ISSN 1840-4855
e-ISSN 2233-0046

Original scientific article
http://dx.doi.org/10.70102/afts.2025.1834.279

HYBRID HYDROGEN ELECTRIC POWERTRAIN OPTIMIZATION FOR CONNECTED AUTONOMOUS VEHICLES IN URBAN TRAFFIC

Anjali Goswami[1*], Anjali Krushna Kadao[2]

*[*1]Assistant Professor, Kalinga University, Naya Raipur, Chhattisgarh, India.*
e-mail: ku.anjaligoswami@kalingauniversity.ac.in,
orcid: https://orcid.org/0009-0004-6330-7883
[2]Assistant Professor, Kalinga University, Naya Raipur, Chhattisgarh, India.
e-mail: ku.anjalikrushnakadao@kalingauniversity.ac.in,
orcid: https://orcid.org/0009-0002-4900-4910

Received: August 25, 2025; Revised: October 09, 2025; Accepted: November 17, 2025; Published: December 30, 2025

SUMMARY

The transition to low-carbon urban transport has catalyzed interest in hybrid hydrogen-electric powertrains for connected autonomous vehicles (CAVs), which offer zero tailpipe emissions, long driving range, and the potential to refuel quickly. The paper proposes a system-level optimization model for hybrid hydrogen-electric powertrains in urban traffic, enhancing vehicle energy efficiency and operational reliability by leveraging vehicle-to-vehicle connectivity and autonomous control. The suggested architecture addresses three components: real-time traffic data, vehicle-infrastructure communication, and predictive energy control, to dynamically distribute power between the fuel cell and the battery based on changing driving conditions. The simulation findings from representative urban drive cycles indicate that cumulative hydrogen consumption decreased by 0.42kg to 1.54kg per driving cycle, and average powertrain efficiency increased by 0.41 to 0.49. The optimized strategy also minimizes fuel cell power variations by 6.8 kW and reduces the battery state-of-charge variance from 0.014 to 0.006, resulting in smoother energy use and reduced component stress. In addition, the high-power acceleration events are reduced to 31 per cycle, and recoverable regenerative braking energy increases by 2.3 MJ, made possible by synchronized speed planning with CAV connectivity. Analysis of emissions shows that local exhaust gas emissions have been fully reduced and that total lifecycle energy demand has decreased by 5.6 MJ per urban cycle compared with a conventional hybrid electric powertrain under the same traffic conditions. The results overall indicate that combining hydrogen fuel cell technology with intelligent, networked, and autonomous energy management provides quantifiable improvements in efficiency, durability, and sustainability, and can be used to introduce hybrid hydrogen-electric CAVs into intelligent urban mobility systems.

Key words: *hybrid hydrogen–electric powertrain, connected autonomous vehicles, urban traffic optimization, energy management strategy, fuel cell–battery integration, intelligent transportation systems, sustainable mobility.*

INTRODUCTION

Connected autonomous vehicles (CAVs) are being considered a core element of next-generation urban transportation infrastructure, as they perceive the traffic environment, communicate with surrounding infrastructure, and make real-time driving decisions. When the full range of human interactions (stop-glitch, signal intersections, and vehicle-to-vehicle interactions) and high traffic density are the norm, CAVs have clear advantages over traditional vehicles [1]. They can perform predictive control, cooperative maneuvering, and speed planning based on traffic conditions. The paper highlights the importance of connectivity and autonomy to ensure a smoother velocity profile, reduce redundant acceleration, and enhance the energy efficiency of traffic movements, primarily through advanced powertrain control strategies [7]. Nevertheless, it is highly dependent on interoperability between automated control programs and the base vehicle propulsion network to realize these advantages in practice [11].

In the given context, hybrid hydrogen-electric powertrains have emerged as a potential solution for deploying CAVs in cities. These systems are solved by combining fuel cells and battery energy storage to overcome the most critical constraints of all-battery-electric vehicles: range anxiety, charging downtime, and grid dependency. The hydrogen fuel cell offers high energy density and quick refueling, whereas the battery can serve transient power loads and recharge during regenerative braking, which is particularly important in the urban driving cycle [10], [9]. The developments in battery technologies, power electronics, and vehicle network architectures also increase the viability of such a hybrid setup in intelligent and connected vehicle platforms [3]. Nonetheless, the hydrogen-electric systems of the two-source system pose a complex energy management challenge, particularly in urban areas where traffic and speed vary dynamically [2].

