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Model-based multi-critical optimisation of combustion engine fuel consumption and emissions

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Model-based multi-critical optimisation of combustion engine fuel consumption and emissions

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Abstract. The combustion engine is a typical nonlinear multi-input multi-output (MIMO) system with strong couplings, actuator constraints, and fast dynamics. This paper addresses a model-based multi-critical optimisation approach in diesel engines, which allows to improve emission performance and to provide a reference for the design and optimisation of the diesel engine system. The first part of this paper introduces a data-based modelling method that appears particularly suitable for emission modelling. The Design of Experiments (DoE) method helps to generate and collect the required measurement for data-based modelling in a short time, despite the increasing number of manipulated variables. The second part establishes a new model-based multi-critical optimisation approach that supports the optimisation of fuel consumption and emissions based on engine models. This proposed model-based framework consists of system identification and multi-critical optimisation. This framework has the ability to achieve the fast and precise solving of multi-critical optimisation problem and is suitable for implementation in the engine control unit. The experiment results illustrate that the model-based multi-critical optimisation significantly improves the engine exhaust emissions and fuel consumption against the original ECU.

1. Introduction

The diesel engine plays a dominant role in heavy-duty vehicles, agricultural machinery, engineering machinery, and other fields due to its high energy efficiency, strong driving performance, and good economic characteristics. Shown in Figure 1 is a common configuration in many modern diesel engines for a power vehicle system, especially when high performance is required. However, the primary problem for the diesel engine is its emissions of nitrogen oxides (NOx) and particulate matter (PM; also called OPAC when measured as opacity) [1]. With increasingly stringent emission regulations, the question of how to improve the economy and emissions of diesel engines has become an important issue for engine development [2]. For diesel engines, this pursuit involves using control optimisation as well as exhaust gas recirculation (EGR) technology to reduce NOx emissions, and employing after-treatment technology, such as three-ways catalytic, diesel particulate soot filters, and other methods, to reduce its particulate emissions [3]. Furthermore, the engine turbocharger technology is an important means to improve engine performance. Variable-geometry turbochargers (VGTs) are a family of turbochargers usually designed to allow the ratio of Area/Radius (A/R) of the turbo to be adapted as engine operations change [4]. Variable-geometry turbochargers can reduce the turbine vane’s variable angle opening when the engine is running at low speed, thus increasing the exhaust gas pressure and flow rate, improving the exhaust energy efficiency, and enhancing the low speed torque performance. The turbine vane’s variable angle opening can be adjusted during high-speed operation, so that it works within the high-efficiency area of the turbocharger. When combined with the EGR system, one can adjust the opening of VGT vanes to improve the pressure difference between the turbine and EGR system, which could further improve the EGR rate and reduce NOx emissions.

