

Analysis and Choice of Input Candidates for a Virtual NO_x Sensor by a Mutual Information Approach

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ABSTRACT

Abatement and control of emissions from passenger car combustion engines have been in the focus for a long time. Nevertheless, to address upcoming real-world driving emission targets, knowledge of current engine emissions is crucial. Still, adequate sensors for transient emissions are seldom available in production engines. One way to target this issue is by applying virtual sensors which utilize available sensor information in an engine control unit (ECU) and provide estimates of the not measured emissions. For real-world application it is important that the virtual sensor has low complexity and works under varying conditions. Naturally, the choice of suitable inputs from all available candidates will have a strong impact on these factors. In this work a method to set up virtual sensors by means of design of experiments (DOE) and iterative identification of polynomial models is augmented with a novel input candidate selection strategy. Therefore, a systematic approach to analyze and determine possible input candidates based on mutual information (MI) analysis is introduced. As application example a virtual NO_x sensor for a passenger car Diesel engine is presented. For input selection, sensor setup and validation, experiments on a hardware-in-the-loop (HIL) test bench under varying operating conditions are used. The validation of the sensor, performed during transient cycles varying environmental conditions, led to promising results.

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INTRODUCTION

Engine emissions have been of great interest in scientific and industrial research over the last decades. Related environmental and health concerns are evident and therefore legislation is becoming more and more strict over time [1]. Lately, focus is shifting on regulating real-driving emissions and this leads to new challenges in engine and aftertreatment control. For these tasks the engine emissions need to be determined or estimated during the normal operation in the vehicle [2]. One way to quantify the actual emissions is the use of physical sensors. However, there exist important quantities, such as nitric oxides (NO_x) or particulate matters, that are not easily measurable in a production-type vehicle, since currently no devices are available which are able to measure these quantities sufficiently fast and accurate while at the same time being suitable in terms of cost and mounting space [3].

Against this background, a commonly proposed solution is the use of so-called virtual sensors. These are essentially mathematical models that estimate the target quantity, NO_x in the case of this contribution, by using input quantities, which are already available in modern engine control units [4], [4], [6]. Concerning virtual sensors there basically can be found two fundamentally different ways to obtain such models. On the one hand, a number of first principle models based on the understanding of chemical processes responsible for

emissions [7] or computational fluid dynamics (CFD) analyses [8] have been developed. However, these have the disadvantage that they are often too complex for control tasks and depend on influencing factors that cannot be determined in a production-type car [9]. On the other hand, data-based modeling techniques are introduced and are able to provide different shades of model complexity. Therefore these models are often the method of choice for control-oriented modeling purposes [10]. Of course the choice of suitable input candidates, model structure and experimental data has a high impact on the achievable quality. Previously proposed data-based modeling approaches for virtual NO_x sensors [5] [6] [9] are relying on either gray-box or black-box structures, where the input candidates have been selected manually by an expert based on assumptions provided by physical understanding of the system and experience.

In contrary to this selection by expert knowledge, this work introduces a systematic procedure, where the target-relevant input signals are automatically selected from a very large amount of available signals. For example it is possible to consider all sensor measurements and modeled quantities which are available in an ECU and to determine the ones with the highest impact on the target automatically. This is done by an input selection approach based on mutual information (MI) [12], which analyses the correlation between the possible input signals and the NO_x target values. Additionally it

should be mentioned that while the use of expert knowledge to determine model inputs is a valid and well established approach, the proposed strategy allows determining unknown or unconsidered relations and effects.

This work utilizes the iterative identification strategy for virtual sensors presented in [6] [9]. Thus, as model class polynomial nonlinear ARX (PNARX) models are utilized. For these type of virtual sensors the MI-based approach is an adequate choice, because the MI is a measure that enables to analyze nonlinear correlations between the inputs and the target values. The function and effectiveness of the proposed strategy for virtual sensors is validated in different transient validation cycles on a HIL test bench and under varying ambient conditions. The identified sensors show a performance similar to the one from fast transient emission measurement devices and also to virtual sensors utilizing expert knowledge for the input selection. In addition to that, by the MI selection criterion a minimum number of input candidates, which are essentially necessary for the model, can be established. Accordingly, this leads to a model with a low complexity while still a good performance can be obtained.

