World Electric Vehicle Journal

MDPI

Article

Advancing Energy Management Strategies for Hybrid Fuel Cell Vehicles: A Comparative Study of Deterministic and Fuzzy Logic Approaches

Mohammed Essoufi [1], Mohammed Benzaouia [2], Bekkay Hajji [1], Abdelhamid Rabhi [3] and Michele Calì [4,*]

1 Laboratory of Energy, Embedded System and Information Processing, National School of Applied Sciences, Mohamed First University, 60000 Oujda, Morocco; m.essoufi@ump.ac.ma (M.E.); hajji.bekkay@gmail.com (B.H.)
2 UniLaSalle, UPJV, GeNumEr, URR 7511, 80000 Amiens, France; mohammed.benzaouia@unilasalle.fr
3 Modelization, Information and Systems Laboratory, Picardie Jules Verne University, 80000 Amiens, France; abdelhamid.rabhi@u-picardie.fr
4 Electric, Electronics and Computer Engineering Department, University of Catania, 95125 Catania, Italy
* Correspondence: michele.cali@unict.it

Abstract

The increasing depletion of fossil fuels and their environmental impact have led to the development of fuel cell hybrid electric vehicles. By combining fuel cells with batteries, these vehicles offer greater efficiency and zero emissions. However, their energy management remains a challenge requiring advanced strategies. This paper presents a comparative study of two developed energy management strategies: a deterministic rule-based approach and a fuzzy logic approach. The proposed system consists of a proton exchange membrane fuel cell (PEMFC) as the primary energy source and a lithium-ion battery as the secondary source. A comprehensive model of the hybrid powertrain is developed to evaluate energy distribution and system behaviour. The control system includes a model predictive control (MPC) method for fuel cell current regulation and a PI controller to maintain DC bus voltage stability. The proposed strategies are evaluated under standard driving cycles (UDDS and NEDC) using a simulation in MATLAB/Simulink. Key performance indicators such as fuel efficiency, hydrogen consumption, battery state-of-charge, and voltage stability are examined to assess the effectiveness of each approach. Simulation results demonstrate that the deterministic strategy offers a structured and computationally efficient solution, while the fuzzy logic approach provides greater adaptability to dynamic driving conditions, leading to improved overall energy efficiency. These findings highlight the critical role of advanced control strategies in improving FCHEV performance and offer valuable insights for future developments in hybrid-vehicle energy management.

Keywords: fuel cell; battery; model predictive control; energy management strategy; deterministic rules; fuzzy logic

Academic Editors: Michael Fowler, Wenming Yang and Anna Pinnarelli

Received: 13 June 2025
Revised: 12 July 2025
Accepted: 29 July 2025
Published: 6 August 2025

Citation: Essoufi, M.; Benzaouia, M.; Hajji, B.; Rabhi, A.; Calì, M. Advancing Energy Management Strategies for Hybrid Fuel Cell Vehicles: A Comparative Study of Deterministic and Fuzzy Logic Approaches. *World Electr. Veh. J.* **2025**, *16*, 444. https://doi.org/10.3390/wevj16080444

1. Introduction

The environmental consequences of fossil fuel consumption, particularly its contribution to global warming and air pollution, have become a major global concern. Fossil fuels have historically played a central role in powering industry and transport, but they are now widely recognised as a primary source of greenhouse gas (GHG) emissions. The transport sector alone contributes around 16.2% of total global GHG emissions, with road transport battery state of charge at 60% and manage the battery and fuel cell currents. Du et al. [10] combine rule-based and dynamic programming to reduce hydrogen consumption and extend battery life. A rule-based approach optimised by genetic algorithm is proposed in [11] that balances several objectives but lacks online recognition of driving cycles. Wang et al. [12] use a Bayes Monte Carlo technique to improve fuel economy and component lifetime. Yang Li et al. [13] integrate Q-learning and deterministic rules to reduce current fluctuations, but the intensive training and model dependence make real-time applications difficult. The second is fuzzy rule-based strategy, which uses fuzzy logic to manage uncertainties and imprecise information [14]. In [15], an approach using fuzzy logic aims to keep the fuel cell in a high-efficiency zone while responding to fast demands. Luciani and Tonoli [16] compare several control strategies, highlighting fuzzy logic, which improves fuel cell efficiency by up to 33% for low-load cycles. In [17], a type-2 fuzzy strategy is used for a hybrid system integrating fuel cell, battery, and supercapacitor. This method improves stability and efficiency through robust control. Zhang et al. [18] integrate driving mode recognition via a neural network with fuzzy adaptive control, optimizing energy distribution in real time. In [19], a strategy combining fuzzy logic, flatness theory, and rule-based algorithms improves energy distribution and stabilizes output voltage. In [20], Ahmadi et al. propose an optimised management approach integrating fuzzy logic and genetic algorithms, balancing fuel economy and performance. The third is the strategy based on frequency separation, which is particularly well suited to FCHEVs due to the fuel cell's low dynamic response characteristics [21]. These strategies separate the power demand into high-frequency and low-frequency components. High-frequency components, corresponding to rapid variations in power demand, are managed by the battery, while low-frequency components, corresponding to steady-state or slow variations, are managed by the fuel cell [22–27].

