Chapter 9

Model-Based Condition and State Monitoring of Large Marine Diesel Engines

Daniel Watzenig, Martin S. Sommer and Gerald Steiner

Additional information is available at the end of the chapter

http://dx.doi.org/10.5772/55267

1. Introduction

Although the history of diesel engines extends back to the end of the nineteenth century and in spite of the predominant position such engines now hold in various applications, they are still subject of intensive research and development. Economic pressure, safety critical aspects, compulsory onboard diagnosis as well as the reduction of emission limits lead to continuous advances in the development of combustion engines.

Condition monitoring and fault diagnosis represent a valuable set of methods designed to ensure that the engine stays in good condition during its lifecycle, [7] and [13]. Diagnosis in the context of diesel engines is not new and various approaches have been proposed in the past years, however, recent technical and computational advances and environmental legislation have stimulated the development of more efficient and robust techniques. In addition, the number of electronic components such as sensors or actuators and the complexity of engine control units (ECUs) are steadily increasing. Meanwhile, most of the software running on the main ECU is responsible for condition monitoring of sensor signals, monitoring parameter ranges, detecting short/open circuits, and verifying control deviations. However, these kinds of condition monitoring systems (CMS) are not designed to detect and clearly identify different engine failures, sensor drifts and to predict developing failures, i.e. to asses degradation of certain components right in time. Especially the reliable detection and separation of engine malfunctions is of major importance in various fields of industry in order to predict and to plan maintenance intervals.

Diesel engines usually consist of a fuel injection system, pistons, rings, liners, an inlet and exhaust system, heat exchangers, a lubrication system, bearings and an ECU. For the design of an efficient CMS it is essential to know as much as possible about the underlying thermodynamical processes and possible faults and malfunctions. This information can be seen as *a-priori* knowledge and can be used to increase the robustness of fault detection algorithms.

In the following, common diesel engine faults and fault mechanisms, and their causes are listed.

- power loss caused by misfire and blow-by.
- emission change caused by loss of compression, turbocharger malfunction, blocked fuel filter, incorrect injector timing, poor diesel fuel, incorrect fuel air ratio, air intake filter blocked, incorrect piston topping, or ECU malfunction etc.
- lubricating system fault due to incorrect oil pressure and oil deterioration
- thermal overload as a result of one or a combination of leaking injection valves, piston ring-cylinder wear or failure, eroded injector holes, too low injection pressure, high engine friction, misfire, leaking intake or exhaust manifold/valves, high coolant or lubricant temperature etc.
- leaks in the fuel injection system, lubrication system, or air intake
- wear of the piston caused by either corrosion or abrasion, or both
- noise and vibration caused by the impact of one engine part against another (mechanical noise), vibrations resulting from combustion, intake and exhaust noise
- other faults like knocking, filter faults, fuel contamination and aeration

The main challenge in engine fault detection is the ambiguity between faults and causes. Certain engine faults may be caused by a combination of causes (with different weightage). The assessment of engine states from sparse measurement data as well as a reliable assignment of failure effects and causes are an active research field. The problems relating to marine diesel engines, especially medium- and high-speed engines, are due mainly to their large size and their high operating speed. Occurring faults of marine diesel engines which are on the high seas for several months may lead to expensive holding times. On the other hand, additional sensors and measurement equipment for condition monitoring are usually undesirable since engines have to be modified to place those additional sensors. Such additional sensors are e.g. viscosity sensors to sense oil degradation as described by [12] and [1], or acoustical sensors to determine faults based on acoustical pressure and vibration signals measurements as can be found in [5], [11], and [2].

A topical review on different fault diagnosis methods for condition monitoring can be found in [7]. Both standard methods (Fourier analysis of pressure, torque, power, crankshaft speed and vibration signals) and advanced methods (neural networks, fuzzy techniques) are encountered and briefly described. [14] discuss the detection of a single fault in a statistical framework (hypotheses testing) by measuring acoustic emission energy signals and applying an independent component analysis. However, most methods usually rely on heuristic knowledge and on a data training phase as well as on the specification of threshold levels in order to assign states as faulty or non-faulty. Since the last decade, a paradigm shift from classical signal processing and feature extraction to computationally expensive model-based CMS can be observed. In contrast to classical condition monitoring, model-based methods can manage distributed and multiple correlated parameters, as described by [16] and [13]. They cover a wide variety of states since the engine behavior is described in terms of physical relationships and hence, parameters that influence certain parts of the first principles equations can be isolated or at least correlations can be determined. Three different methods to estimate the compression ratio from simulated cylinder pressure traces are presented in [8] and compared in terms of estimation accuracy and computation time. By reconstructing only one single failure based on polytropic compression and expansion of the cylinder pressure significant results have been reported. However, the detection of multiple failures from in-cylinder pressure measurements is still an open issue. Different Fuzzy-based methods also provide remarkable results for detecting only one single fault such as in [3], [4], [17], and [18].

In this work the main focus is on a robust model-based identification and separation of two common failure modes of large marine diesel engines by accurately modeling the underlying thermodynamic process. These two failures, which cause very similar changes in the cylinder pressure, are

- changes in the compression ratio primarily leading to emission and power changes
- increased blow-by mainly resulting in a loss of power.

Following a model-based approach, it is possible to identify the above mentioned failures and to clearly separate them given uncertain measurement data with low sampling rate (1° of crank angle). By measuring only cylinder pressure traces of every cylinder, the symptoms due to faults are determined, [8]. Two different approaches – ratiometric and nonlinear parameter estimation – are investigated, validated with measured data and compared to each other in terms of performance, accuracy, and robustness given sensor drift and uncertain measurements, [15].