This paper is organized as follows. In the next section the problem is stated and fundamentals about mutual information, input selection, design of experiments and system identification are given. Subsequently, the specific MI-based approach for input selection is introduced and in the next step the iterative identification approach for polynomial models is applied. The resulting virtual NO_x sensors utilize the previously selected and most important input candidates. Finally, the virtual sensors are validated under different conditions and a conclusion summarizes the results of this work.

PROBLEM STATEMENT

Consider the following identification task. Starting from a complex, nonlinear, dynamic system, a model for a given output y should be established, see Figure 1. In this setup it is often the case that a high number of possible input quantities $u_i, i \in \{1, 2, \dots, N\}$ can be measured or are available for this model and related to the output quantity y . The goal is now to systematically analyze the influence of each possible input candidate on the output, purely based on the captured data in order to identify a model. Obviously this model, should only contain, or be based on, the most significant inputs affecting the chosen output. In other words, the aim is to create a model of limited complexity to be used for control strategies. This choice of suitable input candidates has a significant impact on the quality of the model. The task of choosing the model inputs is typically performed manually by experts with knowledge about the underlying system behavior and relations. On the contrary, the target of the proposed approach is to automatically find relevant inputs from a set of input candidates in a systematic way.

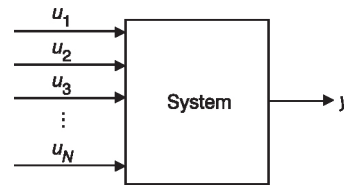


Figure 1. A multi-input single-output system. The system's inputs are $u_1, u_2, u_3, \dots, u_N$. The output is y .

The description above can be further motivated by the following considerations: In a modern ECU a high number of measured and calculated quantities is available. To this end, a systematic method to find input quantities which significantly affect the desired output quantity can be a great advantage in the whole modeling process. Moreover, the strategy purely relies on experimental data and so further can be utilized to reveal, maybe even for the expert unexpected, relations between available input candidates and the output. Of course, the set of relevant inputs can be used to identify a data-based model for the target quantity y .

Fundamentals

The presented approach consists of a data-based identification scheme based on polynomial models. The first part of this section presents this model class. Since for every data-based model a set of suitable input candidates has to be defined, the second part is about the concept of mutual information, which is used for input selection, i.e. the determination of a set of relevant input quantities for the NO_x target. For identification, as well as for the input selection, the generation of sufficiently exciting input data is crucial for the result. Therefore the last part of this section focuses on the basic idea of D-optimal experiment design (input design), which is also part of the presented approach.

Polynomial Model Class

The class of polynomial models of degree p used within this work can be defined by

$$y_k = f_p(x_k)^T \theta + e_k = \varphi_k^T \theta + e_k, \quad (1)$$

where y_k is the system output at time instant k , e_k is the model error and $f_p(x_k)$ represents all polynomial combinations to degree p of the vector x_k , e.g. if

$$x_k = [u_{1,k} \quad u_{2,k} \quad u_{2,k-1} \quad y_{k-1}]^T,$$

where u_1 and u_2 represent the two inputs of the system and $p = 2$, then $f_p(x_k)$ consists of all 15 polynomial combinations of the components in x_k up to a degree of 2, i.e.

$$f_2(x_k) = \begin{bmatrix} 1 \\ u_{1,k} \\ u_{2,k} \\ u_{2,k-1} \\ y_{k-1} \\ u_{1,k}^2 \\ u_{1,k}u_{2,k} \\ u_{1,k}u_{2,k-1} \\ u_{1,k}y_{k-1} \\ u_{2,k}^2 \\ u_{2,k}u_{2,k-1} \\ u_{2,k}y_{k-1} \\ u_{2,k-1}^2 \\ u_{2,k-1}y_{k-1} \\ y_{k-1}^2 \end{bmatrix}.$$

The parameter vector θ is a vector containing 15 components in this example. The structure (1) is summarized in literature under the name polynomial nonlinear ARX (PNARX) models. The class has the property that it is linear in parameters. Consequently, the least squares (LS) method [15] can be used to identify the parameter vector θ , although the model is nonlinear concerning its inputs.

