

Pressure Based Virtual Sensing of Transient Particulate Matter of CI Engines

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ABSTRACT

At the moment, no equipment is available for fast measurements of particulate matter (PM) from production CI engines, especially during transients. Against this background, virtual sensors may be an option, provided their precision can be validated. This paper presents a new approach to estimate PM emission based only on in-cylinder pressure data. To this end, an in-cylinder pressure trace is measured with a high resolution (0.5 CAD) and every trace is divided into 8 segments according to critical cylinder events (e.g. opening of the valves or the beginning of injection). A piecewise principle component analysis (PCA) is used to compress the information. This information is then used for PM estimation via a second order polynomial model structure. The key element is the separate use of pressure trace information before and during the early stages of combustion. The model is parameterized by steady points and transient experiments which include parts of the FTP and the NEDC. In order to confirm the model quality, the remaining parts of these transient cycles and a randomly generated transient cycle were applied for model validation and satisfying result can be achieved.

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INTRODUCTION

Stricter emissions regulations motivate an increased interest in transient PM emission, which can be a very substantial part of the total PM emissions in modern engines, as open-loop smoke restrictions based on fuel-oxygen ratio may be ineffective for many transient PM situations because of large differences between actual and estimated charge flow of fresh air or exhaust gas [1]. A real-time feedback of PM emission for a production engine or road vehicle becomes a plausible way to reduce transient emission and the general method is to mount a PM sensor and monitor the PM emission online. But the existing fast PM measurement devices such as the AVL Opacimeter are large in size and use a secondary flow, which leads to significant total time delays and makes them slow and impossible to mount them on a vehicle - not to mention the costs. Hence, a virtual PM sensor may be a good solution - if it works.

Some studies have proposed transient PM models based on the ECU control parameters, such as [2, 3]. However, in these models, the dynamics or lags from the ECU to the PM generation are difficult to obtain. In other words, the quantities measured at a certain instant such as intake pressure are not the real combustion reactants which generate the PM measured at the same time instant. To avoid these effects (also indicated by Figure 1), in this proposal only the in-cylinder pressure trace which is the direct response of the combustion is used as input for the PM modeling, which proves less sensible to the dynamics and delays of the ECU signals. It also reduces differences between steady state and transient operation,

because the largest part of the difference between steady state and transient operation is due to the gas flow dynamics which is not directly used.

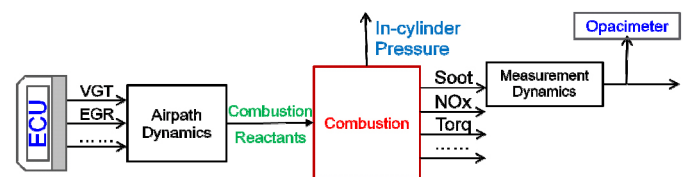


Figure 1. Dynamics between ECU and PM measurement.

Cylinder pressure sensors have been slowly spreading from laboratory use to production engines, for example, a Diesel engine unveiled by General Motors was debuted in Cadillac CTS in 2009 [4]. Extracting useful information from the pressure trace is also becoming established. For instance, Bilal Youssef estimated the mass trapped in cylinder in 2011 based on part of the in-cylinder pressure [5] and M. Amiri Dogahe calculated the mass fraction of residual gases [6]. In addition, there are other potential benefits of using cylinder-pressure data for diagnostics and control, as described in [7]. Estimation of the PM or NOx estimation is always a challenge as their mass only accounts for a tiny fraction of the total mass of the fuel or trapped gas. For NOx, it has already been shown that pressure traces can provide sufficient information, e.g. Simone Formentin built a polynomial model to estimate NOx also based on in-cylinder pressure features and other engine control and status variables [8]. However, the effect of ECU action is also reflected in

the in-cylinder pressure. Therefore, using both ECU settings and in-cylinder pressure has some redundancies. In the case of soot, however, at first it seems impossible to use only in-cylinder pressure data, as some issues, like turbulence, are critical especially for the oxidation of PM [9], but have very little specific effect on the pressure during combustion. Differently from NO_x, using full trace principal component analysis (PCA) will not work as it cannot extract enough information about critical aspects. To solve this problem, we propose a piecewise PCA.

To introduce our method, we shall first present the piecewise PCA and its main advantages. Then, a Design of Experiments (DOE) is conducted to obtain variety of in-cylinder pressure shapes. Based on the DOE data the principal components for each segment of the pressure trace are determined via a piecewise PCA. The third step is the data collection and assignment for both identification and validation. The identification data includes both steady state and a part of the NEDC and FTP cycle while the validation data includes other parts of the FTP and NEDC as well as a randomly generated transient test cycle.

For the calibration of the virtual PM model, the real PM emissions from the target cylinder used in this work are measured by an AVL Opacimeter. Using the identification data and the calibration results, the features of each segment are extracted by projecting on principal components and are used as model inputs. These values are used to parameterize a nonlinear polynomial model of second degree and its parameters are calculated by the least square estimate (LSE). Validation is then used to verify the results.

