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Energy Management for a Fuel Cell Plug-in Hybrid Heavy-duty Vehicle

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Executive Summary

The transition to environmentally responsible land freight transportation is critical to reducing global emissions. This study investigates energy management strategies (EMSs) for a Fuel Cell Plug-in Hybrid Electric Vehicle (FC-PHEV) designed for heavy-duty applications. A backward-facing vehicle model is developed to test several EMSs, including both optimization and rule-based strategies. The EMSs are evaluated in terms of energy consumption, battery degradation, and fuel cell degradation. The Equivalent Consumption Minimization Strategy (ECMS) emerged as a promising option, motivating further testing with a forward-facing model and additional drive cycles. The results show that ECMS can be effective for a heavy-duty FC-PHEV, with the average energy consumption from ECMS across five drive cycles about 1% higher than the consumption from the global optimal solution and 7.5% lower than the consumption from a simple rule-based strategy.

Keywords: Energy Management, Fuel Cell Electric Vehicles, Heavy Duty Electric Vehicles & Buses, Modeling & Simulation, Plug-in Hybrid Vehicles.

1 Introduction

Current road freight infrastructure relies on burning fossil fuels in internal combustion engines which produce carbon dioxide (CO_2) and other emissions. Road freight contributes to about 7% of global CO_2 emissions [1]. These emissions must be reduced or eliminated to mitigate the devastating effects of climate change and to meet climate targets. Fuel Cell Electric Vehicles (FCEVs), which use a fuel cell to convert hydrogen into electricity without producing harmful emissions, are a promising alternative. This paper considers a Fuel Cell Plug-in Hybrid Electric Vehicle (FC-PHEV), which is an FCEVs with a battery that can be charged directly from the fuel cell, through plug-in charging, and from regenerative braking. This configuration can also be referred to as a Battery Electric Truck with Fuel Cell Range Extender (BET-FCRE). Typical Hybrid Electric Vehicles (HEVs) operate in a charge-sustaining mode, meaning the initial and final battery state of charge (SOC) are similar. PHEVs can operate in either a charge-sustaining mode, or a charge-depleting mode where the final battery SOC is lower than the initial battery SOC. The vehicle discussed in this paper operates in a charge-depleting mode and uses a series hybrid powertrain, meaning the fuel cell and battery each provide power to an electric motor that drives the vehicle [2].

Hybrid vehicles use an energy management strategy (EMS) to determine how power sources work together to provide the required power. In an FC-PHEV, the EMS controls the battery and fuel cell behavior. Several EMSs are designed, tested, and evaluated for this paper. Further simulations are done with a subset of the EMSs to quantify effectiveness in additional driving scenarios and to understand the effect of parameter tuning on energy management.

2 Methods

Drive cycle data from five truck routes is used with two simulation models to test different EMSs. A backward-facing model is used to compare EMSs while a forward-facing model is used to further evaluate the strategy that performed the best with the first model. Both models are FC-PHEVs with proton exchange membrane fuel cells and large battery capacity.

2.1 Drive cycles

Data for five driving routes pertaining to the foreseen real-life pilot vehicles of the European Union's ESCALATE project is used to run simulations and evaluate EMSs [3] (Figure 1). The data includes vehicle velocity as well as road slope and elevation. This data was processed utilizing VTT's Smart eFleet simulation toolbox, adapted for trucks for the ESCALATE project [4][5][6].

