Wang, X. M., Zhang, Shujun ORCID logoORCID: https://orcid.org/0000-0001-5699-2676 and Bechkoum, Kamal ORCID logoORCID: https://orcid.org/0000-0001-5857-2763 (2016) Data-Based Gain-Scheduled Modeling and Nonlinear Control of Engine Intake and Exhaust System. Proceedings of the 5th International Conference on Mechanical Engineering, Materials and Energy, 90. pp. 119-124. doi:10.2991/icmeme-16.2016.21

Official URL: https://www.atlantis-press.com/proceedings/icmeme-16/25867491
DOI: http://dx.doi.org/10.2991/icmeme-16.2016.21
EPrint URI: https://eprints.glos.ac.uk/id/eprint/4407

Advances in Engineering Research, volume 90
5th International Conference on Mechanical Engineering, Materials and Energy (ICMEME 2016)

Data-Based Gain-Scheduled Modeling and Nonlinear Control of Engine Intake and Exhaust System

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Keywords: Model-Based Design, Exhaust Gas Recirculation, Variable Geometry Turbocharger, Emissions, Optimization, Gain-Scheduled.

Abstract. In this paper, the parameterized dynamical model of the diesel engine intake and exhaust system using a data-based method, namely a Gain-Scheduled model is proposed and designed based on the data from a virtual engine test bench under normal load conditions. In the first step, the Multiple Input Multiple Output model structure is defined with five inputs and two outputs. Using the constructed model, it is possible to establish the relations between intake Manifold Pressure, Air Mass Flow, the control signals, and changes of the load. Then, the model is further used to design a Nonlinear Model Predictive Control controller, aimed at optimizing the efficiency of the combustion system in terms of the control reference value tracking with respect to emission reduction. This paper follows a model-based design approach to construct the Nonlinear Model Predictive Control objective function for the engine intake Manifold Pressure and Air Mass Flow nonlinear control problem. The proposed data-based dynamical modeling method is shown to increase the flexibility for the modeling of nonlinear plant at a low cost in computational requirements. The experimental results illustrate that the optimized nonlinear control approach significantly improve the control reference tracking performance and the exhaust emissions against the standard decentralized Single Input Single Output control in the standard production Engine Control Unit.

Introduction

This study is motivated by the necessity of improving the performance of diesel engines and reducing their emissions. Research in [1] has shown that both Exhaust Gas Recirculation (EGR) system and Variable Geometry Turbocharger (VGT) are driven through the exhaust gas, thus there is a strong coupling between the two systems. However, in the standard production Engine Control Unit (ECU), the control strategy remains based on gain scheduled Proportional–Integral–Derivative (PID) plus feed forward control for the EGR and VGT, wherein boost pressure is controlled with VGT and the mass flow through the turbine is controlled by the EGR valve. With such a control system, the control performance for transient tracking and adjusting is insufficient, because the effects from the VGT position on the air mass flow and from the EGR rate on the boost pressure are ignored. With transients, the control objective has to provide sufficient Air Mass Flow (MAF) charge at the pedal tip-in such that enough fuel can be burnt without visible smoke to provide the demanded torque while avoiding so called *turbo-lag* [1]. Moreover, at the same time sufficient re-circulated gas is needed to reduce nitric oxide (NOx) and particulate matter (OPAC) emissions. Therefore, the current study proposes and develops an advanced control approach namely, Nonlinear Model Predictive Control (NMPC), for diesel engine intake and exhaust system to generate as much energy as possible per fuel injection while keeping pollutant emissions below a given threshold.

Model-Based Control Design

The design of automotive controls has become increasingly complex and expensive due to several factors 1) the increasing variety of variants of a base engine calibration version; 2) the decreasing availability of test objects (engine, vehicle); and 3) increasingly strict requirements concerning consumption, emissions, and diagnostics. The increasing complexity of the task can no longer be handled using classical methods of controller design [6]. Even if automating controller turning processes, a series of tasks must be iteratively executed: 1) measurement and variation of controller parameters; 2) measurement of responses of the experimental plant with a vehicle and engine; 3) analysis of measurements; 4) step-by-step optimization on the test bench. For model-based control design, one measurement on the real system is sufficient (after creating the experiment plan) [6]. Further steps are performed on the numerical model: 1) control parameters can be changed and the resulting behavior can be predicted in simulation; 2) depending on the specification, optimal results can be achieved.

