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Robust numerical approach to steady-state calibration of mean-value models

Radek Beňo [a,*], Daniel Pachner [b], Vladimír Havlena [a]

[a] Department of Control Engineering, Faculty of Electrical Engineering, Czech Technical University in Prague, Technická 2, 166 27 Prague 6, Czech Republic
[b] Honeywell Automotive Software, Honeywell, V Parku 2326/18, 148 00 Prague 4, Czech Republic

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ABSTRACT

A numerically robust approach to steady-state calibration of nonlinear dynamic models is presented. The approach is based on explicit formulation of the constraints on validity of internal model signals by set of inequalities. The constrained optimization with feasible iterates guarantees that the model will never be evaluated with invalid internal signals. This overcomes numerical difficulties often encountered when dealing with highly nonlinear models. Because the approach uses a large number of slack variables, distributed least squares algorithm is proposed. The robustness of this approach is demonstrated on a steady-state calibration of turbocharged diesel engine model starting from grossly inaccurate initial estimates.

1. Introduction

Control oriented models are gaining popularity in the automotive industry due to the increased complexity of modern engines, stringent emission standards (Hallstrom & Schiavon, 2007; Ohrnberger, Becker, & Doehring, 2012), on-board diagnostics legislation (Regulation (ec) no 595/2009, 2009; Section 1968.2, 2013) and their short innovation cycles. Dynamic models of Internal Combustion Engines (ICE) vary widely in both form and complexity. The model is usually built for a specific subclass of control problems, required accuracy and the time scale, see Guzzella and Onder (2009). The models often combine empirical, mechanical and thermodynamical law and chemical kinetics. The models range from simple local linear models to complex Computational Fluid Dynamics (CFD) models. The high fidelity first-principles models are used mainly for off-line analysis, system optimization, diagnostics design. Besides the dynamic models, the global steady-state nonlinear high fidelity models are often used in set-point optimization. In contrast, the real time feedback control design is still predominantly not model based, or it is based on local linear models. The reason is that it is difficult to develop a first-principles-based model with sufficient accuracy. However, such models would have a clear advantage of global validity and better extrapolation capabilities. With the growing complexity of engines, their interactions with after-treatment systems, and increasing number of actuators, the black box model development is becoming a problem as it is difficult to cover the high-dimensional operating space with experimental data.

The Mean Value Models (MVM) represent an example of such first-principles models potentially useful for model-based controls (Guzzella & Onder, 2009; Isermann, 2014; Nikzadfar & Shamekhi, 2015). They are "zero dimensional" models which consider the average mass and energy flows over the engine cycles, neglecting their pulsations caused by the periodic emptying and filling of cylinders (Heywood, 1988). These models are primarily used for design of air path controls. The model is built mainly around the differential equations of the gas pressure and temperature at certain control volumes, where the pressure and temperature is assumed to be constant.

In automotive industry, it is the common practice that physical models are calibrated component-wise. This is a different situation from the process industry, where ingenious nonlinear model identification methods were developed (Kozma, Savorgnan, & Diehl, 2012). A typical engine test cell is equipped with sufficient number of sensors which provide inputs and output signals to component sub-models. This makes the model calibration problem a static fitting problem; the individual nonlinearities are fitted separately. Such calibration approach is simpler compared to the general nonlinear dynamic model identification.

The minimization of prediction errors on the component level

* Corresponding author.
E-mail addresses: benorade@fel.cvut.cz (R. Beňo), daniel.pachner@honeywell.com (D. Pachner), havlena@fel.cvut.cz (V. Havlena).

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does not guarantee the minimum prediction error of the resulting dynamic model. Accuracy of the model built from separately fitted components may be sub-optimal. There are two reasons for this. Firstly, the model structure is imperfect. The fitted components models may require some adjustment to compensate the effect of the structure simplifications. Secondly, the turbocharged ICE represents a feedback structure where the component errors are propagated and possibly amplified. It is thus necessary to minimize the errors which are most amplified even at the cost of making the component fit worse on a local level.

This is why a system level optimization based calibration approach has been proposed (Pachner, Germann, & Stewart, 2012). The idea is to start from the component level model and run an optimization of model parameters to fit the global model predictions to the data. This automated model calibration is still relatively new in automotive industry and models are often adjusted manually based on physical insight. The reason is that the optimization can drive model parameters to incorrect values or values which make some of the internal signals physically incorrect albeit the prediction errors of the optimized signals are minimized. This could be improved by constraining model parameters during the optimization to certain a priori described sets, regularizing the problem enforcing the prior information about model components (Wahlström & Eriksson, 2011). It is also important to fit all available measurements during the automated calibration. The automotive engineering community often regards such optimized models with some suspicion and their predictions are considered less reliable compared to models built from components.