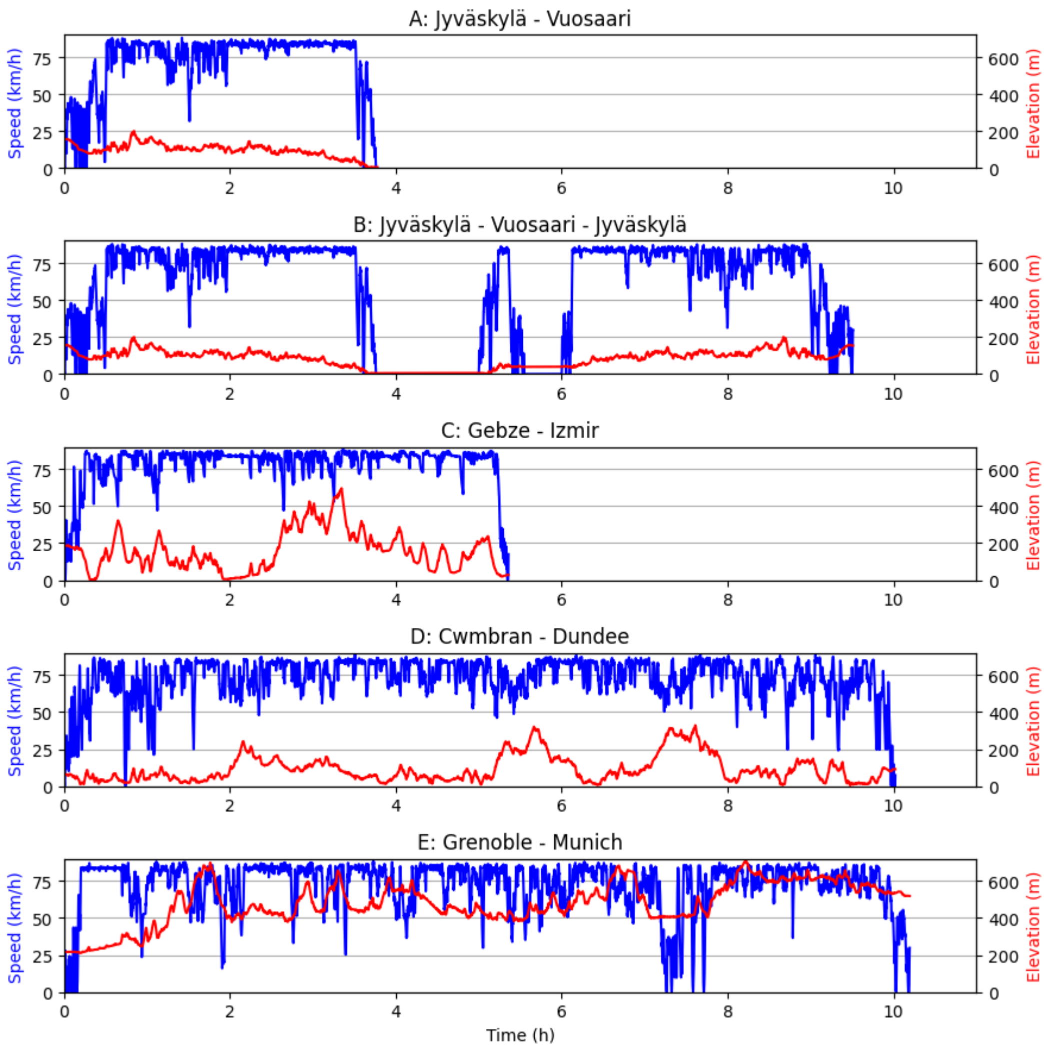

Figure 1: Drive cycle data [3][5].

2.2 Backward-facing model

First, a backward-facing model is built, rather than a forward-facing model, because it allows for fair comparison between EMSs [7]. In a forward-facing model, a control loop attempts to provide the required power. However, the model may sometimes be unable to provide the exact power required, depending on the EMS. For example, if a drive cycle requires sharp acceleration but the EMS does not provide enough power for the vehicle to produce the necessary torque, the vehicle will accelerate slower. As a result, the vehicle performance may differ for the same drive cycle depending on the EMS. Alternatively, a backward-facing model assumes the required power will be provided for all cycles. This ensures the vehicle dynamics are the same for all EMSs.

MATLAB® Simulink is used to build a backward-facing model of a heavy-duty vehicle with a fuel cell battery hybrid powertrain, as shown in Figure 2 [8]. The model is designed to represent a pilot vehicle which is being built for the European Union's ESCALATE project [3]. The vehicle model uses velocity and slope data generated using the SeF toolbox (see Figure 1) to calculate the total power demand [4][5][6]. Key vehicle parameters are shown in Table 1. The energy management system determines the power request from the fuel cell. The fuel cell power output is as close as possible to the power request, within physical limits. The battery provides the remaining power. The vehicle, fuel cell, and energy management models are designed and built for this research, while the battery model is a coupled electrical equivalent and thermal equivalent circuit model that was developed by Hentunen et al. [9][10].

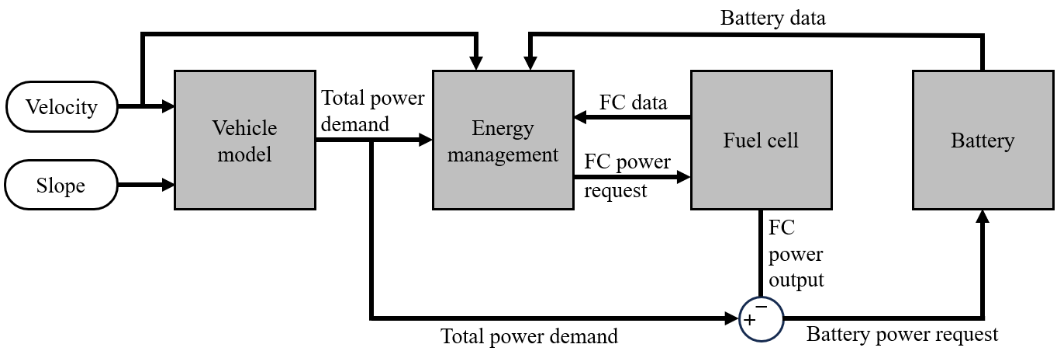

Figure 2: Backward-facing model overview [8].

