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# ENERGY OPTIMIZATION STRATEGIES FOR ZERO EMISSION HEAVY DUTY VEHICLES

Pawel Majecki
*Industrial Systems and Control Ltd*
Glasgow, UK
pawel@isc-ltd.com

Luca Cavanini
*Industrial Systems and Control Ltd*
Glasgow, UK
l.cavanini@isc-ltd.com

Mike J. Grimble
*Industrial Systems and Control Ltd and University of Strathclyde,* Glasgow, UK
m.grimble@isc-ltd.com

***Abstract*—The decarbonization of the commercial transport sector is a crucial part on the pathway to a fully green economy and the use of zero-emission Heavy Duty Vehicles (HDVs) is a major aim. Hydrogen Fuel Cells will probably represent the main technology to provide an alternative future fuel source to replace fossil fuels. This will involve combining fuel cells with batteries in HDVs, exploiting the full potential of these technologies in an economically effective way. To guarantee expected performance from fuel cell-based powertrains, these should be controlled by an appropriate Energy Management System to optimize the performance of the vehicle. This paper illustrates the performance achieved by applying optimal predictive control to the zero-emission Heavy-Duty Vehicles' power management problem.**

***Keywords:*** Fuel Cell, Optimal Control, Heavy-Duty Vehicle.

## NOMENCLATURE

| | |
|---|---|
| EMS | Energy Management System |
| RB | Rule-based |
| ECMS | Equivalent Consumption Minimization Strategy |
| PMP | Pontryagin's Minimum Principle |
| MPC | Model Predictive Control |
| LTI | Linear Time-Invariant |
| LPV | Lnear Parameter-Varying |
| NL | Nonlinear |
| DP | Dinamyc Programming |
| FC | Fuel Cell |
| SOC | State-of-Charge |
| HDV | Heavy-duty Vehicle |
| ICE | Internal Combustion Engine |
| EM | Electric Motor |

## I. INTRODUCTION

Hydrogen has been considered a realistic alternative power source to replace fossil fuel in recent years for several applications including commercial ground transport. At the same time, hydrogen technology has been revolutionized by the development of an efficient and economic system to generate power from hydrogen. Hydrogen Fuel Cell (FC), technology can generate electric power from hydrogen by chemical reactions and without the combustion of the fuel, as in Internal Combustion Engines (ICEs) [1]. Despite their advantages, FCs have limitations, such as the inability to recover energy or the high degradation of the component occurring when the delivered power changes rapidly [2]. To overcome these limitations, FCs are normally used in combination with batteries, to develop zero-emission powertrains that exploit the advantages of both these technologies. Thanks to the features of such hybrid powertrains, and the typical drive profiles involved, FC-based powertrains are particularly suitable for commercial transportation when used for driving Heavy-Duty Vehicles (HDVs) [3]. The maximum system performance can only be achieved when an appropriate policy is applied to drive the different components to work together in the most effective and efficient way. In FC-based powertrains, this goal is performed by a control system termed Energy Management System (EMS) [4]. An EMS is an automatic control system able to maximize the efficiency of different power sources operating together while correctly enforcing constraints guaranteeing the correct behaviour of the overall system [5]. Several techniques have been considered for optimizing FC-based powertrain performance, in commercial transport involving HDVs. A simple approach utilizes rule-based (RB) policies, using a set of if-then statements, that is easy to develop but with limited performance. More sophisticated methods are based on optimization paradigms, to calculate the control signals according to the solution of a constrained optimization problem. The most widely used control method for driving FC-based HDVs is the Equivalent Consumption Minimization Strategy (ECMS) [6]. This optimizes the FC powertrain performance by following Pontryagin's Minimum Principle (PMP) [7]. Recently, advanced optimization methods have been used to develop the EMS for FC-powered vehicles using a Model Predictive Control (MPC) paradigm [8]. MPC is a control technique that makes explicit use of the mathematical model of the system to predict its likely future behavior and solve a constrained optimization problem. The constraints are used to enforce logical and physical bounds characterizing the controlled system. Several MPC techniques provide suitable methods for optimizing the performance of FC-based vehicles. The most common are the linear MPC (LTI-MPC), the Linear Parameter-Varying MPC (LPV-MPC), and the nonlinear MPC (NL-MPC). The LTI-MPC is the simplest policy, less effective for controlling complex nonlinear systems but also characterized by a low computational complexity. This method has limitations and is not suitable for EMS automotive applications [9]. On the other hand, NL-MPC can provide improved optimization performance thanks to the use of the nonlinear model of the system, but it is expensive computationally as a nonlinear non-convex optimization problem must be solved at each sample period [10]. The LPV-MPC approach is a method for limiting the computational complexity of MPC, whilst maintaining the good performance of NL-MPC [11]. This is possible by using the LPV modelling paradigm that approximates the nonlinear dynamics of a real-world system using a family of LTI models scheduled according to the value of a set of time-varying parameters [12]. In the following, the RB approach, ECMS, and LPV-MPC methods are compared in a simulation study. For the comparison, the results of the unrealistic "gold standard" Dynamic Programming (DP) policy has been applied to provide a benchmark in the ideal case when future knowledge is available.

