# A heuristic Engine and EATS supervisory control scheme for heavy-duty vehicles \*

# Ubaldo Tiberi<sup>\*</sup> Esteban R. Gelso<sup>\*</sup>

\* Volvo Group Trucks Technology, Göteborg, Sweden. (e-mail: {ubaldo.tiberi,esteban.gelso}@volvo.com)

**Abstract:** In this paper we present a heuristic supervisory control scheme for jointly controlling the engine and the after-treatment system (EATS) in heavy-duty vehicles. The proposed controller aims at fulfilling emission legislation constraints without penalizing the fluid consumption and the delivered torque. Compared to existing methods, the proposed control scheme is computationally efficient since it does not require the online execution of iterative algorithms as it is typically done for this class of problems. Moreover, it does not require an accurate model identification of the system nor it requires highly skilled personnel for calibrating its parameters, which are two aspects very appealing in an industrial setting. The effectiveness of the proposed approach is evaluated through simulations where a comparison with existing methods is also performed.

*Keywords:* Emission coordinator, heavy-duty vehicles, diesel engines; exhaust after-treatment system; heavy-duty emission legislation.

#### 1. INTRODUCTION

Recently, many control strategies have been proposed to control the tailpipe emissions of diesel engine systems while the consumption of diesel and urea is minimized. In general, the control laws are found by applying optimal control techniques such as dynamic programming (DP) Donkers et al. (2017), Pontryagin's minimum principle Cloudt and Willems (2011); Zentner et al. (2014); Willems et al. (2015); Mentink et al. (2015); Donkers et al. (2017); Karim et al. (2018), model predictive control (MPC) Chen and Wang (2015); Vagnoni et al. (2018). In Elbert et al. (2017), a simpler emission controller is proposed for a passenger car diesel engine system, in order to adapt the Lagrange multipliers of the engine optimization control problem. This adaptation is based on a feed-back scheme using the actual tailpipe emissions. In this way, it is changed the trade off between engine out NOx mass flow, engine out soot and fuel consumption to such that the emission regulation is complied with.

A common limitation of optimal control techniques like DP or MPC resides in their computational burden for implementing complex algorithms that could include iterative methods, or the high memory needed for storing high dimensional maps.

Compared to existing methods, the proposed approach has lower computational complexity since the controller reduces to a gain-scheduled feedback plus feed-forward scheme with saturated limits and it does not require lookahead information, i.e. information of engine utilization in the upcoming kilometers. Moreover, it does not require specific competence of the personnel for understanding, using or maintaining it and it can be easily adapted if there are changes in the underlying hardware, thus providing a substantial benefit in terms of product variant handling. It is worth noting that these aspects are compelling in an industrial settings. We consider the same system setup as in Karim et al. (2018).

## 2. SYSTEM DESCRIPTION

The system under examination includes an internal combustion engine (ICE), an exhaust after-treatment system (EATS) and an engine electronic control unit (EECU). The ICE takes air and hydrocarbons fuel as input and it produces mechanical power and exhaust gases as output whereas the EATS takes the exhaust gases coming from the ICE and a solution made of urea and deionized water (AdBlue) as input and it reduces the amount of particulate matter and NOx at the vehicle tailpipe.

A typical problem in ICE control is to deliver the requested mechanical power with less fuel as possible and to produce less pollutant gases as possible, Kiencke and Nielsen (2000). This is typically achieved through some control strategy for the various ICE sub-systems, including the fuel injection and the air path sub-systems Guzzella and Amstutz (1998). A typical problem in EATS control is to maximize its conversion efficiency defined as

$$r := \frac{\mu - \mu_{tp}}{\mu} \,, \tag{1}$$

where  $\mu$  is the NOx mass flow at the outlet of the ICE and  $\mu_{tp}$  is the tailpipe NOx mass flow, with the minimum amount of AdBlue, Schär et al. (2006). To obtain high conversion efficiency it is necessary that the EATS - in particular its internal component named SCR catalyst operate at sufficiently high temperature. The SCR catalyst temperature  $T_{SCR}$  is almost entirely determined by the exhaust temperature at the ICE outlet T. For a given

 $<sup>^{\</sup>star}$  This work was financed by the Vinnova FFI project MutiMEC, ref. number 2014-06249.

delivered torque M, it is possible to increase T by injecting more fuel after affecting the gas exhange and the combustion processes. However, a change in injected fuel also affects the exhaust NOx mass flow  $\mu$ . More precisely, in high power regions an increase of injected fuel leads to a decrease of  $\mu$  whereas in low power regions an increase of injected fuel also leads to an increase of  $\mu$ , see Figure 1.

