# Model-based Development Methods

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## A key to calibrating modern internal combustion engines

Design of Experiments and model-based parameter optimization are the keys to mastering complex engine management systems. In the following report, Hyundai and ETAS show how model-based development methods can sensibly support the calibration of modern internal combustion engines.

With $CO_2$ and exhaust gas emissions limits getting tougher all the time, engine management systems are becoming increasingly complex in response. The result is a constant increase in the calibration parameters that need to be optimized in the overall system. At the same time, strong competition is forcing manufacturers to shorten development cycles and cut development costs. To be able to carry out engine calibrations that ensure maximum ride comfort, high dynamics, and low emissions under these circumstances, there is a need for new computer-assisted calibration methods to complement conventional ones[1].

Engineers at the Hyundai Motor Europe Technical Center GmbH (HMETC) in Rüsselsheim, Germany, were quick to recognize this need: in powertrain development, they have been making greater use of Design of Experiment (DoE) and model-based optimization methods on top of increased automation levels since 2005. Acceptance of the initial solutions was severely hampered by their lack of user-friendliness and the fact that they did not cover all engine development process steps.

However, the introduction of the ETAS ASCMO[2] software resolved this situation: in addition to a program structure and user interface tailored to model-based ECU calibration, the software provides helpful functions to support inexperienced users. As an example, the following sections describe the use of this new solution in a preproduction engine project at the HMETC Powertrain Division.

### Project scenario

The test candidate was a 2.0-l, four-cylinder diesel engine with preproduction engine hardware and ECU software. At the beginning of the tests, the existing calibration already complied with the Euro 5 emissions standard. The objective was to use the DoE software to further reduce the engine's fuel consumption.

To do this, it was important to find the optimal balance for the following calibration parameters:

- air mass/EGR rate
- start of injection
- swirl flap position
- exhaust back pressure flap position for low-pressure EGR control
- boost pressure
- rail pressure

The relevant target variables are listed below:

- fuel consumption ($CO_2$)
- particulate mass (soot)
- nitrous oxides ($NO_x$)
- hydrocarbons (HC)
- carbon monoxide (CO)
- combustion acoustics (dBA)

All tests were conducted on the engine test bench, with subsequent in-vehicle verification on the emissions chassis dynamometer. During the basic measurement run, the $CO_2$ value was determined as a reference for the optimization. As shown in Figure 1, the relevant operating points for optimization were supplied by the dwell times of rpm and load in the NEDC.



### Planning data acquisition on the test bench

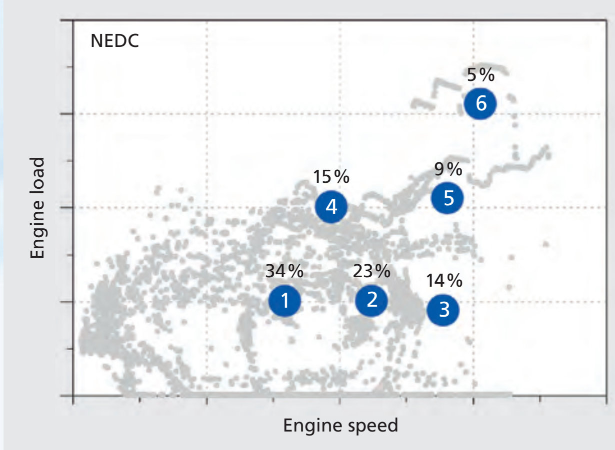
The DoE module used for test planning divides the workflow into eight user-friendly steps. A useful function facilitates the compression of measuring points via selected input variables, Figure 2. In the case at hand, the measuring points were compressed in the vicinity of small air masses, because in addition to greater measuring inaccuracy, less smooth physical dependency was also expected in this area due to high EGR rates.

