

Chapter 2

Exhaust Gas Concentrations Estimation in Diesel Engines

2.1 Introduction

Driven by the advancements in diesel engines and especially due to the stringent regulations in the recent years that have enhanced the introduction of the after-treatment (AT) systems, the control and diagnostic logics in the modern ECU are accomplishing a renewal. The typical configuration of a short route EGR and a variable geometry turbine (VGT) shall be extended to include dual EGR loops, and different systems for eliminating particles, hydrocarbons and NO_x in the exhaust. This modernisation must be run jointly with the improvements in the ways of retrieving information from the states of the engine, particularly from engine-out concentrations. This chapter gives an overview on the actual state on technologies related with diesel engine and the different sources of information from the exhaust gas concentration on diesel engines: sensors, models and adaptive estimators. A specific discussion about the λ and NO_x estimation in CI engines is made due to their relevance in the present dissertation.

2.2 Diesel Engine Subsystems

There exists different possible diesel engine layouts, but they all share at some point the following subsystems (Bosch 2011): the fuel path, the air path, the after-treatment and the control system.

2.2.1 The Fuel Path System

The common-rail (CR) system and the direct injection (DI) is standard in current diesel engines (Schommers et al. 2000). The main advantages of the CR against

other systems, such as the distributor pump and the unit pump injector, are the multiple injections and the control flexibility. A pressurised deposit monitored by a rail pressure sensor is capable of maintaining the pressure highly constant during the injection.

In the ECU, the total injected fuel mass (m_f) is modelled by a look-up table function of the injection duration (t_{id}) and the rail pressure (p_{rail}). The SOI actuation (u_{soi}) is determined by a calibrated look-up table as function of speed (n) and the desired m_f and is measured in degrees with respect to the top dead centre (TDC). In the case of sharp load steps and in order to avoid the excessive emissions of HC and soot, the smoke limiter function limits m_f until the air path responds and supplies the air mass flow (\dot{m}_a) required for the combustion, as depicted later in Fig. 2.2.

$$m_f = f(t_{id}, p_{rail}) \quad (2.1a)$$

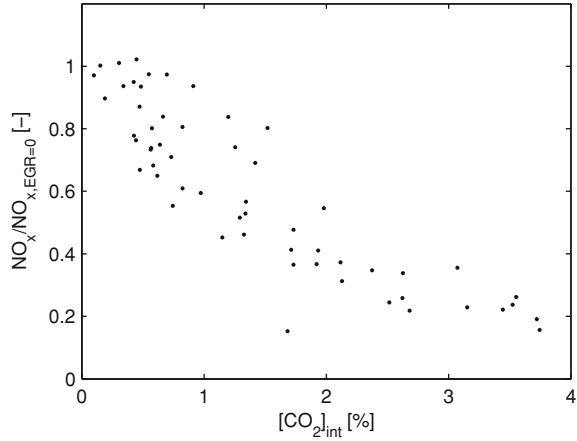
$$u_{soi} = f(n, m_f). \quad (2.1b)$$

2.2.2 The Air Path System

In a commercial CI engine, the following subsystems can usually be found in the air path: the air filter (in order to clean the entering air, although causing a minimum pressure drop in the line), a (single or double stage) turbocharger (TC) including an intercooler for cooling the compressed air (thus increasing the density), the intake and exhaust manifolds, the EGR loops (high and low pressure loops) and the pipe-out line (the after-treatment devices are considered as an independent subsystem because of the different possibilities existing today, even though they are really connected to the pipe-out line).

A single TC is the common layout in commercial engines, but some mount also dual stage TC (Varnier 2012). The main function is increasing the intake air mass flow by increasing the density with a compressor usually powered by a turbine shaft located at the engine exhaust (Saidur et al. 2012). One of the main drawbacks of the system is the turbolag of the TC which is associated with the inertial response of the turbo shaft to accelerations, especially at low speed and low loads, when the exhaust energy is quite low (Park et al. 2010). In order to get the maximum efficiency of the compressor and turbine, two types of control are usual: waste-gate (WG) valves and a variable geometry turbine (VGT), also known as variable nozzle turbine (VNT). The WG configuration is based on the use of a fixed geometry in the turbine with a valve that acts bypassing the flow minimising the effective exhaust flow through the turbine. This solution has practically been replaced by the use of the VGT, which is based on movable nozzles that vary the turbine work depending on the operating point. The VGT allows to increment the engine performance reducing the specific fuel consumption and also adds a major flexibility to the control, admittedly that increments the related complexity and calibration effort. In a dual stage TC, there

Fig. 2.1 Nominal NO_x emissions depending on $[\text{CO}_2]_{\text{int}}$ for nominal tests in the CI engine explained in Chap. 3. Values are normalised with the maximum NO_x value for each operating point, which corresponds to $u_{\text{egr}} = 100$ (fully closed) for each pair of $[n, m_f]$



exists a wide variety of possibilities of combining WG, VGT and fixed geometries in the high pressure (HP) and low pressure (LP) turbines (Galindo et al. 2009).

The exhaust gas recirculation (EGR) is the most widely extended NO_x reduction system (Pla 2009) and is used in CI engines since the middle of the 90s. The basic idea is recirculating a portion of the exhaust gas to the intake. The principal effect of the EGR system is reducing the effective O_2 (increasing effective $[\text{CO}_2]_{\text{int}}$) at the intake and then diminishing the peak temperature in the cylinder and thus reducing NO_x as it is shown in Fig. 2.1.

The EGR rate in steady-state operation can be defined as the quotient between the total EGR mass flow \dot{m}_{egr} and the intake mass flow (\dot{m}_{int})

$$\dot{m}_{\text{int}} = \dot{m}_a + \dot{m}_{\text{egr}} \quad (2.2a)$$

$$\text{EGR} = \frac{\dot{m}_{\text{egr}}}{\dot{m}_{\text{int}}} \quad (2.2b)$$

The work by Ladommatos et al. (1996a, b, 1997a, b, 2000) is a good reference for understanding the effects of the EGR in the combustion and emissions. In addition to the internal EGR (inert gas fraction that stays in the cylinder after the combustion), the external EGR can comprise high pressure EGR (HPEGR) and low pressure EGR (LPEGR) loops. The HPEGR is based on the extraction of a portion of the exhaust gas upstream of the turbine and driven normally to the intercooler output (hot EGR). The LPEGR extracts a portion of the exhaust gas at some point downstream of the turbine (it is usual to locate it downstream of the diesel particulate filter for avoiding damage in the compressor) and is guided at the compressor inlet (after the air filter). Besides the installation of valves for controlling the flow, coolers are installed for increasing the flow density.

The HPEGR, namely EGR for simplification, is the standard in CI engines due to the simple layout and control: the pressure differences between exhaust and intake

facilitate that gas goes to the intake with some exceptions, which can occur for high EGR rates, problem that can be solved e.g. by introducing a throttle valve (van Nieuwstadt 2003). Even though the LPEGR did not enter into massive production, there exists today a certain interest in combining both loops for further reduction of emissions that can push up to relax the AT efficiencies (Millo et al. 2012; Desantes et al. 2013) and thus the cost of complex systems.

2.2.2.1 EGR/VGT Control

The air path is managed independently of the fuel injection system. The effects of the injection settings are considered in the air path as instantaneous inputs for a multiple input multiple output (MIMO) control problem. More concretely, the fuel injection quantity (m_f) and the engine speed (n) are used as scheduling variables for defining the set-points for the EGR and VGT actuation. Then, for a common layout of HPEGR and VGT (or WG), the inputs are the EGR valve position (u_{egr}) and the turbine actuation (u_{vgt} or u_{wg}), besides other actuators such as valves for bypassing the flow over the EGR cooler ($u_{bp,egr}$) if necessary. If the TC is dual stage, it is usual that only one of the turbines can be actuated. For other layouts, different control strategies can be designed, e.g. with a twin turbo sequential parallel configuration, an extra variable is necessary in order to coordinate the switching (Galindo et al. 2009). Varnier (2012) gives a complete review on boosting technologies and its associated control.

The EGR/VGT control strategy basically consists on two maps for determining the set-points for the air mass flow (\dot{m}_a) and the boost pressure (p_{boost}), while u_{egr} and u_{vgt} are commanded for reaching these set-points (Guzzella and Amstutz 1998). The coupling of the EGR/VGT system is avoided by defining control regions, with and without EGR. When engine is working in the EGR area, u_{egr} is controlled in closed loop for reaching the required air mass flow set-point scheduled by m_f and n . The VGT is commanded in open loop by a feed-forward controller that imposes a given u_{vgt} depending also on m_f and n . This structure avoids the problem of the EGR/VGT coupling that can be exemplified as follows: when the EGR valve is opened, a closing on turbine nozzles increments the exhaust backpressure and the turbine regime, this effect produces a higher recirculation of EGR reducing the effective air mass flow at the intake (the EGR mass flow replaces the fresh air). However, when the EGR valve is fully closed, a closing of the turbine nozzles produces an increase of the intake air mass flow. This occurs for medium-high engine loads and u_{vgt} is controlled in closed loop, while the EGR valve keeps closed. The control objective is then reaching the intake air mass flow set-point. Figure 2.2 schematises the air path and the smoke limiter controller.

Furthermore, some corrections or maps switching are applied depending on combustion modes or for cold starting strategies (the references for injection and air path are modified). The engine coolant temperature (T_{cool}) is also used for corrections and for defining the cold starting strategies.

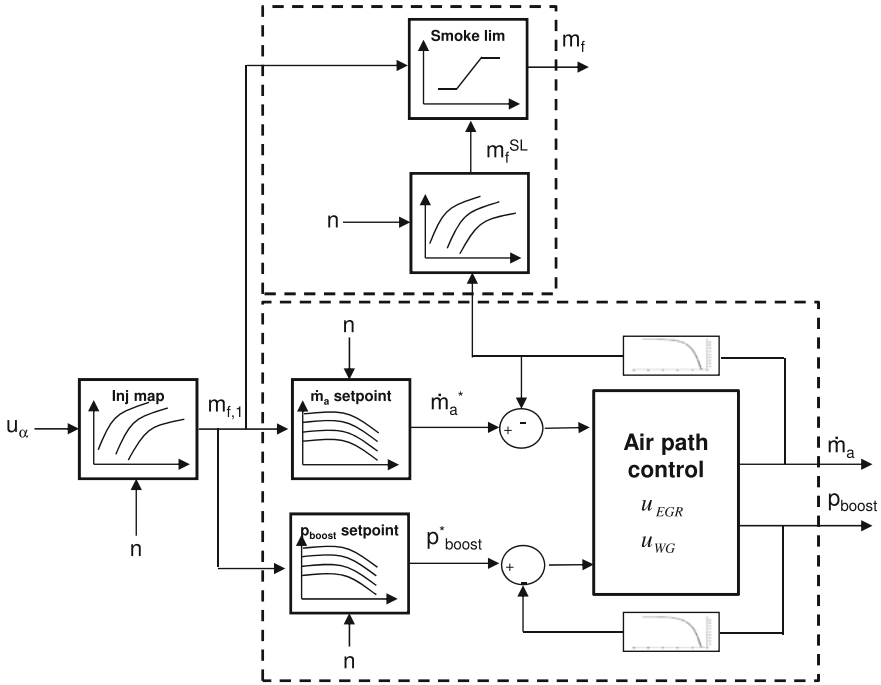


Fig. 2.2 Smoke limiter and air path control blocks

An alternative to the commercial air path control is using virtual and physical sensors or including adaptive strategies by feeding back the controllers with direct measurements of exhaust conditions, e.g. exhaust gas concentrations whose estimation is further discussed in Sect. 2.3. Then, model predictive control (MPC) (Tschanz et al. 2012; Ortner and del Re 2007) or other strategies (Stefanopoulou et al. 2000) can be exploited for such control.