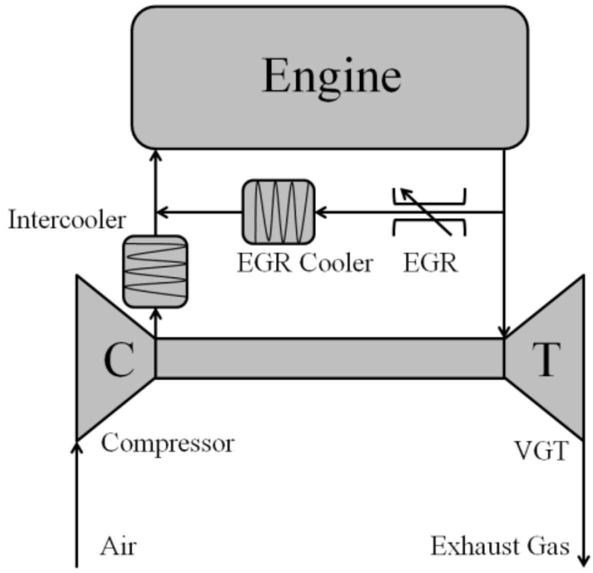

Figure 1. Turbocharged Diesel Engine Equipped with EGR

Therefore, the classic manipulated variables of injection volume and the injection process are joined by further manipulated variables, such as EGR, VGT, injection pressure in common rail systems, variable valve train (VVT), and injection volume modulation. These control variables affect torque, fuel consumption, and emissions. The cross-coupling effect of control variables creates a complex nonlinear multivariable system. The variety of control options and their interactions make it increasingly difficult for engine designers to find an optimal engine setting, and the number of realisable characteristics in modern engine controls rise sharply. For some time, the traditional test-bench approach, which is limited to a stationary assignment of the inputs and outputs variables listed above, has not met all requirements [5]. Hence, model-based methods are required to develop engine control systems further that permit the static and dynamic behaviour of internal combustion engines to be exactly determined with the help of a more precise mathematical simulation. This paper presents an integrated method based on emission modelling to optimise the consumption and emission behaviour of internal combustion engines.

In the first part of the paper, the modelling of emissions will be explained in detail. With the help of the DoE approach, the required measurement data for data-based modelling of emissions can be collected in a short time despite the increasing number of manipulated variables. The validation results of the emission models are then presented and discussed. The second part of this paper describes how the presented emission models form the basis of a model-based optimisation of fuel consumption and emissions.

2. Data-based modelling of emissions

In many real-world situations, it is too difficult to describe a system using known physical laws. With engine exhaust emissions, for example, the system identification method can be used to perform data-based modelling. The goal of system identification is to estimate a model of a system based on observed input-output data [6]. System identification is useful when the only available information from a system is input and output data. The procedure to determine a model of a dynamic system from observed input-output data involves three components: 1) the input-output data; 2) the model structure- possible candidate models; and 3) the identification method (some criterion to select a model in the set, given the information in the data).

Identifying the engine exhaust emission model uses the data set collected from the engine test bench. Figure2 presents the emission model structure, which includes all the inputs and outputs for identification. To obtain this measurement data, a DoE plan was applied to the engine. The input signals are mf: injected fuel mass in mg/cycle; n: engine speed in rpm; MAP: manifold absolute pressure in mbar; MAF: manifold air flow in mg/cycle. The output signals are NOx in ppm and OPAC in %. Figure 3 illustrates the results of the DoE data in 3D. The duration of the measurements for the training data sets was around 0.5 seconds at every operating point, whereby the control variables were changed abruptly in a region around the series setting. The sampling time was 100ms.

