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Adaptive Energy Management Strategy to Avoid Battery Temperature Peaks in Fuel Cell Electric Trucks

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Abstract: Thermal management is essential in electric vehicles to preserve battery life. In particular, avoiding temperature peaks is critical to prevent accelerated degradation. The battery thermal management problem is crucial in fuel cell electric trucks due to the heavy vehicle weight, especially on mountain or hilly roads. Therefore, this paper proposes an energy management strategy that reduces battery degradation by limiting its usage at high temperatures to allow its cooldown and avoid peaks. The energy management strategy is adaptive because the main control parameters for the fuel cell/battery power-split are adjusted depending on the battery temperature. The comparison between adaptive and non-adaptive strategies proves the effectiveness of the proposed formulation in avoiding temperature peaks without hindering fuel consumption or fuel cell degradation. The robustness of the proposed energy management strategy is validated with simulations of several real-world driving cycles with various speed and elevation profiles.

Keywords: Energy Management, Heavy-Duty Fuel Cell Vehicle, Adaptive Control, Battery Temperature, Fuel Cell Degradation, Battery Thermal Management.

1. INTRODUCTION

Extending the lifetime of powertrain components is one of the most challenging issues for the advancement of fuel cell electric vehicles. In the last years, increasing research effort has been focused on designing control strategies for optimal operation of powertrain components to find a good trade-off between system efficiency and lifetime. In this context, energy and thermal management are the control functions with the highest impact on the overall performance of heavy-duty fuel cell vehicles, especially on mountain roads, due to their massive weight. In particular, energy management is essential to obtain a suitable control of the battery state of charge (SoC) without hindering fuel consumption. At the same time, battery thermal management is critical to keep the temperature within a safe operating range to prevent accelerated degradation and preserve battery life.

In Li-ion batteries, the cell temperature influences some of the leading battery degradation mechanisms, such as SEI growth, lithium plating, and active material dissolution, as indicated in Reniers et al. (2019). In particular, higher temperatures determine faster (unwanted) chemical reactions and, thus, accelerated degradation. Reniers et al. (2019) also shows that different degradation models respond very differently to varying operating conditions. Moreover, the degradation mechanisms depend highly on the cell chemistry, making battery degradation modeling challenging and hard to generalize. Alyakhni et al. (2021) present a review of battery degradation mechanisms and modeling oriented towards health-aware energy management strategies. Lam and Bauer (2013) show that the capacity fade rate of a battery operating at 40°C is more than twice higher than at 30°C. Zia et al. (2019) show that the battery cycle life drastically drops for temperature higher than 60°C. Hannan et al. (2017) show that, to improve battery cycle life, the best temperature operating region of Li-ion batteries is between 15°C and 45°C. Diao et al. (2019) experimentally investigate the effect of temperature on capacity degradation, showing extremely poor performance at 60°C and already compromised performance at 45°C.

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A literature review of studies on energy management strategies (EMSs) for fuel cell battery vehicles is proposed in Lü et al. (2020). Recently, predictive EMSs for heavy-duty fuel cell vehicles have been studied to find a good trade-off between fuel consumption, SoC control, and powertrain component degradation: Ferrara et al. (2021) use model predictive control to reduce fuel cell transients while retaining high system efficiency in real-world driving cycles. Zendegan et al. (2021) propose a dual-stage predictive control scheme based on the offline optimization of a predictive SoC reference, which is then used for on-board energy management. Some works have studied the interaction between energy and thermal management, including the battery temperature within the power-split optimization problem: Padovani et al. (2013) use Pontryagin's Minimum Principle to solve an optimization problem that includes a soft constraint on battery temperature. Amini et al. (2018) develop a model predictive control to optimize the energy management while keeping the battery temperature within defined constraints. Song et al. (2021) offer a review of the temperature effect in fuel cell electric vehicles, pointing out that most energy management strategies neglect the role of temperature.

This paper proposes an innovative energy management strategy that adapts to the battery temperature to limit its usage in critical conditions and avoid temperature peaks without compromising system efficiency and SoC control. The adaptive EMS is implemented by suitably adjusting the main control parameters for the fuel cell/battery power-split depending on the battery temperature. The simulations of real-world driving cycles prove that the proposed solution effectively avoids temperature peaks over 45°C, which is considered the threshold for accelerated battery degradation. The effectiveness and robustness of the adaptive EMS are validated in 13 selected real-world driving cycles, which represent different speed, elevation, and vehicle mass scenarios for road freight vehicles. The comparison with a non-adaptive EMS shows significant improvements in terms of battery thermal management. Not only the temperature peaks are avoided, but also the battery operation in its optimal temperature range is increased.

