2017 NDIA GROUND VEHICLE SYSTEMS ENGINEERING AND TECHNOLOGY SYMPOSIUM
POWER & MOBILITY (P&M) TECHNICAL SESSION
AUGUST 8-10, 2017 - NOVI, MICHIGAN

ADVANCED MODELING AND OPTIMIZATION FOR VIRTUAL CALIBRATION OF INTERNAL COMBUSTION ENGINES

Dr. Tobias Gutjahr
ETAS Inc.
Ann Arbor, MI

Dr. Thomas Kruse
ETAS GmbH
Stuttgart, Germany

Thorsten Huber
ETAS GmbH
Stuttgart, Germany

ABSTRACT

Due to the high complexity of modern internal combustion engines and powertrain systems, the proper calibration of the electronic control unit's (ECU) parameters has a strong impact on project targets like fuel consumption, emissions and drivability, as well as development costs and project duration. Simulation methods representing the system behavior with a model can support the calibration process considerably. However, standard physics-based models are often not able to describe all effects with sufficient accuracy, or the effort to set up a detailed model is too high. Physics-based models can also have a high computational demand, so that their simulation is not real-time capable. More suited for ECU calibration are data-driven models, combined with Design of Experiment (DoE). The system to be calibrated is identified with few specific test bench or vehicle measurements. From these measurements, a mathematical regression model is built. This paper describes recently developed machine learning methods based on Gaussian processes. In contrast to polynomial models or neural network regression, Gaussian processes are able to model strongly nonlinear systems with high accuracy, and are robust against measurement noise and outliers. No expert knowledge is required for their practical application, all model parameters are determined automatically by probabilistic principles. The data-driven model replaces the real engine or vehicle in the calibration process, and combined with optimization methods, the best set of ECU parameters with respect to the project targets is identified. The short response time of Gaussian process models further enables their use in real-time environments, e.g. Hardware-in-the-Loop (HiL) test systems or even directly on the ECU. This paper shows the application of the data-driven approach in the calibration process on several examples.

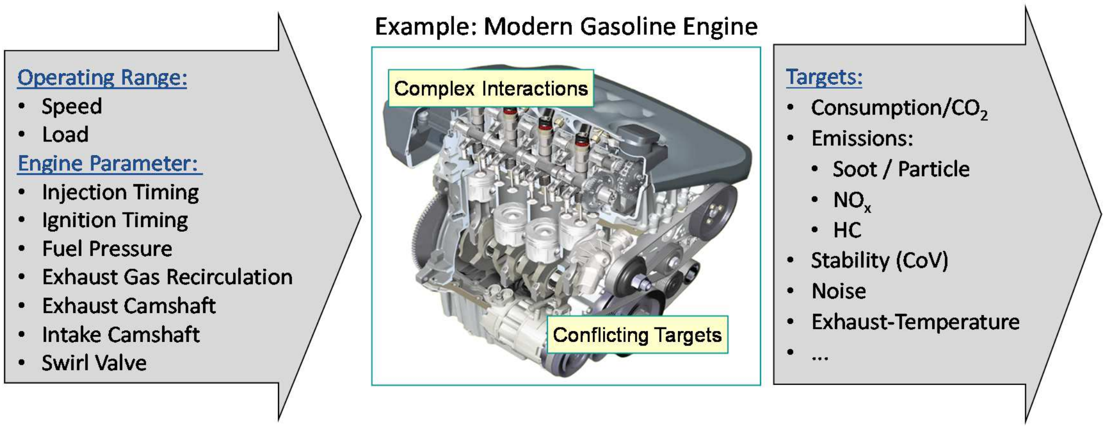

Figure 1: Typical parameter and optimization targets of a modern gasoline engine.

