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Research Article

Bayesian Monte Carlo-assisted life cycle assessment of lithium iron phosphate batteries production for electric vehicles under uncertainty

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Abstract

The environmental performance of electric vehicles (EVs) largely depends on their batteries. However, the extraction and production of materials for these batteries present considerable environmental and social challenges. Traditional environmental assessments of EV batteries often lack comprehensive uncertainty analysis, resulting in evaluations that may not be sufficiently accurate or reliable. To address this issue and quantify uncertainties in the evaluation of EV battery production, based on the foreground data of the lithium-iron-phosphate battery pack manufacturing process, the ReCiPe midpoint methodology was adopted to quantify the lifecycle environmental impacts using eleven environmental indicators. Given the parametric uncertainties in the manufacturing process of lithium-iron-phosphate, a Bayesian Monte Carlo analytical method was developed to determine the probability distribution of global warming potential and acidification potential. Local sensitivity analysis was conducted to identify the influential factors of selected environmental indicators. Results indicated that battery cell production is the largest contributor to the entire emissions and resource utilization (comprising 63.38% of the production of each battery pack), in which cathode electrode paste and anode current collector manufacturing processes were the two predominant components with the highest environmental burdens. Sensitivity analysis showed that environmental indicators were quite sensitive to different substances in the battery pack. The application of Bayesian Monte Carlo uncertainty analysis effectively reduces the uncertainties in life cycle assessment. This study would contribute to uncertainty quantification towards solid life cycle assessment.

INTRODUCTION

The advancement of electric vehicles (EVs) is critical in mitigating greenhouse gas emissions and is essential for achieving carbon neutrality objectives. By replacing internal combustion engines with battery-powered systems, EVs are claimed to have significant potential for emission reduction[1]. Over the past decade, the growth in EV development has been substantial, with the number of available models surpassing 500 by 2022, more than doubling since 2018[2]. The environmental impact of batteries has been a hotspot across academia, industry, and governmental organizations, particularly the European Union which enacted the new EU Batteries Regulation recently[3]. This regulation enforces comprehensive sustainability requirements to ensure lower lifecycle carbon emissions[4]. Thus, accurately estimating the lifecycle emissions of EV batteries is critically important. Life cycle assessment (LCA), widely acknowledged as an environmental management methodology, is the primary tool for such estimation[5].

The manufacturing stage has been identified as the most significant source of environmental impact for EV batteries[6]. This study aims to address the critical challenge of accurately evaluating the environmental impacts of EV battery production and mitigating inconsistencies in LCA results. The burgeoning efforts have been made to investigate the environmental impacts of the EV battery production phase[7]. Amidst these endeavors, many studies commonly adopt an approach grounded in the LCA framework, scrutinizing and listing the life cycle inventory (LCI) of EV batteries. For example, Temporelli *et al.*[6] assessed the ecological impacts of EV batteries throughout their life cycle, including material extraction, manufacturing, use, and end-of-life phases, highlighting the substantial environmental burdens during the production stage. However, the manufacturing phase of EV batteries is fraught with uncertainties. Although the general LCA framework exists[8], studies on batteries of the same type show diverse or even contradictory results. For instance, Hao *et al.*[9] and Shu *et al.*[10] reported 46.43 and 109.32 kg CO_2 eq, respectively, when manufacturing a 1 kWh lithium-iron-phosphate (LFP) battery. However, Marques *et al.*[11] stated a much higher carbon emission during the production stage, with a value of 282.6 kg CO_2 eq. Unsurprisingly, this large variability stems from various uncertainties, such as parameter-related uncertainty (e.g., variations in the energy sources used for manufacturing and the efficiency of material utilization[12,13]). Therefore, integration of uncertainty analysis into LCA is non-trivial for a reliable environmental assessment of EV batteries[14].

The absence of primary and reliable industry data necessitates several assumptions; for example, different energy structures for battery manufacturing can lead to variations in life cycle impact assessment (LCIA) results[15]. Current literature claims that uncertainty could influence the environmental burden significantly. Kim *et al.*[16] discussed the variability in the environmental impacts due to different data sources and assumptions, highlighting that cradle-to-gate emissions from lithium-ion battery (LiB) production could range from 56 to 494 kg CO_2-eq per kWh depending on the manufacturing scenario. Similarly, Hao *et al.*[9] acknowledged the inherent uncertainties in the material sourcing and manufacturing processes of EV batteries, noting that greenhouse gas emissions from LiB production in China can vary by as much as 30% based on the regional energy mix and efficiency of manufacturing processes. Despite recognizing the influence of uncertainty, their study lacks a systematic approach to quantify these uncertainties across different stages of the battery lifecycle. This gap in comprehensive uncertainty analysis is a critical issue, as it undermines the reliability and comparability of LCA results, ultimately affecting policy and decision-making processes aimed at promoting sustainable practices in the EV industry. Thus, there is an urgent need for more rigorous and standardized approaches to uncertainty analysis in LCA studies of EV batteries to ensure more accurate and reliable environmental impact assessments.

Common uncertainty analysis techniques have been applied to the LCA of batteries, such as scenario analysis[17], sensitivity analysis[18], and probability modeling[19]. However, sensitivity analysis often oversimplifies by changing one variable at a time, failing to capture the interplay between multiple factors[20]. Scenario analysis, while useful for exploring different possibilities, does not provide probabilities for the occurrence of each scenario, limiting its predictive power[21]. Probabilistic modeling, although more sophisticated, can be computationally intensive and may still rely on uncertain input data, compounding the uncertainty rather than clarifying it[22]. As a tool for probabilistic modeling, the Monte Carlo (MC) simulation is commonly employed to conduct error propagation in model parameters[23]. Traditional MC simulation methods often face limitations in handling parameter uncertainties due to their reliance on frequentist probability distributions, which may not adequately represent real-world variability[24].

Collectively, research issues that motivated the present study were: (1) accurately evaluating the environmental impacts of EV battery production and (2) mitigating inconsistencies by quantifying uncertainties in the assessment of EV battery production. To address these problems, this study performed an LCA of LFP batteries under multiple uncertainties[25-27]. The system boundary was defined as "cradle-to-gate", specifically, the battery production process. The foreground data stem from multiple relevant literature on LFP production and the background data was rooted in Ecoinvent 3.0[28,29]. Then, the ReCiPe method was adopted and 11 environmental indicators were selected. Additionally, Bayesian inference was incorporated into the MC simulation, also referred to as the Bayesian Monte Carlo (BMC) method, for quantifying the LCI uncertainties of the LFP production process. This leverages prior information and updates our uncertainty estimates as more data becomes available, leading to more robust and accurate quantifications of uncertainties. Further, a local sensitivity analysis was conducted to determine environmentally sensitive parameters. The uncertainty analytics in this study not only reveals the variation of environmental impacts of LFP battery production but also enhances the robustness and reliability of assessment.

The rest of this article is organized as follows: Part 2 presents the methodology of LCA employed in this study. Part 3 describes the final numerical results. Part 4 provides critical discussions, and Part 5 concludes this study.

METHODS

LCA is a systematic and comprehensive methodology employed to evaluate the environmental impacts associated with a product, process, or system throughout its life cycle. In this study, the environmental assessment of one LFP battery pack is conducted using LCA methodology, following the guidelines of the International Organization for Standardization (ISO) 14040 (2006a) and ISO 1404 (2006b)[8,30].