The paper is structured as follows. Section II describes the HDV model, Section III presents the optimal control methods, Section IV reports test results, and Section V concludes the paper.

## II. Fuel Cell Heavy Duty Vehicle MODEL

In this section, the FC HDV simulation model and related components are presented, mostly following the modeling assumptions given in [13]. (the reader is referred to this reference for more details and model parameter values).

### A. Fuel Cell Heavy Duty Vehicle Architecture

The FC vehicle model consists of a battery, a fuel cell, an electric motor, a component representing auxiliary loads, and the drivetrain connecting the electric motor with the wheels. The high-level functional diagram of a complete hybrid vehicle featuring a single fuel cell system and a battery pack is shown in Figure 1, which also illustrates the power flow between the system components: FC provides the $P_{fcs}$ to the power system and the Auxiliary Load absorbs power from the system, whereas the power can be both delivered and absorbed by Battery and Electric Motor (EM). Furthermore, the power generated from the EM flows through the Drivetrain to the wheels in both directions.

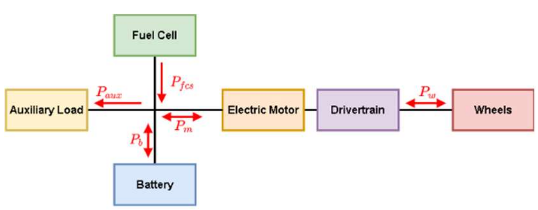


Fig. 1. Fuel Cell Heavy Duty Vehicle Architecture

The mathematical models of the components characterizing the FC HDV are presented in the following:

- Only the longitudinal dynamics of the vehicle is considered, as shown in Figure 2 because turning and lateral motions have a relatively minor effect on the energy management performance. The vehicle dynamics is described by the following equation giving the power at the wheels $P_w$

$$P_w = F_w v = (m_v \dot{v} + F_{res}) v \tag{1}$$

where $m_v$ is the vehicles mass, $\dot{v}$ is the vehicle acceleration, and the resistance force $F_{res}$ is defined as

$$F_{res} = F_{roll} + F_{slope} + F_{drag} \tag{2}$$

with the rolling friction force $F_{roll}$, the gravity force due to road slope $F_{slope}$, and the aerodynamic drag force $F_{drag}$ defined as

$$F_{roll} = m_v g c_r \cos \alpha \tag{3}$$

$$F_{slope} = m_v g \sin \alpha \tag{4}$$

$$F_{drag} = 0.5 A_v c_x \rho_{air} v^2 \tag{5}$$

where $m_v$ is the vehicle mass, $g$ is the acceleration of gravity, $c_r$ is the rolling friction coefficient, $\alpha$ is the road slope, $A_v$ is the vehicle front area, $c_x$ is the drag coefficient, $\rho_{air}$ is the air density, and $v$ is the vehicle longitudinal speed.

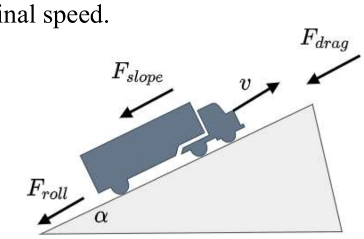


Fig. 2. Vehicle Longitudinal Dynamics Force Diagram

- The powertrain is modeled by a constant efficiency between wheel power $P_w$ and electric motor power $P_m$

$$P_m = P_w \eta_T^{-sgn(P_w)} \tag{6}$$

whereas the total electric power accounts for any additional auxiliary loads (e.g. air conditioning, cooling trailers), which for simplicity are assumed constant and additive

$$P_{el} = P_m + P_{aux}\ . \tag{7}$$

The required electric power $P_{el}$ serves as the reference, or demand, for the vehicle's EMS.

