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Adaptive internal model control with application to fueling control

Daniel Rupp *, Lino Guzzella

Department of Mechanical and Process Engineering, ETH Zurich, ML K, Sonneggstrasse 3, 8092 Zurich, Switzerland

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ABSTRACT

This paper presents an adaptive internal model controller for stable but not necessarily minimum-phase SISO plants and its application to the air/fuel ratio control system of a spark-ignited engine. The internal model of the controller is formulated in an output-error structure that can be adapted by using standard adaptive laws. The method is applied to an air/fuel ratio control system with a reduced-order internal model and unknown sensor dynamics. Experiments on an engine test bench demonstrate the capability of the adaptive controller to recover the performance and robustness properties of the control system in the case of an aged oxygen sensor.

1. Introduction

The most common pollution abatement system for SI port-injection engines is the three-way catalytic converter. It derives its name from its ability to simultaneously reduce NO*x* and oxidize CO and HC. State-of-the-art systems are capable of removing more than 98% of the pollutants. However, this can only be achieved by operating the engine within very narrow air/fuel-ratio (AFR) limits, which requires a very precise control system. Aside from the feedforward controller, which compensates for excursions of the AFR during engine transients, the feedback controller uses the measurement data from a wide-range oxygen sensor (also called lambda sensor) to compensate for all kinds of disturbances.

For several reasons, the dynamic behavior of an AFR sensor may change considerably during its lifetime. To some extent, a robust controller can mitigate this change. However, the trade-off between robustness and performance may be in conflict with the increasing demands on the effectiveness of the control system. This paper presents an adaptive control concept which is capable of sustaining a high level of performance even in the presence of substantial changes in the sensor dynamics.

AFR control has been addressed by many researchers in the field. In Jones, Ault, Franklin, and Powell (1995) and Stroh, Franchek, and Kerns (2001) recursive identification is used to tune a model-based AFR controller online. The authors of Roduner, Onder, and Geering (1997) and Alfieri, Amstutz, and Guzzella (2009) focussed on the design of the feedback controller and its automated design strategy based on H_∞ control. The authors of Guzzella, Simons, and Geering (1997) employed feedback linearization for the control of the air/fuel ratio. Adaptive strategies based on Kalman filtering techniques have been described in Turin and Geering (1995) and recently in Muske, Jones, and Franceschi (2008). Due to the inherent time delay in engine systems Smith predictors, or more generally, internal model controllers (IMC) (Balenovic, Backx, & Hoebihk, 2001; Inagaki, Ohata, & Inoue, 1990) and their adaptive counterparts (Yildiz, Annaswamy, Yanakiev, & Kolmanovsky, 2008) have been gaining interest with the context of AFR control. The requirement for the adaptation of the oxygen sensor dynamics has evolved only recently in the automotive industry. In Rupp and Guzzella (2009) an IMC controller is proposed that is tuned iteratively to cope with changes in the dynamics of oxygen sensors.

This paper deals with the adaptation of the internal model of the IMC that regulates the AFR. The methodology that was developed for the adaptive AFR control is introduced in a general framework, such that the same concept can be applied to practically any other internal model control systems with stable but not necessarily minimum-phase plants. The idea of an adaptive internal model has already been pursued earlier. The authors of Datta and Ochoa (1996) suggest the use of a series–parallel identification model based on the equation error method, which implies that the output of the internal model is calculated based on the input and the measured output of the plant. The method presented in this paper proposes to use the output error method, where the output of the internal model is calculated based on the input to the plant and prior model outputs. As pointed out by the authors of Datta and Ochoa (1996), in contrast to the equation error method, with the output error method a guarantee for global stability often cannot be given. However, the

* Corresponding author. Tel.: +41 44 632 2453; fax: +41 44 632 1139.
E-mail address: daniel.rupp@alumni.ethz.ch (D. Rupp).

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local stability results obtained are shown here to be sufficient in the case of AFR control, which is a representative application of internal model controllers. It is also shown that by foregoing global stability the robustness of the adaptation regarding external disturbances and the control performance can be increased. These are important features when adaptive control methods are used for processes such as AFR control where only a reduced-order model is available.

In contrast to classical adaptive control systems, for the method described in this paper, typically a substantial amount of prior information about the model is available, i.e. the initial internal model is already a good approximation of the dominant plant dynamics. In classical model reference adaptive controllers, the adaptation signals are used to compensate for disturbances in order to match a reference model. With the method presented here, these signals are used solely to improve the internal model of the IMC, while the resulting adapted but static IMC handles the rejection of disturbances. The new method can thus be seen as a stable way to increase controller performance by online closed-loop system identification. This implies that the adaptation needs to be turned on only when the model deviates from the plant.

2. Air/fuel ratio control of SI engines

Lambda sensors are an essential part of modern AFR control systems. Based on the measurement data provided by the oxygen sensor, the controller in the engine control unit (ECU) regulates the correct amount of fuel to be injected. Due to ageing and harsh operating conditions, a wide-range oxygen sensor can undergo substantial changes in its dynamics, which have a detrimental effect on the performance of the control system.

