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Energy management in autonomous hybrid electric vehicles: A review

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Abstract. Hybrid electric vehicles represent a critical step toward sustainable automotive technology. The integration of Advanced Driver Assistance Systems introduces complex challenges in energy demand and management, making Energy Management Systems crucial for optimizing this integration and ensuring overall vehicle efficiency. This review aims to explore the variety of EMS approaches used in HEVs, focusing on their role in managing the heightened energy requirements introduced by ADAS components. The paper examines EMS configurations and their effectiveness in allocating and controlling energy from diverse sources such as fuel cells, batteries, and supercapacitors. The review also highlights the importance of innovative management techniques that adapt to variable power requirements and driving conditions influenced by ADAS. EMS are shown to be instrumental in enhancing the operational efficiency of HEVs. They are essential for accommodating the fluctuating energy demands of ADAS, which can significantly elevate the vehicle's overall energy consumption. EMS are vital for advancing HEVs, ensuring that these vehicles not only meet the complex energy demands of ADAS but also achieve environmental sustainability goals.

Keywords: Hybrid electric vehicles (HEVs); Autonomous vehicles; Energy Management Strategies (EMS); Advanced Driver Assistance Systems (ADAS); Fuel cells; Batteries; Supercapacitors; Energy optimization; Predictive algorithms; Sustainable transportation

1 Introduction

The rapid evolution of hybrid electric vehicles, combining fuel cells, batteries, and supercapacitors, is driving a significant shift toward sustainable transportation [1]. With transportation accounting for 29% of global greenhouse gas emissions [2], HEVs offer a promising solution, reducing emissions by up to 13.4% compared to conventional vehicles [3]. These vehicles blend electric propulsion with traditional fuel systems, positioning them at the forefront of this transformation.

However, the integration of Advanced Driver Assistance Systems [4] introduces new challenges in energy management, complicating vehicle power systems [5]. This paper reviews energy management strategies that balance fuel cells, batteries, and supercapacitors while meeting ADAS's high-energy demands [6]. Systems like adaptive cruise control [7], lane-keeping assist [8], and autonomous emergency braking [9] enhance safety but can increase energy consumption by up to 23% during peak usage [10].

A key focus is hybrid algorithms that combine multiple EMS approaches to improve efficiency and adaptability, distributing energy optimally across vehicle systems. The paper also explores predictive strategies using advanced analytics to forecast energy needs and dynamically manage energy flow [11].

The paper opens with an exploration of the fundamental technologies and configurations that define hybrid electric vehicles. Next, it delves into the energy demands introduced by ADAS and their effect on energy management strategies. The analysis then moves to hybrid algorithms that enhance energy distribution efficiency, as well as predictive strategies for optimizing real-time energy flow. Further, the discussion addresses emerging technologies such as artificial intelligence, V2X, and 5G, which hold great potential for transforming energy management. The paper concludes by synthesizing the findings and offering new directions for future research.

2 Technologies and Hybrid Energy Sources in Autonomous Hybrid Vehicles

Autonomous hybrid vehicles represent a major leap in sustainable transportation, relying on a sophisticated combination of energy systems to meet the diverse demands of modern driving. These vehicles are powered by three main energy sources: fuel cells [12], batteries [13], and supercapacitors [14]. Unlike conventional vehicles [15], which depend solely on internal combustion engines [16], AHVs utilize multiple clean energy technologies to reduce emissions and optimize performance. This combination not only improves energy efficiency but also supports the high power requirements of

Advanced Driver Assistance Systems for features such as real-time navigation [17] and adaptive driving [18].

The decision to combine fuel cells, batteries, and supercapacitors in a hybrid configuration is based on their complementary nature. Batteries, particularly lithium-ion types [19], offer high energy density [20], making them essential for sustained, low-to-medium energy tasks like maintaining speed and powering electronics. However, their slower charge-discharge cycles [21] limit their ability to handle sudden power demands [22]. Fuel cells generate electricity through an electrochemical reaction between hydrogen [23] and oxygen, providing continuous, long-term energy [24] and making them ideal for long-distance driving [25], though they respond more slowly to sudden power demands [26]. Supercapacitors complement both by delivering rapid energy bursts [27] during acceleration, braking, or when powering ADAS sensors. Although supercapacitors store less energy, they release it quickly, making them perfect for managing short-term power needs, especially in scenarios requiring fast energy responses, though their lower storage capacity prevents them from replacing batteries or fuel cells for long-term use [28].