INTRODUCTION

The process of calibrating the parameters of the engine's electronic control unit (ECU) has a strong impact on project targets like fuel consumption, emissions, drivability, as well as development costs. One major challenge is the increasing number of engine parameters, which must be optimized over the entire engine operating range, in order to provide the best compromise between conflicting targets. Figure 1 shows a typical set of inputs and outputs considered during base calibration of a modern direct injection gasoline engine. Each new engine parameter leads to a multiplication of the measurement effort, if classical calibration methods are applied. Simulation methods that represent the system behavior by a model can support the calibration process considerably. Figure 2 shows the different phases of a standard calibration process, from the base calibration at the engine test bench to the test

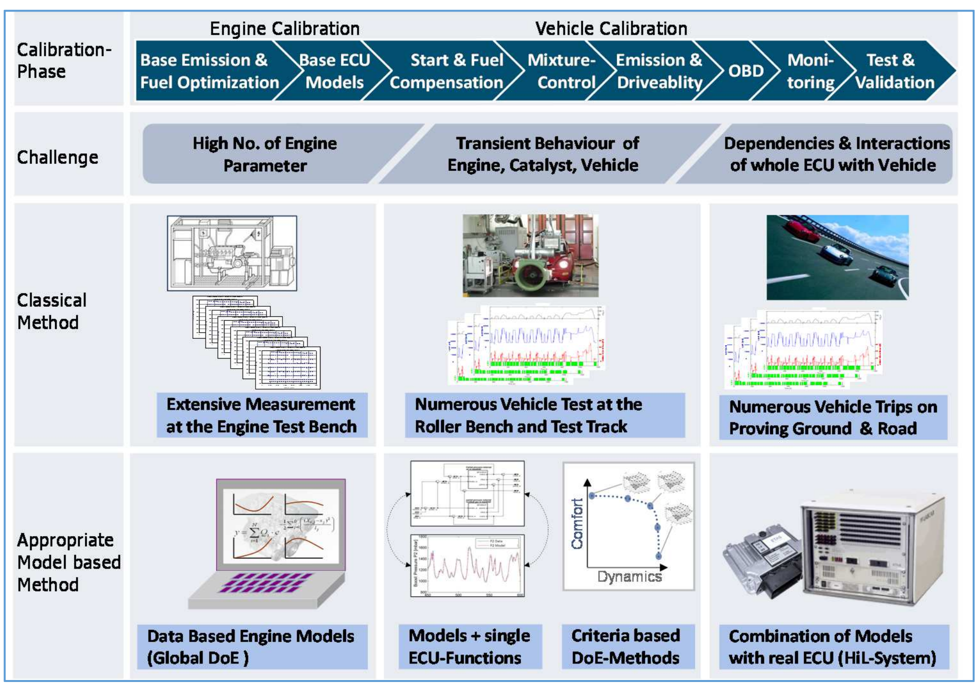

Figure 2: Different phases of the calibration process for a gasoline engine.

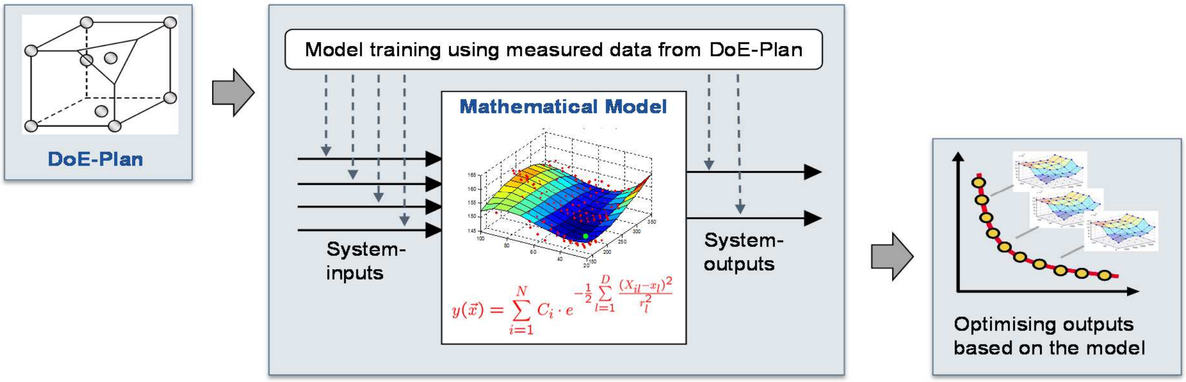

Figure 3: Overview of the DoE process from the test plan to the optimization of the system outputs.

and validation of the entire calibration. In each phase, the calibration engineer struggles with new challenges, leading to a very high measurement effort and an extensive use of prototypes, i.e. engines and complete vehicles. Appropriate simulation methods, where the relevant system behavior is represented by a model, can reduce the calibration effort and demand for real prototypes significantly. An essential prerequisite for the practical application is that the models have to provide a very high accuracy and can be configured with relatively low measurement and time effort. This excludes in most cases the use of physics-based models. More suitable are data-driven models combined with a Design of Experiment (DoE).

