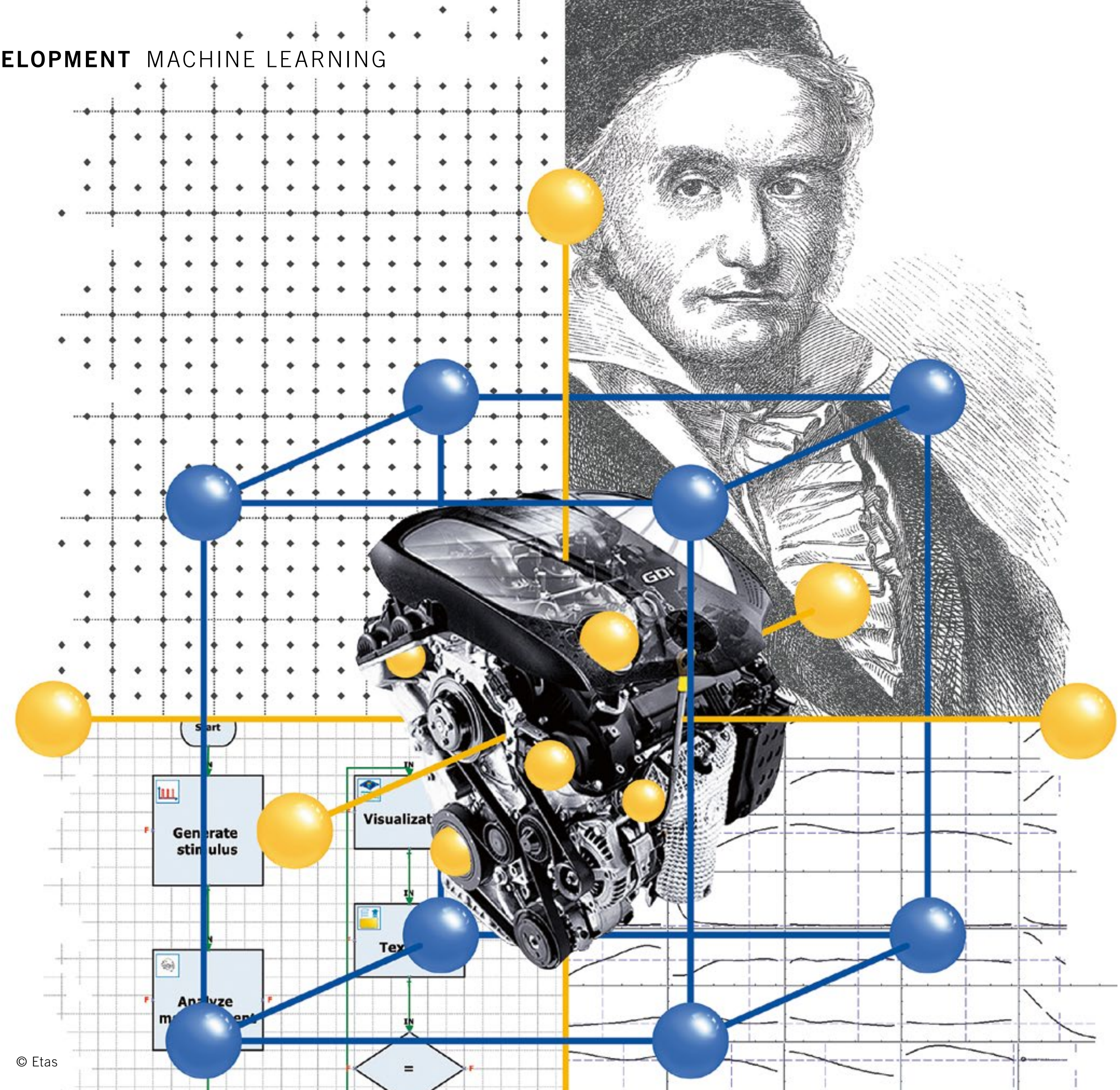

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Optimisation of Gasoline Engines

Automation and Machine Learning Techniques in Calibration

For vehicle emissions and fuel consumption testing, the WLTP (Worldwide-Harmonised Light-Duty Vehicles Test Procedure) and RDE (Real Driving Emissions) regulations will enter into force in Europe this September for type testing. In order to fulfill the strict new test conditions, the behavior of engines must be optimised throughout the speed-load range ("globally"). Etas uses machine learning methods amongst others.

