

Comparison of Virtual and Physical NO_x-Sensors for Heavy Duty Diesel Engine Application

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ABSTRACT

Nitrogen oxide (NO_x) sensing is required both for on-board diagnosis and optimal selective catalytic reduction (SCR)-catalyst control in heavy duty diesel engines. This can be accomplished either by physical solid-state sensors, or by so-called virtual sensors, which estimate the value of the target quantity using other states by means of a model.

Both approaches have advantages and disadvantages. This paper resumes the derivation and the identification of a virtual sensor based on a polynomial structure and optimal experimental design methods and compares its performance to the one of a production physical solid state sensor.

The virtual sensor is compared with a commercially available solid-state sensor in terms of accuracy (stationary as well as dynamic) and operation limits. To this end both sensors were tested on several stationary and transient heavy duty test cycles like the European Stationary Cycle (ESC), the European Transient Cycle (ETC), the World Harmonized Stationary Cycle (WHSC) and the World Harmonized Transient Cycle (WHTC) and on further stationary measurement data to determine their behavior under relevant engine operating conditions. The analysis also included several special cases like driving cycles with increased exhaust-backpressures, warm-up phases of the sensors and different sensor mounting positions.

INTRODUCTION

Meeting the increasingly stringent exhaust gas legislations represents one of the most challenging issues in modern engine development. For Diesel engines, NO_x emissions and

the particulate matter (PM) emissions are especially critical [1]. Over the years several strategies have been developed to reduce NO_x, among them in particular exhaust gas recirculation (EGR) and catalyst after-treatment (e.g. SCR-catalysts and storage catalysts). EGR systems reduce the in-cylinder oxygen partial pressure and increase the thermal capacity of the mixture to decrease the combustion temperatures and as a consequence the NO_x-emissions [2]. For the selective catalytic reduction (SCR) urea is injected into the exhaust pipe to convert the nitrogen oxides into harmless products within the catalyst. NO_x-storage catalysts absorb the NO_x and remove it from the exhaust gas. Once the maximum storage capacity is reached a reduction of the stored NO_x is initiated at higher temperatures (catalyst regeneration) [3]. Both after-treatment systems require information about the untreated NO_x-emissions upstream of the after-treatment device. SCR-catalysts demand exact continuous information of the NO_x-emissions upstream of the catalyst to allow the precise injection of the necessary urea. NO_x storage catalysts require at least the cumulative NO_x-values to detect the momentary charge-level and to determine the correct time for regeneration. Besides these NO_x-after-treatment systems so called on board diagnosis (OBD) systems for trucks were introduced by recent emissions legislations. In many cases OBD requires the knowledge of the NO_x-level before the after-treatment system as well.

To obtain the NO_x-emissions the common approach is to use commercial physical sensors for vehicle-applications. The most established sensor types for these purposes are solid-state sensors based on semi conducting elements. Another possibility to monitor the NO_x-emissions is to use emission-models. Literature provides numerous different modeling

approaches like first principle models based on physical and chemical equations [4] or data based modeling techniques [2, 5, 6, 7, 8, 9]. At the moment data based models provide the most promising results in emission modeling because quite simple model structures are sufficient to create a fast and accurate representation of the NO_x-emissions. Such models are also referred to as virtual sensors. This name indicates that these models are supposed to replace physical sensors. Virtual sensors use signals, which are available in the engine control unit (ECU), to calculate the NO_x-emissions. Data based virtual sensors normally consist of mathematical formulas to calculate the desired signal dependent on a certain set of input variables.

In this work a heavy duty diesel engine was investigated to compare commercial NO_x-sensors to virtual sensors under different operating conditions. Therefore a data-based modeling technique was applied to create a virtual sensor. For the comparison both the virtual and the physical sensor were tested under nominal conditions (test cycles) and under special conditions as well (increased exhaust back pressure, deviant environmental conditions like different charge air temperatures).

