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Impact of Energy Management Strategy Calibration on Component Degradation and Fuel Economy of Heavy-Duty Fuel Cell Vehicles

Julian Kölbl * **Alessandro Ferrara** ** **Christoph Hametner** *

* *Christian Doppler Laboratory for Innovative Control and Monitoring of Automotive Powertrain Systems, TU Wien, Vienna, Austria (e-mail: julian.koelbl@tuwien.ac.at; christoph.hametner@tuwien.ac.at).*
** *Institute of Mechanics and Mechatronics, TU Wien, Vienna, Austria (e-mail: alessandro.ferrara@tuwien.ac.at)*

Abstract: Energy management strategies significantly impact the fuel economy and component degradation of fuel cell electric vehicles by distributing the load demand between the battery and fuel cell systems. Since these are contrasting targets, designing a control strategy that finds a good trade-off is challenging. Therefore, this paper adopts a rule-based energy management strategy to show the significant impact of its calibration on fuel consumption and component degradation. The expected vehicle life is maximized by balancing battery and fuel cell degradation, assuming that individual component replacement is undesired. Moreover, the simulation results highlight the trade-off between fuel consumption and expected vehicle life, revealing that a slight increase in consumption can significantly mitigate the degradation. The study considers a sequence of six ld driving cycles for robust calibration of the energy management strategy. However, analyzing individual cycles reveals that even a robust calibration leads to significantly unbalanced degradation if the vehicle only runs a specific driving cycle. Therefore, this work proposes two potential research directions to cope with the mentioned issues and maintain the balance between fuel cell and battery degradation.

Keywords: Predictive Energy Management Strategy, Heavy-Duty Fuel Cell Vehicles, Optimal Calibration, Fuel Cell Degradation, Hydrogen Consumption, Vehicle Life.

1. INTRODUCTION

The short lifetime of fuel cell electric vehicles (FCEVs) is hindering their market penetration in the road freight transport sector. Hence, the degradation mechanisms of batteries and fuel cells have been studied intensively with several modeling approaches. Empirical models are widely used to estimate the lifetime of powertrain components since they generally present a good trade-off between accuracy and complexity, as shown in Pelletier et al. (2017) and Vichard et al. (2021). They introduce stress indicators that mathematically link operating conditions to degradation effects, such as battery capacity fade or fuel cell voltage degradation.

Energy management strategies (EMSs) distribute the load demand between the fuel cell and battery systems. Therefore, incorporating degradation models within the EMS optimization can lead to significant advantages in mitigating the fuel and battery degradation and, thus, extending the overall vehicle life. Energy management strategies are usually categorized into two groups: optimization-based and rule-based. Optimization-based strategies as in Fares et al. (2015) and Fletcher et al. (2016) minimize an objective function to achieve an optimal power-split. Rule-based strategies rely on a set of rules created with engineering experience to perform the power-split, as in Ahmadi and Bathaee (2015) and Aouzellag et al. (2015). Rule-based strategies are the common choice in the industry because of the simpler design and lower complexity than optimal-based ones, as mentioned in Alyakhni et al. (2021).

This work calibrates a rule-based EMS to show its significant impact on fuel consumption and component degradation in heavy-duty FCEVs. The strategy relies on the rules defined in Ferrara et al. (2021), using a formulation to stay close to optimal fuel cell power and state of charge (SoC) references. In Zendegan et al. (2021), the authors further developed the strategy by including a predictive SoC reference optimized based on basic road information to improve fuel economy and SoC control. Eventually, the rule-based EMS adopted in this work requires the calibration of three main control parameters to define the power-split. This calibration significantly impacts fuel cell and battery degradation, which is not considered within the generation of the predictive references. The overall vehicle life is estimated by adopting fuel cell and battery degrada-

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tion models from literature and assuming that individual component replacement is undesired. The study considers several real-world driving cycles of road freight vehicles to investigate the correlation between road topographies and stress indicators of degradation. The simulation results highlight the trade-off between fuel consumption and expected vehicle life, revealing that a slight increase in consumption can significantly mitigate the degradation. A robust EMS calibration is obtained considering the driving cycles in sequence. However, analyzing individual cycles reveals that even a robust calibration leads to significantly unbalanced degradation if the vehicle only runs a specific driving cycle.

The rest of this paper is structured as follows: Section 2 describes the simulation framework, including energy management strategy, real-world driving cycles, battery capacity fading model, and fuel cell voltage degradation model. Section 3 analyzes the impact of strategy calibration on component degradation indicators, the trade-off between fuel economy and expected vehicle life, and the balance between the fuel cell and battery degradation.

