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Abstract

Electric hybridization of vehicles propelled by gasoline engine proved to be a solution to reduce fuel consumption. Indeed, in Hybrid Electric Vehicle (HEV), the electrical machine and battery offer an additional freedom degree to ensure vehicle displacements, through the control structure, more particularly the energy management system (EMS). Another constraint is to respect more and more stringent standards of pollutant emissions. In this paper, several energy management strategies are proposed to optimize jointly the fuel consumption and pollutant emissions. An accurate simulation HEV model, with parallel architecture and spark-ignition engine, is built with its corresponding control structure and EMS in order to test the different strategies. Some heuristic strategies are proposed, then a mixed criterion is formulated, and Dynamic Programming, for off-line minimization, and on-line strategies, borrowed from optimal control, are described. The different strategies are compared from simulation results on the HEV model. Conclusions for setting the criterion and tuning the on-line strategy are given.

Keywords: Hybrid Electric Vehicle (HEV), energy management, pollution, fuel consumption, optimal control

Introduction

Reducing carbon dioxide emissions is currently a global challenge, and more particularly for the automotive industry. The CO_2 emissions of a vehicle are directly related to its fuel consumption, and the electrical hybridization of traditional vehicles is a main way to reduce this consumption. An Hybrid Electric Vehicle (HEV) includes a reversible electrical power source to supply the power demand of the driver.

Apart from the sizing of the units and the architecture optimization, the fuel consumption of an HEV can be reduced by the energy management system (EMS), which manages the power provided by the thermal engine and the electrical motor. Many energy management strategies have been developed, particularly for minimizing the fuel consumption [2]. The main optimal strategies are the Dynamic Programming (DP) and the minimization strategy based on the Pontryagin Minimum Principle (PMP) [7], derived from optimal control. An on-line version of PMP allowing charge sustaining is called Equivalent Consumption Minimization Strategy (ECMS) [6].

Nevertheless, reducing the fuel consumption of an HEV does not guarantee decreasing pollutant emissions. The optimal control which minimizes fuel consumption leads to some engine operating points with high pollutant emissions. Thus, a second objective for the EMS is to respect the pollutant emissions standards. Strategies minimizing a mixed (pollutant emissions - fuel consumption) criterion have been proposed. In [4] and in [3] an adaptation of the ECMS is build and different trade-offs are tested. In [1] an heuristic strategy based on DP is applied to a mixed criterion. [8] verifies that the PMP-based strategy and DP results are identical.

The paper formalizes the joint optimization of the fuel consumption and pollutant emissions and aims at finding the good setting in the mixed criterion to obtain the best compromise on a realistic HEV model.

In Section 1, an accurate HEV model and a control structure are built to test different energy management strategies. In Section 2, some heuristic strategies are proposed, then a mixed criterion is formulated, next DP, for off-line minimization, and on-line PMP-based strategies are described. The different strategies are compared in the next section from simulation results on the HEV model. Conclusions for tuning the on-line strategy are given.

1 HEV model

An accurate HEV model is developed with a multi-physic modeling software, for a parallel architecture (Fig. 1). It is made up of the five sub-models:

- vehicle (based on the Newton's second law),
- spark-ignition engine (including engine speed/torque look-up tables),

- electric machine (electric motor/generator with its converter),
- electrochemical battery (internal resistance model),
- 3-way catalytic converter.

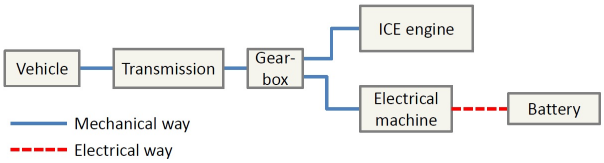

Figure 1: Parallel architecture of HEV

1.1 3-Way Catalytic Converter model

The 3-Way Catalytic Converter (3WCC) is the only current technology ensuring that the vehicles based on spark-ignition engine respect CO, HC and NO_X emission standards.

