Computer Modeling in Engineering & Sciences

Tech Science Press

https://doi.org/10.32604/cmes.2026.081630

ARTICLE

Digital Twin–Based Analysis of Energy Management Strategies for Heavy-Duty Fuel Cell–Battery Electric Vehicles Using a Hybrid Deterministic Decision Framework

Antonio Gimeno and Emilio Larrodé*

Department of Mechanical Engineering, School of Engineering and Architecture, University of Zaragoza, Zaragoza, Spain

*Corresponding Author: Emilio Larrodé. Email: elarrode@unizar.es

Received: 05 March 2026; Accepted: 27 May 2026; Published: 30 June 2026

ABSTRACT: This paper presents the development of a digital twin of a heavy-duty electric truck powered by a hybrid energy system based on a hydrogen fuel cell and a battery pack. The objective of the model is to analyze different energy management strategies and to determine how the power demand of a real route can be shared between both energy sources, while keeping the fuel cell within safe operating limits to preserve its service life. The digital twin simulates vehicle dynamics, traction, and regenerative braking, and the main operational constraints of the fuel cell, including minimum and maximum power limits, power variation constraints, and startup conditions. The input data are obtained from real driving routes, using telemetry data recorded from conventional diesel trucks. These data provide realistic speed, acceleration, and slope profiles, which are used to reconstruct the power and energy demand of the vehicle and to simulate the behavior of an equivalent fuel cell–battery electric truck. Several rule-based energy management strategies are implemented and compared using indicators such as hydrogen consumption, minimum battery state of charge, unused generated energy, and fuel cell power variability. The results show that strategies limiting rapid fuel cell power changes provide a better balance between hydrogen efficiency, battery protection, and smoother fuel cell operation. The proposed digital twin offers a practical framework to evaluate hybrid energy management strategies under realistic operating conditions and to support future intelligent energy management developments.

KEYWORDS: Digital twin; heavy-duty electric vehicle; fuel cell–battery hybrid system; energy management strategy; hydrogen-powered truck; rule-based control

1 Introduction

The global urgency to mitigate climate change has positioned the transport sector at the center of the sustainability debate. To address this, the European Parliament has set ambitious CO_2 reduction targets for heavy-duty vehicles [1].

Furthermore, upcoming regulations will impose limits significantly stricter than current standards [2,3], forcing manufacturers to innovate beyond Internal Combustion Engine Vehicle (ICEV) [4]. Recent policy analyses highlight that achieving these targets requires a rapid shift toward zero-emission powertrains in the logistics sector [5].

While Battery Electric Vehicles (BEV) have proven efficient for light transport, their application in heavy-duty long-haul trucking faces significant barriers. Studies indicate that a 40-t BEV truck with 600 km of autonomy could lose at least 4 t of payload due to battery weight [6], in addition to challenges regarding long charging times and infrastructure costs [7].

Consequently, Fuel Cell Electric Vehicles (FCEV) using hydrogen have emerged as a superior alternative, offering rapid refueling and lower powertrain weight [1,8]. The selection of these electrified architectures is supported by critical reviews that emphasize the need for optimized component sizing to ensure operational viability [9,10].

Recent research emphasizes that the most effective path toward decarbonization is the hybridization of fuel cells and batteries [11,12]. In these systems, the fuel cell system (FCS) acts as the primary power source while a lithium-ion battery pack handles high-energy transients [13,14].

This configuration leverages the high energy density of hydrogen and the high-power density of electrochemical batteries [15,16]. However, managing the power distribution is critical. As noted by Xiao et al. (2025), hierarchical control strategies are essential to optimize energy management in hybrid environments [17]. Furthermore, well-designed EMS have been shown to significantly extend the battery's useful life by maintaining optimal state-of-charge trajectories [18,19].

The main technical challenge for FCEVs is fuel cell degradation caused by dynamic load transients [20,21]. Advanced research has characterized the impact of these fluctuations on the electrochemical surface area and catalyst stability [22,23]. Therefore, sophisticated Energy Management Strategies (EMS) are required to "smooth" the fuel cell's power output.

To explore these strategies, the use of Digital Twins has become a fundamental tool, allowing for Hardware-in-the-Loop (HIL) testing [24,25]. Recent systematic approaches in EMS design highlight the importance of utilizing kinetic energy data and robust drive control to enhance overall system efficiency [26].

Current literature has explored various EMS, from deterministic rules to advanced predictive frameworks [27]. For instance, optimized strategies using machine learning have shown potential in predicting power demands and reducing hydrogen consumption [28].

Additionally, adaptive super-twisting sliding mode control provides robust torque optimization [29]. Despite these advances, there is a need for studies that validate these models using real-world telemetry data [30].

In this context, the developed digital is proposed as a framework for evaluating energy management strategies. This framework provides a digital shadow capable of predicting the energy feasibility of a route based on two critical thresholds: the minimum battery state of charge (SOC) and the hydrogen tank level.

By identifying these limits, the model supports the analysis of hybrid system operating conditions. Since the route profile is a fixed constraint, the digital twin allows for the prospective adjustment of operational variables, such as vehicle speed, to ensure trip viability without compromising the system's lifetime.

This paper presents the necessary base for a Digital Twin for a heavy-duty truck. By using real telemetry data from diesel routes, this study evaluates four EMS under deterministic and rule-based conditions, focusing on reducing transients to extend the fuel cell's lifetime while maintaining battery health and hydrogen efficiency.

The modular structure of the model allows its adaptation to different routes and operating conditions, facilitating the generation of energy-sustainable speed profiles in real-world scenarios characterized by operational variability.

2 Digital Twin Framework and Baseline Definition

The development of a high-fidelity Digital Twin requires the integration of high-resolution, real-world data. The methodology presented in this study begins by replicating the operational parameters of a physical asset, which are subsequently used to validate the virtual model (Fig. 1).

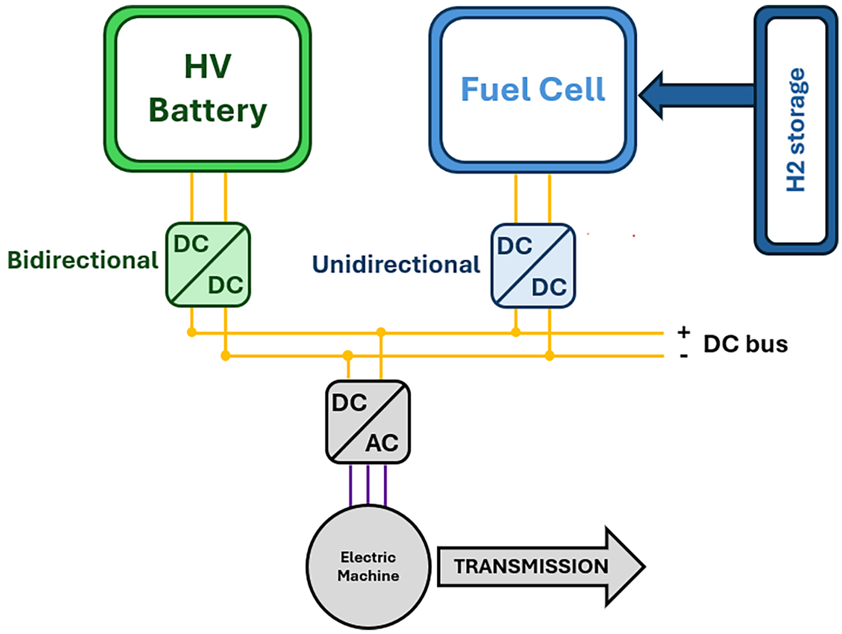

Figure 1: Hybrid powertrain operational layout, combining the fuel cell system and the battery pack.

2.1 Selected Route Description and Diesel Vehicle Specifications

The route is a critical factor in heavy-duty vehicle analysis, as it directly dictates energy consumption and autonomy requirements. To ensure a representative evaluation, the selected route must encompass a diverse range of topographic conditions, including flat segments, steep ascents, and prolonged descents.

The primary testbed for this model is a 380 km corridor connecting El Burgo de Ebro (Zaragoza) and Silla (Valencia), primarily following the A-23 highway, a key segment of the European E-7 'Red E Road' network. The elevation profile (Fig. 2) reveals a challenging terrain for a 40-t vehicle, with altitudes ranging from 1221 m in the province of Teruel to 10 m above sea level at the Mediterranean destination.

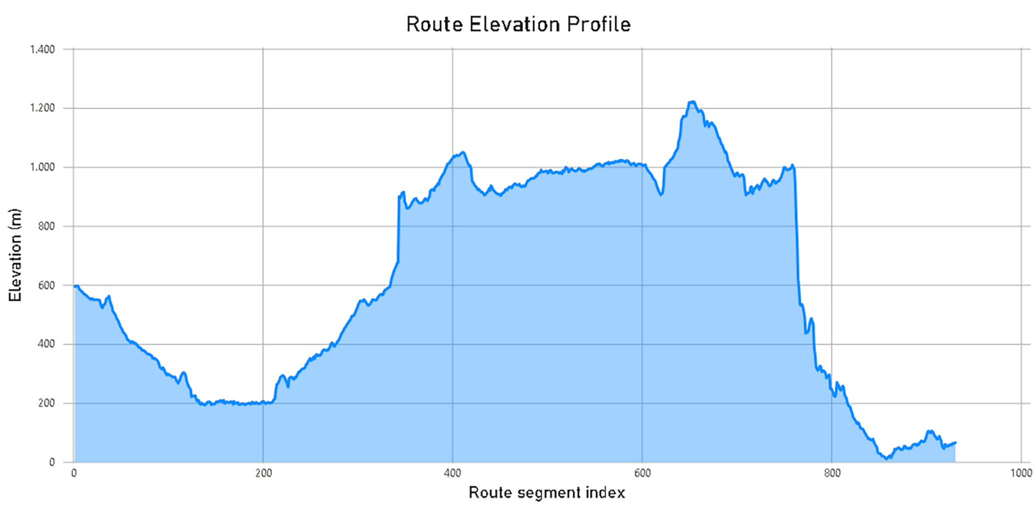

Figure 2: Route elevation profile, where the "Route segment index" represents the sequential discrete path intervals used to analyze elevation changes throughout the route.

