Total Cost of Ownership Analysis in the Development Phase
- Model-Based Fleet Validation over the Useful Life -

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ABSTRACT: In the development phase a typical means of cost saving is the replacement of a sensor with a model. A model-based methodology combined with statistical approaches is presented, enabling a holistic view on the cost and legal consequences of such a decision. It considers production tolerances, environmental conditions and their joint effect on component aging. Additionally, the effect of methodical inaccuracies on the results is reflected by confidence levels. Finally, by means of a use case, the methodology is applied to assess the exchange of a mass flow sensor by a corresponding model in terms of TCO and legal conformity.

KEY WORDS: Vibration, noise, and ride comfort, Model-Based Fleet Validation, Total Cost of Ownership, In-Service Conformity, Noise Factors, Virtual Development Environment, Metamodels, Aging Models, Propagation of Uncertainty [B3]

1. Introduction

The pursuit of a cost-efficient internal combustion engine that is robust over lifetime has never been more intense in the automotive industry than it is today [1]. This process is extensively driven by a fleet-oriented emission legislation, becoming increasingly stringent all around the globe [2, 3]. Secondary to that, competitiveness against direct or substitute competitors requires more and more an outline of all costs of lifetime operation. Here, the ‘Total Cost of Ownership’ (TCO) function – that is the sum of acquisition, usage, service and disposal costs of a product – generates growing awareness and acceptance as a potential competitive advantage in the market [4].

The increasing market pressure lets development engineers often struggle with answering the question which engine parts and associated quality levels are effectivly required. Reducing production cost by the economization of a particular sensor, for instance, might be favorable regarding the prototype engine. However, this does not automatically mean that an overall benefit would be achieved concerning the successive production series, defining the ‘fleet’. In fact, reasonable uncertainty is added to the decision finding process by uncontrollable ‘noise factors’. As these involve the variability of the fleet by component (i.e. production tolerances and aging) and usage tolerances (i.e. individual usage and environmental conditions), the ‘Key Performance Indicators’ (KPI), describing the prototype developed and its TCO to be expected, deviate after ‘Start Of Production’ (SOP) [5]. Figure 1 shows a typical example in this context. An alternative Concept B, although apparently comparable to Concept A, might be less insensitive (or ‘robust’) in the presence of the variability of the fleet. Thus, the vehicle fleet implementing Concept B, is not legally feasible. Since the cause-effect relationship between noise factors and KPIs is normally unknown to the development engineer, the effect of noise factors cannot be fully validated before SOP. In the past we already described a model-based and cost-efficient method, capable of estimating the unknown cause-effect relationship and using the latter to validate the complete production series against potential concepts [6, 7]. We refer to this method as the ‘Model-Based Fleet Validation’ method. The approach is suitable for short time periods, because aging effects are considered to be independent from other noise factors. Owing to a model-based fleet validation over the useful life, as applicable to assessing TCO or legally regulated in-use requirements, we will describe an expansion to the existing approach.

Fig. 1: Uncertainty in the Decision Finding Process

In Section 2, we highlight the challenge of the classical development processes and the need for a systematic analysis of the cause-effect relationship between noise factors and KPIs. On that account, we provide a brief overview of the model-based fleet validation approach as described in our previous work. In Section 3, we expand the scope of that methodology to a long-term horizon over the useful life. Here, we present a systematic integration of component aging models and sketch the final work flow. At the end of that chapter, we discuss the main sources of uncertainty inside the work flow and examine their effect on the confidence in
the results given. In Section 4, we conclude this paper by a use case. Particularly, we want to bring about a TCO-based decision regarding whether or not the ‘Exhaust Gas Recirculation’ (EGR) mass flow sensor of a particular engine concept can be economized, while simultaneously accounting for the emission legislation. In Section 5, a conclusion of this paper is given.

