DOI: 10.1111/jiec.13344

RESEARCH ARTICLE

JOURNAL OF INDUSTRIAL ECOLOGY WILEY

Life cycle greenhouse gas emissions of residential battery storage systems

A German case study

Daniel Fett | **Christoph Fraunholz** | **Philipp Schneider**

Karlsruhe Institute of Technology (KIT), Chair of Energy Economics, 76187 Karlsruhe, Germany

Correspondence
Daniel Fett, Karlsruhe Institute of Technology (KIT), Chair of Energy Economics, Hertzstraße 16, 76187 Karlsruhe, Germany.
Email: daniel.fett@kit.edu

Editor Managing Review: Lynette Cheah

Funding information
Bundesministerium für Bildung und Forschung, Grant/Award Number: 03SFK1F0-2

Abstract

Battery storage systems (BSSs) are popular as a means to increase the self-consumption rates of residential photovoltaics. However, their environmental impact is under discussion, given the greenhouse gas emissions caused by the production and the efficiency losses during operation. Against this background, we carry out a holistic environmental assessment of residential BSSs by combining a partial life cycle assessment for the production phase with a detailed simulation of 162 individual German households for the operational phase. As regards the production phase, we only find small differences between the carbon footprints of different cell chemistries. Moreover, we can show that the balance of plant components have a comparable impact on the global warming potential as the cell modules. In terms of the operational phase, our simulations show that BSSs can compensate at least parts of their efficiency losses by shifting electricity demand from high-emission to low-emission periods. Under certain conditions, the operational phase of the BSSs can even overcompensate the emissions from the production phase and lead to a positive environmental impact over the lifetime of the systems. As the most relevant drivers, we find the exact emissions at the production stage, the individual household load patterns, the system efficiency, and the applied operational strategy.

KEYWORDS
cradle-to-gate assessment, greenhouse gas impact, industrial ecology, life cycle assessment, operational simulation, residential battery storage system

1 | INTRODUCTION

Around two million installed photovoltaic (PV) systems with a nominal capacity of 54 GW_p supplied about 10% of the German net electricity consumption in 2021 (Bundesverband Solarwirtschaft, 2021a). In the past years, increasing retail electricity prices and the reduction of feed-in tariffs have made self-consumption increasingly attractive for many households. As a consequence, every second small-scale PV system in Germany is currently installed with a battery storage system (BSS) (Bundesverband Solarwirtschaft, 2021b). Thereby, with roughly 300 thousand BSSs already installed, Germany alone accounts for about two thirds of the European market for residential BSSs (Bundesverband Energiespeicher Systeme, 2021; d'Halluin et al., 2020).

Some authors argue that BSSs are unreasonable from an environmental point of view, given the greenhouse gas (GHG) emissions caused by the production as well as the efficiency losses during operation (Luczak, 2020). Others argue that highly efficient residential BSSs might be able to compensate both, the carbon footprint of the production process and the efficiency losses, due to diurnal fluctuations of the CO_2 intensity of the German electricity mix (Weniger et al., 2019b).

While a few life cycle assessments (LCAs) of residential BSSs have already been carried out, all of them neglect important aspects relevant for a holistic assessment over the entire production and operational stages. Thus, we propose a novel modeling approach combining a partial LCA (cradle-to-gate) for the production phase with a detailed simulation of 162 individual households for the operational phase. This methodology, applied in a comprehensive case study for Germany, allows us to work out in detail which conditions have to be met for a residential BSS to compensate the emissions from the production stage during its operational life.

The remainder of this paper is structured as follows. In Section 2, we provide an overview of the existing literature on the environmental impact of residential BSSs and outline the research gap our article aims to fill. Section 3 then introduces our novel modeling approach in detail. Based on this, Section 4 presents the results of our environmental assessment. Finally, we discuss the limitations of our work in Section 5 and provide a conclusion in Section 6.

2 | LITERATURE REVIEW AND RESEARCH GAP

Over the past decade, various LCAs for lithium-ion batteries have been conducted, with the vast majority concentrating on the application in electric vehicles (Peters et al., 2017). In contrast, our focus in the following lies on existing work for residential BSSs and here especially on the balance of plant (BOP) components. Relevant studies in this field include Belmonte et al. (2017), Jasper et al. (2022), Le Thomas et al. (2020), Schmidt et al. (2019), and Stolz et al. (2019).

Most of these publications rely on secondary data for the life cycle inventories (LCIs). An exception is Jasper et al. (2022), which use primary data for the BOP components, yet secondary data for the battery cells. They create their own LCI for the inverter and—for the first time—the other BOP components (e.g., the charger) by decomposing a stationary BSS. In contrast, three of the other studies (Belmonte et al., 2017; Schmidt et al., 2019; Stolz et al., 2019) use a 2.5 kW inverter included in Ecoinvent, with the LCI dating back to 2004. According to Tschümperlin et al. (2016), who carry out LCAs for PV inverters with 5–20 kW, this dataset is outdated, and the environmental impacts are probably underestimated. This assumption seems plausible given that the 5 kW inverter from Tschümperlin et al. (2016), which is used by Le Thomas et al. (2020), has twice the GHG impact of the Ecoinvent dataset. Apart from the BOP components, Stolz et al. (2019) and Jasper et al. (2022) are also the only authors to consider a housing for the BSS.

Both Schmidt et al. (2019) and Le Thomas et al. (2020) harmonize the cell components and manufacturing process across different battery chemistries. Furthermore, Le Thomas et al. (2020) base the mass of the battery module and the mass proportion of its cells on data sheets of commercially available residential lithium-ion BSSs.

Summing up, we are not aware of any existing LCA for residential BSSs that takes into account all BOP components, and at the same time considers the peculiarities of different cell chemistries in terms of their energy consumption during production and their supply chains. Providing more profound insights in these regards is one of the major contributions of our article.

Moreover, our analysis puts a particular focus on the operational phase of residential BSSs. So far, mostly attributional LCAs for BSSs have been carried out, such that only the environmental impacts attributable to the product are considered. Thereby, the operational phase is typically only rudimentary, considered in the form of a certain number of battery cycles per day (Hiremath et al., 2015; Jasper et al., 2022; Le Thomas et al., 2020; Schmidt et al., 2019). Additionally, efficiency losses are mostly only modeled through round-trip efficiencies, and stand-by losses are only taken into account by Jasper et al. (2022) and Le Thomas et al. (2020).