The integration of fuel cells, batteries, and supercapacitors allows AHVs to create a dynamic and efficient energy management system, capable of responding to both steady and variable driving conditions. This hybrid configuration ensures that energy sources are utilized according to real-time demand, enhancing overall vehicle performance while efficiently meeting the power-intensive requirements of ADAS systems.

Table 1: Comparative Characteristics of Battery, Fuel Cell, and Supercapacitor with ADAS.

Characteristic	**Battery**	**Fuel Cell**	**Supercapacitor**
Energy Density	High energy density, suited for long-term use	Continuous energy supply but slower to respond	Low energy density, high power output
Power Density	Moderate	Low	Very high
Response Time	Slow	Slow to moderate	Fast
Charge/Discharge Rate	Limited	Steady	Very fast
Best Usage Scenarios	Long-term driving and steady-state operations	Long-range driving	Quick acceleration and regenerative braking
Challenges	Slower charge rate, requires careful management to avoid degradation	Infrastructure issues, slower response to sudden demands	Low energy storage capacity, needs frequent charging
Integration with ADAS	Reliable for sustained ADAS operation	Good for continuous but low-response energy	Ideal for handling ADAS power surges

3 Energy Demands and Optimization in Advanced Driver Assistance Systems

Advanced Driver Assistance Systems are crucial for enabling the autonomous functionalities of Hybrid Autonomous Vehicles, providing enhanced safety and convenience. These systems rely heavily on real-time data collection and processing from various sensors, including cameras [29], radar [30], LiDAR [31], and ultrasonic sensors [32], which constantly monitor the vehicle's surroundings to inform driving decisions. As AHVs become more advanced, the energy demands of ADAS systems increase. These technologies are vital for functions such as navigation, collision avoidance, and adaptive responses to road conditions but significantly contribute to the vehicle's overall energy consumption, especially in dynamic environments like cities [33]. For example, in urban areas with frequent stop-and-go traffic, ADAS systems are continuously active, increasing energy demands by up to 23% [10].

3.1 Sensor Efficiency and Energy Optimization

To address the increased energy demand, advancements in energy management can improve ADAS efficiency [34]. Multi-sensor fusion, which combines data from various sensors into a single processing stream, reduces redundancy and optimizes sensor operations, thereby lowering energy consumption without compromising performance. Additionally, adaptive strategies that adjust sensor scan frequencies according to driving conditions—such as fewer LiDAR scans on highways—can further conserve energy [35].

3.2 Impact of ADAS on Vehicle Range and Overall Energy Management

Higher energy consumption by ADAS can reduce the overall driving range of AHVs, particularly in urban environments where frequent stops and rapid adjustments are required. Urban driving places the greatest strain on energy systems due to continuous sensor activity and frequent acceleration and braking. In contrast, highway driving involves fewer ADAS activations, thereby lessening the energy load. Smart energy management systems can optimize sensor usage based on driving conditions, preserving vehicle range without reducing ADAS functionality.

Research indicates that integrating ADAS into hybrid vehicles enables dynamic energy management, adjusting energy supply to match real-time demands. In highway conditions, where ADAS functions are less frequently needed, these systems can lower energy consumption, enhancing the overall efficiency of the vehicle. By focusing energy on the most critical ADAS functions, such as traffic monitoring or speed adjustment, energy use is optimized. Studies also show that systems like Adaptive Cruise Control help reduce energy waste by maintaining steady speeds and minimizing unnecessary acceleration and braking, especially on highways. AI-powered ADAS systems also offer predictive energy management, adjusting sensor activity based on anticipated driving conditions, further optimizing energy efficiency and extending vehicle range.

4 Energy Management Techniques: Strategies and Algorithms

In hybrid autonomous electric vehicles several energy management strategies are employed to optimize the use of hybrid power sources, including batteries, fuel cells, and supercapacitors. Techniques such as bi-adaptive control with fuzzy logic enhance battery-supercapacitor configurations, improving charge efficiency and reducing stress [36]. Decentralized methods, like Mixed Droop Control, have been effective in increasing energy efficiency and stability in fuel cell-battery systems [37]. Advanced control strategies, such as backstepping sliding mode control, ensure stable DC bus voltage regulation under varying loads [38, 39], while fuzzy logic paired with Direct Torque Control enables smooth power sharing between batteries and supercapacitors, improving motor control response [40].

