Which Battery Chemistry Will Pave the Way for EVs? A Comparison Between Different Battery Chemistries for Electric Vehicles

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Received January 12, 2026
Accepted September 16, 2026
Electronic access October 31, 2026

Electric Vehicles (EVs) have become very popular recently due to their increased availability. However, these vehicles have severe drawbacks, such as reduced range compared to internal combustion engine (ICE) vehicles. In this paper, ten battery chemistries, five current and five experimental, are analysed to determine which one is the most appropriate for electric vehicles regarding environmental impact. Secondary data analysis was used to measure twelve emissions indicators for both battery production and use. Using this data, a model was created to simulate the emissions of all battery chemistries and three energy grid mixes taken into consideration. The cradle-to-gate portion of this study showed that SIBs performed the best out of the whole sample. The use stage part of this study demonstrates that Sweden's energy grid pollutes way less than the world energy grid since it makes use of renewable energy at a larger scale. The results of this study show the direction of future research towards improving battery sustainability should develop SIBs and SSBs to create more reliable and sustainable EV battery packs.

Introduction

Background and context

The transport industry accounts for over 15% of global greenhouse gas (GHG) emissions, with over 8 billion tonnes of GHGs produced in 2022,[1] and presents a great problem: How can we make EVs more sustainable and competitive with internal combustion engine (ICE) vehicles? These vehicles are available at a wide range of prices and have arrived at a broad range of global markets, but they tend to share some common drawbacks: they need longer-lasting batteries to allow this technology to reach its full potential. Currently there are many different battery technologies available, which accentuates the importance of choosing a battery technology to help impulse future development and compare future developments to.

The most common batteries seen in EVs are lithium-ion batteries (LIBs), which use a lithium-based electrolyte to store energy. Different types of Li-ion batteries can be further identified based on the positive electrode, for instance lithium nickel manganese cobalt oxide (NMC), Lithium nickel cobalt aluminium oxide (NCA), and Lithium iron phosphate (LFP).[2] It is worth noting that some of these electrodes contain cobalt, which is being phased out due to its high social and environmental cost.[3,4] Currently, there have been several advancements in EV battery technology, two of which are included in this study: sodium ion batteries (SIBs) and solid-state batteries (SSBs). The main attributes which make SIBs enticing alternatives instead of current battery chemistries are their usage of more abundant materials and their better performance against current battery chemistries.[5] Meanwhile, SSBs appear to be a more viable technology due to their high energy density, which can help reduce a vehicle's total weight.[6]

Literature review

Currently, one of the most common ways of analysing the environmental impact of EV battery chemistries is by using the Life cycle assesment methodology, as it allows for the comprehensive understanding of the effects of a cell on its environment. Regardless of this, it is worth noting that there is no standardized way of conducting these kinds of studies and different ways of modelling a battery can yield vastly different results, even for seemingly identical items.[7] This section presents various findings from primary sources which led to the unique nature of this study. Approaches to ameliorate the discrepancies between sources are detailed in the methods section of this study.

Conventional battery chemistries (NMC, NCA and LFP)

Most of the established literature available tackles these kinds of batteries, as they are the most popular chemistries for use in EVs.[8] These three battery types cover a wide range of use case scenarios and price categories, satisfying the current needs of most vehicle manufacturers. NMC batteries are some of the

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most common batteries in EVs, used by manufacturers such as Volkswagen, Tesla, Ford and Hyundai; and are popular to the extent that there are multiple sub chemistries available with differences between models.[5,6] Their popularity can be attributed to their balance between high capacity and safety compared to NCA and LFP.[9,10] However, their higher emissions hinder the development of a sustainable transportation network in countries such as China.[10] NCA batteries tend to have the largest capacity of the three Li-ion battery categories, with a comparable lifespan to NMC batteries, however, these batteries tend to be less safe than the other two available options and may require additional safety mechanisms.[9] Regarding emissions, this battery type tends to perform better than its contemporaries, with lower emissions in most categories.[9,11]