In this paper we assume that both the ICE and the EATS are already controlled, i.e. we assume that the aforementioned control problems are satisfactorily tackled by a control strategy implemented in the EECU. We refer to such a system as locally controlled system. The available set-points are the NOx mass flow at the ICE outlet  $\mu^*$ , the exhaust gases temperature at the ICE outlet  $T^*$  and the EATS conversion efficiency  $r^*$ , see Figure 2. The available measurements (or estimates) are the tailpipe NOx massflow  $\mu_{tp}$ , the NOx massflow at the ICE outlet  $\mu$ , the exhaust gases temperature at the ICE outlet  $\mu$ , the exhaust gases temperature at the ICE outlet  $\mu$ , the exhaust gases temperature at the ICE outlet  $\mu$ , the speed  $\omega$ , and the ICE torque M. This setup is the same presented in Karim et al. (2018).

Experiments on the described system show that if the setpoint  $\mu^*$  is too large or too small, then there is torque derate, i.e. the ICE will not deliver the requested torque  $M^*$ . A torque derate due to a poor setting  $\mu^*$  is undesirable since it would suddenly slow down the vehicle motion thus penalizing the vehicle driveability. Therefore, to secure the ICE to deliver the requested torque, the set-point  $\mu^*$  must be chosen in a feasible set  $[\mu_{\min}, \mu_{\max}]$ . The limits  $\mu_{\min}$  and  $\mu_{\max}$  are time-varying as they depend on the ICE speed  $\omega$ and torque M.

Concerning the value of the exhaust temperature, we experienced that the identification of a reachable set of T is a very hard task. However, we observed that there are no major drawbacks in poorly selecting the value of the set-point  $T^*$ . At worst the temperature T will not reach the selected set-point. Hence, we can safely choose  $T^*$  in the set  $[0, \infty)$ . However, for too large values of  $T^*$  the ICE may burn unnecessary fuel whereas for too little values the SCR may cool down too much thus reducing the EATS conversion efficiency.

Finally, by the definition of the conversion efficiency r in (1) and given that  $\mu \ge \mu_{tp}$  in normal conditions of no NOx formation over the EATS, it holds  $r^* \in [0, 1]$ .

## 3. PROBLEM FORMULATION

Our goal is to close the loop from the available information of  $\mu$ ,  $\mu_{tp}$ , T, M,  $\omega$  to the set-points  $\mu^*$ ,  $T^*$  and  $r^*$  by designing a supervisory controller named <u>emission coordinator</u> to achieve a threefold objective:

i. The controlled system is compliant with the current emission legislation. The current European Euro VI emission legislation for heavy-duty vehicles requires that the produced tailpipe NOx mass is lower than a certain limit c in the 90-th percentile or higher of valid work-based windows of length  $W_0$ , EC (2018). The valid windows are those with an average power greater than a fraction  $\alpha \in (0, 1)$  of the maximum deliverable ICE power  $P_{\rm max}$ . More precisely, the current legislation requires that



Fig. 1. High and low ICE power regions. In the high power region an increase of the injected fuel results in a reduction of NOx massflow at the ICE outlet, whereas in the low power region an increase of the fuel results in an increase of NOx massflow. The exhaust temperature increases as the injected fuel does, independently of the ICE operating region.

$$m_{tp}^{W_0} := \int_{t_i}^{t_{i+1}} \mu_{tp}(\sigma) \, d\sigma \le c \tag{2}$$

in the 90-th percentile work-based windows of length  $W_0$  defined as

$$W_0 := \int_{t_i}^{t_{i+1}} P(\sigma) \, d\sigma \,, \tag{3}$$

and such that

$$\frac{1}{(t_{i+1}-t_i)} \int_{t_i}^{t_{i+1}} P(\sigma) \, d\sigma \ge \alpha P_{\max} \,, \qquad (4)$$

where P is the instantaneous power produced by the ICE,  $m_{tp}^{W_0}$  is the accumulated tailpipe NOx mass in the current work-based window of length  $W_0$  and c > 0 is the accumulated NOx mass limit imposed by the legislation. It is worth noting that if the ICE is running at sufficiently low-power, then after a sufficiently long time (3) will be satisfied but (4) may not. In such a case, the specific work-based window is discarded and (2) will not be evaluated.