DESIGN OF EXPERIMENT AND DATA-DRIVEN MODELING

The basic idea of DoE is to characterize an unknown system, e.g. an internal combustion engine, by a data-driven mathematical model using a matching test plan to minimize the measurement effort. Compared to a full factorial test plan, the number of required measurements can be reduced by orders of magnitudes with a proper DoE, especially for high dimensional identification problems. The determination of the calibration parameters is done based on a trained model and the use of mathematical optimization algorithms. The overall process is depicted in Figure 3. The first applications of data-driven modeling and DoE in ECU calibration started more than a decade ago [1]. The combination of DoE with modern test bench automation methods allows a fast and simultaneous variation of all parameters, which further increases the efficiency [2].

The key element of the entire DoE process is the mathematical model. Often, polynomials or neural networks are used [3], but both types have significant disadvantages which limit their use in the calibration process. Polynomials are easy to understand and available in many commercial tools. The major drawback is that only a very simple system behavior can be described. Polynomials are also sensitive to single measurement errors, which can deteriorate the model if not detected as outliers. Alternatively, neural networks are theoretically able to describe any complex system behavior, but often require high expertise for the model configuration and additional validation data to avoid model over fitting. As a consequence of the listed drawbacks, DoE methods were only applied by a few experts in the past and limited to a small number of use cases.

A new approach is the use of machine learning methods based on Gaussian processes. From a complete set of basis functions, a Bayesian approach determines automatically the set of functions which represents the training data with highest probability [4]. The function set is characterized by so-called hyperparameters: signal noise, signal strength, and a length scale for each input dimension D which describes the rate of change of the output over the respective input. The hyperparameters are determined automatically from the training data based on maximum likelihood optimization. The final formula for the prediction of an output y depending on the inputs x_1, x_2, …, x_D can be reduced to a summation of overlapping Gaussian kernel functions [5], see Figure 4.

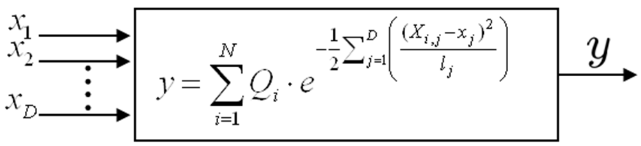

Figure 4: Formula of the Gaussian process model for predicting an output y.

N represents the number of training data points, Q_i is a combination of the signal noise and signal strength hyperparamters for data point i, l_j is the length scale hyperparameter, and $X_{i,j}$ stands for the position of the training data in the input space. This regression model allows a precise description of complex and highly nonlinear systems without over fitting.

A one-dimensional example is given in Figure 5. The training data points for the output (y-axis) show a strong nonlinear behavior with respect to the input (x-axis) including some measurement noise. The upper half of Figure 5 shows the attempt to describe the input-output relationship with a polynomial model, which fails in fitting the data properly even with a high model order of 5. The lower half shows the model fit based on the Gaussian process approach. Here, the true relationship is described very well without fitting the noise in the data. Additionally, a locally resolved model variance can be derived from the Gaussian process algorithm [5]. This can be used to indicate a level of model uncertainty, which increases in areas with insufficiently provided training data points. Based on this, a recommendation for a valid model range can be derived. If the model variance exceeds a certain threshold, the model prediction can be classified as unreliable, as shown with the grey line in Figure 5. These areas can then be excluded from the subsequent calibration optimization. Also, this information can be used to define and collect new measurements to improve the model quality. The available information regarding model accuracy and validity is important for the use in series ECU calibration and for user acceptance.

These highly flexible and accurate Gaussian process models enable an easy generation of global engine models for the entire operating range and all relevant calibration parameters. In contrast to the often used two-stage approach [6], engine speed and load can be included as a normal input variables. The modeling process is done in a few minutes on a standard PC, even for complex problems with more than ten input dimensions and thousands of training data points.