Of course, model complexity must be kept as small as possible, so as a last step a parameter reduction is applied which reduces the regressor number almost by 45 percent, while the model quality remains appropriate.

EXPERIMENTAL FACILITY

The whole experiment was performed at the test bench of the Institute for Design and Control of Mechatronical Systems at Johannes Kepler University Linz, as shown in Figure 2. It includes a highly dynamical engine testbed and a Euro 5, 4 cylinders, 2lt, common rail Diesel production engine, whose air path was equipped with a variable geometry turbocharger (VGT), a variable swirl valve (SwV), an air intercooler and a high pressure exhaust gas recirculation valve (EGR), see Figure 3. INTECRIO is used with INCA for bypassing applications on the engine control unit (ECU) with an ETK interface and all data acquisition and setting is done with dSPACE. In order to monitor the in-cylinder information, all four cylinders are equipped with same indicated pressure sensor sampling every 0.5 CAD. But only the pressure data of cylinder 3 is used for this proposal. In addition, the PM is measured by AVL Opacimeter with a rising time of 0.1s.

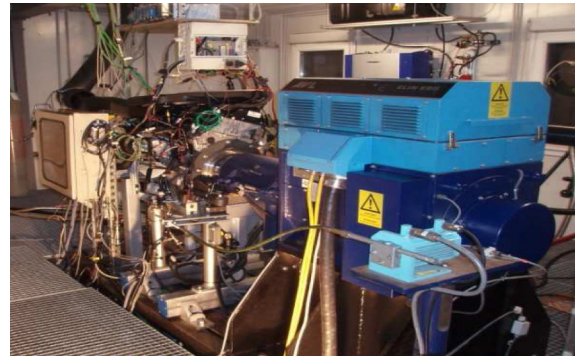


Figure 2. Engine test bench at JKU Linz.

PIECEWISE IN-CYLINDER PRESSURE PRINCIPAL COMPONENTS EXTRACTION

Since the in-cylinder pressure sensor provides a high resolution measurement, the size of raw in-cylinder pressure signal data is huge. The whole in-cylinder pressure trace possesses 1440 recorded points per cycle and cannot be used directly as regressors of a model. Thus, a dimension reduction approach is needed, in our case PCA. But as already mentioned, we do not apply it on the whole pressure trace as usual, but first we divide the pressure profile in 8 segments. A DOE which generates different combustion cases are also introduced in this section. Hence, after applying piecewise PCA on a variety of in-cylinder pressure shapes, the principal components used in identification and validation could be obtained.

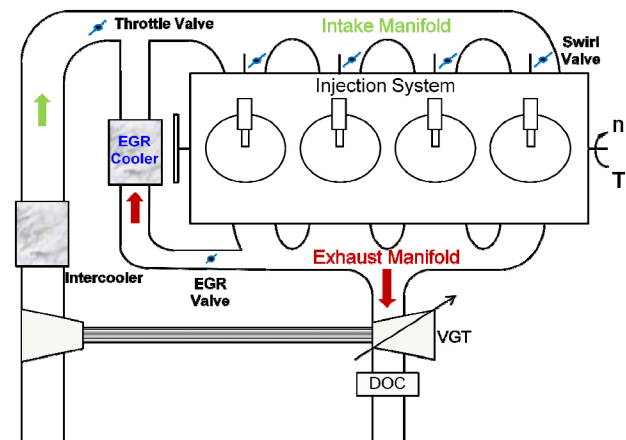


Figure 3. Experimental system scheme.

It is well known that the turbulence level of intake gas has a high effect on PM oxidation [8] and the swirl valve will definitely and immediately affect the intake condition and combustion. However, it does not change the whole in-cylinder pressure trace significantly. To see it, we examine the effect of swirl valve variation to check the difference between the proposed piecewise PCA and the conventional full trace PCA. All other ECU parameters are fixed in this experiment except the swirl valve position. In the left part of Figure 4, the swirl valve position changed via bypassing control and the impact on opacity value is shown in the right part.

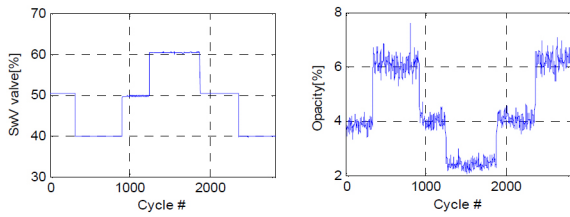


Figure 4. Swirl valve is changed as the left part. Its impact on opacity value is shown in the right part.

