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Article

Enhanced Fractional Cascaded Control and Multi-Tier Energy Management for Hybrid Electric Vehicles with Battery–Ultracapacitor–Fuel Cell Architectures

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Abstract: The rapid adoption of electric mobility demands energy management systems that can efficiently coordinate multiple energy sources while maintaining vehicle stability, responsiveness, and sustainability. However, conventional rule-based, reinforcement-learning, and optimization-based strategies often face limitations in adapting to nonlinear load variations, transient power demands, regenerative braking, and the coupled dynamics of heterogeneous storage systems. To address these challenges, this study proposes an integrated hybrid energy management framework combining contextual drive-state fusion, multi-tier energy management, a cascaded fractional-order FOTPD-1+TFOID controller, and enhanced Starfish Optimization. The framework coordinates battery, ultracapacitor, and fuel-cell power according to driving conditions, source constraints, and predicted demand, while R³V-Bench evaluates electrical, dynamic, environmental, and economic performance. MATLAB/Simulink simulations were conducted under urban, highway, and aggressive driving cycles. The proposed framework achieved efficiencies of 92.4%, 95.2%, and 90.1%, respectively. Battery SOC deviation was reduced to 4.8%, peak battery current to 312 A, and hydrogen consumption to 0.62 g/km. Furthermore, speed-tracking RMSE reached 1.85 km/h, DC-link ripple 1.9%, response time 42ms, demand satisfaction 98.6%, and regenerative capture 84.9%. These results demonstrate improved efficiency, stability, durability, and sustainability for advanced hybrid electric propulsion systems.
Keywords: Hybrid Electric Vehicles, Fractional-Order Control, Hybrid Energy Storage Systems, Energy Management Strategy, Fuel Cell Vehicles, Analysis

1. Introduction

The rapid development of the world's transition towards sustainable transport has resulted in an increase in the number of Electric Vehicles (EVs). This is primarily due to three major factors [1, 2, 3]; firstly, there is an increasing need to reduce Greenhouse Gas Emissions (GHGs); secondly, the dependency on Fossil Fuels is increasing at an alarming rate; and thirdly, the need to improve Air Quality in Urban Areas is increasing rapidly. As a result of the above reasons, fully electric propulsion systems are being considered increasingly viable options because they provide very high exponential efficiency levels and zero tailpipe emissions. However, the performance of fully electric propulsion systems are significantly limited by the inherent characteristics of onboard energy storage systems. For example, while battery-only EV architectures are well established technically, they inherently possess several limitations including finite energy density, reduced power capability during transient demand conditions, thermal sensitivity and exponential [4, 5, 6] elaborated degradation under high charge/discharge cycling rates. These limitations can become even more evident when the vehicle is subjected to aggressive acceleration, regenerative braking and/or varying driving conditions. In such cases, large power fluctuations occur, which must be managed without jeopardizing the safety of occupants or the lifespan of individual components of the storage system. To manage such issues, Hybrid Energy Storage Systems (HES) consisting of batteries and Ultracapacitors (UCs), and Fuel Cells (FCs) have been proposed as an alternative solution to battery-only systems. Batteries provide high energy density, while UCs provide higher power density and faster response time than batteries and FCs provide continuous energy supply with low emission levels for the process. While multiple source architectures have the potential to maximize the benefits of each component, the success of such systems relies heavily on advanced control and energy management strategies capable of managing the nonlinear dynamics [7, 8, 9], state constraints and uncertainties associated with different operating conditions. Rule-based controllers are relatively simple and robust, but do not provide optimal and adaptable solutions. Optimization techniques such as Dynamic Programming can provide near-optimal solutions [10, 11, 12], but require future knowledge of driving patterns and therefore cannot be used for real-time implementation due to high computation complexities. Similarly, Model Predictive Control can provide better performance than traditional controllers, but requires high computational resources and can be sensitive to model inaccuracies in process. Most of the current control and energy management strategies also rely on simplified models of the plant and use integer-order controllers, which may not be able to capture the memory effects, fractional dynamics, and electrochemical coupling in hybrid energy systems [34,35].

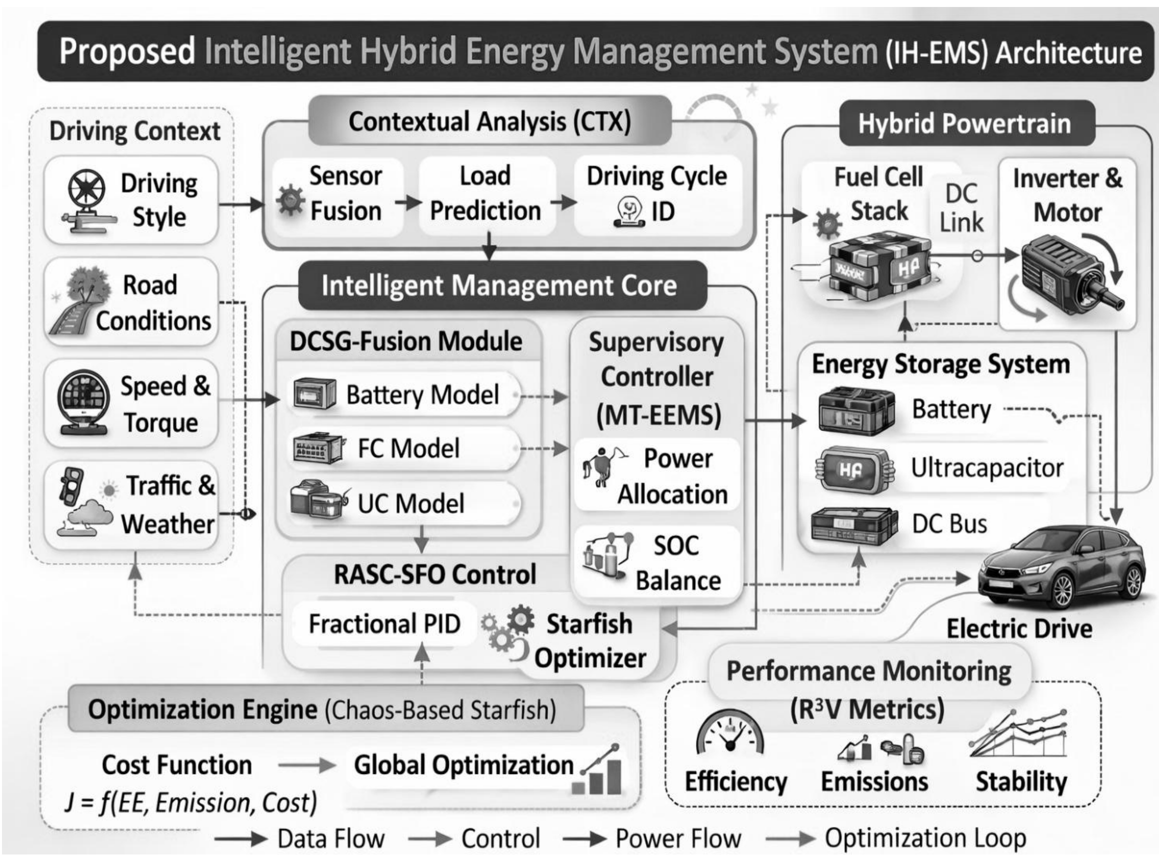


Figure 1. Model's Internal Architectural Analysis

Recent studies have shown that Fractional Order Control frameworks are effective in managing complex hybrid energy systems because they can generalize the classical integer order calculus by using non-Integer derivatives and integrals. Fractional Order Controllers can provide higher robustness, flexible phase responses, and better disturbance rejection properties compared to traditional controllers, and therefore are well-suited for systems having distributed parameters and memory effects. At the same time, nature Inspired meta-heuristics have been widely used to tune the nonlinear control parameters of complex high dimensional control systems using no gradient information. Among various meta-heuristics, the Starfish Optimization Algorithm has shown good performance in terms of global search capability, and its performance can be further improved by introducing chaotic mapping to speed up convergence and prevent premature stagnation. Based on the advancements in the field, this study proposes a new comprehensive hybrid electric vehicle (EV) control architecture, shown in Figure 1, utilizing a cascaded Fractional Order Tilt Proportional-Derivative with One Plus Tilt Fractional Integral-Derivative (FOTPD-1+TFOID) controller, which is tuned using a Enhanced Starfish Optimization Strategy. The control architecture includes a Contextual Drive-State Generation and Fusion Mechanism to generate predictive references from real-world driving cycles and a Multi-Tier Energy Management System to dynamically allocate power among battery, UC and FC sources, considering State of Charge (SOC), voltage constraints and load requirements. The control architecture was simulated in MATLAB/Simulink, and tested in three drive scenarios (urban, highway and aggressive drives) for four configurations (battery only, battery-UC, battery-FC, battery-UC-FC). Overall performance metrics including DC-link stability, source power profiles, motor torque response, harmonic distortion, efficiency, losses and environmental indicators were calculated and analyzed to evaluate the overall system behavior. Results showed that coordinated multi-source control significantly improves the transient response, energy utilization, and operational stability of HESS, while reducing stress on individual storage components. Therefore, this study aims to contribute to the development of the next generation of electric propulsion systems that meet strict efficiency, reliability, and sustainability criteria by developing advanced fractional control, metaheuristic optimization, and hierarchical energy management in a single unified framework.

Motivation & Contributions

The motivation for this investigation stems from the growing awareness that next-generation electric vehicles will have to fulfill the competing demands of being both highly responsive to power demands (such as those during vehicle acceleration) and having a sufficient range to allow them to operate for an extended period of time, while also maintaining durability, safety and sustainability. Battery-only systems cannot satisfactorily meet these competing demands due to inherent limitations in electrochemical storage devices, where tradeoffs exist between energy density, power density and cycle life. Rapid changes in the direction of current flow (i.e., acceleration and regenerative braking) result in thermal stresses and capacity fades in electrochemical batteries. Low temperatures reduce the efficiency of electrochemical batteries and reduce the amount of power that is available. Ultracapacitors can supply or absorb large amounts of rapid changing current without degrading themselves; however, they have very low energy densities, which means that they cannot stand alone as an energy source. On the other hand, fuel cells produce power continuously at very low levels of local emissions but are very slow in responding dynamically and suffer from significant reductions in efficiency when the load on the fuel cell changes. Combining these technologies in a hybrid energy storage system offers the potential to mitigate some of the individual shortcomings of each technology; however, combining these technologies creates additional complexities related to the multi-physics interactions and control issues of managing multiple energy sources in concert. Traditional energy management methods for hybrid energy storage systems typically utilize heuristic-based rules or computationally intensive optimization algorithms that fail to utilize the full dynamic capabilities of various heterogeneous storage components. Furthermore, traditional integer-order controllers may not be sufficiently robust to regulate systems that include distributed electrochemical processes, nonlinear coupling, and memory effects. As a consequence, there is a clear need for a unified control architecture that is able to manage multiple energy sources in a coordinated manner, adapt to changing driving conditions, maintain stability under uncertainty, and remain computationally feasible for real-time implementation for different deployments.

