

Evaluation of Nonlinear Estimation Methods for Calibration of a Heat-Release Model

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ABSTRACT

Model-based analysis of in-cylinder pressure sensor signals has been a key component for internal combustion engine research, diagnostics and controller development during the past decades. This analysis is often based on simple thermodynamic models of the in-cylinder processes. In order for the analysis to give accurate results, the models need to be sufficiently calibrated. This paper investigates the use of the extended Kalman filter and the particle filter for the purpose of online estimation of top-dead-center offset, a convective heat-transfer coefficient and cylinder-wall temperature in a Gatowski heat-release model. Simulation results show that the filters are consistent in estimating the true parameters, that the assumed model uncertainty and heat-release noise density works as filter tuning parameters. The filters were found to be sensitive to errors on pressure-sensor offset and the cylinder compression ratio. The filters were also evaluated against experimental data and the result showed converge times of 200 engine cycles with acceptable steady-state variance for both filters.

CITATION: Ingesson, G., Yin, L., Johansson, R., and Tunestal, P., "Evaluation of Nonlinear Estimation Methods for Calibration of a Heat-Release Model," *SAE Int. J. Engines* 9(2):2016, doi:10.4271/2016-01-0820.

INTRODUCTION

Analyzing the measured in-cylinder pressure trace is probably one of the most common ways of trying to understand the processes occurring inside the combustion chamber. In order to understand these processes, models which relate volume change, combustion heat release, heat transfer, gas composition, temperature and mass flow to the in-cylinder pressure are necessary.

A class of simpler models builds upon the first law of thermodynamics and the ideal gas law in order to model the cylinder gases as a system of one or more homogeneous zones without spatial resolution that exchanges work and heat with its boundaries. These models are popular because of their simplicity and ability to predict measured pressure data. One of the earlier models of this class was presented in [1], they modeled the pressure change as the sum of the effects from the polytropic volume change and the combustion process in order to study the mass-fraction burnt. Matekunas et al. [2] instead chose to study this quantity by computing the ratio of the fired pressure curve to the motored pressure curve.

A very popular and slightly more detailed model was presented in [3] where heat transfer to the cylinder walls, thermodynamic properties of the gases and the mass flow to and from crevice volumes were included. Models like the above mentioned have proven to be important tools for engine diagnostics, research studies, control and simulation, however they all have a set of unknown parameters that have to be tuned in order for the models to perform satisfactorily. The tuning of these parameters can be performed manually using experience of how each component of the model should behave and how physical heat release rates should look like, this is however a time-consuming work, that has to be redone from time to time.

The development of automatic calibration methods has been an active research area for the past decades, where automatic methods for calibrating pressure-sensor offset [4], [5], polytropic coefficient [6], [7], volume-curve offset [8], [9] and compression ratio [10] have been presented. In the thesis by Klein, [11], an offline method for simultaneous calibration of a large set of parameters were presented and

studied in detail. Eriksson, [12], concluded that all parameters might not be simultaneously identifiable, this indicates that the calibration problem involving a large set of parameters is not easily solved.

In this paper, a calibration problem which considers a subset of the model parameters in a simplified Gatowski model is formulated as a non-linear estimation problem where unknown states in a dynamic system are to be estimated given a statistical physics-based model and pressure-sensor measurements. The estimation problem is then solved using the extended Kalman filter and the particle filter which are conventional techniques for solving this type of estimation problem. These filters lend themselves nicely for real-time applications because of their sequential processing of data and the increased amount of available computational power in today's computers.

The outline of the paper is to first present the studied model together with the model assumptions, then, the filter algorithms and configurations are presented. In the last sections, filter performance with respect to simulated and experimental data is presented.

THE MODEL

The model considered in this paper is based on Eq. (1).

$$\frac{dp}{d\theta} = -\frac{\gamma}{V} \frac{dV}{d\theta} p + \frac{\gamma-1}{V} \left(\frac{dQ_c}{d\theta} - \frac{dQ_{ht}}{d\theta} \right) \quad (1)$$

where the right hand side relates the pressure, p , derivative with respect to crank-angle degree, θ , to the cylinder volume, V , the combustion heat-release rate, $dQ_c/d\theta$, the heat-transfer rate, $dQ_{ht}/d\theta$, and the ratio of specific heats $\gamma = c_p/c_v$. More detailed models that also take into account for crevice effects, radiation, boundary layers and multiple cylinder zones as presented in [13] were not considered here.