Table 1: Backward-facing model parameters.

Parameter	**Value**
Gross vehicle weight	40 000 kg
Fuel cell maximum power output	240 kW
Hydrogen tank capacity	58 kg
Battery capacity	497 kWh
Battery nominal voltage	670 V

2.3 Forward-facing model

A forward-facing model is used to further evaluate the best EMS found from the backward-facing simulations. The forward-facing model is more realistic because it does not assume the vehicle is able to perfectly follow the drive cycle. This model is similar to the backward-facing model shown in Figure 2, except that a feedback loop is used to calculate the actual vehicle velocity and input it into the vehicle model along with the drive cycle velocity. The model used is part of VTT's Python-based Smart eFleet simulation toolbox [5]. It is based on the same vehicle as the backward-facing model, but some parameters are changed because of adjustments to the ESCALATE pilot vehicle design. Notably, the maximum fuel cell power output is now smaller and the battery capacity is larger (see Table 2).

Table 2: Forward-facing model parameters.

Parameter	**Value**
Gross vehicle weight	40 000 kg
Fuel cell maximum power output	120 kW
Hydrogen tank capacity	58 kg
Battery capacity	644 kWh
Battery nominal voltage	663 V

2.4 Evaluation metrics

Several EMSs are designed and tested, and their performance is evaluated using three metrics: energy consumption, fuel cell degradation, and battery degradation. The primary goal of the energy management is to minimize the total energy consumed to complete each drive cycle. Total energy consumption is calculated as the sum of the consumed battery energy and the energy of the consumed hydrogen fuel.

In both models, the tank-to-wheel efficiencies of the two prime mover options are quite different. The fuel cell efficiency is approximately 40%-60%, which is much lower than the battery efficiency of approximately 98%. For this reason, the total energy consumption will be lower when more of the required energy comes from the battery and less comes from the fuel cell. To fairly compare EMSs, the initial and final battery SOC should be similar for all simulations on a given cycle. Otherwise, a strategy may appear better if it uses more battery energy, even if its energy management is poor. To address this, an initial SOC and final SOC target are defined for each cycle. For the cycles A, B, and C, the vehicle simulations start with the battery SOC at 80% and aim to discharge it to 20%. The final two cycles are longer, so the SOC starts at 100% and discharges to 15%. However, though the final SOC target is constant between strategies, that target will not be exactly reached. An adjusted energy consumption is calculated for each simulation, using the average fuel cell efficiency and battery efficiency to estimate what the total energy consumption would be if the final SOC target was reached exactly. This adjusted value is used for all energy consumption results, as it allows for fairer comparison between EMSs.

After energy consumption, the next goals are to minimize the fuel cell and battery degradation. The primary factor contributing to fuel cell wear is the ramping up and down of the power generation, known as dynamic loading or load cycling [11]. For this paper, fuel cell degradation is quantified by calculating the average absolute value of the rate of change of fuel cell power, referred to as fuel cell ramp rate. Lower average fuel cell ramp rate corresponds to longer fuel cell lifetime. Battery degradation is largely correlated with the battery charging and discharging rate, with lower rate corresponding to less degradation and longer battery lifetime. The average magnitude of the battery C-rate is calculated to quantify this effect on battery lifetime. Lower C-rate correlates with longer battery lifetime. Additional battery and fuel cell stress factors are out of the scope of this paper.

2.5 Energy management strategies

The basic purpose of the energy management is to decide the power split between the fuel cell and battery, as shown in (1)

$$P_{demand} = P_{FC\_out} + P_{bat\_out}, \tag{1}$$

where P_{demand} is the total power demand from the vehicle model and P_{FC_out} and P_{bat_out} are the power outputs from the fuel cell and battery, respectively. Since this vehicle is a plug-in hybrid with significant battery capacity, the energy management is charge-depleting, meaning the battery SOC drops over the cycle. Six EMSs are considered, including two offline strategies and four online strategies (see Table 3). Offline strategies must be tuned in advance, with complete knowledge of the driving cycle. They cannot be used in real driving scenarios. Online strategies have some parameters that are selected in advance, but make real-time decisions to manage energy consumption as the route is driven. The online strategies described in this paper use an SOC error value, which is calculated as the difference between the current SOC and the target SOC, where the target SOC is calculated as if the battery SOC drops linearly from the initial to final value throughout the drive cycle, as shown in (2) and (3)

$$SOC_{error} = SOC_{current} - SOC_{target}, \tag{2}$$

$$SOC_{target} = SOC_{initial} - (SOC_{initial} - SOC_{final}) * \frac{x}{x_{total}}, \tag{3}$$

where x is the current distance traveled and x_{total} is the estimate of the total route distance, which all the online EMSs in this paper require as an input before the drive cycle is started.

Table 3: Energy management strategies.