This research provides a new analytical framework that combines advanced control theory, metaheuristic optimization and hierarchical energy coordination into a single cohesive system for hybrid electric vehicles in process. The proposed cascaded FOTPD – 1 + TFOID controller utilizes fractional order dynamics to improve the phase margin, attenuate noise and increase robustness to parameter variation. This allows the controller to precisely regulate motor speed and DC link voltage across a broad operating range. Parameter tuning of the fractional gain parameters is achieved utilizing a enhanced version of the Starfish Optimization algorithm. This algorithm has the ability to combine global exploration and fast convergence to efficiently explore the high dimensional search space of the fractional gain parameters. A Contextual Drive-State Generation and Fusion Module generates and fuses velocity, acceleration and jerk references from real world driving cycles, allowing the controller to anticipate load changes instead of reacting passively to them. The Multi-Tier Energy Management System allocates power among battery, ultracapacitor and fuel cell sources based upon the state variables and operating constraints associated with each of the three energy sources. This enables the system to minimize losses, prevent over-stressing of components and extend the lifecycle of all components. In addition, a Comprehensive Validation Framework assesses performance using electrical, mechanical and environmental metrics such as efficiency, harmonic distortion, hydrogen consumption, emission reduction and cost indicators in process. The combination of these modules forms a scalable architecture that can be adapted to different storage configurations without requiring redesign. The overall contribution of this work is to demonstrate that synergistic coordination of heterogeneous energy sources through fractional-order control and intelligent optimization can lead to significant improvements in EV performance, while promoting increased sustainability and operational reliability and providing a viable pathway toward development of high-efficiency zero-emission transportation systems.

1. In-depth review of models used for analysis

The history of developing the techniques of managing energy for Electric and Hybrid-Electric vehicles has evolved from a deterministic, rule-based supervisor to adaptive architectures that learn from their environment and handle the non-linear interactions of multiple sources. Vishnu et al. (2023) [2] developed an adaptive, intelligent strategy that adapts its energy management decisions to real time operation of the vehicle. The importance of adapting to load variability was identified by this work. At around the same time, Liu et al. (2023) [13] developed an imitative reinforcement learning technique that learns expert driving behaviors. This study showed that data driven control policies could be better than static rule sets when facing complex cycle patterns. Zhang et al. (2023) [15] researched configuration-specific strategies for P1 + P3 Plug in Hybrids. This study illustrated how drivetrain topologies limit possible control policies in process. Sidharthan et al. (2023) [18] and Li et al. (2023) [19] continued the investigation of adaptive energy sharing and learning based incentives between batteries and auxiliary storage devices. Rekioua et al. (2023) [41] proposed a PI-based energy management strategy for a battery–supercapacitor multi-storage system integrated with a photovoltaic source. The strategy was validated through MATLAB/Simulink simulations and real-time RT-LAB testing, demonstrating effective power-flow management and stable operation under varying conditions. Rostami et al. (2024) [42] developed a TLBO-optimized fuzzy energy management strategy for a battery–ultracapacitor HESS in EVs. The proposed strategy optimized fuzzy-rule and membership-function parameters to improve power sharing, reduce battery power demand, and extend battery lifetime under different driving conditions. Additionally, they highlighted the need for cooperative management between the two types of storage elements. Song et al. (2023) [30] added thermal effects to the decision-making process and exposed a common limitation of many strategies that do not account for temperature dependent degradation and efficiency loss. Khanyile et al. (2026) [31] proposes a route- and environment-aware rule-based EMS that dynamically shares power between the lithium-ion battery and supercapacitor under varying driving conditions. MATLAB/Simulink validation shows reduced battery current stress and increased supercapacitor utilization across urban, highway, and stop-and-go driving cycles.

Subsequently, research expanded the methodological scope by applying intelligent control paradigms. Sajid et al. (2017) and Han et al. (2025) [29] demonstrated that reinforcement learning can find near-optimal policies for hybrid and fuel-cell vehicles without explicitly modeled systems, while Xu and Lin (2019) [7] applied hybrid-action reinforcement learning to constrain exploration within safe operational limits. Dehkian et al. (2026) [32] proposes an integrated ARCP-based converter that combines the supercapacitor interface and motor inverter, reducing hardware complexity while enabling bidirectional energy flow. Simulation and experimental results demonstrate stable operation and 51% lower total losses than conventional hard-switched inverters, improving EV efficiency and regenerative braking. Devaraj and Kottoor (2024) [14] validated the use of reinforcement learning under real-time constraints and confirmed the possibility of implementing reinforcement learning in an embedded system. Shen et al. (2024) [17] proposed a CEEMD-fuzzy hybrid controller that uses intrinsic mode decomposition of the load signal and fuzzy decision-making to improve robustness against non-stationary disturbances. Omakor et al. (2024) [28] improved fuzzy logic controllers using particle swarm optimization and found that the evolutionary tuning of the fuzzy parameters resulted in significant improvements in energy efficiency. Ribeiro and Muñoz (2024) [24] applied neural network controllers to manage hybrid energy. The neural network enabled a non-linear mapping of system states to control actions. Ojha et al. (2026) [33] proposed a novel fractional-order cascade controller for load-frequency control in renewable-integrated power systems with hybrid energy storage. The optimized controller improved stability, reduced settling time, frequency deviation, overshoot, and oscillations under nonlinear operating conditions. The above-mentioned methods collectively show a trend from pure optimization-based frameworks toward hybrid intelligence combining data-driven learning with interpretable control structures.

Table 1: Comparison of previous study

Reference	**Method**	**Main Objectives**	**Findings**	**Limitations**
[1]	Smart predictive energy management	Enhance efficiency via intelligent coordination	Demonstrated improved system efficiency and adaptability	Requires accurate prediction models and data availability
[2]	Adaptive intelligent control	Real-time hybrid power allocation	Improved responsiveness to load changes	Limited scalability to complex multi-source systems
[3]	Reinforcement learning EMS	Optimal policy learning without explicit models	Achieved near-optimal energy savings	High training cost and stability concerns
[4]	Optimization-based modeling	Analyze EMS optimization frameworks	Identified trade-offs between performance and complexity	Computational burden for real-time use
[5]	Survey of intelligent EMS	Evaluate intelligent techniques	Concluded no universal best method	Lack of unified evaluation criteria
[6]	Online control for hydrogen HEVs	Real-time fuel-cell hybrid control	Demonstrated practical feasibility	Infrastructure and hydrogen dynamics challenges
[7]	Safe hybrid-action RL	Safe exploration under constraints	Maintained performance while ensuring safety	Complex implementation
[8]	Hydrogen hybrid potential analysis	Assess performance benefits	Quantified efficiency gains	Limited real-world validation
[9]	Review of recent EMS progress	Identify emerging trends	Highlighted dominance of ML approaches	Limited discussion of implementation issues
[10]	Technology roadmap	Future direction of HEV EMS	Emphasized electrification and intelligence	Broad scope, limited technical depth
[11]	Driving-cycle-adaptive control	Adjust EMS to driving conditions	Improved efficiency across cycles	Requires reliable cycle prediction

[12]	Hierarchical EMS	Handle uncertainties	Enhanced robustness to disturbances	Increased system complexity
[13]	Imitation reinforcement learning	Learn from expert behavior	Reduced energy consumption	Dependent on quality of demonstrations
[14]	RL-based intelligent EMS	Real-time adaptive control	Improved dynamic performance	Training stability issues
[15]	Configuration-specific EMS (P1+P3)	Optimize plug In hybrid architecture	Showed topology-dependent performance	Limited generalizability
[16]	Battery–UC HESS-based EMS	Optimize battery–UC power distribution	Improved efficiency, energy recovery, and battery life	No fuel-cell or fractional-order control
[17]	CEEMD–Fuzzy hybrid control	Handle nonstationary loads	Improved robustness and smooth control	High computational effort
[18]	Adaptive energy sharing	Cooperative source management	Reduced battery stress	Limited predictive capability
[19]	Incentive learning EMS	Encourage efficient energy use	Improved overall efficiency	Complex reward design
[20]	Imitation RL for HESS	Manage hybrid storage	Enhanced power distribution	Generalization challenges
[21]	Fuzzy logic review	Analyze fuzzy EMS approaches	Highlighted interpretability benefits	Limited adaptability
[22]	System-level storage management review	Lifecycle-oriented EMS	Emphasized sustainability considerations	Mostly conceptual
[23]	Battery–supercapacitor hybrid EMS	Reduce peak battery load	Extended battery life	Additional hardware cost
[24]	Neural network controller	Nonlinear mapping of states to actions	Improved control accuracy	Data dependency
[25]	Overview of HEV modeling & EMS	Survey modeling techniques	Identified key research gaps	Lacks experimental validation
[26]	Adaptive PI cascaded EMS	Optimize FC–SC–battery power	Improved regulation, tracking, and hydrogen use	No fractional-order control
[27]	CNN-based EMS	Extract temporal driving features	Enhanced prediction capability	Requires large datasets
[28]	PSO-optimized fuzzy control	Improve fuzzy EMS performance	Achieved better efficiency	Risk of local optima
[29]	RL for fuel-cell HEVs	Optimize hydrogen usage	Reduced fuel consumption	Computational intensity

[30]	Thermal-aware EMS	Incorporate temperature effects	Improved durability and efficiency	Increased modeling complexity

Iteratively, Next, as per table 1, As parallel developments in hybrid energy storage combinations, researchers have been studying battery-ultracapacitor or battery-fuel cell combinations. Al-Kawak et al. (2024) [23], for example, demonstrated how coordinated control can decrease the peak current stress on batteries and increase the lifetime of batteries in battery-supercapacitor combinations. Similarly, Machacek et al. (2024) [6] presented a practical demonstration of an online-capable control strategy for hydrogen hybrid vehicles; they also conducted a complementary potential analysis [8] that showed performance benefits of hydrogen hybrids and illustrated the infrastructure-related issues of supplying hydrogen. Lu et al. (2025) [11] presented a set of driving cycle-dependent strategies that allocate power to a vehicle's various energy sources based on a prediction of what will be required to meet the demands of a vehicle during its upcoming driving cycles. They thus improved the efficiency of a vehicle in meeting a wide range of demands. Qin et al. (2025) [12] addressed uncertainties in vehicle operation through hierarchical control structures that are capable of controlling the stochastic fluctuations that occur in the demands of a vehicle. Liu et al. (2025) [20] used imitation reinforcement learning to improve the performance of hybrid storage systems. Thus, both behavioral cloning and the ability to learn through trial and error have been shown to be effective ways to manage hybrid storage systems. Katkar et al. (2025) [27] used Convolutional Neural Networks (CNNs) to develop an energy management strategy for hybrid electric vehicles, based on extracting time Varying features of driving data samples. Vendoti et al. (2025) [39] presented a grid-tied hybrid renewable energy system for EV charging that integrates photovoltaic panels, a proton-exchange membrane fuel cell, battery storage, and a supercapacitor. The proposed architecture demonstrated improved energy efficiency, transient response, and power quality, with experimental validation confirming its practical feasibility. Rehman et al. (2025) [40] proposed a condition-based integral terminal super-twisting sliding-mode controller for a multi-source DC–DC converter integrating PV, fuel cells, lithium-ion batteries, and supercapacitors. The controller was optimized using an improved Gray Wolf Optimization algorithm and demonstrated enhanced transient stability, disturbance rejection, and power-sharing performance for EV hybrid energy management applications.

