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Model Error Compensation in ODE and DAE Estimators

with Automotive Engine Applications

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To My Family

Abstract

Control and diagnosis of complex systems demand accurate information of the system state to enable efficient control and to detect system malfunction. Physical sensors are expensive and some quantities are hard or even impossible to measure with physical sensors. This has made model-based estimation an attractive alternative.

Model based observers are sensitive to errors in the model and since the model complexity has to be kept low to enable use in real-time applications, the accuracy of the models becomes limited. Further, modeling is difficult and expensive with large efforts on model parametrization, calibration, and validation, and it is desirable to design robust observers based on existing models. An experimental investigation of an engine application shows that the model have stationary errors while the dynamics of the engine is well described by the model equations. This together with frequent appearance of sensor offsets have led to a demand for systematic ways of handling operating point dependent stationary errors, also called biases, in both models and sensors.

Systematic design methods for reducing bias in model based observers are developed. The methods utilize a default model, described by systems of ordinary differential equations (ODE) or differential algebraic equations (DAE), and measurement data. A low order description of the model deficiencies is estimated from the default model and measurement data, which results in an automatic model augmentation. The idea is then to use the augmented model in observer design, yielding reduced stationary estimation errors compared to an observer based on the default model. Three main results are: a characterization of possible model augmentations from observability perspectives, a characterization of augmentations possible to estimate from measurement data, and a robustness analysis with respect to noise and model uncertainty.

An important step is how the bias is modeled, and two ways of describing the bias are analyzed. The first is a random walk and the second is a parameterization of the bias. The latter can be viewed as an extension of the first and utilizes a parameterized function that describes the bias as a function of the operating point of the system. By utilizing a parameterized function, a memory is introduced that enables separate tracking of aging and operating point dependence. This eliminates the trade-off between noise suppression in the parameter convergence and rapid change of the offset in transients. Direct applications for the parameterized bias are online adaptation and offline calibration of maps commonly used in engine control systems.

The methods are evaluated on measurement data from heavy duty diesel engines. A first order model augmentation is found for an ODE of an engine with EGR and VGT. By modeling the bias as a random walk, the estimation error is reduced by 50 % for a certification cycle. By instead letting a parameterized function describe the bias, better estimation accuracy and increased robustness is achieved. For an engine with intake manifold throttle, EGR, and VGT and a corresponding stiff ODE, experiments show that it is computationally beneficial to approximate the fast dynamics with instantaneous relations, transforming the ODE into a DAE. A main advantage is the possibility to use more than 10 times longer step lengths for the DAE based observer, without loss of estimation accuracy. By augmenting the DAE, an observer that achieves a 55 % reduction of the estimation error during a certification cycle is designed.

Populärvetenskaplig Sammanfattning

I dagens samhälle har transporter av olika slag en betydande roll och på land står den tunga lastbilen för en majoritet av dessa. Samtidigt som transportbehovet ständigt ökar ställer både emissionslagstiftning och kunder allt högre krav på minskade utsläpp och minskad bränsleförbrukning. För dieselmotorer är det utsläpp av partiklar, det vill säga oförbränt bränsle och smörjoljerester, samt utsläpp av kväveoxider och koldioxid som omfattas. Kraven innebär både att hålla förbränningsemissionerna nere under normal drift och att fel som medför risk för förhöjda emissioner måste kunna upptäckas, vilket driver den tekniska utvecklingen framåt. Med introduktionen av nya tekniska lösningar samt hårdare emissionskrav följer behovet av tillförlitlig information om motorns interna tillstånd för att möjliggöra robust och säker drift. Till exempel behöver information om tryck, temperatur och syre/bränsle-förhållande tas fram.

Dock är det inte ekonomiskt eller praktiskt möjligt att använda fysiska sensorer för att mäta alla dessa parametrar. Det här har medfört introduktionen av matematiska modeller över motorn, vilka tillsammans med tillgängliga sensorer används för att ta fram information om motorns tillstånd. Modellerna baseras ofta på fysikaliska samband för exempelvis energi- och massbevarande. De är dyra att utveckla då det tar tid att ta fram de matematiska samband som krävs. Dessutom tillkommer aktiviteter såsom parametrisering, kalibrering och validering. Oavsett hur mycket tid som läggs på att ta fram modellen kommer den aldrig att bli perfekt. I de fall där kraven på modellens beräkningskomplexitet är höga blir detta extra tydligt, vilket är fallet i de flesta realtidsapplikationer. Resultatet från modellen kommer alltså att avvika från de verkliga värdena, och det blir viktigt att reducera fel i skattningar som uppkommit till följd av fel i modellen.

Det har därför vuxit fram ett intresse för metoder som möjliggör användning av modeller behäftade med fel för att beräkna motorers interna tillstånd med hög noggrannhet. Syftet med forskningen som presenteras i avhandlingen är därför att utveckla systematiska metoder som, utan att involvera extra modellering, höjer noggrannheten i skattningar baserade på modeller som innehåller fel. Metoderna hjälper ingenjören, som har god kännedom om systemet, modellen och dess brister, att svara på frågan om kompensation för ett visst fel är möjlig, samtidigt som metoderna kan peka ut andra potentiella felkällor. Ur metoderna fås en felbeskrivning som används för att utöka modellen. Genom att nyttja denna modell, utökad med felbeskrivning, kan information om motorns tillstånd beräknas med högre noggrannhet. I motorstyrenheter är dessutom uppslagstabeller för att beskriva komplicerade fenomen där fysikaliska modeller saknas vanligt förekommande. Dessa är ofta i behov av kontinuerlig anpassning för att kompensera för drift, åldrande och slitage av motorns fysiska komponenter och de framtagna metoderna lämpar sig väl även för detta ändamål.

Sammanfattningsvis förenar metoderna teori, som garanterar tillförlitliga och stabila skattningar, med industriella tillämpningar såsom anpassning av uppslagstabeller. Metoderna är utvärderade med hjälp av mätdata från standardiserade certifieringscykler insamlade i motorprovceller på Scania i Södertälje. I dessa cykler uppvisas minskningar av skattningsfel på i medel omkring 50 %. Reduktionen av skattningsfel möjliggör noggrann reglering, med minskade emissioner och bränsleförbrukning, samt förbättrar möjligheterna att upptäcka små fel.

Acknowledgments

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First, I would like to thank my supervisors Erik Frisk and Lars Eriksson for their guidance and many interesting, and often very fruitful, discussions. I would also like to thank professor Lars Nielsen for letting me join his research group.

All colleagues at Vehicular systems also deserve a place in this acknowledgment for creating such a nice research atmosphere and a special thanks goes to Jan Åslund for his guidance in the theory of matrices. Some of the characters in the world of enlightenment that made the weeks go scary fast are; my roommates Andreas Myklebust and Peter Nyberg, the "baljan" crew composed by Oskar "toe-kick/proof-reader" Leufvén, Emil "pony-tail" Larsson, and Christoffer "orienteer" Sundström, all of whom participated in several intriguing, seldom research related, discussions.

I would also like to thank my colleagues at Scania for showing great interest in the project and for all valuable inputs. Special thanks goes to my managers Peter Madsen and Mats Jennische for letting me be a part of this project, and Mats Jennische, David Elfvik, Anders Larsson, and Ola Stenlåås for providing valuable insights and measurement data. During my short detour to the engine calibration department, made possible by Christer Eriksson, I met Martin Jonsson and Anders Gau who guided me in the world of engine maps, for which I am deeply grateful. While in the Scania department, I would also like to acknowledge my former supervisors Björn Völcker and Erik Geijer Lundin, and my project manager Lars Dahlén, whom contributed gratefully to the project. A special thanks goes to Carl Svärd, Tommy Sahi, and Dan Hallgren, for making my visits to Scania joyful and for introducing me to the Gröndal facility, which made the evenings go fast.

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Erik Höckerdal
Linköping, April 2011

Contents

Chapter 1

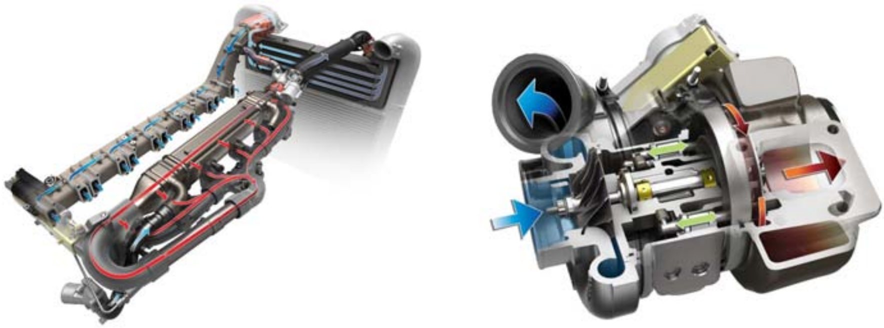
Introduction

Transportation is of vital importance in the modern economy and a major part of these transportations are carried out by trucks, e.g., in Europe and United States road vehicles account for more than 70 % of the inland freight transport (Noreland, 2008; Bradley, 2000). As a consequence, a major part of the emissions from the vehicular traffic is from trucks. It is therefore necessary to reduce the emissions and fuel consumption.