2. Model-Based Fleet Validation

2.1. The Challenge of the Classical Development Process

Forthcoming limitations in the emission framework have put a noticeable challenge into the development process of the internal combustion engine and the exhaust aftertreatment system (8), ‘Real Driving Emissions’ (RDE) as well as more restrictive ‘In-Service Conformity’ (ISC) and ‘On-Board Diagnostics’ (OBD) regulations demand for validating the assembled engines against a large multiplicity of usage conditions until ‘Full Useful Life’ (FUL), yet almost impossible to cover by the classical development process (9). The same usually foresees an experience-based test sequence, where multiple prototype engines are repeatedly tested under particular use and environmental conditions over certain time periods. A complete validation of the legally regulated (or soon to become regulated) ‘factor space’, as spanned by the axes ‘Produced Engines’, ‘Lifetime’ and ‘Usage Conditions’, is, by nature, not achievable with hardware testing only (see Figure 2). Similarly, as a consequence of untested variability, TCO calculus was not entirely reliable in the concept finding process.

![Fig. 2: Legally Regulated Scope versus Hardware Testing](image)

As shown in Section 4, production tolerances and varying environmental conditions could have a different influence on the aging behavior of the engine and on the performance associated. Thus, vehicles assembled with identical engines may differ in fuel or garage cost, and so in TCO, even in spite of identical usage.

In the concept phase, experience and expertise often need to balance the incompleteness of experimental data. Due to the absence of the cause-effect relationship between noise factors and KPIs, potential engine concepts cannot be completely validated regarding the successive fleet. As a consequence, this involves the risk of over-engineered or even error-prone concepts. The model-based fleet validation methodology (10), gives the basic fundament for overcoming that challenge in a quantitative way.

2.2. Approximating the Unknown Cause-Effect Relationship

In the classical development process, the cause-effect relationship between an individual noise factor and a particular KPI is sometimes linearly approximated. Nevertheless, a good fit of reality needs, in general both, a more complex than linear model and the possibility to consider the joint effect of all noise factors at once. Deliberately changing noise factors while observing their effect on the particular KPIs is the key for ‘understanding’ the real cause-effect relationship. It can be found when using a ‘Virtual Development Environment’ (VDE) wherein the cause-effect relationship is implicitly modelled. There, multiple system boundaries of the vehicle can be investigated (10, 11). In the course of this paper we focus on the system engine including the exhaust aftertreatment and ‘Engine Control Unit’ (ECU). All major effects of the noise factors on TCO and the regulated pollutants can be thereby validated.

2.2.1. The Virtual Development Environment

The VDE is a CAE software platform, consisting of physical and semi-physical equations. The term ‘semi-physical’ approach means the application of empirical models, where necessary, in order to retain (faster-than-)real-time simulation capability in ‘Software in the Loop’ (SiL) or ‘Hardware in the Loop’ (HiL) test environments. The physics-based part of the equations ensures extrapolation capability. This property proves to be advantageous, particularly in the concept finding process where test bench data is rarely available, if at all.

For the purpose of this paper, the VDE consists of the engine model and a virtual ECU. The engine model can already be set up by a few hardware specification parameters, although it remains tunable to measurement data, if later available. The virtual ECU comprises models and control loops for the most essential systems of the engine that are the air path, the injection and the exhaust aftertreatment system. The resultant working environment allows the engineer to early test feasible hardware concepts including their controls in transient driving cycles. Additionally to the KPIs, the combustion as well as temperatures, pressures, mass flows, and emissions in the whole air path become assessable. At the same time, combinations of noise factors, further denoted as ‘factor combinations’, can be implemented in a quick and cost-efficient way, by simply changing model parameters (see Figure 3). Beside its reproducibility, other advantages of the VDE, such as its capability of automation and replication enhance the exploration of the unknown cause-effect relationship.

![Fig. 3: Exploration of the Unknown Cause-Effect Relationship between Noise Factors and KPIs using the VDE](image)
The model prediction accuracy plays a central role in the model-based engineering task. The same and its impact on the decision finding process shall be therefore separately discussed in chapter 3. The next subsection describes how to use the VDE in order to transfer the variability of the noise factors to the KPIs.