2.2.2.2 Dual EGR/VGT Control

When using a dual EGR loop, in addition to the control variables presented for the single loop, the following inputs are necessary: LPEGR valve (u_{lp}), intake throttle valve (u_{it}) and/or the backpressure valve positions (u_{bp}). The total EGR rate is calculated as in (2.2b) but considering mass flows of the low and high pressure loops respectively \dot{m}_{lp} and \dot{m}_{hp}

$$\dot{m}_{egr} = \dot{m}_{lp} + \dot{m}_{hp} \quad (2.3)$$

Depending on the engine conditions and control needs, the EGR split ($\dot{m}_{lp}/\dot{m}_{hp}$) is selected, i.e. the set-points for \dot{m}_{lp} and \dot{m}_{hp} . The control is similar to that of the single EGR/VGT control but designing an appropriate algorithm for defining the

Table 2.1 Approximate characteristic response times for the main actuation variables in a CI engine

Command	Response time
$u_{p_{rail}}, u_{soi}, u_{id}$	100–600 μ s
$u_{hp} (u_{egr})$	0.2–0.5 s
u_{lp}	0.2–1 s
u_{vgt}, u_{wg}	0.5–1.5 s

EGR split (Shutty et al. 2007). A common solution in steady-state is controlling u_{lp} and if necessary opening u_{hp} for reaching the \dot{m}_a set-point (EGR is not directly measured). Indeed, the LP loop itself might be sufficient for getting the required \dot{m}_a set-point. For transient operation, the discussion must evaluate the characteristic response times of the systems: the HPEGR line is faster than the LPEGR line due to the higher pressure differences and the shorter length. This produces that different trade-offs between u_{hp} and u_{lp} may be stated during transients. An intrinsic benefit of using a dual loop EGR is that for the EGR engine area, the total \dot{m}_{egr} quantity may be increased leading to further reductions on NO_x , which can alleviate the needs of AT or could move the deNO_x ¹ trade-off to select a lean NO_x trap (LNT) rather than a selective catalyst reduction (SCR) system. Model based and optimal approaches to the control problem of dual EGR loops can be found in (Haber and Wang 2010; Chauvin et al. 2011; Desantes et al. 2013).

2.2.2.3 Control of the Air and Fuel Paths

Some authors have proposed a joint control of the air and fuel paths for optimising the engine transient operation. For that, fast acting variables linked to the fuel path (u_{soi} or p_{rail}) are able to track NO_x or soot while u_{egr} and u_{vgt} are arranged to improve the engine transient response while keeping the engine operation (ensuring the torque on wheels) without exceeding emission limits. This can be made by feeding back the controllers with real time measurements of exhaust gas concentrations (typically NO_x and soot, or exhaust oxygen) (Deng et al. 2012; Tschanz et al. 2012). Table 2.1 sums up the characteristic response times for step variations in the inputs, showing how the associated fuel path responses are quite faster than the air path ones. Furthermore, the response times of the TC are in general higher than those related to the EGR loop due to the turbolag problem.

Some authors have proposed a transient operation optimization of the engine management strategy (EMS), see e.g. (Alberer and del Re 2009b). However, manufacturers are still reluctant to change the actual implementation in the fuel and air path system: the EMS is confided to fixed calibrations and optimised for steady-state operation with a validation in transient operation without feedback on exhaust engine states.

¹ The term deNO_x refers in general to an AT system for reducing NO_x , see Sect. 2.2.3.

2.2.3 The After-Treatment Systems

The new stringent regulations have forced to get an impressive development in diesel engines, and particularly with the after-treatment devices (AT); Johnson (2012) and Twigg (2007) present complete reviews on emissions control and available AT technologies. The standard configuration for AT in diesel engines for EURO 6 will comprise

- a diesel oxidation catalyst (DOC) for three main functions: oxidising CO and HC, heating the exhaust gas and oxidising NO to NO₂, which is useful in the DPF regeneration and also facilitates the SCR performance;
- a diesel particulate filter (DPF) for eliminating soot; and
- a deNO_x system for reducing NO_x that it is usually a selective catalyst reduction (SCR) or a lean NO_x trap (LNT).

The DPF and LNT action is based on substrate materials that store the pollutants through mechanisms or chemical principles. When the system is full, a regeneration by means of post-injections and thus increasing exhaust heat is necessary. The DOC system is built from ceramic and catalytic noble metals, such as platinum or rhodium, for enhancing the oxidation of CO and HC as well as NO to NO₂. SCR systems eliminate NO_x by dosing urea and water (principle component is ammonia) and reacting with NO_x for obtaining N₂ and water, where a dedicated control management is necessary for optimising its dosing (Chi and Da Costa 2005; Roberts 2011). The SCR requires an specific installation for the urea storage that increases the cost and weight, and for this reason, the SCR is more extended in HD than in LD. Major concerns in SCR are the light-off related with the minimum temperature for guarantying the efficiency of the system (critical when the engine is cold or it is working in low-load operation); and the ammonia slip, due to the excessive injection of urea, which does not react with NO_x, constituting an economical cost and affecting the output of the NO_x sensors based on ZrO₂ (see Sect. 2.3.1).

DPF and DOC are standard in EURO 5 cars, and deNO_x systems will also be with the application of EURO 6. Anyway, the trade-off between SCR and LNT is not solved (Bickerstaffe 2009), and different factors influence the final decision. Thinking of future regulations, manufacturers struggle between getting lower removal efficiencies (around 85 %) by using LNT or allowing the engines to work on much higher efficiencies and then higher NO_x production but with the use of a SCR with a removal efficiency nearly 98 % (Johnson 2012).

The selection of the layout of the ATs in the engine is another important trade-off and influence the correct operation of the systems. Some possibilities are later shown in Fig. 5.1; however this is a trending discussion. It seems logical that the DOC should be located first because it is required for a proper performance of DPF and SCR, but the trade-off between DPF and SCR or LNT present advantages and drawbacks. Indeed, there are some research on moving the DPF upstream of the turbine for preventing turbine and compressor damage (if it is located before the EGR loop) (Payri et al. 2011b) or doing something similar with the DOC

(Carberry et al. 2005). There are also some alternatives that combine some of the systems for reducing the packaging and final weight (Frobert et al. 2012).

With respect to the feedback, the knowledge of the concentrations upstream and downstream of the AT systems allows to diagnose the performance, and is required for direct control of the final emissions. The temperature also influences the regeneration of the DPF and LNT as well as it is critical for the SCR light-off (key reactions are inhibited at low temperatures). The pressure drop in the line could also be used for detecting failures or when the DPF or LNT are full. The decision on the sensor set for a proper control and diagnosing is a challenging problem that requires a specific study out of the scope of this work. The use of sensors and models for estimating exhaust gas concentrations, especially NO_x and exhaust oxygen, is discussed in Sect. 2.3.

2.2.4 The Control System

As presented in previous sections, the modern diesel engine has evolved until reaching today an important and increasing complexity, which is reflected with the introduction of different subsystems for improving the performance and minimising the emissions. The vehicle electronics in the 80s were reduced to the radio plus simple engine controllers. At the same time, these were based on mechanical and hydraulic devices with a simple electronic assistant, and dedicated to specific functions such as the ignition in the case of SI engines. However, the evolution of the engines has been closely related with the rise of complexity of the modern embedded electronics in automotive, as it is well depicted in (Ebert and Jones 2009). Nowadays, safety performance, fuel efficiency and comfort are major demands and these are achieved by installing proper control units. Modern cars have between 20 and 70 control units with a size of 10^8 in object instructions, while in the first 90s this was in the order of 10^6 , according to Ebert and Jones (2009).

From all the control units in the vehicle, the ECU is in charge of managing the engine. Others work with the braking systems, the air conditioning in the cabin or the gear shifting management (Bosch 2011). In the beginning of the 00s, the ECU EDC16 model by Bosch for diesel engines changed the view of the diesel control by using the final torque demand on the wheels as the feedback for a proper air and fuel path management. This ECU also included a fully flexible control of the common-rail (pilot, main and post-injections), the VGT and the EGR, all in the same processor. The current EDC17 (Hammel et al. 2003) model coordinates a bigger number of data from sensors, actuators and models in order to get a full management of the diesel engine.

From all the requirements and purposes of the ECU, the on-board diagnostics (OBD) standards were applied to engines in order to implement safety routines for detecting sensors or engine systems malfunctions (van Basshuysen and Schaefer 2004). Currently, about 40% of the automotive electronics are devoted to OBD functions. The gradual introduction of the AT systems in diesel engines, especially with the current trade-off between selecting SCR (more complex due to the urea

dosing but effective) or LNT (more simple but less effective), is requiring a renewal of the current diesel air path control (Bickerstaffe 2009), and new functions and managing strategies are being developed; see for instance (Yang et al. 2009) who propose an independent control unit for the AT line separated from the main ECU.

2.2.4.1 Summary on the Information Required for a Global Diesel Management

The commercial diesel engine management focuses on references measured upstream of the combustion chamber, with no direct feedback from the exhaust line. This makes that emissions are controlled in open loop and possible changes and the ageing are not taken into account. The sensors set used in the automotive in the beginning of 00s (Fleming 2001) had hardly changed until the end of the last decade. A major factor is the unnecessary of increasing the number and the type of sensors due to the current control logic. Furthermore, other important factor is the low cost of pressure, temperature and rotational motion sensors (bellow 3\$ per unit) against the higher cost (minimum > 10–20 \$) of more sophisticated sensors, such as NO_x or in-cylinder pressure ones [references obtained from (Fleming 2001) and conversations with engine manufacturers].

Table 2.2 summarises the usual inputs and sensors that are installed in current diesel engines, while indicating possible alternatives in a short future (Turner 2009), which are essentially driven by the emission standards (the need of ATs control and diagnosis). It is rather complicated establishing an universal sensor set and some discrepancies can be found, e.g. GM is starting to include p_{cyl} sensors in engines and some AUDI and BMW vehicles already install NO_x sensors before and/or after the SCR system.

Alternatively, model based strategies present different advantages: models can be used for engine calibration saving costs (Arsie et al. 2011); models can easily be linked in control and diagnosis algorithms as they present faster responses than sensors; and the fusion of sensors and models permits to estimate variables or update parameters on real time solving the drift and ageing and improving the dynamic responses of the original signals.

This section has emphasised the importance of the information about engine states and how to correctly retrieve them on-board. Next section deals with the topic of exhaust gas concentration estimation in CI engines, stressing the variables NO_x and λ .

2.3 Dynamic Exhaust Gas Concentration Estimation

Previous section has made a review on the different technologies in order to manage the diesel engine and has underlined the need of reliable methods for estimating variables online. Test-bed measurement systems are usual for testing and research but these present in general deficient dynamic responses and overall limited on-board

Table 2.2 Summary of the on-board sensors and control inputs used in a commercial LD diesel engine for control and feedback, and split between the main engine subsystems

System	Inputs	Standard sensors	Expected sensors
Injection	u_{prail} $[u_{soi}, u_{id}]_{pilot, main, post}$	n, p_{rail}	p_{cyl}^* $fuel\ quality$
Air path	u_{vgt}, u_{hp}, u_{lp} u_{it}, u_{bp}	$p_{boost}, \dot{m}_a, T_{cool}$ $T_{boost}, p_{amb}, T_{amb}$	\dot{m}_{egr}, T_{egr} n_{vgt}, λ_{int}^*
AT	$[u_{soi}, u_{id}]_{post}, u_{urea}$		$NO_x^*, soot, \lambda_{exh}^*$

The inputs column defines the main actuator signals in the diesel engine. The remaining columns show the variables that are measured by sensors, differentiating between standard for EURO 5 cars and the possible expectations in a short future. Admittedly, some discrepancies can exist between this distinction depending on the considered car and sector (luxury, utility, etc.). The symbol * represents sensors that can be found in some actual engine models but with less probability. The injection settings are defined by the rail pressure control u_{prail} , the injection timing command (u_{soi}) and the injection duration u_{id} , and these settings can be specified for pilot injections main injections and possible post injections (variable u_{tmi} makes reference to the duration of the main injection only). A detailed summary on the symbols and acronyms used in this work appears in the beginning of this document. The interested reader is also referred to Turner (2009) for finding basic comprehensive explanations about the principles of measurement of the main automotive sensors

capabilities. However, in the last years, and forced by the stringent emission laws, developments of on-board gas concentration sensors have proliferated and some of them are a reality today, such as NO_x or wide-band lambda sensors. Furthermore, COMs and data fusion (DF) techniques that combine different information sources can also be used for real-time (RT) estimations.

Current section gives a review on the different methods for the estimation of the exhaust gas concentration in CI engines, emphasising the on-board methods. Therefore, in addition to being feasible from the point of view of cost and engine implementation, the accuracy and dynamic responses of these estimators should be issued. Hereinafter the following three main possibilities are discussed:

- sensors,
- models and/or virtual sensors, and
- DF techniques for combining different information sources.

2.3.1 Sensors

A subsequent division is made between test bed measurements systems and on-board gas concentration sensors, such as exhaust gas oxygen (EGO), universal exhaust gas oxygen (UEGO) sensors, fast soot sensors and finally innovative solution for monitoring e.g. NO_x by using the substrate materials of the AT systems.