2. The thermodynamical process model

Various approaches to model diesel engines have been proposed in literature, however, the main focus is on small-size engines that are commonly used in the automotive industry. The typical differential equations that represent the thermodynamic processes, i.e. the interrelationship between system pressure, temperature and mass can be found in [6], [9], and [10].

Since in this work, identification of blow-by and compression ratio is of primary interest, a simplified thermodynamical model capable of running in real-time is developed. Note that a list of symbols used in the following equations is given at the end of this chapter. The main reason for compression losses are referred to as damages of the piston crown during the combustion phase leading up to an increasing volume V_0 in the top dead center (TDC) of the piston. In the equation for the volume V in the cylinder the constant volume fraction V_0 is represented by the term $h_0 \cdot A$ with h_0 being the compression parameter and A the cross-sectional area of the cylinder. In the time-varying fraction of the volume equation ω denotes the instantaneous angular velocity of the crankshaft and ΔV the maximum volume deviation related to the movement of the piston. By also taking into account the ratio λ of the crank radius to the length of the connecting rod regarding to the equation of a standard crank mechanism the equation for the volume and its time derivative can be summarized as follows

$$V = h_0 \cdot A + \frac{\Delta V}{2}\left[(1-\cos(\omega t)) + \frac{1}{\lambda}\cdot\left(1-\sqrt{1-\lambda^2\sin^2(\omega t)}\right)\right] \tag{1}$$

$$\frac{\mathrm{d}V}{\mathrm{d}t} = \frac{\Delta V}{2}\cdot\omega\cdot\sin(\omega t)\left(1+\frac{\lambda\cos(\omega t)}{\sqrt{1-\lambda^2\sin^2(\omega t)}}\right) \tag{2}$$

For the length of the connceting rod being large compared to the crank radius the terms including λ in Equation (1) and (2) can be neglected.

The time derivative of the mass fraction passing by the piston is described by

$$\frac{\mathrm{d}m}{\mathrm{d}t} = \tilde{k}\frac{1}{\sqrt{T}}p \tag{3}$$

with $\tilde{k}$ denoting the parameter for blow-by. For simplicity, for the *healthy state* of the cylinder it is assumed that the effect of blow-by as well as wear of the piston can be neglected. Because of the fact that blow-by is rapidly increasing when it comes to a tear-off of the oil film between piston and liner due to the loss of the sealing function of the oil the simple model of $\tilde{k}$ as a constant is not sufficient. To model this nonlinear behavior a sigmoid function described by

$$\tilde{k}(p) = \frac{\tilde{k}_{\mathrm{max}}}{1 + \mathrm{e}^{-a(p-b)}} \tag{4}$$

is used where b describes the pressure when 50% of the maximum blow-by is reached and a denotes the ascending slope of the sigmoid function as illustrated in Figure 1, [15]. For the

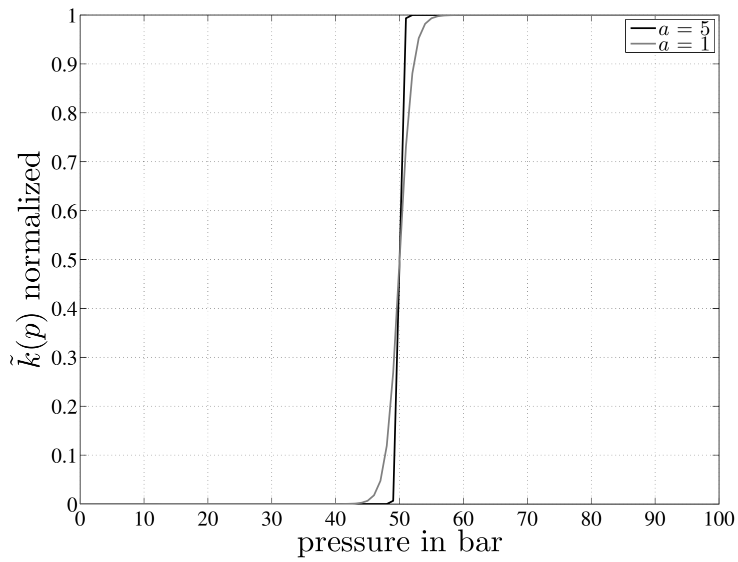

Figure 1. Sigmoid function to describe the nonlinear behavior of blow-by related to the cylinder pressure. The rapid increase of the mass passing by the cylinder results from the tear-off of the oil film at the piston crown.

complete thermodynamical description the equations for the temperature T as well as the in-cylinder pressure p represented by

$$\frac{\mathrm{d}T}{\mathrm{d}t} = T_{\mathrm{in}} - \frac{p}{mc_v}\frac{\mathrm{d}V}{\mathrm{d}T} - \frac{kV^{\alpha_1}T^{\alpha_2}p^{\alpha_3}}{mC_v} \tag{5}$$

$$\frac{\mathrm{d}p}{\mathrm{d}t} = \left(RT\frac{\mathrm{d}m}{\mathrm{d}t} + R\frac{\mathrm{d}T}{\mathrm{d}t}m - p\frac{\mathrm{d}V}{\mathrm{d}t}\right)\frac{1}{V} \tag{6}$$

are needed containing the isochore heat capacitance C_v and the rapid increase of the temperature in the cylinder during the combustion phase T_{in} in Equation 5 and the ideal gas constant R in Equation 6. Since during our investigations only the failure parameters during the compression phase are of interest, T_{in} can be neglected. Regarding our assumption of the *healthy state* of the diesel engine with blow-by and piston wear being negligible the pair $[h_0\ \tilde{k}] = [0.15\ 0]$ for the compression and blow-by parameter has been identified.