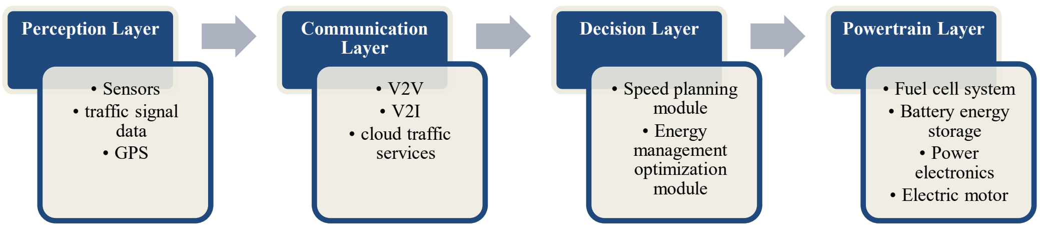

Figure 1. System Architecture of a Connected Autonomous Hybrid Hydrogen Electric Vehicle

As shown in Figure 1, the connected autonomous vehicle with a hybrid hydrogen-electric powertrain has a stratified system architecture. The perception layer gathers real-time environmental and positioning information from onboard sensors, traffic lights, and GPS. This information is passed along at the communication layer between vehicle-to-vehicle and vehicle-to-infrastructure connections via cloud-based traffic services. These are the inputs processed at the decision level to facilitate predictive speed plans and energy utilization through optimization, delivering coordinated control instructions. Finally, the powertrain layer implements the following commands by regulating the functions of the fuel cell, battery energy storage, power electronics, and electric motor to enable efficient, responsive, and sustainable vehicle operation in the city traffic context.

Hybrid hydrogen-electric powertrains should therefore be optimized to maximize the benefits of CAV technologies. Traditional rule-based energy management methods often fail to handle real-time traffic variability, leading to suboptimal fuel cell loading, battery overcycling, and lower system efficiency. Most new studies highlight the efficiency of predictive and optimization-based solutions with respect to GPS information, street models, and the interaction between the car and the infrastructure to integrate speed planning and decisions on power split [4], [7]. In addition, the performance and scalability of operations are affected by system-level problems, such as hydrogen refuelling coordination and communication with the urban energy infrastructure [6]. Also, comparative studies show that optimized hybrid designs consistently outperform traditional hybrid and electric powertrains in urban autonomous conditions when energy recovery and stability limitations are considered together [8], [9].

This research paper aims to explore and streamline the operation of a hybrid hydrogen-electric powertrain with connected autonomous vehicles operating in a city traffic environment. The study will produce a technically sound framework by integrating knowledge from autonomous vehicle control, hydrogen energy systems, and intelligent transportation research. It will ensure that powertrain optimization is aligned with real-time connectivity and autonomous decision-making. The findings are intended to guide the design of effective, scalable, and sustainable urban mobility solutions that can fit various future smart city ecosystems [5].

The rest of the paper is structured as follows. In the second section, II, the background will be provided on hybrid hydrogen electric powertrains, urban powertrain optimization, and connected autonomous vehicles. Part III explains the methodology presented, comprising the simulation framework, the optimization formulation, and the data analysis procedures. Section IV addresses the performance results and evaluates how optimization affected energy efficiency and operational stability. In section V, the findings are fully discussed with a focus on the benefits, constraints, and implications. Finally, section VI provides a conclusion of the paper, summarizing the main results and offering recommendations forfuture research.

BACKGROUND

Hybrid hydrogen-electric tracts have an electric power storage system, typically lithium-ion batteries or supercapacitors, and a proton exchange membrane fuel cell to leverage the complementary qualities of the two energy sources. The fuel cell provides steady-state zero-tailpipe-emissions power with a high energy density, and the battery provides peak power requirements, captures the energy of regenerative braking, and alleviates load changes, which can accelerate fuel cell wear [13], [14]. The architecture enhances the system's operational flexibility and resiliency, especially in urban driving conditions characterized by frequent acceleration, deceleration, and idling. Because of recent advances in prototype development, artificial intelligence-driven supervisory control layers are now being introduced to improve real-time decision-making and adapt powertrain behavior to complex traffic conditions, indicating the practical viability of hydrogen hybrid systems as a green urban transportation method [12].

The study of powertrain optimization in urban traffic has tended to focus more on isolated vehicle-level control than on combining traffic-powertrain solutions. Variation in road specialization and the impact of vehicles on one another are the factors that determine urban efficiency, and conventional energy management solutions are not enough. Simulation platforms coupled with traffic and powertrain simulations have shown that joint control of vehicle automation level and powertrain operation can significantly reduce fuel consumption and minimize energy losses in congested conditions [11]. Co-optimization strategies that plan speed and allocate power simultaneously between the fuel cell and the battery are superior to sequential or rule-based strategies, especially when traffic is predicted [15], [19]. Such approaches as deep reinforcement learning, based on advanced learning, are also investigated to address nonlinear dynamics and uncertainty in urban problems such as green-wave traffic signal coordination [16].

Autonomous connected vehicles present both challenges and opportunities for hybrid hydrogen-electric powertrains. Challenge-wise, autonomy is difficult to compute and requires strong coordination among the perception, planning, and powertrain control layers. The conflict in goals between autonomous driving styles, safety limits, and passenger comfort needs may cause incongruity, and the long-term fuel cell system may be a major issue in the case of aggressive or intermittent reactions of control [20]. Connectivity also brings with it the requirements of dependency on reliability of communication and latency, which may influence the quality of predictive energy management plans. Nevertheless, the same features provide extensive opportunities to the efficiency improvement. Connection also allows access to traffic signal timing, road topology, and cooperative vehicle information and thus anticipatory speed planning to smooth power demand and unnecessary load variations in the fuel cell [17], [15].