2.3.1.1 Test Bed Sensors

Some of the most common test bed sensors are the following: gas analysers (Horiba 2001) for different gas concentrations; opacimeters based on Beer-Lambert law (Lapuerta et al. 2005) and smoke meters for soot; and gravimetric devices or spectrometers for PM (Mamakos et al. 2013), among others. But these are expensive, require from specific installations and their dynamic responses are questionable. Nevertheless, there have been some developments for fast response emissions analysers for NO_x, CO₂ or particles and portable emission measurement systems (PEMS) (Franco et al. 2013) are being generalised for on-board inspections but with limited dynamic accuracy (Mrosek et al. 2011) and packaging. Finally, standard procedures for measuring emissions in test-cells can show representative errors in the dynamic cycles with respect to the actual transient emissions (Mamakos et al. 2013; Viskup et al. 2011) and this should be taken into account when processing the data (Geivanidis and Samaras 2008; Chan et al. 1997; Arrègle et al. 2006b; Bedick et al. 2009) (see Sect. 2.3.2.3).

2.3.1.2 On-board Gas Concentration Sensors

Oxygen Sensors

In 1968, the introduction of EGO sensors (Dueker et al. 1975) was the key for the implantation of the primary three way catalyst (TWC) control in SI engines. These sensors offered a binary lean/rich resolution for measuring oxygen concentration and thus the equivalent air-to-fuel ratio or lambda, which represents the excess air factor with respect to the stoichiometric air-to-fuel ratio (approximately 14.5 in diesel engines)

$$\lambda = \frac{\dot{m}_a}{\dot{m}_f} \frac{1}{14.5} \quad (2.4)$$

In the end of the 90s, planar UEGO sensors were implemented for SI and CI engines. It is common to use directly the term lambda probe for referring to these sensors. The term lambda is due to the characteristic shape of the signal output in narrow-band lambda sensors, which is similar to the λ letter from the Greek alphabet (see Fig. 2.3). Furthermore, these are also known as switching-type sensors. UEGO sensors present full and linear resolution on oxygen over a wide range, hence the term wide-band. UEGO and EGO response characteristics are shown in Fig. 2.3.

λ measurement in CI engines is used for correcting injector drift. In the case of low temperature combustion (LTC) processes (Lu et al. 2011), intake charge composition, and hence λ is important for the combustion stability and control (Chiang et al. 2007; Agrell et al. 2005). Some studies about wide-band lambda sensors performance can be found in (Regitz and Collings 2008b; Klett et al. 2005).

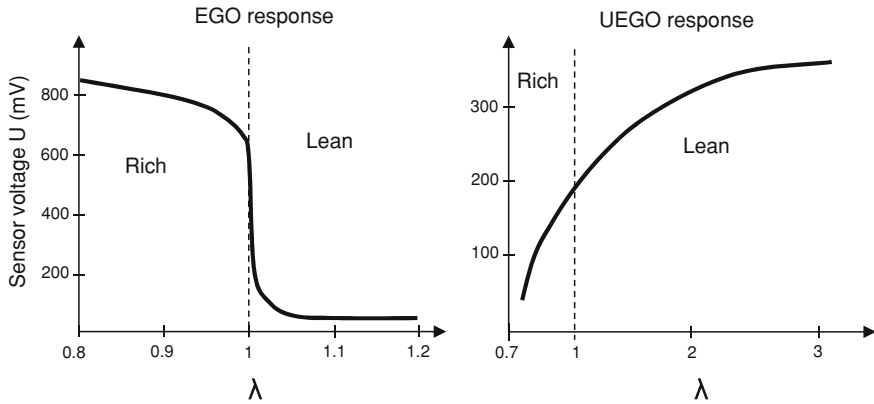


Fig. 2.3 Characteristic outputs of oxygen lambda sensors. *Left* Narrow-band lambda or EGO sensors. *Right* Wide-band lambda or UEGO sensors

NO_x – ZrO_2 Sensors

The development of on-board NO_x sensors has been driven by those which are based on ZrO_2 layers (Kato et al. 1996; Nakanouchi et al. 1996) and able to measure gas at wet condition (i.e. without removing exhaust gas water steam content as gas analysers do). These sensors have suffered an evolution over the last 15 years (Zhuiykov and Miura 2007) and now are manufactured using the planar ZrO_2 multilayer technology (Moos 2005), which combines thick film screen printing and ceramic tape casting (Riegel et al. 2002). Modern versions offer reduced warmup time, smaller size, lower weight and cost-effective production, which encourage their implementation on commercial engines. This kind of sensors simultaneously provides a measurement of the relative air-to-fuel ratio (λ) and NO_x concentration and must play a major role in the SCR control and diagnosis (Hofmann et al. 2004; Hsieh and Wang 2011; Künkel 2001; van Nieuwstadt and Upadhyay 2005).

The working principle is well explained in Riegel et al. (2002) and layout is schematised in Fig. 2.4. This sensor presents two cavities with membranes for measuring oxygen and NO_x , respectively. In a first outer cavity, an electrochemical pump adjusts the oxygen concentration from the diffusing gas to a predefined value (pump intensity I_{p1}) by reducing O_2 to O^{2-} with an electrode (usually Pt), thus providing a linear amperometric measurement of λ . At the same time, a faster binary output is provided, differentiating between rich and lean conditions in the exhaust gases (similar to EGO sensor output). The measurement principle of this first cavity is similar to that of a wide-band UEGO sensor. In addition, NO is oxidised to NO_2 , and then the NO_2 is diffused to a second inner cavity, where the oxygen produced through the dissociation of the NO_2 is pumped out in a similar way by means of a second electrochemical pump (I_{p2}). The output of this pump is proportional to the NO_x concentration in the exhaust gases. A heater is necessary for keeping the sensor at high temperatures, where the device gets good resolution, i.e. the sensor needs

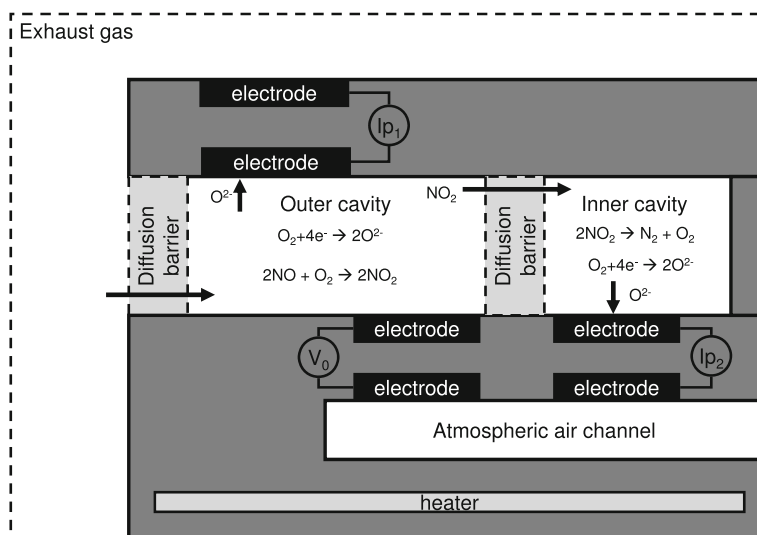


Fig. 2.4 Schematic representation of a $\text{NO}_x\text{-ZrO}_2$ sensor, where the main reactions in the chambers and diffusion barriers are shown

some lag for starting to measure when switching on (the same occurs for UEGO sensors). Therefore, these sensors provide three signal outputs: a fast binary λ (around 100 ms), lean or rich, suitable e.g. for TWC diagnosis, a slower (around 500 ms of response time) full resolution λ and NO_x (with a response around 750 ms).

NO_x and UEGO Sensor Limitations

Because of the importance of NO_x and UEGO sensors in the present work, response limitations of these sensors are underlined. Several studies have evaluated the accuracy and response times of real time NO_x sensor measurements for different applications, such as Smith (2000), Manchur and Checkel (2005) and Galindo et al. (2011).

Conventional UEGO sensors exhibit fast response times around 70 ms with sufficient accuracy (Schilling et al. 2008). This can be improved, as proposed in Alberer and del Re (2009a), moving the O_2 sensor upstream of the turbine and using a Kalman filter (1960) for taking into account pressure effect on the output signal. If the NO_x sensor is placed downstream of the AT systems, its response is affected by a considerable transport delay and filtering. Figure 2.5 compares λ^{-1} signals from a UEGO sensor located upstream of the AT systems, and from a NO_x sensor located downstream of an AT line including DOC, DPF and SCR in a turbocharged diesel engine. The NO_x sensor signal is significantly slower and more filtered than that of a UEGO sensor, although the steady-state accuracy seems to be sufficiently accurate in both devices at a glance. Due to the measurement principles of both UEGO and

Fig. 2.5 λ^{-1} measurement from a UEGO sensor located at the turbine outlet and from a NO_x sensor downstream the after-treatment systems

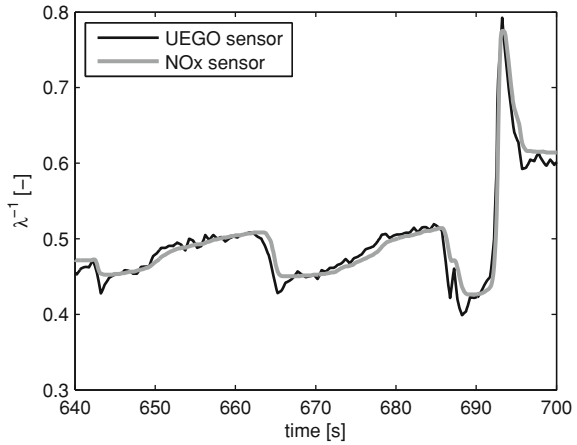
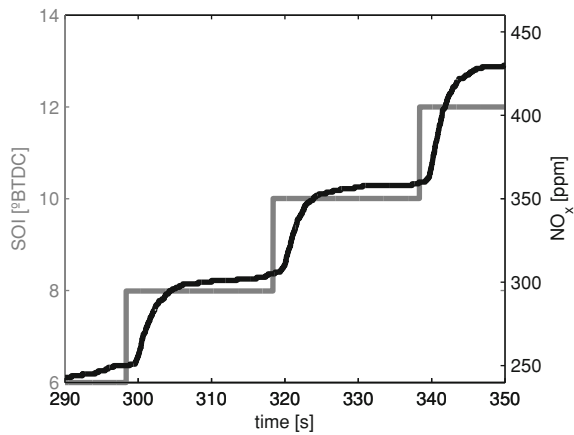


Fig. 2.6 NO_x sensor response to SOI steps (*black-right axis*). NO_x presents a clear delay and filtering with respect to the SOI signal (*gray-left axis*). The dynamic response could be fitted with a first order delayed discrete filter. SOI units are crank angle degrees before the top dead centre (°BTDC), while NO_x is measured in ppm. The delay is in the order of 1 s while the response time is around 0.75 s



NO_x sensors, the pressure in the runners also compromises the steady-state accuracy of the sensor.

Concerning NO_x output from NO_x sensors, the delay is variable, depends on operating conditions, and is in the order of 1 s. This delay is caused for both transport and physical motives, which are difficult to model and can vary with the engine operating conditions. This issue makes difficult to use the raw sensor signals for RT critical functions. For illustrating sensor response, see Fig. 2.6: the actual NO_x is expected to respond instantaneously when performing start of injection (SOI) steps where the delay and response time in the sensor are attributed to the sensor. Several studies have evaluated the accuracy and response times of RT NO_x sensor measurements (Smith 2000; Manchur and Checkel 2005; Mrosek et al. 2011).

Finally, since sensors are subjected to unit-to-unit manufacturing discrepancies, and can be affected by significant drift during their lifespan, methods for the online

characterisation of sensors would improve the application of these for automotive control purposes. Usual calibration methods consist of a specific test rig which generates known composition synthesis gas which is used for the static and dynamic calibration of the sensor, while high speed valves are needed for dynamic calibration (Regitz and Collings 2008a); or some solutions based on openly mounted sensors with valves allocated before the sensor, where gas composition is changed within milliseconds (Tobias et al. 1999). However, these calibration methods are restricted to laboratory use and cannot be performed during the operation phase on the engine. Chapter 3 presents a contribution for the online characterisation of NO_x output by means of SOI steps (Galindo et al. 2011); furthermore, λ^{-1} output from wide-band lambda sensors may be characterised by means of load steps.