Stricter emission legislations and customer demands on low fuel consumption drive the technical development of engines and force new solutions to be introduced. To cope with reduced emission limits on diesel engines, for example intake manifold throttle, exhaust gas recirculation (EGR), and variable geometry turbine (VGT) are introduced, see Figure 1.1. This technical development, with increased system complexity and tightened requirements from customers and legislators, increase the demands on the control and diagnosis systems. Two examples of important quantities that significantly affect the emissions from diesel engines are: air to fuel ratio (λ) and EGR-fraction (x_{egr}). The increased demands on the control and diagnosis systems, increase the required information quality of λ and x_{egr}. At the same time it is desirable to have as few and cheap sensors in the system as possible to keep the cost down. This has made estimation an important and active research area, see e.g. Colin et al. (2009); Lino et al. (2008); García-Nieto et al. (2008); Andersson and Eriksson (2004).

Model based estimators are often used to achieve cost-effective estimation with high accuracy. This has driven the development of new models that are suitable for estimator design. These models have to be simple enough to be evaluated in real time, by for example an engine control unit (ECU), and at the same time describe the system behavior accurately enough for the estimation task. Development of these models is a delicate balance between computational complexity of the model and how well it manages to describe the true system. Typically, a large engineering effort is spent on modeling, often combining first law physics and system identification techniques.

In all model based control or diagnosis systems, the performance of the system is directly dependent on the accuracy of the model. In addition, as stated above, modeling



(a) Exhaust gas recirculation (EGR) system (b) Variable geometry turbine (VGT)

Figure 1.1: Technical solutions introduced on modern diesel engines to be able to fulfill the stricter emission legislations. *Courtesy Scania CV AB.*

is time consuming and even if much time is spent on physical modeling, there will always be errors in the model. The causes of these model errors can be quite varying; the model accuracy can depend on the operating point (Zimmerschied and Isermann, 2010), changes in ambient conditions (Won et al., 1998), the aging of components (Rupp and Guzzella, 2010), etc., all of which affect the system properties and hence the model errors. Model deficiencies are especially common if there are constraints on the model complexity, as is the case in most real time applications. Another scenario is that a model developed for some purpose, for example control, exists but needs improvement before it can be used for other purposes, for example diagnosis. That is, there exists a lot of models, on which much modeling time is spent, that needs improvement before they can be used in an estimation application. A common situation is that, while the dynamics is well captured by the model, there are stationary errors, possibly operating point dependent (Höckerdal et al., 2008). Hereafter, these already available models will be called default models. Since modeling is time consuming, and hence expensive, methods that enable use of these default models in estimation without involving extensive modeling efforts are needed.

In engine control and diagnosis, it is crucial to have good and unbiased estimates. In model based diagnosis (Ceccarelli et al., 2009) the true system is monitored using residuals, formed as the difference between estimated and measured signals. If the residual exceeds a threshold, it is concluded that something is wrong (Blanke et al., 2003; Isermann, 2011). In engine control (Stefanopoulou et al., 2000; Ortner and del Re, 2007; Plianos and Stobart, 2011), one objective is to control torque output while keeping the emissions below legislated levels and the fuel consumption as low as possible (Guzzella and Amstutz, 1998). Here, unbiased estimates are crucial since fuel consumption and emissions are often in conflict with each other. The hard constraints on the emissions force the engine operation away from the most fuel efficient operating point. With reduced stationary estimation errors the control system can balance closer to the fuel optimal operating point without the risk of violating the emission limits. For diesel engines this is especially difficult since the control system normally does not have any feedback information from a λ or nitrogen oxides (NO_x) sensor and have to rely on estimated signals instead (Wang, 2008). In both cases, biased estimates impair the performance.

Finally, the development of engines and engine control systems involves extensive testing, both during the development of the control strategies and the engine calibration. Data is collected in engine test cells as well as in laboratory vehicles. This means that it is fairly easy to obtain system measurements. The sensors available are often both production sensors, that will be available on the commercial product, and high grade laboratory sensors added to enable extra monitoring. These laboratory sensors provide valuable information that can be used during the development phase, allowing estimation of model errors not possible to find with only production sensors.

1.1 Problem Statement

The objective is to develop systematic methods for reducing estimation errors given a default model and measurement data, without involving extensive modeling efforts.

The starting point is a default model and measurement data from the true system. From this it can be determined if the model describes the system sufficiently well or if it has to be modified to be applicable to the intended estimation application. The focus is on adjustments with respect to operating point dependent stationary estimation errors.

If it is concluded that the model suffers from too large stationary errors and cannot be used for estimation in its current state, then the methods developed for reducing stationary estimation errors can be applied. The ideas in the developed methods are to augment the default model with bias states that compensate for operating point dependent stationary errors. This augmented model can then be used in any suitable estimator design to get an adaptive estimator with reduced stationary errors compared to using the default model directly.

1.2 Thesis Outline

The theme throughout the thesis is the successive development of methods for compensating operating point dependent stationary model errors in the design of estimators. The studied topics originate from estimation of gas flows in heavy duty diesel engines using existing mean value engine models (MVEM) (Hendricks, 1986; Jensen et al., 1991; Hendricks, 2001; Eriksson et al., 2002), referred to as default models.

Chapter 2 is based on Höckerdal et al. (2008) and describes an important estimation problem from the automotive industry. It gives an overview of the heavy duty diesel engine and model used for evaluation throughout the dissertation. This particular system is used to analyze how the quality of a sensor signal can be improved as well as how the quality can be assessed. The chapter illustrates the effect that a model with stationary errors has on the estimates when used in estimator design. Chapter 2 ends with a compilation of the contributions and their relation to other scientific work.

Papers A and E, based on Höckerdal et al. (2009) and Höckerdal et al. (Submitted), present systematic methods for bias compensation in model based estimator design for ordinary differential equation (ODE) and differential algebraic equation (DAE) models respectively. The methods apply the idea of introducing extra states, $q \in \mathbb{R}^{n_q}$, for adjusting the stationary operating point of the model, i.e. $x^\circ \to (x^\circ - A_q q)$, according to

$$\dot{x} = f(x - A_q q, u) \tag{1.1a}$$
$$\dot{q} = 0 \tag{1.1b}$$
$$y = h(x), \tag{1.1c}$$

where $x \in \mathbb{R}^{n_x}$ are the states, $u \in \mathbb{R}^{n_u}$ the inputs, and $y \in \mathbb{R}^{n_y}$ the outputs. In (1.1a), q represent the underlying cause of the bias, A_q its affection of the original states, x, and $A_q q$ shifts the stationary point of the model. Automatized methods for estimating low order augmentations, A_q, from measurement data are developed.

An operating point dependent bias can exhibit both fast and slow dynamics, arising from, for example, operating point dependent bias (Zimmerschied and Isermann, 2010) and aging (Rupp and Guzzella, 2010). Papers B and C address this problem in an integrated way by modeling the bias as a parameterized function,

$$q_{\text{fcn}}(x, u, \theta), \tag{1.2}$$

of known states and/or inputs instead of as an extra state

$$\begin{aligned} \dot{x} &= f(x, u, q_{\text{fcn}}(x, u, \theta)) \\ \dot{\theta} &= 0 \\ y &= h(x). \end{aligned} \tag{1.3}$$

The idea with a construction like (1.3) is to capture the operating point dependence of the bias by the parametrization (1.2), and use the parameters, $\theta \in \mathbb{R}^{n_\theta}$, introduced as new states, to track the aging. Paper B presents a solution and establishes necessary conditions for observability in the case the parameterized function is described by 1-D linear interpolation and an interpolation variable that is measured. Paper C extends the results with a simulation example using a 2-D cubic spline interpolation.

Paper D analyzes computational issues that arise when designing an observer for a stiff ODE system, containing both slow and fast dynamics, and especially what can be gained by approximating the fast dynamics with instantaneous relations resulting in a DAE system, i.e.

$$\begin{aligned} \dot{x}_{\text{slow}} &= f(x_{\text{slow}}, x_{\text{fast}}, u) \\ \dot{x}_{\text{fast}} &= g(x_{\text{slow}}, x_{\text{fast}}, u) \end{aligned} \quad \Rightarrow \quad \begin{aligned} \dot{x}_{\text{slow}} &= f(x_{\text{slow}}, x_{\text{fast}}, u) \\ 0 &= g(x_{\text{slow}}, x_{\text{fast}}, u) \end{aligned}.$$

In an observer, efficient and accurate solution of these continuous-time models is necessary and has to be done in discrete-time. The properties of forward and backward Euler for discretization of the continuous-time model are also analyzed.