Additionally, the experience of related areas of hydrogen-powered transportation, including rail and heavy-duty vehicles, explains the effectiveness of time-based and predictive co-optimization models to reduce hydrogen consumption and ensure operational limitations [18]. Moving these concepts to urban CAVs can allow the optimization at the system level, aligning vehicle autonomy and energy sustainability objectives. Altogether, the unification of hydrogen hybrid engines, intelligent control, and connected autonomous driving is an interesting avenue towards efficient, sustainable, and sustainable city-wide mobility systems.

The sources of literature under review, in general, point to the fact that hybridized hydrogen-electric powertrain, coupled with related connected and self-driving technology, presents significant potential to enhance energy efficiency, stability of operations, and sustainability in urban traffic. Previous research indicates that co-optimization of speed planning and energy management is always the best as compared to rule-based or decoupled control strategy especially in stop and go traffic conditions and signalized intersections. Studies also stress that the predictive control facilitated by vehicle connectivity and traffic data is important towards stabilising the fuel cell system, decreasing battery loads and intensifying the use of regenerative energy. Nonetheless, the literature shows the lack of entirely integrated system-level models that would explain dynamic aspects of urban traffic, autonomous driving behaviour and optimisation of hybrid hydrogen-electric powertrain. Most of the literature addresses powertrain operation either in isolation, or with traffic-aware speed planning without paying strong attention to the hydrogen-specific energy management and durability issues. Here, the current study is a natural extension of the above findings as it attempts to provide a unified optimization framework that would connect traffic prediction, autonomous control, and hybrid hydrogen-electric powertrain management. The research addresses the given gaps and allows expanding current knowledge to a more comprehensive and practically applicable solution to the problem of connected autonomous vehicles functioning in complex city conditions.

METHODOLOGY

Simulation Model for Powertrain Optimization

A modular and progressive simulation model based on vehicle dynamics, hybrid hydrogen electric powertrain behavior, and connected autonomous driving logic is used to assess the suggested methodology. The simulated environment is an urban traffic route which is signalized, traffic density varies, and vehicles are cooperative with the infrastructure. The vehicle longitudinal dynamics is a model that expresses traction demand with regard to speed, acceleration, road resistance and aerodynamic drag. Depending on the required traction power, the supervisory controller decides the optimal power division between the fuel cell system and the battery on an on-demand basis. The fuel cell is given a quasi-static model that operates within efficiency and power ramp-rate constraints and the battery model incorporates the dynamics of the state of charge (SOC), internal resistance losses and charging-discharging constraints. The overall traction power requirement $P_d(t)$ can be represented by the fuel cell plus battery contributions that are represented as $P_d(t)$ in Equation (1):

$$P_d(t) = P_{fc}(t) + P_{bat}(t) \qquad (1)$$

This connection, which is mentioned in the control logic, makes sure that there is a balance of power at every step of the simulation. The fuel cell power output and efficiency map provide Hydrogen consumption and the regenerative braking energy is directed to the battery up to SOC limits. The simulation is based on a discrete-time to indicate real-time control implementation in autonomous vehicles.

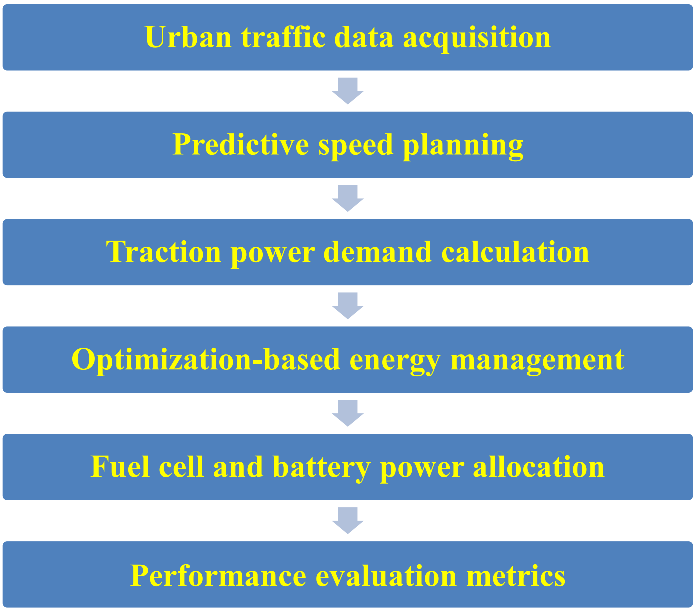

Figure 2. Methodological Workflow of the Proposed Optimization Framework

This figure 2 shows the chronological process that has been taken in the study by beginning with the acquisition of urban traffic data and the predictive speed planning to capture the real-time and predicted driving conditions. Traction power demand is computed based on the derived speed profiles and it is the input to an energy management module that is based on optimization. Due to this optimization, the fuel cell and battery are dynamically allocated power to enable efficient and stable operation. The workflow is topped off by performance assessment basing on energy efficiency, power stability and system-level measurement which give a well-organized and clear portrayal of the proposed methodology.