Goal and scope definition
Goal of this study
The research object in this study is an LFP battery pack. According to Gaines *et al.*[31] and Ellingsen *et al.*[32], a single battery pack comprises several distinct components, including battery modules, a battery management system (BMS), a cooling system, and battery packaging. Within this framework, battery cells are consolidated into individual modules. Figure 1 illustrates the fundamental model of the battery pack, showcasing the pack level to modules and further down to individual cells. The goal of this study is to ascertain LCI data pertaining to an LFP battery, assess the environmental implications of LFP batteries within the manufacturing life cycle, and examine the influence of uncertainties in key parameters on environmental indicators for further environmental performance improvement. Meanwhile, these analysis results will furnish support for investigating the environmental impact of the subsequent use and recycling
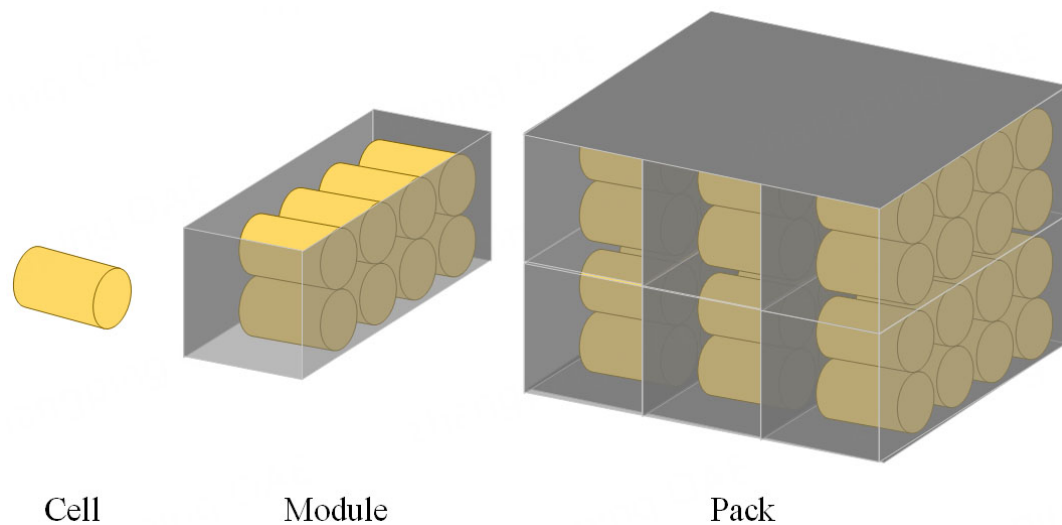
Figure 1. EV battery compositions: from battery cell to pack. EV: Electric vehicles.

of LFP batteries in different scenarios.

Scope of this study

As a medium for energy storage and transfer, LFP battery plays a fundamental role in the power supply for EVs. Scrutinizing 241 EVs in China, Wang and Yu[33] found that the average weight of LiBs for these EVs approximates 298 kg. It is assumed that the average weight of the LFP battery pack in this study is 300 kg. Table 1 specifies the component ratios within a battery pack.

The functional unit (FU) serves as the basis for the calculation of every intake of raw materials, energy consumption, waste gas produced, and effluent emitted during the battery production process. The FU in this study is defined as "producing one complete LFP battery pack, with a weight of 300 kg, designed for an electric vehicle". As shown in Figure 2, the system boundary is in the form of "cradle-to-gate", primarily covering the production stages of LFP batteries and including material preparation, transportation, assembly, manufacturing, and package phases. The LFP battery can be classified into eight main components, namely the positive electrode, negative electrode, separator, cell container, electrolyte, BMS, battery cooling system, and battery package. Of these main components, the manufacturing processes of four critical ones are depicted in Figure 3. The energy consumption, heat generation, transportation, atmospheric emissions, and effluents occurring within the system boundary were primarily considered, while the usage and end-of-life disposal phases are ignored due to the issue of data availability in practical situations.

Data cutoff criteria and data collection

In this study, foreground data are the primary concerns on the production of LFP batteries, encompassing information gathered from diverse literature databases. The background data for raw material extraction, transportation, assembly, and manufacturing processes stem from the Ecoinvent 3.0 database. A 0% cutoff criterion was employed in the LCA practice, allowing for a comprehensive consideration of all relevant factors in the assessment. For the foreground data on specific materials missing in the LCA databases, data from similar materials were directly employed for imputation. Specific inventory information regarding the material substitution is detailed in the following chapter.

Table 1. Battery pack configurations

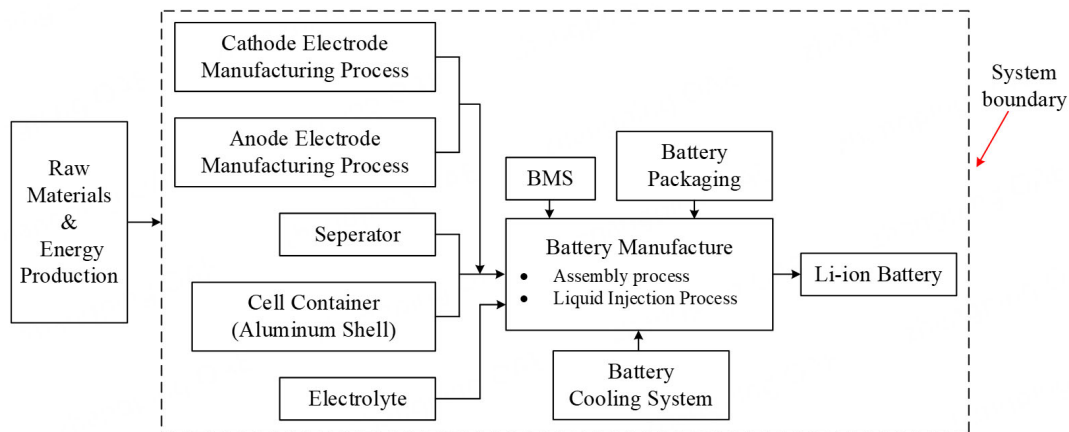| Components	Mass (%)
Battery cell	60.1
Battery cooling system	4.1
BMS	3.7
Battery packaging	32.1

BMS: Battery management system.

Figure 2. System boundary of LCA. LCA: Life cycle assessment; BMS: Battery management system.

Life cycle inventory analysis

The LCI of the complete LFP battery pack was compiled in conjunction with data from various studies. Primary data on raw materials during the production of individual battery cells stemmed from the study of Notter *et al.*[34]. Energy consumption during assembly was obtained from Baars *et al.*[35], while inventories for battery packaging, cooling system, and the BMS were sourced from the research by Ellingsen *et al.*[32] and Crenna *et al.*[4]. The main components of these parts are detailed in Tables 1 and 2. Additionally, the Supplementary Materials provides a detailed summary of these tables, outlining the inventory for battery masses and the sources of the data. Our inventory employed Ecoinvent 3.0 as a background system.

The cathode, a critical component of the LFP battery, consists of the positive electrode paste and the cathode current collector. The positive electrode paste is made from LFP as the primary material, with Polyvinylidene Fluoride (PVDF) as the binder, carbon black as the conductive agent, and N-methyl-2-pyrrolidinone (NMP) as the solvent to impart a slurry texture to the mixture. The cathode current collector is primarily composed of aluminum foil, supplemented with a pre-treatment process using sulfuric acid (H_2SO_4) and sodium hydroxide (NaOH) to eliminate impurities and enhance corrosion resistance. The aluminum foil thickness ranges between 10 to 18 μm[35]. Due to the absence of an inventory for PVDF in both the Ecoinvent database and existing literature, Polyvinyl Fluoride (PVF) inventory from Ecoinvent is used as a substitute, a practice commonly adopted in related studies[35,36]. In this study, raw materials related to PVDF are substituted with PVF. The manufacturing of LFP follows the synthetic route proposed by Majeau-Bettez *et al.*[37]. The materials involved in this chemical reaction include $FeSO_4$ with phosphoric acid (H_3PO_4) and lithium hydroxide (LiOH). The quantities of these materials can be estimated through stoichiometric calculations[35-37].