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REASONS FOR EFFICIENT CALIBRATION PROCESSES

In order to meet the high requirements with respect to performance, fuel consumption, and pollutant emissions, increasingly efficient engines and systems are being developed. Current gasoline engines from Hyundai are equipped with systems such as dual continuous variable valve timing, continuous variable valve lift, gasoline direct injection, a variable intake system, and electrically actuated variable turbine geometry. The many degrees of freedom afforded by the large number of systems are reflected in the wide range of parameters that have to be adjusted and optimised in the course of calibration. Simultaneously, companies must fulfill a huge variety of customer requirements in order to compete internationally. Consequently, manufacturers are bringing out new vehicle models and engine variants at an accelerating rate. In order to efficiently calibrate the complex engines in all their variety with regards to production ramp-up deadlines, available engine test beds, and acceptable man-hour investment, conventional approaches are no longer adequate.

In its research and development center in Namyang, South Korea, the Hyundai Motor Cooperation (HMC) therefore introduced a new, model-based calibration process that is both efficient and covers the engine's operating range globally. The new process is based on advanced modelling and automation methods, which are supported by the Etas Ascmo [1] and Inca-Flow [2] software tools. In this article, we present Hyundai's new calibration process, describe how the methods work, and set out the advantages of the tools used.

PROJECT SCENARIO

Hyundai determined the measurement effort saved compared to the previous process and the quality of the results based on standard calibration packages for gasoline engines. The target engine was a naturally-aspirated V6-3.0-l GDI engine with a three-stage intake system, dual continuously variable valve timing, and a Continental engine control unit. To this end, the following elements were optimised:

- intake and exhaust camshaft timing
- injection timing
- ignition angle.

In addition, the models for the following elements were pre-calibrated in the ECU:

- air charge
- torque
- exhaust temperature.

CONVENTIONAL METHOD

For basic calibration of the individual models and functions, the engine used to be measured on the test bed for all combinations of relevant parameter values at various speed-load points. For example, in order to pre-calibrate the air charge model, measurements had to be performed at 16 engine speeds, ten engine torques, eight intake camshaft settings, six exhaust camshaft settings, and three settings of the intake system. When we multiply these settings, we arrive at a total number of approximately 23,000 individual measurements. Assuming that each measurement takes an average of two minutes, the basic calibration of the air charge model alone used to take a total of some 800 h, or 80 measurement days.

NEW CALIBRATION PROCESS

When redesigning its calibration process, Hyundai introduced two new methods, namely design of experiments (DoE) and the fully automated measuring of the engine on the test bed. Using machine learning techniques, models that simulate the behavior of engines with high accuracy on computers are generated on the basis of the measurement results. The test plans and the models based on measurement data are generated using the Etas Ascmo tool. The measurement points for the test plans can be worked through fully automatically on the test bed with the aid of a newly developed measurement control system based on the Inca-Flow tool.

DESIGN OF EXPERIMENTS

With a test plan generated using the DoE method, a maximum amount of information can be obtained from the smallest possible number of individual measurements. To this end, the measuring points are distributed in a statistically optimum manner through the space formed by the