2. SIMULATION FRAMEWORK

This section describes the simulation framework adopted to evaluate the impact of EMS calibration on fuel cell and battery degradation. The simulations consider a heavy-duty fuel cell electric vehicle and real-world driving cycles for road freight transport. The rule-based EMS, battery capacity fading model, and fuel cell voltage degradation model adopted in this work are described below.

2.1 Vehicle simulation and energy management strategy

The heavy-duty vehicle under consideration has a maximum weight of 42 tonnes, and its model derives from the work of Ferrara et al. (2022). The fuel cell system has a nominal power of 310 kW and the battery a nominal capacity of 52 kWh. Fig. 1 shows the simulation results for a real-world driving cycle in terms of vehicle speed v, route elevation z, battery SoC, battery temperature T_{bat}, electric load demand P_{el}, battery power P_{bat}, fuel cell system power P_{fc}, and hydrogen consumption rate $\dot{m}_{H_2}$.

The EMS performs the power-split between the fuel cell and battery systems such that:

$$P_{el} = P_{fc} + P_{bat} \ . \tag{1}$$

This work studies the impact of EMS calibration on component degradation and fuel economy by adopting the predictive EMS from Zendegan et al. (2021), which includes an offline optimization of the predictive SoC and fuel cell power references and a rule-based strategy for on-board control. The predictive references are optimized to obtain minimum fuel consumption while keeping the SoC between 50% and 80%. On the other hand, the on-board rule-based EMS performs the power-split by defining the fuel cell power with the following rules:

$$P_{fc} = P_{fc,ref} + r_1(P_{el} - P_{fc,ref}) + r_2(\mathrm{SoC}_{ref} - \mathrm{SoC}), \tag{2}$$

$$|\dot{P_{fc}}| \leq r_3 \ , \tag{3}$$

where $P_{fc,ref}$ and SoC_{ref} are the predictive fuel cell power and SoC references. In (2), the fuel cell setpoint is defined based on the deviation from the references. Moreover, the rate of change of the fuel cell power is limited in (3). The parameters r_1, r_2, and r_3 are constant and need to be calibarated to find a good balance between fuel economy, fuel cell degradation, and battery degradation. For a more detailed description of the predictive EMS, the reader is referred to Zendegan et al. (2021).