- The FC system is modeled as a quasi-static system ignoring underlying internal electrochemistry and hydrogen flow dynamics such that the FC efficiency is given by the characteristics shown in Figure 3, with the hydrogen consumption rate $\dot{m}_{H_2}$ and specific hydrogen consumption $\mu_{H_2}$ given by

$$\dot{m}_{H_2} = \mu_{H_2} P_{fcs} \tag{8}$$

$$\mu_{H_2} = \left(\eta_{fcs} \cdot LHV_{H_2}\right)^{-1} \tag{9}$$

where the hydrogen lower heating value $LHV_{H_2}$ is assumed constant. The FC is controlled by the power command signals $P_{fcs,cmd}$ driving the component to supply the required power $P_{fcs}$ bounded by the following magnitude and rate constraints (operating conditions defined according to component specifications):

$$P_{fcs,idle} \leq P_{fcs} \leq P_{fcs,nom} \tag{10}$$

$$-\dot{P}_{fcs,max} \leq \dot{P}_{fcs} \leq \dot{P}_{fcs,max} \tag{11}$$

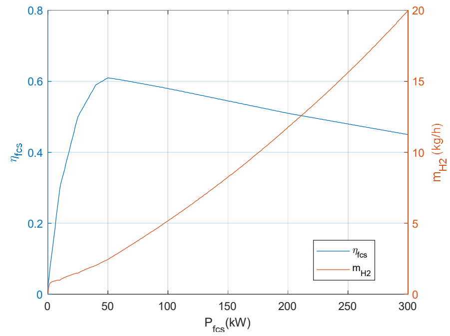


Fig. 3. FC hydrogen consumption/efficiency characteristics

- The battery is modelled by an equivalent circuit model, as shown in Figure 4, where the battery power $P_b$ is given by:

$$P_b = V_b I_b = (V_{oc} - R_{int} I_b) I_b \tag{12}$$

with $V_b$ the battery voltage, defined according to the battery open-circuit voltage $V_{oc}$, the battery internal resistance $R_{int}$, and the battery current $I_b$. Battery power $P_b$ is bounded to the maximum charge $P_{b,ch}$ and discharge $P_{b,dis}$ values:

$$P_{b,ch} \leq P_b \leq P_{b,dis} \tag{13}$$

From Eq.(12), the battery current is computed as [14]

$$I_b = \frac{V_{oc} - \sqrt{V_{oc}^2 - 4P_b R_{int}}}{2R_{int}} \tag{14}$$

and the power loss due to internal battery resistance is calculated as:

$$P_\Omega = R_{int} I_b^2 \tag{15}$$

The battery state of charge ($SoC$) dynamic model is defined as an integrator driven by the battery current, such that the $SoC$ derivative is given by

$$\dot{SoC} = \frac{-I_b}{Q_{nom}} = -\frac{V_{oc} - \sqrt{V_{oc}^2 - 4P_b R_{int}}}{2R_{int} Q_{nom}} \tag{16}$$

where $Q_{nom}$ is the battery nominal (maximum) charge.

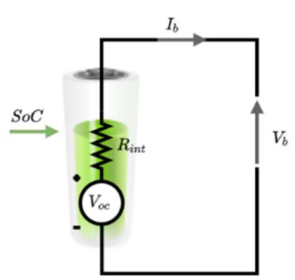


Fig. 4. Battery equivalent circuit model

## III. Energy Management System

The EMS policies considered in this paper are now introduced and the performance indices are used to compare the different control methods presented.

### A. Dynamic Programming

In order to provide a performance benchmark, Dynamic Programming (DP) was applied to the problem [15]. The DP algorithm is a recursive method of solving optimal control problems that can be used to find an optimal trajectory of a nonlinear dynamic system over a given time period. The key idea is optimization in stages backwards over time. The approach reveals that at any point on the optimal trajectory, the remaining trajectory is also optimal for the corresponding subproblem initiated from that point. That is, any segments of the optimal paths are optimal in themselves. This is the so-called Principle of Optimality.