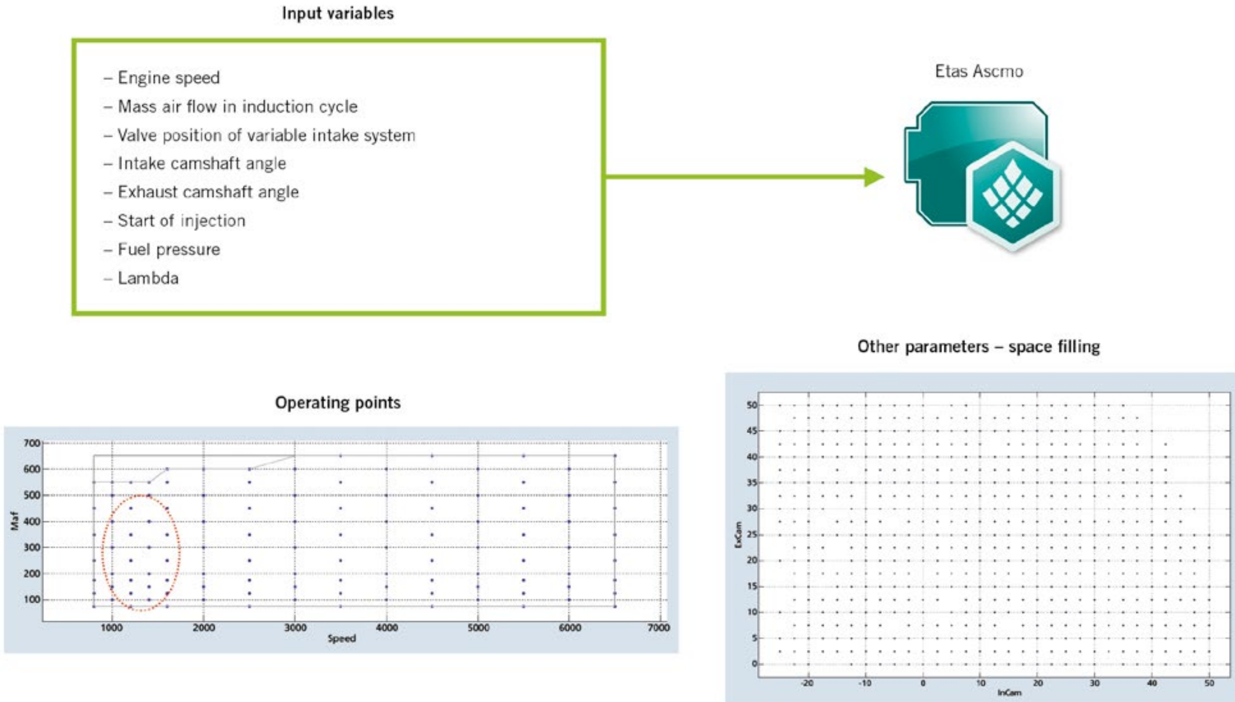


FIGURE 1 Test planning with Etas Ascmo. Relevant input variables (above left). Distribution of measuring points for speed and load, which are clustered into a reduced number of operating points and concentrated in the low rpm range (see red ellipse) (below left); even distribution of measuring points across two further input variables (below right) (© Etas)

measurement parameters. **FIGURE 1** shows the DoE input variables along with two-dimensional projections of the test plan generated using Etas Ascmo.

To accelerate the test run, Etas Ascmo can be used to cluster speed-load measuring points while leaving unchanged the distribution of the measuring points in relation to the other parameters.

MEASUREMENT AUTOMATION

High-performance measurement automation is the key to efficient measurement of engines on the test bed. Hyundai's new automation solution based on Inca-Flow is illustrated in **FIGURE 2**. It shows the interplay between ECU, test bed controller, AVL IndiCom combustion analysis, Etas Inca, and Inca-Flow.

The flow diagram from Inca-Flow, a graphically programmable control sequence, determines the measurement procedure based on the individual measuring point and the sequence in which the measuring points of the test plan are processed on the test bed. During the