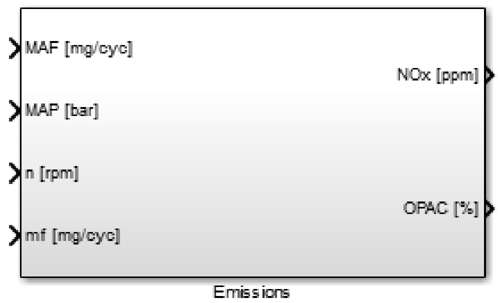

Figure 2. Emission Simulink Model

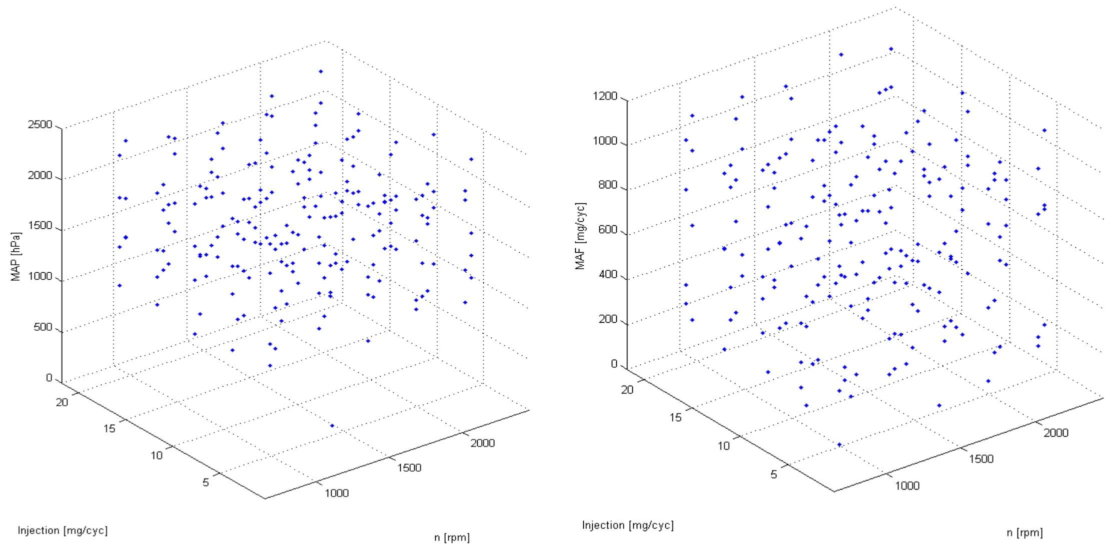

Figure 3. DoE-Data (Engine Injection, Engine Speed, MAP, and MAF) in 3D

System identification can be performed from these measurements. The engine emission model is identified in one step, with a MIMO structure to catch the interactions between all inputs and outputs. The system identification toolbox from Matlab enables to estimate models of different types and orders. To perform the validation, Figure 4 shows that the NLARX model estimations yield a reasonably close response to the original measurement data. The average error of NLARX model was between 5% and 10%. Thus, the identified model is able to represent the real behaviour of the engine emissions in the given operating range. So far, the output variables (NOx and OPAC) were modelled with the engine control variables as model inputs. This emission model is further connected to a mean-value engine model which was modelled in a previous work [7]. Alternatively, internal variables from the measurement dataset, such as MAF and MAP can be used as input variables for the models. The MAF and MAP used as input are useful when the optimisation aim introduced in the second part is not the calculation of control characteristics for the manipulated variables but when calculating command variable mapping characteristics for secondary control (VGT or EGR) [7].