The DP approach is a popular method for assessing the performance of EMS designs in hybrid electric vehicles and has also been used in this project to determine the theoretical minimum hydrogen consumption for a given driving scenario (the component degradation term was not included in the DP cost as the absolute minimum fuel consumption was sought in this case). The DP optimal controller is not causal and cannot be implemented in practice, due to the assumption that full future system knowledge is available. However, it still provides a useful benchmark to judge whether a more sophisticated solution or further tuning of the existing algorithm may be justified.

### B. Rule-based Scheme

A simple rule-based approach is considered as the baseline policy to be compared with the following methods for showing the improvement given by optimization-based techniques. In fact, the approach does not contain if-then statements, but is described by the following simple formula:

$$P_{fcs,cmd} = P_{fcs,\eta_{max}} + r_1\left(P_{ref} - P_{fcs,\eta_{max}}\right) + r_2\left(SOC_{ref} - SOC\right)V_{oc}Q_{nom} \tag{17}$$

subject to the constraint defined as $\left|\dot{P}_{fcs}\right| \leq \dot{P}_{fcs,max}$ to compute the power command signal driving the FC power generation, with $r_1$ and $r_2$ calibration parameters characterizing the policy.

### C. Equivalent Consumption Minimization Strategy

The Equivalent Consumption Minimization Strategy (ECMS) is a policy exploiting Pontryagin's Minimum Principle to determine the necessary conditions for optimality. In FC vehicles, the EMS problem can be simplified to include a single state variable representing the battery $SOC$, and one control $P_{fcs}$. The Hamiltonian [14] is defined as:

$$H\left(P_{fcs}, \lambda, P_{el}\right) = W_{H2}\left(P_{fcs}\right) + \lambda \dot{SOC}\left(P_{fcs}, P_{el}\right) \tag{18}$$

where $W_{H2}\left(P_{fcs}\right) = \frac{P_{fcs}}{\eta_{fcs}(P_{fcs}) LHV_{H_2}}$ with $\eta_{fcs}$ the FC efficiency for a given FC power $P_{fcs}$, $LHV_{H_2}$ the hydrogen lower heating value. By minimizing it w.r.t. $P_{fcs}$ gives the absolute minimum vehicle fuel consumption. The optimal control depends on the electrical power demand and the co-state:

$$P_{fcs}^*(\lambda, P_{el}) = \mathrm{argmin}_{P_{fcs}} H\left(P_{fcs}, \lambda, P_{el}\right). \tag{19}$$

The battery state of charge evolves according to

$$\dot{SOC}(P_{fcs}, P_{el}) = -\frac{V_{oc} - \sqrt{V_{oc}^2 - 4(P_{el} - P_{fcs}^*)R_{int}}}{2R_{int}Q_{nom}} \quad (20)$$

whereas the co-state is constant throughout the driving cycle because the Hamiltonian does not depend on the battery state of charge:

$$\dot{\lambda} = -\frac{\partial H}{\partial SOC} = 0. \quad (21)$$

In practice, the Hamiltonian is minimized numerically over a grid of e.g. 100W steps in $P_{fcs}$, resulting in simple and efficient calculations. The theoretical PMP solution requires that $\lambda$ be 'tuned' for any given driving cycle so that SOC remains within bounds, without the battery depleting or overcharging. One way of achieving this is to use the so-called Adaptive ECMS (A-ECMS), which introduces a feedback loop around the battery SOC and so attempts to maintain this variable close to its nominal reference value. A simple PI controller was used here and the PI gains considered as tuning parameters.

### D. Linear Parameter-Varying Model Predictive Control

As mentioned, the issue with the NL-MPC approach is that it leads to a general nonlinear optimization problem that can be hard and time-consuming to solve (making it unsuitable for real-time implementation), as well as relatively sensitive to solver settings and initial conditions. One approach used to address these problems is to use a Linear Parameter-Varying (LPV) model to represent the nonlinear system dynamics. The LPV-modelled systems are locally linear dynamical systems whose mathematical description depends on so-termed scheduling parameters that may change over time. The LPV model considered here follows [16] and is defined in the state-space form as:

$$x(k+1) = A(k)x(k) + B(k)\Delta u(k) + G(k)\Delta w(k) \quad (22)$$

$$y(k) = C(k)x(k) \quad (23)$$

with the following definition of signals and time-varying system matrices evaluated at the $k$-th time instant

