

Evaluation of Virtual NO_x Sensor Models for Off Road Heavy Duty Diesel Engines

Stephan Stadlbauer, Daniel Alberer and Markus Hirsch
Johannes Kepler University Linz

Simone Formentin
Politecnico di Milano

Christian Benatzky
Liebherr Machines Bulle SA

Luigi del Re
Johannes Kepler University Linz

ABSTRACT

NO_x and PM are the critical emissions to meet the legislation limits for Diesel engines. Often a value for these emissions is needed online for on board diagnostics, engine control, exhaust after treatment control, model based controller design or model in the loop simulations. Besides the obvious method of measuring these emissions, a sensible alternative is to estimate them with virtual sensors.

A lot of literature can be found presenting different modeling approaches for NO_x emissions. Some are very close to the physics and the chemical reactions taking place inside the combustion chamber, others are only given by adapting general functions to measurement data. Hence, generally speaking, there is not a certain method which is seen as the solution for modeling emissions. Finding the best model approach is not straightforward and depends on the model application, the available measurement channels and the available data set for calibration.

This paper evaluates three different already published virtual sensor approaches for NO_x engine raw emissions of a heavy duty Diesel engine in off-road applications. The three proposals consist of a black box polynomial mean value model using available data from the electronic control unit (ECU), a black box mean value model using mainly the measured indicated pressure profile and a crank angle based gray box model also based on the indicated pressure profile.

The final evaluation of the three models was done with measurements of a highly dynamical test cycle for HD engines, coming from a wheel-loader application and conducted on a dynamical engine test bench, whereas dynamical behavior, integral error as well as transient deviations were analyzed.

CITATION: Stadlbauer, S., Alberer, D., Hirsch, M., Formentin, S. et al., "Evaluation of Virtual NO_x Sensor Models for Off Road Heavy Duty Diesel Engines," *SAE Int. J. Commer. Veh.* 5(1):2012, doi:10.4271/2012-01-0358.

INTRODUCTION

Nitrogen oxides (NO_x) - the sum of nitrogen oxide NO and nitrogen dioxide NO₂ - are besides particulate matter the primary and for manufactures most demanding pollutants of Diesel engines. The legislation limits can be met either by in cylinder measures like exhaust gas recirculation (EGR) and multiple fuel injections or otherwise by the use of after treatment devices like selective catalytic reduction (SCR) or lean NO_x traps (LNT). For on-board diagnosis as well as for

control of these systems the value of the NO_x raw emissions is essential. Hence, in [1] it is concluded that development in engine control will depend crucially on the availability of sensors and on their reliability, robustness, immunity to noise and capacity to operate in harsh environment - especially important for off-road applications.

There are two basic possibilities to determine the value the NO_x raw emissions: Obviously, the first one is to measure NO_x with a physical sensor usually based on solid-state

principles (see e.g. [1]). The second way is to compute a NO_x quantity from already available data (other sensor signals of engine states, or engine control variables) by means of a model, i.e. to design a virtual sensor. However, modeling emissions is not straightforward and, although it was part of many works before, it is still not a solved issue and has substantial potential for improvement. The presented approaches reach from detailed three dimensional computational fluid dynamics (CFD) models with chemical reaction kinetics [2] over phenomenological models [3] and zero dimensional one and multi zone models [4] to purely empirical models [5]. From a theoretical point of view the CFD models with a detailed spatial description should be closest to the real process, however, the many degrees of freedom which coincide with the complicated model structure lead to poorly conditioned problems, i.e. in the end a lot of parameters need to be empirically tuned. Furthermore, the computational burden is extremely high. In other words, the selected degree of detail essentially depends on the intended use of the model - in this case a virtual sensor for online emission prediction - and the available measurements.

In this paper three different NO_x modeling approaches are presented and evaluated. All models are of simple structure to be applicable on a standard engine control unit (ECU).

The first approach describes the mean NO_x raw exhaust concentration - hence, the name *mean value model* (MVM) - with available ECU signals as inputs [6]. A black box model does not include any system or process information, which in this case would be given in terms of physical or chemical first principles relevant for NO_x formations but the whole information for setting up the model comes from measurement data. Common black box model classes for describing engine emissions are artificial neural networks (ANN) [7],[8] and models applying genetic algorithms [9] also brought valuable results. In the approach presented below, the black box model is of a general polynomial structure [6], whereas the polynomial parameters are adapted by means of data based identification to represent the certain engine.