Table 2. Battery cell configurations

Components	Mass (%)
Cathode electrode paste	22.8
Cathode current collector	2.9
Anode electrode paste	9.9
Anode current collector	13.3
Separator	1.3
Electrolyte	9.5
Battery cell container	0.4
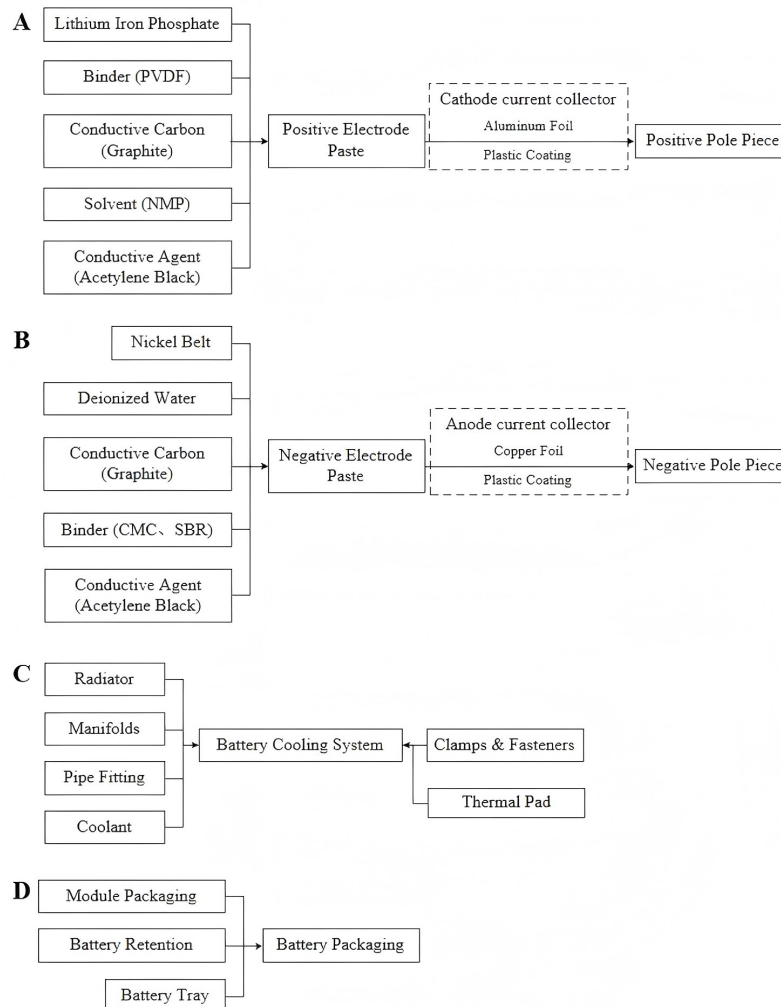
Figure 3. The manufacturing process of main components: (A) cathode electrode; (B) anode electrode; (C) battery cooling system; and (D) battery package. PVDF: Polyvinylidene fluoride; NMP: N-methyl-2-pyrrolidinone; SBR: Styrene-butadiene rubber; CMC: Carboxymethyl cellulose.

Similar to the cathode, the anode comprises the negative electrode paste and anode current collector. The negative electrode paste uses carboxymethyl cellulose and styrene-butadiene rubber (SBR) as binders, graphite as the conductive carbon, and NMP as the solvent to provide a slurry texture to the mixture. Notably, non-metallic graphite serves as the primary component, exhibiting thermal and electrical

conductivity akin to metals. The production of SBR, modeled using the inventory suggested by Peters *et al.*[38], includes materials such as butadiene, styrene, soap, deionized water, cyclohexane, and sodium persulfate. The separator inventory, sourced from the work by Notter *et al.*[34], includes polyethylene, phthalic anhydride, hexafluoroethane (C_3F_6), polyvinyl fluoride, and silica sand, with C_2F_6 replacing C_3F_6 in some cases. The electrolyte commonly comprises a lithium salt dissolved in an organic solvent and includes additives[39]. Building on the study by Baars *et al.*[35], the model employs lithium hexafluorophosphate ($LiFP_6$) as the conductive salt, with ethylene carbonate (EC) and dimethyl carbonate (DMC) as solvents, and vinyl carbonate (VC) as an additive. The inventory data on these solvents and additives are available in the Ecoinvent 3 database.

The cell container's composition involves materials such as polyethylene terephthalate (PET), aluminum, polypropylene, and copper[4]. Existing LCA studies[40] on the BMS were performed in various degrees. In this study, the environmental inventory of BMS was grounded in the Ecoinvent 3 framework, encompassing the integrated battery interface system (IBIS), high-voltage system, low-voltage system, battery module boards (BMB), and electronic components. The BMB and fasteners in BMS were approximated by printed wiring boards and low-alloyed steel in the Ecoivent database, respectively. The cooling system of the battery pack is composed of a radiator, manifolds, clamps and fasteners, pipe fittings, a thermal pad, and coolant. Among these six sub-components, the radiator stands out as the most critical element, being constructed from aluminum metal. The environmental profile of the cooling system has been investigated by Ellingsen *et al.*[32].

Battery packaging is divided into three parts: module packaging, battery tray, and battery retention, with inventory data sourced from the work by Ellingsen *et al.*[32]. One battery pack comprises 12 modules, and one module consists of 30 cells. Each cell is encased in a protective cassette, featuring an outer and inner frame, with the outer frame made from nylon 66, and the inner frame is similarly constructed. The assembly needs steel fasteners (retention rods, bolts, nuts), nylon washers produced via injection molding, and busbars welded to cell tabs, all under a protective ABS plastic lid. The heat transfer plate is crafted from anodized aluminum. Bimetallic busbars, with 30% aluminum and 70% copper composition, and washers feature both aluminum and copper sides. Module components such as the busbar holder and end-busbar holder are made from ABS plastic through injection molding.

Within the framework of the model, the assembly phase encompasses the integration of anode material, cathode material, battery cells, battery modules, the battery cooling system, battery packaging, and the ultimate assembly of the battery pack itself. The energy consumption required for the assembly process is derived from the Ecoinvent 3 database and has been estimated based on data provided by Ellingsen *et al.*[32].

Analyzing the "cradle-to-gate" of EV batteries allows the identification of environmental hotspots within the production phase, which consistently constitutes the largest proportion of the overall environmental footprint. This approach facilitates early mitigation of resource usage, emissions, and environmental impacts during the product's life cycle[41,42]. Thus, transportation considerations are limited to the conveyance of raw materials to chemical plants and to factories where related components are manufactured, as well as the transportation of materials and prefabricated components to the battery production facilities. Given China's significant role in the production of raw materials for lithium batteries[43], it was assumed that the manufacturing phase occurs within the country. Consequently, the China Statistical Yearbook 2023 (Yearbook 2023) was referenced based on the assumptions made by the National Bureau of Statistics of China (NBSC)[44]. It was assumed that the raw materials and components are typically transported at an average distance of 180 km using diesel trucks with a capacity of over 32 metric

tons.

The foreground data (data identified in the LFP battery manufacturing process) and background data (corresponding data in the LCA database) are integrated to prepare the LCIs in Table 3 based on the processes and the components of each part within the system boundary described above.

