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APPLIED RESEARCH

Optimization of Fuel Consumption for Rule-Based Energy Management Strategies of Hybrid Electric Vehicles: SOC Compensation Methods

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ABSTRACT To optimize the fuel consumption of hybrid electric vehicles (HEV) controlled by rule-based energy management strategies (EMS), multiple driving cycles are simulated. These driving cycles are simulated with different EMS calibrations and the optimizer compares the corresponding fuel consumptions. A drive cycle simulation usually ends with a different end state of charge (SOC) compared to the start SOC. Such an unbalanced SOC for the secondary energy source (battery) affects the consumption of the primary energy source (fuel). Therefore, it is crucial to consider the battery SOC difference when comparing fuel consumption in a drive cycle. In this paper, six different methods are presented to compensate the SOC difference or to achieve a balanced SOC, such as *Multiple Sequential Drive Cycle Simulation*, *Variation of Start SOC*, *Linear Regression*, *Static Correction Factor*, *Individual Correction Factor* and *Linear Interpolation*. These methods are compared in their applicability within a numerical optimization and, for a subset, also in their accuracy in SOC compensation using an exemplary hybrid electric vehicle model. It was determined, that *Linear Interpolation* requires twice as much computing time as either *Static* or *Individual Correction Factor*, but it is the most accurate method. In addition, it supports robust EMS behavior without strongly restricting the boundary conditions within the optimization.

INDEX TERMS Fuel consumption optimization, state of charge (SOC) compensation, energy management strategy (EMS), hybrid electric vehicle (HEV).

I. INTRODUCTION

So-called *alternative propulsion systems* have become increasingly important in recent years. Hybrid vehicles are part of this group, consisting of at least two different energy storage and conversion devices [1]. Hybrid electric vehicles (HEV) are typically a combination of an internal combustion engine (ICE) and one or more electric motors (EM). This freedom raises the question of which energy converter should be used for propulsion. A number of energy management strategies (EMS) exist for this decision-making process [2], [3], [4].

A. EMS OPTIMIZATION

Many researchers have applied various types of strategies to HEVs to optimize the fuel consumption of these vehicles [5], [6], [7], [8], [9], [10], [11], [12], [13], [14]. In addition, component sizing, emissions or total cost are considered for optimization [15], [16], [17], [18], [19].

Besides the increasing complexity due to multicriteria optimization, there is the challenge (for causal EMS) to determine a fuel consumption value of a drive cycle simulation that can be used within a numerical optimization. Even in a single objective optimization, it is not advisable to purely use the resulting fuel consumption (without SOC compensation) as an objective function value. Due to the second energy storage device of HEVs, the state of charge (SOC) of this additional device should be considered to make the fuel consumption of differently calibrated EMSs comparable. Figure 1 shows that the end SOC of a drive cycle simulation is not only dependent on the start SOC, but that the calibration of the EMS itself is of significant importance. Therefore, the fuel consumption of these two EMS calibrations is not comparable due to different end SOCs compared to the start SOC. However, for fuel consumption optimization of rule-based EMS, it is crucial

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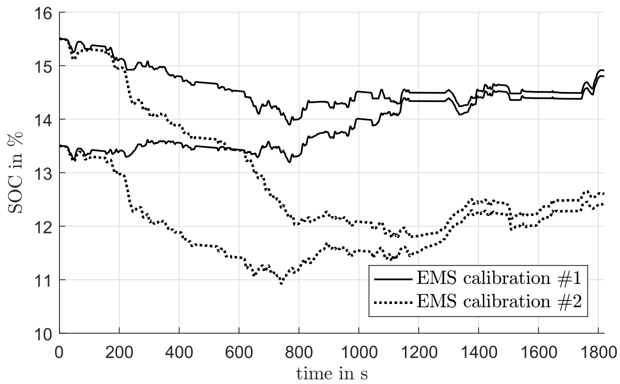

FIGURE 1. SOC trajectories of two EMS calibration variants for the same vehicle within the same driving cycle and two different start SOCs.

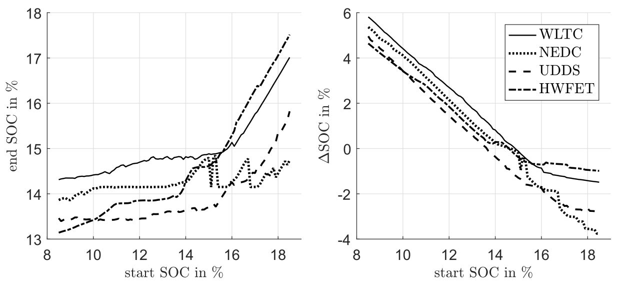

FIGURE 2. Behavior of end SOC versus start SOC for different drive cycles and same EMS calibration. ***Left:*** end SOC based on start SOC ***Right:*** ΔSOC based on start SOC.

to have comparable fuel consumption between drive cycle simulations to select the best EMS calibration.

B. HEV SOC CHARACTERISTICS AND EMS OPERATING MODES

The change in SOC between the start and end of a drive cycle depends on several factors, including the calibration of the EMS, the type of drive cycle and the start SOC of the drive cycle. Figure 2 left and right shows how the end SOC of an exemplary plug-in HEV behaves based on different start SOCs and drive cycles with an identically calibrated EMS. ΔSOC is the difference between end SOC and start SOC. Driving cycles considered are the well-known Worldwide Harmonized Light Vehicles Test Cycle (WLTC), New European Drive Cycle (NEDC), Urban Dynamometer Driving Schedule (UDDS) and Highway Fuel Economy Test (HWFET). The corresponding speed profiles are visualized in Figure 15 in the Appendix. Plug-in HEVs can operate in charge sustaining (CS) mode, where the SOC may fluctuate, but the intention of the EMS is to maintain the current SOC on average (for very low SOCs the battery is charged towards the CS target SOC value). Or in charge depleting (CD) mode, where the intention of the EMS is to deplete the SOC from a higher level down to the CS target SOC value [20]. In Figure 2 left it can be seen that for starting SOCs higher around 14 % to 15 % a CD strategy is implemented, while for lower SOCs a CS strategy is implemented. It can also be seen that it is difficult to achieve a balanced SOC level while operating in CS mode.

C. SOC COMPENSATION

To achieve a balanced SOC level (end SOC equals start SOC) within an EMS fuel consumption optimization, it is possible to define a boundary condition for the objective function that the $|\Delta\text{SOC}|$ should be less than a certain threshold ε. Therefore, a ΔSOC of $\pm 0.5\,\%$ was accepted in [7], $\pm 1\,\%$ in [21], $\pm 1.5\,\%$ in [22] and $\pm 5\,\%$ in [17]. The disadvantage of this method is that on the one hand, ε should be as small as possible to maximize the comparability of two different drive cycle simulations. On the other hand, ε should be as large as possible to increase the feasible search space and thus the chances for the optimizer to find a calibration that minimizes fuel consumption without being influenced by an arbitrarily selected start SOC within the CS SOC range. A start SOC equal to the CS target SOC is considered as an arbitrary value, because the end SOC also depends on the drive cycle (Figure 2 left) and the EMS calibration itself (Figure 11 left, explained later in Section III-A).