All aforementioned studies apply yearly averaged values for the CO_2 emissions of the electricity mix, which neglects the crucial impact of diurnal fluctuations. Hourly emission time series, in contrast, have so far mainly been used to evaluate different charging strategies for electric vehicles (Arvesen et al., 2021; Braeuer et al., 2020). Only Weniger et al. (2020) analyze the emissions of the operational phase of residential BSSs with a simulation model and an hourly time resolution. However, the authors only analyze one model household with two different BSS configurations. The influence of different operational strategies, as well as different household load profiles are not considered. Furthermore, Weniger et al. (2020) neglect the GHG emissions of the production phase.

Against the background of the identified drawbacks in the existing literature, we develop a novel methodological approach, which—as outlined in the subsequent section—offers a number of benefits as compared to previous standard LCA studies on residential BSSs.

3 | METHODOLOGY

In order to provide a realistic assessment of the GHG emissions of residential BSSs, we apply a two-stage modeling approach consisting of a partial LCA—more precisely a cradle-to-gate assessment—and a detailed simulation of 162 individual households for the operational phase (see Figure 1).

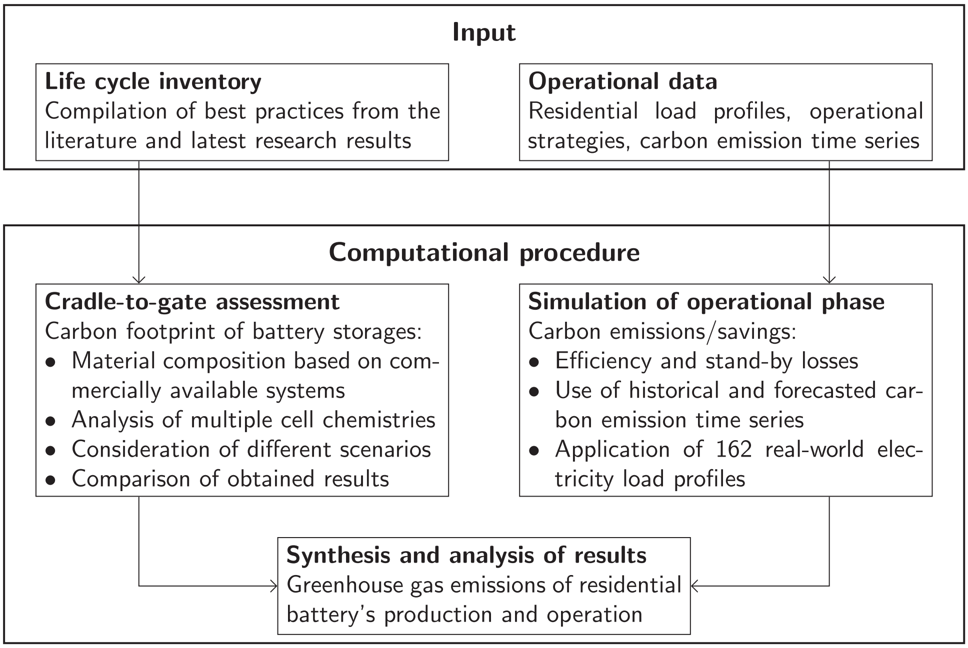

FIGURE 1 Overview of the applied modeling framework.

The innovative combination of a partial life cycle assessment (cradle-to-gate) and a detailed simulation of 162 individual households for the operational phase enables a holistic environmental assessment of residential BSSs.

TABLE 1 Input data and assumptions used for the overall environmental assessment.

Parameter	Value/source
Simulation horizon	20 years (2018–2037)
Technical lifetime	15 years (inverter), 20 years (battery cells)
Cradle-to-gate emissions	*Scenario specific* (cf. Table 3)
Carbon emission factors	Time series (Agora Energiewende, 2019, and own simulations)
Household load profiles	162 empirical time series (Kaschub, 2017; Tjaden et al., 2015)
PV system size	1 kW_p per 1000 kWh of electricity consumption (Weniger et al., 2015)
Battery size	1 kWh per 1000kWh of electricity consumption (Weniger et al., 2015)
Battery operation	Default/delayed charging/dynamic feed-in limitation
System efficiency	*Scenario specific* (cf. Table 3)

In order to adequately account for uncertainties in terms of emissions during production and system efficiency, three different scenarios are set up (cf. Table 3).

This allows us to account for the diversity of households and therefore derive robust conclusions regarding the range of GHG emissions related to the operation of residential BSSs. Finally, the results of both analyses are synthesized to derive overall conclusions for the whole lifetime of the residential BSSs. Please note, however, that we do not consider the end-of-life phase in our analysis, since recycling of lithium-ion batteries is still in its early stages (Le Thomas et al., 2020). Details on the cradle-to-gate assessment are provided in Section 3.1, while Section 3.2 focuses on the simulation of the operational phase. An overview of the main input data and assumptions used for the overall environmental assessment are provided in Table 1.

3.1 | Cradle-to-gate assessment

3.1.1 | Framework

Our partial LCA follows a cradle-to-gate approach. This implies that raw material extraction and processing, product manufacturing, as well as all energy inputs involved in these phases are considered. As previously mentioned, the operational phase of the residential BSSs is analyzed separately (see Section 3.2), while the end-of-life phase is not included in our analysis. Following the standard procedure of LCAs, the two main steps consist in carrying out an LCI analysis and a subsequent life cycle impact assessment (LCIA).

For our analysis, the LCI data are given in relation to the mass of the BSS in kilograms. The functional unit is defined as 1 kWh of nominal battery capacity, calculated on the basis of given energy densities of the different cell chemistries in Wh/kg. Thereby, we consider three of the most common battery chemistries for residential BSSs (Le Thomas et al., 2020), namely lithium nickel cobalt aluminum oxide (NCA), lithium nickel manganese cobalt oxide (NMC), and lithium iron phosphate (LFP).

We apply International Reference Life Cycle Data System (ILCD) midpoint as LCIA method and choose the global warming potential (GWP) as impact category. Thereby, the GWP is measured in kilograms of carbon dioxide equivalent (kg CO_2e) and calculated using the IPCC 2013 GWP 100a method (Intergovernmental Panel on Climate Change, 2014). For the implementation and calculation of results we use OpenLCA 1.9 combined with data from Ecoinvent 3.6 (Wernet et al., 2016).

