Powertrain Digital Twinning for Real-World Emissions Compliance

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A digital twin is a digital representation of a planned or real physical system, product, or process that functions as its practically identical digital counterpart for tasks such as testing, integration, monitoring, and maintenance. Creating digital twins allows the 'digital system' or 'digital product' to be tested faster-than-real-time improving the overall efficiency and reducing programme's timescales. The HORIBA Intelligent Lab virtual engineering toolset has been used produce Empirical Digital Twins (EDT) of several contemporary Internal Combustion Engine (ICE) propulsion systems. Digital twinning in its current format can supplement real-world testing methods for the development, calibration, optimisation, and certification of powertrains and vehicles. Given the move to ever more stringent pollutant criteria over wider test conditions, which is expected to put additional strain on Original Equipment Manufacturers (OEMs), the HORIBA EDT approach is expected to increase efficiency and reduce time when taking a vehicle or powertrain to market.

Keywords
Digital Twin, Dynamic DoE, DoE, Empirical modelling,
Data driven model

Introduction

Amid growing international concern over the impact of automotive exhaust emissions on human health and global warming, the introduction of more stringent environmental regulations such as Europe's Euro 7 is being considered [1],[2].

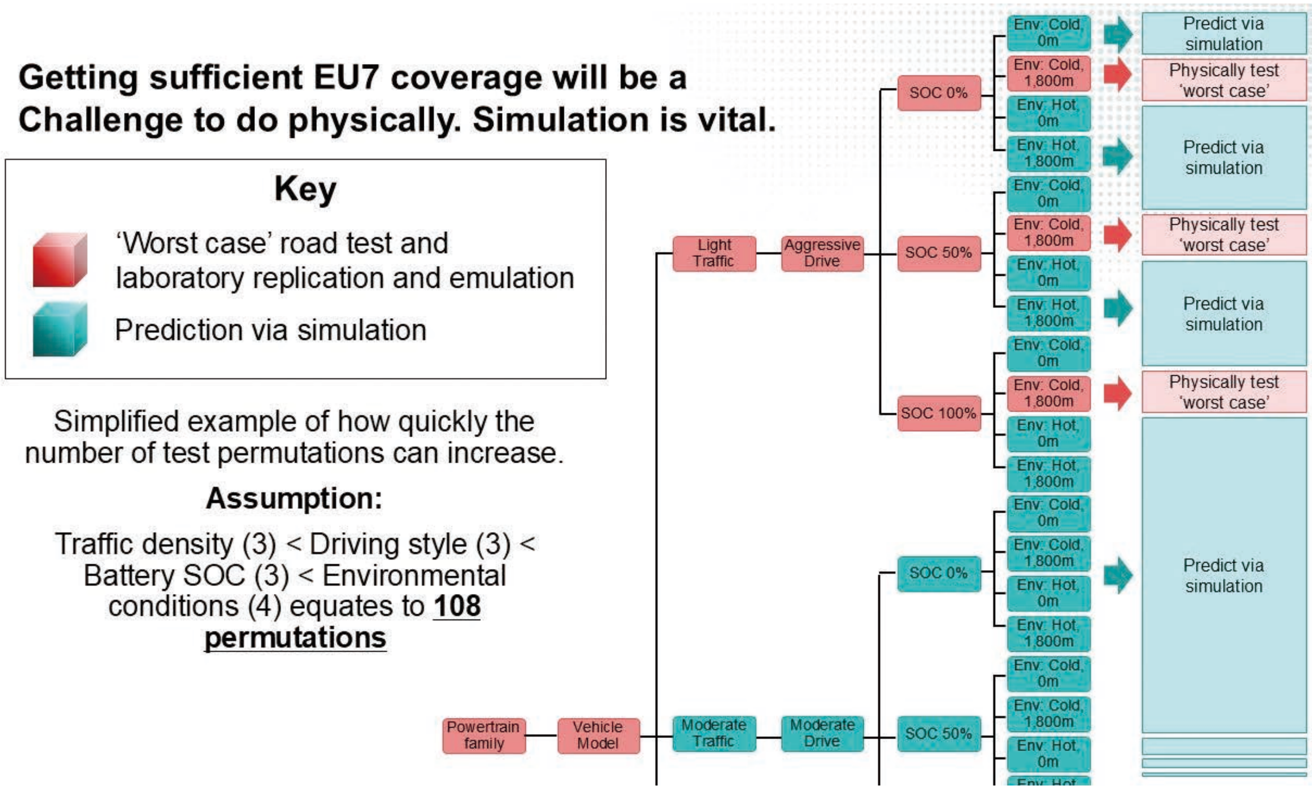
Consequently, the field of engine technology development faces increasing demands for performance evaluation under increasingly diverse testing conditions, alongside further tightening of emission regulations. For automotive OEMs, this presents significant challenges in both technical and financial aspects.

