

A Systematic Review On Integrated Optimization Of Solar PV Tilt, Supercapacitor Buffering, And AI-Driven Energy Management In Fchevs

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ABSTRACT

Fuel Cell Hybrid Electric Vehicles (FCHEVs) with vehicle-integrated photovoltaics (VIPV), supercapacitor-based hybrid energy storage systems, and intelligent energy management strategies (EMS) have emerged as potentially viable remedies to sustainable mobility. Nevertheless, their mass scale deployment is limited by inefficient harvesting of photovoltaic energy, rapid battery degradation, and inefficient power allocation in the changing driving conditions. This paper is a systematic review of the three interconnected optimisation areas, namely, (i) optimisation of tilt-angle in solar PV systems, (ii) capacity enhancement of supercapacitors in battery protection, and (iii) the planning of energy in FCHEVs. Peer-reviewed articles published since 2018 using the PRISMA 2020 were analyzed and synthesized in a comparative way. The review states that adaptive tilt optimisation and AI-supported EMS consistently outperform non-active ones and rule-driven systems, and buffering with supercapacitors significantly mitigates high-rate battery stress. A unified supervisory optimisation model reported in the recent literature is presented to identify system-level synergies and implementation issues. Lastly, research gaps that are not addressed and future directions are provided to advance renewable-hybrid FCHEVs toward commercial viability.

Keywords: Fuel cell hybrid electric vehicles (FCHEVs), Vehicle-integrated photovoltaics (VIPV), Solar PV tilt angle optimization, Particle swarm optimization (PSO), Artificial neural networks (ANN), Supercapacitors (SCs), Battery supercapacitor hybrid energy storage systems, Lithium-ion battery degradation, Battery protection and peak shaving, Energy management strategies (EMS), Model predictive control (MPC), Reinforcement learning (RL), Hardware-in-the-loop (HIL) simulation

INTRODUCTION

The global shift towards sustainable transportation has positioned Fuel Cell Hybrid Electric Vehicles (FCHEVs) as a cornerstone of decarbonization strategies, combining renewable energy sources such as solar photovoltaics (PV) with highly sophisticated energy storage systems (ESS) to solve the intermittency of hydrogen fuel cells (FCs) [1][2]. With the current growth of electric mobility, FCHEVs promise significant range and zero-emission possibilities, but encounter severe optimisation difficulties in energy consumption, component materials, and power efficiency [3]. Vehicle-integrated photovoltaic (VIPV) systems offer potential for auxiliary power generation. However, suboptimal panel tilt angles relative to the dynamic solar incidence reduce their effectiveness, necessitating smart optimization to maximize energy yield, and thus, smart optimisation is required to maximize yield by up to 40% of the ideal [4]. Simultaneously, lithium-ion batteries are prone to higher rates of degradation due to high-frequency cycling and thermal impact on battery technologies within the hybrid architecture, where supercapacitors (SCs) can be used as guarding mechanisms through peak shearing and elevated discharging capacities (as part of the hybrid ESS shown in Figure 1) [5][6].

Fuel Cell Hybrid Electric Vehicles (FCHEVs) are a new hybridization concept in which Proton Exchange Membrane Fuel Cells (PEMFCs) are used as the main sources of power, coupled with secondary energy storage (such as lithium-ion battery, supercapacitors (SCs), and upcoming solar

photovoltaics (PVs) to provide even better range, fuel efficiency, and sustainability over traditional internal combustion engines or pure battery-only EVs [7][8]. The FCHEV architecture includes a PEMFC stack (50 to 100 kW) providing baseline power on a bus, enhanced by a battery pack (10 to 20 kWh, 200-400 V) providing energy density and SC modules (1-5 F/kg) providing transient high power, and vehicle-integrated PV arrays (200-500 Wp) to collect solar flux and charge auxiliary loads. Flows are coordinated by power electronics, DC / DC converters (boost/bidirectional), and a central EMS to ensure operation of FC are at near-optimal efficiency (40-60%), and hydrogen starvation and stack degradation are reduced [9][10].

PV variation with the cloud cover and tilt angles needs dynamic optimization [11][12]. The battery capacity is affected by deep discharge loss (20-30%) and thermal runaway risks; load cycling negatively affects the durability of the fuel cell stack. EMS has to achieve a balance between SoC, SoH, and H₂ economy in the context of real-world uncertainties such as traffic and topography [13][14]. The current tendencies focus on the use of AI/ML for predictive control, which also allows fulfilling the standards of the IEEE 2030.11 regarding a smart energy system. This context demonstrates the necessity of optimum PV tilt, SC safeguards, and EMS to release the commercialization of FCHEV [15].