Life cycle impact assessment
LCIA evaluates potential environmental impacts and resource consumption highlighted by an LCI. According to the ISO standards, impact category selection, classification, and characterization are three mandatory stages, while the normalization, grouping, and weighting steps are optional within the framework[29]. The ReCiPe midpoint (H) model[45] was employed to evaluate the environmental footprint of battery production. LCIA in this study covered a total of 11 impact categories, including global warming potential (GWP), ozone depletion potential (ODP), ozone formation potential (OFP), fine particulate matter formation (FPMF), acidification potential (AP), freshwater eutrophication (EP), marine eutrophication (EP), marine ecotoxicity (ME), urban land use (LU), fossil resource scarcity (FRS), and water consumption (WC). The excerpt of characterization factors related to these environmental impact categories is listed in Table 4.

BMC-based uncertainty analysis
This study employs the BMC method to conduct a robust uncertainty analysis for the LCA of LFP battery production[46]. The methodological framework [Figure 4] begins with defining a deterministic LCA model. To capture the inherent uncertainties in the LCA, a sensitivity analysis was performed to identify critical uncertain parameters.

The prior probability distributions of these parameters were determined based on literature and expert judgment. An initial round of MC simulations is then conducted using these prior distributions, transforming the deterministic LCA model into a probabilistic one and confidence intervals. This could provide quantitative uncertainty of the environmental impact results. The subsequent phase involves Bayesian updating, wherein observed data is used to update the prior distributions. This process integrates observed data with prior distributions through Bayesian inference to produce posterior distributions, reflecting refined uncertainty estimates. For a practical implementation, the integral evaluated is:

$$\overline{f_p} = \int f(x) \, p(x) \, dx \tag{1}$$

where x is the material input, $f(x)$ is the function representing the input parameter and $p(x)$ is the probability density function (PDF) of x. BMC views the integral as a Bayesian inference problem, where $\overline{f_p}$ is treated as a random variable. The process involves placing a Gaussian Process (GP) prior on $f(x)$, enabling a smooth interpolation of function values between observed data points. The joint distribution of the function values under the GP prior is Gaussian, as given by:

$$f = (f(x_1), f(x_2),..., f(x_n))^T \sim N(0,K) \tag{2}$$

where K is the covariance matrix defined by a covariance function, such as:

$$K_{pq} = \text{Cov}\,(f(x_p), f(x_q)) = w_0 \exp\left(-\frac{1}{2}\sum_{d=1}^{D} \frac{(x_{pd} - x_{qd})^2}{w_d^2}\right) \tag{3}$$

Table 3. Main resource consumption and emissions in the life cycle of LFP battery manufacturing

Pollution type	Resources/emissions	unit	LFP battery manufacturing
Resource consumption	Coal	kg	177
	Natural gas	m^3	382
	Oil	kg	178
Water emission	Nitrate	kg	2.26
	Phosphate	kg	9.78
Atmospheric emission	CO_2	kg	3154.67
	CH_4	kg	0.40
	N_2O	kg	0.12

LFP: Lithium-iron-phosphate.

Table 4. Characterization factors of resources and emissions (excerpt)

Impact category	Resources/Emissions	Characterization factor	Unit
Global Warming Potential	CO_2	1	kg CO_2-eq/kg
	CH_4	34	kg CO_2-eq/kg
	$CHCl_3$	20	kg CO_2-eq/kg
	N_2O	298	kg CO_2-eq/kg
Ozone depletion potential	CFC-11	1	kg CFC-11 -eq/kg
	Halon-1301	14.066	kg CFC-11 -eq/kg
	CCl_4	0.895	kg CFC-11 -eq/kg
Ozone formation potential	NO_x	1	kg NO_x-eq/kg
	NMVOC	0.18	kg NO_x-eq/kg
Fine particulate matter formation	SO_2	0.29	kg $PM_{2.5}$-eq/kg
	$PM_{2.5}$	1	kg $PM_{2.5}$-eq/kg
Acidification potential	NO_x	0.36	kg SO_2-eq/kg
	NH_3	1.96	kg SO_2-eq/kg
	SO2	1.00	kg SO_2-eq/kg
Freshwater eutrophication	Phosphorus	1	kg P-eq/kg
	Phosphate	0.33	kg P-eq/kg
Marine ecotoxicity	1,4-Dichlorobenzene	1	kg 1,4-DCB -eq/kg
	Nickel	32	kg 1,4-DCB -eq/kg
Water consumption	CF watershed median	6.04E-13	species·yr/m^3
	CF area-weighted country average	1.74E-12	species·yr/m^3
Fossil resource scarcity	Crude oil	0.457	kg USD2013/kg
	Hard coal	0.034	kg USD2013/kg
	Natural gas	0.301	kg USD2013/kg

with hyperparameters w_0 and w_d. The posterior distribution over the function values, given the observed data, is also Gaussian. The posterior mean and covariance are:

$$\overline{f_D}(x) = k(x, X)K^{-1}f \tag{4}$$

$$Cov_D(f(x), f(x')) = k(x, x') - k(x, X)K^{-1}k(X, x') \tag{5}$$

where $k(X, x')$ is the covariance between new data points and observed data. The BMC estimate of the integral $\overline{f_p}$ and its variance are then given by:
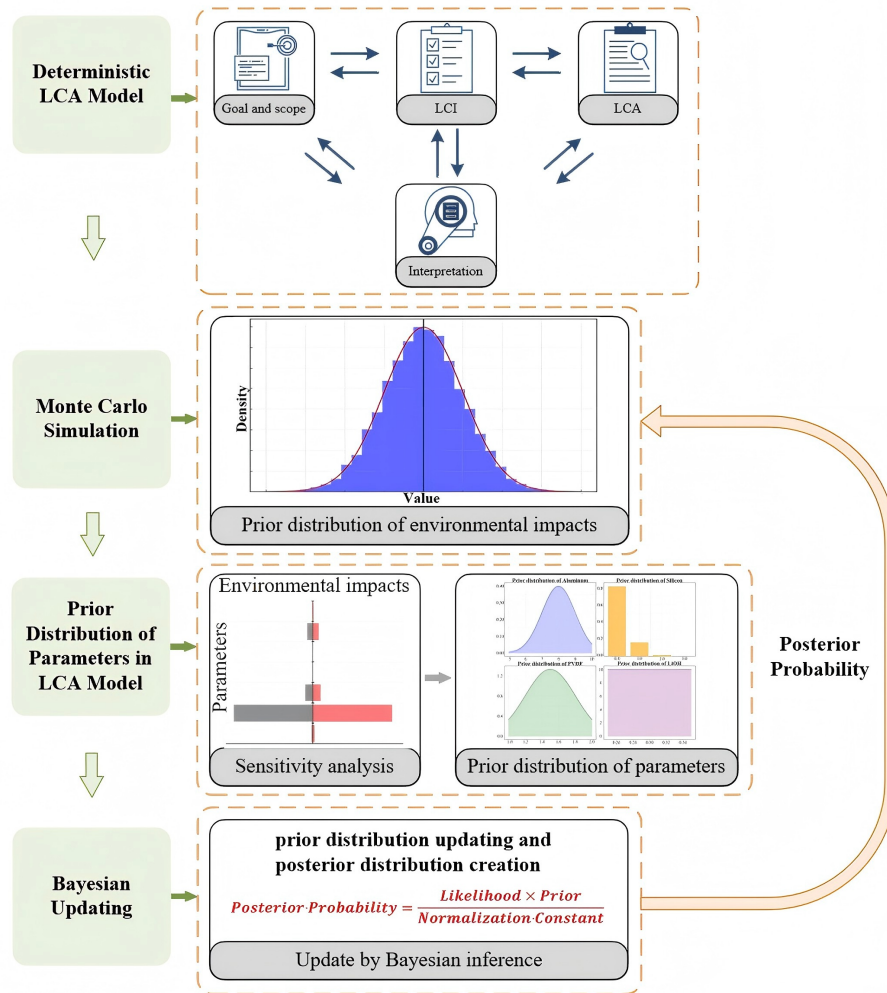
Figure 4. BMC-based uncertainty analysis for LCA of LFP battery production. BMC: Bayesian Monte Carlo; LCA: Life cycle assessment; LFP: Lithium iron phosphate.

$$E_{f/D}[\overline{f_p}] = \int (x)\, p(x)dx \qquad (6)$$

$$V_{f/D}[\overline{f_p}] = \iint Cov_D\,(f(x), f(x'))\, p(x)\, p(x')dxdx' \qquad (7)$$

where $\overline{f_D}$ is the posterior mean function. These expressions capture the mean and variance of the integral, providing a probabilistic description of the uncertainty. Following Bayesian updating, a second round of MC simulations is performed using the posterior distributions. This simulation yields more reliable results by incorporating updated uncertainty estimates, reflected in new confidence intervals and variances.