Offline strategies	Constant Fuel Cell Power (CFCP)
	Pontryagin's Minimum Principle (PMP)
Online strategies	On/Off
	Equivalent Consumption Minimization Strategy (ECMS)
	PI control (PI)
	Nonlinear optimization (NLO)

The offline strategies act as baselines to compare the other strategies against. A basic option is the Constant Fuel Cell Power (CFCP) strategy. To tune this strategy, simulations are run iteratively with different constant fuel cell power values until a value is found that results in the battery dropping exactly to the desired final SOC at the end of the cycle. This EMS is a good baseline for comparison because it uses the fuel cell in a stable manner. Pontryagin's Minimum Principle (PMP) is a common offline optimization-based strategy used to minimize energy consumption in hybrid systems. It uses a cost function to decide the optimal power split at each step in time, as shown in (4)

$$H_{PMP} = E_{H2\_consumed} + \lambda * E_{bat\_consumed}, \tag{4}$$

where the cost H_{PMP} is calculated by summing the hydrogen energy $E_{H2\_consumed}$ and battery energy $E_{bat\_consumed}$ while using a coefficient lambda (λ) to define the cost ratio. At each moment in time, there are multiple ways to provide the vehicle with the power required (1). By minimizing the cost function at each step in time, PMP not only finds the minimum cost at that moment but also minimizes the cost over the whole driving cycle. Therefore, this strategy provides the global optimal solution in terms of energy consumption. The value of lambda is tuned in advance for each drive cycle so that the battery reaches the final SOC target exactly as the vehicle completes the drive cycle.

The remaining four methods are online strategies, meaning they operate in real-time without advanced knowledge of the route, except for an estimate of the total route distance. Two of the online strategies are rule-based. In the On/Off strategy, the fuel cell turns on whenever the SOC error drops too low, and then turns off when the battery has been sufficiently charged and the SOC error is high. In the PI control strategy, the fuel cell power output is adjusted based on the SOC error. The final two strategies are optimization-based. The Equivalent Consumption Minimization Strategy (ECMS) is a common online EMS based on PMP. ECMS finds the combination of fuel cell and battery use that has the lowest cost, using the same equation as PMP (4). A PI controller is used in real-time to adjust the cost ratio (λ) based on the SOC error, as shown in (5)

$$\lambda = \lambda_{initial} - k_p * SOC_{error} - k_i * \sum SOC_{error} \Delta t, \quad (5)$$

where $\lambda_{initial}$ is a pre-determined initial lambda value and k_p and k_i are the proportional and integral gains, respectively. This cost function encourages use of the fuel cell and battery near their highest efficiency zones. The final strategy is nonlinear optimization (NLO), which takes inspiration from the nonlinear programming strategy presented by Ferrara et al. [7]. It uses a nonlinear cost function to simultaneously minimize energy consumption, maximize fuel cell lifetime, maximize battery lifetime, and keep the SOC near its target, as shown in (3)

$$H_{NLO} = w_1 \left(\eta_{FC} - \eta_{FC\_max}\right)^2 + w_2 \left(\frac{P_{FC} - P_{FC\_prev}}{t_{sample}}\right)^2 + w_3 \left(P_{bat}\right)^2 + w_4 \left(SOC - SOC_{target}\right)^2, \quad (6)$$

which contains four terms corresponding to the goals of the strategy, each with its own weight coefficient (w_1, w_2, w_3, and w_4) which can be tuned depending on control priorities. The fuel cell efficiency (η_{FC}), fuel cell power (P_{FC}), battery power (P_{bat}), and battery SOC (SOC) are inputs to the equation which are estimated in real-time using equations modeling the system. The maximum possible fuel cell efficiency (η_{FC_max}) and sample time (t_{sample}) are known constants and the previous fuel cell power (P_{FC_prev}) is known from the last time step.

3 Results

The backward-facing model is used to test all six EMSs on drive cycles A and B. Cycle A represents a one-way journey from Jyväskylä to Vuosaari in Finland, while B represents a round-trip journey from Jyväskylä to Vuosaari and back to Jyväskylä. For the backward-facing model, all three evaluation metrics are considered. Results from the online EMSs are show in Figure 3.

