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A Comprehensive Survey on Fuel Consumption Optimization: Machine Learning, Energy Management, and Emerging Powertrain Technologies

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Abstract—This paper presents a comprehensive survey of recent advances in fuel consumption optimization across multiple transportation domains, synthesizing findings from 18 peer-reviewed studies published between 2007 and 2025. The reviewed literature spans data-driven prediction models for marine vessels, equivalent consumption minimization strategies (ECMS) for fuel cell hybrid vehicles (FCHVs), fuzzy logic and particle swarm optimization for range extender vehicles, alternator control strategies for conventional vehicles, energy consumption standard analysis, hydrogen consumption studies under varying state-of-charge (SOC) conditions, sail-assisted ship routing, real-time fuel monitoring systems, comparative powertrain analysis across battery electric (BEV), fuel cell (FCEV), and internal combustion engine (ICEV) vehicles, machine learning models for fuel prediction, eco-driving cooperative strategies, and hardware-in-the-loop (HIL) validation of hybrid architectures. Key findings demonstrate that hybrid machine learning and physics-informed approaches consistently outperform purely rule-based strategies, achieving fuel savings of 7–20% across diverse vehicle and vessel classes. Emerging trends include connected vehicle intelligence (V2X), reinforcement learning-based energy management, and federated learning for privacy-preserving fleet optimization. This survey identifies critical research gaps and outlines a unified framework for next-generation fuel consumption optimization systems.

Index Terms—Fuel Consumption Optimization, Machine Learning, Energy Management, Hybrid Electric Vehicles, Fuel Cell Vehicles, Eco-Driving, Neural Networks, ECMS, Particle Swarm Optimization, V2X, Maritime Energy Efficiency.

I. INTRODUCTION

The global transportation sector is a dominant contributor to greenhouse gas emissions, accounting for approximately 24% of direct CO_2 emissions from fuel combustion. Road transport, maritime shipping, and commercial vehicle fleets collectively consume billions of barrels of petroleum annually, creating simultaneous pressures on operational costs, energy security, and environmental sustainability. Reducing fuel consumption is therefore not merely an engineering objective but a socioeconomic and regulatory imperative that spans automotive manufacturers, fleet operators, maritime authorities, and policymakers worldwide.

The past two decades have witnessed a dramatic transformation in approaches to fuel efficiency. The classical paradigm—optimizing engine design, aerodynamics, and mechanical drivetrain components through physics-based models and empirical testing—is increasingly being supplemented, and in some domains replaced, by data-driven and learning-based methodologies. The rise of onboard diagnostics (OBD-II), telematics systems, GPS-enabled route data, and connected vehicle platforms has generated unprecedented streams of high-resolution operational data, providing the substrate for machine learning models that can discover and exploit complex, nonlinear relationships between driving conditions and fuel consumption that rule-based approaches routinely miss.

Simultaneously, the emergence of alternative powertrain architectures—hybrid electric vehicles (HEVs), plug-in hybrids (PHEVs), fuel cell hybrid vehicles (FCHVs), battery electric vehicles (BEVs), and fuel cell electric vehicles (FCEVs)—has introduced entirely new optimization dimensions. Energy management strategy (EMS) design for these multi-source systems is a nontrivial control problem: the objective is to allocate power between energy sources dynamically, in real time, subject to battery state-of-charge (SOC) constraints, component thermal limits, driver demand, and route context, while minimizing total energy cost or hydrogen consumption over a complete drive cycle.

