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Development of an FC Controls Optimization Method for FC Hybrid Trains Based on a Driving Energy Simulator: A Comparison of Control Methods

Yida Bao[1], Takashi Yoneyama[1,2], Wei-hsiang Yang[1], Yushi Kamiya[1]
[1]*Waseda University, Tokyo, Japan*
[2]*Railway Technical Research Institute, Tokyo, Japan*
Corresponding Author: gitatsu.hou@toki.waseda.jp (Yida Bao)

Executive Summary

In the fuel cell hybrid test train, increasing the number of full cell control input variables, such as battery SOC, speed, track data, and power demand, enhances the system's adaptability to various operational scenarios, including track geometry, local, and rapid services. However, this increase in input variables complicates the assessment of their individual impacts, making it challenging to determine optimal control strategies based purely on engineering experience. This paper discusses optimized multivariable control methods, including PI and feedforward (PI+FF) and Fuzzy control, using a driving energy simulator for the test train. The study compares the performance and adaptability of each method for implementation.

Keywords: Fuel Cell electric vehicles, Railway vehicles, Fuel Cell systems, Energy management, Modelling & Simulation

1 Introduction

1.1 Background and Motivation

Rail transport offers significantly higher passenger transport efficiency and lower greenhouse gas emissions compared to automobiles and aircraft. However, to meet carbon neutrality goals, further emission reductions are essential [1]. The development of fuel cell (FC)-based railway systems presents a promising solution by utilizing hydrogen to reduce environmental impact and improve energy efficiency. This approach also offers benefits such as replacing diesel trains, reducing overhead line maintenance for electric trains, and enabling catenary-free electric train operation, which further reduces maintenance requirements. Consequently, many countries are actively promoting the development of FC-powered trains [2].

In FC-battery hybrid trains, control of the FC output is critical to energy management, as it directly impacts hydrogen consumption, traction performance, and dynamic response. This critical role is challenged by the fact that the discharge and charge power capabilities of battery are constrained by its state of charge (SOC) [3]. Although adding more battery or FC modules could mitigate these limitations, space and weight restrictions in heavy-duty FC-battery hybrid vehicles often make this impractical [4][5]. For example, when the SOC is either too low or too high, the required power cannot be provided or the regenerative energy cannot be fully absorbed. In such cases, the system must rely on the FC to provide additional power [6]. However, since the FC operates most efficiently in the mid-to-low output range, Frequent high-output operation degrades the FC efficiency and leads to an increase in SOC. An excessively high SOC restricts the capacity of battery to absorb regenerative power due to its limited charging capability, thereby reducing the regeneration rate. This reduction, combined with lower FC efficiency, results in worsened fuel economy.

Achieving an appropriate multi-objective balance between fuel economy and acceleration capability under these operational constraints remains a key challenge. Advanced control strategies, such as multi-objective reinforcement learning, have been proposed to address this challenge. For instance, Wu et al. developed a method that simultaneously optimizes fuel efficiency and lifecycle cost in FC-battery hybrid vehicles [7]. However, the practical application of such approaches is often limited due to high computational complexity and insufficient real-time feasibility.

1.2 Objectives

To address these challenges, this study proposes an optimization framework for two rule-based control strategies: a combined proportional-integral (PI) and feedforward (FF) control system, and a fuzzy logic-based control system. Both strategies are designed to handle multiple control variables relevant to FC-battery hybrid train systems. The objective of the optimization is to minimize hydrogen consumption while meeting acceleration performance constraints. Additionally, a comparative evaluation was conducted between the two optimized control strategies to assess their impact on key performance metrics, including acceleration capability, fuel economy, and the degree of fuel cell degradation. The goal is to clarify the advantages and limitations of each control approach in improving the overall energy efficiency and operational reliability of FC-battery hybrid train systems.

2 Configuration of the FC Hybrid Test Train and Simulator

The FC-battery hybrid test train consists of one trailer car and one motor car, as illustrated in Figure 1. The configuration of its traction circuit is shown in Figure 2, and the main specifications are summarized in Table 1. The powertrain incorporates an FC system composed of two polymer electrolyte membrane fuel cell (PEMFC) systems, each rated at 90 kW, along with a lithium-ion battery system that provides a total energy capacity of 45.3 kWh and a maximum output power of 540 kW. Both the traction and auxiliary converters operate at 1,500 V DC, which corresponds to the standard overhead line voltage of the base train before modification.