NOMENCLATURE

h_0	compression parameter	m
A	cylinder cross–sectional area	m^2
V	cylinder volume	m^3
ΔV	maximum volume deviation	m^3
m	mass of the mixture	kg
T	temperatur of the mixture	$^\circ$K
p	cylinder pressure	bar
R	ideal gas constant	J/(mol·K)
c_v	isochore heat capacitance	J/(kg·K)
$\tilde{k}$	blow–by parameter	
k	constant	
α_1	power of volume	
α_2	power of temperature	
α_3	power of pressure	

3. Measurement noise model

In order to obtain the goals of reliability and estimation robustness common perturbations of the cylinder pressure signal like detection uncertainties of the TDC, pressure offset p_0, and measurement noise $\mathbf{n}_k$ have to be analyzed and characterized. While the TDC offset is corrected by the manufacturer and the pressure offset can be included in the nonlinear parameter estimation approach, the task lies in finding an adequate probability density function (PDF) of the measurement noise. According to Figure 2 the measurement noise is modeled using a *Gaussian* PDF represented by

$$p(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{(x-\mu)^2}{2\sigma^2}\right], -\infty < x < \infty \tag{7}$$

where μ denotes the mean and σ^2 the variance of the random variable x. Figure 2 shows the noise data extracted from several measurements of the cylinder pressure together with the Gaussian distribution $\mathcal{N}(0,\ \sigma^2)$. Therefore, there exists no additional offset in the pressure signal due to measurement noise. The range of the analysis window of $[-90,\ -40]$ degrees to the TDC for the determination of the noise PDF was selected according to the reasonable signal to noise ratio (SNR) in this area.

4. Condition monitoring algorithms

Within this section two different model-based algorithms for condition monitoring of large diesel engine states are introduced and discussed. In the following both failures types – increased blow-by and decreased compression ratio – are denoted as errors. Thus the term compression error is used for a decreased compression ratio.

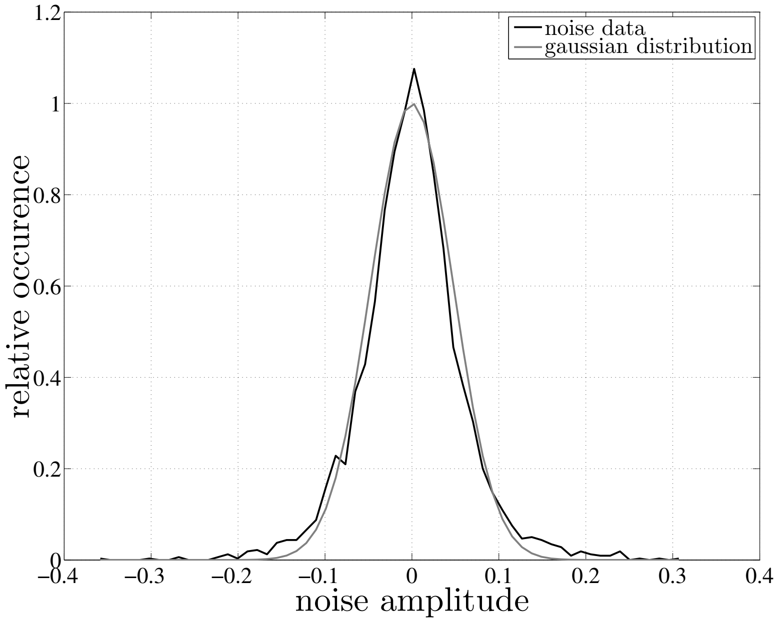

Figure 2. Histogram of the measurement noise (repeated measurements) compared to a *Gaussian* PDF (both curves are normalized by $1/\sqrt{(2\pi\sigma^2)}$).

4.1. Ratiometric approach

The main advantages of using a ratiometric approach lie in the independency of a pressure offset in the measurement data and therefore there is one disturbance variable less to be determined, the simple implementation of the method and the calculation speed. In Figure 3 all parameters for the determination of the ratiometric parameter

$$q = \frac{P_{\max} - P_{\min}}{P_2 - P_1} \tag{8}$$

are displayed together with two typical traces of the in-cylinder pressure of a large diesel engine. The dashed curve represents the *healthy state* whereas the solid curve reflects a cylinder state with increased compression error. The ratiometric parameter q allows to find dependencies between the error parameters h_0 and $\tilde{k}$ and the position of the analysis window $[\varepsilon_1, \varepsilon_2]$ within the compression phase. Due to the fact that blow-by has a strong nonlinear behavior causing its main influence only at hight pressures near the TDC, two analysis windows were used with the lower window being placed before and the upper window behind the inflection point of the cylinder pressure trace. To gain additional information the pressure traces in the two intervals of interest are approximated by polynomials of the form

$$P(\theta) = P_1 + a_1\theta + a_2\theta^2 + a_3\theta^3 \,. \tag{9}$$

As before, the *healthy state* (0% error) of the engine is described by the pair $\left[h_0\ \tilde{k}\right] = [0.15\ 0]$. Additionally, the maximum error (100% error) is defined by $\left[h_0\ \tilde{k}\right] = \left[0.16\ \ -2 \times 10^{-5}\right]$. The procedure is described by a case study with simulated data with 70% compression and 10% blow-by error. (see Figures 4 to 6).