This survey synthesizes findings from 18 peer-reviewed studies to provide a structured overview of the state of the art. The papers span: (i) data-driven fuel prediction models for controllable-pitch propeller (CPP) maritime vessels; (ii) real-time ECMS with V2X information for FCHVs; (iii) adaptive chaotic particle swarm optimization of fuzzy control parameters; (iv) intelligent alternator control for conventional passenger cars; (v) analysis of FCEV energy consumption standards in China; (vi) SOC-dependent hydrogen consumption characterization; (vii) sail-assisted ship route optimization; (viii) real-time ship fuel monitoring systems; (ix) driving-cycle-dependent energy analysis of FCHVs; (x) powertrain comparison across BEV, FCEV, and ICEV for autonomous heavy-duty vehicles; (xi) hydrogen-to-wheels efficiency characterization; (xii) ant colony optimization for delivery vehicle routing; (xiii) DIRECT algorithm optimization for parallel hybrid vehicles; (xiv) machine learning regression models for vehicle fuel prediction; (xv) fuel cell vehicle fuel consumption rate analysis by body type; (xvi) cooperative eco-driving with V2V information sharing; and (xvii) hardware-in-the-loop validation of a diesel parallel mild-hybrid vehicle.

The remainder of this paper is organized as follows. Section II describes the taxonomy and scope of the reviewed literature. Sections III through VII present thematic analysis across five domains: data-driven prediction models, energy management strategies, vehicle electrification and powertrain comparison, route and logistics optimization, and monitoring and standards. Section VIII synthesizes cross-cutting themes and identifies research gaps. Section IX presents a unified optimization framework. Section X concludes with future research directions.

II. TAXONOMY AND SCOPE OF REVIEWED LITERATURE

The 18 papers reviewed in this survey were selected from IEEE Xplore, published between 2007 and 2025, and cover five primary thematic domains as illustrated in Table I. Papers were categorized according to their primary optimization objective, the vehicle or vessel platform studied, the methodological approach, and the key performance metric reported.

TABLE I Classification of Reviewed Papers by Domain

Ref.	Domain	Platform	Method	Key Metric
[1]	Maritime Fuel Prediction	CPP Ro-Pax Ship	Improved BP Neural Network + Sliding Avg. Filter	RMSE: 1.71%
[2]	FCHV Energy Management	Fuel Cell Hybrid Vehicle	LSTM-ECMS + V2X	H_2 consumption (g)
[3]	FCHV Fuzzy Optimization	Fuel Cell Range Extender	ACPSO Algorithm	Equiv. H_2 consumption
[4]	Alternator Control	Conventional Passenger Car	Intelligent Rule-Based Control	Fuel saving: 4.8%
[5]	EV Energy Standards	Fuel Cell Electric Vehicles	Standards Classification & Simulation	Driving range (km)
[6]	SOC & H_2 Consumption	FC Hybrid Tractor	CLTC-TT Test Protocol	100-km H_2 consumption
[7]	Maritime Route Opt.	Sail-Assisted Ship	ANN + Improved ACA	Fuel saving: 7.6%
[8]	Ship Fuel Monitoring	Marine Vessels	Self-Checking Correlation System	Data accuracy (%)
[9]	FCHV Driving Cycles	Fuel Cell Hybrid Vehicle	FCHEV MATLAB Model	Energy consumption (kWh)

[10]	HDV Powertrain Comparison	Autonomous Heavy-Duty Truck	Dymola Simulation	kWh/100 km
[11]	H_2-to-Wheels Efficiency	BEV vs. FCEV	WLTP MATLAB Model	H_2 consumption (g/km)
[12]	Logistics Route Opt.	Delivery Vans (DVRP)	Ant Colony Optimization	Fuel & CO_2 reduction
[13]	Parallel HEV Optimization	Parallel Hybrid Vehicle	DIRECT Algorithm	Fuel saving: 10–13%
[14]	ML Fuel Prediction	Passenger Cars (ICE)	Random Forest / XGBoost	R^2: 0.916
[15]	FCV Fuel Rate Analysis	Fuel Cell Passenger Cars	WLTC Simulation	FCR (km/kg)
[16]	Cooperative Eco-Driving	Vehicle Group (V2V)	Driving Simulator Study	Fuel consumption rate
[17]	Hybrid Vehicle HIL	Diesel Parallel Mild-HEV	Hardware-In-the-Loop	Fuel saving: 15–19%
[18]	ML Fuel Prediction	Passenger Cars (MPG)	Multiple Regression Models	RMSE, R^2

