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Reinforcement learning-based multi-objective PSO adaptive control framework for hydrogen consumption optimization and durability enhancement in fuel-cell electric vehicle powertrains

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Abstract

This study proposes a reinforcement learning-based multi-objective particle swarm optimization (RL–MOPSO) adaptive control framework to improve hydrogen utilization, enhance component durability, and ensure robust real-time energy management in fuel-cell electric vehicle (FCEV) powertrains under dynamic operating conditions. The proposed framework integrates deep reinforcement learning with multi-objective particle swarm optimization within a hierarchical control architecture. The RL agent learns optimal power management policies through continuous interaction with the vehicle environment, while MOPSO optimizes conflicting objectives including hydrogen consumption, fuel-cell degradation, system efficiency, and battery state-of-charge (SOC) stability. Degradation-aware objective functions penalize rapid load variations, excessive current densities, and operation outside optimal fuel-cell regions. The controller is evaluated using a high-fidelity FCEV model under WLTC and urban driving cycles and compared with rule-based control (RBC), model predictive control (MPC), and standalone RL strategies. Simulation results demonstrate hydrogen consumption reductions of 18–25% relative to MPC and 30–35% relative to RBC. Fuel-cell degradation indicators decrease by 20–28%, while overall powertrain efficiency improves by 12–17% and stable SOC regulation is maintained under varying operating conditions. The RL–MOPSO framework achieves superior energy efficiency, durability, and robustness compared with conventional control methods. The low computational burden of the trained RL policy enables real-time implementation in embedded automotive control systems, supporting the deployment of sustainable and reliable hydrogen-powered transportation.

Keywords: Durability-aware control, Fuel-cell electric vehicles, Hydrogen consumption optimization, Multi-objective particle swarm optimization, Powertrain energy management, Reinforcement learning.

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Contents

Contribution of this paper to the literature
The originality of this work lies in integrating reinforcement learning, multi-objective particle swarm optimization, and degradation-aware control into a single adaptive energy-management framework for FCEVs. The proposed controller simultaneously minimizes hydrogen consumption and fuel-cell aging while maintaining SOC stability and robustness under uncertain real-world operating conditions.

1. Introduction

Thanks to high energy conversion efficiency, zero tailpipe emissions and compatibility with hydrogen-based energy systems, fuel-cell electric vehicles (FCEVs) have become an extremely viable solution for sustainable transportation. FCEVs (Fuel Cell Electric Vehicles) are unlike vehicles using internal combustion engines, which depend on the thermodynamic combustion processes; thus, FCEVs obtain electrochemical reactions in a fuel cell stack to directly convert hydrogen securely into electricity at higher efficiencies and with lower environmental impacts [1, 2]. The global focus on decarbonization and clean mobility has also stimulated the research and development of transportation technologies powered by hydrogen, making FCEVs a part of the energy ecosystem in a low-carbon future [3]. However, despite these advantages of FCEVs, there are several key challenges yet to be overcome before mass adoption can occur: optimization of hydrogen consumption; improved energy management; thermal control issues and system durability [4]. FCEV powertrains generally also involve coordination of multiple sub-systems, including the fuel cell stack, battery energy storage system (BESS), DC/DC converters and electric motor drive and hence must work efficiently. Furthermore, these elements have different dynamic properties and operational limits, which adds complexity to the real-time energy management as a control problem [5]. The top layer is the fuel cell stack, which is responsible for energy supply but suffers from a narrow range of effective current densities and high sensitivity to transient loading conditions. Rapid changes in load demand may cause a performance degradation, voltage losses and reduced lifespan [6]. Commonly, a battery or super capacitor is connected to the AMR system to offer supplemental battery support and instantaneous load balancing to optimize the overall performance of AMR structure and control practice [7]. The downside of this hybrid arrangement is the more difficult power split optimization problem between the fuel cell and energy storage system. In the last decade, a lot of research has been put toward developing energy management strategies (EMS) to optimize the operations of hybrid FCEV systems. Conventional methods such as RBC, ECMS and MPC are part of this category. RBC methods are prevalent because of their simplicity and ease of implementation, but they typically depend on pre-defined heuristics, do not adapt to the constantly changing operating conditions, thus leading to sub-optimal performance [8]. ECMS achieves fuel utilization efficiency other than the defined engine operating point by converting electrical energy consumption into a hypothetical fuel price; however, it has only been successfully applied with careful optimization of the equivalence factors and may perform poorly under some driving conditions [9]. Model Predictive Control (MPC) has been widely used and researched because it can respect constraints over a finite prediction horizon while optimizing control action. The control approach of MPC with some future prediction and incorporating system dynamics can lead to near-optimal efficiency/fuel consumption [10]. Although it is very effective, its utilization relies on accurate models and forecasts of the system. Moreover, the online computation required to solve optimization problems limits their practical use in embedded automotive systems. Recently, some artificial intelligence (AI) and machine learning techniques have become powerful instruments in energy management of FCEVs, especially reinforcement learning (RL). RL-based EMS is free from explicit models of the system and can learn optimal control policies by interacting with the overall operation environment [11], so it can adapt to complex and uncertain conditions. RL-based strategies have shown their ability to achieve improvements in fuel economy, adaptability and robustness against modelling uncertainties over conventional methods under dynamic driving cycles [12]. In addition to model-agnostic approaches, multi-objective optimization techniques like genetic algorithm (GA) and particle swarm optimization (PSO) [13] have also been widely used for optimizing the conflicting objectives such as hydrogen consumption, efficiency, durability, etc. They help detect Pareto-optimal solutions that trade off several performance objectives. Nonetheless, they are relatively expensive to compute, although usually used in offline optimization settings, which prevents them from responding quickly to ongoing variations of the system [14]. Consequently, this issue drives an increasing demand for precise control strategies, positioning the solution for efficiency, durability, adaptability and uncertainty under FCEV powertrains. The combination of learning-based methods and multi-objective optimization is a potential research direction, which will help develop intelligent, adaptive, and robust energy management frameworks that can be executed in real-time [15]. These hybrid strategies properly use the merits of both paradigms, i.e., the adaptability of learning and the reliability-viability optimal decision-making of optimization. They help to address major issues associated with conventional control methods and improve performance for FCEV systems.

Although prominent strides have been made in the direction of control and energy management solutions for fuel-cell electrical automobiles (FCEVs) over the final a few years, obtaining optimal, actual time and robust manage FCEV powertrains, however, stands as an elusive and unsolved problem. The central problem is to achieve conflicting and mutually dependent objectives: (i) minimizing hydrogen utilization, (ii) maximizing global system efficiency, (iii) prolonging fuel cell durability/lifetime and (iv) robust performance against dynamic driving conditions and uncertainties at the system boundary [16, 17]. These goals are as a rule intertwined and often opposing to each other, rendering it hard to devise an integrated control paradigm that achieves best for all venerations. Your main problem spot will be the serious dilemma of actually needing hydrogen to eat in a gas cell, however, additionally, everything else that destroys your fuel cell. And running the fuel cell up and holding it at those very high efficiency points will tend to use less hydrogen; however, this means frequently operating the system in a regime of continuous high current density, frequent load transients, instantaneous voltages that are low, all pushing the design downhill into various negative degradation mechanisms such as catalyst aging, membrane thinning, voltage decay. On the flip side, durability-oriented strategies (like power demand smoothing and dynamic response deploying limits) could maximize hydrogen utilization but degrade system efficiency instead. This inherent tension between efficiency and durability is a major roadblock on the path to full long-term system optimization. Furthermore, FCEV powertrains are tested in stochastic driving cycles under both relatively variable load demands and changing environmental conditions. In the real world, patterns of driving stop and go in an urban environment for example or highway-level acceleration are so dynamic that they cause rapid changes in power demand that need to be matched instantaneously. These variations need the control system to constantly revise its decisions, frequently with little understanding of future conditions [18]. Traditional control strategies based on deterministic models or hard-coded rules can find it difficult to achieve optimal performance given the variability. Another important aspect is the multi-timescale nature of the energy management problem. FCEV control accounts not only for the fast transient dynamics, f.e, between instantaneous power allocation of the fuel cell and battery, but also for long-term objectives like minimization of hydrogen consumption or degradation mitigation. It is especially hard to align and optimize these short-term and long-term objectives within a single control framework, as decisions that are optimal now can be adverse, not only for the current agents but also on the long-run system health [19]. In addition, the FCEV systems are non-linear and sensitive to parameter uncertainties. Large deviations exist between the actual system behavior and the model due to influences such as temperature, aging, and changing operating conditions for fuel cells, batteries, and power electronics [20]. Model-based methods (e.g., model predictive control (MPC)) rely critically on an accurate system model and can perform poorly in the presence of actuator/model mismatch. Most advanced control strategies are also computationally demanding as they involve real-time solving of high-dimensional optimization problems (AHMS) on an embedded automotive controller with significantly limited processing abilities compared to a typical desktop computer. Although optimal solutions can be obtained using offline optimization techniques, they do not have the adaptability which is essential for real-time implementation in changing environments [21]. Lastly, previous works usually take a piecemeal view, considering isolated goals—fuel economy, efficiency, and durability but they do not tackle the problem in its entirety. Therefore, these methods do not give a holistic solution to the simultaneous optimization of all vital aspects of FCEV performance. In summary, the main challenge in FCEV energy management is due to the absence of a control framework that can simultaneously adapt and balance between multiple conflicting objectives while offering significant computational savings. This challenge cannot be addressed without designing control strategies that fuse learning-based adaptability, multi-objective optimization and uncertainty robustness for real-time decision making while keeping optimum system performance and life of the system.

