# Optimal cost-NO$_x$ trade-off in Diesel Engines by Integrated Emission Management

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## Introduction

To meet emission legislation limits, several new technologies have been introduced in heavy-duty trucks in the last two decades. This has caused the truck's engine and aftertreatment system to become increasingly complex as well as the application of supervisory control to exploit the synergy between the engine and aftertreatment system. As a result, fuel efficiency has barely improved over these years. Traditional supervisory control strategies often include heuristic rules, not leading to optimal solutions. We propose Integrated Emission Management (IEM), which is an improved supervisory control strategy that uses ideas from optimal control theory, to increase fuel efficiency.

## Objectives

In this paper, we present the global optimal solution to the IEM problem for a Euro VI truck. In IEM, the goal is to *minimize fuel and AdBlue costs* over a drive cycle while *satisfying emission constraints* imposed by legislation. In Cloudt and Willems [2011], a real-time implementable solution to the IEM problem has been proposed and this approach reduces fuel consumption up to 2 [%] during engine demonstration [Willems et al., 2013]. The objective of the current work is to find the most cost-efficient solution to the IEM problem and to compare this strategy with the aforementioned real-time implementable solution. To arrive at this most cost-efficient solution, Dynamic Programming (DP) algorithms are compared and extended.

## System Description

An overview of the control structure of the considered powertrain is given in Fig. 1. The AdBlue dosing strategy is tuned to autonomously maximize NO$_x$ conversion. The supervisory controller provides setpoints to the air management system that controls the Variable Turbo Geometry (VTG) and Exhaust Gas Recirculation (EGR) valve, later represented by $u_1$ [kg/s] and $u_2$ [kg/s], respectively. The supervisory controller also provides setpoints to the fuel control system, so that the engine receives the amount of fuel required to deliver the desired power. In this study, the applied engine model is a steady-state mean value engine model based on Wahlström and Eriksson [2011] and combines mass and energy balances with empirical relations. The relatively slower dynamics of the Engine Aftertreatment System (EAS) are described by a dynamical model. Both models are adapted from Cloudt and Willems [2011] and Willems et al. [2013].

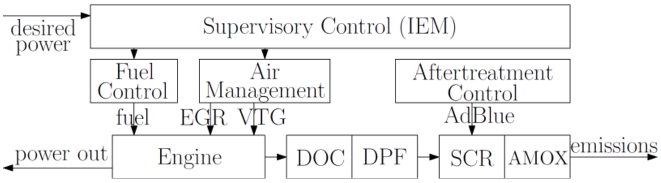

Fig. 1. Block diagram of the engine plus aftertreatment.

## Optimal Control Problem

The objective of IEM can mathematically be expressed as

$$J\big(x(t_s)\big) = \min_{u_1,u_2} \int_{t_s}^{t_f} \pi_f \dot{m}_f(u,t) + \pi_A \dot{m}_A(T_{EAS},u,t)\mathrm{d}t, \tag{1}$$

subject to the EAS dynamics and $m_{NO_{x,tp}}\big(t_f\big) \leq \bar{m}_{NO_{x,tp}}$, where $T_{EAS}$ [K] is the EAS temperature, $m_{NO_{x,tp}}$ [kg] is the cumulative amount of engine-out NO$_x$ emissions, $\pi_f$ [euro/kg] and $\pi_A$ [euro/kg] are the price of fuel and AdBlue, respectively, $\dot{m}_f$ [kg/s] and $\dot{m}_A$ [kg/s] are the mass flow of fuel and AdBlue used for the engine and the SCR system, respectively, and $\bar{m}_{NO_{x,tp}}$ [kg] is the final state constraint on NO$_x$ emissions and its value is imposed by emission legislation.