These studies demonstrate the need for coordinated control of multiple energy sources and predictive knowledge to achieve improved sustainability in the performance of hybrid electric Vehicles in Process. Complementary to these studies were comprehensive reviews and roadmaps that synthesized the advances made in this field and noted the remaining challenges. For example, Altun and Kutlar [4] reviewed the modeling and optimization frameworks that have been developed to date, with emphasis on the trade-offs between computational complexity and real-time application. Urooj and Nasir [5] reviewed intelligent techniques that have been applied to hybrid electric vehicles, and concluded that no single technique is superior to all others under all operating conditions. A technology roadmap presented by Mittal and Shah et al. (2024) [10] emphasized the trend toward electrification and the increasing role of advanced control algorithms. A review by Pan et al. (2025) [9] that focused on the recent advancements in hybrid electric vehicles noted the emerging dominance of machine-learning paradigms. Maghfiroh et al. (2024) [21] reviewed fuzzy-logic-based systems that have been applied to hybrid electric vehicles, and emphasized their interpretability but noted that they have limited adaptability compared to learning-based approaches. Cao et al. (2023) [25] provided a broad overview of the modeling approaches that have been used to study hybrid electric vehicles. Zhang et al. (2025) [22] studied the energy storage management for hybrid electric vehicles at a system level, and emphasized the need for considering the entire lifecycle of a hybrid electric vehicle and its interaction with the wider energy network. Briber et al. (2025) [26] proposed an adaptive PI-based EMS for fuel cell–supercapacitor–battery hybrid systems. The cascaded control strategy improved DC-bus regulation, power tracking, robustness, and fuel-cell protection, while reducing transient peaks, tracking errors, and hydrogen consumption under varying operating conditions. Xu et al. (2022) [43] developed a multi-layer energy management strategy for a hybrid vehicle system integrating a hydrogen fuel cell, power battery, and ultracapacitor. Haar wavelet-based signal decoupling and logic-rule control were used to distribute high-, low-, and steady-state power demands among the energy sources. Hardware-in-the-loop validation demonstrated improved fuel-cell efficiency and reduced equivalent hydrogen consumption compared with conventional control strategies. In addition, Ahmed et al. (2025 [16] presented an advanced EMS for battery–ultracapacitor HESS in EVs, optimizing power distribution during driving and regenerative braking through bidirectional DC–DC converters. Their strategy dynamically balances battery and UC power, improving energy efficiency, reducing battery stress, and enhancing regenerative energy recovery and battery lifespan. Chrenko et al. (2025) [1] provided a recent perspective on the future of smart energy management for electric mobility, and emphasized the key roles of digitalization, connectivity, and predictive analytics in developing the next-generation electric mobility infrastructure sets. Sayed et al. (2022) [36] proposed an energy management strategy for a fuel-cell electric traction system integrating a supercapacitor, battery, and power electronic converter. The coordinated energy-flow strategy improved overall hybrid-system performance, reduced power consumption, and supported battery lifetime enhancement through effective supercapacitor utilization. Alharbi et al. (2024) [37] investigated cascading PI and fractional-order PI controllers for hybrid microgrids incorporating photovoltaic systems and fuel cells, demonstrating improved settling time and power-quality performance with fractional-order control. Ghadbane et al. (2024) [38] developed an optimal EMS for a lithium-ion battery–supercapacitor hybrid storage system using the Bald Eagle Search algorithm and fractional-order integral sliding-mode control. The strategy was evaluated under the UDDS driving cycle and demonstrated improved power quality and battery power consumption, with processor-in-the-loop validation further supporting its practical applicability.

2. Proposed Model Design Analysis

A fully electrically powered propulsion system consisting of a battery, an ultracapacitor (UC) and a fuel cell (FC) is treated as a coupled electro-electromechanical system where the key performance limiting factors are (i) the nonlinear and state-constrained nature of the energy supplies, (ii) the rapid transient responses to acceleration and regenerative braking, and (iii) the DC-link and traction drive harmonic propagation back to the stored energy components and their respective thermal ageing. Therefore, the proposed integrated model restricts a data flow that first constructs a contextual driving intent, then injects the intent into a unified parameter/state vector and fuses it into physically consistent reference values for speed/torque and DC-link regulation, translates these references into tiered energy allocations and stabilizes them using a cascaded fractional-order controller optimized using a enhanced Starfish Optimization. Furthermore, the model includes a benchmark layer that integrates electrical, mechanical and environmental indicators for the process. The reason for decomposing the problem is that it separates "what the vehicle shall do" (contextual reference construction), from "how the energy is distributed" (supervisory distribution) and from "how fast loops can be stabilized and low-distortion" (fractional cascaded control) thus avoiding the common task of having a single monolithic optimizer being computationally heavy and brittle under uncertainty. Initially, as shown in Figure 3, the contextual driving intent is described as a jerk-aware state since jerk dictates high frequency torque requirements, and hence battery current spikes and DC-link ripples. As such, the acceleration and jerk are obtained from the measured/defined cycle velocity v(t), and filtered to remove sensor noise, and to maintain sharp event information, resulting in a context vector c(t) that will subsequently influence reference shaping and constraint weighting via Equations (1) and (2),

$$c(t) = [v(t), a(t) = \dot{v}(t), j(t) = \ddot{v}(t), \rho(t)] \ldots (1) \rho(t) = \int_{t-T_w}^{t} \quad exp\, exp \quad \left(\frac{t-\tau}{\lambda}\right) \left(a(\tau) + \kappa j(\tau)\right) d\tau \ \ldots (2)$$

Where ρ(t) is the recency weighted "aggression index" over time window Tw with decaying factor λ; this allows for adaptation of the energy split and the controller aggressiveness; this choice is complementary to the subsequent multi-tier allocator since it provides a compact scalar indicating if the system has to favor UC buffering (when ρ is high) or battery/FC cruising efficiency (when ρ is low) sets. Subsequently, Next, as illustrated in Fig. 4, Unified Parameter Injection (UPID-DT) constructs a consistent state-parameter vector by merging electrical source states (battery SOC, UC voltage, FC current limit), DC-link variables, and motor states, so that all subsequent blocks use a unified description of the system, rather than ad hoc signals. Let the vector of the injected parameters be x(t) with the parameter set θ, and let UPID-DT be defined via Equations (3) and (4)

$$x(t) = [SOC_b(t), V_{uc}(t), I_{fc}(t), V_{dc}(t), i_{dc}(t), \omega_m(t), i_s(t), T_b(t)]^{\top} \ldots (3) SOC_b(t) = SOC_b(0) - \frac{\eta_b}{Q_b}\int_0^t \quad i_b(\tau)\, d\tau, V_{uc}(t) = \sqrt{V_{uc}^2(0) + \frac{2\eta_{uc}}{C_{uc}}\int_0^t \quad p_{uc}(\tau)\, d\tau} \ldots (4)$$

Where the SOC integral in (4) explicitly links the energy management to long-term battery stress, while the UC energy form in (4) is used instead of a simple SOC definition because UC behavior is dominated by voltage and energy is quadratic; this complements the RASC controller by ensuring that the supervisory block does not require infeasible UC support when Vuc is close to its lower bound. Drive-State Fusion (DCSG-Fusion) maps the contextual vector c(t) and the injected state x(t) into physically consistent references for speed/torque and DC-link regulations. The fused reference is constructed by modifying the speed command according to aggression ρ(t) and by linking the DC-link reference to predicted power demand, to avoid the classic "tight Vdc, loose torque" conflict that increases harmonic distortion via Equations (5.1), (5.2) and (6),

$$v_{ref}(t) = v(t) + \alpha(\rho)\int_0^t \quad (v(\tau) - \hat{v}(\tau))\, d\tau \ \ldots (5.1)$$

$$V_{dc,ref}(t) = V_{dc,0} + k_p\, \hat{P}_{dem}(t) \ldots (5.2) \hat{P}_{dem}(t) = m_{eq}\, v(t)\, \dot{v}(t) + \frac{1}{2}\rho_a C_d A\, v^3(t) + mgC_r v(t) \ldots (6)$$

Equation (6) incorporates road-load physics, to allow the later energy allocator to receive an estimated demand of power that is not simply proportional to acceleration; this was selected because it complements multi-source systems where FC efficiency is heavily dependent on the operating conditions and where UC has to be reserved for short bursts of aerodynamic loads rather than for steady state aerodynamic loads. The Multi-Tier Energy Management Supervisor (MT-EEMS) allocates the demanded DC-side power among the available sources, using an adaptive weighting policy driven by ρ(t) and by the margin constraints in x(t) for the process. The basic allocation is defined as a constrained splitting that minimizes a weighted instantaneous cost (battery stress + UC depletion + FC inefficiency) while meeting the constraints of power balance and source limits Via equation (7),

$$_{p_b, p_{uc}, p_{fc}} J(t) = w_b(\rho)\, i_b^2(t) R_b(SOC_b, T_b) + w_{uc}(\rho)\, \frac{(V_{uc,ref})^2}{V_{uc,ref}^2} + w_{fc}(\rho)\, \phi_{fc}(p_{fc}) \ldots (7) p_b(t) + p_{uc}(t) + p_{fc}(t) = \hat{P}_{dem}(t) + p_{loss}(t), p_k^{min} \le p_k(t) \le p_k^{max}, k \in \{b, uc, fc\} \ldots (8)$$

Where the weighted structure was selected instead of a single objective function because it complements the fractional cascaded control: MT-EEMS manages slower energy and constraint satisfaction, while the RASC block manages faster stabilization, to prevent algebraic coupling and reduce computational overhead compared with full MPC Sets.