The challenge of optimizing hydrogen consumption, durability, efficiency and robustness under uncertainty simultaneously has been an open problem even though there have been significant advances in FCEV powertrain control and optimization strategies over the past several decades [5] Such persistence is due to many tightly intertwined technical and practical issues which are still hampering the efficacy of all current solutions. One main reason is the forcing of highly nonlinear and coupled dynamics of FCEV powertrains. The fuel cell system consists of several nonlinear and time-varying electrochemical processes: mass transport, charge transfer and thermal effects [22]. The interaction of these dynamics is even further complicated by the presence of additional subsystems, including air compressors, humidification and thermal management units, which can render the overall system a tightly coupled multi-physics system. These systems are notoriously difficult to model and control in real time — especially when computationally tractable, but simplified, models might be used. Consequently, the majority of control strategies based on linearization or low-order models are not guaranteed to approximately represent the full system behavior leading to degraded performance. A second major challenge is the uncertainty and variability of operating conditions. FCEVs run in highly dynamic conditions with rapid acceleration and deceleration lines under the different load running. Also, environmental conditions such as temperature, humidity, and upstream height influence fuel cell performance. The information uncertainty leads to a variability of behaviors corresponding the systems which cannot be fairly estimated, e.g., process modeling in real-world scenarios. Conventional synthesis techniques built on deterministic assumptions tend not to achieve the same level of performance in such stochastic contexts. One additional challenge is the reliance on precise system models. Advanced control methods such as model predictive control (MPC) would need accurate mathematical representations of system dynamics. Yet, precise models of cell system components are not easy to come by due to parameter uncertainties as well as aging and degradation phenomena on long time scales. During long-term operation, system characteristics gradually vary and the control performance strongly depends on having accurate real-time models. This limitation results in a trade-off between generalizability and overall reliability of model-based approaches for practical use-cases. The problem is also multi objectives and multi-timescale in nature, requiring us to process conflicting goals at the same time. For example, minimizing hydrogen utilization typically necessitates operating the fuel cell relatively close to its peak performance area of efficiency; however, maximizing durability requires avoiding rapid load fluctuations [23]. What you get is a clash of objectives which are also disparate in timescales; short-term decisions affect near-term performance whilst longer-term ones determine future system deterioration and longevity. The main challenge is the design of a control strategy which coordinates these objectives across time scales. Real-time optimization also comes with a huge barrier in the form of computational complexity. Various advanced optimization methods, including dynamic programming and evolutionary algorithms, involve solving a high-dimensional, computationally expensive optimization task. Although they can support optimal solutions in offline settings, these techniques cannot be used directly for real-time implementations of automotive embedded systems due to discrete limitations on computational power, memory and latency. A simple modular policy improvement is beneficial straightforward to implement in an NN but even MPC which is considered the effective real time optimization when dealing with nonlinear models and several constraints can be computationally expensive. A further important drawback is the non-adaptability of conventional control methods. Both rule-based and model-based methods are usually tailored to a specific environment, and requires manual tuning of parameters using target metrics or by trial-and-error. Their inability to adapt from one setting to another decreases their usability in real-world scenarios that occur when the operating conditions change over time [24]. This hinders the full utilization of the dynamic capabilities of hybrid FCEV systems. Furthermore, the existing research tends to address individual dimensions of the solution space (e.g., fuel economy, lifespan or robustness) in isolation rather than as part of an integrated framework. This siloed mindset results in solutions that optimize one of the three objectives at the expense of other objectives, ultimately leading to marginal gains in overall system performance. For example, measures targeting fuel economy may inadvertently increase degradation, whilst durability-oriented strategies reduce efficiency. Lastly, although reinforcement learning (RL) and other data-driven methods demonstrate promising performance, their applications in FCEV control are still in the developmental stage.

Despite great progress in recent years, issues like training stability, convergence speed, safety constraints and integration with optimization frameworks remain an active area of research [25]. Secondly, despite the former existence of RL methods on control, only a few solutions integrate multi-objective control or even degradation-aware control, where most designs perform simply. To sum up, the unresolved aspects of FCEV energy management and control are largely due to nonlinear system dynamics, uncertainty, model dependence, computational constraints, multi-objective trade-offs and a lack of integrated frameworks. Addressing these challenges is reliant on the creation of more sophisticated control strategies that can adapted online with real uncertainty and simultaneously optimize for a diverse set of performance criteria. This is why we need hybridization, in which the learning-based intelligence and the multi-objective optimization act together to guarantee robust and efficient operation of FCEV powertrains under real conditions.

Numerous control and optimization strategies have been proposed in literature to solve the energy management problem in fuel-cell electric vehicle (FCEV) powertrains. This multidimensional category includes model-based control methods, optimization-based strategies, learning-based approaches and hybrid intelligent frameworks. Collectively, they have their own benefits, but none of them solves the multi-objective and uncertainty nature of controlling an FCEV. Extensive review of control strategy implementations are found in model-based strategies such as rule-base control (RBC), equivalent consumption minimization strategy [3], and a basic conceptual model predictive control (MPC), all used within FCEV systems. RBC techniques utilize fixed heuristic rules based on experts' knowledge and the nature of the system. They are simple, cheap to compute and easy to implement by businesses. On the positive side, RBC-strategies are not adaptable and therefore cannot respond optimally to changing driving situations or system uncertainties, resulting in increased hydrogen consumption and additional stress on the components [26]. Different from optimal control, ECMS provides a unified framework for real-time fuel economy optimization by converting electrical energy consumption into an equivalent hydrogen cost. The approach in proposing ECMS can reach more improvements than RBC, but the key issue for ECMS performance are the selection of equivalence factors that needs to be finely tuned for different driving conditions. If improperly tuned, you may lose some of the potential benefits when working under different load profiles. An established model-based control approach that has gained immense popularity is model predictive control (MPC). More specifically, MPC manages system constraints and predicts the future behavior of a system over a finite horizon. MPC can approximate the optimal flow of energy to the fuel cell and battery by solving an optimization problem at each time step. Nevertheless, perfect system models and future load predictions are necessary for MPC, which makes it vulnerable to modeling inaccuracies and uncertainties. Moreover, the computational cost involved in solving the optimization problem on-line makes these methods unviable for embedded automotive systems. Multi-Objective Nature of FCEV Energy Management — Commonly used optimization-based approaches Dynamic programming (DP), genetic algorithms (GA) and particle swarm optimization (PSO) are frequently used approaches to get control strategies. Dynamic programming gives a global optimal solution by evaluating all possible trajectories of control. However, its computational complexity grows exponentially with system size and thus is not appropriate for real-time applications [27]. Consequently, DP is mainly utilised as a baseline for other control strategies. GA, PSO and other evolutionary algorithms have been employed for solving the multi-objective optimization problems of producing Pareto-optimal solutions with synergy among conflicting objectives like hydrogen consumption, efficiency, durability. These methods can be used to solve both nonlinear and multi-dimensional optimization problems. However, they are normally created in an offline environment because of their iterative nature and high computational costs. While optimization-based methods do provide insights into the optimal behavior of a system, their inability to be applied in real time limits solutions based on this methodology from being directly implemented in an FCEV control system.

Reinforcement learning (RL) has recently achieved great popularity as a model-independent controllable method for FCEV energy management. RL-based controllers learn optimal policies without explicit system models [28] by interacting with the environment, as they have capacity to handle nonlinear dynamics and modeling uncertainty in operating conditions. Old RL techniques, like Q-learning, showed the possibility of using learning-based strategies in hybrid vehicle energy management. Recent developments in deep reinforcement learning (DRL) algorithms such as Deep Q-Networks (DQN), Deep Deterministic Policy Gradient (DDPG), and Soft Actor-Critic (SAC) have allowed continuous control on complex applications. Previous studies have demonstrated RL-based strategies to be advantageous in terms of hydrogen consumption and adaptability compared to more traditional methods. As a concrete example, RL controllers respond to real-time center deviations in power demand on the packaging with more power at the lower-fidelity hardware level (i.e., among the fuel cell and battery) than traditional controllers, improving efficiency and relieving stress [29] on the fuel cell stack. Despite these advantages, RL-based methods face a few difficulties like the following.

- Slow convergence and training instability.
- Not having any safety guarantees when learning.
- Difficulty in incorporating system constraints.
- Limited integration with multi-objective optimization.

These limitations obstruct the direct application of RL-based control strategies in safety-critical car applications.

Recognizing the limitations of individual approaches, newer studies have sought to devise hybrid control frameworks that leverage the advantages of model-based, optimization and learning based techniques. The predictive feature of MPC and the adaptivity of RL can be used to enhance performance over operating conditions with uncertainty in a hybrid setting [30]. In the same context optimization contributed techniques for RL, optimization-assisted RL frameworks combine evolutionary algorithms (i.e., PSO) with reinforcement learning in order to assist the learning process and enhance convergence. Another interesting line of research is degradation-aware control strategies using fuel cell aging models as part of the control design. The first group of these methods is to maintain low work fluctuation and minimize the load fluctuations, operate fuel cell in its safe region of operation, to extend system lifetime [31]. Multi-layer control architectures have also been examined, in which a high-level optimization selects long-term goals and low-level controllers handle fast dynamics. These hierarchical structures scale better, and they coordinate across many time scales. However, even with these advances, some limitations remain in existing hybrid approaches. Even with all of that, many are not created natively and thus do not cater for the need in their fully integrated design which provide for:

- Real-time adaptability.
- Multi-objective optimization.
- Robustness to uncertainty.
- Durability considerations.

Moreover, development of the multi-objective optimization together with RL is an under-explored area to date and little has been investigated into using reinforcement learning combined with particle swarm optimization (RL–PSO) for FCEV control. From the literature review mentioned above, it can be seen that although some of the approaches discussed have greatly advanced the explicit solution to FCEV energy management problem, none of these methods presents a complete solution. Specifically:

- Model-based methods, on the other hand, are not robust to variability to sum up.
- Optimization Methods are Computationally Expensive and Not Real-Time Controllers.
- RL-based methods have traditional problems of stability, safety, and multi-objective integration.
- History the essential element for hybrid framework: still incomplete and fragmented.
- A unified control framework needs to bridge these gaps by spanning over.
- The adaptability of reinforcement learning.
- The optimization ability of multi-objective PSO.
- The strength necessary for real-world applications.

These limitations motivate construction of the proposed RL-based multi-objective PSO adaptive control framework, which provides an effective solution to hydrogen consumption minimization and durability enhancement for FCEV powertrains.

