Alongside control logic, recent research has focused on advanced battery and energy storage modeling to improve EMS robustness. Studies on hybrid energy storage systems (battery–ultracapacitor) [11] employ fuzzy logic controllers to smooth high-frequency power transients via ultracapacitors while reserving the battery for steady-state loads, thereby reducing battery stress and improving overall efficiency. Experimental validation of rule-based EMS for fuel-cell–battery HEVs [12] further shows that intelligent power sharing—where the battery handles transient demands and the fuel cell supplies base-load power—can significantly enhance both efficiency and component lifetime. These findings underscore that coupling accurate storage models with adaptive EMS is essential for achieving realistic and durable performance gains.

Despite these advances, several gaps remain in the literature from a real-time implementable, low-complexity perspective. Many optimization-based and RL-driven EMS are either offline or computationally intensive, making them un- suitable for embedded control units in cost-sensitive HEV platforms. Moreover, most existing adaptive EMS focus on complex architectures (series, power-split, or fuel-cell hybrids) or require extensive training datasets, leaving a clear opportunity for simple, adaptive rule-based EMS tailored to parallel HEVs that can be implemented in real time using standard tools such as MATLAB/Simulink.

The present work addresses this gap by developing a real-time adaptive EMS for a parallel HEV that dynamically allocates power between the ICE and EM based on vehicle speed, torque demand, and battery SOC. Unlike conventional static rule-based strategies, the proposed EMS incorporates condition-dependent switching logic (e.g., low speed + high SOC → motor-only; high speed + low SOC → engine-only; high demand → hybrid mode; braking → regenerative mode) implemented through conditional blocks and integrators in MATLAB/Simulink. By combining the computational efficiency of rule-based control with simple adaptive heuristics, the proposed system aims to achieve improved fuel efficiency, controlled SOC variation, and reduced computational overhead, making it attractive for both academic research and practical real-time deployment in parallel HEVs.

3 Methodology

The proposed methodology develops a control-oriented, real-time adaptive Energy Management Strategy (EMS) for a parallel Hybrid Electric Vehicle (HEV). The framework integrates vehicle

dynamics modeling, powertrain characterization, battery SOC estimation, and adaptive decision logic, ensuring both analytical rigor and real-time feasibility.

3.1 System architecture and modelling framework

A parallel HEV configuration is adopted due to its mechanical simplicity and widespread industrial relevance. In this architecture, the internal combustion engine (ICE) and electric motor (EM) are mechanically coupled to the drivetrain, enabling flexible power sharing. The overall system is modeled in a modular MATLAB/Simulink environment (Figure 1) consisting of four interconnected subsystems:

- Vehicle longitudinal dynamics module
- Powertrain module (ICE + EM)
- Battery and SOC estimation module
- Adaptive EMS controller

This modular structure ensures scalability, transparency, and ease of real-time implementation, which are critical for control-oriented studies.