The second approach is similar to the first one. It describes also a black-box MVM but is based on information derived from the measured indicated pressure profile. To this end, a principal component analysis was applied to the high dimensional information of the crank angle resolved indicated pressure signal in order to extract the "relevant information" and to reduce the dimensionality for the NO_x -MVM. Finally, four relevant signals were derived from the pressure measurement and together with the engine speed as link between the crank angle domain and time domain a polynomial NO_x -MVM was designed (for details see [10]).

The third approach is a gray box one, which means that the main model structure is given by first principle considerations (see [4],[11]). By means of a thermodynamic process calculation, which is based on the indicated pressure measurement, and the use of the well known Zeldovich

mechanism, NO formation rates inside the combustion chamber were computed in the crank angle domain. Hence, this zero-dimensional model does not only predict the mean NO_x concentration in the exhaust but also provides a crank angle resolved NO signal during combustion.

The evaluation presented in this paper was done with a HD off-road Diesel engine on a dynamical engine test bench with fuel and temperature conditioning. Finally, all methods were tested on a highly dynamical test cycle, coming from a wheel-loader application, and a comparison is presented considering dynamical as well as cumulative prediction quality.

SYSTEM SETUP

The measurements for model parameterization as well as for validation were carried out on a highly dynamical engine test bench at the Johannes Kepler University in Linz (Figure 1). The considered test candidate was a 4 cylinder 7 liter heavy duty off-road Diesel engine with a maximum torque of 1115Nm (BMEP = 2MPa) @ 1500 rpm and a maximum power of 175kW @ 2000 rpm. This engine is equipped with a common rail injection system, an external exhaust gas recirculation and a waste gate turbocharger. For the stationary NO_x analyses a Horiba Mexa 7100 was used and for the dynamical analyses a Cambustion $f\text{NO}_x400$ (with a response time in the range of 10ms), hence it was possible to detect also transient NO_x peaks. Several tests also included variations of the engine air system control inputs, which were done with an ECU bypass and the use of a dSpace rapid prototyping system. The data acquisition was done with the dSpace system, too.

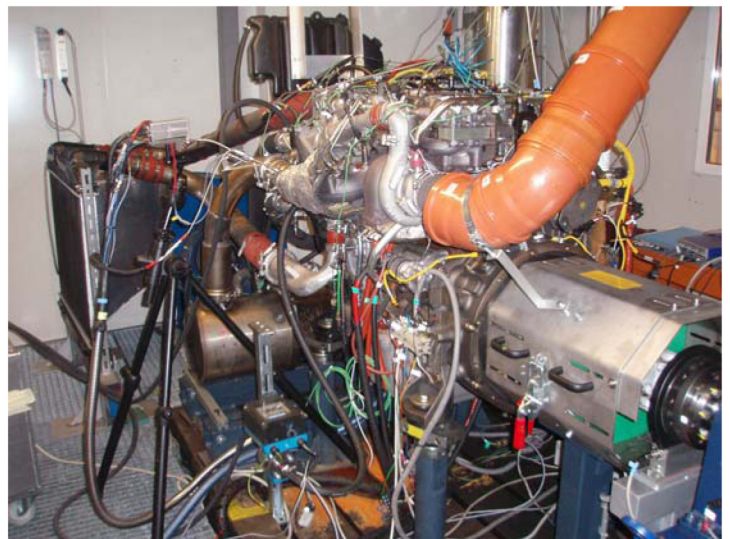


Figure 1. Dynamical engine test bench at the Johannes Kepler University Linz

MODELING APPROACHES

As already mentioned above, three different modeling approaches were implemented and compared in this study. In the following paragraph the proposed methods are introduced and their basic ideas are presented.

Black box polynomial mean value model

The main idea behind the black box approach (shown in [12]) is to use signals as inputs for the NO_x model that are already available in standard ECUs for HD engines. Moreover, the goal was to develop a simple mean value model which is straight forward to implement on an ECU and which should capture all relevant effects in the whole engine operating range. Due to the fact that for a certain model complexity¹ black box models are the least constraint model class², they offer the potential of the best approximation quality for a given measurement data set. However, this potential also has a downside, namely that black box models strongly rely on the availability of “good” measurement data, i.e. if the data used for model identification is poor, the probability of getting a poor model is high, too. To this end, in this work a Design of Experiments (DoE) method was applied for measurement data generation [12]. After defining the main inputs, an optimal design is generated for these inputs and the assumed model structure. For the proposed model a polynomial structure $f(u(k), \theta)$ is used. Since this structure is linear in parameters it can be represented by the product of a parameter vector θ with a data vector $\varphi(k)$ [6].