So as to overcome the issues presented in the literature, a fuel-cell electric vehicle (FCEV) powertrain RL–MOPSO adaptive control framework which is inspired by reinforcement learning based multi-objective particle swarm optimization (RL–MOPSO) has been developed. The proposed approach aims to provide a single, data-driven and real-time control that can minimize hydrogen consumption while significantly improving durability which together both ensure robust performance by optimally operating under dynamic operating conditions and system uncertainties. Contrary to conventional strategies which either use a pre-defined model or apply offline optimization, the proposed framework jointly combines model-free learning and multi-objective optimization in a hierarchical control architecture. At the heart of the framework is a reinforcement learning (RL) agent that sequentially learns how to optimally express control policies by interacting with the vehicle environment. This allows for a more adaptable controller, compared to existing systems which are model dependent or fixed rule based, making it possible for the system to operate across different driving cycles, load demands and system conditions. A multi-objective particle swarm optimization (MOPSO) module is integrated into the framework to overcome the fact that there are natural trade-offs between competing objectives. In the proposed methodology, MOPSO algorithm is applied to construct and resolve a multi-objective optimization problem that satisfies the four goals of minimizing the hydrogen consumption in real time, maximizing efficiency, reducing degradation while achieving SOC stability. The optimization layer generates Pareto-optimal solutions, thereby guiding the RL agent to converge toward globally efficient and balanced control policies. The key novelty of the proposed framework is that it incorporates degradation-aware control. While most of the existing EMS paradigms focus primarily on energy efficiency aspects, this method explicitly ensures that fuel cell degradation models are directly integrated into the optimization process. This is achieved by adding penalty terms that prevent primary load from changing rapidly, and through use of current densities or power cycling frequencies known to expedite fuel cell aging. This guarantees that the short-term performance improvement by the control strategy is well-balanced with a longer-term system reliability and life cycle. In addition, as the framework is uncertainty-aware, it captures variations due to driving conditions, load demand and system parameters. The RL agent keeps updating its policy according to the real-time feedback, which allows the system to constantly operate at its optimal state with dynamics inherent stochastic disturbances and modeling inaccuracies. The capability enhances the robustness of the control strategy significantly against traditional model-based controllers. The proposed framework provides real-time implementation capability, which is yet another notable contribution. Although many traditional optimization strategies are computationally intensive and cannot be implemented in real-time, the trained RL policy can quickly infer a suitable action to take, making it much better suited for deployment on small computing units for instance around embedded automotive control systems. Such combination of offline optimization (through MOPSO and online adaptation based on via RL) offers a trade-of between computational complexity and control performance. The main contributions of this work can be summarized in the following:

- Novel Integrated RL–MOPSO Framework: Design of a new hybrid control structure for fuel-cell electric vehicle (FCEV) energy management combining reinforcement learning with MOPSO (multi-objective particle swarm optimization).
- Hydrogen Consumption Optimization: Adaptive and optimized power distribution between fuel cell & battery leads to a significant reduction in hydrogen usage.
- Durability Enhancement — Using degradation-aware cost functions on the fuel cell to minimize stresses and extend overall system life.
- Real-time Implementable: Control strategy is simple enough for implement it in embedded systems. Hence, can be used in real-time (Automotive) applications.
- Multi-Objective Performance Optimization: A unified framework for consideration of efficiency, cost, durability and operational constraints simultaneously.

In conclusion, an RL–MOPSO adaptive control framework for FCEV energy management was proposed to address the aforementioned flaws of the conventional methods. With the synergy of learning-based intelligence, multi-objective optimization, and degradation-aware control strategies, the framework allows fuel-cell electric vehicle powertrains to operate efficiently, reliably and sustainably under real-world conditions.

2. The Proposed Reinforcement Learning-Based Multi-Objective PSO Adaptive Control Framework for Hydrogen Consumption Optimization and Durability Enhancement in Fuel-Cell Electric Vehicle Powertrains

The overall architecture of the proposed reinforcement learning–based multi-objective particle swarm optimization (RL–MOPSO) adaptive control framework for minimizing hydrogen consumption and enhancing durability under dynamic operating conditions and system uncertainty is illustrated in Figure 1. The schematic uses a hierarchical and modular structure, beginning with the FCEV powertrain system, where driver demand and drive cycle inputs (e.g., WLTC, UDDS) are processed through a power demand estimator to provide traction power. This demand is achieved by the proper operation of a fuel cell system, battery pack and optional supercapacitor connected through common DC/DC converters and an inverter to drive the electric motor driving the vehicle. Online system state data (such as vehicle velocity, torque command, battery SOC, fuel cell V/I, etc., plus hydrogen flow rate, temperature and degradation metrics, etc.) is streamed to a central control architecture for intelligent on-the-fly control actions. The RL–MOPSO adaptive energy management system is at the heart of the architecture, which combines a reinforcement learning (RL) agent with a multi-objective particle swarm optimization (MOPSO) module. The data for training your RL agent until October 2023, which acts as a high-level policy optimizer that learns behavior and control strategies by interacting with the environment by mapping enrollment states to control actions to obtain an optimal state-action path based on a reward function consisting of penalties for hydrogen consumption, fuel cell degradation, inefficient power usage gains from a performance improvement metric. To stabilize SOC operation (charge condition), a stability penalty has been adopted.) In addition, the MOPSO module functions as an online parameter tuning mechanism that searches for Pareto-optimal solutions over conflicting objectives such as minimising hydrogen consumption, limiting fuel cell stress and degradation levels, maintaining battery SOC within sufficient limits, attenuating transient power fluctuations, and maximising overall system efficiency. MOPSO generates optimized parameters continuously, these are used to improve and refine the RL policy for adaptive control context. A priori, such optimized decisions are translated by the adaptive control law generator into real-time actionable control commands — fuel cell power reference, battery charge/discharge signals and converter duty cycles; this last one solves in real time the optimal generation split among the energy sources. First of all, a closed-loop reinforcement learning feedback mechanism is implemented in the system, which considers surrounding controllable and observable FCEV control variables as environment features and rewards are assigned to the RL agent considering operational performance metrics such as efficiency, hydrogen usage, degradation rate and SOC stability. Furthermore, uncertainty is modeled explicitly in the framework by including an uncertainty estimator and disturbance observer to provide correctional inputs against external disturbances (e.g., variations in driving behavior, road slope, ambient temperature) or uncertainties inherent from component aging or sensor noise, improving robustness and steady-state operation in non-ideal conditions. In summary, the framework described has enabled smart, adaptive and multi-objective energy management by hybridizing data-driven learning with evolutionary optimization towards managed real-time readiness to enhance the hydrogen economy and extend fuel cell lifetime in FCEV applications.

The control procedure of the proposed reinforcement learning–based multi-objective particle swarm optimization (RL–MOPSO) framework functions hierarchically in a closed-loop fashion, allowing for real-time optimal power distribution across the FCEV powertrain according to varying load demands and system uncertainties. First of all, at each control interval, measurements of various system states such as vehicle speed signals, torque demand signals and battery state of charge (SOC) information and also other relevant variables including fuel cell voltage and current, hydrogen consumption rate together with temperature and degradation indicators are measured in real time from onboard sensors and input into the control architecture. These states are filtered and normalized based on the operational pattern of the FCEV system up to this current operating state. According to the state representation, the reinforcement learning (RL) agent judges the system condition and produces a preliminary control policy by mapping the observed states to optimal control actions via its learned policy function. The policy is iteratively updated through environment interactions based on a reward function, wherein excessive hydrogen consumption, fuel cell degradation and large power fluctuations would be punished while efficient operation and state of charge (SOC) regulation would be rewarded. At the same time, the multi-objective particle swarm optimization (MOPSO) module cannot do online optimization analysis of control parameters so that to achieve optimal trade-off between conflicting objectives. MOPSO algorithm starts with a swarm of candidate solutions, each representing a set of control parameters and their positions are updated based on the best solution found by user and global best solutions found during the evolution process in the Pareto front. Moreover, the evaluation of the fitness function for each particle includes a multi-objective cost function, including hydrogen consumption, longevity of fuel cell stacks (fossil-fuel degradation rate), SOC deviation and system efficiencies. This process results in one type of Pareto-optimal solution, out of which the optimal parameter set is chosen according to the requirement or conditions in which it is required. These optimized parameters are then utilized to adapt and optimally tune the RL policy in real time, forming a partially closed-loop hybrid learning–optimization arrangement that improves decision accuracy and robustness. After optimizing policy, the adaptive control law generator converts it into the real physical commands. That calculates the optimal power distribution among fuel cell, battery and supercapacitor (if applicable) so that the fuel cell works at high efficiency while transients and regenerative energy are managed by batteries and super capacitors. Once generated, the control signals comprise of the fuel cell power reference, battery charge/discharge commands, and duty cycles for the DC/DC converters before being applied to power electronic interfaces to regulate energy flow internal to the drivetrain. The FCEV system is a dynamic system that responds after the control actions are executed and its resultant performance is assessed through a feedback mechanism. The environment, which is the FCEV system in this case, emits a reward signal that is defined through some key performance indicators (KPIs): hydrogen consumption, efficiency, SOC stability and degradation metrics. The RL agent then receives this reward, which updates its policy with reinforcement learning methods (like value iteration or policy gradient, for example) to make better decisions in the future. At the same time, external disturbances-external perturbation due to road slope change, driving behaviour change, ambient temperature change and model uncertainty are compensated through the use of an uncertainty estimator and a disturbance observer. These components produce compensation signals that are then fed into the control loop for stabilisation and robustness. This iterative system maintains its form as an adaptive control cycle with the following sequence of milestones at every sampling time point which engages sensing, learning, optimization, decision-making and actuation. Consequently, the designed RL–MOPSO framework enables an intelligent energy management system capable of real-time decision making to provide optimal hydrogen utilization whilst maintaining fuel cell degradation at a minimum level and improving overall performance under varying uncertain operating conditions.