COMPUTATIONAL RESULTS AND DISCUSSION
Results
The LCA results for the production of the four major components comprising the battery pack across eleven environmental impact categories are detailed in Table 5. In this study, environmental indicators such as GWP, ODP, and OFP were primarily considered to present the main results of the environmental impacts. As indicated, the resources and energy consumption during the cradle-to-gate LCA of the LFP

Table 5. LCA results for per LFP battery pack [ReCiPe Midpoint (H)/World Recipe H]

Impact category	Unit	Battery cell	Battery cooling system	BMS	Battery packaging	Total
Global warming potential	kg CO_2 eq	1.86E+03	1.77E+02	7.89E+02	8.54E+02	3.68E+03
Ozone depletion potential	kg CFC-11 eq	8.04E-04	4.37E-05	4.06E-04	3.40E-04	1.59E-03
Ozone formation potential	kg NO_x eq	6.35E+00	4.59E-01	2.72E+00	2.13E+00	1.17E+01
Fine particulate matter formation	kg $PM_{2.5}$ eq	8.81E+00	3.52E-01	2.30E+00	1.80E+00	1.33E + 01
Acidification potential	kg SO_2 eq	2.50E+01	7.87E-01	5.22E+00	4.23E+00	3.52E+ 01
Freshwater eutrophication	kg P eq	2.58E+00	7.42E-02	1.20E+00	4.17E-01	4.27E+00
Marine eutrophication	kg N eq	3.71E-01	4.26E-03	4.30E-02	5.56E-02	4.74E-01
Marine ecotoxicity	kg 1,4-DCB	1.39E+03	1.81E+01	7.42E+02	1.45E+02	2.30E+03
Land use	m2a crop eq	1.03E+02	2.49E+00	4.56E+01	1.72E+01	1.68E+02
Fossil resource scarcity	kg oil eq	5.16E+02	3.86E+01	1.97E+02	2.11E+02	9.63E+02
Water consumption	m^3	4.36E+01	2.38E+00	8.10E+00	8.81E+00	6.29E+01

LCA: Life cycle assessment; LFP: Lithium-iron-phosphate; BMS: Battery management system.

battery are predominantly attributed to the production of battery cells, which consume the highest number of resources within a battery pack. Therefore, all the environmental impact categories associated with battery cell production significantly surpass those of other components' production, accounting for more than 54% of the total value, respectively. Thus, Figure 5 illustrates the environmental impact of the more detailed breakdown of battery component production within a battery pack. The primary contributors to the total environmental impacts, as shown in Figure 5, are the cathode electrode paste production, which dominates GWP, ODP, OFP, EP, FRS, and WC (29.67%, 21.56%, 26.64%, 65.88%, 28.94%, and 36.53%, respectively). This is followed by the battery packaging, BMS, anode current collector, and anode electrode paste, which contribute in descending order to these impacts. For AP and EP, the anode current collector manufacturing has the highest impact (48.39% and 28.22%, respectively), followed by the cathode electrode paste, BMS, battery packaging, and other cell assembly processes.

Overall, the cathode electrode paste energy requirements are the biggest contributor to the impacts of GWP, ODP, marine eutrophication, Photochemical Ozone Creation Potential (POCP), water depletion, and fossil depletion, whereas the anode current collector is the biggest contributor to the impacts of AP, EP, Particulate matter formation, Human Toxicity Potential (HTP), freshwater ecotoxicity, ME, LU and metal depletion [Figure 5].

Since the environmental burdens of LFP battery production are largely driven by energy consumption[42], the energy consumption during the production procedure is further quantified. Figure 6 shows the cradle-to-gate energy consumption data expressed in mega joules (MJ) per production step, wherein nearly 40,800 MJ of energy is utilized in the manufacturing process of an LFP battery pack. The highest electricity consumption occurs during the production of cathode electrode paste, accounting for approximately 11,822 MJ, followed by the manufacturing of the BMS at approximately 8,387 MJ, and battery packaging at approximately 9,065 MJ. This characteristic of the LCA findings is consistent with observations made in other EV battery analyses[4]. Conversely, the battery container and separator production processes require the least amount of energy.