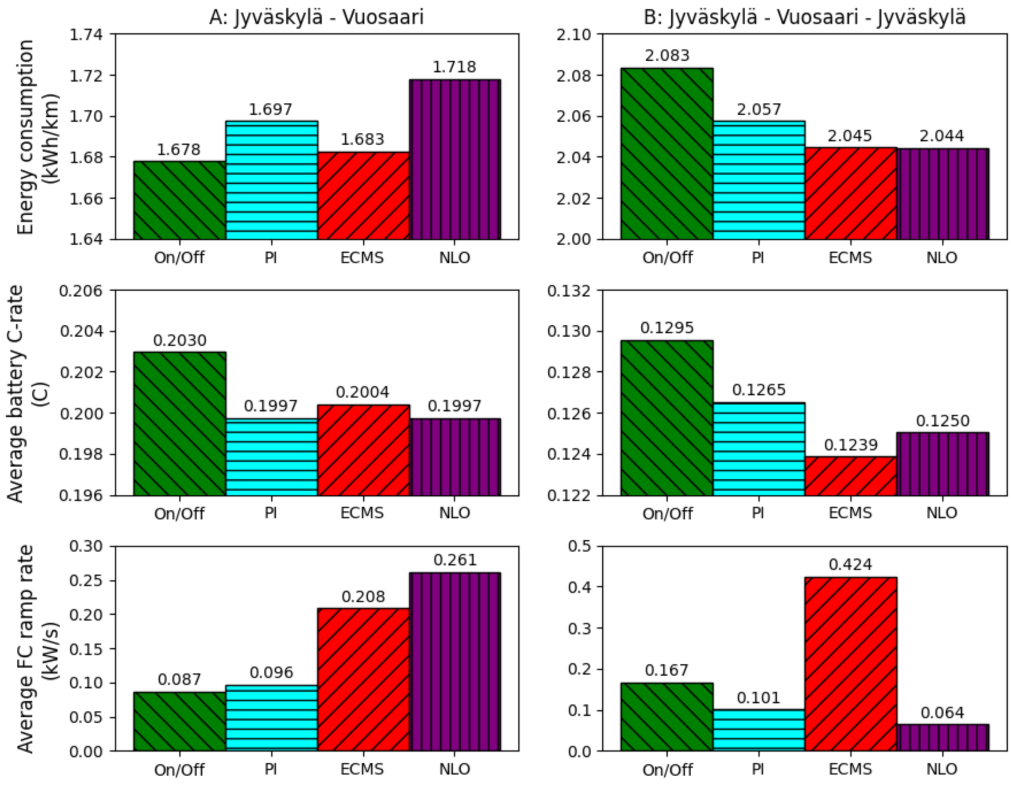

Figure 3: Backward-facing simulation results for online EMSs. On all plots, lower values are desirable. The scale on the first four plots is truncated to improve readability.

In terms of energy consumption, the On/Off strategy and ECMS perform best for cycle A, and for cycle B ECMS and NLO have the lowest consumption. For cycle A, the PI and NLO strategies have the lowest C-rate, with ECMS close behind. For cycle B, ECMS has the lowest C-rate result. Finally, regarding the fuel cell ramp rate, the On/Off strategy is best for cycle A and the NLO strategy is best for cycle B. A spider plot is used to visually compare all three metrics together (Figure 4). In this format, the best strategy should be represented with a small triangle at the center of each plot. For cycle A, NLO has the largest triangle and generally appears to be the worst. The other three cycles each have their own strengths and weaknesses. For cycle B, the On/Off strategy is the worst, while again the other three strategies each have their own tradeoffs, with NLO being the best with the smallest triangle. If we eliminate NLO and On/Off since they each performed poorly on one cycle, we are left with PI and ECMS as candidates for the best strategy. ECMS has lower energy consumption on both cycles. Though it does have high fuel cell ramp rates, it has low battery C-rates. Minimizing energy consumption is the primary evaluation goal, so ECMS is deemed the best all-around strategy based on these results.

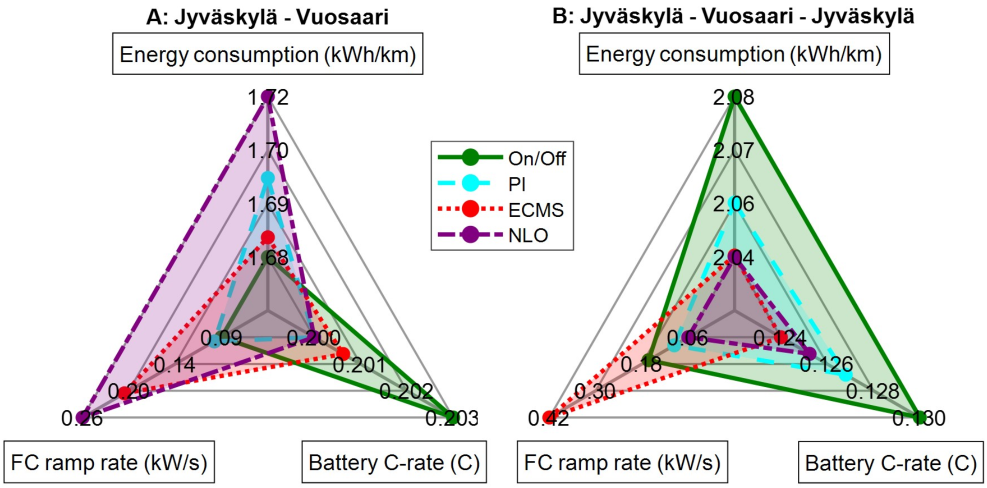

Figure 4: Spider plots with backward-facing simulation results for online EMSs. Lower values on each axis represent desirable results.