Model-Based Multiple-Target Optimization

It is well known in engine application that emissions optimization is a true multiple-target optimization that leads to a set of Pareto-optimal solutions [6]. At that point, the selection of the solution can also be performed by means of some criteria (e.g. trade-off between NOx and OPAC). Here the optimization procedure is carried out simultaneously using a simulation model at all operating points. The results are calibration maps as is the case with successive optimization at several Operation Points (OPs). Regarding the target criteria, driving cycle data as well as smoothness of the resulting maps can be considered. In this paper, the optimization problem is transformed into following relationship as in Eq.1. The contribution of a component to the target weights can be adapted to individual requirements.

$$Optimization\,J = Weight_{nox}(OP)\left(\sum NOx\right)^2 + Weight_{opac}(OP)\left(\sum OPAC\right)^2 \qquad (1)$$

Nonlinear Model Predictive Control (NMPC)

Model Predictive Control (MPC) is a control approach in which a current control signal is calculated by solving an optimization problem. The optimization problem is solved by predicting the future system output using a model of the plant. The model can be a state space system, transfer function, or any other representation. A large challenge in implementing an NMPC is the need of an accurate nonlinear model. In this work, a Gain-Scheduled modeling approach is used. This approach is introduced in a previous study, [2], under the term *parameter varying*. The model is related to a Gain-Scheduled structure which separates the working area of a nonlinear plant in several regions. For each of these areas linearized models must be evaluated. With this approach, the nonlinear identification problem is transformed into a quasi-linear relationship:

$$x_{i+1} = A_i(x_i,\rho)x_i + B_i(x_i,\rho)u_i + m_k \qquad (2)$$
$$y_i = C_i(x_i,\rho)x_i,$$

where *y*, *x* and *u* are the output, state and input of the system; *A*, *B*, and *C* are the system matrixes; m_k denotes the modeling error; and ρ is the gain scheduling parameter.

This Gain-Scheduled model provides increased prediction accuracy compared to the linear case. In a discrete time case, the system input space is expanded with feedback from past input and output values up to a certain time horizon, as shown in Eq. 3. The NMPC principle is characterized by the following cost function:

$$NMPC\ J = min_u \sum_{i=0}^{n_{PH}} (y_i - y_{ref})^T Q (y_i - y_{ref}) + \sum_{i=0}^{n_{CH}} u_i^T R u_i \quad (3)$$
$$y_{min} \le y_i \le y_{max}$$
$$u_{min} \le u_i \le u_{max},$$

where *PH* and *CH* denote the prediction horizons and control horizons, respectively; and *Q* and *R* are the weight factors. Detailed researches about NMPC can be found in [3, 4, and 7].

Application: Nonlinear Model Predictive Control of Engine Intake and Exhaust System