An alternative approach is to compensate the ΔSOC by calculating a corrected fuel consumption. Without further restrictions, the possibility to find an EMS calibration with a lower fuel consumption is increased. In addition, the optimization process is simplified, because no ε has to be chosen. Therefore, this paper focuses on methods without the use of ε in the optimization constraints.

D. HEV TOPOLOGIES AND MODEL USED

Hybrid vehicles can be categorized in several ways. A rough classification is often made by the degree of hybridization and a finer distinction is made by the topology of the powertrain [2], [23], [24]. The powertrain topology describes the arrangement of the ICE, EM, battery and gearbox, as well as their interaction and connection to the drive wheels. These components are usually mechanically or electrically coupled (Figure 3). A common classification of parallel hybrids is based on the position of the electric motor in the drivetrain. Figure 4 compares the major types of parallel hybrids.

A complete vehicle simulation model based on MATLAB/Simulink was used for the investigations in this paper. The real EMS of Mercedes-Benz vehicles is part of the model. This EMS is rule-based and consists mainly of load point shift maps and power thresholds for engine start. The powertrain studied is a P2 parallel hybrid (provided formulas refer to this topology), but the methods presented have no limitations for use on other hybrid vehicle topologies.

This paper provides a holistic overview and novel accuracy considerations of SOC compensation methods with a focus on EMS parameter optimization of HEVs. Such battery ΔSOC compensations, resulting from drive cycle simulations, are crucial when comparing corresponding fuel consumptions. Therefore, several SOC compensation methods are presented in Section II and the accuracy of three selected methods is evaluated in Section III. Section IV compares the accuracy of these three methods and Section V provides the conclusion.

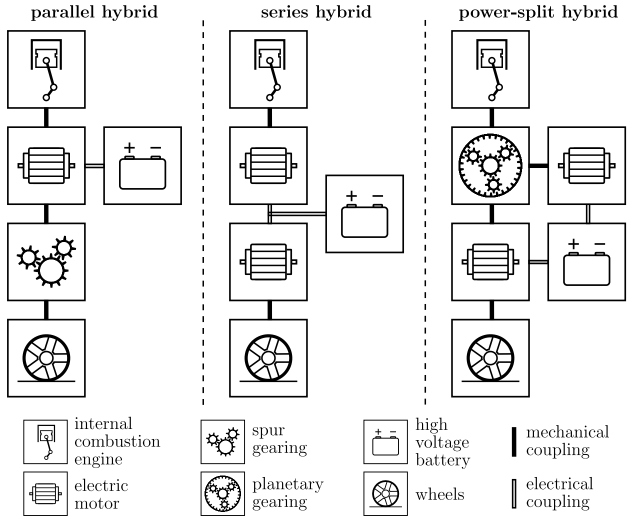

FIGURE 3. **Hybrid vehicle topologies: *Parallel hybrid:* ICE and EM have mechanical access to the wheels. *Series hybrid:* The ICE drives a generator-operated EM. A second motor-operated EM has exclusive access to the wheels. *Power-split hybrid:* One EM is always used as a generator and the other as a motor. The torque of the ICE can only be transmitted to the wheels by the counter torque of the generator.**

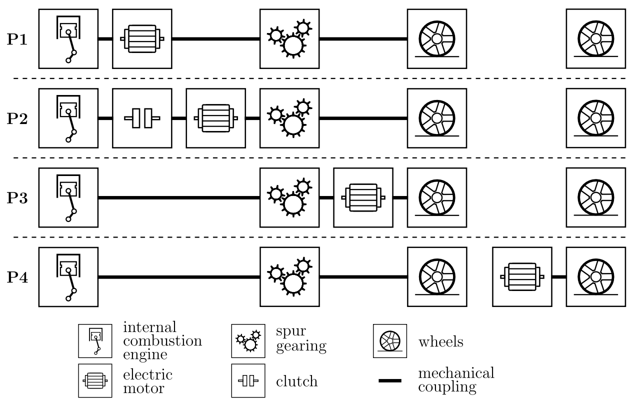

FIGURE 4. **Parallel hybrid topologies: The position of the EM in the powertrain determines the parallel hybrid topology. Gearbox input- or output-side clutches and the high voltage battery are not shown here because they are not relevant for differentiation.**

II. SOC COMPENSATION METHODS

This section describes several methods to make the fuel consumption of different driving cycles comparable. This is achieved either by correcting the fuel consumption based on a ΔSOC or by achieving a balanced SOC without using ε in the optimization constraints.

When a plug-in HEV drives a cycle with an initially full battery (CD mode), the focus is typically on the electric driving experience and the vehicle is operated purely electrically. SOC compensation is required when the vehicle is operated in CS mode.

A. MULTIPLE SEQUENTIAL DRIVE CYCLE SIMULATION

Since all hybrid vehicles must have an EMS that prevents deep discharge of the high voltage battery (due to component protection), this automatically results in a certain SOC range within which the state of charge moves up and down during a drive cycle. This applies to both: a full battery (in which

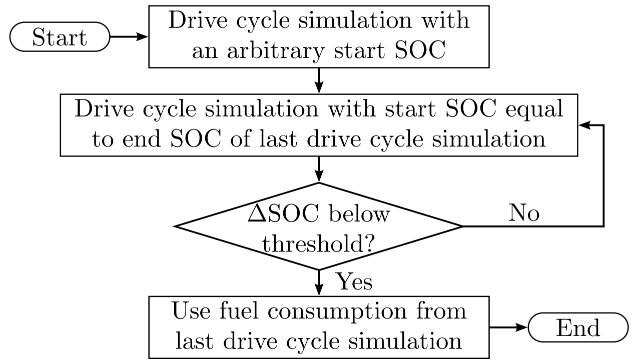

FIGURE 5. **Flowchart for *Multiple Sequential Drive Cycle Simulation* method.**

case the battery is first severely discharged until the CS mode begins) and an extremely discharged battery (which is then severely charged). Thus, a drive cycle only needs to be run often enough (with the start SOC always equal to the end SOC of the previous cycle) to result in an approximately balanced SOC [25]. Once the SOC is balanced over a drive cycle, the sequence can be terminated and the fuel consumption from that drive cycle can be used Figure 5. This procedure is very simple, but requires an indefinite number of drive cycle simulations, making it impossible to estimate the required computation time. In [26], as a compromise, the drive cycle is repeated until $\Delta\text{SOC} \leq 0.35\,\%$ is reached, and then a static correction factor is applied.