The values of c and  $W_0$  depend on the ICE under examination. For the considered ICE and the EU VI Step D legislation, it holds c = 15.18 g,  $\alpha = 0.2$  and  $W_0 = 33$  kWh. This means that the accumulated tailpipe NOx  $m_{tp}^{W_0}$  in the 90-th percentile of all the energy windows of length 33 kWh and such that the average delivered power is above the 20% of the maximum ICE power shall not exceed 15.18 g, EC (2018).

- ii. The total fluid consumption defined as the sum of fuel and AdBlue consumption is not worst when compared to the fluid consumption when the locally controlled system is run with fixed values of  $\mu^*, T^*$  and  $r^*$ .
- iii. The vehicle driveability is not penalized. That is, the ICE shall be able to produce the torque requested by the driver  $M^*$  in short time in front of an acceleration.



Fig. 2. The control system architecture. The locally controlled system includes an ICE, an EATS and an EECU. The emission coordinator sets the values of the set-points  $\mu^*, T^*$  and  $r^*$  based on feed-back information to achieve a threefold goal: to be emission legislation compliant, to have good fuel economy and to secure a certain driveability.

Feedback controllers are typically designed by devising a plant model and then by designing a controller based on some specifications of the closed-loop system. However, the identification of a white box model in our case is not possible since there are no available first principles that completely capture the input-output behavior of the locally controlled system. In-fact, despite it would be possible to exploit some first principle to get models of the ICE and EATS systems, to get a complete white box model of the locally controller system we would also need information of the controller running on the EECU. Unfortunately, this is typically proprietary information which is not accessible since local controllers may be outsourced from external suppliers.

The utilization of a grey or black-box identification technique may not be scalable. In-fact, a change in any component of the locally controlled system may require the execution of a large set of experiments for re-identifying a new model which is a high cost operation. In the light of these issues, we attempt at designing a heuristic controller based solely on the information provided in Section 2.

Finally, we need a standing assumption that secure the existence of an emission coordinator. For instance, let  $P_{\min}$  and  $P_{\max}$  the minimum and maximum deliverable ICE power, respectively, and let us define

$$\Lambda := \{ M(t), \omega(t) : P_{\min} \le P(t) \le P_{\max} \}.$$
(5)

We assume that by setting  $\mu^* = \mu_{\min}$  the constraints (2)–(4) are satisfied for all  $(M(t), \omega(t)) \in \Lambda$ . Such an assumption means that if the legislation constraints (2)–(4) are not met in-spite the system is run in open-loop with  $\mu^* = \mu_{\min}$  for all the time, then there is no hope to meet legislation constraints without derating torque, no matter what emission coordinator is used.

## 4. PROPOSED METHOD

The proposed approach consists in setting  $r^* = 1$  for all the time and to consider two decoupled control loops, namely a NOx and a temperature control loop as depicted in Figures 3–4.

#### 4.1 NOx control loop

The first control loop is composed by a system that takes the NOx at the ICE outlet set-point  $\mu^*$  as input and it produces the accumulated tailpipe NOx in the current work-based window  $m_{tp}^{W_0}$  as output. The controller goal is to regulate the system out to satisfy the legislation constraints without burning too much fuel and without reducing the delivered torque, see Figure 3. We construct such a controller through successive refinements as we explain next.

To satisfy (2)-(4) is enough to enforce that

$$\mu_{tp}(t) \le \frac{c}{W_0} P(t), \quad \forall t \ge t_0.$$
(6)

In-fact, by taking the integral of both sides of (6) it holds

$$m_{tp}^{\infty} := \int_{t_0}^{t_f} \mu_{tp}(\sigma) d\sigma \le \frac{c}{W_0} \int_{t_0}^{t_f} P(\sigma) d\sigma := \frac{c}{W_0} W^{\infty} ,$$
(7)

where  $m_{tp}^{\infty}$  and  $W^{\infty}$  are the accumulated tailpipe NOx and the delivered ICE energy in the time interval  $[t_0, t_f]$ , respectively.