Fast Soot Sensors

According to (Kasper 2004), particles with lower diameters affect more to alveolar deposition after healthy tests with persons, which underline the risk of underestimating the effect of the residual soot downstream of the DPF. This carries out a sensitive problem for sensors: in addition to robustness, packaging and dynamic limitations, on-board soot sensors must measure with high resolution at low-soot values (this sensitive problem is also linked with NO_x sensors). Another problem with soot sensors is the selection of an appropriate metric as different metrics can be used depending on the physical measuring principle: particle number, total mass, sizes or light absorbing properties (opacity). A common solution for fast soot sensors, described in Warey and Hall (2005), is measuring the electrical conductivity of the carbonaceous fraction of the PM, which acts as a resistance between two electrodes located in the sensor. One of them is feed with a high voltage DC, while the current generated in the other is transformed to voltage, conditioned and then acquired for being converted into a soot estimation. This layout is similar to other fast soot sensors, see e.g. Steppan et al. (2011) and Nelson (2011). Even though these sensors have not reached the maturity of UEGO or NO_x sensors, some companies have already introduced them in the market or are targeted for start of production in 2013.

Sensors in Development, Other Alternatives

A relevant problem of fast NO_x -ZrO₂ sensors is the low sensitivity when the NO_x concentration is small, i.e. downstream of SCR or LNT systems; and the related cross-sensitivity to ammonia. In that field, it can be underlined the work by Moos (Moos et al. 2008; Moos and Schönauer 2008; Moos 2010; Geupel et al. 2011; Schönauer et al. 2011; Groß et al. 2012).

An alternative is using the catalysts and/or substrate materials of the AT devices for determining the NO_x , soot or ammonia by means of measuring the impedance variance of the material. This allows to profit the proper AT device for measuring, developing an integrated device. These are often called in situ monitoring devices.

Moos (2010) show results for in situ sensors in order to detect loadings of oxygen in TWC, NO_x in LNT, NH_3 in SCR-catalyst and soot in DPf, among others. The principal advantage of the approach is the simple and inexpensive setup required as the devices themselves are used as sensors.

Concretely for NO_x sensing, see Geupel et al. (2011) and Groß et al. (2012) who extend the use of integrating-type NO_x sensors for measuring instantaneous NO_x concentration, especially in the low ppm range (where NO_x concentration is low), incorporating temperature based corrections in the measurements. Groß et al. 2012 also present results with respect to NO/NO_2 differentiation and cross-sensitivities with other gas components. Other alternatives for innovative sensors could be using electromagnetic waves (Moos 2010) or radio-frequency signals which coincide with the oxidation/reduction rate of a TWC for determining oxygen loading without using lambda sensors (Moos et al. 2008).

NH_3 on-board sensors (Moos and Schönauer 2008) are also being developed for closed loop urea dosing control, based on the same principles of the wide-band lambda sensors: the mixed-potential principle between electrodes, separated by a solid electrolyte, where an electric force is created. Delphi has already marketed a commercial version where the reference electrode is in direct contact with exhaust gas (Wang et al. 2008). Schönauer et al. (2011) show results with mixed potential ammonia sensors and suggest some improvements in the technology.

2.3.2 Models and Virtual Sensors

Modelling or virtual sensing² is an important tool in the design, analysis and control of IC engines. It is not in vain that model-based strategies in ECU have each time higher responsibilities, overall in control and OBD functions (Stewart et al. 2010). Furthermore, models are quite helpful in the analysis and design phases: hardware and software in the loop (HIL and SIL) are usual because of the reduced cost and time-to-implement with respect to a pure experimental approach. However, the accuracy, reliability, computational cost and time effort of models depend highly on the structure, data used for calibration and the dynamic conditions. A classification on models for automotive is made in Guardiola et al. (2012) and these are compared in Table 2.3:

- Mean value models (MV), which average the physical quantities over a time range, neglecting in-cycle variations. They can be further subdivided in data driven models (DDM) and physical mean value engine models (MVEM).
- Emptying-and-filling models (E&FM), based on first-principle equations and with certain capability for estimating in-cycle variations. They are usually crank-angle solved.

² The term virtual sensing is often used for RT on-board models for estimating variables that cannot be measured easily or their measurements are not reliable, in contrast with using physical sensors.

Table 2.3 Summary of the characteristics of different type of models used in the automotive, reproduced from Guardiola et al. (2012)

	DDM	MVEM	E and FM	WAM	CFD
Spatial resolution	0D	0D	0D	1D	3D
Time resolution	MV	MV	CAS	CAS	CAS
Typical acq. rates	0.5–100 Hz	1–200 Hz	> 1 MHz	> 10 MHz	1–100 MHz
Physical description	No/Very low	Low	Low	Medium	Complex
Prediction capabilities	No	Low	Medium	Medium	High
Computational cost	Very low	Low	Medium	High	Very high
Main application	Control	Control	CAE	CAE	CAE

MV mean value, *acq.* acquisition, *CAS* crank angle solved, *CAE* computer aided-engineering

- Wave Action Models (WAM), able to quantify variables in 1D space and based on an Euler equation balance. These allow to represent wave effects (useful e.g. for valve lifting tuning).
- Computational fluid dynamics models (CFD), based on a detailed geometrical description of the engine volumes and the application of the Navier-Stokes equations. Due to the 3D nature of this approach, this tool is effective for simulating mixing models, i.e. EGR distribution around the cylinders or injection spray models. However, CFD characteristic times of computation can range from seconds to days, preventing its use for RT purposes.

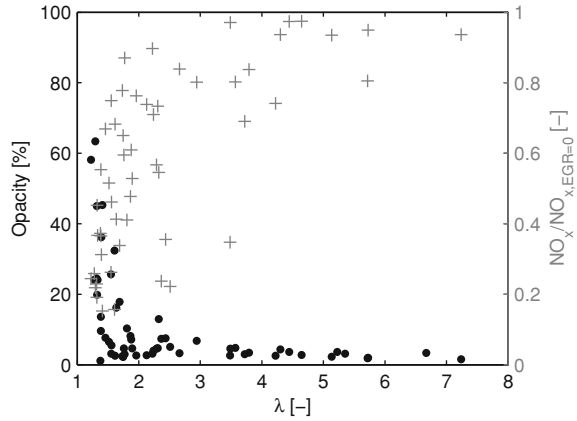
In order to design control oriented models (COMs), MVEM and DDM are the predominant approaches (Calendini and Breuer 2010), basically for the relatively simple computation and the good accuracy achieved, especially when the training data set is appropriate, getting indeed higher accuracy than more complex models. MVEM and DDM rely on two main hypothesis: variables are averaged over the time, with computation (and acquisition) rates about 50 Hz,³ and the number of states that these models can manage are reduced due to the limited computational resources available (mainly the ECU limitations). A straightforward classification of COMs is:

- Physical models,
- gray box models, which combine first principle equations with parameters, curves and maps to be fitted with engine data, and
- black box models, which are fitted only by data and with no physical based structure.

These approaches present advantages and drawbacks. In the following, COMs for λ and NO_x are discussed, as being core variables of the present work. The interested reader can find a review on proposed models for these variables in the dissertation by (Schilling 2008) with application to failure detection and isolation (FDI).

³ For an engine that is spinning at 3,000 rpm, that is equivalent to a rate of 1–100 Hz. A typical frequency for getting changes inside the combustion chamber could be in the order of 1° if talking about crank angle, and this makes a required frequency (at 3,000 rpm) of $50 \times 360 = 18 \text{ MHz}$, quite higher than the typical rates used in MV models.

Fig. 2.7 Opacity (left axis and black points) and nominal NO_x (gray +) emissions depending on λ for nominal tests in the TCCI engine used in Chap. 3. NO_x is normalised with the maximum NO_x value for each operating point, which corresponds to $u_{egr} = 100$ (fully closed) for each pair of $[n, m_f]$



2.3.2.1 λ Models

λ , although not measuring emissions itself, is a key variable in order to control emissions in CI engines. Figure 2.7 shows the opacity and NO_x with respect to λ showing the clear opposite trade-off between both variables. λ can be directly estimated in the basis of \dot{m}_a and \dot{m}_f , see (2.4). Both signals can be measured from the ECU or estimated by a model. In the first case, \dot{m}_a is measured by a sensor and \dot{m}_f , inferred by the p_{rail} and u_{tmi} (2.1a). This computation is simple and no specific model is necessary.

Alternatively, MVEMs can be proposed for calculating λ , which will be reduced to estimate the air mass flow at intake as \dot{m}_f is often considered as an input for control models (Guardiola et al. 2013c). Basic literature for principle equations of CI engines is in Heywood (1988), Guzzella and Amstutz (1998) and Guzzella and Onder (2004) while Wahlström (2009) develops and tune a MVEM for control of EGR and VGT in diesel engines. In addition, other model types with higher or lower ability to compute on RT can be proposed, Tunestsl and Hedrick (2003) estimate λ using net heat release data and (Arsie et al. 2006) use neural networks (NN) (with SI application), among other examples (Nyberg and Stutte 2004; Cesario et al. 2005).

2.3.2.2 NO_x Models

The case of emissions, such as NO_x , is more complex than for λ . NO_x can be inferred by using predictive models that can be implemented on-engine for RT purposes such as engine or AT control and diagnosis. Furthermore, such models can be useful in an off-line basis for NO_x simulation and prototype design. The physical based approach presents difficulties to be applied on RT but can be the basis for grey box approaches (Arsie et al. 2003). First, some words on NO_x physics.

NO_x Physical-Based Models

The term NO_x includes all nitrogen oxides but the nitric oxide (NO) is the predominant in diesel engines (Heywood 1988). NO_x formation is affected by three different mechanisms: thermal, prompt and from fuel-bound nitrogen (Arrègle et al. 2010). The thermal mechanism is the most important in diesel engines where high temperatures benefit reaction of N and O₂ from air producing NO_x. NO_x formation physics in combustion and explosion processes were modelled by Zeldovich (1946) in 1946, and formulated for IC engines by Lavoie et al. (1970) in 1970 with the well-known extended-Zeldovich mechanism



According to Heywood (1988), the typical characteristic times of the NO formation in diesel engines combustion is in the order of seconds and thus under the hypothesis of equilibrium of certain species, the $d\text{NO}/dt$ can be fitted with the initial NO formation rate by the Arrhenius equation

$$\frac{d\text{NO}}{dt} = \frac{k_1}{T^{0.5}} e^{-k_2/T} [\text{O}_2]^{0.5} [\text{N}] \quad (2.6)$$

The strong dependency with the temperature T is clear: when T increases, NO (and thus NO_x) increases exponentially. The other mechanisms can be relevant in some specific conditions such as LTC (Andersson 2006; Desantes et al. 2012).

Cylinder conditions such as temperature, pressure and oxygen concentration (Brand 2005; Luján et al. 2008; Timoney et al. 2005) are the most important variables for determining NO_x concentration.

Because of the cylinder severe conditions, price and signals problems have prevented to use in-cylinder sensors in commercial vehicles. Although in-cylinder pressure cost is one of the main factors burdening its application for automotive engines, the continuous improvements of pressure sensors and its applications are justifying its nearby implementation (Powell 1993). The case of the temperature sensors is more complicated (Fleming 2001), and their use is not foreseen in applications. Therefore, the solution for estimating the in-cylinder conditions on RT is then using virtual sensors.

Physical models for NO_x estimation are often based in the heat release, using pressure sensor signal for estimating flame temperature (T_f) in the cylinder. The problem is not trivial and a multi-zone discretisation is advisable. Furthermore, the residual gases (internal EGR) affect the process and these are not always easy to estimate. An usual solution to the problem is applying mass and energy conservation equations to each zone (walls, injector neighbourhood, etc.) in conjunction with heat transfer equations, among them it stands out the heat transfer to cylinder wall (Payri et al. 2005), which can be approached by using Woschni equation (Woschni 1967).

Finally, NO_x emissions for both Diesel and gasoline engines are calculated by using the extended Zeldovich mechanism. Good examples for estimating NO_x by using heat release are Arrègle et al. (2006a), Payri et al. (2011a), Guardiola et al. (2011) and Westlund et al. (2008). In the case of SI engines, some authors use the ionisation current on the spark for approaching the pressure (Andersson and Eriksson 2002, 2009), but this is not available on the diesel engine. Nevertheless, the accuracy of the prediction is not as satisfactory as expected, and the drift cannot be eliminated.

There is an open discussion about using time or crank angle based models for the NO_x prediction. For the case of pressure based models, crank angle sampling seems more logical as volume can be easily linked with pressure trace. However, these models require heavy calculations and big memory resources. The time required for completing one engine cycle is often bigger than the characteristic time of the engine. In order to overcome this limitation some authors have proposed simplifications. Guardiola et al. (2011) develop a semi-physical discrete event model based on the heat release calculation but considering only one zone as the main contributor to the NO_x formation; and the process is supposed adiabatic, approaching T_f with the adiabatic temperature of the process. This approach requires specific corrections, especially when the combustion temperature is low. Other examples are Westlund (2011) who present a fast physical model for NO_x and soot, or Arsie et al. (2003) who present a hierarchical model structure for engine control design with different models and layers, ranging from physical based to mean value approaches.