Sodium Ion batteries

Compared to literature on established chemistries, SIB literature is smaller in size and tends to focus on more experimental battery models rather than using data from large-scale battery production.[12–15] This battery type stands out due to its lower cost and lower environmental impact, since it uses more widely available materials in its construction, such as the possibility of replacing copper with aluminium as a current collector.[13] Salami found that, when comparing the emissions of a Li-ion battery pack with an SIB, there was a 40% difference between both chemistries in favour of the SIB.[13] Currently studied SIB battery chemistries include NaNFM, NaPBA, NaNMMT and NaNVPF, whose main difference is the cathode material.[5,14] Of these, NaPBA and NaNFM proved to be significantly superior to LIBs in multiple categories, such as ecotoxicity and human toxicity, however, it is worth noting that NaNVPF performed worse than other SIBs due to its use of vanadium, a relatively scarce metal. Overall, most SIB lack one crucial aspect compared to current chemistries: energy density, as even the most energy-dense SIBs struggle to match the energy density of LFP, however, in a study by Guo et al, it was found that SIBs have a higher energy conversion efficiency than LIBs.[14,15]

Solid state batteries

Most studies which tackle SSB battery emissions use data from lab models or simulations, since this technology is still in development .[16–18] The main advantage of SSBs is that they nearly double the energy density of some of the most energy dense battery packs available.[16] Furthermore, due to the absence of flammable liquids in SSBs, they are less likely to catch on fire, making them a safer alternative to current chemistries.[16] It is worth noting that SSBs are at a more mature state of development, as they are set to be produced by Samsung both for EVs and electronics by 2027.[16] A disadvantage to SSB batteries is that they produce slightly elevated carbon emissions when compared to traditional chemistries due to their increased usage of electricity in their production. It is worth noting that this study was done in China, which mostly relies on non-renewable energy sources.[17]Pell et al. suggest that SSBs may produce less pollution when compared to their current counterparts when using the European energy grid, however, it takes a more conservative approach to SSB battery parameters.[18] When comparing the results from both of these studies, they suggest that SSB battery production emissions can undercut traditional battery technologies in less-polluting energy grids.

Electricity generation

Research in this area has two different scopes: a region-wide approach, which takes into account a particular energy mix (some examples of region-specific LCAs include those made in Iran, Canada, France and Mexico) or a technology-specific approach (such as those done in Nuclear, Solar and Wind energy).[19–22] Fossil-fuel based electricity generation sources produce considerably more air-related pollutants than renewable energies which do not rely on combustion.[19] The main emissions sources for Fossil fuel-based powerplants are electricity generation and fossil fuel value chains.[19] It is worth noting, however, that combined-cycle gas power plants show lower emissions than other non-renewable energy sources.[20] Regarding renewable energy sources their environmental impact tends to be lower than those of conventional technologies, however, these are not low enough to the point of being trivial due to the high construction emissions of renewables.[20] Regarding specific alternative electricity generation methods, nuclear has been shown to be a low-emission energy source with a very high energy efficiency, even at a sub-optimal utilization rate.[21] The main source of nuclear energy pollution is not energy production, but rather initial infrastructure costs, leading to lower emissions per kWh as the power plant sees more use.[21] In the case of photovoltaic solar energy generation, its main environmental cost occurs in the production of cells and modules, however, advancements in solar panel recycling and improved cell efficiency are anticipated to decrease this technology's environmental impact.[22] Wind power shows increased environmental impact during both its manufacturing and installation phase, as their size implies a large resource requirement in addition to the large amount of cement used in the foundation of a wind turbine.[22] It is worth noting that some materials involved in wind energy production are recyclable, such as the steel used in the towers and the materials used in the nacelle, the part of the wind turbine responsible for turning kinetic energy into electrical energy.[22] Emissions from Hydropower energy generation can be quite variable and are region-dependent, as they rely on several factors such as the total organic content of inundated soil or the shape and depth of a given reservoir.[23] Regardless of this fact, the main driving factor of this technology's emissions is construction,

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making both reservoir longevity and efficiency crucial to lowering hydropower electricity production emissions.[23]

Problem statement

The main issue with previous studies is mainly that they observe per cell/kg emissions rather than the emissions of a vehicle's battery as a whole, since it does not allow for a complete picture of an EV's emissions, especially regarding the importance of each life cycle phase relative to each other. By calculating the emissions of a whole vehicle's battery cells, it is possible to compare these factors more objectively and fairly, especially when factoring in battery size and vehicle efficiency. Another benefit of comparing emissions in this way is that, by using articles with emission breakdowns for each chemistry, the main emissions factors for different scenarios can be highlighted, such as a specific battery part or energy source. This provides a more actionable result rather than results focused on only one part of the battery's life cycle, which could be less helpful than they seem when considering the bigger picture.