Apart from compromise solutions, the fundamental difficulty of this procedure is to define a ΔSOC threshold (similar like ε, but not as limiting constraint) for stopping the multiple driving cycle simulation. If the threshold is too high, the comparability of the determined fuel consumption suffers. If the threshold is too low, it cannot be guaranteed that the criterion will be reached in a finite time, because in principle a continuous oscillation (alternating start SOCs around the CS target SOC) can also occur. Furthermore, parameter constellations can be simulated during the optimization, which show an undesired behavior of the EMS (e.g., no control towards the CS target SOC, therefore never a balanced SOC).

So far, there is no reproducible method (except compromise solutions) to define this threshold so that a balanced SOC can be achieved with a defined number of drive cycle simulations. Therefore, the multiple drive cycle simulation method is less suitable for optimizing an energy management strategy, but can be well applied to a final calibrated EMS.

B. VARIATION OF START SOC

A balanced SOC can also be achieved by running multiple parallel drive cycle simulations, each with a deliberately different initial SOC (e.g. gridding over a certain range as in Figure 2) [7], [25]. After all drive cycle simulations are completed, the fuel consumption of the simulation run with the smallest ΔSOC is taken (Figure 6).

This method is more targeted than the Multiple Sequential Drive Cycle Simulation, but it also requires a large number of

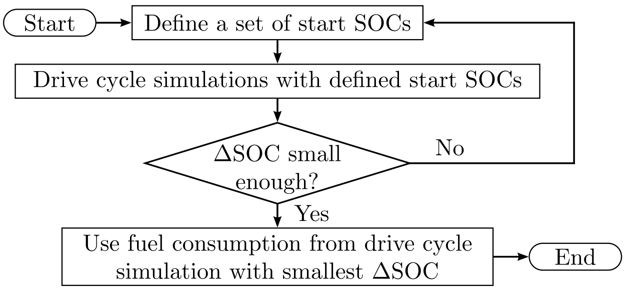

FIGURE 6. **Flowchart for *Variation of Start SOC* method.**

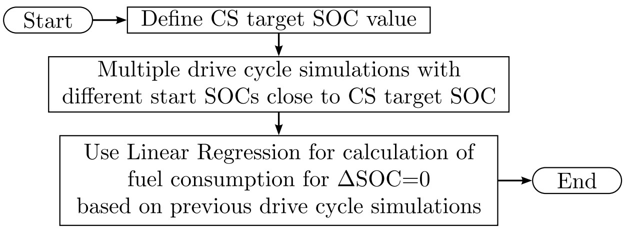

FIGURE 7. **Flowchart for *Linear Regression* method.**

simulations to obtain an exactly balanced SOC. Specifying a certain number of iteration steps (as few as possible) does not guarantee that the ΔSOC will be small enough. For this reason, this procedure is also not favorable in a numerical optimization, but it is useful to find the optimal start SOC (which perfectly balances the SOC for a specific driving cycle) for a final calibrated EMS. Since the SOC could be perfectly balanced with this procedure, it is possible to determine the real fuel consumption without error from any correction algorithm.

C. LINEAR REGRESSION

After simulating several drive cycles with different start SOCs that are close to the CS target SOC (and therefore with high probability for small ΔSOC values), Linear Regression can be used to calculate fuel consumption for a balanced SOC [27], Figure 7.

This procedure is also used for vehicle measurements according to the Worldwide harmonized Light vehicles Test Procedure (WLTP) specifications, where three to five measurements are required before Linear Regression can be used [20]. This procedure allows comparability between different calibrations or vehicle variants, but still requires multiple simulation runs, which increases computation time.

D. LINEAR INTERPOLATION

The Linear Interpolation method differs from Linear Regression in that exactly two drive cycle simulations are performed. One with an initial SOC high enough to produce a negative ΔSOC and one with an initial SOC low enough to produce a positive ΔSOC [25]. Using these two points, the fuel consumption for $\Delta\text{SOC} = 0\,\%$ can then be calculated by Linear Interpolation (Figure 8). Since there are no measurement errors in the simulation compared to real measurements, no averaging is necessary and the number of

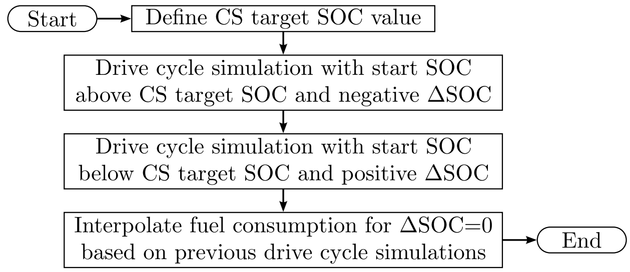

FIGURE 8. **Flowchart for *Linear Interpolation* method.**

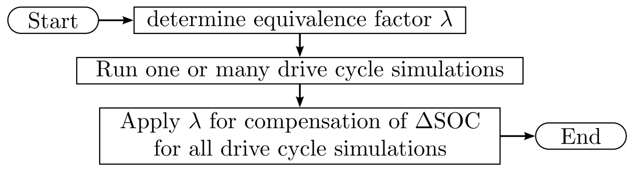

FIGURE 9. **Flowchart for *Static Correction Factor* method.**

drive cycle simulations can be reduced to two. This reduction in computation time for the objective function is the reason why this method is listed here, even though it is only a subset of Linear Regression. However, Linear Interpolation assumes that the fuel consumption of the vehicle is truly linear within the two ΔSOC support points. If this is the case, then this procedure allows a high accuracy of the corrected fuel consumption with only twice the computation time for the objective function value.

E. STATIC CORRECTION FACTOR

A common approach for correcting the fuel consumption V_{fuel} is to use an a priori determined correction factor λ to convert the ΔSOC of the battery to an equivalent amount of fuel (Figure 9)

$$V_{\text{cor}} = V_{\text{fuel}} - \lambda \cdot \Delta\text{SOC}. \tag{1}$$

This correction factor can be based on empirical values or calculated using specific component properties such as fuel density and conversion efficiencies [13], [21], [26], [28]. This method requires the least amount of computation during optimization because a single drive cycle simulation is sufficient to calculate the corrected fuel consumption based on the ΔSOC. It also assumes linear behavior without knowing up to what SOC difference linear behavior exists. It is tolerated that the correctness of the correction factor used is affected by parameter changes within the EMS.

F. INDIVIDUAL CORRECTION FACTOR

Compared to the Static Correction Factor method, an Individual Correction Factor is calculated for each simulation run by analyzing each drive cycle simulation (efficiency considerations) without using prior knowledge or specific analyses in advance [29], Figure 10.

The claim is an increased accuracy of the fuel correction compared to the Static Correction Factor method, because the influence of the respective EMS calibration is taken into account, as well as a low optimization time, because (as

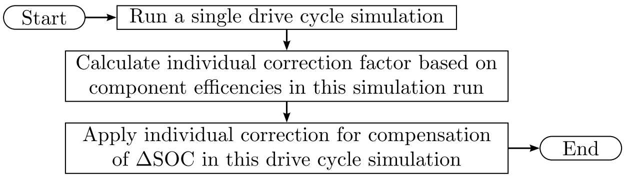

FIGURE 10. Flowchart for *Individual Correction Factor* method.