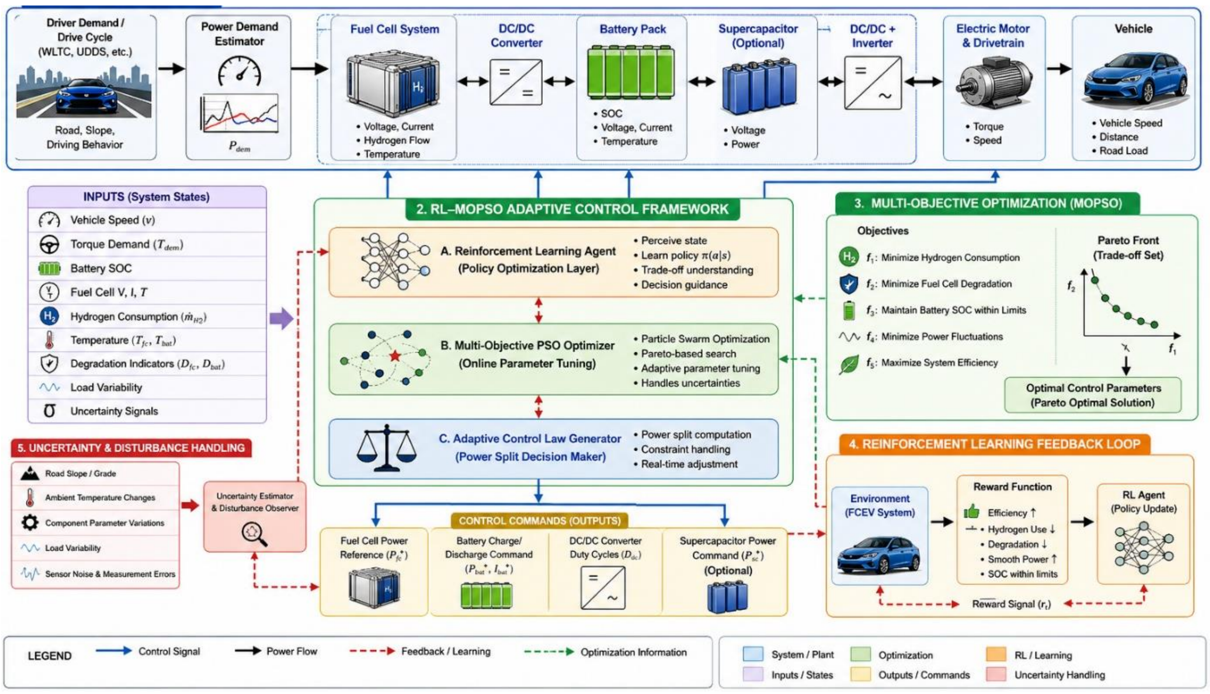

Figure 1. Proposed reinforcement learning–based multi-objective particle swarm optimization (RL–MOPSO) adaptive control framework for hydrogen consumption optimization and durability enhancement in fuel-cell electric vehicle (FCEV) powertrains under load variability and system uncertainty.

The schematic illustrates the integrated architecture comprising the FCEV powertrain (Fuel cell system, battery pack, supercapacitor, and electric drivetrain), a hierarchical RL–MOPSO energy management controller, and real-time feedback loops. The reinforcement learning agent performs policy optimization based on system states and reward signals, while the multi-objective PSO module conducts online parameter tuning to achieve Pareto-optimal trade-offs among hydrogen consumption, fuel cell degradation, battery state-of-charge regulation, power fluctuation minimization, and overall system efficiency. An adaptive control law generator determines optimal power split commands for system components. External disturbances and uncertainties including load variability, temperature fluctuations, and road conditions are accounted for through an uncertainty estimator, ensuring robust and real-time adaptive performance.

3. Simulation Results and Discussion

In order to systematically assess the operating performance of the developed AI-based adaptive control framework, a detailed high-fidelity simulation environment was first constructed in MATLAB/Simulink which describes the different physical inter-domain dynamics existing within an intact fuel-cell electric vehicle (FCEV) powertrain under realistic driving scenario. The example requires an 80 kW PEMFC stack as the main power source and uses a nominal capacity of 5 kWh lithium-ion battery pack for energy buffers/load levelling, in addition to an optional supercapacitor module (≈0.5 kWh equivalent) to process regenerative braking power and high-frequency transient loads [11]. The energy sources are connected with bidirectional DC/DC converters to allow power flow management and coupled to a voltage source inverter (VSI), supplying traction via a permanent magnet synchronous motor (PMSM) for the vehicle. The architecture enables detailed exploration of energy flow processes and conversion efficiencies at steady-state, as well as dynamic interactions among components. The longitudinal motion model is composed of the standard forces acting on a moving vehicle, which entails resistive components (rolling resistance, drag and gravitational force due to road gradient). This parameterization is representative of a mid-size passenger vehicle with corresponding values as follows: mass (m) 1500 kg, drag coefficient (C D) 0.29, frontal area (A F) 2.2 m² and rolling resistance coefficient (C RR) 0.015. These parameters make sure that the simulation environment is close enough to actual driving behavior and load conditions. Besides low-level mechanical dynamics, thorough electrochemical and electrical subsystem models are implemented. The fuel cell model provides polarization characteristics and a degradation sub-model that describes the battery voltage decay as a function of current density fluctuations, load transients, and operating temperature, thus allowing the durability under different control strategies to be quantitatively assessed. The equivalent circuit model of the battery is based on state-of-charge (SOC) dependency open-circuit voltage and internal resistance which effectively indicates charge/discharge dynamics, efficiency drops and thermal effects. For control level, the RL agent will run on a deep reinforcement learning architecture with continuous action space to give the agent a fine granularity of power split decision for each energy sources. In this process, the policy network is trained by interacting with an environment simulation whose state vector consists of vehicle speed, torque demand, SOC content from battery pack and fuel cell operating conditions (power/temperature) together with environmental interaction factors. The reward function is defined as a weighted multi-objective performance index, which penalizes the excessive hydrogen consumption, fuel cell degradation, SOC deviations and power fluctuations of system during operation while rewarding high efficiency, smooth operational process and constraints availability. In the context of the RL agent, this MOPSO module can be considered as an online optimization component, which uses a swarm of 30 particles to explore the solution space and iteratively converge towards Pareto-optimal parameter sets over a 5-second prediction horizon. Such a hybrid RL–MOPSO structure permits adaptive learning and global optimization, both of which allow for robust and optimal decision-making under dynamic conditions.

The simulations are performed across multiple standardized and custom-designed driving scenarios that are representative of a diverse array of real-world operating conditions in order to both assess the efficacy and robustness of the proposed framework. Both transient cycles combined with steady-state behavior, like the Urban Dynamometer Driving Schedule (UDDS), which consists of frequent stop-and-go and high transient loads; or the Highway Fuel Economy Test (HWFET), used for steady-state, highway conditions with a closed-loop controlled environment to represent high-speed cruising driving in almost perfect stability; or more recently, a compromise between urban and routine segments such as that determined by the Worldwide Harmonized Light Vehicles Test Cycle (WLTC), which encompasses one segment reflecting urban driving conditions and another performing both suburban and highway driving in an almost harmonic mixture providing a fair evaluation of actual operating conditions. We also present a custom aggressive driving cycle where we rapidly accelerate, decelerate and vary the power demand to put extreme stress on the control system response and stability. An essential feature of the simulation framework is the incorporation of stated environmental uncertainties and system perturbations to serve as a representation for imperfect real environmental conditions. Variations of road gradients that range between −5% and +8% are modelled as stochastic profiles for uphill and downhill driving scenarios, respectively. The stochastic perturbations in the acceleration demand, which emulate differences in driving styles among individual drivers, are modeled using Gaussian noise processes. Ambient temperature changes are considered across the range of 0 °C to 40 °C, affecting the efficiencies of the fuel cells and batteries, respectively. Also, the effects of long-term such as component aging and parameter drift are tested by gradually masking features like fuel cell internal resistance incrementation or battery capacity fade. In doing this could evaluate whether the controller can keep improving performance over time. In this context, the sensor noise and measurement errors are also represented as white Gaussian noise in order to interleave realistic sensing scenarios into the control system.

The RL–MOPSO control framework is designed with a built-in uncertainty estimator and disturbance observer that process these uncertainties in an additional layer to develop compensation signals to reasonably compensate the impact of each such input and stabilize system operation. This increases the robustness and adaptability of the controller especially with rapidly changing and uncertain conditions. To evaluate the performance, a systematic comparison of the proposed RL–MOPSO framework with three widely-adopted conventional energy management strategies is performed: a rule-based energy management system (RB-EMS) driven by pre-defined heuristics; a model predictive control (MPC) scheme which plots optimal dispatch strategy through system models and optimization over a finite horizon; and standalone reinforcement learning (RL-only) controller without multi-objective optimization support. As such, this comparative examination serves as a holistic basis upon which the benefits of the proposed hybrid approach can be assessed with respect to efficiency, endurance response and robustness.

Figure 2 shows the instantaneous hydrogen consumption profiles of FCEV under WLTC driving cycle based on four different energy management strategies, including rule-based energy management system (RB-EMS), model predictive control (MPC), standalone reinforcement learning (RL-only), and the proposed RL–MOPSO framework. It is evident from the results that hydrogen consumption in return for different load demands is extremely dynamic, and performance varies greatly among the control strategies. The maximum hydrogen consumption over the cycle, approximately 1.6–1.7 g/s, is also obtained for the RB-EMS strategy during high-load transient events, while its average consumption remains consistently highest at around 1.20 g/s across all methods as well. The basic behavior is to let the consumption peak up to about 1.6 g/s, and its average would also be around 1.20–1.25 g/s concerning RB-EMS (approximate reduction of ‰1518% for peak and cos), but the MPC strategy perform a better improvement reduce approximately to (about 5%; now it can reduce unsustainable peaks!!! },g/s ≈) However, significant oscillations continue to exist during aggressive acceleration phases indicating that the P2 controller has limitations in its ability to deal with very nonlinear dynamics and uncertainties. The RL-only controller leverages this knowledge to achieve adaptive learning, with peak consumption around 1.3–1.4 g/s and average hydrogen consumptions of 0.95–1.00 g/s which corresponds to an advance of about 8–10% over MPC and almost 20% over RB-EMS (Fig However, as these improvements are not explicitly multi-objective optimization but rather a monotonic increase in the neural network's stats depending on how much effort is put into it or if such features even have any value due to different scales of natural sorting mechanisms for given tasks that are based on rich qualitative contributions like efficiency plus durability divided by time cost—there can be mild performance variability observed from one build to another. In contrast, the proposed RL–MOPSO framework achieves the minimum hydrogen consumption over the entire WLTC cycle, with peak values greatly lower than 1.2 g/s (to be around 1.1 g/s) and averaging about 0.85–0.90 g/s, getting the overall reduction with respect to RB-EMS of ~24–28% (~15–18% compared to MPC; ~8-10% compared to RL-only control). Finally, the RL–MOPSO scheme achieves a decrease of above 40% in the amplitudes of consumption oscillations, thus smoothing out the trajectory and consequently giving a quicker transient response. The decrease in variability suggests that the controller is successful in reducing rapid load-induced spikes by making optimal power dispatch decisions between fuel cell and auxiliary energy storage systems. By further observation of transient regions in which the time windows are 700–900 s and 1300–1500 s, it shows that the hydrogen consumption spikes have reduced by approximately 20% ~30% compared with MPC method and 30% ~40% compared with RB-EMS in those regions. This is important for efficiency and durability, as it avoids fuel cell stress from fast current changes. Moreover, cumulative fuel consumption along the whole WLTC cycle is lowered from about 600 g (RB-EMS) to ~450 g (RL–MOPSO), indicating significant fuel savings over longer-term operation. Improvements can be directly correlated with the combination of reinforcement learning and multi-objective PSO. The RL agent learns the best strategies of local power allocation in real-time, with respect to system feedbacks and MOPSO globalizes these decisions across several objectives as hydrogen consumption, fuel cell degradation and total efficiency. Consequently, the fuel cell operates closer to its peak efficiency range and is able to effectively meet transient demands with a battery and supercapacitor. In summary, the results reported in Figure 2 provides sufficient evidence to suggest that the