As illustrated in the gradient analysis (Fig. 3), the route features significant slope variations, with maximum positive gradients of +4.46% and peak negative gradients of −4.96%, providing a robust scenario for testing both traction demand and regenerative braking capacity.

Figure 3: Slope in each route segment, where the "Route segment index" represents the sequential discrete path intervals used to analyze elevation changes throughout the route.

Following the route definition, a conventional diesel-powered heavy-duty truck was selected to serve as the baseline for the digital model. The reference vehicle is a Scania R450, powered by a 13-L six-cylinder in-line engine delivering 450 hp (331 kW) at 1900 rpm. These mechanical characteristics, combined with a total fuel capacity of 1250 L (800 and 450 L dual-tank configuration), define the operational capabilities used to characterize the original powertrain in the virtual environment.

To avoid information overload and ensure computational efficiency, the data extraction from the vehicle's Electronic Control Unit (ECU) was strategically limited to six essential parameters.

1. Altitude and Speed: To assess the impact of topographical changes and driving dynamics on energy demand.
2. Odometer and Payload Sensor: To accurately calculate the instantaneous work required based on the transported mass and distance.
3. Fuel Tank Level and Engine RPM: To establish a rigorous fuel consumption baseline and synchronize the angular velocity of the original engine with the equivalent electric traction motor.

2.2 Modeling of Resistive Forces for Heavy-Duty Dynamics

To determine the instantaneous power demand that the hybrid powertrain must deliver, the Digital Twin resolves the balance of forces opposing the vehicle's motion at each time step (Δt). The total resistive force (F_{total}) is decomposed into four fundamental vectors:

2.2.1 Rolling Resistance (F_{roll})

Rolling resistance arises from tire hysteresis and road surface deformation. In heavy-duty vehicles, this factor is critical due to the high vertical load on the axles. It is calculated as follows Eq. (1):

$$F_{roll} = C_{rr} \cdot m \cdot g \cdot \cos\alpha \tag{1}$$

where C_{rr} is the rolling resistance coefficient, calibrated for low-resistance truck tires on standard asphalt; m is the total vehicle mass (including payload); and α is the road inclination angle.

2.2.2 Aerodynamic Drag (F_{aero})

At cruising speeds (80–90 km/h), aerodynamic drag becomes a predominant energy consumer. To address concerns regarding wind influence, the model employs a relative velocity formulation Eq. (2):

$$F_{aero} = \frac{1}{2} \cdot \rho \cdot C_D \cdot (A \cdot C_S) \cdot (v + v_{wind})^2 \tag{2}$$

where:

- ρ: Air density, adjusted according to the route's altitude.
- C_D: Drag coefficient, specific to the Scania R450 profile.
- $A \cdot C_S$: Effective frontal area, where C_S is a surface correction factor for standard trailer configurations.
- $(v + v_{wind})$: Resulting relative velocity, considering both vehicle speed and frontal wind speed, allowing for the required sensitivity analysis.

2.2.3 Inertial Resistance (F_{iner})

Based on Newton's second law, this quantifies the force required to modify the vehicle's kinetic state during acceleration and braking Eq. (3):

$$F_{inercia} = a \cdot m \tag{3}$$

This force is crucial for the Digital Twin to determine the power peaks that the battery must either absorb (regeneration) or supply (fuel cell assistance).

2.2.4 Gradient Resistance (F_{grad})

Given the 40-t Mass of the Vehicle, the Gravitational Component on Slopes Is the Most Variable Factor of the Route. for "E-Road" Network Infrastructures (Such as the A-23), Where Gradients Are Strictly Regulated (Typically between 4% and 8%), a Small-Angle Approximation (Cos$\alpha \approx$ Tan$\alpha = \theta$) Is Applied Eq. (4):

$$F_{grad} = m \cdot g \cdot \theta \tag{4}$$

where θ is the dimensionless slope obtained from the altitude difference between telemetry points.

2.2.5 Total Resistive Force and Energy Demand

The resulting total force that the electric powertrain must overcome is the algebraic sum of the previous components Eq. (5):

$$F_{Total} = F_{roll} + F_{aero} + F_{iner} + F_{grad} \tag{5}$$

2.3 Powertrain Efficiency Analysis

To ensure the high fidelity of the Digital Twin, it is imperative to evaluate the powertrain's efficiency through a dynamic rather than a static lens. In this study, efficiency is defined as the system's capacity to transform input energy into useful mechanical work while minimizing losses from friction and thermal dissipation. To achieve this, critical components—including the electric motor, transmission, inverter, and battery pack—are modeled individually, assuming optimal Beginning-of-Life (BoL) operating conditions.

The core of the energy model lies in the bidirectional nature of power flow within the electric motor. It is essential to distinguish between two distinct operational regimes: traction efficiency (driving mode) (Fig. 4) and regeneration efficiency (generator mode) (Fig. 5).

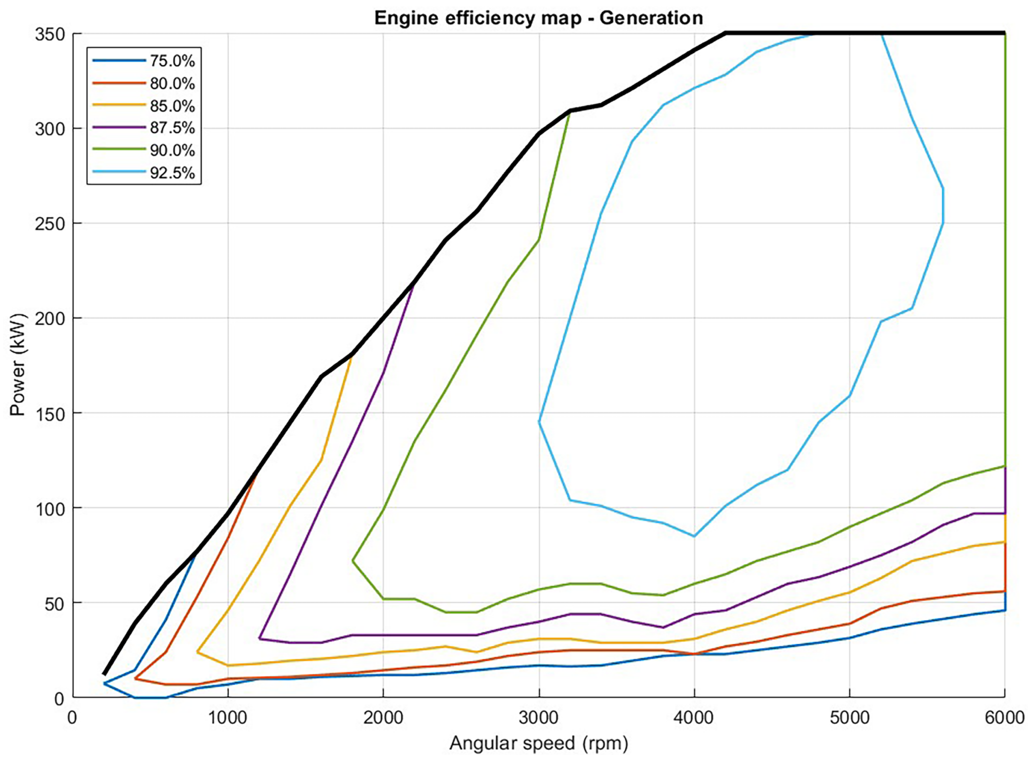

Figure 4: Engine efficiency map–traction scenario.

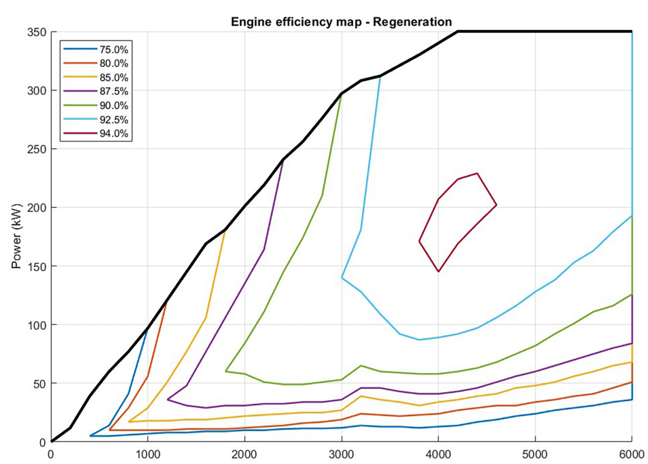

Figure 5: Engine efficiency map–regeneration scenario.

The efficiency maps utilized in this simulation are derived from an extensive experimental characterization phase. By conducting empirical evaluations and benchmarking several heavy-duty motor models under established laboratory conditions, a standardized 'generic motor' profile was established to represent current industrial performance standards.

2.4 Energy Balance and System Dynamics

Once the instantaneous traction power and the resistive forces acting on the vehicle are quantified using these laboratory-derived maps, the model determines the energy required to maintain the dynamic conditions of the route. The algorithm distinguishes two scenarios based on the sign of the total force applied to the truck:

1. Positive Force (Traction): The vehicle requires energy to overcome gradient, rolling, and aerodynamic resistance, as shown in Eq. (6):

$$E_{traction} = \frac{F_{Total} \cdot v}{\eta_{traction}} \cdot t \tag{6}$$

where $\eta_{traction}$ is the overall system efficiency derived from the dynamic maps.

2. Negative Force (Deceleration/Downhill): The electric motor operates in regenerative mode, enabling partial recovery of kinetic energy, as expressed in Eq. (7):

$$E_{regenerated} = \frac{F_{Total} \cdot v}{\eta_{traction}} \cdot \eta_{regen} \cdot t \tag{7}$$

where η_{regen} denotes the regeneration efficiency, considering that the battery can only absorb energy within its instantaneous charging limits.

This unified treatment of traction and regeneration enables an accurate representation of the battery's energy dynamics throughout the route.

As seen in the State of Charge (SOC) evolution (Fig. 6), it can be observed that the battery may start the route at a high level, discharge during segments with higher demand, and subsequently recover energy both through regenerative braking on downhill sections and by absorbing surplus energy supplied by the fuel cell.

