

Robust, Cost-Optimal and Compliant Engine and Aftertreatment Operation using Air-Path Control and Tailpipe Emission Feedback

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ABSTRACT

Heavy-duty diesel engines are used in a wide range of applications. For varying operating environments, the engine and aftertreatment system must comply with the real-world emission legislation limits. Simultaneously, minimal fuel consumption and good drivability are crucial for economic competitiveness and usability.

Meeting these requirements takes substantial development and calibration effort, and complying with regulations results in a trade-off between emissions and fuel consumption. TNO's Integrated Emission Management (IEM) strategy finds online, the cost-optimal point in this trade-off and is able to deal with variations in operating conditions, while complying with legislation limits. Based on the actual state of the engine and aftertreatment system, an optimal engine operating point is computed using a model-based optimal-control algorithm.

A novel feature introduced in this work is the addition of a feedback scheme to control the tailpipe NO_x emissions through modification of the Lagrange multiplier in the optimal control algorithm. The Lagrange multiplier represents the penalty on tailpipe NO_x emissions in the optimal control problem. This feature provides In-Service Conformity (ISC) in real-life operation and adds robustness, in terms of emissions, to system disturbances, such as production tolerances, system ageing and sensor or actuator errors.

The IEM strategy is a generic toolkit and can incorporate additional optimization variables, provided their effects are accurately represented by the online models of the engine and aftertreatment system. This can be used to include additional degrees of freedom such as fuel injection timing, pressure, pre- and post-injections and power-splits for hybrid drivelines. IEM is capable of real-time implementation and has previously been operated on an engine testbed, showing up to 2% reduction in fuel consumption that can be translated into a corresponding CO₂ emission reduction.

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INTRODUCTION

With the introduction of heavy-duty diesel Euro-VI emission regulations in 2013/2014, again a major step in the reduction of pollutant emissions was made. These European standards contain more real-world emission focus by stricter OBD requirements, off-cycle emission limits (OCE), In-Service Conformity testing (ISC), and extended emission durability life-time periods. Also, new Type Approval (TA) cycles (World Harmonized Transient and Steady-state Test Cycle, WHTC and WHSC respectively) with tighter limits [1] were introduced.

In addition to this, significant CO₂ reduction has been set as a main target by the European Commission and Environmental Protection Agency (EPA), like in [2] and [3] to further reduce CO₂ footprints from heavy-duty trucks. Heavy-duty truck manufacturers face a strong challenge to comply to these standards and simultaneously develop engines, which have low operational cost and good

performance. To meet these requirements, the vast majority apply both Exhaust Gas Recirculation (EGR) and exhaust gas aftertreatment system, which contains a Diesel Particulate Filter (DPF) and urea-based Selective Catalytic Reduction (SCR) system. Exceptions exist from Iveco and Scania, who offer SCR-only solutions [4], [5]. However, they all need to deal with engine and aftertreatment interaction under real-world circumstances, which is challenging and not straightforward, due to the growing number of sensors, actuators, sub-systems and extensive variety of operating conditions. This sets new targets for on-road performance robustness while maintaining low operational cost.

TNO has been developing an integrated control strategy for engine and aftertreatment, called Integrated Emission Management (IEM), for several years. This model-based control strategy continuously (in real-time) minimizes fuel and urea consumption within the emission constraints. Engine air-path settings are determined based on the actual state of engine and aftertreatment. Several IEM topics have

been addressed the past years, ranging from concept demonstration [6], experimental demonstration [7] and real-world cycle performance evaluation using ISC [8].

This work is a direct extension of previous work [8], focusing on the robustness under real-world circumstances. A sensitivity analysis is conducted in the form of a Monte Carlo simulation study, to introduce sensor and actuator uncertainties in the system and evaluate the system performance by calculating the ISC factor (Conformity Factor, CF). To guarantee real-world robustness in terms of tailpipe emissions, the IEM strategy is extended with a feedback loop from the tailpipe NO_x sensor that controls the emission output from the system. Such an extension is made without significantly compromising on the performance of the system in terms of fuel consumption.