$$x(k) = [SoC(k), \Delta SoC(k-1), P_b(k-1), P_{fcs}(k-1)]';$$

$$\Delta u(k) = [\Delta P_{fcs}(k)]; \ \Delta w(k) = [\Delta P_{ref}(k)];$$

$$A = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}; B = \begin{bmatrix} -f_\Delta(P_{b,0}) \\ -f_\Delta(P_{b,0}) \\ -1 \\ 1 \end{bmatrix}; \ G = \begin{bmatrix} f_\Delta(P_{b,0}) \\ f_\Delta(P_{b,0}) \\ 1 \\ 0 \end{bmatrix};$$

$$y(k) = [P_{fcs}(k-1), \ SOC(k)]'; C = \begin{bmatrix} 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \end{bmatrix} \quad (24)$$

The function $f_\Delta(P_{b,0})$ is obtained from the Jacobian linearization of the $SoC$ model with respect to the battery power $P_b$:

$$f_\Delta(P_b) = \frac{\partial \Delta SOC}{\partial P_b} = -\Delta t \cdot \frac{1}{Q_{nom}\sqrt{V_{oc}^2 - 4P_bR_{int}}} \quad (25)$$

where

$$SOC(k+1) = SOC(k) + \Delta SOC(k) \quad (26)$$

The operating point $P_{b,0}$ is taken as the previous battery power $P_b(k-1)$. The quadratic cost function is defined as:

$$J_{LPV-M} = \sum^{N_p}(Y_{ref} - Y)^T Q (Y_{ref} - Y) + \sum^{N_u} \Delta U^T R \Delta U \quad (27)$$

where $Y$ is the vector of predicted outputs and $Y_{ref}$ is the vector of future reference values over the prediction horizon $N_p$, $\Delta U$ is the vector of future controls over the control horizon $N_u$, and $Q, R$ are diagonal weighting matrices. The control increments can be defined to be zero beyond the control horizon $N_u \leq N_p$, which reduces the complexity of the optimization problem. The optimization is performed subject to the system constraints. As an additional design factor, gain scheduling is introduced for the penalty on the SOC deviation from reference represented by the weight $w_2$ computed as:

$$w_2 = w_{2,0} \times f(SOC(k)) \quad (28)$$

A typical shape of the function $f$ as in Eq. (37) is shown in Figure 5. That is, a larger penalty is used for large SOC deviations, and smaller penalty when SOC is close to reference. The motivation for such a policy is that the battery should be used as an energy buffer, and while it is good to reduce variations and depth of discharge (to limit degradation), tight regulation around the nominal is not essential or desirable.

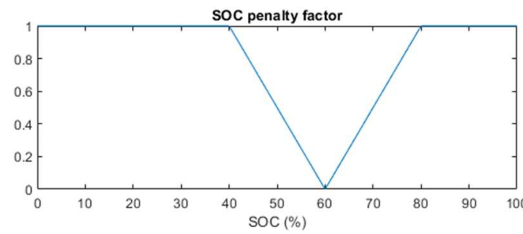


Fig. 5. Gain-scheduling of the SOC penalty factor

### E. Performance Criteria

The following performance indices were considered:

- Fuel Economy index. The total hydrogen consumption $m_{H_2}$ computed as

  $$m_{H_2} = \int \dot{m}_{H_2} \, dt \quad (29)$$

  and average hydrogen consumption is given by

  $$\bar{m}_{H_2} = \int \dot{m}_{H_2} \, dt \times \frac{100}{d} \quad (30)$$

  with $d$ the driven distance in km. To account for the difference between the initial and final battery SOC, a correction term can be added to the $m_{H_2}$ index [14], resulting in the SOC-independent index $J_H$ defined as

  $$J_H = m_{H_2} + \bar{\mu}_{H_2}(SOC_I - SOC_F)V_{oc}Q_{nom} \quad (31)$$

  where $\bar{\mu}_{H_2} = \mu_{H_2}(\bar{P}_{el} + \bar{P}_\Omega)$ is the equivalent specific consumption involving the average load and ohmic losses.
- Equivalent lifetime hydrogen consumption $m_L$ measuring the FC degradation [16] computed as

