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Virtual Multi-Criterial Calibration of Operating Strategies for Hybrid-Electric Powertrains

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Abstract: In hybrid vehicle development, the operating strategy has a decisive role in meeting the development goals, such as compliance with emission standards and high energy efficiency. A considerable number of interactions and cross-influences on other topics, such as emissions, on-board diagnostics, or drivability, must be considered during the calibration process. In this context, the given time constraints pose further challenges. To overcome these, approaches for virtualization of the calibration process are an effective measure. For this purpose, in the current study, a real engine control unit is embedded into a virtual simulation environment on so-called hardware-in-the-loop (HiL) testbenches, which allow virtual calibration and validation of the complete target vehicle. In this context, the paper presents a novel method for virtual calibration of operating strategies for hybrid-electric propulsion systems. This includes an innovative multi-criterial approach that considers the requirements of several development tasks, such as emission and OBD calibration. Measurement data for this optimization is generated on a HiL testbench setup tailored for the described methodology, including both the electrical setup and the simulation environment. To validate the selection of modeling approaches and the parametrization, the simulation environment is operated in open loop. The results of the open loop validation show promising behavior regarding the proposed use case. Finally, the presented methodology is evaluated regarding time and cost savings compared to a conventional approach.

Keywords: virtual calibration; HiL testbench; P2-hybrid operating strategy; multi-criteria evaluation; virtualization

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1. Introduction

1.1. Motivation

The automotive sector is under increasing pressure due to continuous social, technological, and legal changes (Figure 1). The most important drivers are ongoing climate change and increased environmental awareness worldwide [1,2]. Accordingly, governments and legislators are working on regulations to limit the emission of gases harmful to the climate and human health [1]. As early as 2019, the European Union defined a path to reduce CO_2 emissions in the transportation sector over the next decade, specifically for passenger cars and light commercial vehicles. With the introduction of regulation (EU) 2019/631 [3] in 2021, the CO_2 fleet target was set to 95 g/km, which will be reduced in a first step to 80 g/km in 2025 and then further to 60 g/km in 2030 [3]. If manufacturers do not comply with these targets, they will be subject to significant fees [3]. In addition, the EU Commission has published a proposal for the adapted pollutant emission regulation of the European market [4] under the name "Euro 7". The aim of the EU Commission is to further limit the environmental pollution from harmful emission components. The limits that already exist in the current Euro 6d-ISC-FCM will be further reduced in some cases [4]. Moreover, the emissions of further components, such as NH_3, N_2O, and CH_4, will be limited [4]. The scope of real driving scenarios in which the legislation applies will also significantly expand [4,5]. According to current information, the Euro 7 legislation will come into effect as early as July 2025 [4]. This, in combination with the accelerated technological progress, will result in a shorter time to market [6].

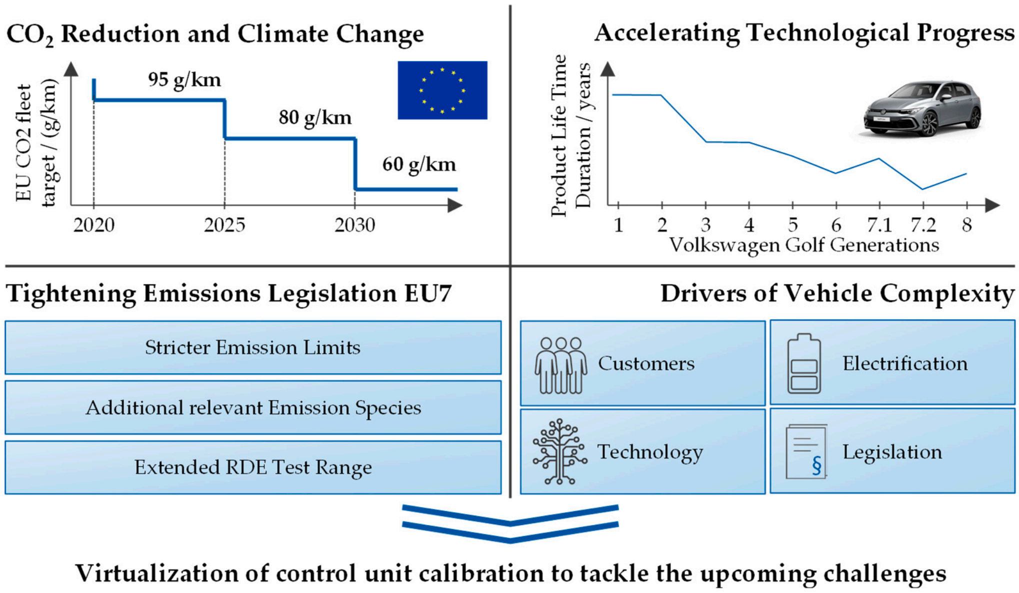

Figure 1. Motivation for Virtual Calibration.

Automotive manufacturers must respond to these short-term changes, specifically by adapting vehicle concepts and adding improved emission-reducing systems [7,8]. The electrification of conventional powertrains has the potential to significantly reduce fuel consumption and pollutant emissions from internal combustion engines (ICE) [7,9]. Such powertrains pose further challenges to the development process due to their increased system complexity compared to conventional powertrains [10]. An increased number of states, in which the powertrain can be operated leads to a higher number of interrelated control functions [11,12]. Finding a calibration that meets the requirements of all development disciplines requires further testing and validation on the road and in existing testing facilities, such as chassis dynamometers. Increased customer expectations and accelerating technological progress drive vehicle complexity [6].

To counteract this trend, automotive manufacturers must develop and implement robust and flexible processes and methods for development and calibration tasks [13–15]. In this context, implementing virtualized test environments is an important focus of current research. By shifting development tasks into a virtualized test environment, the time and cost associated with the calibration process can be reduced by up to 20% [16,17].

1.2. Virtual Calibration of Automotive Control Units

The vehicle development process can typically be divided into four main stages, as shown in Figure 2. Following the conception and definition of hardware and software, the system calibration phase begins, typically divided into three substages. The results achieved in the calibration are often generated and validated on different testbenches. For this purpose, component testbenches and prototype vehicles on chassis dynamometers are used. In later phases, the prototype vehicle is operated on the road to assess close-to-customer operation. All collected measurement data are ideally stored centrally in a measurement database.