Optimisation-based strategies, using mathematical models, are being developed to manage the energy of hybrid vehicles by balancing the distribution of power between fuel cells and batteries [28]. These strategies aim to improve performance in terms of fuel economy, sustainability of energy sources, emissions reduction, and vehicle efficiency [29]. Energy management is based on a cost function that integrates these objectives, and the optimisation process can be achieved via two methods: global (offline) or local (online) optimisation. Global optimisation strategies play a crucial role in hybrid vehicle energy management, despite their high computational demands and dependence on prior knowledge of the driving cycle [30]. These strategies aim to identify optimal solutions in the entire search space, minimising or maximising a cost function while respecting predefined constraints. Although they are difficult to implement directly in real scenarios, they serve as a valuable reference for evaluating other control approaches [31]. In addition, global optimisation techniques help refine rule-based strategies and optimise the sizing of vehicle components, thus contributing to advances in the theoretical and practical design of energy management systems [32–34]. Local optimisation strategies, designed for real-time energy management, replace global optimisation with instantaneous decisions, reducing the computational load and enabling rapid adaptation to the dynamic requirements of hybrid vehicles [35]. Among the key approaches, the Equivalent Consumption Minimization Strategy (ECMS) optimises global consumption by translating electrical energy into fuel equivalent [36]. The Pontryagin Minimum Principle (PMP) solves the Hamiltonian function to minimise instantaneous costs while managing the non-linearities of hybrid systems [37]. Model predictive control (MPC), although more computationally demanding, anticipates future states and adjusts power distribution to optimise energy utilization under complex conditions [38,39].

independent control of the DC bus voltage, better protection of the energy sources, and efficient regulation of the energy flow. It ensures optimum energy management and system performance by taking advantage of the complementary strengths of each energy source under varying driving conditions.

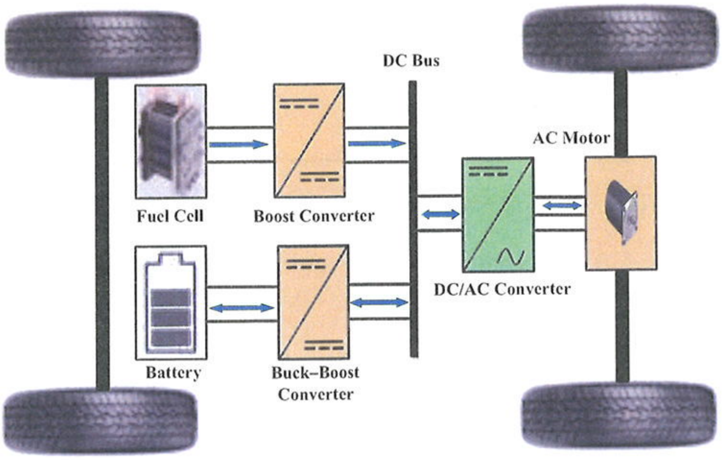

Figure 1. Fuel cell–battery hybrid electric vehicle topology.

2.2. Vehicle Model

All the forces acting on a moving vehicle are illustrated in Figure 2. Vehicle dynamics takes into account the specific characteristics and coefficients of the vehicle under study, as well as the required dynamic performance. Based on Newton's second law and as shown in Figure 2, vehicle motion can be expressed mathematically by Equation (1):

$$M_v \frac{d\overrightarrow{v}}{dt} = \overrightarrow{R_r} + \overrightarrow{F_{air}} + \overrightarrow{F_r} + \overrightarrow{F_t} + \overrightarrow{P} \tag{1}$$

The principal forces acting on the vehicle are:

$$\overrightarrow{F_{air}} = -\frac{1}{2}\rho_{\text{air}} V^2 A C_x \vec{x} \tag{2}$$

$$\overrightarrow{F_r} = -P C_r \cos(\alpha) \vec{x} \tag{3}$$

$$\overrightarrow{P} = -M_v g \sin(\alpha) \vec{x} \tag{4}$$

where

- $\overrightarrow{F_{air}}$ is the aerodynamic force, which is the air resistance in the direction of the vehicle's motion;
- $\overrightarrow{F_r}$ is the rolling resistance force between the wheels and the ground;
- $\overrightarrow{P}$ is the gravitational force of the vehicle;
- M_v is the total mass of the vehicle;
- $\overrightarrow{R_r}$ is the rolling resistance force vector due to tire–road interaction;
- $\overrightarrow{F_t}$ is the mechanical tensile force.

The mechanical tensile force $\vec{F_t}$ is expressed by Equation (5):

$$F_t = M_v \frac{dv}{dt} + \frac{1}{2}\rho_{\text{air}} V^2 A C_x + M_v g \sin\alpha + M_v g C_r \cos\alpha \tag{5}$$

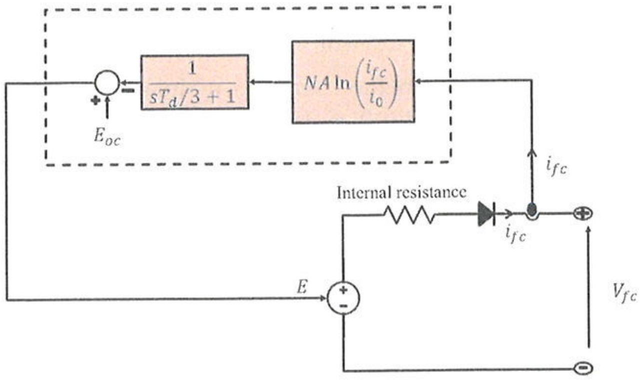

Figure 3. Model of the fuel cell.

2.4. Battery Model

Battery modelling forms the basis of battery design and control. A large number of battery models have been developed in the literature. These models can generally be classified into electrochemical models or equivalent electrical circuit models.

The equivalent electrical circuit model of the battery used in this study is shown in Figure 4 [49].

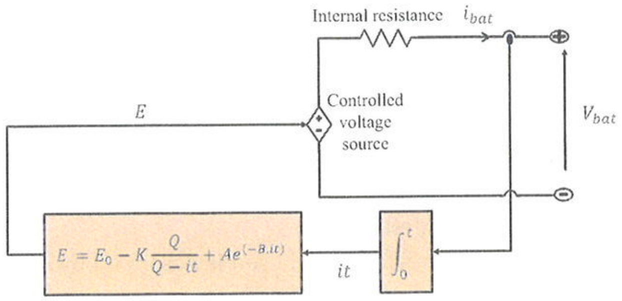

Figure 4. Model of the battery.