The remainder of the paper is structured as follows. Section 2 outlines the fuel cell electric vehicle simulation framework with a particular focus on the battery thermal management system. Section 3 describes the proposed adaptive energy management strategy. Section 4 analyzes the simulation results and highlights the benefits of the adaptive EMS compared to the non-adaptive one.

2. SIMULATION OF FUEL CELL ELECTRIC TRUCK

This study evaluates the performance of a heavy-duty vehicle with nominal fuel cell system (FCS) power of 310 kW and battery capacity of 53 kWh. The simulation framework considers realistic driving scenarios and a complex vehicle model, which was extended from Ferrara et al. (2021) to include cooling systems and thermal dynamics. This section offers only a brief model description because detailed modeling of vehicle components is beyond the scope of the paper.

The vehicle acceleration is calculated as in (1), adopting longitudinal dynamics and forward facing modeling approach. Here, m_v is the vehicle mass, v is the speed, P_w the power at the wheels, and F_{res} the resistant force.

$$m_v\, \dot{v} = P_w/v - F_{res}(v, \alpha) \tag{1}$$

The resistant force considers the aerodynamic drag, the road slope α, and the wheels rolling friction, as in Ferrara et al. (2021). The power at wheels is calculated based on the electric motor power P_m using (2). The total efficiency η_T includes all the power losses of the motor, inverter, and drivetrain.

$$P_w = P_m\, \eta_T^{\mathrm{sgn}(P_m)} \tag{2}$$

The electrical motor power is determined depending on the fuel cell and battery power as in (3). Here, the auxiliary power P_{aux} includes the radiator fan losses for fuel cell cooling, the chiller compressor losses for battery cooling, and all the external loads outside of the electric powertrain (e.g. cabin conditioning, power-steering pump).

$$P_m = P_{fcs} + P_{bat} - P_{aux} \tag{3}$$

The battery system considered in this work has the highest efficiency in the temperature range between 35°C and 40°C. Indeed, the battery cell characteristics (e.g. the internal resistance) depend on the temperature. On the other hand, this study assumes that 45°C is the threshold for safe operation, and after that, the battery degradation is accelerated. The battery thermal management system (BTMS) is divided into two cooling circuits, as depicted in Fig. 1. The battery pack exchanges heat with oil flowing through liquid cooling plates. At the same time, the oil exchanges heat with a coolant fluid, which is cooled down by a chiller system. A hysteresis controller regulates the chiller operation depending on the battery temperature. In particular, the chiller is switched on - at maximum cooling power - when the battery temperature reaches 40°C and off at 35°C. The thermal dynamics of the BTMS are described in (4), assuming that the battery, oil, and coolant temperatures are uniform. C_{bat} is the thermal capacity of the battery system. h_{bo} is the heat exchange coefficient at the battery-oil interface.

$$C_{bat}\, \dot{T}_{bat} = \dot{Q}_{loss} - h_{bo}(T_{bat} - T_{oil}) \tag{4a}$$

$$C_{oil}\, \dot{T}_{oil} = h_{bo}(T_{bat} - T_{oil}) - h_{oc}(T_{oil} - T_{cool}) \tag{4b}$$

$$C_{cool}\, \dot{T}_{cool} = h_{oc}(T_{oil} - T_{cool}) - \dot{Q}_{cool} \tag{4c}$$

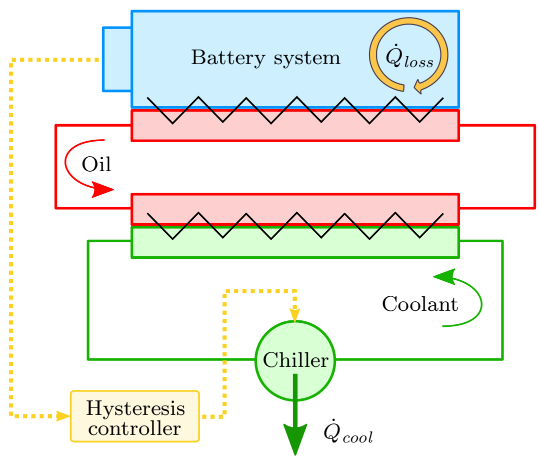

Fig. 1. Layout of the battery thermal management system.