HORIBA has proposed the Empirical Digital Twin (EDT) approach[3] as a solution to the issues outlined above, which is attracting attention as a robust technological foundation for streamlining the entire process from vehicle and powertrain design to market introduction, and for shortening development cycles.

At the time of writing (May 2025), light-duty vehicles (LDVs) sold in Europe (passenger cars and other vehicles under 3.5 tons) must comply with the current Euro 6[4] regulations by undergoing the Worldwide Harmonized Light Vehicles Test Procedure (WLTP) and Real Driving Emissions (RDE) testing.

WLTP testing is conducted in a laboratory under controlled atmospheric conditions, whereas RDE testing is based on actual road driving conditions, requiring evaluation under more uncertain circumstances. Specifically, Euro 6 provides detailed specifications for the proportion of urban, rural, and highway driving, as well as operating conditions. Under these real-world testing regimes, powertrain and emissions aftertreatment systems must be designed to function reliably. Looking ahead to even stricter future emission standards, it is theoretically possible to comprehensively verify all operating conditions through physical testing, but in practice, this is extremely inefficient and challenging for development teams and is likely infeasible for many OEMs.

Simulation tools capable of predicting performance and emissions during edge-case boundary conditions that are physically difficult to achieve will become essential for future compliance. In this context, the authors propose a method whereby OEMs will still physically conduct tests under "worst-case" boundary conditions then use the results to build predictive models that, when combined with simulation, supplement RDE testing (**Figure 1**).



Getting sufficient EU7 coverage will be a Challenge to do physically. Simulation is vital.

Key

🟥 'Worst case' road test and laboratory replication and emulation

🟦 Prediction via simulation

Simplified example of how quickly the number of test permutations can increase.

Assumption:

Traffic density (3) < Driving style (3) < Battery SOC (3) < Environmental conditions (4) equates to **108 permutations**

Figure 1 An example for the need for combined physical testing and simulation

In this study, a Plug-in Hybrid Electric Vehicle (PHEV) was subjected to simulated RDE tests on a single route, combining three types of traffic conditions, three driving styles, three battery states of charge (SOC), and four environmental conditions, with the same powertrain installed in multiple vehicle platforms. Physical testing of >100 conditions would be hugely time consuming; hence the use of supplementary simulation data proves indispensable.

EDT Principle — Overview

HORIBA have developed a simulation tool utilizing digital twins to support future emission compliance for automotive OEMs[5]. Here, a digital twin refers to empirical models that accurately replicate physical units. The HORIBA toolkit consists of proprietary modules for transient experimental design, modeling, prediction, and optimization, employing an approach similar to Dynamic Design of Experiments (Dynamic DoE)[6].

These standalone modules operate according to the following process:

1. Design a transient experiment using statistical methods.
2. Conduct the designed transient experiments with the powertrain or vehicle and acquire training data.
3. Generate models to predict performance and emission characteristics based on the training data.
4. Validate the accuracy of the generated models.
5. Predict performance and emission behavior under real-world or synthetic driving conditions.
6. Identify undesirable powertrain characteristics ("hotspots") such as excessive emissions, poor fuel economy, or increased energy consumption.
7. Recalibrate to address identified issues.

These seven processes are depicted in **Figure 2** (**Figures 2-1 to 2-4**) and **Figure 3** (**Figures 3-5 to 3-7**).

EDT combines the empirical model created in process 3 with real-world RDE driving cycles generated by virtual vehicle simulation tools such as IPG CarMaker™*1 (process 5). HORIBA's EDT approach builds upon semi-dynamic testing methods from previous studies[7]-[12], employing new modeling techniques that combine empirical models and simulation for greater immersion and extensibility across broader domains.