Figure 4 shows the battery model with a controlled voltage source in series with an internal resistor. The model is used to calculate the battery's output voltage (V_{bat}), which varies according to the battery's charging or discharging mode. During discharge, the output voltage is calculated by Equation (10). During charging, however, the output voltage is determined by Equation (11).

Discharge mode:

$$V_{\text{discharge}} = E_0 - Ri - K\frac{Q}{Q-it} \cdot (it + i^{*}) + Ae^{-Bit} \tag{10}$$

Charge mode:

$$V_{\text{charge}} = E_0 - Ri - K\frac{Q}{it - 0.1Q} \cdot i^{*} - K\frac{Q}{Q-it} \cdot it + Ae^{-Bit} \tag{11}$$

The estimated state of charge (SOC_{bat}) of the battery is calculated by Equation (12):

$$SOC_{\text{batt}} = 100\left(1 - \frac{\int i(t)\,dt}{Q}\right) \tag{12}$$

An additional cost function, presented in Equation (19), is introduced to reduce the switching frequency.

$$g_{sw}(k+1) = \lambda[u_{(k+1)} - u_{(k)}]^2 \tag{19}$$

where ($\lambda = 0.1$) is an adjustable weighting factor.

The total cost function combining these two objectives is expressed by Equation (20):

$$g_t(k+1) = g_i(k+1) + g_{sw}(k+1) \tag{20}$$

The MPC selects the optimal control $u^*(k)$ presented by Equation (21), by minimising the cost function among the possible switching states.

$$u^*(k) = \arg\min_{u(k)} g_t(k+1) \tag{21}$$

3. Energy Management System

Hybridization of fuel cell electric vehicles with batteries offers a promising solution for improving overall system efficiency and extending the lifespan of energy sources. However, this potential can only be fully exploited by implementing an appropriate energy management strategy that optimally distributes power between the sources to ensure energy efficiency and performance. In this context, two critical degradation factors are specifically considered in this study: the frequent and rapid variation in the fuel cell's reference power, and its operation outside the optimum efficiency range. These conditions impose dynamic stress on the membrane–electrode assembly and accelerate ageing by increasing irreversible losses, highlighting the crucial role of power management in protecting the longevity of fuel cells.

Two approaches for energy management in hybrid fuel cell vehicles are then developed and compared: a deterministic rule-based and a fuzzy logic-based strategy.

3.1. Deterministic Energy Management Strategy

The principle of deterministic rule-based energy management strategies for fuel cell and battery electric vehicles is based on the use of predefined "if-then" rules to manage energy distribution between the fuel cell, battery, and electric motor. These rules are established on the basis of prior knowledge of the system and technical experience, to ensure reliable operation under various driving conditions. The strategy consists in determining the energy source according to certain predefined conditions, such as battery state of charge, power demand, and vehicle speed.

An energy management strategy (EMS) was developed, combining two deterministic rule-based approaches—power tracking and optimal efficiency region—with critical state-of-charge (SOC) management. This integration guaranteed operational efficiency, power balance, and optimal battery condition.

The power tracking method aims to effectively balance the power distribution between the fuel cell and the battery to meet the vehicle's energy demand P_{dem}. When $P_{\text{dem}} > 0$, the system evaluates the battery's state of charge (SOC) against defined thresholds and adjusts the fuel cell's power, taking into account its minimum and maximum limits. In the event of regenerative braking, the energy recovered is stored in the battery. This mechanism guarantees optimum energy distribution, keeps the SOC within an ideal range, and preserves the battery's health. The fundamental formula for this method is defined by Equation (22):

$$P_{\text{dem}} = P_{\text{fc}} + P_{\text{bat}} \tag{22}$$

3.2. Fuzzy Logic Energy Management Strategy

A fuzzy logic rule-based energy management strategy for a fuel cell hybrid electric vehicle exploits the strengths of fuzzy logic to effectively manage the uncertainties and non-linearities inherent in the system. Contrary to traditional deterministic rule-based approaches that follow fixed if–then instructions, fuzzy logic uses a more flexible and adaptive control strategy. This flexibility is achieved through the use of fuzzy sets and membership functions, which allow the system to manage different degrees of truth and integrate a wider range of input conditions.

In a fuel cell–battery electric vehicle, power demand and battery state of charge can fluctuate considerably depending on driving conditions, load requirements, and other dynamic factors. Fuzzy logic is excellent in this context, as it enables smooth transitions between different energy sources (fuel cell and battery) and nuanced control of energy distribution. This ability to adapt is essential for optimizing vehicle performance, as it ensures that the powertrain operates efficiently under diverse and changing conditions.

The fuzzy controller shown in Figure 8 was employed. That controller uses two inputs: the power demand and the battery state of charge. The output of the fuzzy controller is the fuel cell's reference power, which determines the power to be delivered by the fuel cell at any given time to optimise system performance and efficiency.

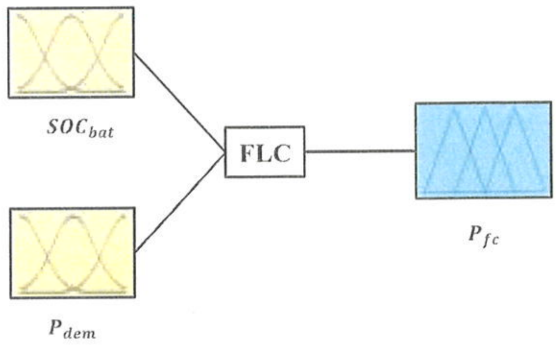

Figure 8. Fuzzy controller structure used in energy management.

The fuzzy logic rules were designed using the same methodology as that applied to the deterministic rule-based strategy. That approach was based on expert knowledge and analysis of system behaviour, incorporating criteria such as fuel cell efficiency zones, battery state-of-charge limits, and energy demand characteristics. Both strategies used predefined thresholds derived from the power tracking and the optimal efficiency region approach to ensure that the fuel cell operated within its ideal dynamic range while preserving the state of health of the battery. This ensured consistency between the two EMS designs and enabled a close comparison of performance.