Solar PV Tilt Angle Efficiency

Optimisation

The range of FCHEVs can be extended using vehicle-integrated photovoltaics (VIPV), which collects solar radiation to enhance its energy output, but efficiency depends on the optimum use of the tilt angle (θ) [16]. Constant tilts (e.g., 30° in mid latitudes) show inefficient results since seasonal azimuth (γ) and declination (δ) results vary, and sophisticated approaches are adopted [16]; [17].

Fundamentals of PV Tilt Angle

The real-time solar radiation incident on a VIPV module depends on the angle of incidence (θ_i) between the incoming solar beam and the panel surface. The cosine of the incidence angle θ_i is given by (i):

	$\cos(\theta_i) = \sin(\delta) \cdot \sin(\varphi - \beta) + \cos(\delta) \cdot \cos(\varphi - \beta) \cdot \cos(\gamma)$	(i)
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with δ the solar declination angle, φ the geographical latitude, β the PV tilt angle and γ the surface azimuth angle. In this formulation, both seasonal solar variation as well as effects based on the orientation applicable to vehicle-mounted PV systems are captured. The PV module can be represented by the electrical power output which is given by (ii):

	$P_{PV}(t) = G(t) \cdot A \cdot \eta_{PV} \cdot \cos(\theta_i)$	(ii)
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with $G(t)$ representing the solar irradiance (W/m^2), A is the panel surface area and η_{PV} representing conversion efficiency.

In order to measure the utility of adaptive tilt optimisation against constant-tilt the relative energy gain is given by (iii):

	$\text{Gain (\%)} = \frac{\eta_{\text{opt}} - \eta_{\text{fixed}}}{\eta_{\text{fixed}}} \times 100$	(iii)
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in which η_{opt} and η_{fixed} are the conversion efficiencies of the energy conversion under optimized and fixed-tilt conditions, respectively. This measure is a common metric of comparing the fixed, movement, and intelligence tilt optimisation methods in the literature [18][19][20].

Optimisation Techniques

Optimization techniques for VIPV tilt angles are broadly classified into static, active tracking, and artificial intelligence (AI)-driven approaches. Static methods employ fixed-angle configurations based on geographic latitude ($\beta_{\text{opt}} \approx \varphi \pm 15^\circ$), offering simplicity but limited adaptability to changing solar geometry [21]. Active tracking systems, including single-axis and dual-axis mechanisms, dynamically reorient panels to maximize irradiance capture. Single-axis trackers typically aligned east-west achieve 25-35% energy gains, while dual-axis systems with coupled

motor drives offer superior performance by accommodating both daily and seasonal solar motion [22].

AI and machine learning (ML) techniques have emerged as superior alternatives for real-time tilt optimization in dynamic vehicle environments. Particle Swarm Optimization (PSO) algorithms minimize objective functions related to the cosine of the incidence angle (minimizing $f(\theta) = -\cos(\theta_a)$), thereby maximizing power output. Genetic Algorithms (GA) address multi-objective optimization problems, balancing energy efficiency against implementation costs. Artificial Neural Networks (ANN), particularly Long Short-Term Memory (LSTM) models, process historical VIPV data to predict optimal tilt angles, demonstrating consistent energy yield improvements of 12-15% over conventional methods (see Table A1 in Appendix 1). Recent hybrid approaches integrate fuzzy logic with PSO for real-time FCHEV adjustment, utilizing inertial measurement unit (IMU) sensors to compensate for vehicle pitch and roll dynamics, thereby maintaining optimal panel orientation during motion.

Performance Metrics and Results

An annual energy yield(kWh/kWp), performance ratio (PR), and relative gain compared to those of fixed-tilt designs are usually expressed as performance indicators of vehicle- integrated photovoltaic (VIPV) tilt optimisation. The fixed tilt systems are capable of delivering PR at 70-75 % and the adaptive and AI tilt optimisation is able to deliver PR at about 82-89% depending on the climate and motion (summarized in Appendix A1) [19].