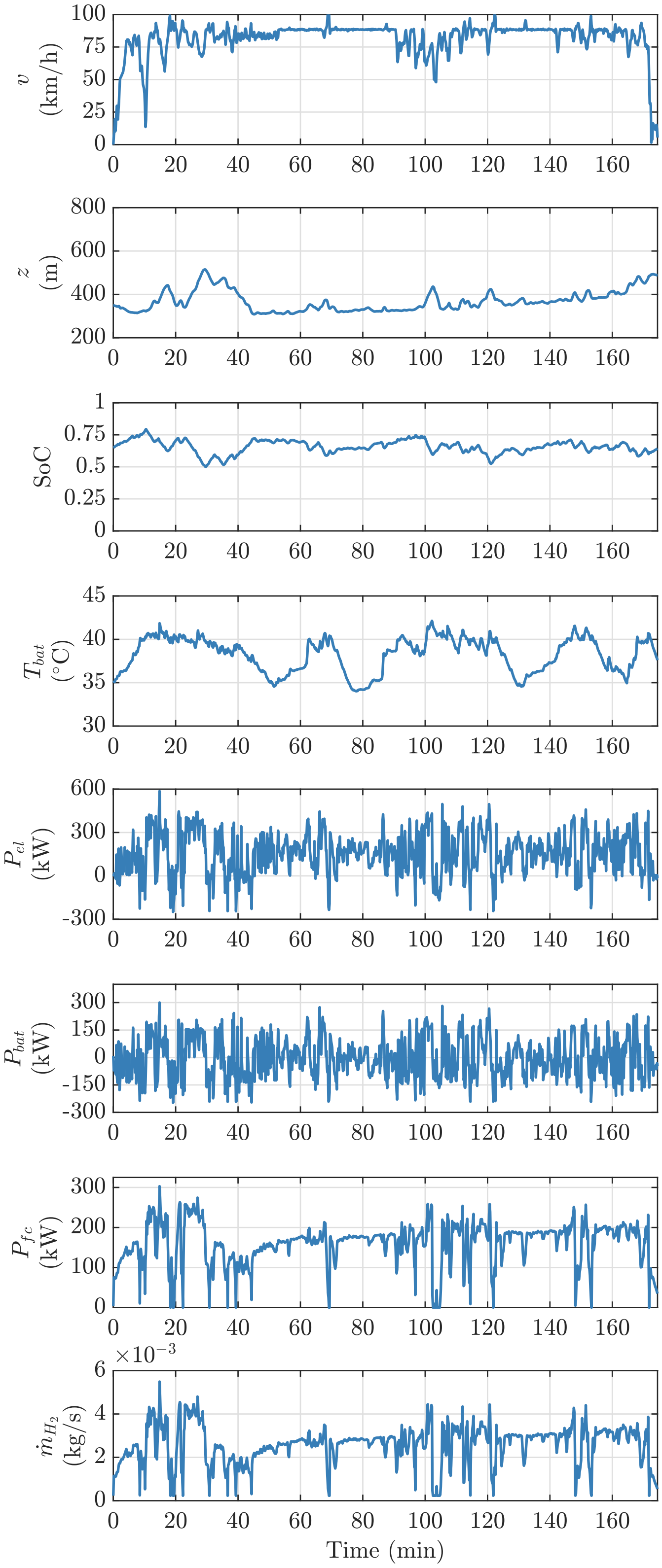

Fig. 1. Simulation of a heavy-duty fuel cell electric vehicle in a real-word driving cycle.

2.2 Battery capacity fading model

This work considers the empirical capacity fading model proposed by Lam and Bauer (2013) to determine the battery degradation based on the operating conditions. The model has the distinct advantage that its stress indicators derive from commonly available data of the vehicle, and their physical interpretation is straightforward. The parametrization of the original model is valid for a cell with nominal capacity: $Q_{bat,ref} = 1.1$ Ah. However, using an equivalent circuit model, the operating conditions of the whole battery pack can be easily scaled to a single cell. Eventually, the total capacity loss is determined as:

$$\Delta Q_{bat} = Ah \cdot f_1(\mathrm{SoC}_\sigma, \mathrm{SoC}_{avg}) \cdot f_2(T_{bat,avg}) \quad (4)$$

$$f_1 = k_1\ \mathrm{SoC}_\sigma\ e^{k_2\ \mathrm{SoC}_{avg}} + k_3\ e^{k_4\ \mathrm{SoC}_\sigma} \quad (5)$$

$$f_2 = e^{-E_a/R(1/T_{bat,avg} - 1/T_{bat,ref})} \quad (6)$$

where Ah is the charge processed by each cell, SoC_{avg} the average state of charge, SoC_σ the normalized standard deviation from SoC_{avg}, and $T_{bat,avg}$ the average temperature. The values of k_1, k_2, k_3, and k_4 are taken as in Lam and Bauer (2013). The reference temperature is: $T_{bat,ref} = 35°\mathrm{C}$. In general, higher SoC_{avg}, SoC_σ, and $T_{bat,avg}$ determine higher degradation.

The battery cell reaches end of life (EoL) conditions when the capacity fade is 20% of the nominal one: $\Delta Q_{bat,EoL} = 0.20\ Q_{bat,ref}$. The expected battery life for a given driving cycle is estimated as:

$$L_{bat} = \frac{\Delta Q_{bat,EoL}}{\Delta Q_{bat}}\ L_{dc}\ , \quad (7)$$

where $L_{dc} = \int v\ dt$ is the distance traveled by the vehicle in a driving cycle. Here, it is assumed that the degradation is always the same if the driving cycle is repeated until EoL conditions. Additionally, it is assumed that the capacity loss is distributed equally across all cells, implying that (7) remains equal for both single-cell and battery pack calculations.

The comparison of two different EMS calibrations in Fig. 2 shows that energy management strategies significantly impact battery degradation. Here, the expected battery life resulting from each calibration, L_{bat_1} and L_{bat_2}, are computed using (4) and (7). In particular, calibration 1 results in a significantly lower processed charge and, in turn, three times higher battery life. Moreover, calibration 1 follows the predictive SoC reference stricter than the other one, resulting in lower SoC_σ and longer battery life.