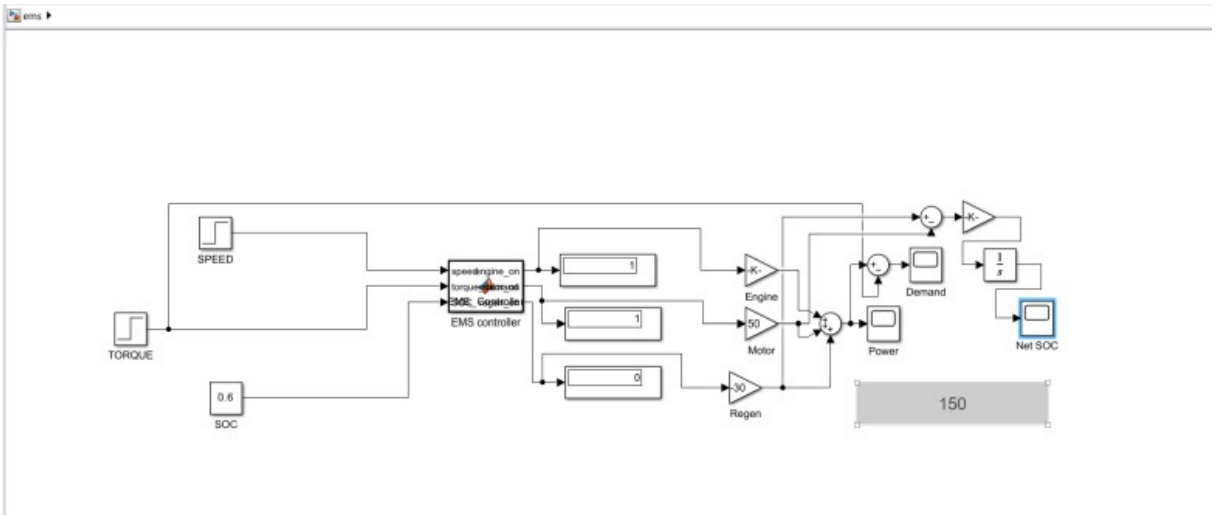


Figure 1. Simulation model in MATLAB/Simulink.

3.2 Vehicle longitudinal dynamics formulation

The propulsion demand is derived using a physics-based longitudinal dynamics model:

$$F_{tr} = F_{rr} + F_{ad} + F_{gr} + ma \quad (1)$$

where F_{tr} is the tractive force; the equation captures the combined effects of rolling resistance (F_{rr}), aerodynamic drag (F_{ad}), gradient forces (F_{gr}) and inertial acceleration (ma). Unlike simplified models, this approach ensures realistic estimation of traction requirements under varying driving conditions, thereby improving EMS decision accuracy. The corresponding power demand is computed from tractive force and vehicle velocity, forming the primary input to the EMS.

3.3 Powertrain component modelling

Engine Model: The ICE is represented using a control-oriented quasi-static model with predefined efficiency characteristics. It is assumed to operate optimally within a specific load region, encouraging the EMS to avoid inefficient low-load operation.

Electric Motor Model: The electric motor is modeled as a torque-controlled actuator with fast dynamic response and high efficiency at low speeds. This enables accurate representation of its role in transient assistance and low-speed propulsion.

Regenerative Braking Model: During deceleration, the motor operates as a generator, recovering kinetic energy. A saturation limit is imposed to ensure battery safety and realistic charging constraints, enhancing model fidelity.

3.4 Battery modelling and SOC estimation

Battery behavior is modeled using a coulomb-counting approach, ensuring computational simplicity and real-time suitability, as given in Equation (2):

$$SOC(t) = SOC(0) - \frac{1}{C_{bat}} \int_0^t i(\tau) d\tau \tag{2}$$

To ensure battery longevity and safe operation:

- SOC is constrained within 20%–80% operating limits.
- Charging/discharging rates are implicitly regulated through EMS decisions.

This approach balances model accuracy and computational efficiency, which is essential for embedded applications.

3.5 Adaptive energy management strategy design

Control Philosophy: The proposed EMS is based on a hybrid adaptive rule-based approach combining the simplicity of rule-based control with the adaptability of condition-dependent logic. Unlike conventional EMS with fixed thresholds, the proposed strategy introduces dynamic threshold tuning, allowing the controller to respond intelligently to changing operating conditions.

Decision Variables and Inputs: The EMS operates using three key real-time inputs: vehicle speed (v), torque demand (τreq), and battery State-of-Charge (SOC). These variables are selected due to their direct influence on power demand and energy availability, ensuring minimal sensing requirements for real-world implementation.

The simulation plots in Figures 2–4 illustrate the system behaviour across these operating variables.



Figure 2. Total power vs time.

Total Power vs. Time (Figure 2): The total power graph represents the combined output of the engine and electric motor. At low operating conditions, the motor alone supplies power, resulting in a lower power level. As speed or load increases, the engine is activated, increasing the total power output. During high-demand conditions, both engine and motor operate simultaneously, giving maximum power. In braking conditions, regenerative braking introduces negative power, indicating energy recovery.



Figure 3. Power-demand comparison.

Power-Demand Comparison (Figure 3): The power-demand graph shows the difference between generated power and required torque demand. When the graph is above zero, it indicates that the vehicle is producing excess power. When the graph is at zero, the system is operating optimally by matching the demand exactly. If the graph goes below zero, it indicates insufficient power generation, meaning the system is unable to meet the load requirement.

