Higher Efficiency with Model-based Predictive Knock Control

Today's knock control systems generally neglect the stochastic character of knocking phenomena and react to individual knocking working cycles with a retarded ignition timing. A control approach developed in the FVV project "Fast Knocking Prediction for Gasoline Engines" (No. 1370) in cooperation with the University of Stuttgart and RWTH Aachen University reduces the frequency of ignition retardation and thus increases the efficiency by this alone.

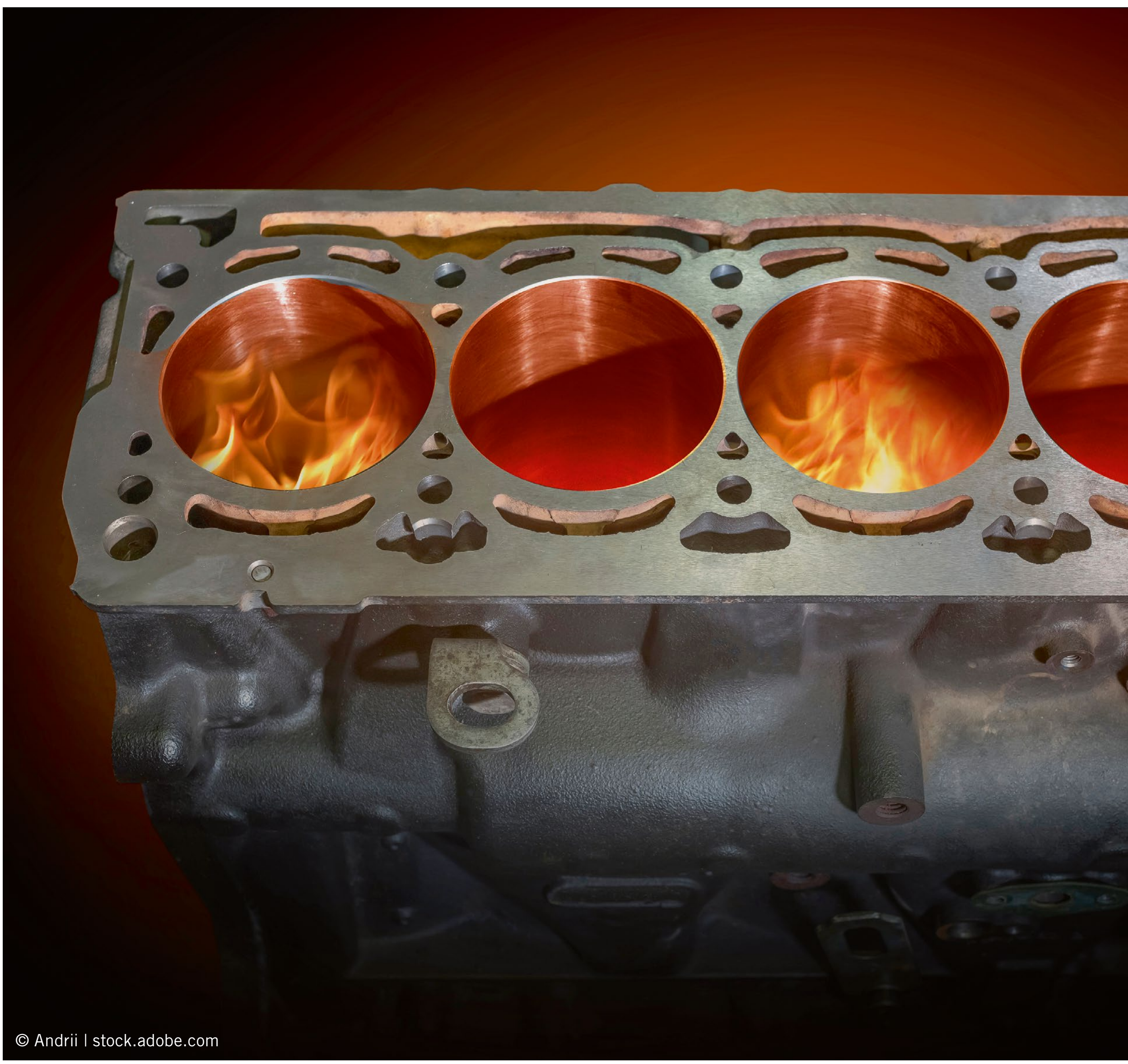
WRITTEN BY

Dr.-Ing. Michael Grill is Head of Artificial Intelligence & Simulation at the Research Institute of Automotive Engineering and Powertrain Systems Stuttgart (FKFS).