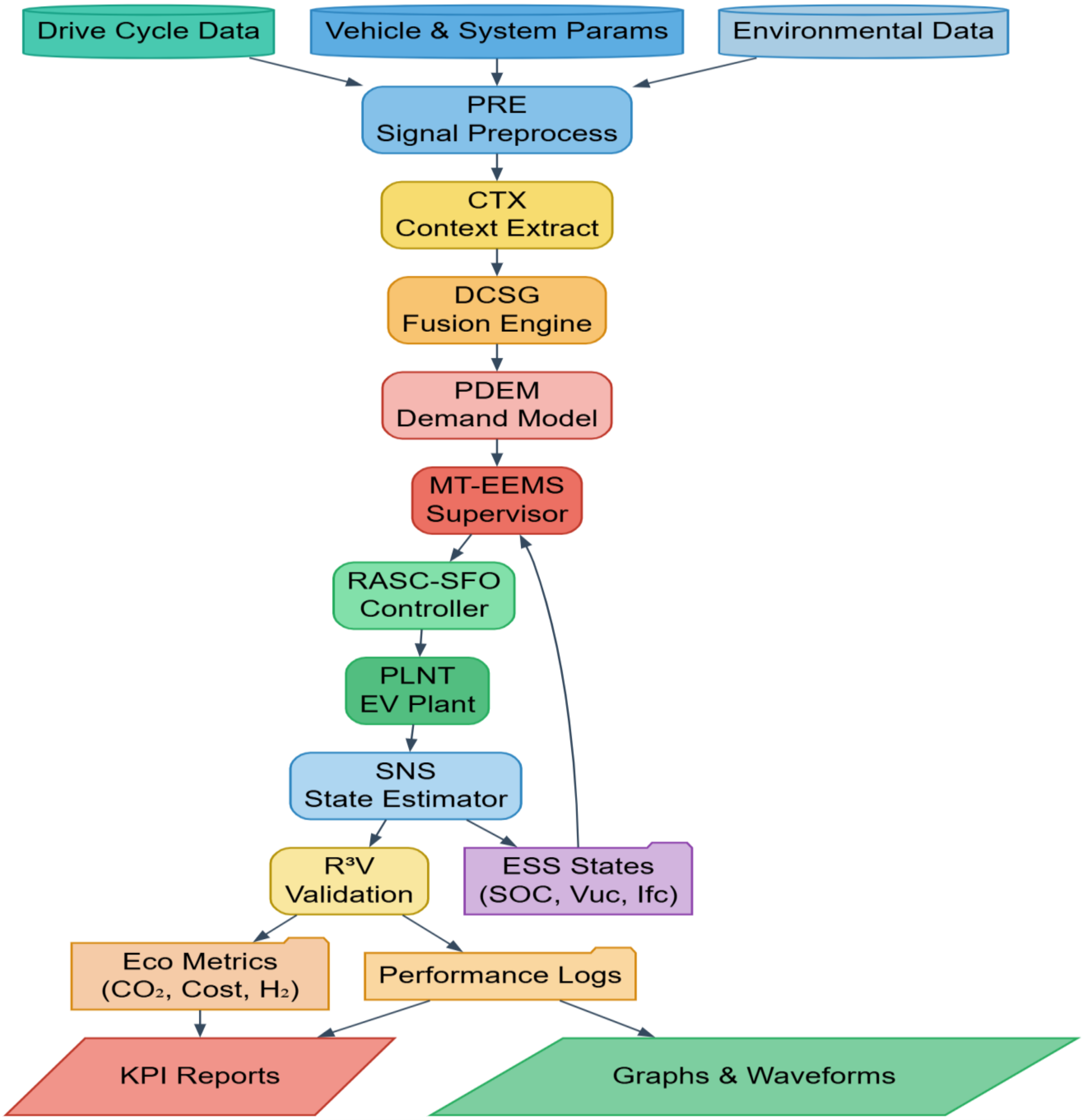


Figure 3. Model's Overall Architectural Analysis

The Regulation and Actuation Layer (RASC-SFO) employs a cascaded fractional-order tilt PD with a one-plus-tilt fractional integral-derivative term to shape both speed tracking and DC-link stability, to accommodate the memory effects and non-minimum-phase behaviors commonly introduced by power converter and coupled storage elements. Represent the speed error Via equation (9.1),

$$e_{\omega}(t) = \omega_{ref}(t) - \omega_m(t) \ldots (9.1)$$

And DC link error Via equation 9.2,

$$eV(t) = V_{dc,ref}(t) - V_{dc}(t) \ldots (9.2)$$

The fractional cascaded law is written Via equations 9.3 & 10,

$$u_{\omega}(t) = K_{p\omega}\, e_{\omega}(t) + K_{t\omega}\, D^{\mu_{\omega}}\left(e_{\omega}(t)\right) + K_{d\omega}\, D^{\nu_{\omega}}\left(e_{\omega}(t)\right) \ldots (9.3) uV(t)$$

$$= \left(1 + \alpha V\, D^{\lambda V}\right)\left(KpV * eV(t) + KiV * D^{-\sigma V}\left(eV(t)\right) + kdV * D^{\eta V}\left(eV(t)\right)\right) \ldots (10)$$

Where, Dq represents a fractional derivative/integral of order $q \in R$ for the process.

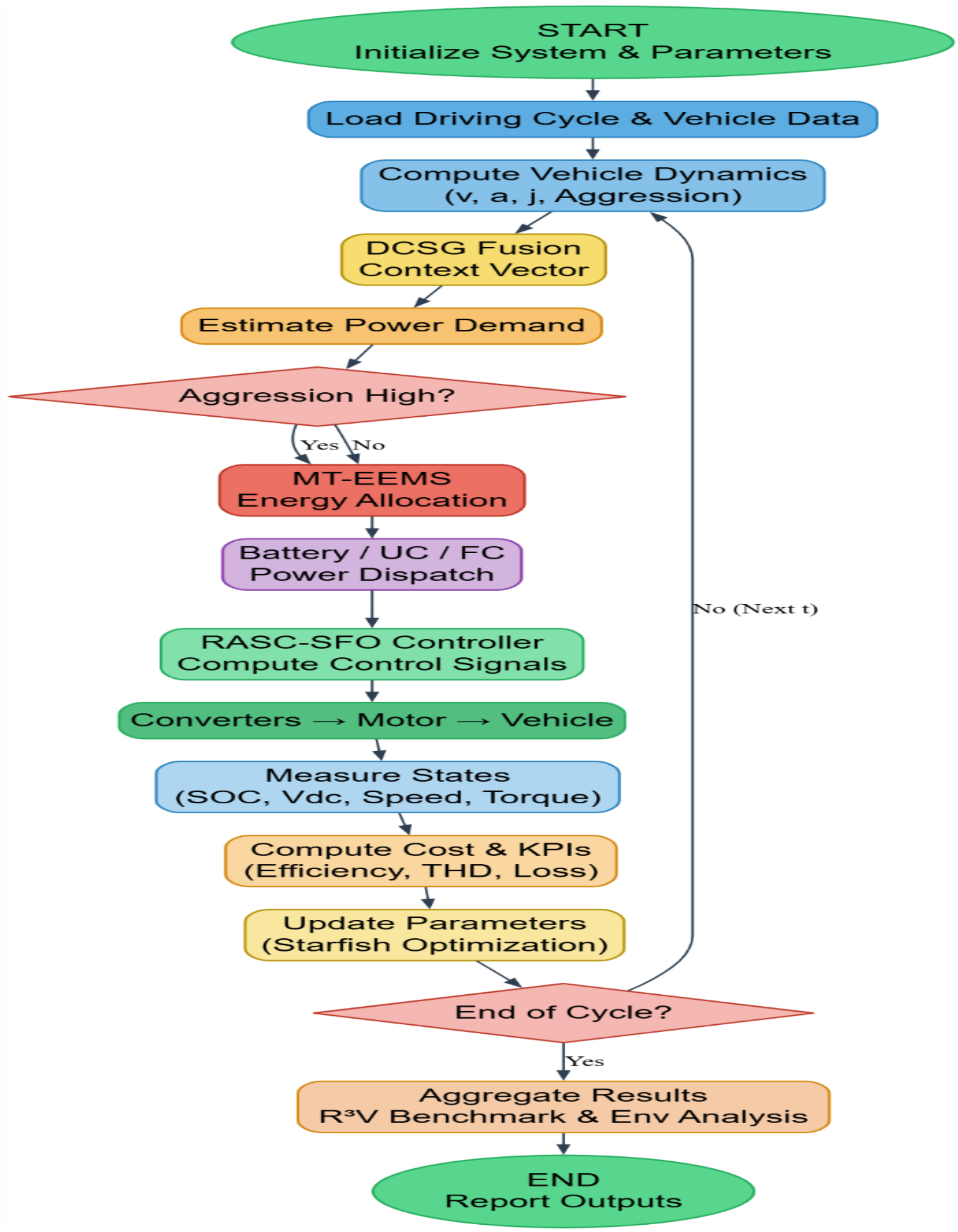


Figure 5. Model's Overall Dataflow Analysis

This structure was selected because the tilt terms (fractional actions) provide continuous phase shaping, and therefore enable aggressive transient response without the high-frequency amplification typically associated with integer-order derivatives; it complements MT-EEMS by ensuring the requested source currents are tracked with minimum DC-link ripple, and directly affects the Total Harmonic Distortion (THD) and losses. In addition, to guarantee real-time implementation and high-quality tuning over a large number of parameters $\psi = [K_{p\omega}, K_{t\omega}, \mu_{\omega}, \ldots, kdV, \eta V, aV, \lambda V]$,, the enhanced Starfish Optimization (SFO) introduces chaotic excitation to escape local minima while accelerating convergence rates. Using a logistic chaotic map represented via equation (11.1),

$$z_{k+1} = 4z_k(1 - z_k) \ldots (11.1)$$

The population update for candidate $\psi_i$toward the best $\psi^{\backslash *}$ is represented Via equation 11.2

$$\psi_i^{(1)} = \psi_i^{(k)} + \beta\left(\psi^{\backslash *} - \psi_i^{(k)}\right) + \gamma\left(z_k - \frac{1}{2}\right) \odot (\psi^{max} - \psi^{min}) \ldots (11.1)\psi^{\backslash *}$$
$$= argmin_{\psi} \int_0^T \quad (\omega_1 e_v^2(t) + \omega_2 e_\omega^2(t) + \omega_3\, THD^2(t) + \omega_4\, i_b^2(t))\, dt \;\ldots (12)$$