By observing that it holds  $\mu_{tp} = (1 - r)\mu$  and that  $\mu \in [\mu_{\min}, \mu_{\max}]$ , we set  $\mu^* = \hat{\mu}^*$  where

$$\hat{\mu}^* := \operatorname{sat}\left(\frac{1}{1-r}cK_fP\right), \quad 0 \le K_f \le 1, \qquad (8)$$

and where

$$\operatorname{sat}(z) := \begin{cases} \mu_{\max} & \text{if } z \ge \mu_{\max} ,\\ z & \text{if } \mu_{\min} \le z \le \mu_{\max} ,\\ \mu_{\min} & \text{if } z \le \mu_{\min} . \end{cases}$$
(9)

Controller (8) is a only feed-forward type of controller and therefore it has two main drawbacks. The first is that it lacks robustness since it will not react if the actual value of  $m_{tp}^{W_0}$  is above the legislation limits. The second is that it may be too conservative since it attempts to secure  $m_{tp}^{\infty}$  for all the time which is a more strict condition compared to what the legislation actually requires and that is  $m_{tp}^{W_0} \leq c$ . To cope with such shortcomings, we add a feedback term that consider the actual accumulated tailpipe NOx mass in the current work-based window  $m_{tp}^{W_0}$  as feedback information and it compares it with a desired value  $m_{tp}^{W_0*}$ .

Unfortunately, we cannot directly measure  $m_{tp}^{W_0}$  and therefore we need to estimate it. A convenient way is to construct an event-based estimator where its output is updated in correspondence of every unit of energy produced by the ICE instead of every time a fixed unit of time has elapsed, as it is typically done in computer-controlled systems. This allow us an easy implementation on digital platforms since the estimator has a fixed dimension. Let us divide the work-based window in N energy samples of length  $W_0/N$ . The proposed estimator has the form



Fig. 3. NOx control-loop.

$$\begin{bmatrix} x_1(t_{j+1}) \\ x_2(t_{j+1}) \\ \vdots \\ x_N(t_{j+1}) \end{bmatrix} = \begin{bmatrix} 0 & \dots & \dots & 0 \\ 1 & & & \\ & \ddots & & \\ & & 0 & 1 \end{bmatrix} x(t_j) + \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} u(t_j)$$
(10)
$$= Ax(t_j) + Bu(t_j)$$
(11)

$$\hat{m}_{tp}^{W_0}(t_j) = \frac{W_0}{N} \begin{bmatrix} 1 \ 1 \ \dots \ 1 \end{bmatrix} x(t_j) = Cx(t_j)$$

where  $\hat{m}_{tp}^{W_0}(t_j)$  is an estimate of  $m_{tp}^{W_0}(t_j)$  in the *j*-th workbased window,  $x_k(t_j)$  is the amount of tailpipe NOx mass accumulated during the *k*-th energy sample within the *j*th work-based window,  $u(t_j)$  indicates the accumulated tailpipe NOx mass in the first energy sample of the (j+1)th work-based window and it is defined as

$$u(t_j) := \int_{t_j}^{t_{j+1}} \mu_{tp}(\tau) \, d\tau, \, t_j, t_{j+1} : \int_{t_j}^{t_{j+1}} P(\tau) \, d\tau = \frac{W_0}{N}.$$
(12)

Through exploitation of the estimator (10) we refine then the only feed-forward controller (8) by adding a feedback term. For instance, we set  $\mu^* = \hat{\mu}^*$  where this time it holds

$$\hat{\mu}^{*}(t) = \operatorname{sat}\left(\frac{P(t)}{1 - r(t)} (cK_{f} + K_{P}(m_{tp}^{W_{0}*} - \hat{m}_{tp}^{W_{0}}(t_{j})))\right),$$
(13)

where  $K_P > 0$  is the feedback gain.

Although the controller (13) should be sound enough for coping with the problem stated in Section 3, it can be further improved. In-fact, if the EATS is operating with a conversion efficiency r near to 1 and if the ICE power P(t)is small, then the controller (13) would set high values  $\mu^*$ . This is undesirable because we would burn unnecessary fuel.