Figure 1: Exterior view of FC test train

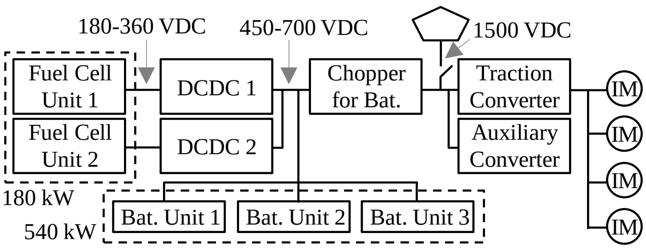

Figure 2: Circuit diagram of FC test train

Table 1: Specifications of test train

	Value	
Type of Train	Commuter	
Train Configuration	2 Cars in 1 Train Set	
Mass of Train	Trailer Car	31.8 t
	Motor Car	37.2 t
Dimension (1 car)	19,670 × 2,950 × 3,702 mm	
Traction Motor	Induction Motor 95 kW × 4	
Power Converter	Traction Converter IGBT 2Level	
	Auxiliary Converter IGBT 3Level	
	DC/DC Converter for Battery step-up Chopper	
DC/DC Converter for FC	Boost Chopper and High-frequency Isolated DC-DC Converter	
Fuel Cell (FC)	PEFC 90 kW × 2	
Battery for Traction	Lithium Ion Battery (540 kW・45.3 kWh)	

As the FC system generates approximately 300 V DC, this voltage is first stepped up to around 600 V DC using a galvanically isolated DC/DC converter. The output is then integrated with the battery system. To meet the inverter's power demand and control battery charging and discharging, a bidirectional DC/DC converter further boosts the voltage to 1,500 V DC.

To support control strategy development and performance evaluation, a forward-type energy simulator has been developed for this test train, as shown in Figure 3. The simulator includes a driver behavior model that determines traction force commands by calculating acceleration and braking notches to reach the target speed or stop at station platforms. The target speed is set according to the train's service type. These commands are fed into detailed dynamic models of the FC system, battery, and DC/DC converters. As a result, the simulator computes key operating parameters such as motor torque, SOC, DC link voltage (i.e., the voltage supplied to the traction converter), motor output power, and speed.

To reproduce the acceleration and regenerative braking limitations under realistic conditions, the simulator imposes variable voltage variable frequency (VVVF) traction converter power limits within the FC, bat. and DC/DC Converter Model shown in Figure 3, based on the SOC-related charge and discharge capabilities of battery and FC output, as shown in Figure 4. Acceleration performance is limited when SOC is below 30%, and regenerative braking is restricted when SOC is outside the 30%-45% range due to battery charging limitations. These constraints reflect the inherent characteristics of the battery and FC system.

Additionally, as illustrated in Figure 3, the simulator incorporates key operational variables such as passenger occupancy rate, track gradient, and interstation distance. A comparison with actual test track data confirms that the simulator maintains speed, distance and fuel consumption errors all within 4%, indicating sufficient accuracy for practical use [8].

Driving simulations were conducted on a virtual 18 km route that incorporates these operational variations, as shown in Figure 5. This route reflects typical service conditions, including different stopping patterns, gradients, and passenger load profiles depending on the train service type. The simulation results were used to evaluate energy consumption and traction performance under representative scenarios.