Dr.-Ing. Marco Günther is Chief Engineer and Lecturer at the Chair of Thermodynamics of Mobile Energy Conversion Systems (tme) at RWTH Aachen University.

Univ.-Prof. Dr.-Ing. André Casal Kulzer is Member of the Board of the Research Institute of Automotive Engineering and Powertrain Systems Stuttgart (FKFS) and Full Professor for Automotive Powertrain Systems at the Institute for Automotive Engineering Stuttgart (IFS) of the University of Stuttgart.

Univ.-Prof. Dr.-Ing. (USA) Stefan Pischinger is Head of the Institute at the Chair of Thermodynamics of Mobile Energy Conversion Systems (tme) at the RWTH Aachen University.



1 OPTIMIZED CENTER OF COMBUSTION

At the knock limit, generally 4 to 10 % knocking operating cycles are permitted. Due to the retardation of the ignition timing after a knocking working cycle and advancing in smaller steps, a conventional knock control operates a large number of cycles with an unnecessarily late center of combustion. Approaches that include the intensity of the knocking event in the decision to retard also remain reactive approaches.

Predictive knock control enables an optimized center of combustion for operation at the knock limit, increases efficiency and thus reduces fuel consumption and CO_2 emissions. The prerequisite for this is a model that can precisely and very quickly predict the knock probability for the current engine operation. Through the FVV research project [1], which was carried out at the Chair of Thermodynamics of Mobile Energy Conversion Systems (tme) at RWTH Aachen University and at the Institute of Automotive Engineering Stuttgart (IFS) at the University of Stuttgart, it was possible to expand knowledge about knocking combustion and to develop a model for predicting knocking probabilities. A knock controller is thus enabled to predictively control the ignition timing.

2 KNOCK FREQUENCY MODEL

The high complexity and stochastic nature of knocking phenomena are a challenge for the development of knock models. Inhomogeneities in the cylinder charge that promote knock cannot be captured on the test bench and cannot be investigated in two-zone combustion models due to averaging over the entire burned and unburned zone. Knock-relevant conditions can be identified with 3-D flow simulations (Computational Fluid Dynamics, CFD) and coarse structure simulations (Large Eddy Simulations, LES), in particular temperature and mixture inhomogeneities and their cyclic variations. Regime boundaries within the detonation diagram will be verified with CFD simulations, and the applicability of the detonation diagram to auto-ignition assessment will be investigated in 0-D simulations to assess the impact of combustion cycle-to-cycle variations in terms of knock. For model-based control, the 3-parameter approach from [2] was further developed to enable application to ECUs.

3 KNOCK CONTROL

Based on the knowledge gained from the previous investigations, a predictive knock control was developed which models the expected knocking probability for the boundary conditions of the next working cycle. The ignition timing is adjusted in such a way that the modeled knocking probability corresponds to a targeted maximum knocking frequency of, for example, 5 % of knocking working cycles at the knock boundary. Knock events detected by the knock sensor no longer lead to direct intervention by the controller, instead, the knock sensor first only monitors the actual knock frequency. If it deviates from the modeled knock frequency, this information can be used in a later implementation to recalibrate the knock model. If it deviates from the modeled knock frequency, this information can be used to recalibrate the knock model. The created concept was compared to a conventional knock control by means of 0-D/1-D simulations, especially to demonstrate the robustness even under fast load changes, **FIGURE 1**.

4 VALIDATION

In order to evaluate the potential of the newly developed predictive knock control model under real conditions, steady-state validation measurements were performed on a single-cylinder research engine. For this purpose, the new model concept must