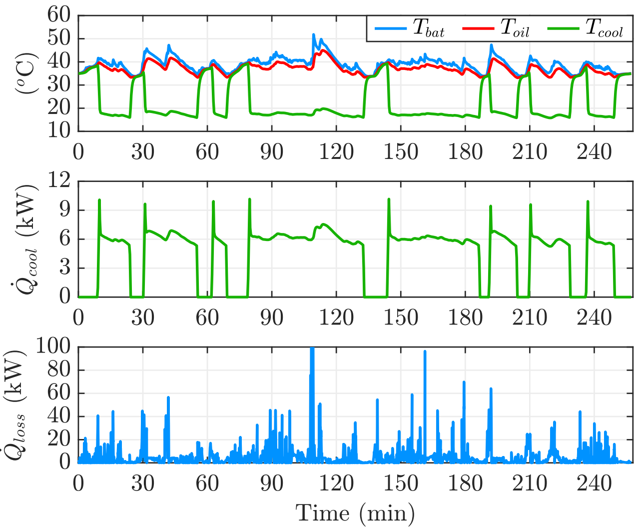

Fig. 2. Simulation results of the battery thermal management system.

The simulation results in Fig. 2 help visualize the cooling system dynamics during a driving cycle. The coolant quickly reaches the oil temperature when the chiller is off, showing that battery, oil, and coolant have different thermal capacities. The second tile of the figure shows that the maximum cooling power is not constant, as it depends (among other things) on the coolant temperature. The third tile shows the battery heat generation due to ohmic losses, which reach significant peaks at high C-rate operation. Eventually, the simulation results show that the cooling system is not powerful enough to avoid battery temperature peaks.

Since it is challenging to model the degrading effect of temperature peaks, the battery capacity fade is not directly quantified in this work. On the other hand, the maximum battery temperature represents the key performance indicator, although the specific fuel consumption and fuel cell voltage degradation are also considered. In (5), a quasi-static model is adopted to calculate the hydrogen consumption of the fuel cell system. The efficiency η_{fcs} includes the stack, balance of plant components, and converter losses. Therefore, P_{fcs} represents the net FCS power after all these losses. The maximum fuel cell efficiency is 55% at 56 kW, with an efficiency characteristic similar to the one in Ferrara et al. (2020).

$$\dot{m}_{\mathrm{H}_2} = P_{fcs}/(\eta_{fcs}\ \mathrm{LHV}_{\mathrm{H}_2}) \tag{5}$$

The fuel cell voltage degradation, ΔV_{fcs}, is calculated in (6) considering start-up/shut-down cycles, dynamic loading, low-power and high-power operation, using the quick evaluating method developed by Pei et al. (2008).

$$\Delta V_{fcs} = \Delta V_{fcs,ss} + \Delta V_{fcs,dl} + \Delta V_{fcs,lp} + \Delta V_{fcs,hp} \tag{6}$$

It is assumed that the fuel cell system can idle at zero net power to avoid shut-down cycles (consequently, there is one start-up/shut-down cycle per driving cycle). The thresholds for low and high-power operation are 10% and 80% of the fuel cell nominal power, as in Ferrara and Hametner (2021).

3. ADAPTIVE ENERGY MANAGEMENT STRATEGY

This study adopts the predictive energy management system developed by Zendegan et al. (2021), proposing an improved formulation of the control strategy to avoid high battery temperatures and limit accelerated degradation. The predictive EMS consists of two control stages: route-references optimization and on-board control. Every time a new route is inserted into the navigation system, the expected electric load is estimated based on the speed and elevation forecasts over the entire route. The power-split is then optimized using quadratic programming to find the best trade-off between hydrogen consumption and SoC control. The optimization results are saved as maps of the SoC and FCS power references. Then, an on-board control strategy uses the predictive references to perform the power-split during the driving cycle. For more details on the predictive energy management system, refer to Zendegan et al. (2021). However, it should be mentioned that the battery temperature is not considered within the optimization problem to reduce its complexity.

