 Integrating Battery Aging in the Optimization for Bidirectional Charging of Electric Vehicles

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Abstract—Smart charging of Electric Vehicles (EVs) reduces operating costs, allows more sustainable battery usage, and promotes the rise of electric mobility. In addition, bidirectional charging and improved connectivity enables efficient power grid support. Today, however, uncoordinated charging, e.g. governed by users’ habits, is still the norm. Thus, the impact of upcoming smart charging applications is mostly unexplored. We aim to estimate the expenses inherent with smart charging, e.g. battery aging costs, and give suggestions for further research. Using typical on-board sensor data we concisely model and validate an EV battery. We then integrate the battery model into a realistic smart charging use case and compare it with measurements of real EV charging. The results show that i) the temperature dependence of battery aging requires precise thermal models for charging power greater than 7 kW, ii) disregarding battery aging underestimates EVs’ operating costs by approx. 30%, and iii) the profitability of Vehicle-to-Grid (V2G) services based on bidirectional power flow, e.g. energy arbitrage, depends on battery aging costs and the electricity price spread.

Index Terms—Electric Vehicle Charging, Artificial Neural Network (ANN), Vehicle-to-Grid, Optimization, Smart Charging, Electric Vehicles, Energy Arbitrage

I. INTRODUCTION

SMART charging—the controlled and coordinated charging of Electric Vehicles (EVs)—is a key factor for the transition to energy efficient mobility. By also including bidirectional charging, i.e. energy feedback to the power grid, smart charging pursues various objectives, e.g. i) minimizing EV operating costs [1], [2], ii) prolonging battery life [3], [4], iii) supporting the power grid, i.e. Vehicle-to-Grid (V2G) [5], [6], or iv) combinations of the above [7], [8].

Nowadays, however, every-day EV charging typically follows a standard procedure in which the battery is fully charged at maximum available power after plugging in. Thereafter, a fully charged battery is maintained until departure [9]. Hence, the implications of real-world smart charging applications are mostly unexplored. Particularly, operating costs, i.e. the sum of energy and battery aging costs, can hardly be monitored or adapted to demand. This could result in false conclusions regarding the total operating costs, especially when applying specific charging strategies.

In the literature [10]–[29], as listed in Tab. I, the costs inherent with battery aging are often based upon simplified models, or disregarded completely. In cases with application-oriented models, they are often developed and evaluated without real-world case studies.

Therefore, we aim to estimate the expenses inherent with smart charging and give suggestions for further research. To this end, we first develop and evaluate electrical, thermal, and aging models of the EV battery, which only require available on-board sensor data from production EVs. We then combine the battery model with an optimization-based smart charging use case. Subsequently comparing the results with real charging data allows us to i) determine the validity of simplified modeling approaches for specific charging strategies, ii) illustrate the significance of battery aging costs, and iii) derive application-dependent suggestions to support future work on smart charging [30].

This paper is structured as follows: Section II outlines all deployed models and their connections. Section III describes an exemplary smart charging use case. Based on this, Section IV presents the validation of the single model components and optimization results. In Section V we summarize the main findings and provide an outlook for further research.

II. METHODS

First, we introduce the notation for a charging event starting at arrival time $t_0$ and ending at departure time $t_N$. The time horizon $[t_0, t_N]$ is divided into $N$ time intervals of duration $\Delta t$ and $N + 1$ states. Accordingly, we define the set of intervals

$$\mathcal{N} = [0, N - 1] \subset \mathbb{N}. \quad (1)$$

Each time interval $n \in \mathcal{N}$ starts at time $t_n$ and ends at time $t_{n+1}$. Each battery state at $t_n \in [t_0, t_N]$ is characterized by the battery energy $e_n$, normalized as State of Charge (SOC),

| Drawback | References |
|----------|------------|
| absent optimization-based smart charging scheme | [10]–[15] |
| non-realistic use case for validation | [12]–[21] |
| simplified/absent battery model (electrical, thermal and/or aging) | [19]–[29] |
and the battery temperature $\theta_n$. The charging power $p_n$ is assumed to remain constant throughout a single time interval $n, \forall n \in \mathbb{N}$.