To find the *global* optimal solution to the dynamic optimization problem in (1), Dynamic Programming (DP) is used. As conventional DP (CDP) is sensitive to numerical errors that appear close to the boundary of the feasible sets, we propose Boundary-Surface DP (BSDP), which is an extension of Sundström et al. [2010] towards higher-order systems. The numerical errors are caused by determining the costs for points near the boundary by interpolating between the costs of feasible and non-feasible points, where the latter are assigned a large cost. In the novel BSDP method, we keep track of the boundary of the feasible sets, thereby reducing the numerical errors significantly.

Besides several DP algorithms, the optimal control problem is also solved using Pontryagin's Minimum Principle, which we will denote by Optimal PMP (OPMP). Furthermore, the real-time implementable heuristic strategy (HPMP) of Cloudt and Willems [2011], based on PMP, is used to find a solution. However, an optimal solution found with PMP is not guaranteed to be a global optimal solution. Therefore, we compare these results with the DP approaches.

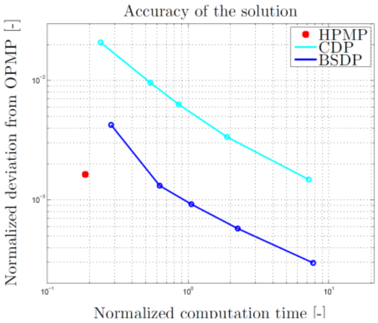

Fig. 2. Operational costs versus computation time.

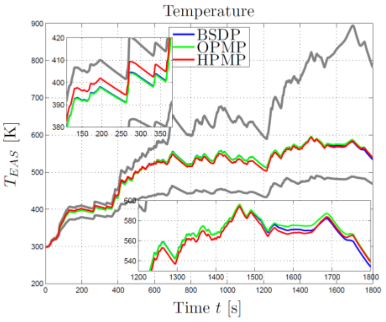

Fig. 3. Temperature EAS as a function of time.

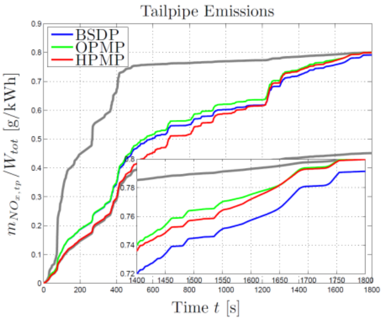

Fig. 4. $NO_x$ tailpipe emissions as a function of time.

## Simulation Study

Simulations are performed on a cold-start World Harmonized Transient Cycle (WHTC). We consider a cold start, because this cycle is more challenging from a thermal management and emissions perspective. In Fig. 2, normalized costs for BSDP, CDP and HPMP are shown using OPMP as a reference for both computation time, which equals 150 minutes, and resulting operational cost. From Fig. 2, we conclude that OPMP gives the most cost-efficient result for the cold-start WHTC. BSDP has a higher numerical accuracy than CDP (for the same computation time) and its minimal cost deviates 0.03 [%] from OPMP. HPMP is a good approximation of OPMP, with a deviation of 0.16 [%].

In Fig. 3-4, EAS temperature and tailpipe emissions are shown as a function of time. Note that the grey lines in Fig. 3 and Fig. 4 show the minimum and maximum feasible values found with BSDP. For BSDP, owing to some remaining numerical issues, the tailpipe emissions do not reach the final state emission constraint, see Fig. 3. HPMP is more expensive than OPMP, because it uses more fuel for EGR instead of cheaper AdBlue in the SCR system to convert $NO_x$, as can be derived from the low tailpipe emissions during the first 600 seconds in Fig. 4. It can be seen in Fig. 3 that all strategies increase the EAS temperature almost as fast as possible. When the EAS is cold, engine-out emissions are kept low with EGR. After 600 seconds, when the temperature of the EAS reaches approximately 525 [K], the SCR system's maximum efficiency increases towards 99 [%]. Consequently, engine-out $NO_x$ emissions can be increased by reducing EGR, which leads to reduced fuel consumption. This so-called EGR-SCR balancing results in applying optimal engine settings for given operating conditions, while satisfying emission constraints.

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