

Optimal Sensor Selection and Configuration, Case Study Spark Ignited Engine

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ABSTRACT

The selection and configuration of sensors can strongly influence the closed-loop dynamics of a system. Therefore a methodology for finding the best sensor placement is a valuable tool. This paper deals with this problem by formulating an optimization problem and applies the new method on an SI engine.

The best sensor configuration is one that minimizes the overall system costs, yet still meets the system constraints. Before solving the optimization problem, the system is modeled, different sensor configurations are defined, the appropriate controller and the feedback term are developed, and the locations and size of the various errors present in the model are determined. Then, the objective function and the system constraints are defined and the optimization problem is solved considering the worst-case combination of modeling errors, which is computed using genetic algorithms. The objective function is defined as the sum of the sensor costs and of a penalty term. This term describes additional costs that depend on the control quality achieved, which is a function of the worst-case modeling error combination.

The new method is then applied to the case of the AF ratio control in an SI engine. In this application various sensor configurations are possible. The feedforward term is important for a fast compensation of changes in the engine's operating point, but due to the complexity of the plant various modeling errors are present that can strongly influence its effect. The objective function includes the costs of the sensors and of the catalytic converter. The latter represents the penalty term that depends on the performance of the control structure and therefore on the worst-case modeling error combination. The larger the transients are, the larger the catalytic converter has to be for fulfilling the emissions legislation and the higher the resulting costs are. The proposed method is then validated with test bench measurements.

INTRODUCTION

Previous investigations in the field of optimal sensor and actuator placement have focused on applications in the area of flexible structures. Several publications deal with

applications in the area of aerospace and active structural acoustic control problems [1], [2]. Two different methods exist, an open-loop and a closed-loop approach. Since closed-loop methods consider the feedback loop, the dynamics of the system can be evaluated. A given sensor and actuator location is considered to be optimal if the attenuation of vibrations over a set of modes is maximized. A near-optimal solution for these problems can be found using different heuristic optimization methods such as simulated annealing, tabu search, or genetic algorithms [3]. Open-loop methods solve this problem by only considering the system itself (i.e. without a controller). Some algorithms try to increase the observability and the controllability of the system [4], while others attempt to locate the poles and the zeros of the plant in such a way as to improve the closed-loop dynamics of the system [5].

These methods all have certain drawbacks and cannot be used for solving this problem. They solve the problem of optimal sensor and actuator location by minimizing a closed-loop function (minimization of vibration modes) that cannot be adopted for this kind of system, and they often neglect the importance of the feedforward term that could in some cases dramatically improve the performance of the control structure. Moreover, the resulting costs are often not taken into account. In an SI engine system the feedforward term plays an important role. For the AF-ratio control in gasoline engines, the minimum requirements on the lambda transients ($0.7 < \lambda < 1.3$) cannot be met without a feedforward term to compensate for the fast variations of air mass flow $\dot{m}_\beta$ entering into the cylinders.

Both the controller robustness and its feedforward quality are affected by the accuracy of the model used for the design of the control structure. In the case of a gasoline engine an error-free model can ideally be used to design an open-loop observer of the air mass flow $\dot{m}_\beta$ entering into the cylinder. This value is then used to invert the wall-wetting dynamics and ideally inject exactly the right mass of fuel. But, if the timing error is considered, i.e. the time-lag between the calculation of $\dot{m}_\beta$ and the fuel injection, no perfect inversion of the fuel path dynamics is possible, and some feedback structure is needed. Moreover, in real cases, the model always

contains parametric and dynamic errors that have to be compensated.

This paper presents a new approach for solving the problem of optimal sensor location and selection. Given an engine, the objective is to minimize the overall system costs, i.e. the costs of the sensors and the cost of the catalytic converter necessary to meet the emissions legislation. First, a mathematical model of the engine is created, and different modeling errors are inserted in order to consider the plant uncertainties. Then three different feedforward structures for the estimation of $\dot{m}_\beta$ and various positions of the lambda sensor (feedback) are defined and analyzed. Each of these configurations utilizes different sensors and performs differently. For each sensor combination, the worst-case modeling error combination, i.e. the modeling error combination that causes the highest oxygen transients in the catalytic converter, is used to determine its oxygen capacity necessary to compensate for any possible transient. Then the system costs of the different sensor combinations are computed, and the optimization process is completed by selecting the least expensive solution that satisfies all the constraints.