2.1. The air/fuel ratio dynamics of an SI engine

Fig. 1 shows the fuel path of an SI engine. Its dynamics comprise several delays, the wall-wetting dynamics, the gas mixing dynamics, and the sensor dynamics. The input u_ϕ to the plant is a multiplicative factor for the nominal injection duration, and the output λ_s is the signal produced by the lambda sensor, which is assumed to measure the lambda value λ_{mC} at the main confluence point of the exhaust pipes. A detailed analysis of this system can be found in Onder, Roduner, and Geering (1997). However, for control purposes, the complete fuel path from the fuel injector to the main confluence point can be approximated fairly well by a first-order low-pass element with a time constant τ and a transport delay δ (Guzzella & Onder, 2004)

$$P_e(s) = \frac{\Delta\lambda_{mC}}{\Delta u_\phi} = \frac{-1}{\tau \cdot s + 1} \cdot e^{-s\cdot\delta}, \tag{1}$$

where s is the Laplace variable and Δ stands for a small deviation from the nominal value. For small deviations of the nominal injected fuel mass the linear model $P_e(s)$ also covers the wall-wetting dynamics. This can be seen in Guzzella and Onder (2004, p. 190) where the injected fuel mass is varied from -10% to $+10\%$ of the nominal fuel mass without any compensation of the wall-wetting dynamics. The two parameters of this model are dependent on the operating point of the engine, as determined by the engine speed and the mass of air in the cylinders. The values of the two parameters are typically available from engine-specific maps that are identified off-line. A typical range for both parameters is from 30 ms for high speed and high air mass up to 0.5 s for low speed and low air mass. The relative errors of the maps that are used in production-type cars are less than 20% for all operating points except very low air mass and speed. The wide-range lambda sensor can also be modeled as a first-order low-pass element with the time constant τ_s:

$$P_s(s) = \frac{\Delta\lambda_s}{\Delta\lambda_{mC}} = \frac{1}{\tau_s \cdot s + 1}. \tag{2}$$

The time constant of a new state-of-the-art wide-range lambda sensor is about 50 ms, but during its lifetime this time constant τ_s can increase to 1 s.

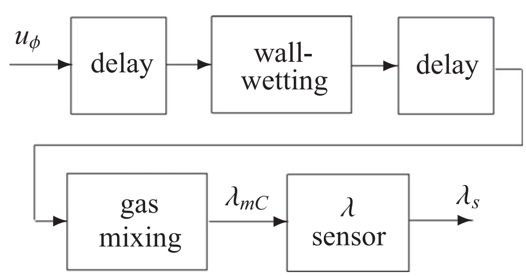

Fig. 1. Main dynamic subsystems in the fuel dynamics of a spark-ignited engine.

2.2. Internal model controller

The main goal of the feedback controller is to compensate for the disturbances in the AFR as a result of potentially rapidly varying torque commands issued by the driver. For several reasons, such as easy tunability and parametrization as well as robustness, an IMC as illustrated in Fig. 2 is used. The performance and robustness of a control system governed by a model-based controller obviously is strongly connected to the quality of the model available. To illustrate this, let us assume that the relative uncertainty of the model $\hat{P}(s)$ with respect to the plant $P(s)$ satisfies the inequality

$$\left|\frac{P(j\omega) - \hat{P}(j\omega)}{\hat{P}(j\omega)}\right| < W_2(\omega), \quad \forall\omega$$

for all frequencies ω, where $W_2(\omega)$ is the frequency-dependent uncertainty bound. The IMC control system is robustly stable if the inequality

$$|Q(j\omega)| < \frac{1}{|\hat{P}(j\omega)|} \cdot \frac{1}{W_2(\omega)}, \quad \forall\omega \tag{3}$$

holds for all frequencies ω (Morari & Zafiriou, 1989). In the ideal case, when no disturbances or model uncertainties are present, the internal controller $Q(s)$ acts as a pure feedforward controller. It is thus typically designed to invert the plant, at least in the control-relevant frequency range. However, (3) shows that the model uncertainty $W_2(\omega)$ acts as a border line in the tradeoff of robustness versus performance. Specifically, given a fixed internal controller $Q(s)$, the robustness can be increased or recovered by improving the precision of the model.

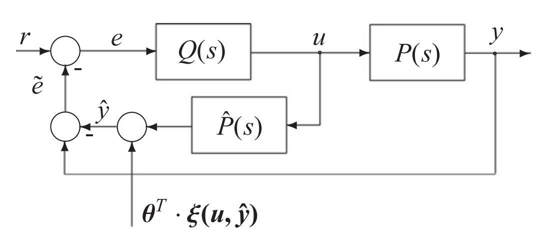

Fig. 2. Internal model control system with correction signal $\theta^T \cdot \xi(\boldsymbol{u}, \hat{\boldsymbol{y}})$ for the internal model, which will be defined in Section 3.1 below.