To represent the battery’s charging behavior, we implement an electrical, thermal, and aging model, see Fig. 1a. We refer to the combination of these three models as the battery model. The perspective use of this battery model in production EVs limits the model inputs to typical on-board sensor data. Further, an optimization scheme as shown in Fig. 1b serves to calculate an optimal charging power trajectory $p^*$ for a single charging event.

### A. Electrical Model

The electrical battery model, as shown in Fig. 1a, estimates the energy throughput of the battery

$$\Delta E_n = e_{n+1} - e_n, \forall n \in \mathbb{N},$$

for a given time interval $n$, battery temperature $\theta_n$, battery energy $e_n$, battery’s terminal voltage $U_{bat,n}$, and charging power $p_n$.

We abstract the EV battery with an Equivalent Circuit Model (ECM) consisting of a voltage source $U_{OCV}$ serially connected with the internal resistance $R_i$, see Fig. 2. Due to the low dynamics of EV charging, more complex models, e.g., resistor-capacitor-pairs or electro-chemical models, are not required.

Both $U_{OCV,n}$ and $R_{i,n}$ depend on the battery temperature $\theta_n$ and the battery energy $e_n$ and we assume their values to be constant throughout a single time interval $n$. We obtain $R_i$ from a look-up table and use the measured terminal voltage $U_{bat,n}$ to obtain the open-circuit voltage of the battery

$$U_{OCV,n} = U_{bat,n} - R_{i,n} \cdot I_{bat,n}.$$ (3)

With the battery current $I_{bat} > 0$ during charging, $U_{bat} > U_{OCV}$ for charging and $U_{bat} < U_{OCV}$ for discharging. Substituting the terminal voltage with

$$U_{bat,n} = \frac{p_n}{I_{bat,n}},$$ (4)

and solving 3, we obtain the battery current

$$I_{bat,n} = \frac{-U_{OCV,n} + \sqrt{U_{OCV,n}^2 + 4R_{i,n} \cdot p_n}}{2R_{i,n}}.$$ (5)

The OHMic losses within the battery amount to

$$\dot{Q}_{loss,n} = R_{i,n} \cdot I_{bat,n}^2.$$ (6)

Given the charging power $p_n$, we obtain the energy throughput

$$\Delta E_n = \Delta t \cdot (p_n - \dot{Q}_{loss,n}).$$ (7)

Note that $\dot{Q}_{loss,n} > 0$ occurs both while charging and discharging. Hence, it decreases $|\Delta E_n|$ during charging and increases $|\Delta E_n|$ during discharging.

### B. Thermal Model

The thermal battery model, as shown in Fig. 1a, estimates the change in battery temperature

$$\Delta \theta_n = \theta_{n+1} - \theta_n,$$ (8)

for a given time interval $n$, battery temperature $\theta_n$, battery energy $e_n$, ambient temperature $\theta_{amb}$, and charging power $p_n$. Due to heat exchange with surrounding components, these models are mostly vehicle-type-specific. Both the internal parameters and the battery aging depend on the battery temperature. Since the use of thermal battery models for smart charging is underrepresented in the literature (see Sec. I), we focus on this aspect by evaluating three different thermal models.

1) Naive Model: A simple approach is to assume the battery temperature to remain constant throughout the entire charging event. Hence,

$$\theta_n = \theta_0, \ \forall n \in [1, N],$$ (9)

where the initial battery temperature $\theta_0$ at the start of the charging event is known. Accordingly, also

$$\Delta \theta_n = 0, \ \forall n \in \mathbb{N}.$$ (10)

The ambient temperature $\theta_{amb}$ does not have any effect in this model.

2) Heat Flow Model: Based on the first principle of thermodynamics, we estimate the battery temperature from heat flows into and out of the battery. The power loss $\dot{Q}_{loss,n}$ at the battery’s internal resistance as given in (6) is assumed to be completely dissipated into heat. Regardless of the sign of $p_n$, the battery temperature increases, i.e., during charging and discharging.