3.1.2 | Life cycle inventory

The considered residential BSS consists of module casings, the battery management system (BMS), the battery cells, as well as the BOP components (inverter, power electronics, and battery casing).

Similar to Le Thomas et al. (2020), we determine the mass of the battery module and the mass proportion of its cells based on data sheets of residential lithium-ion batteries commercially available in Germany. In total, we analyze 11 LFP, 6 NCA and 20 NMC residential BSSs (see Supporting Information for more details). All BSSs are scaled to 9 kWh of nominal battery capacity, which is the average installed capacity of residential BSSs in Germany (Figgener et al., 2018). The allocation of the module weight to the different components is carried out in accordance to Jasper et al. (2022). For all cell chemistries, the cell comprises 68.7%, the casing 28.5%, and the BMS 2.8% of the module weight.

The LCI and the mass ratio of the cells are based on Le Thomas et al. (2020). However, a few adjustments are made to represent the currently dominant supply chain for residential BSSs installed in Europe. For example, LFP/NCA and NMC are modeled with the Japanese and South Korean electricity mix, respectively, and Asian aluminum is assumed for all systems (Schmidt et al., 2019). Moreover, due to the harmonization of assumptions regarding the cell components and our own, thus different, market overview, we have to update the energy density of the different cell chemistries. The updated mass ratios for the cell modules are obtained by combining the calculated module weights/mass fractions of the cells with the material composition of the cell components from Le Thomas et al. (2020).

As in Le Thomas et al. (2020), we assume the same process for the manufacturing of the battery cells across all battery chemistries while taking into account the different energy densities. Values for the mass proportions of the solvents for the positive electrode as well as the energy and water usage for the cell production are updated with values retrieved from Dai et al. (2017, 2019).

Since Ecoinvent 3.6 does not include an entry for cobalt sulfate, the dataset from the LCI in Majeau-Bettez et al. (2011) is used instead. As a substitute of the LCIs from Ecoinvent, the more recent datasets from the GREET model presented in Dai et al. (2019) are used for lithium nickel cobalt manganese oxide and nickel cobalt manganese hydroxide. Moreover, the graphite in the negative electrodes is replaced with the dataset "graphite, battery grade" from Ecoinvent and the water that is used as a solvent in the anode is already included in the factory's water consumption (Dai et al., 2019).

As a simplification, we assume that all battery chemistries use the same BOP components. We scale the material fraction of the housing based on the energy density and the battery capacity for each chemistry, as cells with a lower energy density can be expected to require a larger housing. Based on the market overview, the average combined mass of the charger and system controller is 13.6 kg. The ratio between the two components is taken from Jasper et al. (2022). Since the residential BSSs with the highest market share from "Sonnen" are *made in Germany* (Hannen, 2020), we assume that the production of the housing and the assembly of the BSS takes place in Germany. The transport distance of the different cell modules from the largest port in the country of manufacturing to the production site in Germany is estimated using Sea-Distances (2020). The detailed LCIs can be found in the Supporting Information.

3.2 | Simulation of operational phase

3.2.1 | Framework

In order to analyze the energy flows (and the resulting GHG impact) involved in the operation of a residential BSS, we use a simulation model implemented in MATLAB (Fett et al., 2021). The model features a time resolution of 15 min and uses average path efficiencies to represent technical parameters of the PV system and BSSs. Additionally, stand-by losses, which occur when the battery is neither being charged nor discharged are implemented. In order to account for uncertainties, different efficiency parameters are investigated as shown in Table 2. To avoid biases resulting from aggregated or synthesized data and in order to account for the diversity of households' load curves (Quoilin et al., 2016; Schopfer et al., 2018), we use 162 empirically measured household load profiles. Additional information about these load profiles (e.g., electricity consumption and peak load) is available in the Supporting Information. Determining an optimal size of PV system and BSS is out of the scope of our analysis. There-

TABLE 2 Assumed efficiencies of the battery storage systems for the simulation of the operational phase.

Component	Parameter	High	Medium	Low
Inverter	Charging efficiency	95.1%	93.5%	91.7%
	Discharging efficiency	98.0%	95.1%	92.6%
Battery	Storage efficiency	95.4%	93.6%	92.0%
System	Round-trip efficiency	88.9%	83.2%	78.1%
	Stand-by consumption	5.0 W	10.0 W	20.0 W

In order to account for uncertainties, the efficiency parameters of different components are varied resulting in three systems with different round-trip efficiency and stand-by consumption. *Source*: based on Weniger et al. (2020).

fore, we use a simplified approach as in Weniger et al. (2015) and base the system sizes on the respective household's energy consumption with 1 kW_p of PV and 1 kWh of battery storage being installed per 1000 kWh of electricity consumption. Since the way the batteries are operated may have a substantial impact on the related GHG emissions, three operational strategies are implemented in the model, which are briefly described in the following.

Default

This relay-based operational strategy is designed to maximize self-consumption. The PV generation is first used to cover the household's electricity demand. Excess PV generation charges the battery or is fed into the grid, if the battery is already fully charged. If the household's electricity demand exceeds the PV generation, the battery supplies electricity to the household, until fully discharged. Demand not covered through PV and battery is supplied through the electricity grid. No exchange between battery and the grid is allowed. This is the most common operational strategy for current residential BSSs (Klingler, 2017).

Delayed charging

This alternative operational strategy was proposed by Williams et al. (2014). Its basic idea is to move the battery charging into the time of the day, where on average the peak PV generation occurs. From May to September, the battery is charged at a constant rate from 9 a.m. to 3 p.m., which is determined for each day based on the state of charge (SOC) at 9 a.m. Before 9 a.m., excess PV generation is fed into the grid and after 3 p.m., the default strategy is used. The behavior for supplying the household's electricity demand stays the same as in the default strategy.

Dynamic feed-in limitation

The aim of this forecast-based operational strategy by Bergner et al. (2014) is to lower the peak feed-in as much as possible, while having a minimal impact on the self-sufficiency. While the behavior for supplying the household's electricity demand again stays the same as in the default strategy, the charging behavior of the battery is controlled differently. The battery is only charged if the excess PV generation is above a virtual feed-in limit, otherwise the PV surplus is fed into the grid. This virtual feed-in limit is determined such that considering the current SOC, the expected PV generation, and the expected household demand, the battery is fully charged at the end of the day. In this work, perfect foresight is assumed for the PV and load forecast.