Sensitivity analysis and uncertainty analysis
To exemplify the uncertainty analysis conducted on the environmental impacts of LFP battery production, the MC simulation results for GWP were focused on. Figure 7 presents the distribution of GWP and closely resembles a Gaussian distribution. Statistical examination reveals that both the mean and median values
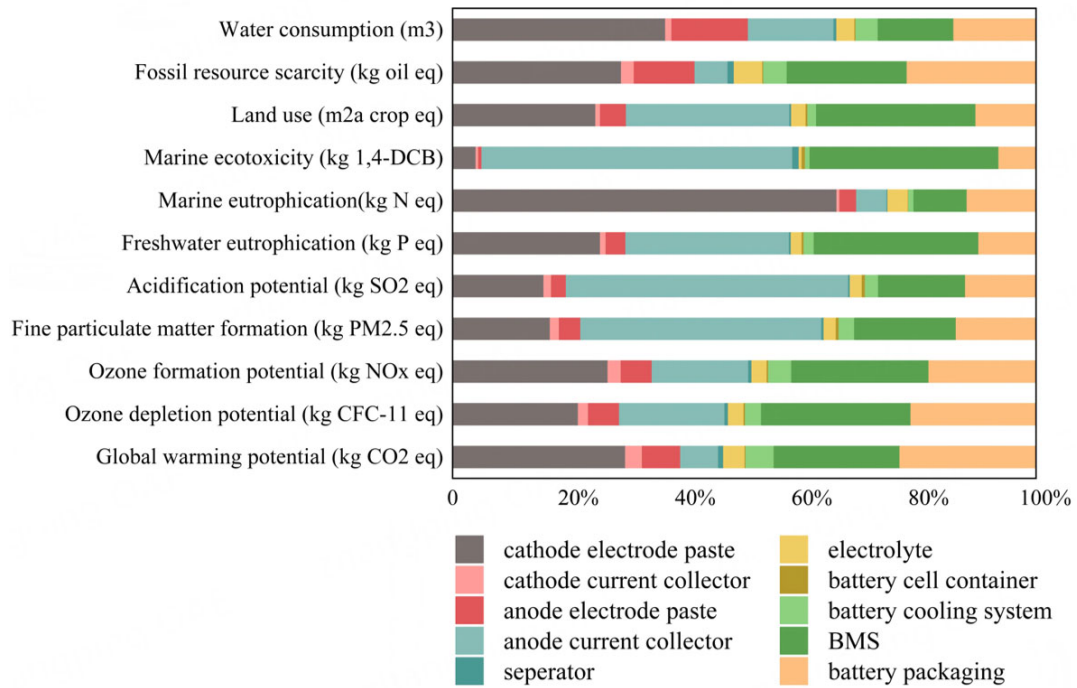
Figure 5. Relative contributions per LFP battery pack. LFP: Lithium-iron-phosphate.
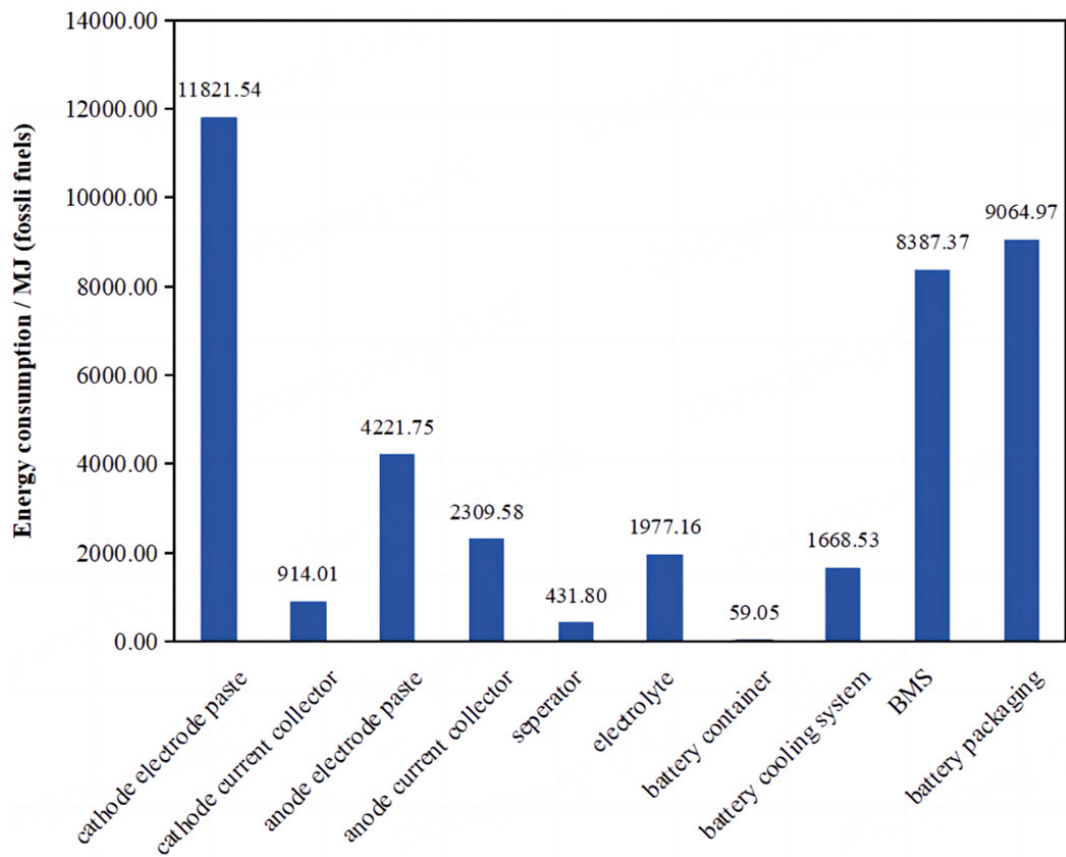

Figure 6. Energy consumption for each production in MJ per LFP battery pack. MJ: Mega joules; LFP: Lithium-iron-phosphate.
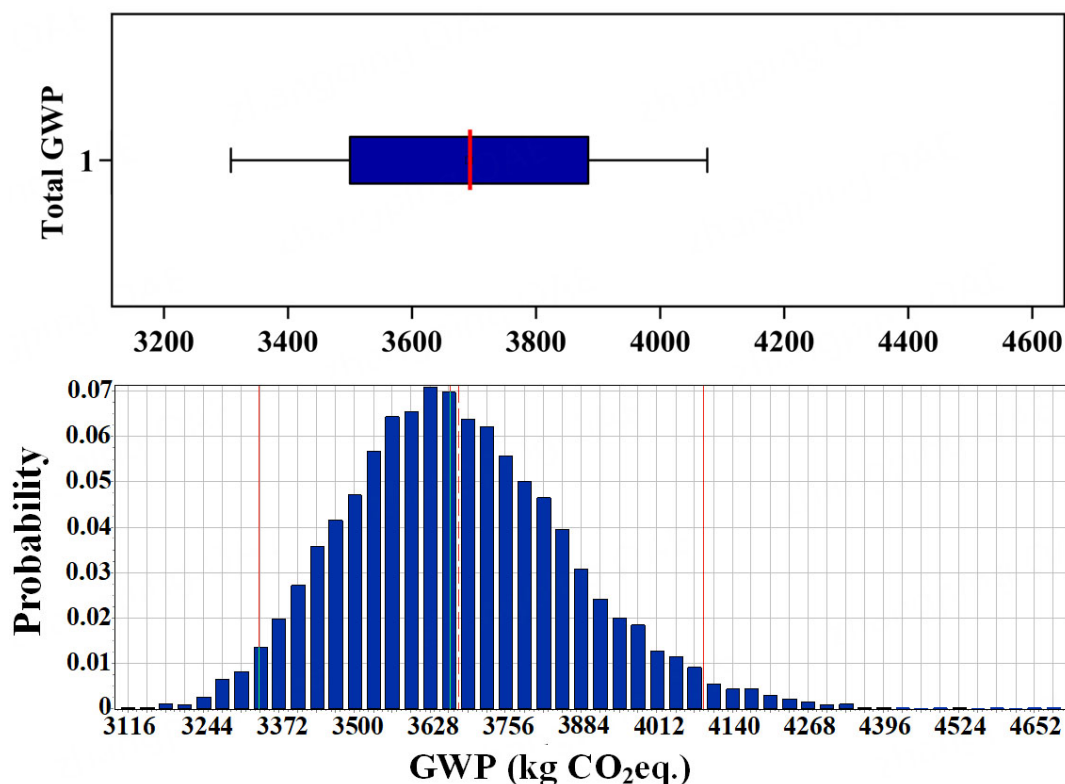
Figure 7. Output distribution of 10,000 MC runs for GWP; top diagram: box plot diagram; bottom diagram: histogram with red bars that indicate the 95% confidence interval. MC: Monte Carlo; GWP: Global warming potential.

stand at around 3,675 kg and 3,662 kg CO_2 eq. per LFP battery pack, respectively, with negligible deviation from the deterministic LCA final value. The standard deviation is approximately 194 kg CO_2 eq., with a coefficient of variability of 5.27%. The 95% confidence interval spans from 3,338 to 4,092 kg CO_2 eq. per battery pack, as depicted by red bars in the visualization. Additionally, the box plot presents percentiles at 2.5%, 25%, 75%, and 97.5%. Further statistical details are provided in Table 6.

To further identify key substances affecting the GWP, we employed a stepwise tracing approach to identify key material parameters generating environmental impacts. In this study, the sensitivity analysis was carried out by changing ± 5% material input, and the results are shown in Figure 8.