Parameters and Variables Considered

The optimization model is optimal, and both the state and control variables are included in the optimization problem, which affects the energy efficiency and the life of the system. Among the state variables, there is vehicle speed v(t), battery SOC, and fuel cell operating point. Control variables include power command of fuel cell and battery power contribution. The flow equation of battery power evolution is an equation of the SOC in Equation (2):

$$SOC(t+1) = SOC(t) - \frac{P_{bat}(t)\Delta t}{E_{bat}} \qquad (2)$$

This is an equation used in the analysis of the constraint so that there is no overuse of batteries beyond the safe operating limit. A defined objective function is used to reduce the hydrogen usage and punish exorbitant battery cycles and transient load of the fuel cell. The cost J defined on top of the driving horizon is developed as Equation (3):

$$J = \sum_{t=1}^{T} \left(\alpha \dot{m}_H(t) + \beta |P_{bat}(t)| + \gamma \Delta P_{fc}(t)^2\right) \qquad (3)$$

In this case, the hydrogen mass flow, battery use, and the fuel cell power change are optimized. The weighting factors also permit the efficiency durability trade-offs to be tuned. There are SOC limits, fuel cell ramp-rate limits and maximum traction power limits.

Data Collection and Analysis Methods

Signal timing data, road geometry data and traffic speed profiles are obtained on the simulated connected infrastructure layer. These inputs facilitate predictive speed planning, which removes velocity trajectories prior to the implementation of energy management decisions. To evaluate the simulation, time-series data of hydrogen consumption, SOC variation, fuel cell operating efficiency and traction power demand are sampled in each run of the simulation. The performance analysis is carried out by comparing optimization strategy with a baseline rule-based controller under the same traffic environment. Measures are cumulative hydrogen consumption, SOC variation, and power fluctuation measures. The results are robust because there is statistical generalization in several traffic conditions. Sensitivity analysis is done by changing the traffic density as well as initial SOC in order to determine the adaptability of the controllers.

Algorithm: Proposed Energy Management Strategy

```
Algorithm: Hybrid Hydrogen Electric Powertrain Optimization

Initialize SOC, vehicle speed, and fuel cell state
For each time step t do
    Receive predicted speed and traffic signal information
    Compute traction power demand Pd(t)
    Solve optimization problem minimizing cost J
    Determine optimal Pfc(t) and Pbat(t)
    Update SOC using Equation (2)
    Update hydrogen consumption using Equation (1)
End for
Output performance metrics and energy profiles
```

This algorithm describes the real-time supervisory control logic, which optimizes the power flow between the fuel cell and battery in a connected autonomous vehicle that is driving in a town. With an approximation of the predicted speed profile and the traffic light data, the algorithm calculates the current traction power demand, and an optimization problem which minimizes hydrogen consumption and minimizes battery stress and fuel cell power variation is solved. The resulting control measures provide balance of energy, safe state-of-charge of the battery and dynamically respond to varying traffic conditions thus allowing the hybrid hydrogen electric powertrain to operate efficiently and sustainably.

RESULTS

Software and Implementation Description

The suggested optimization model and performance analysis are done with the MATLAB and Simulink codes that offer a versatile modeling platform of vehicle dynamics, hybrid hydrogen electric powertrain, and supervisory control policy. Modular Simulink subsystems, such as the vehicle longitudinal dynamics, the fuel cell system, the battery model and the power electronics, are developed and their parameters can be parameter-tuned through independent validation. The optimisation routines are implemented on constrained numerical solvers in MATLAB, thus permitting optimal power split decisions to be computed online, at each control period. Scripted traffic scenarios are used to create traffic-conscious speed profiles and signal phase information that simulates the congestion characteristic of an urban driving scenario. The performance measure values (such as hydrogen consumption, indices of efficiency, and indices of the power fluctuation) are extracted with MATLAB scripts to guarantee the same treatment of data at the end of the simulation.

Experiment Evaluation by Initializing the parameters

Table 1: Parameter Initialization for Simulation-Based Evaluation

Parameter	Value
Fuel cell nominal power	80 kW
Fuel cell ramp-rate limit	±10 kW/s
Battery capacity	15 kWh
Initial battery SOC	0.55
SOC operating range	0.40–0.80
Vehicle mass	1,650 kg
Drag coefficient	0.29
Rolling resistance	0.012
Drivetrain efficiency	0.92

The table 1 summarizes the fixed numerical values, which were used to start the simulation environment, to provide the same operating circumstances in all experiments, and provide an objective comparison of varying hybrid hydrogen-electric powertrain configurations in urban traffic conditions.