Purpose

The results of this study can help determine the relative impact of different variables in both the production and usage stage of the battery, which can help determine which are the more significant factors in lowering EV emissions, providing a more concrete direction to current and future research in battery technologies and electrification as a whole. Furthermore, this data also paints a picture of the changing priorities to lower battery emission depending on a country's energy grid, which can play a large role in vehicle usage emissions depending on the energy grid. Additionally, presenting this information as a per-vehicle total can allow for a more direct comparison between EVs and even other kinds of vehicles, such as plug-in hybrids (PHEV) or ICE vehicles. This is especially important when a battery's emissions are scaled, as a relatively minor increase in emissions per cell could drastically affect overall emissions once these are scaled up.

Objectives

Through the comparison of various battery chemistries, the main questions the study aims to answer are: How do new battery technologies' emissions compare to existing technologies? Which battery chemistry is the least polluting of the sample? How do electricity emissions impact the overall emissions of an EV? Which variables, such as battery parts and energy mix, have the largest impact on emissions.

Scope

The main battery chemistries included in this article are the following: LFP, NCA, NMC (622, 811 and 532), and SSB NMC as current battery chemistries, and NaNFM, NaNVPF, NaPBA and NaNMMT as upcoming battery chemistries. All 12 impact categories considered in this study come from sources which use the ReCiPe 2016 (H) framework, as it is one of the most common frameworks present in the source sample. The only category where results from multiple frameworks were mixed is Global warming potential (GWP), as GWP100 characterization factors are derived from the IPCC and can be reliably compared between them. The main functional unit used in the study for data normalization was 1 kWh of gross battery capacity, as this was the most common unit present in all sources. Furthermore, the vehicle database used to obtain data on current EVs, EVKX[24], provides essential information in this unit. This study is limited to only two life cycle assessment phases: battery production and usage. This was done to provide a fair comparison to new battery chemistries, as these have not had enough time to develop accurate end-of-life (EOL) emission models. Furthermore, pack overhead was not considered for similar reasons, since the newer battery chemistries analysed in this article have not seen widespread commercial use with more established battery management system (BMS) models. Both of these factors could heavily influence battery emissions, however, the final emissions models for newer battery chemistries would be inaccurate. Due to the unavailability of the software and databases typically used to carry out LCA research, secondary data analysis of various primary sources was done to create accurate models.

Theoretical framework

The Life Cycle Assessment (LCA) methodology was used to determine the emissions produced by the batteries assessed in this study, as it considers various factors involved in the creation of a product, such as resource extraction, material processing, etc. to output an accurate measurement of its environmental impact. The research does consider a source's life cycle inventory (LCI) for inclusion, as it must only include the inputs and outputs of the battery cell. Regarding the life cycle impact assessment (LCIA), all sources have either equal or comparable models for the impact categories tested to ensure data comparability with the same time frame. All of these measures ensure that the data gathered is both accurate and comparable to current battery emissions.

Methodology overview

To gather the data for this study, several articles and data sources were filtered through the following criteria: a publication date no earlier than 2020, the usage of the ReCiPe 2016 (H) framework and per-component battery/energy grid

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emission breakdowns. With these sources, all data points were normalized to 1 kWh to create both production and use models which simulate real life conditions. The production model was separated into six cell components: cathode, anode, separator, electrolyte, casing and manufacturing. The use model only considers electricity as a source of emissions and uses an energy mix consisting of three fossil-based and five fossil-free energy sources in different percentages for each scenario: coal, gas, oil, nuclear, hydropower, wind, solar and bioenergy. Finally, the emissions of these models were compared to pinpoint the main factors contributing to EV emissions.