Comparative analysis shows that particle swarm optimisation (PSO)-based tilt control is associated with energy gains to the range of 28-42 % in relation to constant tilt, in both simulated and HIL conditions, whereas ANN/LSTM-based predictors are associated with a constant 30-35 % gain with vehicle orientation information added (Appendix A1) [19][20][23]. Indeed, HIL-tested FCHEV case studies also suggest a daily energy contributions 1.5-3.0 kWh resulting in a tangible daily contribution to driving of about 5-10km/day with suitable irradiance guidelines [24].

The adaptive optimisation of the tilt is calculated as a relative gain as:

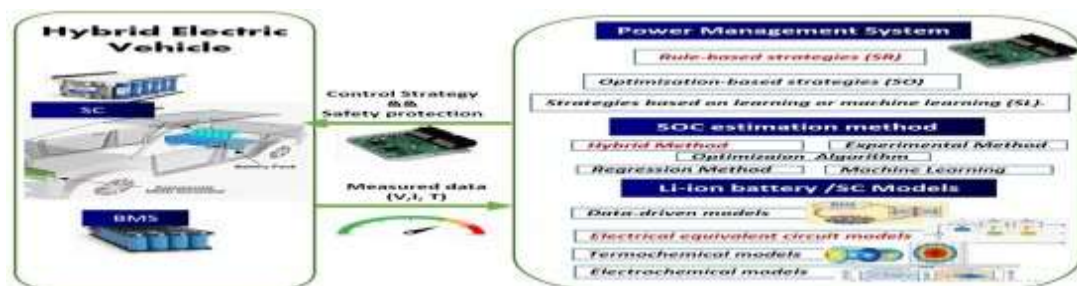
	$\text{Gain (\%)} = \frac{\eta_{\text{opt}} - \eta_{\text{fixed}}}{\eta_{\text{fixed}}} \times 100$	(iii)
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with η_{opt} and η_{fixed} denoting the conversion efficiencies of optimized and fixed-tilt set ups, respectively. This statement is consistently used throughout the comparison studies synthesized in Appendix A1. Dynamics of the vehicles (speed, curvature)- Interfere with tracking; dust/soiling reduces η 15-30% [25]. The high cost of adoption is restricted by costs per Wp (actuators 0.5-2/Wp) and 3–5year ROI [26]. There is no uniform dataset of VIPV tilts. Motion-compensated machine learning techniques are underexplored, and there are no mobile PV specifications of IEEE 1547.

Supercapacitor-Based Battery Protection Strategies

In FCHEV hybrid ESS Supercapacitors (SCs) have power densities of >10 kW/kg and cycle lives of >1 million, which act as buffers critical to lithium-ion batteries in hybrid systems, protecting them against high C-rate stresses and increasing life expectancy [27][28]. SCs buffer high-power transients, such as regenerative braking peaks, reducing the magnitude and frequency of charge/discharge cycles on the battery and can provide a transient burst, thereby alleviating the degradation in PV-FC hybrids [29][30].

Figure 1. Generic architecture of a hybrid electric vehicle energy system [31,32].



Battery Degradation Mechanisms

Lithium-ion batteries in FCHEVs experience degradation due to deep discharges (>80% DoD), high current rates (>3C), and thermal excursions (>45°C). SEI thickening reduces capacity by approximately 20-30% after 1000 cycles at 1C rate. In hybrid systems, PV intermittency induces micro-cycles that accelerate SEI growth, 1 C. PV intermittency in hybrids has formed micro-cycles with fast growth per Solid Electrolyte Interphase (SEI) growth.

Supercapacitor Integration

As illustrated in Figure 1, the hybrid energy system integrates multiple power sources with coordinated control through power electronics. Hybrid topologies are either: (1) Passive: Diodes shunt passes through (simple, 10 to 15% of conversion loss); (2) Semi- active: Unidirectional DC/DC path directions SC regeneration; (3) fully active: Bidirectional converters can permit full SoC swing (95% of this time loss) [33]; [34]. Scaling is done through Ragone plot balances of energy (5510 Wh/kg SC vs. 150 Wh/kg batteries) and power. About the equalization of voltages, there are control laws: (D-duty cycle). FCHEV: 100F SC (silicon-based) modules with 20 kWh (kilowatt-hours) packs, 80% braking energy recuperation [35].