1.3 Contributions

The main contributions are:

- The experimental analysis of model and sensor errors of heavy duty diesel engines [Chapter 2].
- Methods for estimating a low order bias compensating model augmentation using a default ODE or DAE model and measurements from the true system [Papers A and E].
- Necessary and sufficient conditions for model augmentations that maintain system observability for ODE:s and DAE:s [Paper A, Theorem 4.2, and Paper E, Theorem 4.2].
- Parametrization of all model augmentations that are possible to obtain with the proposed estimation algorithms [Paper A, Theorem 5.1].
- An algorithm for engine map adaptation with variable parameter update rate [Paper B], with an additional 2-D cubic spline application example [Paper C].
- An analysis of the benefits of approximating fast dynamics with instantaneous relations, transforming an ODE model into a DAE model, for EKF:s [Paper D].

1.4 Publications

The dissertation is based on the work presented in the following publications.

Journal Papers

Erik Höckerdal, Erik Frisk, and Lars Eriksson. EKF-based Adaptation of Look-Up Tables with an Air Mass-Flow Sensor Application. In: *Control Engineering Practice*, 19(5):442–453, 2011. [**Paper B**]

Erik Höckerdal, Erik Frisk, and Lars Eriksson. Observer Design and Model Augmentation for Bias Compensation With a Truck Engine Application. In: *Control Engineering Practice*, 17(3):408–417, 2009. [**Paper A**]

Erik Höckerdal, Lars Eriksson, and Erik Frisk. Air mass-flow measurement and estimation in diesel engines equipped with EGR and VGT. In: *SAE Int. J. Passeng. Cars – Electron. Electr. Syst.*, 1(1):393–402, 2008.

Submitted

Erik Höckerdal, Erik Frisk, and Lars Eriksson. DAE and ODE Based EKF:s and their Real-Time Performance Evaluated on a Diesel Engine. In: *IEEE Transactions on Industrial Electronics*, 2011. [**Paper D**]

Book Chapter

Erik Höckerdal, Lars Eriksson, and Erik Frisk. Off- and On-Line Identification of Maps Applied to the Gas Path in Diesel Engines. In: *Identification for Automotive Systems*, Linz, Accepted for Publication, 2010. [**Paper C**]

Conference Papers

Erik Höckerdal, Erik Frisk, and Lars Eriksson. Model Based Engine Map Adaptation Using EKF. In: *6th IFAC Symposium on Advances in Automotive Control*. Munich, Germany, 2010.

Erik Höckerdal, Erik Frisk, and Lars Eriksson. Observer Design and Model Augmentation for Bias Compensation Applied to an Engine. *IFAC World Congress*. Seoul, Korea, 2008.

Erik Höckerdal, Lars Eriksson, and Erik Frisk. Air mass-flow measurement and estimation in diesel engines equipped with EGR and VGT. In: *Electronic Engine Controls*. SAE Technical Paper 2008-01-0992. SAE World Congress, Detroit, USA, 2008.

Submitted

Erik Höckerdal, Erik Frisk, and Lars Eriksson. Bias Reduction in DAE Estimators by Model Augmentation: Observability Analysis and Experimental Evaluation. In: *50th IEEE Conference on Decision and Control and European Control Conference*, Orlando, Florida, 2011. [**Paper E**]

Chapter 2

Model Error Compensation

As a prelude to the publications, some additional background is given with the purpose of putting the contributions into context. Even though the developed methods are general and applies to non-linear ODE and DAE models they are evaluated on automotive engine examples. A main challenge in engine control and diagnosis is accurate estimation of the internal state of the engine and was briefly described in Chapter 1 together with the contributions. This chapter elaborates on this, pointing out the necessity of unbiased estimates in engine control, and presenting some common properties of ordinary engine models. An overview of the heavy duty diesel engine with intake manifold throttle, EGR, and VGT is given in Section 2.1. Section 2.2 presents important control variables, the necessity of unbiased estimates, and the need for continuous adaptation in engine control and diagnosis, while Section 2.3 briefly describes the effect of biased models in model based estimation. Section 2.4 presents the publications with focus on the contributions and their relation to other scientific work.

2.1 Application Example

This section serves as an overview of the system and the default models that are used for evaluation of the developed methods throughout the thesis. It also introduces the nomenclature, and presents important control quantities used in the control of diesel engines. Even though the methods developed are not specially devoted to engine applications, they are all applied and evaluated on the gas flow system of a Scania heavy duty diesel engine, like the one presented in Figure 2.1.

The default models used in the evaluations of the methods are developed in Wahlström and Eriksson (Accepted for publication), and Wahlström and Eriksson (2010). The main difference between the models are that the latter includes an intake manifold throttle, accompanied by an extra state for the intercooler pressure, and a state for the exhaust manifold temperature.

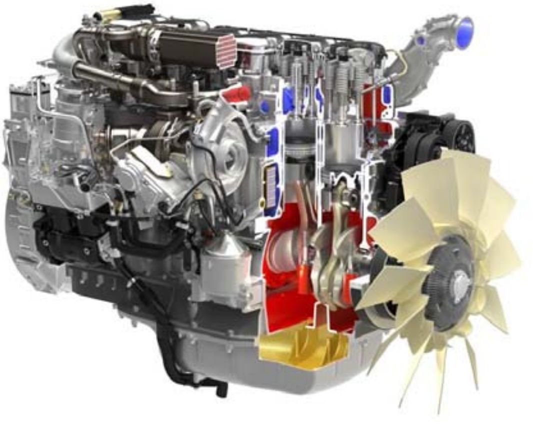


Figure 2.1: Cutaway view of the Scania inline six cylinder engine with VGT and EGR used for evaluation. *Courtesy Scania CV AB.*

Schematics of the more complex model from Wahlström and Eriksson (2010) is presented in Figure 2.2, where most of the modeled variables are presented. Control inputs to the model are injected amount of fuel u_δ and the positions of EGR, VGT, and throttle valves; u_{egr}, u_{vgt}, and u_{th}. The engine speed n_{e} is used as a parameterization input beside the control inputs, and thus the engine model can be expressed in state space form as

$$\begin{aligned} \dot{x} &= f(x, u, n_{\text{e}}) \\ y &= h(x). \end{aligned}$$

In these applications n_{e} is an input to the model which is due to the fact that the modeling is focused on the gas flows and does not include modeling of the produced torque and drive line. States are pressures in the intercooler, intake manifold and exhaust manifold, p_{ic}, p_{im} and p_{em}, turbine speed ω_{t}, and exhaust manifold temperature, T_{em}. Also presented are modeled signals for the, compressor mass-flow W_{c}, throttle mass-flow W_{th}, EGR mass-flow W_{egr}, mass-flow into the engine W_{ei}, mass-flow out of the engine W_{eo}, and turbine mass-flow W_{t}. Outputs from the model are the states, p_{im}, p_{em}, p_{ic}, and ω_{t}, and the compressor mass-flow W_{c}. Equations (2.1) and (2.2) presents a summary of the model and measurement equations and more details are presented in Appendix A.

$$\begin{aligned} \dot{p}_{\text{im}} &= f_{p_{\text{im}}}\big(p_{\text{im}},\ p_{\text{em}},\ p_{\text{ic}},\ T_{\text{em}},\ u_\delta,\ u_{\text{egr}},\ u_{\text{th}},\ n_{\text{e}}\big) \\ \dot{p}_{\text{em}} &= f_{p_{\text{em}}}\big(p_{\text{im}},\ p_{\text{em}},\ \omega_{\text{t}},\ T_{\text{em}},\ u_\delta,\ u_{\text{egr}},\ u_{\text{vgt}},\ n_{\text{e}}\big) \\ \dot{p}_{\text{ic}} &= f_{p_{\text{ic}}}\big(p_{\text{im}},\ p_{\text{ic}},\ \omega_{\text{t}},\ u_{\text{th}}\big) \\ \dot{\omega}_{\text{t}} &= f_{\omega_{\text{t}}}\big(p_{\text{em}},\ p_{\text{ic}},\ \omega_{\text{t}},\ T_{\text{em}},\ u_{\text{vgt}}\big) \\ \dot{T}_{\text{em}} &= f_{T_{\text{em}}}\big(p_{\text{im}},\ p_{\text{em}},\ \omega_{\text{t}},\ T_{\text{em}},\ u_\delta,\ u_{\text{egr}},\ u_{\text{vgt}},\ n_{\text{e}}\big) \end{aligned} \tag{2.1}$$

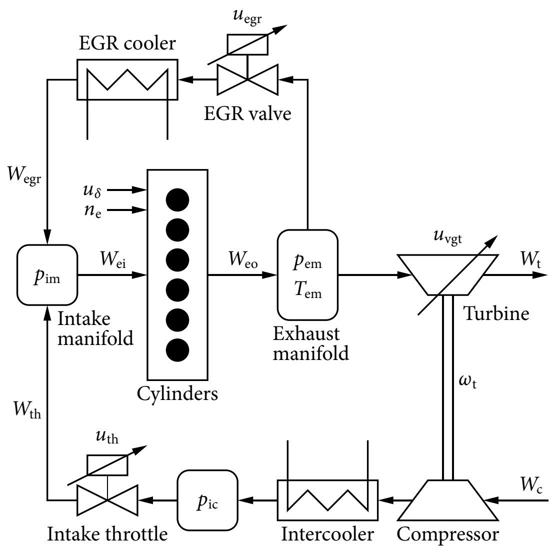


Figure 2.2: Schematic of the diesel engine model (Wahlström and Eriksson, 2010) with intake manifold throttle, EGR, and VGT, showing model states (p_{im}, p_{em}, p_{ic}, ω_t, and T_{em}), control inputs (u_{egr}, u_{vgt}, u_δ, and u_{th}), parametrization input (n_e), and flows between the different components (W_c, W_{th}, W_{egr}, W_{ei}, W_{eo}, and W_t). Rectangles with rounded corners represent control volumes.

$$y_1 = p_{im} \tag{2.2a}$$
$$y_2 = p_{em} \tag{2.2b}$$
$$y_3 = p_{ic} \tag{2.2c}$$
$$y_4 = \omega_t \tag{2.2d}$$
$$y_5 = W_c\left(p_{ic},\ \omega_t\right) \tag{2.2e}$$

The data used is collected in engine test cells at Scania CV AB in Södertälje, Sweden, and a detailed sensor setup that includes accuracy and placement of the sensors used is presented in Appendix B.