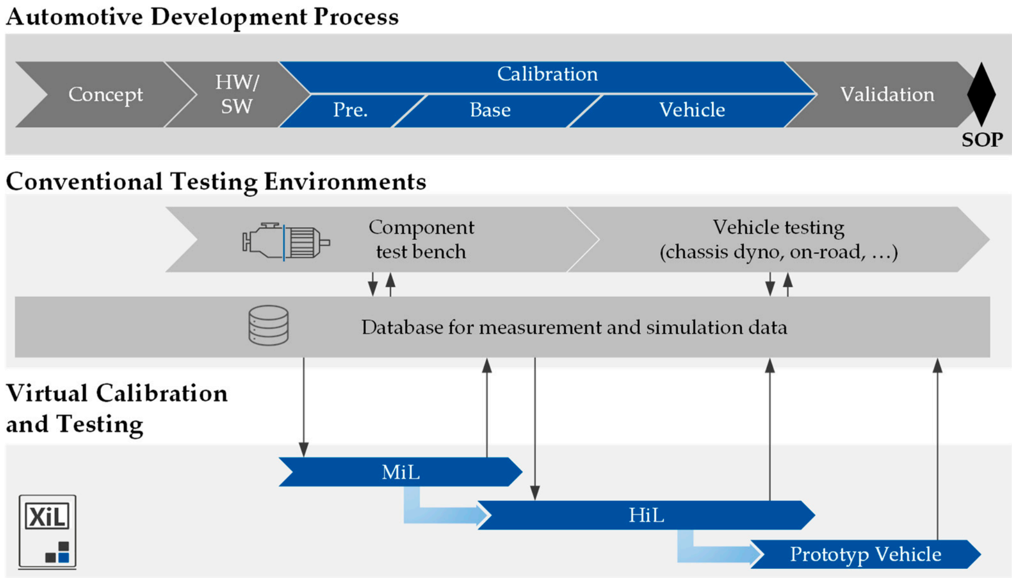

Figure 2. Development process in the automotive industry supported by virtual methods.

Virtualized methods on X-in-the-loop (XiL) test rigs can be integrated into the existing processes (Figure 2). These virtualized testbenches comprise a real target hardware component—device under test (DUT)—and a simulation environment. In principle, different setups for XiL testbenches are possible, which differ in the degree of virtualization and their accuracy in relation to the real system. A detailed description of the individual test environments has been reported previously [18,19]. Existing measurement data from both conventional and virtualized sources are used for efficient generation and evolution of the simulation environment. The simulation environment is continuously optimized and refined by the available measurement data during the development process.

In early phases of the development process, when little or no target hardware is available, highly virtualized testbenches, such as the model-in-the-loop (MiL) or the software-in-the-loop (SiL) setups, are used. During development, additional parts of the target hardware are integrated to increase the reliability of the generated results. Thus, so-called hardware- (HiL), engine- (EiL), or powertrain-in-the-loop (PiL) testbenches can be derived from existing testbenches (Figure 2). Integrating such testbenches with different virtualization degrees into the calibration process has been achieved for different calibration disciplines [20–24]. However, a final release or homologation of the target hardware and software can currently only be achieved with a prototype vehicle. The virtualized testbenches should, therefore, be seen as complementary measures that reduce the overall cost and time expenditure in a holistic approach.

1.3. Use Case: Virtual Calibration of the Operating Strategies of a Hybrid-Electric Vehicle

The calibration of the operating strategy for hybrid powertrains represents a specific use case for virtual calibration with high potential. This has been partially demonstrated in various studies by Wu et al. [25], Merl et al. [26] Kuznik et al. [27], and Schmidt et al. [28], among others. For P2-plug-in hybrid vehicles (PHEVs) considered in this paper (Chapter 2.2), the operating strategy controls the interface between the electric and conventional drive systems (Figure 3). Among other factors, the hybrid operating strategy is responsible for the start/stop decisions of the internal combustion engine, load point shifting during hybrid operation, and the predictive operating strategy. P2-PHEVs have many possible states compared to other hybrid topologies and are, therefore, complicated in terms of optimal calibration. Hence, the hybrid operating strategy calibration is well suited for the use of virtual methods during the development process.

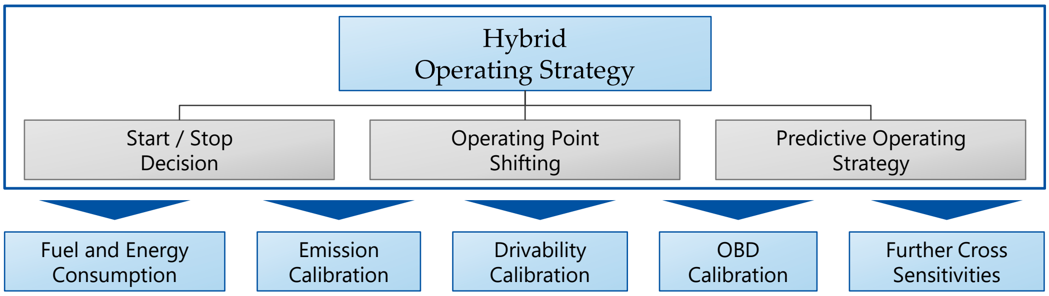

Figure 3. Scope of hybrid operating strategy and influence on other calibration disciplines.

Further, the hybrid operating strategy calibration of a P2-PHEV powertrain is characterized by a high degree of cross-influences on other calibration disciplines, including the emissions or drivability calibration [29] (Figure 3). This motivates a holistic approach to calibration. Relevant quality criteria of other disciplines must be considered from the start of the optimization process. Similar approaches in control function development and open-loop simulation have been investigated by Wang et al. [30], Duan et al. [31], and Görke et al. [32]. However, in contrast to the proposed methodology, these approaches used simulation setups without real target hardware. Compared to a conventional iterative calibration approach, this holistic method can significantly reduce development time and cost.

In the early phases of the development process, when no control unit or final software is available, the MiL approach can be used to generate an initial pre-calibration. In this case, the entire vehicle is replicated in a simulation environment. The control functions to be calibrated, and all other functions relevant to representative operation are simulated (Figure 2). To enable time-efficient optimization, the model should run faster than the real-time criterion. The parameterization of the overall system model is based primarily on measurement data from a database and simulation results of more detailed and complex models.

When a real engine control unit (ECU) with software close to series production is available, the calibration process can be transferred to a HiL testbench (Figure 2). In contrast to the MiL setup, this is characterized by using real target hardware and software to control the system model. Thus, the transferability to the target system is improved, and the maturity of the calibration is further increased. However, due to the use of target hardware, a real-time capable simulation environment is necessary, and an acceleration of the simulation is no longer possible. Nevertheless, a time advantage can be achieved with this setup as different test environments can be assessed without having to condition the real components beforehand. Furthermore, the calibration can be optimized based on the pre-calibration from the MiL environment. The virtually obtained results are finally validated in tests with a prototype vehicle and released for the homologation process.

1.4. Need for Scientific Research

To address the described challenges in the calibration of hybrid electric vehicle operating strategies, virtualization methods are promising. However, these must be combined with a holistic optimization that considers requirements from other calibration disciplines. Existing publications on the virtual calibration of hybrid operating strategies on XiL testbenches focus primarily on reducing fuel consumption and, thus, do not include a multi-criterial calibration approach. Furthermore, studies focused on the holistic optimization of a hybrid operating strategy and rely fully on virtual simulation environments. The results of these investigations can only be partially transferred to a real calibration process due to the limitations of simulating the relevant control functions. Hence, this paper presents a virtual multi-criterial calibration methodology for operating strategies of hybrid-electric powertrains on a HiL testbench. In Chapter 2.1 this methodology and the tailored testbench are described in detail, including the hardware setup and simulation environment. In

Chapter 3, an extract of the results from the first validation of the model environment is presented. In Chapter 4, the results are discussed in the context of the complete methodology as well as the described use case. Furthermore, the potential benefits of the proposed methodology are derived. In Chapter 5, the content of the paper is summarized, and an outlook is provided.