TABLE 1. Overview of SOC compensation methods. Evaluated is the computation time or whether a result is available in a given time as well as the accuracy that can be expected with the method. Used symbols: + + /+ ...(very) beneficial, ∘ ...neutral, – –/– ...(very) detrimental.

	computation time / determinism	accuracy
Multiple Sequential Drive Cycle Simulation	– –	∘
Variation of Start SOC	– –	++
Linear Regression	–	+
Linear Interpolation	+	+
Static Correction Factor	++	–
Individ. Correction Factor	++	∘

with the Static Correction Factor) only a single drive cycle has to be performed to calculate the respective correction factor. This approach offers the possibility to model nonlinear behavior, but the question remains whether this procedure is generally applicable or whether there are conditions that reduce the accuracy.

G. SUMMARY

The most important advantages and disadvantages of the above mentioned methods are summarized in Table 1. The *computation time / determinism* criterion evaluates how many drive cycle simulations are required to achieve a balanced SOC or to correct the fuel consumption. The *accuracy* describes the degree of accuracy that can be achieved for the fuel consumption correction, taking into account the findings of the following sections. Variation of Start SOC is the method with the highest probability of achieving a perfectly balanced SOC and thus complete accuracy (at least in theory), so it is given the highest rating.

For numerical optimization (especially for large complex vehicle models) it is crucial to have a low and deterministic computation time. The methods Variation of Start SOC and Multiple Sequential Drive Cycle Simulation get the worst rating in this category, because much more than two simulation runs are needed or the termination criterion may never be met. Therefore, these algorithms are discussed only theoretically, without detailed accuracy analysis.

The calculation of the corrected fuel consumption for Linear Regression and Linear Interpolation is very similar. The main difference is the higher number of drive cycle simulations for Linear Regression, which is beneficial for real vehicle testing with measurement error. For numerical optimization, the Linear Regression method has no benefits if there is linearity in fuel consumption versus ΔSOC, which is the case for the vehicle model used. Thus, Linear Regression is not considered further.

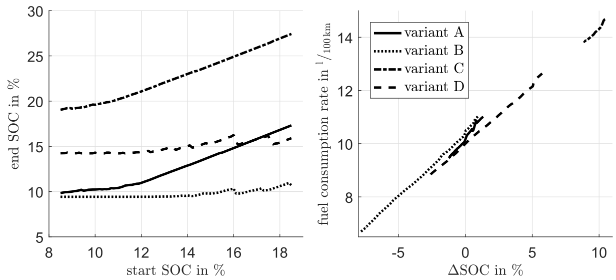

FIGURE 11. SOC behavior and fuel consumption rate for four very different EMS calibrations (Table 2) for the same vehicle within a WLTC drive cycle simulation. *Left:* end SOC based on start SOC *Right:* fuel consumption rate based on ΔSOC.

Linear Interpolation, Static Correction Factor, and Individual Correction Factor appear to be the most favorable within a numerical parameter optimization. This is because drive cycle simulations usually have high computational requirements and these methods allow the shortest simulation time. Therefore, these methods are discussed in more detail in the following sections.

III. ACCURACY OF SELECTED METHODS

After providing an overview of different fuel consumption compensation methods in Section II, this section discusses in more detail three of them that are appropriate for determining objective function values in EMS parameter optimizations. The focus is not on the accuracy of the modeled fuel consumption, but on the pure error of the objective function for the fuel consumption correction. The analysis was performed using a MATLAB/Simulink implementation of a P2 plug-in HEV simulation model, but the methods are applicable to other HEV models as well.

A. ACCURACY OF STATIC CORRECTION FACTOR

Probably the most commonly used method of compensating for a ΔSOC is to convert the ΔSOC to an equivalent amount of fuel via a constant value (the equivalence factor). This equivalent amount of fuel is then added/subtracted from the fuel consumed by the ICE, resulting in a corrected fuel consumption. However, the question is how to determine this factor and in what range (small signal vs. large signal behavior) can this factor be used with sufficient accuracy? Therefore, a maximum allowable ΔSOC was defined in [26], up to which the equivalence factor is used. In addition, a specific equivalence factor for the NEDC and FTP-72, i.e. the driving cycles used, was determined by several tests.

Figure 11 shows the end SOC over the start SOC (on the left) and the fuel consumption rate over the ΔSOC (on the right) for four exemplary and very different EMS calibrations. In each case, a WLTC was simulated. It can be seen that despite identical start SOCs, the respective calibrations lead to very different end SOCs. Despite these large deviations, the fuel consumption rate over the ΔSOC shows an approximately linear behavior. If a static equivalence factor were generally applicable for consumption correction, the gradient of these linear curves should be identical.

TABLE 2. Overview of the combinatorics of the simulated EMS calibrations and the resulting equivalence factor λ (gradient in Figure 11 on the right). High *load point increase* means faster battery charging due to higher electric motor generative torque. High *engine start power* means that a high power demand from the driver is required to start the engine.

variant	load point increase	engine start power	λ in l/100 km/%
A	low	low	≈ 0.61
B	low	high	≈ 0.50
C	high	low	≈ 0.56
D	high	high	≈ 0.46

A rough description of the EMS calibration variants from Figure 11 and their corresponding equivalence factors is given in Table 2. The factors determined here show a difference of up to 0.15 l/100 km/%, which results in a fuel difference of up to 0.15 l/100 km for a ΔSOC of 1 % for the vehicle model used here. With an uncorrected fuel consumption rate of 10 l/100 km, this results in an error in the corrected fuel consumption rate of up to approximately 1.5 %. Since improvements in fuel consumption rate of 1 % or 0.1 l/100 km are already significant, the use of a general static correction factor seems to be imprecise.

Since the calibration variants listed above were chosen arbitrarily, larger or smaller errors in the equivalence factor are in principle possible for other parameter combinations. Furthermore, the Table 2 shows mean values, although a closer look at the Figure 11 shows that there are indeed deviations from linear behavior in the small signal behavior. Among the four variants, only variant D shows behavior similar to the EMS reference calibration in that an end SOC close to the CS target SOC is adjusted independently of the start SOC. Interestingly, the linear behavior of variant D (fuel consumption rate over ΔSOC) is particularly pronounced. This may indicate that this method leads to better results when the undesired behavior of the EMS (variants A, B and C) is directly discarded via constraints during the optimization process.

Ultimately, the challenge of this method is to find the most appropriate equivalence factor, which means that the actual problem (optimizing the EMS parameters) is burdened with this additional development task for each new vehicle variant.