Hence, we perform a final refinement of the proposed by ultimately setting

$$\mu^* = \vartheta(\hat{\mu}^* - \mu_{\min}) + \mu_{\min} , \qquad (14)$$

where

$$\vartheta := \frac{1}{1 + e^{-K_{\vartheta}(P - \tilde{P})}}, \ K_{\vartheta} > 0, \qquad (15)$$

and where  $\tilde{P}$  denotes the boundary between the low and high power region of the ICE. We use the logistic function (15) for compensating the uncertain delimitation between the "high" and "low" ICE power regions since in reality their boundary is rather fuzzy. By this modification, the controller always set low values of  $\mu^*$  when the ICE is operating in low-power regions.

The controller (14) is a gain-scheduled feed-back plus feedforward scheme with saturated limits. The gain scheduling variables are the ICE power P(t) and the EATS conversion efficiency r(t). The feed-forward terms attempts to enforce (6) whereas the feed-back term adjusts the control action



Fig. 4. Temperature control-loop.



Fig. 5. Validation of the  $\hat{T}_{SCR}$  model.

depending on how well we are fulfilling the legislation constraints.

We wish to remark that the proposed controller is computationally high efficient in terms of CPU load and memory footprint since it only requires the implementation of the estimator (10) and the control strategy (14).

#### 4.2 Temperature control loop

In the second control loop we use the ICE out temperature  $T^*$  as a manipulated variable to track a desired value of the SCR temperature  $T^*_{SCR}$  for securing a good EATS conversion, see Figure 4. Tests on the system showed that  $T_{SCR}$  is a filtered and delayed version of T, see Figure 5. Hence, we approximate the dynamics of  $T_{SCR}$  with

$$\hat{T}_{SCR}(t) = -a(\hat{T}_{SCR}(t) - T(t-\tau))$$
 (16)

where  $a, \tau > 0$  are parameters that are set from experimental data. Given the dynamics (16) and given the control objective of tracking a desired value  $T^*_{SCR}$ , a natural solution would be to use a PI controller along with a Smith predictor for compensating the time-delays. However, to avoid wind-up of the integrator we need to know the upper and lower limits for the possible choices of  $T^*$ . This means to find the reachable set of T which is a very complex task. Nevertheless, differently from the NOx control loop, we observed that here there are no major side effects in setting  $T^*$  too high or too low.

For these reasons, the proposed controller only attempts to secure  $T_{SCR}$  to be sufficiently high for securing an acceptable EATS conversion efficiency, but not too high to avoid consuming too much fuel. Hence, we propose the following dynamic controller

$$\begin{cases} \tilde{T}_{SCR}(t) = -a(\tilde{T}_{SCR}(t) - T(t)), \\ T^*(t) = K_T(T^*_{SCR}(t) - \tilde{T}_{SCR}(t)) + T^*_{SCR}(t), K_T \ge 0 \end{cases}$$
(17)

It is worth noting that  $\tilde{T}_{SCR}(t) = \hat{T}_{SCR}(t+\tau)$ , i.e.  $\tilde{T}_{SCR}(t)$ is an estimate of the SCR temperature  $T_{SCR}$  at time  $t + \tau$  and its value only depends on the ICE out exhaust temperature T(t) which is an available information.

When the set-point  $T^*_{SCR}$  is constant and  $T^*$  is reachable, it holds  $T(t) = K_T(T^*_{SCR} - \hat{T}_{SCR}(t + \tau)) + T^*_{SCR}$ . By using this expression into (16) it follows  $\dot{T}_{SCR} = -a(K_T + 1)(\hat{T}_{SCR} - T^*_{SCR})$ .

When the set-point  $T^*_{SCR}$  is constant and  $T^*$  is not reachable, then the controller simply tries to minimize the distance between  $T^*_{SCR}$  and  $T_{SCR}$ .

The implementation of the controller (17) adds a tiny computational complexity to the overall control that now has to implement only (10), (14) and (17).

# 5. EVALUATION

The proposed control strategy is compared versus a baseline scenario where the set-points  $\mu^*/P$ ,  $T^*$  and  $r^*$  are kept constant. In this way we are implicitly requesting a production of NOx at the ICE outlet in terms of mass over unit of energy rather than mass over unit of time. We consider two different baselines: one where  $\mu^*/P$  is set to a fairly low value and one where  $\mu^*/P$  is set to a fairly high value. Finally, we compare the proposed method with the economic nonlinear MPC (E-NMPC) based supervisory control algorithm from Karim et al. (2018) as it considers the same system configuration described in this paper. For such a comparison, we configure the E-NMPC with a prediction horizon length equal to 100 s.