$$y(k) = f(u(k), \theta) + e(k) = \varphi^T(k)\theta + e(k) \quad (1)$$

Subject to the assumption of an error $e(k)$ uncorrelated to $f(u(k), \theta)$, standard analytic least squares parameter estimation routines can be applied [12] to get an estimate $\hat{\theta}$ of the parameter vector.

$$\begin{aligned} \hat{\theta} &= \arg \min_{\theta} \sum_{k=1}^N (y(k) - \varphi^T(k)\theta)^2 \\ &= \left(\frac{1}{N} \sum_{k=1}^N \varphi(k)\varphi^T(k) \right)^{-1} \frac{1}{N} \sum_{k=1}^N \varphi(k)y(k) \\ &= (\Phi^T \Phi)^{-1} \Phi^T Y \end{aligned} \quad (2)$$

The applied D-optimal DoE uses the minimization of the determinant of the covariance matrix $\Sigma(\hat{\theta})$ to get an optimal input design.

$$\Sigma(\hat{\theta}) \approx \hat{\sigma}^2 (\Phi^T \Phi)^{-1} \quad (3)$$

The determinant is the product of the eigenvalues of $\Sigma(\hat{\theta})$, thus it corresponds to the volume of the confidence ellipsoid. Therefore, minimizing $\Sigma(\hat{\theta})$ is equivalent to minimizing the volume of the confidence ellipsoid as shown in Figure 2. In this figure other different optimization methods (A-optimality, M-optimality and E-optimality) are shown as well as the used D-optimal optimization method.

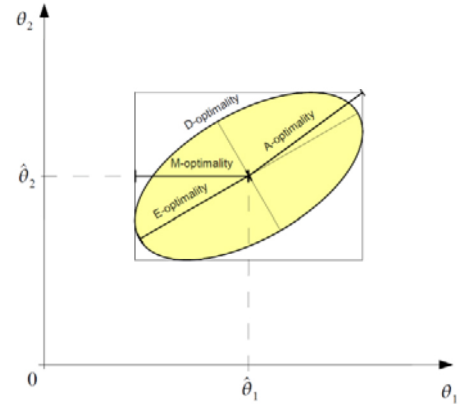


Figure 2. Confidence ellipsoid with measures of optimal criteria

Table 1 depicts the considered system inputs, which were optimized by the DoE method.

Table 1. Considered inputs for DoE (left) and for the polynomial model (right)

DoE inputs	Model inputs
Engine speed (N)	Engine speed (N)
Accelerator pedal position (α)	Injected fuel amount (mf)
EGR valve position (EGR)	Air mass flow (MAF)
Waste gate position (WG)	Intake manifold absolute pressure (MAP)
Rail pressure (p_{RAIL})	Rail pressure (p_{RAIL})
Angle of the main injection (φ_{MI})	Angle of the main injection (φ_{MI})
	Oxygen concentration (O_{2exh})

Based on the data generated by DoE, seven ECU signals were selected for the identification of the NO_x model, consisting of the engine speed (N), the injected fuel amount (mf), the air mass flow (MAF), the intake manifold absolute pressure (MAP), the exhaust oxygen concentration (O_{2exh}), the angle of the main injection (φ_{MI}) and the rail pressure (p_{RAIL}). Note that since most of these signals are no direct inputs to the engine, different signals were used for the DoE method (see Table 1). However, the considered DoE inputs have a strong correlation with the model inputs, whereas a

¹subject to the model structure and the number of model parameters

²For instance, first principles based models have a fixed model structure and therefore can qualitatively be seen as a constrained subclass of the generic modeling class represented by black box models.