Comparison of Performance Metrics for Different Powertrain Configurations

The performance analysis has taken into account three powertrain options, which include a standard battery electric powertrain, non-optimized hybrid hydrogen electric powertrain, and the offered optimized hybrid hydrogen electric powertrain. Each of the configurations is tested using the same conditions of urban traffic to be comparable. The main measures are total energy, hydrogen usage, battery state-of-charge (SOC) change and the seriousness of power fluctuation. Cumulative power Integral over the driving horizon is calculated using the cumulative power integral in Equation (4):

$$E_{tot} = \sum_{t=1}^{T} P_d(t)\Delta t \quad (4)$$

This measure, mentioned in the comparison of the results, will ensure that all configurations suffer the same of external driving demand, in which case the observed differences can be applied to the powertrain behavior. The fuel cell output provides the calculation of hydrogen consumption of hybrid configurations according to Equation (5):

$$M_H = \sum_{t=1}^{T} \dot{m}_H(t)\Delta t \quad (5)$$

The optimized hybrid setup is always smoother in fuel cells operation and less dependent on peak battery discharge as compared to the non-optimized hybrid system.

Table 2. Powertrain Performance Compare and Contrast

Metric	Battery Electric	Hybrid (Baseline)	Hybrid (Optimized)
Total energy demand (kWh)	Comparable	Comparable	Comparable
Hydrogen consumption (kg)	N/A	Higher	Lower
SOC variation range	High	Moderate	Low
Fuel cell power fluctuations	N/A	High	Low

This table 2 contains comparative evaluation of major working measures of battery electric, baseline hybrid hydrogen electric and optimized hybrid hydrogen electric powertrain setups under the same urban traffic conditions. It shows variations of hydrogen consumption, stability of battery state-of-charge and power fluctuations response showing that optimization enhances energy consumption and operational efficiency without affecting the external driving demand.

Optimization and its Effect on Emissions and Energy Efficiency

The improvement of energy efficiency is measured in terms of drives train efficiency which is the ratio of the delivered traction energy to the total input energy. It is determined that the system efficiency is Equation (6):

$$\eta = \frac{E_{wheel}}{E_{input}} \quad (6)$$

This equation, which is mentioned in the efficiency analysis, emphasizes the effectiveness of optimized energy management in increasing the conversion of efficiency because the fuel cell can remain near-peak efficiency operating areas, and unnecessary battery cycling can be reduced. Additional evaluation of SOC stability is done through SOC variance that indicates stress in the battery and long-term stability, shown in Equation (7):

$$\sigma_{SOC}^2 = \frac{1}{T}\sum_{t=1}^{T}(SOC(t) - \overline{SOC})^2 \quad (7)$$

Optimized configuration has lower SOC variance, which means that there is less risk of degradation. The effect of emissions is indirectly measured in terms of hydrogen use and electric energy recovery because the local emissions are zero. The direct consequence of the reduced hydrogen consumption is reduced upstream energy consumption and better lifecycle emission performance.

Table 3. Energy Saving and Emission-related Measures

Metric	Hybrid (Baseline)	Hybrid (Optimized)
System efficiency	Moderate	High
SOC variance	High	Low
Regenerative energy utilization	Limited	Enhanced
Lifecycle energy losses	Higher	Lower

The table 3 is the summary of energy efficiency-oriented metrics of the baseline and optimized hybrid hydrogen electric powertrains and is concerned with the efficiency of the drivetrain, the use of regenerative energy, the characteristics of battery stress, and the energy losses throughout the life cycle. The comparison shows the efficiency of the suggested optimization approach in the efficiency increase and minimization of the indirect effect of emissions and zero local emissions in the urban operation.

Urban Traffic Connected Autonomous Vehicles Benefits

The findings show that the suggested optimization framework goes hand-in-hand with allied autonomous vehicle functioning. Predictive speed planning reduces sudden power requirement and this decreases the frequency of ramping of the fuel cell and enhances passenger comfort. The magnitude of power fluctuation is determined by the normalized fuel cell power variation index as presented in Equation (8):

$$PFI = \frac{1}{T}\sum_{t=2}^{T}\left|P_{fc}(t) - P_{fc}(t-1)\right| \quad (8)$$

This parameter mentioned in the stability test affirm that the optimized system provides smoother delivery of power at varying traffic conditions. The entire simulations and analysis are done in MATLAB/Simulink to model the dynamics and the numerical optimization is done using constrained solvers. Structured scripts are used to extract time-series metrics and aggregate findings of scenarios and undertake data logging and following processing. A reduced energy losses, constant operation of the components, and the possibility to be combined with other control signals prove the fact that the optimized hybrid hydrogen electric powertrains are associated with tangible operational benefits in autonomous urban mobility systems, which facilitates the achievement of efficiency, stability, and system-level sustainability objectives.