*1 Registered trademarks or trademarks of IPG Automotive GmbH

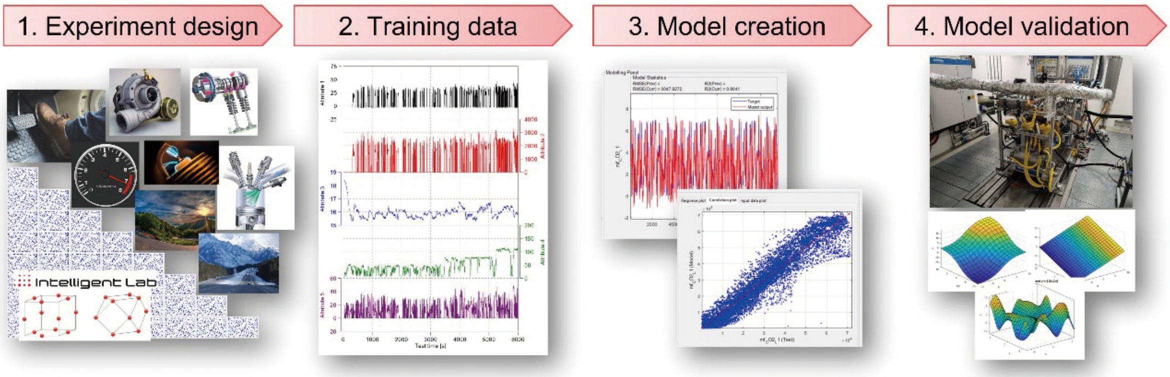


Figure 2 Stages of the HORIBA EDT approach (1) ; experiment design, generation of training data, modelling, and model validation.

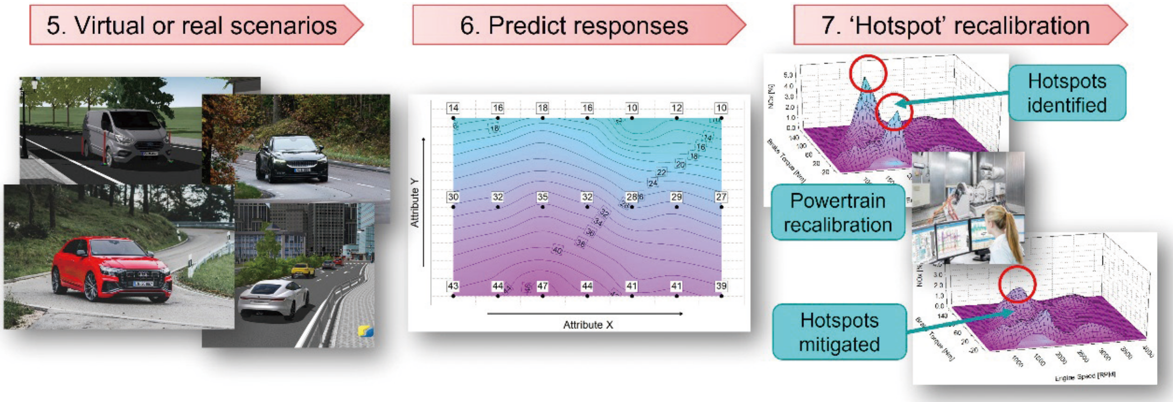


Figure 3 Stages of the EDT approach (2) ; establishing real or virtual scenarios to couple with empirical models, prediction of responses, and 'hotspot' determination.

EDT Principle—Dynamic Experimentation (Training Data Acquisition)

To build the empirical models in process 3, transient experimental design tools were used to generate training cycles covering the full operating range for both PHEV and commercial vehicle powertrains.

This enabled the construction of models that accurately replicated performance and emissions behavior under various operating conditions.

Figure 4 presents examples of powertrain bench experiments, while Figure 5 shows examples from chassis bench experiments.

The test cycles used to acquire training data for model generation required approximately 1.5 hours on both powertrain or chassis benches. For the powertrain test bench, input parameters included accelerator pedal position, brake pedal position, and drive shaft speed. For the chassis bench, input parameters were accelerator pedal position and vehicle speed. In the latter tests, HORIBA's automated driving system (ADS EVO) was used to automate accelerator pedal operation, with the chassis dynamometer controlling vehicle speed.

The dynamic experimental design, like traditional design of experiments (DoE) for steady-state conditions[13], consists of multiple target points within the operational constraints of the physical system (the engine, in this case; see Figure 2-1). However, in dynamic design, these points are passed in a specific sequence, sometimes revisited multiple times in different orders with brief stops.