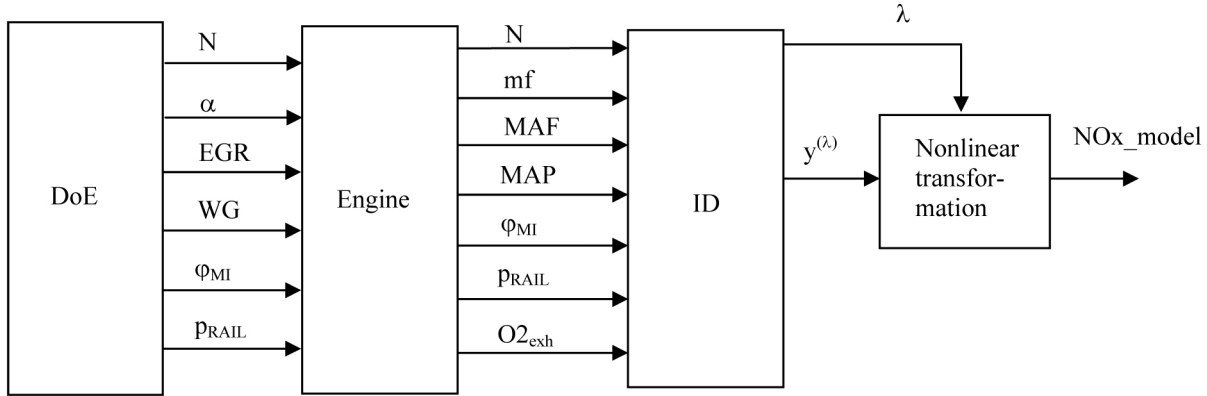


Figure 3. Structure of the black box identification

sufficient excitation of the model inputs could be realized. It turned out that a polynomial approach of second degree was sufficient to capture the nonlinear emission behavior of the engine:

$$\begin{aligned}
 y^{(\lambda)} = & \theta_0 + \theta_1 N + \theta_2 N^2 + \theta_3 N mf + \theta_4 N MAP + \theta_5 N MAF + \\
 & \theta_6 N O_{2exh} + \theta_7 N \phi_{MI} + \theta_8 N p_{RAIL} + \theta_9 mf + \theta_{10} mf^2 + \\
 & \theta_{11} mf MAP + \theta_{12} mf MAF + \theta_{13} mf O_{2exh} + \theta_{14} mf \phi_{MI} + \\
 & \theta_{15} mf p_{RAIL} + \theta_{16} MAF + \theta_{17} MAF^2 + \theta_{18} MAF MAP + \\
 & \theta_{19} MAF O_{2exh} + \theta_{20} MAF \phi_{MI} + \theta_{21} MAF p_{RAIL} + \\
 & \theta_{22} MAP + \theta_{23} MAP^2 + \theta_{24} MAP O_{2exh} + \theta_{25} MAP \phi_{MI} + \\
 & \theta_{26} MAP p_{RAIL} + \theta_{27} O_{2exh} + \theta_{28} O_{2exh}^2 + \theta_{29} O_{2exh} \phi_{MI} + \\
 & \theta_{30} O_{2exh} p_{RAIL} + \theta_{31} \phi_{MI} + \theta_{32} \phi_{MI}^2 + \theta_{33} \phi_{MI} p_{RAIL} + \\
 & \theta_{34} p_{RAIL} + \theta_{35} p_{RAIL}^2
 \end{aligned}
 \quad (4)$$

Note that in (4) $\theta_0 \dots \theta_{35}$ represent 36 identification parameters. To guarantee the homoscedasticity of the error, which is important for parameter selection algorithms, a nonlinear transformation (Box-Cox transformation [12]) of the output described by a parameter λ was included too:

$$y^{(\lambda)} = \begin{cases} (y^\lambda - 1) / \lambda & \lambda \neq 0 \\ \log y & \lambda = 0 \end{cases}
 \quad (5)$$

Hence, in total 37 parameters had to be estimated with an identification model structure as shown in (4). Figure 3 depicts an overview of the black box model structure. In order to keep the number of parameters as low as possible and to reduce the uncertainty of the identified parameter values, an f-test [12] based method was applied, which eliminated insignificant terms of (4).

Indicated pressure based black box mean value model [10]

The initial motivation behind this approach was based on the assumption that all phenomena during combustion - including the NO_x emission formation - are captured by the indicated pressure measurement signal. To this end, a 2 step approach based on the indicated pressure measurement was applied, whereas in the first step by use of a principal component analysis (PCA) the “relevant information” of the pressure signal is extracted and in the second step a polynomial mean value model is designed (similar to the black box approach presented above). In other words, a low dimensional mean value information is generated from the high dimensional crank angle resolved pressure signal trajectory and then used as basis for NO_x modeling. As it turned out in practice, besides the indicated pressure measurement based PCA, additional information was required in order to get a satisfactory prediction quality of the NO_x model over a large operating range. To this end, engine speed was selected (see also [10]) because it creates a link between the crank angle domain and the time domain.

For the model the pressure profile around ± 100 CAD of the combustion top dead center was considered, i.e. with a resolution of 0.5 CAD in total 400 pressure data values were considered at each combustion cycle. As mentioned above, in the first step a PCA was applied to determine the number of inputs which are required to capture the 400 points with a sufficient accuracy. PCA, also known as Karhunen-Loève (KL) transform [13], projects the data onto a lower dimensional subspace in a way that the mean squared distance between the data points and their projection is minimized. Consider the pressure matrix P built using the profiles characterizing r different cycles (the size of P is then $r \times 400$). P can be rewritten as

$$P = U \Sigma V^T = \sum_{i=1}^r \sigma_i u_i v_i^T
 \quad (6)$$