Figure 8A highlights significant variations in GWP impacts during the battery pack manufacturing process, particularly in the fabrication of the cathode electrode paste, cathode current collector, and the battery cooling system. The respective GWP changes for these components range from -17.62% to -14.15%, -25.63% to 1.62%, and -14.41% to 8.87%. A focused analysis reveals that in the production of cathode electrode paste, the materials PVDF and $LiFP_4$ exhibit notable GWP shifts of -15.70% to 15.7% and -13.16% to 13.16%, as detailed in Figure 8B). Further scrutiny of $LiFP_4$ production material impacts reveals a notable influence from LiOH, with GWP variations of -14.90% to 14.9%, as detailed in Figure 8C. Similarly, the manufacturing of the cathode current collector shows significant GWP impacts from aluminum and NaOH with changes of -13.90% to 13.9% and -3.49% to -6.51%, as presented in Figure 8D. Further examination in Figure 8E indicates that during the battery cooling system manufacturing, the thermal pads and cooling manifolds lead to GWP shifts of -28.08% to 28.08% and -19.92% to 19.92%, respectively. The analysis extends to the specific materials used in the production of these components. For instance, silicon in the

Table 6. Statistical evaluation of GWP impacts distribution

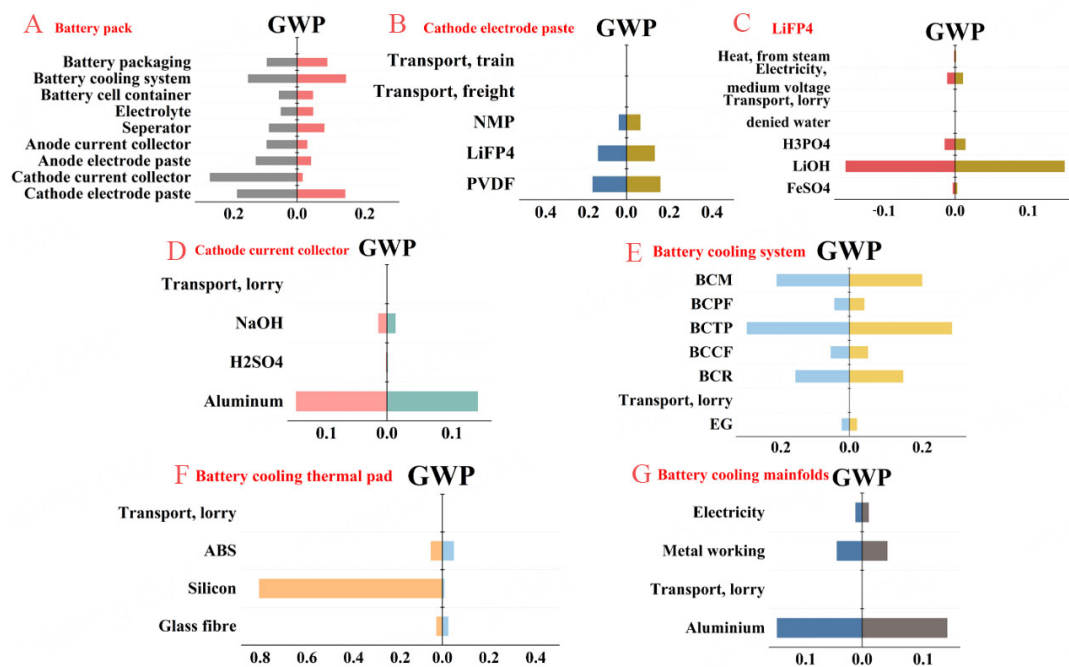|	Values	Unit
Trials	10000	-
Base case	3682.03	kg CO_2 eq
Mean	3675.68	kg CO_2 eq
Median	3661.69	kg CO_2 eq
Standard deviation	193.86	kg CO_2 eq
2.5% percentile	3338.04	kg CO_2 eq
97.5% percentile	4091.80	kg CO_2 eq
Coefficient of variability	5.27	%
Minimum	3016.40	kg CO_2 eq
Maximum	4705.72	kg CO_2 eq

GWP: Global warming potential.

Figure 8. Sensitivity analysis of GWP impacts of (A) Battery pack; (B) Cathode electrode paste; (C) LiFP$_4$; (D) Cathode current collector; (E) Battery cooling system; (F) Battery cooling thermal pad; (G) Battery cooling manifolds with respective parameters. GWP: Global warming potential; LiFP$_4$: Lithium iron phosphate.

thermal pad manufacturing processes emerges as the most impactful material, with a GWP change range from -78.40% to 0.82%, as shown in Figure 8F. Moreover, aluminum used in the cooling manifold fabrications maintains a consistent GWP influence of -13.90% to 13.9%, as illustrated in Figure 8G. This analysis underscores the substantial GWP impacts of specific LFP EV battery manufacturing materials and processes. It becomes evident that key variables such as PVDF, LiOH, aluminum, and silicon play critical roles in shaping the environmental footprint of battery pack production.

In this study, the prior distributions used for estimating environmental impact in LCA were based on the Global EV Outlook provided by International Energy Agency (IEA)[2] and were subsequently updated using the likelihood distributions resulting from the results of the MC analysis. Table 7 shows the mean values

Table 7. Summary of prior, likelihood, and posterior distributions for impact categories and the changes in CV values

Parameters	Prior		Likelihood		Posterior		%change in CV
	Mean	**CV**	**Mean**	**CV**	**Mean**	**CV**	
LiOH	30	0.096	24.34	0.0222	24.53	0.021	-78.13%
Aluminum	8	0.125	1.1	0.019	1.105	0.019	-84.8%
Silicon	0.2	2.236	0.22	0.18	0.22	0.18	-91.95%

CV: Coefficients of variation; LiOH: Lithium hydroxide.

and coefficients of variation (CV) for both the prior and refined (posterior) parameter distributions relevant to the inventory and impact assessment phases. The reduced CV values in the posterior distributions demonstrate that incorporating more precise likelihood information effectively decreased uncertainty. For example, the CV of the posterior probability distribution for LiOH was reduced to less than a quarter of its initial value (0.021), and similar reductions were observed for aluminum and silicon. The posterior distributions of these three key parameters were significantly shaped by the likelihood distributions due to their higher precision compared to the initial distributions.

Figure 9 illustrates the comparison of the prior and posterior probability density distribution (PDFs) for LiOH [Figure 9A], aluminum [Figure 9B], and silicon [Figure 9C]. It is shown that the posterior distribution is narrower than the prior distribution. The uncertainty associated with the parameters had been reduced due to the incorporation of more accurate observed data.

Figure 10 presents the PDFs of the GWP in both prior and posterior distributions, represented by the blue and yellow lines, respectively. The mean, 2.5%, and 97.5% percentile values show minimal differences between the prior and posterior distributions. However, the posterior distribution is narrower, with a smaller standard deviation. Incorporating observed data into the prior probability distribution in this study effectively reduces uncertainty, enhancing the reliability of the GWP estimations.

Discussion

In this study, we analyzed the environmental impacts associated with LFP EV battery production, placing particular emphasis on data precision and inventory reliability. The findings reveal that the cathode electrode paste and anode current collector emerge as the primary contributors to emissions and resource utilization, primarily due to energy demands in battery cell manufacturing. This energy-intensive production phase accounts for 58.99% and 12.91% of total energy use, respectively, underscoring the CO_2 reduction potential through optimizations in these components. Our result aligns with previous literature on LIBs, which similarly highlights energy consumption in cell manufacturing as a substantial factor in overall emissions[47].