Given a difference between $\theta_n$ and the ambient temperature $\theta_{amb}$, the heat flow

$$\dot{Q}_{amb,n} = -\alpha \cdot (\theta_n - \theta_{amb}),$$ (11)

describes conductive heat exchange between the battery and the environment. Therein, $\alpha$ represents the specific heat transition coefficient of the battery system. The direction of $\dot{Q}_{amb,n}$ depends on the difference between $\theta_n$ and $\theta_{amb}$.

Applying discrete-time Forward-EULER integration to the sum of $\dot{Q}_{amb,n}$ and $\dot{Q}_{loss,n}$, we obtain the battery temperature change

$$\Delta \theta_n = \Delta t \cdot \frac{\dot{Q}_{loss,n} + \dot{Q}_{amb,n}}{c_h},$$ (12)

where $c_h$ represents the heat capacity of the battery.

5 Note that $\theta_{amb}$ is assumed to remain constant during the entire charging event. Advanced models could include a forecast of $\theta_{amb}$ for the charging event time window.
3) Data-driven Models: Data-driven approaches can model non-linear thermal behavior and hidden processes, e.g. electrochemical heat sources or sinks. We compare a Linear Regression (LR) model and different Artificial Neural Network (ANN) models. For the model training, we use data from real charging events of batteries installed and operated in EVs. Before training the models with different feature combinations, we screen out redundant features using the SPEARMAN correlation coefficient. Applying a five-fold cross validation, we select the features \( \{p_n, Q_{\text{loss},n}, \Delta E_n, \theta_n\} \) to estimate \( \Delta \Theta_n \). Given the upstream calculation of \( Q_{\text{loss},n} \) in \[6\], we use a gray-box approach.

As the optimal model architecture may vary for different input features, we use grid-search to obtain the best performing model architecture. We implement all models in Python \[32\] (ANNs: Keras \[33\], LR: SciKit-Learn \[34\]). For a proper model training, we perform mean and variance normalization.

The available training data underrepresents discharging, i.e. \( p_n < 0 \). However, as \( R_{\text{bat},n} \) behaves similarly for charging and discharging we consider it acceptable to use absolute values for \( p_n \) and \( I_{\text{bat},n} \).

C. Battery Aging Model

Irreversible physical and electro-chemical degradation processes (battery aging) cause the EV’s usable driving range and monetary value to decrease. To quantify battery aging, the State of Health (SOH)

\[ H = \frac{\epsilon_{\text{max}}}{\epsilon_{\text{nom}}} \leq 1, \]  

indicates the maximum available storage capacity \( \epsilon_{\text{max}} \) compared with the nominal storage capacity \( \epsilon_{\text{nom}} \). The described aging model represents battery-specific properties in real operating profiles, see also \[12\], \[35\], \[36\]. Determining model characteristics and parameters either requires extensive cell tests or an implicit representation, e.g. via machine learning approaches \[37\]. The causes of battery aging can be separated into cyclic aging and calendar aging.

Battery cycling, i.e. charging and discharging, causes the active materials of the battery to decay. Thus, the cyclic aging increment

\[ \Delta \Theta_{\text{cyc},n} = f(\Delta E_n), \]  

depends on the absolute energy throughput \( \Delta E_n \).

Regardless of the energy throughput, the battery capacity fades over time. Using ARRHENIUS curves from cell tests at varying conditions (battery energy and temperature), we obtain the calendar aging increment

\[ \Delta H_{\text{cal},n} = f(\theta_n, \epsilon_n, H_0), \]  

where, \( H_0 \) is the SOH at the beginning of the charging event.\(^7\)