Methods

The study is a cross-sectional, comparative LCA which uses a secondary data analysis framework to source information. Both production and use emissions are only analysed for current battery manufacturing techniques and energy grid emissions, specifically sourcing data published no earlier than 2020. To ensure a fair comparison between data sources, a functional unit of 1 kWh was established for both life cycle phases, as it can represent battery capacity regarding the production stage and km driven in the use stage by using a vehicles efficiency ratio (kWh per km driven). Once the data was normalized, two types of models were created: a production model and a use model. The production model is based on the cells of an average EV battery pack, while the use model represents electricity production emissions for the energy used up by the car considering different energy grids. Finally, all the battery models were compared to each other to determine which battery chemistry is the least polluting. Likewise, all use models were compared against each other for the same reason.

Search strategy

To define the scope of this study, data from multiple articles was gathered to determine the available information on the field. This not only allows the study to cover a larger amount of battery chemistries but also makes every data point more accurate by providing more points of reference. To select sources of information, multiple research articles were analysed to obtain the data required for the study. Google Scholar was used to look for sources of information using the keywords: “ReCiPe battery LCA”, “LIB battery LCA”, “SIB battery LCA”, “SSB battery LCA” and “Electricity production LCA”. In addition to these keywords, only sources published no earlier than 2020 were considered to ensure the data was relevant and up to date. Review articles were excluded from the data gathering process as they may contain data from before 2020. The focus was articles which evaluated multiple chemistries under one framework, as this allowed for greater data availability and reliability, however, articles which focused on one experimental battery technology were allowed in the sample as long as they met all of the inclusion criteria. Any cradle-to-grave articles were excluded, as these tend to mix production and EOL emissions into one rubric. For vehicle-related information, EVKX was chosen as the only source of information, as it contains both government and manufacturer-provided data for over 700 vehicles as of 18-07-2026, ranging from low-capacity city cars to large pickup trucks and 3 row SUVs.

Inclusion Criteria

There were three inclusion criteria applied to the articles obtained from this process:

- Only studies with per-component battery breakdowns (production)/ per technology emissions breakdowns (use) were included. Articles with a wider scope, such as pack overhead, were only considered if they included a way to separate pack overhead emissions from cell emissions.
- The studies chosen must follow one framework: ReCiPe 2016 (H). This was done to ensure data availability and comparability, as this proved to be a very widely used framework in the sample. It is worth noting that sources outside this framework were taken into consideration for GWP as long as they met the other two criteria and used GWP100 characterization factors for this rubric, as these data points follow IPCC guidelines. All data not corresponding to this framework outside of GWP was excluded.
- The functional unit of the source must be either 1 kWh or convertible to this unit. This allows the data to be more easily scaled up to an EV’s battery capacity or range using data from EVKX.

After the application of these criteria, 28 sources were excluded from a 40-source sample for battery production, while 8 sources were excluded from a 12-source sample for battery usage. This data was used to build a dataset for selecting battery chemistries and parameters. This process is summarized in Figure 1. The articles included in the study are shown in Table 1.

Battery chemistry selection

The battery chemistries available in these articles were separated into five groups to provide a wider picture of the current battery landscape: Liquid LIBs, NMC sub-chemistries, liquid SIBs, Solid state batteries (SSBs) and others. Only NMC was separated into sub-chemistries as most articles which cover

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Table 1 Shows all the articles included in the study. Those in green were fully considered for production, those in yellow were only considered for GWP production emissions and those blue were considered for use emissions.