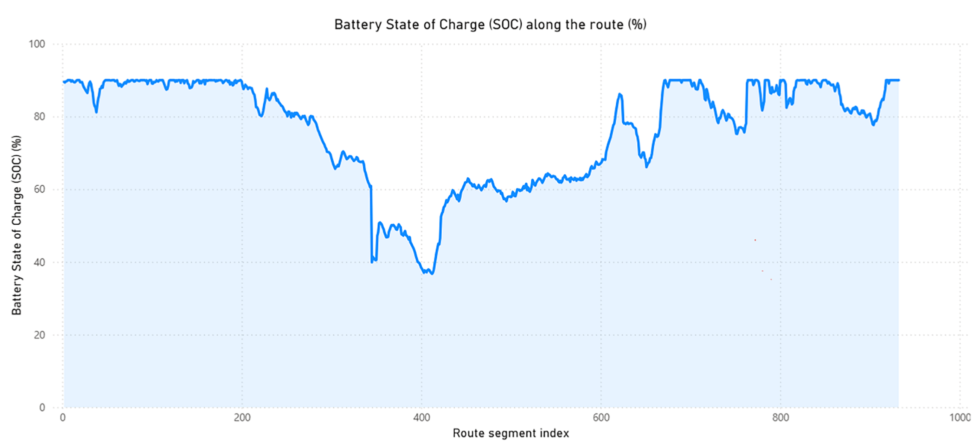

Figure 6: Battery State of Charge (SOC) evolution considering energy regeneration.

At each instant, the system applies an energy management strategy (EMS) that distributes the power demand between the battery and the fuel cell. Four main configurations are evaluated:

1. Use of the fuel cell as a primary traction energy source.
2. Operation of the fuel cell at a constant nominal power.
3. Dynamic adjustment of the fuel cell usage based on battery SOC.
4. Limitation of the fuel cell's response dynamics.

For each scenario, variables such as electric energy consumption, hydrogen consumption, overall efficiency, final SOC, and total dissipated energy are obtained. These results are subsequently analyzed through comparative assessments and multi-criteria evaluation of strategies.

The main objective is to determine which strategy provides the optimal balance between energy efficiency, range, and system durability.

3 Code Algorithmic Structure

The algorithm implemented in MATLAB follows a modular architecture comprising several distinct stages to ensure computational efficiency and scalability.

The execution flow begins with the ingestion of high-resolution telemetry data—including vehicle speed, altitude, payload, hydrogen tank level, and engine rotational speed—which serve as the primary boundary conditions for simulation.

These data originate from real-world tests and allow the representation of driving scenarios with varying slopes, loads, and energy demands. Based on these input signals, the model computes the instantaneous traction power required, integrating the resistive forces (slope, rolling resistance, and aerodynamic drag) and efficiency maps previously defined.

At the core of the execution, the algorithm evaluates the instantaneous State of Charge (SOC) and the available hydrogen at each sampling interval. The power split between energy sources is managed through a hybrid control framework that combines deterministic rules with a qualitative interpretation of fuzzy logic. In this approach, "if-then" heuristics operate as a preliminary interference engine, where decisions depend on continuous variables and vary according to the selected Energy Management Strategy (EMS). Typical operational rules include:

- High Demand Phase: If power demand is high and SOC is below the operational threshold, the fuel cell acts as the primary power source to maintain system balance.
- Energy Recovery & Replenishment: If power demand is low and stored energy is high, the fuel cell operates within its optimal efficiency range to replenish battery reserves, simulating a flexible threshold approach.

The model iteratively quantifies subsystem efficiencies, hydrogen consumption rates, and thermal losses for each interval. Finally, the system exports the processed datasets for post-processing and multi-criteria validation.

This modular architecture allows the modification of control thresholds or strategies without altering the core kernel of the model. By establishing this hybrid logic, the digital twin provides a robust baseline that facilitates the future transition toward fully formalized fuzzy logic controllers and advanced optimization techniques in subsequent research phases.

4 Energy Management Strategy

The model's decision-making process is based on the systematic evaluation of the energy required to maintain the dynamic conditions of the route in relation to the power availability of the fuel cell at any given operational point.

The three input variables of the model (speed, slope, and traveled distance) exhibit continuous and variable behavior. To manage these fluctuations, the control algorithm categorizes the route conditions into discrete operational regimes through a deterministic threshold-based approach, ensuring smooth transitions between speed-dependent regimes, topographical profiles, and power demand levels.

To determine the necessary power and energy levels within these regimes, the model utilizes a hybrid approach. This method combines fixed qualitative parameters with variable factors that do not have a strictly predefined set point.

These operational parameters and technical constraints were established through a dedicated experimental phase. By testing various fuel cell models under controlled laboratory conditions, a set of representative values was synthesized to define a standardized "base-type" fuel cell, allowing the simulation to represent representative operating limits of currently available fuel cell systems.

- Operating Range: The fuel cell is restricted from operating below 25 kW under nominal conditions to prevent efficiency losses, with a maximum instantaneous power capped at 85 kW.
- Dynamic Limits: To ensure system longevity, power variation is strictly limited to a maximum rate of 30 kW/s.
- Thermal & Lifecycle Protocols: A specific cold-start protocol requires a steady 15 kW for one minute. Additionally, as a degradation-aware constraint, the maximum power is reduced to 70 kW in advanced lifecycle stages.

Based on this empirical foundation, the model currently operates using deterministic logic, where specific route conditions trigger the pre-defined modes mentioned above to split the energy between power sources.

However, this structure is viewed as a preliminary step. For the subsequent control phase, implementing formal fuzzy logic controllers could provide greater adaptability under variable driving conditions than remaining with strictly fixed rules, as it would allow the system to adapt more fluidly to real-world driving variability.

In this regard, the current relationship to fuzzy decision-making is more of an interpretation than a formal methodological contribution, serving as a preliminary basis for future developments.

Before analyzing the dynamic response of the fuel cell to the route's requirements, a key indicator is defined to evaluate its operational performance: the utilization ratio.

This ratio serves as a quantitative measure of the alignment between the power actually required by the vehicle at each instant and the power the fuel cell is capable of delivering within its predefined constraints. It is important to clarify that this metric does not reflect the electrochemical or thermodynamic efficiency of the system; instead, it characterizes the adequacy of energy generation relative to instantaneous demand, expressed as a percentage.

The determination of this ratio follows a bifurcated logic depending on the relationship between demand and generation:

- Scenario A: Optimal or Surplus Supply. If the fuel cell generates power equal to or greater than the vehicle's requirement, the ratio is calculated as the quotient of the power demanded divided by the power generated. This yields values equal to or below 100%, indicating the extent to which the fuel cell's current output is being effectively utilized by the traction system.

- Scenario B: Insufficient Generation. If the power demand exceeds the maximum power generated by the fuel cell due to its operational limits, the relationship is inverted. In this case, the ratio is computed as the quotient of the power generated divided by the power demanded. The resulting value below 100% quantifies the degree of power insufficiency, directly representing the fraction of the load that must be compensated by the battery pack to ensure route viability.

Based on these conditions, the logical relationships implemented in the code can be formulated as rules of the following type:

1. Power demand below the fuel cell's minimum threshold

   If power demand is low and the slope is descending or flat, then the fuel cell operates at its minimum (25 kW), and the energy generated exceeds the required amount.
   Utilization ratio < 100%

2. Power demand equal to generated power

   If speed and slope require power close to the fuel cell's nominal operating range, then generation matches demand.
   Utilization ratio = 100%

3. Power demand is lower than the generated power

   If the slope increases slightly or the speed is moderate, and the fuel cell operates above its minimum constraints, then energy generation exceeds demand.
   Utilization ratio < 100%

4. Power demand greater than generated power

   If the slope is steep or the required speed is high, demand may exceed the power the fuel cell can deliver without violating its operational limits.
   Utilization ratio < 100%

With all these conditions defined, a graph is generated to reflect the actual behavior of the fuel cell (Fig. 7). The visualization allows identifying the utilization ratio values as a function of generated and demanded power at each moment.

Although the algorithm is implemented through deterministic logical structures in MATLAB, these rules are designed to effectively manage the continuous and non-linear fluctuations of the input variables. By avoiding discrete or simplistic transitions, the system ensures operational stability across the entire mission profile.

Consequently, this energy management framework is modeled as a robust rule-based system, where the interplay between energy demand, available power, and the inherent physical constraints of the fuel cell results in non-linear response characteristic. This approach allows the digital twin to simulate progressive and non-linear power distributions, accurately reflecting the complex coupling between the hybrid energy sources and the route's requirements.

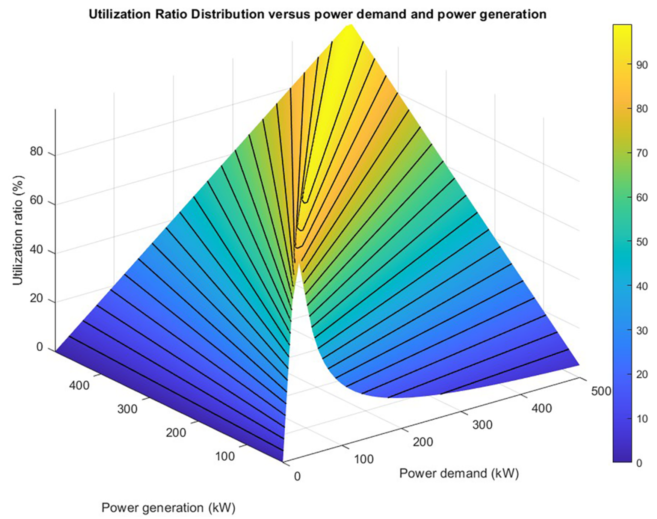

Figure 7: Utilization ratio distribution vs. power demand and power generation.

5 Methodology and Structure of the Simulation Model

The proposed model has been fully implemented in MATLAB, leveraging its capabilities for vectorized computation, efficient handling of large datasheets, and graphical representation of results.

The code structure follows a methodological sequence designed to realistically reproduce the energy behavior of the hybrid truck along each route segment (Fig. 8).