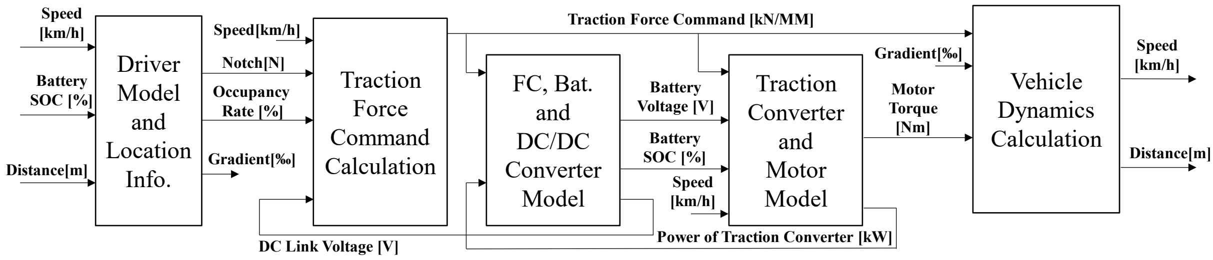

Figure 3: Overview of the driving energy simulator

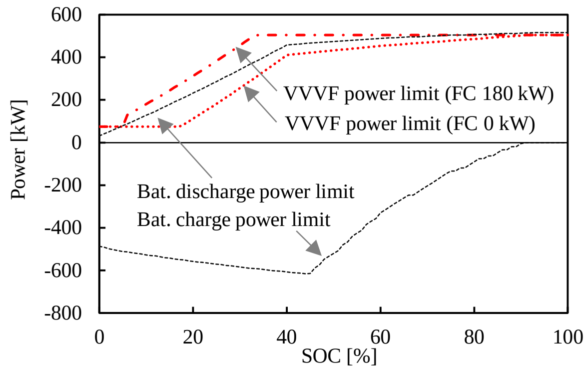

Figure 4: Battery and VVVF Power limits depending on SOC

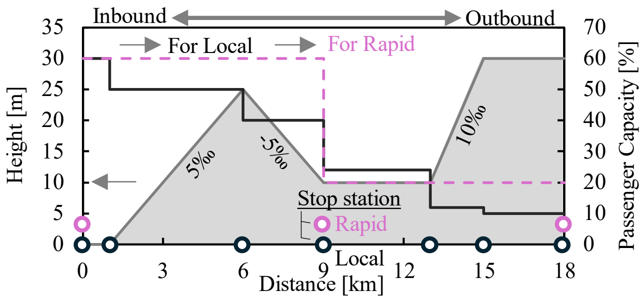

Figure 5: Virtual route profile

3 Fuel Cell Output Control Methods

3.1 Parameters Subject to Optimization in PI+FF Control

PI+FF control enables flexible adjustment of control parameters based on the performance characteristics of onboard devices. As shown in Figure 6, the PI+FF control is based on PI control targeting a battery SOC of 50%. This approach is designed to fully utilize the battery while supplementing the power shortfall with the fuel cell. Specifically, between the PI limiter and the FC output limiter, the PI output command is computed by subtracting the battery discharge limit (i.e., the battery output constraint), which is determined based on SOC, from the sum of the traction converter (VVVF) power demand and the SIV (auxiliary power supply inverter) power demand. This allows the fuel cell to meet the VVVF power demand.

In PI control, only the proportional gain (Kp) and integral gain (Ki) influence the FC output characteristics. As shown in Figure 7, to ensure appropriate FC output characteristics for different SOC levels, the current PI control divides the FC output range into three zones using two thresholds, Mid_{thre} [kW] and Hi_{thre} [kW], based on the SOC deviation (ΔSOC) from the target value. These parameters affect both acceleration performance and fuel economy, and therefore require optimization.

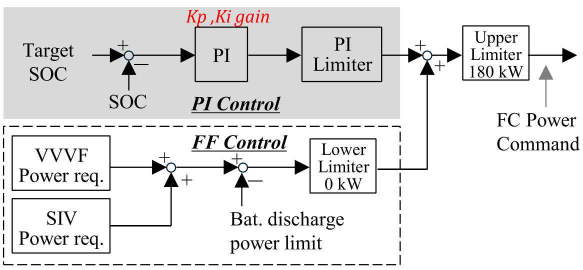

Figure 6: PI+FF control

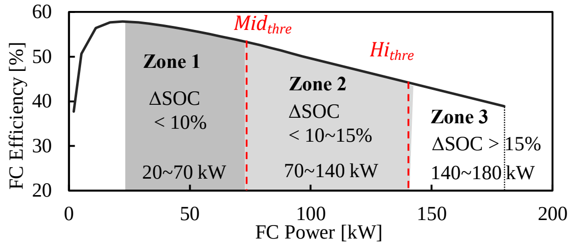

Figure 7: Efficiency of FC module & control zone

3.2 Parameters Subject to Optimization in PI+FF Control

Fuzzy control, as a multivariable control method, is widely applied to vehicle control optimization owing to its logic that generates output surfaces based on input variables and allows high flexibility in parameter tuning. However, in many previous studies, Fuzzy rules have been constructed based on engineers' experience, with optimization limited only to membership functions (MFs) [9]. Under such circumstances, this study proposes a new approach that simultaneously optimizes both a subset of Fuzzy rules and MFs that particularly where experience alone cannot determine optimal settings.

Specifically, for FC hybrid rail vehicles, Fuzzy control is designed to control FC output [kW] based on two inputs: SOC and VVVF power [kW] (traction converter power). This control logic is structured so that FC output increases when SOC decreases or VVVF power increases. As shown in Figure 5, the input MFs for SOC and VVVF power, and the output MFs for FC output, were designed. As the shape of MFs significantly effects on the output surface, the threshold values ($x_1 \sim x_4$) of the input MFs were selected as optimization parameters.

Considering the performance constraints of onboard devices, the design policy dictates that FC output should be high when VVVF power is high, and low when SOC is high. Based on this policy, Fuzzy rules were established as shown in Table 2. Specifically, when SOC is extremely low (VL), FC output is set to high (HO) to prevent battery discharge limits and degradation. When SOC is extremely high (VH), FC output is set to low (LO) to reduce light-load regenerative braking. Furthermore, considering that maximum traction converter power demand exceeds the maximum FC output, fuzzy rules were designed to ensure sufficient acceleration performance. Concretely, the gray areas in Table 2 represent rules where FC output is fixed at high or low. The blue areas limit the output to medium (MO) or higher, while the green areas have no restrictions. The fuzzy rules in the blue and green areas are subject to optimization.