Piecewise PCA

Because different segments of in-cylinder pressure include different conditions or states of combustion, the main idea of the piecewise PCA is dividing the whole pressure profile into many pieces and extracting features for each piece. In this paper, we divide the pressure profile into 8 segments according to the working process of one cylinder. Figure 5 shows a typical in-cylinder pressure curve and the 7 division points. These division points respectively are exhaust valve close angle (EVC), intake valve close angle (IVC), the earliest advance angle of pilot injection (EAPI) in the controlling map, top dead center (TDC), the combustion ending angle (CEA), exhaust valve open angle (EVO) and intake valve open angle (IVO). In addition, the CEA is determined by empirical analyzes of pressure traces and is fixed to the maximum value of CA95 found among all records plus a fixed offset of 5 CAD. According to the division, the first 3 segments before fuel injection only contain the information of intake gas, the last 3 pieces only possess information of the burnt gas and the other 2 pieces include information of combustion and injection.

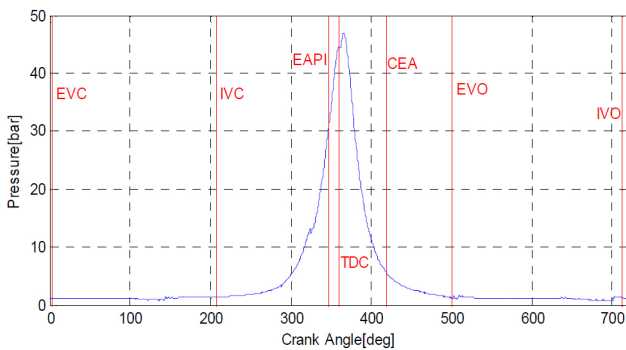


Figure 5. 8 pieces divided in a typical in-cylinder pressure profile.

After the segmentation, singular value decomposition (SVD) is applied to extract principal components of each segment according to Equation 1. Afterwards, raw data of each segment project to its principal components and their features are extracted according to Equation 2.

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

$$feature_i = P \cdot v_i \quad (2)$$

In Equation 1, each row of P corresponds to one segment of one in-cylinder measurement and each column represents one resolution. U is an $m \times m$ unitary matrix; Σ is an $m \times n$ diagonal matrix with related eigenvalues of every principal component on the diagonal; and the $n \times n$ unitary matrix V denotes the principal components of P [10]. The whole profile of in-cylinder pressure can be reconstructed approximately by Equation 3.

$$P(0 \leq CAD < 720) \approx \begin{cases} \sum_{i=1}^{r1} feature_i \cdot v_i^T & CAD \in [0, EVC) \\ \sum_{i=1}^{r2} feature_i \cdot v_i^T & CAD \in [EVC, IVC) \\ \sum_{i=1}^{r3} feature_i \cdot v_i^T & CAD \in [IVC, EAPI) \\ \sum_{i=1}^{r4} feature_i \cdot v_i^T & CAD \in [EAPI, TDC) \\ \sum_{i=1}^{r5} feature_i \cdot v_i^T & CAD \in [TDC, CEA) \\ \sum_{i=1}^{r6} feature_i \cdot v_i^T & CAD \in [CEA, EVO) \\ \sum_{i=1}^{r7} feature_i \cdot v_i^T & CAD \in [EVO, IVO) \\ \sum_{i=1}^{r8} feature_i \cdot v_i^T & CAD \in [IVO, 720) \end{cases} \quad (3)$$

Equation 3 illustrates the reconstruction of the whole pressure profile by selected principal components of each segment and their corresponding features. More principal components of segment 4 and segment 5 are selected because these two pieces correspond to injection and combustion and possess more complicated profiles. For the other segments, their corresponding physical processes are simple and only 3 principal components are used. We indicate with $r1 \sim r8$ the selected principal components of each segment. The preliminarily selected principal components and the size reductions of each segment are listed in Table 1.

Table 1. Principal components used as model inputs from each segment are listed in this table. $r1 \sim r8$ are the selected principal components of each segment.

Segment No.	Preliminary Selection of Principal Components
1	Principal Component 1~3, $r1=3$, Segment Size Reduction: $R^2 \rightarrow R^3$
2	Principal Component 1~3, $r2=3$, Segment Size Reduction: $R^{107} \rightarrow R^3$
3	Principal Component 1~3, $r3=3$, Segment Size Reduction: $R^{281} \rightarrow R^3$
4	Principal Component 1~7, $r4=7$, Segment Size Reduction: $R^{25} \rightarrow R^7$
5	Principal Component 1~7, $r5=7$, Segment Size Reduction: $R^{120} \rightarrow R^7$
6	Principal Component 1~3, $r6=3$, Segment Size Reduction: $R^{161} \rightarrow R^3$
7	Principal Component 1~3, $r7=3$, Segment Size Reduction: $R^{123} \rightarrow R^3$
8	Principal Component 1~3, $r8=3$, Segment Size Reduction: $R^{16} \rightarrow R^3$

Features of each segment can be extracted via projecting every segment to their selected principal components, and the features are considered as substitute of combustion information and used as