The accurate model of the 3WCC is based on physics equations particularly to compute the temperature. A particularly interesting variable to describe the functioning of a 3WCC is its pollutant conversion efficiency defined by:

$$\eta_x = (1 - \frac{q_{xin}}{q_{xout}}) * 100, \tag{1}$$

where q_{xin} and q_{xout} are the flow rates of the chemical species x, respectively at the entrance and exit. The predominant variables influencing this conversion efficiency are the temperature of the monolith T_{mono}, the Air-Fuel Ratio (AFR) of the mixture in the spark-ignition engine, and the flow rate of exhaust gas through the monolith Q_{exh}. The model includes a conversion function for each pollutant species, e.g. for NO_X:

$$\eta_{NO_X} = f(T_{mono})\ g(AFR)\ h(Q_{exh}),$$

with $f(T_{mono}) = \frac{1+tanh(0{,}2(T_{mono}-250))}{2}$.

In the case considered here, the temperature T_{mono} is the only variable really influencing the conversion efficiency, for the following reasons.

- The conversion is only possible above a certain temperature threshold of the monolith.
- The influence of AFR differs for the considered pollutant species, as shown in Fig. 2, but stays weak during simulations, where AFR is maintained close to the stoichiometric value of 14.7.
- The conversion is not possible for a too high flow rate, that is not the case for a well sized 3WCC.

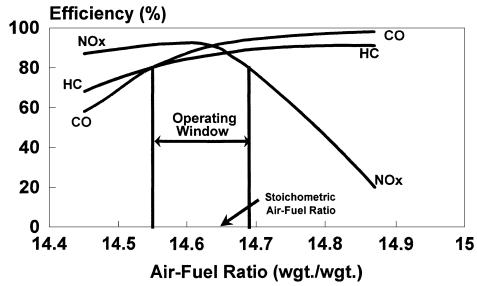

Figure 2: Influence of the AFR on the conversion efficiency of a 3WCC

1.2 Control structure

To test different energy management strategies on the physical model, a control structure has been developed in order that the vehicle follow the speed set-point of a driving cycle. The control structure is based on a simplified backward model adjusted by a proportional controller. From the speed of a driving cycle, this backward model calculates the acceleration and estimates the corresponding requested torque used to manage the power distribution.

First, the Newton's second law is applied to the vehicle:

$$m_v\gamma = F_{res} + F_r, \tag{2}$$

where F_{res} are the resistive forces (aerodynamic and rolling friction), F_r the requested force at the wheels provided by the engine and the motor through the gearbox , m_v the mass of the vehicle and γ its acceleration, directly deduced from the desired speed. Then:

$$F_r = m_v\gamma - F_{res}. \tag{3}$$

Therefore the requested torque at the wheels is given by:

$$T_r = F_r R_w, \tag{4}$$

where R_w is the wheel radius. Then the requested torque at the entrance of the gear box is:

$$T_0 = \frac{T_r}{k_{GB}}, \tag{5}$$

where k_{GB} is the gearbox transmission ratio.

To ensure a good tracking of the speed set-point, a proportional controller is applied, giving:

$$T_{req} = T_0 + k\ (v_d - v_v), \tag{6}$$

where v_d is the desired driving cycle speed and v_v the vehicle speed. The value of the parameter k is not sensitive and its tuning very quick and simple.

In HEV's, the requested torque T_{req} can be supplied by the engine (T_{eng}) or the electric motor (T_{mot}), with simply $T_{req} = T_{eng} + T_{mot}$. Thus, a "torque split" control variable u is introduced:

$$u = \frac{T_{mot}}{T_{req}}. \tag{7}$$

This torque split can be determined according to different cases. **If** $T_{req} \leq 0$, the maximum energy is

recuperated by regenerative braking. If regenerative braking is not sufficient due to electric machine constraints, braking with brake pads is assured. Then $T_{req} \leq 0$ implies $u = 1$. **If** $T_{req} > 0$, the different propulsion modes are:

- $u = 1$: full electric. The engine is turned off;
- $1 < u < 0$: hybrid. The propulsion is provided by the engine and electric motor and $0 < T_{eng}, T_{mot} < T_{req}$;
- $u = 0$: full engine;
- $u < 0$: regeneration. The engine produces a torque higher than requested and the surplus of torque is dedicated to the battery regeneration. Then $T_{eng} > T_{req}$ and $T_{mot} < 0$.

For a torque split given by the EMS, the proposed control structure provides the vehicle model with control values ensuring the tracking of the driving cycle speed set-point.

2 Optimal energy management

Energy management aims at determining the torque split u according to some objectives. Because of the control structure, energy management strategies are only active if $T_{req} > 0$. If not, simply $u = 0$.

