

Estimation of Cylinder-Wise Combustion Features from Engine Speed and Cylinder Pressure

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ABSTRACT

Advanced engine control and diagnosis strategies for internal combustion engines need accurate feedback information from the combustion engine. The feedback information can be utilized to control combustion features which allow the improvement of engine's efficiency through real-time control and diagnosis of the combustion process.

This article describes a new method for combustion phase and IMEP estimation using one in-cylinder pressure and engine speed. In order to take torsional deflections of the crankshaft into account a gray-box model of the crankshaft is identified by subspace identification. The modeling accuracy is compared to a stiff physical crankshaft model. For combustion feature estimation, the identified MISO (multiple input single output) system is inverted. Experiments for a four-cylinder spark-ignition engine show the superior performance of the new method for combustion feature estimation compared to a stiff model approach.

INTRODUCTION

The necessity to reduce greenhouse gas emissions in order to combat climate change has lead to higher demands being made of today's combustion engines. In order to reduce CO₂ emissions, the efficiency of today's combustion engines needs to be significantly improved. As part of this process, new homogenous combustion processes are being investigated in or-

der to reduce fuel consumption in spark-ignition engine. In this particular combustion mode, the fuel is auto-ignited by compression of the air-fuel mix. This mode is also referred to as controlled auto ignition (CAI). A higher feedback rate of exhaust gas allows a more homogenous and, therefore, more thermodynamically efficient combustion. Furthermore, de-throttling reduces gas exchange losses. One challenge is the stability of the combustion process wherefore closed-loop control strategies are being investigated. A closed-loop control approach needs highly-accurate feedback information from the combustion process. Cylinder pressure sensors provide the information required for accurate determination of necessary combustion features for control and diagnosis strategies

However, considering the costs of a fully equipped engine, alternative sensor types and configurations must be evaluated for combustion feature reconstruction.

Since the engine speed sensor at the flywheel is part of the standard sensor configuration of today's combustion engines and since the engine speed fluctuations contain important information about the combustion in each cylinder, this signal is prominent in the literature for pressure or torque reconstruction [1] [2] [3] [4]. Alternatively, a torque sensor mounted on the crankshaft is used by Larsson et al. [5] for pressure reconstruction. Wagner and Villarino [6] [7] examined structure-borne sound, currently used for knock detection in spark ignition engines, for pressure reconstruction. In order to further improve the accuracy of combustion feature estimation Hamedovic et al. [8] [9] introduced the key-cylinder approach eval-

uating one cylinder pressure signal in combination with the engine speed signal at the flywheel. They used a stiff crankshaft model to describe the relationship between engine speed and pressure neglecting torsional deflections of the crankshaft. At higher engine speeds the influence of torsional deflections increases and degrades combustion feature estimation. Consequently, this work investigates how torsional deflections can be compensated for, in order to improve key-cylinder based combustion feature estimation.

Earlier work already described a physical multi-body model of the crankshaft in order to take torsional deflections into account [10]. One difficulty of this modeling approach is that knowledge of the parameters of the physical model is critical to its accuracy. Identification of these parameters does not always lead to well-conditioned optimization problems and parameters may also vary between operating points. Furthermore, the physical modeling structure requires a high system order.

A subspace identification approach for gray-box modeling of the crankshaft promises a lower system dimension through higher flexibility in the system description and a more user-friendly identification procedure through better conditioned optimization criteria.

Additionally, in this article a different inversion strategy for the reconstruction of the combustion features is considered. In contrast to [10] which uses a parametric torque model, this strategy is not limited by torque modeling inaccuracies.

This article is structured as follows. First, the equations for physical torsional crankshaft modeling are summarized and the assumptions and ideas of the gray-box modeling approach are described. Then, it is shown how to invert the identified linear time invariant MISO system using the separation algorithm. Through this, the key-cylinder pressure measurement is used to estimate the compression torque. The procedure for combustion feature estimation is illustrated next. In the following, the spark-ignition engine test bed is described including an improved tooth wheel with a better resolution for engine speed measurements at the flywheel. Finally, the results of the model identification, system inversion and combustion feature estimation are presented. A conclusion is given in the last section.

GRAY-BOX MODEL OF THE CRANKSHAFT

In earlier work [10], a white-box model of the crankshaft describing torsional effects was described and evaluated through experiments. A white-box model uses purely physical information in contrast to a black-box model which is purely data based.

This work aims to show higher accuracy in crankshaft modeling, using a gray-box model approach. It is referred to as gray-box model because input and structural information comes from physical insight, whereas the identification is driven by measurement data.