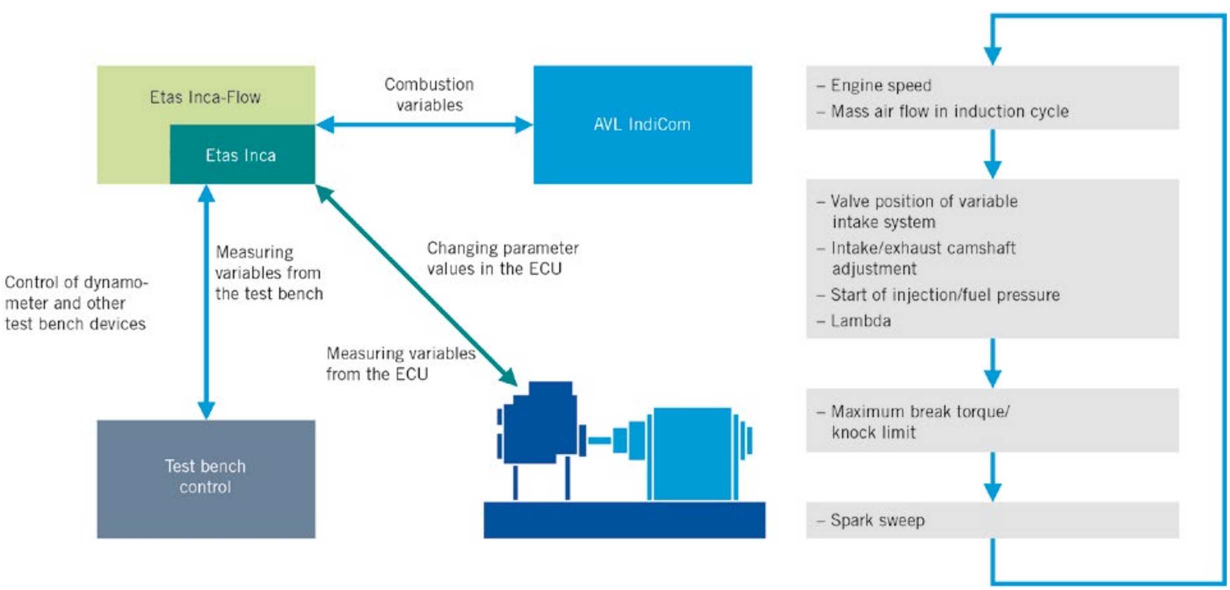
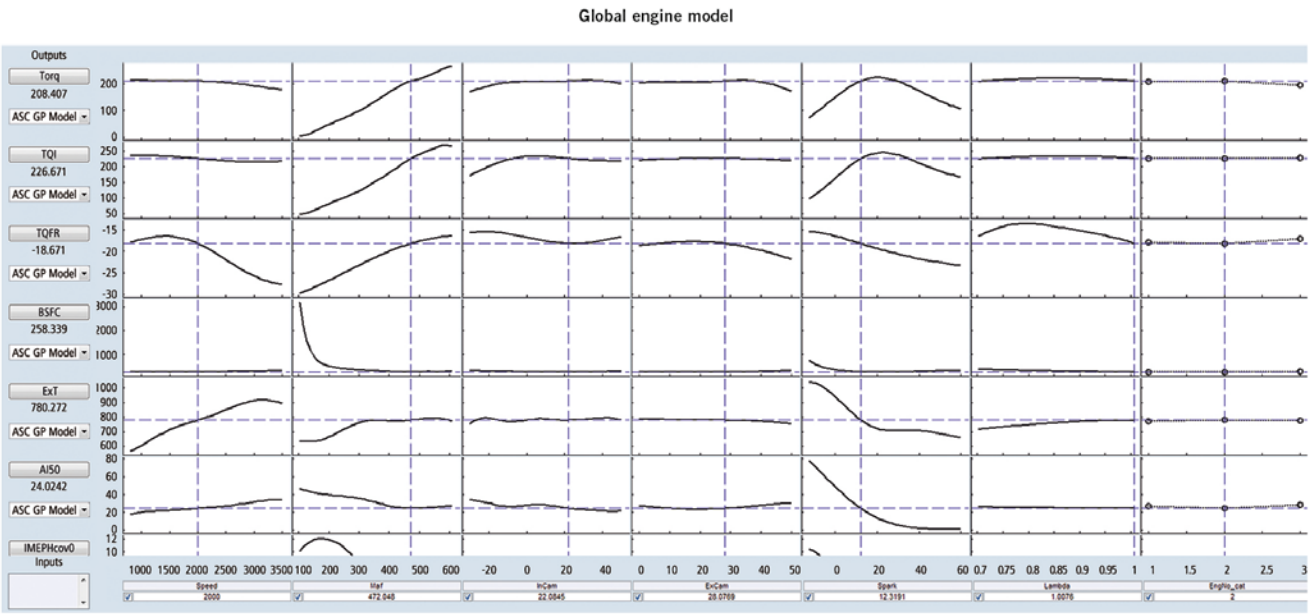