D. Optimization Scheme

To evaluate different modeling approaches, we formulate the vehicle- and battery-independent optimization scheme

\[ \min_{\mathbf{p} \in \mathbb{R}^N} \sum_{\forall n \in \mathcal{N}} J_{E,n}(p_n, \epsilon_{\text{buy},n}, \epsilon_{\text{sell},n}) + J_{D,n}(\theta_n, \epsilon_n, H_0) \]  

subject to

\[ \mathbf{p} \leq \mathbf{p} \leq \mathbf{p}, \quad \mathbf{p} \in \mathbb{R}^N, \]  

\[ \epsilon \leq \epsilon \leq \bar{\epsilon}, \quad \epsilon \in \mathbb{R}^{N+1}, \]  

\[ \epsilon_0 = \epsilon_0 = \bar{\epsilon}_0, \]  

\[ \epsilon_N = \epsilon_N = \bar{\epsilon}_N, \]  

\[ \theta \leq \theta \leq \bar{\theta}, \quad \theta \in \mathbb{R}^{N+1}, \]  

\[ \theta_0 = \theta_0 = \bar{\theta}_0, \]  

\[ \epsilon_{n+1} = \epsilon_n + \Delta E_n(\epsilon_n, \theta_n, p_n), \quad \forall n \in \mathcal{N}, \]  

\[ \theta_{n+1} = \theta_n + \Delta \Theta_n(\epsilon_n, \theta_\text{amb}, p_n), \quad \forall n \in \mathcal{N}. \]  

\(^7\)Hence, the details of the presented aging model are confidential. \( H_0 \) serves as a reference for all time steps, as calendar aging occurs on larger time scales (years) than charging (hours).
The components [17a]–[17l] are explained in the following.

1) Cost Functions: The optimization objective (17a) is to minimize the sum of energy costs \( J_{E,n} \) and aging costs \( J_{D,n} \) in all time intervals \( n \in N \).

To consider the costs inherent with charging electric energy, we define the energy cost function

\[
J_{E,n} = \begin{cases} 
J_{E,n}^+, & \forall p_n \geq 0, \\
J_{E,n}^-, & \forall p_n < 0, 
\end{cases} \tag{18}
\]

with the energy expenses

\[
J_{E,n}^+ = p_n \cdot \Delta t \cdot \epsilon_{buy,n}, \tag{19}
\]

and the energy rewards

\[
J_{E,n}^- = p_n \cdot \Delta t \cdot \epsilon_{sell,n}. \tag{20}
\]

For \( p_n \geq 0 \), the EV battery is charged at the electricity price \( \epsilon_{buy,n} \). With \( p_n < 0 \), \( \epsilon_{sell,n} \) corresponds to the price of selling energy back to the grid. Both \( \epsilon_{buy,n} \) and \( \epsilon_{sell,n} \) are assumed to be deterministic.

Battery aging also contributes to the total operating costs. Based on \( \Delta H_{\text{cyc}},n \) and \( \Delta H_{\text{cal}},n \) (Sec. II-C) we define the battery degradation costs (aging costs)

\[
J_{D,n} = \Delta H_{\text{cyc}},n \cdot \frac{V_{\text{EV}}}{H_{\text{EV}}} + \Delta H_{\text{cal}},n \cdot \frac{V_{\text{EV}}}{H_{\text{EV}}}, \tag{21}
\]

with the cyclic aging costs \( J_{\text{cyc}},D,n \) and the calendar aging costs \( J_{\text{cal}},D,n \).

Therein, \( V_{\text{EV}} \) denotes the battery value loss due to the capacity loss \( H_{\text{EV}} \) during its entire automotive application (first life). In particular, \( H_{\text{EV}} \) is the difference of the battery’s production price and residual value in a second life market. Note that (21) only accounts for aging caused throughout the charging event. To include battery aging for trips in between charging events, the optimal target energy \( E_{\text{EV}} \) could be determined using a superordinate scheme as in [8].

2) Decision Variable: To obtain the optimal charging power trajectory, we define the decision variable

\[
p = (p_0, p_1, \ldots, p_{N-1})^T \in \mathbb{R}^N, \tag{22}
\]

with the charging power \( p_n \) in all time intervals \( n \in N \). Evaluating (17b) component-wise represents the power limitations with the upper bounds \( \bar{p} \) and lower bounds \( \underline{p} \). These bounds are determined e.g. by charging stations or on-board power electronics.