Source	Article title	Year	LCA phase	Chemistries / Technologies covered	LCA framework	GWP version	Functional unit	Emissions breakdown
Chen et al.	Prospective environmental and resource sustainability assessment of advanced matching technologies for sodium-ion and lithium-ion batteries	2026	Production	NMC111/532/622/811, LFP, NaNFM, NaNMMT, NaNVPF, NaPBA	ReCiPe 2016	GWP 100	1 kg cell	(Graphical breakdown) Cathode (active material + binder), anode, separator, current collectors/tabs, cell container, production energy
Degen et al.	Comparative life cycle assessment of lithium-ion, sodium-ion, and solid-state battery cells for electric vehicles	2025	Production	NMC532/622/811/900, NCA, LFP, NaNFM, SSB (NMC900|Li)	ReCiPe 2016 (H)	GWP 100	1 kWh	Cathode, anode, electrolyte, separator, cell casing, current collectors, cell production energy
Le Varlet et al.	Comparative life cycle assessment of lithium-ion battery chemistries for residential storage	2020	Production	NMC, NCA, LFP, LMO, LCO	ReCiPe Endpoint (H)	GWP100a	1 kWh	Cathode, anode (both split into active material, binder, conductive carbon and current collector), electrolyte, separator and cell packaging
Xu et al.	Comparative LCA of energy and environmental impacts in sulfide-based all-solid-state battery manufacturing: Wet vs. dry processes	2026	Production	SSB (NMC95 solid, Li-metal anode), LFP	ReCiPe 2016 Midpoint	GWP 100	1 kWh	Cathode, solid electrolyte, anode, cell assembly
Accardo et al.	Prospective LCA of Next-Generation Cells for Electric Vehicle Applications	2024	Production	NMC (not specified), Li-S, SiNWs, SiCPAN, SSB NMC (NMC900|Li)	ReCiPe/EF	GWP 100	1 kWh	(Graphical breakdown) Cathode, anode, electrolyte, separator, current collectors, cell housing
Arshad et al.	Life cycle assessment of lithium-ion and secondary batteries: A comparative analysis on environmental impacts and graphite recycling	2026	Production	NCM811, NCA, LFP, NiMH, Li-S, Mg-S, Na-ion (SIB)	GWP-focused in dataset (GWP100a)	GWP100a	1 kWh	Cathode, anode, electrolyte, separator, current-collector foils, binder, cell tabs
Lai et al.	Comprehensive assessment of carbon emissions and environmental impacts of sodium-ion batteries and lithium-ion batteries at the manufacturing stage	2023	Production	LFP, NMC111, NMC532, NMC622, NMC811, NaNMMO, NaNMMC, NaNMMT, NaPBA, NaNMVP, NaS	ReCiPe/EF	GWP 100	1 kg cell and 1 kWh	Cathode, anode, electrolyte, separator, current collectors, cell housing
Liu et al.	Are solid-state batteries absolutely more environmentally friendly compared to traditional batteries - analyzing from the footprint family viewpoint	2024	Production	LFP, NMC (not specified), LTO, SSB (Li-FeS2 / LLZO)	GWP only	GWP 100	1 kg cell and 1 kWh	Cathode, anode, electrolyte, separator, current collectors (foils), BMS
Nibelius et al.	Life cycle assessment on sodium-ion cells for energy storage systems (cradle-to-gate, 16 environmental perspectives)	2023	Production	SIB (not specified)	EF 2.0	GWP 100	1 kWh	Cathode (active material), anode, electrolyte, separator, current collectors, cell casing, BMS
Rietdorf et al.	Cradle-to-gate life cycle assessment of cylindrical sulfide-based solid-state batteries	2024	Production	SSB (NMC811/622, LFP)	EF 3.1 midpoint	GWP 100	1 kWh	Cathode, anode, solid electrolyte, separator, current collectors, cell casing
Zhang et al.	Future climate impacts of sodium-ion batteries	2024	Production	NMC811, LFP, NaNMMT, NaNVPF, NaPBA	GWP only	GWP 100	1 kg cell	Cathode, anode, electrolyte, separator, current collectors, cell container
Diemer	Some Digressions on the Life Cycle Analysis of a Nuclear Power Plant in France	2024	Use	Nuclear (GWP)	GWP only	GWP 100	1 kWh	Partial — nuclear detailed; other technologies as GWP comparison only
Mohsen / Hosseini et al.	Midpoint and endpoint impacts of electricity generation by renewable and nonrenewable technologies: A case study of Alberta, Canada	2022	Use	Coal, Natural gas, Hydropower, Wind, Bioenergy	ReCiPe 2016 (midpoint + endpoint)	GWP 100	1 kWh	Yes — 9 technologies, full numeric tables
San Miguel	External environmental costs of electricity generation using a life cycle approach: A case study of Spain	2024	Use	Coal, Natural gas, Oil, Nuclear, Hydropower, Wind, Solar, Bioenergy	ReCiPe 2016 v1.1 (midpoint World 2010 H + endpoint H/A)	GWP 100	1 MWh	Yes — 14 technologies (totals numeric; per-category in figures)
Yousefi	Integrated energy, cost, and environmental life cycle analysis of electricity generation and supply in Tehran, Iran	2023	Use	Natural Gas, Hydropower, Solar, Bioenergy	ReCiPe 2016 (midpoint + endpoint)	GWP 100	1 kWh	Yes — 6 technologies, full numeric table