3.2.2 | Greenhouse gas emissions

Please note that contrary to the cradle-to-gate assessment, we consider direct CO_2 emissions as the sole GHG related to electricity generation and thus indirectly the operation of the BSSs. Given the lack of reliable data on technology-specific upstream emission per unit of electricity generated, this is common practice in the research field of energy economics. Data from Ecoinvent for the average German electricity mix in 2016 suggests that this approach may underestimate emissions by roughly 10% as compared to the emissions data from Agora Energiewende (2019) that we apply in our analysis. Yet, part of these upstream emissions stems from the construction phase of the conventional power plants and utility-scale renewables like wind and solar. It is reasonable to assume that the expansion of these technologies would not be affected by the amount of residential BSSs installed (Fett et al., 2021). Consequently, the installation and operation of residential battery storages only affects the operation of the utility-scale electricity system, but not its construction. Moreover, in our analysis, we are only interested in *deltas* of emissions between different time periods. Therefore, we would expect the small error caused by not accounting for upstream emissions of electricity generation to be further reduced.

In order to determine the carbon emissions of the operational phase, it is essential to first select an appropriate definition of the emission factor.

Ryan et al. (2018) recommend using an average rather than a marginal emission factor when evaluating an existing electricity demand. This is clearly given in the case of residential BSSs, as they reduce the household's existing electricity demand by increasing self-consumption. Furthermore, average factors are the established method for ecological assessments in the building sector, especially when considering exchange with the electricity grid (Clauß et al., 2019).

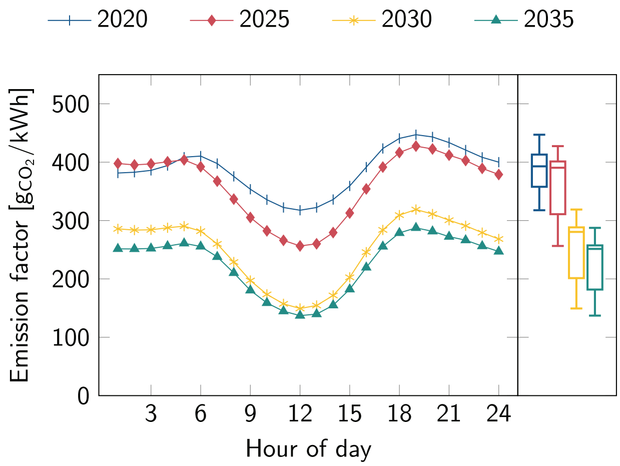

FIGURE 2 Average diurnal pattern of the applied carbon emission factors.

The assumed strong expansion of renewables leads to decreasing emissions in the overall electricity supply. Underlying data for all Figures are available in Supporting Information S2.

In terms of the temporal dimension, most studies apply yearly averaged values. Since this approach neglects the crucial impact of diurnal fluctuations, we rely on hourly resolved emission factors instead. We use both historical emission factors for the year 2018 obtained from Agora Energiewende (2019) as well as future time series simulated with the agent-based electricity market model PowerACE (Fraunholz, 2021) for the period 2020 through 2040. For the latter, similarly as in Hein and Hermann (2019), we divide the hourly direct emissions originating from electricity generation by the total hourly electricity demand in Germany including electricity exchange with neighboring countries.

Figure 2 depicts the average diurnal pattern of the emission factors for selected simulation years. Most notably, the simulations with PowerACE show a strong overall decline of the emission factors until 2035, with the lowest values around noon. These trends can be attributed to the assumed strong expansion of renewable electricity sources in general and the typical diurnal generation patterns of PV in particular. Apart from the absolute level of the emission factors, their diurnal fluctuations are also an important aspect when evaluating BSSs. The higher these fluctuations are, the more emissions can be reduced by storing electricity at times of low emission factors and releasing it at times of higher ones. The box plots on the right part of Figure 2 illustrate that diurnal fluctuations increase from 2020 up to 2025, yet decrease between 2030 and 2035.

For the calculation of the CO_2 emissions during the operational phase, we follow the approach by Weniger et al. (2019b). Based on the interaction of the household with the public grid, we calculate two indicators. First, the CO_2 balance $E_{h,o}^{CO_2}$ is determined for each household h and operational strategy o as shown in Equation (1). For this purpose, the delta of power exports to the public grid ($P_{h,o,t}^{exp}$) and power imports ($P_{h,o,t}^{imp}$) is determined for each time step t, and multiplied by the time step length Δt as well as the respective emission factor $e_t^{CO_2}$. Using this definition, a negative value of $E_{h,o}^{CO_2}$ indicates emission savings due to the operation of the PV system and BSS.

$$E_{h,o}^{CO_2} = \Delta t \cdot \sum_{t=1}^{T} \left[\left(-P_{h,o,t}^{exp} + P_{h,o,t}^{imp} \right) \cdot e_t^{CO_2} \right] \quad \forall h, o \tag{1}$$

In order to isolate the impact of the BSS, the emissions obtained by the first indicator need to be related to those of a PV system without battery storage. Thus, we define a second indicator which calculates this CO_2-delta $\Delta E_{h,o}^{CO_2}$ for each household h and operational strategy o as shown in Equation (2). Here, $E_{h,base}^{CO_2}$ denotes the respective emissions of a given household h in the base case with only a PV system, but no battery storage installed. The interpretation of the second indicator is straightforward. If $\Delta E_{h,o}^{CO_2}$ takes a negative value, the household would emit less CO_2 through the operation of the PV and BSS as compared to a PV system without battery.

$$\Delta E_{h,o}^{CO_2} = E_{h,o}^{CO_2} - E_{h,base}^{CO_2} \quad \forall h, o \tag{2}$$

4 | RESULTS AND DISCUSSION

In the following, we present and discuss the results of our analyses. In line with the structure of our applied methodology, Section 4.1 focuses on the cradle-to-gate assessment and Section 4.2 on the operational phase, while the final Section 4.3 provides an overall assessment.