Before discussing the gray-box model approach in detail, the physical equations of the stiff and torsional crankshaft model are illustrated. A linearization leads to the subspace identification approach which will be the basis of the inversion algorithm described in the next section.

PHYSICAL TORSIONAL CRANKSHAFT MODEL

A physical model of the crankshaft neglecting torsional effects can be described by the following torque balance equation:

$$\Theta \ddot{\varphi} = \tau_{ind}(\varphi) + \tau_{mass}(\varphi, \dot{\varphi}, \ddot{\varphi}) + \tau_{load}(\varphi) + \tau_{fric}(\varphi) \quad (1)$$

where Θ is the rotating moment of inertia of the crankshaft, $\ddot{\varphi}$ is the crank angle acceleration and the driving torques are the indicated torque τ_{ind} of all cylinders, the mass torque τ_{mass} , the friction torque τ_{fric} and the load torque τ_{load} . Indicated torque $\tau_{ind,l}$ of cylinder l at crank angle φ is caused by the in-cylinder pressure p_l

$$\tau_{ind,l}(\varphi) = (p_l(\varphi) - p_0) h \left(\varphi - (l-1) \frac{4\pi}{z} \right) \quad (2)$$

$$\text{with } h(\varphi) = A r \left(\sin \varphi + \frac{\lambda \sin \varphi \cos \varphi - \mu \cos \varphi}{\sqrt{1 - \lambda^2 \sin^2 \varphi + 2 \lambda \mu \sin \varphi - \mu^2}} \right),$$

where p_0 is the ambient pressure, z the number of cylinders, l the cylinder index according to the firing order, A the piston area, r the crank radius, λ the connecting rod ratio, and μ the axial offset ratio. In the following, $z = 4$ is used, since the test bed is a four-cylinder spark-ignition engine.

The mass torque results from the oscillating parts of the crankshaft, such as pistons and rods and increases with engine speed $\dot{\varphi}$. The mass torque of cylinder l is calculated as follows:

$$\begin{aligned} \tau_{mass,l}(\varphi, \dot{\varphi}, \ddot{\varphi}) &= -\theta_l(\varphi) \frac{d\dot{\varphi}}{d\varphi} \dot{\varphi} - \frac{1}{2} \frac{d\theta_l(\varphi)}{d\varphi} \dot{\varphi}^2 \\ &\approx -\frac{m_l}{2} r^2 \frac{d\dot{\varphi}}{d\varphi} \dot{\varphi} - \frac{1}{2} \frac{d\theta_l(\varphi)}{d\varphi} \dot{\varphi}^2 \end{aligned} \quad (3)$$

where $\theta_l(\varphi)$ stands for the moment of inertia of the oscillating parts of a cylinder l and m_l for the corresponding mass. The moment of inertia $\theta_l(\varphi)$ can be approximated by $\frac{m_l}{2} r^2$ according to Schagerberg [11]. For the stiff crankshaft model, the mass torques of each cylinder $\tau_{mass,l}$ are summed up to the total mass torque τ_{mass} in equation (1). Friction and load torque

are assumed to be constant and can be estimated from the mean value of the indicated torque. Introducing spring and damping elements, as well as splitting up the total moment of inertia in more detailed parts according to figure 1 allows the modeling of torsional effects on the crankshaft [11]. The spring,

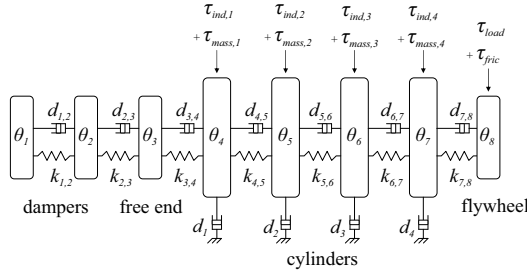


Figure 1: Crankshaft model for $z = 4$

damping and inertia elements can be summarized in damping and stiff matrices $\mathbf{D}$ and $\mathbf{K}$ and leads to the following differential equations:

$$\begin{aligned} \Theta \ddot{\underline{\varphi}} + \mathbf{D} \dot{\underline{\varphi}} + \mathbf{K} \underline{\varphi} \\ = \underline{\tau}_{ind}(\underline{\varphi}) + \underline{\tau}_{mass}(\underline{\varphi}, \dot{\underline{\varphi}}, \ddot{\underline{\varphi}}) + \underline{\tau}_{load}(\underline{\varphi}) + \underline{\tau}_{fric}(\underline{\varphi}). \end{aligned} \quad (4)$$