Control-Oriented Models for NO_x

Literature about COMs for NO_x is extensive. Schilling (2008) gives a short review on different COMs for NO_x and presents a NO_x virtual sensor (see also references therein). His work is based on deriving maps from complex models (Schilling et al. 2006, 2008) or engine data (Lughofer et al. 2011; Desantes et al. 2011), building a model that is easy to integrate into the engine ECU, but with limited extrapolation capabilities. In commercial ECUs the prevailing approach is to use look-up tables to model nonlinear and operating point dependent behaviours because of the simple programming in spite of the intensive tuning effort (Guardiola et al. 2013a); even though other possibilities can be commented. Winkler-Ebner et al. (2010) design a virtual NO_x sensor for SCR control and diagnosis. Black box models rely on system identification (Karlsson et al. 2010) but are often operating point dependent and its adaptation is not an easy task. Hirsch et al. (2008) present a gray box model for NO_x and PM. Other non-linear approaches are Takagi-Sugeno fuzzy models (Takagi and Sugeno 1985; Lughofer et al. 2011), Hammerstein-Wiener (HW) (Falck et al. 2012), or NN (Yen and Michel 1991; Alonso et al. 2007; Maaß et al. 2009; Arsie et al. 2010).

2.3.2.3 Identification of Sensor and Physical Dynamics

Dynamic models describe the evolution of a state vector x along the time t and subjected to a specific set of inputs u

$$\dot{x} = f(x, u, t) \quad x \in \mathbb{R}^{n_x}, \quad u \in \mathbb{R}^{n_u} \quad (2.7a)$$

$$y = g(x, u, t) \quad (2.7b)$$

The identification is the technique of designing and tuning the dynamic models by means of a data set $\{u, y\}_{t_1}^{t_{end}}$ over a certain time t_{end} ; see (Johansson 1993; Ljung 1999) for comprehensives references on system identification. A common procedure for identification is defining different black box linear model structures (AR, ARX, ARMAX, etc.) based on polynomial relationships with a certain order and solving the linear regression problem, usually by means of a least squares (LS) formulation. In addition to the model parameters, the selection of an appropriate order of the system is key for an adequate solution. If the system is non-linear, specific structures should be utilised, e.g. piece-wise affine (PWA), linear parameter varying (LPV) or HW models, among others.

Sensors Identification for On-board Strategies

Most of the dynamic models with physical meaning used in engineering, as for instance sensor models, respond to n-order linear filters with a certain delay τ (Ogata 2001), at least in the selected areas of performance. In the case of exhaust gas concentration sensors, 1st order linear models can be sufficient for representing the sensor response in the s-domain (Galindo et al. 2011; Mrosek et al. 2011)

$$G(s) = e^{-s\tau} \frac{k}{1 + Ts} \quad (2.8)$$

where T is the response time and k is the gain. Parameters can be fitted by LS. However, actual sensor responses are non-linear and parameters usually vary, especially the delay or dead-time τ , due to the hardware itself, the engine operating conditions and ageing. These variations can be modelled by scheduling strategies, where parameters are stored in look-up tables, or functions (Trimboli et al. 2012) typically depending on n and m_a .

Another possibility is using model structures with physical insight: e.g. Wang (2007) identifies the oxygen sensors dynamics by means of a physical based model and Zhuiykov (2010) describes and models the electrochemistry of ZrO_2 gas sensors. Adaptive filtering can also be used for taking into account the ageing and dispersion. Furthermore, if the signal processing is made off-line, non-causal deconvolution techniques may also be used, see e.g. Henningsson (2012).

DDMs are often based on static relationships such as look-up tables and algebraic equations. In addition, the dynamics are often modelled by linear filters and

the correct identification is critical for the adaptive filtering algorithms presented hereinafter.

2.3.3 Adaptive Filtering

Sensors present problems when using the raw output signal in RT functions, in particular the delay from engine to sensor and the response time of the sensor. With respect to models, two problems can be underlined when working with COMs. On one hand, the model accuracy is driven by the collection of the appropriate data and calibration of all the parameters. This is a hard and time consuming task. In fact, ECU has a big number of maps and parameters for engine and vehicle management. On the other hand, independently of how well the model has been calibrated there is inevitably a drift between the system and the model as the surrounding conditions changes and the engine ages. DDMs are highly sensitive to the calibration data set and will have problems with the ageing, manufacturing discrepancies, slowly varying parameters and other non-modelled variables. These affects also to dynamic models identified for both sensor and physics filtering.

2.3.3.1 Data Fusion

Data fusion (DF) utilises information from different sources for providing a better estimation of a given variable. These information sources can come from sensors, models and/or other DF algorithms. DF has been used for many years in different engineering fields, such as e.g. inertial navigation of satellites and missiles (Wagner and Wieneke 2003) or automotive applications in intelligent transportation systems (Faouzi et al. 2011; Stiller et al. 2011) related with traffic and driver/road assistance, among others. Different DF methods can be used as (Faouzi et al. 2011) propose: statistical, ranging from the simplest arithmetic mean to weighted combinations or data mining techniques (Henningsson 2012); probabilistic, such as Bayesian approaches, maximum likelihoods methods and Kalman filter (KF); and artificial intelligence including NN or genetic algorithms. A more exhaustive classification and discussion on challenging problems of multisensor DF is in (Khaleghi et al. 2013). From DF methods, those which are applied adaptively for bounding error of parameters, signals and parameters can be included as methods for adaptive filtering, fusion or learning (Mehra 1970).

The present work centres on the use of Kalman filter (KF) (1960) based tools in order to observe exhaust gas concentration variables in CI engines (Guardiola et al. 2013b, c). The KF is probably the most extended adaptive filtering algorithm used in engineering (Gao and Harris 2002) and provides a systematic and simple way of manipulating linear dynamic models and engine variables by supposing a priori knowledge of the measurement and noise statistics, modelled by Gaussian distributions. This property allows to track the estimation error by means of a covariance

matrix \mathbf{P} that also tracks the ageing of the states, i.e. if the error in a given state is foreseen to be higher or lower depending on when was updated the last time and how much. The KF minimises this expected error by solving an iterative Riccati matrix equation and setting out a Kalman gain (K) for correction. The linear structure of the filter makes it appropriate to ECU-oriented approaches, even though simplifications shall be considered when manipulating large state vectors. Furthermore, depending on the available data, different fusion structures can be programmed as Gao and Harris (2002) show.

Other filtering alternatives, such as RLS (recursive least squares) or proportional methods can also be applied and in some cases lead to similar solutions. Input observers by means of measurements of the states and outputs can also be addressed for estimating engine variables (Chadli et al. 2009; Stotsky and Kolmanovsky 2002). The interested reader is referred to Simon (2006) and Höckerdal (2011), the former for finding a complete and broader view on optimal state estimation and KF-based algorithms for engineering applications, and the latter for a key precedent and motivation for the current work.

In the next, and due to the importance of the KF in this work, main equations are recalled although the reader familiarised with control engineering could skip this paragraph.

2.3.3.2 Kalman Filter

In the setting the data are assumed to be generated by the following discrete time system

$$x_k = f(x_{k-1}, u_k) + w_k \quad (2.9a)$$

$$y_k = g(x_k, u_k) + v_k \quad (2.9b)$$

where $x_k \in \mathbb{R}^{n_x}$ represents the state vector, $u_k \in \mathbb{R}^{n_u}$ the input vector, $y_k \in \mathbb{R}^{n_y}$ the output vector. If f and/or g are non-linear, a previous linearisation step is required for the filter and then, elements ij of \mathbf{F}_k and \mathbf{H}_k are obtained

$$\mathbf{F}_{k,ij} = \frac{\partial \mathbf{f}_i}{\partial \mathbf{x}_j} \Big|_{\mathbf{x}=\hat{\mathbf{x}}_k} \quad \mathbf{H}_{k,ij} = \frac{\partial \mathbf{g}_i}{\partial \mathbf{x}_j} \Big|_{\mathbf{x}=\hat{\mathbf{x}}_k} \quad (2.10)$$

being \mathbf{F} the linearised process matrix and \mathbf{H} the linearised output matrix. From now, the discussion is valid both for linear and non-linear systems and KF will be used referring to Kalman filter based methods, including the non-linear Extended Kalman Filter (EKF) (Simon 2006) and the standard one.

Noises in (2.9) $w_k \in \mathbb{R}^{n_x}$ and $v_k \in \mathbb{R}^{n_y}$ are assumed to be independent and both generated by Gaussian distribution with zero mean and covariance matrices \mathbf{Q}_k resp. \mathbf{R}_k , defined by

$$E[w_k w_k^T] = \mathbf{Q}_k \quad (2.11a)$$

$$E[v_k v_k^T] = \mathbf{R}_k \quad (2.11b)$$

In many applications these are often chosen to be constant, i.e. \mathbf{Q} and \mathbf{R} , and diagonal.

Then, $\hat{x}_k \in \mathbb{R}^{n_x}$ is the observation of the state vector x_k

$$\hat{x}_{k|k-1} = f(\hat{x}_{k-1}, u_k) \quad (2.12a)$$

$$e_k = y_k - g(\hat{x}_{k|k-1}, u_k) \quad (2.12b)$$

$$\hat{x}_k = \hat{x}_{k|k-1} + K_k e_k \quad (2.12c)$$

where Kalman gain K_k is solved by the following iterative equation

$$\mathbf{P}_{k|k-1} = (\mathbf{F}_k \mathbf{P}_{k-1} \mathbf{F}_k^T + \mathbf{Q}) \quad (2.13a)$$

$$K_k = \mathbf{P}_{k|k-1} \mathbf{H}_k^T (\mathbf{H}_k \mathbf{P}_{k|k-1} \mathbf{H}_k^T + \mathbf{R})^{-1} \quad (2.13b)$$

$$\mathbf{P}_k = (\mathbf{I} - K_k \mathbf{H}_k) \mathbf{P}_{k|k-1} \quad (2.13c)$$

and matrix \mathbf{P}_k is the covariance matrix of the state estimate error (Ljung 1999)

$$\mathbf{P}_k = E[x_k - \hat{x}_k][x_k - \hat{x}_k]^T. \quad (2.14)$$

2.3.3.3 About the Methods in this Work

From all the possible applications of the KF for the gas concentration estimation, the following are exploited in the present work:

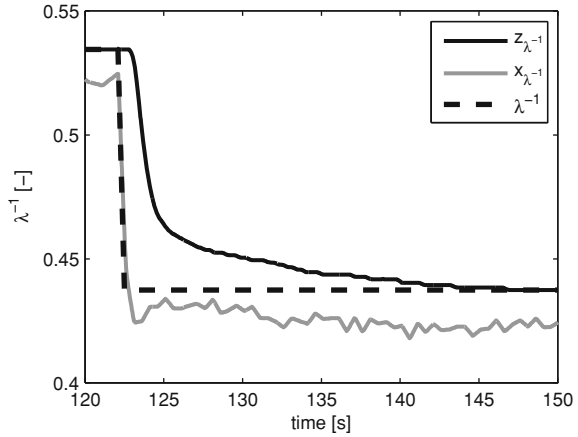
- Dynamic estimation of engine variables by means of fusing a fast reference, often a model, and a slow but accurate sensor, for developing robust virtual sensors or bias tracking algorithms; and
- on-line adaptation of models, especially the online updating of look-up tables as basic structures in COMs.

These algorithms, although applied in the present work to λ and NO_x , can be used for estimating other relevant engine quantities, such as the intake air mass flow or the volumetric efficiency (Höckerdal et al. 2009, 2011), just considering the appropriate state-space model. In the following, the state of the art related with these applications on automotive is reviewed.

2.3.3.4 Adaptive Estimators Based on the KF

Figure 2.8 shows a model signal for λ^{-1} , based on the injected fuel mass \dot{m}_f estimated by the electronic control unit (ECU) and the air mass flow \dot{m}_a determined from a

Fig. 2.8 Different λ^{-1} estimations during a load transient in the tested diesel engine (see Sect. 3.2): $z_{\lambda^{-1}}$ is the output of a NO_x sensor located at the turbine outlet, $x_{\lambda^{-1}}$ is the output of the model presented in Sect. 4.2 and λ^{-1} is the foreseen actual value



hot wire anemometer. Comparing to the sensor, model is faster and non-delayed but presents a bias with respect to the sensor steady-state value.