FIGURE 2 Diagrams for measurement automation (left) and sequence control using Inca-Flow (right) (© Etas)



Abbreviation	Explanation
Torq (Nm)	Torque (Nm)
Map (hPa)	Intake manifold pressure (hPa)
BSFC (g/kWh)	Brake specific fuel consumption (g/kWh)
ExT (°C)	Exhaust temperature (°C)
IMEPcov (%)	Coefficient of variation of indicated mean effective pressure in combustion chamber (%)

FIGURE 3 Graphs showing the dependencies between output and input variables; the Etas Ascmo model simulates the dependencies very well across the entire parameter space (© Etas)

measurement run, the values of the relevant calibration parameters and measurement variables are automatically set or recorded using Inca. The automation protects the engine against knock and excessively high exhaust temperatures. Knock is prevented by adjusting the ignition timing. The exhaust temperature is limited by adjusting the injected fuel mass.

MACHINE LEARNING TECHNIQUES FOR GLOBAL ENGINE MODELLING: GAUSSIAN PROCESSES

Based on the data measured on the engine test bed, a machine learning technique is used to define a mathematical model that simulates the engine behavior across the entire operating range. To do this, Etas Ascmo uses Gaussian processes. The basic idea behind Gaussian processes is to simulate measurement data by means of a probabilistic model with maximum probability. Unlike conventional methods based on minimising squares of errors, the values of the variables calculated using the model are assigned via a probability distribution. Accordingly, the method is very robust in its handling of outliers and is very suitable in practice for modelling noisy engine measurement data [3, 4]. The model structure is determined by the number of measurement data, which means that users do not have to specify any model parameters from outside. As the number of measurement data increases, so the ability of Gaussian processes to model complex non-linear relationships grows. The model structure adapts to the number of measurement data. Unlike traditional methods, the technique is free from the risk of overfitting. In this way, it always guarantees optimum model quality and generates plausible models, even for small data sets. The computing overhead for the model training of standard Gaussian processes scales at the rate of the cube of the number of measurement points, in a way that the use of Gaussian processes for data volumes > 8000 ceases to be practicable. For this reason, an advanced version of Gaussian processes was implemented in Etas Ascmo. Using special approximations, these algorithms can model even very large data sets quickly. The mathematical foundations of Gaussian processes are elaborated extensively in the literature [5].

CALIBRATION BASED ON ENGINE MODEL

The engine model created from the test bed measurements simulates the behavior of the engine with high accuracy across the entire parameter space, **FIGURE 3**. On the basis of the model, both the fuel consumption and the full-load torque were optimised, **FIGURE 4**. At the same time, the knocking limit and the maximum exhaust temperature were observed. Pre-calibration of the air charge, torque, and exhaust temperature model in the ECU requires large volumes of data. Unlike standard practice with conventional methods, this data was not laboriously measured at the engine test bed, but derived by Etas Ascmo from the empirical engine model ("screening"). When compared against validation measurements, the deviation of the results that were calculated using the models pre-calibrated in this way amounted to under 5 % for the air charge model, under 5 % – or a