A rule-based EMS defines the fuel cell power setpoint as:

$$P_{fcs} = P_{ref} + r_1(P_{el} - P_{ref}) + r_2(\mathrm{SoC}_{ref} - \mathrm{SoC})\ , \tag{7}$$

to provide the electric load P_{el} demanded by the driver during the driving cycle. Even though the control strategy consists of a simple rule, the energy management is still highly effective thanks to the predictive references P_{ref} and SoC_{ref}. In this study, the references are optimized to have the SoC within the 50%-80% range. Moreover, the fuel cell power is subject to the constraints defined in (8). Here, the rate of change is limited to reduce the degradation associated with transient fuel cell operation.

$$|\dot{P}_{fcs}| \le r_3 \tag{8a}$$

$$0 \le P_{fcs} \le P_{fcs,max} \tag{8b}$$

$$P_{bat,min} \le P_{el} - P_{fcs} \le P_{bat,max} \tag{8c}$$

The battery system operates as a buffer between the electric load and the fuel cell power. Therefore, its setpoint is defined to ensure that the demanded load is always provided by the two power sources:

$$P_{bat} = P_{el} - P_{fcs}\ . \tag{9}$$

This paper proposes an innovative solution to avoid battery temperature peaks through an adaptive energy management strategy. In particular, at critical temperatures, the power-split criterion changes from optimal powertrain operation to low battery usage, limiting the heat generation due to ohmic losses and allowing its cooldown.

The EMS is adaptive because the main control parameters for the fuel cell/battery power-split depend on the battery temperature. Therefore, the parameters in (7) and (8) are implemented as a function of the battery temperature:

$$r_1 = r_1(T_{bat}),\ \ r_2 = r_2(T_{bat}),\ \ r_3 = r_3(T_{bat})\ . \tag{10}$$

The characteristics of the parameters are defined based on heuristic considerations to avoid temperatures above 45°C. It is essential to understand that the most critical power-split parameter is r_1 because it significantly impacts the battery operation. Indeed, combining (7) and (9), the battery power setpoint becomes:

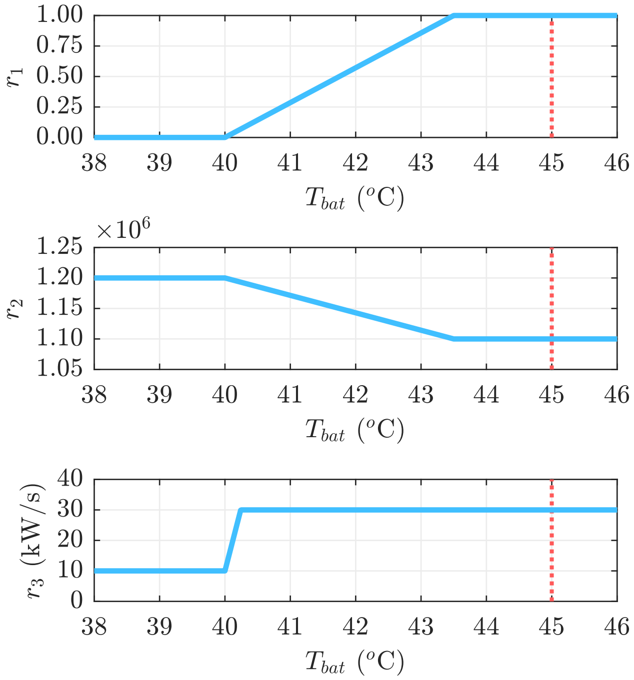

Fig. 3. Characteristics of the adaptive EMS parameters as function of the battery temperature.

$$P_{bat} = (1 - r_1)(P_{el} - P_{ref}) - r_2(\mathrm{SoC}_{ref} - \mathrm{SoC}) \; . \quad (11)$$

When $r_1 = 1$, the fuel cell is operated in load-follower mode. On the other hand, the battery operates to:
– provide the loads exceeding the maximum FCS power,
– absorb regenerative braking energy,
– stay close to the optimal SoC reference.

This study proposes the adaptive power-split parameter characteristics depicted in Fig. 3, which allow for a gradual reduction of the battery usage for increasing temperatures. The values were heuristically tuned until the battery temperature stayed below 45°C. In particular, the parameter r_1 linearly changes from 0 (at 40°C) to 1 (at 43.5°C), which marks the transition to load-follower operation. The parameter r_2 is slightly lower at high temperatures to reduce the SoC reference tracking term in (11). The parameter r_3 rapidly increases to allow faster fuel cell transients for better load-follower energy management.