Optimization strategies like Adaptive Equivalent Consumption Minimization Strategy improve battery state-of-charge and fuel efficiency [41, 42], while genetic algorithms further optimize fuel consumption and extend the lifespan of hybrid energy systems [43]. Real-time control strategies, such as Pontryagin's Minimum Principle, significantly reduce fuel cell degradation and hydrogen consumption [44]. Dynamic programming approaches, including Advisory Dynamic Programming, achieve up to a 29% improvement in energy efficiency through real-time power distribution [45].Other strategies, including wavelet-based power management [46] and frequency decoupling with fuzzy control [47], improve battery longevity and fuel efficiency by optimizing power distribution and reducing fluctuations. Finally, Model Predictive Control is widely used to minimize fuel cell degradation and optimize power management based on real-time constraints and vehicle dynamics [48].

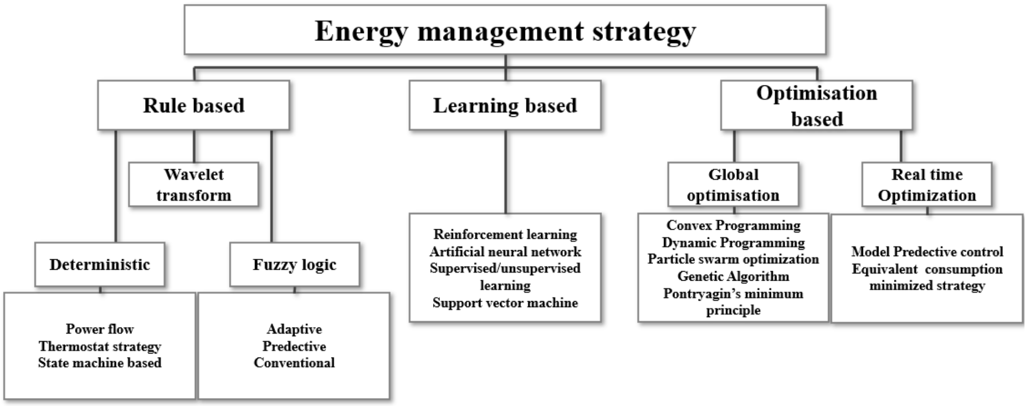

Fig. 1: Hybrid energy management strategies for AHVs.

Table 2: Summary of energy management strategies for hybrid power sources.

Ref	Strategy	Hybrid power sources	Optimized parameters and output
[36]	Bi-adaptive control based on a low-pass filter and an adaptive proportional integrative charge controller, using fuzzy logic for real-time management	Battery and Supercapacitor	Reduction of stress, temperature, and power losses in the battery. Improved charge and discharge management during acceleration and braking. Stable performance of the supercapacitor with charge efficiency rates of 98%, 95%, and 96% for the tested driving cycles.

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Ref	Strategy	Hybrid power sources	Optimized parameters and output
[37]	Decentralized energy management strategy using a composite control scheme combining Mixed Droop Control and Disturbance Observer-Based Control	Fuel Cell and Battery	Enhanced dynamic load power allocation, extended service life, improved energy efficiency, and robust system stability.
[38, 39]	Backstepping-based sliding mode control for nonlinear HESS control	Fuel Cell, Supercapacitor	DC bus voltage regulation under varied load demand. Reference tracking of fuel cell and supercapacitor current. Improved stability, zero initial overshoot, fast convergence.
[40]	Fuzzy logic-based power management combined with Backstepping Direct Torque Control	Battery, Supercapacitor	Smooth power-sharing between battery and supercapacitor. Regulation of DC bus voltage and supercapacitor voltage. Chattering reduction in motor control and improved dynamic response.
[49]	Integral Backstepping Control	Fuel Cell, Ultracapacitor	Removes steady-state error and provides robust regulation of DC bus voltage.
[41, 42]	Optimization-oriented adaptive equivalent consumption minimization strategy	Fuel Cell, Battery	Optimized SOC stability, rapid SOC recovery, low SOC fluctuation (0.36%), and improved fuel economy (8.003 L/100 km).
[43]	Genetic Algorithm-based optimization	Fuel Cell, Battery, Supercapacitor	Optimized fuel consumption, reduced current fluctuation, improved system efficiency, and extended component lifespan.
[50]	Model Predictive Control combined with Multi-Objective Particle Swarm Optimization	Fuel Cell, Supercapacitor, Battery	Optimized energy efficiency, reduced battery current variation, minimized SC SOC fluctuations, minimized hydrogen consumption, and enhanced system performance during different driving cycles.
[44]	Real-time energy management based on Pontryagin's minimum principle	Fuel Cell, Li-ion Battery	Reduced hydrogen consumption by 13.8%, reduced fuel cell degradation by 93%, improved durability.
[51]	Genetic Algorithm - Pontryagin Minimum Principle	Fuel Cell, Battery, Supercapacitor	Reduced hydrogen consumption by approximately 9%, minimized SOC variation.
[45]	Advisory Dynamic Programming	Fuel Cell, Battery, Supercapacitor	Up to 29% improvement in energy efficiency through real-time adjustments in power split.
[52]	Pontryagin's Minimum Principle	Batteries and supercapacitors	Reduced battery RMS current by 50% during real-world driving cycles.
[53]	Co-optimization of speed trajectory and power management using Pontryagin's Minimum Principle	Fuel cell, battery	Total energy savings from co-optimization range from 5.3% to 24.2% for aggressive driving on hilly terrain and 0.5%-5.3% on flat roads. Reduced computational cost achieved.
[54]	Convex Programming	Fuel cell, battery	CP-based EMS results in 3.9%-7.0% higher hydrogen consumption than DP. Optimal battery size is 2.803 kWh for DP and 2.081-2.165 kWh for CP. DP ensures global optimality, while CP provides faster computation.
[46]	Wavelet-based power management	Battery, Ultracapacitor	Improved battery lifetime by 120%, cost reduction of $1500 over 10 years.
[55]	Multi-dimensional dynamic programming	Fuel Cell, Battery	Hydrogen consumption reduced by 3.10%. Durability improved by 1.08% for fuel cell and 0.13% for battery.
[56]	Wavelet-Fuzzy Energy Management + Particle Swarm Optimization	Fuel Cell, Battery, Ultra-capacitors	Optimized power distribution, reduced hydrogen consumption, increased system durability, extended battery life, and reduced system cost.
[57]	Mutative Fuzzy Logic Control	Fuel Cell, Battery	Prolonged fuel cell lifetime by up to 32.8%, optimized power distribution, and reduced degradation rates.