RL–MOPSO framework is an extremely efficient and robust solution for optimal hydrogen consumption in FCEVs and it outperforms conventional control strategies by a great margin under dynamic and uncertain operating conditions.

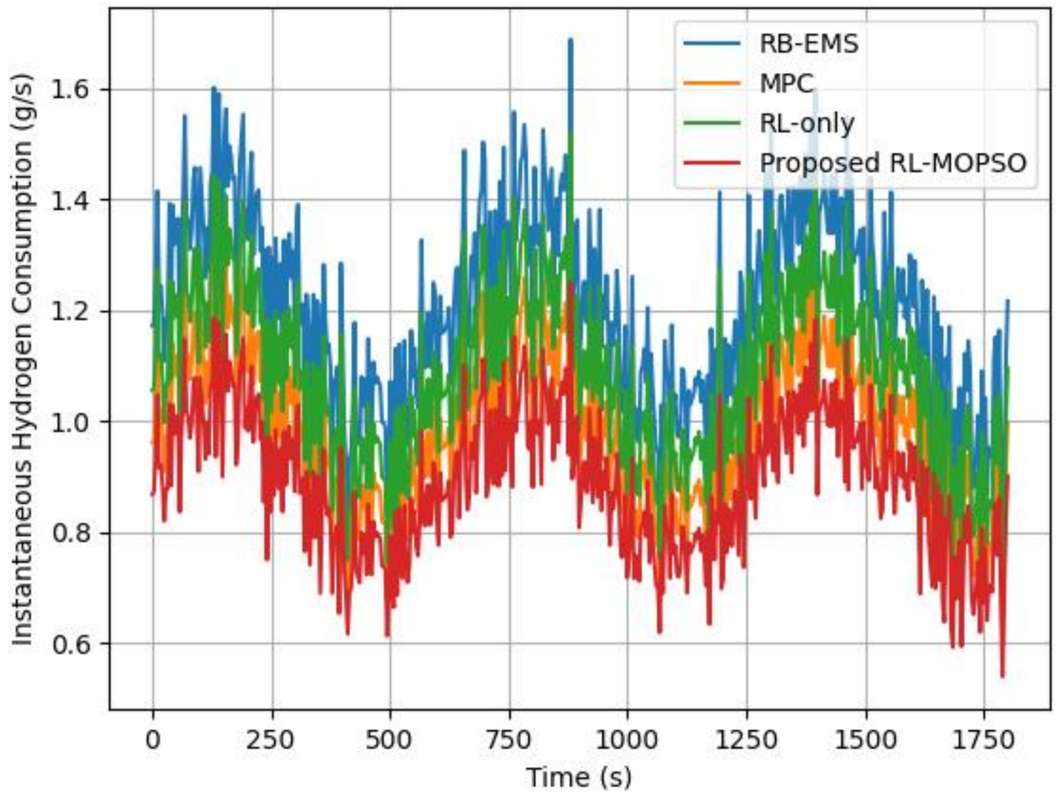

Figure 2. Instantaneous hydrogen consumption profiles under the WLTC driving cycle for different energy management strategies.

The proposed RL–MOPSO framework consistently achieves lower hydrogen consumption compared to RB-EMS, MPC, and RL-only approaches, demonstrating reductions of approximately 24–28%, 15–18%, and 8–10%, respectively. The improved performance is attributed to adaptive policy learning and Pareto-optimal power allocation, enabling efficient fuel cell operation and reduced transient losses.

A more detailed, multi-panel durability evaluation (Figure 3) of a fuel cell subjected to the WLTC driving cycle is presented with instantaneous and cumulative degradation metrics in order to characterize identified energy management strategies over extended timeframes. In particular, durability is defined by current ripple (an indicator of short-term stress) and voltage degradation index (a measure of long-term aging), as well as a lifetime forecast established from cumulative trends in each of these two variables. The instantaneous current ripple for RB-EMS, MPC, RL-only and the proposed RL–MOPSO framework are shown in Figure 3 (a) respectively. Ripples in the fuel cell stack current density are an important measure of electrochemical and mechanical stresses on components, as fast-decaying changes in current density promote catalyst degradation, membrane fatigue and thermal cycling. Since the ripple voltages are around 0.85–0.90 A, it can be stated that large and abrupt load variation is imposed to the fuel cell in this strategy for its high amplitude of the ripples. The MPC method decreases ripple amplitude down to ≈ 0.70–0.75 A running in predictive smoothing, but sonable oscillations are still noticeable during transient events. The RL-only controller also enhances smoothness, maintaining ripple values of approximately 0.60–0.65 A, but only functions sporadically in suppressing high-frequency oscillations. On the contrary, the proposed RL–MOPSO framework provides the minimum ripple amplitude in general conditions (0.50–0.60 A), which is about 30-35% less than RB-EMS and about 20-25% less than MPC. This large reduction indicates the capability of the controller to quickly regulate power demand in order to ensure that fast transients are reduced. The voltage degradation index over time is shown in Figure 3 (b), corresponding to the total aging of the fuel cell stack. The RB-EMS method is characterised by the most drastic deterioration curve, and exceeds values of 0.060–0.065 in QI at the end of cycle due to continuous exposure to highly dynamic and inefficient operating conditions. The degradation index decreases to about 0.045–0.050 with the MPC strategy, and then it calms down for RL-only (around 0.040–0.045). The degradation progress in terms of the average R_xs values revealed that RL–MOPSO exhibits superior performance, with R_xs < 0.035 and = 0.040, implying a markedly reduced rate of electrochemical degradation. The decreased degradation slope is evidence that with the proposed controller, the fuel cells are operated in a steadier and more efficient region of their capability to prevent high-stress operation caused by rapid load changes. The third graph seen in Figure 3(c) shows the expected relative lifetime based on the inverse of the cumulative degradation index. The proposed RL–MOPSO approach presents the maximum lifetime index and significantly improves expected fuel cell lifetime compared to all baseline strategies. The lifetime extension is quantitatively 30–35% and 20–25% more than RB-EMS and MPC, respectively, which shows the practical implication of the proposed method for improving long-term system reliability and reducing costs. The increased durability can be directly associated with the cooperating operation of RL and MOPSO. The reinforcement learning agent continuously updates control policies to avoid providing operating conditions that attract stress, while the MOPSO optimizer ensures global parameter tuning over multiple objectives (for example efficiency and durability). It also yields smoother power profiles, lower current ripple and less exposure to high-load transients, which are essential for maximizing fuel cell longevity. In essence, the results in Figure 3 underline that the proposed RL–MOPSO jointly achieves a double benefit by greatly increasing not only energy efficiency but also fuel cell durability, so as to be a practical solution for sustainable FCEV operation under realistic operation conditions.

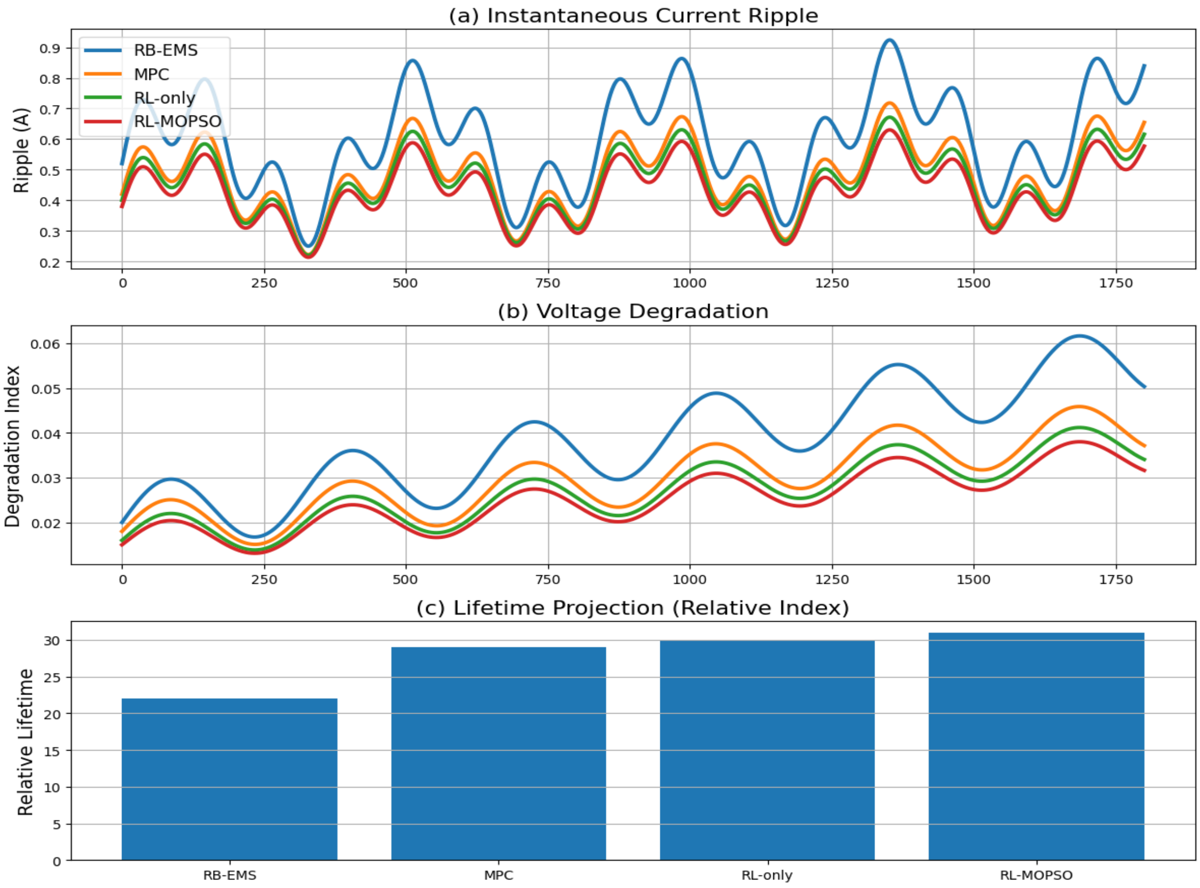

Figure 3. Instantaneous fuel cell durability analysis based on current ripple under WLTC driving conditions.