Unlike steady-state experiments, in dynamic systems, even identical steady-state points may exhibit different behavior depending on the approach path (e.g., changes in engine speed or load i.e., history). Thus, trajectory information leading to measurement results is important and must be considered in model construction.

Data obtained by effectively covering the system's entire operational space enables the construction of highly-accuracy models that can accommodate any scenario expected in real-world operation.

In this study, to reduce the required amount of training data and physical testing burden, a dynamic experimental design unique to the target system was formulated (Figure 2-2). This design accurately captured the system's dynamic behavior and generated a high-density dataset while covering the entire operational space.

Using the training data acquired from these experiments, transient empirical models for multiple performance and emission characteristics were constructed (Figure 2-3).

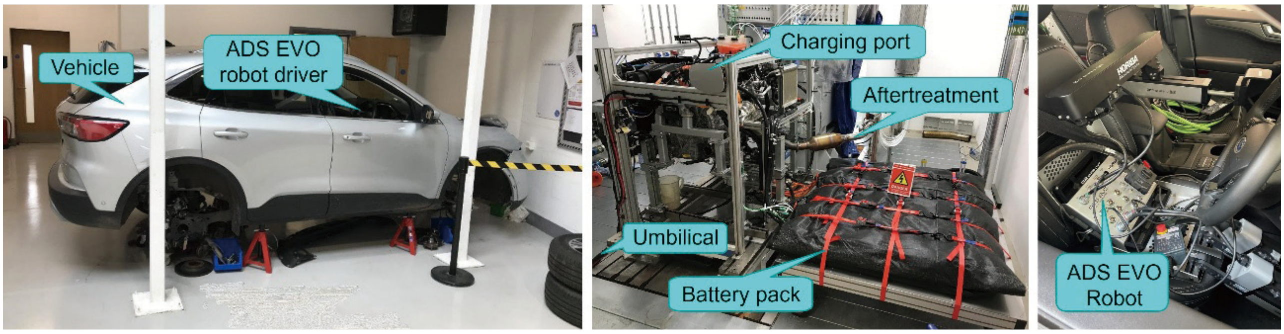


Figure 4 PHEV powertrain tested at HORIBA MIRA in the UK

Figure 5 Vehicle and corresponding diesel engine tested at an OEM in the UK.

EDT Principle—Model Creation, Validation, and Prediction

For modeling, a recurrent neural network (RNN)[14] with a long short-term memory (LSTM)[15] architecture was adopted.

RNNs were chosen for their flexibility in handling dynamic systems that change over multiple time scales. However, standard RNNs struggle to maintain long-term dependencies when handling long sequence data, often suffering from the vanishing gradient problem[15]. LSTM mitigates these issues with enhanced long-term memory retention and a structure that resists gradient vanishing.

LSTM features cell states and multiple gate mechanisms (input, output, forget gates), enabling temporary storage and appropriate output generation by combining past information with current inputs. This allows important past information to be reused even if similar values do not reappear in the current sequence; stored values are deleted only when learned conditions are met.

Training data collected during planned experiments includes both input and output variables as time-series data for the algorithm. During training, sequences are processed step-by-step in a moving window format.

RNN training is computationally intensive and time-consuming, but the use of high-density training data and general-purpose graphics processors (GPGPU) enables significant reduction in processing time. For example, even with multiple variables input at 10 Hz over a 90-minute driving scenario, model training and prediction is completed in only a few minutes.

All generated models are validated by comparing predictions with actual measurements (**Figure 2-4**). **Figure 6** shows examples of model quality from HORIBA's EDT toolkit, visually demonstrating differences between measured and predicted values for several performance and emission characteristics.

To reproduce real-world driving scenarios in a virtual domain, IPG CarMaker was used. Following steps described in previous literature[16], virtual drivers were programmed to drive multiple virtual RDE cycles in IPG CarMaker.

A major advantage of virtual scenarios is the ability to run simulations much faster than real time, enabling hundreds of RDE tests for a single vehicle to be completed in a very short period. Data generated by these simulations, combined with corresponding EDT models, allow for large-scale predictions of performance and emissions while greatly reducing the need for physical testing. **Figure 7** shows examples of scenarios generated using IPG CarMaker. These virtual tests enable detailed analysis of how factors such as driving style, traffic density, and route characteristics affect engine, powertrain, or overall vehicle performance.