The comparison is done using a high-fidelity simulation platform including a model of a 13 L turbo compound diesel engine and a model of an EATS, over a vehicle driving cycle called Borås-Landvetter-Borås cycle. This cycle was recorded from a heavy-duty truck driven from Borås to Landvetter and back to Borås in the area of Gothenburg in Sweden. To have a quantitative measurement of the vehicle driveability we define the <u>driver-disappointment</u> index (DDI) as

 $DDI := \frac{1}{\tau} \int |M^*(s) - M(s)| \, ds \,,$ 

where

$$-\frac{d}{d} = \frac{d}{d} + \frac{d}{d} = \frac{d}{d} + \frac{d}{d} = \frac{d}{d} + \frac{d}{d} = \frac{d}{d} + \frac{d$$

$$\mathcal{T} := \left\{ t \ge t_0 : \frac{a}{dt} M^*(t) \ge 0 \right\}.$$
(19)

The DDI is essentially an Integral Absolute Error (IAE) measure between the requested torque  $M^*$  and the delivered torque M, but, differently than the classic notion of IAE, it only considers the vehicle acceleration phase.

Table 1 shows that the Brake Specific Total Fluid Consumption (BSTC) of the proposed control strategy is 0.4% higher than the baseline control strategy with a high ICE out brake specific NOx emissions demand. However, such a baseline strategy does not fulfill the Euro VI emission



Fig. 6. Comparison of the NOx emissions over the workbased-windows, with the different control strategy.

legislation, see Figure 6. The baseline control strategy calibrated with a low ICE out brake specific NOx emissions demand fulfills the legislation, but the BSTC is higher than the proposed strategy and the DDI is also much worse.

Hence, it appears necessary to dynamically adapt the set-points of the locally controller system to meet legislation constraints without penalizing fluid consumption and vehicle driveability. Compared with the E-NMPC, the proposed method shows about 0.4% higher BSTC. Such difference may be further increased by using a longer prediction horizon at a cost of increasing the computational complexity, Karim et al. (2018). The Brake Specific Fuel Consumption (BSFC) is very similar as also shown in Figure 7. The legislation constraints are met in both the cases with a slightly larger margin for the E-NMPC. Nevertheless, the DDI of the proposed controller is much lower, which also reflects in a higher delivered energy for this driving cycle. This traduces in a better vehicle driveability.

Regarding the computational complexity, the proposed method is more efficient since it only requires the implementation of (10), (14) and (17) contrarily to the E-MPC that requires the execution of some online iterative method along with look-ahead information.

Table 1. Comparison between a baseline strategy with a high and a low NOx demand calibration, an economic nonlinear MPC, and the proposed strategy.

Control	Baseline	Baseline	Economic	Proposed
performance	high NOx	low NOx	NMPC	strategy
BSFC [%]	100.0	102.0	100.9	102.1
AdBlue [%]	100.0	58.4	69.1	49.0
BSTC [%]	100.0	100.7	100.0	100.4
Deliv. energy [%]	100.0	99.8	97.4	100.6
DDI [%]	100.0	118.2	215.0	92.7
90th percentile				
tailpipe NOx [g]	74.9	13.9	8.7	11.6

#### 6. DISCUSSION

In this paper we presented a heuristic control scheme named emission coordinator that establishes the set-points

(18)



Fig. 7. Normalized total mass of fuel and tailpipe NOx emissions, with a baseline, economic nonlinear MPC, and the proposed supervisory control strategy.

for a locally controlled system composed by an ICE and EATS, and an EECU, and it uses measurements which are typically available in every heavy-duty truck. Such emission coordinator aims at tackling NOx emissions constraints provided by the current legislation without penalizing fluid consumption and vehicle driveability and it reduces to a gain-scheduled proportional plus feed-forward controller with saturation limits.