Figure 9 shows the membership functions of the input variable "power demand". The power demand on a vehicle's motor can vary considerably depending on driving conditions. To manage this variability, power demand was divided into different linguistic categories covering all possible cases.

Figure 10 illustrates the membership functions of the input variable "Battery state of charge". The battery's state of charge is another essential indicator of the battery's current state of charge.

Figure 11 presents the membership functions of the output variable "Fuel cell reference power". Fuel cell power output was determined to ensure optimum performance and efficiency. The membership functions associated with the fuel cell's reference power were defined according to the optimal efficiency region.

Table 2. Fuzzy logic controller rules.

		SOC		
		L	M	H
Pdem	N	ZE	ZE	ZE
	ZE	L	ZE	ZE
	L	M	L	ZE
	M	H	M	L
	H	H	M	M

4. Simulation Results and Discussion

The simulation model for the energy management system of a fuel cell–battery hybrid vehicle, developed in MATLAB Simulink R2016a, is presented in Figure 12. It is based on a three-layer architecture, enabling in-depth analysis and optimisation of energy management strategies. The first layer, dedicated to the energy management system (EMS), uses two algorithms, the first based on deterministic rules and the second based on fuzzy rules. A look-up table converts this power into a reference current, serving as input to the second layer. The second layer generates PWM signals to control the converters via model predictive control (MPC) and a PI controller, guaranteeing a stable voltage of 500 V on the DC bus and efficient energy conversion. The third layer, called the powertrain, integrates the energy sources, converters, and motor, converting electrical energy into mechanical energy to propel the vehicle. This model was tested with two standard driving cycles, the NEDC and the UDDS, offering a variety of scenarios for evaluating the performance and efficiency of the energy management strategy under dynamic and stable load conditions.

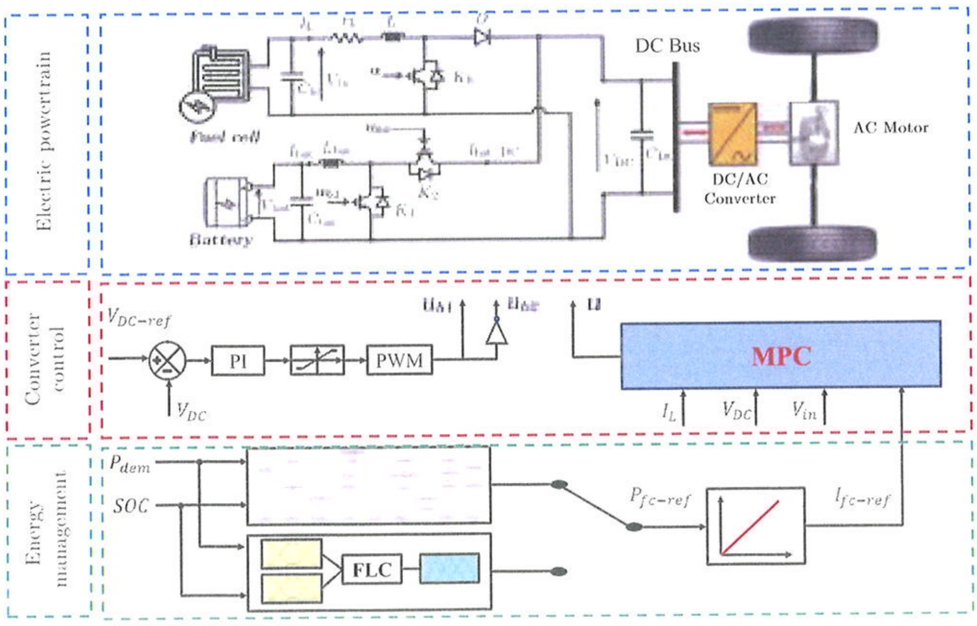

Figure 12. Overall simulation structure.

Figures 13 and 14 present vehicle speeds for the UDDS and NEDC driving cycles, respectively.

In both cases, the vehicle speed closely followed the reference speed with minimal error, demonstrating the high performance of the system. The figures also highlight three zones: Z1, Z2, and Z3. Each zone illustrates a crucial aspect of vehicle control, from achieving maximum speed to precise response under hard deceleration, as well as smooth manage-system's ability to manage energy distribution in real time and optimise consumption in a variety of driving scenarios.

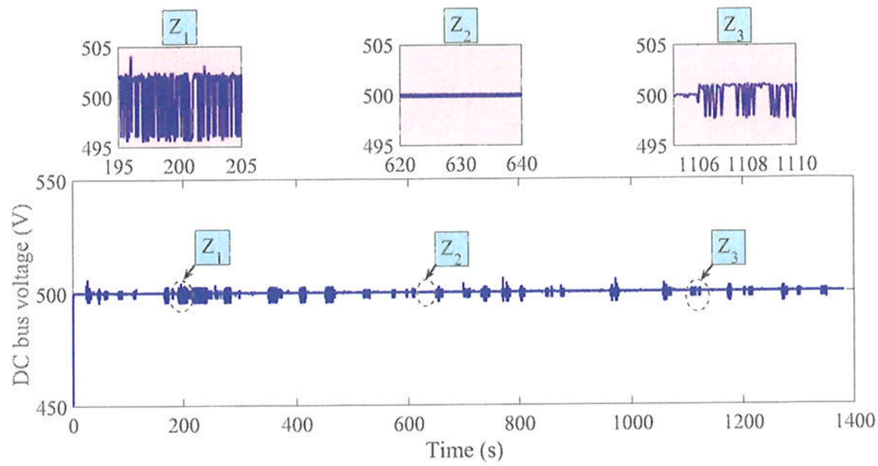

Figure 15. DC bus voltage evolution for the UDDS drive cycle.