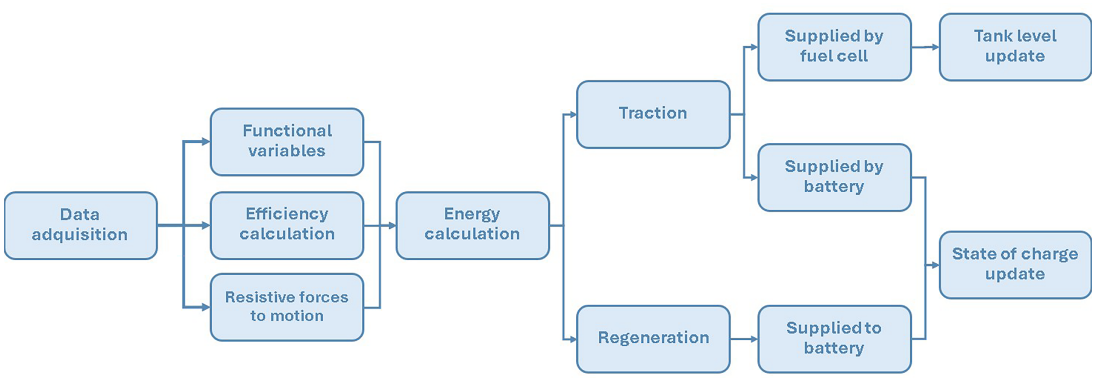

Figure 8: Simulation model structure.

The computational workflow followed by the model in each case is described below:

1. Data acquisition

The code begins by reading external files containing route conditions: speed, traveled distance, and slope.

2. Calculation: functional variables, efficiency, and resistive forces

For each time step, the forces acting on the vehicle are determined: aerodynamic drag, rolling resistance, and the gravitational component associated with the slope. Simultaneously, traction and regeneration efficiencies are computed, which condition the usable or recoverable energy.

3. Energy calculation

Based on dynamic parameters, the model calculates the energy required to maintain speed or the energy recovered during braking or downhill segments. This stage determines whether the vehicle is in energy demand mode (traction) or regenerative mode.

4. Traction

When the required energy is positive, the system decides how to meet the demand: the fuel cell may act as the primary source within its operational limits, or the battery must supply additional energy.

5. Regeneration

In this case, the system calculates the energy that can be recovered and sent back to the battery. This value is limited by regeneration efficiency and the battery's absorption capacity.

6. Tank level and State of Charge update

After each cycle, the model updates the hydrogen level consumed by the fuel cell and the battery's state of charge (SOC).

6 Results

6.1 Model Validation

Prior to the evaluation of the energy management strategies, a validation of the Digital Twin's physical consistency was performed by benchmarking its results against real-world diesel powertrain performance. The model determines that the theoretical ideal energy required to overcome the resistive forces of the analyzed route (ignoring powertrain losses) is 614 kWh.

Telemetry data from a conventional heavy-duty diesel truck completing the same mission shows a total energy consumption of 1400 kWh. This comparison results in an overall powertrain efficiency of approximately 44%. This value serves as a robust validation of the model, as it aligns with current high-efficiency standards for modern Euro VI heavy-duty engines.

Recent research on advanced internal combustion engines indicates that while peak brake thermal efficiencies (BTE) can reach up to 50% in controlled environments, average operational efficiencies typically range between 40% and 45% in real-world long-haul logistics [4]. This consistency confirms that the resistive force modeling and the energy demand calculations of the Digital Twin provide a reliable baseline for the subsequent hybrid powertrain analysis.

6.2 Energy Management Strategies Evaluation

Four strategies for power distribution between the fuel cell and the battery were evaluated to analyze how different control criteria influence performance. Each strategy modifies how the fuel cell responds to variations in input parameters, enabling comparison under a deterministic decision-making rule-based framework.

6.2.1 Dynamic Power Strategy

In this strategy, the fuel cell operates as the main source and adjusts its power within a range, reaching up to 90% of the maximum allowed. The battery only intervenes during demand peaks or when the required power exceeds the fuel cell's instantaneous capacity.

Simulations show flexible operation but also a pattern of rapid oscillations in generated power, which increases dynamic stress on the fuel cell (Fig. 9).

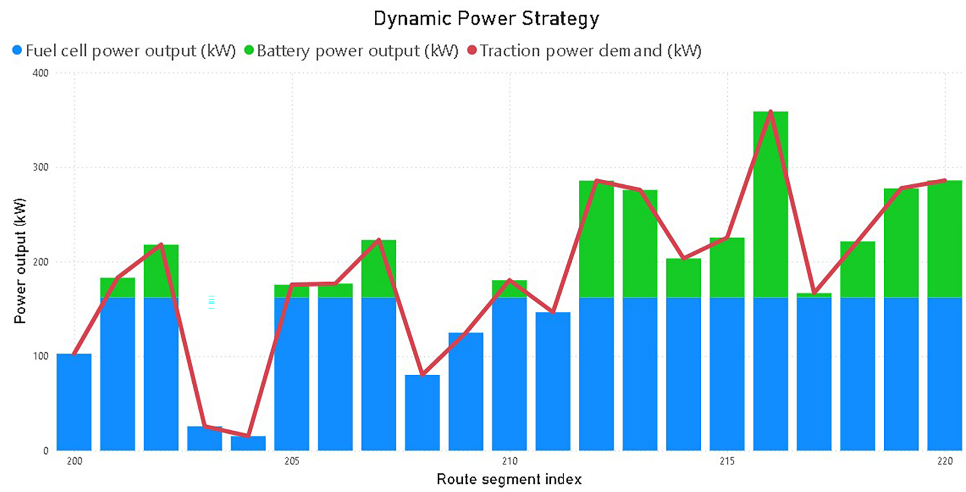

Figure 9: Dynamic power strategy: power output scope (kW).

6.2.2 Fixed Power Strategy

In this case, the fuel cell operates at an almost constant value of 85% of its nominal power, minimizing power fluctuations.

The battery covers demand peaks and absorbs surplus energy when the system requires less power than generated.

This approach reduces the number of oscillations (Fig. 10) but results in a significant amount of unused energy, as the fuel cell continues producing even when demand is low (Fig. 11).

6.2.3 Interval-Based Power Strategy

The power supplied by the fuel cell depends directly on the battery's state of charge (SOC), applying ranges (lower and upper thresholds) that define when to increase or reduce the fuel cell's contribution (Table 1).

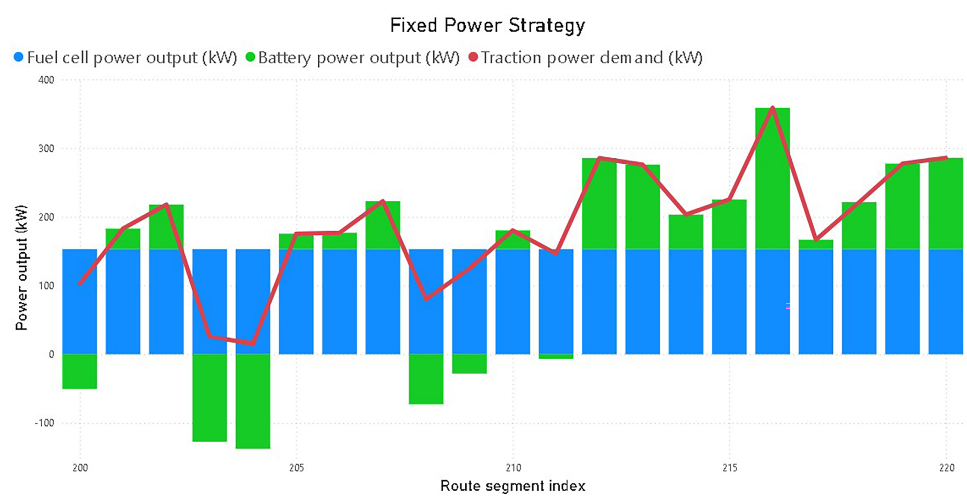

Figure 10: Fixed power strategy: power output scope (kW).

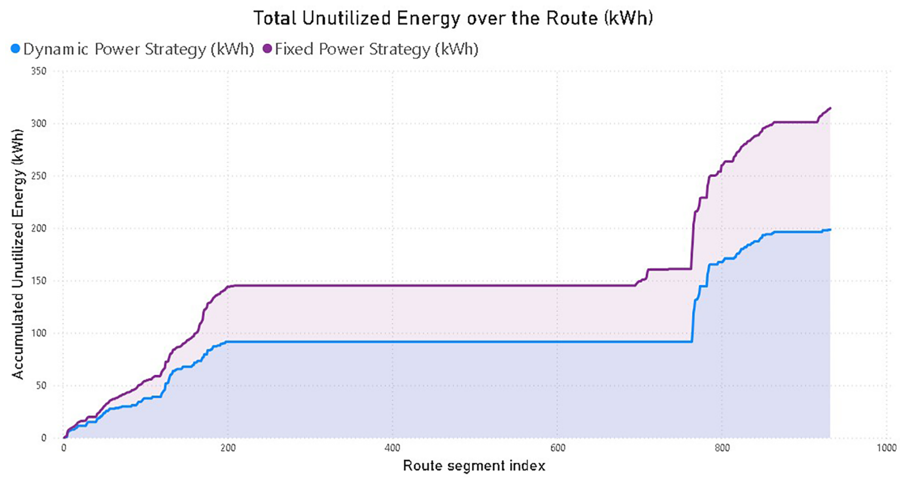

Figure 11: Total unutilized energy over the route comparison (Dynamic power vs. Fixed power strategy).

Table 1: Fuel cell nominal power rate vs. battery state of charge (SOC).

Battery State of Charge (SOC) (%)	Fuel Cell Nominal Power Rate (%)
Above 80%	84%
70%–80%	86%
60%–70%	88%
Below 60%	90%

This mechanism prevents excessive oscillations, as the fuel cell does not react to every minor variation in demand but only when SOC crosses a significant threshold. The result is a more stable operation (Fig. 12), achieving a better balance between consumed and stored energy.