For sensitivity analysis, key materials influencing the GWP were identified. Specifically, PVDF, LiOH, aluminum, and silicon demonstrated significant influence over GWP. PVDF and $LiFePO_4$, integral to cathode paste, showed notable GWP variability, with LiOH prominently affecting GWP in $LiFePO_4$ production. Aluminum's impact spans cathode collectors and cooling manifold components, while silicon significantly contributes to the GWP variation within battery thermal pads. These findings corroborate previous environmental impact assessments and further elucidate the roles of specific materials in shaping the environmental footprint of battery production.
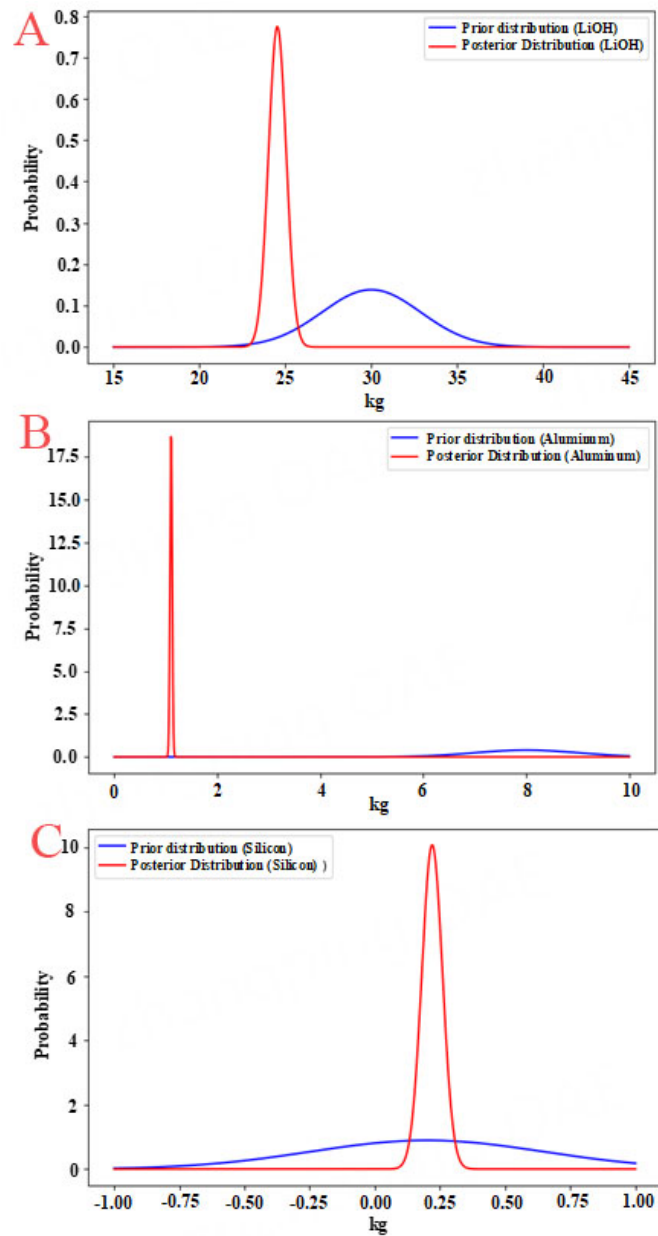
Figure 9. Comparison of prior and posterior distributions of the mass of (A) LiOH; (B) Aluminium; and (C) Silicon. LiOH: Lithium hydroxide.

Moreover, the BMC method, applied to evaluate uncertainty, effectively reduced the CV values for GWP, validating its practicality for handling uncertainties in LCA studies. However, this analysis encountered limitations due to missing data, which constrained correlation assessments among input parameters. Future studies may benefit from physical process models that incorporate variable interactions, thereby allowing for enhanced assumptions in uncertainty analysis and improving the LCA's robustness and accuracy for LFP EV batterie[48,49].

CONCLUSIONS

In this study, a BMC-based uncertainty analysis method for LCA of LFP battery production was developed.
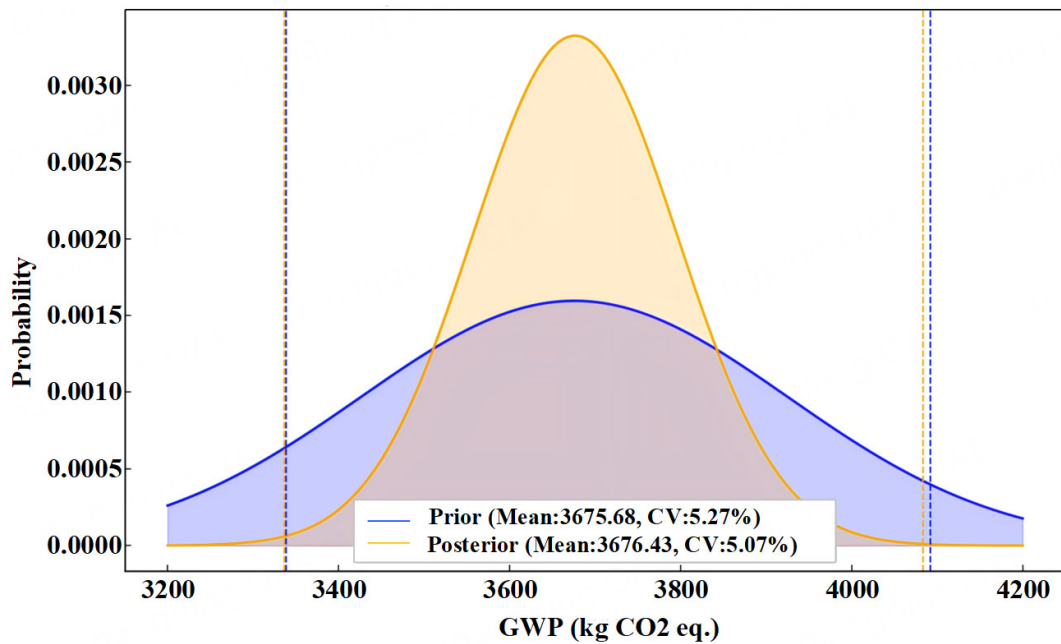
Figure 10. Comparison of prior and posterior distributions of GWP. GWP: Global warming potential.

The results show that the production of battery cells has the largest environmental impact. Consistent with the energy consumption analysis of the various components of LFP batteries, the production of the cathode electrode paste consumes the most electricity and exerts the greatest environmental impact. Sensitivity analysis reveals that the GWP is most sensitive to the production of the cathode electrode paste, the cathode current collector, and the battery cooling system. The key parameters influencing GWP are identified as LiOH, aluminum, and silicon. By incorporating observational data for these key parameters into the corresponding prior distributions, the CV for their posterior distributions was significantly reduced. As a result, the posterior distribution of GWP became notably narrower compared to the prior distribution, enhancing the overall reliability of the LCA results.

However, the limitation of this paper is that the potential for recycling and reuse of several raw materials used in LFP batteries was not considered. Follow-up studies can extend this "cradle-to-gate" case to "cradle-to-grave" assessment that incorporates the usage and end-of-life stages of an LFP battery pack. The results of this LCA could benefit LFP battery manufacturers by pinpointing the hotspots to mitigate environmental impacts across diverse manufacturing processes. Additionally, it is important to note that other types of uncertainty need to be considered, such as the scenario uncertainties that include market demand, fluctuations in raw material prices, changes in policies and regulations, and variations in recycling rates to obtain relatively accurate environmental assessment results. The EV batteries are still constantly developing and evolving. Their environmental impact and cost assessment will remain subjects of great concern to support sustainable production.

DECLARATIONS

Author's contributions
Conceptualization, methodology and experiments, writing-original draft, data collection: Gao B
Methodology and experiments: Yang S

Editing and funding: Peng S

Conflicts of interest
Peng S is the Guest Editor of the Special Issue "Development of Green Manufacturing Technology for Batteries" of the journal of *Green Manufacturing Open*. The other authors declared that there are no conflicts of interest.

Ethical approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

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