B. ACCURACY OF INDIVIDUAL CORRECTION FACTOR

In the previous section, a static constant value was used for the consumption correction, even if the calibration of the EMS has changed. Since inaccuracies have been shown in this method, an advanced approach to reduce these inaccuracies is determining a correction factor that is based on the individual operation of the vehicle and does not require any further prior knowledge. For this purpose, the energy flow of the fuel from the tank into the battery is considered in this section. The delta amount of battery energy is recalculated into a corresponding amount of fuel based on the physical conversion processes during a drive cycle simulation. Therefore, only data that can be collected during the drive cycle simulation or that has been stored in the simulation model as characteristic component properties are used.

The corrected fuel consumption V_{cor} is calculated by subtracting the equivalent amount of fuel ΔV_{fuel} from the real fuel consumption V_{fuel} determined directly in the driving cycle simulation

$$V_{\text{cor}} = V_{\text{fuel}} - \Delta V_{\text{fuel}}. \tag{2}$$

The equivalent fuel quantity is obtained from the chemical energy content of the fuel E_{fuel}, the density of the fuel ρ_{fuel} and its lower heating value $H_{\text{l,fuel}}$ [30]

$$\Delta V_{\text{fuel}} = \frac{\Delta E_{\text{fuel}}}{\rho_{\text{fuel}} \cdot H_{\text{l,fuel}}}. \tag{3}$$

Using the ICE efficiency η_{ICE}, the clutch efficiency η_{Cl}, the EM efficiency η_{EM}, the high voltage (HV) system efficiency η_{HV} and the battery efficiency η_{Bat}, the equivalent fuel can be traced back to a battery energy quantity ΔE_{Bat}

$$\Delta V_{\text{fuel}} = \frac{\Delta E_{\text{Bat}}}{\rho_{\text{fuel}} \cdot H_{\text{l,fuel}} \cdot \overline{\eta}_{\text{ICE}} \cdot \overline{\eta}_{\text{Cl}} \cdot \overline{\eta}_{\text{EM}} \cdot \overline{\eta}_{\text{HV}} \cdot \overline{\eta}_{\text{Bat}}}. \tag{4}$$

In (4), average efficiencies were considered because the average component efficiency correlates to the corresponding fuel consumption or ΔSOC in the battery within a drive cycle simulation. The efficiency calculation is generally based on the quotient of the extracted power divided by the supplied power respectively the extracted energies divided by the supplied energy quantity per component during a drive cycle simulation [31]. In the case of ICE, mechanical and chemical energy are considered, and in the case of EM, mechanical and electrical energy are considered. The clutch converts mechanical energy to mechanical energy, but is also be set to 1 if this component is not available. The efficiency of the HV system allows to take into account the transmission losses between the electric motor and the battery, if they are modeled. Finally, the battery converts electrical energy to chemical energy. For this calculation, the terminal voltage of the battery can be set in relation to the open circuit voltage (OCV), which is SOC dependent. Further details on the component efficiency calculation are given in the Appendix.

The change in battery energy is given by

$$\Delta E_{\text{Bat}} = C_{\text{Bat}} \int_{\xi_{\text{start}}}^{\xi_{\text{end}}} U_{\text{OCV}}(\xi) \mathrm{d}\xi \,, \tag{5}$$

i.e., the surface area under the OCV curve in the range from the start SOC ξ_{start} to the end SOC ξ_{end} multiplied by the battery capacity C_{Bat}.

To evaluate the accuracy of the above formulas, a graphical analysis is performed (as was done for the Static Correction Factor method). The main element of this evaluation is the plot of the corrected fuel consumption rate versus the ΔSOC. Since the fuel correction is intended to compensate for the influence of the ΔSOC on the fuel consumption rate, it is expected that an approximately horizontal line will be visible in the graphical representation, at least for small ΔSOC.

Figure 12 on the left shows the real (uncorrected) fuel consumption of the ICE. Once again we see the largely linear curve of the fuel consumption rate over the ΔSOC,

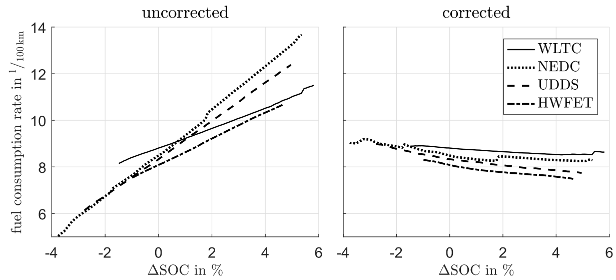

FIGURE 12. **Fuel consumption rate over ΔSOC for four different driving cycles. *Left:* The uncorrected fuel consumption rate of the ICE. *Right:* The fuel consumption rate of the ICE corrected by ΔSOC using the Individual Correction Factor.**

but with different gradients for each driving cycle. The right graph shows the fuel consumption rate corrected by the individual factor. Basically, you can see a clear flattening of the curves, which is the desired effect. However, a closer look shows that this expectation is not fully met. The desired horizontal curve around $\Delta SOC = 0\,\%$ is not visible. For the WLTC, $\Delta SOC = 1\,\%$ results in a corrected fuel consumption of $8.842\,\mathrm{l/100\,km}$, which is $0.09\,\mathrm{l/100\,km}$ less than the fuel consumption rate with a balanced SOC. Related to $8.932\,\mathrm{l/100\,km}$ at $\Delta SOC = 0\,\%$ there is an error of about $1\,\%$. This means that the calculation of the individual correction factor also has some inaccuracies.

C. ACCURACY OF LINEAR INTERPOLATION

The Static and Individual Correction Factor methods determine a corrected fuel consumption based on a single drive cycle simulation run. For the fuel consumption correction by Linear Interpolation, the same drive cycle is simulated twice with identical EMS calibration, only the start SOC is chosen differently, so that once a positive energy difference occurs and once a negative energy difference occurs within the battery. An interpolation of the fuel consumption for $\Delta SOC = 0\,\%$ is then performed over these two fuel consumption respectively ΔSOC support points.

Figure 13 in the upper left shows the resulting ΔSOC as a function of the start SOC when simulating the WLTC with the EMS reference calibration. With a start SOC just below $15\,\%$, there is a balanced SOC such that the uncorrected fuel consumption rate of approx. $8.81\,\mathrm{l/100\,km}$ is identical to the corrected fuel consumption rate. Starting with a SOC higher than approx. $15\,\%$ will result in a negative ΔSOC (B) and starting with a lower SOC will result in a positive ΔSOC (A). A pair of negative and positive ΔSOC values is needed to perform an interpolation. The possible value pairs are shown in Figure 13 in the upper right corner. In addition to the allowed value pairs, the distance in %-points SOC between the two interpolation support points is also shown. When the corrected fuel consumption is interpolated for different start SOC value pairs, subtracting the fuel consumption rate for a balanced SOC of $8.81\,\mathrm{l/100\,km}$ gives the absolute error as shown in Figure 13 on the lower left and the relative error on the lower right. It can be seen that for the majority of possible start SOC combinations the relative error is below $0.2\,\%$.