2. Material and Methods

2.1. Methodology for Virtual Calibration of Hybrid Electric Vehicles

A calibration methodology that considers a holistic approach in a virtualized environment and is tailored to calibrate hybrid operational strategies is presented in Figure 4.

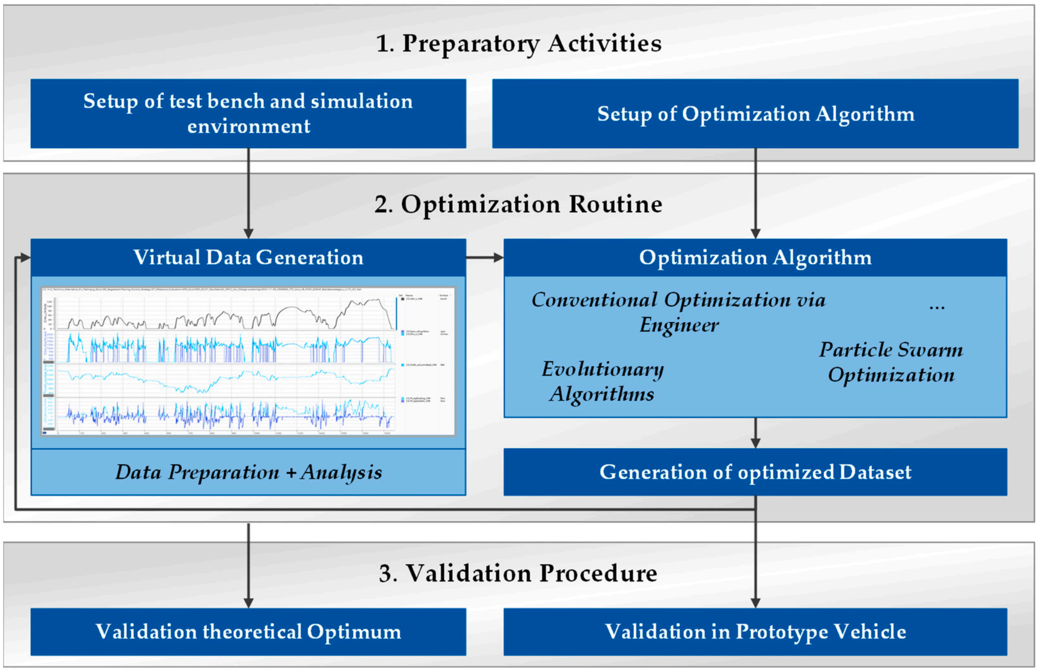

Figure 4. Schematic representation of the methodology for virtual optimization of operating strategies of hybrid electric powertrains.

Fundamentally, the methodology presented here comprises three components. Before optimization, all preparatory measures must be conducted. This includes the setup of the testbench and preparation of the optimization process. The testbench build-up phase consists of several validation steps for both the simulation model and the hardware setup. First, hardware and simulation model requirements must be derived from the calibration use case. Using available measurement and parametrization data, suitable simulation models must be defined and parametrized. The standalone models are then validated in an open-loop environment to confirm the model behavior. In parallel, the electrical hardware of the testbench is planned and realized according to the requirements. In the next validation step, the simulation environment and hardware are aggregated. The behavior of the resulting XiL testbench is investigated in a closed-loop environment. The test bench is assessed regarding the simulation of the system response to calibration changes. If the complete validation is successful, the XiL testbench is released for virtual calibration tasks.

To prepare for optimization, objectified quality criteria must be defined for the relevant calibration disciplines. These criteria are weighted and transformed into a quality function. Furthermore, the set of valid solutions of the optimization problem must be restricted by the definition of constraints. Likewise, reasonable limits of the calibration variables are to be defined.

After completion of the first component, the optimization routine begins. Based on one or more initial calibration data sets, measurement data are generated on the virtual testbench. For this purpose, it is important to select the scenarios to be examined according to the function to be applied. The approaches described by Claßen et al. [33], Krysmon et al. [34] and Roberts et al. [35,36] can be applied.

The generated testbench data must be evaluated in an automated and standardized manner with respect to the defined quality criteria. In the next step, the evaluated measurement data is passed on to an optimization algorithm, such as the Particle Swarm Algorithm (PSA) [37,38] or the evolutionary algorithm (EA) [39,40]. However, not only automated algorithms, but also manual optimization can be performed by the calibration engineer. For this purpose, the engineer uses the results of the automated measurement data preparation and analysis to define the optimized calibration datasets. These are then fed back to the testbench environment in an optimization loop. Despite the possibility of complete automation of the optimization, supervision by a calibration engineer remains necessary.

The optimization loop is iterated until the system behavior has reached the desired quality. The calibration is then released for validation. The evaluation is conducted based on a comparison with a theoretical optimum, e.g., determined by dynamic programming [41,42], and with validation in a prototype vehicle. In the current state, final approval of the calibration for homologation in accordance with legal requirements can only be obtained by validation in the vehicle [43].

2.2. Testbench Setup and Target Vehicle

In the following, a tailored HiL testbench setup for the virtual calibration of operating strategies for hybrid electric powertrains is described in detail; the setup is illustrated in Figure 5.

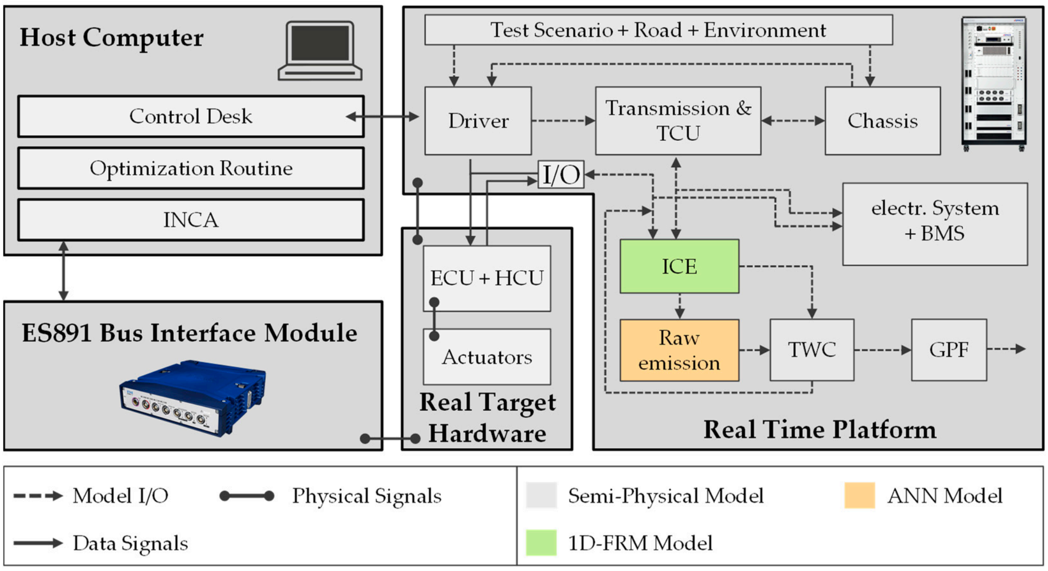

Figure 5. Setup of a hardware-in-the-loop testbench for virtual calibration of hybrid electric vehicles.