At the same time, the MVM of turbocharged engines contain nonlinear functions with singularities and constrained domains. In Jankovic, Jankovic, and Kolmanovsky (1998), it has been proven that the states of this physical system remain in certain invariant set Ω within the singularities and argument to functions remain in their domains. An accurate simulation of a properly calibrated model started in Ω should stay there. Nonetheless, a numerical simulation of the model can fail if the solution will fall outside Ω due to discretization errors; crossing the singularity. System level calibration of such a model is difficult. As the set Ω can depend on model parameters, the optimization can hit infeasible signal values when optimizing the parameters which makes the numerical properties of the optimization problematic. The model Jacobians can be ill-conditioned close to singularities, models can be unstable or even have finite escape time outside Ω. How system level model calibration can be approached in such situation is studied in this paper. The idea is to use constraints on both parameters and model internal signals as a regularization of the optimization process to prevent the optimization from exploring infeasible areas.

The model singularities also affect the numerical solution of the differential equations. Close to a singularity, or to a point where the right-hand side of the differential equation is not differentiable, the model Jacobian is ill-conditioned which is a manifestation of model stiffness (Hairer & Wanner, 1999). The numerical solution may then be difficult and special implicit solvers are required. At a singularity, the differential equations are even not guaranteed to have unique solution (Picard Lipschitz Theorem). A typical example of a point where the right-hand side of the model differential equation is not differentiable is a model with the valve flow equation when the pressure ratio across the valve is one. A regularization of the valve flow function for such pressure ratios is discussed by Guzzella and Onder (2009). There has been shown how a smooth polynomial approximation can replace the non-differentiable function close to the point of non-differentiability. The model differential equations treated in this way will be less stiff, and will definitely be Picard Lipschitz, which means easier numerical solution. The approach proposed by this paper is different as it is steady-state only. It constrains the model signals to be always in certain ϵ distance from the singularities. The model is not allowed to enter "forbidden ground" during the steady-state calibration. This avoids not only singularities but also other undesired or physically implausible signal values. Very often slow and problematic model simulations are avoided.

2. Problem formulation

Model calibration: The nonlinear continuous-time dynamical model is defined in the usual form (Khalil, 2002):

$$dx_t/dt = f(x_t, u_t, p), \tag{1}$$

$$y_t = g(x_t, u_t, p). \tag{2}$$

The model calibration problem is formulated as a deterministic nonlinear least squares optimization solved with respect to vector of model parameters p considering measured sampled sequences of model input and output vectors, u_k and y_k respectively; $k = 1, \ldots, K$. Here y_k and u_k denote signal values of the continuous time signals y_t and u_t sampled at discrete sampling instants $t_k = \lim_{\epsilon\to 0^+}(kT_s - \epsilon)$; with sampling period T_s. The minimized sum of prediction error squares will be referred as the cost function:

$$\hat{p} = \arg\min_{p,x_0} \sum_{k=1}^{K} \|g(x_k, u_k, p) - y_k\|_2^2. \tag{3}$$

Here g is the output function of (2) and $\hat{p}$ denotes the vector of parameter estimates.

Steady-state calibration: For stable nonlinear models, one of the steps of model calibration can be fitting the model steady-state responses towards steady-state data. The steady-state data are often obtained by sampling the signals after a sufficient time from the last change of inputs; thus allowing the process to settle. It assumes that the system is strictly stable and the effect of unmeasured disturbances is negligible. The steady-state calibration problem is easier to solve and it is easier to represent the global steady-state response by a limited data size which spans the whole operating range. Following text will concentrate on the steady-state calibration only because the transient calibration is usually easier once the model steady-state is reasonable. In the steady-state, the model equations (1) will become a set of equality constraints for each of the steady state responses fitted: $f(x_k, u_k, p) = 0$.

Constrained optimization approach: The proposed approach focuses on functions f, g which were derived from first principles and which can have limited domains: $(x_t,\ u_t,\ p) \in \Omega$. The functions should be differentiable in a closed set Ω and they are supposed to represent the correct physics there. As an example, the oxygen concentration in the combustion products can be evaluated as a simple fraction, provided both numerator and denominator are positive. For negative values, the formula does not represent reality:

$$[O_2]_o = (\dot{m}_i[O_2]_i - \xi\dot{m}_{\text{fuel}})/(\dot{m}_i + \dot{m}_{\text{fuel}}),$$
$$\Omega = \{\dot{m}_i[O_2]_i \geq \xi\dot{m}_{\text{fuel}},\ \dot{m}_{\text{fuel}} \geq \epsilon\}. \tag{4}$$

Outside Ω functions f, g represent some formal continuation of the physical formulae. The model optimization can become difficult outside Ω. The possibility of exploring exterior of Ω also increases risk of finding incorrect local optimum. In general, f, g can contain fractions of functions, square roots of certain nonlinear expressions, etc. It can be usually proven that the fraction denominators and square root arguments at physical formulae must be positive. This defines certain constraints on internal signals.

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