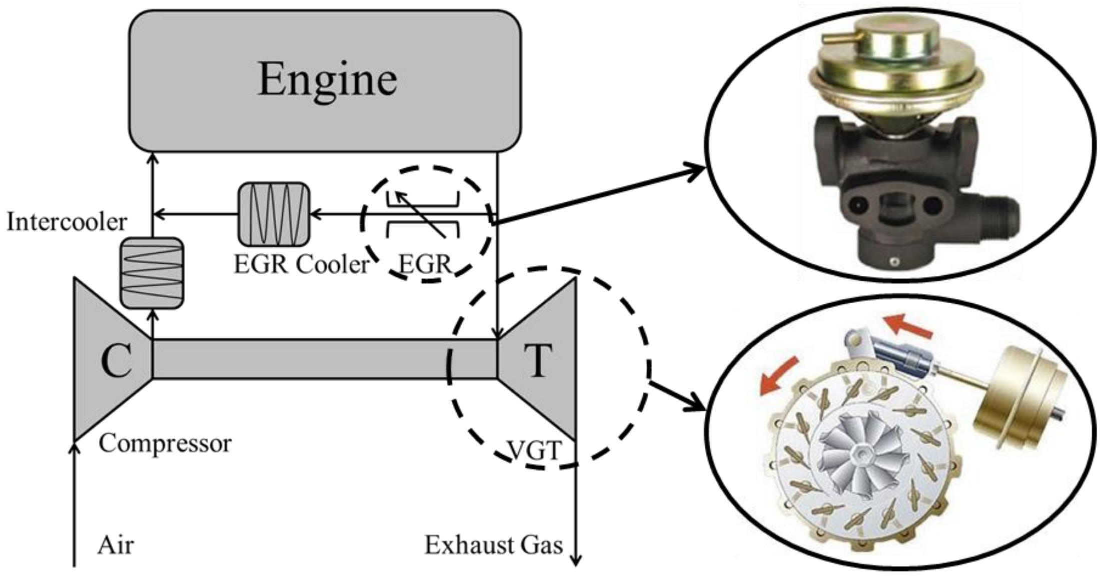

Figure 1. Engine layout, Variable Geometry Turbocharger and Exhaust Gas Recirculation

System Description and Control Objectives. As shown in Fig. 1, this is a common configuration in many modern engines for a power vehicle system, especially when high performance is required. The reduction of fuel consumption and the regulated emissions of components is one of the most important issues in engine development. A significant contribution to these goals can be delivered by EGR and VGT actions according to given reference values of Manifold Pressure (MAP) and MAF. However, the extreme nonlinearity of the combustion system makes it difficult to accurately control the VGT and EGR actuators. Then questions arise, why are MAF and MAP the only variables of interest? The reasons for this are widespread. The aim of modern engines is the minimization of fuel consumption while providing the demanded torque and keeping emissions below legal limits. One approach would be to use emission quantities (e.g. NOx and OPAC) in the control algorithm. However, the online measurement of these variables is not currently possible in a production engine and the use of online emission models is in a developmental phase [5]. There must be quantities which, on the one hand, can be easily measured, and on the other correlate to emissions. Until now, MAP and MAF are the two most popular quantities [1, 5].

Engine Intake and Exhaust System Modeling. To optimize the engine system efficiency as described by MAP and MAF control tracking and emissions reduction, an advanced control approach NMPC is necessary. To design and tune such a control system, a real time precise prediction model must be developed, thus the system is identified with the Gain-Scheduled approach. The chosen inputs for the identified model with feed forward input selection are: Exhaust Pressure (Pex), EGR valve position (Xegr), VGT valve position (Xvgt), engine speed (n), and fuel injection (mf). The outputs are MAF and MAP. This system is identified in one step with a Multiple Input Multiple Output (MIMO) structure to determine the interactions between all inputs and outputs. The identification of MAP and MAF highly depends on the special behavior of input and output signals, therefore in this case, a preprocessed Federal Test Procedure (FTP) -75 driving cycle measurement is prepared as the identification and validation data set. The model is then identified using the previously discussed Gain-Scheduled identification approach. Fig. 2 presents a comparison of the measured data and the simulation results based on the identified models. It can be deduced that the Gain-Scheduled model could give good identification precision results.