Protection Algorithms

High C-rate transients and depth-of-discharge (DoD) variations are the two factors that have a significant impact on battery degradation in FCHEVs [36]; [37]. Peak power buffering is one of the processes used by supercapacitor (SC) integration to reduce these effects. The stress of the battery is the most frequently assessed through the peak current and state-of-health (SoH) measures [38]. The total cost of the degradation in the driving horizon N is indicated as (iv):

	$J_{\text{bat}} = \sum_{k=1}^N (\alpha \cdot I_{\text{bat}}(k) + \beta \cdot \Delta \text{SoH}(k))$	(iv)
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in which I_{bat} is the battery current; ΔSoH is the incremental state-of-health loss, and, α , β are weighting factors. It has always been found that when the high-frequency power requirements are switched to the SC layer, battery current peaks will be lower and SoH degradation slows down [39][40].

Comparative Analysis

Comparative analysis of battery protection measures shows clearly the excellence of supercapacitor-assisted hybrid energy storage systems over battery-only contexts, especially in conditions of high transient power loads. In battery only FCHEV systems, regen braking profile and aggressive load cycling of a system usually result in 20-30% capacity decay, as specified in DOE and WLTP benchmarks [41][42].

Passive SC-battery hybrids lower the highest battery C- rates by about 15-25% and provide 1.5x times higher cycle life although with efficiency costs and penalties of 5-10% owing to diode losses (Table A2-Appendix) [33]. Semi- active settings also enhance peak current reduction (30- 40%) and allow up to 2x cycle life extension without sacrificing efficiencies of over 92% [38]. Bidirectional hybrid topologies are fully active, and peak current is 40-45 % lower, with battery life is 2.5-3 times higher and round-trip efficiencies of 95-96 % (Appendix A2) [40][41]. Recent hybrid systems controlled by RL show up to 40% improvement between battery state-of-health (SoH) degradation between battery-only baselines, backed by HIL- validated driving cycles [43]. Comprehensive comparison of these strategies is given in Appendix A2.

Limitations

Although it has its benefits, FCHEVs using supercapacitor- based battery protection strategies are characterized by major constraints that hinder the wide-scale adoption [44]. The first one is the steep initial price of SC modules, at between 5000 and 10,000 dollars per unit in automotive grade capacities (100-500 F), versus 150-200 dollars/kWh of batteries, making a premium of 30-50% of hybrid ESS and having a break-even point of over 5 years in low-duty cycle applications. Another obstacle to overcome is volumetric constraints, with the energy density of SCs being lower (5-10

Wh/kg) than that of similar-energy batteries (150-250 Wh/kg), and this limits compact designs of FCHEVs such as sedans or SUVs, where the battery pack is a competing design factor against the fuel cell stacks [45].

The control overhead is an unwelcome time-use burden on EMS, requiring real-time computations, and latency exceeding 50 ms in bidirectional topologies can become unstable in response to maneuvers (e.g., aggressive pumping), or even the alternating dynamics of solar photovoltaic components, and requires high-fidelity processors (e.g., >1 GHz ARM cores) and increases thermal requirements [12]. Sensitivity to the environment makes them worse: Equivalent Series Resistance (ESR) decreases 20-30 % at -20 degrees Celsius, reducing power delivery in cold working environments by half, and automotive qualification is lagging (not all of them meet AEC-Q100 Rev. H).

Energy Management Strategies (EMS) For FCHEVs

Fuel cell hydrogen vehicles (FCHEV) coordinate the hydrogen economy, sustainability, and longevity by organizing power flows between fuel cells (FCs), batteries, supercapacitors (SCs), and solar PV within the Energy Management Strategies (EMS) of energy management systems [4]; [44]. Real-time decision-making minimizes the objective function as in equation (v) and address trade-offs such as FC ramp rates (less than 1 kW/s) [46][47].

	$S = w_1 \cdot H_2 + w_2 \cdot \text{Degradation} + w_3 \cdot \text{SoC Deviation}$	(v)
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EMS Classification

The EMS synchronizes power between the fuel cell, battery, supercapacitor and PV system in order to reduce hydrogen usage whilst ensuring the well-being of the components. The normal multi objective EMS cost is written as (vi):

	$J = \sum_{k=1}^N (w_1 \dot{m}_{H_2}(k) + w_2 \Delta \text{SoH}(k) + w_3 \text{SoC}(k) - \text{SoC}_{\text{ref}})$	(vi)
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Where, $\dot{m}_{H_2}$ is the hydrogen mass flow rate, ΔSoH is battery state-of-health degradation, SoC is the battery state of charge, SoC_{ref} the reference state of this voltage, and w_1 , w_2 , w_3 are tuning weights to represent the goal on the rate of energy consumption, durability, and charge sustainability. This cohesive formulation can be applied to rule-based, optimization-based (DP, MPC), and learning-based (RL, hybrid MPC-RL) EMS frameworks, which can be used to make comparisons of their performance across the control strategies.