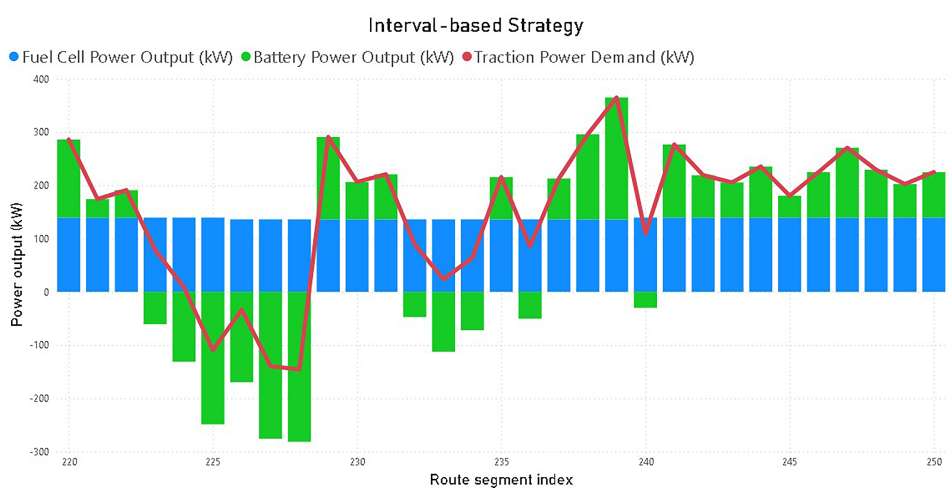

Figure 12: Interval-based strategy: power output scope (kW).

6.2.4 Variation Rate Strategy

This strategy introduces a limit on the rate at which the fuel cell can increase or decrease power, simulating a real ramp-based control.

Different rate values were tested (from 5 to 0.1 kW/s), showing a significant smoothing of the power profile (Table 2). The results indicate that a rate of 0.3 kW/s provides the best balance between hydrogen consumption, minimum battery SOC, and energy efficiency.

Table 2: Indicator values obtained in the simulation.

Variation Rate (kW/s)	Tank Load (%)	Minimum Battery SOC (%)	Unutilized Energy (kWh)
5	53.8	27.7	122.5
3	54.3	28.9	125.6
1	55.0	30.1	130.2
0.8	55.2	30.6	134.3
0.5	55.4	30.0	141.0
0.4	55.4	30.3	141.8
0.3	55.2	36.7	144.4
0.2	55.5	32.0	144.7
0.1	57.3	12.1	150.7

The fuel cell operates more progressively, reducing internal stress and better adapting to typical behaviors of real systems. This strategy produces the most stable operating profile, consistent with the manufacturer's specified lifetime.

6.3 Key Indicators Comparison

To objectively evaluate each strategy, three fundamental indicators were analyzed: hydrogen consumption, minimum battery SOC, and unutilized energy.

6.3.1 Hydrogen Consumption

The results show significant differences among strategies, see Fig. 13 and Table 3.

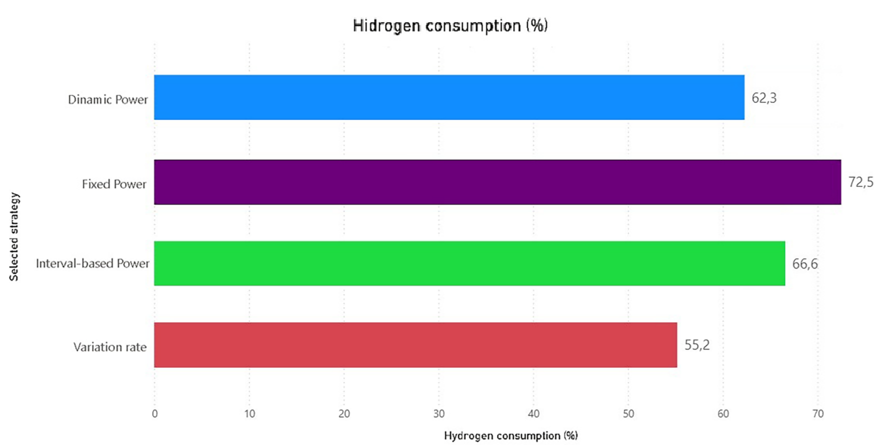

Figure 13: Hydrogen consumption comparison.

Table 3: Strategy comparison.

Analyzed Parameter	Dynamic Power	Fixed Power	Interval-Based Power	Variation Rate
Remaining fuel percentage in the tank at the end of the route (%)	37.7	27.5	33.4	44.8

- The Fixed Power strategy shows the lowest remaining hydrogen percentage (27.5%) because the fuel cell operates constantly, even during low-demand segments.
- The Variation Rate strategy achieves the highest percentage (44.8%), indicating more efficient hydrogen use, as the fuel cell operates only when necessary and with a controlled profile.

This behavior is consistent with a rule-based decision-making system, leading to stabilized operating conditions and reduced fuel consumption.

6.3.2 Minimum Battery State of Charge (SOC)

The minimum SOC reached provides an indicator of the battery's operational safety, see Fig. 14 and Table 4.

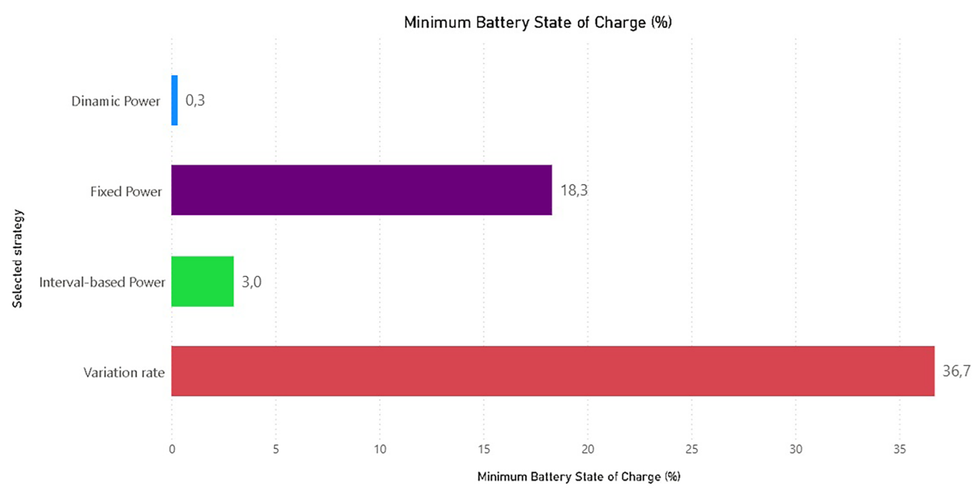

Figure 14: Minimum battery State of Charge (SOC) comparison.

Table 4: Strategy comparison.

Analyzed Parameter	Dynamic Power	Fixed Power	Interval-Based Power	Variation Rate
Minimum battery SOC at the end of the route (%)	0.3	18.3	3.0	36.7

- Dynamic Power: Minimum SOC of only 0.3%, indicating highly intensive and potentially harmful battery usage.
- Variation Rate: Minimum SOC of 36.7%, ensuring the battery never reaches dangerously low states.

This demonstrates that stability in fuel cell response reduces the need for battery support, avoiding deep discharge cycles.

6.3.3 Unutilized Energy

The energy generated by the fuel cell but not utilized shows clear contrasts among strategies, see Fig. 15 and Table 5.

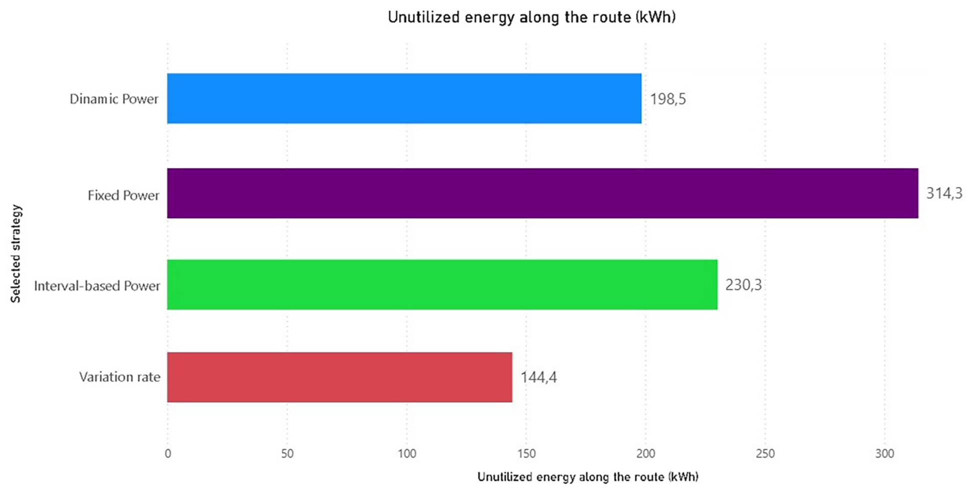

Figure 15: Unutilized energy comparison.

Table 5: Strategy comparison.

Analyzed Parameter	Dynamic Power	Fixed Power	Interval-Based Power	Variation Rate
Unutilized energy along the route (kWh)	198.5	314.3	230.3	144.4

- The Fixed Power strategy is the least efficient, with 314.3 kWh of unused energy.
- The Variation Rate strategy reduces this figure to nearly half (144.4 kWh).

This reinforces the idea that smooth and gradual control improves the utilization of generated energy.

6.3.4 Power Variations and Fuel Cell Lifetime

The durability of a fuel cell is strongly influenced by both the frequency and magnitude of the power variations it experiences during operation [20,21].

As established during the dedicated experimental phase previously discussed, the operational parameters and technical constraints of the standardized "base-type" fuel cell were synthesized from empirical laboratory data. This foundational characterization ensures that the model reflects the average performance limits of current industrial technology.

Consistent with these, the deterministic control logic ensures that power ramps remain strictly below thresholds on the order of 30 kW/s. This constraint is implemented as a hard rule within the system to prevent accelerated degradation phenomena. Consequently, the energy management strategy is designed to actively limit sharp power peaks, maintaining the fuel cell's operation well below this critical limit to prioritize system longevity and operational stability.

In the case of the variation rate strategy, power variations were kept below 0.3 kW/s, resulting in a significant reduction in the severity of transients compared to the other strategies analyzed.

Although this approach leads to a higher number of power adjustments, their low magnitude reduces the electrochemical and thermal stress on the fuel cell.

From a durability perspective, this behavior is more favorable, as it prioritizes smooth transitions over abrupt power changes.

6.4 Comparison with a Conventional Diesel Powertrain

In order to contextualize the obtained results, a comparison is made between the performance of the analyzed hybrid system and that of an equivalent diesel powertrain, both evaluated under the same route and operating conditions, see Fig. 16.