Pressure-Sensor Model

This paper considers in-cylinder pressure measurements using piezo-electric sensors. This measurement technique has good linearity, high cut-off frequency and can handle the tough environment inside the combustion chamber. The relation between the measured pressure p_{meas} and p is given on the form

$$p_{meas} = kp + \Delta p \quad (2)$$

where Δp is a sensor offset and k is a scaling factor. Methods for determining k and Δp are presented in [7]. Here it is assumed that k is known and that Δp is determined by pegging the in-cylinder pressure at inlet-valve closing (IVC) to the measured intake manifold pressure, p_{in} . The measured signal p_{meas} might also be corrupted by current leakage and thermal shocking [14], compensation for such phenomena was not considered here. High-frequency noise in p_{meas} that usually is more significant during the combustion event was attenuated using a zero-phase digital filter.

Cylinder Geometry

The cylinder volume V was modelled as a crank-sliding mechanism

$$V = V_c + \frac{V_d}{2} \left(R - \cos\left(\frac{\pi}{180}\theta\right) + 1 - \sqrt{R^2 - \sin^2\left(\frac{\pi}{180}\theta\right)} \right) \quad (3)$$

where V_d , V_c are displacement and clearance volume, R is the ratio of the connecting rod to the crankshaft length. In this paper this volume curve is assumed to be accurate with known parameters. There is however an unknown crank-angle offset between the assumed volume curve and the true volume curve, this is known as the top-dead center offset, $\theta_{\Delta TDC}$, an offset which greatly degrades the quality of the model in Eq. (1), [15]. Here, $\theta_{\Delta TDC}$ is assumed to be an unknown parameter to be estimated.

Ratio of Specific Heats

The ratio of specific heats, $\gamma = c_p/c_v$, has shown to have a great impact on the model-output error of Eq. (1), [16]. Physically it is determined by the composition and temperature, T , of the in-cylinder gases. In this work it was decided to model this parameter physically using NASA specific-heat tables [13] and the in-cylinder gas temperature. The temperature, T , was determined from intake conditions at IVC,

$$T = \frac{p_{IVC} T_{IVC}}{p_{IVC} V_{IVC}} \quad (4)$$

The gas composition during compression and expansion was determined from the measured EGR- and air-to-fuel ratio. The gas composition is of course non-trivial to determine during combustion, so, the composition during combustion was chosen as an interpolation between the unburnt and burnt gas composition. The species considered were N_2 , O_2 , CO_2 , and H_2O .

Heat-Transfer Model

The convective heat-transfer rate was modelled using Newton's law of cooling

$$\frac{dQ_{ht}}{d\theta} = \frac{h_c A}{60 N_{Speed}} (T - T_w), \quad (5)$$

with wall-surface temperature T_w , combustion-chamber area A and an empirical expression for the convection coefficient h_c

$$h_c = 3.26 B^{0.2} p^{0.8} T^{-0.55} \omega^{0.8}, \quad (6)$$

derived from a Nusselt-Reynolds relation as presented by [17], N_{Speed} is the engine speed in rpm.

In Eq. (6) B is the cylinder bore and ω the cylinder-gas velocity modelled as

$$\omega = C_1 S_p + C_2 \frac{V T_{ivc}}{p_{ivc} V_{ivc}} (p - p_m), \quad (7)$$

where C_1 and C_2 are engine dependent empirical parameters, S_p is the mean piston speed and p_m is the assumed motored pressure curve, alternatives to this model are presented in the works of [18] and [19]. It was discovered that the accumulated heat-transfer rate was much more sensitive to the choice of C_2 than C_1 , this was also found in [16]. The coefficient C_1 was therefore here set fixed to 2.28 while C_2 was being viewed as an unknown parameter to be estimated.

Cylinder Wall Temperature

The cylinder-wall temperature, T_w , is physically determined by the heat transfer from the in cylinder gases, and the heat transfer to the engine coolant with temperature T_c . The cylinder wall and piston head was here modeled as a single mass with conductive coefficient k_c , thickness L_c , mass and specific heat m_c and c_p . Assuming that the wall is in steady state and that the outer wall surface has fixed temperature T_c gives the dynamical equation for T_w

$$\frac{dT_w}{d\theta} = -\frac{2A(h_c + k_c/L_c)}{60N_{Speed}m_c c_p} T_w + \frac{2Ah_c}{60N_{Speed}m_c c_p} (T + T_c), \quad (8)$$

or on more compact form

$$\frac{dT_w}{d\theta} = A_w(\theta)T_w + B_w(\theta)(T + T_c), \quad (9)$$

this model was previously presented in [20], [21].

During the intake (exhaust) stroke, T was assumed to take a constant temperature equal to the measured intake (exhaust) temperature.