Further tests are done to evaluate ECMS using the forward-facing model with all five drive cycles, since the backward-facing model results point towards ECMS as the best strategy. Fuel cell and battery lifetime factors are not evaluated for the forward-facing simulations. As designed, the ECMS method requires an initial lambda value, a proportional gain, and an integral gain. However, testing with the forward-facing model showed that the integral gain was ineffective and so it is set to zero. An important quality of an effective EMS is its ability to perform in different scenarios, even without advanced tuning, so the impact of lambda and the proportional gain on ECMS is investigated. Simulations are run with all five drive cycles with ten initial lambda values and ten gain values, and the energy consumptions and final SOC errors are reported. Figure 5 shows these results for drive cycle A. The subplot on the left shows a strong correlation between the proportional gain and energy consumption, as lower gain values result in lower energy consumption. However, the subplot on the right shows that final SOC error can become large if the gain is too small.

These tests are also completed for the other drive cycles, as shown in Figure 6. All energy consumption heat map plots show a correlation between low gain and low energy consumption. There is also a correlation between higher lambda and higher energy consumption. By definition, higher lambda values mean the cost of using the battery is higher than the cost of using the fuel cell. Since the fuel cell is less efficient than the battery, it makes sense that penalizing battery usage increases energy consumption. All SOC error heat map plots show mostly low error, except for with the lowest gain values. To select parameters for ECMS, the lambda and gain combination that results in the average lowest energy consumption, while never having an SOC error magnitude of greater than 1%, is selected. The selected lambda value is 1.8 and the selected gain value is 0.3.

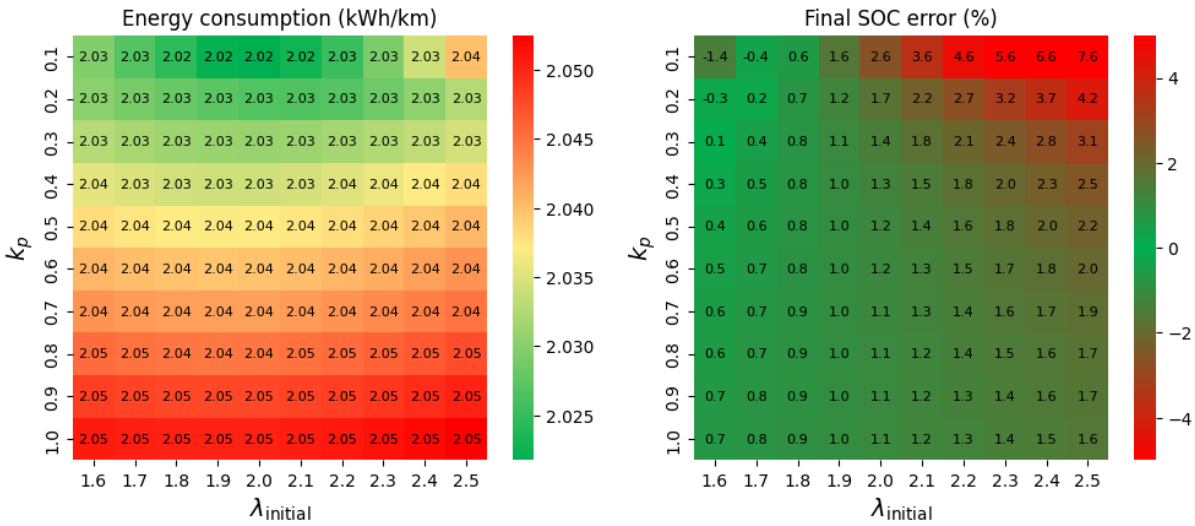

Figure 5: Heat map of energy consumption and final SOC error based on ECMS parameters, for cycle A.