In this section, two heuristic energy management strategies are presented as basic references, then the optimal control is obtained off-line by Dynamic Programming (DP) on a simplified HEV vehicle model, then on-line strategies are presented for the complete physical model.

2.1 Introduction

Heuristic strategies are simple rules-based on-line strategies. A first heuristic strategy ("h1") aims at sustaining the battery State Of Charge (SOC) around 50% to ensure a Zero Battery Balance (ZBB). Several rules are considered:

- if $SOC > 70\%$, then $u = 1$,
- if $70\% > SOC > 50\%$, then $u = 0.4$,
- if $50\% > SOC > 20\%$, then $u = -0.05$,
- if $20\% > SOC$, then $u = -0.2$.

As this fairly simple strategy does not consider the pollutant emissions, a second heuristic strategy ("h2") is built. A new rule considers the evolution of the 3WCC monolith temperature and aims at warming up the monolith if necessary, the most intelligibly:

- if $T_{mono} < 250°C$ then $u = -0.5$ else h1.

A torque split of -0.5 corresponds to high torque operating points, where the exhaust gas temperature is high allowing to warm up the 3WCC.

These two strategies are given as basic references to illustrate the contribution of the more elaborate strategies described in the following. In addition, the differences in the results of h1 and h2 (see Table 4) highlight in a simple way the interest of including pollutant emissions in EMS. However, the tuning of the parameters (SOC thresholds and torque split values) is very sensitive to the considered driving cycle.

2.2 Optimal control

The primary objective of the EMS is the reduction of the fuel consumption. This amounts to minimizing a performance index J_{fuel} over the time interval $[t_0, t_f]$ corresponding to a given driving cycle:

$$J_{fuel} = \int_{t_0}^{t_f} LHV \dot{m}_{fuel} dt, \tag{8}$$

where $\dot{m}_{fuel}$ is the fuel flow rate and LHV the Lower Heating Value. Taking into account the reduction of pollutant emissions leads to a mixed performance index [1] [4] [3]:

$$J_{mixed} = \int_{t_0}^{t_f} \dot{m}_{mixed} dt, \tag{9}$$

where, for the example of the NO_X emissions, $\dot{m}_{mixed} = \alpha \dot{m}_{fuel} + \beta \dot{m}_{NO_X}$. It is worth noting that NO_X is the only pollutant species in the criterion because HC and CO emissions vary in the same sense as the fuel consumption. Introducing

$$\gamma = \frac{\beta}{\alpha} \tag{10}$$

yields to the notation J_γ, with $J_{fuel} = J_0$ for $\alpha = 1$ and $\beta = 0$, and $J_{NO_X} = J_\infty$ for $\alpha = 0$ and $\beta = 1$. To produce comparable results, all minimizations must ensure a ZBB over the driving cycle, i.e.:

$$SOC_{t_0} = SOC_{t_f}. \tag{11}$$

2.2.1 Dynamic Programming

For the considered problem, Dynamic Programming (DP) [2] finds off-line the optimal solution minimizing the performance index during a driving cycle. Nevertheless, due to a heavy computational burden, DP is implementable only on a backward simplified model.

The accurate physical model is replaced by a quasi-static model, which is simply the control structure backward model without the proportional controller. To limit the computational cost of DP, the only one dynamics considered is the evolution of the SOC given by:

$$\dot{SOC}(t, u) = SOC(t, u) + 100 \frac{I(t, u)}{Q_{max}} \Delta t, \tag{12}$$

where Q_{max} is the maximum battery capacity and I the intensity of the battery current computed by:

$$I(t, u) = \frac{OCV}{2R_i} - \sqrt{\frac{OCV^2 - 4P_{bat}(u)R_i}{4R_i^2}}, \tag{13}$$

where OCV is the Open Circuit Voltage of the battery, R_i the internal resistance of the battery, both depending on $SOC(t)$, and $P_{bat}(u)$ is the power delivered by the battery to the electric machine.