Mutual Information

Mutual information (MI) is a measure that indicates the mutual dependence between two random variables X and Y [11] [12]. Unlike the correlation coefficient it is able to determine nonlinear relationships between two quantities. For two continuous random variables X and Y , the MI is defined by

$$MI(X, Y) = MI(Y, X) = \int_Y \int_X p_{XY}(x, y) \log \left(\frac{p_{XY}(x, y)}{p_X(x)p_Y(y)} \right) dx dy,$$

where $p_X(x)$ is the probability density function (PDF) of X , $p_Y(y)$ is the probability density function of Y and $p_{XY}(x, y)$ is the joint probability density function of X and Y . In this paper MI is used to determine the impact of each possible input candidate on the target quantity (NO_x emissions). Since the assumed model is nonlinear, it is important to use a measure that is able to detect also the nonlinear relations between two quantities. For more details concerning MI the reader is referred to [12].

D-optimal Design of Experiments

Concerning model identification utilizing the least squares method, it is important to use sufficiently exciting data, such that the information in input and output signals is high. Especially when using nonlinear models, it is important to use well-designed input signals, since biased information leads to poor models [13]. The term design of experiments (DOE) denotes such an optimal generation of input signals for identification.

This work uses the determinant criterion (D-criterion) [9] [14] as criterion for a static model design of the input signals. It is defined as the maximization of the determinant of the information matrix H

$$H = \Phi^T \Phi,$$

where the data matrix Φ consist of N measurements of the vector φ_k^T , see e.g. [15]. This leads to a well-invertible matrix H and therefore to a precise parameter estimation $\hat{\theta}$ of the LS solution

$$\hat{\theta} = (\Phi^T \Phi)^{-1} \Phi^T Y$$

with Y being the vector of all outputs y_k for $k \in \{1, \dots, N\}$.

Experimental Setup

All measurements were captured on a 4-cylinder 120 kW BMW N47 Diesel engine at the institute's engine test bench in Linz. The engine is equipped with a common rail injection system, an exhaust gas recirculation (EGR) and a variable-geometry turbocharger (VGT). Figure 2 shows a picture of the test bench equipped with an electric dynamometer and fast transient emission measurement devices.

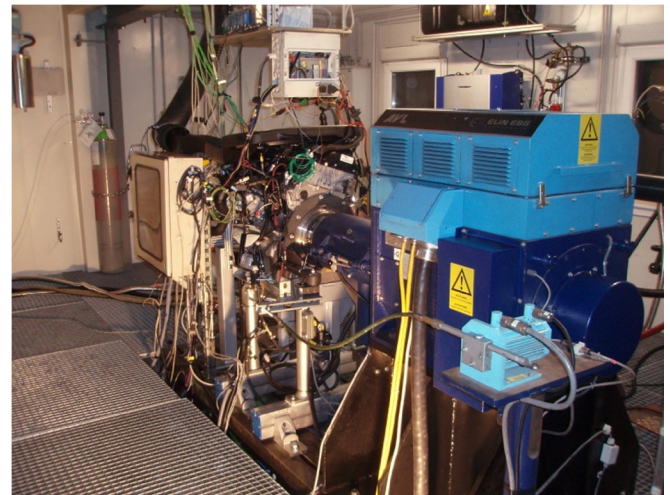


Figure 2. Dynamic engine test bench equipped with a BMW N47 Diesel engine at Johannes Kepler University in Linz.

The test bench is controlled via a *dSpace* rapid prototyping environment, which is also utilized to capture the available physical sensor data as well as quantities that are computed and measured within the ECU. The NO_x measurement devices include a transient NO_x *Cambustion fNOx400* with a response time of 10 ms and a *Horiba Mexa 7100* for stationary analysis. Both devices are mounted downstream of the turbine of the turbocharger and measure the NO_x raw emissions of the engine.

INPUT SELECTION STRATEGY

Experiment Design

For input selection measurement data from all input candidates and the output has to be captured first. Therefore a D-optimal static DOE has been used for input data generation. However, it is infeasible to vary the whole set of more than 140 possible input candidates. First, not all variables measured by the ECU are directly manipulable such as the mass air flow (MAF) and the manifold air pressure (MAP). However, a strong correlation between them and the manipulable position of the EGR and VGT position can be found. Second, quantities such as the cylinder or the exhaust temperature, which in fact a result of the combustion can only be influenced indirectly by