The real ECU, with the control functions to be calibrated, forms the core of the testbench with several real actuators from the vehicle. Simulation models replace all components of the vehicle that are not present on the testbench. A wiring harness connects the real ECU to a Scalexio real-time platform (RTP) from dSPACE. All simulation models are executed on this platform. Electrical signals and necessary bus systems are simulated on the I/O boards based on the vehicle simulation and transmitted to the ECU in real time [22]. This allows the ECU to be operated in a virtual environment without error substitution reactions.

Various modeling approaches are used to simulate the overall system. The complete simulation model must guarantee real-time execution on the target hardware due to the testbench setup [44]. A major part of the model environment is based on a semi physical approach. An example of this is the electrical system simulation (electric machine and battery). The simulation is fundamentally based on physical relationships and equations as well as empirical findings.

The internal combustion engine, on the other hand, is modeled by a one-dimensional simulation with GT-Suite from Gamma Technologies. The model is converted into a fast-running model (FRM) for real-time capability and compiled for use in a MATLAB s-function. Similar approaches have been implemented on HiL testbenches [45]. Moreover, an artificial neural network (NN) is used to simulate the raw emissions of the internal combustion engine. This approach was validated by Dorscheidt et al. [46] and evaluated regarding its use for virtual calibration. Real-time emission simulation with alternative simulation approaches has been performed by Picerno et al. [24], among others. All other simulation models and their respective approaches are presented in Figure 5.

The host PC is used to control the simulation model and RTP hardware via dSPACE ControlDesk. The PC also runs INCA from ETAS for communication with the ECU. The ECU is equipped with a FETK interface for calibration and validation purposes, allowing measurement and calibration access to the control unit via an ETAS ES891 bus interface module. The optimization process is also performed on the host PC. Similar setups for virtual calibration of control units are presented by Dorscheidt et al. [17] and Xia et al. [47], among others.

Figure 6 shows the practical implementation of the theoretical structure from Figure 5. Depicted are the real ECU and hardware, the real time platform, the host PC, and the bus interface module. A PHEV vehicle was employed as the testing vehicle, which belongs to EEC Segment J (SUV) and complies with the current EU6d legislation. The electric machine is located on the transmission input shaft (P2 configuration). The V8 gasoline engine with a variable valve train is coupled to the powertrain via a clutch (K0).

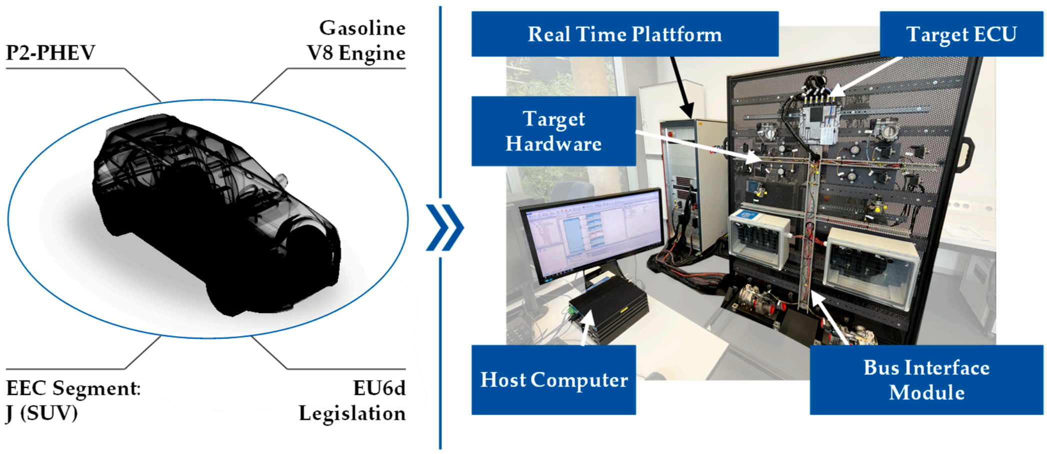

Figure 6. Overview of the experimental vehicle and realized testbench setup.

The capacity of the battery is >20 kWh, while the electric machine has a power output >150 kW. The total system has a combined output of ~600 kW, reaching a maximum torque >900 Nm.

3. Results

Multiple validation steps must be performed successfully before releasing the testbench for virtual calibration (Chapter 2.1). In the following chapter, the first validation step for the described testbench is completed, and the results are presented. The identified simulation models are parametrized to the target vehicle and executed in an open-loop environment. For this purpose, the input variables required by the individual model are taken from real vehicle measurements. The output variables of the simulation model are then compared with the real vehicle measurements. Hence, there is no corrective control of the system behavior, allowing a better evaluation of model deviations from reality.

As described in Chapter 2.1, the requirements for the operating strategy of a hybrid electric vehicle are complex and are influenced by different disciplines. The criteria for fuel consumption, electrical energy consumption, and exhaust emissions are vital for the approval and legally-prescribed battery charge-sustaining exhaust emission tests. In such tests for the European market (EU6d), the so-called net energy change (NEC) criterion [48] must be met, which is expressed as follows:

$$-0.01 \leq \frac{\Delta \mathrm{E}_{\mathrm{REESS}}}{E_{\mathrm{fuel,CS}}} \leq 0.01 \tag{1}$$

$\Delta \mathrm{E}_{\mathrm{REESS}}$: Change in the electrical energy of the rechargeable electrical energy storage system (REESS) in the charge sustaining test
$E_{\mathrm{fuel,CS}}$: Fuel energy consumption in the charge sustaining test

$$\Delta \mathrm{E}_{\mathrm{REESS}} = U_{\mathrm{Nenn}} \cdot \int_0^{t_{\mathrm{end}}} I(t)\, dt \tag{2}$$

U_{Nenn}: Nominal voltage of the high voltage battery
$I(t)$: Electrical current of the battery during the charge sustaining test

$$E_{\mathrm{fuel,CS}} = 10 \cdot HV \cdot FC_{\mathrm{CS,nb}} \cdot d_{\mathrm{CS}} \tag{3}$$

HV: Heating value of the fuel used, for E10 gasoline = 8.640 kWh/l
$FC_{\mathrm{CS,nb}}$: Uncorrected fuel consumption in the charge sustaining test
d_{CS}: Distance driven in the charge sustaining test

From these operating strategy criteria, requirements for the virtual environment, particularly the simulation environment, can be derived. For the application, a high model quality is required regarding the operating points of the individual powertrain components [49]. Since the gaseous emissions of the internal combustion engine must be considered in the optimization, raw emission and exhaust after-treatment system models with sufficient accuracy are required.

The utilized simulation models for the internal combustion engine, electric system components, and raw emissions are described in the following subsections. In addition, the respective results in the first level of validation are presented. The scenarios used for validating each simulation model are summarized in Table 1.

Table 1. Experimental plan for the open-loop validation of simulation models.