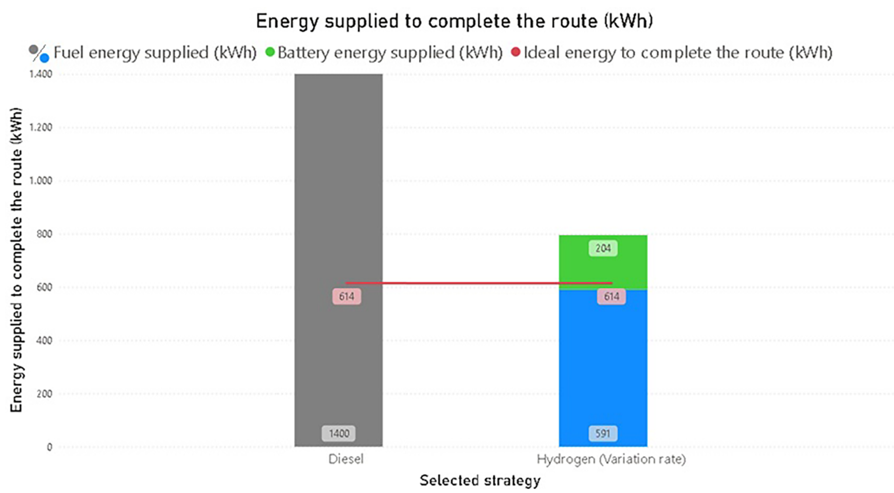

Figure 16: Energy supplied to complete the route comparison (Diesel vs. Hydrogen + Battery).

It is important to emphasize that this comparative assessment is intended strictly for contextualization and model validation purposes. Consequently, the analysis does not delve deeply into the internal combustion engine's characteristics, as the primary objective of this work is to evaluate the energy management strategies (EMS) and power distribution logic within the proposed hydrogen-electric propulsion system.

The estimated energy efficiencies of both systems reveal differences mainly associated with the powertrain architecture.

- Diesel powertrain: 44% energy efficiency
- Hydrogen-based powertrain: 77% energy efficiency

The results obtained by the digital twin show an energy saving of approximately 44% compared to the diesel baseline (Fig. 15). These values are highly consistent with recent empirical studies in the field of sustainable logistics. Specifically, research on heavy-duty logistics vehicles has reported energy consumption reductions of 46.91% for fuel cell systems and 47.22% for pure electric configurations when compared to diesel counterparts [31].

The slight difference between these literature values and the 44% saving predicted by the current model can be attributed to the specific hybrid architecture and the restrictive operational constraints imposed on the fuel cell to ensure durability. This alignment with external data serves as a preliminary validation of the model's ability to realistically simulate the energy benefits of hydrogen-electric hybridization.

The hybrid system based on a fuel cell and battery benefits from its ability to recover energy during braking or downhill phases, to modulate instantaneous power demand through battery support, and to reduce internal losses by allowing each subsystem to operate within more favorable ranges.

As a result of these characteristics, the energy supplied by the fuel cell using hydrogen as a fuel can fall below the theoretical minimum energy required to complete the route when considering a system without intermediate storage.

This is enabled by the presence of the battery pack and the operational flexibility it provides, allowing more efficient use of the available energy throughout the journey.

7 Sensitivity Analysis

The sensitivity analysis was conducted to evaluate the robustness of the model against variations in two external parameters directly related to operational uncertainty: total vehicle mass and frontal wind speed.

These specific variables were selected because they introduce the highest degree of variability into the system and, crucially, are the parameters over which the operator has the least control. Their nature is inherently stochastic, as they depend on fluctuating environmental conditions and the specific requirements of the service provided, changing with every alternative route analyzed.

Both variables significantly modify the energy demand along the route, allowing for an assessment of the deterministic control system's response under non-nominal conditions. By evaluating these random operational factors, the results can be effectively extrapolated to a wider range of real-world scenarios, ensuring the reliability of the energy management strategy across diverse driving environments.

The indicators analyzed to quantify this impact were hydrogen consumption, minimum battery state of charge (SOC), and unutilized energy generated by the fuel cell.

7.1 Influence of Total Vehicle Mass Variation

Total vehicle mass is a key factor in energy performance, as it directly affects rolling resistance and the gravitational component on slopes. A range between 30,000 and 38,000 kg was evaluated, representative of typical freight transport configurations.

7.1.1 Hydrogen Consumption

Results show that hydrogen consumption exhibits moderate variation with increasing mass (Fig. 17). Although energy demand rises with weight, the fuel cell can absorb this increase without abrupt changes in its operation.

This behavior indicates that the system maintains stable performance under reasonable load increments, suggesting that hydrogen consumption is not the most sensitive parameter to changes in total mass.

7.1.2 Mimimum Battery State of Charge (SOC)

In contrast, minimum SOC shows a significantly more pronounced trend: the higher the mass, the deeper the SOC drops (Fig. 18).

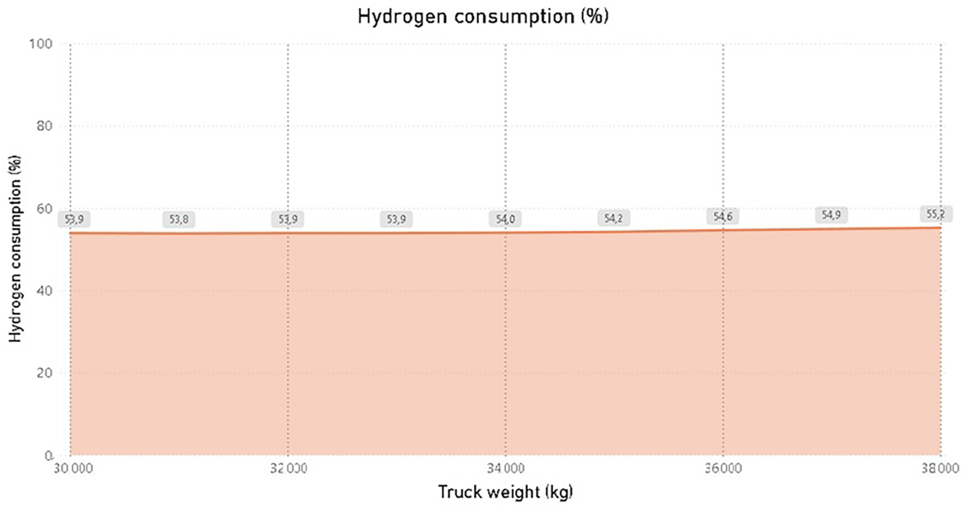

Figure 17: Hydrogen consumption relative to the vehicle's total weight.

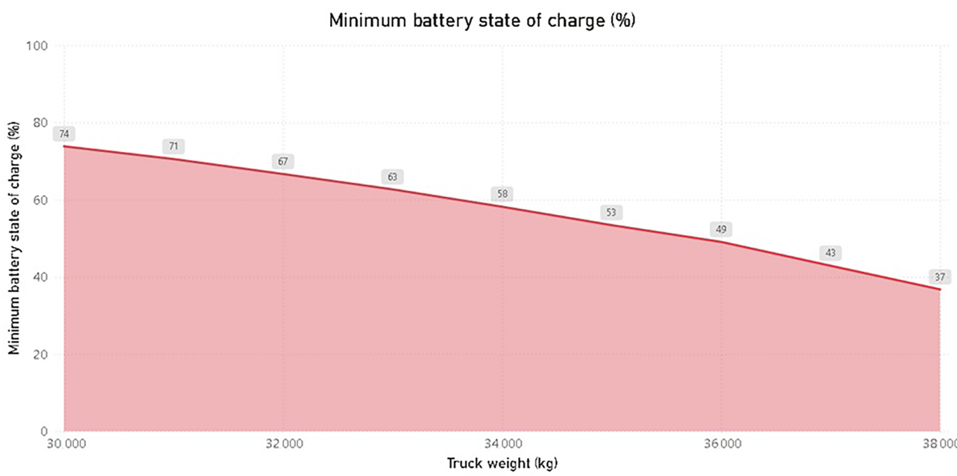

Figure 18: Minimum battery State of Charge (SOC) relative to the vehicle's total weight.

This occurs because an increase in mass generates more frequent and higher demand peaks, forcing the battery to intervene more intensively to complement the fuel cell when required power exceeds its instantaneous capacity.

From an operational robustness perspective, this result highlights mass as a critical parameter in energy management, as it directly influences discharge depth and, therefore, the lifetime of the storage system.

7.1.3 Unutilized Energy

Unutilized energy generated by the fuel cell shows a non-linear behavior, with a minimum around 36,000 kg (Fig. 19).

This point can be interpreted as an optimal operational balance zone, where the fuel cell's generated power reaches a maximum alignment with the vehicle's actual demand, minimizing energy surplus.

Below this value, the system tends to generate more energy than needed. Above it, demand becomes so high that surpluses nearly disappear, though at the cost of greater stress on the battery.

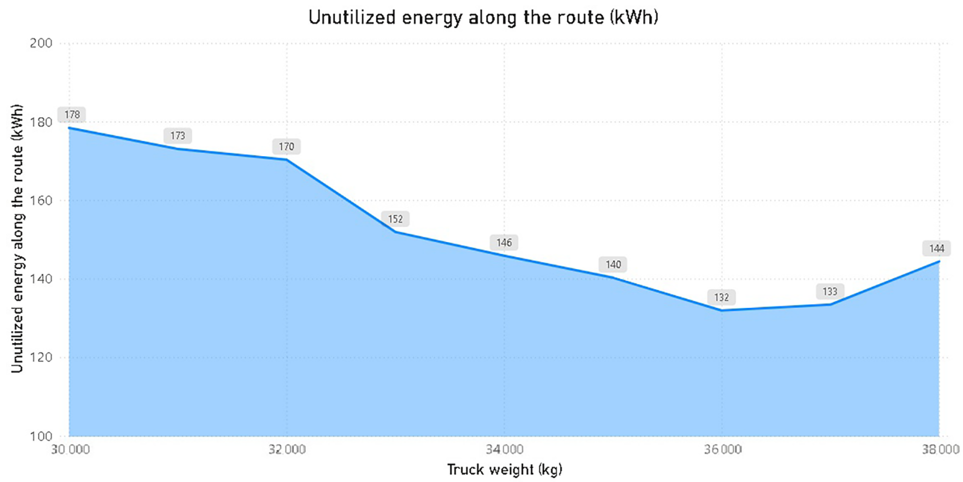

Figure 19: Unutilized energy along the route relative to the vehicle's total weight.