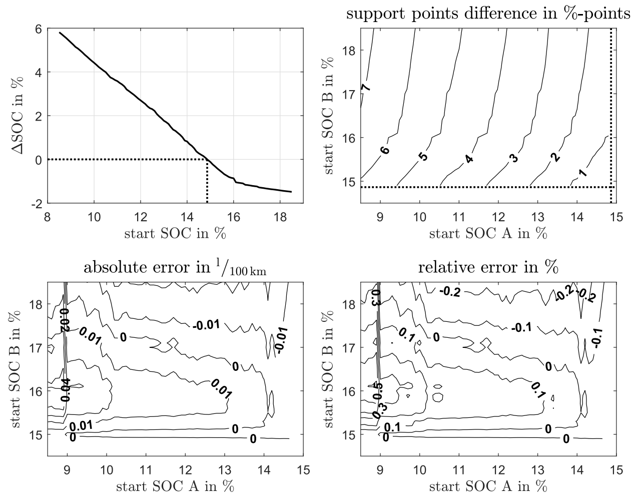

FIGURE 13. **Error values when using fuel consumption rate compensation by Linear Interpolation and simulation of WLTC. *Top Left:* Resulting ΔSOC depending on start SOC *Top Right:* Visualization of the distance between the support points for the interpolation for the pairs of start SOC values for which an interpolation is possible. For each start SOC (A and B) an end SOC is given by drive cycle simulation. The sum of the corresponding ΔSOC (for A and B) is called the support points difference. *Bottom Left:* Absolute error of Linear Interpolation method related to fuel consumption rate with balanced SOC. *Bottom Right:* Corresponding relative error.**

Only when using start SOCs below $9\,\%$ does the relative error increase abruptly, peaking at about $0.6\,\%$. However, since battery SOCs below $9\,\%$ are already below the minimum allowed SOC for the simulated vehicle, this behavior is not relevant.

1) INTERPOLATION VS. EXTRAPOLATION

The above considerations assume that the corrected fuel consumption is always calculated by interpolation. If any two different ΔSOC value pairs are available, the corrected fuel consumption could in principle also be determined by linear extrapolation. Usually, the estimation error for extrapolation is higher than for interpolation, so interpolation is recommended. To avoid extrapolation, these constraints could be added to the optimization: low start SOCs should have a positive ΔSOC and high start SOCs should have a negative ΔSOC. This ensures the possibility of interpolation by using only weak constraints and additionally supports desired EMS behavior: control to the CS target SOC.

2) CHOICE OF START SOC COMBINATIONS

Now that it is known which start SOC combinations allow high quality interpolation of corrected fuel consumption, the question remains which choice should be made? The following issues should be considered:

- To optimize parameters that depend on the battery SOC, it is generally necessary to cover the widest possible SOC range.
- Above the CS target SOC, electric driving should be used primarily, i.e., for the high start SOC, placement only slightly above the CS target SOC is sufficient. However, the high start SOC should be chosen high

TABLE 3. Resulting equivalence factor λ for different driving cycles based on the gradient in Figure 12 on the left.

drive cycle	λ in l/100 km/%
WLTC	≈ 0.43
NEDC	≈ 0.85
UDDS	≈ 0.81
HWFET	≈ 0.56

enough to result in a negative ΔSOC in all relevant driving cycles.

- The low start SOC should be set as low as possible (within the allowed SOC range) to cover an as wide SOC range as possible and still result in a positive ΔSOC.

A start SOC combination of 10 % and 15 % was chosen to optimize the EMS of this exemplary plug-in hybrid. In this case, only a relative error of 0.027 % results from Figure 13 lower right.

IV. DISCUSSION

After detailed description of the algorithms, the focus is now on comparing the accuracy of the compensation methods.

A. COMPENSATION METHOD ACCURACY: OVERVIEW

The previous section discussed three methods of compensating the fuel consumption rate for a ΔSOC. The first is the *Static Correction Factor*, which is easy to use but requires additional analysis to determine the most appropriate correction factor. Once determined, however, the inevitable change in the calibration of the EMS as part of a parameter optimization will affect the accuracy of the factor. In the numerical example presented, a relative error of up to 1.5 % was found. If the correction factor is well chosen (the mean of the values provided in Table 2), the relative error can also be reduced to 0.75 % or less.

The previously determined error values are based on Figure 11 and Table 2 by simulation of a WLTC. Using Figure 12 on the left (simulation of different drive cycles), Table 3 can be generated analogously. This gives a maximum difference of the factors of 0.42 l/100 km/%, which results in a relative error of up to 5 % for a fuel consumption of 8.5 l/100 km and a ΔSOC of 1 %. This shows how much the error value depends on a proper preliminary analysis when using the Static Correction Factor method.

Subsequently, the *Individual Correction Factor* was presented. No prior knowledge is required for its calculation and a relative error of approx. 1 % was found for the WLTC. The additional effort consists in determining the different component efficiencies of the respective driving cycle. However, the computational effort for this is small compared to the driving cycle simulation itself.

Finally, the fuel consumption calculation by *Linear Interpolation* was discussed. For the relevant start SOC combinations, the relative error is less than 0.2 %, which means that this method has the smallest error values. However, this increased accuracy comes at the cost of twice the computational time because a drive cycle is run not once, but twice with different start SOCs.

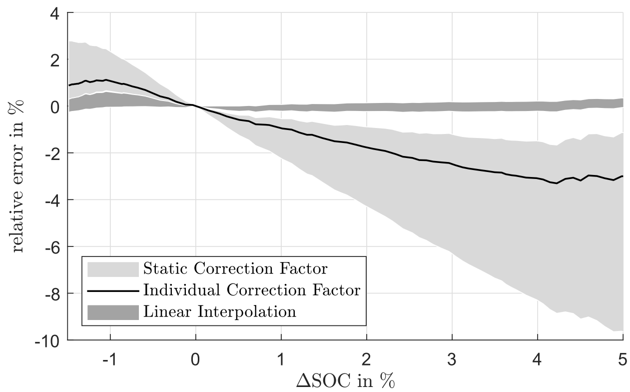

FIGURE 14. Relative error of the fuel consumption correction using the same EMS calibration for a WLTC driving cycle.

B. COMPENSATION METHOD ACCURACY: DIRECT COMPARISON

Each of the three methods presented for fuel consumption correction has its own strengths and weaknesses. The performance of the methods is shown in the Figures 11 (with Table 2), 12 and 13, but the diagrams are not directly comparable with each other. For a direct comparison, Figure 14 shows how the relative error behaves as a function of a ΔSOC to be corrected, using the same EMS calibration and simulating a WLTC driving cycle. A specific equivalence factor for the Static Correction must be defined for the visualization. For this purpose, the maximum and minimum equivalence factors from Table 2 have been selected to define a range for the relative error calculation. The relative error for the Individual Correction can be determined directly from the Formulas in Section III-B and in the Appendix or from Figure 12. For Linear Interpolation, it is necessary to specify a pair of start SOC values. As this choice allows a certain degree of freedom, a bandwidth of the relative error is shown accordingly in Figure 14. For this purpose, the start SOC associated with a ΔSOC was determined from Figure 13 at the top left. For this start SOC (A or B), all possible start SOC combinations (B or A) from Figure 13 at the bottom right were considered and the smallest and largest relative error was determined in each case.