Compared to Karim et al. (2018), which uses the same system setup, the proposed control scheme exhibits slightly lower closed-loop performance in terms of fuel consumption and NOx emissions, but better vehicle driveability. It further provides a number of additional benefits which are compelling in industry. For instance, the proposed approach is computationally more efficient than Karim et al. (2018) and other existing methods which are often based on MPC. In addition to that, it does not require an accurate identification of the plant model which is a very expensive - and sometimes not even possible - operation, but it only requires the estimation of some bound. This fact is central in an industrial setting where different components of the vehicle are often outsourced from external suppliers which hide information to secure their Intellectual Property. Moreover, the proposed controller is inherently robust and it can be easily adapted to other underlying hardware. This fact positively influences the product variant handling as it requires the adaptation and re-tuning of few parameters to make it work. In fact, the proposed method does not work only if the available setpoint of the locally controlled system are  $\mu^*, T^*$  and  $r^*$ . but, with few adaptations, it may work with any set of inputs that produce a change in  $\mu$  and T. Finally, it does not require personnel with advanced skills in control to understand and to tune it.

We wish to conclude by highlighting that the proposed method works satisfactorily without using look-ahead information as done in a number of existing methods. Nevertheless, look-ahead information can be exploited for example for scaling the value of the set-point  $m_{tp}^{W_0^*}$  based on future estimates of the EATS conversion efficiency  $\hat{r}(t+T)$  and ICE power  $\hat{P}(t+T)$ . This provides room for future Research.

#### ACKNOWLEDGEMENTS

The authors wish to thank Ricard Blanc at Volvo Group for the number of inspiring discussions on powertrain control and to Mohammed R. Karim from Chalmers University of Technology.

#### REFERENCES

- Chen, P. and Wang, J. (2015). Nonlinear model predictive control of integrated diesel engine and selective catalytic reduction system for simultaneous fuel economy improvement and emissions reduction. Journal of Dynamic Systems, Measurement, and Control, 137(8), 081008.
- Cloudt, R. and Willems, F. (2011). Integrated emission management strategy for cost-optimal engineaftertreatment operation. <u>SAE International Journal of</u> Engines, 4(1), 1784–1797.
- Donkers, M., Van Schijndel, J., Heemels, W., and Willems, F. (2017). Optimal control for integrated emission management in diesel engines. <u>Control Engineering</u> Practice, 61, 206–216.
- EC (2018). Commission regulation (EU) 582/2011. Official Journal of the European Union, 02011R0582.
- Elbert, P., Amstutz, A., and Onder, C. (2017). Adaptive control for the real driving emissions of diesel engines. MTZ worldwide, 78(12), 68–74.
- Guzzella, L. and Amstutz, A. (1998). Control of diesel engines. IEEE Control System Magazine, 18(5), 53–71.
- Karim, M.R., Egardt, B., Murgovski, N., and Gelso, E.R. (2018). Supervisory control for realdriving emission compliance of heavy-duty vehicles. IFAC-PapersOnLine, 51(31), 460–466.
- Kiencke, U. and Nielsen, L. (2000). <u>Automotive Control</u> Systems: For Engine, Driveline and Vehicle. Springer-Verlag, Berlin, Heidelberg, 1st edition.
- Mentink, P., van den Nieuwenhof, R., Kupper, F., Willems, F., and Kooijman, D. (2015). Robust emission management strategy to meet real-world emission requirements for hd diesel engines. <u>SAE International Journal of</u> <u>Engines</u>, 8(3), 1168–1180.
- Schär, C., Onder, C., and Geering, H. (2006). Control of an scr catalytic converter system for a mobile heavyduty application. <u>IEEE Trans. Contr. Syst. Tech.</u>, 14(4), 641–653.
- Vagnoni, G., Petri, S., Aubeck, F., Lindberg, J., Gelso, E., Murgovski, N., et al. (2018). Predictive engine and aftertreatment control concepts for a heavy-duty long haul truck. 27th Aachen Colloquium Automobile and Engine Technology, Institute for Automotive Engineering, RWTH Aachen (Germany).
- Willems, F., Kupper, F., Rascanu, G., and Feru, E. (2015). Integrated energy and emission management for diesel engines with waste heat recovery using dynamic models. <u>Oil & Gas Science and Technology–Revue dIFP</u> <u>Energies nouvelles</u>, 70(1), 143–158.
- Zentner, S., Asprion, J., Onder, C., and Guzzella, L. (2014). An equivalent emission minimization strategy for causal optimal control of diesel engines. <u>Energies</u>, 7(3), 1230–1250.