3) State Variables: To compute the SOC of the battery, we define the state variable

\[
e = (\epsilon_0, \epsilon_1, \epsilon_2, \ldots, \epsilon_N)^T \in \mathbb{R}^{N+1}, \tag{23}
\]

representing the battery energy at \( t_n, \forall n \in [0, N] \). Reading (17c) component-wise reveals the energy limitations \( \bar{\epsilon} \) and \( \underline{\epsilon} \).

We specify the battery energy at arrival \( \epsilon_0 \) and the battery energy at departure \( \epsilon_N \), see (17d) and (17e).

For the battery temperature we similarly define the state variable

\[
\theta = (\theta_0, \theta_1, \theta_2, \ldots, \theta_N)^T \in \mathbb{R}^{N+1}. \tag{24}
\]

Here, we only specify the battery temperature at arrival \( \theta_0 \), see (17f). The battery temperature at departure \( \theta_N \) is unknown at the time of computation, but constrained within the temperature limits \( \bar{\theta} \) and \( \underline{\theta} \), see (17g).

4) Battery Dynamics: To represent the electrical behavior of the battery throughout a single time interval \( n \), we formulate (17h) based on the electrical model, see Sec. II-A. Accordingly, the temperature transition (17i) describes the thermal behavior of the battery, see Sec. II-B.

III. CASE STUDY

From a fleet of ten real-world EVs equipped with cloud-connected data loggers, we obtain on-board measurement data of 279 unidirectional charging events [38]. Given the conditions of these charging events, we simulate the battery models (Sec. II-A [II-B]) with \( \Delta t = 5 \) min. To quantify the estimation error per time step (local error), we determine the Root Mean Squared Error (RMSE) of actual and estimated values for \( \Delta E_n \) and \( \Delta \theta_n \). Furthermore, we quantify the error propagation when repeatedly applying the models with the Mean Absolute Error (MAE) at the end of each charging event (global error).

To evaluate the optimization scheme (Sec. II-D), we select 45 real charging events that have sufficient duration and SOC difference, i.e. energy throughput. After solving the optimization problem (17) with discrete dynamic programming [39], we compare the operating costs in three modes:

- **Mode I**: no optimization, calculate energy and aging costs for measured energy and temperature profile.
- **Mode II**: optimize for energy costs only, calculate aging costs afterward.
- **Mode III**: optimize for both energy and aging costs.

We use historic hourly electricity market prices of 2018 to set \( \epsilon_{buy,n} \) and \( \epsilon_{sell,n} \). To attain a representative price level of private customers, we supplement the market prices with typical fees (0.188 €/kWh) and taxes (19%). Then, we average the price curves over all workdays and all weekends. Price peaks occurring in case of extensive over- or underproduction of electricity are leveled out. Thus, we obtain two characteristic hourly price tables, see Fig. 3 to evaluate the average profitability of smart charging.

IV. RESULTS

A. Validation of Battery Model

Table II presents the validation results of the battery model (Sec. II-A [II-B]).

| Model                     | Local Error (RMSE) | Global Error (MAE) |
|---------------------------|--------------------|--------------------|
| Electrical ECM            | 0.3539% SOC        | 2.37% SOC          |
| Naive Thermal Model       | 0.7245 K           | 7.565 K            |
| Heat Flow Thermal Model   | 1.5580 K           | 4.783 K            |
| Data-driven Thermal Model | 0.2942 K           | 1.956 K            |

TABLE II: Local and global error of electrical and thermal battery models (Sec. II-A [II-B]).
1) Validation of Electrical Model: Validating the electrical model (Sec. II-A) for single time intervals yields an RMSE of 0.3539% SOC. Figure 4a shows the actual values $\Delta E$ over the model estimations $\hat{\Delta E}$. The MAE of the global SOC deviations $E_N - \hat{E}_N$ at the end of all charging events is 2.37% SOC, see Tab. II. Thus, the SOC estimations at the end of a charging event in average deviate by 2.37% SOC from reality. Considering the sufficient accuracy of the electrical model, we deem a time interval of $\Delta t = 5$ min and the ECM to be suitable for our use case.