The optimization parameters for fuel efficiency improvement in this study are the MF thresholds ($x_1 \sim x_4$) and the selected fuzzy rules ($R_1 \sim R_6$).

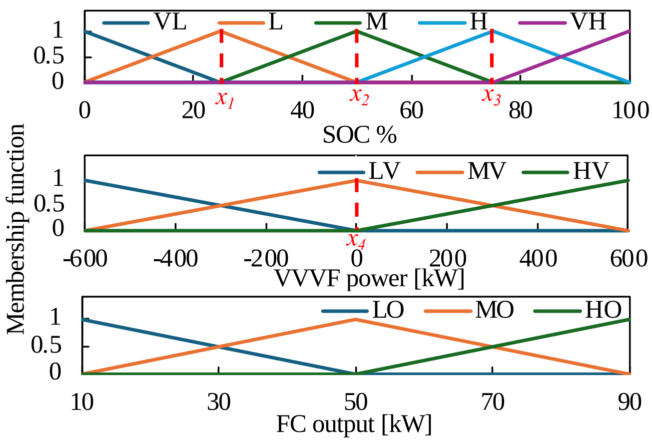

Figure 8: Input and output MFs of Fuzzy control

Table 2: Fuzzy rules

	VL	L	M	H	VH
HV	HO	HO	HO	R_4	LO
MV	HO	HO	R_2	R_5	LO
LV	HO	R_1	R_3	R_6	LO

4 Optimization Method for FC Control Parameters

4.1 Simplified Modeling of Energy Simulator Using Neural Networks

Unlike automobiles, trains operate on the same routes back and forth every day. Therefore, in this study, it was assumed that control parameters need not be modified during operation, which allows for a reduction in computational cost. Specifically, various combinations of FC control parameters were set using a simulator to perform a round-trip operation on a representative route. The resulting hydrogen fuel economy [km/kg-H_2] was used as an index to evaluate the effectiveness of each parameter set.

However, when using a high-fidelity train energy simulator, repeating simulations for each parameter combination significantly increases the total computation time. To address this problem, a simplified model of the simulator was constructed in this study. As shown in equation (1), for PI+FF control, a neural network model was built with the FC control parameters Kp, Ki, Mid_{thre} [kW], and Hi_{thre} [kW] as input variables, and the hydrogen fuel economy C_{fuel} [km/kg-H_2] and operation time T_{travel} [s], which reflects acceleration performance, as output variables. Similarly, for Fuzzy control, as shown in equation (2), the input variables consisted of MFs thresholds (x_1~x_4) and selected Fuzzy rules (R_1~R_6). The model was constructed using the Backpropagation (BP) method.

$$[C_{fuel}, T_{travel}] = BPmodel(Kp, Ki, Mid_{thre}, Hi_{thre}) \quad (1)$$

$$[C_{fuel}, T_{travel}] = BPmodel(R_1 \sim R_6, x_1 \sim x_4) \quad (2)$$

To enhance the generalizability of the model, the diversity of the training data was ensured by explicitly incorporating three types of service patterns-local, rapid, and a combined pattern in which both services are performed using the same control parameters. This design choice reflects real-world scenarios in which some trains are required to perform both local and rapid services within a single day without adjusting FC control parameters.

For the PI+FF control, a total of 2,248 simulations were conducted for each service type, using diverse parameter sets. The FC control parameter ranges and simulation settings used in the training data are listed in Table 3. For the Fuzzy control, which involves a greater number of adjustable parameters, 2,880 simulations were conducted per service type, following the same approach. The parameter ranges and conditions are summarized in Table 4.

Table 3: Simulation conditions of the training data for BP model (PI+FF)

FC control parameters	Range	Division
Kp	0.1~4.9	0.3
Ki	0.1~1.0	0.3
Mid_{thre} [kW]	20~140	20
Hi_{thre} [kW]	80~180	20

Table 4: Simulation conditions of the training data for BP model (Fuzzy)

FC control parameters	Range	Division
x_1	10~50	20
x_2	15~85	35
x_3	50~90	20
x_4	-400~400	400
R_1	MO, HO	-
R_2	MO, HO	-
R_3	LO, MO, HO	-
R_4	LO, MO, HO	-
R_5	LO, MO, HO	-
R_6	LO, MO, HO	-

4.2 Optimization Using Island Model Genetic Algorithm

In this study, an island model Genetic Algorithm (GA) was employed to optimize the input variables of the BP model. For each round-trip operation on the virtual route (36 km), the operation time which directly reflects acceleration performance and hydrogen fuel economy were used to evaluate the effectiveness of FC control parameters.