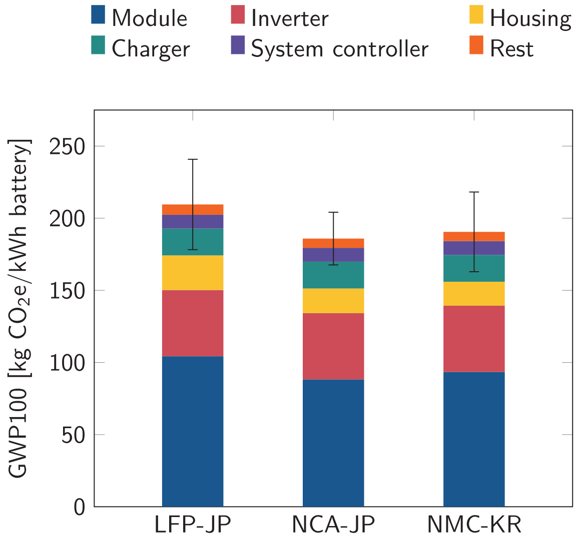

FIGURE 3 Greenhouse gas impact resulting from the cradle-to-gate assessment.

The values for all three battery chemistries lie within a rather small range. The error bars account for the uncertain weights of the cell modules. GWP, global warming potential; JP, Japan; KR, Republic of Korea, LFP, lithium iron phosphate; NCA, lithium nickel cobalt aluminum oxide; NMC, lithium nickel manganese cobalt oxide. Underlying data for all Figures are available in Supporting Information S2.

4.1 | Cradle-to-gate

Figure 3 shows the results of the GHG impact assessment of the full production phase (cradle-to-gate). The error bars result from the standard deviations of the cell module weights for each of the battery chemistries found in the market survey. Overall, we find the GHG impacts of the LFP, NCA, and NMC residential BSSs to be within a close range of 210 ± 31, 186 ± 18, and 191 ± 28 kg CO_2e/kWh of nominal battery capacity, respectively.

Thereby, the cell modules show the largest impact of all components, accounting for 49.8% (LFP), 47.5% (NCA), and 49.1% (NMC) of the GWP100, respectively. A more detailed analysis shows that across all cell chemistries, more than 75% of the GWP100 of the cell module is caused by the battery cells, while the impacts of the other components are significantly lower. The module casing accounts for 10.6–13.7% and the BMS for 3.9–5.1%.

Combined, the peripheral components have a similar impact as the cell modules. Since the material balances of the BOP components are assumed identical for all cell chemistries and only the material share of the housing is adjusted to the different energy densities, the contribution of the periphery is similar for all battery chemistries. Amongst the peripheral components, the battery inverter has the highest GHG impact with 45.9 kg CO_2e/kWh of nominal battery capacity. Depending on the cell chemistry, this is followed by either the charger (18.6 kg CO_2e/kWh), or the housing (16.6–24.0 kg CO_2e/kWh). Due to the lowest energy density, the GHG impact of the housing is highest for LFP BSSs. With a GWP100 of only 9.6 kg CO_2e/kWh, the system controller has the lowest GHG impact. The category "rest" includes, amongst others, the transport of the BSS as well as cables and electronics required for the final assembly.

4.2 | Operational phase

The magnitude of carbon emissions during the operational phase is strongly affected by the respective household's generation and demand pattern, the way the BSS is operated, the efficiency of the BSS, and the carbon intensity of the electricity mix from the grid. Thus, in order to obtain reasonable estimates across the entire lifetime of a BSS, we consider empirical electricity demand profiles of 162 individual households, 3 operational strategies (see Section 3.2.1), 3 system efficiencies (see Table 2), and empirical, respectively simulated, time series for the emission factors (see Section 3.2.2).

Given these assumptions and input data, Figure 4 provides an overview of the resulting deltas in carbon emissions for all 162 considered households as compared to the base case without operating a BSS[1]. The most significant findings can be summarized as follows.

First, the broad range of the box plots shows substantial differences between the households. This supports our statement that taking into account the variability of electricity demand patterns is essential for a thorough assessment of residential BSSs' environmental impact. Supplementary regression analyses (see see Supporting Information S3) show that in particular the total electricity consumption of an individual household can be a major driver. When relying on advanced operational strategies for the BSS (see later), a higher electricity consumption generally results

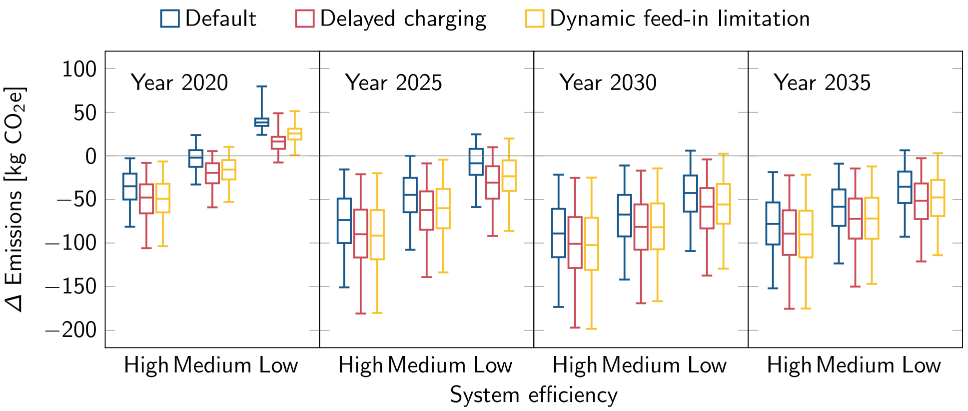

FIGURE 4 Simulated impact of the different operational strategies on carbon emissions.

The box plots show the deltas in emissions of all 162 considered households as compared to the case without operating a BSS. Thereby, the boxes represent the data for the lower quartile, the median, and the upper quartile of the investigated households; the whiskers the households with the minimum and maximum delta in emissions, respectively. Negative values correspond to a reduction of the carbon emissions through the battery operation. The different system efficiencies refer to the data shown in Table 2. Following Weniger et al. (2015), we assume each household to install 1 kW_p of PV and 1 kWh of battery storage per 1000 kWh of electricity consumption. Underlying data for all Figures are available in Supporting Information S2.

in a higher potential for carbon emission reductions through the use of the BSS, whereas no clear relationship can be observed for the default operational strategy.