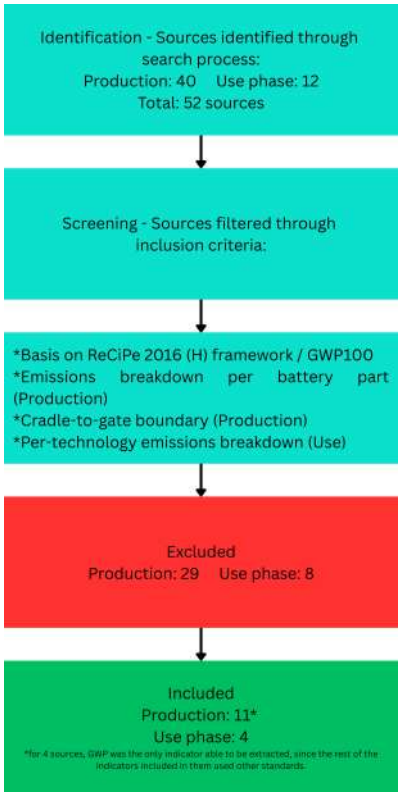

Figure. 1 Shows the summary of the source selection process and selection criteria.

this type of battery identify the NMC sub-chemistry analysed or even present multiple different types of NMC. For the SSBs covered in this article, they were grouped together by their cathode, even though their electrolytes may vary due to the recency of the technology and multiple types of electrolytes which are being tested. Up to three batteries were chosen per group if they had over ten parameters covered. The only group where more than three batteries were selected is Liquid SIBs, as information for NaNMMT, NaPBA and NaNVPF is equally available in the dataset. Table 2 shows all of the groups broken down by battery chemistry with the number of parameters covered per battery type.

Parameter selection

To select the parameters covered in this study, these were filtrated by number of batteries covered, as only those which covered all ten battery types were considered. Afterwards, those indicators which did not provide an emissions-specific output were not selected. Additionally, all indicators which did not provide any emission specific data, but rather focused on battery production were excluded. Indicators with only one source were also excluded, as these did not have any other data

Table 2 Shows all the batteries studied in the previous sources selected separated into five categories. The chemistries selected for the study were coloured in green, while those which were not are coloured in red. In total, ten chemistries were selected: NMC (811, 532 and 622), LFP, NCA, NaNFM, NaNMMT, NaPBA, NaNVPF and NMC SSB