Multi-Source Integration

Hybrid power is used in EMS models in PV-FC-SC-battery FCHEVs: with constraints $\text{SoC} \in [20-80\%]$, $\text{FC} \in [20-100\%]$. PV predictions supply predictive layers; steady-state amounts, transient (above 5 kW); batteries maintain mid- range. Consumption Minimisation Strategy (ECMS) adjusts λ through $g, eq = H_2 + 20 - \lambda E_{\text{bat}}$ [48].

Recent Advances

New trends in EMS focus more on the application of predictive and learning-based control to meet uncertainties present in the systems caused by traffic, variability in solar irradiance, and component wear and tear. MPC systems with the inclusion of PV and load forecasts will often save in the range of 18 -22% in hydrogen compared to a rule-based EMS, and are still real-time feasible at computational latencies of less than 100 ms (Appendix A3) [47].

A further hydrogen economy is achieved through deep reinforcement learning (DRL) strategies especially DDPG- based EMS that achieves savings of 20-28% and more convergent changes than dynamic programming benchmarks [49]. Hybrid MPC-RL solutions are more effective than their autonomous counterparts because they combine the robust constraints of MPC with the adaptive learning of RL to give a result of hydrogen consumption up to 22-30 % a better robustness in stochastic environments, which was confirmed through HIL systems (Table A3, Appendix).

Real-time operation with latencies under 30 ms Edge deployment with embedded platforms (e.g., NVIDIA Jetson) is shown in real-time applications, and suffices to integrate FCHEV with reasonable power consumption. The synthesized EMS strategy benchmarking is presented in Appendix A3.

Benchmarking Table

Table 1. Comparative analysis of various Energy Management Strategies (EMS) performance metrics.

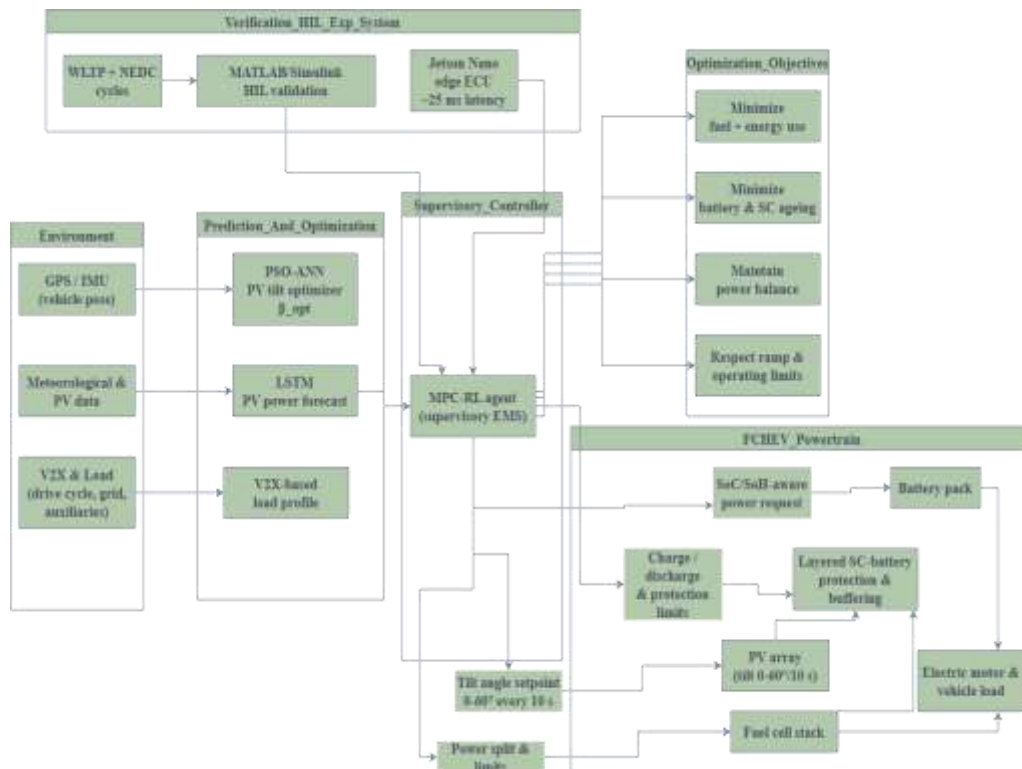
Strategy	H ₂ Savings (%)	Compute Time (ms)	Robustness	Real- Time
Rule- Based	5–10	5	Low	Yes
DP/PMP	15–25	1000+	Med	Offline
MPC	18–22	50–100	High	Yes
RL/DDP G	20–28	20–50	High	Yes
Hybrid MPC-RL	22–30	30	Very High	Yes