Second more sophisticated operational strategies can reduce carbon emissions as compared to the *Default* strategy with the sole objective of maximizing self-consumption. This is mostly because *Delayed Charging* and the *Dynamic Feed-In Limitation* shift the battery charging to the hours of peak PV generation whereas surplus electricity in the early morning and late afternoon hours is directly fed into the grid. Given the diurnal pattern of the carbon emission factor (cf. Figure 2), we can observe that this leads to a higher emission bonus as compared to a feed-in of surplus PV electricity at times of peak PV generation—as is the case in the *Default* strategy. A small additional impact arises from the fact that less curtailment of PV generation needs to be carried out when using the alternative operational strategies. These results are crucial, since the current German regulation provides little incentives to use more sophisticated operational strategies. Finally, also small differences between *Delayed Charging* and the *Dynamic Feed-In Limitation* are visible. These are related to stand-by losses: By charging at a constant rate between 9 a.m. and 3 p.m., the *Delayed Charging* strategy reduces the idle time of the BSS as compared to the *Dynamic Feed-In Limitation*. Naturally, this effect is most pronounced in case of low system efficiencies (see later).

Third, the carbon emissions are strongly reduced from 2020 through 2030, which is due to the increasing share of renewables in the system. Yet, in 2035, emissions slightly increase again. This is despite an ongoing expansion of renewables and driven by the lower diurnal fluctuations in emissions as described in Section 3.2.2. These results illustrate that it is essential to consider the changes in carbon emission factors not only on a diurnal scale, but also in the long-term perspective.

Fourth, the system efficiency also plays an important role. However, the increasing diurnal spreads between low-emission and high-emission periods (see Figure 2) allow to compensate parts of the efficiency losses. Consequently, the impact of the system efficiency on emissions is more pronounced in 2020 than the other presented years. Nevertheless, for a holistic analysis, it is essential to account for the variability in BSSs' efficiencies and the respective impact on carbon emissions.

4.3 | Overall assessment

In this final results section, we combine the findings from both, the cradle-to-gate assessment and the simulation of the operational phase to an overall environmental assessment of residential BSSs. For this purpose, the input data and assumptions summarized in Table 1 are used.

A PV BSS in Germany only completes about 200–250 cycles per year, therefore usually the calendaric aging is the limiting factor (Klein, 2020). The feed-in tariff for PV installations in Germany is guaranteed for a 20 year period. The calendaric lifetimes for all considered battery chemistries are within a close range (Le Thomas et al., 2020). As regards the GHG emissions during production, we therefore assume a constant technical lifetime of 20 years for all battery cells, which corresponds to our considered simulation horizon to simplify the comparison. However, the inverter has to be replaced after 15 years.

Since we are confronted with substantial uncertainties, we set up three different scenarios that combine *optimistic*, *best guess*, and *pessimistic* assumptions from the production and the operational stage. We first define an *average system*, which is calculated as the arithmetic mean of all

TABLE 3 Investigated scenarios in the overall environmental assessment.

Scenario	Production (Section 4.1)	Operation (Section 4.2)
Optimistic	Lower bound	High system efficiency
Best guess	Average system	Medium system efficiency
Pessimistic	Upper bound	Low system efficiency

In order to cover a broad range of uncertainties, optimistic, moderate, and pessimistic assumptions from both, the cradle-to-gate assessment and the simulation of the operational phase are combined.

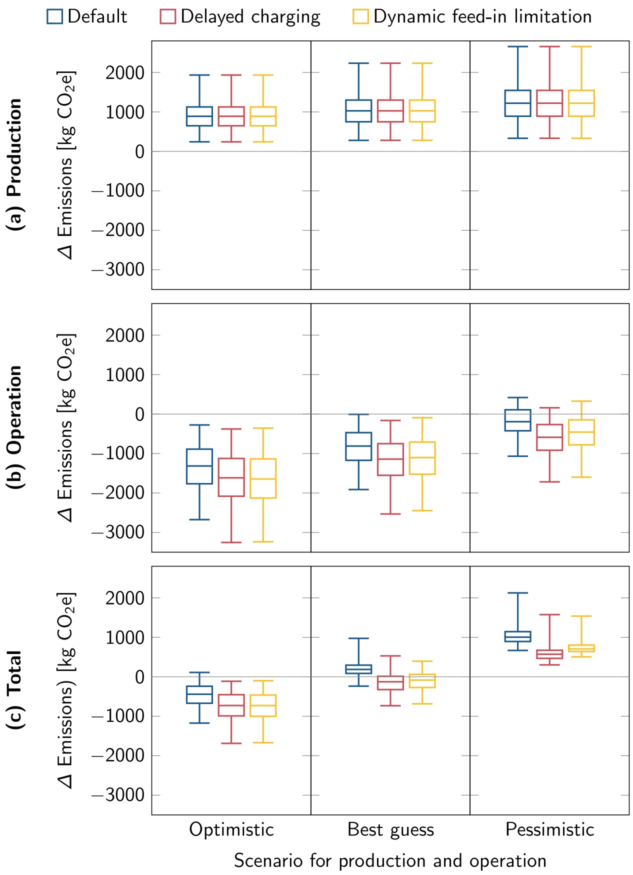

FIGURE 5 Greenhouse gas impact of (a) production, (b) operation, and (c) both stages combined in different scenarios.

The box plots show the deltas in emissions of all 162 considered households as compared to the case without operating a BSS. Thereby, the boxes represent the data for the lower quartile, the median, and the upper quartile of investigated households; the whiskers the households with the minimum and maximum delta in emissions, respectively. Negative values correspond to a reduction of the greenhouse gas emissions through the battery operation. Following Weniger et al. (2015), we assume each household to install 1 kW_p of PV and 1 kWh of battery storage per 1000 kWh of electricity consumption. Underlying data for all Figures are available in Supporting Information S2.

three considered cell chemistries (cf. Section 4.1). Moreover, we use the minimum value across all cell chemistries (NMC) as *lower bound* proxy for the emissions during production, and likewise the maximum value across all cell chemistries (LFP) as *upper bound* proxy. Under consideration of the inverter replacement, this leads us to cradle-to-gate emissions ranging from 208.84 kg CO_2e/kWh of nominal battery capacity (*lower bound*), over 241.25 kg CO_2e/kWh (*average system*), and up to 286.79 kg CO_2e/kWh (*upper bound*). These three values for the emissions at the production stage are then combined with different BSS efficiencies at the operational stage (cf. Table 2) to form the final three scenarios to be analyzed as shown in Table 3.