2.2 Gas Flow Measurement

The air mass-flow into the engine is a central quantity in the engine control systems and is hence often measured. It is used for many purposes and influences both the engine performance and emissions, and it is therefore essential to have an air mass-flow signal of good quality. One important issue with the air mass-flow sensor is its characteristics and

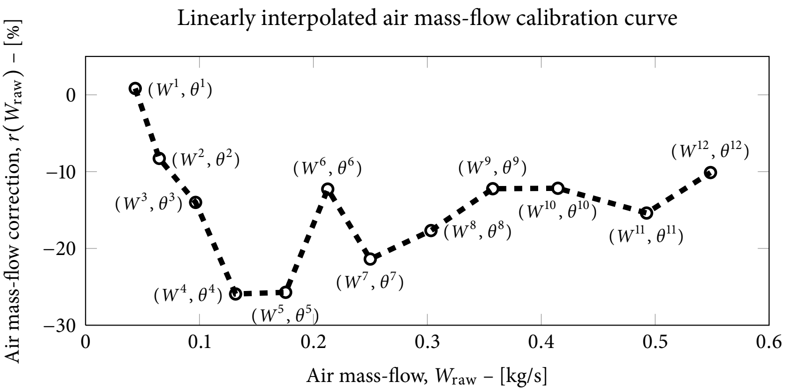


Figure 2.3: Air mass-flow sensor calibration curve with 12 grid points.

long term stability. To analyze this, two questions are addressed: how does the sensor characteristic evolve over time, and how does it vary between engine configurations?

To answer these questions, systematic engine test cell measurements have been conducted on a limited range of air mass-flow sensors over the span of several weeks. A central piece of information is a sensor calibration curve that has been recorded and stored for all days and tests. The data is analyzed with respect to day-to-day variations, aging, and changes between configurations. The calibration curve $r(W_{raw})$ is defined by

$$r(W_{raw}) = \frac{W_{ref}}{W_{raw}} - 1, \tag{2.3}$$

where W_{ref} is a reference sensor mass-flow sensor and W_{raw} is the raw engine air mass-flow measurement. The calibration curve is found by comparing the production air mass-flow sensor W_{raw} to a reference mass-flow sensor W_{ref}, for a long series of engine measurements. The reference sensor W_{ref} is available only in the engine test cell for the purpose of accurately being able to measure the air mass-flow into the engine, and has an uncertainty of less than 1 % and a response time of 12 ms. It is mounted on a straight pipe in the test cell, where the air mass-flow over the cross section of the pipe is orthogonal to the sensor and cylindrically symmetric, and is considered to give accurate measurements of the air mass-flow. The calibration curve is implemented as a lookup-table consisting of 12 grid points, see Figure 2.3 for an example. Using this calibration curve to adjust the raw sensor measurement an adapted sensor signal can be computed

$$W_{adapt} = (1 + r(W_{raw}))\, W_{raw}, \tag{2.4}$$

which gives a more accurate estimate of the true air mass-flow into the engine.

The air mass-flow signal is needed for computations of air to fuel ratio, λ, and EGR-fraction, x_{egr}. Both are important quantities that significantly affect the emissions. The air to fuel ratio is defined as

$$\lambda = \frac{W_{air}}{W_{fuel}\,(A/F)_s},$$

where W_{air} is the air mass-flow into the engine, W_{fuel} the fuel mass-flow, and $(A/F)_s$ the stoichiometric air to fuel ratio. In diesel engine control it is important to keep λ above a certain limit, $\lambda_{\text{smoke lim}}$, to avoid generating smoke. Normally, when λ is greater than $\lambda_{\text{smoke lim}}$, W_{fuel} is determined by the desired torque. However when the desired torque forces λ to $\lambda_{\text{smoke lim}}$, the control law enters a mode where W_{fuel} is proportional to W_{air}, (Wahlström, 2006). This is particularly important during transients where the torque demand is high, e.g. during acceleration. In these cases, an error in the air mass-flow signal results in either creation of smoke or reduced torque output. The other important quantity, is the EGR-fraction defined as

$$x_{\text{egr}} = \frac{W_{\text{tot}} - W_{\text{air}}}{W_{\text{tot}}},$$

where W_{tot} is the total gas mass-flow into the engine, i.e. $W_{\text{air}} + W_{\text{egr}}$. The x_{egr} is used in the engine control to reduce the NO_x emissions, and is governed by the EGR-valve and the VGT position. The following small example gives a rough estimate of the consequence of an incorrect air mass-flow measurement for the control of x_{egr}.

Example 1 Assume that the engine control system controls x_{egr} to 30 % based on the air mass-flow sensor and that the air mass-flow sensor signal is incorrect and reads $W_{\text{air}} \cdot 0.9$. That is,

$$x_{\text{egr}} = \frac{W_{\text{tot}} - W_{\text{air}} \cdot 0.9}{W_{\text{tot}}} = 30\,\%.$$

Then the true fresh air-fraction would become

$$(1-0.3) \cdot W_{\text{tot}} = W_{\text{air}} \cdot 0.9 \quad \Rightarrow \quad W_{\text{air}} = \frac{1}{0.9} \cdot (1-0.3) \cdot W_{\text{tot}} \approx 0.78 \cdot W_{\text{tot}},$$

and thereby the true $x_{\text{egr}} \approx 22\,\%$, which would have a significant effect on the NO_x emissions (Heywood, 1988). That is, in this example the control system controls the engine to run with less EGR than needed to fulfill the legislated NO_x levels. ◇

An analogous analysis can be made for λ close to $\lambda_{\text{smoke lim}}$ which further supports the statement that an accurate estimate of the air mass-flow is important.

Both λ and x_{egr} are important for the emissions and the air mass-flow W_{air} is central in their control. Hence, it is important to have a high quality measurement or estimation of the air mass-flow. Note that the x_{egr} estimate also depends on W_{tot}, which is computed using the volumetric efficiency of the engine and is, by experience, considered to be accurate.

2.2.1 Air Mass-Flow Sensor Variations

Calibration curves from two diesel engines, one inline 6 cylinder and one V8, are gathered from test runs in an engine test cell. 13 calibration curves are collected over a total time of about two weeks for the 6 cylinder engine and 21 calibration curves over four weeks for the V8 engine. Figure 2.4 presents the typical appearance of a calibration curve, the upper for a 6 cylinder engine and the lower for a V8 engine. These calibration curves are used to analyze the quality of the air mass-flow sensor.

The difference between engine configurations can be seen by comparing the upper and lower plot in Figure 2.4 and Figure 2.5, where Figure 2.4 presents the day-to-day variations of the calibration curve and Figure 2.5 presents the trend of the four grid points, θ^2, θ^5, θ^8, and θ^{11}, in the calibration curves, see Figure 2.3.

Figure 2.4 shows that the day-to-day variations are quite large, especially for the V8 engine where the standard deviation varies between 2 – 3 %-units. For the 6 cylinder engine the variations are smaller. Further, the difference between the minimum and maximum values for each parameter in the calibration curve varies between approximately 1.5 – 4 %-units for the inline six cylinder engine and 3 – 12 %-units for the V8 engine. Another difference between the two engine configurations is the appearance of the calibration curve. For the 6 cylinder engine the line starts at approximately 5 %, has a slightly positive slope, and ends at approximately 10 %, which corresponds to the computations in Example 1. For the V8 engine the line is quite different, it starts at about 1 %, varies quite a bit, and ends at -1 %. These investigations indicate that the air mass-flow sensor has to be continuously monitored and adapted, to ensure safe and clean engine operation over time.

The large spread among the calibration curves for the V8 engine plot, of about 10 %-units from min to max, indicates that an ad hoc approach for compensating the sensor signal using only a calibration curve (2.4) might not be enough, see Example 1. The quality has to be improved in a way that the spread is reduced as well. These observations together with the importance of the estimates of λ and x_{egr} necessitate an accurate estimate of the air mass-flow.