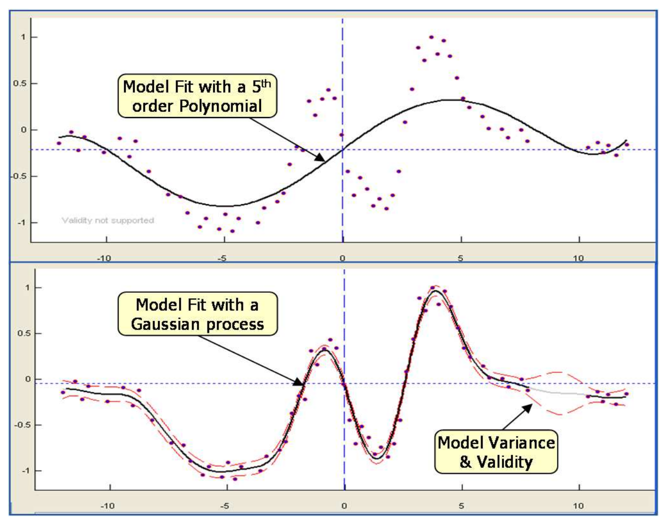

Figure 5: Modeling of a complex one-dimensional relationship with a polynomial model of 5th order (upper half) and the Gaussian process algorithm (lower half). The dashed lines indicate the model variance.

Since the model accuracy depends mainly on the local density of the training data in the input space, an equal distribution of the data points is desired. This is provided best by a space filling DoE test plan such as a Sobol sequence [7].

GAUSSIAN PROCESS MODELING AND ITS APPLICATION IN ECU CALIBRATION

The capability of building easily very precise data-driven models, e.g. of a global engine, enables the use of model-based methods for a broad range of calibration tasks. Therefore, in a joint project between ETAS and the Robert Bosch GmbH, the described modeling algorithms were implemented in a tool called ETAS ASCMO (Advanced Simulation for Calibration, Modeling and Optimization). In addition to the modeling and test planning, the tool provides powerful optimization algorithms [8, 9], an interactive visualization, and prognosis features tailored to different calibration needs.

Engine Base Calibration: Emissions and Fuel Optimization

The first step in the calibration process (Figure 2) is the steady-state optimization of the engine base parameters over the entire operating range with respect to targets like fuel consumption, raw emissions and combustion stability. The use of an accurate model based on only some hundred test points can reduce here the required test bench time significantly.

Figure 6 shows a screenshot of a global engine model for a spray-guided direct injection gasoline engine created with ETAS ASCMO based on 500 training data points. The shown graphs are belonging horizontally to the four relevant engine outputs and vertically to engine speed, load, and the different calibration parameters. The calibration engineer can choose any operating point of the engine, in this case 2000 rpm and an engine load of 4 bars of mean effective pressure (PME), and analyze the influence of the calibration parameters regarding the relevant engine outputs. In this example, the seven calibration parameters are: injection and ignition timing, fuel pressure, rate of exhaust gas recirculation (EGR), timing of exhaust and inlet camshaft, and the swirl control valve (SCV). The relevant engine outputs are: fuel consumption, combustion stability (CoV), soot, and NOx emissions. The values of the calibration parameters, indicated by the vertical dashed lines,