As can be seen in Figure 14, the performance of the Static Correction Factor is highly dependent on the choice of the equivalence factor. The Individual Correction Factor has a smaller relative error on average, but is in a similar order of magnitude. Linear Interpolation provides the smallest relative error for SOC compensation.

V. CONCLUSION

Six different methods for compensating a ΔSOC in the simulation of a hybrid vehicle in a specific driving cycle were presented. The three methods, Static and Individual Correction Factor, as well as the correction by Linear Interpolation, are particularly suitable for use in the context of EMS parameter optimization due to their deterministic and low computation time.

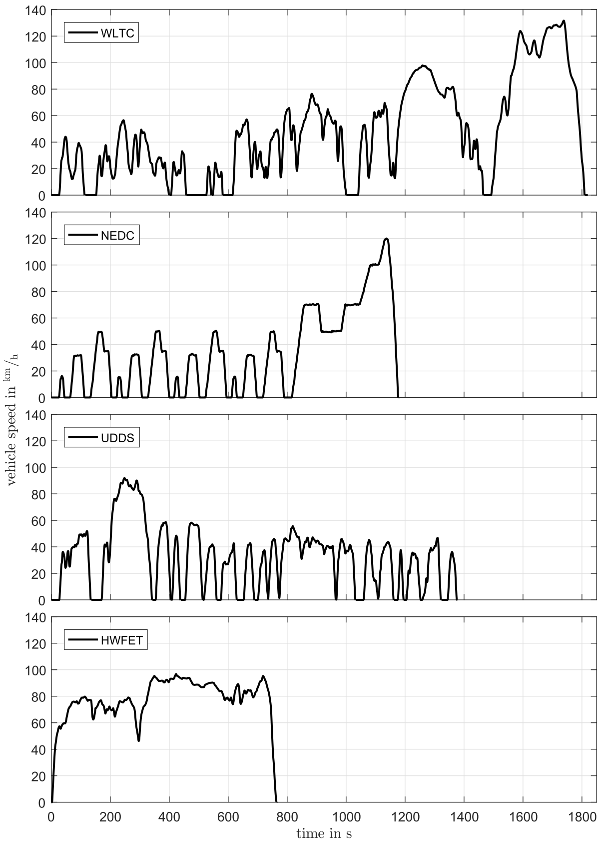

FIGURE 15. Vehicle speed over time for the WLTC, NEDC, UDDS and HWFET driving cycles used.

For the Static Correction Factor method with a ΔSOC of 1 % a relative error in the corrected fuel consumption of about 0.75 % to 1.5 % was determined, for the Individual Correction Factor of about 1 % and for the Linear Interpolation of less than 0.2 % for the Worldwide Harmonized Light Vehicles Test Cycle (WLTC).

Compensation by Linear Interpolation is the most accurate method, but requires twice the computation time. This method supports robust EMS behavior (control towards the CS target SOC), although only weak constraints are required during optimization. This gives the optimizer more freedom to determine the most fuel-efficient EMS calibration.

The error values given in this paper may vary depending on the vehicle model, specific EMS implementation and driving cycle. For this reason, all of the above is intended primarily as a guide for determining the error values individually for each specific application. Unfortunately, many EMS optimization papers do not specifically mention if or how SOC compensation is performed. This may be due to space limitations or other priorities. In these cases, this paper can be used as a reference on how the compensation is done.

APPENDIX A
DRIVE CYCLES

For a better understanding of the characteristics of the driving cycles used, the vehicle speed is plotted for each of them in Figure 15.

APPENDIX B
COMPONENT EFFICIENCY CALCULATION

To make the calculation of the Individual Correction Factor based on a driving cycle simulation easier to understand, the formulas used for the efficiency calculation are given here. Since the focus of this paper is to compare SOC compensation methods (and Linear Interpolation is the preferred method), the efficiency calculation is not fully derived here and only the resulting formulas are provided. More detailed insights can be found in [30] and [31].

A fundamental challenge in calculating the efficiency of individual powertrain components is the dynamic operation during a driving cycle simulation. The vehicle is partly electrically driven and partly dominated by the ICE. There are phases of driving and standstill, but only the driving is relevant for the efficiency calculation. For this reason, the instantaneous efficiencies and their averaging in the relevant operating states are considered.

INTERNAL COMBUSTION ENGINE

During engine operation, the ICE delivers mechanical power $P_{\mathrm{ICE,mech}}$ (based on torque T and speed N), while it absorbs chemical power $P_{\mathrm{ICE,chem}}$ (based on fuel mass flow $\dot{m}_{\mathrm{fuel}}$ and lower heating value $H_{\mathrm{l,fuel}}$) through the combustion of fuel

$$\overline{\eta}_{\mathrm{ICE}} = \left. \frac{\int_{t_{\mathrm{start}}}^{t_{\mathrm{end}}} P_{\mathrm{ICE,mech}}\,\mathrm{d}t}{\int_{t_{\mathrm{start}}}^{t_{\mathrm{end}}} P_{\mathrm{ICE,chem}}\,\mathrm{d}t} \right|_{P_{\mathrm{ICE,mech}}>0\,\cap\,P_{\mathrm{ICE,chem}}\neq 0}, \quad (6)$$

$$P_{\mathrm{ICE,chem}} = \dot{m}_{\mathrm{fuel}} \cdot H_{\mathrm{l,fuel}}\,, \quad (7)$$

$$P_{\mathrm{ICE,mech}} = T_{\mathrm{ICE}} \cdot 2\pi N_{\mathrm{ICE}}. \quad (8)$$

Only phases in the drive cycle where the combustion engine is active ($P_{\mathrm{ICE,chem}} \neq 0$) and delivers torque ($P_{\mathrm{ICE,mech}} > 0$) are considered.

CLUTCH

The specific mechanical implementation of the coupling between the ICE and EM may vary in practice, but the calculation of efficiency for P2 hybrids is based on Figure 4 by

$$\overline{\eta}_{\mathrm{Cl}} = \left. \frac{\int_{t_{\mathrm{start}}}^{t_{\mathrm{end}}} P_{\mathrm{EM,mech}}\,\mathrm{d}t}{\int_{t_{\mathrm{start}}}^{t_{\mathrm{end}}} P_{\mathrm{ICE,mech}}\,\mathrm{d}t} \right|_{P_{\mathrm{ICE,mech}}>0\,\cap\,P_{\mathrm{ICE,chem}}\neq 0}, \quad (9)$$

$$P_{\mathrm{EM,mech}} = T_{\mathrm{EM}} \cdot 2\pi N_{\mathrm{EM}}. \quad (10)$$

The clutch efficiency is determined in the same drive cycle phases as the ICE efficiency.