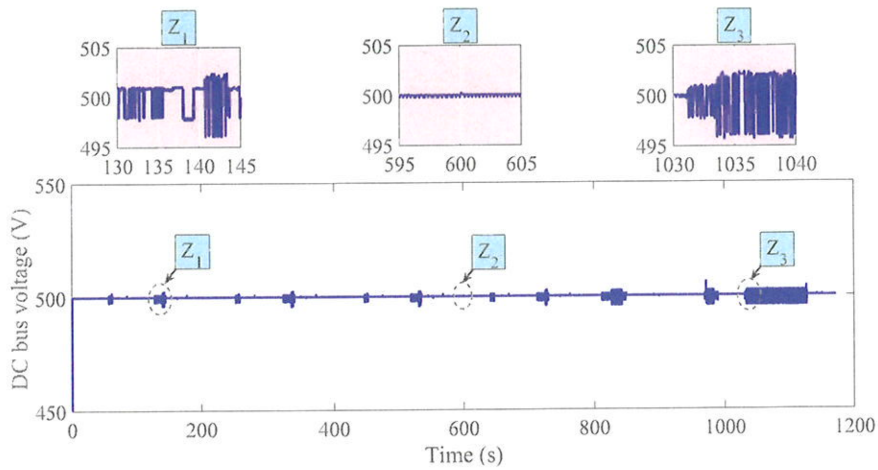

Figure 16. DC bus voltage evolution for the NEDC drive cycle.

Figures 19 and 20 illustrate the power evolution of the fuel cell, battery and electric motor using a fuzzy logic-based energy management strategy, applied to the UDDS and NEDC cycles. In contrast to deterministic strategies, this approach ensured smoother power variations, enhancing the system's adaptability. The fuel cell adjusted its power smoothly, while the battery compensated acceleration and recovered energy from braking. Zoomed-in areas highlight critical transitions, showing how fuzzy logic optimised energy distribution. These results confirm improved flexibility and energy performance in different driving scenarios.

Figures 21 and 22 show the evolution of the battery's state of charge (SOC) during the UDDS and NEDC driving cycles, respectively. In both figures, the state of charge remains within the predefined range of 40% to 80%, fluctuating around an average state of charge (60%), demonstrating the effectiveness of the energy management strategy in maintaining the state of charge within a safe and efficient operating range. The difference in state of charge between the initial and final state of charge was +3% for the UDDS cycle and −4% for the NEDC cycle. These results demonstrate the ability of the energy management system to adapt to different driving conditions, while maintaining the battery's SOC within the desired range.

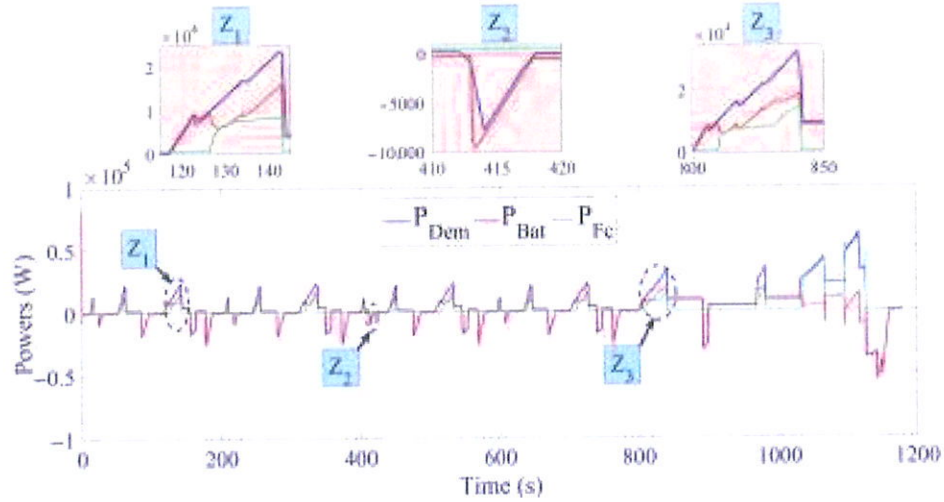

Figure 20. Power evolution of fuel cell, battery, and power demand during the NEDC driving cycle (fuzzy logic).

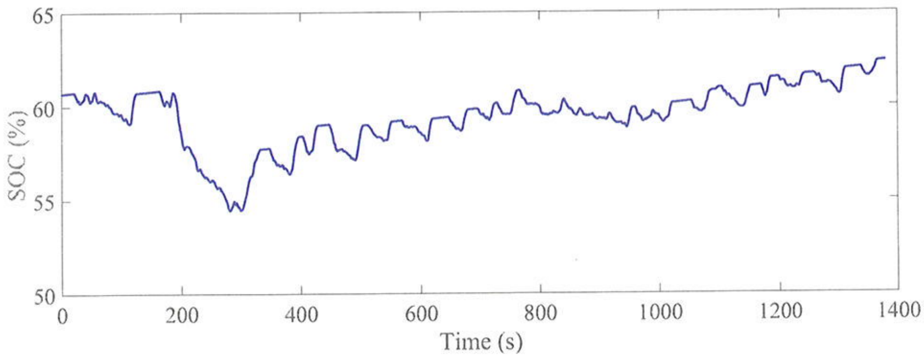

Figure 21. Evolution of the battery's state of charge during the UDDS driving cycle (deterministic rules).

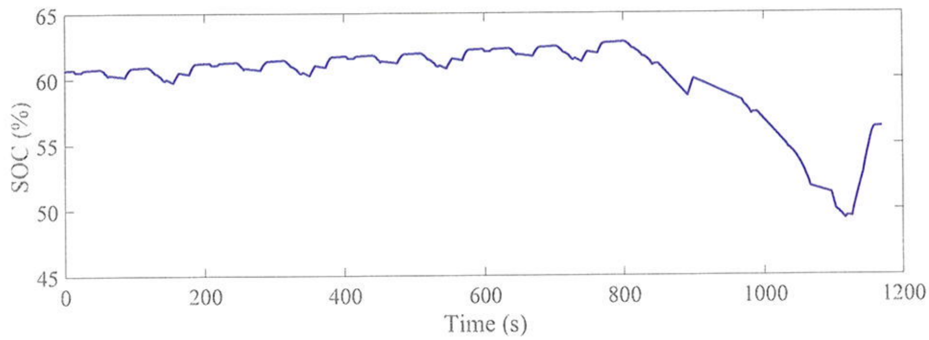

Figure 22. Evolution of the battery's state of charge during the NEDC driving cycle (deterministic rules).