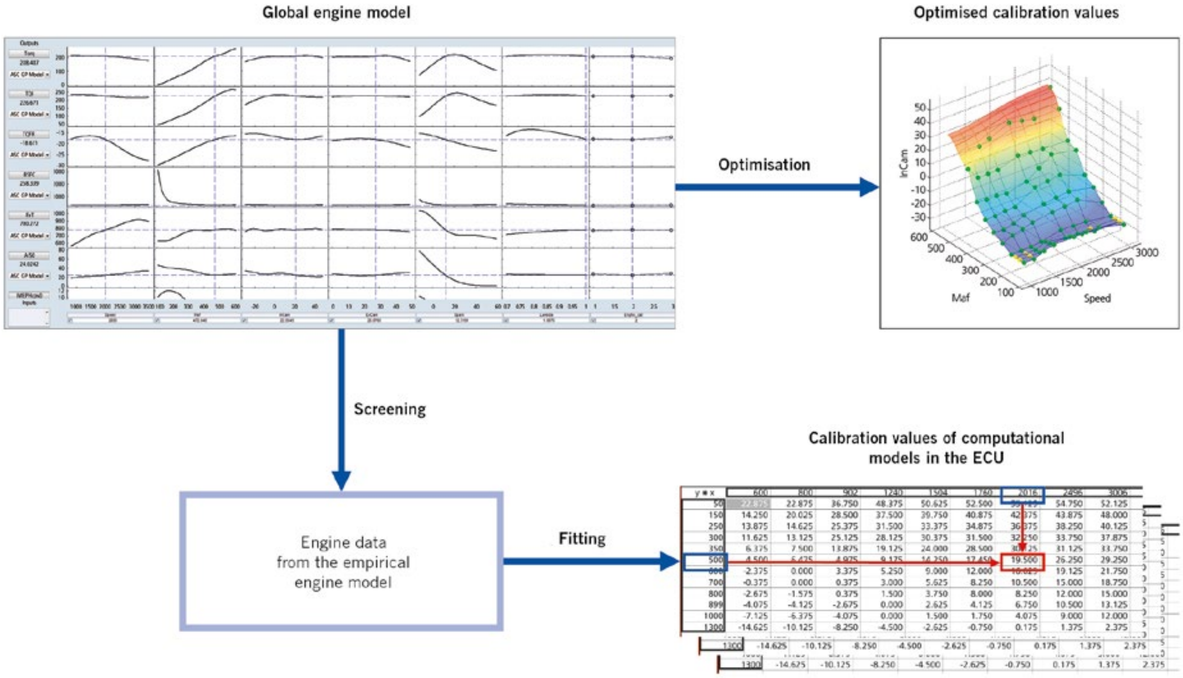


FIGURE 4 Optimisation of parameter values of models in ECU ("optimisation function") by adjusting ("fitting") the output of these models to data derived from the empirical engine model using Etas Ascmo ("screening") (© Etas)

maximum of 5 Nm – for the torque model, and under 15 °C for the exhaust temperature model. Consequently, the physical behavior is simulated very well by the models in the ECU in each case. **TABLE 1** and **FIGURE 5** show the simulation accuracy of curves for selected physical variables by ECU models. The second column shows the variance (RMSE) of the model calculations, while the third column shows their coefficient of determination (R2). R2 is a relative measure that indicates the proportion of measuring points explained by the model.