As Figure 2.5 shows there are no obvious trends in the data over time. However, due to the relatively short time span over which the data is collected, it is hard to draw any conclusions regarding long term aging of the air mass-flow sensors.

2.3 Gas Flow Estimation

In the previous section it was shown that a sensor is not sufficient for acquiring an accurate air mass-flow signal, and the main two reasons were; i) the sensor needs to be calibrated to compensate for its positioning in the intake system, ii) it needs continuous adaptation to compensate for system aging and different operating conditions caused by geographical location, for example pressure, temperature, and humidity of the surrounding air. This section presents some basic approaches to cope with sensor adaptation and include ad hoc mapping, according to (2.4), and Kalman filtering (Kalman, 1960). The investigation analyzes the effect model quality has on the estimates from a model based estimator, and is the topic of Section 2.3.1.

2.3.1 Methods for Improving Sensor Signals

There exist several ways of acquiring accurate estimates of these control and diagnosis variables, e.g., direct measurement via physical sensors and model based estimation, and

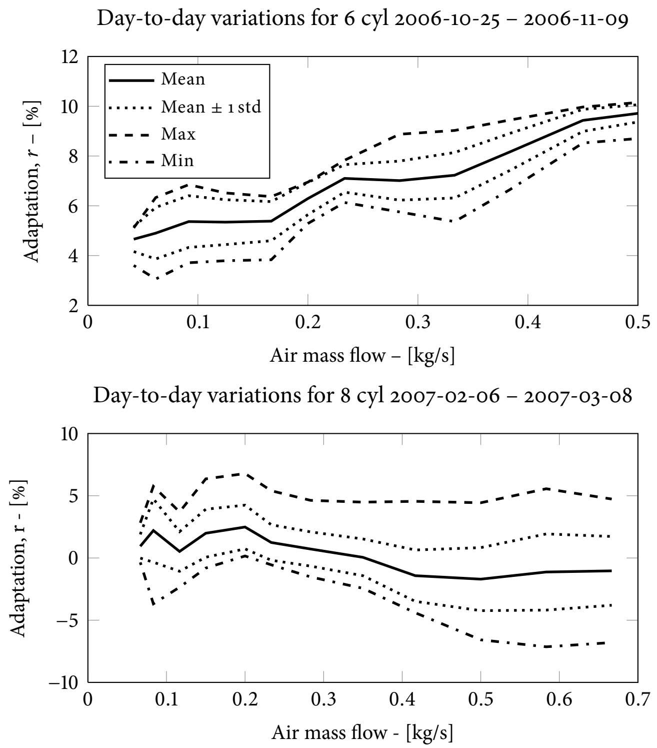


Figure 2.4: Min, max, mean, and standard deviation over all collected calibration curves are presented for a 6 cylinder engine (upper plot) and a V8 engine (lower plot). It can be seen that the variations are quite large for both engine configurations, especially for the V8 engine.

all model based estimators are highly dependent on the accuracy of the model used. This becomes especially apparent if the assumptions in the design method do not hold. If for example an EKF (Jazwinski, 1970) is used, the measurement and model errors are assumed to be described by zero mean white noise processes, i.e. biased measurements is not handled. Figure 2.6 presents estimates of the air mass-flow from five different sources; raw measurement from the production sensor, adapted production sensor (2.4), model output, EKF, i.e. combing the model and the adapted measurement, and a cell installed reference sensor. All representing means of acquiring estimates of the air mass-flow into the intake system of an engine.

One observation from Figure 2.6 is that the model output $\hat{W}_{\text{model}}$, computed using (2.1) and (2.2e), does not agree well with W_{ref}. It has an obvious offset that is different for low and high air mass-flows, but it manages to capture the system dynamics. From this observation it is clear that the model does not fully describe the engine and these model errors violate the assumptions made when utilizing the model to design an EKF,

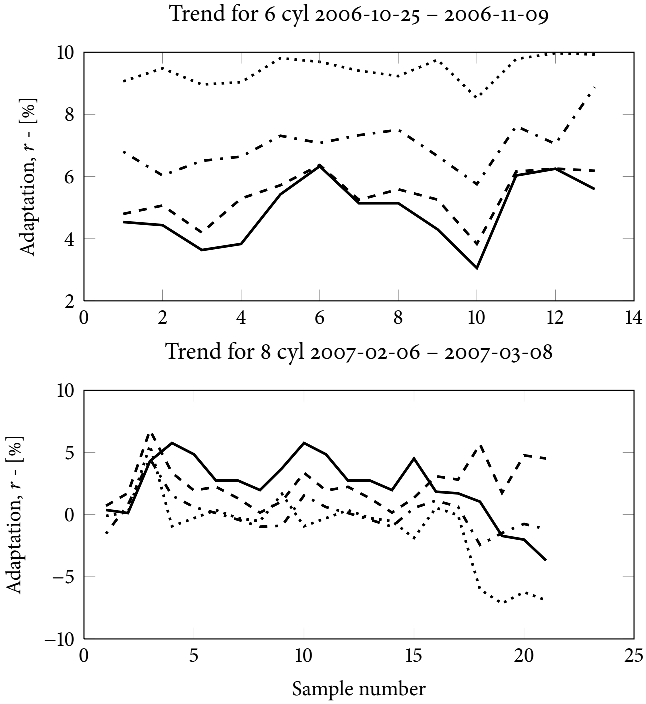


Figure 2.5: The trend of four support points for a 6 cylinder engine (upper plot) and a V8 engine (lower plot). It shows that there is no particular trend in either of the engine configurations. Note that the samples are not equidistant.

i.e. zero mean Gaussian system and measurement errors. Another observation is that also the raw measurement has an error that depends on the mass-flow. In this case a simple adaptation according to the calibration curve (2.3) in Section 2.2.1 significantly improves the estimation accuracy, see $\hat{W}_{\text{adapt}}$.

Obviously the model output and the raw measurement performs poorly, and by applying an adaptation scheme to the measurement much better estimates are acquired. Similarly, by combining the model with the adapted measurement in an EKF, even better estimates are achieved, see $\hat{W}_{\text{EKF}}$.

These estimators, the adapted mass-flow sensor and the EKF, compile the essence of the problems addressed in this thesis, i.e. the need for a systematic way of reducing operating point dependent stationary estimation errors in model based estimators, and the online adaptation of engine maps, or lookup-tables.

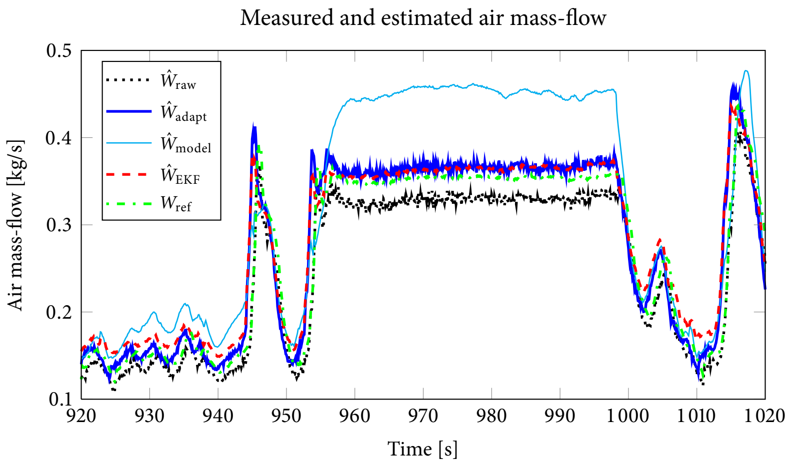


Figure 2.6: Typical example of model output from a biased model (Höckerdal et al., 2008), where W_{ref} is the air mass-flow measured by a reference sensor. As often is the case, the model captures the dynamics well but suffers from operating point dependent stationary errors. As comparison, the raw and adapted air mass-flow sensor measurements are presented, and an EKF using feedback from the adapted measurement is included as well.

2.4 Publications and Contributions

The overall goal with the work is the development of systematic methods that allow use of models with errors, referred to as default models, for estimator design. The focus is on models based on first principles physics and a primary condition on the methods is the preservation of the physical structure, or properties, of the models.

In system identification, model error modeling (MEM) is treated in for example Ljung et al. (1991); Stenman and Tjärnström (2000). However, since the focus here is on default models that have biases, or other stationary errors, and aims at preserving the physical structure of the model, the MEM path is not pursued. Methods that address the issue of biased default models for estimation exist in e.g. model augmentation using physical knowledge (Andersson and Eriksson, 2001) and proportional-integral (PI) observers (Söffker et al., 1995; Koenig and Mammar, 2002). The methods developed in this thesis unify these ideas with the idea of estimating a minimal description of the model bias.