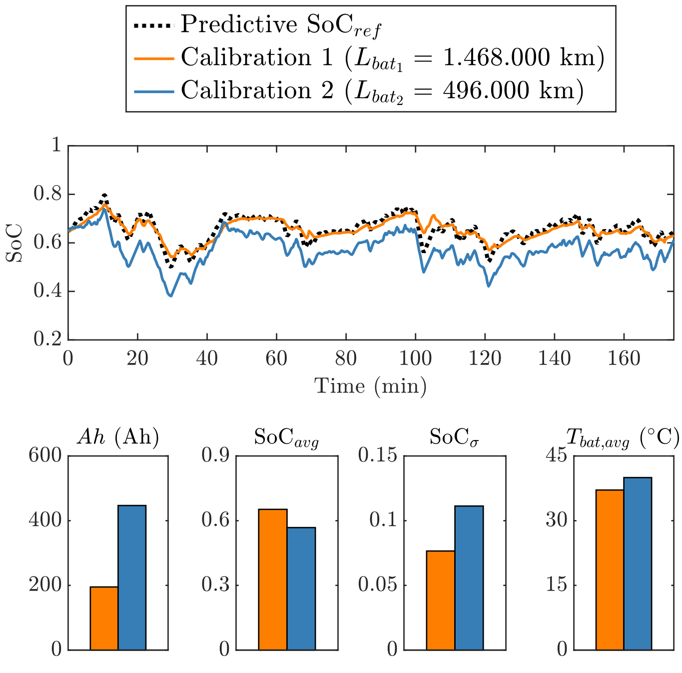

Fig. 2. Comparison of different calibration in terms of SoC profile and the stress indicators for battery degradation.

2.3 Fuel cell voltage degradation model

Pei et al. (2008) developed a simple empirical model that evaluates the lifetime of fuel cells in automotive applications based on the real-word operating conditions of the vehicle. In particular, the fuel cell voltage degradation is expressed as a function of load cycling (n_1), start-up/shut-down cycles (n_2), low power operating time (t_1) and high power operating time (t_2). The relative voltage loss from the nominal fuel cell voltage is computed as:

$$\Delta V_{fc} = k_p(p_1 n_1 + p_2 n_2 + p_3 t_1 + p_4 t_2)\ , \quad (8)$$

where p_1, p_2, p_3, p_4 are deterioration rates and k_p is an accelerating coefficient which compensates differences between laboratory and real-world operating environment. However, in this paper, ideal conditions are assumed, i.e., $k_p = 1$. Due to the EMS design, all investigated driving cycles only have one start-stop cycle ($n_2 = 1$). The low power threshold is 10% of the nominal fuel cell power, whereas the high power one is at 80%, as in Ferrara et al. (2022). Load cycling are defined as the number of load changes from low power to the rated power of the fuel cell and are calculated as:

$$n_1 = \frac{\int |\dot{P}_{fc}|\ dt}{2 P_{fc,nom}}. \quad (9)$$

The end-of-life criterion is $\Delta V_{fc,EoL} = 10\%$, at which the performance of the fuel cell start to deteriorate significantly faster. The expected fuel cell life is estimated as:

$$L_{fc} = \frac{\Delta V_{fc,EoL}}{\Delta V_{fc}}\ L_{dc}\ , \quad (10)$$

similarly to the expected battery life calculation in (7).

The impact of the different EMS calibrations on fuel cell degradation is shown in Fig. 3. In this case, the difference in fuel cell operation is even more evident than in the previous comparison. In particular, the expected fuel cell life resulting from calibration 2 is almost seven times higher than the other. The main reason is that the load cycling is significantly lower for calibration 2. Additionally, the low and high power operating times are negligible.

Comparing the results shown in Fig. 2 and Fig. 3, it is evident that the different calibrations have a contrasting effect on battery and fuel cell life. Comparing these two extreme cases paves the way for a deeper analysis of the EMS calibration impact on the degradation of both components. Eventually, the calibration target is to find a good trade-off between fuel economy, battery life, and fuel cell life.

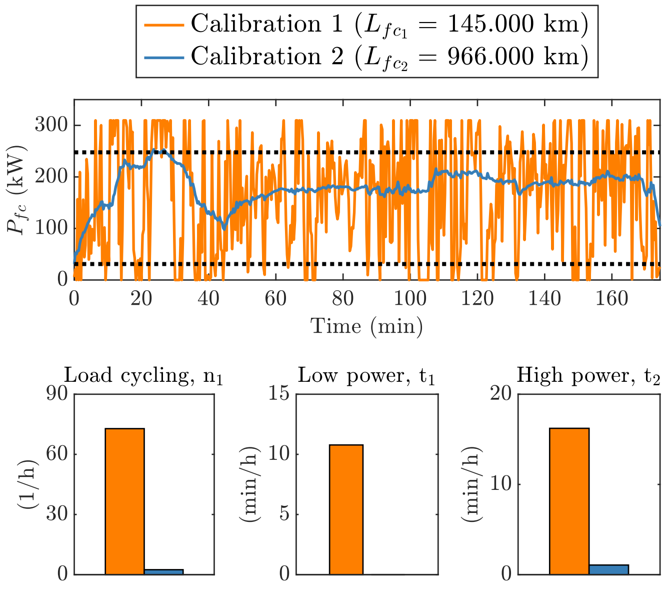

Fig. 3. Comparison of different calibration in terms of fuel cell power profile and the stress indicators for fuel cell degradation.