This behavior evidences that mass introduces compensatory effects between energy utilization and electrical system wear.

7.2 Influence of Frontal Wind Speed

Frontal wind speed was analyzed in a range from −5 to +5 m/s, representing sustained tailwind to headwind throughout the route. This parameter directly affects aerodynamic resistance and, consequently, the power required to maintain vehicle speed.

7.2.1 Hydrogen Consumption

Results show high sensitivity of hydrogen consumption to frontal wind (Fig. 20).

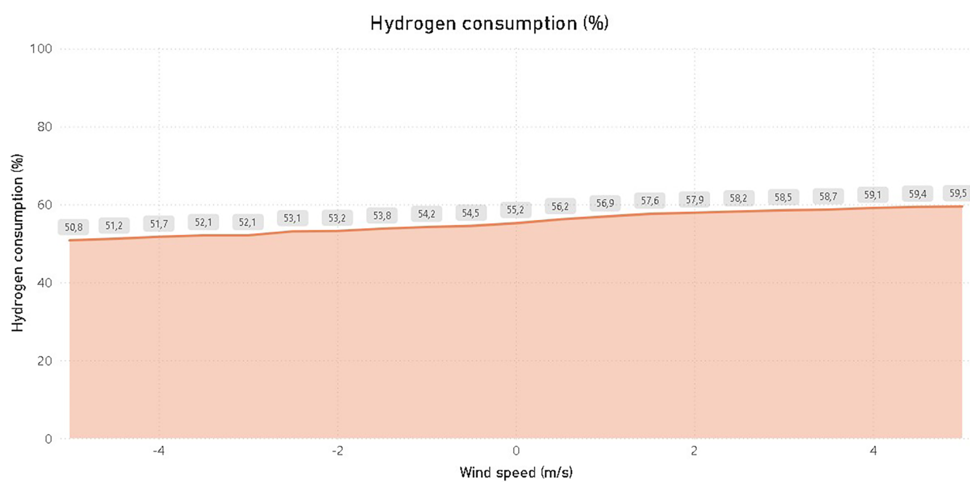

Figure 20: Hydrogen consumption relative to frontal wind speed.

For values near +5 m/s, consumption can increase by approximately 9%, demonstrating that headwind is a highly relevant factor for industrial vehicles due to its direct influence on aerodynamic resistance.

7.2.2 Minimum Battery State of Charge (SOC)

Minimum SOC exhibits a sharp downward trend as headwind increases (Fig. 21).

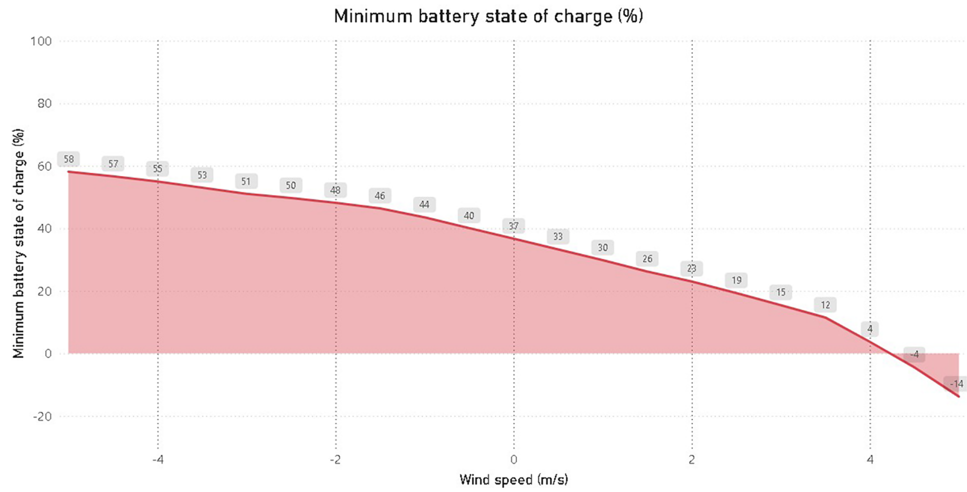

Figure 21: Minimum battery State of Charge (SOC) relative to frontal wind speed.

For speeds above 4 m/s, the system may completely deplete the battery, indicating that instantaneous demand repeatedly exceeds the fuel cell's capacity.

This behavior reveals that frontal wind can push the system outside its safe operating zone, affecting stability and autonomy.

7.2.3 Unutilized Energy

Unutilized energy decreases progressively with increasing headwind (Fig. 22).

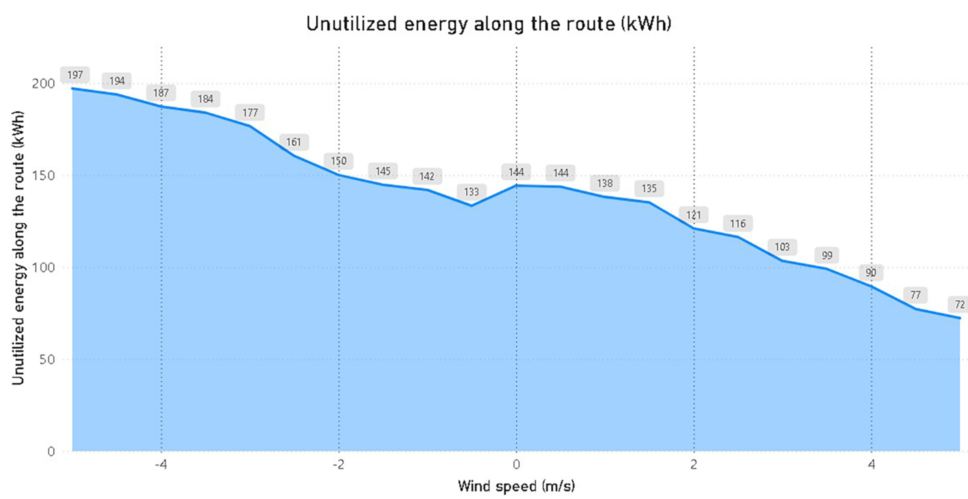

Figure 22: Unutilized energy along the route relative to frontal wind speed.

This result can be explained by the fact that higher demand reduces the likelihood of the fuel cell generating surplus energy compared to what is required.

7.3 Synthesis of the Analysis

The results obtained indicate that:

- Total vehicle mass mainly affects minimum SOC and energy balance, while its influence on hydrogen consumption is limited.
- Frontal wind has a significant impact on all three indicators, especially on consumption and SOC stability.
- Both parameters create more favorable and more demanding operating zones, allowing the identification of a continuum of operational states. Instead of a single critical threshold, the system exhibits gradual and deterministic transitions between optimal, stable, and high-demand conditions based on the specific parameter combinations.

8 Conclusions and Future Directions

This work presents a digital twin developed to analyze the energy behavior of a heavy-duty truck powered by a hybrid system based on a hydrogen fuel cell and a battery pack. Real driving data obtained from telemetry of conventional diesel trucks are used to represent realistic routes and driving conditions. Based on this foundational data, the model simulates the power and energy demand that would be required if the vehicle were equipped with a fuel cell–battery electric powertrain.

The digital twin includes the main physical and operational aspects of the system, such as vehicle dynamics, traction, and regenerative braking, and the most relevant operating constraints of the fuel cell. These constraints include power limits, power variation rates, startup conditions, and the effect of aging on the maximum available power. This allows evaluating different energy management strategies under conditions close to real operation, without the need to perform experimental tests with electric vehicles.

Several energy management strategies were analyzed and compared, revealing clear differences among them. Strategies that involve rapid power variations in the fuel cell lead to a very low battery state of charge and high battery usage. Such behavior can be detrimental to the battery and does not ensure stable operation. In contrast, strategies that limit the fuel cell power ramp rate result in smoother operation, a higher minimum battery state of charge, and reduced stress on the fuel cell.

From a decision-making perspective, the energy management problem addressed in this work is not limited to binary choices. Power demand and system states change continuously along the route. Therefore, the implemented strategy adopts a hybrid approach that combines deterministic control rules with qualitative interpretations based on fuzzy logic. This enables smooth transitions between operating modes, allowing gradual changes across different operating conditions by blending fixed technical constraints with flexible operational thresholds.

The sensitivity analysis indicates that vehicle mass and frontal wind speed have a strong impact on the minimum battery state of charge and hydrogen consumption. These parameters can drive the system toward more demanding operating conditions and must be taken into account when assessing the feasibility of a given route.

This feasibility is determined by two key indicators identified by the model: the minimum battery state of charge and the remaining hydrogen tank level. If any of these parameters reaches a critical value during the simulation, the route cannot be completed under the defined conditions.

In the current model, the main input variables are the route slope and the assigned vehicle speed for each segment. Since the slope is a fixed parameter associated with the real route, the only variable that can be modified is the vehicle speed.

This opens the possibility for future research to develop an automatic procedure based on full fuzzy logic controllers that progressively adjust the speed in selected route segments to ensure that neither the battery SOC nor the hydrogen tank level reaches critical values.

Moving beyond the current hybrid interpretation toward a formalized fuzzy inference system will enable these adjustments to avoid abrupt changes or extreme decisions, maintaining realistic driving conditions. In this context, adaptive and energy-sustainable speed profiles could be generated, suitable for real operating scenarios with high variability.

The combination of dynamic speed adjustment and the digital twin's ability to anticipate the energy behavior of a route provides the basis for future developments oriented toward assisted route optimization and planning, ensuring the energy viability of each trip.

Despite its benefits, certain limitations of the current study should be acknowledged. First, the digital twin operates under deterministic rule-based control and a qualitative interpretation of fuzzy logic rather than a fully dynamic optimization algorithm. Second, the model assumes stable Beginning-of-Life (BoL) conditions for components like the battery pack, without fully coupling real-time electrochemical degradation rates during the driving cycle. Finally, environmental factors such as ambient temperature, which affect fuel cell thermal management and efficiency, were kept constant. Addressing these boundary conditions will be essential to further enhance the model's predictive fidelity.