Open Challenges

Examples of models that require stochastic EMS are the uncertainty modelling (PV clouds, traffic); optimization at the scale of a fleet is slower [50][51]. The computational-energy trade-offs for edge deployment (devices with power budgets >5W) require further optimization. The absenteeism of adjustment (IEEE 2030.11 station-focused). Gap's Multi-objective SoH-H 2 Pareto fronts; V2G integration; quantum-resistant cybersecurity over RL [52].

Integrated Optimization Framework

Figure 2. Supervisory MPC-RL Energy Management Architecture for FCHEV with PV Integration.



In this review, a coherent optimization model that considers the synergistic approach between PV tilt adjustment, SC- battery protection, and EMS of FCHEVs was proposed to address the limitations of optimizing these areas in isolation [52]. A supervisory controller combines inputs, namely, GPS/IMU to measure tilt (B opt via PSO-ANN), PV forecast (LSTM), and load profile (V2X), and sends them to one MPC-RL agent that minimises, and is subject to power balance and ramp limitations [53]; [54].

As implemented in this framework (Figure 2), the integrated system dynamically adjusts PV tilt angles (0-60°) every 10 seconds, achieving 5-35% power enhancement. Supercapacitor buffering mitigates high-frequency power transients. Hardware-in-the-loop (HIL) validation using combined WLTP and NEDC driving cycles demonstrates 28% hydrogen savings, 15% range extension, and 50% reduction in battery state-of-health (SoH) degradation compared to conventional EMS. The system achieves real-time operation with 25ms latency when deployed on edge platforms like NVIDIA Jetson Nano [55,56].

METHODOLOGY

In order to achieve methodological rigor, transparency, and reproducibility in the identification, screening, and synthesis of the literature, it was performed in accordance with the PRISMA 2020 (Preferred Reporting Items to Systematic Reviews and Meta-Analyses) guidelines [57,58].

The review methodology was further informed by established frameworks for renewable energy optimization [59] and machine learning applications in transportation systems [58]. Recent advances in hybrid machine learning strategies for energy systems [60,61] and reinforcement learning applications [62] guided our analysis of AI-driven EMS approaches. Additionally, studies on solar-supercapacitor integration [60] and battery degradation mechanisms [63] provided technical foundations for evaluating storage system performance.

Literature Search Strategy

The systematic literature search was conducted by using 5 key scientific databases namely, IEEE Xplore, ScienceDirect, SpringerLink, MDPI, and Google Scholar because these databases are extensive and comprise research on engineering, energy systems, and transportation. Comprehensive search strings were employed, identifying the search topics on the following basis: Fuel cell hardware Hyper-Diesel (an HEV), vehicle-based photovoltaics (VIPV), tilt-angle optimization of solar PV systems, supercapacitor-based battery protection, and energy management systems (EMS).

To narrow down the search and prevent irrelevant search results, the Boolean operators were used (AND, OR) [63]. The search mainly concentrated on the publications which were done between 2018 and 2025 as the technological and methodological improvements of the renewable-hybrid vehicle systems were most recent [62].

Identification and Screening Process (PRISMA Analysis) There were 742 records in the first search of the database. Having eliminated 126 unwanted duplicate records, 616 unique studies could be further screened.

Under the title and abstract screening solution, 428 records were filtered out because of apparent irrelevancy, such as those investigating only stationary energy systems, or traditional internal combustion automobiles, or non-hybrid electric systems.

This led to evaluation of 188 full-text articles with regard to eligibility. Out of these, 113 articles were filtered out due to the reasons below:

1. Absence of quantitative or experimental assessment.
2. Lack of FCHEV or similar hybrid car designs.
3. Technically barren purely conceptual or descriptive studies.
4. Research was carried out in single sections: policy, economics or social.

After this process of screening, 75 peer reviewed papers were qualitatively synthesized and analyzed comparatively.