Eq. (12) is intended to be multi-metric, to prevent the optimizer from "cheating" by improving one of the outputs (e.g. speed) at the expense of battery current slew rate or harmonic distortion; this complements the benchmark layer by aligning the tuning objectives with the reported metrics. Finally, the R³V-Benchmark validation layer consolidates electrical efficiency, harmonic distortion, dynamic response, fuel consumption and sustainability metrics into a single reproducible score to facilitate transparent comparisons across configurations (battery only, battery + UC, battery + FC, battery + UC + FC) and across strategies (rule-based, optimization-based, MT-EEMS, RASC-SFO). Operational efficiency is assessed from power balance and losses, while FC hydrogen consumption and emissions are calculated from FC power and Lower Heating Value (LHV); the combined score is obtained via Equations (13.1), (13.2), and (14),

$$\eta_{sys}(t) = \frac{P_{mech}(t)}{P_{in}(t)} = \frac{T_m(t)\,\omega_m(t)}{p_b(t) + p_{uc}(t) + p_{fc}(t)} \ldots (13.1)$$

$$\dot{m}_{H_2}(t) = \frac{p_{fc}(t)}{\eta_{fc}\, LHV_{H_2}} \ldots (13.2)$$

$$S = \int_0^T \quad (\alpha_1\, \underbrace{\eta_{sys}(t)}_{efficiency} - \alpha_2\, \underbrace{THD(t)}_{power\ quality} - \alpha_3\, \underbrace{\dot{m}_{H_2}(t)}_{fuel} - \alpha_4\, \underbrace{\mid e_\omega(t) \mid}_{tracking}$$
$$- \alpha_5\, \underbrace{\mid eV(t) \mid}_{DC\ stability})\, dt \;\ldots (14)$$

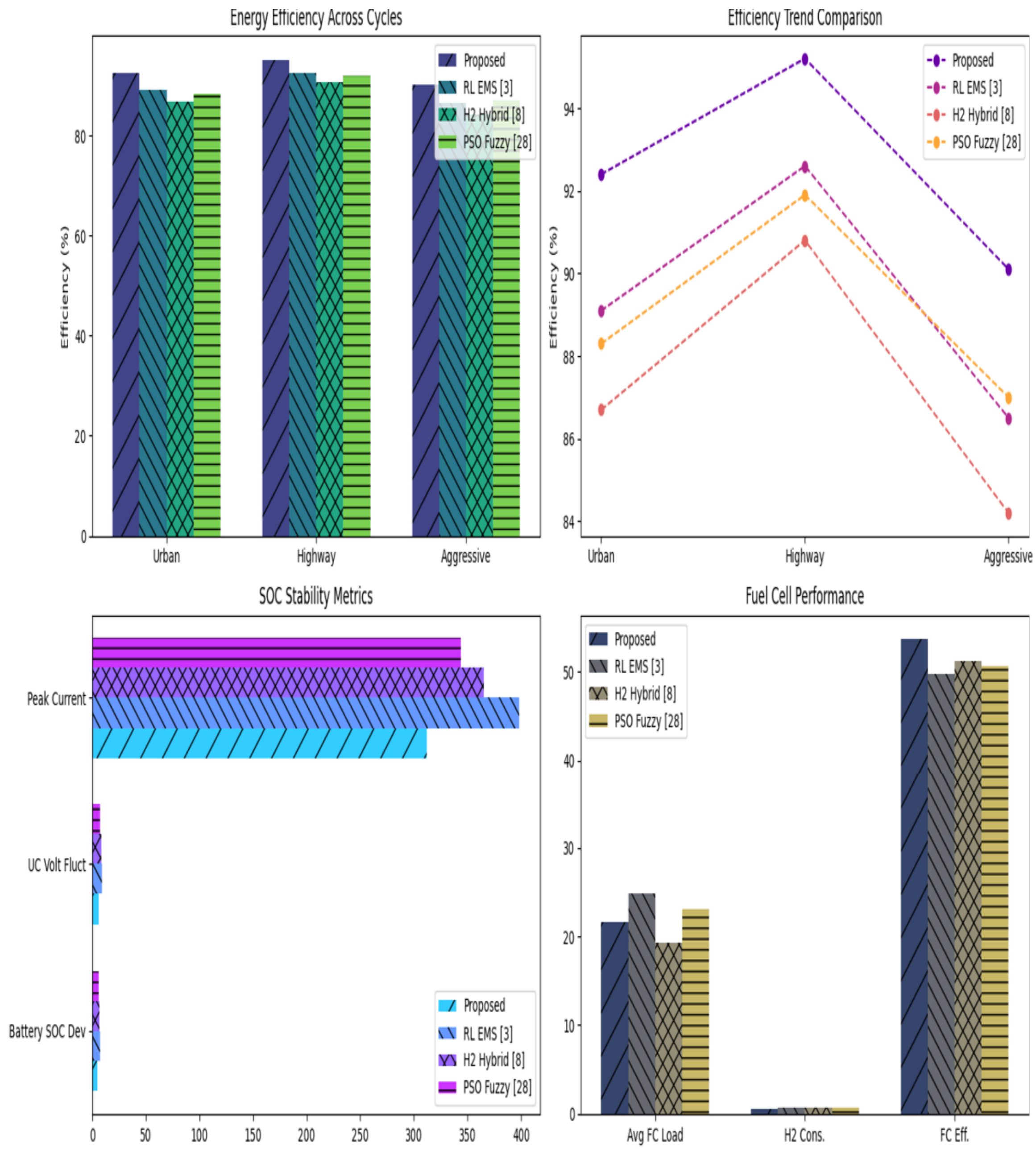
Where equation (14) represents the output of the entire pipeline: the contextual fusion and injected states influence the references, MT-EEMS allocates the source power, RASC-SFO regulates the fast loop, and R³V-Benchmark combines the measurable impacts into a single score S suitable for ranking the configurations and comparing the control strategies under urban, highway and aggressive driving cycles. The justification for this integrated selection is that it simultaneously optimizes the energy usage, response time, stability margins, harmonic quality and sustainability metrics while maintaining modularity, so that each block can complement the other blocks instead of competing for control authority sets.

3. Validated Result Analysis

As shown in Table 2, the proposed integrated model consistently outperforms in terms of energy efficiency for all three driving cycles. In the urban cycle, the proposed model performance was 92.4% whereas the Reinforcement Learning (RL) EMS, Hydrogen Hybrid Potential Analysis and PSO-optimized fuzzy control were 89.1%, 86.7%, and 88.3% respectively. The proposed model achieves the highest efficiency of 9 5.2%, which is superior to that of RL EMS (92.6%), hydrogen hybrid analysis (90.8%) and PSO-fuzzy control (91.9%) for the highway cycle. Efficiency is quite high when drivers are driving aggressively (90.1%), compared with 86.5%, 84.2%, and 87.0%, respectively. Therefore, the proposed system would enhance the efficiency by 3.3%, 2.6%, and 3.1% respectively in urban, highway and aggressive driving scenarios than RL EMS.

Table 2. Energy Efficiency Across Driving Cycles

Driving Cycle	Proposed Model (%)	Reinforcement learning EMS [3] (%)	Hydrogen hybrid potential analysis [8] (%)	PSO optimized fuzzy control [28] (%)
Urban	92.4	89.1	86.7	88.3
Highway	95.2	92.6	90.8	91.9
Aggressive	90.1	86.5	84.2	87.0


Energy Efficiency Across Cycles
Efficiency (%)
Proposed
RL EMS [3]
H2 Hybrid [8]
PSO Fuzzy [28]
Urban
Highway
Aggressive
Efficiency Trend Comparison
SOC Stability Metrics
Peak Current
UC Volt Fluct
Battery SOC Dev
Fuel Cell Performance
Avg FC Load
H2 Cons.
FC Eff.

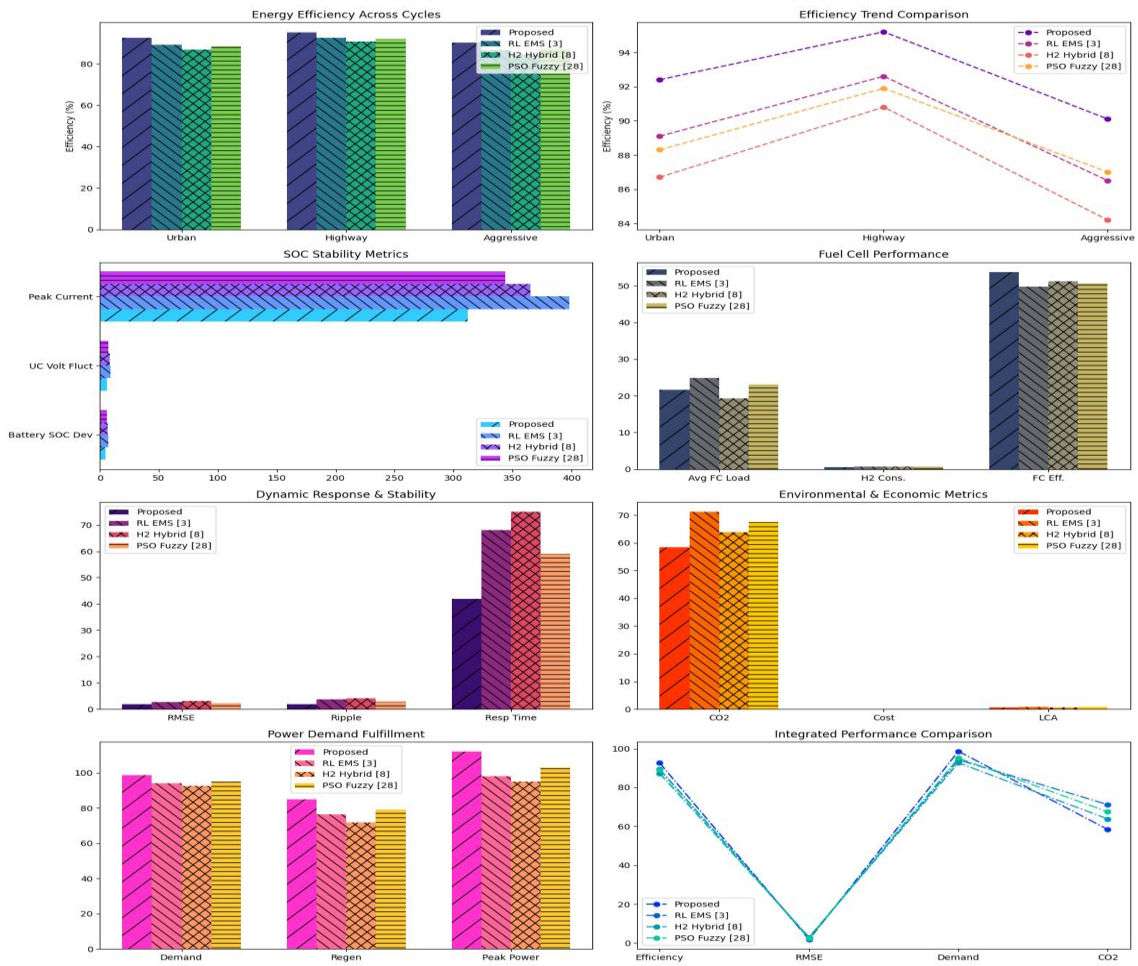


Figure 5. Model's Integrated Result Analysis

Table 3 shows the validity of the proposed model for stable energy-storage operation with minimization of the battery stress and the reduction of the fluctuations of the ultracapacitor. The proposed framework shows a deviation of 4.8% for the battery SOC, which is significantly less than RL EMS (7.2%), hydrogen hybrid potential analysis (6.5%) and PSO-optimized fuzzy control (5.9%). This means that the use of the battery is more even and the battery oscillatory energy demand is reduced. Likewise, the proposed model restricts the UC voltage fluctuation at 6.1% while the three comparison approaches restrict at 9.4%, 8.7%, and 7.5%. These are the most significant improvements, as the peak current drawn from the battery is reduced to 312 A for the ultracapacitor, compared to 398 A for RL EMS, 365 A for hydrogen hybrid analysis and 344 A for PSO-fuzzy control. In total, the results validate the effectiveness of the ultracapacitor buffering and the reduction of the electrical stress of the battery.