The rotating moment of inertia matrix Θ represents the dampers at the beginning of the crankshaft, the main bearing journal at the free end, the connecting rod journals and counterweights at the cylinders, as well as the flywheel which is the connection to the drive train. These rotating moments of inertia are summarized in the diagonal matrix Θ as follows:

$$\Theta = \begin{pmatrix} \Theta_1 & 0 & \dots & 0 & 0 \\ 0 & \Theta_2 & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & \Theta_7 & 0 \\ 0 & 0 & \dots & 0 & \Theta_8 \end{pmatrix} \quad (5)$$

The engine speed sensor is mounted in front of the flywheel. Therefore, the flywheel inertia is chosen as the model output for engine speed simulation. The matrices for the damping and stiffness elements have the following symmetric structure:

$$\mathbf{D} = \begin{pmatrix} d_{1,2} & -d_{1,2} & 0 & \dots & 0 & 0 \\ -d_{1,2} & d_{1,2}+d_{2,3} & -d_{2,3} & \dots & 0 & 0 \\ 0 & -d_{2,3} & d_{2,3}+d_{3,4} & \ddots & 0 & 0 \\ \vdots & \vdots & \ddots & \ddots & -d_{6,7} & 0 \\ 0 & 0 & \dots & -d_{6,7} & d_{6,7}+d_{7,8}+d_4 & -d_{7,8} \\ 0 & 0 & \dots & 0 & -d_{7,8} & d_{7,8} \end{pmatrix} \quad (6)$$

$$\mathbf{K} = \begin{pmatrix} k_{1,2} & -k_{1,2} & 0 & \dots & 0 & 0 \\ -k_{1,2} & k_{1,2}+k_{2,3} & -k_{2,3} & \dots & 0 & 0 \\ 0 & -k_{2,3} & k_{2,3}+k_{3,4} & \ddots & 0 & 0 \\ \vdots & \vdots & \ddots & \ddots & -k_{6,7} & 0 \\ 0 & 0 & \dots & -k_{6,7} & k_{6,7}+k_{7,8} & -k_{7,8} \\ 0 & 0 & \dots & 0 & -k_{7,8} & k_{7,8} \end{pmatrix} \quad (7)$$

These spring and damping elements are responsible for torque transmission related to torsion in the crankshaft.

The second order ordinary differential equations in (4) can be transformed into first order ordinary differential equations by a state transformation. The crank angle and the crank angle speed vectors are combined to a state vector $\underline{x}$:

$$\underline{x} = (\underline{\varphi}^T \dot{\underline{\varphi}}^T)^T. \quad (8)$$

The multi-body dynamic crankshaft model can then be described by the following nonlinear differential state space equations:

$$\begin{aligned} \dot{\underline{x}} &= \mathbf{A}(\underline{x})\underline{x} + \mathbf{b}(\underline{x}, \underline{u}) \\ \underline{y} &= \mathbf{H}\underline{x}. \end{aligned} \quad (9)$$

The nonlinear effects are caused by the mass torque. The input vector $\underline{u}$ and the output vector $\underline{y}$ are chosen as follows:

$$\begin{aligned} \underline{u} &= [\tau_{ind1}, \dots, \tau_{ind4}, \tau_{load}]^T \\ \underline{y} &= [\dot{\varphi}_{fe}, \dot{\varphi}_{flwh}]^T. \end{aligned} \quad (10)$$

Then the crank angle velocities at the free end $\dot{\varphi}_{fe}$ and at the flywheel $\dot{\varphi}_{flwh}$ can be simulated. The accuracy of this physical model approach depends highly on the knowledge of the parameters which can be gained from the manufacturer or by parameter identification.

GRAY-BOX MODEL OF THE CRANKSHAFT USING SUBSPACE IDENTIFICATION The main disadvantages of the physical torsional model are the high system order (system order for the example in figure 1 is 16) and the reduced flexibility in the nonlinear state space description through the assumed system structure using the stiffness and damping matrices $\mathbf{D}$ and $\mathbf{K}$. Furthermore, the parameter identification of a nonlinear system is computationally expensive. In order to avoid these difficulties and to achieve higher modeling accuracy, this work focuses on a gray-box modeling identification approach.

In the first step, the model equations (9) need to be linearized. To do this, the mass torque of each cylinder is assumed to be identical. Torsional differences represented in the crank angle are negligible. The