DP requires to discretize the criterion. For example, for (8):

$$J_{fuel\ discrete} = \sum_{t=0}^{t_f} LHV\dot{m}_{mixed}\Delta t. \qquad (14)$$

DP uses a cost-to-go matrix $J(t, SOC)$. The state space is discretized in a finite number of states. If sufficiently fine, the discretization has no influence on the solution. Starting from

$$J(t_f, SOC) = \begin{cases} 0 & \text{if } SOC = SOC_{t_0} \\ \infty & \text{else,} \end{cases} \qquad (15)$$

DP computes backward the cost-to-go matrix from $t_f - \Delta t$ to t_0, with

$$J(t, SOC) = \min_u \{J(t + \Delta t, SOC + \Delta SOC(\Delta t)) + LHV\dot{m}_{mixed}\Delta t\}, \qquad (16)$$

with $\Delta SOC(\Delta t)$ computed from the discrete version of (12). Fig. 3 shows the cost-to-go matrix J for the road ARTEMIS driving cycle.

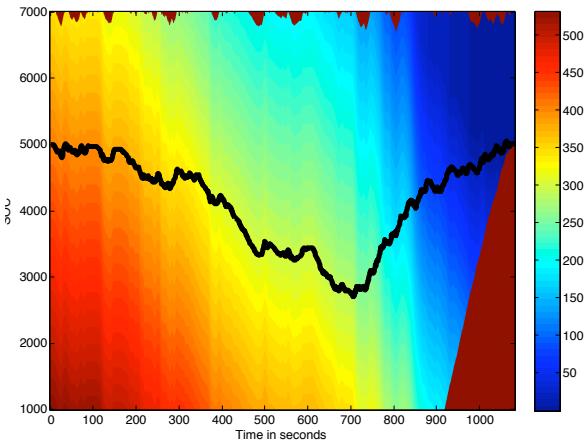

Figure 3: Cost-to-go matrix $J(t, SOC)$ and SOC trajectory

The value $J(0, SOC_{t_0})$ is the minimum of the performance index considered. For each discrete-time point and each discrete value of the state SOC, an optimal value of the torque split u can be computed and stored in a matrix U_{opt}, as presented in Fig. 4. To find the optimal SOC trajectory, the model has to be run forward from:

$$u(t) = U_{opt}(t, SOC)\ \forall t \in [t_0, t_f]. \qquad (17)$$

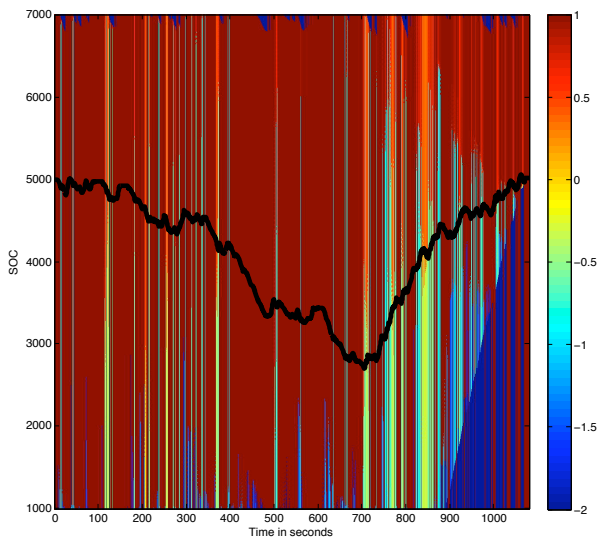

Figure 4: Optimal torque split matrix $U_{opt}(t, SOC)$ and SOC trajectory

2.2.2 Strategy based on optimal control

Generically, the goal is to find the control $u(t)$ which minimizes, on the interval $[t_0, t_f]$, the criterion

$$J = \int_{t_0}^{t_f} L(u(t), t)dt, \qquad (18)$$

where $L(u(t), t)$ is a cost function, subject to the constraint on the state x:

$$\dot{x}(t, u) = f(x(t, u), t, u). \qquad (19)$$

An Hamiltonian function is introduced:

$$H(t, u, \lambda(t)) = L(u, t) + \lambda(t)\dot{x}(t, u), \qquad (20)$$

where $\lambda(t)$ is the Lagrange multiplier. The optimal control solution $u_{opt}(t)$ obtained by the Pontryagin Minimum Principle (PMP) is then:

$$u_{opt}(t) = \min_u [H(t, u, \lambda(t))]. \qquad (21)$$

The optimization problem can be recast for the fuel consumption to the performance index J_{fuel} (8) to find the optimal torque split control variable u (7). The system state is the SOC evolving with (12) and constrained by the ZBB equation (11). The control minimizing J_{fuel} is given by (21), with:

$$H(t, u, \lambda(t)) = LHV\dot{m}_{fuel} + \lambda(t)S\dot{O}C(t). \qquad (22)$$