Additionally, by incorporating the effects of environmental factors such as altitude and extreme ambient temperature into the EDT model, it is possible to predict driving performance and emission behavior for virtual environments at sea level or in regions of very high or low temperature. As an example, research described in[17] used HORIBA's altitude simulator Multi-function Efficient Dynamic Altitude System (MEDAS) to integrate the

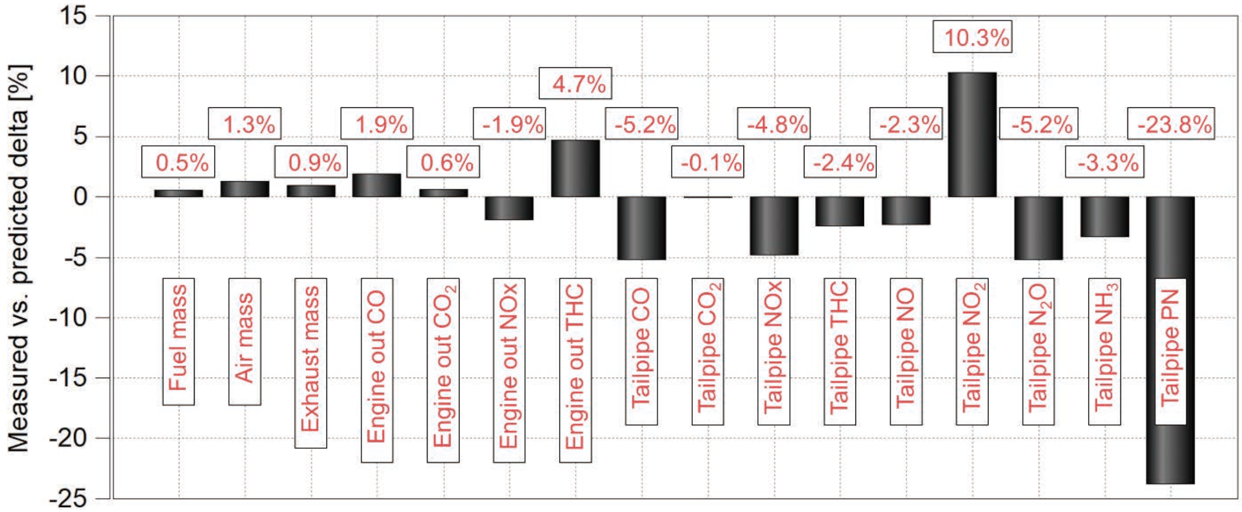


Figure 6 Measured vs. predicted deltas for performance and emissions attributes for a PHEV SUV tested on a powertrain dynamometer.

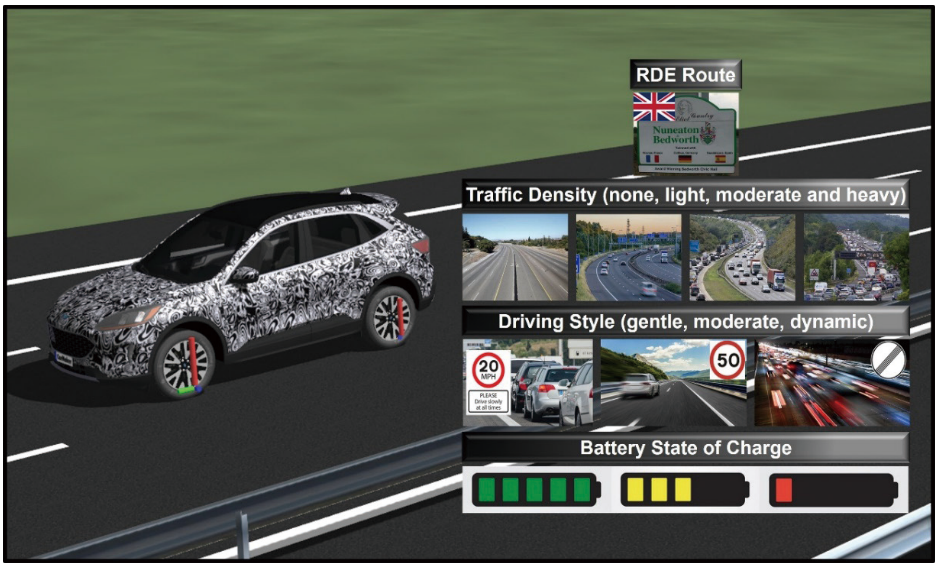


Figure 7 IPG CarMaker scenario definition for the light-duty PHEV SUV.

effects of altitude and temperature on engine performance and emissions into the EDT models.