2.2.2. The Mathematical and Statistical Analysis

The VDE facilitates a deliberate manipulation of noise factors and the observation of the changes in the KPIs, which theses combinations produce. In order to determine the robustness of a feasible engine concept, it needs to be tested for all factor combinations possible after SOP.

The Monte-Carlo sampling approach is an intuitive and popular methodology on how to include noise factors in engineering tasks (12). Particularly, the variability of a KPI shall be determined while alternately operating the engine under feasible combinations of noise factors. Although well known in the art, that approach entails two major disadvantages. On the one hand, the unknown cause-effect relationship is only investigated in probable regions of the factor space. On the other hand, the engineer needs to account for the statistical ‘representativeness’ of the experiments performed (13). This means the experiments may not reveal all critical factor combinations, nor cover the real occurrence probabilities of the same in the fleet. When the experimental procedure is expensive, either in time or cost, representative testing is often not possible, even when compensating expenses with the VDE. On this account, it is proposed, as a first step, to aim all experiments available at the exploration of the unknown cause-effect relationship (7). The described strategy of experimentation consists of a stepwise sequence of space-filling ‘Designs of Experiments’ (DoE), which usually comprise in total about 500 factor combinations. In contrast to the Monte-Carlo sampling approach, there, importance is attached to regions in the factor space, where the relationship between noise factors and the KPIs appears to be more complex. The data established allows to approximate the cause-effect relationship independently of factor occurrences after SOP. In doing this, a so called ‘metamodel’ is built for every KPI.

As shown in Figure 4, the variability of the fleet becomes instantly transferable to every KPI. Moreover, since the metamodel approach works independently of factor occurrences, other than the primarily considered variability assumption becomes assessable. Hence, the robustness of concepts may be investigated under selective usage conditions or under more restrictive component tolerances.

The model-based fleet validation approach is a useful method to estimate the effect of noise factors on KPIs in a representative way. In order to make it optimally applicable to the early concept phase in matters of TCO and a lifetime-oriented legally regulated scope, the method needs to be enhanced in two ways. At first, aging shall not be treated as an independent noise factor. It is more realistic to introduce component aging, as a function of operation and the remaining noise factors. Secondly, the major methodological uncertainties shall be analyzed, as they will realize and propagate differently from one to the other use case.

3. Model-Based Fleet Validation over the Useful Life

3.1. Aging Models and the Virtual Development Environment

During regular use, the internal combustion engine and its subsystems are subject to aging in form of deterioration and degradation of all kinds. Its aging phenomena typically include mechanical abrasion of movable parts, the degradation of actuator and sensor functionalities, cooler fouling or performance losses in the exhaust aftertreatment system. Hence, an engine shall be denoted as ‘aged’, if one or multiple components deviate from their original characteristics, as existent at the time of their assembly.

A differentiated and systematic consideration of engine aging in the presence of noise factors shall be achieved through the use of component ‘aging models’. An aging model can be considered as a function, instantly transferring one or multiple time series of damaging data points into an aged state of a component. The VDE, as briefly described in the last chapter, brings a twofold advantage for the integration of aging models compared to a real test bench. As shown in Figure 5, the engine model provides the damaging data necessary for the aging models without any expensive measurement equipment. In addition to that, the output of the engine model allows to quickly set the aged state of a component characteristic. At last, the simulation of the aged engine state is enabled by expanding or updating the original factor combination with the absolute aging parameters.

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**Fig. 4:** Model-Based Fleet Validation

In a second step, the empirical nature of the metamodels is utilized to assess a set of Monte-Carlo factor combinations, large enough to be representative for the variability assumed for the fleet. Carrying out a number of experiments that equals to a production volume of one million engines is so easily achieved for example.
Aging models and the VDE are outstandingly suitable for a joint methodological consideration. In the next step, aging models shall be therefore integrated into the model-based fleet validation methodology.