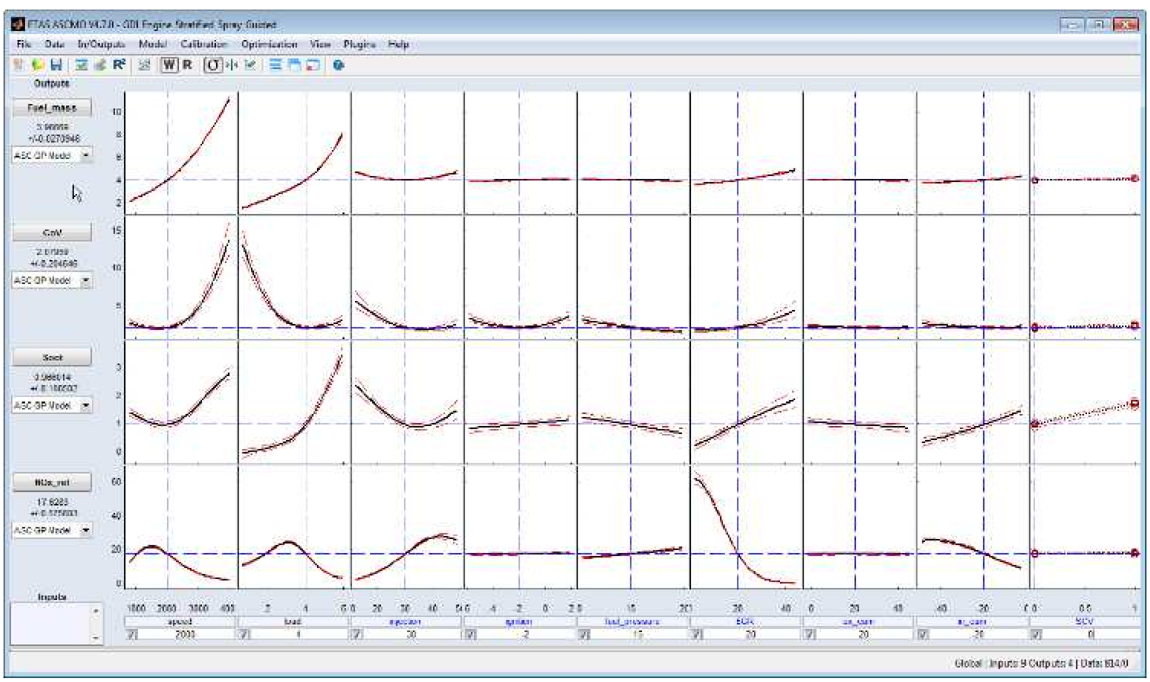

Figure 6: Visualization of the global engine behavior in ETAS ASCMO with respect to engine speed, load, and all ECU calibration parameters.

can be changed interactively. The dashed lines around the model prediction graph indicate the confidence interval, which is an important quality information.

An optimization over the entire engine operating range can now be performed, e.g. minimizing fuel consumption while keeping limits for the other outputs. As a result, the user will get a proposal for the calibration of all calibration maps. Figure 7 shows how the global engine model can be combined in ETAS ASCMO with vehicle and driving cycle data. The speed and load trajectories, resulting from vehicle data, and the relevant driving cycle can either be reduced to a list of weighted operating points, reflecting the duration in the corresponding speed/load area, or considered point by point. This allows a prediction of the total fuel consumption and cycle emissions depending on the current calibration. Further, a simultaneous optimization of all maps can be performed with respect to fuel consumption, emissions, local constraints such as noise or combustion stability, and a smoothness factor for the calibration maps. By using the analytic gradient of the model prediction from the Gaussian process algorithm, the optimization process is very fast. This allows the calibration engineer to create different calibration proposals for various trade-off scenarios within a few minutes. Compared to classical DoE approaches, significant improvements in the overall driving cycle fuel consumption and emissions of up to 4% could be proven in many applications [10, 11]. Since a global engine model is built in ETAS ASCMO, a prediction and optimization for any real driving cycle can be performed without new test bench measurements.

Transient Calibration: Criteria-based Drivability Calibration

The proposed modeling approach can also be used for transient calibration tasks such as drivability. One important part of the drivability calibration is the optimization of the so-called tip-in, a very quick positive actuation of the accelerator pedal (Figure 8). Without countermeasures, the fast built up of the engine torque would lead to strong and uncomfortable oscillations of the powertrain. The calibration task is a multi-criteria optimization problem, namely to find a compromise between comfort and driving dynamics by determining the appropriate control parameters in the drivability function. In this case, it is sufficient to build a