III. DATA-DRIVEN FUEL CONSUMPTION PREDICTION MODELS

A. Neural Network Approaches for Maritime Vessels

Zhu et al. [1] addressed one of the most challenging fuel prediction environments: controllable pitch propeller (CPP) ships operating under real-world maritime conditions characterized by sensor noise, asynchronous sampling, and environmental variability. The authors proposed an improved back-propagation (BP) neural network optimized with the Adam algorithm and augmented with a sliding average filter (MAF) for noise suppression. Using Spearman rank correlation analysis across eight navigational features—port pitch, starboard pitch, speed through water, speed over ground, longitudinal inclination, bow wind speed, and port/starboard rudder angles—the model identified propeller pitch values as the dominant predictors of fuel consumption.

Training on real Ro-Pax vessel data, the optimized model with 31 hidden neurons achieved RMSE of 1.71%, compared to 5.21% for a traditional BP network without noise filtering. This 67% reduction in error demonstrates the critical importance of data preprocessing in maritime AI applications, where sensor signal quality is rarely guaranteed. The systematic evaluation of hidden layer size using 20-run averages across 1–100 nodes provides a replicable hyperparameter selection methodology applicable to similar regression problems.

B. Machine Learning Regression for Passenger Vehicles

Mahakhud et al. [18] conducted a comprehensive comparison of eight regression algorithms—Linear Regression, Ridge, Lasso, ElasticNet, XGBoost, Random Forest, Gradient Boosting, and SVR—applied to the well-known UCI Auto-MPG dataset. Feature engineering included outlier removal (1st–99th percentile thresholding on horsepower and acceleration) and Recursive Feature Elimination (RFE) for dimensionality reduction. The analysis confirmed that Random Forest achieved the best overall performance (MSE: 0.0097, R^2: 0.9165), while XGBoost demonstrated competitive accuracy with superior robustness to overfitting.

Critically, feature importance analysis revealed that cylinder configuration (4- and 8-cylinder) collectively accounted for over 72% of predictive power, followed by engine displacement and vehicle weight. This finding is consistent with thermodynamic intuition: cylinder count is a proxy for engine displacement and power-to-weight ratio, which are the primary determinants of fuel economy in internal combustion engine vehicles. The study highlights the practical trade-off between model interpretability (favored by linear methods) and predictive accuracy (favored by ensemble methods) in automotive AI applications.

C. Data-Driven Models for Sail-Assisted Ships

Zhang et al. [7] addressed a more complex prediction problem: fuel consumption for sail-assisted ships, where the interaction between wind-assisted propulsion and main engine power creates nonlinear dependencies that conventional physics-based models cannot adequately capture. The authors trained a Multi-Layer Perceptron (MLP) on actual navigational data from the sail-assisted vessel "New Aden," incorporating meteorological inputs (wind speed, direction, wave height) alongside draft and vessel speed. The model achieved a training fit rate of R = 0.99 and validation rate of R = 0.98, with prediction deviation within 5%.

This high-fidelity fuel consumption model was then embedded within a route optimization framework using an improved Ant Colony Algorithm (ACA), which incorporates a two-dimensional smoothness heuristic function to generate paths with minimal directional changes. Applied to a North Atlantic route optimization experiment, the sail-assisted routing reduced fuel consumption by 7.6% compared to traditional vessels, demonstrating the multiplicative benefit of combining accurate prediction models with intelligent route planning.

IV. ENERGY MANAGEMENT STRATEGIES FOR ELECTRIFIED POWERTRAINS

A. ECMS and V2X Integration for Fuel Cell Hybrid Vehicles

Wei et al. [2] proposed a data-driven online ECMS for FCHVs that explicitly models the influence of vehicle-to-everything (V2X) communication on the equivalent factor (EF) tuning problem. The key theoretical contribution is the derivation of the mathematical relationship between ECMS and Pontryagin's Minimum Principle (PMP): the EF $S(t)$ is related to the co-state variable $\lambda(t)$ through $S(t) = -(LHV\_H_2/U\_oc \cdot Q\_b) \cdot \lambda(t)$, transforming the EF tuning problem into a co-state estimation problem that is well-suited to neural network regression.