4. SIMULATION RESULTS

This section offers a detailed analysis of the simulation results to highlight the benefits of the adaptive EMS in realistic driving scenarios compared with a non-adaptive strategy. First, Fig. 4 shows the simulation results of a real-world driving cycle in terms of speed, elevation, fuel cell power, SoC, battery temperature, and cooling power. The figure provides a good visualization of the predictive energy management references adopted in (7). In particular, the SoC is kept within the 50%-80% range by adequately charging the battery in anticipation of long uphills and discharging it before the downhills to maximize regeneration. The battery temperature and cooling power clearly show a behavior typical of hysteresis control. Moreover, at minute 110, the fuel cell operates in load-follower mode ($r_1 = 1$) to limit the battery usage, successfully keeping the temperature below the accelerated degradation threshold.

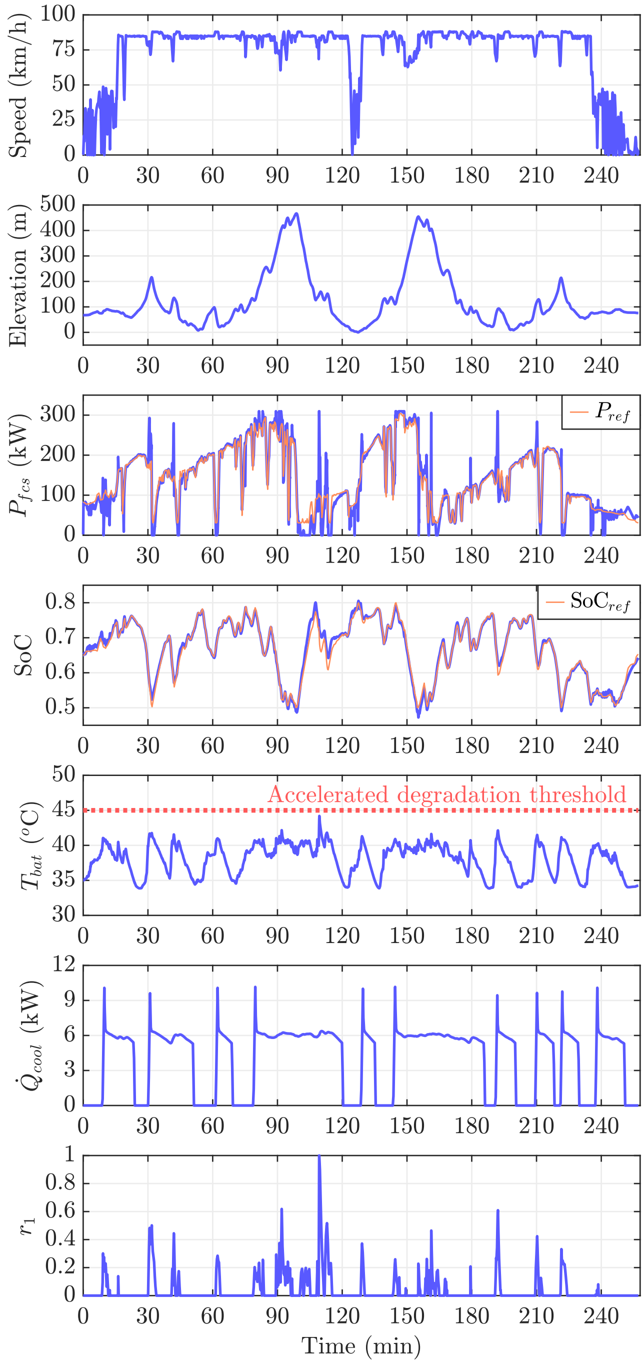

Fig. 4. Simulation results of a real-world driving cycle using the adaptive EMS to avoid temperature peaks above the accelerated degradation threshold.

It is meaningful to compare the results with those of a non-adaptive EMS, which has constant parameters in (7) and (8). For a fair comparison, the constant values are obtained from the corresponding characteristics in Fig. 3 at 40°C. The comparison is depicted in Fig. 5 using red lines for the non-adaptive EMS and blue lines for the adaptive one. The figure shows evident benefits of the adaptive EMS to avoid the temperature peaks at minutes 30, 40, 90, 110, and 190. In particular, by briefly changing the fuel cell power in these events, the adaptive EMS reduces the heat generation due to ohmic losses and allows the battery to cool down.