In terms of a control problem, the disturbances acting on the system are at different time scales as shown in Figure 1. Production tolerances and sensor offsets act as constant disturbances (frequency is 0 Hz) on the system while ageing of the system occurs over longer durations. A typical drive cycle lasts from a few hours to a few days. Climatic effects also occur over a similar time scale. Different time scales of disturbances provide a challenge from a control perspective. That is, it is challenging to design a single control system that is capable of being robust towards disturbances over all time scales. In this paper, focus is made on studying the sensor and actuator effects (short time scales) over a drive cycle. System ageing effects and changes in climatic conditions have not been considered here.

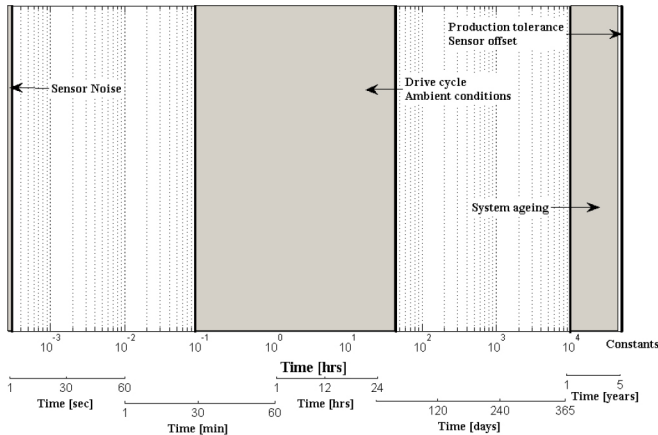


Figure 1. Control problem definition - time scales of disturbances shown on a logarithmic scale

This paper is organized as follows: first a brief description of the IEM strategy is given, together with its control approach. Second, the simulation set-up, containing descriptions of the applied engine and aftertreatment models, high-level and low-level controls and real-world cycles. Subsequently, the Monte Carlo method is described, including the applied sensor and actuator tolerances. The results of this Monte Carlo study are described afterwards. Then, the novel tailpipe NO_x feedback in the IEM control strategy is described. The performance of the extended IEM strategy, evaluated by again a Monte Carlo study is successively described. The final section contains the conclusions and outlook for future work.

IEM MODEL BASED OPTIMAL CONTROL STRATEGY

The main idea behind the development of the IEM control strategy is to integrate the control of the engine and aftertreatment components, thereby extracting performance benefits from the overall powertrain. The IEM strategy, thus acts as a supervisory controller, that, based on the current state of the aftertreatment system, adjusts the engine settings, such that the fuel and AdBlue costs are minimized and the emission levels are kept below the legislative limits.

The layout of the IEM strategy and its interaction with low-level controllers is shown in Figure 2. The IEM is a model based control strategy. Models of the engine and aftertreatment system are used to formulate a cost function that is optimised in real-time in the optimiser. For real-time implementation, the models should be able to run and process calculations quickly. For this purpose, a steady-state implementation of the dynamic engine model from [9] is used.

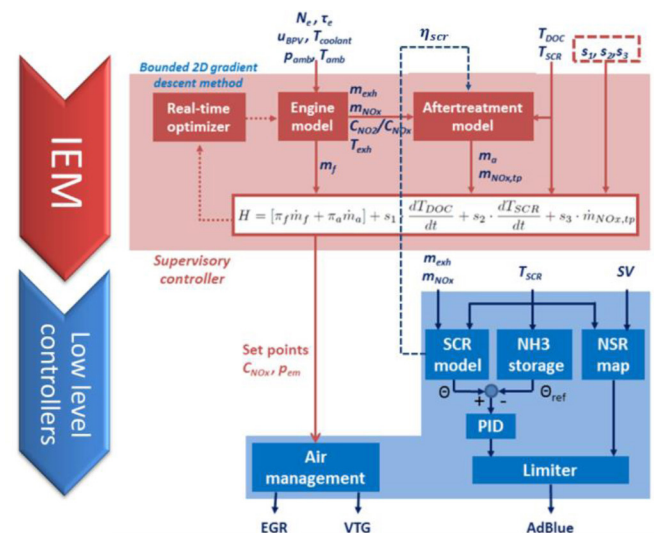


Figure 2. Control architecture of the supervisory (IEM) and low-level (air-path and urea dosing) controllers. Figure adapted from [10]