3.2. Integration of Aging Models into the Methodology

The cause-effect relationship between a set of uncontrollable noise factors and a KPI becomes estimable by the model-based fleet validation methodology, as discussed in chapter 2. There, noise factors relating to component aging were considered independently of all other noise factors. It is self-evident that this hypothesis is hardly tenable when considering a variable usage in the fleet. Indeed, varying production tolerances and environmental conditions yield a different aging procedure, even if the driving cycle would be fixed. Thus, engine aging that depends on noise factors demands a cause-effect relationship that changes over time.

The exploration of a cause-effect relationship that is time-dependent naturally requires experiments under aged engine statuses. Hence, the stepwise sequence of space-filling DoEs, as proposed in (7), needs to be resumed for different aged statuses. The starting point should be the new engine state. For every experiment, all KPIs of note and also damaging data for the aging models involved can be recorded (see Figure 3). The length of the respective time series corresponds to the duration of the drive cycle in the simulated factor combination. An aging model accordingly transforms this information into an estimated state of component aging that would be reached after having similarly operated the engine for one-time. The most intuitive approach on how to resume the aging procedure, would be to directly adapt the aging parameters of the respective factor combination and rerun the simulation. However, as this would mean looping through Figure 5, that approach is very time-consuming, even in a simulation environment faster-than-real-time. Depending on the duration of the cycle, obtaining an aged state after years of operation would require hundreds or even thousands repetitions for each of the factor combinations simulated. Here, a more practicable way is the replication of the damaging data available to a desired aging length before passing it to the aging model. In doing so, an arbitrary aged state can be rapidly reached with damaging data of a unique simulation run-through. Taking this ‘shortcut’ means, however, that the usage conditions are fixed and one misses the amplifying effect of aged components on the aging behavior itself. Those disadvantages can be compensated by a stepwise approach, where the factor combination is updated a manageable number of times and considered under different usage conditions until a desired aged state is reached.

A fleet validation methodology treating with the long-term horizon requires repeating every experiment under multiple aged statuses of the engine, however at least for the new and ultimate aged state legally regulated (at FUL). Figure 6 sketches our final proposal regarding the work flow necessary to enable model-based fleet validation over the useful life. There, metamodels approximating the unknown cause-effect relationship and regression models are generated for every aged state. As apparent, the latter are capable of transferring factor combinations from the new to the individual aged state. Except for the new state, a path of two empirical functions follows, consisting of an aging regression model, nested into the KPI metamodel. This path is capable of transferring the fleet variability, as generated by the Monte Carlo approach, to the KPIs of the particular aged statuses covered.

The model-based fleet validation methodology established, allows assessing the KPIs in the presence of uncontrollable noise factors for arbitrary aged statuses. Hence, the conformity with legally regulated in-use requirements or TCO becomes estimable for the whole fleet before SOP. In the next subsection, we want to describe how the errors of the models used inside the work flow effect the confidence in the final results.

3.3. Propagation of Uncertainty and Confidence in the Results

The model-based fleet validation methodology in the early development phase of an engine involves a chain of errors, influencing the confidence in the final result. For this paper, the error sources can be clearly divided into two separate classes. The first class are errors coming from inputs to the models. That is the class of errors entering the proposed methodology. It comprises all deviations between the assumed variability of the noise factors and, respectively, the same as it would be realizing for the vehicle fleet over lifetime in reality. The second error class consists of all errors associated with the methodology introduced in the previous chapters. As described, the main prerequisites for a model-based
fleets validation over the useful life are the VDE, component aging models and appropriate empirical (meta) models.