Simulation Model	Validation Scenario
One-dimensional combustion engine model	Charge sustaining WLTC driving cycle
Raw emission model	Charge sustaining WLTC driving cycle
Electric propulsion system model	Charge depleting driving cycle Charge increasing road driving cycle

3.1. One-Dimensional Internal Combustion Engine Simulation

The one-dimensional internal combustion engine model uses test results from a world-wide harmonized light vehicles test cycle (WLTC) as input for the investigation. The engine model requires the following inputs and actuator positions of the real system:

- Engine speed in min^{-1}
- Throttle valve position in %
- Turbocharger wastegate position in %
- Variable intake valve position in °CA bTDC (gas exchange)
- Variable exhaust valve position in °CA bTDC (gas exchange)
- Ignition timing in °CA bTDC (firing)

- Injection timing in °CA bTDC (firing)
- Injection duration in °CA

The investigated output variable of the engine model is the torque of the internal combustion engine. The simulation results for a WLTC are shown in Figure 7. The simulated engine torque follows the trace of the vehicle measurement with high quality over the entire driving cycle. This is confirmed by the simulation and measurement results in the scatter plot (Figure 8). The model achieved a coefficient of determination of R^2 = 0.9935. The deviations in the scatter plot occur primarily in highly dynamic phases, for example, during engine start and stop and during the transition to fuel cut-off phases. However, these phases are less relevant than the normal operation due to their low statistical relevance.

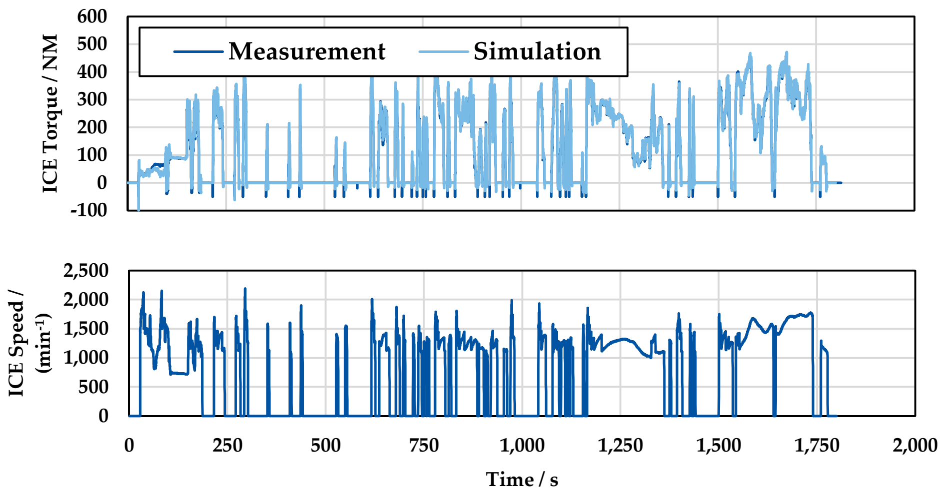

Figure 7. Open-loop simulation results of the one-dimensional FRM engine model in a WLTC.

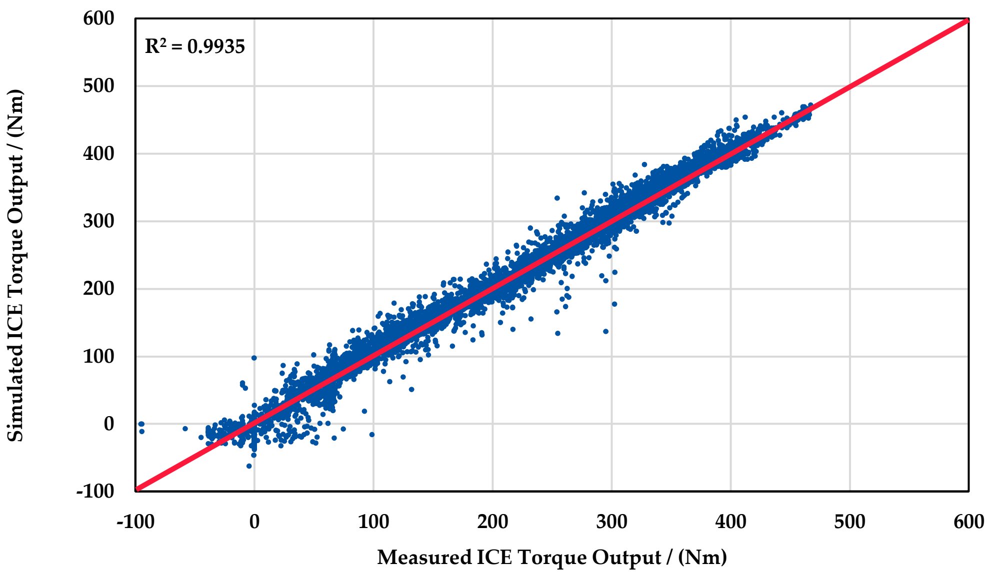

Figure 8. Scatter plot of the simulated versus measured ICE torque in a WLTC.

The most significant deviation is observed shortly after the first engine start at t ≈ 50 s. This results from the retarded ignition timing combined with the specific camshaft phasing during the catalyst heating. These operating points cannot be simulated with an appropriate model quality due to the lack of measurement data in the parameterization of the simulation model.

3.2. Artifical Neural Network for Gasous Emission Simulation

NNs are used to simulate gaseous emissions. The applicability of this approach has been demonstrated by Dorscheidt et al. [46]. The NNs use the following input variables to determine the molar mass fractions of the emission components:

- Engine speed in min^{-1}
- Engine inner torque in Nm
- Variable intake valve position in °CA bTDC (gas exchange)
- Variable exhaust valve position in °CA bTDC (gas exchange)
- Ignition timing in °CA bTDC (firing)
- Variable valve lift position (small lift or large lift)

The molar mass fractions of the individual exhaust components are converted into an emission mass flow using the following equation:

$$\dot{m}_{\mathrm{i}} = \dot{m}_{\mathrm{exh}} \cdot \psi_i \cdot \frac{M_{\mathrm{i}}}{M_{\mathrm{exh}}} \tag{4}$$

$\dot{m}_{\mathrm{i}}$: exhaust mass flow of component i
$\dot{m}_{\mathrm{exh}}$: mass flow of the complete exhaust gas
ψ_{i}: molar mass fraction of exhaust component i
M_{i}: molar mass of exhaust component i
M_{exh}: molar mass of complete exhaust gas

To determine the fuel consumption, the proportionality between fuel consumption and CO_2 emissions can be used, assuming almost complete combustion using the following equation:

$$v_{\mathrm{Kr}} = m_{\mathrm{CO2}} \cdot C_{\mathrm{E10}} \tag{5}$$

v_{Kr}: fuel volume in L
m_{CO2}: mass of CO_2 in kg
C_{E10}: Constant fuel volume per kg CO_2, for E10 $= 0.4349 \frac{\mathrm{L}}{\mathrm{kg\ CO2}}$ [50]

The molecules that are not completely oxidized can be neglected due to their small absolute mass compared to the CO_2 molecules. For this reason, the results of the CO_2 emission simulation are analyzed in more detail below to evaluate the consumption simulation.