The first parameter to be evaluated is the ratiometric parameter q. As can be seen in Figure 4, q alone is not sufficient to distinguish between the two failure modes. Therefore the additional

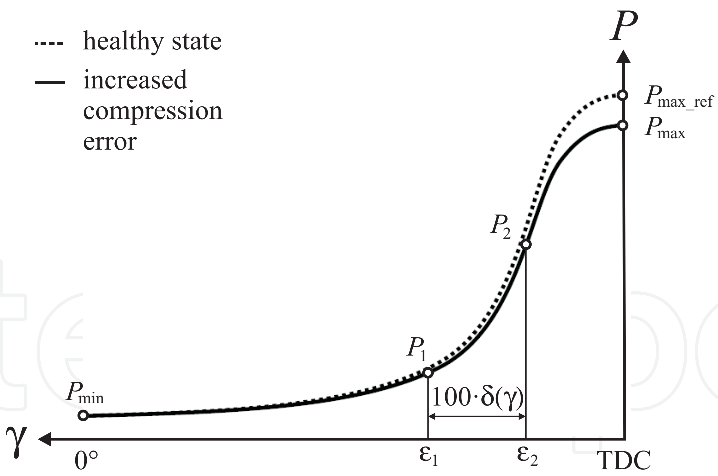

Figure 3. Typical cylinder pressure traces representing a *healthy state* (dashed) and a cylinder with increased compression error (solid). The analysis window $\delta(\gamma)$ is applied within the well-defined compression phase in order to avoid the influence of combustion effects as well as measurement noise at low signal levels.

parameters slope a_1 and curvature a_2 need to be evaluated for failure separation. As can be seen in Figure 5 the compression failure is overestimated by $\sim$ 10% and a separation of the two failure modes is still not possible, respectively. The evaluation of the curvature information a_2 depicted in Figure 6 allows the distinction between compression and blow-by error but the compression error is still overestimated. Because of the small values of a_2 the disturbance of the curve by measurement noise with $\sigma = 0.047354$ bar becomes visible. In this sensitivity to measurement noise lies the main drawback for this method. Therefore, for the utilization of the ratiometric principle on real measurement data, Equation 8 for the calculation of the ratiometric parameter has to be modified to

$$q_{\text{mod}}(\theta) = \frac{P_{\text{defect}}}{P_{\text{healthy}}} \tag{10}$$

with P_{defect} representing a cylinder with either blow-by or compression failure.

In Figure 7 the different curvature of q_{mod} can be determined. As can be seen the greatest differences occur at crank angles close to the TDC which are partly outside of the observation window limited by the upper bound of -8° to the TDC.

In Table 1 the coefficients according to Equation 9 are summarized for three cylinders with known failure sources of two different engines excluding the pressure offset. Here the different signs for the coefficients a_1 and a_3 for blow-by and compression failure have to be noted.

occurred failures	a_1	a_2	a_3
increased blow-by	-3.99×10^{-4}	-3.57×10^{-6}	-1.09×10^{-8}
changed compression ratio	5.38×10^{-3}	-4.99×10^{-4}	1.62×10^{-5}
	3.32×10^{-3}	-3.98×10^{-4}	1.29×10^{-5}

Table 1. Coefficients of the fitting polynomial.

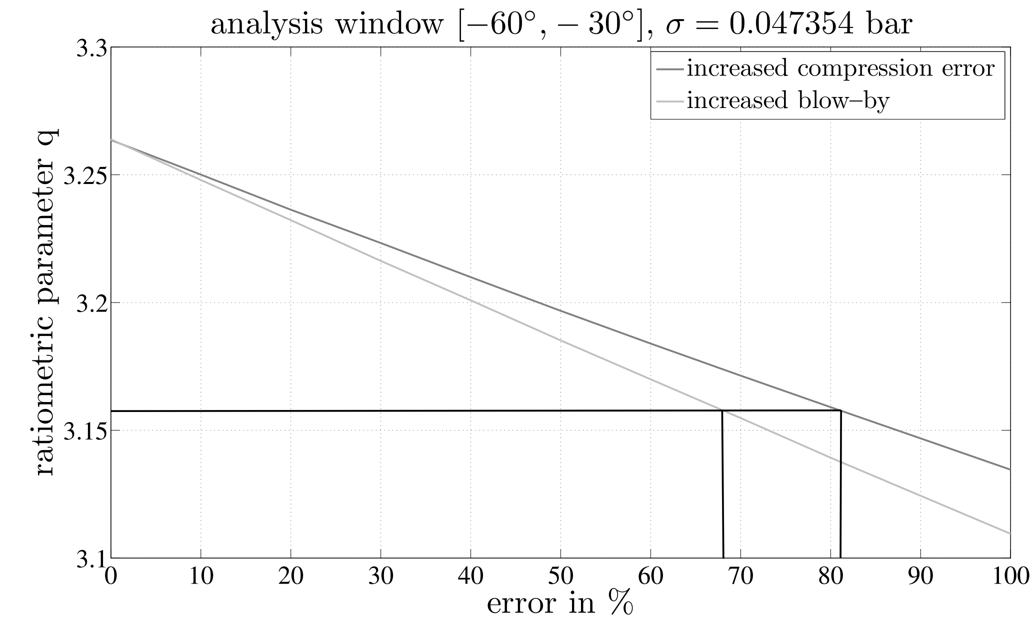

Figure 4. Ratiometric parameter q for the lower analysis window $[-60°, -30°]$ to TDC ($q = 3.1587$). The lines for compression and blow-by error are proceeding too close for a failure separation.