In estimation, observability of the system is central to ensure consistent state and parameter estimates. This have made preservation of the default models' observability properties, in the developed methods, central. One method to check global observability is for example Ljung and Glad (1994) which is applied to an engine example in Sokolov and Glad (1999). However, this method applies to polynomial models and is not applicable to the models addressed in this dissertation. Hence, local analyses using model linearizations, such as the Popov-Belevitch-Hautus (PBH)-test for ODE models (Kailath, 1980) and its DAE analogues (Dai, 1989), are used throughout the publications. An important observation is that the system (2.1) is coupled, meaning that several states have dependencies on both intake and exhaust states, which makes the default system locally observable from any output.

2.4.1 Paper A – Model Augmentation for ODE:s

The principal idea in the model augmentation is that local errors in the model may affect several model states. Consider for example an observer based on the engine model (2.1) consisting of three coupled volumes with one pressure state for each volume. Then an error in one of the mass-flow equations would, possibly, affect all three pressures. Some possibilities are then to, introduce a model augmentation using physical intuition (Andersson and Eriksson, 2001), or apply a PI-observer (Söffker et al., 1995). The first requires deep understanding of the modeled system while the latter only compensates for bias in measured states used for feedback and does not bother about the origin of the bias. The developed method applies a separate step in the observer design that estimates a low order model error description, which is used for model augmentation. The main contributions are a characterization of possible augmentations from observability perspectives, a parameterization of the augmentations from the method, and a robustness analysis of the proposed augmentation estimation method.

An advantage of the developed method, compared to e.g. PI observers, is its ability to incorporate information from extra sensors during the bias estimation. In this way compensation of states not available for feedback in the final application is made possible. It is also worth to note that both the model augmentation using physical knowledge and the PI-observer fits into the framework of the developed method.

2.4.2 Papers B and C – Map Adaptation

The ideas above address the bias compensation through model augmentation, by describing the bias as a random walk, and thus does not store any information about the bias in different operating points. A common technique to handle operating point dependencies in automotive applications is to introduce maps or look-up tables, (Guzzella and Amstutz, 1998; Peyton Jones and Muske, 2009). These maps are frequently used to describe relations when physical models are unavailable, e.g., sensor and actuator characteristics, cooler efficiency, injector characteristics, and aftertreatment systems. Common for these maps is that they benefit from continuous online adaptation to prevent undesired system behavior. Routines for online map adaptation have been considered in Wu (2006); Peyton Jones and Muske (2009), and a primary contribution in Paper B and Paper C is simultaneous bias compensation and online map adaptation.

2.4.3 Paper D – ODE vs. DAE in Estimation

Using models with both fast and slow dynamics, i.e. stiff models, in real time estimation may be numerically problematic. The problem of stiff models, described by ordinary differential equations (ODE), for engine control is closely connected to the embedded system in which it is implemented and its computational limitations. In engine control units (ECU), a main difficulty with stiff models is that the model execution is scheduled in loops with fixed frequencies, that limits the ECU:s capability of satisfactory solving the differential equations. A possible solution (Hairer and Wanner, 2000, Chapter 6), used in for example electrochemical and reactive distillation processes (Mandela et al., 2010), is to approximate fast dynamics with instantaneous relations, i.e. algebraic conditions. With this approach a stiff ODE would be transformed into a system of differential algebraic equations (DAE), while keeping the overall model structure. This is exploited for a diesel engine model with intake manifold throttle, EGR, and VGT in Paper D. The stability and estimation accuracy of an EKF based on the default stiff ODE is compared to that of an EKF based on the corresponding DAE. It is shown that even though the ODE, for each time-update, is less computational demanding than the resulting DAE, an EKF based on the DAE achieves better estimation performance with less computational effort. The main gain with the DAE based EKF is that it allows significantly increased step lengths without degrading the estimation performance compared to the ODE based EKF.

2.4.4 Paper E – Model Augmentation for DAE:s

The number of models described by DAE:s have increased, partly due to modern modeling tools such as Dymola, or similar tools using the Modelica®modeling language, and Simscape that often deliver DAE models and since DAE:s are a way of describing systems with both slow and fast dynamics. As more and more DAE models are available, it is natural to use them for observer or estimator design. Also these models may suffer from deficiencies that make them unsuitable for direct use in estimation and Paper E extends the model augmentation results for ODE:s from Paper A to DAE:s. The main contributions are necessary and sufficient conditions for the preservation of the observability properties of the default model during the augmentation.

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Appendix A

Model Details

Below follows a summary of the model equations using the symbols and indices presented in Tables A.1 and A.2. The model states, inputs, and outputs are presented in Table A.3 and more details about the model is found in Wahlström and Eriksson (2010).

Manifolds

Intake manifold

$$\frac{d}{dt}p_{\mathrm{im}} = \frac{R_{\mathrm{a}}\,T_{\mathrm{im}}}{V_{\mathrm{im}}}\left(W_{\mathrm{th}} + W_{\mathrm{egr}} - W_{\mathrm{ei}}\right)$$

Exhaust manifold

$$\begin{aligned}
\frac{d}{dt}p_{\mathrm{em}} &= \frac{R_{\mathrm{e}}\,T_{\mathrm{em}}}{V_{\mathrm{em}}}\left(W_{\mathrm{eo}} - W_{\mathrm{egr}} - W_{\mathrm{t}}\right) + \frac{p_{\mathrm{em}}}{T_{\mathrm{em}}}\frac{d}{dt}T_{\mathrm{em}}\\
\frac{d}{dt}T_{\mathrm{em}} &= \frac{R_{\mathrm{e}}\,T_{\mathrm{em}}}{p_{\mathrm{em}}\,V_{\mathrm{em}}\,c_{\mathrm{ve}}}\Big(\left(W_{\mathrm{eo}} - W_{\mathrm{egr}} - W_{\mathrm{t}}\right)c_{\mathrm{ve}}\left(T_{\mathrm{em,in}} - T_{\mathrm{em}}\right)+\\
&\quad R_{\mathrm{e}}\left(T_{\mathrm{em,in}}\left(W_{\mathrm{eo}} - W_{\mathrm{egr}} - W_{\mathrm{t}}\right) - T_{\mathrm{em}}\left(-W_{\mathrm{eo}} + W_{\mathrm{egr}} + W_{\mathrm{t}}\right)\right)\Big)
\end{aligned}$$

Intercooler

$$\frac{d}{dt}p_{\mathrm{ic}} = \frac{R_{\mathrm{a}}\,T_{\mathrm{im}}}{V_{\mathrm{ic}}}\left(W_{\mathrm{c}} - W_{\mathrm{th}}\right)$$

Intake Throttle

$$W_{\text{th}} = \frac{p_{\text{ic}}\,\Psi_{\text{th}}(\Pi_{\text{th}})A_{\text{th,max}} f_{\text{th}}(u_{\text{th}})}{\sqrt{T_{\text{im}}\,R_{\text{a}}}}$$

$$\Psi_{\text{th}}(\Pi_{\text{th}}) = \begin{cases} \Psi^*_{\text{th}}(\Pi_{\text{th}}) & \text{if } \Pi_{\text{th}} \le \Pi_{\text{th,lin}} \\ \Psi^*_{\text{th}}(\Pi_{\text{th,lin}})\frac{1-\Pi_{\text{th}}}{1-\Pi_{\text{th,lin}}} & \text{if } \Pi_{\text{th,lin}} < \Pi_{\text{th}} \end{cases}$$

$$\Psi^*_{\text{th}}(\Pi_{\text{th}}) = \sqrt{\frac{2\,\gamma_{\text{th}}}{\gamma_{\text{th}}-1}\left(\Pi_{\text{th}}^{2/\gamma_{\text{th}}} - \Pi_{\text{th}}^{1+1/\gamma_{\text{th}}}\right)}$$

$$\Pi_{th} = \begin{cases} \left(\frac{2}{\gamma_{\text{th}}+1}\right)^{\frac{\gamma_{\text{th}}}{\gamma_{\text{th}}-1}} & \text{if } \frac{p_{\text{im}}}{p_{\text{ic}}} < \left(\frac{2}{\gamma_{\text{th}}+1}\right)^{\frac{\gamma_{\text{th}}}{\gamma_{\text{th}}-1}} \\ \frac{p_{\text{im}}}{p_{\text{ic}}} & \text{if } \left(\frac{2}{\gamma_{\text{th}}+1}\right)^{\frac{\gamma_{\text{th}}}{\gamma_{\text{th}}-1}} \le \frac{p_{\text{im}}}{p_{\text{ic}}} \le 1 \\ 1 & \text{if } 1 < \frac{p_{\text{im}}}{p_{\text{ic}}} \end{cases}$$

$$f_{\text{th}}(u_{\text{th}}) = b_{\text{th1}}(1-\cos(\min(a_{\text{th1}}\,u_{\text{th}} + a_{\text{th2}}, \pi))) + b_{\text{th2}}$$