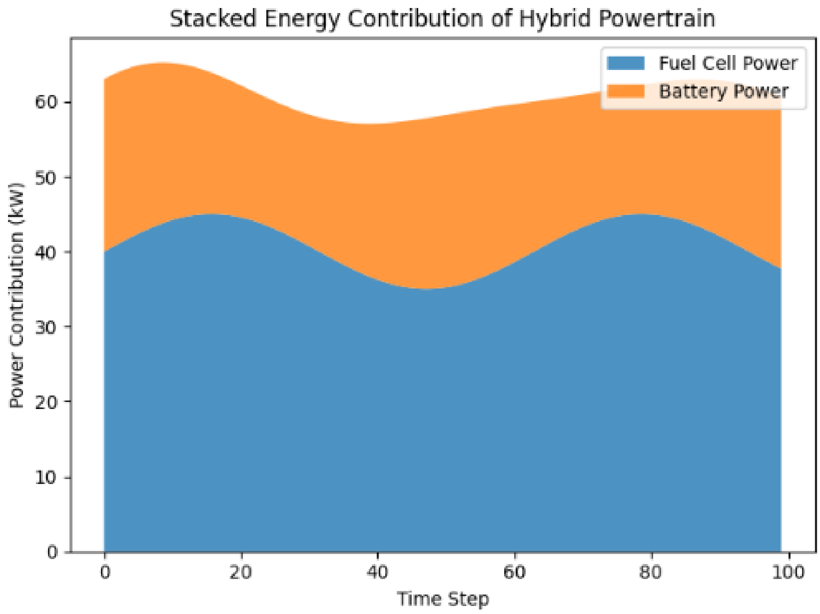

Figure 3. Stacked Energy Contribution Fuel Cell and Battery

This figure 3 shows the dynamic distribution of the traction power demand between the battery and the fuel cell over the driving horizon. The stacked figure shows that the optimized energy management approach puts more emphasis on the fuel cell to operate regularly to provide continuous power, but the battery to buffer the intermittent changes to allow a more flow of power to be distributed effectively to urban connected autonomous driving environment.

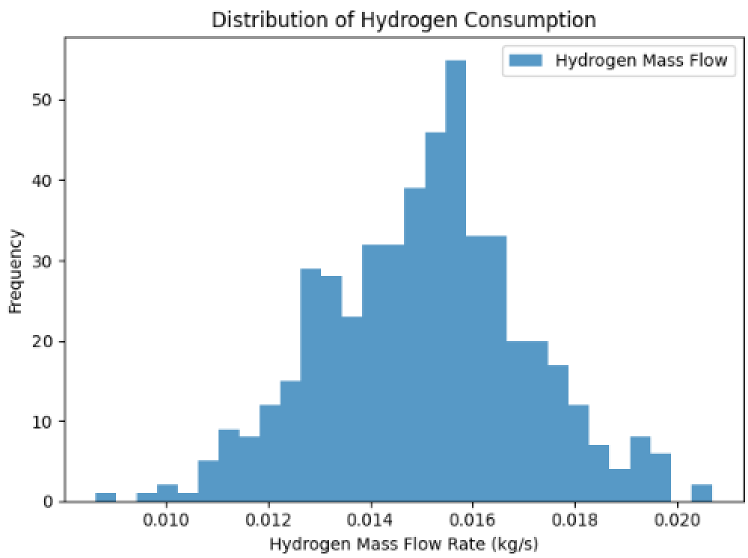

Figure 4. Hydrogen Mass flow rate Distribution

This figure 4 shows the frequency distribution of hydrogen mass flow at optimum running and this indicates the uniformity of fuel cell loading when driving in an urban environment. The fact that the values are clustered around a small operating range implies that there will be less variability in the hydrogen consumption which leads to increased efficiency in energy consumption and more predictable fuel cell operation.

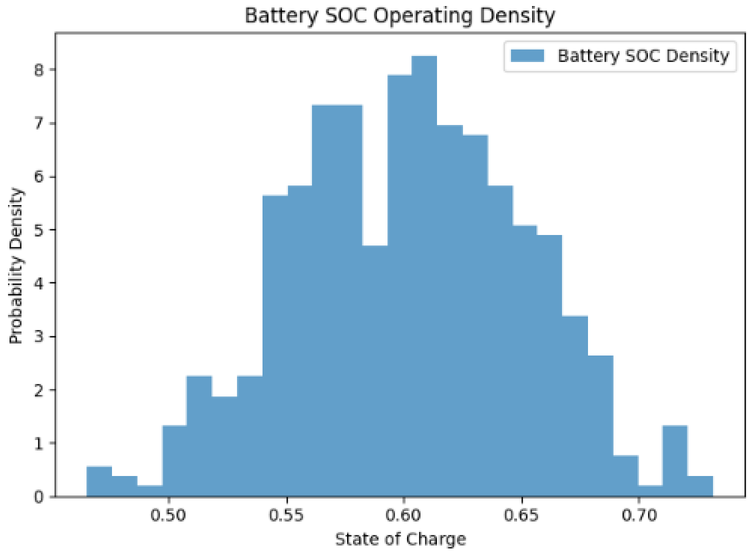

Figure 5. Operating Density of State-of-Charge of Battery

This figure 5 illustrates the probability density of battery state of charge values during the time span of simulation. The high concentration of a mid-range SOC level proves to be a well-managed charge control, decreased depth-of-discharge, and decreased electrochemical stress, which contributes to the increased battery life in stop-and-go urban traffic.