The paper is structured as follows. In the second section a mean-value model of the plant with different modeling errors is created. In the third section a driving cycle (FTP-75) is analyzed to determine the most critical transients for the catalytic converter. In the fourth section the control structure is defined and analyzed and finally, in the fifth section, simulation results with different sensor configurations are compared with results obtained on the test bench. Moreover, using the theory of fundamental limitations in control [6], the controller quality is compared with the best theoretically achievable controller.

PHYSICAL MODEL AND ERROR DEFINITIONS

A V6 2.8l port-fuel-injected engine serves as the basis for the physical model.

PHYSICAL MODEL OF THE PLANT

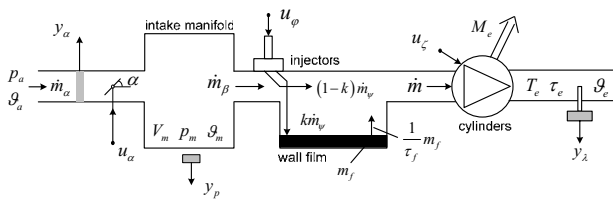


Figure 1: Schematic Diagram of a Mean-Value SI Engine (diagram taken from [7]).

For the design of the feedback and the feedforward terms, both the fuel and the air path have to be modeled (Fig. 1). The model of the plant is consistent with the description in [7]. A brief summary of the most important

formulas and assumptions is given in the next subsections.

Air Path

The air mass flow $\dot{m}_\alpha$ entering into the intake manifold can be calculated with

$$\dot{m}_\alpha(t) = c_d \cdot A(t) \cdot \frac{p_a(t)}{\sqrt{R \cdot \varrho_a(t)}} \cdot \psi\left(\frac{p_a(t)}{p_m(t)}\right), \quad (1)$$

where the flow function $\psi(\cdot)$ can be adequately approximated with

$$\psi\left(\frac{p_a(t)}{p_m(t)}\right) \approx \begin{cases} 1/\sqrt{2} & \text{for } p_m < \frac{1}{2} p_a \\ \sqrt{\frac{2p_m}{p_a} \left[1 - \frac{p_m}{p_a}\right]} & \text{for } p_m \geq \frac{1}{2} p_a \end{cases}. \quad (2)$$

For the modeling of the intake manifold an isothermal formulation is used. The following differential equation describes this behavior:

$$\frac{d}{dt} p_m(t) = \frac{R \cdot \varrho_m(t)}{V_m} \cdot (\dot{m}_\alpha(t) - \dot{m}_\beta(t)). \quad (3)$$

The air mass flows that are aspirated into the engine can be approximated as follows:

$$\dot{m}_\beta(t) = \rho_m(t) \cdot \lambda_i(p_m, \omega_e) \cdot V_d \cdot \frac{\omega_e(t)}{4\pi}. \quad (4)$$

Fuel Path

The fuel is injected into the intake port. A part of the fuel evaporates and enters immediately into the cylinder, while another part accumulates on the intake port walls and only enters into the cylinder during the subsequent intake strokes. This is the so-called wall-wetting phenomenon which can be modeled as described below. The advantage of this formulation is that the fuel mass conservation is guaranteed.

$$\dot{m}_\varphi(t) = (1 - \kappa) \cdot \dot{m}_\psi(t) + \frac{m_f(t)}{\tau_f}, \quad (5)$$

$$\frac{d}{dt} m_f(t) = \kappa \cdot \dot{m}_\psi(t) - \frac{m_f(t)}{\tau_f}. \quad (6)$$

Gas Mixing and Transport Delays

Especially at low loads, a significant part of the burned gas (i.e. the residual gas fraction) remains in the cylinder. This phenomenon can strongly influence the value of λ at the exhaust. The discrete behavior is modeled as in [7], [8], and [9] (Fig. 2).