In general, acceleration performance and fuel economy are in a trade-off relationship. Therefore, it is necessary to improve fuel economy while satisfying the operation time limit required for each train operation pattern. For this purpose, operation time limits were defined for each operation mode. These were calculated based on route length and scheduled speed using equation (3):

$$T_{limit} = \frac{L_{route}}{v_{schedule}} \times 3600 \text{ [s]} \quad (3)$$

Here, T_{limit} is the operation time limit [s], L_{route} is the round-trip route distance [km], and $v_{schedule}$ is the scheduled speed [km/h]. The scheduled speed was set to 45 km/h for rapid trains and 41.5 km/h for local trains. Based on equation (3), the resulting time limits were 3,160 seconds for local and 2,350 seconds for rapid trains. For the mixed operation evaluation, where both rapid and local operations are performed once each, the total operation time limit was set to 5,510 seconds.

Figure 9 shows the process of the island model GA, and Table 5 summarizes the initial settings. The GA aims to maximize hydrogen fuel economy C_{fuel} [km/kg-H_2] defined in equation (1)(2). The algorithm runs GA independently on 15 islands. Each island evolves a population by selection, crossover, and mutation, searching for FC control parameters that yield better fuel economy. If an individual violates the operation time limit, it is regenerated to ensure compliance. Every 40 generations, the best-performing individuals are exchanged between islands. Through this migration process, information is shared across islands, enhancing search performance and promoting convergence to a global optimum.

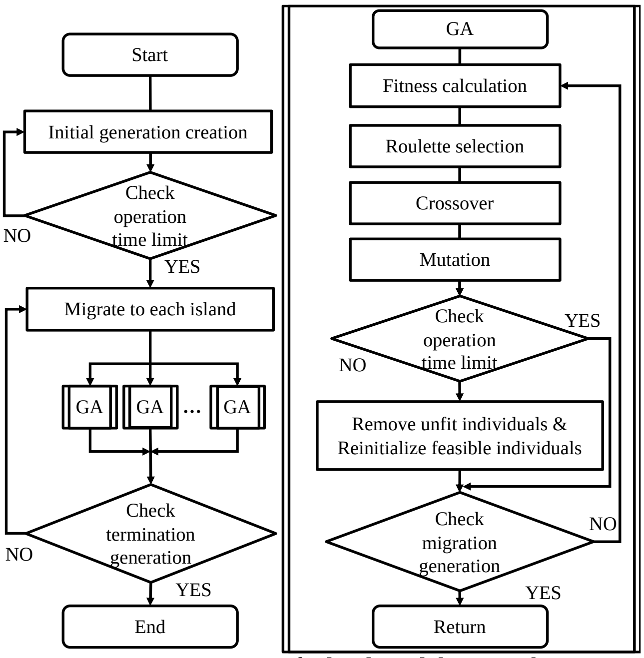

Figure 9: Process of island model GA with operation time limit

Table 5: Initial settings of island GA

	GA initial settings
Number of islands	15
Number of populations per island	40
Islands migration generation	40 generations
Crossover probability	70%
Mutation probability	10%
Optimization objective	Maximum fuel economy [km/kg-H_2]

5 Results of FC Control Parameter Optimization

5.1 Optimization Results for PI+FF Control

Conventional FC output control parameters were designed based on hardware performance constraints. Specifically, they were configured to utilize the maximum allowable battery charge/discharge power defined by SOC, aiming to maximize both acceleration capability and regenerative energy recovery.

Table 6 presents the optimized FC control parameters that achieved the highest fuel economy through GA, while Table 7 summarizes the corresponding simulation results. The application of the proposed optimization method led to a clear improvement in fuel economy. Notably, the results confirmed that operation time was reduced across all driving patterns, while fuel economy was simultaneously improved.

Figure 10 illustrates the frequency distribution of FC operating efficiency points during rapid operation of a single FC module, where PI+FF control achieved the most significant fuel economy improvement. Under conventional parameter settings based on empirical rules, the FC operating points were dispersed over a wide range of efficiency levels, indicating that FC output control was conducted in a pointwise manner without prioritizing efficiency. In contrast, the GA-optimization results suggest that improvements in both acceleration performance and hydrogen economy were achieved by concentrating FC operation in two specific regions: the high-efficiency zone around 45 kW and the high-output zone around 85 kW for strong acceleration. However, PI+FF control offers limited degrees of freedom, as its feedforward logic primarily tracks the power demand from the traction converter, thereby reducing the effectiveness of parameter tuning.