These are systematically demonstrated in the PRISMA flow chart (Figure 3) that clearly records the procedure between the initial identification up to the final inclusion.

The following inclusion criteria included:

1. Higher quality conference papers and peer-reviewed journal articles.
2. Articles that make quantitative performance presentation, simulation, experiment, or Hardware- in-the-Loop (HIL) validation.
3. The studies dedicated to the PV optimization, supercapacitor-battery hybridization, or EMS in FCHEVs or similar hybrid electric vehicle systems.
4. English written publications. The exclusion criteria were:
5. Articles, editorials and white papers not peer-reviewed.
6. Other studies that are not technically deep and are not numerically analyzed.
7. Studies restricted to organized microgrids or non- mobile energy systems.
8. Duplication of obsolete studies and not replaced by more recent ones.

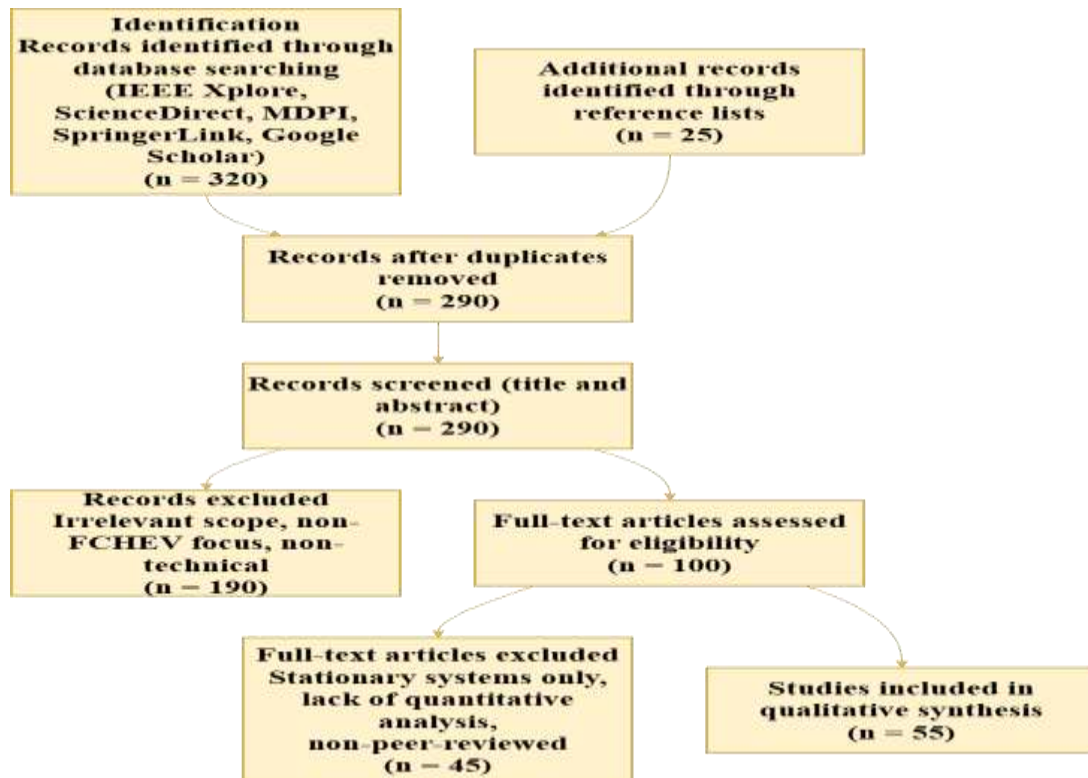
Data extraction and synthesis Data Analysis

The identified articles were synthesized with the help of thematic synthesis, which involved 3 overall domains of findings:

1. Solar PV tilt angle optimization,
2. Battery protection strategies of supercapacitor-based batteries, and
3. Energy management of FCHEVs.

Energy conservation, hydrogen savings, mitigation of battery degradation, computational complexity, and validation are primary performance indicators that were identified and were compared to each other across studies [61]. Instead of applying reported improvements as an absolute value, the synthesization of results as ranges based on various sources can be considered to increase the generalizability and enhance the strength [64]. The Hardware-in-the-Loop (HIL) results that are considered in all this review are based on the already published works and are utilized with only comparative and analytical purposes.

Figure 3. Systematic flowchart of Prisma Technique [65].