EQUIPMENT

EXPERIMENTAL FACILITIES

All experiments were performed on a MAN D2676LF heavy duty common rail Diesel engine with an external exhaust gas recirculation and a two staged turbocharger. The engine's nominal power is 320 kW. The turbocharger is equipped with waste gates for boost-pressure control and boost pressure limitation. The control of the exhaust gas recirculation is based on the measured λ (relative air fuel ratio) in the exhaust pipe. Moreover an EGR-cooler is used to reduce the temperature of the recirculated exhaust gas. [Figure 1](#) shows the engine configuration and [Table 1](#) explains the relevant measuring variables. For the tests the engine was mounted on a dynamic Kristl, Seibt&Co test bench. The NO_x emissions measurement equipment consisted of two Continental Smart NO_x Sensors (SNS 18) and a PEUS measuring device for engine test benches. The working principle of the solid state SNS 18 sensor will be explained in the next section. The PEUS measuring device is a highly accurate chemiluminescence NO_x analyzer. Here, ozone (O₃) is combined with nitric oxide (NO), to form nitrogen dioxide in an activated state NO₂*. As the activated NO₂* reverts to the lower energy state NO₂, it emits electromagnetic radiation which is measured by photoelectrical detectors. To determine the amount of all nitrogen oxides NO_x, NO₂ first has to be converted to nitric oxide NO. This is done by passing the sample through a converter before the ozone activation reaction is applied. The three measuring positions for the upstream NO_x-concentration of any after-treatment device

are shown in [Figure 1](#), indicated by the labels NOX_HP, NOX_LP and NOX.

<[figure 1](#) here>

Table 1. description of variables of [figure 1](#)

name	unit	description
NOX	ppm	PEUS NO _x -signal
O2_EX	%	oxygen concentration
NOX_LP (SNS 18)	ppm	signal of the SNS 18 solid state NO _x -sensor in the exhaust pipe
P4, T4	mbar, °C	pressure and temperature in the exhaust pipe
P3N, T3N	mbar, °C	pressure and temperature between the turbines
NOX_HP (HP-SNS 18)	ppm	signal of the SNS 18 solid state NO _x -sensor between the turbines
MAF_2	kg/h	air flow sensor near the engine intake
P22_EDC, T22	mbar, °C	pressure and temperature after charge air intercooler 2
MAF_1	kg/h	air flow sensor upstream of the inlet air conditioning

SOLID STATE NOX-SENSOR

The applied NO_x-sensor for vehicle applications is a SNS 18 solid state sensor from Continental. This sensor is commonly used in vehicles like trucks and passenger cars to measure NO_x-concentrations in the exhaust gas. [Table 2](#) shows the characteristics of the SNS 18 NO_x-sensor. The SNS 18 is calibrated for NO_x-concentrations up to 1500 ppm. Nevertheless, it is possible to measure NO_x-values up to 3012 ppm with reduced accuracy.

Table 2. SNS 18 - characteristics

Measuring range	0 – 1500 ppm
Stationary accuracy	at 0 ppm: +/- 10 ppm 100 – 1500 ppm: +/-10 %
Response time (33%-66%)	1300 ms (new) 1650 ms (aged)

Like wide-range lambda sensors this sensor is based on the ion conductivity of certain semi conducting metal oxides like zirconium (ZrO_2) or titanium (TiO_2) at temperatures of 350 °C and higher. These materials are doped with Y_2O_3 to generate a defect-structure, which allows oxygen-ions (O_2^-) to penetrate the solid structure. This leads to an oxygen-ion-conductivity which can be used to measure oxygen concentrations. If such materials are equipped with two electrodes, O_2^- -ions will drift from the electrode at a high oxygen partial pressure to the electrode with lower oxygen partial pressure. If a voltage is applied across the electrodes it is possible to create an electrochemical oxygen pump. The SNS 18 uses such an electrochemical pump to remove all the oxygen in a first chamber which is filled with exhaust gas. Afterwards the almost oxygen free exhaust gas enters a second chamber where NO_2 is transformed into NO. In the next step a reaction accelerated by catalytic materials transforms the NO-molecules into N_2 and O_2 . Finally the resulting oxygen concentration is measured like in ordinary wide-range lambda sensors and functions as an indicator for the NOx-level. A more detailed description of the working principle can be found e.g. in [10].