Figure 9 shows the cumulative CO_2 mass over a WLTC in charge sustaining operation. It can be seen that CO_2 emissions can be simulated with high accuracy over the cycle. The maximum deviation over the complete cycle is 1.061 g, leading to a relative deviation of 1.465%. At the end of the emission test, the total deviation is 0.017 g, corresponding to a relative deviation of 0.0235%.

Figure 10 shows the simulation results from Figure 9 in a scatter plot. Deviations from the measurement are observed during low load events, resulting in low emission intensity. This typically occurs during engine stop phases, shortly after the injection is deactivated. The NN does not provide information on the current state of the injection; hence, simulation accuracy is lower during these events.

3.3. Semi Physical Electric Motor and Battery Simulation

To validate the simulation models for the high-voltage battery and electric motor, the two sub-models were tested while connected in an open loop. The virtual components were controlled by a model of the battery management system and the inverter. The following input signals to the composite model are required:

- Torque demand of the electric motor provided by the operating strategy in Nm
- Actual speed of the electric motor in min^{-1}

From this, all other output variables are calculated based on physical and empirically determined correlations, including the required battery power and the state of charge (SoC) of the high-voltage (HV) battery.

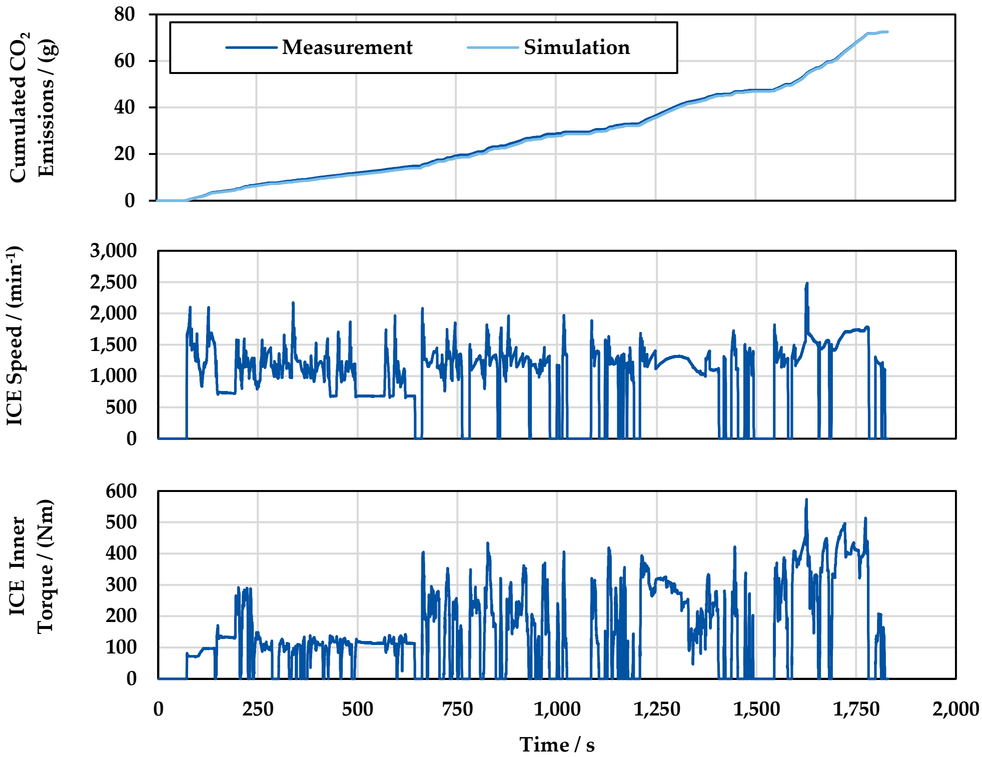

Figure 9. Simulation results of the ANN for the cumulated CO_2-emissions in a WLTC.

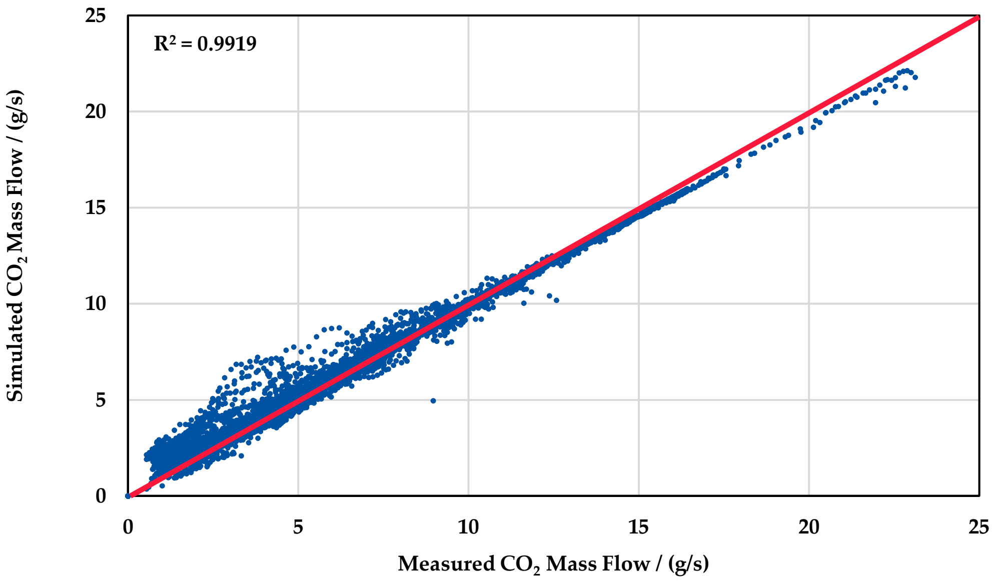

Figure 10. Scatter plot of the simulated versus the measured CO_2 emission in a WLTC.

Here, the simulation results from two different scenarios are evaluated in detail. The first scenario is a depleting emissions test, in which nine cycles are executed in succession, with the HV battery fully charged at the start of the test sequence (Figure 11). As soon as the vehicle has changed from the depleting behavior to the sustaining behavior, the current driving cycle is completed. This cycle is followed by a confirmation cycle in which the vehicle must comply with the charge-sustaining criterion (Equation (1)).

Figure 11 presents the SoC over the entire scenario. The simulation results follow the trend of the vehicle measurements with high quality over the complete 12,000 s scenario. During the investigated scenario, the maximum deviation of the SoC is 1.05%. At the end of the depleting scenario, the SoC deviation of the simulation from the vehicle measurement is 0.59%. The actual battery power, which must be calculated as an intermediate result for the calculation of the SoC, is also presented with high simulation quality. A coefficient of determination of $R^2 = 0.9874$ can be achieved for the battery power.