Table 1. Characteristics of the real-world driving cycles under investigation.

	Driving cycle ID number					
	1	2	3	4	5	6
Vehicle mass (t)	28	35	36	41	42	42
Average speed (km/h)	61	79	80	77	82	69
Traveled distance (km)	173	347	161	188	238	385
RPA (m/s^2)	0.09	0.03	0.03	0.04	0.03	0.01
Total climb (m/km)	9.1	7.2	3.2	3.1	5.3	7.6
Max-min elevation (m)	293	694	73	267	207	1526
Average load (kW)	84	136	139	126	155	123

3. IMPACT OF EMS CALIBRATION ON COMPONENT DEGRADATION

Six different real-world driving cycles for freight road transportation were selected from the work of Ferrara et al. (2021) to conduct the powertrain degradation study, including different speed and elevation profiles and varying vehicle mass. Table 1 reports meaningful characteristics of the driving cycles under investigation, such as vehicle mass, average speed, traveled distance, relative positive acceleration (RPA), total climb, maximum minus minimum elevation, and average electric load. Driving cycle no. 1 corresponds to final delivery in a suburban environment, with the lowest vehicle mass and average speed but the highest RPA (i.e. heavy traffic). The remaining cycles show low RPA (i.e. stable cruising in motorways). In particular, the last driving cycle stands out for its elevation difference, as it corresponds to a motorway in the Alps. The driving cycle no. 5 is the one corresponding to the simulation results shown in Fig. 1.

3.1 Analysis of battery and fuel cell degradation indicators

In order to investigate the influence of different strategy parametrizations on battery and fuel cell degradation, 12000 strategies with different combinations for r_1, r_2, and r_3 have been simulated. Fig. 4 shows the boxplot distribution of the stress indicators for battery degradation, revealing that while the variance in the average SoC (SoC_{avg}) over a full driving cycle remains similar, the variation of the normalized standard deviation (SoC_σ) and Ah-throughput for cycles with a higher total climb like 1, 2, 5, and 6 increases. It indicates that in the case of uphill driving, the efficacy of SoC control is more sensitive to changing parameters in the rule-based strategy compared to cycles with relatively flat elevation profiles. Further, the distribution of the average temperature ($T_{bat,avg}$) shows little variance across all six cycles despite some outliers between 36 and 40 °C. When considering only the battery system, it can be concluded that road profiles with distinct elevation profiles show a large degree of freedom in reducing battery degradation stress indicators.

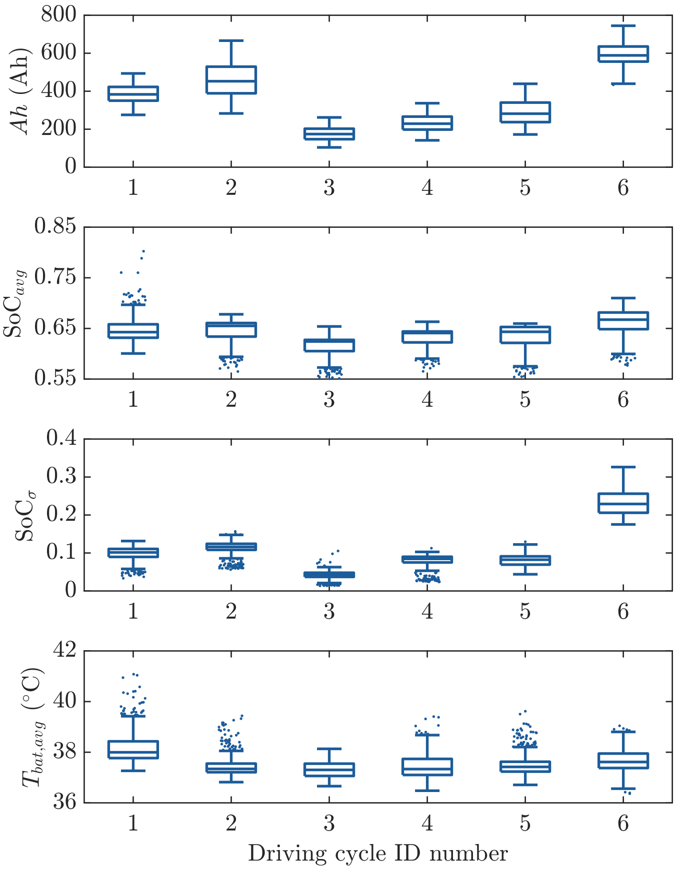

Fig. 4. Boxplot distribution of the stress indicators for battery degradation.