Figure 11 shows the time-series variations of SOC and FC output during rapid operation. Both before and after optimization, SOC remained above 20%, and the SOC variation (ΔSOC) between the start and end points was within 5%, demonstrating good SOC stability. Moreover, PI+FF control effectively tracked the power demand from the traction converter, successfully meeting the uphill traction power requirement and adhering to the operation time constraints, thereby confirming its superior acceleration performance. However, the results also indicated that large FC output fluctuations in FC output may accelerate FC degradation [10][11][12].

Table 6: Results of FC control parameters through optimization

	Kp	Ki	Mid_{thre} [kW]	Hi_{thre} [kW]
Local	0.224	0.553	87.5	88.1
Rapid	1.30	0.933	91.5	94.7
Combined (Local & Rapid)	1.22	0.508	80.1	92.2

Table 7: Improvement in vehicle performance through optimization
(Red: Compare with the results without optimization)

	Time limit [s]	Operation time [s]	Fuel economy [km/kg-H_2]
Local	3,160	3,107 -0.06%↑	7.78 +1.43%↑
Rapid	2,350	2,289 -0.09%↑	7.70 +1.99%↑
Combined (Local & Rapid)	5,510	5,396 -0.06%↑	7.75 +1.84%↑

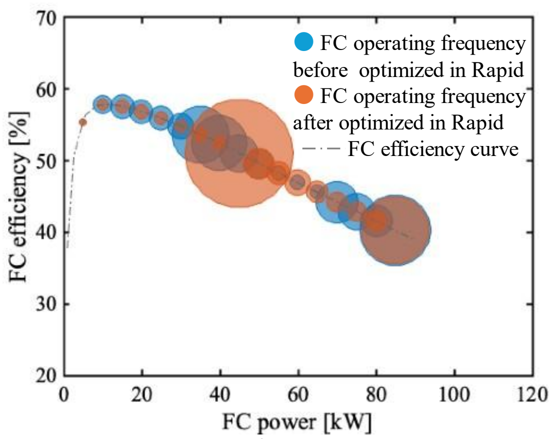

Figure 10: Frequency of FC operation points (Rapid)

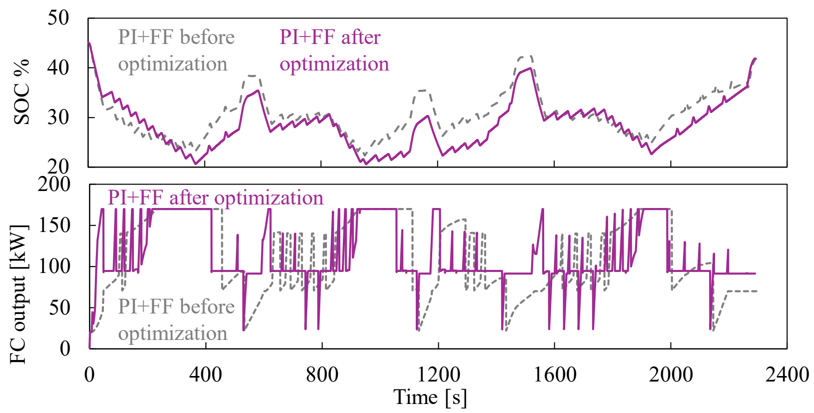

Figure 11: Simulation results of time variation (Rapid) before & after Optimization

5.2 Optimization Results for Fuzzy Control

Similar to PI+FF control, the conventional fuzzy control parameters were originally configured according to hardware performance constraints, aiming to maximize both acceleration capability and regenerative energy recovery. Tables 8 presents the optimized fuzzy rules and MF parameters, respectively, obtained through GA, while Table 9 shows the simulation results using these optimized parameters. These results demonstrate that GA-based optimization using the BP model significantly improved the fuel economy. The method successfully optimized the trade-off between acceleration performance and hydrogen fuel economy within the predefined operation time limits, achieving significant fuel economy improvement.

Figure 12 and Figure 13 display the FC output surface corresponding to the VVVF power and SOC during local service operation before and after optimization. The optimized fuzzy control suppressed FC output fluctuations and concentrated the operating points within the high-efficiency range (yellow area), as illustrated in Figure 13.