EDT Principle—Identification of Hotspots

Figure 8 presents an example of identifying problematic operating conditions ("hotspots") for powertrains or vehicles using the EDT approach. The figure shows cumulative NOx emission predictions from the tailpipe for four RDE cycles on the same virtual route and traffic density, with an SUV-type PHEV set to zero battery SOC for all cycles. Black lines indicate calm (solid) and dynamic (dashed) driving styles at sea level and 35°C intake temperature; red lines show the same styles at 1,800 meters elevation and 35°C intake temperature.

The black box in the figure represents the proposed EU7 mass limit requirement during the 2021 Euro 7 discussions (since removed as of 2025), which stipulates cumulative NOx emissions must not exceed 600 mg within the first 10 km of testing. All predictions are based on training data collected after engine warm-up. For sea level driving (black lines), cumulative NOx emissions remain around 400 mg, within the black box, and per-distance emissions are below 60 mg/km, meeting both gasoline and diesel standards at the time.

In contrast, predictions for 1,800 meters elevation (red lines) exceed 600 mg NOx emissions between 6–7 km, violating the mass limit. Interestingly, these high-altitude emissions remain below 60 mg/km, still compliant with Euro 6.

As demonstrated in **Figure 8**, HORIBA's EDT method enables identification of problematic powertrain operating conditions even before vehicle mass production. Since all predictions are based on post-warm-up engine data, cold-start conditions could result in exceeding 600 mg within

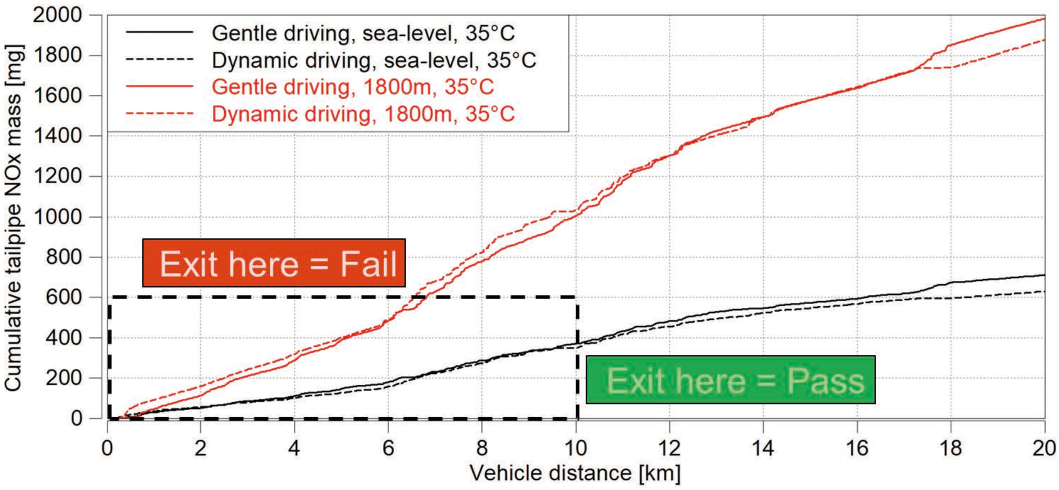


Figure 8 Predicted tailpipe NOx emissions for the PHEV SUV at sea-level and 1,800m.

10 km even at sea level. Thus, cold-start conditions, though permissible under Euro 6, become a crucial consideration for compliance if the EU7 10-km mass limit is introduced.

With the introduction of stricter emissions regulations, automotive OEMs must strengthen simulation activities to ensure product compliance under a wider range of operating conditions.

HORIBA's transient EDT method is therefore highly effective for predicting performance and emissions for various powertrains, engines, and vehicles over a vast number of cycles at faster-than-real-time.

Conclusion

By adopting the EDT approach, automotive OEMs can verify product reliability and regulatory compliance under "worst-case" and "edge-case" conditions – such as temperature and altitude extremes or operating characteristics near RPA, V.apos[95][4] boundaries – defined by RDE regulations, even before conducting real-world vehicle tests.