Table 1: Sources of Errors inside the Work Flow

| Label | Sources of Error |
|-------|------------------|
| a     | Test Bench vs Virtual Development Environment (KPIs) |
| b     | Test Bench vs Virtual Development Environment (Damaging Data) |
| c     | Component Test Bench vs Aging Models |
| d     | Aging Models vs Regression Models (modeling aging) |
| e     | Virtual Development Environment (KPIs) vs Metamodels |

For reasons of efficiency and feasibility, these are intended to economize testing procedures with the real engine. We see it as a scientific obligation to perform an error propagation analysis of all errors introduced by our methodology. In the following we focus on an approach that considers these second sources of errors, as shown in Figure 6 and listed in Table 1. The starting point of the error propagation analysis should be a KPI result, as predicted by the corresponding metamodel for a particular factor combination regarding the new state. There, the error ‘e’ gives an absolute estimate of the deviation to be expected when repeating the experiment with the VDE. When further replacing the VDE by a real test bench, the error of the VDE ‘a’ becomes additionally effective. Hence, when referring the results of the model-based fleet validation methodology to the real test bench, the error ‘e’ needs to be corrected by the effect of error ‘a’. At least this applies to the KPIs for the new state. Figure 7 shows that the error chain becomes more complex, when including aged statuses.

According to the previous subsection, the KPI result is derived by the sequential execution of an aging regression model and a metamodel. The shortcut of the aging procedure by using the regression model additionally incorporates an error ‘d’, which needs to be considered. When referring result confidence to the real test bench, error ‘d’ must be corrected by the error of the aging model ‘c’. In turn, that error needs to be adjusted concerning the error of the damaging data ‘b’ respectively, as produced by the VDE for the preceding aged state. Similarly to the new state, error ‘c’ needs to be corrected by error ‘a’. However, for an aged state, both errors ‘c’ and ‘a’ need to be revised regarding the error ‘c’ (and consequently on ‘b’), as associated to the aging procedure of the simulated experiments. Indeed, the error sources ‘a’ and ‘b’ need to be corrected by error ‘c’, since the factor combination entering the VDE is already biased. Hence, the error chain also propagates through the successive aged statuses. All these error corrections need to be taken into consideration for a confidence statement in the KPI result, as obtained by the methodology.

The error propagation analysis allows to refer the KPI results of the model-based fleet validation methodology with regard to the real test bench. In doing that, the predicted KPI is framed by a confidence interval, wherein the real test bench is expected to realize for the corresponding experiment. In the next chapter, the findings of this paper will be summarized in the course of a use case.

4. USE CASE: TOTAL COST OF OWNERSHIP ANALYSIS IN THE DEVELOPMENT PHASE

The purpose of this investigation was to derive, already in the development phase, a TCO assessment of an engine concept, when the EGR mass flow sensor is replaced by a sensor model. The goal was achieved by a model-based fleet validation over the useful life. Moreover, the confidence in the KPI results was adapted to the final TCO assessment for both concepts.

The starting point of the TCO study was a VDE, modeling a EURO VI commercial on-road truck application with a 6-cylinder diesel engine, equipped with the usual exhaust aftreatment system components, using the ‘Selective Catalytic Reduction’ (SCR) technology. A virtual ECU was included too, which contained calibrated controls regarding the air mass, boost pressure, fuel injection, ‘Diesel Exhaust Fluid’ (DEF) injection and ambient conditions. Additionally, three calibrated OBD monitors were provided, namely the ‘EGR high flow’, ‘EGR low flow’ and the ‘SCR efficiency monitor’. The EGR Venturi air mass flow sensor was of particular interest, whose signal was used by the air mass controller.

The question was whether the economization of that sensor by a sensor model would yield, not only less production cost, but also savings in the TCO given the component and usage variability of the fleet. All cost should be considered at net sales level, where the sensor concept was with 80€ per vehicle by 70€ more expensive than the sensor model concept. The production volume was planned with 25,000 vehicles per year. A model-based fleet validation over the useful life should be performed in order to find the best solution from the viewpoint of the original vehicle owners.