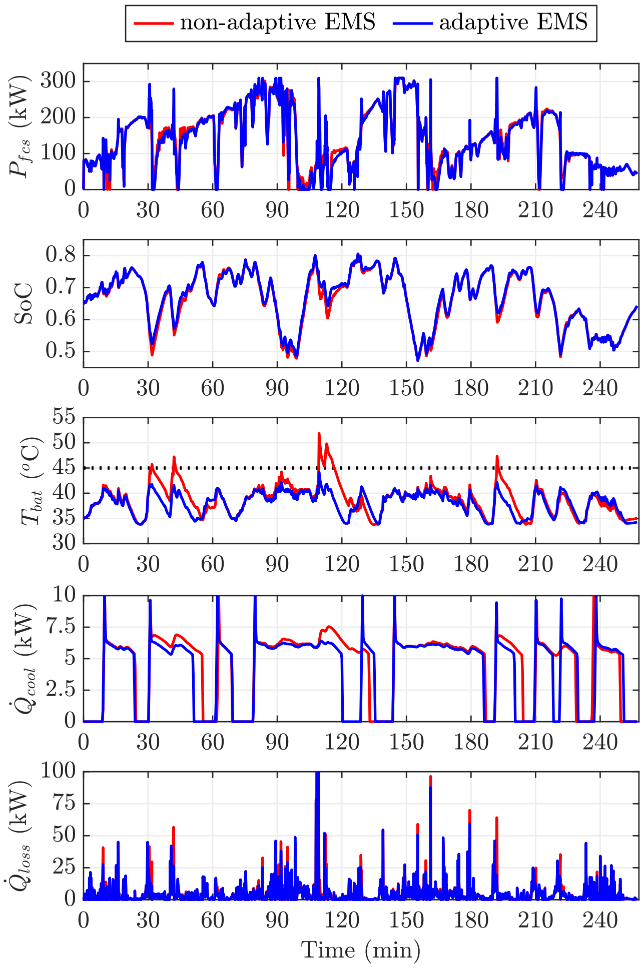

Fig. 5. Comparison between the adaptive and non-adaptive energy management strategies.

The robustness and effectiveness of the adaptive EMS are validated in 13 selected driving cycles, which represent different speed, elevation, and vehicle mass scenarios for road freight vehicles. The left side of Fig. 6 shows performance indicators related to the battery thermal management, which are the maximum temperature and the timeshare above 45, 43, and 40°C. For all cycles, the adaptive EMS can keep the battery temperature below the accelerated degradation threshold, which this work assumed as the design target. It can be expected that such a result has significant benefits for battery life because, depending on the cycle, the non-adaptive strategy operates above 45°C for 4 to 13% of the total time. Moreover, the timeshare above 43°C, in which the adaptive EMS operates the fuel cell in load-follower mode, is negligible. The operation between $35°C - 40°C$, which is optimal for the battery, is increased. The right side of Fig. 6 compares the specific fuel consumption (SFC) and voltage degradation of the two strategies. The SFC considers the hydrogen consumption of the fuel cell system and the equivalent battery consumption due to the SoC change compared to the initial charge. The results show that the adaptive EMS is also beneficial in terms of SFC, which is counterintuitive because the load-follower operation is generally less efficient. However, in this case, the SFC improvement is due to two reasons. Firstly, the battery operates longer in its optimal temperature range. Secondly, the total ohmic and battery cooling losses are reduced, resulting in lower energy consumption. On the other hand, the adaptive EMS impact on fuel cell voltage degradation compared to the non-adaptive strictly depends on the cycle. However, the overall degradation is slightly higher (approximately 3%) for the adaptive EMS because the load-follower mode generally results in higher cycling and high-power operation. This result was expected because mitigating fuel cell and battery degradation are contrasting targets, and improving the life of one component usually results in lowering the other one.

5. CONCLUSION

This paper proposed an innovative solution to exploit the interaction between energy and thermal management in fuel cell electric trucks. The simulation results show that the proposed adaptive energy management strategy developed can effectively avoid battery temperature peaks by limiting its usage in critical conditions. Although the adaptive control parameters are designed based on heuristic considerations, the effectiveness of the adaptive EMS is proved in multiple cycles, confirming the robustness of its design.