Figures 23 and 24 illustrate the evolution of the battery state of charge during the UDDS and NEDC driving cycles using a fuzzy logic-based energy management strategy. The state of charge in both cases remained within the predefined range of 40% to 80%, fluctuating around an average value of 60%. This demonstrates the effectiveness of the system in adaptively regulating the state of charge, guaranteeing safe and optimal vehicle operation. The variation in state of charge between the start and end of cycles was −0.5% for the UDDS cycle and −1% for the NEDC cycle. These results clearly tively adjusts its energy behavior according to the initial SOC and systematically achieves the targeted SOC of 60% at the end of the cycles, whatever the initial value.

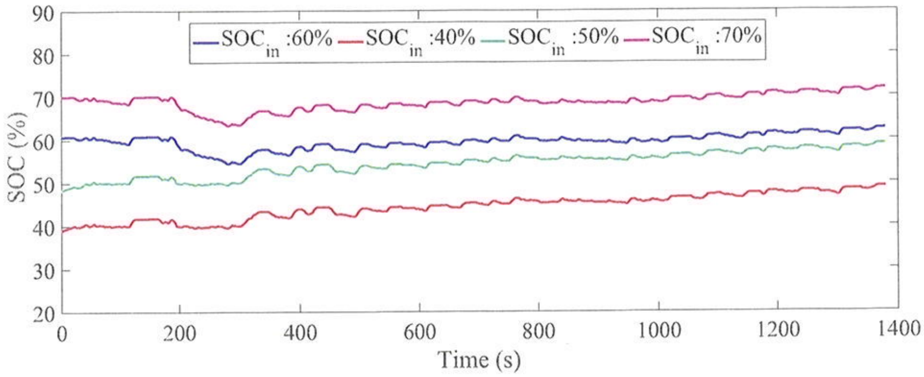

Figure 25. SOC evolution during the UDDS driving cycle with different initial values (deterministic rules).

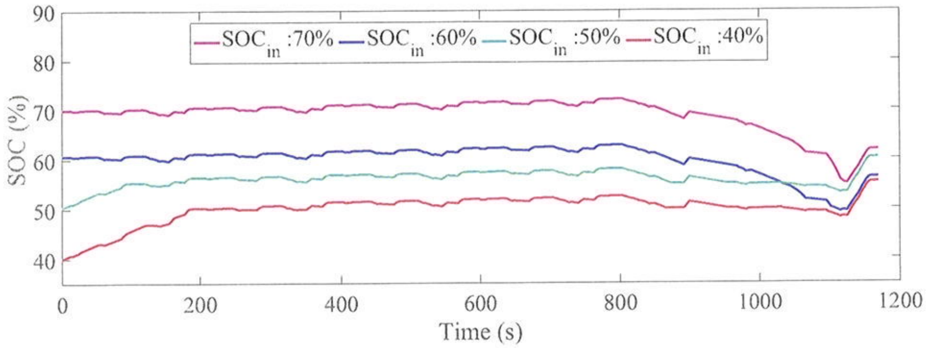

Figure 26. SOC evolution during the NEDC driving cycle with different initial values (deterministic rules).

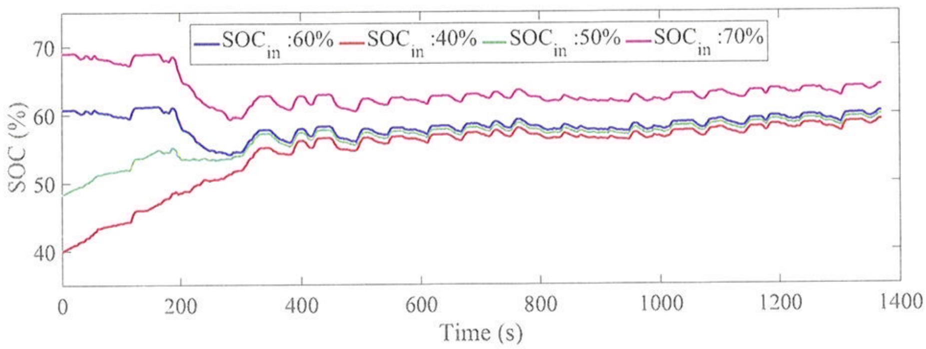

Figure 27. SOC evolution during the UDDS driving cycle with different initial values (fuzzy logic).

Simulations showed that fuzzy logic-based energy management effectively regulated the SOC to 60% at the end of the UDDS cycle when the initial SOC was 40%, 50%, or 60%. However, a small deviation (final SOC of 64%) was observed for an initial SOC of 70%, indicating the need for improvements to better manage high levels under dynamic urban conditions. In the NEDC cycle, on the other hand, the SOC systematically reached 60%, whatever its initial level, confirming the system's effectiveness in more stable driving conditions.

hydrogen consumption. In comparison, the deterministic rule-based (DR) strategy offered acceptable performance but remained less flexible, with more marked power peaks, impacting load management and hydrogen consumption.