Another function allows users to divide the test plan into a variable number of sections ("blocks"). Given a sufficient number of measuring points, each individual block offers optimum distribution for modeling. During live measurement on the test bench, it is therefore possible to quickly determine after each block has been run whether the requisite model quality has been achieved and the test run can be completed early. This can significantly reduce the amount of time and effort required for measuring. As an example, Figure 3 plots modeling accuracy for the smoke number as a function of the number of measuring points used for model generation.

### Key element: Raw data analysis

Once the measurement data has been gathered, the next phase is raw data analysis. This often proves to be the most important data evaluation step. As well as identifying faulty measurements and drifts, it also provides insight into optimization potential.

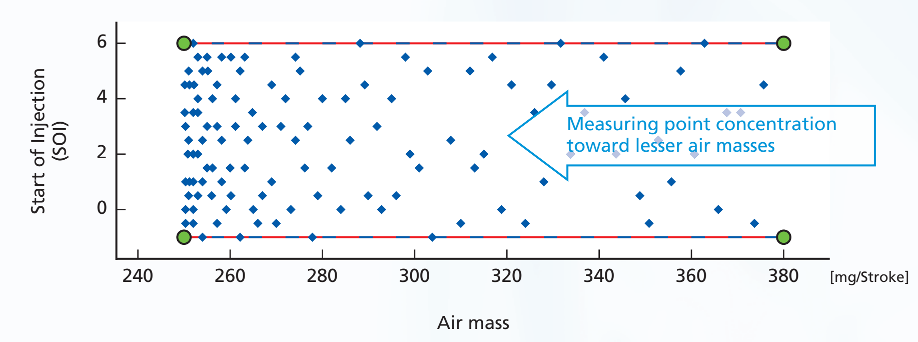
The DoE software supports this process very efficiently: interactive diagrams allow users to display