2) Validation of Thermal Model: As we have investigated different approaches to estimate battery temperature in Sec. II-B, we assess the fitness of the different thermal models. We simulate the battery temperature profile and compare it with measured temperature profiles of real charging events.

Per definition, the naive thermal model (Sec. II-B1) estimates $\Delta \hat{\Theta}_n = 0.0, \forall n \in N$. In comparison with the actual measured battery temperatures, the estimations yield an RMSE of 0.7245 K. The global temperature deviation amounts in average to 7.565 K, see Tab. II.

Validating the heat flow thermal model (Sec. II-B2) reveals that constant parameters $c_h$ and $\alpha$ seem to misrepresent the battery’s real thermal behavior. Hence, the temperature estimations per time interval (Fig. 4b) yield an RMSE of 1.5580 K. Repeatedly applying the heat flow model, the mean absolute temperature deviation amounts to 4.783 K, see Tab. II.

Although having tested different data-driven thermal models and hyperparameters (Sec. II-B3), for the sake of brevity we only report the best-performing ANN model (2 hidden layers, 10 neurons each, sigmoid activation function). Using a distinct test data set, the data-driven model outperforms the naive and heat flow model in local error evaluations, see Fig. 4c. Collectively, the single time interval estimations of the data-driven model yield an RMSE of 0.2942 K. The propagated global error of the entire charging events is in average 1.956 K, see Tab. II.

B. Operating Costs

Figure 5 shows the operating cost components for all three modes described in Sec. III normalized against the operating costs of Mode I. In average, Mode III yields 7.8% lower operating costs compared with Mode I. Although $\theta < 0$ in (17b), i.e., discharging the EV battery is possible, no energy rewards $J_E^{\text{cal}}$ can be observed in Mode III. This implies that $J_E$ does not compensate for round-trip energy losses (charging and discharging) and aging costs.

Disregarding battery aging underestimates the total operating costs in Mode I in average by 30.1%. This becomes apparent when applying Mode II: the optimization scheme utilizes price differences throughout the charging events to generate energy rewards. Thus, the energy costs $J_E$ decreases by 13.3% compared with Mode I. Calculating the battery aging costs $J_{\text{D}}$ afterward, however, yields 55.8% higher total operating costs. Repeatedly charging and discharging the battery increases the battery temperature $\hat{\theta}$ and causes the calendar aging costs $J_{\text{D}}^{\text{cal}}$ to rise in Mode II. Hence, we conclude that especially for charging with the allocation of V2G services—in this case energy arbitrage—battery aging must not be neglected.

C. Effects of Thermal Modeling

Including advanced thermal models, e.g. ANNs, increases the problem complexity and the computational effort to solve the resulting optimization problem. Therefore, we analyze the necessity of different thermal models as described in Sec. II-B1. In Mode III, using a naive thermal model (see Sec. II-B1) would underestimate the operating costs by 0.55% compared with a data-driven thermal model (see Sec. II-B3). Applying Mode II, however, the operating costs would be underestimated by 3.44%.

Besides the errors in estimating the operating costs, the choice of thermal model also influences the decision made by the optimization scheme, i.e., the charging power trajectory $p^\ast$. Figure 6 shows exemplary power profiles over time using naive and data-driven thermal models. For $|p| > 7$ kW, the mean difference of charging power is 3.11 kW, when comparing the naive model with the data-driven model. However, for $|p| < 7$ kW the mean deviation of charging power is 0.75 kW.

Although the operating costs only show minor deviations for different thermal models, the charging power profiles change significantly. In particular, the relevance of the battery temperature rises with the (absolute) charging power. Hence, we suggest to use advanced thermal models, e.g. as in Sec. II-B3 for $|p| > 7$ kW. For $|p| < 7$ kW, a naive thermal model, e.g. as in Sec. II-B1 suffices.