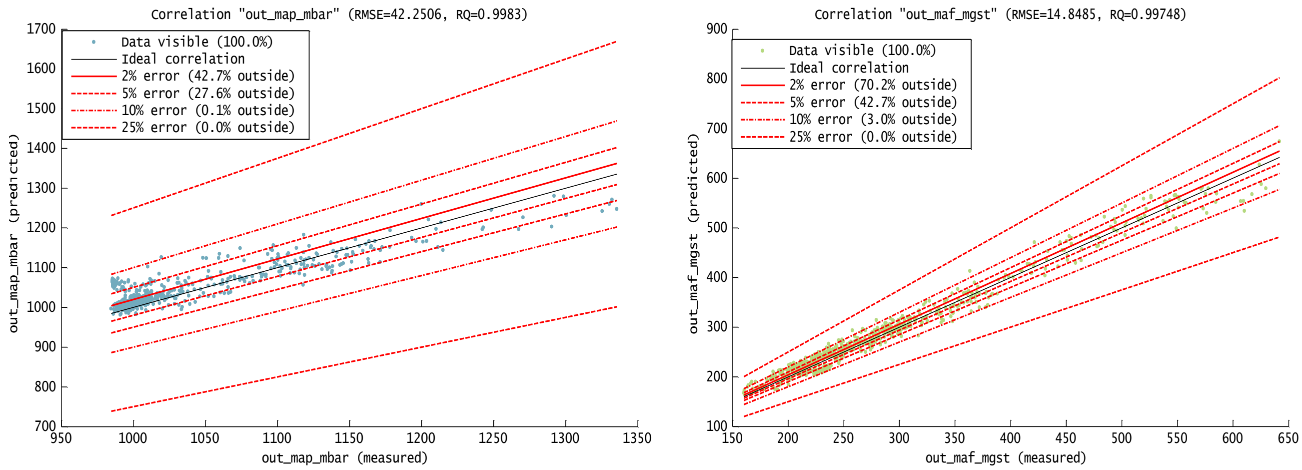

Figure 2. Validation of model outputs of Air Mass Flow and Manifold Pressure

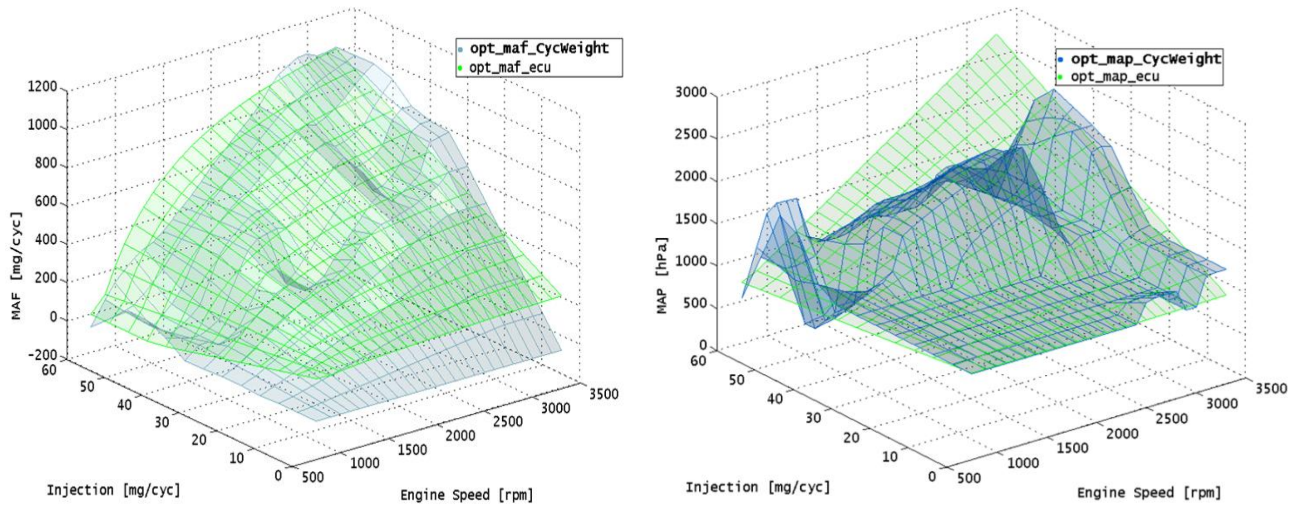

Figure 3. Optimized reference values of Air Mass Flow and Manifold Pressure

Nonlinear Model Predictive Control of Engine Intake and Exhaust System. The combustion engines manufactures must be able to prove that legally prescribed thresholds for emissions are adhered to (e.g. in accordance with the Euro 6 standard) in various test cycles [6]. The task of optimization is thus both to adhere to these thresholds and attain the best possible consumption rates while subject to any other constraints, such as thresholds for pressure and temperature. Some drive cycles are prescribed by the legislator as a list of stationary operation points, others are defined as transient drive cycles via speed and load. To make reliable predictions about dynamic results from stationary information, it is a common practice to reduce the transient drive cycles to a list of operating points that are as representative as possible [6]. In this case, the optimized reference values of MAP and MAF, according to minimized emissions, are shown in Fig. 3.