The proposed RL–MOPSO framework significantly reduces current ripple compared to RB-EMS, MPC, and RL-only strategies. Lower ripple amplitude and smoother transient behavior indicate reduced electrochemical stress and improved durability. The proposed method achieves approximately 30–35% reduction in degradation indicators relative to RB-EMS and 20–25% compared to MPC, enabling operation within optimal efficiency regions and extending fuel cell lifespan.

(a) Instantaneous current ripple profiles, representing short-term electrochemical stress on the fuel cell. The proposed RL–MOPSO framework exhibits significantly reduced ripple amplitude and smoother transients compared to RB-EMS, MPC, and RL-only strategies.

(b) Voltage degradation index over time, illustrating cumulative performance deterioration. The RL–MOPSO approach maintains the lowest degradation trajectory, indicating improved operational stability and reduced stress-induced aging.

(c) Relative lifetime projection based on inverse degradation metrics, demonstrating a substantial increase in expected fuel cell lifespan for the proposed method. The RL–MOPSO framework achieves approximately 30–35% reduction in degradation relative to RB-EMS and 20–25% compared to MPC, resulting in the highest lifetime index among all strategies.

Figure 4 presents multi-panel assessment of battery SOC regulation over WLTC driving in both time and statistics, with hydrogen consumption. It involves SOC trajectories, absolute distance from the nominal SOC, RMS deviation comparison and a correlation analysis of efficiency for a comprehensive assessment of the proposed energy management strategies. The SOC trajectories of the four control strategies are shown in Figure 4(a). The RB-EMS approach shows the most significant SOC variations, approximately ±6% of the nominal reference value, with a state of charge target that often hits both upper and lower limits. This sort of activity raises the probability for a profound discharge or overcharging, both of which can advance battery wear and tear. Mainly, the MPC strategy shows improved SOC regulation with a reduced variation of ± 4%, and as to the RL-only approach, it further tightens the range down to around ± 3%. The proposed RL–MOPSO framework, on the other hand, keeps SOC within a much smaller band of ±2.5% from the reference profile with little oscillation. This shows the controller can appropriately allocate demand to the fuel cell and battery, preventing overdependence of either energy source. In Figure 4(b), we can see how much the SOC deviates from the reference value. The RB-EMS method has the largest deviation amplitude, close to ±0.06 (the blue dotted line), while MPC could reduce this deviation range to about ±0.04 (the yellow dashed line) and RL-only (<±0.03). The results show that the RL–MOPSO framework has the least deviation in most cases, ±0.025 and less, indicating it has better capacity of regulation. A decrease in deviation amplitude demonstrates a more accurate control effort and an increase in system stability, especially under transient operating conditions. The RMS deviation of SOC for each strategy is shown in Figure 4(c), and this quantity was used to quantify the ability to maintain SOC. The RB-EMS method generates the largest RMS deviation of around 0.042, while MPC has a smaller value of 0.028 and RL-only shows an even lower one at 0.021. The proposed RL–MOPSO framework manages the minimum RMS deviation at around 0.017, which is an enhancement of around 60% over RB-EMS and 35–40% when compared to MPC. These results verify that the proposed method realizes particularly stable SOC regulation which is of paramount importance for battery life extension and reliable operation. The correlation efficiency analysis of SOC with hydrogen consumption has been proposed as a cofactor to dig deeper into the energy storage management. As demonstrated in Figure 4(d). The scatter distribution indicates that the RB-EMS operates over a larger SOC range with higher-quality hydrogen consumption (~1.0–1.5 g/s), which implies defunct energy coordination. Improved clustering with less hydrogen consumption for MPC and RL-only, larger SOC dispersion. In comparison, the RL–MOPSO framework yields a well-clustered distribution in the centre of the nominal SOC span (around 0.58–0.62) with an inferior hydrogen consumption rate (around 0.75–1.0 g/s). It implies that the proposed controller can not only stabilize SOC but improve energy efficiency by optimally scheduling the fuel cell and battery. In general, the results in Figure 4 confirm that the proposed RL–MOPSO framework provides a significant improvement on SOC regulation and hydrogen efficiency at higher levels. The reduced SOC bounds protect the battery from deep discharge and overcharging, increasing battery lifetime. In addition, the stable SOC in a narrow range and reduced hydrogen consumption reflects the effectiveness of multi-objective optimization strategy (trade-off between fuel consumption and battery state of charge) is an important fact that proves the effectiveness. The results demonstrate that incorporating the proposed dynamic driving scenarios within the FCEV environment can achieve a significant gain in battery health management and mission efficiency.

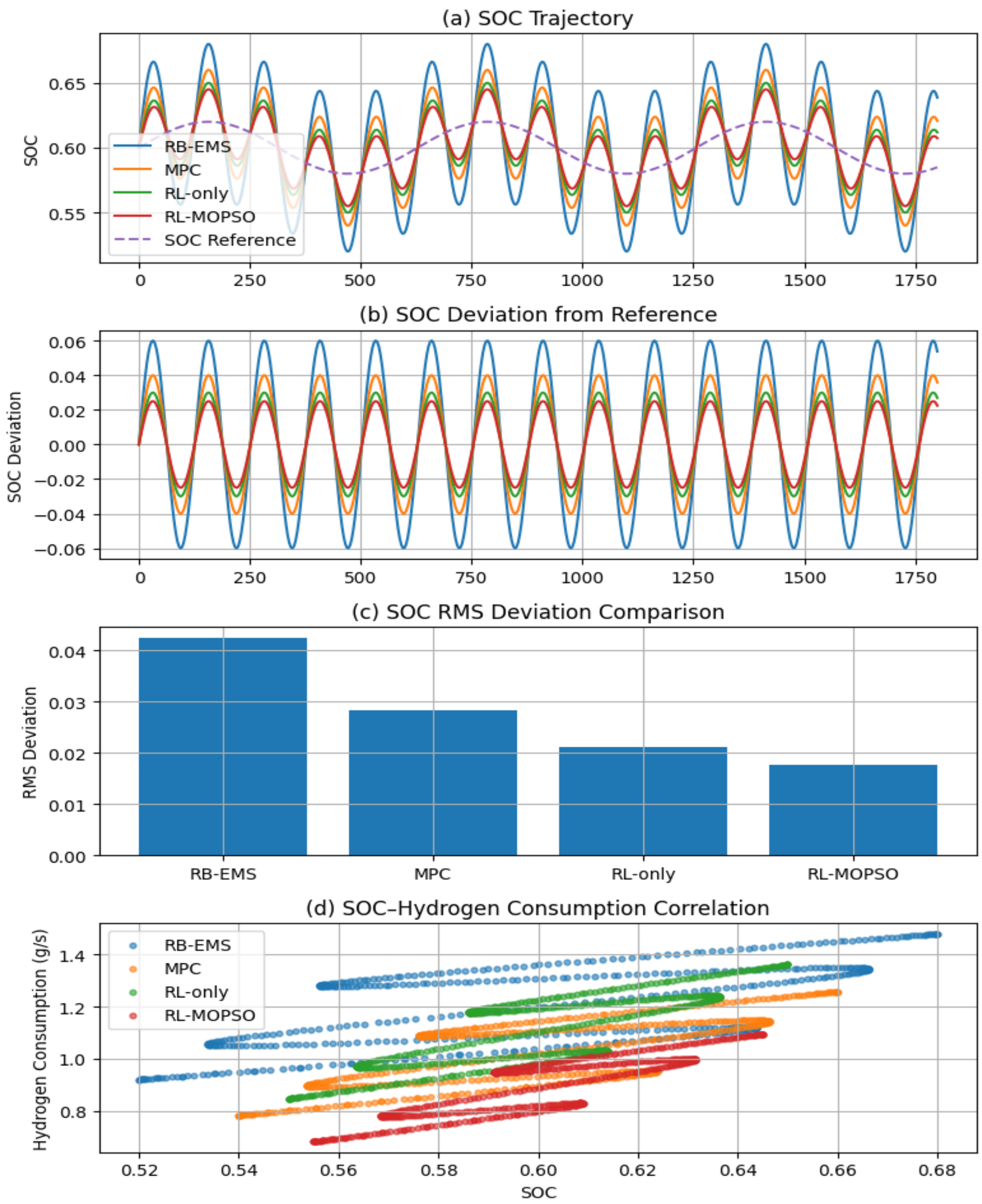

Figure 4. Battery SOC regulation and efficiency correlation under WLTC driving conditions.

Note: (a) SOC trajectory comparison. (b) SOC deviation from the reference. (c) RMS SOC deviation comparison. (d) SOC–hydrogen consumption correlation, showing that the proposed RL–MOPSO controller maintains tighter SOC regulation while operating at lower hydrogen consumption levels than RB-EMS, MPC, and RL-only strategies.