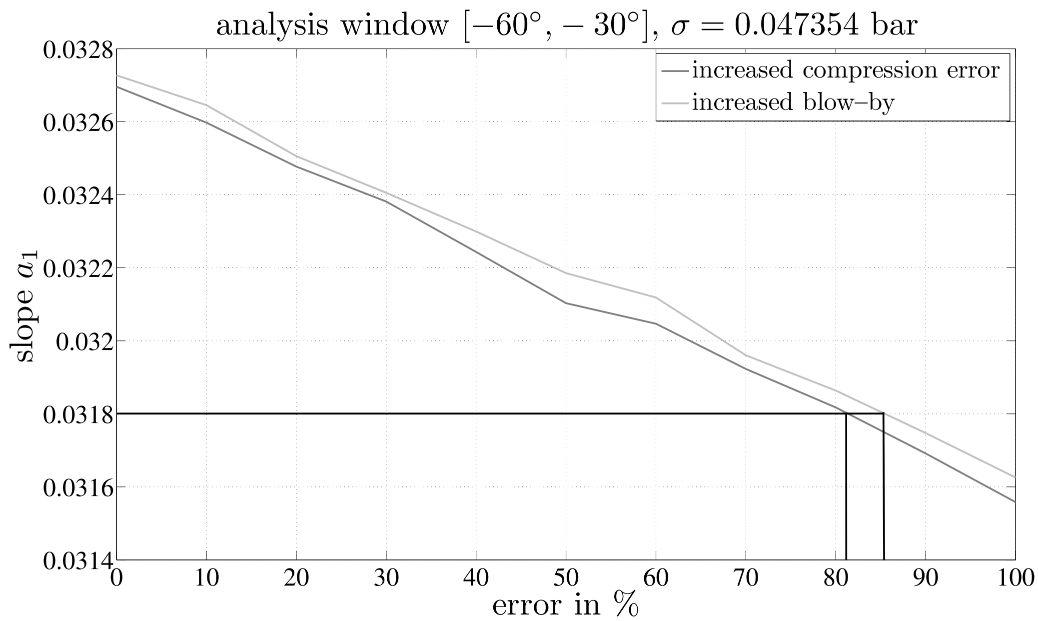

Figure 5. Slope parameter a_1 for the lower analysis window $[-60°, -30°]$ to TDC ($a_1 = 3.180 \times 10^{-2}$). The lines for compression and blow-by error are still too close together for a separation of the failure modes.

Due to the limitations and the fact that the ratiometric approach only allows a qualitative statement led to the development of a nonlinear parameter estimation approach.

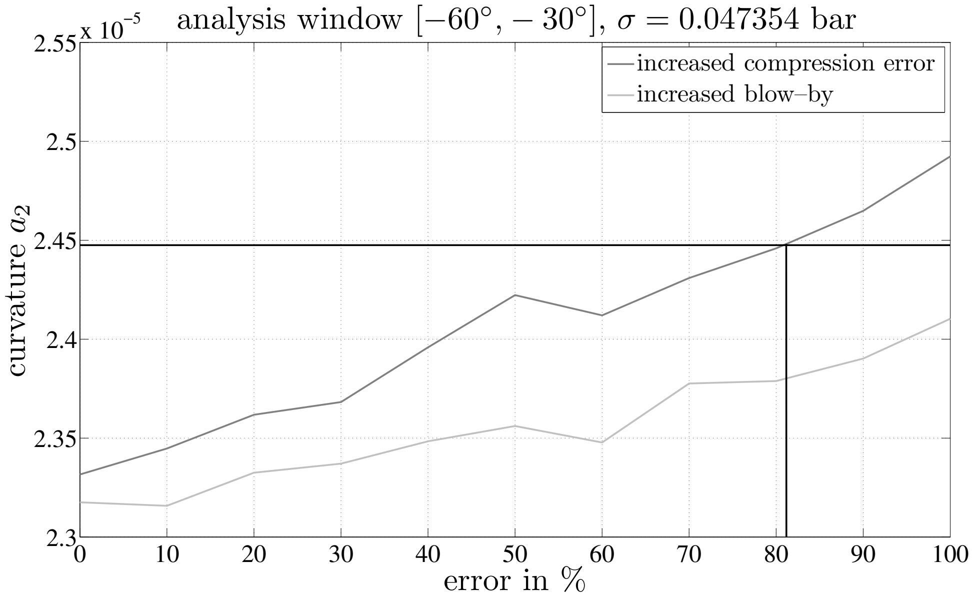

Figure 6. Curvature parameter a_2 for the lower analysis window $[-60°, -30°]$ to TDC ($a_2 = 2.447 \times 10^{-5}$). Because there is only one failure mode in the allowed range a_2 allows the separation between blow-by and compression error.