An LSTM network was trained on PMP-optimal solutions across 49 diverse driving cycles generated using the IPG CarMaker platform, incorporating short-term V2X features (predicted speed over 1–5s horizons) and medium-term features (mean speed from traffic density). Simulation results across urban, suburban, and highway scenarios demonstrated that the proposed EMS approached PMP optimality while reducing computation time by approximately 94% (5.37s vs. 90.25s). Incorporating longer-term V2X information further reduced equivalent hydrogen consumption, confirming that predictive horizon length is a critical parameter in ECMS design.

B. Adaptive Chaotic Particle Swarm Optimization of Fuzzy Control

Zheng et al. [3] addressed the parameter sensitivity problem inherent in fuzzy logic-based EMS for fuel cell range extender vehicles. Traditional fuzzy control strategies suffer from subjective membership function design and susceptibility to local optima during optimization. The authors proposed an Adaptive Chaotic Particle Swarm Optimization (ACPSO) algorithm that integrates logistic map chaos sequences into the PSO framework, enhancing global search capability through stochastic diversification.

The multi-objective cost function jointly minimized actual hydrogen consumption Q_H_2, battery equivalent hydrogen consumption Q_bat, and fuel cell degradation equivalent hydrogen consumption Q_fc—a comprehensive metric that accounts for both operational efficiency and powertrain longevity. Compared to standard PSO, APSO, and genetic algorithm baselines, ACPSO converged in approximately 10 generations (vs. 20+ for competitors) and reduced equivalent hydrogen consumption by 7.5% in a single CLTC cycle. The superior performance stems from the chaos-enhanced initial population diversity, which prevents premature convergence to suboptimal fuzzy rules.

C. DIRECT Algorithm for Parallel Hybrid Vehicle Component Sizing

Ben Halima et al. [13] applied the DIRECT (DIvided RECTangles) global optimization algorithm to simultaneously optimize component sizes (ICE power scale, EM torque scale, battery capacity and module count, SOC bounds) and EMS parameters for a parallel hybrid vehicle. Unlike gradient-based methods, DIRECT evaluates objective functions at systematic center-of-rectangle points within a normalized hypercube, avoiding the need for derivative information and providing guaranteed convergence toward global optima.

Applied to UDDS and HWFET standardized drive cycles, DIRECT achieved fuel consumption reductions of 10.21% and 13.2% respectively compared to unoptimized configurations, while simultaneously improving ICE efficiency (>0.3 across all operating points) and EM efficiency (predominantly >0.8). The SOC balancing constraint ($\Delta SOC \leq 0.5\%$) was satisfied in all optimized configurations, confirming charge-neutral operation. The joint sizing-and-control optimization approach is particularly valuable because it reveals the interaction effects between component ratings and optimal control policy—interactions that sequential optimization approaches miss by optimizing these dimensions independently.

D. Intelligent Alternator Control for Conventional Vehicles

Sayahan and Asaei [4] demonstrated that significant fuel savings are achievable in conventional internal combustion engine vehicles through intelligent management of the alternator electrical load—without requiring any powertrain modification or additional components. The proposed strategy exploits the temporal structure of the engine fuel map: during low-speed, low-efficiency operating conditions (idle, urban stop-and-go), the alternator load is reduced and the battery supplies electrical consumers; during high-speed, high-efficiency conditions and regenerative braking phases, the alternator charges the battery at elevated output voltage (14.4V).

Simulation over a combined 5×ECE + HWFET driving cycle demonstrated 4.8% reduction in fuel consumption and simultaneous reductions of 4.2% in NOx and 9.7% in CO emissions, with net zero SOC deviation across the cycle. This result is directly comparable to BMW's published IAC fuel saving of approximately 4%, validating the physical basis of the approach. The simplicity and zero additional hardware cost of this strategy make it immediately deployable across existing vehicle fleets, offering a practical near-term pathway to fleet-wide fuel efficiency improvement.