Fig. 5 presents the distribution of the fuel cell stress indicators. The influence of start-stop cycles is negligible under the assumption that the fuel cell only starts at the beginning and stops operating at the end of each driving cycle. However, the variance of load-cycling is significant, indicating improvement potential regarding fuel cell life even if degradation due to high and low power operation is neglected. Only cycle 6 stands out with a small variance compared to the other cycles caused by the considerable distance of driving downhill during which the battery recharges through regenerative braking, and the fuel cell is idling most of the time. Overall, it is evident that the complexity of reducing system degradation increases when multiple driving cycles are considered.

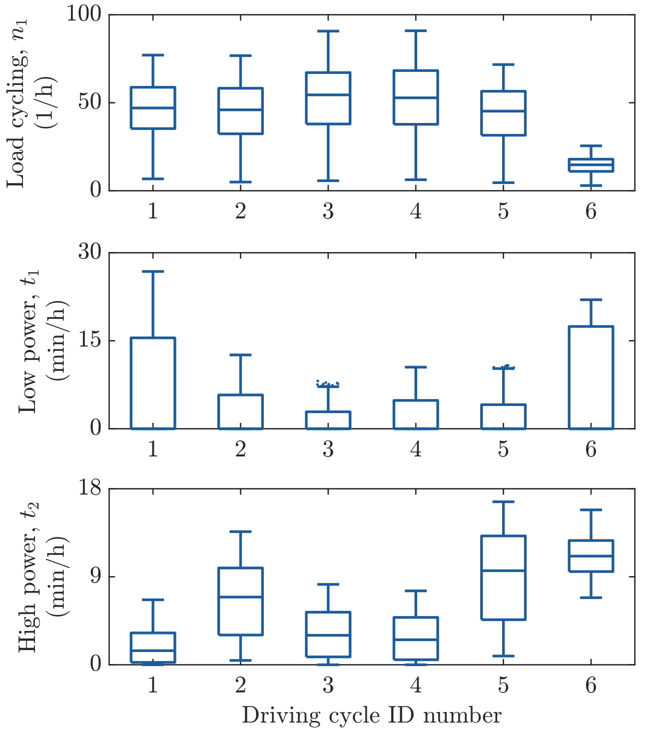

Fig. 5. Boxplot distribution of the stress indicators for fuel cell degradation.

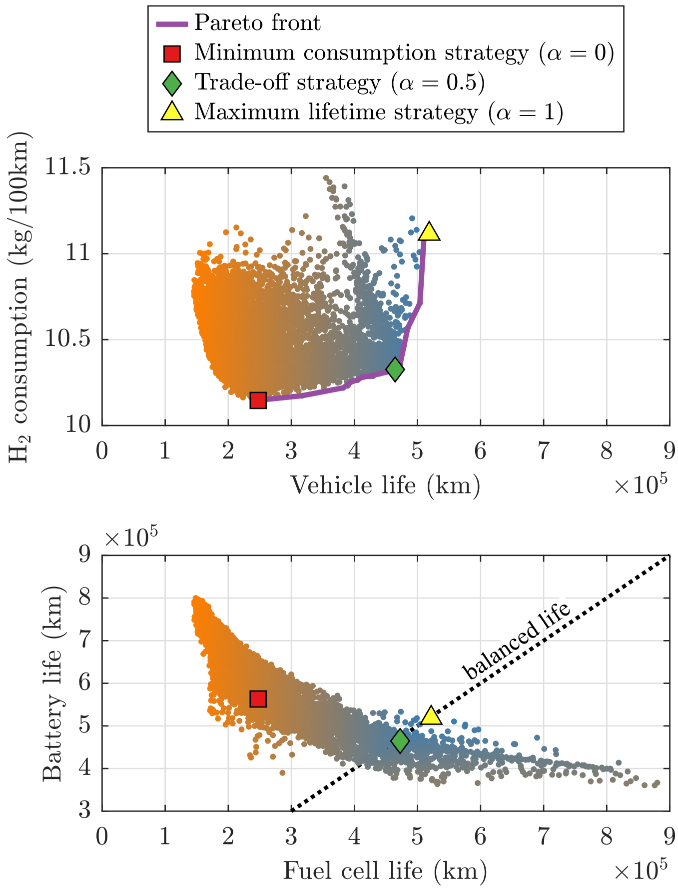

Fig. 6. Trade-off between fuel consumption and vehicle life (top); and battery and fuel cell life (bottom).