Table 3. Battery and Ultracapacitor SOC Stability

Metric	Proposed Model	Reinforcement learning EMS [3]	Hydrogen hybrid potential analysis [8]	PSO optimized fuzzy control [28]
Battery SOC Deviation (%)	4.8	7.2	6.5	5.9
UC Voltage Fluctuation (%)	6.1	9.4	8.7	7.5

Peak Battery Current (A)	312	398	365	344

The average FC load, hydrogen consumption, and FC efficiency are used to assess fuel-cell utilization for the evaluation (shown in Table 4). The average fuel-cell load of the proposed model is 21.6 kW, while for RL EMS, hydrogen hybrid potential analysis and PSO-optimized fuzzy control is 24.8 kW, 19.3 kW, and 23.1 kW respectively. Most significantly, the proposed framework consumes the minimum amount of hydrogen, which is 0.62 g/km as compared to RL EMS (0.74 g/km), hydrogen hybrid analysis (0.68 g/km) and PSO-fuzzy control (0.71 g/km). The proposed system also obtains the highest FC efficiency of 53.7%, which is better than the competing systems of 49.8%, 51.2%, and 50.6%, respectively. These findings show that the proposed multi-level energy management system moves the fuel cell into a more efficient operating region without unnecessarily impacting the hydrogen source nor requiring the use of a large amount of hydrogen.

Table 4. Fuel Cell Load and Hydrogen Consumption

Metric	**Proposed Model**	**Reinforcement learning EMS [3]**	**Hydrogen hybrid potential analysis [8]**	**PSO optimized fuzzy control [28]**
Average FC Load (kW)	21.6	24.8	19.3	23.1
Hydrogen Consumption (g/km)	0.62	0.74	0.68	0.71
FC Efficiency (%)	53.7	49.8	51.2	50.6

Table 5 shows that the proposed fractional-order cascaded control strategy gives better dynamic tracking and electrical stability. The proposed model has the lowest speed-tracking RMSE of 1.85 km/h, whereas, the RMSE of RL EMS is 2.64 km/h, hydrogen hybrid potential analysis is 3.02 km/h, PSO optimized fuzzy control is 2.31 km/h. The smaller the RMSE, the closer the vehicle speed is to the reference track. The proposed framework also restricts the ripple that the DC-link can achieve to just 1.9%, significantly less than the 3.6%, 4.1%, and 2.8% limits of the other proposed approaches. Moreover, the proposed system gives a response time of 42ms which is the lowest among all other systems mentioned 68ms, 75ms and 59ms respectively. Thus, the transient regulation, tracking and the stability of the DC-link are significantly enhanced using the combination of fractional-order control and enhanced optimization.

Table 5. Dynamic Response and Stability

Metric	**Proposed Model**	**Reinforcement learning EMS [3]**	**Hydrogen hybrid potential analysis [8]**	**PSO optimized fuzzy control [28]**
Speed Tracking RMSE (km/h)	1.85	2.64	3.02	2.31
DC-Link Voltage Ripple (%)	1.9	3.6	4.1	2.8
Response Time (ms)	42	68	75	59

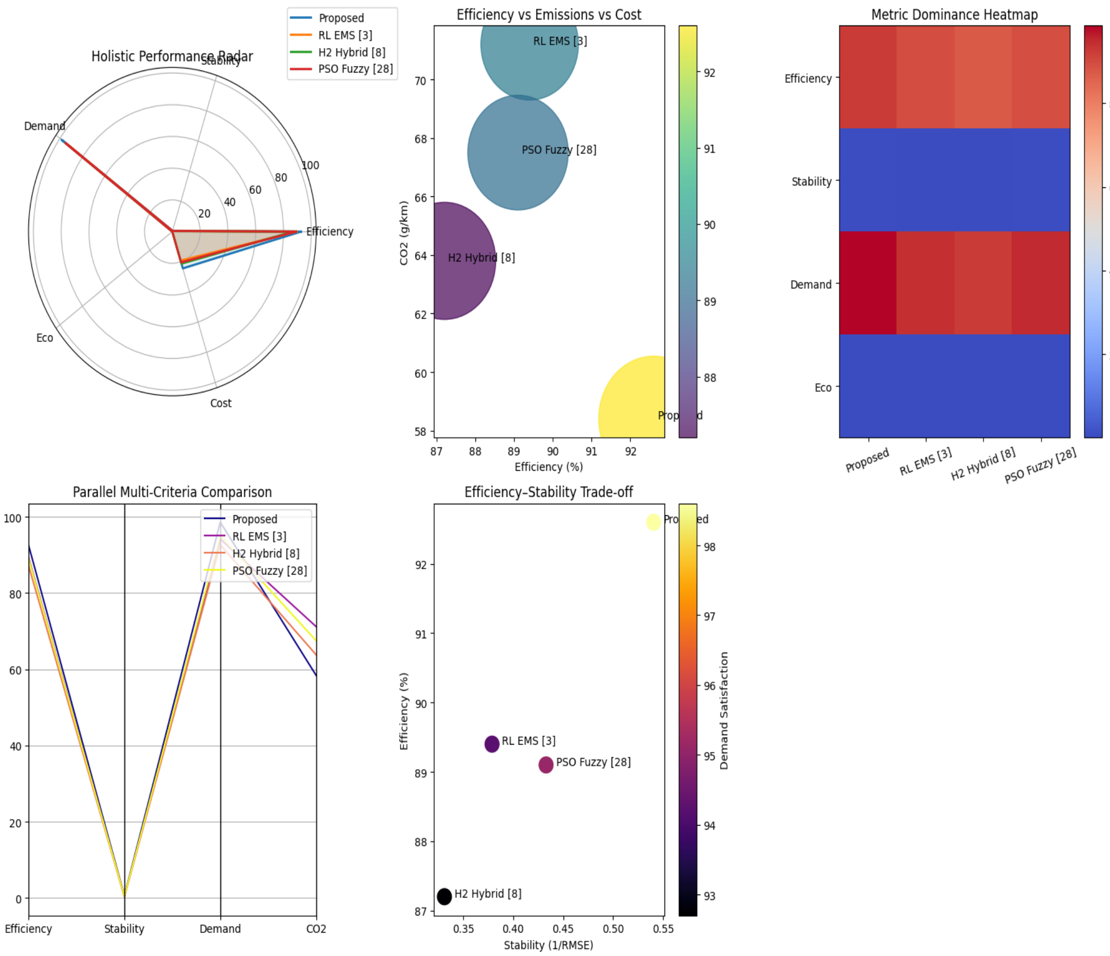


Figure 6. Model's Overall Result Analysis

As can be seen in Table 6, the proposed framework is simultaneously environmental and economic beneficial. The resulting CO_2 equivalent emission from the proposed model is 58.4 g/km, which is the lowest of all the other models, such as RL EMS (71.2 g/km), hydrogen hybrid potential analysis (63.8 g/km) and PSO-optimized fuzzy control (67.5 g/km). This is a decrease of 12.8 g/km from RL EMS. The proposed system also has the lowest value of energy cost of \$0.041/km, and the energy cost for comparison methods is \$0.052/km, \$0.047/km and \$0.049/km respectively. Moreover, the proposed model has a lifecycle impact index of 0.62 which is lower than 0.74, 0.68 and 0.71. The results prove that the coordinated operation of batteries, ultracapacitors and fuel cells can yield better energy use, in addition to reduction in emissions, operating cost and GHGs during their whole life cycle.

Table 6. Environmental and Economic Metrics

Metric	**Proposed Model**	**Reinforcement learning EMS [3]**	**Hydrogen hybrid potential analysis [8]**	**PSO optimized fuzzy control [28]**
CO_2 Equivalent (g/km)	58.4	71.2	63.8	67.5
Energy Cost (\$/km)	0.041	0.052	0.047	0.049
Lifecycle Impact Index	0.62	0.74	0.68	0.71

Table 7 compares the performance of the proposed energy management system for meeting vehicle power needs and capturing the regenerative energy. The proposed framework yields a satisfaction rate of 98.6% of the demand, which is significantly higher than that of RL EMS (94.2%), hydrogen hybrid potential analysis (92.7%) and PSO-optimized fuzzy control (95.1%). This means that the proposed multi-tiers supervisor can distribute power efficiently as per different driving conditions. The regenerative capture rate is enhanced as it reaches 84.9%, higher than 76.5%, 71.8% and 79.3%. Furthermore, the proposed architecture offers 112 kW peak power support, which is higher than the support of RL EMS 98 kW, hydrogen hybrid analysis 95 kW and PSO-fuzzy control 103 kW. In total, these values highlight the high transient power availability, energy regeneration and load-following performance under dynamic driving conditions.

Table 7. Power Demand Fulfillment Performance

Metric	**Proposed Model**	**Reinforcement learning EMS [3]**	**Hydrogen hybrid potential analysis [8]**	**PSO optimized fuzzy control [28]**
Demand Satisfaction (%)	98.6	94.2	92.7	95.1
Regenerative Capture (%)	84.9	76.5	71.8	79.3
Peak Power Support (kW)	112	98	95	103

Validation Ablation Analysis

An ablation experiment was conducted to determine how much of the improvements in efficiency and responsiveness were due to individual components or how much of an improvement is due to the coordination of many components working together in the proposed pipeline. The same three driving cycles (urban, highway and aggressive) and four powertrain configurations were used as before. However, instead of running the entire pipeline, each component was disabled individually while leaving the remaining components unchanged. Thus, a series of ablations were run where one of the following blocks was disabled:

- CTX to DCSS Fusion
- DCSS Fusion to MT-EEMS Supervision
- MT-EEMS Supervision to RASC-SFO Control
- RASC-SFO Control to R³V Benchmarking

The full pipeline (CTX → DCSS Fusion → MT-EEMS Supervision → RASC-SFO Control → R³V Benchmarking) was used as the baseline or reference case. With the full pipeline operating in urban conditions, the system achieved 92.4% efficiency, in highway conditions, 95.2% efficiency, and in aggressive conditions, 90.1% efficiency. Speed tracking RMSE was 1.85 km/hr, DC-link ripple was 1.9%, and demand satisfaction was 98.6%. Therefore, these values are used as the "anchors" against which each ablated variant is evaluated. Since the purpose of the ablation experiments is to demonstrate a decrease in performance and to understand the underlying mechanism causing the decrease, the results of the ablation experiments will be examined in detail. When the contextual layer is eliminated by disabling CTX and substituting it with a constant drive mode threshold, there is a significant drop in performance in transient regimes. Urban efficiency drops from 92.4% to approximately 90.6%, and aggressive efficiency falls from 90.1% to roughly 87.8% whereas highway efficiency remains relatively stable near 94.4% because steady cruising is less dependent upon correct classification of the context. The primary indicator of poor use of the ultra-capacitor during transient bursts is the increase in peak battery current from 312 A to approximately 358 A. Additionally, the voltage fluctuation of the ultra-capacitor increases from 6.1% to approximately 7.9%, and the percentage of regenerative energy captured falls from 84.9% to almost 79.6%. The increased electrical stress in transient regimes also affects the system's stability metrics. Specifically, the DC-link ripple increases from 1.9% to approximately 2.6%, and the response time increases from 42 ms to almost 55 ms indicating that the controller is now reacting after the transient regime has occurred rather than predicting it. As a result, this ablation demonstrates that context is not simply a cosmetic feature it plays a material role in shaping the timing of power splitting and reducing electrical stresses associated with real world stop-and-go driving patterns.