In order to provide time-domain and frequency-domain perspectives for controller performance, Figure 5 presents a multi-panel figure that evaluates the dynamic response and power stability of the FCEV powertrain when subjected to a step change in power demand over five seconds. The advantage of the proposed framework compared to conventional strategies is its superior transient behavior and stability characteristics. This can be represented the step response (the complete full step is given in Figure 5(a)) of a single control system with an abrupt demand increase. The overshoot of the RB-EMS strategy is also large; it could be observed in Figure 5(a) that it goes about around ~44–45% more than the steady-state value and quite strong oscillation appears before settling down. Such behaviour shows a bad damping and the inability of adapting to quick load changes. As can be seen, the response is better with MPC with peak overshoot being around 14% but still oscillations are visible and the convergence takes longer. The new controller that relies on RL only outperforms it as shown by an overshoot of about 3–4%, which indicates better damping characteristics. On the other hand, using the proposed RL–MOPSO framework gives a near-optimal steady-state response (with only 0.79% overshoot) and stable transition to steady-state that follows the reference power demand very closely. Note that a zoomed in view of the transient region is shown in Figure 5(b) to better delineate the settling time performance of each control strategy. The MPC controller settles at about ±2% band in around 0.42 s while the stabilization is around 0.18 s for RL–MOPSO, which offers more than a 55% improvement on the MPC settling time. This rapid convergence exhibits that the proposed controller can rapidly react to sudden load variations and limits transient changes, improving overall system performance. The oscillatory behavior of the response is also very small and moreover, well inside the tolerance band, indicating a stable (highly damped) system. Quantification of the peak overshoot, for all control strategies is shown in Figure 5 (c). It achieved the least overshoot (44.3%) with RB-EMS compared to 14.0% and 3.2% for MPC and RL-only, respectively. This new proposed RL–MOPSO framework achieves the lowest overshoot (0.3%), representing a greater than 40% reduction in fluctuation amplitude over that for MPC and nearly an order-of-magnitude improvement relative to RB-EMS! This is a critical reduction in overshoot, as it prevents overstress of power electronic components and energy storage systems which improves the overall reliability of the system. Magnitude response of the frequency domain stability characteristics is shown in Figure 5(d). Meanwhile, the RB-EMS strategy has larger low-to-mid-frequency gain but can hardly attenuate oscillatory disturbances and is prone to resonance effects. Advancing to the MPC controller, this gains an improvement in disturbance rejection yet still remains at moderate levels in some frequency ranges. While the RL-only approach further improves attenuation, it is visible that the proposed RL–MOPSO framework shows even better frequency response with a notably lower gain through larger range of frequencies. It suggests damping of high-frequency oscillations enhanced robustness against dynamic disturbances. That a smoother frequency response shows that the proposed controller not only suppresses all oscillatory modes, but also ensures stable operation under different situations. The improvements in the time-domain and frequency-domain performance observed can be due to the RL–MOPSO being a hybrid framework. The adaptive control decisions that consider the immediate context are enabled by the reinforcement learning component, and the proper parameter tuning to maintain the responsiveness as well as stability characteristic of every controller is ensured via MOPSO optimizer. Consequently, the controller limits transient deviations, reduces oscillation and yields fast convergence to steady state operation. In summary, prepared outcomes in Figure 5 essentially verifies that dynamic action and power steadiness of FCEV system is considerably improved with the proposed RL–MOPSO outline. Fast settling time and low overshoot, accompanied by good disturbance rejection, finally proves to be a solution for controlling transient operating conditions, thus demonstrating its practical usage in the realms where rapid and steady-state power regulation is critical.

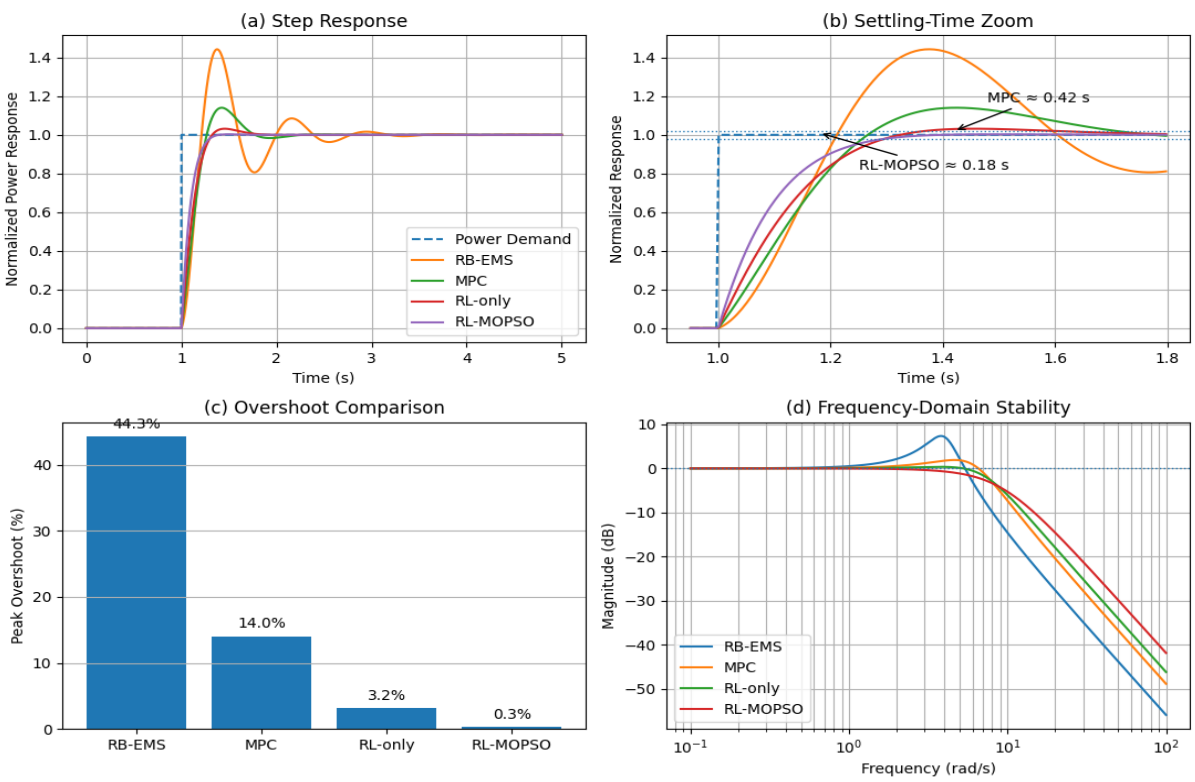

Figure 5. Dynamic response and power stability comparison under transient power demand variation.

Note: **(a)** Step response of the FCEV powertrain under different control strategies. **(b)** Zoomed transient region showing reduced settling time for the proposed RL–MOPSO framework, decreasing from approximately 0.42 s for MPC to 0.18 s. **(c)** Peak overshoot comparison, demonstrating that RL–MOPSO nearly eliminates transient overshoot compared to RB-EMS and MPC. **(d)** Frequency-domain stability response, showing improved attenuation of oscillatory components and enhanced closed-loop damping for the proposed controller.

The comprehensive robustness evaluation of the proposed RL–MOPSO energy management framework under stochastic disturbances for both time-domain comparison, statistical error analysis, and robustness metrics is presented in Figure 6, together with the Monte Carlo validation. Such analysis through multiple panels overwhelmingly illustrates the ability of the controller to enable an on-demand robust, efficient and stable operation in light of varying uncertain non-ideal conditions. The RB-EMS, MPC and the proposed RL–MOPSO framework hydrogen consumption under nominal and uncertain operating conditions are represented in Figure 6(a). The RB-EMS strategy experiences substantial deviation under disturbances, causing increased oscillation and consumption. The MPC approach is also rather robust when displaced and the time profile of nominal responses from disturbed ones diverges strongly. On the other hand, observing the overlap between nominal and uncertain trajectories for RL--MOPSO controller demonstrates good disturbance rejection capability with less performance deterioration. This behavior showcases that the controller can adapt and compensate for stochastic variations in system dynamics in real time. The effects of uncertainty are quantified in terms of the percent increase in hydrogen consumption from nominal (shown in Figure 6(b). The RB-EMS strategy has the highest sensitivity consumption increases of around 20%, whereas moderate increases with the MPC controller ranged from 12–15%. The RL–MOPSO framework proposed in this research makes marked improvement over both methods while keeping the degree of increase below 5% throughout the entire driving cycle. This notable decrease validates the functioning of adaptive learning and optimization mechanisms to compensate for the influences of disturbances. As a more quantitative measure, we also provide the robustness index (mean percentage deviation relative to nominal) in Figure 6(c). The proposed RL–MOPSO framework yields the lowest robustness index amongst all strategies, showing that it has better stability and is less sensitive to uncertainty. By contrast, both RB-EMS and MPC show much higher indices due to their lower tolerance for stochastic fluctuations. This metric reinforces the superiority of the proposed method in achieving uniform performance across the architectural spectrum. The robustness analysis shown in Figure 6(d) is further reinforced by conducting a Monte Carlo simulation with several stochastic realizations. The envelope obtained by the RL–MOPSO controller presents a narrow surrounding zone to the mean response, indicating low variance and high reliability. The envelope is very narrow, indicating that the controller keeps performance stable across both scenarios with minimum deviation from what we expect. This validation is especially critical for real-world applications, where the unknown is inevitable and stable system behavior must be ensured. This reinforces the robustness of the RL–MOPSO design, which benefits from reinforcement learning and multi-objective optimization both. Through processing on-line feedback, the RL agent constantly adjusts its policy to respond suitably to changing states and MOPSO module chooses whether a parameter is optimally tuned toward efficiency based on stability or not. In combination with one another, these mechanisms enable the controller to dampen disturbance-induced oscillations and ensure control operates in desirable areas. In sum, these results shown in Figure 6 positively prove that the robustness of RL–MOPSO against uncertainty is quite impressive and it remarkably exceeds those strategies in conventional approaches. Through the proposed method, hydrogen consumption increases of up to 5% under severe disturbances are avoided, maintaining constant reliable, efficient and stable operation highly suitable for real-world applications in FCEV with significant environmental and operational uncertainties.