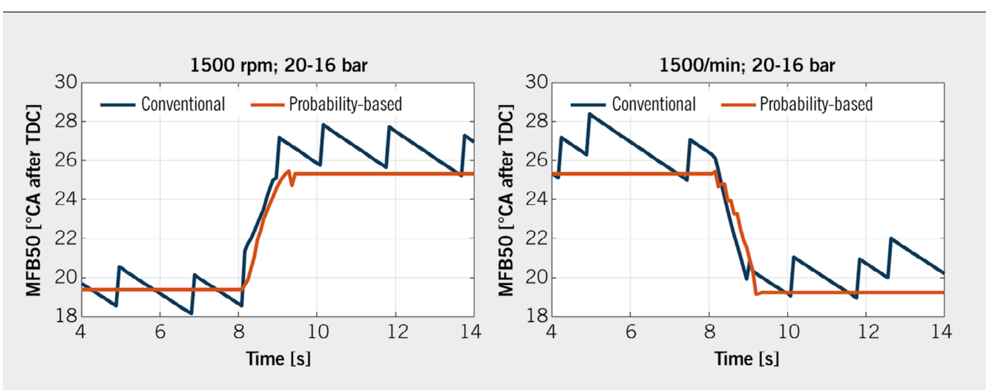


FIGURE 1 Visualization of the robustness of the new approach for fast load changes (left and right) compared to conventional control (© IFS | FKFS)

be transferred into a real-time, compilable Rapid Control Prototyping (RCP) software model, which is done in three steps as part of the model integration. For the application on the RCP hardware, it must be considered that the requirements for model complexity in terms of real-time capability are, however, different from those for the 0-D simulation model used, so that the previous model must be simplified for simulation purposes in terms of computational complexity. In order to increase the computational speed, selected highly complex calculations are transferred to a map-based approach that has been previously parameterized offline. In a first step, the functional description of the model is transferred into a Simulink model. Through Simulink, the model can be tested in an open-loop environment to validate the model behavior with imposed values from previous simulations. Converting the simulation model to a Simulink model also ensures compilability to dedicated RCP hardware and delivery of the same results as from the previous simulation investigations of the predictive model-based control approach.

After completion of the model tests, the compiled model was implemented on the dedicated RCP hardware, firstly to determine the time for the calculation (task time, T_{task}) and secondly to validate the real-time capability of the model on the final target hardware at the engine test bench. For this purpose, the RCP hardware with the required software and the implemented new knock model is connected to all the required inputs from the engine test bench and put into operation for the investigations. The main inputs for the calculation of the control parameters are the engine speed (n), the Indicated Mean Effective Pressure (IMEP) and the actual ignition timing. In addition, the initial pressure and temperature in the cylinder are used as input for the calculation. They are not determined by the ECU sensors but are taken from a calibrated map.

FIGURE 2 shows the alignment of the models in the open-loop environment. The exemplary operating point proves that the calculated values of the RCP model and the simulated values of the 0-D/1-D simulation show a deviation of less than 0.1 %. Preliminary investigations of the computation time to ensure real-time capability showed that for a task time of T_{task} = 1 ms, only a small computational load of 4 % is caused by the predictive knock control model, while for the lower task time of T_{task} = 0.1 ms, a computational load of 45 % is occupied by the model. It must be considered that for operation on the single-cylinder test bench not only the predictive knock control model must be run on the RCP hardware, but also all other models required for the operation of the engine. For this reason, a task time of T_{task} = 0.5 ms was selected for further use of the new knock control model.

The simulation studies showed a maximum CO_2 reduction potential of up to ΔCO_2 = 1 % and a possible reduction of the exhaust gas temperature of $\Delta T_{exhaust}$ = 20 K. This potential was finally validated in the evaluation of the measurements on the single-cylinder test bench. For this purpose, the measurements were evaluated in terms of the mean exhaust gas temperature $T_{exhaust,\ mean}$ and the mean cycle efficiency η_{cycle} for operation with both a conventional knock control and the predictive model-based knock control model. In addition, the peak cylinder pressure was evaluated to assess implications for a possible difference in mechanical stress between the two control approaches.

FIGURE 3 shows the comparison of the control approaches for a representative load point with n = 2500 rpm and IMEP = 21 bar. The evaluation of the conventional controller showed an average cycle efficiency of η_{cycle} = 34.3 %. The average cylinder pressure was $p_{cylinder,\ mean}$ = 76.91 bar with a maximum value of $p_{cylinder,maximum}$ = 100.85 bar and a minimum value of $p_{cylinder,minimum}$ = 56.27 bar peak pressure. The measured exhaust gas temperature before the turbine was $T_{exhaust}$ = 502.0 °C. With the predictive knock control approach, the cycle efficiency at this operating point improves by $\Delta\eta_{cycle}$ = 0.54 % to η_{cycle} = 34.84 %. The average cylinder pressure increases to $p_{cylinder,mean}$ = 80.87 bar. In addition, the exhaust gas temperature before the turbine is reduced by $\Delta T_{exhaust}$ = 20 K to $T_{exhaust}$ = 481.25 °C. This evaluation confirms that the controller can also verify its potential shown in the simulation in real tests on the engine test bench under steady-state operating conditions.