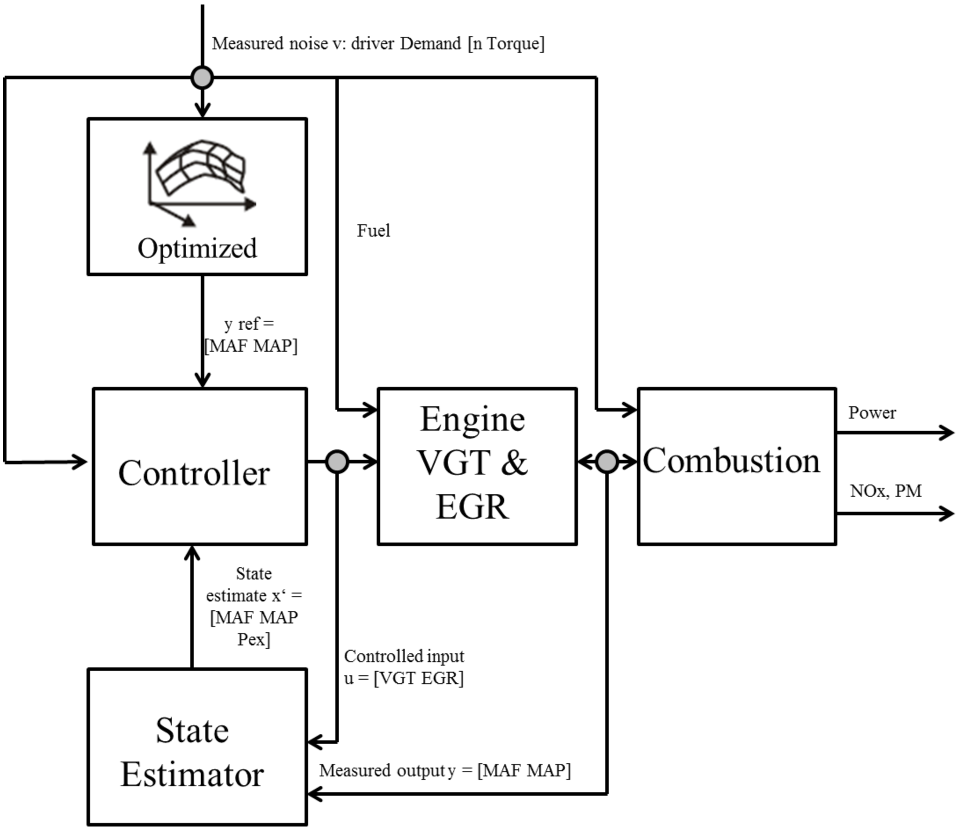

Figure 4. Nonlinear Model Predictive Control closed loop control structure

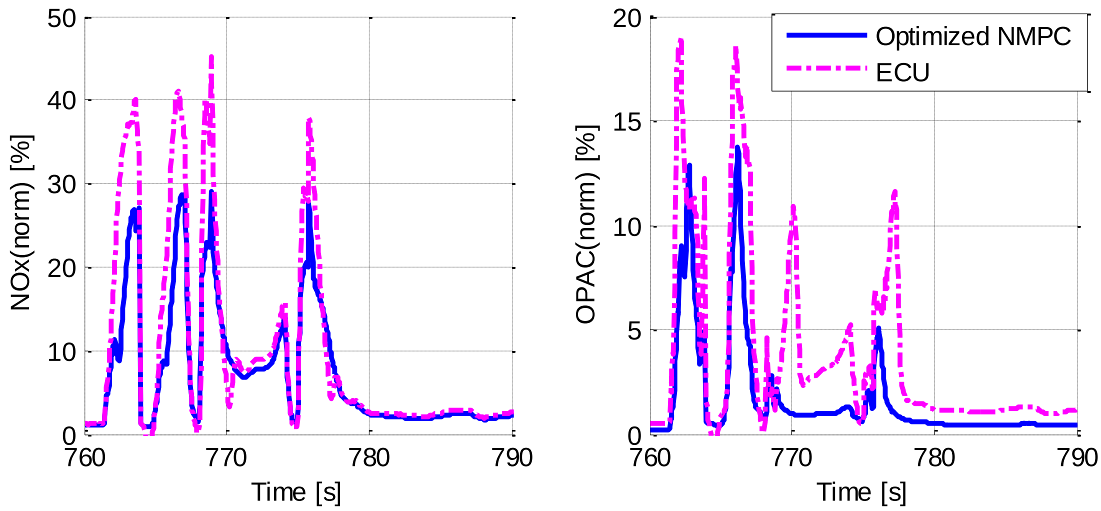

Figure 5. Comparison of exhaust emissions of nitrous oxide and particular matter

As discussed, the chosen controller design is an NMPC controller design to determine a suboptimal robust control. The algorithm of the implemented NMPC is integrated with a matlab programmed real time quadratic problem (QP) solver, by calculating different discrete solution regions and choosing the best within the limits of prescribed tolerances. The closed loop control structure is depicted in Fig. 4. For a comparison between the performance of optimized NMPC and

ECU, experiments were performed with identical conditions. The results of this closed loop simulation are presented in Fig. 5 and 6.

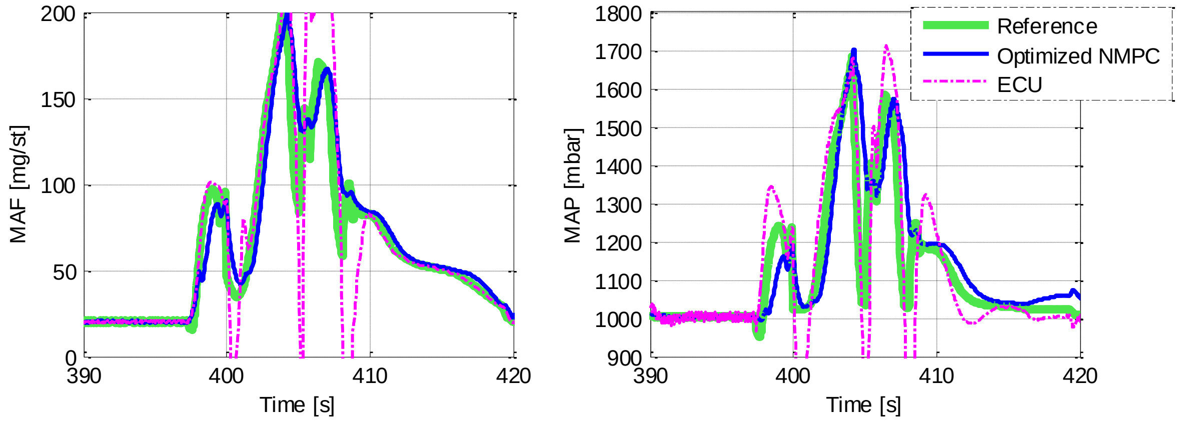

Figure 6. Comparison of tracking results of Air Mass Flow and Manifold Pressure

Conclusion

Studies have shown that a large operation point changing value leads to a transient state, increasing the emissions. Therefore, optimizing and maintaining control tracking results under the given references are the main task in engine control. In this research, the transient behavior caused by operation changes was approximated with a dynamic model, identified with a Gain-Scheduled approach. The excitation of the engine was completed under closed loop conditions. The results, as shown in Fig. 5 and 6, clearly show that the optimized NMPC approach has a corresponding set of advantages over the standard ECU control as it achieves the better reference tracking performance and lower emissions. Another important fact is that the proposed model-based optimization method is offline and would not require changes in the current structure of the control hardware. However the disadvantage is the large amount of memory required to store the control laws and description of the polyhedral partition. If the number of regions is high, the computing time necessary to determine the proper control law must not be neglected. That should be improved for future research.

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