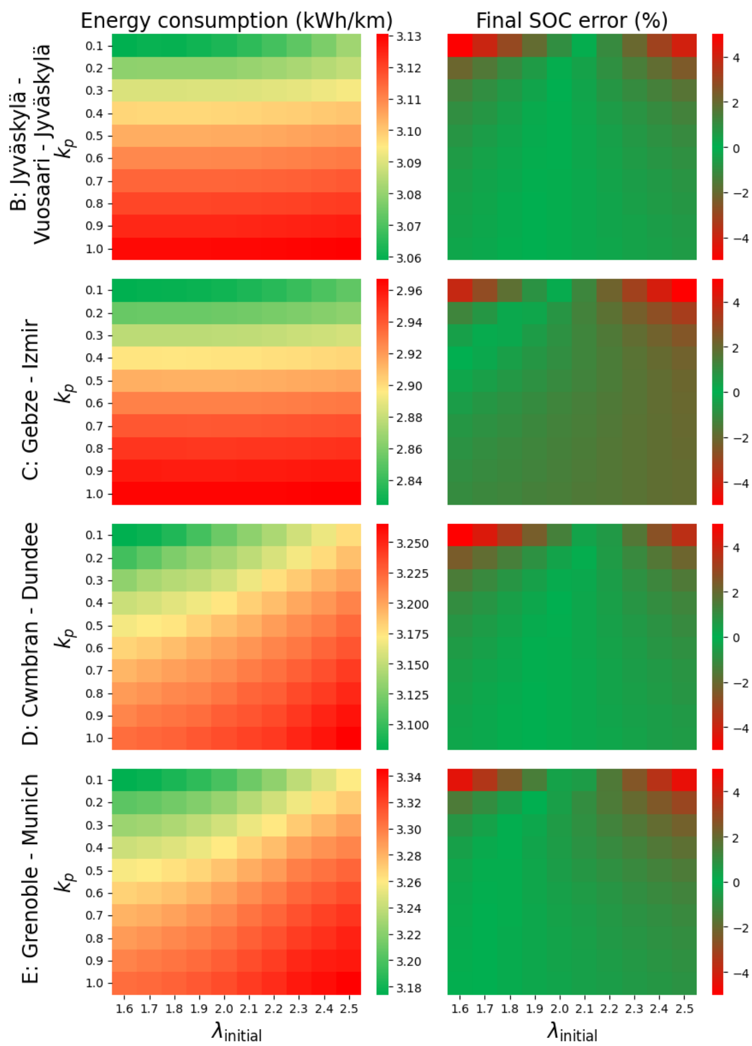

Figure 6: ECMS parameter heat maps for cycles B, C, D, and E.

In addition to ECMS, the PMP, CFCP, and On/Off strategies are evaluated so that ECMS can be compared with them. Recall that PMP and CFCP are offline strategies that cannot be used in real time since they must perfectly know the whole route in advance, which is only possible in a simulation. The On/Off strategy is one of the simplest possible EMSs, so it gives perspective to the ECMS results. Energy consumption is recorded for each simulation and the results are shown in Figure 7. On average, ECMS consumed a similar amount of energy as PMP, only 1.1% more energy. Compared to the simple On/Off rule-based strategy, EMS consumed on average 7.5% less energy. The CFCP strategy performed very similarly to PMP, consuming only 0.15% more energy on average.

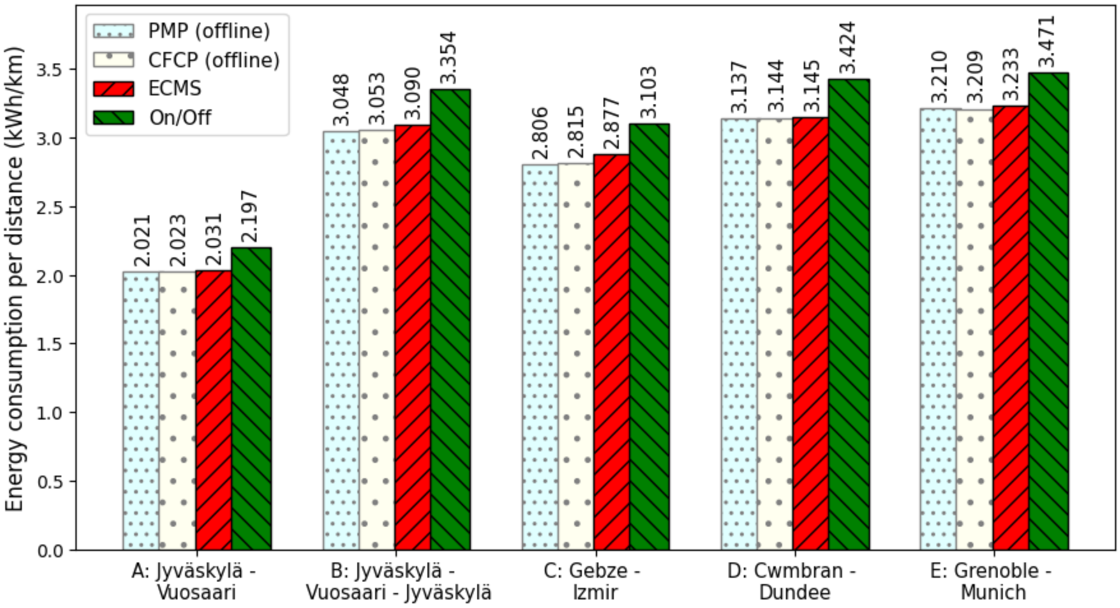

Figure 7: Forward-facing simulation energy consumption.