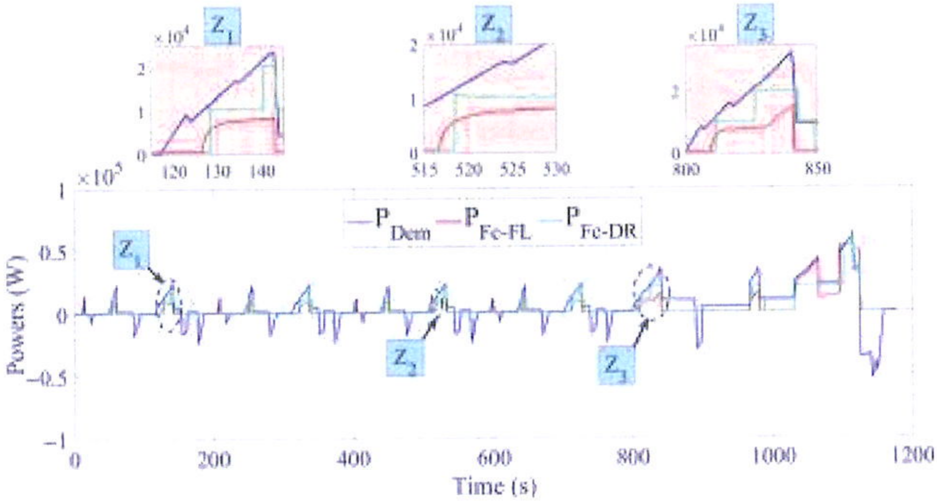

Figure 30. Fuel cell reference power for the NEDC driving cycle (FL and DR comparison).

Table 3 presents an overall comparison of the performance of the two energy management strategies, FL and DR, for both the UDDS and NEDC driving cycles in terms of key criteria such as initial and final SOC, hydrogen consumption, quality of power transitions, and system reactivity.

Table 3. Performance comparison of FL and DR energy management strategies for UDDS and NEDC driving cycles.

Strategy	Cycle	Speed (km/h)	Dyn. FC	SOC_{min}	SOC_{moy}	SOC_{max}	SOC_{final}	H_2 (g)	Rob.
Ref.			Yes	40	60	80	60	Min	Yes
DR	UDDS	0–91.2	No	54.44	59.32	62.4	62.36	62.49	No
	NEDC	0–120	No	49.26	59.21	62.77	56.25	61.30	No
FL	UDDS	0–91.2	Moderate	54.12	58.24	61.18	60.24	57.65	Yes
	NEDC	0–120	Moderate	51.95	57.79	60.18	59.10	68.42	Yes

The strategy based on fuzzy logic (FL) was more respectful of fuel cell dynamics, offering progressive power adjustments, while the strategy based on deterministic rules (DR) was more rigid and led to sudden variations that put more stress on components.

In regard to battery state-of-charge management, the FL strategy approached the 60% target at the end of cycles, with final state-of-charge values of 60.24% for the UDDS and 59.10% for the NEDC, thus extending battery lifetime. In comparison, the DR strategy showed a lower final state of charge in the NEDC cycle, at 56.25%, indicating that the battery had compensated for some of the energy required, thus reducing apparent hydrogen consumption. The target of 60% state of charge was chosen as a compromise between energy availability and preserving the health of the battery. Operating the battery within an intermediate SOC window helps to minimise degradation mechanisms such as lithium plating and electrolyte decomposition, which are more pronounced at the high and low SOC extremes. Maintaining the state of charge around that level reduces stress on the battery and extends its life, helping to improve SOH over a long period of use. This choice is aligned with industry practice for improving battery durability in hybrid systems.

vehicles. Furthermore, the integration of artificial intelligence techniques—in particular reinforcement learning—offers a promising route for the development of adaptive energy management strategies.

Author Contributions: M.E.: Conceptualization, Formal Analysis, Writing—Original Draft Preparation. M.B.: Writing—Review and Editing. B.H.: Supervision, Review and Editing. A.R. and M.C.: Review and Editing. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data presented in this study are available in the article.

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

Abbreviations

The following abbreviations are used in this manuscript:

BAT	Battery
DC	Direct Current
DR	Deterministic Rule-based Strategy
EMS	Energy Management Strategy
FC	Fuel Cell
FCHEV	Fuel Cell Hybrid Electric Vehicle
FL	Fuzzy Logic Strategy
MPC	Model Predictive Control
NEDC	New European Driving Cycle
PEMFC	Proton Exchange Membrane Fuel Cell
PI	Proportional–Integral (Controller)
PMP	Pontryagin Minimum Principle
SOC	State of Charge
UDDS	Urban Dynamometer Driving Schedule

References

1. Maciejczyk, P.; Chen, L.C.; Thurston, G. The role of fossil fuel combustion metals in PM2. 5 air pollution health associations. *Atmosphere* **2021**, *12*, 1086. [CrossRef]
2. Aminzadegan, S.; Shahriari, M.; Mehranfar, F.; Abramović, B. Factors affecting the emission of pollutants in different types of transportation: A literature review. *Energy Rep.* **2022**, *8*, 2508–2529. [CrossRef]
3. Sanguesa, J.A.; Torres-Sanz, V.; Garrido, P.; Martinez, F.J.; Marquez-Barja, J.M. A review on electric vehicles: Technologies and challenges. *Smart Cities* **2021**, *4*, 372–404. [CrossRef]
4. Alanazi, F. Electric vehicles: Benefits, challenges, and potential solutions for widespread adaptation. *Appl. Sci.* **2023**, *13*, 6016. [CrossRef]
5. Togun, H.; Aljibori, H.S.S.; Abed, A.M.; Biswas, N.; Alshamkhani, M.T.; Niyas, H.; Mohammed, H.I.; Rashid, F.L.; Paul, D. A review on recent advances on improving fuel economy and performance of a fuel cell hybrid electric vehicle. *Int. J. Hydrogen Energy* **2024**, *89*, 22–47. [CrossRef]
6. Nnabuife, S.G.; Hamzat, A.K.; Whidborne, J.; Kuang, B.; Jenkins, K.W. Integration of renewable energy sources in tandem with electrolysis: A technology review for green hydrogen production. *Int. J. Hydrogen Energy* **2024**, *107*, 218–240. [CrossRef]
7. Zhao, X.; Wang, L.; Zhou, Y.; Pan, B.; Wang, R.; Wang, L.; Yan, X. Energy management strategies for fuel cell hybrid electric vehicles: Classification, comparison, and outlook. *Energy Convers. Manag.* **2022**, *270*, 116179. [CrossRef]
8. Sorlei, I.S.; Bizon, N.; Thounthong, P.; Varlam, M.; Carcadea, E.; Culcer, M.; Iliescu, M.; Raceanu, M. Fuel cell electric vehicles—A brief review of current topologies and energy management strategies. *Energies* **2021**, *14*, 252. [CrossRef]
9. Fadel, A.; Zhou, B. An experimental and analytical comparison study of power management methodologies of fuel cell–battery hybrid vehicles. *J. Power Sources* **2011**, *196*, 3271–3279. [CrossRef]
10. Du, C.; Huang, S.; Jiang, Y.; Wu, D.; Li, Y. Optimization of energy management strategy for fuel cell hybrid electric vehicles based on dynamic programming. *Energies* **2022**, *15*, 4325. [CrossRef]
11. Yuan, H.B.; Zou, W.J.; Jung, S.; Kim, Y.B. A real-time rule-based energy management strategy with multi-objective optimization for a fuel cell hybrid electric vehicle. *IEEE Access* **2022**, *10*, 102618–102628. [CrossRef]