Table 2: Aging Models Considered in the Validation Study

| Aging Models                        | Charge Air Cooler Efficiency | Irreversible Injector Deposits | NOx Sensor Accuracy | SCR Efficiency |
|-------------------------------------|------------------------------|-------------------------------|---------------------|----------------|
| EGR Valve Position                  |                              |                               |                     |                |
| EGR Cooler Efficiency               |                              |                               |                     |                |
| EGR Mass Flow Sensor / Model Accuracy|                              |                               |                     |                |
| High Pressure Compressor Efficiency  |                              |                               |                     |                |
| Low Pressure Compressor Efficiency   |                              |                               |                     |                |

For these, a usage period of four years had been presumed (see Figure 8). Thereby, the TCO should be analyzed in terms of fuel
cost, DEF cost, OBD maintenance cost and legal testing effort. The 73 minutes long-lasting driving cycle was chosen to be typical for the regular vehicle owner and consisted of 20% urban driving followed by 25% rural and 55% motorway driving. That cycle therefore enabled additionally a comparison of both concepts in terms of the testing effort necessary for passing the ISC procedure, as legally prescribed every two years (14).

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In the second step, 10 million Monte-Carlo factor combinations, which had been identified to be representative for the variability assumed for the fleet, could be instantly evaluated in their effect on the KPIs considered. The resultant variabilities of the KPIs obtained were appropriately recalculated so that the cost targets could be derived.

The noise factors involved into the study incorporated non-standard environmental conditions and production tolerances, which were assumed to be mostly decisive for the cost targets.

In the end, production tolerances were considered for 21 parts, dividable into sensors, actuators, coolers and parts of the turbo charger, the injection and the exhaust aftertreatment system respectively. The aging models, vitally important for a model-based fleet validation over the useful life, were available as specified in Table 2. In accordance with chapter 2 and 3 of this paper, the first step was the experimental exploration of the time-dependent cause-effect relationship between noise factors and the KPIs using the VDE. Figure 9 gives an overview of that procedure.

Fig. 9: Exploration of the Unknown Time-Dependent Relationship between Noise Factors and KPIs using the VDE

In that respect, the KPIs under investigation were selected so that the cost targets of Figure 8 became calculable. The whole simulation procedure conformed to the process in Figure 6, whereas there the aged state represented the end of the 4th year of operation. Thus, metamodels could be built for every KPI and aged state. A regression model, capable of aging factor combinations was built too.

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The expected measurement effort estimated for the two concepts and all corresponding cost positions at OEM side are summarized

Table 3: Probabilities of an OBD Event due to Uncontrollable Factors in the Fleet

| Probability of an OBD Event | New Status | Aged Status (and of 4th year) | Cost of Maintenance & Dwell Time |
|-----------------------------|------------|------------------------------|---------------------------------|
| SCR Efficiency              | 0.0%       | 0.0%                         | 1200€ + 500€                    |
| EGR Mass Flow Above         | 0.0%       | 0.0%                         | 30.5                         |
| EGR Mass Flow Below         | 0.0%       | 0.0%                         | 150€ + 500€                    |

| Event                      | Cost for First Vehicle | Cost for Additional Vehicle |
|----------------------------|------------------------|----------------------------|
| PEMS* setup                | 5,000 €/vehicle       | 5,000 €/vehicle            |
| PEMS* calibration          | 5,000 €/unit           |                            |
| Measurement                | 12,000 €/vehicle      | 4,000 €/vehicle            |
| Evaluation                 | 6,000 €/vehicle       | 2,000 €/vehicle            |

*PEMS = Portable Emission Measurement System

Table 4: Final Result of the Use Case

| Event                      | Cost* per vehicle @ 4 years** |
|----------------------------|-------------------------------|
| SCR Efficiency             | 100,000€                      |
| EGR Mass Flow Above        | 154,000€                      |
| EGR Mass Flow Below        | 154,000€                      |

* All costs considered in € before taxes
** 4 years: ~ 400,000 km; ECD = 700,000 km (or 7 years)
*** Fuel 0.97€/l, DEF 0.45€/l

Costs provided by the OEM
in Figure 11. There, the plot at the right side shows the effort to be expected for the sensor model concept for example. The requirement to start the test with three vehicles is visible by the starting point of the orange line. As passing the test was not possible with an odd number of engines and the failure probability was equal to two, in 98 percent of the cases an additional vehicle needed to be tested. Then, in 47 percent of the cases it could be expected that the ISC would be passed with four vehicles. Testing more than four vehicles needed to be planned for the remaining 51 percent of the cases, which distributed up to ten vehicles as apparent from the plot.