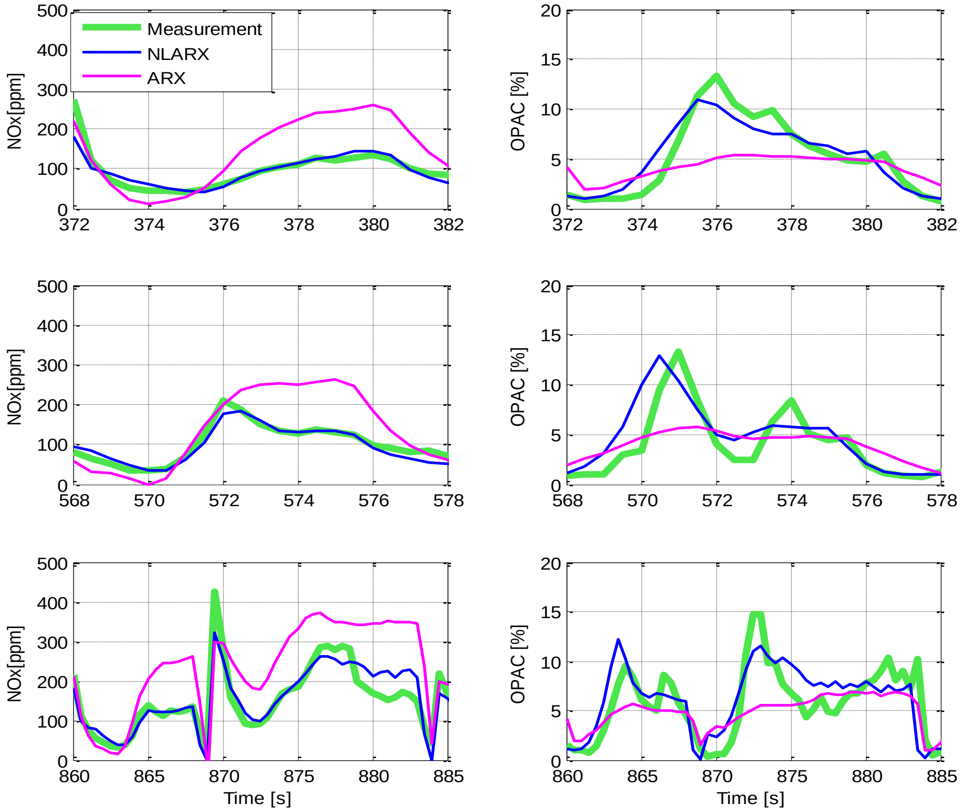

Figure 4. Comparison of Measurement, NLARX and ARX Model

3. Model-based multi-critical optimisation of fuel consumption and emissions

With engine optimisation, the exhaust emissions must be restricted for the duration of an operating cycle to the legally permissible limit for each emission component with minimal fuel consumption. These two requirements often contradict each other and reducing certain exhaust gas constituents typically entails an increase in consumption, which is why an appropriate compromise must be found. Experienced test engineers traditionally carry out optimisation based on test-bench conditions [7]. This procedure is time consuming and is impossible to implement when the number of manipulated variables rises. In this paper, the engine behaviour is presented with a mathematical model (mean-value engine model connected with emission model); offline optimisation can be performed on this model to determine the optimum manipulated variables [8].

Optimisation is based on cost function J (Eq. 1) to determine fuel consumption and emissions. Engine control variables should minimise this cost function through optimisation algorithms. Optimisation tasks frequently lead to a situation where a reduction (e.g. of an emission variable) is associated with an increase of other values, such as consumption. The model-based multi-critical optimisation is available for the optimisation of such ‘opposite’ outputs.

$$J = k_1(n, mf)(norm(NOx))^2 + k_2(n, mf)(norm(OPAC))^2 + k_3(n, mf)(norm(fuel))^2 \quad (1)$$

Table 1. Elements of cost function

Name	**Weight**	**Target**
NOx	k_1	Low NOx Emission
OPAC	k_2	Low OPAC Emission
Fuel	k_3	Low Fuel Consumption $_{\text{Equivalent Power}}$

In order to achieve comparable sensitivity of the cost function for the respective components, it is necessary to first normalise them within each operating point. To this end, for any reference values, the respective behaviour can be used in the series products. The weighting factors are defined in the offline application of this procedure by different value combinations that appear useful. To prevent inhibiting the drivability of the vehicle, the engine torque must be not smaller than a predetermined moment represents an additional condition. Optimisation for each operating point means that Eq. 1 must be solved by an optimisation method. For this purpose, the method SQP (sequential quadratic programming) was used [9], which is designed for non-linear, multivariable problems with constraints and, for example, as a function called 'fmincon' in MATLAB's Optimisation Toolbox.