VIRTUAL NOX-SENSORS

THE MODEL STRUCTURE

To model the highly nonlinear process of NOx-formation a data based modeling approach was chosen. Representatives of this kind of models are for example artificial neuronal networks (ANN) [8], polynomial models [2, 5, 6, 9] or models based on genetic algorithms [7]. In this work a polynomial model structure of second order (see equation (1)) was chosen. y is the output of the model, u_i are the n different

model inputs and Θ_i , Θ_{ij} are the model parameters. This structure includes nonlinear combinations of inputs but the regression function is linear in parameters [5, 6].

$$y = \Theta_0 + \sum_{i=1}^n u_i \Theta_i + \sum_{\substack{i,j=1 \\ i \leq j}}^n u_i u_j \Theta_{ij} \quad (1)$$

y ... model output

u_i ... model inputs

Θ_i , Θ_{ij} ... model parameters

Due to the nonlinearities of the process a subdivision of the engine map into 4 different regions was necessary (see Figure 2). One polynomial model of second order was identified for each region. Otherwise a polynomial of this low order would be overstrained in representing the NOx-emissions in the whole engine operating range. The model output is generated by switching between the outputs of the local models [5, 6]. In overlapping regions of the local models the outputs are interpolated linearly. Figure 2 shows the subdivision of the engine map and the overlapping regions of the resulting local models.

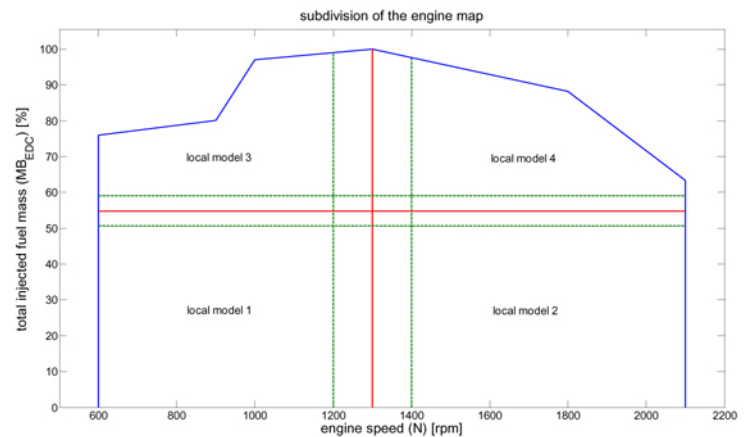


Figure 2. subdivision of the engine map

MODEL IDENTIFICATION

Equation (2) shows the least squares identification formula, which was used to determine the model parameters out of measurement data. The vector Θ includes all the model parameters, the matrix Φ (data matrix) includes vectors of measured model inputs u_i and the vector Y includes the measured outputs. The vector e in the matrix Φ is a vector of ones ($e = [1 \dots 1]^T$).

$$\Theta = (\Phi^T \Phi)^{-1} \Phi^T Y \quad (2)$$

$\Theta = [\Theta_0 \quad \Theta_1 \quad \dots \quad \Theta_n \quad \Theta_{11} \quad \Theta_{12} \quad \dots \quad \Theta_{nn}] \dots$ parameter vector

$\Phi = [e \quad u_1 \quad \dots \quad u_n \quad u_1 u_1 \quad u_1 u_2 \quad \dots \quad u_n u_n] \dots$ data matrix

$Y \dots$ vector of measured outputs

To improve the robustness of the identified model a variable selection of the identified parameters was performed. A statistical t-test was used to neglect insignificant model parameters with an expectancy value of 0 [6, 11].