  $$m_L = \int w_L \dot{P}_{fcs}^2 dt \quad (32)$$

  with the coefficient $w_L$ that can be adjusted to achieve a meaningful trade-off between the actual and equivalent lifetime consumption.
- Multiobjective index $J_{HL}$ can be used that combines fuel consumption and FCS degradation:

  $$J_{HL} = J_H + m_L. \quad (33)$$
- Battery degradation index $D_b$ defined according to the Rainflow counting algorithm [17]. The Rainflow

counting algorithm is typically considered to extract cycles from the analysis of a signal trajectory which can be obtained from measurements or simulations. In this work, the battery $SOC$ trajectory has been evaluated a posteriory for evaluating the stress affecting the battery due to the counted cycles.

- Equivalent number of battery charge/discharge cycles $N_b$ calculated as

$$N_b = \frac{\int|\dot{Q}|dt}{2Q_{nom}}. \quad (34)$$

- The standard deviation of the FC power rate of change is $\sigma(\dot{P}_{fcs})$.

## IV. Simulation Results

The EMS algorithms are now compared by evaluating the performance criteria over an example test scenario.

### *A. Test Scenario*

A driving scenario is defined here by trajectories representing the vehicle speed, road grade, vehicle mass (varying to represent lorries loading/unloading) and auxiliary power demand. The driving test scenario considered here was defined by combining the New European Driving Cycle (NEDC) with time-varying road grade and constant vehicle mass and auxiliary power trajectories. The characteristics of this test scenario are shown in Fig. 6 and are collected in Table 1.

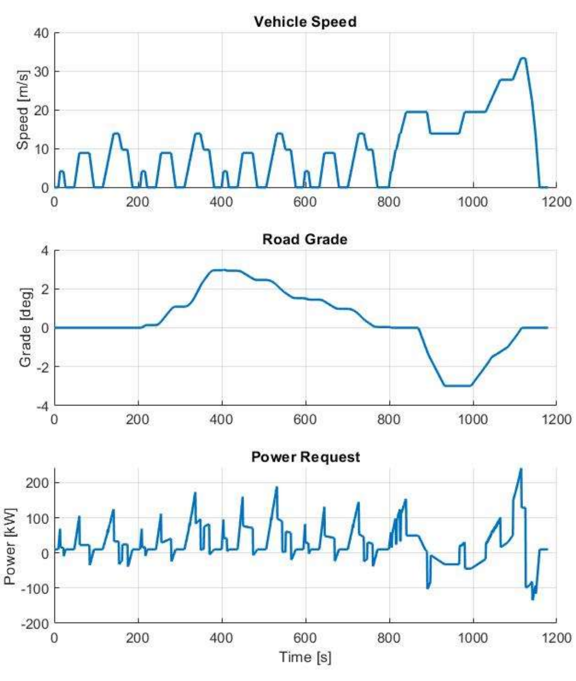


Fig. 6. Modified NEDC Driving Scenario

This test can simulate a short trip with several starts and stops, representing bus or garbage truck operations in hilly terrain. There is no constraint enforcing equal initial and final SOC values; however, thanks to the form of the cost function the SOC variations are relatively limited and the SOC is accounted for in the definition of the $J_H$ index.

Table. 1. Modified NEDC Driving Scenario Parameters

| ***Parameter*** | ***Value*** | ***Unit*** |
|---|---|---|
| Vehicle Mass | 10000 | *kg* |
| Duration | 1179 | *s* |
| Distance | 10.93 | $km$ |
| Average speed | 33.38 | $km/h$ |
| Maximum speed | 120 | $km/h$ |
| Averaged total power | 34.91 | *kW* |
| Max total positive power | 241.28 | *kW* |
| Max total negative power | $-134.84$ | *kW* |
| Averaged total power | 27.69 | *kW* |

### *B. Results*

The simulation results are shown in Figure 7 and the related performance indices are collected in Table 2. The MPC horizons were selected as $N_p = 20$ and $N_u = 6$, which was found to achieve a satisfactory trade-off between computational complexity and the control performance. The results indicate that the MPC design can provide improvement in fuel economy relative to the simpler baseline solutions. The potential improvements are relatively small, but they will build up to more significant amounts over many journeys. For the scenario considered, the MPC fuel savings are increased by 6.7% compared with the RB policy (in terms of the $J_H$ index). It was also interesting to find that the fuel savings were noticeably larger on short city journeys than on long journeys involving long stretches of motorway driving (latter scenario is not described in this paper). This is in part because the EMS is only effective when the balance between power sources needs to be changed, and MPC's predictive capabilities then come to therfore.