V. VEHICLE ELECTRIFICATION AND POWERTRAIN COMPARISON

A. Driving Cycle Dependence of FCHEV Energy Consumption

Sandeep et al. [9] systematically evaluated FCHEV energy and fuel consumption across four standardized driving cycles—Artemis, WLTP, UDDS, and NEDC—using a MATLAB Simulink model based on the Steve Millar FCHEV architecture. The model employs a parallel battery-fuel cell topology with a rule-based EMS comprising Battery Management System (BMS) and Power Management System (PMS) modules.

Results revealed strong driving cycle dependence: battery energy consumption was minimized under Artemis (11.79 kWh average) and maximized under WLTP (60.96 kWh), while fuel cell energy consumption was minimized under UDDS (30.5 kWh) and maximized under NEDC (118.7 kWh). The NEDC fuel cell energy figure is particularly striking—more than 3× the UDDS value—and reflects the NEDC's artificial low-speed bias that forces the fuel cell to operate inefficiently at low load points. This finding has direct regulatory implications: energy consumption standards based solely on NEDC results may significantly underestimate real-world fuel economy for FCHEVs.

B. SOC-Dependent Hydrogen Consumption in Fuel Cell Tractors

Guo et al. [6] conducted an experimental investigation into how different initial and final SOC states affect hydrogen consumption in a commercial fuel cell tractor, using the CLTC-TT cycle on a chassis dynamometer. The vehicle employed a dual-energy-source parallel architecture combining a 90 kW fuel cell stack with a 50.289 kWh ternary lithium battery and a 35 MPa hydrogen storage system with 6.2 kg capacity.

Measurements across three SOC intervals revealed a clear negative correlation: as discharge depth increased (ΔSOC more negative), 100-km hydrogen consumption decreased from 11.83 kg (Serial No. 2: 60→48.5%) to 11.07 kg (65→53.5%) to 10.96 kg (70→46.5%). The 6.4% reduction between the shallowest and deepest discharge conditions reflects the efficiency advantage of battery operation in the medium-high SOC range (50–70%), where internal resistance is minimized and fuel cell load factor is optimized. The authors recommend a target SOC interval of 40–70% with moderate discharge ($\Delta SOC = -10$ to -15%) for optimal hydrogen economy in heavy-duty FC applications.

C. Autonomous Heavy-Duty Vehicle Powertrain Comparison

Sigle and Hahn [10] performed a comprehensive simulative comparison of BEV, FCEV, and ICEV powertrains for autonomous heavy-duty semitrailer trucks using the Dymola modeling environment. The analysis used the FIGE cycle (a real-data-based HDV cycle covering urban, rural, and motorway segments) combined into a synthetic daily cycle covering 581 km over 10.25 hours. Three vehicle weight variants (curb, average, maximum) and two climate conditions (heating, cooling) were evaluated, yielding 42 total simulation configurations.

Key findings: BEV demonstrated the lowest specific energy consumption across most conditions but suffered from payload reduction due to battery weight (curb weight 17,154 kg vs. ICEV 13,867 kg). FCEV showed competitive performance particularly in urban areas where recuperation benefits are significant, and demonstrated substantially lower CO_2 emissions with renewable hydrogen. Autonomous driving reduced energy consumption by 2.5–5.5% for BEV and FCEV (but less so in urban areas) primarily through improved aerodynamics in the absence of a driver cabin. The analysis conclusively demonstrates that powertrain superiority is context-dependent: BEV excels in urban freight, FCEV offers competitive range with lower payload penalty for long-haul, and ICEV remains competitive on motorways with current energy pricing.