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Ref	Strategy	Hybrid power sources	Optimized parameters and output
[58]	Hierarchical Energy Management Strategy combining fuzzy logic and status regulator	Fuel Cell, Battery, Ultracapacitor	Reduced hydrogen consumption by up to 54.5%, increased energy efficiency by 61.3%.
[59]	Fuzzy logic with Super-twisting Sliding Mode Control	Fuel Cell, Battery, Supercapacitor	Hydrogen fuel consumption reduced by 29%, achieving an average fuel consumption of 3.427 liters.
[47]	Frequency decoupling-based energy management strategy with fuzzy control	Fuel Cell, Battery, Ultracapacitor	Optimization of fuel cell lifespan, reduction of power fluctuations (-200W/s to 200W/s), 7.94% reduction in hydrogen consumption compared to ECMS.
[60]	Adaptive Neuro-Fuzzy Inference System rule-based controller	Li-Ion Battery, Electric Double-Layer Supercapacitor	Improved battery lifespan, faster tracking rate, 16.96% and 9.81% better performance than RFOSMC under heavy and light load conditions.
[61]	Fuzzy Logic Control optimized using Genetic Algorithm	Fuel-Cell , Battery, Ultra-Capacitor	Improved fuel economy, enhanced dynamic performance, battery SOC variation ¡ 2%, optimized power distribution.
[62]	Multi-level EMS combining rule-based and optimization-based approaches	Fuel Cell, Battery, Ultracapacitor	Optimized fuel consumption, battery power fluctuations, SOC, hydrogen consumption, and system performance.
[63]	Sequential quadratic programming based equivalent consumption minimization strategy	Fuel Cell, Battery, Supercapacitor	Hydrogen consumption, fuel cell current stability, SOC, power split, and system efficiency.
[64]	Finite State Machine based energy management and PID-controlled	Battery, Supercapacitor, Fuel Cell	Extended battery and fuel cell life, reduced power fluctuations, improved fuel economy, hydrogen consumption reduced to 0.583 kg.
[48]	Switched Model Predictive Control	Fuel Cell, Battery	Hydrogen mass flow rate control, pressure regulation, and stable operation of PEMFC. The MPC strategy efficiently manages pressure and flow dynamics with two operating points (150 A, 350 A) to achieve optimized hydrogen circulation for enhanced fuel cell durability.

5 Predictive Energy Management Algorithms

Predictive energy management algorithms in autonomous hybrid vehicles optimize energy use by reducing power fluctuations and extending component life. Techniques like LSTM-based predictors and neural networks improve energy efficiency and extend battery life by up to 51.85% [65, 66]. Reinforcement learning methods, including fast RL and deep RL, reduce fuel consumption, minimize power fluctuations, and extend fuel cell lifespan [67, 68]. Q-learning strategies further enhance vehicle range and reduce battery degradation [69].