ELECTRIC MOTOR

The EM can be operated in motor mode, producing mechanical power ($P_{\mathrm{EM,mech}} > 0$) while absorbing electrical power ($I_{\mathrm{EM}} > 0$), or in generator mode, producing electrical power ($I_{\mathrm{EM}} < 0$) while absorbing mechanical power ($P_{\mathrm{EM,mech}} < 0$). To calculate the efficiency of the electric motor, only the phases of the driving cycle in motor or generator mode are taken into account

$$\overline{\eta}_{\mathrm{EM}} = \frac{\int_{t_{\mathrm{start}}}^{t_{\mathrm{end}}} P_{\mathrm{EM,mech}}\,\mathrm{d}t\Big|_{I_{\mathrm{EM}}>0,\ P_{\mathrm{EM,mech}}>0}}{\int_{t_{\mathrm{start}}}^{t_{\mathrm{end}}} P_{\mathrm{EM,el}}\,\mathrm{d}t\Big|_{I_{\mathrm{EM}}>0,\ P_{\mathrm{EM,mech}}>0}} \frac{+\int_{t_{\mathrm{start}}}^{t_{\mathrm{end}}} -P_{\mathrm{EM,el}}\,\mathrm{d}t\Big|_{I_{\mathrm{EM}}<0,\ P_{\mathrm{EM,mech}}<0}}{+\int_{t_{\mathrm{start}}}^{t_{\mathrm{end}}} -P_{\mathrm{EM,mech}}\,\mathrm{d}t\Big|_{I_{\mathrm{EM}}<0,\ P_{\mathrm{EM,mech}}<0}}, \tag{11}$$

$$P_{\mathrm{EM,el}} = U_{\mathrm{EM}} \cdot I_{\mathrm{EM}}. \tag{12}$$

The electrical power of the EM is the result of voltage U_{EM} and current I_{EM}.

HIGH VOLTAGE SYSTEM

The efficiency of the HV system is intended to describe the fact that energy is transferred from the electric motor to the battery (or in the opposite direction) with certain losses. The causes of these transmission losses are, for example, the voltage drop across the cable resistance or auxiliary devices such as the DCDC converter.

$$\overline{\eta}_{\mathrm{HV}} = \begin{cases} \dfrac{\int_{t_{\mathrm{start}}}^{t_{\mathrm{end}}} |I_{\mathrm{Bat}}|\ \mathrm{d}t}{\int_{t_{\mathrm{start}}}^{t_{\mathrm{end}}} |I_{\mathrm{EM}}|\ \mathrm{d}t}, \text{ for } \Delta E_{\mathrm{Bat}} > 0 \\ \dfrac{\int_{t_{\mathrm{start}}}^{t_{\mathrm{end}}} |I_{\mathrm{EM}}|\ \mathrm{d}t}{\int_{t_{\mathrm{start}}}^{t_{\mathrm{end}}} |I_{\mathrm{Bat}}|\ \mathrm{d}t}, \text{ for } \Delta E_{\mathrm{Bat}} < 0 \end{cases}. \tag{13}$$

In the formula above, the current integral was deliberately chosen instead of a power integral so that the battery efficiency (different voltage levels during charge and discharge) does not affect the efficiency of the HV system. In addition, the voltage drop across the cable resistance is ignored in the above formula because most vehicle models do not account for this effect.

BATTERY

Similar to the EM, the battery efficiency calculation distinguishes between charge ($I_{\mathrm{Bat}} < 0$) and discharge ($I_{\mathrm{Bat}} > 0$)

$$\overline{\eta}_{\mathrm{Bat}} = \frac{\int_{t_{\mathrm{start}}}^{t_{\mathrm{end}}} U_{\mathrm{Bat}}\,\mathrm{d}t\Big|_{I_{\mathrm{Bat}}>0,\ U_{\mathrm{Bat}}<U_{\mathrm{OCV}}}}{\int_{t_{\mathrm{start}}}^{t_{\mathrm{end}}} U_{\mathrm{OCV}}(\xi)\,\mathrm{d}t\Big|_{I_{\mathrm{Bat}}>0,\ U_{\mathrm{Bat}}<U_{\mathrm{OCV}}}} \frac{+\int_{t_{\mathrm{start}}}^{t_{\mathrm{end}}} U_{\mathrm{OCV}}(\xi)\,\mathrm{d}t\Big|_{I_{\mathrm{Bat}}<0,\ U_{\mathrm{OCV}}<U_{\mathrm{Bat}}}}{+\int_{t_{\mathrm{start}}}^{t_{\mathrm{end}}} U_{\mathrm{Bat}}\,\mathrm{d}t\Big|_{I_{\mathrm{Bat}}<0,\ U_{\mathrm{OCV}}<U_{\mathrm{Bat}}}}. \tag{14}$$

To distinguish between charging and discharging, the ratio of U_{OCV} and U_{Bat} at time t was evaluated in addition to the sign of I_{Bat} at time t. The reason for this is that real batteries have not only an ohmic internal resistance, but also at least two RC elements (double layer capacity and diffusion [32]). This leads to polarization effects, so that for small currents (after high currents) the efficiency of the above calculation can be greater than one, which is not plausible.

APPENDIX C
NOMENCLATURE

SYMBOLS

η	Efficiency (unitless).
λ	Equivalence factor in $^{l}/_{100\,\mathrm{km}}/\%$.
ξ	State of charge in %.
ρ	Density in $^{\mathrm{g}}/_{\mathrm{cm}^3}$.
C	Capacity in As.
E	Energy in Wh.
H_{l}	Lower heating value in $^{\mathrm{Ws}}/_{\mathrm{g}}$.
I	Current in A.
m	Mass in g.
N	Speed in $^{1}/_{\mathrm{min}}$.
P	Power in W.
T	Torque in Nm.
t	Time in s.
U	Voltage in V.
V	Fuel consumption in l.

ABBREVIATIONS

Bat	Battery
CD	Charge depleting
chem	Chemical
Cl	Clutch
cor	Corrected
CS	Charge sustaining
DCDC	Direct current to direct current converter
el	Electrical
EM	Electric motor
EMS	Energy management strategy
HEV	Hybrid electric vehicle
HV	High voltage
HWFET	Highway Fuel Economy Test
ICE	Internal combustion engine
mech	Mechanical
NEDC	New European Drive Cycle
OCV	Open circuit voltage
SOC	State of charge
UDDS	Urban Dynamometer Driving Schedule
WLTC	Worldwide Harmonized Light Vehicles Test Cycle
WLTP	Worldwide Harmonized Light Vehicles Test Procedure

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