NMC derivatives	Number of parameters covered	Number of sources (Including GWP only)	Number of sources (for non-GWP parameters)
NMC811	17	5	2
NMC532	17	3	2
NMC622	17	3	2
NMC111	17	2	1
NMC900	17	1	1
NMC (generic)	1	3	0
Liquid LIBs	**Number of parameters covered**	**Number of sources (Including GWP only)**	**Number of sources (for non-GWP parameters)**
LFP	17	6	2
NCA	17	3	1
LMO (LiMn2O4)	17	2	1
LTO	1	1	0
NCO-LTO (Li-titanate anode)	1	1	0
Liquid SIB	**Number of parameters covered**	**Number of sources (Including GWP only)**	**Number of sources (for non-GWP parameters)**
SIB – NaNFM (Fe-Mn LO)	17	2	2
SIB – NaNVPF (V-polyanionic)	17	3	1
SIB – NaNMMT (Ni-Mn-Mg-Ti LO)	17	3	1
SIB – NaPBA (Prussian Blue)	17	3	1
SIB – generic / unspecified	1	2	0
SIB – NaMMO (Mn-based LO)	1	1	0
SIB – NaNMC (Ni-Mn-Co LO)	1	1	0
Solid state batteries	**Number of parameters covered**	**Number of sources (Including GWP only)**	**Number of sources (for non-GWP parameters)**
SSB-NMC (A-NCM / NMC900|Li)	17	4	2
Li-FeS2	1	1	0
LLZO	1	1	0
Others	**Number of parameters covered**	**Number of sources (Including GWP only)**	**Number of sources (for non-GWP parameters)**
NiMH	1	1	0
Li–S	1	2	0
Mg–S	1	1	0
NaS (Na-S)	1	1	0
Si-anode LIB (SiNWs / SiCPAN)	1	1	0
Lead-acid (PbA)	0	0	0
NiCd	0	0	0
Vanadium redox flow (VRFB)	0	0	0

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to compare against. Table 3 shows all of the emissions indicators available in the dataset.

Table 3 Shows all the parameter included in the dataset. The parameters selected for the study were coloured in green, while those which were not are coloured in red. In total, twelve indicators were selected: GWP, AC, FEUP, FETP, MEUP, HTPc, HTPnc, PMFP, POF IR, METP and TETP

Parameters	Number of sources	Chemistries covered (of 10)
GWP / Climate Change	11	10
AC / Acidification	3	10
FEUP / Eutrophication – Freshwater	3	10
RU-MM / Resource Use – Minerals & Metals	3	10
FETP / Ecotoxicity – Freshwater	3	10
MEUP / Eutrophication – Marine	3	10
HTPc / Human Toxicity – Cancer	3	10
PM / Particulate Matter	3	10
POF / Photochemical. Ozone Formation	3	10
HTPnc / Human Toxicity – Non-Cancer	3	10
LU / Land Use	3	10
RU-F / Resource Use – Fossils	3	10
IR / Ionizing Radiation	3	10
WU / Water Use / Consumption	3	10
METP / Ecotoxicity – Marine	3	10
TETP / Ecotoxicity – Terrestrial	3	10
OD / Ozone Depletion	3	9
TEUP / Eutrophication – Terrestrial	1	1

Data Extraction

To obtain per component values for all battery chemistries, the data collected from these sources was placed into a template designed to capture both quantitative data points and relevant details of each source. For every data point, the following were also recorded: publication year, first author name, battery chemistry assessed, functional unit, impact assessment method, model components and system boundary. Each data point was extracted in its component level form, comprising of the battery's cathode, anode, separator, electrolyte, casing and production. If a source had further breakdowns of these parts, the data points were added up to comply with these categories. This process was done for each of the twelve impact indicators discussed in this study. Values outside the system boundary were excluded from the study.

Synthesis Methods

Once all values were extracted, they were harmonized through a three-stage process to obtain the final data points: normalization, aggregation and scaling. Data normalization of all data was done to 1 kWh. For production emissions, most sources already displayed data for a 1 kWh cell, however, all data points displayed in a per-kg basis were normalized using the average battery energy density per-kWh displayed in Degen et al., Chen et al., Zhang et al., Rietdorf et al. and Xu et al.[6,12,25–27] All use emission data points extracted were already displayed per kWh. The data from the template was averaged out per data point (per parameter, chemistry and battery part for the production phase, per parameter and technology for the use phase) once all the data was normalized. These values were aggregated to display the emissions per kWh of each stage. Regarding production emissions, all data points corresponding to the same battery chemistry and parameter were added up to obtain the emissions per kWh cell. In the case of use emissions, the data points were first applied to three energy mixes: Optimistic (Sweden, since most of its electricity comes from carbon-free sources), Average (World average) and Pessimistic (China, as it depends on coal for over 50% of its energy) by multiplying each technology's emissions per category by their share in each energy mix, which were obtained from Our World in Data.[28] These data points were added up to obtain the total emissions per kWh for all three energy mixes. The per-scenario values were converted from kWh to km, since it provides a more tangible unit of measurement. For this conversion, the average vehicle efficiency from a vehicle sample obtained from the EVKX database was used. From this database, only currently available fully electric vehicles with listed battery capacities and ranges were chosen, creating a sample of 749 EVs with listed range and battery capacity. Since the database only reports the energy efficiency of some models, this value was calculated individually for every vehicle dividing each EV's battery capacity by its range. The average of these values was calculated to obtain the conversion factor of 0.150 kWh/km, which was applied to all use phase data points. To scale up energy emissions for battery production, the EVKX database sample was used to obtain the average EV battery capacity. All battery capacity values from this sample were averaged out to obtain the mean EV battery capacity of 81.2kWh. All production emissions were scaled up linearly using this value by multiplying the emissions per cell by the average EV battery capacity. To scale up use emissions, each data point was calculated for different vehicle usage every 50,000 km, considering the average vehicle lifetime is around 200,000 km, by multiplying each per-km data point by the usage of each milestone.[29]