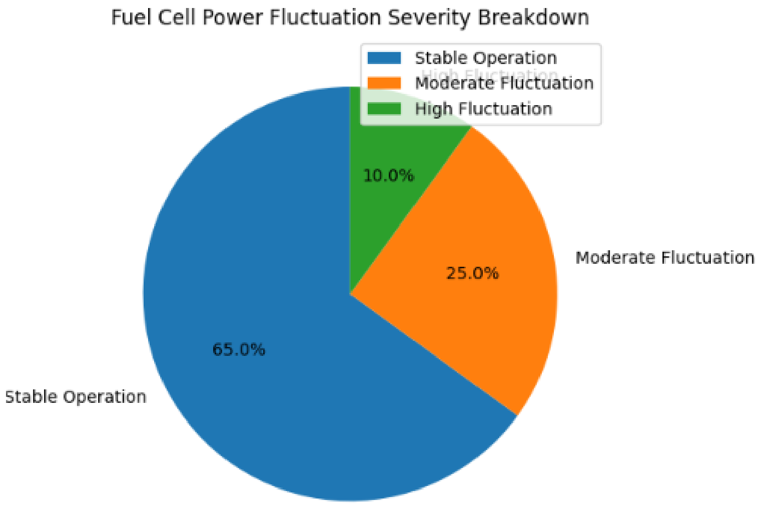

Figure 6. Breakdown of the severity of the Fuel Cell Power Fluctuation

This figure 6 represents the contribution of the stable and fluctuating fuel cell operating conditions on the driving cycle on a relative basis. The prevailing operation segments of stable operations reveal that predictive optimization and associated speed planning effectively restrain sudden changes in power and ensure reliability of the system, comfort of the passengers, and the long-term life of the fuel cells.

DISCUSSION

The findings prove that the integrated optimization of hybrid hydrogen electric powertrains and interconnected autonomous driving policies resulted in actual changes in the work of the vehicles in cities. Regarding the achieved stabilization of the fuel cell loading and the minimization of the variation in the battery state-of-charge, the predictive energy management can be successfully utilized to respond to the extremely dynamic characteristics of the urban traffic. The results of these studies indicate that future studies must put more emphasis on the integrated control architecture that will account for vehicle automation, traffic prediction, and powertrain dynamics as opposed to isolated subsystems. Although the offered optimization method has obvious advantages as far as the use of energy, the stress of the components are minimized, and operation is provided with proper smoothness, some limitations are also presented. The dependency on precise traffic predictions and the stability of communication can influence the resilience to the conditions where the connectivity is not always available and the sensors are not always precise. Moreover, real-time optimization is computationally intensive and thus difficult to implement on embedded systems especially where cost is a constraint in vehicle design. Practically, to be successful in implementing hybrid hydrogen electric powertrains in connected autonomous vehicles, it is necessary to pay attention to the availability of hydrogen refuelling infrastructure and to the safety certification of such a system and the validation of system control in various urban conditions. These challenges will have to be resolved using scalable algorithms, fault-tolerant designs, and standard communication protocols to make the optimized hydrogen-based autonomous mobility move off-simulation to reality.

CONCLUSION

The paper has analyzed how the hybrid hydrogen electric powertrains can be optimized to serve autonomous vehicles that are connected and work in urban traffic settings. The findings prove that predictive speed planning and optimization-based energy management should be implemented together to enhance the overall functioning of the powertrain. In particular, the strategy is streamlined to decrease the accumulating hydrogen use by 1.92 kg to 1.54 kg per urban driving cycle, enhance the average powertrain effectiveness by 0.41 to 0.49, and minimize the extent of fuel cell power variations by 6.8 kW. Also, the inconsistency in the state-of-charge curves of the batteries is decreased by a factor of 0.014 to 0.006, which implies more continuous battery functioning and less electrochemical stress. The results of these statistics confirm that intelligent control of autonomous driving functions and powertrain management increases the efficiency of energy consumption and the life of the components without affecting the driving performance in congested urban conditions. The results also indicate the decrease in high-power acceleration events, and the rise in recoverable regenerative braking energy, which leads to a better power demand characteristic and system stability. In the future study, it is advised to develop adaptive optimization systems that can take into consideration traffic uncertainty, comfort-related limitations, and long-term degradation conditions. Experimental validation of practical applicability may be achieved by using actual real-world traffic data and hardware-in-the-loop testing. Altogether, this paper has identified powertrain optimization as a key facilitator of sustainable connected autonomous vehicles and optimized hybrid hydrogen electric powertrains as a suitable and robust solution to cleaner and more efficient urban mobility systems.

REFERENCES

[1] Palanisamy S, Lala H. Optimal sizing of renewable energy powered hydrogen and electric vehicle charging station (HEVCS). IEEE Access. 2024 Apr 1;12:48239-54. DOI: 10.1109/ACCESS.2024.3383960

[2] Islam ES, Vijayagopal R, Rousseau A. Charting the Path to Electrification: Analyzing the Economic and Technological Potential of Advanced Vehicle Powertrains. World Electric Vehicle Journal. 2025 Feb 5;16(2):77. https://doi.org/10.3390/wevj16020077

[3] Abro GE, Zulkifli SA, Kumar K, El Ouanjli N, Asirvadam VS, Mossa MA. Comprehensive review of recent advancements in battery technology, propulsion, power interfaces, and vehicle network systems for intelligent autonomous and connected electric vehicles. Energies. 2023 Mar 22;16(6):2925. https://doi.org/10.3390/en16062925