3.2 Trade-off between vehicle life and fuel consumption

This work considers the vehicle life as the minimum between the battery and fuel cell life:

$$L_{veh} = \min(L_{bat}, L_{fc}) \ . \qquad (11)$$

Therefore, it is assumed that the individual replacement of one of the components is undesired. On the other hand, it is better to balance the component degradation to maximize the overall vehicle life. The impact of different EMS calibrations is analyzed for a combined driving cycle, consisting of a sequence of the others. This approach was adopted to increase the robustness of the EMS calibration to unknown driving cycles.

The trade-off between fuel consumption and vehicle life is analyzed by defining a multi-objective cost function as:

$$J = -\alpha \ L_{veh,norm} + (1-\alpha) H_{2,norm} \ , \qquad (12)$$

following the approach described by Yang (2014). The vehicle life and fuel consumption are normalized between 0 and 1, obtaining $L_{veh,norm}$ and $H_{2,norm}$, respectively. The parameter α is a weighting parameter to define the trade-off between vehicle life and fuel consumption.

The overall simulation results for all the EMS calibrations investigated are depicted in Fig. 6. The top plot shows the trade-off between fuel consumption and vehicle life, whereas the bottom plot shows the trade-off between battery and fuel cell life. The optimal strategy calibration for each α value is located on the Pareto frontier, which is defined by minimizing (12) for $0 \leq \alpha \leq 1$. The vehicle life can increase significantly for $0 \leq \alpha \leq 0.5$, with a relatively small increase in fuel consumption. On the other hand, for $\alpha > 0.5$, the lifetime can be slightly increased but with a substantial cost in fuel economy. In the bottom plot of Fig. 6, it is shown that the cases with α equal to 0.5 and 1 have both balanced component life. On the other hand, it is evident that some EMS calibrations can significantly increase the life of the battery or fuel cell individually, but not simultaneously.

Table 2. Optimal trade-off between fuel consumption and vehicle life.

α	H_2 cons. (kg/100km)	Vehicle life (km)
0	10.14	247.000
0.5	10.33 (+1.9%)	465.000 (+88%)
1	11.11 (+9.6%)	519.000 (+110%)

The optimal fuel consumption and vehicle life for selected values of α are reported in Table 2, indicating the relative change compared with the minimum fuel consumption tuning. In particular, vehicle life can increase by 88% with a 1.9% increase in fuel consumption or even by 110% with a 9.6% consumption increase.

Lastly, this work investigates the robustness of the optimal EMS calibration with $\alpha = 0.5$ on the individual cycles, assuming that the vehicle always runs them individually. In particular, the question is if the calibration that ensures balanced life on the sequence of all cycles retains balanced life when considering the cycles individually. The results of this investigation are shown in Fig. 7. Here, it is evident that for some driving cycles (i.e. no. 3, 4, and 6), there is a significant imbalance in component life, even though

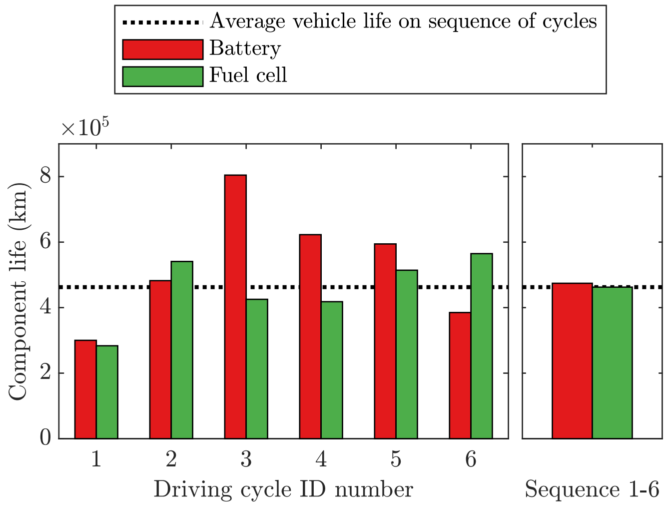

Fig. 7. Robustness to unknown driving conditions of the optimal EMS calibration for balanced component life.

the driving cycles were considered on average for the calibration. Such an issue could eventually be even worse in driving cycles that are entirely unknown during the EMS calibration process.

4. CONCLUSION

This paper shows the significant impact of rule-based energy management strategy calibration on battery and fuel cell degradation and fuel consumption for FCEVs. Component life is estimated with parametrized empirical degradation models from the literature that link degradation effects to stress indicators. The significant variance in stress indicators for different calibrations and road profiles highlights the complexity of choosing a single calibration that can increase battery and fuel cell life for different operating conditions.