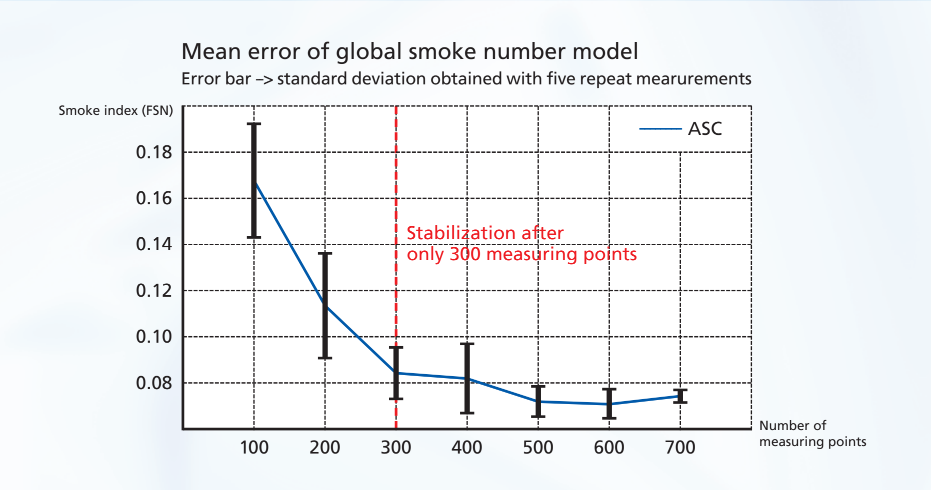


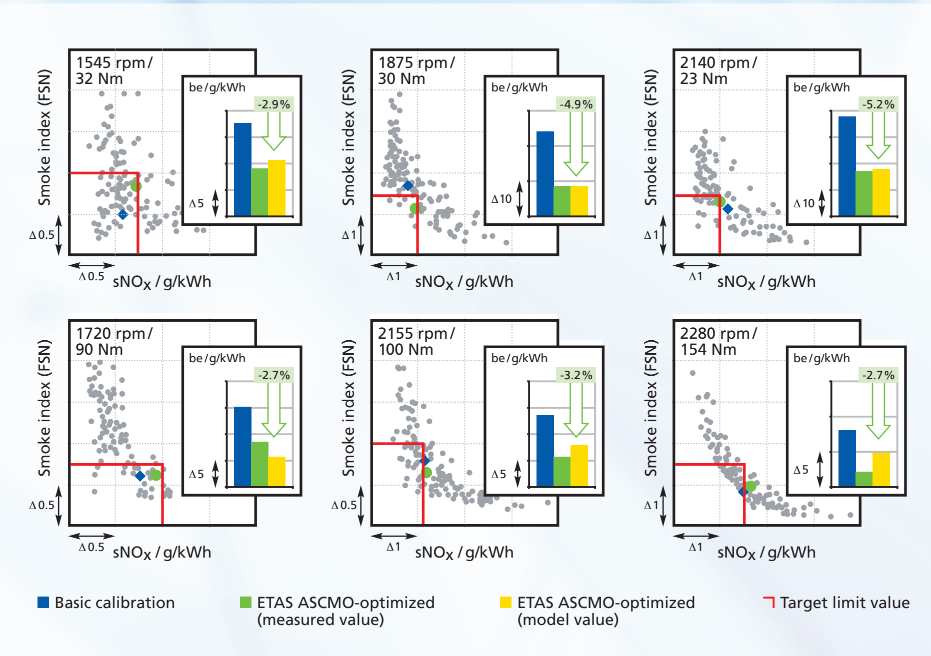

| No. | Engine speed | Load |
|---|---|---|
| | RPM | Nm |
| 1 | 1545 | 32 |
| 2 | 1875 | 30 |
| 3 | 2140 | 23 |
| 4 | 1720 | 90 |
| 5 | 2155 | 100 |
| 6 | 2280 | 154 |

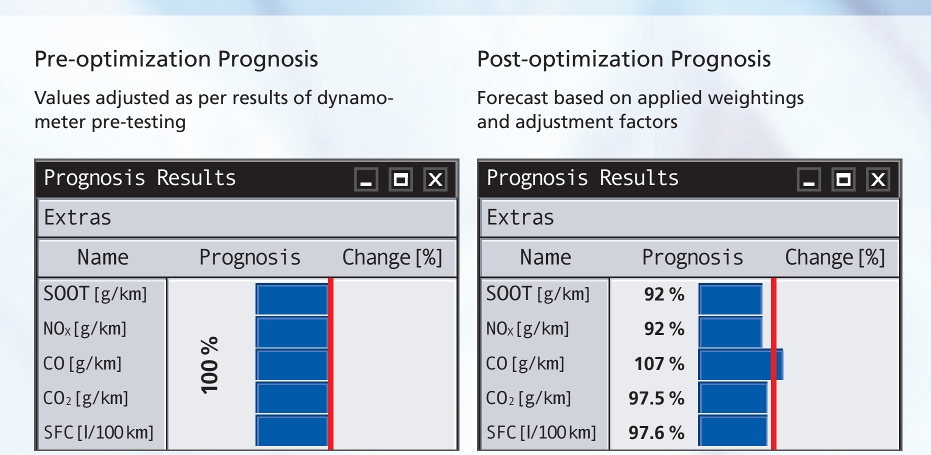
Figure 1: Distribution and weighting of operating points in the NEDC test.

Figure 2: Experiment planning using local measuring point concentration.






| | $NO_X$ / g/km | CO / g/km | Soot / g/km | $CO_2$ / g/km | FC / l/100 km |
|---|---|---|---|---|---|
| Deviation ETAS ASCMO vs. in-vehicle meas. | -3.7 % | -4.0 % | -12.5 % | +0.2 % | +0.3 % |
| Tendency | + | + | - | ++ | ++ |

calibration parameters and/or target variables in relation to each other and, for example, to isolate the areas in which target variables display their optimal values. This facilitates the effective visual evaluation of measurement data and the identification of good parameter combinations.