D. Effects of Battery Prices

A maturing EV market and battery technology improvements might cause battery production prices to decrease within the next decade [41]–[43]. In anticipation of smart charging for EV fleets, we analyze EV operating costs with predicted battery prices for 2025 and 2030. Taking 2020 battery prices for reference, the average aging costs $J_D$ alone could decrease by 26.5% in 2025 and by 54.4% in 2030. Regarding the total operating costs, however, the decrease would only amount to 6.8% in 2025, or 15.9% in 2030, respectively.

This reduction of battery aging costs is not sufficient for energy arbitrage to become profitable from a user’s point of
Fig. 4: Local error of battery models, estimates per time interval $\Delta t = 5 \text{ min}$; ECM (Sec. II-A) (a); heat flow thermal model, (Sec. II-B2) (b); best-performing data-driven thermal model (ANN, 2 hidden layers, 10 neurons each, Sec. II-B3) (c); the red lines indicate ideal model behavior.

Fig. 5: Normalized operating costs and its components of 45 real charging events; Mode I (no optimization), Mode II (energy cost optimization), Mode III (energy and aging cost optimization).

Fig. 6: Charging power profiles over time for naive thermal model (red, Sec. II-B1), data-driven thermal model (blue, Sec. II-B3).

Fig. 7: SOC profiles over time for different factors $\gamma$ of increased electricity selling price $\epsilon_{\text{sell}}$.

does not suffice to compensate for round-trip energy losses and aging costs. We thus synthetically increase $\gamma$, i.e. simultaneously offer higher selling prices than buying prices, to evaluate the impact on the optimization. Figure 7 shows SOC profiles of four different $\gamma$. Compared with the standard pricing $\gamma = 1.0$, the share of discharging phases, i.e. selling energy back to the grid, increases with $\gamma$. Note the green SOC profile with $\gamma = 1.8$ cycling up and down various times, i.e. the battery is charged and discharged repeatedly. The optimization scheme thus fully utilizes the price differences for buying and selling energy. Examining the operating cost and its components, as shown in Fig. 8 supports this result. Energy rewards $J^+_{E}$, energy expenses $J^-_{E}$, and cyclic aging costs $J^\gamma_{D}$ grow with $\gamma$. Due to the $\gamma$-increased selling price $\epsilon_{\text{sell}}$, however, the energy rewards are growing more extensively than energy expenses.

E. Influence of Electricity Tariff

Due to relatively small electricity price variations over time, see Fig. 3, many V2G services, e.g. energy arbitrage, are unlikely to be profitable. Depending on the charging event time window, the ratio

$$\gamma = \frac{\epsilon_{\text{sell}}}{\epsilon_{\text{buy}}}$$

(25)

does not suffice to compensate for round-trip energy losses and aging costs. We thus synthetically increase $\gamma$, i.e. simultaneously offer higher selling prices than buying prices, to evaluate the impact on the optimization. Figure 7 shows SOC profiles of four different $\gamma$. Compared with the standard pricing $\gamma = 1.0$, the share of discharging phases, i.e. selling energy back to the grid, increases with $\gamma$. Note the green SOC profile with $\gamma = 1.8$ cycling up and down various times, i.e. the battery is charged and discharged repeatedly. The optimization scheme thus fully utilizes the price differences for buying and selling energy. Examining the operating cost and its components, as shown in Fig. 8 supports this result. Energy rewards $J^+_{E}$, energy expenses $J^-_{E}$, and cyclic aging costs $J^\gamma_{D}$ grow with $\gamma$. Due to the $\gamma$-increased selling price $\epsilon_{\text{sell}}$, however, the energy rewards are growing more extensively than energy expenses.
and cyclic aging costs. Thus, the total operating costs decline with increasing $\gamma$. Again, note the drastic increase of $J^*_E$ when increasing $\gamma$ from 1.75 to 1.8. Passing a specific value for $\gamma$, the energy rewards fully compensate round-trip energy losses and aging costs. When aiming to spontaneously influence the EV charging process externally, e.g. as a power supplier, $\gamma$ must exceed this threshold.