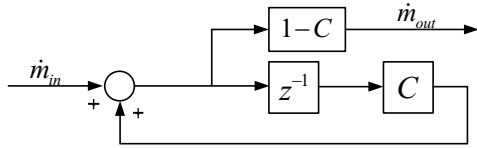


Figure 2: In-cylinder mixing (diagram taken from [8]).

With a value of C of 0.10, 10% of the burnt gases remain in the cylinder during each cycle. The variable $z = e^{j\omega T}$ is the variable of the Z transformation, and the sampling time T can be calculated as follows

$$T = \frac{120}{\omega_e [rpm] \cdot n_{Ci}} \quad (7)$$

where n_{Ci} is the number of cylinders considered in the measurement.

The gas mixing and transport delay phenomena are modeled with a first-order lag and a transport delay

$$\lambda_s(s) = e^{-T_e \cdot s} \cdot \frac{1}{1 + \tau_e \cdot s} \cdot \lambda(s) \quad (8)$$

with

$$\lambda(s) = \frac{\dot{m}_{out \beta}}{\sigma_0 \cdot \dot{m}_{out \varphi}} \quad (9)$$

Torque Generation

Since the plant inputs (i.e. the throttle angle u_α and the engine speed ω_e) on the test bench are given, there is no need for modeling the engine torque.

Sensors

Various signals are measured. For the feedforward term different combinations of temperature, pressure and HFM sensors are used. Both the ambient and the intake manifold pressure are measured. For the feedback only a λ sensor mounted upstream of the catalytic converter is used. For the optimization problem three lambda sensor positions are considered. In order to get an appreciable and measurable difference between the various positions, the LSU wide-range lambda sensors are located at 7cm (λ_1), 40cm (λ_2), and 85cm (λ_3) after the confluence part of the exhaust gases of the individual cylinders.

The sensor dynamics are well approximated with a first-order lag.

ERROR MODELING

The engine model cannot exactly reproduce the behavior of the plant at all operating points and during all the transients. The causes are sensor and actuator

inaccuracies, sensor noise, and physical modeling errors. A higher order model leads to a higher agreement of the results obtained by simulation and measurements, but such a model is inappropriate for control purposes. In this paper the effect of the various modeling errors on the control structure is analyzed. The results are then used to select the best sensor configuration, which is the one that minimizes the overall costs and meets all the constraints.

As expected, measurements show that not all the feedforward structures perform equally well. Therefore, for their investigation and their simulation (see section 4), the open-loop observer that approximates the air mass flow $\dot{m}_\beta$ into the cylinder has to yield a signal with another level of precision for each feedforward structure. This is only possible with the introduction of modeling errors into the air path model. Error modeling allows distinguishing among the various feedforward structures for the estimation of the air mass flow entering into the cylinder and allows investigating the effect of model parameter uncertainties.

For the selection and the definition of the modeling errors the following assumptions have been made:

- The model does not contain any physical modeling error.
- Only parametric errors are modeled.

The first criterion means that the assumptions for using a given physical model are correct. This condition is not always entirely fulfilled, but it allows the process of error modeling and identification to be greatly simplified.

Parametric errors are described as follows. Consider a proper plant family $G(s, r)$, where r is a vector of length m of all uncertain parameters. Then the vector r lies in the rectangle R given by:

$$r \in R = \{r : r_i^- < r_i < r_i^+ \mid i = 1, \dots, m\} \quad (10)$$

The vector r can describe both the plant and the actuator / sensor uncertainties.

The next subchapter presents methods for the identification of the various modeling errors, i.e. the identification of r_i^- and r_i^+ .

Identification of Modeling Errors

In general, due to the restricted availability of measurement data, i.e. not all signals can be directly measured, and due to measurement imprecision, it is difficult to precisely identify the location and the size of each modeling error. This difficulty can be partially avoided by renouncing to identify the modeling error of each parameter, but instead condensing the description of the error in only a few of them. In the following, a few intuitive methods and examples are presented.