## Automated modeling

The core of ETAS ASCMO is its user-friendly modeling function, which is largely automated. Unlike the model-based calibration tools available on the market until now, users are not required to select a specific type of model from a large number of options. Instead, the tool suggests a single, particularly flexible and powerful model type for them based on Gaussian processes (GP). This approach makes it possible to model even highly nonlinear behavior by very complex systems to a high degree of accuracy without overfitting. To do this, users do not have to parameterize the model. A critical issue for GP models is often the computing times and memory capacities required for processing large measuring ranges. However, the efficient GP implementation allows to generate models from tens of thousands of measuring points even on a standard PC in an acceptable time.

The high flexibility of the GP models also enables users to create global engine models with rpm and load as additional input variables. In order to assess the maximum attainable quality in our sample project, the measurement data of the six operating points was used to create a global model in addition to local models. In both instances, the quality of the models was satisfactory and the modeling of physical dependencies was largely correct. In some cases, the global model provided even better characteristics than its local counterparts. Only the modeling of CO emissions, with a value range of up to 16 g/kWh and a standard deviation of 0.57 g/kWh, remains somewhat too inaccurate. The table shows the statistical quality levels of the global models based on verification measurements.

Figure 3 (top): Model accuracy of ETAS ASCMO model (ASC) versus data record size: mean error of global smoke number model (determined by means of verification measurements, error bar = standard deviation obtained with five repeat measurements).

Figure 4 (center): Optimization results based on measurements taken at six operating points on the engine test bench.

Figure 5 (bottom): Prognosis based on cycle extrapolations before and after optimization (partly screenshot).

## Optimization results

While ETAS ASCMO's range of functions for local optimization is comparable with that of other commercial tools, its strength lies in its global modeling and evaluation capabilities, which enable it to automatically optimize entire engine maps with respect to drive cycles. Then, based on a list of weighted operating points, a current cycle prognosis is calculated online for each change of the characteristic maps. This means that a powerful optimizer can be used to automatically generate calibration data, which achieves minimal fuel consumption while staying within the cycle's limit values and respecting local limit values and map smoothness. The optimization results achieved in this way based on the analyses are summarized in Figure 4. During verification on the dynamometer, the vehicle with optimized calibration achieved a 2.5 percent reduction in fuel consumption compared to the base data, accompanied by slightly reduced smoke and $NO_X$ emissions. When we consider that the base data version was mature to start with, we can see these increases for the impressive achievement that they are. Moreover, the value measured is very close to the DoE model forecast. Figure 5 shows the results of pre- and post-optimization cycle extrapolations.

## Summary

Overall, the evaluation of ETAS ASCMO had a very positive outcome. Particularly in the area of engine calibration, the tool quickly achieved a high degree of acceptance among calibration engineers on account of its advanced task-centered functionality and its user-friendliness. Whereas many publications on model-based optimization have tended to emphasize the time and cost savings it delivers, the focus for HMETC was more on the measurable increase in quality and the improved documentation of calibration results.

References

[1]) Klar, H.; Klages, B.; Gundel, D.; Kruse, T.; Huber, T.; Ulmer, H.: Neue Verfahren zur effizienten modellbasierten Motorapplikation (New methods for efficient model-based engine calibration). 5th International Symposium for Development Methodology, Wiesbaden, 2013

[2]) Huber, T.; Kruse, T.; Lauff, U.: Modellbasierte Applikation komplexer Systeme (Model-based calibration of complex systems). In: Hanser automotive, 10/2013, pp. 33-35

Quality of global model within the limits of definition range established by verification measurements.

| | $sNO_X$/g/kWh | sCO/g/kWh | Smoke/FSN | $CO_2$/FSN | Combustion noise/ dBA | be/g/kWh |
|---|---|---|---|---|---|---|
| Model range | 0.4 - 2.5 | 0.7 - 16 | 0 - 6 | 4 - 13 | 75 - 95 | 210 - 460 |
| RMSE | 0.058 | 0.57 | 0.089 | 0.059 | 0.23 | 5.32 |
| $R^2$ | 0.97 | 0.98 | 0.97 | 0.99 | 0.98 | 0.99 |