Table 3: Summary of Predictive Energy Management Algorithms for hybrid power sources.

Ref	Strategy	Hybrid power sources	Optimized parameters and output
[65]	LSTM-based with wavelet transform and rule-based SOC control strategy	Fuel Cell, Battery, Ultra-capacitor	Reduced power frequency of fuel cell and battery, maintained SOC of ultra-capacitor, overall better energy efficiency and improved vehicle performance.
[66]	Neural network-based	Fuel Cell, Battery, Ultra-capacitor	Convex optimization to split power among the energy sources, aiming to extend battery life (5 years), efficiently utilize UC and FC. NN-based algorithm achieved 92.5% efficiency of the convex optimization.

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Ref	Strategy	Hybrid power sources	Optimized parameters and output
[67]	Speedy Reinforcement Learning-Based	Fuel Cell, Battery	Optimized fuel cell and battery power distribution, considering FCS lifetime. Reduced fuel consumption by 5.59% and reduced power fluctuation in the FCS by 13%, improving system longevity.
[68]	Longevity-Conscious EMS based on PER-DQN (Deep Reinforcement Learning)	Fuel Cell, Lithium-ion Battery	Improved fuel economy by balancing hydrogen consumption and fuel cell degradation. Achieved 91.04% of DP-based EMS's fuel economy and reduced fuel cell degradation by adjusting hydrogen consumption and degradation weights. Computational efficiency improved by 70%.
[69]	Q-learning based	Battery, Ultracapacitor	Q-learning minimizes battery degradation by 13-20% and increases vehicle range by 1.5-2% compared to baseline without ultracapacitor. Q-learning converged after 300 iterations and optimized energy management by balancing power distribution between battery and ultracapacitor.

6 New Approaches and Innovative Technologies

6.1 Emerging Strategies

One of the most promising trends in energy management for autonomous vehicles is the integration of machine learning and artificial intelligence with traditional energy management systems. By leveraging AI, vehicles can dynamically adapt their energy usage based on real-time driving conditions and sensor data. For example, using algorithms that combine both rule-based and AI-driven approaches, systems can adjust power usage across various components, such as the sensors and processors in ADAS. These AI-based strategies allow the system to decrease the frequency of sensor scans or even deactivate certain ADAS features when the vehicle is in a low-risk environment, such as cruising on an empty highway.

6.2 Promising Technologies

5G connectivity is becoming a game-changer for energy management in autonomous hybrid electric vehicles. With the increased speed and low latency provided by 5G networks, vehicles can now communicate seamlessly with everything (V2X), allowing vehicles to receive data from surrounding objects, this connectivity enables better traffic prediction, reducing the need for sudden acceleration or braking, which in turn optimizes energy consumption. Additionally, 5G enables real-time updates to the vehicle's systems, allowing ADAS to adjust its operations based on the upcoming road conditions, minimizing energy waste.

6.3 Combining Multiple Strategies

The future of energy management in autonomous vehicles lies in the ability to combine multiple strategies. By integrating AI-based algorithms with predictive energy management and traditional rule-based systems, vehicles can achieve a more flexible and adaptive approach to energy distribution. For example, a hybrid energy management system might utilize AI to predict the vehicle's future energy needs based on historical driving patterns, while simultaneously using rule-based control to regulate power between fuel cells, batteries, and supercapacitors. Additionally, combining predictive algorithms with real-time optimization methods, such as Model Predictive Control and fuzzy logic, can enhance overall system efficiency.

These combined strategies help balance immediate energy demands with long-term sustainability, ensuring that all vehicle systems operate at peak efficiency without sacrificing performance.

7 Conclusion

The evolution of energy management systems in autonomous hybrid electric vehicles is essential to meet the increasing energy demands of advanced driver assistance systems. This review has explored various methods for managing fuel cells, batteries, and supercapacitors, highlighting the importance of balancing these energy sources for optimal efficiency and performance. EMS dynamically allocate energy based on real-time needs, especially in response to ADAS requirements.

AI-driven predictive algorithms, such as reinforcement learning, have proven highly effective in reducing energy consumption and extending component lifespan. However, no single strategy fully addresses the complexities of AHEVs. The best approach combines multiple methods, such as hybrid control, AI algorithms, and real-time optimization, to enhance energy management and adapt to fluctuating demands.

Future progress will rely on integrating AI with traditional rule-based strategies and leveraging new technologies like 5G and V2X communication for more precise control. As AHEVs advance, continuous innovation in EMS will be key to achieving sustainable and efficient energy management.

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