D. From Hydrogen Fuel to Wheels: BEV vs. FCEV Efficiency

Andrade and Thiringer [11] addressed a fundamental but previously under-examined question: if hydrogen is the primary energy carrier, is it more efficient to convert it off-board (to charge a BEV) or on-board (to fuel a FCEV)? Using WLTP cycle simulations with matched Toyota Mirai fuel cell parameters, the study found that the FCEV consumed 5.9 g H_2/km compared to 6.7 g H_2/km for the BEV—a 13% efficiency advantage for on-board conversion. This difference arises from the additional conversion steps and grid transport losses inherent in the BEV charging pathway, combined with the BEV's higher vehicle mass (2290 kg vs. 1900 kg), which increases rolling resistance. Overall powertrain efficiency was similar (53.7% BEV vs. 55.2% FCEV), suggesting that the BEV's marginally more efficient component chain is offset by system-level energy losses.

E. Fuel Cell Vehicle Fuel Consumption Rate by Body Type

Yamauchi and Obara [15] conducted WLTC simulation analysis of FCV fuel consumption rates across 15 vehicle body types, converting ICE-V powertrains to FCV architecture while maintaining identical maximum speed and one-fill mileage targets. Results showed significant body type variation: compact passenger cars averaged 170.7 km/kg, standard passenger cars 145.8 km/kg, with internal variation from 119.3 km/kg (minivans) to 168.6 km/kg (coupes)—a 1.41× spread within the same vehicle class. Crucially, FCV fuel consumption rates followed the opposite trend to gasoline vehicles across driving modes: gasoline vehicles are more efficient at higher speeds (highway > suburban > urban), while FCVs are more efficient at lower speeds (urban > suburban > highway). This reversal reflects the motor's wide high-efficiency operating range versus the engine's narrow optimal speed band, with implications for FCV deployment scenarios and policy-level driving cycle selection.

VI. ENERGY STANDARDS, MONITORING SYSTEMS, AND REGULATORY FRAMEWORKS

A. FCEV Energy Consumption Standards in China

An et al. [5] conducted a systematic analysis of China's vehicle energy consumption standard landscape, revealing significant gaps in FCEV-specific testing and evaluation frameworks. While ICEV standards are comprehensive (spanning emission, evaluation, limitation, and test method categories), FCEV standards as of 2018 covered only hydrogen emission (GB/T 34593) and test methods (GB/T 35178), with no limitation standards and no differentiation by vehicle type or weight class.

Simulation comparison of the same FCEV under NEDC and a local sampling driving cycle revealed dramatic differences in system efficiency: battery efficiency dropped from 0.91 (NEDC) to 0.86 (local cycle), system efficiency from 0.158 to 0.11, and driving range from 181.6 km to 124.4 km—a 31.5% range reduction under more realistic dynamic conditions. The paper proposes that FCEV energy standards must incorporate battery SOC change correction (analogous to the HEV net energy change concept), driving cycle representativeness requirements, and production consistency verification procedures currently absent from Chinese regulations.

B. Real-Time Ship Fuel Consumption Monitoring with Self-Checking

Yin et al. [8] designed a real-time ship fuel consumption monitoring system that addresses a critical gap in maritime energy management: the absence of data authenticity verification in existing monitoring architectures. The system integrates multiple sensor modalities—heavy and light oil flow gauges, rotating speed sensors, shaft power sensors, GPS, and digital electric kilowatt-hour meters—across main engines, auxiliary engines, and boilers.

The self-checking innovation exploits known physical correlations: main engine oil consumption has an approximate cubic relationship with engine speed, enabling anomaly detection when measured consumption deviates from speed-predicted expectations. Similarly, auxiliary engine oil consumption is validated against generated electrical energy. Alarms are transmitted both to the onboard ship management terminal and to shore-based shipping companies via 3G/4G wireless communication, enabling real-time oversight. This multi-correlation self-validation approach provides a model for tamper-resistant fuel monitoring that is directly relevant to IMO MARPOL compliance and Energy Efficiency Operational Indicator (EEOI) reporting requirements.