Accumulated Heat-Release Assumptions

Using the obtained pressure signal p from Eq. (2) and p_{meas} , Eq. (1) can be inverted in order to estimate the heat-release rate,

$$\frac{dQ_c}{d\theta} = \frac{\gamma}{\gamma-1} p \frac{dV}{d\theta} + \frac{1}{\gamma-1} V \frac{dp}{d\theta} + \frac{h_c A}{60N_{Speed}} (T - T_w). \quad (10)$$

Now if the model is correctly tuned, the accumulated heat release $Q_c = \int dQ_c$ will be flat and zero before the event of combustion, after the combustion event it should be flat at the level given by the burnt fuel energy. Measurement noise and model uncertainty will of course induce errors, therefore, the accumulated heat release before and after combustion, given the correct model parameters, is modeled stochastically according to

$$Q_c(\theta) = \begin{cases} \varepsilon_1 & \theta < \theta_{SOC}, \\ Q_{tot} + d + \varepsilon_2 & \theta > \theta_{EOC}, \end{cases} \quad (11)$$

where $\varepsilon_1 \sim N(0, \sigma_1^2)$, and $\varepsilon_2 \sim N(0, \sigma_2^2)$, are i.i.d normally distributed noise, with standard deviations σ_i , $d \sim N(0, \sigma_d^2)$ is a random offset accounting for variations in the injected fuel energy. A realization of the model output given the correct parameters is presented in Fig. 1.

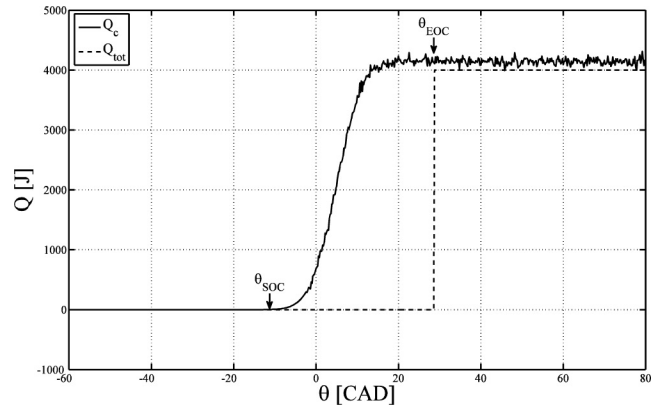


Figure 1. A realization of the statistical model in Eqs. (11), (12), (13). The dashed line represents the expected accumulated heat release before and after combustion without the stochastic variations, the solid line represents an actual accumulated heat release with an offset d and noise ε_2 , here $\sigma_1^2 = 0$, $\sigma_2^2 = 2500$.

The Nonlinear State-Space Model with Gaussian Noise

In order to estimate the unknown model parameters C_2 , $\theta_{\Delta TDC}$ and T_w on a cycle-to-cycle basis using estimation theory, the parameters are assumed to be driven by a Gaussian-noise process v_k which represents the assumed parameter uncertainty, this gives the complete model

$$\begin{bmatrix} C_2^{k+1} \\ \theta_{\Delta TDC}^{k+1} \\ T_w^{k+1} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & \Phi \end{bmatrix} \begin{bmatrix} C_2^k \\ \theta_{\Delta TDC}^k \\ T_{wall}^k \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \Gamma_1 T + \Gamma_2 T_c \end{bmatrix} + v_k, \quad (12)$$

$$\frac{dQ_c}{d\theta} = \frac{\gamma}{\gamma-1} p \frac{dV}{d\theta} + \frac{1}{\gamma-1} V \frac{dp}{d\theta} + \frac{h_c A}{60N_{Speed}} (T - T_w),$$

$$Q_c(\theta) = \begin{cases} \int dQ_c + \varepsilon_1 & \theta < \theta_{SOC}, \\ \int dQ_c & \theta_{SOC} \leq \theta \leq \theta_{EOC}, \\ \int dQ_c + d + \varepsilon_2 & \theta > \theta_{EOC}, \end{cases} \quad (13)$$

where

$$v_k \sim N(0, \Sigma_1), \quad \Phi = e^{\int_{\theta_{BDC}}^{\theta} A_w(\theta) d\theta},$$

$$\Gamma_1 T + \Gamma_2 T_c = \oint e^{\int_{\theta_{BDC}}^{\theta} A_w(\theta) d\theta} B_w(\theta) (T + T_c) d\theta,$$

here, k denotes cycle index and the covariance matrix Σ_1 gives a measure of the model uncertainty. An initial distribution is also assumed according to