This Hamiltonian can be expressed as a sum of powers, where $s(t)$ arbitrates between electrical and fuel power sources:

$$H(t, u, \lambda(t)) = P_{fuel}(t, u) + s(t)P_{elec}(t, u), \qquad (23)$$

where

$$P_{fuel}(t, u) = LHV\dot{m}_{fuel},$$

$$P_{elec}(t, u) = S\dot{O}C(t)\ OCV\ Q_{max},$$

with OCV the Open Circuit Voltage, or:

$$P_{elec}(t,u) = \frac{I(t,u)}{Q_{max}}\ 100\ OCV\ Q_{max},$$

with Q_{max} the maximum battery capacity and the intensity of the battery current $I(t,u)$ given by (13),

$$s(t) = \lambda(t)\frac{LHV}{OCV\ Q_{max}}. \tag{24}$$

$s(t)$, called the equivalence factor, can be obtained by different ways. It can be maintained constant during a driving cycle. To find this value $s(t) = s_c$, a dichotomy method can be used, but only off-line. Many works can be found in the literature for on-line adapting $s(t)$. In the Equivalent Consumption Minimization Strategy (ECMS) [6], it is computed proportionaly to P_{elec}. It can be computed with a PID controller from the difference $SOC_{target} - SOC$, or even with the adaptive algorithm A-ECMS [5].

DP and PMP approaches have been presented for the minimization of fuel consumption from the J_{fuel} criterion (8). The extension to the joint minimization of fuel consumption and pollutant emissions is straightforward by considering J_{mixed} (9).

3 Results

In this section, two driving cycles are considered, the ARTEMIS urban and road cycles, shown on Fig. 5.

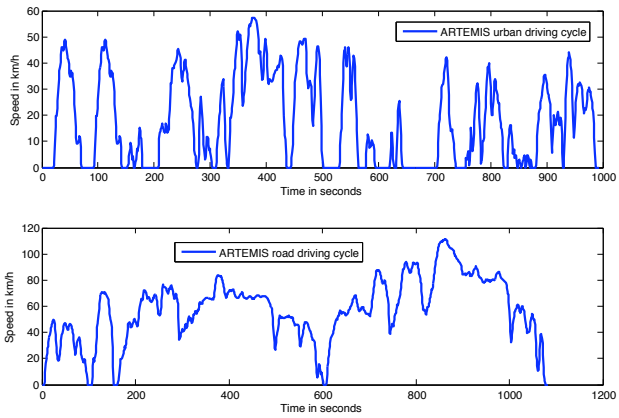

Figure 5: ARTEMIS driving cycles

3.1 Quasi-static model

Simulation results with the simple quasi-static model are presented in Tables 1 and 2 with the reference DP method and PMP strategies, for several mixed performance criteria (9), from J_{fuel} to J_{NO_X} through J_γ with several values of γ (10). For the PMP optimal control approach, simulations have been carried out with a constant equivalence factor (24) ensuring ZBB (11). It can be noticed that the results are very close for both DP and PMP strategies.

Table 1: Fuel consumption (l/100km) and NO_X engine emissions (mg/km) on road cycle

Perf. index	J_{fuel}	J_3	J_9	J_{19}	J_{49}	J_{NO_X}
DP						
Consumption	3.13	3.14	3.19	3.24	3.34	3.4
NO_X eng. em.	961	947	892	861	834	830
PMP						
Consumption	3.17	3.19	3.21	3.26	3.32	3.66
NO_X eng. em.	966	964	942	892	852	851.1

Table 2: Fuel consumption (l/100km) and NO_X engine emissions (mg/km) on urban cycle

Perf. index	J_{fuel}	J_3	J_9	J_{19}	J_{49}	J_{NO_X}
DP						
Consumption	2.23	2.23	2.28	2.35	2.48	2.56
NO_X eng. em.	646	635	559	493	414	408
PMP						
Consumption	2.21			2.31	2.38	3.3
NO_X eng. em.	644			555	454	315

3.2 Accurate physical model

ZBB simulations are run on the accurate physical HEV model. To compare the results, two strategies are added, full-engine propulsion, i.e. $u = 0\ \forall t \in [t_0, t_f]$, full-engine with Start And Stop ("SAT"), where the engine is turned off when the vehicle is stopped and regenerative braking is possible. The results are presented in Tables 3 and 4, with these two reference strategies, the two heuristic ones "h1" and "h2" (section 2.1), and on-line PMP strategies, for several mixed performance criteria (9), from J_{fuel} to J_{NO_X} through J_γ with several values of γ (10). The significant gains in fuel consumption and pollutant emissions can be noticed.