Algorithms based on bias tracking take a fast model that keeps high frequency components of the considered variable while a slow but steady-state accurate sensor permits to correct model drift. The vector $x_m(t) \in \mathbb{R}^{n_x}$ contains model signals and $z(t) \in \mathbb{R}^{n_z}$ the sensor signals. The drift is modelled with a vector $\theta(t) \in \mathbb{R}^{n_x}$, which contains model biases and varies with time often slowly. If $x_r(t) \in \mathbb{R}^{n_x}$ is the vector containing the actual values of the states, then the true bias θ is

$$\theta(t) = x_r(t) - x_m(t) \quad (2.15)$$

but the problem here is that x_r is usually measured by a sensor z

$$z(t) = g(x_r(t - \tau)) \quad (2.16)$$

and in general will have a certain delay τ . The discussion on identifying the function g and delay τ was made before in Sect. 2.3.2.

In order to design a drift correction algorithm, an augmented state-space model is written. An extra-state is used for tracking the given error (θ), creating a wide state vector x^w with drift vectors and the original state vector $x \in \mathbb{R}^{n_x}$, which contains the estimations of x_m ,

$$x^w(t) = \begin{bmatrix} \theta(t) \\ x(t) \end{bmatrix} \quad (2.17)$$

and the state-space model

$$\dot{x}^w = f(x^w, x_m, W, t) \quad (2.18a)$$

$$z = g(x^w, x_m, V, t) \quad (2.18b)$$

is solved by adding noises $W(t) \in \mathbb{R}^{2n_x}$ and $V(t) \in \mathbb{R}^{n_z}$ to the model and sensor output respectively.

This formulation, with different variations, is made by different authors in order to observe the bias between two references, usually a model and a sensor. Alternatively, the bias can be applied to the model and/or sensor by shifting the references when proceeding; for the latter the sensor is not steady-state accurate and a steady-state accurate reference is required (Chen and You 2008).

The classical approach for modelling the drift is supposing a slow variation of the state by the dynamic equation

$$\dot{\theta} = 0 \quad (2.19)$$

and supposing that states noise W is low with respect to output noise V , for having a smooth correction.

There exist different references with similar models as described above for estimating engine variables. The majority of them uses the EKF due to the non-linear equations involved, some references from 2005 are commented below:

- Hsieh and Wang (2011) use an EKF in order to estimate NO_x up, in between and downstream of a two-series SCR configuration and consider the ammonia cross sensitivity of a NO_x sensor located in between.
- Höckerdal et al. (2009) uses an augmented model for observing the sensor bias with an air mass flow sensor application.
- Alberer and del Re (2009a) use a KF for correcting an oxygen measurement made by a UEGO sensor located upstream of the turbine in a TCCI engine, where pressure effects in the sensor are taken into account.
- Polóni et al. (2012) compare two different sensors configuration in a TCCI engine for correcting states in a MVEM of the air path, designing a closed loop MVEM. They use an EKF for tracking the bias on the considered states and then simulate the model with the corrected variables. References included in this work are interesting and show other different observer designs.
- Other examples are Yan and Wang (2012), Surenahalli et al. (2012), Chauvin et al. (2006), Grünbacher et al. (2005), Trimboli et al. (2012), Tschanz et al. (2012), Benaïcha et al. (2011), and Zhou et al. (2012) who design observers for different relevant engine quantities, such as intake manifold temperature, soot, individual in-cylinder air to fuel ratio or engine torque among others, with diagnosis or control applications.

Drift Models

However, there are cases where the considered bias, e.g. model bias θ variation does not depend only on time

$$\frac{d\theta}{dt} = \frac{\partial\theta}{\partial t} + \frac{\partial\theta}{\partial n} \frac{dn}{dt} + \frac{\partial\theta}{\partial m_f} \frac{dm_f}{dt} + \dots \quad (2.20)$$

and although the bias variation associated with the system drift ($\partial\theta/\partial t$) is expected to be slow, the actual variation of the bias may be very fast, due to the ability of the engine of performing fast transition between operating conditions (usually defined by n and m_f). This can be solved by using specific models for the bias, where a possible solution may be using look-up tables.

In the following, the use of adaptive virtual sensors is discussed.

2.3.3.5 Online Adaptation of Models

In addition to the bias and ageing, the basic structure of models lead to errors due to uncertainties and non-considered inputs. Therefore, the model error might be tracked and distributed between the model parameters. This could be made on an offline basis if the variables are stored, and then the model signals and parameters might be updated by means of executing an optimisation method. An alternative is using adaptive filtering for directly updating the model parameters online. Schilling (2008) makes a selection on parameters from a virtual sensor for NO_x and λ ; and designs an adaptive virtual sensor for their online adaptation. Another possibility is introduced by Polóni et al. (2012) where a set of individual observers are designed for some states of the model. However, MVEMs often pose a mixed structure with different parameters, curves, tables and dynamic equations. The problem of updating all elements is not straightforward and must be faced carefully. The design of observers for updating parameters and tables can be used for tuning or updating DDMs and MVEMs, although stability and robustness of the solution should be issued. Due to the relevance on the present work, the updating of look-up tables is considered.

Look-up tables⁴ allow engineers to easily model systems that present complex expressions by means of mapping outputs with a set of nD heuristic array structures. Look-up tables are used in automotive for different purposes (Vogt et al. 2004): maps of engine parameters as function of the operating-point conditions, often m_f (or torque) and n ; in order to provide set-points for the controllers; or for gain scheduling, among others. Furthermore, the manipulation and interpretation of look-up tables is simple and the usual offline procedures for calibration are based on LS methods. Linear interpolation is usual for computing the outputs. Anyhow, the tables are of course subjected to drift and ageing when running online. Adaptive filtering can be used for correcting the drift and/or tuning parameters in an offline basis.

⁴ Usual dimensions of look-up tables are 2D, while 1D tables are often named as curves, but in fact they can be considered as 1D look-up tables. Using higher dimensional grids is not usual due to the involved computational burden, excepting specific cases such as for representing different combustion modes.

EKF for Updating Look-up Tables

Höckerdal et al. (2011) propose an EKF for updating table elements where they are treated as states to be observed and updated by measuring the considered output. In this approach, \mathbf{P} represents the ageing of the states, defining a proper K for updating in such sense that locally inactive elements see how their related variance grows monotonically and active elements see how this is modified depending on the weighted distance to the considered element. The interpolation principle weights the correction and \mathbf{P} updating: more excited elements will tend to have lower variance than the less excited ones. A bounded limit on \mathbf{P} should be applied for engineering applications in order to avoid robustness problems.

The first limitation of this algorithm is that although inactive elements do not really affect the updating in a given iteration, EKF manipulates all elements of \mathbf{P} . The global stability of the method relies on the observability (linked with activeness) of the states and although during each iteration only 4 elements (in a 2D example) are locally observable and the remaining are unobservable, the calculation involves all grid areas. A second limitation is that system matrices vary with time making impossible to derive a steady-state Kalman filter (Payri et al. 2012). This forces to solve the Riccati equation at every instant for inferring K , involving a huge memory and computational resources. By utilising a numerical example, an EKF for updating a look-up table with 20-by-20 elements gives rise to a covariance matrix of 400-by-400 elements and thereby also a significant computational burden when solving the Riccati equations, which grows rapidly with the grid dimensions. Therefore an important discussion of the work is how the KF can be used or modified to get an efficient updating procedure for look-up tables without an important loss of properties.

RLS and Other Approaches

An alternative solution for estimation is the use of LS techniques, see e.g. Peyton Jones and Muske (2009) who use a RLS with a forgetting factor for updating look-up tables. The programming of a RLS is fairly simple and requires that table grid and data is well distributed for avoiding robustness problems (as the authors literally claim). Vogt et al. (2004) present the normalised least mean square (NMLS) method optimised for online-adaptation of tables and propose an interesting simplification on this method by separating non-active and active elements of the considered table, aspect that is also exploited in this work but for EKF-based methods. The results are good with much lower computation involved but with a slower convergence with respect to the standard RLS.

Another interesting contribution due to the simplicity of the formulation is made by Wu (2006), who treats the problem of table updating as a reverse interpolation problem. A proportional weighting is then used for updating all the elements that were involved in the previous interpolation calculation. The author cites it literally as *multiple nodes proportional distribution*. This weighting is calculated only from

the inputs and previous outputs. In that way, the method does not take into account any noise in the measurement, and can be considered as sub-optimal if comparing with the KF, but with a much lower computation and memory weight because only the table values related with observable elements are updated.

This work presents two approaches (SKF and SSKF) with some characteristics of the commented above in order to update look-up tables efficiently.

References

- Agrell F, Angström HE, Eriksson B, Wikander J, Linderyd J (2005) Transient control of HCCI combustion by aid of variable valve timing through the use of a engine state corrected CA50-controller combined with an in-cylinder state estimator estimating lambda. In: SAE technical paper 2005-01-2128
- Alberer D, del Re L (2009a) Fast oxygen based transient diesel engine operation. In: SAE technical paper 2009-01-0622
- Alberer D, del Re L (2009b) Optimization of the transient diesel engine operation. In: SAE technical paper 2009-24-0113
- Alonso JM, Alvarruiz F, Desantes JM, Hernández L, Hernández V, Moltó G (2007) Combining neural networks and genetic algorithms to predict and reduce diesel engine emissions. *IEEE Trans Evol Comput* 11(1):46–55
- Andersson M (2006) Fast NO_x prediction in diesel engines. PhD Thesis, Lund University
- Andersson I, Eriksson L (2009) A parametric model for ionization current in a four stroke SI engine. *ASME*
- Arrègle J, López JJ, Martín J, Mocholí E (2006a) Development of a mixing and combustion zero-dimensional model for diesel engines. In: SAE technical paper 2006-01-1382
- Arrègle J, Bermúdez V, Serrano JR, Fuentes E (2006b) Procedure for engine transient cycle emissions testing in real time. *Exp Thermal Fluid Sci* 30(5):485–496
- Arrègle J, López JJ, Guardiola C, Monin C (2010) On board NO_x prediction in diesel engines: a physical approach. In: del Re L et al. (ed) *Automotive model predictive control: models, methods and applications*. Springer, London. ISBN-1849960704
- Archie I, Pianese C, Rizzo G (2003) An integrated system of models for performance and emissions in SI engines: development and identification. In: SAE technical paper 2003-01-1052
- Archie I, Pianese C, Sorrentino M (2006) A procedure to enhance identification of recurrent neural networks for simulating air-fuel ratio dynamics in SI engines. *Eng Appl Artif Intell* 19(1):65–77
- Archie I, Pianese C, Sorrentino M (2010) Development of recurrent neural networks for virtual sensing of NO_x emissions in internal combustion engines. *SAE Int J Fuels Lubricants* 2(2):354–361
- Archie I, Crisculo I, Pianese C, De Cesare M (2011) Tuning of the engine control variables of an automotive turbocharged diesel engine via model based optimization. In: SAE technical paper 2011-24-0146
- Bedick CR, Clark NN, Zhen F, Atkinson RJ, McKain DL (2009) Testing of a heavy-duty diesel engine schedule for representative measurement of emissions. *J Air Waste Manage Assoc* 59(8):960–971
- Benaïcha F, Bencherif K, Sorine M, Vivalda JC (2011) Model based mass soot observer of diesel particle filter. In: *IFAC proceedings volumes (IFAC-PapersOnline)*, vol 18, pp 10647–10652
- Bickerstaffe S (2009) No one ideal solution. *Automot Eng* 34(9):44–46
- Bosch R (2011) *Automotive handbook*. In: Bosch handbooks, 8th edn. Robert Bosch GmbH
- Brand D (2005) Control-oriented modeling of NO emissions of SI engines. PhD Thesis, ETH, Zürich
- Calendini PO, Breuer S (2010) Mean value engine models applied to control system design and validation. *Lecture notes in control and information sciences*, vol 402. Springer, London