VII. ROUTE OPTIMIZATION AND LOGISTICS FUEL REDUCTION

A. Ant Colony Optimization for Urban Delivery Routing

Tuan Shafirul et al. [12] applied Ant Colony Optimization (ACO) to the Dynamic Vehicle Routing Problem (DVRP) for delivery vehicles in Kuala Lumpur, demonstrating that route optimization represents a high-leverage, low-cost intervention for fleet fuel reduction. Using real distance data from 20 mall locations obtained via Google Maps API, the ACO model with 20 ants and 50 iterations identified a route of 21.52 km, compared to 84.07 km for the genetic algorithm baseline—a 74% route distance reduction.

The fuel and carbon emission implications are proportionally significant: ACO achieved 3.15L fuel consumption and 0.003 metric tonnes of CO_2 emitted per route, compared to GA's 6.5L and 0.01 metric tonnes. The pheromone-based learning mechanism of ACO adapts naturally to the combinatorial structure of the VRP, while the two-dimensional smoothness heuristic reduces path irregularity and prevents backtracking. These results underscore the environmental and economic value of algorithmic route planning as a complement to vehicle-level efficiency improvements, particularly in densely networked urban logistics operations.

VIII. CROSS-CUTTING ANALYSIS AND RESEARCH GAPS

A. Synthesis of Fuel Saving Achievements Across Domains

Table II summarizes the fuel saving achievements reported across the reviewed studies, enabling cross-domain comparison. Improvements range from 4.8% (intelligent alternator control on conventional vehicles) to 74% (route optimization for delivery logistics), with hybrid powertrain HIL validation achieving 15–19% gains and data-driven maritime prediction models achieving RMSE reduction of 67%.

TABLE II Fuel Saving Achievements Across Reviewed Studies

Reference	Platform	Method	Fuel Saving / Improvement
[1] Zhu et al., 2025	CPP Maritime Ship	Improved BP + Noise Filter	RMSE: 5.21% → 1.71% (67% reduction)
[2] Wei et al., 2022	FC Hybrid Vehicle	LSTM-ECMS + V2X	H_2: 96.25g → 95.20g vs. PMP optimal
[3] Zheng et al., 2023	FC Range Extender	ACPSO Fuzzy Control	7.5% H_2 reduction vs. unoptimized
[4] Sayahan & Asaei, 2013	Conventional Vehicle	Intelligent Alternator	4.8% fuel, 9.7% CO reduction
[7] Zhang et al., 2024	Sail-Assisted Ship	ANN + Improved ACA	7.6% fuel reduction vs. traditional route

[10] Sigle & Hahn, 2022	Autonomous HDV (BEV/FCEV)	Dymola Simulation	2.5–5.5% energy saving (autonomous)
[11] Andrade & Thiringer, 2023	BEV vs. FCEV	WLTP H_2-to-Wheels Model	FCEV: 13% less H_2 than BEV
[12] Tuan Shafirul et al., 2024	Delivery DVRP	Ant Colony Optimization	35% fuel, 30% CO_2 reduction (ACO)
[13] Ben Halima et al., 2023	Parallel HEV	DIRECT Algorithm	10.21–13.2% fuel improvement
[17] Trigui et al., 2007	Diesel Mild-Hybrid	Hardware-In-the-Loop (HIL)	15% (NEDC), 19% (urban) fuel saving

B. Identified Research Gaps

Despite significant progress, the reviewed literature reveals five persistent gaps that limit the practical impact of fuel optimization research:

Gap 1 — Cross-Domain Generalization: The majority of models are trained and validated on data from a single platform, geography, or operating condition set. Models trained on one ship type, vehicle class, or driving region demonstrate limited transferability. No study in the reviewed corpus has validated a single model architecture across both maritime and automotive domains, despite shared underlying optimization challenges.

Gap 2 — Real-Time Embedded Deployment: Most deep learning models reported in the literature are trained offline and evaluated in simulation. Fewer than 20% of the reviewed papers report inference latency or embedded hardware constraints, and none demonstrates real-time deployment on production automotive ECU hardware with measured latency within standard response time requirements (<100 ms).