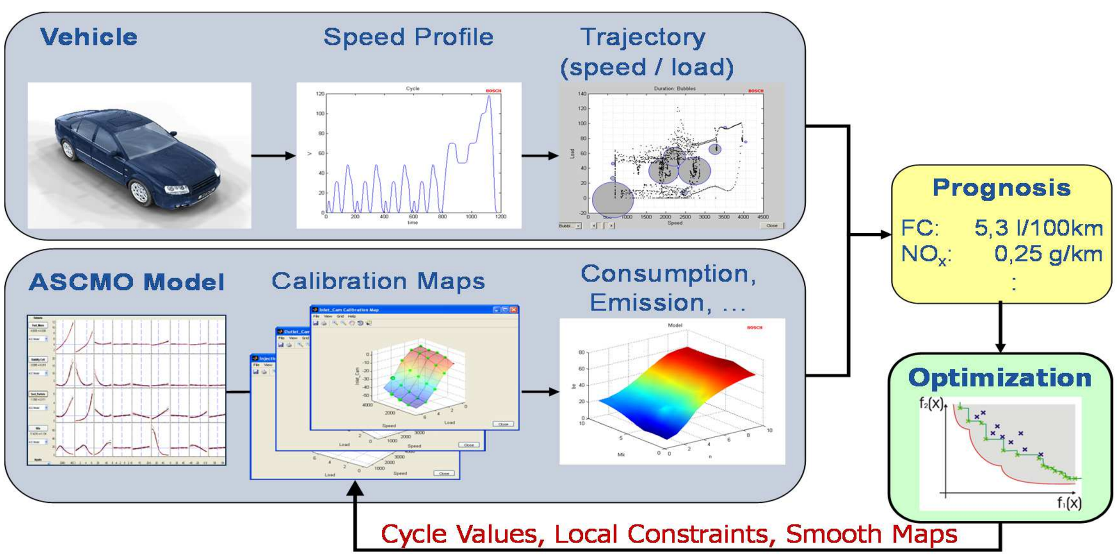

Figure 7: Driving cycle optimization in ETAS ASCMO. Combining a global engine model with vehicle data for cycle prognosis and calibration map optimization.

model for defined criteria describing the comfort and the dynamics. The comfort can be characterized by the surface area of the oscillations S_O and the dynamics by the rise time T_r. While running a DoE test plan in the vehicle for the variations of the relevant control parameters, a data-driven model for S_O and T_r can be built. The results of the multi-criteria optimization in ETAS ASCMO provide a trade-off curve between comfort and dynamics from which a best compromise can be selected [12]. As additional benefit, variant calibrations with different drivability characteristics can be derived without any new measurements.

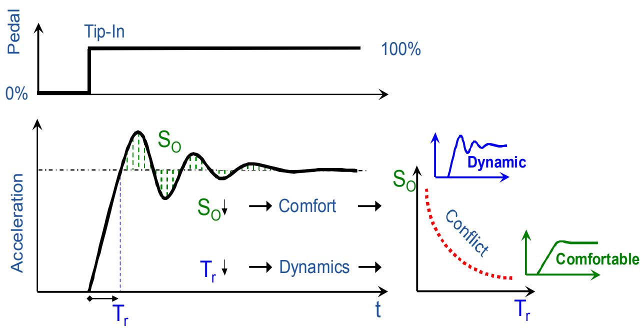

Figure 8: Vehicle response for a load step (tip-in) and the resulting criteria-based optimization problem.

Transient Calibration: Model-based Prediction of Transient Emissions for Real Driving Emissions (RDE) Cycles

Regarding possible upcoming legislatives guidelines for Real Driving Emissions (RDE), time dependent (transient) effects, e.g. in the air system of an engine, have a major impact on driving cycle emissions and have to be considered for the engine calibration. To model transient effects, the Gaussian process algorithm can be combined with a feedback model structure. As shown in Figure 9, past input and output values up to a certain time horizon are included as additional inputs for the model training. Often, the time dependencies of the system to be identified are not known in advance and it remains an open question how many time steps need to be fed back to support the highest possible model quality. To solve this, a so-called iterative feature selection was developed. Starting with one time lag (feature) at a time, a model is built for all input combinations. Only the one feature resulting in the best model quality is kept. Then, new features are added one by one to the set of selected features until there is no more significant improvement in model quality [13]. This process is implemented in the Dynamic Modeling module of ETAS ASCMO and provides an automatic and robust modeling of transient effects.

To minimize the required measurement effort for the model training, a suitable transient DoE approach needs to be applied. It turned out that a space filling design, where the amplitudes and gradients of all inputs are varied according to a Sobol sequence, will result in a very good model quality. In order to consider known limits of the system under test and the desired test duration, the transient DoE in ETAS ASCMO further allows to constraint the maximum (and minimum) gradients and amplitude values in the test plan.