Model Improvements

The IEM control architecture is similar to the one presented in previous publications [7], [8] and [10]. An extension has been made to the aftertreatment model inside the IEM strategy. Previous versions of the IEM strategy included steady-state efficiency maps of the SCR system as can be seen in Figure 3. However, the use of efficiency maps resulted in differences between actual and modelled SCR efficiencies. This is illustrated in Figure 4. It can be observed that the cumulative tailpipe NO_x value of the IEM model and the actual value diverges throughout the cycle. Another factor to be considered is that the steady-state maps cannot adapt themselves to system ageing, which is also shown in Figure 4. Ageing of the SCR catalyst is simulated here by adapting the calibration parameters related to adsorption and desorption reaction kinetics and the ammonia storage capacity of the catalyst. In Figure 4, the actual value of tailpipe NO_x for an aged SCR system (30% aged) is much higher than that for a new SCR system. However, the IEM model predicted tailpipe NO_x value does not show a difference between the new and aged systems.

The error in prediction for a new SCR system is 26.4% and for an aged SCR system is 35.7%. This means that the IEM model assumes a different tailpipe NO_x emission compared to the actual value, resulting in model errors, which affect the performance of the optimal controller.

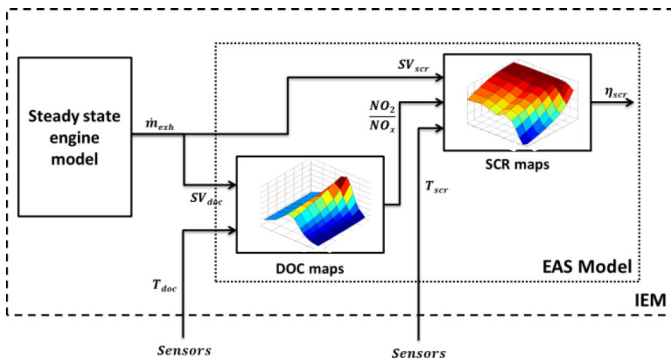


Figure 3. Aftertreatment model inside IEM using steady-state DOC and SCR maps

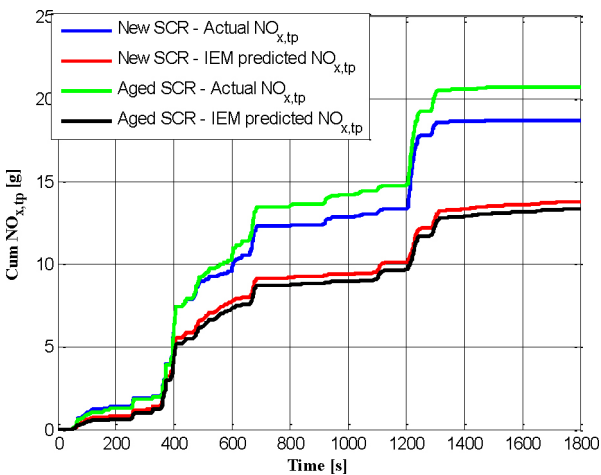


Figure 4. Comparison of $\text{NO}_{x,tp}$ prediction using SCR maps with actual $\text{NO}_{x,tp}$ for a new and 30% aged SCR on a (hot) WHTC cycle

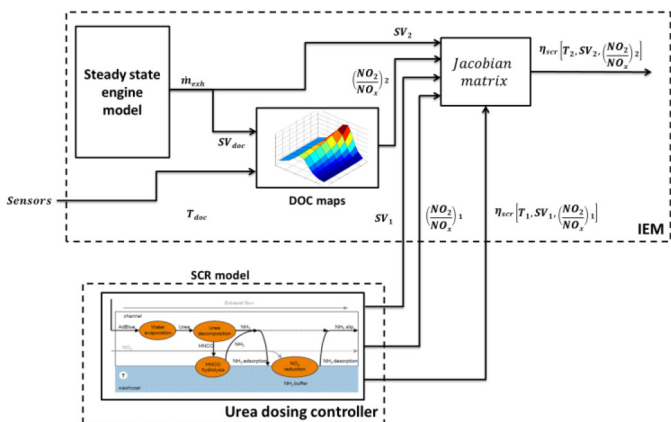


Figure 5. IEM aftertreatment model using feedback from low-level controller to predict SCR efficiencies

In order to improve accuracy of prediction of the efficiency of the SCR in the IEM strategy (and thus improve the tailpipe NO_x prediction accuracy), the efficiency maps of the SCR is replaced by feedback signals from the low-level urea dosing controller. The urea

dosing controller uses a dynamic SCR storage model to determine the amount of Adblue dosing required by the system. Efficiency of the SCR can be calculated by this model and this signal is used by the IEM controller. The updated SCR model inside the IEM strategy is presented in Figure 5.