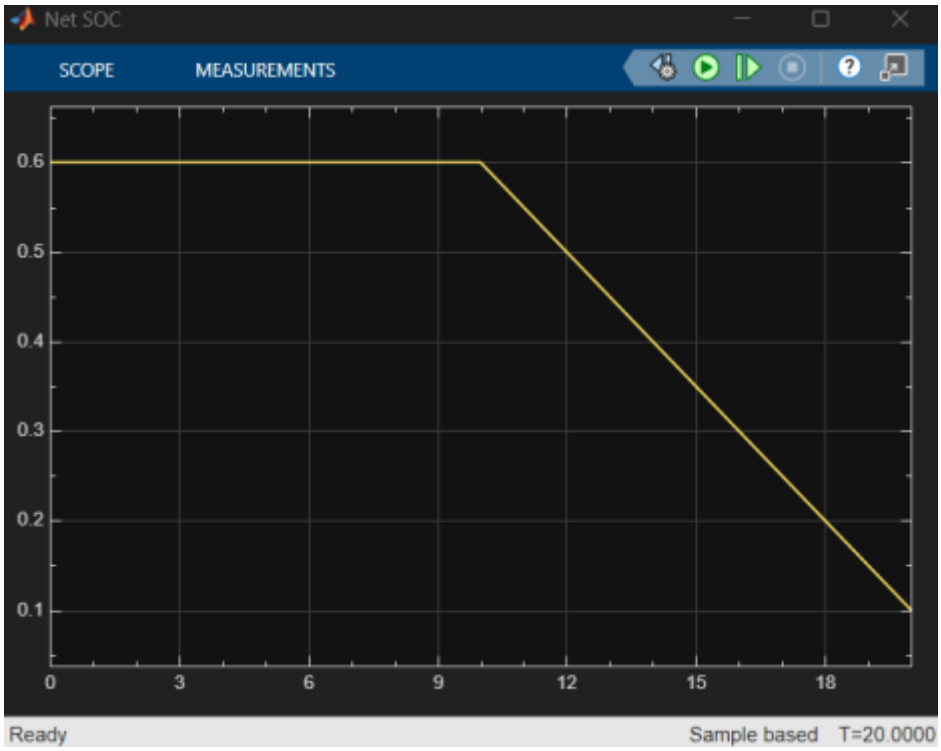


Figure 4. Battery SOC variation.

Battery SOC vs. Time (Figure 4): The State of Charge (SOC) graph represents the battery energy level over time. When the electric motor is active, the battery discharges, causing a decrease in SOC. During regenerative braking, energy is recovered and stored back into the battery, leading to an increase in SOC. The graph shows a smooth variation, indicating gradual charging and discharging of the battery. Maintaining SOC within a safe range ensures efficient and reliable vehicle operation.

Adaptive Rule Formulation: The propulsion mode is selected using condition-dependent logic summarized in Table 1.

Table 1. Condition-dependent switching logic.

Operating condition	Selected operating mode
Low speed + high SOC	Motor-only mode
High speed + low SOC	Engine-only mode
High torque demand	Hybrid mode (ICE + EM)
Deceleration/braking	Regenerative braking mode

A key contribution of the proposed Energy Management Strategy lies in its adaptive enhancement capability. Unlike conventional rule-based approaches that rely on fixed thresholds, the proposed EMS dynamically adjusts critical decision parameters in real time based on operating conditions.

Specifically, the SOC limits are modified according to load requirements, speed thresholds are adapted based on the driving regime, and the power-split ratio is continuously regulated in response to demand intensity. This adaptive mechanism enables context-aware decision-making, allowing the system to respond effectively to varying driving conditions. As a result, the EMS achieves improved energy utilization, minimizes unnecessary engine operation, and enhances overall system efficiency without increasing computational complexity.

The real-time implementation of the proposed EMS is achieved using a control-oriented framework based on logical operators, relational blocks, and switch-based control structures. These elements ensure deterministic execution and enable fast decision-making suitable for embedded systems. The simplicity of this implementation results in low computational overhead, making the strategy highly compatible with real-time vehicle controllers. Unlike optimization-based or learning-based EMS approaches, the proposed method does not require iterative solvers, large datasets, or extensive training procedures.