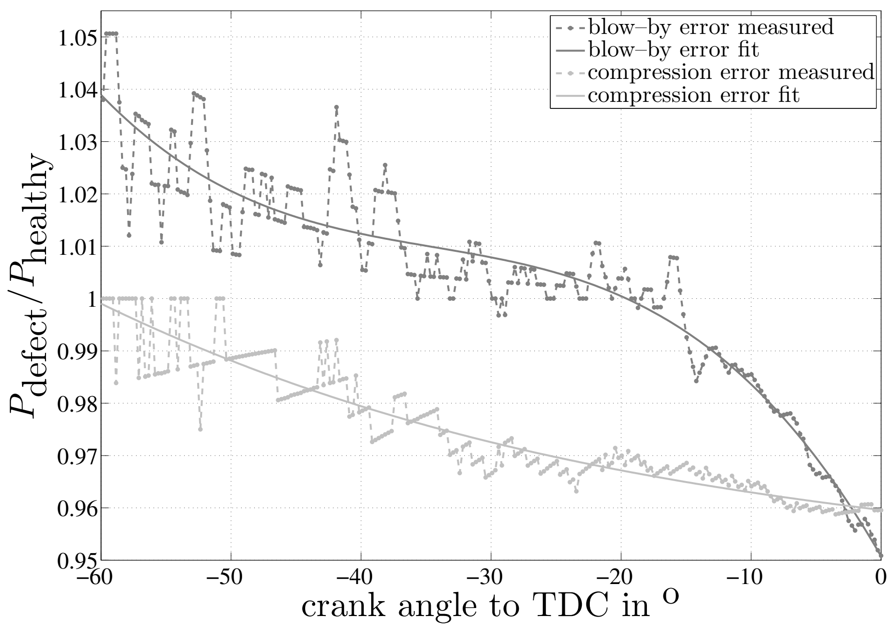

Figure 7. Comparison of the ratio $P_{defect}/P_{healthy}$ for an engine showing blow-by error and compression error respectively showing different curvature in their slopes especially in the interval $[-40°, 0°]$.

4.2. Nonlinear parameter estimation

The proposed approach aims at finding a parameter vector $\boldsymbol{\theta} = [h_0\ \tilde{k}\ p_0]^T$ which is comprised of the compression ratio h_0, the blow-by parameter $\tilde{k}$ and the pressure offset p_0 by minimizing the L_2-norm of the error $\|e\|_2^2 \rightarrow \min$ between measured data and computed cylinder pressure in a nonlinear least squares sense for each cycle. The block diagram is shown in Figure 8. The disturbance of the data $\tilde{\mathbf{y}}_k$ due to measurement noise $\mathbf{n}_k$ is considered by an additional summation node with the output $\mathbf{y}_k$ representing the corrupted data. The thermodynamic

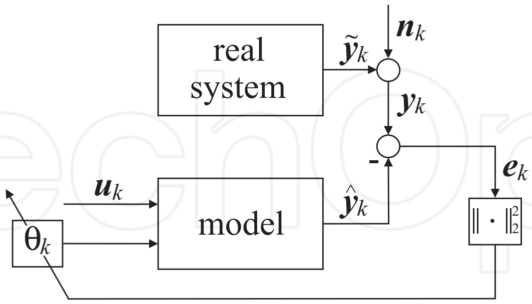

Figure 8. Block diagram of the parameter identification of large diesel engines. The index k indicates the iterative nature of the optimization procedure. By minimizing the residual error between measured and calculated cylinder pressure, the optimal parameter configuration for blow-by and compression ratio is found. Based on the *a priori* known limits of the parameters, the engine state can be assessed and monitored.

model is calibrated for a measured *healthy state* prior to the parameter identification by adapting the parameter vector $\boldsymbol{u} = [\alpha_1\ \alpha_2\ \alpha_3\ R\ c_v\ k]^T$. The parameter identification problem consists of finding the set of parameters $\boldsymbol{\theta} \in \mathbb{R}^n$ that minimizes the target function $f(\boldsymbol{\theta})$ at a single point. The inequality constraints simultaneously have to be satisfied at this single point where both the target and constraint functions depend on the parameter vector. The objective is to find a parameter configuration that satisfies

$$\begin{aligned} &\min_{\boldsymbol{\theta}}\ f(\boldsymbol{\theta}) = \min_{\boldsymbol{\theta}} \|\mathbf{y}_k - \hat{\mathbf{y}}_k(\boldsymbol{\theta})\|_2^2 \\ &\text{s.t.}\quad \mathbf{b}_l \leq \boldsymbol{\theta} \leq \mathbf{b}_u \end{aligned} \tag{11}$$

where $\mathbf{y}_k$ denotes the measured cylinder pressure and $\hat{\mathbf{y}}_{\mathbf{k}}(\boldsymbol{\theta})$ represents the estimated cylinder pressure based on the thermodynamic model. The bounds $\mathbf{b}_l$ and $\mathbf{b}_u$ are the lower and the upper bound for the unknown parameter vector, i.e. the imposed constraints on the parameters to be reconstructed from measured data.

In order to mask out undesired effects of the starting combustion close to the TDC and the low SNR at small cylinder pressures, a window function $\delta(\gamma)$ is applied to the measured cylinder pressure $\mathbf{y}_k$ according to Equations (12) and (13). The proposed rectangular window is mainly restricted to the compression phase. If the entire signal $\mathbf{y}_k$ is provided to the parameter identification problem, a robust detection and identification of blow-by and compression ratio failures is impossible since various other effects influence the cylinder pressure during combustion.

$$\mathbf{z}_k = \delta(\gamma)\mathbf{y}_k \tag{12}$$

$$\delta(\gamma) = \begin{cases} 1 & \text{if } \varepsilon_1 \leq \gamma \leq \varepsilon_2 \\ 0 & \text{else} \end{cases} \tag{13}$$

where $\gamma \in [0\ 360]$ denotes the crank angle in degrees. The lower and upper bound for the analysis window are given by $\varepsilon_1 = \text{TDC} - 120°$ and $\varepsilon_2 = \text{TDC} - 8°$. The model-based estimation of $\boldsymbol{\theta}$ is based on the windowed signal $\mathbf{z}_k$ by solving the constrained nonlinear optimization problem (11). Signal parts with low signal magnitude as well as the signal part that corresponds to the combustion phase depicted in Figure 3 are cut off for the estimation procedure. The dashed curve representing the *healthy state* is used to calibrate the thermodynamical model by adapting the model parameter vector $\mathbf{u}$.