The current efficiency of the SCR, $\eta_{scr,t}$, is calculated in the low-level controller. Inside the IEM controller, the current SCR efficiency is used to predict the SCR efficiency at the next time step, given the temperature, space velocity and pre-SCR NO_2 - NO_x ratio at the next step from the engine model inside the IEM controller. This is done through the use of the first order Taylor series expansion as shown in Equation (1). The derivatives of the SCR efficiency with respect to temperature, space velocity and NO_2 - NO_x ratio are based on offline maps.

The efficiency of the SCR as predicted by the IEM controller needs to be calculated several times at each time step corresponding to the chosen air path setting of the engine model (which subsequently affects the space velocity of exhaust gas and DOC efficiency). This requires that the SCR efficiency calculation needs to be done very quickly. This prevents the usage of high fidelity SCR models inside the IEM which would have been ideally desirable. The usage of Taylor series expansion is an approximation which is computationally less expensive while being accurate enough for this purpose.

$$\eta_{SCR,IEM\ predicted} = \eta_{SCR,DynamicModel} + \left[\frac{\partial \eta_{SCR}}{\partial T_{SCR}} \quad \frac{\partial \eta_{SCR}}{\partial SV_{exh}} \quad \frac{\partial \eta_{SCR}}{\partial \left(\frac{C_{NO_2}}{C_{NO_x}} \right)} \right] \cdot \begin{bmatrix} \Delta T_{SCR} \\ \Delta SV \\ \Delta \left(\frac{C_{NO_2}}{C_{NO_x}} \right) \end{bmatrix} \quad (1)$$

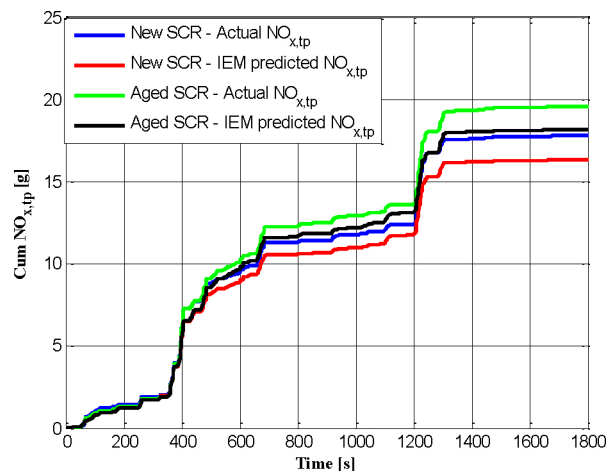


Figure 6. Comparison of $\text{NO}_{x,tp}$ prediction using updated IEM model with actual $\text{NO}_{x,tp}$ for a new and 30% aged SCR on a (hot) WHTC cycle

Using this model update, the plot shown in Figure 4 is recomputed and is presented in Figure 6. It can now be seen that the model predicted error in tail-pipe NO_x has been reduced to 8.2% for a new SCR system and to 7.1% for an aged SCR system. The error, however, has not yet converged to zero. A possible reason for this is the use of Taylor series approximation for calculation of the new efficiency, which is accurate only in a region close to the current SCR efficiency. A possible way to overcome this is to use physics based

models of the SCR inside the IEM controller, but this comes at the cost of additional computational effort.

IEM and Optimal Control

The IEM strategy is steeped in the concept of the optimal control theory and uses the Pontryagin's Minimum Principle in order to minimize a cost function - fuel and Adblue costs, under the constraints of emission limits set by legislation. Thus, the following objective function can be formulated:

$$\min_{NO_{x,eo}, p_{em}} \int_0^{t_e} (\pi_{fuel} \cdot W_{fuel} + \pi_{adblue} \cdot W_{adblue}) dt \quad (2)$$

Subject to:

$$\frac{\int_0^{t_e} W_{NO_{x,tp}} dt}{\int_0^{t_e} \frac{P_d}{3.6} \cdot 10^6 dt} \leq Z_{NO_{x,tp}} \quad (3)$$

Where,

- π_{fuel} is the fuel price [€/kg];
- π_{adblue} is the Adblue price [€/kg];
- P_d is the power required for the drive cycle [kW];
- $Z_{NO_{x,tp}}$ is the legislative emission limit for TA cycle [g/kWh]