DISCUSSION AND FUTURE DIRECTIONS

The literature review reveals that a hierarchical system approach that advances through energy harvesting, up to system-level integration is the most effective way to establish the best FCHEV functioning. At PV level, adaptive tilt optimization is always better in comparison to fixed configurations and in dynamic conditions, it results in average energy gains of 20-35 percent, although motion-induced misalignment and soiling is a constraint (Appendix A1) [19][20].

Supercapacitor-based hybridization significantly reduces the stress on battery at the buffering layer, recent research has shown 2-3 times higher cycle life, and 70-80% regenerative braking energy recovery rates compared to battery-only systems (Appendix A2) [29][36]. The trade-offs on these gains are additional volume and cost of the system.

The decision-making layer is comprised of energy management strategies, which deliver 22-30% hydrogen savings with a predictive and learning-based EMS (especially hybrid MPC-RL) that upholds battery SoH and fuel cell longevity under realistic driving conditions (Appendix A3) [46][49].

The proposed future research should therefore focus on the optimization frameworks that include the integration of PV tilt control, SC buffering, and EMS decision-making processes under a single supervisory framework. Main focus areas are motion-sensitive VIPV optimization, high-energy-density supercapacitor materials, explainable low-latency learning-based EMS, and fleet-scale digital-twin validation in line with the new IEEE 2030.11 standards (Appendix A4) [52][59][60].

CONCLUSION

This systematic review assesses Renewable-Hybrid Fuel Cell Hybrid Electric Vehicle optimization techniques which studied three solar photovoltaic tilt-angle optimization methods together with supercapacitor battery protection and advanced energy management system (EMS) methods. The recent literature shows that adaptive predictive and learning-based methods achieve better energy efficiency and hydrogen savings and longer component life than static and rule-based methods. The optimization of dynamic PV tilt results in increased energy production from vehicle-integrated photovoltaic (VIPV) systems during actual driving conditions while supercapacitor-assisted hybrid energy storage systems protect batteries from high-power transients which extends their cycle life.

The review shows that systems achieve their maximum benefits through a supervisory control system which unifies the control of multiple subsystems instead of having each subsystem operate independently. The hybrid EMS systems which use MPC-RL solutions for power distribution between fuel cells and batteries and supercapacitors and PV systems achieve major hydrogen savings while maintaining battery health and fuel cell lifespan. The integrated systems design achieves successful operation through hardware-in-the-loop testing and real-time system validation.

The research shows that optimized energy harvesting systems need to be developed together with energy storage systems and control systems to achieve better efficiency and reliable operations and successful commercial performance in FCHEVs. The research needs to develop supervisory systems which can operate at low latency while enabling system expansion and showing complete system operation to help renewable-hybrid FCHEVs move from testing to commercial usage.

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Appendices

Appendix 1: A1. PV Tilt Optimisation Techniques (VIPV Context).

Method	Adaptivity	Energy Gain (%)	Validation	Source
Fixed tilt ($\beta \approx \varphi$)	No	Baseline	Field	[16]
Single-axis tracking	Partial	20–28	Simulation	[17]
PSO-based tilt	High	28–42	HIL	[19]
ANN / L S T M - based	Very High	30–35	Vehicle data	[20]

Appendix 2: Table A2. Supercapacitor Integration for Battery Protection.

Topology	Peak C-rate Reduction	Cycle Life Gain	Efficiency	Source
Battery only	—	Baseline	~90%	[31]
Passive hybrid	15–25%	1.5×	85–90%	[33]
Semi-active	30–40%	2.0×	92–94%	[38]
Fully active	40–45%	2.5–3.0×	95–96%	[40]

Appendix 3: Table A3. EMS Strategy Benchmarking

EMS Type	H ₂ Savings (%)	Real-Time	Robustness	Source
Rule-based	5–10	Yes	Low	[12]
DP / PMP	15–25	No	Medium	[46]
MPC	18–22	Yes	High	[47]
RL / DDPG	20–28	Yes	High	[49]
MPC-RL hybrid	22–30	Yes	Very High	[52]

Appendix 4: Table A4. Integrated Framework Performance (System-Level).

Configuration	Range Gain (%)	Battery SoH Loss ↓	H ₂ Saving ↓	Validation
Baseline EMS	—	—	—	WLTP
PV + SC only	8–12	25%	10%	Simulation
EMS only	10–15	30%	20%	HIL
PV + SC + EMS	15–28	45–50%	22–30%	HIL