5. Condition monitoring results

In the following, results for two measured data sets of different engines containing single blow-by and single compression ratio failure are presented. For the evaluation of the source of defect the engines were disassembled by the manufacturer. The reason for lower compression ratios was identified as burn-off of the piston crown whereas increased blow-by occurred due to defects of the crankcase cover gasket. The model limits for the parameters to be estimated are $h_0 = [0.15 \;\; 0.16]$ and $\tilde{k} = [0 \;\; -2 \times 10^{-5}]$ corresponding to [0% 100%] of failure. The main objective is to identify and to quantify the occurring failures. Figure 9 illustrates the pressure traces of a five cylinder diesel engine, respectively.

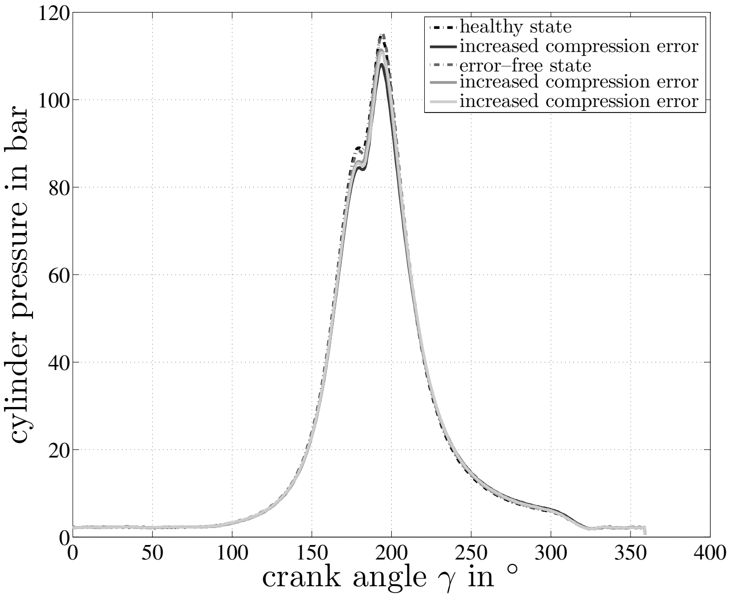

Figure 9. Measured cylinder pressure traces representing a *healthy state* and cylinders with increased compression error of one specific engine.

In both cases the sources of defect were known. Because blow-by errors often lead to severe damages of the engine most of the time the crankcase cover gaskets are replaced before the error occurs and therefore there exist only a few data sets where blow-by is documented.

Figure 10 shows such a case for one cylinder of a seven cylinder diesel engine. As can be seen the single pressure traces are close together up to the TDC. As the observation window is limited by -8° to the TDC, the area with the greatest change in the cylinder pressure cannot be used which makes the detection and separation of the interesting failures a challenging task. For quantification the model limits for the parameters to be estimated are again $h_0 = [0.15 \;\; 0.16]$ for compression and $\tilde{k} = [0 \;\; -2 \times 10^{-5}]$ for blow-by corresponding to [0% 100%] of failure. Table 2 summarizes the results of the estimated parameter vector $\boldsymbol{\theta}$ with varying upper bound ε_2 of the analysis window. The first block indicates increased blow-by given the

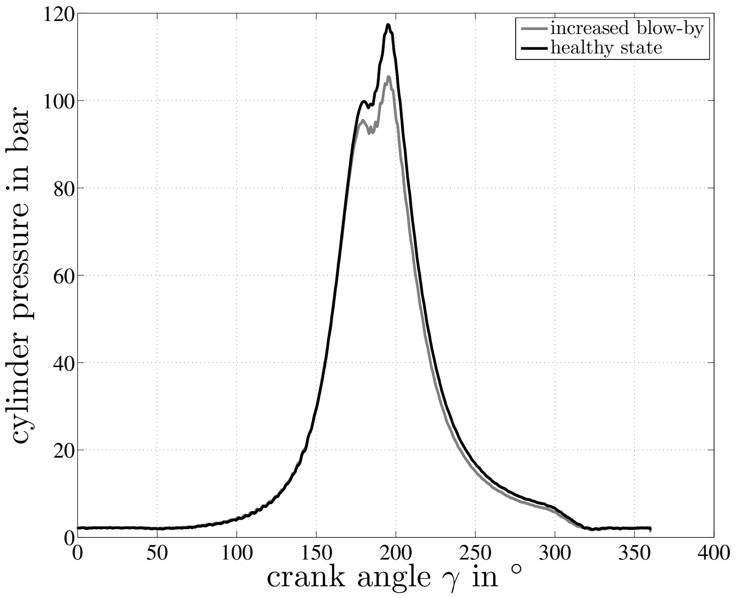

Figure 10. Measured cylinder pressure representing a *healthy state* and one cylinder with increased blow-by of a different engine. The sources of defect were in both cases documented by the manufacturer after disassembly of the machine.

desired compression ratio while in the second block a changed compression ratio is clearly identified.

occurred failures	γ−TDC	h_0	$\tilde{k}$
increased blow-by	−8°	0.150	$\mathbf{-1.84 \times 10^{-5}}$
	−9°	0.150	$\mathbf{-1.67 \times 10^{-5}}$
	−10°	0.150	$\mathbf{-1.99 \times 10^{-5}}$
changed compression ratio	−8°	**0.154**	-3.01×10^{-15}
	−9°	**0.154**	-2.72×10^{-15}
	−10°	**0.154**	-1.72×10^{-15}

Table 2. Results for estimated blow-by and compression ratio.

The blow-by estimate remains very small denoting that blow-by has not increased. In addition, the nonlinear approach exhibits a robust parameter estimation behavior given uncertainties in TDC within a certain range.