Table 1 lists the fluid prices used in this study. The prices are taken from [11] and [12]:

Table 1. Fluid prices

Fluid	Price [€/kg]
Fuel (π_{fuel})	1.485
Adblue (π_{adblue})	0.24

The fuel quantity, W_{fuel} used, is determined by a low-level fuel path controller, while the desired Adblue quantity, W_{Adblue} is calculated assuming all of the injected urea is available for conversion of engine out NO_x emissions. Using this assumption, W_{Adblue} is determined as:

$$W_{adblue} = 2.0067 \cdot \eta_{scr} \cdot W_{NO_{x,eo}} \quad (4)$$

Where, 2.0067 represents the stoichiometry between urea and NO_x gas. The $W_{NO_{x,eo}}$ term in Equation (4) is determined from the engine model inside the IEM strategy as shown in Figure 2. Using Equations (2) and (3), a Hamiltonian is formulated wherein, the objective function is augmented with state dynamics and constraints using Lagrange parameters. The following Hamiltonian function is obtained:

$$H(x, u) = (\pi_{fuel} \cdot W_{fuel}(x, u) + \pi_{adblue} \cdot W_{adblue}(x, u)) + \lambda^T \cdot f(x, u) \quad (5)$$

With state dynamics $f(x, u)$ and Lagrange parameters: $\lambda^T = [\lambda_1; \lambda_2; \lambda_3]$.

The state dynamics are given by:

$$\dot{x} = f(x, u) = \begin{bmatrix} W_{exh} \cdot C_{p,exh} \cdot \frac{T_{exh} - T_{DOC}}{C_{DOC}} \\ W_{exh} \cdot \frac{C_{p,exh} \cdot (T_{DOC} - T_{SCR}) - h \cdot (T_{SCR} - T_{amb})}{C_{SCR}} \\ (1 - \eta_{SCR}) \cdot W_{NO_{x,eo}} \end{bmatrix} \quad (6)$$

With states : $x^T = [T_{DOC}; T_{SCR}; m_{no_{x,tp}}]$ and $u^T = [p_{em}; NO_{x,eo}]$

In order to minimize the above Hamiltonian, optimal trajectories of the Lagrange parameters have to be determined. This means that the drive cycle needs to be known a priori which is not possible in a real time implementable situation. In order to have a real-time implementable controller, approximations of the Lagrange parameters have been used through application of heuristic rules. The heuristic rules and the physical interpretation of the applied Lagrange parameters have been detailed in [7], [8] and [10].

SIMULATION SETUP

In the previous work [8], the performance of the Integrated Emission Management strategy in real-world conditions is studied and compared with a state-of-the-art Euro-VI strategy, containing several discrete engine calibrations to enable the desired NO_x conversion in the SCR as well as low fuel consumption when NO_x conversion is sufficient. As an extension of this, the robustness of the IEM strategy to sensor and actuator tolerances is studied. This paper covers the findings of this analysis, while also providing an extension to the IEM strategy to make the controller robust towards such tolerances.

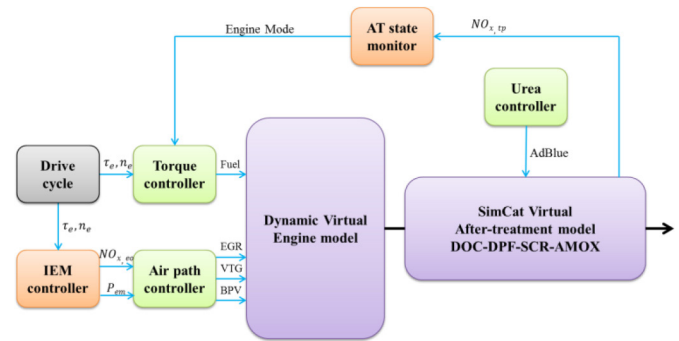


Figure 7. Simulation setup showing the various control and hardware models used in this study.

Figure 7 shows the simulation setup used for this study. The IEM controller block has been previously explained. The other controller and simulation models are explained in the next section. The virtual engine model and the virtual aftertreatment models used here represent an engine and aftertreatment system and are validated high fidelity models. The control models used in the IEM strategy consist of low fidelity physics based models and map based models.