- Carberry B, Grasi G, Guerin S, Jayat F, Konieczny R (2005) Pre-turbocharger catalyst—Fast catalyst light-off evaluation. In: SAE technical paper 2005-01-2142
- Cesario N, Di Meglio M, Pirozzi F, Moselli G, Tagliatela F, Carpentieri F (2005) Air/Fuel control system in SI engines based on virtual lambda sensor. In: SAE technical paper 2005-24-058
- Chadli M, Akhenak A, Ragot J, Maquinc D (2009) State and unknown input estimation for discrete time multiple model. *J Franklin Inst* 346:593–610
- Chan SH, Chen XS, Arcoumanis C (1997) Measurement and signal reconstruction of transient nitric oxide emissions in the exhaust of a turbocharged diesel engine. *J Dyn Syst Meas Control, Trans ASME* 119(4):620–630
- Chauvin J, Moulin P, Corde G, Petit N, Rouchon P (2006) Kalman filtering for real-time individual cylinder air fuel ratio observer on a diesel engine test bench. In: Proceedings of the American control conference, pp 1886–1891
- Chauvin J, Grondin O, Moulin P (2011) Control oriented model of a variable geometry turbocharger in an engine with two EGR loops. *Oil Gas Sci Technol-Revue D IFP Energies Nouvelles* 66(4, SI):563–571
- Chen TS, You RZ (2008) A novel fault tolerant sensor system for sensor drift compensation. *Sens Actuators A: Phys* 147:623–632
- Chiang CJ, Stefanopoulou AG, Jankovic M (2007) Transitions in homogeneous charge compression ignition engines. *IEEE Trans Control Syst Technol* 15(3):438–448
- Chi J, Da Costa H (2005) Modeling and control of a urea-SCR aftertreatment system. In: SAE technical paper 2005-01-0966
- Deng J, Stobart R, Liu C, Winward E (2012) Explicit model predictive control of the diesel engine fuel path. In: SAE technical paper 2012-01-0893
- Desantes JM, Luján JM, Guardiola C, Blanco-Rodríguez D (2011) Development of NO_x fast estimate using NO_x sensors. In: EAEC 2011 congress, Valencia
- Desantes JM, López JJ, Redón P, Arrègle J (2012) Evaluation of the thermal NO formation mechanism under low-temperature diesel combustion conditions. *Int J Engine Res* 13(6):531–539
- Desantes JM, Luján JM, Pla B, Soler JA (2013) On the combination of high-pressure and low-pressure exhaust gas recirculation loops for improved fuel economy and reduced emissions in high-speed direct-injection engines. *Int J Engine Res* 14(1):3–11
- Dueker H, Friese KH, Haecker WD (1975) Ceramic aspects of the bosch lambda-sensor. In: SAE technical paper 750223
- Ebert C, Jones C (2009) Embedded software: facts, figures, and future. *IEEE Comput* 42(4):42–52
- Eriksson L, Andersson I (2002) An analytic model for cylinder pressure in a four stroke SI engine. In: SAE technical paper 2002-01-0371
- Falck T, Dreesen P, De Brabanter K, Pelckmans K, De Moor B, Suykens JAK (2012) Least-squares support vector machines for the identification of Wiener-Hammerstein systems. *Control Eng Pract* 20(11):1165–1174
- Fauzi N-E, Leung H, Kurian A (2011) Data fusion in intelligent transportation systems: progress and challenges—A survey. *Inf Fusion* 12(1):4–10
- Fleming WJ (2001) Overview of automotive sensors. *IEEE Sens J* 1(4):296–308
- Franco V, Kousoulidou M, Muntean M, Ntziachristos L, Hausberger S, Dilara P (2013) Road vehicle emission factors development: a review. *Atmos Environ* 70:84–97
- Fröbert A, Raux S, Lahougue A, Hamon C, Pajot K, Blanchard G (2012) HC-SCR on silver-based catalyst: from synthetic gas bench to real use. *SAE Int J Fuels Lubricants* 5(1):389–398
- Galindo J, Climent H, Guardiola C, Doménech J (2009) Strategies for improving the mode transition in a sequential parallel turbocharged automotive diesel engine. *Int J Automot Technol* 10(2):141–149
- Galindo J, Serrano JR, Guardiola C, Blanco-Rodríguez D, Cuadrado IG (2011) An on-engine method for dynamic characterisation of NO_x concentration sensors. *Exp Thermal Fluid Sci* 35(3):470–476
- Gao JB, Harris CJ (2002) Some remarks on Kalman filters for the multisensor fusion. *Inf Fusion* 3:191–201

- Geivanidis S, Samaras Z (2008) Development of a dynamic model for the reconstruction of tailpipe emissions from measurements on a constant volume sampling dilution system. *Meas Sci Technol* 19(1).doi:10.1088/0957-0233/19/1/015404
- Geupel A, Kubinski DJ, Mulla S, Ballinger TH, Chen H, Visser JH, Moos R (2011) Integrating NO_x sensor for automotive exhausts—A novel concept. *Sens Lett* 9(1):311–315
- Groß A, Beulertz G, Marr I, Kubinski DJ, Visser JH, Moos R (2012) Dual mode NO_x sensor: measuring both the accumulated amount and instantaneous level at low concentrations. *Sensors (Basel)* 12(3):2831–2850
- Grünbacher E, Kefer P, del Re L (2005) Estimation of the mean value engine torque using an extended Kalman filter. In: SAE technical paper 2005–01-0063
- Guardiola C, López JJ, Martín J, García-Sarmiento D (2011) Semiempirical in-cylinder pressure based model for NO_x prediction oriented to control applications. *Appl Thermal Eng* 31(16):3275–3286
- Guardiola C, Gil A, Pla B, Piqueras P (2012) Representation limits of mean value engine models. *Lecture notes in control and information sciences*, vol 418, pp 185–206
- Guardiola C, Pla B, Blanco-Rodriguez D, Cabrera P (2013a) A learning algorithm concept for updating look-up tables for automotive applications. *Math Comput Model* 57(7–8):1979–1989
- Guardiola C, Pla B, Blanco-Rodriguez D, Eriksson L (2013b) A computationally efficient Kalman filter based estimator for updating look-up tables applied to NO_x estimation in diesel engines. *Control Eng Pract* 21(11):1455–1468
- Guardiola C, Pla B, Blanco-Rodriguez D, Mazer A, Hayat O (2013c) A bias correction method for fast fuel-to-air ratio estimation in diesel engines. In: *Proceedings of the Institution of Mechanical Engineers. Part D: J Automobile Eng* 227(8):1099–1111
- Guzzella L, Amstutz A (1998) Control of diesel engines. *IEEE Control Syst Mag* 8:55–71
- Guzzella L, Onder CH (2004) Introduction to modeling and control of internal combustion engine systems. Springer, Berlin
- Haber B, Wang J (2010) Robust control approach on diesel engines with dual-loop exhaust gas recirculation systems. In: ASME 2010 dynamic systems and control conference, DSCC2010, vol 1, pp 711–718
- Hammel C, Jessen H, Boss B, Traub A, Tischer C, Hönninger H (2003) A common software architecture for diesel and gasoline engine control systems of the new generation EDC/ME(D)17. In: SAE technical paper 2003–01-1048
- Henningsson M (2012) Data-rich multivariable control of heavy-duty engines. PhD Thesis, Department of Automatic Control, Lund University, Sweden, Mayo 2012
- Heywood JB (1988) Internal combustion engine fundamentals. McGraw Hill, New York
- Hirsch M, Alberer D, del Re L (2008) Grey-box control oriented emissions models. In: *Proceedings of the 17th world congress, The International Federation of Automatic Control*, Seoul, Korea, 6–11 July 2008
- Höckerdal E (2011) Model error compensation in ODE and DAE estimators with automotive engine applications. PhD Thesis, Linköping University Institute of Technology
- Höckerdal E, Frisk E, Eriksson L (2009) Observer design and model augmentation for bias compensation with a truck engine application. *Control Eng Pract* 17(3):408–417
- Höckerdal E, Frisk E, Eriksson L (2011) EKF-based adaptation of look-up tables with an air mass-flow sensor application. *Control Eng Pract* 19:442–453
- Hofmann L, Rusch K, Fischer S, Lemire B (2004) Onboard emissions monitoring on a HD truck with an SCR system using NO_x sensors. In: SAE technical paper 2004–01-1290
- Horiba (2001) Horiba MEXA-7000DEGR instruction manual, Aug 2001
- Hsieh M-F, Wang J (2011) Design and experimental validation of an extended Kalman filter-based NO_x concentration estimator in selective catalytic reduction system applications. *Control Eng Pract* 19(4):346–353
- Johansson R (1993) System modeling and identification. Prentice Hall information and system sciences series. Prentice Hall, Englewood Cliffs
- Johnson TV (2012) Vehicular emissions in review. In: SAE technical paper 2012–01-0368, vol 5(2)

- Kalman RE (1960) A new approach to linear filtering and prediction problems. *J Basic Eng* 82 (35–45)
- Karlsson M, Ekholm K, Strandh P, Tunestål P, Johansson R (2010) Dynamic mapping of diesel engine through system identification. In: *Proceedings of the American control conference*, Baltimore, MD
- Kasper M (2004) The number concentration of non-volatile particles—Design study for an instrument according to the PMP recommendations. In: *SAE technical paper 2004–01-0960*
- Kato N, Nakagaki K, Ina N (1996) Thick film ZrO_2 NO_x sensor. In: *SAE technical paper 960334*
- Khaleghi B, Khamis A, Karray FO, Razavi SN (2013) Multisensor data fusion: a review of the state-of-the-art. *Inf Fusion* 14(1):28–44
- Klett S, Piesche M, Heinzelmann S, Weyl H, Wiedenmann H-M, Schneider U, Diehl L, Neumann H (2005) Numerical and experimental analysis of the momentum and heat transfer in exhaust gas sensors. In: *SAE technical paper 2005–01-0037*
- Künkler C (2001) Catalytic reduction of NO_x on heavy-duty trucks. PhD Thesis, Lund University
- Ladommatos N, Abdelhalim S, Zhao H, Hu Z (1996a) The dilution, chemical, and thermal effects of exhaust gas recirculation on diesel engine emissions. In: *Part 1: Effect of reducing inlet charge oxygen*. *SAE technical paper 961165*
- Ladommatos N, Abdelhalim S, Zhao H, Hu Z (1996b) The dilution, chemical, and thermal effects of exhaust gas recirculation on diesel engine emissions. In: *Part 2: Effects of carbon dioxide*. *SAE technical paper 961167*
- Ladommatos N, Abdelhalim S, Zhao H, Hu Z (1997a) The dilution, chemical, and thermal effects of exhaust gas recirculation on diesel engine emissions. In: *Part 3: Effects of water vapour*. *SAE technical paper 971659*
- Ladommatos N, Abdelhalim S, Zhao H, Hu Z (1997b) The dilution, chemical, and thermal effects of exhaust gas recirculation on diesel engine emissions. In: *Part 4: Effects of carbon dioxide and water vapour*. *SAE technical paper 971660*
- Ladommatos N, Abdelhalim S, Zhao H (2000) The effects of exhaust gas recirculation on diesel combustion and emissions. *Int J Engine Res* 1(1):107–126
- Lapuerta M, Martos FJ, Cárdenas MD (2005) Determination of light extinction efficiency of diesel soot from smoke opacity measurements. *Meas Sci Technol* 16(10):2048–2055
- Lavoie GA, Heywood JB, Keck JC (1970) Experimental and theoretical study of nitric oxide formation in internal combustion engines. *Combust Sci Technol* 1(4):313–326
- Ljung L (1999) *System identification: theory for the user*. Prentice Hall PTR, Upper Saddle River
- Lu X, Han D, Huang Z (2011) Fuel design and management for the control of advanced compression-ignition combustion modes. *Prog Energy Combust Sci* 37:741–783
- Lughofer E, Macián V, Guardiola C, Klement EP (2011) Identifying static and dynamic prediction models for NO_x emissions with evolving fuzzy systems. *Appl Soft Comput* 11:2487–2500
- Luján JM, Pla B, Moroz S, Bourgoin G (2008) Effect of low pressure EGR on gas exchange processes and turbocharging of a HSDI engine. In: *THIESEL 2008 conference on thermo- and fluid-dynamic processes in diesel engines*
- Maaß, Stobart R, Deng J (2009) Diesel engine emissions prediction using parallel neural networks. In: *Proceedings of the American control conference*, pp 1122–1127
- Mamakos A, Bonnel P, Perujo A, Carriero M (2013) Assessment of portable emission measurement systems (PEMS) for heavy-duty diesel engines with respect to particulate matter. *J Aerosol Sci* 57:54–70
- Manchur TB, Checkel MD (2005) Time resolution effects on accuracy of real-time NO_x emissions measurements. In: *SAE technical paper 2005–01-0674*
- Mehra RK (1970) Approaches to adaptive filtering. In: *IEEE symposium on adaptive processes*, Austin
- Millo F, Giacominetto PF, Bernardi MG (2012) Analysis of different exhaust gas recirculation architectures for passenger car diesel engines. *Appl Energy* 98:79–91
- Moos R (2005) A brief overview on automotive exhaust gas sensors based on electroceramics. *Int J Appl Ceram Technol* 2(5):401–413