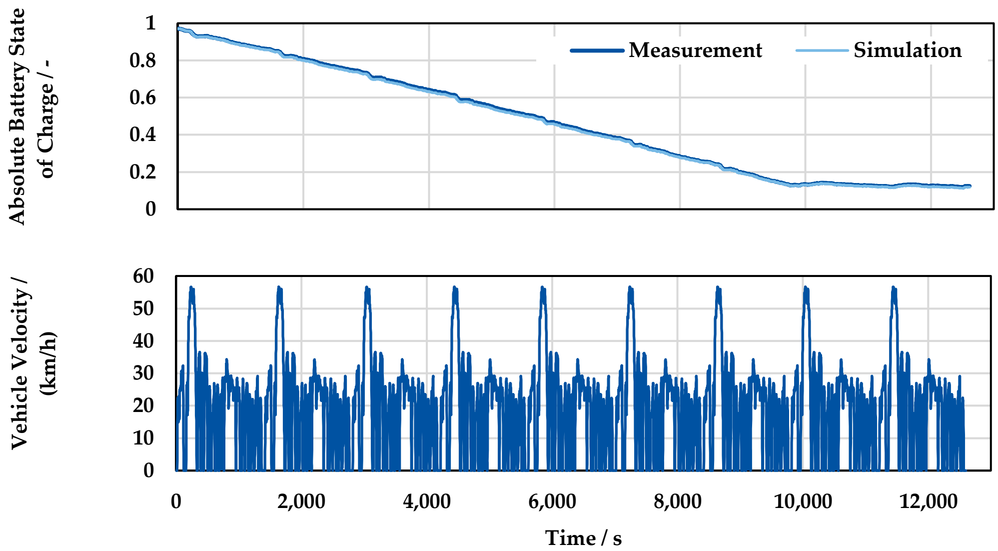

Figure 11. Open-loop simulation result of the electric system compound model in a WLTC depleting test.

The second scenario evaluates the charge-increasing operation. Here, a road measurement was used in which the battery was charged by load point shifting of the internal combustion engine while driving. Figure 12 shows the HV battery SoC and the speed of the electric machine. The SoC of the battery can also be simulated with high quality while the battery is being charged. The maximum deviation of the SoC between simulation and vehicle measurement during the 1400 s long scenario is +0.208%.

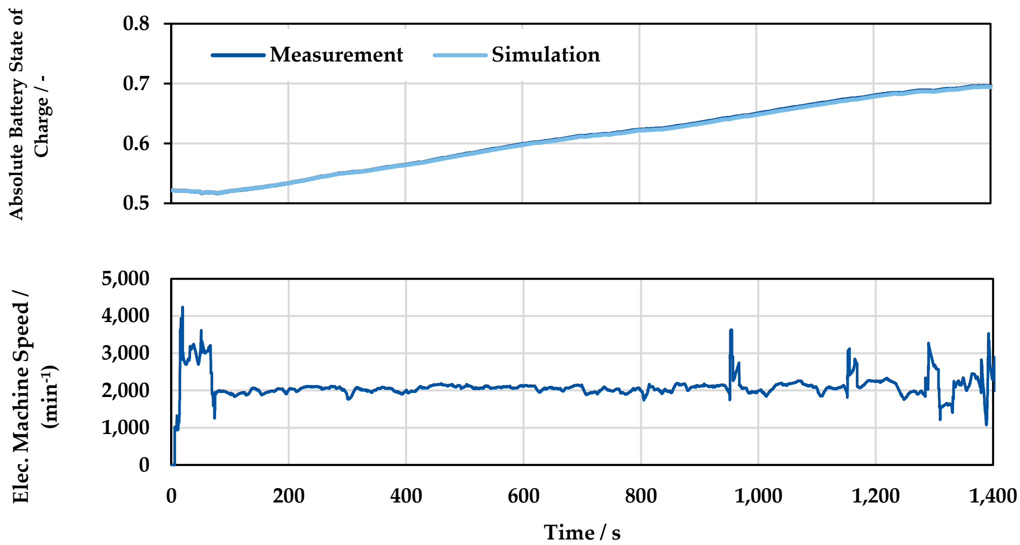

Figure 12. Open-loop simulation result of the electric system compound model in a charge increasing driving cycle.

In Figure 13, the simulation results for the actual battery power are presented in a scatter plot over the measurement results. The simulation can follow the real measurement even in a wide-load range. The coefficient of determination of $R^2 = 0.9685$ supports this statement.

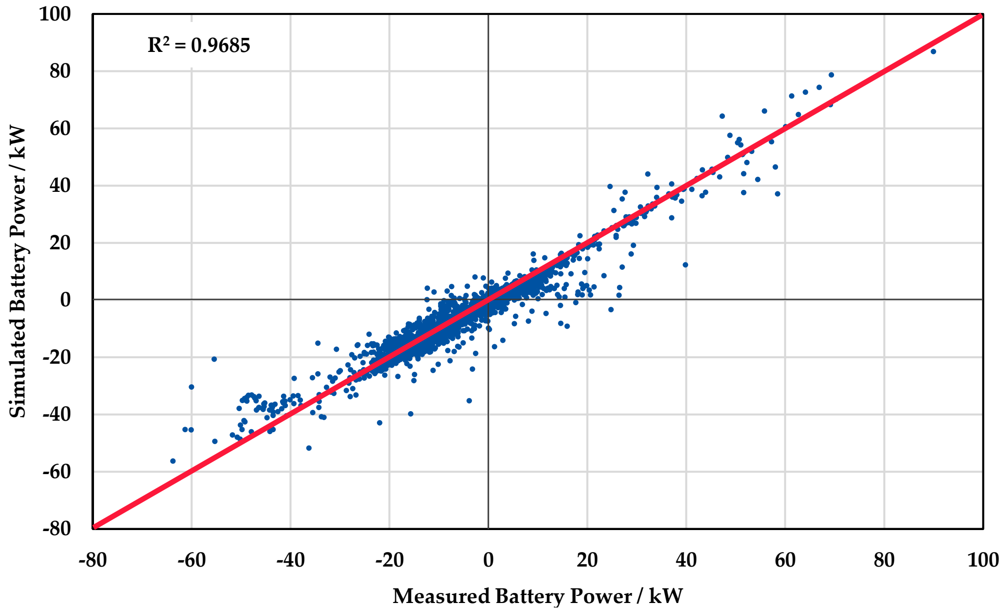

Figure 13. Scatter plot of the simulated versus the measured battery power in a charge increasing driving cycle.

Overall, the results show promising behavior regarding the simulation accuracy of the internal combustion engine, the electrical system, and the gaseous raw exhaust gas emissions. The described models must be combined in a complete system model, which can be used to assess the usability of XiL testbenches for the virtual calibration of a hybrid operating strategy. Moreover, the extent to which the system model represents the system response to calibration changes must be determined.

4. Discussion and Conclusions

Given that the results of the first validation step in an open-loop environment have shown promising behavior, the individual simulation models are integrated into a complete vehicle model for the purpose of integration into an HiL testbench. Subsequently, the HiL testbench is investigated in a closed loop to determine the simulation accuracy of the compound system (Chapter 2.1).

The advantages of the described methodology and testbench setup for the proposed use case are diverse. Figure 14 illustrates these advantages using the chronological progression of the development process. By employing virtualization methods, such as the virtual calibration on HiL testbenches, development tasks can be started earlier in the development process (frontloading). This increases the maturity of the ECU calibration at an early stage. Furthermore, extensive time is saved for vehicle preconditioning, which is required for chassis dynamometer tests.