Cylinder

Cylinder Flow

$$W_{\text{ei}} = \frac{\eta_{\text{vol}}\,p_{\text{im}}\,n_{\text{e}}\,V_{\text{d}}}{120\,R_{\text{a}}\,T_{\text{im}}}$$

$$\eta_{\text{vol}} = c_{\text{vol1}}\frac{r_{\text{c}} - \left(\frac{p_{\text{em}}}{p_{\text{im}}}\right)^{1/\gamma_{\text{e}}}}{r_{\text{c}}-1} + c_{\text{vol2}}\,W_{\text{f}}^2 + c_{\text{vol3}}\,W_{\text{f}} + c_{\text{vol4}}$$

$$W_{\text{f}} = \frac{10^{-6}}{120}\,u_{\delta}\,n_{\text{e}}\,n_{\text{cyl}}$$

$$W_{\text{eo}} = W_{\text{f}} + W_{\text{ei}}$$

Exhaust Manifold Temperature

Cylinder out temperature

$$T_{\text{e}} = T_{\text{im}} + \frac{q_{\text{HV}}\,f_{\text{Te}}(W_{\text{f}}, n_{\text{e}})}{c_{\text{pe}}\,W_{\text{eo}}}$$

$$\begin{aligned} f_{\text{Te}}(W_{\text{f}}, n_{\text{e}}) &= f_{\text{TeWf}}(W_{\text{f}}) \cdot f_{\text{Tene}}(n_{\text{e}}) \\ f_{\text{TeWf}}(W_{\text{f}}) &= c_{\text{fTeWf1}}\,W_{\text{f,norm}}^3 + c_{\text{fTeWf2}}\,W_{\text{f,norm}}^2 + c_{\text{fTeWf3}}\,W_{\text{f,norm}} + c_{\text{fTeWf4}} \\ f_{\text{Tene}}(n_{\text{e}}) &= c_{\text{fTene1}}\,n_{\text{e,norm}}^2 + c_{\text{fTene2}}\,n_{\text{e,norm}} + 1 \end{aligned}$$

$$W_{\text{f,norm}} = W_{\text{f}} \cdot 100, \quad n_{\text{e,norm}} = \frac{n_{\text{e}}}{1000}$$

Heat losses in the exhaust pipe

$$T_{\mathrm{em,in}} = T_{\mathrm{amb}} + \left(T_{\mathrm{e}} - T_{\mathrm{amb}}\right) e^{-\frac{h_{\mathrm{tot}}\,\pi\, d_{\mathrm{pipe}}\, l_{\mathrm{pipe}}\, n_{\mathrm{pipe}}}{W_{\mathrm{eo}}\, c_{\mathrm{pe}}}}$$

EGR-Valve

$$W_{\mathrm{egr}} = \begin{cases} \dfrac{A_{\mathrm{egr}}\, p_{\mathrm{em}}\, \Psi_{\mathrm{egr}}\left(\frac{p_{\mathrm{im}}}{p_{\mathrm{em}}}\right)}{\sqrt{T_{\mathrm{em}}\, R_{\mathrm{e}}}} & \text{if } p_{\mathrm{em}} \geq p_{\mathrm{im}} \\ -\dfrac{A_{\mathrm{egr}}\, p_{\mathrm{im}}\, \Psi_{\mathrm{egr}}\left(\frac{p_{\mathrm{em}}}{p_{\mathrm{im}}}\right)}{\sqrt{T_{\mathrm{egr,cool}}\, R_{\mathrm{a}}}} & \text{if } p_{\mathrm{em}} < p_{\mathrm{im}} \end{cases}$$

$$\Psi_{\mathrm{egr}}(\Pi_{\mathrm{egr}}) = 1 - \left(\frac{1 - \Pi_{\mathrm{egrlim}}(\Pi_{\mathrm{egr}})}{1 - \Pi_{\mathrm{egropt}}} - 1\right)^2$$

$$\Pi_{\mathrm{egrlim}}(\Pi_{\mathrm{egr}}) = \begin{cases} \Pi_{\mathrm{egropt}} & \text{if } \Pi_{\mathrm{egr}} < \Pi_{\mathrm{egropt}} \\ \Pi_{\mathrm{egr}} & \text{if } \Pi_{\mathrm{egr}} \geq \Pi_{\mathrm{egropt}} \end{cases}$$

$$A_{\mathrm{egr}} = A_{\mathrm{egrmax}}\, f_{\mathrm{egr}}(u_{\mathrm{egr}})$$

$$f_{\mathrm{egr}}(u_{\mathrm{egr}}) = b_{\mathrm{egr1}}(1 - \cos(\min(a_{\mathrm{egr1}} u_{\mathrm{egr}} + a_{\mathrm{egr2}}, \pi))) - b_{\mathrm{egr1}}(1 - \cos(\min(a_{\mathrm{egr2}}, \pi)))$$

Turbocharger

Turbo Inertia

$$\frac{d}{dt}\omega_{\mathrm{t}} = \frac{P_{\mathrm{t}}\,\eta_{\mathrm{m}} - P_{\mathrm{c}}}{J_{\mathrm{t}}\,\omega_{\mathrm{t}}}$$

Turbine Efficiency

$$P_{\mathrm{t}}\,\eta_{\mathrm{m}} = \eta_{\mathrm{tm}}\, P_{\mathrm{t,s}} = \eta_{\mathrm{tm}}\, W_{\mathrm{t}}\, c_{\mathrm{pe}}\, T_{\mathrm{em}} \left(1 - \Pi_{\mathrm{t}}^{1-1/\gamma_{\mathrm{e}}}\right)$$

$$\eta_{\mathrm{tm}} = \eta_{\mathrm{tm},BSR}(BSR) \cdot \eta_{\mathrm{tm},\omega_{\mathrm{t}}}(\omega_{\mathrm{t}}) \cdot \eta_{\mathrm{tm},u_{\mathrm{vgt}}}(u_{\mathrm{vgt}})$$

$$\eta_{\mathrm{tm},BSR}(BSR) = 1 - b_{BSR}\,(BSR^2 - BSR_{\mathrm{opt}}^2)^2$$

$$BSR = \frac{R_{\mathrm{t}}\,\omega_{\mathrm{t}}}{\sqrt{2\, c_{\mathrm{pe}}\, T_{\mathrm{em}} \left(1 - \Pi_{\mathrm{t}}^{1-1/\gamma_{\mathrm{e}}}\right)}}$$

$$\eta_{\mathrm{tm},\omega_{\mathrm{t}}}(\omega_{\mathrm{t}}) = \begin{cases} 1 - b_{\omega\mathrm{t1}}\,\omega_{\mathrm{t}} & \text{if } \omega_{\mathrm{t}} \leq \omega_{\mathrm{t,lim}} \\ 1 - b_{\omega\mathrm{t1}}\,\omega_{\mathrm{t,lim}} - b_{\omega\mathrm{t2}}(\omega_{\mathrm{t}} - \omega_{\mathrm{t,lim}}) & \text{if } \omega_{\mathrm{t}} > \omega_{\mathrm{t,lim}} \end{cases}$$

$$\eta_{\mathrm{tm},u_{\mathrm{vgt}}}(u_{\mathrm{vgt}}) = b_{\mathrm{vgt1}}\, u_{\mathrm{vgt}}^3 + b_{\mathrm{vgt2}}\, u_{\mathrm{vgt}}^2 + b_{\mathrm{vgt3}}\, u_{\mathrm{vgt}} + b_{\mathrm{vgt4}}$$

$$\Pi_{\mathrm{t}} = \frac{p_{\mathrm{t}}}{p_{\mathrm{em}}}$$

Turbine Mass-Flow

$$W_{\mathrm{t}} = \frac{A_{\mathrm{vgtmax}}\, p_{\mathrm{em}}\, f_{\Pi\mathrm{t}}(\Pi_{\mathrm{t}}) f_{\omega\mathrm{t}}(\omega_{\mathrm{t,corr}})\, f_{\mathrm{vgt}}(u_{\mathrm{vgt}})}{\sqrt{T_{\mathrm{em}}\, R_{\mathrm{e}}}}$$

$$f_{\Pi\mathrm{t}}(\Pi_{\mathrm{t}}) = \sqrt{1 - \Pi_{\mathrm{t}}^{K_{\mathrm{t}}}}$$

$$f_{\omega\mathrm{t}}(\omega_{\mathrm{t,corr}}) = 1 - c_{\omega\mathrm{t}}\,(\omega_{\mathrm{t,corr}} - \omega_{\mathrm{t,corropt}})^2$$

$$\omega_{\mathrm{t,corr}} = \frac{\omega_{\mathrm{t}}}{100\sqrt{T_{\mathrm{em}}}}$$

$$f_{\mathrm{vgt}}(u_{\mathrm{vgt}}) = c_{\mathrm{f2}} + c_{\mathrm{f1}}\sqrt{\max\left(0, 1 - \left(\frac{u_{\mathrm{vgt}} - c_{\mathrm{vgt2}}}{c_{\mathrm{vgt1}}}\right)^2\right)}$$