6. Conclusions

This book chapter addresses different methods for robust detection of increased blow-by and compression faults from measured cylinder pressure traces of large marine diesel engines. By modeling the underlying thermodynamic process, including prior knowledge about the system, and characterizing the measurement noise, faults can be detected and isolated from each other even in the presence of sensor drift.

The ratiometric approach allows only qualitative statements and can not clearly distinguish between the two failure modes blow-by and compression losses. The main drawbacks of the algorithm are its sensitivity to measurement noise and the fact that crank angles close to the TDC are required to see a proper curvature in the ratio of the pressure. On the other hand, the method is very fast due to its simplicity and independent to a pressure offset in the measurement signal. In contrast, the nonlinear parameter estimation methodology features higher accuracy in estimation results and allows to distinguish between certain types of faults, however, introducing a greater modeling effort and computational costs.

The applicability of the model-based approaches is verified by measurement data given information about the sources of defect of the engine. Due to the low sampling interval of 1° of the crank angle the condition monitoring system (CMS) exhibits real-time performance. The robustness is investigated by analyzing the statistics of the estimated parameters of blow-by and compression ratio. Furthermore, the influence of the upper limit of the analysis window close to the TDC is examined. The detection of these failures can be used in order to predict maintenance intervals. Based on cylinder pressure traces the proposed methods feature the applicability to other domains including large trucks, rail vehicles, and stationary power stations.

Author details

Daniel Watzenig
Graz University of Technology and Virtual Vehicle Research Center, Austria

Martin S. Sommer
Graz University of Technology, Austria

Gerald Steiner
Graz University of Technology, Austria

7. References

[1] Agoston, A., Ötsch, C. & Jakoby, B. [2005]. Viscosity sensors for engine oil condition monitoring–application and interpretation of results, *Sensors and Actuators A: Physical* Vol. 121: 327–332.

[2] Barelli, L., Bidini, G., Buratti, C. & Mariani, R. [2009]. Diagnosis of internal combustion engine through vibration and acoustic pressure non-intrusive measurements, *Applied Thermal Engineering* Vol. 34: 1707–1713.

[3] Çelik, M. & Bayir, R. [2007]. Fault detection in internal combustion engines using fuzzy logic, *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering* Vol. 221: 579–587.

[4] Cruz-Peragon, F., Jimenez-Espadafor, F., Palomar, J. & Dorado, M. [2008]. Combustion faults diagnosis in internal combustion engines using angular speed measurements and artificial neural networks, *Energy & Fuels* Vol. 22: 2972–2980.

[5] Geng, Z. & Chen, J. [2005]. Investigation into piston-slap-induced vibration for engine condition simulation and monitoring, *Journal of Sound and Vibration* Vol. 282: 735–751.

[6] Heywood, J. B. [1988]. *Internal Combustion Engine Fundamentals*, McGraw-Hill.

[7] Jones, N. B. & Li, Y.-H. [2000]. A review of condition monitoring and fault diagnosis for diesel engines, *Tribotest Journal* Vol. 6(No. 3): 267–291.

[8] Klein, M. & Eriksson, L. [2006]. Methods for cylinder pressure based compression ratio estimation, 2006-01-0185, *SAE Technical Paper Series, SAE World Congress, Detroit, USA, April 3-6*.

[9] Kouremenos, D. A. & Hountalas, D. T. [1997]. Diagnosis and condition monitoring of medium-speed marine diesel engines, *Tribotest Journal* Vol. 4(No. 1): 63–91.

[10] Liu, H.-Q., Chalhoub, N. G. & N.Henein [2001]. Simulation of a single cylinder diesel engine under cold start conditions using simulink, *Journal of Engineering for Gas Turbines and Power* Vol. 123: 117–124.

[11] Liu, S., Gu, F. & Ball, A. [2006]. Detection of engine valve faults by vibration signals measured on the cylinder head, *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering* Vol. 220: 379–386.

[12] Macián, V., Tormos, B., Olmeda, P. & Montoro, L. [2003]. Analytical approach to wear rate determination for internal combustion engine condition monitoring based on oil analysis, *Tribology International* Vol. 36: 771–776.

[13] McDowell, N., Wang, X., Kruger, U., McCullough, G. & Irwin, G. [2006]. Fault diagnosis for internal combustion engines, *Automation Technology in Practice* Vol. 3: 19–26.

[14] Pontoppidan, N. H., Sigurdsson, S. & Larsen, J. [2005]. Condition monitoring with mean field independent components analysis, *Mechanical Systems and Signal Processing* Vol. 19: 1337–1347.

[15] Watzenig, D., Steiner, G. & Sommer, M. S. [2008]. Robust estimation of blow-by and compression ratio for large diesel engines based on cylinder pressure traces, *Instrumentation and Measurement Technology Conference, IMTC 2008*, pp. 974–978.

[16] Woud, J. K. & Boot, P. [1993]. Diesel engine condition monitoring and fault diagnosis based on process models, *20th International Congress on Combustion Engines, London*.

[17] Wu, J.-D., Chiang, P.-H., Chang, Y.-W. & j. Shiao, Y. [2008]. An expert system for fault diagnosis in internal combustion engines using probability neural networks, *Expert Systems with Applications* Vol. 34: 2704–2713.

[18] Yong, X., Guiyou, H., Chunrong, S., Zhibing, N. & Wu, Z. [2010]. Reconstruction of cylinder pressure of i.c. engine based neural networks, *2010 First International Conference on Pervasive Computing, Signal Processing and Applications*.