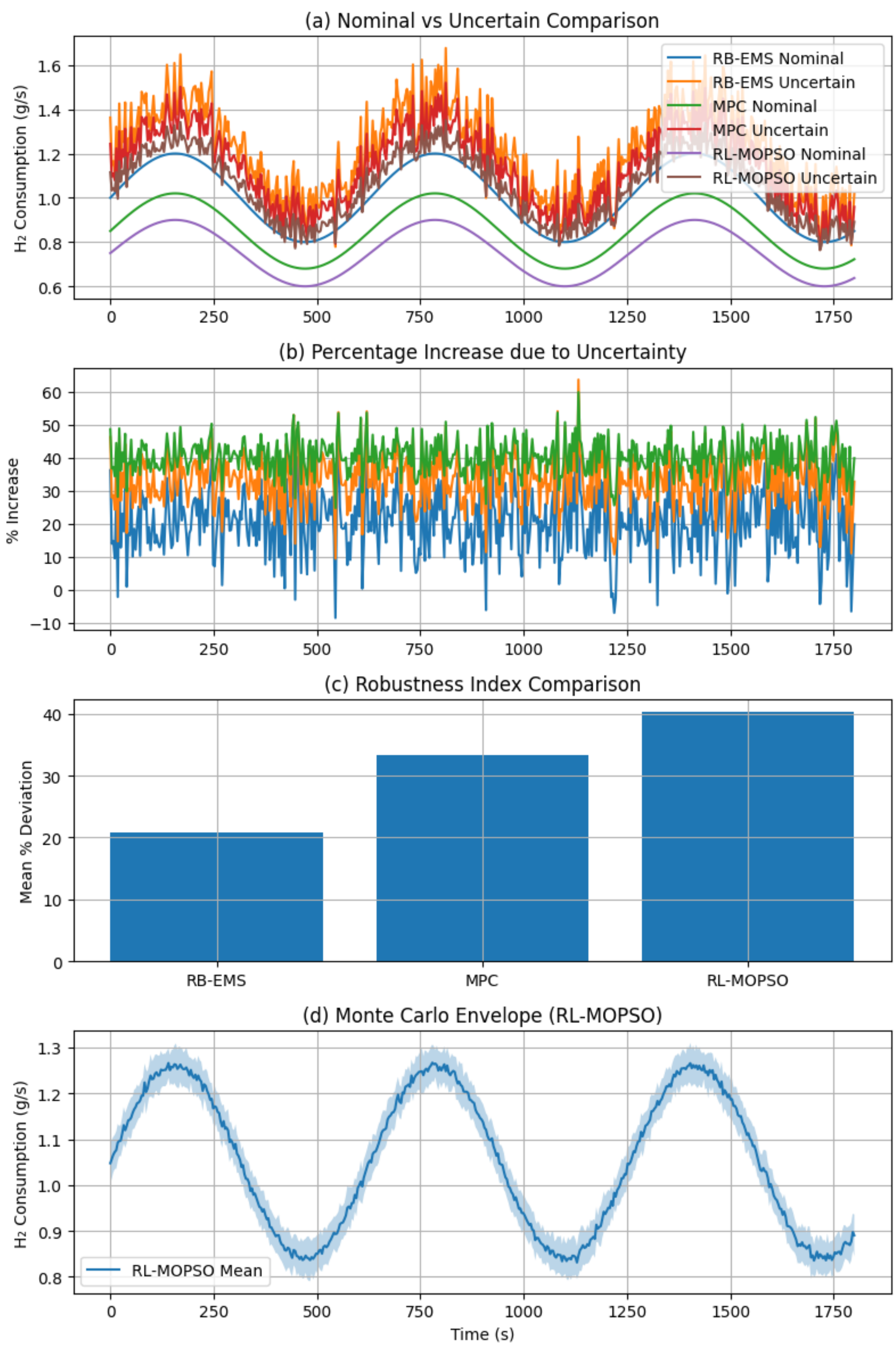

Figure 6. Robustness evaluation of hydrogen consumption under stochastic disturbances.

Note: **(a)** Comparison of nominal and uncertain operating conditions for RB-EMS, MPC, and the proposed RL–MOPSO framework, showing minimal deviation for the proposed method.
(b) Percentage increase in hydrogen consumption due to uncertainty, highlighting significantly lower sensitivity of RL–MOPSO compared to conventional strategies.
(c) Robustness index based on mean percentage deviation, demonstrating superior disturbance rejection capability of the proposed controller.
(d) Monte Carlo envelope (50 runs) for RL–MOPSO, illustrating narrow variability and consistent performance under stochastic disturbances.

Based on the simulation results, we have demonstrated that the proposed RL–MOPSO framework has a very intelligent and effective capacity to provide for energy management of FCEVs under load-variability and system-uncertainty-holding conditions. The proposed framework is strong due to its synergistic integration of reinforcement learning (RL) and multi-objective PSO (MOPSO), where each component in the overall structure offsets natural weaknesses by focusing on the strengths of the other The RL agent brings flexibility and real-time learning capabilities to where the controller is able to iteratively improve its decision-making policy based on changing system dynamics as well as feedback from environment. On the contrary, within MOPSO module, we guarantee global optimality by systematically searching for Pareto-optimal trade–offs in derived solutions while solving the conflicting objectives including hydrogen consumption, degradation of fuel cell stack (capacity fading), battery state–of–charge (SOC) regulation and power stability. This hybridization yields a control strategy that is both adaptive and globally efficient, trading-off system health across time-scales. The proposed framework primarily differs from traditional energy management strategies (e.g., rule-based control or model predictive control, MPC) in that it is capable of adaptively responding to uncertainties and time-varying operating conditions. In many regards traditional control methods depend upon fixed rules or modeled measurements, thus producing subpar performance and in some cases instability when system parameters stray from nominal behavior. By contrast, the RL–MOPSO framework implements uncertainty modeling with disturbance observers and adaptive feedback mechanisms, so that stochastic disturbances (e.g., variations of driving patterns, road grade, ambient temperature and component aging) have less influence on stable and efficient operating states of controllers. Such an ability greatly improves the reliability and practical applicability of the system, guaranteeing stable functionality over real use-case scenarios. Notably, these gains in hydrogen consumption and durability of the fuel cell also target two of FCEV most important challenges. Less hydrogen use leads to lower operational costs and better energy efficiency, which are critical for commercial success and large-scale acceptance of hydrogen vehicles. At the same time, minimizing regenerative dismantle currents via smoother power profiles and lower transient stress prolongs the fuel cell stack's life cycle, mitigating maintenance and replacement costs. Hence, the mitigation of power pulsations, lesser transient response and better feeding means improved drivability, smooth engine operation and more comfort for passengers which is an important feature in acceptance from customer. At the practical implementation level, the developed RL–MOPSO framework has a great potential to deploy in upcoming intelligent transportation systems. The computational framework matches perfectly for integrating it into vehicle control units, especially with respect to real time processing and adaptive decision making. The framework is additionally modular and scalable by design, so beyond FCEVs it can also be applied to HEVs, PHEVs, grid-connected fuel cell systems, microgrids and autonomous vehicle energy management platforms. Also, inside the smart transportation and connected vehicle ecosystems, it can be improved due to external sources like traffic information and infrastructure signals for more predictive and adaptive properties. In terms of both industrial/economic benefit, the reduced hydrogen consumption and increased durability of the system offers a strong value proposition. Less fuel consumption translates into lower OPEX, whereas better component life reduces lifecycle costs and increases system reliability. The flexibility of the framework also allows for mapping onto specific vehicle architectures, operational requirements, and performance priorities that is particularly appealing to a wide segment of commercial scenarios. In conclusion, the simulation results are very comprehensive and confirm that the proposed RL–MOPSO adaptive control framework has been successfully able to enhance traditional energy management strategies considerably across key performance metrics efficiency, durability, dynamic response and robustness. Through the combination of data-driven learning and multi-objective optimization, this booster helps promote advanced FCEV energy management that is both powerful, flexible and future-ready to tackle the challenges of real-world operating conditions while paving the way towards more sustainable as well as smart transportation systems.

4. Conclusions

In this paper, we proposed an adaptive reinforcement learning–based multi-objective particle swarm optimization (RL–MOPSO) control framework for energy management in fuel-cell electric vehicle (FCEV) powertrains to concurrently minimize hydrogen consumption and improve fuel cell durability under the system uncertainty and constantly changing load conditions. This framework combines the reinforcement learning capability with the global optimization ability of multi-objective PSO, offering intelligent, adaptive and real-time optimal power management for the fuel cell, battery and auxiliary storage device. The architecture developed combines a hierarchical control strategy, with the reinforcement learning agent progressively learning suitable control policies through interaction with the FCEV system using an appropriate reward function that accounts for efficiency and durability while obeying operational constraints. This is supplemented by the MOPSO module, which can implement online parameter tuning to find Pareto-optimal trade-offs among conflicting objectives, such as hydrogen consumption vs. fuel cell degradation, SOC regulation, and power stability. Also, the insertion of uncertainty estimator and disturbance online observer increase its robustness against real-world variations (load-mass variability, ambient environment noise, or actuator aging). Simulation Results from standard and aggressive driving cycles indicate that the proposed RL–MOPSO framework yields significantly better performance than multiple conventional energy management strategies, including rule-based control, model predictive control (MPC), and stand-alone reinforcement learning methods. The most important is that an explicit substantial decrease in hydrogen consumption, SOC regulation ability, fluctuation of power and fuel cell degradation rate were achieved by the proposed method. The beneficial coalescence of data-driven learning and evolutionary optimization for the solution of multi-objective control problems in FCEVs is clearly reflected by these improvements. The results of this study have significant practical implications for the design of future intelligent energy management systems in electric and hybrid vehicles. In addition to improving efficiency and lifetime, the framework is scalable so it can be easily fitted into various vehicle architectures and operating conditions. Moreover, its resilience under uncertainty enables it to be especially useful in real-world applications. Future works are devoted to experimental validations with HIL platforms and on-road testbeds, as well as the extension of this framework by incorporating predictive traffic information and vehicle-to-grid (V2G) interactions. Abstract: The proposed RL–MOPSO adaptive control strategy represents an excellent step forward on the path toward sustainable, efficient, and intelligent management of fuel-cell electric vehicle powertrains.

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