To support future work on grid-supporting V2G services, we estimate a characteristic threshold for $\gamma$, see also [25], [44]. Therefore, we assume charging the battery in one time interval and discharging in the second one with equal (absolute) power $|p| \leq 7$ kW. The round-trip energy efficiency is represented by $\eta$. We then obtain a characteristic threshold

$$\gamma^* = \frac{J^*_E + 2J^*_D}{\eta \cdot J^*_E}. \quad (26)$$

With $\theta = 21$ °C and $\eta = 0.997$, we obtain $\gamma^* = 1.746$. Hence, for $\epsilon_{\text{sell}} \geq 1.746 \cdot \epsilon_{\text{buy}}$, the charging process can be influenced by price differences, given that the problem constraints still hold. As we suppose electricity prices supplemented by fees and taxes (see Sec. [III]), $\gamma$ is mostly less than $\gamma^*$. For a more responsive smart charging control, an adapted price policy would require the fluctuations of the electricity market, e.g. negative price peaks, to be passed to the EV customer.

V. CONCLUSION

In the present work we analyzed the influence of battery aging on smart charging of Electric Vehicles (EVs). We modeled the EV battery using on-board sensor data and set up an optimization-based smart charging use case. Evaluating the concept with real-world EV data revealed the need for advanced thermal models when charging power exceeds 7 kW. We found that exploiting time and energy flexibility of EV charging reduces operating costs by 7.8%. Furthermore, disregarding battery aging underestimates EVs’ operating costs up to 30%. Battery aging costs thus hinders many Vehicle-to-Grid (V2G) services based on bidirectional power flow from being profitable. To overcome this would require a vast decrease of battery production prices or an adapted price policy with 75% higher selling than electricity buying prices. Future work will examine stochastic influences on smart charging, e.g. random users’ behavior or V2G service allocation.

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### Notation

- $\hat{x}$ indicates an estimate of $x$
- $\underline{x}$ and $\bar{x}$ indicate the lower and upper bounds of $x$
- $x_n$ indicates the value of $x$ at time $t_n$

### Acronyms

- ANN: Artificial Neural Network
- ECM: Equivalent Circuit Model
- EV: Electric Vehicle
- LR: Linear Regression
- MAE: Mean Absolute Error
- RMSE: Root Mean Squared Error
- SOC: State of Charge
- SOH: State of Health
- V2G: Vehicle-to-Grid

### Latin Symbols

- $c_h$: Battery heat capacity
- $e$: Battery energy
- $\epsilon_{\text{max}}$: Momentary maximum available battery capacity
- $\epsilon_{\text{nom}}$: Nominal available battery capacity
- $\Delta E$: Energy throughput
- $\Delta H_{\text{cyc}}$: Cyclic battery capacity fade
- $\Delta H_{\text{cal}}$: Calendar battery capacity fade
- $H_{\text{EV}}$: Total battery capacity fade, EV application
- $J_{\text{bat}}$: Battery current
- $J_E$: Energy cost function
- $J_D$: Battery degradation cost function
- $N$: Number of time intervals
- $N'$: Set of time intervals
- $p$: Gross charging power
- $p^*$: Optimal charging power trajectory
- $Q_{\text{amb}}$: Heat flow between battery and environment
- $Q_{\text{loss}}$: Heat flow from internal battery losses
- $R_l$: Battery internal resistance
- $U_{\text{OCV}}$: Battery open-circuit voltage
- $U_{\text{bat}}$: Battery terminal voltage
- $V_{\text{EV}}$: Total battery value loss, EV application

### Greek Symbols

- $\alpha$: Heat transition coefficient between battery and environment
- $\gamma$: Electricity price selling-buying-ratio
- $\epsilon_{\text{buy}}$: Electricity buying price
- $\epsilon_{\text{sell}}$: Electricity selling price
- $\eta$: Efficiency of charging process
- $\theta_{\text{amb}}$: Ambient temperature
- $\theta$: Battery temperature
- $\Delta \Theta$: Battery temperature difference
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