Overall, the available development time is used more efficiently, leading to an increased calibration quality and reduced total development time. The necessary capacity of prototype vehicles and test facilities (e.g., chassis dynamometers) can also be reduced and substituted by HiL testbenches. However, the final validation of the virtually-developed calibration for the target system cannot be entirely avoided.

However, not all calibration disciplines are equally suited for virtualization. In many cases, the measurement data required to generate and parameterize the simulation models overlap considerably with those required for calibration. Thus, no added value can be generated by virtualization. Examples include the complex physical processes of forming fuel wall film during a cold engine start and particulate formation and filtration through particulate filters. However, alternative virtualization methods can be used, as described by Dorscheidt et al. [51]. Since physical effects that are complex to simulate cannot be implemented in the virtual environment, robustness measurements with vehicles on the road are required for all boundary conditions.

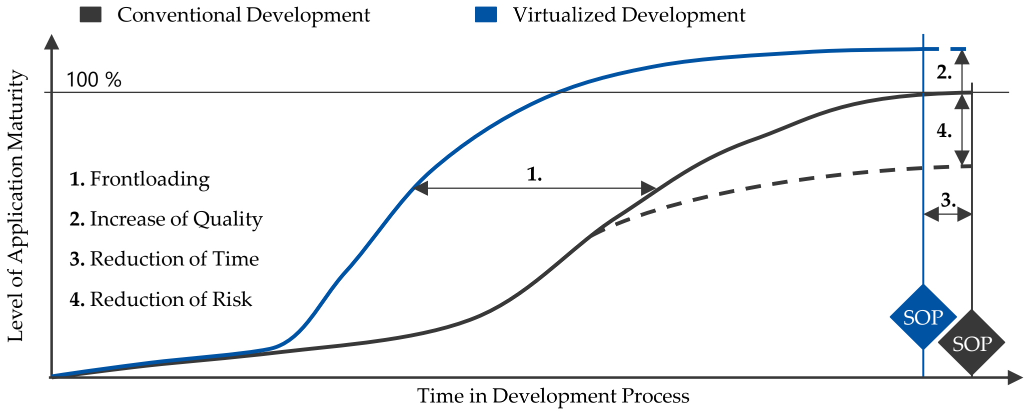

Figure 14. Potentials of virtualized development, such as virtual calibration, in the development process.

The use of virtual testbenches involves added costs, particularly for hardware, software, and testbench commissioning. However, the cost advantage of virtual testbenches over conventional approaches increases when they are used for calibration and testing of several disciplines [17,52]. A cost reduction estimation for a virtual calibration in the development of the test vehicle described in Chapter 2.2 is shown in Figure 15. By using a HiL testbench, cost-intensive exhaust gas emission tests on a chassis dynamometer and preparatory measures can be avoided, realizing a cost reduction of up to 25%.

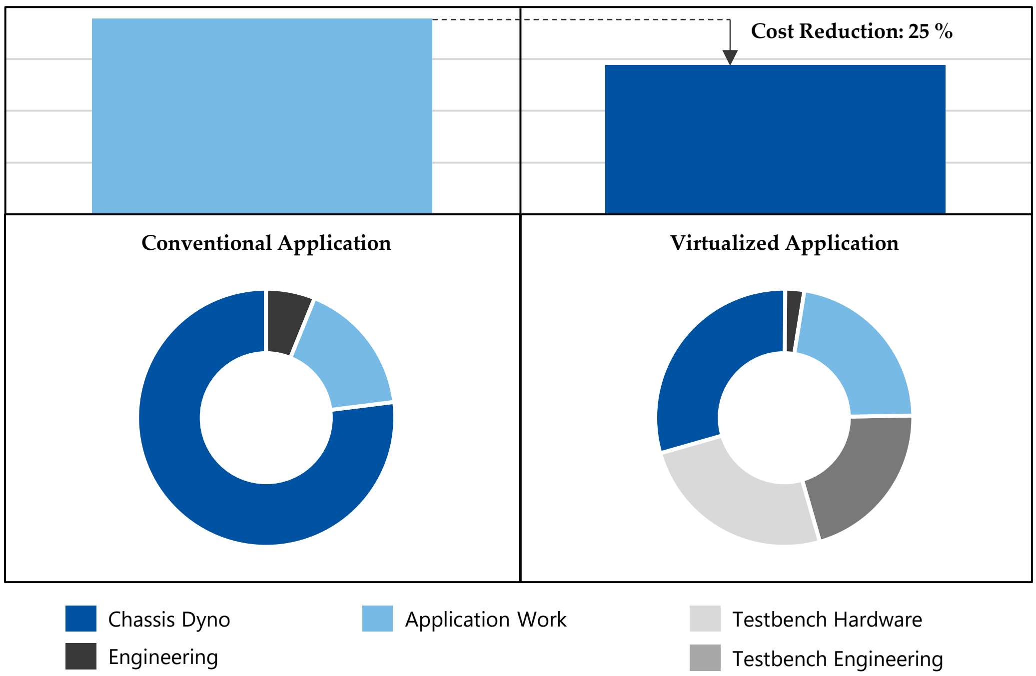

Figure 15. Development cost distribution for conventional and virtualized calibration.

5. Summary

With the tightening of global standards for CO_2 pollutant emissions, the electrification of conventional powertrains is advancing. Accordingly, vehicle and powertrain complexity continues to increase. Moreover, the accelerating pace of technological progress is steadily shortening the time-to-market. These trends motivate the application of more efficient and robust methods in the development process, particularly in the calibration of hybrid electric powertrains.

This paper presents a method for the virtual calibration of operating strategies for hybrid-electric powertrains. It includes a multi-criterial approach to incorporate requirements from different calibration disciplines into a holistic optimization. A hardware-in-the-loop testbench setup with a hardware and simulation environment tailored to the use case of virtual calibration is also presented.

For the first validation level, subcomponent models are identified and parametrized. The validation of this step is performed in an open-loop simulation using real-world measurements as input:

- The one-dimensional internal combustion engine model is assessed in a charge-sustaining WLTC driving cycle. The simulated engine torque follows the measurement over the complete driving cycle and reaches a coefficient of determination of $R^2 = 0.9935$.
- Representative for the raw emission neural network, the CO_2 emission results are taken. The model is again tested in a charge sustaining WLTC driving cycle. The cumulated CO_2 mass over the test and the continuous emissions are simulated with high accuracy. At the end of the scenario, the total deviation is 0.017 g, corresponding to a relative deviation of 0.0235%.
- The electrical system simulation is evaluated as a compound model combining the electrical machine, high-voltage battery, and the respective controllers. The compound model is assessed in a charge-depleting WLTC driving cycle and a charge-increasing driving cycle on the road. The differences between simulation and measurements are <1.0% in both scenarios.

Due to these promising simulation results, the presented model can be released for integration into the closed-loop environment. The potential of a virtualized calibration method has been demonstrated, and an estimation of the cost and time savings of a virtualized method compared to a conventional approach has been presented. A cost reduction of ~25% is achievable in the use case presented.

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