5 SUMMARY AND OUTLOOK

In the FVV project, the potential for a small but not insignificant increase in efficiency was demonstrated simply by means of more advanced control software in the control unit and was proven on the stationary test bench at various operating points. The improvements achieved in terms of efficiency and exhaust gas temperature were within the range of the simulated prediction. For the further development of the control approach for a series applica-

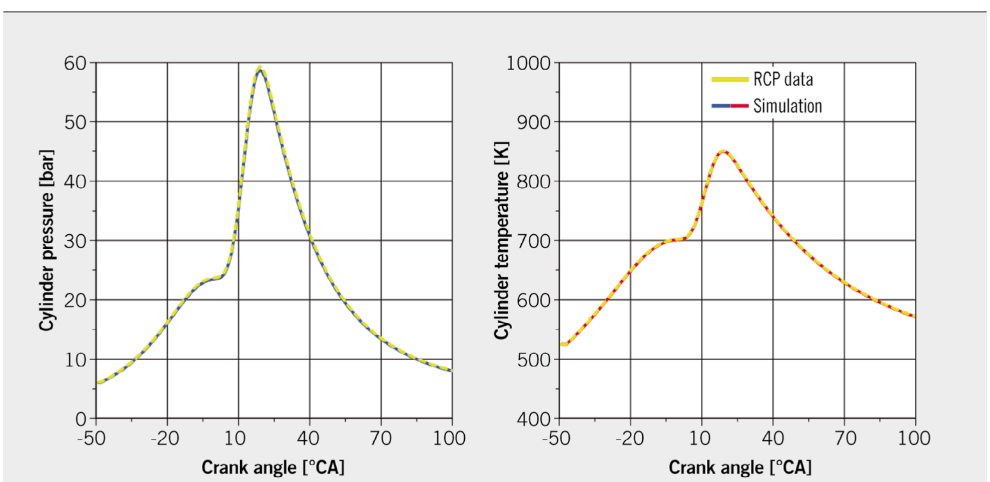


FIGURE 2 Comparison of the cylinder pressure (left) and the cylinder temperature (right) between simulation model and Simulink model (RCP) for an operating point of n = 1500 rpm, IMEP = 12 bar and ignition angle = 6.9 °CA before firing TDC (© tme)

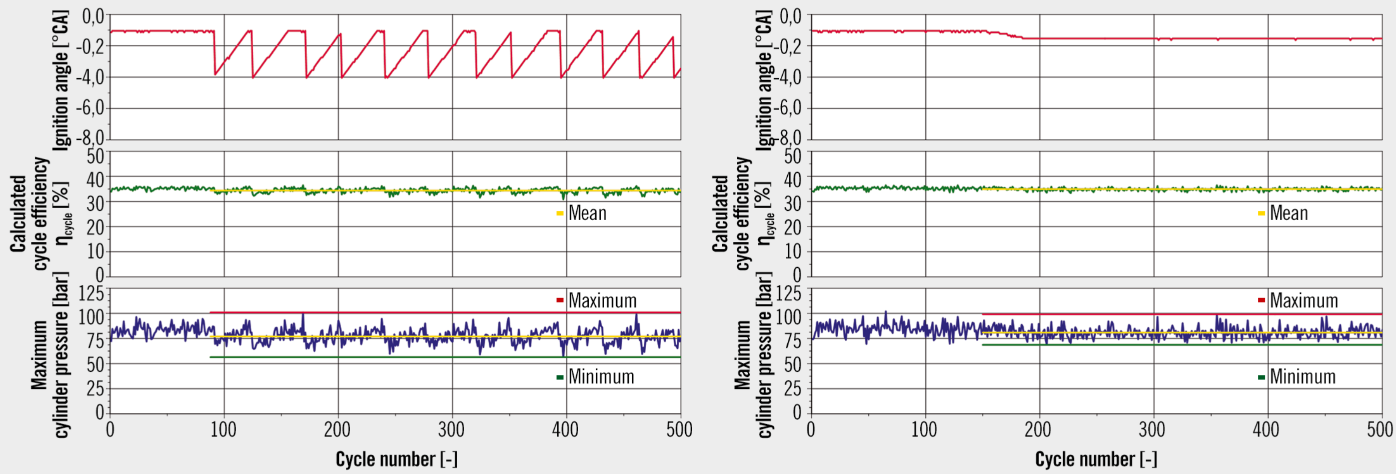


FIGURE 3 Comparison of control approaches for the main parameters for an operating point of n = 2500 rpm and IMEP = 21 bar: conventional knock control (left) and predictive model-based knock control (right) (© tme)