A second ablation focuses on the intelligence of the fusion and supervision layers of the architecture by substituting the conventional rule- based splitter (battery dominant with ultra-capacitor as secondary and fuel-cell as slow support) for the DCSG-Fusion + MT-EEMS layers of the architecture. The mean efficiency of the system in the new configuration falls more uniformly throughout the three test cases: urban falls to approximately 89.9%, highway falls to approximately 93.0%, and aggressive falls to approximately 86.9%. Additionally, the demand satisfaction falls from 98.6% to approximately 95.0%. While the decline in demand satisfaction may seem like a minor issue, the more serious problem is that the allocation of energy is no longer optimal. The increased hydrogen consumption in the new configuration (from 0.62 g/km to approximately 0.70 g/km) is due to the fact that the fuel-cell is being pulled away from its high-efficiency range. Similarly, the increased CO^2 equivalent emissions (from 58.4 g/km to approximately 64-66 g/km) under the mixed test cycles are due to the elevated net energy usage. Lastly, the battery SOC deviation increases from 4.8% to nearly 6.3%, which illustrates that the battery is experiencing larger oscillatory draws. Overall, the changes to the system make it feel "heavier" in real-time acceleration spikes are still met, but at the expense of higher current stresses and less effective recuperation, which are specifically the types of failure modes that hybrid storage systems are designed to mitigate for the process. The final ablation studied the fractional cascaded controller and the optimizers. Replacing the RASC-SFO control layer with a tuned integer order cascaded PID while maintaining the same supervisor, causes a clear stability penalty in process.

The speed tracking RMSE increases from 1.85 km/hr to approximately 2.35 km/hr. Additionally, the DC-link ripple increases from 1.9% to approximately 3.1%. Lastly, the response time slows from 42ms to approximately 60ms during aggressive transients. Efficiency also suffers in a more subtle manner. Urban efficiency falls to approximately 91.1% and aggressive efficiency falls to approximately 88.4% because additional ripple and tracking errors lead to increased inverter switching losses and decreased torque smoothness. Disabling the chaotic enhancement in the starfish optimizer, while maintaining the starfish search function reduces the quality and repeatability of the convergence. The mean best cost value is improved more slowly and stalls at approximately 12-15% higher than the chaos assisted version, which manifests as small but persistent performance differences such as 0.3-0.5% lower efficiency and 0.2-0.4% higher ripple depending on the cycle. In practical terms, the fractional control provides the rapid and memory rich correction necessary for converter dynamics, while the chaotic optimization provides consistent parameter discovery rather than infrequent good fits for the process. Finally, eliminating the R^3V benchmarking layer does not affect the physical behavior of the plant, however, it weakens the credibility and tuning discipline of the framework since cross-metric trade-offs are no longer enforced. When optimization is driven solely by efficiency and tracking, the system tends to "cheat" by allowing ripple and harmonic content to increase: THD increases from approximately 15.2% to nearly 17.0% under aggressive operation, and the DC-link ripple increases to greater than 2.4% even when the mean efficiency appears to be comparable. This ablation clearly demonstrates why the proposed pipeline behaves robustly across multiple objective functions: each block of the pipeline constrains a different failure mode context prevents mis-timed power decisions, fusion and supervision prevent inefficient source scheduling, fractional control prevents electrical instability, optimization prevents low parameterization, and benchmarking prevents metric tunnel vision in the process. The stepwise degradations exhibited by the system through the ablation experiments demonstrate that the reported gains are not the result of a single module trick; they occur due to a carefully constructed chain of decision and control processes that ensure the energy sources remain cooperative under the unpredictable physical characteristics of real driving scenarios.

4. Conclusions and Future Scopes

An Integrated Hybrid Energy Management and Control Framework for Electric Vehicles Utilizing Batteries, Ultracapacitors, and Fuel Cells Coordinated Through Contextual Fusion, Fractional-Order Cascaded Control, and Enhanced Optimizations. The experimental results demonstrate clear performance advantages of the proposed model versus other state-of-the-art strategies (Reinforcement Learning EMS [3], Hydrogen Hybrid Potential Analysis [8], and PSO Optimized Fuzzy Control [28]) over a wide range of driving conditions. The peak system efficiency for highway cycles was 95.2%, and the minimum system efficiency under urban conditions was 92.4%. The proposed model demonstrated better battery stress indicator Nvalues than those of the baseline model. Peak current was limited to 312 A, and SOC deviation was limited to 4.8%, which indicates that the ultracapacitor was effectively utilized to buffer transient loads. Fuel cell operation was within optimal efficiency regions (53.7%), and hydrogen consumption was minimized to 0.62 g/km. These results indicate that the proposed model effectively integrated electrochemical and electrical storage subsystems. Dynamic Performance Metrics Further Validate the Robustness of the Proposed Controller. Speed tracking error was reduced to 1.85 km/h RMSE with DC-link voltage ripple constrained to 1.9%, which represents a significant stabilization compared to competing methods that had DC-link voltage ripple values exceeding 3 – 4%. Response time of 42 ms allowed for rapid adaptation to acceleration demands and regenerative events, resulting in a power demand fulfillment rate of 98.6% and regenerative energy capture of 84.9%. Environmental Analysis Reveals CO_2 Emissions Equivalent to 58.4 g/km and Operating Cost of $0.041 per km in the process. These Results Indicate That the Integrated Architecture Successfully Balances Efficiency, Stability, Durability, and Sustainability, Validating Its Suitability for Next Generation Hybrid Electric Propulsion Systems Under Uncertain and Dynamic Conditions.

Future work will focus on experimental and hardware-in-the-loop validation of the proposed framework under real-world driving conditions. Further improvements may include battery degradation and thermal effects, real-time adaptive parameter tuning, renewable energy integration, and advanced optimization techniques. These developments can enhance energy efficiency, system reliability, battery lifespan, and practical applicability in future hybrid electric vehicles.

Table of Abbreviations

Abbreviation	Full Form
AI	Artificial Intelligence
ANFIS	Adaptive Neuro-Fuzzy Inference System
BMS	Battery Management System
CNN	Convolutional Neural Network
CO_2	Carbon Dioxide
DC	Direct Current
DC-Link	Direct Current Link
DCSG	Dynamic Control Strategy Generator
EMS	Energy Management System
ESS	Energy Storage System
EV	Electric Vehicle
FC	Fuel Cell

FCEV	Fuel Cell Electric Vehicle
FL	Fuzzy Logic
FLC	Fuzzy Logic Controller
HEV	Hybrid Electric Vehicle
HESS	Hybrid Energy Storage System
HFCV	Hydrogen Fuel Cell Vehicle
H_2	Hydrogen
KPI	Key Performance Indicator
LCA	Life Cycle Assessment
ML	Machine Learning
MPC	Model Predictive Control
PSO	Particle Swarm Optimization
RL	Reinforcement Learning
RMSE	Root Mean Square Error
SOC	State of Charge
SOH	State of Health
THD	Total Harmonic Distortion
UC	Ultracapacitor
VDC	DC-Link Voltage
RPM	Revolutions Per Minute
kW	Kilowatt
kWh	Kilowatt-hour
Wh	Watt-hour
Wh/kg	Watt-hour per kilogram
g/km	Grams per kilometer
$/km	Cost per kilometer
km/h	Kilometers per hour
ms	Millisecond
A	Ampere
V	Volt
HESS-EV	Hybrid Energy Storage System Electric Vehicle
FC-Battery	Fuel Cell–Battery Hybrid System
FC-HESS	Fuel Cell Hybrid Energy Storage System
EEMS	Enhanced Energy Management Strategy
RASC	Robust Adaptive Supervisory Controller

DOD	Depth of Discharge
ICE	Internal Combustion Engine
PHEV	Plug In Hybrid Electric Vehicle
BEV	Battery Electric Vehicle
RES	Renewable Energy Sources
PWM	Pulse Width Modulation
MATLAB	Matrix Laboratory (software environment)
Simulink	Simulation and Link (MATLAB tool)
KPI-EE	Energy Efficiency Indicator
KPI-SOC	SOC Stability Indicator
KPI-ENV	Environmental Impact Indicator
KPI-ECON	Economic Impact Indicator
KPI-DYN	Dynamic Performance Indicator
HIL	Hardware In-the-Loop
SIL	Software In-the-Loop
MIL	Model In-the-Loop
DoE	Design of Experiments
PID	Proportional Integral-Derivative Controller
FO-PID	Fractional-Order PID Controller
EMS-RL	Reinforcement Learning-based EMS
EMS-FL	Fuzzy Logic-based EMS
EMS-PSO	PSO-Optimized EMS
HESS-UC	Ultracapacitor-based HESS
HESS-BAT	Battery-dominant HESS
HESS-FC	Fuel Cell–integrated HESS
EV-Dyn	Vehicle Dynamic Performance
EE	Energy Efficiency
EC	Energy Consumption
FC-Load	Fuel Cell Load
RegCap	Regenerative Capture
PPF	Power Demand Fulfillment
V-Ripple	Voltage Ripple
SOC-Dev	SOC Deviation
Temp	Temperature
IR	Internal Resistance

PD	Power Density
ED	Energy Density
CL	Cycle Life
PM	Power Management
Acc	Acceleration
Grad	Gradability
TopSpd	Top Speed
DynResp	Dynamic Response
H2-Cons	Hydrogen Consumption