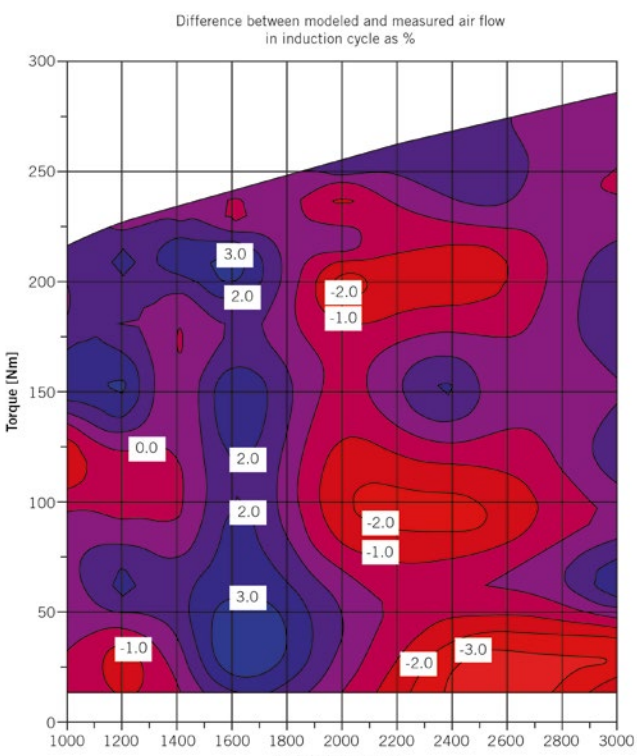


FIGURE 5 The difference between modeled and measured mass air flow in the induction cycle is less than ±5 % across the entire operating range (© Etas)

CONCLUSION AND SUMMARY

By introducing the global, model-based process in the research and development center in Namyang in South Korea, Hyundai achieved a dramatic efficiency increase in engine calibration. In a specific calibration project, the company was able to reduce the measurement effort on the test bed using the new process to a quarter of what it was using the conventional method, **FIGURE 6**. At the same time, it achieved the project goals defined at the outset. A new measurement automation system created on the basis of Etas Ascmo and Inca-Flow facilitated the fast, easy implementation of the measurements on the test bed. Generated from the test bed measurement data using Etas Ascmo with the aid of Gaussian processes, the empirical model of the gasoline engine simulates the dependencies of measurements of the input variables very well. The same applies for the models for calculating physical variables in the ECU, whose

Measurement variable	RMSE	R^2
Torque [Nm]	0.679	0.999
Intake manifold pressure (MAP) [hPa]	0.854	0.999
Brake specific fuel consumption (BSFC) [g/kWh]	2.445	0.999
Exhaust temperature (ExT) [°C]	1.885	0.999
Coefficient of variation of indicated mean effective pressure in combustion chamber (IMEP COV) [%]	0.171	0.990

TABLE 1 The simulation accuracy of curves for selected physical variables by ECU models; the second column shows the variance (RMSE) of the model calculations, while the third column shows their coefficient of determination (R2); R2 is a relative measure that indicates the proportion of measuring points explained by the model

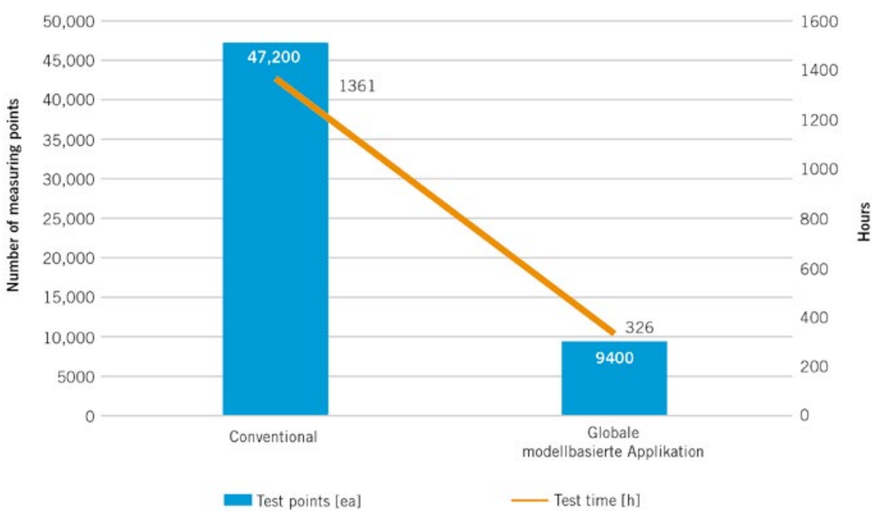


FIGURE 6 Using design of experiments (DoE) methodology, the total number of test points and the total test time can be reduced by 76 % (© Etas)

parameters were optimised very efficiently using the engine model.

In summary, we conclude that the global, model-based process enables engineers to efficiently calibrate complex engines with high-quality results.

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