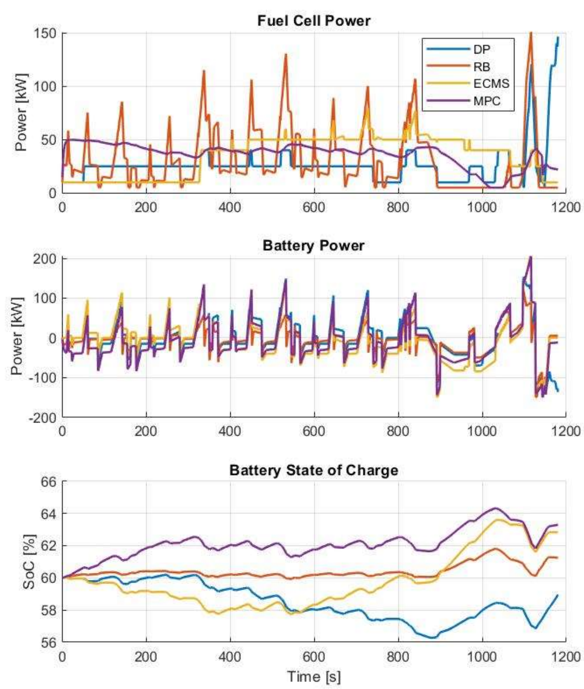


Fig. 7. Compared EMSs Results

Table. 2. Performance comparison

| ***Performance Index*** | ***DP*** | ***RB*** | ***A-ECMS*** | ***MPC*** |
|---|---|---|---|---|
| H2 consumed [kg] | 0.522 | 0.620 | 0.629 | 0.581 |
| Avg H2 cons. [kg/100km] | 4.777 | 5.669 | 5.756 | 5.311 |
| Equiv. Lifetime Cons [kg] | 0.029 | 0.120 | 0.015 | 0.004 |
| $\sigma(\dot{P}_{fcs})$ [kW/s] | 2.11 | 4.28 | 1.53 | 0.76 |
| Final SOC [%] | 58.95 | 61.24 | 62.83 | 61.27 |
| Nb index | 0.075 | 0.047 | 0.083 | 0.081 |
| Db index | 0.465 | 0.144 | 0.756 | 0.343 |
| $J_H$ index [kg] | 0.554 | 0.584 | 0.552 | 0.545 |
| $J_{HL}$ index [kg] | 0.583 | 0.704 | 0.568 | 0.548 |

Of course, the choice of "fixed" cost-function weightings will also influence the fuel savings achieved. The MPC also has the lowest FC degradation indices, at the expense of slightly higher battery degradation indices. In principle, for a given powertrain, it should be possible to translate performance metrics into more meaningful quantities (such as FC lifetime extension in hours, or distance for the battery capacity to drop to 80% of the nominal). The A-ECMS design gives better fuel economy and lower FC degradation index with respect to RB policy (but also higher battery stress) on the considered short journey test scenario. Several possibilities can be considered to improve the ECMS performance e.g., gain-scheduled tuning of the A-ECMS controller may be desirable, depending on the type of driving conditions Furthermore. this gives good robustness and the practical merits of the simplest RB approach. Finally, the Dynamic Programming (DP) benchmark indicates that it is theoretically possible to achieve 5-10% fuel savings over the MPC results. On the other hand, the DP falls short of the MPC in terms of component degradation, since those factors were not included in its cost-function.

## V. CONCLUSIONS

The problem of optimizing the performance of a zero-emission Heavy Duty Vehicle (HDV) using a Fuel Cell (FC) system as the main power source was considered. Several Energy Management System (EMS) design methods were considered and their performance was compared. The results enable the capabilities of the different methods to be assessed, highlighting their limitations and advantages. The MPC approach provides improved performance with respect to the baseline control policies and achieved results close to the idealised benchmark Dynamic Programming policy.

Future research directions will consider the development of a commercial EMS based on the proposed methods. It will involve the evaluation of the performance on an NXP GreenBox platform and development of a Rapid Prototyping environment.

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