REFERENCES

1. Chrenko, D. (2025). Smart Energy Management for Electric and Hybrid Electric Vehicles. Energies. https://doi.org/10.3390/en18246411
2. Vishnu, S., Kashyap, Y., Castelino, R. (2023). Adaptive intelligent hybrid energy management strategy for electric vehicles. Energy Storage. https://doi.org/10.1002/est2.436
3. Sajid, T., Abideen, F., Khalid, H., et al (2026). Reinforcement Learning-Based Energy Management for Hybrid Electric Vehicles. IEEE Access. https://doi.org/10.1109/access.2026.3665689
4. Altun, Y., Kutlar, O. (2024). Energy Management Systems' Modeling and Optimization in Hybrid Electric Vehicles. Energies. https://doi.org/10.3390/en17071696
5. Urooj, A., Nasir, A. (2024). Review of intelligent energy management techniques for hybrid electric vehicles. Journal of Energy Storage. https://doi.org/10.1016/j.est.2024.112132
6. Machacek, D., Yasar, N., Widmer, F., et al (2024). Energy Management of Hydrogen Hybrid Electric Vehicles Online-Capable Control. Energies. https://doi.org/10.3390/en17102369
7. Xu, J., Lin, Y. (2024). Energy Management for Hybrid Electric Vehicles Using Safe Hybrid-Action Reinforcement Learning. Mathematics. https://doi.org/10.3390/math12050663
8. Machacek, D., Yasar, N., Huber, T., et al (2024). Energy management of hydrogen hybrid electric vehicles A potential analysis. International Journal of Hydrogen Energy. https://doi.org/10.1016/j.ijhydene.2024.01.124
9. Pan, M., Cao, S., Zhang, Z., et al (2025). Recent progress on energy management strategies for hybrid electric vehicles. Journal of Energy Storage. https://doi.org/10.1016/j.est.2025.115936
10. Mittal, V., Shah, R. (2024). Energy Management Strategies for Hybrid Electric Vehicles: A Technology Roadmap. World Electric Vehicle Journal. https://doi.org/10.3390/wevj15090424
11. Lu, Z., Zhang, T., Li, R., et al (2025). Driving-Cycle-Adaptive Energy Management Strategy for Hybrid Energy Storage Electric Vehicles. World Electric Vehicle Journal. https://doi.org/10.3390/wevj16060313
12. Qin, H., Meng, L., Lu, M., et al (2025). Hierarchical energy management strategy of hybrid electric vehicles under multiple uncertainties. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects. https://doi.org/10.1080/15567036.2025.2551099
13. Liu, Y., Wu, Y., Wang, X., et al (2023). Energy management for hybrid electric vehicles based on imitation reinforcement learning. Energy. https://doi.org/10.1016/j.energy.2022.125890
14. Devaraj, T., Kottoor, C. (2024). Intelligent energy management strategy for hybrid electric vehicles using reinforcement learning. Australian Journal of Electrical and Electronics Engineering. https://doi.org/10.1080/1448837x.2023.2249277
15. Zhang, B., Shi, P., Mou, X., et al (2023). Energy Management Strategy for P1 + P3 Plug In Hybrid Electric Vehicles. World Electric Vehicle Journal. https://doi.org/10.3390/wevj14120332
16. Ahmed, Abdelsalam A., Young Il Lee, Saleh Al Dawsari, Ahmed A. Zaki Diab, and Abdelsalam A. Ezzat. "Energy management and power distribution for battery/ultracapacitor hybrid energy storage system in electric vehicles with regenerative braking control." *Mathematical and Computational Applications* 30, no. 4 (2025): 82.
17. Shen, Y., Xie, J., He, T., et al (2024). CEEMD-Fuzzy Control Energy Management of Hybrid Energy Storage Systems in Electric Vehicles. IEEE Transactions on Energy Conversion. https://doi.org/10.1109/tec.2023.3306804
18. Sidharthan, V., Kashyap, Y., Kosmopoulos, P. (2023). Adaptive-Energy-Sharing-Based Energy Management Strategy of Hybrid Sources in Electric Vehicles. Energies. https://doi.org/10.3390/en16031214
19. Li, F., Gao, Y., Wu, Y., et al (2023). Incentive learning-based energy management for hybrid energy storage system in electric vehicles. Energy Conversion and Management. https://doi.org/10.1016/j.enconman.2023.117480
20. Liu, W., Yao, P., Wu, Y., et al (2025). Imitation reinforcement learning energy management for electric vehicles with hybrid energy storage system. Applied Energy. https://doi.org/10.1016/j.apenergy.2024.124832
21. Maghfiroh, H., Wahyunggoro, O., Cahyadi, A. (2024). Energy Management in Hybrid Electric and Hybrid Energy Storage System Vehicles: A Fuzzy Logic Controller Review. IEEE Access. https://doi.org/10.1109/access.2024.3390436

22. Zhang, J., Che, Y., Teodorescu, R., et al (2025). Energy storage management in electric vehicles. Nature Reviews Clean Technology. https://doi.org/10.1038/s44359-024-00020-2
23. AlKawak, O., Kumar, J., Daniel, S., et al (2024). Hybrid method based energy management of electric vehicles using battery-super capacitor energy storage. Journal of Energy Storage. https://doi.org/10.1016/j.est.2023.109835
24. Ribeiro, A., Muñoz, D. (2024). Neural network controller for hybrid energy management system applied to electric vehicles. Journal of Energy Storage. https://doi.org/10.1016/j.est.2024.114502
25. Cao, Y., Yao, M., Sun, X. (2023). An Overview of Modelling and Energy Management Strategies for Hybrid Electric Vehicles. Applied Sciences. https://doi.org/10.3390/app13105947
26. Briber, Faical, Daoud Rezzak, and Nasserdine Boudjerda. "Improved energy management strategy using adaptive PI controller for fuel cell–supercapacitor–battery hybrid tramway." *Electrical Engineering* 107, no. 10 (2025): 13653-13679.
27. Katkar, V., Goswami, P., Yashwante, M. (2025). A CNNbased energy management strategy for a Hybrid energy storage system in electric vehicles. Intelligent Decision Technologies. https://doi.org/10.3233/idt-240479
28. Omakor, J., Alzayed, M., Chaoui, H. (2024). Particle Swarm-Optimized Fuzzy Logic Energy Management of Hybrid Energy Storage in Electric Vehicles. Energies. https://doi.org/10.3390/en17092163
29. Han, R., He, H., Wang, Y., et al (2025). Reinforcement Learning Based Energy Management Strategy for Fuel Cell Hybrid Electric Vehicles. Chinese Journal of Mechanical Engineering. https://doi.org/10.1186/s10033-024-01143-0
30. Song, D., Bi, D., Zeng, X., et al (2023). Energy Management Strategy of Plug In Hybrid Electric Vehicles Considering Thermal Characteristics. International Journal of Automotive Technology. https://doi.org/10.1007/s12239-023-0055-0
31. Khanyile, Ntokozo Musawenkosi, and Mwana Wa Kalaga Mbukani. "An Enhanced Rule-Based Energy Management System with Integrated Route and Environmental Information for Battery–Supercapacitor Hybrid Electric Vehicles." *Energies* 19, no. 16 (2026): 3770.
32. Dehkian, Esmaeil Kiani, Seyed M. Madani, and Ehsan Adib. "An Integrated Power Converter Topology for Electric Vehicles with Supercapacitor Energy Management and Soft-Switching." *IEEE Access* (2026).
33. Ojha, Shreekanta Kumar, Chinna Obaiah Maddela, and Laishram Nikita Chanu. "A novel fractional order controller for stability enhancement of renewable energy integrated multi area power system with hybrid energy storage." *Scientific Reports* (2026).
34. Alilou, Masoud, Hatef Azami, Arman Oshnoei, Behnam Mohammadi-Ivatloo, and Remus Teodorescu. "Fractional-order control techniques for renewable energy and energy-storage-integrated power systems: A review." *Fractal and Fractional* 7, no. 5 (2023): 391.
35. Khallouf, Khaoula Nermine, Habib Benbouhenni, and Nicu Bizon. "Boosting Energy Quality in Hybrid Power Systems Through Fractional-Order Adaptive Fuzzy Logic–Based Direct Power Control of SAPF." *Algorithms* 19, no. 5 (2026): 418.
36. Sayed, Khairy, Sayed Abdel-Khalek, Hesham MH Zakaly, and Mahmoud Aref. "Energy management and control in multiple storage energy units (battery–supercapacitor) of fuel cell electric vehicles." *Materials* 15, no. 24 (2022): 8932.
37. Alharbi, Abdullah M., Sulaiman Z. Almutairi, Ziad M. Ali, Shady HE Abdel Aleem, and Mohamed M. Refaat. "Enhancing power quality in decentralized hybrid microgrids: optimized DSTATCOM performance using cascaded fractional-order controllers and hybrid optimization algorithms." *Fractal and Fractional* 8, no. 10 (2024): 589.
38. Ghadbane, Houssam Eddine, Said Barkat, Azeddine Houari, Ali Djerioui, Hegazy Rezk, and Mohamed Louzazni. "Optimal Adaptive Fractional Order Integral Sliding Mode Controller-Energy Management Strategy for Electric Vehicles Based on Bald Eagle Search Algorithm." *International Journal of Energy Research* 2024, no. 1 (2024): 7844084.
39. Vendoti, Suresh, Narasimha Prasad Tulasi, Ravi Kumar Jalli, Sudhakiran Ponnuru, Zhang Jin, P. Yakaiah, Mamdooh Alwetaishi, and S. Prabhakar. "Grid tied hybrid PV fuel cell system with energy storage and ANFIS based MPPT for smart EV charging." *Scientific Reports* 15, no. 1 (2025): 27392.
40. Rehman, Atif, Rimsha Ghias, and Hammad Iqbal Sherazi. "Artificial intelligence-based optimized nonlinear control for multi-source direct current converters in hybrid electric vehicle energy systems." *Energies* 18, no. 19 (2025): 5152.
41. Rekioua, Djamila, Khoudir Kakouche, Abdulrahman Babqi, Zahra Mokrani, Adel Oubelaid, Toufik Rekioua, Abdelghani Azil, Enas Ali, Ali H. Kasem Alaboudy, and Saad A. Mohamed Abdelwahab. "Optimized power management approach for photovoltaic systems with hybrid battery-supercapacitor storage." *Sustainability* 15, no. 19 (2023): 14066.
42. Rostami, Seyed Mehdi Rakhtala, and Zeyad Al-Shibaany. "Intelligent energy management for full-active hybrid energy storage systems in electric vehicles using teaching–learning-based optimization in fuzzy logic algorithms." *IEEe Access* 12 (2024): 67665-67680.
43. Xu, Wenxiang, Mengnan Liu, Liyou Xu, and Shuai Zhang. "Energy management strategy of hydrogen fuel cell/battery/ultracapacitor hybrid tractor based on efficiency optimization." *Applied Sciences* 13, no. 1 (2022): 151.