The interpolation of the results obtained for the new and aged state yielded the results for the entire observation period.

Table 4 summarizes all the considered cost positions for both concepts, when accounting for the fleet variability.

![Fig. 12: Effect of Error Sources on the Confidence of the Fuel Cost Results](image)

The purchase price of the truck and the major independent TCO positions inside that table were provided by the OEM. The sensor model would have been lowered the production cost by 70€ and the legal testing effort by an additional 1€ per vehicle. In fact, according to our analysis, it could be expected that the regular original vehicle owner needed to pay in total by 777€ more for the sensor model concept. This corresponded to 0.12% of the TCO or 0.78% of the purchase price. Despite accounting for all error sources of the methodology regarding fuel and DEF costs, the difference in the results remained significant. The addition of the error sources and their influence on the confidence in the final result is shown by the example of the fuel cost in Figure 12. The model-based fleet validation over the useful life could prevent from following the misleading sensor model concept.

5. CONCLUSION

This paper responds to the increasing need in the automotive market for a method, capable of validating developed prototypes against all eventualities possible from start of production over the useful life. A use case in the early development phase is given, which is a typical means of lowering production costs. That is the decision problem of assembling a virtual sensor instead of a real sensor. We present a model-based validation methodology combined with statistical approaches that enables, for both options, a holistic view of the entire vehicle fleet regarding the total cost of ownership and legal consequences. By establishing a complex but also fast calculating approximation of the cause-effect relationship between the uncontrollable noise factors modeling the fleet, and the key performance indicators describing the development, a key challenge of the classical development process is overcome. Nevertheless, despite the numerical complexity, we even achieve a time-dependent approximation through a systematic interplay of a virtual development environment, aging models and statistics. Particularly, the targeted application of aging models allows considering component aging in a more realistic manner, as a function of operation and noise factors. At last we use the approximation found to transfer the variability of the fleet to the KPIs of both sensing concepts. For that use case, we identify the sensor model concept, although preferable in production cost, as significantly more expensive in TCO as the concept implementing the real sensor. Despite the application of numerous models instead of the engine test bench, the results given are thoroughly validated by an error propagation analysis. The model-based fleet validation over the useful life, as introduced in this paper with well defined assumptions and boundary conditions, can indeed prevent from misleading concepts already before start of production. The application of the method presented is conceivable for technical systems of any other internal combustion engine. The components of the EGR system, the nozzle configuration or the design of the exhaust aftertreatment system could be assessed in a comparable way, for example.

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**LIST OF ABBREVIATIONS**

| Abbreviation | Definition                                      |
|--------------|-------------------------------------------------|
| CAE          | Computer-Aided Engineering                      |
| DEF          | Diesel Exhaust Fluid                            |
| DoE          | Design of Experiments                           |
| ECU          | Engine Control Unit                             |
| EGR          | Exhaust Gas Recirculation                       |
| FUL          | Full Useful Life                                |
| HiL          | Hardware in the Loop                            |
| ISC          | In-Service Conformity                           |
| KPI          | Key Performance Indicator                       |
| NOx          | Nitrogen Oxides                                 |
| OBD          | On-Board Diagnostics                            |
| OEM          | Original Equipment                               |
| RDE          | Real Driving Emissions                          |
| SCR          | Selective Catalytic Reduction                   |
| S/L          | Software in the Loop                            |
| SOP          | Start Of Production                             |
| TCO          | Total Cost of Ownership                         |
| VDE          | Virtual Development Environment                 |