Furthermore, as powertrain sharing becomes common in modern vehicle development, intentional dynamic cycle testing is required to ensure proper functionality across multiple vehicle platforms.

Initial estimates suggest that applying the EDT approach to a single vehicle can reduce the time required for certification and verification processes by at least 70%. This effect becomes even more pronounced as common powertrains are introduced across multiple vehicles.

The EDT approach introduced herein has already been applied to established mass-production powertrains and is also effective during early development stages when hardware and calibration optimization are required. For example, during selection of air supply systems or exhaust aftertreatment, EDT can potentially reduce the number of required prototype systems and vehicles.

Current research focuses on conventional and electrified powertrains using liquid fossil fuels, but the methodology is also applicable to battery electric vehicles (BEVs), fuel cell vehicles, and carbon-neutral alternative fuels, enabling understanding of how energy consumption and driving range vary with different operating characteristics, environmental conditions, and load states.

Traditionally, evaluation of energy consumption and driving range using chassis dynamometers has been complex and time-consuming. However, the EDT approach can significantly reduce this burden. Moreover, the flexibility of this method – developed as a cross-functional toolset spanning multiple engineering and scientific fields – means it is widely applicable to systems beyond automotive.

* Editorial note: This content is based on HORIBA's investigation at the year of publication unless otherwise stated.

References

[1] Nicole Egerstrom et al. Emission reductions and public health benefits from timely Euro 7 standards

[2] 森川多津子, 2030年における自動車からの大気汚染物質排出量推計, JRJ20241001. (in Japanese)

[3] Phil Roberts et al. Powertrain Digital Twinning for Real-World Emissions Compliance 2024-01-2602, SAE

[4] COMMISSION REGULATION (EU) 2016/646 of 20 April 2016 amending Regulation (EC) No 692/2008 as regards emissions from light passenger and commercial vehicles (Euro6)

[5] Phil Roberts et al. The Prediction of Performance and Emissions for Synthetic Machine Handling Cycles Utilising a Powertrain Empirical Digital Twin 2024-01-4271, SAE

[6] Karsten ROEPKE, Design of Experiments for Engine Calibration

[7] Gutjahr, T et al. "Advanced Modelling and Optimization for Virtual Calibration of Internal Combustion Engines," NDIA Ground Vehicles Systems Engineering and Technology Symposium, 2017.

[8] Shishido, T et al. "Dynamic Modelling for Gasoline Direct Injection Engines," *Keihin Technical Review*, Volume 6, 2017.

[9] Le Corre, S.D. et al. "Application of Multi-Objective Optimization Techniques for Improved Emission and Fuel Economy over Transient Manoeuvers," *SAE Technical Paper* 2019-01-1177, 2019, DOI:10.4271/2019-01-1177.

[10] Tulpule, P et al. "Model Based Design (MBD) and Hardware In The Loop (HIL) Validation: Curriculum Development," *American Control Conference*, 2017, DOI:10.23919/ACC.2017.7963788.

[11] Xiaohang et al. "On the application of artificial neural networks for the prediction of NOx emissions from a high-speed direct injection diesel engine," *International Journal of Engine Research*, Volume 22, Issue 6, Pages 1808-1824, 2021, DOI:10.1177/1468087420929768.

[12] Katreddi, S et al. "Trip based modelling of fuel consumption in modern heavy-duty vehicles using artificial intelligence,". *Energies* 2021, 14, 85–92, DOI: 10.3390/EN14248592.

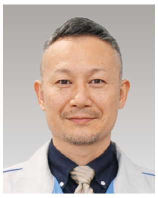
[13] Mohammed Reza Kianifar et al. Sequential DoE Framework for Steady State Model Based Calibration 2013-01-0972, SAE

[14] Ronald J et al. A Learning Algorithm for Continually Running Fully Recurrent Neural Networks, *Neural Computation* (Volume: 1, Issue: 2, June 1989)

[15] Sepp Hochreiter et al. Long Short-Term Memory, *Neural Computation* 9(8):1735-1780, 1997

[16] Phil Roberts et al. RDE Plus - A Road to Rig Development Methodology for Whole Vehicle RDE Compliance: Overview 2020-01-0376, SAE

[17] Phil Roberts et al. RDE Plus - Rapid Characterisation of Vehicle and Powertrain Performance and Emissions using Dynamic Design of Experiments, Digital Twin and Virtual Driving Methodologies 2022-01-0580, SAE



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