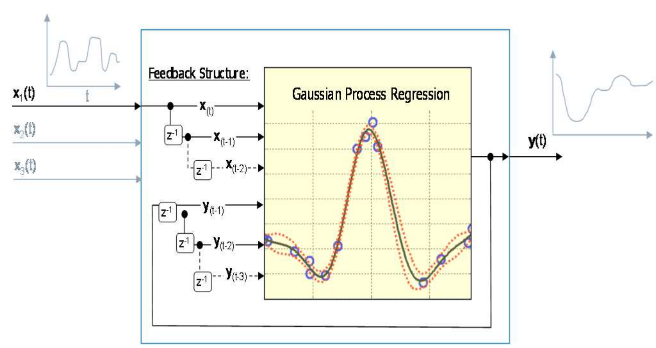

Figure 9: Feedback structure for the data-driven modeling of dynamic (transient) relationships.

For example, Figure 10 shows the model prediction of the transient engine emissions CO2, NOx, and soot during an arbitrary RDE driving cycle. The model was built with a short transient DoE measurement sequence collected on an engine test bench. The availability of such a model allows to significantly reduce the number of test bench runs for the validation of different emission calibrations for various driving cycle.

Data-driven Models in Real-time Environments: Hardware-in-the-Loop Systems

In the final phases of the calibration process (Figure 2), all interactions of the ECU with the vehicle must be validated and tested. If model-based methods are applied to reduce the number and duration of tests with real prototypes, it is insufficient to test single ECU functions against the model. Instead, a Hardware-in-the-Loop (HiL) system, e.g. ETAS LABCAR, is used to simulate the ECU's entire environment with vehicle and engine models running on a real-time PC.

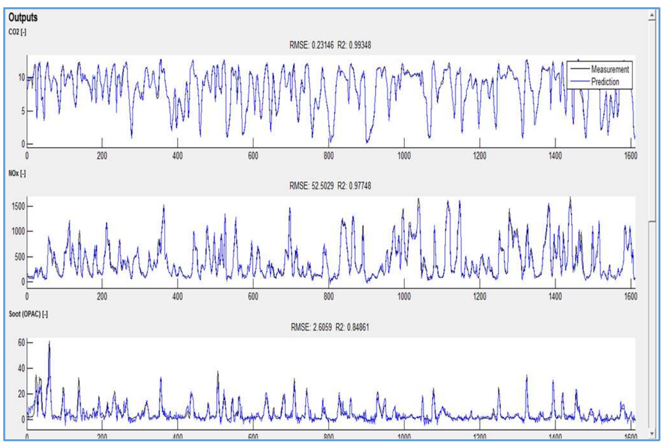

Figure 10: Model prediction of CO2, NOx, and soot for an RDE driving cycle.

In the classical HiL use case, the software testing, qualitative vehicle and engine models are sufficient. However, in case of using a HiL system for testing calibration parameters, quantitative models with high prediction accuracy especially for vehicle emissions and fuel consumption are required. This can be achieved by exporting the engine model from ETAS ASCMO and integrating it in the overall HiL model (Figure 11). Besides the data-driven engine model, additional project specific parameters and component models can also be integrated, e.g. the catalyst or sensor models. With a simulation step size of only a few microseconds, data-driven models generated in ETAS ASCMO provide the necessary real-time capabilities for HiL applications.

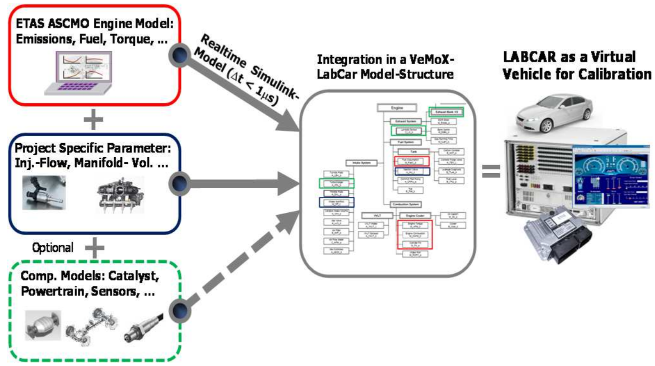

Figure 11: Integrating an ETAS ASCMO engine model in an ETAS LABCAR HiL system.