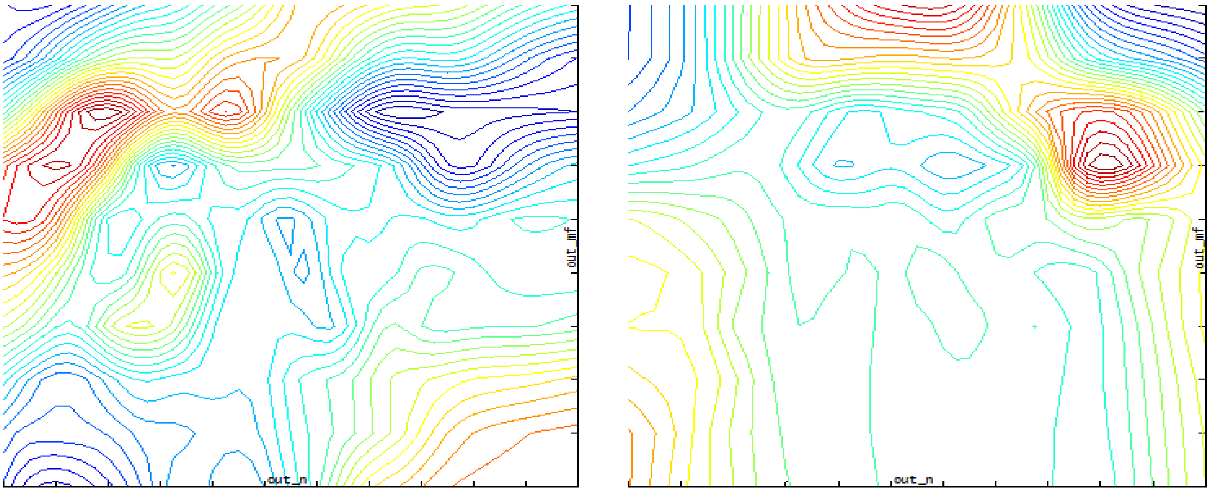

Figure 5. FTP-75 Cycle-Based Weighting Factors for OPAC (left) and NOx (right)

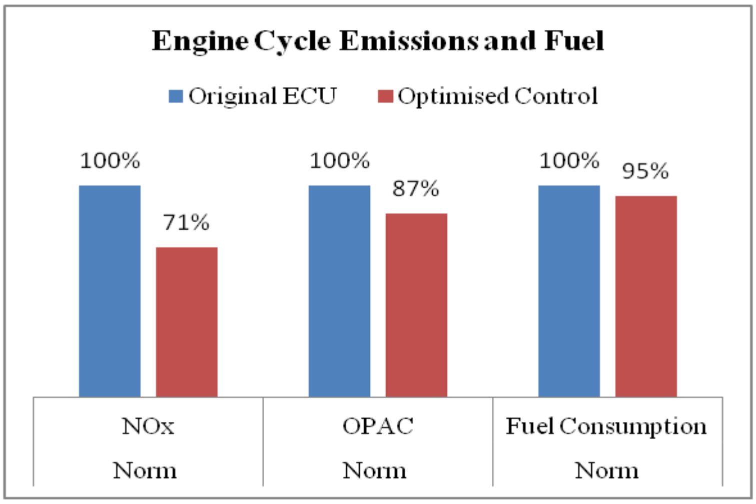

Figure 6. Comparison of Engine Cycle Emisisons and Fuel Consumption

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After optimising, a control map is selected for driving that complies with the emission limit values for a particular driving cycle and that achieves the lowest consumption. If further optimised control maps for other weightings are defined in the control unit then a different emissions and fuel consumption composition can be set (e.g. depending on the driving situation while in operation). This cycle-based weighting, as shown in Figure 5 and positioning of the operation points, *k (n, mf)*, with the reference to the calculation rules can now be used for the global optimization. These optimised manipulated variable maps are further applied to the engine-air-path control. The results of the optimisation compared with the original ECU are shown in Figure 6. The simulation results showed that the NOx emission, OPAC and fuel consumption were decreased by 29%, 13% and 5% respectively against the original ECU.

4. Summary

To meet the increasing demands on modern diesel engines in terms of low consumption and minimal exhaust emissions, it is necessary to control the engine more optimally. The presented model-based multi-critical optimisation methods are carried out for multiple manipulated variables (Engine Injection, Engine Speed, MAP, and MAF) and outputs (fuel consumption and emissions) with cycle-based weighting factors in a relatively short time whereby any driving cycles and either stationary or transient engine models can be used. Optimisation, therefore, does not require a lengthy online engine test, but can be performed offline with simulation engine models. Overall, a model-based framework is thus available, which helps achieve optimisation of engine control within a relatively short amount of time.

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