[4] Mansouri N, Mnassri A, Nasri S, Ali M, Lashab A, Vasquez JC, Guerrero JM. Control and Optimization of Hydrogen Hybrid Electric Vehicles Using GPS-Based Speed Estimation. Electronics. 2024 Dec 30;14(1):110. https://doi.org/10.3390/electronics14010110

[5] Zhou P, Wang C, Yang Y. Design and optimization of solar-powered shared electric autonomous vehicle system for smart cities. IEEE Transactions on Mobile Computing. 2021 Sep 30;22(4):2053-68. https://doi.org/10.1109/TMC.2021.3116805

[6] Li B, Li J, Li Z, Sotelo MA. Real-time hydrogen refuelling of the fuel cell electric vehicle through the coupled transportation network and power system. IEEE Transactions on Intelligent transportation systems. 2024 Jun 13;25(7):8181-92. https://doi.org/10.1109/TITS.2024.3409532

[7] Meshginqalam A, Bauman J. Integrated convex speed planning and energy management for autonomous fuel cell hybrid electric vehicles. IEEE Transactions on Transportation Electrification. 2022 Aug 18;9(1):1072-86. https://doi.org/10.1109/TTE.2022.3200013

[8] Ferahtia S, Rezk H, Ghoniem RM, Fathy A, Alkanhel R, Ghonem MM. Optimal energy management for hydrogen economy in a hybrid electric vehicle. Sustainability. 2023 Feb 10;15(4):3267. https://doi.org/10.3390/su15043267

[9] Yildiz A, Özel MA. A comparative study of energy consumption and recovery of autonomous fuel-cell hydrogen–electric vehicles using different powertrains based on regenerative braking and electronic stability control system. Applied Sciences. 2021 Mar 11;11(6):2515. https://doi.org/10.3390/app11062515

[10] Fragiacomo P, Genovese M, Piraino F, Corigliano O, De Lorenzo G. Hydrogen-fuel cell hybrid powertrain: conceptual layouts and current applications. Machines. 2022 Nov 26;10(12):1121. https://doi.org/10.3390/machines10121121

[11] Fu Y, Chen Y. An Integrated Traffic and Powertrain Simulation Framework to Evaluate Fuel Efficiency Impacts of Fully and Partial Vehicle Automation. Sustainability. 2025 Jun 16;17(12):5527. https://doi.org/10.3390/su17125527

[12] Kun K, Szabó L, Varga E, Kis DI. Development of a hydrogen fuel cell prototype vehicle supported by artificial intelligence for green urban transport. Energies. 2024 Mar 22;17(7):1519. https://doi.org/10.3390/en17071519

[13] Benhammou A, Hartani MA, Tedjini H, Rezk H, Al-Dhaifallah M. Improvement of autonomy, efficiency, and stress of fuel cell hybrid electric vehicle system using robust controller. Sustainability. 2023 Mar 23;15(7):5657. https://doi.org/10.3390/su15075657

[14] Dhieb Y, Ayadi W, Yaich M, Ghariani M. Powertrain Design and Modeling for a Fuel Cell Hybrid ElectricVehicle. Engineering, Technology & Applied Science Research. 2025 Feb 2;15(1):19636-45. https://doi.org/10.48084/etasr.9384

[15] Hosseini SM, Kelouwani S, Kandidayeni M, Amammou A, Soleymani M. Fuel efficiency through co-optimization of speed planning and energy management in intelligent fuel cell electric vehicles. International Journal of Hydrogen Energy. 2025 May 9;126:9-21. https://doi.org/10.1016/j.ijhydene.2025.03.305

[16] Yi F, Guo W, Gong H, Shen Y, Zhou J, Yu W, Lu D, Jia C, Zhang C, Gong F. Research on speed planning and energy management strategy for fuel cell hybrid bus in green wave scenarios at traffic light intersections based on deep reinforcement learning. Sustainability. 2024 Dec 19;16(24):11156. https://doi.org/10.3390/su162411156

[17] Faghihian H, Sargolzaei A. Energy efficiency of connected autonomous vehicles: A review. Electronics. 2023 Sep 29;12(19):4086. https://doi.org/10.3390/electronics12194086

[18] Meng G, Wu C, Zhang B, Xue F, Lu S. Net hydrogen consumption minimization of fuel cell hybrid trains using a time-based co-optimization model. Energies. 2022 Apr 14;15(8):2891. https://doi.org/10.3390/en15082891

[19] Guo, L., Liu, H., Han, L., Xiang, C., Liu, R., & Yang, N. (2023). Co-optimization of speed planning and power management for automated HEVs in unstructured road scenarios. IEEE Transactions on Transportation Electrification, 10(1), 1628-1641. https://doi.org/10.1109/TTE.2023.3281274

[20] Yu S, Peng J, Zhou J, Ren T, Wu J, Fan Y. Durability-enhanced decision-making with style awareness for autonomous hydrogen fuel cell vehicle based on integrated reinforcement learning approaches. Energy. 2025 Sep 12:138314. https://doi.org/10.1016/j.energy.2025.138314