4 Discussion

The backward-facing model results indicate that all EMSs have strengths and weaknesses, with each cycle having the best value for at least one evaluation metric on one cycle. The On/Off strategy has low average fuel cell ramp rate for both cycles because it operates the fuel cell at a constant rate, except for when it is turning on and off. However, the C-rate is high because it forces the battery to take care of transient power demand. The energy consumption depends largely on the pre-defined point that the fuel cell operates at when it is turned on. While it is not the best overall, this strategy could be a good option if long fuel cell lifetime is a priority or if a simple rule-based strategy is desired, especially if the fuel cell set-point can be close to the fuel cell's maximum efficiency point. The PI strategy results show it is a good middle-of-the-road strategy. It is either second or third best for all three evaluation metrics on the two drive cycles, except for the C-rate on cycle A where it ties for the best result. It is a consistent rule-based strategy, though it performs poorly in terms of energy consumption, which is the primary evaluation metric.

Cycle B requires more power from the fuel cell because the same amount of battery energy is available for both cycles, but cycle B requires about twice as much total energy as cycle A. The optimization strategies perform well in these conditions, particularly in terms of energy consumption. ECMS has the lowest average energy consumption across the cycles and has good C-rate results, but uses the fuel cell aggressively. The NLO strategy performed well for cycle B regarding all evaluation metrics but poorly for cycle A in terms of energy consumption and fuel cell ramp rate, indicating that strategy selection should consider route characteristics. The results from all EMSs, especially NLO, depend on how the strategies are tuned, so perfect comparison is difficult. In particular, the weights used in the NLO equation can be adjusted to change the NLO results based on energy management priorities. Furthermore, the evaluation metrics do not consider the higher computational requirements of the optimization-based strategies.

Further testing with the forward-facing model showed that ECMS can be an effective strategy for a variety of driving routes, even when the same lambda and gain parameters are used. The ECMS method produced results very close to the global optimal solutions found by PMP. If minimizing final SOC error is not a priority, the ECMS gain parameter could be decreased to further reduce energy consumption. Also, the results are not very sensitive to the initial lambda value. For example, using a gain of 0.3 with an initial lambda value of 1.6 or 2.0 (instead of 1.8) results in only a 0.2% change in energy consumption, on average across the five cycles. While significant testing has been done with ECMS in Fuel Cell Hybrid Electric Vehicles (FC-HEVs) [7][12], the results in this paper show that it can be an effective strategy for an FC-PHEV.

Additional work could be done to test the PI and NLO strategies using the forward-facing model, including parameter tuning analysis. Also, the forward-facing model results (see Figure 7) show that the CFCP strategy performed very similarly to PMP, so a new online EMS that runs the fuel cell at a more-constant rate could be developed. This strategy could provide a contrasting alternative to ECMS, which requires high ramp rates from the fuel cell. The battery and fuel cell lifetime evaluation metrics could also be improved and included in the forward-facing model evaluation. The C-rate results varied only slightly between strategies with the largest difference between C rates being only 1.6%. A better model, such as the battery degradation model developed by Rehan, could be used to quantify degradation [13]. Thermal management could also be included, such as by incorporating work by Singh et al. [14].

In further work, additional SOC target estimation methods could be developed. The linear estimation used in this paper worked well for the five drive cycles that were tested but may be less effective when the driving route is less homogeneous, for example if the truck is driving over a large mountain pass and requires significantly more energy for a part of the route. In this case, a non-linear SOC target estimation method could be developed.

Furthermore, all strategies could be tested alongside a digital twin and in various operating conditions, for example, under cold weather where auxiliaries such as cabin or freight compartment heating require additional energy. Operational data from the ESCALATE pilot demonstrations could support this analysis. Digital twins could be used to run simulations and suggest EMS parameter updates in real time.

5 Conclusion

This study explored various EMSs for an FC-PHEV operating in a charge-depleting mode. Results using a backward-facing model were collected to understand which traits make a good EMS and which strategies are best for different scenarios. Among the strategies tested, ECMS emerged as the most effective, achieving the lowest average energy consumption. In subsequent studies with the forward-facing model, ECMS consumed on average only 1.1% more energy than the global optimal solution found by PMP and 7.5% less energy than a simple rule-based strategy. Previous research has shown that ECMS can be a good energy management strategy for fuel cell hybrid electric vehicles (FC-HEVs). The results in this paper show that it can also be an effective and adaptable strategy for a heavy-duty fuel cell *plug-in* hybrid electric vehicle (FC-PHEV) operating in a charge depleting mode.

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Presenter Biography

Erik earned his BSc in mechanical engineering from the University of Washington, USA and his MSc in mechanical engineering from Aalto University, Finland. He is currently working as a Research Scientist at VTT Technical Research Center of Finland. He has previously worked as a marine engineer on projects including designing the electrical system for a hybrid electric ferry and developing and troubleshooting ballast water treatment systems. He also has experience working in a renewable energy lab as well as a micro-robotics research lab. His current interests include powertrain design and optimization, hydrogen fuel cell vehicles, and hardware-in-the-loop testing.