Figure 5 shows the results of the overall environmental assessment, comprising both the production and operational stages. Apart from the three introduced scenarios, we also distinguish between the three operational strategies for the BSSs (cf. Section 3.2.1), and account for the 162 individual households.

Starting with scenario *Pessimistic* and the *Default* operational strategy, we observe a mean increase of GHG emissions of 1043 kg CO_2e across all 162 simulated households as compared to the base case without operating a BSS. Thereby, none of the households is able to compensate the initial emissions from the production stage of the BSS, and for 56 of the households, the operation of the BSS even increases the initial emissions further. Switching to the *Delayed Charging* or the *Dynamic Feed-In Limitation* operational strategies reduces the mean emission surplus to 596 and 735 kg CO_2e, respectively. However, even here, 11 and 24 households, respectively, face additional emissions through the operation of the BSS which add to those from the production stage. The *Delayed Charging* strategy performs slightly better than the *Dynamic Feed-In Limitation* due to less idle time and therefore stand-by losses (cf. Section 4.2). However, regardless of the operational strategy, none of the considered households is able to compensate the emissions from the production of the BSS in scenario *Pessimistic*.

In the *Best Guess* scenario, none of the households faces additional emissions caused by the operation of its BSS. Nevertheless, not all households can compensate the initial emissions from the production stage. With the *Default* operational strategy, only 23 households are able to do so. Switching to the *Delayed Charging* or the *Dynamic Feed-In Limitation* operational strategies reduces the mean emissions by 344 and 304 kg CO_2e, respectively, as compared to the *Default* strategy. In consequence, 117 and 111 households, respectively, can compensate the initial emissions from the production of the BSS, if these operational strategies are used.

For the *Optimistic* scenario, we find mean emission reductions of 463 (*Default*), 751 (*Delayed Charging*), and 762 kg CO_2e (*Dynamic Feed-In Limitation*) as compared to the reference case without operating a BSS. Thereby, even when using the *Default* operational strategy, 159 households are able to compensate the initial emissions from the production of the BSS over its lifetime. Given the higher system efficiency in this scenario, the impact of stand-by losses is less important. Thus, the emissions using the *Dynamic Feed-In Limitation* are slightly lower here than under the *Delayed Charging* strategy.

In conclusion, our results show that the GHG impact from production and operation of a BSS may—depending on the scenario-specific assumptions—range from an average increase of emissions over the entire life time of 1043 kg CO_2e to a reduction of 762 kg CO_2e. Thereby, we can identify several important drivers, including the exact emissions at the production stage, the individual household load patterns, the system efficiency, and the applied operational strategy of the BSS. Finally, let us note that installing a replacement inverter with the same efficiency after 15 years in order to extend the lifetime of the BSS to 20 years leads to lower overall emissions than using the BSS for 15 years only. This is driven by the higher diurnal spreads of the carbon emissions toward the end of the considered lifetime (cf. Figure 2), which allow to compensate the additional emissions emerging from the production of a new inverter.

4.4 | Sensitivity analysis

In addition to the input parameters already varied within our scenarios (see Table 3), we conduct sensitivity analyses to demonstrate the robustness of our results. More specifically, we test for the impact of some updated calculation methods and datasets for the GWP as well as the impact of varying our initial lifetime assumptions. In the following, we only provide a brief summary, while the full results of the sensitivity analyses are included in the Supporting Information S3.

In the cradle-to-gate assessment, we use the updated IPCC 2021 AR 6 100a method as an alternative to the IPCC 2013 100a method for the calculation of the GWP. Furthermore, we analyze the impact of exchanging the datasets for cobalt sulfate and synthetic graphite with the potentially more reliable ones recently published by Crenna et al. (2021). All of the aforementioned changes result in negligible changes of less than 2% of the total GWP of the residential BSS for all battery chemistries.

Moreover, we vary our assumptions regarding battery lifetime. First, a scenario with 15 rather than 20 years of lifetime is investigated. In this setting, the savings from the inverter replacement that is no longer required are lower than the losses of 5 years less operational time.

Second, as in Kaschub (2017), the battery is oversized by 20% to account for battery degradation, thus also increasing the emissions from the production phase by 20%. Even here, almost all households are able to offset the emissions from production during operation in the *Optimistic* scenario. Under the *Best Guess* scenario, this still holds for about half of the households for the operational strategies *Delayed Charging* or *Dynamic Feed-In Limitation*.

Third, an additional scenario with individual lifetimes for each battery chemistry is considered. As the assumed lifetimes from Le Thomas et al. (2020) (19 years for LFP, 18 years for NMC, 21 years for NCA) are rather close to the previously assumed 20 years, also the resulting changes in the total GWP are comparably small. Again, almost all households can compensate the emissions from production in the *Optimistic* scenario. Under the *Best Guess* scenario, this applies to 21 out of 162 households for the *Default* operational strategy and over 100 households for both, *Delayed Charging* and *Dynamic Feed-In Limitation*.

Fourth, we assume that not only the inverter, but also the cells have to be replaced once within the 20 years under consideration. The resulting total GWPs are the highest among all considered scenarios and sensitivities. Nevertheless, 129 households can compensate the initial emissions from the production of the BSS in the *Optimistic scenario* using the *Default* operational strategy and still almost all households when using *Delayed Charging* or *Dynamic Feed-In Limitation*. Under the *Best Guess* scenario this is only the case for very few households.

Finally, two scenarios with constant grid emission factors for the operational phase for the entire period under consideration are analyzed (see Figure 2 for the emission factors). The grid emission factors from 2020 lead to a significant increase in the GWP. None of the households is able to offset the GWP from production in the *Best Guess* scenario. For 70 households under the *Default* operational strategy, 16 under *Delayed Charging* and 26 under *Dynamic Feed-in Limitation* the operation of the BSS even increases the initial emissions further. In contrast, the grid emission factor from 2030 leads to a significant reduction in the GWP. In the *Best Guess* scenario the operation reduces the GWP for all households. The 141 households under the *Default* operational strategy, all households under *Delayed Charging*, and 160 under *Dynamic Feed-in Limitation* are also able to compensate the GWP of the production.