Table 8 Results of Fuzzy rules & MFs parameters through optimization

	R_1	R_2	R_3	R_4	R_5	R_6	x_1	x_2	x_3	x_4
Local	MO	MO	MO	LO	LO	LO	17.4	17.4	65.6	299
Rapid	HO	MO	MO	LO	LO	LO	11.0	15.5	81.4	-42.1
Combined (Local & Rapid)	MO	MO	MO	MO	LO	LO	18.1	18.1	72.8	279

Table 9 Improvement in vehicle performance through optimization
(Red & Blue: Compare with the results without optimization)

	Time limit [s]	Operation time [s]	Fuel economy [km/kg-H_2]
Local	3,160	3,141 +1.22%↓	8.19 +10.7%↑
Rapid	2,350	2,299 +0.57%↓	8.09 +7.72%↑
Combined (Local & Rapid)	5,510	5,437 +0.87%↓	8.05 +7.91%↑

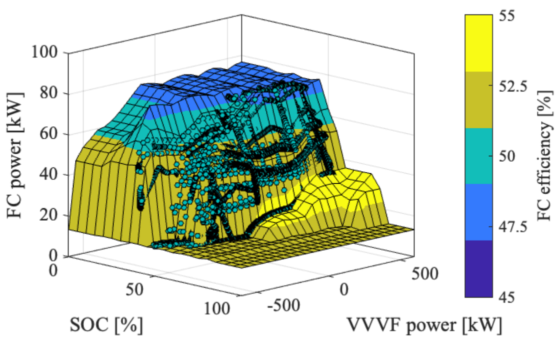

Figure 12: FC operating points efficiency before optimization (Local)

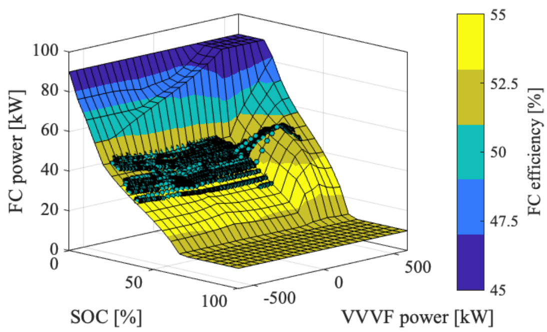

Figure 13: FC operating points efficiency after optimization (Local)

5.3 Comparison of Vehicle Performance between Fuzzy Control and PI+FF Control

By employing fuzzy control, the trade-off between acceleration performance and hydrogen fuel economy was successfully optimized, resulting in improved fuel economy. In contrast, PI+FF control-characterized by its ability to closely follow the VVVF power demand of the traction converter-demonstrated superior acceleration performance. However, due to its effectiveness of PI control parameters tuning, instances were observed where the train arrived earlier than the operation time limit even after optimization. To ensure a fair comparison between the two control strategies, a re-optimization was conducted for the fuzzy control such that its operation time limit matched the optimized operation time obtained from the PI+FF control. The results are summarized in Table 10. Even under the unified operation time, fuzzy control outperformed PI+FF control in terms of fuel economy. This advantage is attributed to the greater degree of parameter tunability in fuzzy control, owing to its flexible control logic. Fuzzy control can be adjusted through parameter tuning to create a surface where each input variable corresponds to a specific output based on its control logic. This enables enhanced optimization benefits compared to PI+FF control, which operates on a fundamentally different logic.

Figure 14 presents the time-series results of SOC and FC output during rapid operation for both strategies. Although SOC stability of fuzzy control was slightly inferior to that of PI+FF control, the operation times were consistent. In addition, fuel economy was corrected by ΔSOC. In contrast, PI+FF control exhibited significant fluctuations in FC output when tracking the VVVF power demand from the traction converter, suggesting a potential risk for accelerated FC degradation. Furthermore, fuzzy control further suppressed FC output fluctuations, as shown on Figure 14. According to previous studies, key factors contributing to FC degradation include the number of on/off cycles, output fluctuations, and output load intensity [10][11][12].

Table 11 summarizes these degradation-related parameters for the FC output during rapid operation shown in Figure 14. It was confirmed that by adopting fuzzy control, the average FC output was reduced by 2.11% and the cumulative power fluctuation was suppressed by 41.1%. These results indicate that fuzzy control is also advantageous from the perspective of FC degradation prevention.

A comparative summary of the optimized results is provided in Table 12. PI+FF control demonstrated advantages in training efficiency and SOC stability, whereas fuzzy control showed better performance in FC degradation suppression and fuel economy through greater parameter tunability. These results suggest that each control strategy offers distinct advantages depending on the operation plan and route conditions. In this study, fuzzy control met the required acceleration performance while achieving greater fuel economy and FC degradation suppression, making it well-suited to the current operation plan. Given its high parameters tunability, it is expected to be adaptable and optimizable for other operation scenarios as well.