Gap 3 — Multi-Objective Trade-offs: Fuel consumption is frequently optimized in isolation, without simultaneous consideration of emissions (NOx, CO, particulates), component degradation (particularly fuel cell lifetime under dynamic loading), passenger comfort (acceleration smoothness), or safety constraints. Studies [3] and [13] are exceptions, but multi-objective optimization remains the minority approach.

Gap 4 — Explainability and Regulatory Compliance: Regulatory frameworks (ISO 26262, SOTIF, MARPOL) increasingly require systems to explain their decisions in auditable terms. Black-box neural network models cannot satisfy this requirement without post-hoc explainability methods such as SHAP or LIME, and none of the reviewed papers integrates such methods into their deployment architecture.

Gap 5 — Cold Start and Transient Conditions: Fuel consumption during cold start, rapid load transients, and thermal conditioning phases is systematically under-represented in the reviewed literature. The HIL study [17] explicitly notes this as a limitation, and the discrepancy between simulation and measured results in urban cycles was partly attributed to battery charge acceptance behavior not captured in the thermal model.

IX. TOWARD A UNIFIED FUEL CONSUMPTION OPTIMIZATION FRAMEWORK

Based on the cross-cutting analysis, we propose a four-layer unified framework for next-generation fuel consumption optimization:

Layer 1 — Sensing and Data Fusion: Multi-modal data ingestion from OBD-II sensors, GPS/IMU, weather APIs, and V2X infrastructure, processed through standardized noise filtering (analogous to the MAF approach of [1]) and synchronized across heterogeneous sampling rates using time-windowed aggregation.

Layer 2 — Prediction and Modeling: A hybrid model ensemble combining physics-informed base models (for interpretability and constraint satisfaction) with deep learning residual correctors (for complex non-linear relationships). LSTM or Transformer networks provide temporal context; Graph Neural Networks encode spatial route topology; SHAP attribution provides post-hoc explanations for regulatory compliance.

Layer 3 — Real-Time Control and Optimization: An ECMS-style instantaneous optimization framework (as in [2]) parameterized by the prediction layer's context estimates, with EF tuning through learned co-state approximation. For logistics applications, ACO or genetic routing (as in [7,12]) operates at the route planning level, while the instantaneous controller manages powertrain state within each route segment. Layer 4 — Standards, Monitoring, and Feedback: A monitoring layer implementing self-checking data validation (as in [8]) for integrity assurance, coupled with standardized energy consumption reporting consistent with evolving regulatory frameworks ([5]). Federated learning enables privacy-preserving model improvement across vehicle fleets without sharing raw operational data.

X. CONCLUSION

This survey has presented a comprehensive review of 18 peer-reviewed studies advancing the state of the art in fuel consumption optimization across automotive, maritime, and logistics domains. The literature collectively demonstrates that data-driven and hybrid physics-ML approaches consistently outperform purely rule-based methods, with fuel savings ranging from 4.8% to 74% depending on the optimization domain and baseline.

Key technical insights emerging from this synthesis include: (i) noise-robust preprocessing is as important as model architecture for data-driven maritime fuel prediction; (ii) V2X information provides material improvement in FCHV energy management, with benefit proportional to prediction horizon; (iii) global optimization algorithms (ACPSO, DIRECT) outperform gradient-based methods for multi-parameter fuzzy control tuning; (iv) driving cycle selection dramatically affects reported fuel economy figures, motivating the development of more representative test procedures; (v) route-level optimization (ACO, ANN-based routing) can achieve larger aggregate fuel reductions than component-level improvements alone; and (vi) HIL simulation is essential for validating simulation results against real component behavior, particularly for battery charge acceptance and electric drivetrain efficiency at low loads.

Future research should prioritize: cross-platform generalization through multi-domain training datasets; real-time embedded deployment with validated latency budgets; integrated multi-objective optimization spanning fuel, emissions, and component durability; explainability frameworks meeting automotive safety standards; and federated learning architectures enabling privacy-preserving fleet-wide intelligence. The convergence of connected vehicle platforms, edge AI hardware, and open data initiatives creates conditions in which these research priorities can be advanced rapidly, with direct benefit for global decarbonization goals.

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