5 | LIMITATIONS

Despite substantial modeling effort, our work has certain limitations, which we briefly address and discuss in the following.

First, the sizing of the PV and BSS is out of the scope of this publication. Therefore, the system sizes are assumed to be purely based on the respective household's electricity consumption. In reality, many factors (including economic considerations, and the desire for a high self-sufficiency rate) influence the investment decision (Figgener et al., 2018), leading to bigger systems than in this paper. However, according to Weniger et al. (2019a), the system efficiency is more important for the CO_2 impact than the system size.

Second, the mass of the battery module and the mass proportion of its cells are determined based on data sheets of BSSs commercially available in Germany. Due to harmonization, we neglect that the structure of the BSSs is not necessarily the same, for example, the module casing can be made from different materials like aluminum or steel. The same is true for the housing of the BSS, there are even systems which do not have a housing.

Third, for the operational phase, we assume a constant operation over the 20 years. This implies that household load profiles remain constant throughout the period of observation. Efficiency improvements as well as the electrification of heat and transport are likely to induce changes to the temporal patterns of the household demand (Boßmann and Staffell, 2015). These effects are not taken into account in our work and battery degradation is also neglected. We did, however, include a scenario in the Supporting Information, where as in Kaschub (2017) the battery is oversized by 20% to compensate degradation.

Fourth, the *Dynamic Feed-In Limitation* operational strategy uses perfect foresight for the forecasts of PV generation and electricity demand. In reality, the households' self-sufficiency would be slightly lower due to forecasting errors (Bergner et al., 2014). However, additional adjustments to the regulatory framework, for example, a reduction of the feed-in limit, could account for this aspect and create an incentive for households to apply such an operational strategy nevertheless.

Fifth, as already mentioned in Section 3.1.1, Ecoinvent 3.6 was used for this analysis. Ecoinvent 3.7 and 3.8 contain updated datasets for different metals including cobalt, which probably would lead to increased GHG emission values from the production phase.

Finally, we have decided not to include the end-of-life phase in our analysis. As recycling of lithium-ion batteries is in its early stages (Le Thomas et al., 2020), the uncertainty about possible gains or losses is still high. A factor generally limiting the benefits from recycling is the high energy demand for cell manufacturing which cannot be recovered (Mohr et al., 2020). For LFP batteries, pyrometallurgical recycling adds burdens (Ciez & Whitacre, 2019; Mohr et al., 2020), whereas the reported values for NMC and NCA range between small burdens (Ciez & Whitacre, 2019) or small gains (Mohr et al., 2020). While in general hydrometallurgical recycling shows a higher potential for GWP reductions, gains for LFP are still small with about 3.5% (Mohr et al., 2020). For NMC and NCA, on the other hand, reductions of up to 25% are reported (Ciez & Whitacre, 2019; Mohr et al., 2020). Therefore, as soon as more research on the recycling of lithium-ion batteries has been carried out, our analysis should be extended in this direction.

6 | CONCLUSION AND POLICY IMPLICATIONS

In this article, we carried out a holistic environmental assessment of residential BSSs. Given some drawbacks in the existing literature, we developed a novel modeling approach combining a partial life cycle assessment for the production phase with a detailed simulation of 162 individual households for the operational phase. This methodology was then applied in a comprehensive case study for Germany, the most important European market for residential BSSs.

As regards the production phase, we only find small differences between the carbon footprints of different cell chemistries. Moreover, we can show that the BOP components have a comparable impact on the GWP as the cell modules. This result is crucial since the existing literature mostly neglects at least some BOP components—thus underestimating the carbon footprint of the battery production.

In terms of the operational phase, our simulations show the important impact of diurnal fluctuations in the carbon intensity of the electricity mix. While most of the literature neglects this aspect and relies on yearly averaged emission time series, we use data from an electricity market model to account for both long-term developments and diurnal fluctuations of the carbon emissions. By shifting electricity demand from high-emission to low-emission periods, BSSs can compensate at least parts of their efficiency losses. In detailed analyses, we find the magnitude of this effect to depend on the respective household load patterns, the system efficiency, and the operational strategy of the battery.

Under certain conditions, the operational phase of the BSSs can overcompensate the emissions from the production phase and lead to a positive environmental impact over the lifetime of the systems. As the most relevant drivers, we find the exact emissions at the production stage, the individual household load patterns, the system efficiency, and the applied operational strategy. If emissions from the production phase and the system efficiency are both assumed to be at the optimistic end of our determined range, the environmental impact of the BSSs is positive for (almost) all investigated households. For the majority of the households, this finding still holds when taking average assumptions on production phase and system efficiency. However, advanced operational strategies for the batteries would then need to be used. Based on these results, we recommend to invest in research and development to further improve both, the manufacturing processes and system efficiencies. Moreover, proper economic incentives for advanced operational strategies should be established, which would support the system integration of renewables and reduce GHG emissions during the operational phase.

ACKNOWLEDGMENTS

We would like to thank Jana Späthe and Manuel Baumann for providing us with additional information about their publication.

Open access funding enabled and organized by Projekt DEAL.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Most data that supports the findings of this study are available in the supporting information of this article (including inventory tables, technical specifications of commercially-available residential battery storage systems, time series of future carbon emission factors and the numerical results as underlying data for the plotted figures).

Additionally part of the residential load profiles used in this study are publically available at [https://solar.htw-berlin.de/elektrische-lastprofile-fuer-wohngebaeude]. The other residential load profiles are not publicly available due to privacy restrictions.

Some data that support the findings of this study are available from ecoinvent. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from https://ecoinvent.org with the permission of [ecoinvent] or directly from the third party.

ORCID

Daniel Fett https://orcid.org/0000-0003-4477-4748

Christoph Fraunholz https://orcid.org/0000-0002-0743-080X

NOTE

[1] Please note that only selected simulation years are depicted, whereas all years between 2018 and 2038 are considered individually in the overall assessment of Section 4.3.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Fett, D., Fraunholz, C., & Schneider, P. (2022). Life cycle greenhouse gas emissions of residential battery storage systems: A German case study. *Journal of Industrial Ecology*, 1–14. https://doi.org/10.1111/jiec.13344