Analyzing the vehicle life, the study balances component degradation to find a robust trade-off calibration between component degradation and fuel economy for six real-world driving cycles. It turns out that a single EMS calibration can significantly extend the vehicle life with a limited impact on fuel consumption. However, further robustness analysis of individual cycles reveals unbalanced degradation of components if the vehicle only operates on specific cycles.

Therefore, this paper proposes two potential research directions to cope with the unbalanced degradation that inevitably results from unknown driving cycles. Firstly, degradation unbalance could be prevented with cycle-specific EMS calibrations whenever a new destination is planned for the vehicle. Secondly, health-conscious EMS could be designed to adapt the calibration to the current fuel cell and battery degradation state to reestablish a balanced component life.

REFERENCES

Ahmadi, S. and Bathaee, S. (2015). Multi-objective genetic optimization of the fuel cell hybrid vehicle supervisory system: Fuzzy logic and operating mode control strategies. *International Journal of Hydrogen Energy*, 40(36), 12512–12521. doi:10.1016/j.ijhydene.2015.06.160.

Alyakhni, A., Boulon, L., Vinassa, J.M., and Briat, O. (2021). A comprehensive review on energy management strategies for electric vehicles considering degradation using aging models. *IEEE Access*, 9, 143922–143940. doi:10.1109/access.2021.3120563.

Aouzellag, H., Ghedamsi, K., and Aouzellag, D. (2015). Energy management and fault tolerant control strategies for fuel cell/ultra-capacitor hybrid electric vehicles to enhance autonomy, efficiency and life time of the fuel cell system. *International Journal of Hydrogen Energy*, 40(22), 7204–7213. doi:10.1016/j.ijhydene.2015.03.132.

Fares, D., Chedid, R., Panik, F., Karaki, S., and Jabr, R. (2015). Dynamic programming technique for optimizing fuel cell hybrid vehicles. *International Journal of Hydrogen Energy*, 40(24), 7777–7790. doi:10.1016/j.ijhydene.2014.12.120.

Ferrara, A., Jakubek, S., and Hametner, C. (2021). Energy management of heavy-duty fuel cell vehicles in real-world driving scenarios: Robust design of strategies to maximize the hydrogen economy and system lifetime. *Energy Conversion and Management*, 232, 113795. doi:10.1016/j.enconman.2020.113795.

Ferrara, A., Zendegan, S., Koegeler, H.M., Gopi, S., Huber, M., Pell, J., and Hametner, C. (2022). Optimal calibration of an adaptive and predictive energy management strategy for fuel cell electric trucks. *Energies*, 15(7), 2394. doi:10.3390/en15072394.

Fletcher, T., Thring, R., and Watkinson, M. (2016). An energy management strategy to concurrently optimise fuel consumption & PEM fuel cell lifetime in a hybrid vehicle. *International Journal of Hydrogen Energy*, 41(46), 21503–21515. doi:10.1016/j.ijhydene.2016.08.157.

Lam, L. and Bauer, P. (2013). Practical capacity fading model for li-ion battery cells in electric vehicles. *IEEE Transactions on Power Electronics*, 28(12), 5910–5918. doi:10.1109/tpel.2012.2235083.

Pei, P., Chang, Q., and Tang, T. (2008). A quick evaluating method for automotive fuel cell lifetime. *International Journal of Hydrogen Energy*, 33(14), 3829–3836. doi:10.1016/j.ijhydene.2008.04.048.

Pelletier, S., Jabali, O., Laporte, G., and Veneroni, M. (2017). Battery degradation and behaviour for electric vehicles: Review and numerical analyses of several models. *Transportation Research Part B: Methodological*, 103, 158–187. doi:10.1016/j.trb.2017.01.020.

Vichard, L., Steiner, N.Y., Zerhouni, N., and Hissel, D. (2021). Hybrid fuel cell system degradation modeling methods: A comprehensive review. *Journal of Power Sources*, 506, 230071. doi:10.1016/j.jpowsour.2021.230071.

Yang, X.S. (2014). Multi-objective optimization. In *Nature-Inspired Optimization Algorithms*, 197–211. Elsevier. doi:10.1016/b978-0-12-416743-8.00014-2.

Zendegan, S., Ferrara, A., Jakubek, S., and Hametner, C. (2021). Predictive battery state of charge reference generation using basic route information for optimal energy management of heavy-duty fuel cell vehicles. *IEEE Transactions on Vehicular Technology*, 70(12), 12517–12528. doi:10.1109/tvt.2021.3121129.