In summary, the developed digital twin is a useful framework to compare energy management strategies, reduce experimental testing, and support the design of hybrid systems. The model can be easily adapted to analyze other routes, operating conditions, or advanced non-deterministic control strategies.

As a natural continuation of this research, future developments will focus on the implementation of a formal fuzzy logic–based energy management controller. The current rule-based framework provides a validated baseline for defining membership functions, inference rules, and defuzzification strategies based on real operating data. This future approach is expected to improve system adaptability under uncertain driving conditions, allowing smoother transitions between operating modes and more flexible power distribution between the fuel cell and the battery.

Acknowledgement: Not applicable.

Funding Statement: The authors received no specific funding for this study.

Author Contributions: The authors confirm contribution to the paper as follows: Conceptualization, Antonio Gimeno and Emilio Larrodé; methodology, Antonio Gimeno and Emilio Larrodé; software, Antonio Gimeno and Emilio Larrodé; validation, Antonio Gimeno and Emilio Larrodé; formal analysis, Antonio Gimeno and Emilio Larrodé; investigation, Antonio Gimeno and Emilio Larrodé; resources, Antonio Gimeno and Emilio Larrodé; data curation, Antonio Gimeno and Emilio Larrodé; writing—original draft preparation, Antonio Gimeno and Emilio Larrodé; writing—review and editing, Antonio Gimeno and Emilio Larrodé; visualization, Antonio Gimeno and Emilio Larrodé; supervision, Antonio Gimeno and Emilio Larrodé; project administration, Antonio Gimeno and Emilio Larrodé; funding acquisition, Antonio Gimeno and Emilio Larrodé. All authors reviewed and approved the final version of the manuscript.

Availability of Data and Materials: Data not available due to commercial restrictions.

Ethics Approval: This study does not involve human participants, clinical trials, or animal subjects. The research is strictly based on computational modeling, vehicle dynamics simulation, and anonymized vehicle telemetry data.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Cunanan C, Tran MK, Lee Y, Kwok S, Leung V, Fowler M. A review of heavy-duty vehicle powertrain technologies: diesel engine vehicles, battery electric vehicles, and hydrogen fuel cell electric vehicles. Clean Technol. 2021;3(2):474–89. doi:10.3390/cleantechnol3020028.
2. European Parliament, Council of the European Union. Regulation (EU) 2023/851 of the European Parliament and of the Council of 19 April 2023 amending Regulation (EU) 2019/631 as regards strengthening the CO_2 emission performance standards for new passenger cars and new light commercial vehicles in line with the Union's increased climate ambition. Off J Eur Union. 2023;66(L 110):5–20.
3. Breed AK, Speth D, Plötz P. CO_2 fleet regulation and the future market diffusion of zero-emission trucks in Europe. Energy Policy. 2021;159:112640. doi:10.1016/j.enpol.2021.112640.
4. Reitz RD, Ogawa H, Payri R, Fansler T, Kokjohn S, Moriyoshi Y, et al. IJER editorial: the future of the internal combustion engine. Int J Engine Res. 2020;21(1):3–10. doi:10.1177/1468087419877990.
5. Müller C. Transition to battery-electric and fuel cell heavy-duty trucks: a multi-level, multi-dimensional approach. Transp Res Part D Transp Environ. 2024;127:104052. doi:10.1016/j.trd.2024.104052.
6. Verbruggen FJR, Hoekstra A, Hofman T. Evaluation of the state-of-the-art of full electric medium and heavy-duty trucks. In: Proceedings of the 31st International Electric Vehicle Symposium and Exhibition (EVS 31); 2018 Sep 30–Oct 3; Kobe, Japan.
7. Çabukoglu E, Georges G, Küng L, Pareschi G, Boulouchos K. Battery electric propulsion: an option for heavy-duty vehicles? Results from a Swiss case-study. Transp Res Part C Emerg Technol. 2018;88(5):107–23. doi:10.1016/j.trc.2018.01.013.
8. Pardhi S, Chakraborty S, Tran DD, El Baghdadi M, Wilkins S, Hegazy O. A review of fuel cell powertrains for long-haul heavy-duty vehicles: technology, hydrogen, energy and thermal management solutions. Energies. 2022;15(24):9557. doi:10.3390/en15249557.
9. Hu X, Han J, Tang X, Lin X. Powertrain design and control in electrified vehicles: a critical review. IEEE Trans Transp Electrif. 2021;7(3):1990–2009. doi:10.1109/TTE.2021.3056432.
10. Kasimalla VKR, Srinivasulu GN, Rahul JR, Velisala V. Optimal component sizing and performance of Fuel Cell-Battery powered vehicle over world harmonized and new european driving cycles. Energy Convers Manag. 2024;300(1):117992. doi:10.1016/j.enconman.2023.117992.
11. Das HS, Tan CW, Yatim AHM. Fuel cell hybrid electric vehicles: a review on power conditioning units and topologies. Renew Sustain Energy Rev. 2017;76:268–91. doi:10.1016/j.rser.2017.03.056.
12. Sulaiman N, Hannan MA, Mohamed A, Majlan EH, Wan Daud WR. A review on energy management system for fuel cell hybrid electric vehicle: issues and challenges. Renew Sustain Energy Rev. 2015;52(6):802–14. doi:10.1016/j.rser.2015.07.132.
13. Marzougui H, Amari M, Kadri A, Bacha F, Ghouili J. Energy management of fuel cell/battery/ultracapacitor in electrical hybrid vehicle. Int J Hydrogen Energy. 2017;42(13):8857–69. doi:10.1016/j.ijhydene.2016.09.190.
14. Mukherjee S, Chowdhury K. State of charge estimation techniques for battery management system used in electric vehicles: a review. Energy Syst. 2025;16(4):1521–64. doi:10.1007/s12667-023-00631-x.
15. Jawad NH, Yahya AA, Al-Shathr AR, Salih HG, Rashid KT, Al-Saadi S, et al. Fuel cell types, properties of membrane, and operating conditions: a review. Sustainability. 2022;14(21):14653. doi:10.3390/su142114653.
16. Inal OB, Zincir B, Deniz C. Investigation on the decarbonization of shipping: an approach to hydrogen and ammonia. Int J Hydrogen Energy. 2022;47(45):19888–900. doi:10.1016/j.ijhydene.2022.01.189.
17. Xiao F, Zhang L, Li G. Scenario-level hierarchical energy management control strategy for hybrid electric vehicles in mixed driving environments. Facta Univ Ser Mech Eng. 2025.
18. Tang L, Rizzoni G, Onori S. Energy management strategy for HEVs including battery life optimization. IEEE Trans Transp Electrif. 2015;1(3):211–22. doi:10.1109/TTE.2015.2471180.
19. Fang B, Li B, Li X, Jia Y, Xu W, Liao Y. Multi-objective comprehensive charging/discharging scheduling strategy for electric vehicles based on the improved particle swarm optimization algorithm. Front Energy Res. 2021;9:811964. doi:10.3389/fenrg.2021.811964.

20. Ferrara A, Jakubek S, Hametner C. Energy management of heavy-duty fuel cell vehicles in real-world driving scenarios: robust design of strategies to maximize the hydrogen economy and system lifetime. Energy Convers Manag. 2021;232(7):113795. doi:10.1016/j.enconman.2020.113795.
21. Mayur M, Gerard M, Schott P, Bessler WG. Lifetime prediction of a polymer electrolyte membrane fuel cell under automotive load cycling using a physically-based catalyst degradation model. Energies. 2018;11(8):2054. doi:10.3390/en11082054.
22. Pei P, Chen H. Main factors affecting the lifetime of Proton Exchange Membrane fuel cells in vehicle applications: a review. Appl Energy. 2014;125(C):60–75. doi:10.1016/j.apenergy.2014.03.048.
23. Li HW, Qiao BX, Hou ZC, Liu JN, Yang Y, Lu GL. An interpretable data-driven method for degradation prediction of proton exchange membrane fuel cells based on temporal fusion transformer and covariates. Int J Hydrogen Energy. 2023;48(66):25958–971. doi:10.1016/j.ijhydene.2023.03.316.
24. Dufour C, Soghomonian Z, Li W. Hardware-in-the-loop testing of modern on-board power systems using digital twins. In: Proceedings of the 2018 International Symposium on Power Electronics, Electrical Drives, Automation and Motion (SPEEDAM); 2018 Jun 20–22; Amalfi, Italy. doi:10.1109/SPEEDAM.2018.8445302.
25. Li X, Niu W, Tian H. Application of digital twin in electric vehicle powertrain: a review. World Electr Veh J. 2024;15(5):208. doi:10.3390/wevj15050208.
26. Benhammou A, Hartani MA, Tedjini H, Guettaf Y, Soumeur MA. Breaking new ground in HEV energy management: kinetic energy utilization and systematic EMS approaches based on robust drive control. ISA Trans. 2024;147:288–303. doi:10.1016/j.isatra.2024.01.037.
27. Daud WRW, Rosli RE, Majlan EH, Hamid SAA, Mohamed R, Husaini T. PEM fuel cell system control: a review. Renew Energy. 2017;113:620–38. doi:10.1016/j.renene.2017.06.027.
28. Cervone D, Sicilia M, Pandolfi A, Polverino P, Sementa P, Arsie I, et al. Machine learning based design of optimal energy management strategy for hydrogen-fueled hybrid vehicle powertrain. In: Proceedings of the Conference on Sustainable Mobility; 2024 Sep 18; Catania, Italy. doi:10.4271/2024-24-0001.
29. Venkatesh A, Kumar SP, Nizami TK. An adaptive super-twisting sliding mode control strategy for energy and torque optimisation in hydrogen fuel cell electric vehicles. IJMMNO. 2026;1(1):10073644. doi:10.1504/ijmmno.2026.10073644.
30. Sery J, Leduc P. Fuel cell behavior and energy balance on board a Hyundai Nexo. Int J Engine Res. 2022;23(5):709–20. doi:10.1177/14680874211059046.
31. Qian S, Li L. A comparison of well-to-wheels energy use and emissions of hydrogen fuel cell, electric, LNG, and diesel-powered logistics vehicles in China. Energies. 2023;16(13):5101. doi:10.3390/en16135101.