A natural follow-up investigation to this work is the validation of the adaptive EMS on real components to assess the benefits on degradation and overall powertrain performance. Another research direction is the design of energy management strategies that are also adaptive to the state of health of the powertrain components. In this way, for example, if the expected fuel cell life is lower than the battery life, the energy management strategy could be adapted to rebalance the degradation of the components.

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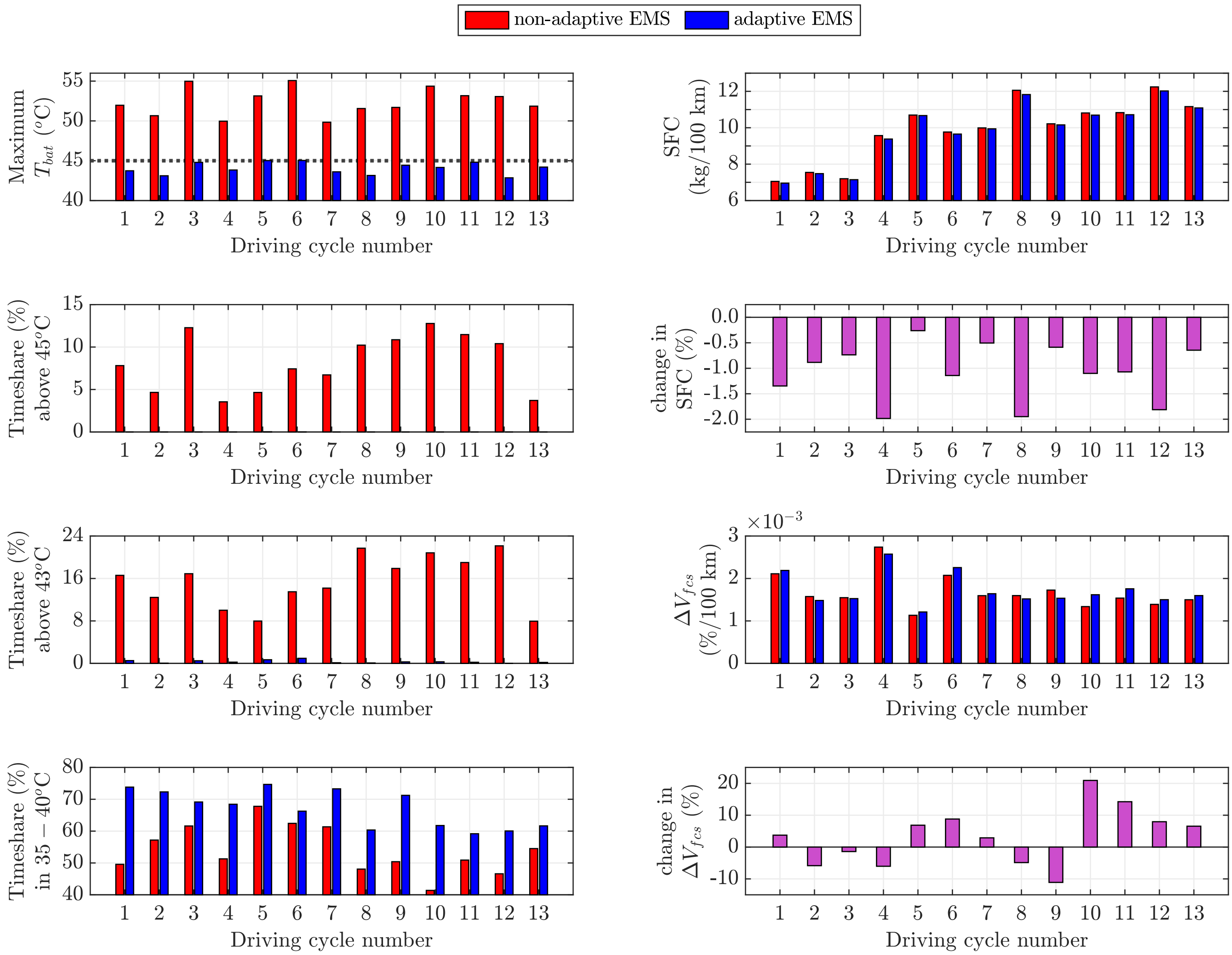

Fig. 6. Comparison of key performance indicators between adaptive and non-adaptive EMS in 13 driving cycles.

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