Table 10: Optimization results in unified operation time

	Unified operation time [s]	Fuel economy [km/kg-H_2]	
		PI+FF	Fuzzy
Local	3,107	7.78	7.90 +1.54%↑
Rapid	2,289	7.70	8.01 +3.87%↑
Combined (Local & Rapid)	5,396	7.75	7.87 +1.55%↑

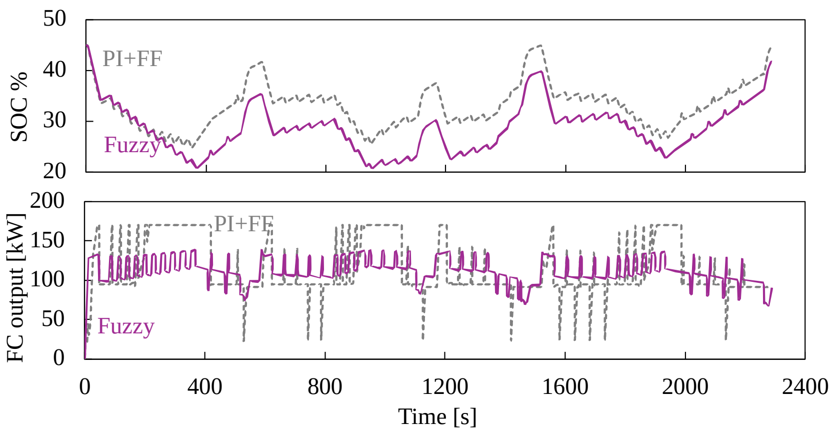

Figure 14: Simulation results of time variation (Rapid)

Table 11: Comparison of the FC damage parameters

	PI+FF	Fuzzy
Cumulative power change [kW]	2923.7	1721.8 -41.1%↑
Average FC power [kW]	113.6	111.2 -2.11%↑
Number of start-ups and shutdowns	1	1

Table 12: Comparison of PI+FF control and Fuzzy control after optimization

	Reference	PI+FF	Fuzzy
Required training data collection time	Different parameters dataset (Table 3, Table 4)	Shorter 2,248 [set]	Longer 2,880 [set]
SOC stability	Final ΔSOC (Figure 14)	Better -0.16%	Worse but acceptable -3.13%
FC degradation suppression	Cumulative power change: ∑FC output [kW] (Table 11)	Worse 2923.7 [kW]	Better 1721.8 [kW] -41.1%↑
Parameters tunability	Fuel economy in unified operation time (Table 10)	Lower -	Higher +3.87%↑ in Rapid

6 Conclusion

This study developed a simplified model for a fuel cell hybrid test train by utilizing a driving energy simulator and a BP neural network. The model takes FC control parameters as input variables and outputs hydrogen consumption and operation time. Based on this model, GA optimization was conducted under the constraint of maintaining scheduled speed, targeting two multivariable control methods-PI+FF control and fuzzy control with the SOC and VVVF traction converter power as input variables. The results confirmed that optimal control parameters could be obtained for various driving patterns to improve fuel economy.

PI+FF control demonstrated excellent SOC stability and acceleration performance. Notably, PI+FF control enhanced fuel economy while reducing operation time across all patterns. However, due to its feedforward logic that closely tracks the VVVF power demand from the traction converter, it exhibited sharp FC output fluctuations, raising concerns about potential degradation risks. Furthermore, as PI+FF control involves a relatively small number of tunable parameters, its degrees of freedom are limited, resulting in a lower optimization margin.

In contrast, fuzzy control offered a greater degree of parameter tunability owing to its flexible control logic. It effectively optimized the trade-off between acceleration performance and hydrogen fuel economy. Moreover, when the operation time for both control methods was unified-i.e., when acceleration performance was identical-fuzzy control not only improved fuel economy but also significantly suppressed fluctuations in FC output. This suppression contributes to the reduction of degradation factors such as output variation and output load intensity. The results suggest that control strategies with a larger number of parameters, which are typically difficult to tune based on human experience, tend to benefit more from optimization owing to their higher degrees of freedom.

In conclusion, fuzzy control was demonstrated to be an effective strategy in simultaneously enhancing hydrogen economy and mitigating FC degradation. Future work will aim to further develop the proposed optimization method and improve FC output control strategies with consideration of equipment durability and FC aging characteristics.

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Presenter Biography

Yida Bao received his B.E. degree in Engineering from Tokyo University of Science, Tokyo, and his M.E. degree in Engineering from Waseda University, Tokyo. He is currently pursuing a Ph.D. degree at the Electric Vehicle Research Laboratory, Graduate School of Environment and Energy Engineering, Waseda University, Tokyo. His research interests include fuel cell vehicle (FCV) systems, fuel cell (FC) control, FCV equipment capacity design, system optimization, and vehicle powertrain modeling.