For the ARTEMIS urban cycle, Fig. 6 gives the NO_X emissions of the whole vehicle and engine with respect to the fuel consumption. The difference of the shapes can be noticed when the parameter γ (10) in the mixed performance index (9) varies. Thus, the best γ value has to be determined from the NO_X emissions of the whole vehicle.

Table 3: Consumption (l/100km) and and pollutant emissions (mg/km) on the ARTEMIS road cycle

Performance index or strategy	J_{fuel}	J_3	J_7	J_9	J_{19}	J_{NO_X}	h1	h2	SAT	full-engine
Consumption	3.63	3.63	3.66	3.7	3.81	4.18	4.56	4.58	5.29	6.18
NO_X **motor emissions**	1110	1100	1070	1060	1060	1100	1160	1160	1400	1560
CO **vehicle emissions**	118	121	206	236	247	265	200	205	213	266
HC **vehicle emissions**	24	25	27	29	31	39	45	50	51	71
NO_X **vehicle emissions**	117	114	106	106	107	112	119	130	133	144

Table 4: Consumption (l/100km) and pollutant emissions (mg/km) on the ARTEMIS urban cycle

Performance index or strategy	J_{fuel}	J_3	J_7	J_9	J_{19}	J_{NO_X}	h1	h2	SAT	full-engine
Consumption	4.99	5.01	5.14	5.21	5.39	5.96	6.7	6.81	8.22	11.8
NO_X **motor emissions**	1450	1450	1420	1410	1400	1400	1540	1560	2008	2360
CO **vehicle emissions**	377	405	610	762	1040	1174	880	680	845	1240
HC **vehicle emissions**	81	81	90	97	118	143	243	160	205	359
NO_X **vehicle emissions**	316	312	305	306	325	316	432	365	424	461

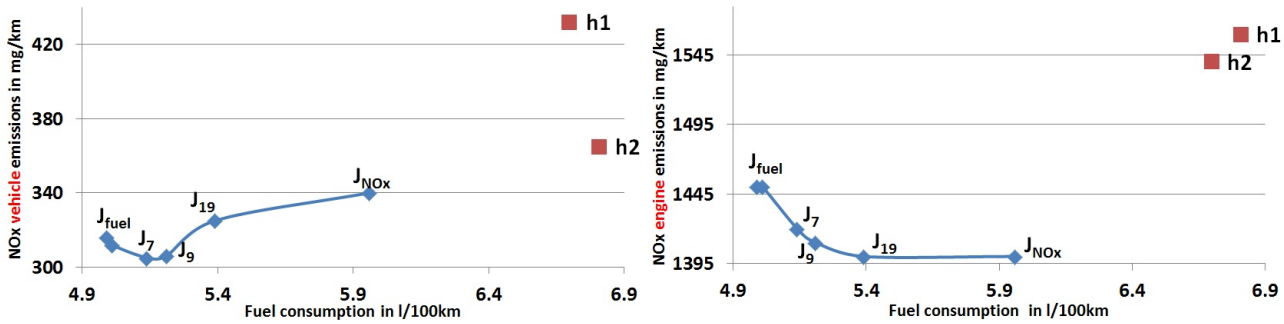

Figure 6: NO_X vehicle (left) and engine (right) emissions (mg/km) vs. fuel consumption (l/100km)

Conclusion

It has been shown that the results obtained with DP and PMP on a simplified static model are very close. Implemented with only the SOC as state, DP allows to get fast results and gives good insights on the setting of the mixed criterion.

To be conclusive, an energy management strategy must be applied on a realistic accurate vehicle model, that is only possible with PMP approaches. Compared to full engine operation, even with Stop and Start, or to heuristic strategies, the gains obtained for the reduction of both fuel consumption and pollutant emissions are very significant. But the results show also the need to include the post-treatment of exhaust gases in the optimization problem.

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