tion, it must be considered that the quality of the modeled knock frequency determines the quality of the control. In this context, the modeling of the knock frequency is exponentially dependent on the modeled temperatures of the combustion of the working process, so that high accuracy requirements must also be placed on these submodels and issues such as series scattering and aging must be balanced. Furthermore, the available computing capacity on a current series ECU can be a limiting factor, although improvements can be expected here thanks to continuous further development.

The model quality is to be improved in an already planned FVV follow-up project using so-called gray box models. As part of the project, the entire approach is also to be validated on an actual multi-cylinder engine. In parallel, an Artificial Intelligence (AI)-based approach is to be pursued in which there is no longer an explicit separation between model, feedforward, and control. Reinforcement learning is to be applied as the AI method. This learning method will be used to determine feedforward and control strategies from a very large amount of training data, as well as to learn new strategies to compensate for fuel quality fluctuations after refueling and long-term aging processes. To train the reinforcement learning system, a virtual test environment is required in which it can gain experience independently. To ensure high model quality, the powertrain must be modeled as accurately as possible in the virtual test environment. Since the reinforcement learning system is slow to recognize basic relationships because it tests out very many decisions in the high-dimensional transient parameter space, high computing capacity is required. Preliminary investigations show that a simulation performance of 20 million km of virtual test drives per day is required to successfully train a reinforcement learning system on a complex problem in the powertrain. For this purpose, an AI-based virtual simulation environment capable of providing such enormous computing capacity is to be set up in the planned follow-up project.

REFERENCES

[1] Blomberg M.; Fajt N.; Leyens L.: Fast Knocking Prediction for Gasoline Engines. Final report FVV project no. 1370, 2022
[2] Blomberg M.; Hess M.; Hesse R.; Morsch P.: Engine Knock Model. Final report FVV project no. 1313, 2021

THANKS

The FVV research project (Project No. 1370) was carried out at the Chair of Thermodynamics of Mobile Energy Conversion Systems (tme) at RWTH Aachen University under the direction of Univ.-Prof. Dr.-Ing. (USA) Stefan Pischinger and at the Institute of Automotive Engineering Stuttgart (IFS) at the University of Stuttgart under the direction of Prof. Dr.-Ing. Michael Bargende and Prof. Dr.-Ing. André Casal Kulzer. It was financially supported by the FVV e. V. with its own funds and accompanied by a working group headed by Dr.-Ing. Michael Fischer (Tenneco GmbH). The authors would like to thank the FVV and all those involved in the project for their support.

international

11th

engine congress

Meeting Place for the Powertrain and Sustainable Fuels Community

PC | **CV** | **Fuels**

27 and 28 February 2024 | Baden-Baden

MAIN TOPICS

Carbon-neutral IC engines from a global perspective | CO_2 recycling as a key topic for reFuels | Further development potentials for the IC engine | Hydrogen and other sustainable energy sources | Legal and technological differences in the markets

PANEL DISCUSSION

No climate protection without IC engines!

TOP SPEAKER

Jonathan Atkinson, Cummins Inc., UK | **Dina Bacovsky,** BEST – Bioenergy and Sustainable Technologies GmbH, Austria | **Michael Fleiss,** Aurobay, Sweden | **Prof. Dr. Uwe Dieter Grebe,** AVL List GmbH, Austria | **Dr. Monika Griefahn,** eFuel Alliance e. V. | **Thorsten Herdan,** HIF EMEA GmbH | **Benjamin Krieger,** CLEPA, Belgium | **Peter Müller-Baum,** VDMA e. V. | **Takahiro Nagai,** National Research and Development Agency / New Energy and Industrial Technology Development Organization (NEDO), Japan | **Benoit Poulet,** Shell Global Solutions (Deutschland) GmbH | **Prof. Dr. Peter Schöggl,** AVL List GmbH, Austria | **Dr. Markus Schwaderlapp,** DEUTZ AG

PROGRAM AND REGISTRATION:
www.ATZlive.com

ATZ live

VDI Wissensforum