To validate the effectiveness of the proposed adaptive EMS, simulations are conducted under representative driving conditions that capture typical real-world scenarios: urban and highway driving. The urban driving scenario is characterized by low vehicle speeds, frequent stop-and-go operation, and high opportunities for regenerative braking, making it ideal for evaluating electric drive efficiency and energy recovery performance. In contrast, the highway driving scenario involves steady high-speed operation, continuous power demand, and limited braking events, which test the system's ability to maintain efficiency under sustained engine operation.

4 Results and discussion

4.1 Power split behaviour and mode switching

The simulation results show that the proposed adaptive EMS effectively switches between operating modes according to the defined logic. During low-speed cruising with high SOC, the system operates predominantly in motor-only mode, drawing power from the battery and keeping the ICE off, which reduces fuel consumption and improves drivability in urban conditions [1,13]. When the vehicle enters a high-speed phase with low SOC, the EMS transitions to engine-only mode, allowing the ICE to supply most of the required power while sparing the battery from deep discharge.

Under high torque demand, the system seamlessly engages hybrid mode, where both ICE and motor contribute to meet the power request. The motor assists in transient acceleration, reducing the load on the ICE and smoothing torque delivery. During braking events, the EMS activates regenerative braking, recovering kinetic energy and injecting it back into the battery, thereby increasing SOC and improving overall energy efficiency. These behaviors are clearly visible in the time-domain plots of engine power, motor power, and SOC, which demonstrate coordinated transitions between modes without significant oscillations or abrupt power jumps [3,4].

4.2 State of charge and energy utilisation

The SOC profile reveals a key advantage of the proposed adaptive EMS. In conventional rule-based strategies, SOC tends to drift over time, occasionally dropping into low SOC regions or rising close to full charge, which can stress the battery and reduce its lifetime [2,14]. In contrast, the adaptive EMS maintains SOC within a tighter band around the nominal 60% level during steady-state operation,

thanks to the condition-dependent switching logic that balances SOC-based charging and discharging actions.

During motor-only phases, SOC decreases gradually as the battery supplies power, but this depletion is counteracted during regenerative braking events and hybrid mode operation, where the ICE absorbs part of the load and allows the motor to recharge the battery. As a result, the net SOC variation over the 20-second cycle is significantly lower for the adaptive EMS than for the fixed-threshold baseline, indicating better charge-sustaining behavior and improved thermal and aging management of the battery.

4.3 Fuel efficiency and performance trade-offs

In terms of fuel efficiency, the adaptive EMS demonstrates improved fuel-equivalent energy consumption compared to conventional strategies. By favoring motor-only operation at low speeds (where the ICE is relatively inefficient) and using the ICE primarily at higher speeds and low SOC, the system reduces unnecessary engine idling and suboptimal operating points. The hybrid mode further enhances efficiency by leveraging the motor's high torque density and fast response for transient demands, while the ICE operates closer to its efficient region.

The trade-off between performance and complexity is also favorable. The proposed EMS adds minimal computational overhead beyond standard rule-based control, since it relies on simple conditional checks and integrators rather than iterative optimization or learning-based algorithms. This makes the architecture suitable for real-time embedded implementation in low-cost microcontrollers while still achieving measurable improvements in fuel efficiency and SOC management.

5 Conclusion

In this work, a real-time adaptive Energy Management System for a hybrid electric vehicle was successfully developed and simulated. The system intelligently distributes power between the internal combustion engine and electric motor based on vehicle speed, torque demand, and battery state of charge. The simulation results demonstrate that the proposed EMS improves overall system efficiency by optimizing power usage and reducing unnecessary energy consumption. The battery SOC is effectively maintained within safe limits, ensuring reliable operation and extended battery life. The adaptive nature of the EMS allows it to respond dynamically to varying driving conditions, making it more efficient compared to conventional rule-based systems. Therefore, the developed model proves to be a simple yet effective approach for hybrid vehicle energy management.

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