For the identification of the air path modeling errors, the measurement of the air mass flow $\dot{m}_a$ and the intake manifold pressure p_m are available. To identify the modeling errors, these measurement data can be compared with the steady-state and the dynamic behavior of the model. The value of the air mass flow $\dot{m}_a(1)$ is determined by the multiplication of four terms. Each of them contains uncertainties, but the available data do not allow locating them. Without loss of generality it can be assumed that the modeling errors are condensed into the first multiplicand c_d . Using a similar approach for the intake manifold pressure $p_m(3)$, the steady-state error between the measurement results of the two signals and the model can be condensed into exactly two parameters, namely the discharge coefficient c_d and the volumetric efficiency λ_l , and the dynamic behavior into just one parameter, the resulting intake manifold volume V_m .

Sensor and actuator inaccuracy and sensor noise influence the process of parameter identification. Sensor imprecision does not influence directly the system state. Actuator inaccuracy influences the operating point of the system. In both cases parameter identification will be affected, since it is not possible to obtain exactly the same measurement results twice.

Repeated measurement of the same process can therefore be used to determine the size of the parameter uncertainty, i.e. the values of r_i^- and r_i^+ . The idea can be applied to the case of the wall-wetting parameter identification. Constant mass flow and fuel steps are used to excite the wall-wetting dynamics.

Another idea for identifying uncertain parameters is to slightly vary the operating point of the system and to investigate the sensitivity of the various parameters with respect to these changes.

These methods do not allow a precise identification of all the modeling errors, but they provide a good idea of the model precision and are useful for investigating the worst-case model behavior.

Identified Modeling Errors

Three different errors have been taken into account. The error modeling process includes modeling errors of the feedforward path (air path), the gas mixing process, and the wall-wetting parameters.

For the modeling of the exhaust gas dynamics, modeling errors were introduced into the time lag τ_e and the delay T_e (eq. (8)). The two errors were assumed to be constant over time.

Concerning the error modeling of the wall-wetting dynamics, simulations and measurements showed that the resulting λ transients are really sensitive to variations of the parameters κ and τ_f . Due to the difficulty of correctly identifying these parameters, the modeling

error can vary from one operating point to another. When driving a test cycle, the system goes through various operating points, which means that the modeling errors can vary over time. Therefore, the modeling errors are not assumed to be constant over time. The same apply for the gas mixing parameters, but in that case the modeling errors have a smaller influence on the resulting λ dynamics and can therefore, as a first approximation, assumed to be constant.

In the case of feedforward error modeling, each sensor configuration has to be considered separately. For SC1 (see section 4), modeling errors are introduced into the parameters that describe the intake manifold volume V_m , and into the volumetric efficiency λ_l . For SC2, errors are introduced into the two previous parameters and into the discharge coefficient parameter c_d too. For the third and last sensor configuration, modeling errors are only introduced into the volumetric efficiency. In all cases constant errors were modeled.

Two sizes of modeling errors (ME1 and ME2) are taken into account. They are summarized in Table 1.

Table 1: Modeling Errors

	Modeling error [%]	
	ME1	ME2
Intake manifold volume V_m	5	5
Discharge coefficient c_d	2.5	5
Volumetric efficiency λ_l	2.5	5
Wall-wetting parameter κ	1.5	5
Wall-wetting parameter τ_f	1.5	5
Gas mixing delay T_e	5	10
Gas mixing time lag τ_e	5	10

While the selected modeling errors (ME1) can look quite small at first glance, it must be remembered that the solution of the optimization problem uses the worst-case error combination. At the end of the optimization process, these errors are summed up, and even if the single modeling errors are small, they can reproduce the measurements results quite well. The column ME2 more accurately reflects the reality, but worst-case considerations can cause very conservative results. This will be illustrated in section 5 (Optimization Problem).

DRIVE CYCLE

One important constraint for each specific sensor configuration is the adherence to the existing emissions