Data-driven Models in Real-time Environments: Direct Implementation on the ECU

Today's ECUs contain many complex map-based models serving as virtual sensors for important engine reference values, e.g. engine torque, air-mass or temperatures. Due to the increasing engine complexity, the development and calibration of such map-based models is getting more and more time consuming. Using data-driven models directly on the ECU instead of the classical map structures can lead to a significant gain in efficiency and quality. Unfortunately, standard Gaussian process models as used in offline calibration would require too much of the ECU's available memory and CPU resources. To solve this problem, two measures were undertaken in a joint project between ETAS and the Robert Bosch GmbH:

1. The original Gaussian process model (Figure 4) contains as many exponential functions as the number of data points used for model training. This number can be significantly reduced by a mathematical optimization allowing a free relocation of the exponential kernel functions in the input space. Only a small subset of kernel functions is needed to maintain the original model quality. This Model Compression feature is available as add-on to ETAS ASCMO.
2. The Robert Bosch GmbH has developed an Advanced Modeling Unit (AMU) for efficiently calculating Gaussian process

models. This AMU is implemented on the latest ECU generation MDG1 [14].

With these two measures, even complex models can be run on series engine ECUs with very low demand of CPU resources.

CONCLUSION

This paper presented data-driven modeling methods based on Gaussian processes and their use in different phases during the calibration of internal combustion engines. In practical applications, these methods help to reduce the required calibration time and the demand for engine and vehicle prototypes. With the integration in an easy to use tool environment, model-based calibration is no longer restricted to modeling experts and can be made available to a wide audience of calibration engineers. The developed approaches not only address use cases from steady-state engine calibration, but can also be applied to transient calibration and validation tasks. Furthermore, the implementation of compressed Gaussian process models directly on real-time targets has a high potential to significantly reduce the effort for future engine development and calibration.

REFERENCES

[1]J. Kuder, T. Kruse, "Parameteroptimierung an Ottomotoren mit Direkteinspritzung", Motortechnische Zeitung (MTZ), 2000.

[2]K. Schnellbacher, "Rapid Measurement and Calibration Utilizing the Fast ECU Access", 3rd International Symposium on Development Methodology, Wiesbaden, 2009.

[3]K. Roepke et al., 5th Conference on Design of Experiment (DoE) in Engine Development, Berlin, 2009.

[4]C. M. Bishop, "Pattern Recognition and Machine Learning", Springer, 2006.

[5]C. Rasmussen, C. Williams, "Gaussian Processes for Machine Learning", MIT Press, 2006.

[6]The MathWorks, "Model-Based Calibration Toolbox: Model Browser User's Guide", 2011.

[7]I. M. Sobol, "On the Distribution of Points in a Cube and the Approximate Evaluation of Integrals", Computational Mathematics 7(4), pages 86-112, 1967.

[8]T. Kruse, S. Kurz, T. Lang, "Modern Statistical Modelling and Evolutionary Optimisation Methods for the Broad Use in ECU Calibration", IFAC-AAC, Munich, 2010.

[9]K. Deb, S. Agrawal, A. Pratab, T. Meyarivan, "A Fast Elitist Non-Dominated Sorting Genetic Algorithm for Multi-Objective Optimization: NSGA-II", 2000.

[10] H. Klar, B. Klages, D. Gundel, "Automation of Model-Based Calibration in Engine Development", 6th Conference on Design of Experiment (DoE) in Engine Development, Berlin, 2011.

[11] S. Hoffmann, M. Schrott, "Model-based Methods for the Calibration of Modern Internal Combustion Engines", MTZ Worldwide, volume 76, issue 4, pages 24-29, 2015.

[12] M. Reger, R. Diener, V. Imhof, T. Lang, A. Powrosnik, H. Schmidt, H. Ulmer H, "Extension of the Classical DoE Method to Dynamic Conditions by Means of Characteristic Numbers", 6th Conference on Design of Experiment (DoE) in Engine Development, Berlin, 2011.

[13] T. Gutjahr, H. Ulmer, C. Ament, "Sparse Gaussian Processes with Uncertain Inputs for Multi-Step Ahead Prediction", IFAC Symposium on System Identification, vol. 16, 2012.

[14] R. Diener, M. Hanselmann, T. Lang, H. Markert, H. Ulmer, "Data-based Models on the ECU", 8th Conference on Design of Experiment (DoE) in Engine Development, Berlin, 2015.