Preliminary investigations were performed to determine the necessary model inputs for a correct representation of the NOx-emissions. Therefore the ECU-variables with the greatest impact on the NOx-emissions were chosen. [Table 3](#) shows the selected model inputs.

Table 3. model inputs

name	unit	description
N	rpm	engine speed
MB_EDC	mg/inj	total injected fuel mass
P22_EDC	mbar	boost pressure
O2_EX	%	O ₂ -concentration in the exhaust gas
SB	°CA	start of main injection
MAF	kg/h	air mass flow
PCR	MPa	rail pressure
T22	°C	charge air temperature

Additionally to the inputs in [Table 3](#) the humidity of the intake air was considered according to the formula ISO/WD 16183, which is shown in [equation \(3\)](#). This linear formula is used to describe the influence of the intake air humidity H_f [g H₂O/kg dry air] and the intake air temperature T_{11} [°C] on the modeled NOx-emissions. More details on the influence of the humidity can be found in [2].

$$K_f = 1 - 0.0182(H_f - 10.71) + 0.0045(T_{11} - 298)$$

$$NOx_{corr} = \frac{NOx}{K_f} \quad (3)$$

DESIGN OF EXPERIMENT

To generate the required data for the identification process, optimal DoE (Design of Experiment) methods were applied. The great advantage of this method is the possibility to take the chosen structure and polynomial order of the model into account for the calculation of the set of measuring points. An optimality criterion, in this case the D-criterion, is used to determine the set of optimal experimental points. This strategy ensures the calculability of the model parameters and improves the model robustness. [Equation \(4\)](#) shows the cost function of the applied D-criterion. Normally the cost function includes the determinant of the information matrix $\Phi^T \Phi$ but in this case the cost function was additionally extended with the Euclidean distance between the experiments x included in the experimental design. An experiment x consists of a certain combination of the inputs at certain input-levels. This extension guarantees a minimum distance between two points and avoids that one point is included in the experimental set twice [5, 12].

$$J_D^* = -|\Phi^T \Phi| + w \cdot \min_{i=1 \dots k} (\sqrt{(x^j - x_i) \cdot (x^j - x_i)^T}) \quad (4)$$

$\Phi^T \Phi \dots$ information matrix

$w \dots$ weighting factor

$x^j = [u_{1j}, u_{2j}, \dots, u_{nj}] \dots$ new experiment

$x_i = [u_{1i}, u_{2i}, \dots, u_{ni}] \dots$ old experiments

Furthermore D-optimal DoE allows handling asymmetric borders of the experimental region. As a consequence it is possible to consider limitations of the engine speed, the injected fuel mass, the boost pressure and the exhaust-oxygen concentration for every engine operating point. This is a decisive advantage of optimal DoE-methods for engine applications because it ensures that the calculated experimental points lead to a safe and stable operation of the engine during the measurement. To determine the borders of the experimental region or in other terms the limitations of the engine variables, a method presented in [5] was used. By measuring operating points at the edges of the experimental region (e.g. point 1: minimum engine speed, minimum injected fuel mass, minimum boost pressure and minimum oxygen concentration) it is possible to create an

approximation of the experimental space with a hyper-polygon. The hyper polygon can be described by a set of inequalities ($Ax \leq b$), which define if an experiment ($x = [N \text{ MB_EDC } P22_EDC \text{ O2_EX } SB]$) is within the valid experimental region or outside.

MEASUREMENT

In this case, 5 variables were varied to generate a sufficient excitation for the identification. Therefore the calculated experiment included variations of 5 different engine variables: the engine speed (N), the total injected fuel mass (MB_EDC), the boost pressures (P22_EDC), the oxygen concentration in the exhaust gas (O2_EX) and the start of the main injection (SB). For further improvements of the model accuracy it is possible to vary the rail pressure (PCR) and the charge air temperature (T22) as well. To perform the manipulation of these quantities the set points of the engine control unit were partly bypassed or in some cases simply changed. The measuring itself was executed by an automated measuring program.