35. Aiteur, I.E.; Vlad, C.; Godoy, E. Energy management and control of a fuel cell/supercapacitor multi-source system for electric vehicles. In Proceedings of the 2015 19th International Conference on System Theory, Control and Computing (ICSTCC), Cheile Gradistei, Romania, 14–16 October 2015; IEEE: Piscataway, NJ, USA, 2015; pp. 797–802.
36. García, P.; Torreglosa, J.P.; Fernández, L.M.; Jurado, F. Viability study of a FC-battery-SC tramway controlled by equivalent consumption minimization strategy. *Int. J. Hydrogen Energy* **2012**, *37*, 9368–9382. [CrossRef]
37. Zhang, S.; Xiong, R.; Zhang, C. Pontryagin's minimum principle-based power management of a dual-motor-driven electric bus. *Appl. Energy* **2015**, *159*, 370–380. [CrossRef]
38. Ławryńczuk, M.; Marusak, P.M.; Chaber, P.; Seredyński, D. Initialisation of optimisation solvers for nonlinear model predictive control: Classical vs. hybrid methods. *Energies* **2022**, *15*, 2483. [CrossRef]
39. Sultana, W.R.; Sahoo, S.K.; Sukchai, S.; Yamuna, S.; Venkatesh, D. A review on state of art development of model predictive control for renewable energy applications. *Renew. Sustain. Energy Rev.* **2017**, *76*, 391–406. [CrossRef]
40. Yavasoglu, H.A.; Tetik, Y.E.; Ozcan, H.G. Neural network-based energy management of multi-source (battery/UC/FC) powered electric vehicle. *Int. J. Energy Res.* **2020**, *44*, 12416–12429. [CrossRef]
41. Liu, Y.; Liu, J.; Qin, D.; Li, G.; Chen, Z.; Zhang, Y. Online energy management strategy of fuel cell hybrid electric vehicles based on rule learning. *J. Clean. Prod.* **2020**, *260*, 121017. [CrossRef]
42. Lin, X.; Zeng, S.; Li, X. Online correction predictive energy management strategy using the Q-learning based swarm optimization with fuzzy neural network. *Energy* **2021**, *223*, 120071. [CrossRef]
43. Reddy, N.P.; Pasdeloup, D.; Zadeh, M.K.; Skjetne, R. An intelligent power and energy management system for fuel cell/battery hybrid electric vehicle using reinforcement learning. In Proceedings of the 2019 IEEE Transportation Electrification Conference and Expo (ITEC), Detroit, MI, USA, 19–21 June 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 1–6.
44. Li, W.; Ye, J.; Cui, Y.; Kim, N.; Cha, S.W.; Zheng, C. A speedy reinforcement learning-based energy management strategy for fuel cell hybrid vehicles considering fuel cell system lifetime. *Int. J. Precis. Eng.-Manuf.-Green Technol.* **2021**, *9*, 859–872. [CrossRef]
45. Tang, X.; Zhou, H.; Wang, F.; Wang, W.; Lin, X. Longevity-conscious energy management strategy of fuel cell hybrid electric Vehicle Based on deep reinforcement learning. *Energy* **2022**, *238*, 121593. [CrossRef]
46. Jouda, B.; Al-Mahasneh, A.J.; Mallouh, M.A. Deep stochastic reinforcement learning-based energy management strategy for fuel cell hybrid electric vehicles. *Energy Convers. Manag.* **2024**, *301*, 117973. [CrossRef]
47. Njoya M., S.; Tremblay, O.; Dessaint, L.A. A generic fuel cell model for the simulation of fuel cell vehicles. In Proceedings of the 2009 IEEE Vehicle Power and Propulsion Conference, Dearborn, MI, USA, 7–10 September 2009; IEEE: Piscataway, NJ, USA, 2009; pp. 1722–1729.
48. Essoufi, M.; Bekkay, H.; Rabhi, A. Modeling and Analysis of a Fuel Cell-Battery Hybrid Electric Vehicle. In Proceedings of the International Conference on Electronic Engineering and Renewable Energy Systems, Saidia, Morocco, 20–22 May 2022; Springer: Berlin/Heidelberg, Germany, 2022; pp. 583–597.
49. Tremblay, O.; Dessaint, L.A.; Dekkiche, A.I. A generic battery model for the dynamic simulation of hybrid electric vehicles. In Proceedings of the 2007 IEEE Vehicle Power and Propulsion Conference, Arlington, TX, USA, 9–12 September 2007; IEEE: Piscataway, NJ, USA, 2007; pp. 284–289.