Compressor Efficiency

$$P_{\mathrm{c}} = \frac{P_{\mathrm{c,s}}}{\eta_{\mathrm{c}}} = \frac{W_{\mathrm{c}}\, c_{\mathrm{pa}}\, T_{\mathrm{amb}}}{\eta_{\mathrm{c}}}\left(\Pi_{\mathrm{c}}^{1-1/\gamma_{\mathrm{a}}} - 1\right)$$

$$\Pi_{\mathrm{c}} = \frac{p_{\mathrm{ic}}}{p_{\mathrm{amb}}}$$

$$\eta_{\mathrm{c}}(W_{\mathrm{c,corr}}, \Pi_{\mathrm{c}}) = \eta_{\mathrm{c,W}}(W_{\mathrm{c,corr}}, \Pi_{\mathrm{c}}) \cdot \eta_{\mathrm{c},\Pi}(\Pi_{\mathrm{c}})$$

$$\eta_{\mathrm{c,W}}(W_{\mathrm{c,corr}}, \Pi_{\mathrm{c}}) = 1 - a_{\mathrm{W}3}(W_{\mathrm{c,corr}} - (a_{\mathrm{W1}} + a_{\mathrm{W2}}\,\Pi_{\mathrm{c}}))^2$$

$$\eta_{\mathrm{c},\Pi}(\Pi_{\mathrm{c}}) = \begin{cases} a_{\Pi 1}\,\Pi_c^2 + a_{\Pi 2}\,\Pi_{\mathrm{c}} + a_{\Pi 3} & \text{if } \Pi_{\mathrm{c}} < \Pi_{\mathrm{c,lim}} \\ a_{\Pi 4}\,\Pi_c^2 + a_{\Pi 5}\,\Pi_{\mathrm{c}} + a_{\Pi 6} & \text{if } \Pi_{\mathrm{c}} \geq \Pi_{\mathrm{c,lim}} \end{cases}$$

$$a_{\Pi 6} = \Pi_{\mathrm{c,lim}}^2(a_{\Pi 1} - a_{\Pi 4}) + \Pi_{\mathrm{c,lim}}(a_{\Pi 2} - a_{\Pi 5}) + a_{\Pi 3}$$

$$W_{\mathrm{c,corr}} = \frac{W_{\mathrm{c}}\sqrt{(T_{\mathrm{amb}}/T_{\mathrm{ref}})}}{(p_{\mathrm{amb}}/p_{\mathrm{ref}})}$$

Compressor Mass-Flow

$$W_{\mathrm{c}} = \frac{p_{\mathrm{amb}}\,\pi\, R_{\mathrm{c}}^3\,\omega_{\mathrm{t}}}{R_{\mathrm{a}}\, T_{\mathrm{amb}}}\Phi_{\mathrm{c}}$$

$$\Psi_{\mathrm{c}} = \frac{2\, c_{\mathrm{pa}}\, T_{\mathrm{amb}}\left(\Pi_{\mathrm{c}}^{1-1/\gamma_{\mathrm{a}}} - 1\right)}{R_{\mathrm{c}}^2\,\omega_{\mathrm{t}}^2}$$

$$\Phi_c = \frac{k_{\mathrm{c1}} - k_{\mathrm{c3}}\,\Psi_{\mathrm{c}}}{k_{\mathrm{c2}} - \Psi_{\mathrm{c}}}$$

$$k_{ci} = k_{ci1}\,(\min(Ma, Ma_{\max}))^2 + k_{ci2}\,\min(Ma, Ma_{\max}) + k_{ci3}, \quad i = 1, \ldots, 3$$

$$Ma = \frac{R_{\mathrm{c}}\,\omega_{\mathrm{t}}}{\sqrt{\gamma_{\mathrm{a}}\, R_{\mathrm{a}}\, T_{\mathrm{amb}}}}$$

Table A.1: Symbols used in the plant model.

Symbol	Description	Unit
A	Area	m^2
BSR	Blade speed ratio	–
c_p	Spec. heat capacity, constant pressure	J/(kg·K)
c_v	Spec. heat capacity, constant volume	J/(kg·K)
J	Inertia	kg· m^2
n_{cyl}	Number of cylinders	–
n_e	Rotational engine speed	rpm
p	Pressure	Pa
P	Power	W
q_{HV}	Heating value of fuel	J/kg
r_c	Compression ratio	–
R	Gas constant	J/(kg·K)
R	Radius	m
T	Temperature	K
u_{egr}	EGR control signal†	%
u_{th}	Throttle control signal†	%
u_{vgt}	VGT control signal†	%
u_δ	Injected amount of fuel	mg/cycle
V	Volume	m^3
W	Mass flow	kg/s
γ	Specific heat capacity ratio	–
η	Efficiency	–
Π	Pressure quotient	–
ρ	Density	kg/m^3
Φ_c	Volumetric flow coefficient	–
Ψ_c	Energy transfer coefficient	–
ω	Rotational speed	rad/s

† 0 – closed, 100 – open

Table A.2: Indices used in the plant model.

Index	Description
a	air
amb	ambient
c	compressor
d	displaced
e	exhaust
egr	EGR
ei	engine cylinder in
em	exhaust manifold
eo	engine cylinder out
ic	intercooler
f	fuel
im	intake manifold
t	turbine
th	throttle
vgt	VGT
vol	volumetric
δ	fuel injection

Table A.3: States, inputs, and outputs of the plant model.

States	Inputs	Outputs
p_{im}	u_{δ}	p_{im}
p_{em}	u_{th}	p_{em}
p_{ic}	u_{egr}	p_{ic}
ω_{t}	u_{vgt}	ω_{t}
T_{em}	n_{e}	W_{c}

Appendix B

Experimental Setup and Data

The data are collected in engine test cells at Scania CV AB in Södertälje, Sweden and are from two inline six cylinder Scania diesel engines with EGR and VGT. One of the engines was also equipped with an intake manifold throttle. The data were collected during a European transient cycle (ETC) (Council of European Parliament, 2005) for the engine without throttle, and a World harmonized transient cycle (Economic Commission for Europe – Inland Transport Committee, 2010) for the engine with throttle. The sensor signals used in all experimental evaluations are; intake and exhaust manifold pressures, turbine speed, and engine speed. Actuator signals used are; VGT and EGR positions, and injected amount of fuel. All these signals are available on a standard engine, i.e. no extra laboratory sensors were used, and collected at a sampling rate of 100 Hz.

An extra air mass-flow sensor, W_{ref}, is used as a reference for the experimental evaluation in Chapter 2. This signal is logged using a different measurement system at a sampling frequency of 10 Hz. The measurements from the different measurement systems are synchronized for the evaluation. The synchronization is made by comparing measurements of the engine speed which is logged with both systems, and performing a time shift.

Sensor Dynamics

To justify that it is the system dynamics that is captured in the measurements, i.e. the sensors are fast enough to be able to track the system dynamics, a brief presentation of the sensor data is presented. The sensor specifications are provided by Scania.

The pressure sensors are capacitive pressure sensors and have a first order step response time constant of approximately 15 ms for the intake manifold pressure, and 20 ms for the exhaust manifold pressure. The intake manifold and intercooler pressure sensors are mounted directly in the intake manifold and right before the throttle, while the exhaust manifold sensor is mounted on an 0.4 m long pipe to avoid heat and soot.

The mass-flow sensor measuring the air mass-flow through the compressor is a hot-wire sensor also with a first order response and a time constant of 20 ms. The closed-loop control circuit maintains a constant temperature differential between the passing air stream and a platinum wire. The current required to heat the platinum wire provides an index of the air mass-flow.

The rotational speed sensors are inductive and measure the periodic variation in the magnetic flux generated by ferromagnetic ring gears passing induction coils. For the engine speed a cog passes the coil every sixth crankshaft degree and the signal used throughout this thesis is the mean value of 20 consecutive cog passes. This gives a time constant of approximately $20\cdot(1-e^{-1}) \approx 13$ samples. For the turbo speed there is only one cog on the ring gear and the signal used throughout the thesis is the median of three consecutive coil passes. That is, the maximum lag is roughly 13 times six crankshaft degrees and 2 times 360 turbo shaft degrees respectively. For the engine idle speed of 500 rpm, this gives a maximal time constant of approximately $13\cdot(500/60\cdot(360/6))^{-1} = 26$ ms, and for turbo speeds over 20 000 rpm, which is the minimum revolution speed for which the sensor works, this gives a maximum time delay of approximately $2\cdot(20\,000/60)^{-1} = 6$ ms. Since these sensor responses are significantly faster than the dynamics seen in measurements they are neglected throughout the thesis.

Reference Signal – W_{REF}

The measured reference output W_{ref} is a cell sensor measuring the air mass flow into the engine. It is a Sensyflow P-Tube hot-wire sensor with type no. 14241-7962638 and a measuring range of 0.055-1.111 kg/s. The uncertainty is less than 1 % of reading and the sensor has a response time of 12 ms. This sensor is placed approximately 4 meters in front of the engine air mass-flow sensor on a straight pipe with a diameter of 0.28 m. The sensor reading is assumed to be without errors, due to the almost ideal sensor placement. The volume and distance between the two sensors give rise to unwanted dynamics. Calculations show that the filling and emptying dynamics from this volume has a time constant of approximately 10 ms and the effect from wave propagation has approximately the same traveling time, which is small in comparison to the time constants of the system.