- Moos R (2010) Catalysts as sensors—A promising novel approach in automotive exhaust gas aftertreatment. *Sensors (Basel)* 10(7):6773–6787
- Moos R, Schönauer D (2008) Recent developments in the field of automotive exhaust gas ammonia sensing. *Sens Lett* 6(6):821–825
- Moos R, Spörl M, Hagen G, Gollwitzer A, Wedemann M, Fischerauer G (2008) TWC: lambda control and OBD without lambda probe—An initial approach. In: SAE technical paper 2008-01-0916
- Mrosek M, Sequenz H, Isermann R (2011) Identification of emission measurement dynamics for diesel engines. In: IFAC proceedings volumes (IFAC-PapersOnline), vol 18, pp 11839–11844
- Nakanouchi Y, Kurosawa H, Hasei M, Yan Y, Kunimoto A (1996) New type of NO_x sensors for automobiles. In: SAE technical paper 961130
- Nelson CS (2011) Particulate matter sensor. US patent 8225648
- Nyberg M, Stutte T (2004) Model based diagnosis of the air path of an automotive diesel engine. *Control Eng Pract* 12:513–525
- Ogata K (2001) Modern control engineering, 4th edn. Prentice Hall, Englewood Cliffs
- Ortner P, del Re L (2007) Predictive control of a diesel engine air path. *IEEE Trans Control Syst Technol* 15(3):449–456
- Park S, Matsumoto T, Oda N (2010) Numerical analysis of turbocharger response delay mechanism. In: SAE technical paper 2010-01-1226
- Payri F, Margot X, Gil A, Martín J (2005) Computational study of heat transfer to the walls of a DI diesel engine. In: SAE technical paper 2005-01-0210
- Payri F, Olmeda P, Martín J, García A (2011a) A complete 0D thermodynamic predictive model for direct injection diesel engines. *Appl Energy* 88(88):4632–4641
- Payri F, Serrano JR, Piqueras P, García-Afonso O (2011b) Performance analysis of a turbocharged heavy duty diesel engine with a pre-turbo diesel particulate filter configuration. *SAE Int J Engines* 4(2):2559–2572
- Payri F, Guardiola C, Blanco-Rodríguez D, Mazer A, Cornette A (2012) Methodology for design and calibration of a drift compensation method for fuel-to-air ratio estimation. In: SAE technical paper 2012-01-0717
- Peyton Jones JC, Muske KR (2009) Identification and adaptation of linear look-up table parameters using an efficient recursive least-squares technique. *ISA Trans* 48(4):476–483
- Pla B (2009) Análisis del Proceso de la Recirculación de los Gases de Escape de Baja Presión en Motores Diesel Sobrealimentados. PhD Thesis, Universitat Politècnica de València, Departamento de Máquinas y Motores Térmicos
- Polóni T, Rohal'-Ilkiv B, Alberer D, del Re L, Johansen TA (2012) Comparison of sensor configurations for mass flow estimation of turbocharged diesel engines, vol 418 of Lecture notes in control and information sciences
- Powell JD (1993) Engine control using cylinder pressure: past, present, and future. *J Dyn Syst Meas Control*, Trans ASME 115(2 B):343–350
- Regitz S, Collings N (2008a) Fast response air-to-fuel ratio measurements using a novel device based on a wide band lambda sensor. *Meas Sci Technol* 19(075201)
- Regitz S, Collings N (2008b) Study of cycle-by-cycle air-to-fuel ratio determined from the exhaust gas composition and a novel fast response device based on a wide band lambda sensor. In: SAE technical paper 2008-01-2439
- Riegel J, Neumann H, Wiedenmann HM (2002) Exhaust gas sensors for automotive emission control. *Solid State Ion* 152–153:783–800
- Roberts C (2011) The pursuit of high efficiency engines—SwRI programs. In: Emissions conference (2011), Ann Arbor, MI
- Saidur R, Rezaei M, Muzammil WK, Hassan MH, Paria S, Hasanuzzaman M (2012) Technologies to recover exhaust heat from internal combustion engines. *Renew Sustain Energy Rev* 16(8):5649–5659

- Schilling A (2008) Model-based detection and isolation of faults in the air and fuel paths of common-rail DI diesel engines equipped with a lambda and a nitrogen oxides sensor. PhD Thesis, ETH-Zürich
- Schilling A, Amstutz A, Onder CH, Guzzella L (2006) A real-time model for the prediction of the NO_x emissions in DI diesel engines. In: Proceedings of the 2006 IEEE international conference on control applications, Munich, Germany
- Schilling A, Amstutz A, Guzzella L (2008) Model-based detection and isolation of faults due to ageing in the air and fuel paths of common-rail direct injection diesel engines equipped with a λ and a nitrogen oxides sensor. In: Proceedings of the Institution of Mechanical Engineers. Part D: J Automobile Eng 222:101–117
- Schommers J, Duvinage F, Stotz M, Peters A, Ellwanger S, Koyanagi K, Gildein H (2000) Potential of common Rail injection system for passenger car DI diesel engines. In: SAE technical paper 2000–01-0944
- Schönauer D, Nieder T, Wiesner K, Fleischer M, Moos R (2011) Investigation of the electrode effects in mixed potential type ammonia exhaust gas sensors. Solid State Ion 192(1):38–41
- Shutty J, Benali H, Daeubler L, Traver M (2007) Air system control for advanced diesel engines. In: SAE technical paper 2007–04-16
- Simon D (2006) Optimal state estimation: Kalman, H infinity, and nonlinear approaches. Wiley, New York
- Smith JA (2000) Demonstration of a fast response on-board NO_x sensor for heavy-duty diesel vehicles. SwRI Project No. 03–02256 Contract No. 98–302. In: Technical report, Southwest Research Institute Engine and Vehicle Research Division PO Box 28510 San Antonio, Texas 78228–0510
- Stefanopoulou AG, Kolmanovsky I, Freudenberg JS (2000) Control of variable geometry turbocharged diesel engines for reduced emissions. IEEE Trans Control Syst Technol 8(4):733–745
- Steppan J, Henderson B, Johnson K, Yusuf Khan M, Diller T, Hall M, Lourduhasamy A, Allmendinger K, Matthews R (2011) Comparison of an on-board, real-time electronic PM sensor with laboratory instruments using a 2009 heavy-duty diesel vehicle. In: SAE technical paper 2011–01-0627
- Stewart G, Borrelli F, Pekar J, Germann D, Pachner D, Kihás D (2010) Toward a systematic design for turbocharged engine control, vol 402. Lecture notes in control and information sciences. Springer, London
- Stiller C, Puente León F (2011) Information fusion for automotive applications—An overview. Inf Fusion 12(4):244–252
- Stotsky A, Kolmanovsky I (2002) Application of input estimation techniques to charge estimation and control in automotive engines. Control Eng Pract 10(12):1371–1383
- Surenahalli HS, Parker GG, Johnson JH, Devarakonda MN (2012) A Kalman filter estimator for a diesel oxidation catalyst during active regeneration of a CPF. In: Proceedings of the American control conference, pp 4969–4974
- Takagi T, Sugeno M (1985), Fuzzy identification of systems and its applications to modeling and control. IEEE Trans Syst Man Cybern SMC-15, no 1
- Timoney DJ, Desantes JM, Hernández L, Lyons CM (2005) The development of a semi-empirical model for rapid NO_x concentration evaluation using measured in-cylinder pressure in diesel engines. In: Proceedings of the Institution of Mechanical Engineers. Part D: J Automobile Eng 219(5):621–631
- Tobias P, Mårtensson P, Göras A, Lundström I (1999) Moving gas outlets for the evaluation of fast gas sensors. Sens Actuators B: Chem 58(1–3):389–393
- Trimboli S, Di Cairano S, Bemporad A, Kolmanovsky IV (2012) Model predictive control with delay compensation for air-to-fuel ratio control. Lecture notes in control and information sciences, vol 423. Springer, Berlin
- Tschanz F, Amstutz A, Onder CH, Guzzella L (2012) Feedback control of particulate matter and nitrogen oxide emissions in diesel engines. Control Eng Pract (in press)
- Tunestål P, Hedrick JK (2003) Cylinder air/fuel ratio estimation using net heat release data. Control Eng Pract 11(3):311–318

- Turner JD (2009) Automotive sensors. In: Sensor technology series. Momentum
- Twigg MV (2007) Progress and future challenges in controlling automotive exhaust gas emissions. Appl Catal B: Environ 70(1–4):2–15
- van Basshuysen R, Schaefer F (2004) Internal combustion engine handbook—Basics. SAE Int Comp Syst Perspect
- van Nieuwstadt M (2003) Coordinated control of EGR valve and intake throttle for better fuel economy in diesel engines. In: SAE technical paper 2003–01–0362
- van Nieuwstadt M, Upadhyay D (2005) Diagnosis of a urea SCR catalytic system
- Varnier O (2012) Trends and limits of two-stage boosting systems for automotive diesel engines. PhD Thesis, Universitat Politècnica de València, Departamento de Máquinas y Motores Térmicos
- Viskup R, Alberer D, Oppenauer K, del Re L (2011) Measurement of transient PM emissions in diesel engine. In: SAE technical paper 2011–24–0197
- Vogt M, Müller N, Isermann R (2004) On-line adaptation of grid-based look-up tables using a fast linear regression technique. J Dyn Syst Meas Control, Trans ASME 126(4):732–739
- Wagner JF, Wieneke T (2003) Integrating satellite and inertial navigation—Conventional and new fusion approaches. Control Eng Pract 11(5):543–550 (Automatic Control in Aerospace)
- Wahlström J (2009) Control of EGR and VGT for emission control and pumping work minimization in diesel engines. PhD Thesis, Linköpings Universitet. LiU-TEK-LIC-2006:52, Thesis no 1271
- Wang DY, Yao S, Shost M, Yoo J-H, Cabush D, Racine D, Cloudt R, Willems F (2008) Ammonia sensor for closed-loop SCR control. In: SAE technical paper 2008–01–0919
- Wang DY (2007) Real-time dynamics of amperometric exhaust oxygen sensors. Sens Actuators B: Chem 126(2):551–556
- Warey A, Hall MJ (2005) Performance characteristics of a new on-board engine exhaust particulate matter sensor. In: SAE technical paper 2005–01–3792
- Westlund A (2011) Simplified models for emission formation in diesel engines during transient operation. PhD Thesis, KTH Industrial Engineering and Management
- Westlund A, Winkler N, Diotallevi F, Ångström H (2008) Predictions and measurements of transient NO emissions for a two-stage turbocharged HD diesel engine with EGR. In: Thiesel conference on thermo-fluid dynamics processes in diesel engines, Valencia, Spain
- Winkler-Ebner B, Hirsch M, del Re L, Klinger H, Mistelberger W (2010) Comparison of virtual and physical NO_x-sensors for heavy duty diesel engine application. SAE Int J Engines 3(1): 1124–1139
- Woschni G (1967) A universally applicable equation for the instantaneous heat transfer coefficient in the internal combustion engine. In: SAE technical paper 670931
- Wu G (2006) A table update method for adaptive knock control. In: SAE technical paper 2006–01–0607
- Yan F, Wang J (2012) Pressure-based transient intake manifold temperature reconstruction in diesel engines. Control Eng Pract 20(5):531–538
- Yang H, Tsourapas V, Prakash AK, Yuan Q, Rugge R, Mhaskar U, Rao PN (2009) Hardware-in-the-loop (HIL) modeling and simulation for diesel aftertreatment controls development. In: SAE technical paper 2009–01–2928
- Yen G, Michel AN (1991) A learning and forgetting algorithm in associative memories: results involving pseudo inverses. In: IEEE international symposium on circuits and systems, vol 2, pp 778–781
- Zeldovich J (1946) The oxidation of nitrogen combustion and explosions. Acta Physicochim 21(4):577–628
- Zhou G, Jørgensen JB, Duwig C, Huusom JK (2012) State estimation in the automotive SCR deNO_x process. In: IFAC proceedings volumes, vol 8, pp 501–506
- Zhuiykov S (2010) Electrochemistry of zirconia gas sensors. Taylor & Francis, London
- Zhuiykov S, Miura N (2007) Development of zirconia-based potentiometric NO_x sensors for automotive and energy industries in the early 21st century: what are the prospects for sensors? Sens Actuators B: Chem 121(2):639–651

Modelling and Observation of Exhaust Gas
Concentrations for Diesel Engine Control

Blanco-Rodriguez, D.

2014, XVII, 190 p. 89 illus., 1 illus. in color., Hardcover

ISBN: 978-3-319-06736-0