COMPARISON

For the comparison of the sensors the measured NOx-values were scaled with the maximum measured NOx-value. To measure the model quality the RMSE (Root Mean Square Error) and R^2 (coefficient of determination) were used. A definition of both values is given in the [appendix](#) of this paper.

STATIONARY COMPARISON

The evaluation of the stationary accuracy under nominal operating conditions was performed on the ESC-truck test cycle, see also [Table A1](#). As the PEUS test bench measurement device is the most accurate one this signal presents the reference for the comparison. Therefore all errors are defined by the difference to this signal. [Figure 3](#) and [Figure 4](#) prove that the virtual sensor provides a good representation of the stationary NOx-emissions. Nevertheless these results indicate a superior stationary accuracy of the physical SNS 18 sensor compared to the data based model. The absolute error of the SNS 18 normally is lower than 10 ppm and the maximum relative error is 4 %, the only exception is the first point. This point is characterized by a quite low NOx-level. An analysis of the stationary accuracy of the SNS 18 showed that the accuracy of the sensor decreases significantly with decreasing NOx-levels. [Figure 5](#) shows the relative error dependence on the momentary NOx-level. Investigations of further sensors indicated that even higher errors (up to 15 %) are possible for NOx-levels lower than 200 ppm. This reveals a drawback of the physical sensors, as in this case the stationary accuracy of the virtual sensor is higher. Another restriction of the SNS 18 is the

limited measuring range. For NOx-emissions beyond 1500 ppm the 10 % maximum relative error cannot be guaranteed anymore and emissions beyond 3012 ppm cannot be detected at all, which leads to errors up to 25 %. The virtual sensor is not limited in its measuring range. NOx-levels which were included in the identification data can be represented by the virtual sensor. On the other hand NOx-levels up to 3000 ppm do not occur in vehicle applications if the engine and the exhaust-gas recirculation work properly.

<[figures 3, 4, 5](#) here>

DYNAMIC COMPARISON

Before the results of the dynamic evaluation are discussed, the dynamic characteristics of the different sensors and the model are presented. If the signal of the model is compared to the signals of the physical sensors, the model shows the smallest dead times and response times. This indicates fast model dynamics, which can be explained by the fact that the dynamics of the model are only limited by the dynamics of the input channels of the model. In other terms this means that the model input with the worst measuring dynamics limits the dynamics of the model output. As a consequence low response times are achieved. Furthermore the low dead time of the model output can be explained by the applied preprocessing of the measurement data for the model identification. The preprocessing included a dead time compensation of the measured NOx signal and the model was then identified on the dead-time compensated data, which lead to a model with a minimum dead time. Due to the fast dynamics of the model, the model signal was used as reference to analyze the dynamics of the physical sensors, see also [Table 4](#). To compare the model with the physical sensors different sensor-dynamics models were added to the virtual sensor, according to the characteristic values of [Table 4](#). These sensor dynamics models are necessary to compensate the different measuring dynamics and to ensure comparability between the sensors and the model. The values of [Table 4](#) were identified in experiments. [Figure 6](#) shows the structure of the sensor dynamics models, which consist of a dead time and a first-order-low-pass filter with a certain response time. [Figure 7](#) shows a comparison of the virtual sensor without the sensor dynamics model and the SNS 18. The figure proves the significant differences in the dynamic behavior. These sensor dynamics models have an important impact on the comparisons of the virtual sensor with the physical sensors. Especially during fast transients and for different engine operating regions these dead and response times vary, which leads to errors in the comparison. To reduce these errors, a fast NOx-measurement, close to the exhaust manifold is necessary. This reduces dead times and response times in the measurement signals and diminishes the dependence on sensor dynamics models for the comparison of the different signals.