Sensitivity analysis

The main assumptions presented in the article (battery capacity, vehicle energy efficiency and lifetime) were tested for sensitivity using two different methods. Vehicle lifetime sensitivity was calculated by adding an additional milestone to the model's lifetime at 500,000km, considering this is the max-

imum mileage depicted in Weymar and Finkbeiner's vehicle sample.[29] Using the milestone markers, shorter vehicle lifespans can be measured. Battery capacity and vehicle energy efficiency sensitivity was tested by creating two additional model variants separate from the average EV: a small EV and a large EV. To build each model, two additional sub-samples were created by filtering the vehicles in the main sample using tags included in EVKX. The tags used correspond to vehicle classifications to make these models directly applicable to real world vehicle categories. The tag "hatchback" was used to create the small vehicle sample, while the tags "Pickup" and "Third row seats" were used to create the large vehicle sample. From the 749 vehicles in the main sample, the small vehicle sample contains 78 vehicles, while the large vehicle sample contains 104 vehicles (17 pickups and 87 SUVs). Regarding the values used for the sensitivity analysis, these were gathered in the same way as the main values, only with a smaller data set. The small vehicle sample has an average battery capacity of 48.8 kWh and an average energy efficiency of 0.125 kWh/km, while the large vehicle sample has an average battery capacity of 105.5 kWh and an average efficiency of 0.187 kWh/km. The assumptions and sensitivity values are shown in Table 4.

Uncertainty propagation

To accurately portray the uncertainty of the data points presented in the study, all data points are presented alongside their min/max values and number of sources, since most data points have around 3-5 sources whose value ranges vary. It is worth noting that some data points only have one source, which may provide multiple data values, and therefore were marked appropriately. These data points are still included in the study, as they can help signal where these developing chemistries stand amongst the rest of the data. Table 5 shows the number of source articles per data point, as to portray their trustworthiness.

Quality Assessment

To judge the reliability and completeness of the sources presented in the sample, all sources were compared across four criteria: life cycle inventory transparency, clarity of the system boundary, recency of LCI data and disclosure of background data base along with its version. Each study was rated in a scale of 1-5 against these criteria and the results of this assessment are displayed on Table 6. It is worth noting that some battery chemistries may be overrepresented in the sample since the inclusion criteria require component level reporting, leading to chemistries with more component level reporting being more common. This imbalance is noted here as a limitation. Table 6 displays the resulting scores from this process.

Results

The harmonized data points obtained for ten battery chemistries and three energy grids across twelve parameters were processed from eleven production phase sources and four use phase sources. This data is displayed on Figure 2. From all chemistries, NaNFM seems to have overall less emissions than the rest of the sample, with ten out of twelve green cells. Furthermore, most SIBs present low toxicity emissions, with the exception of NaNVPF in HTPc. Conversely, most conventional battery technologies exhibit lower MEUP emissions than upcoming technologies. The rubric with the smallest deviation is GWP, while the one with the highest was MEUP, followed by the rest of toxicity indicators. When analysing use indicators, most rubrics show Sweden with the lowest emissions, China with the highest emissions and the world average in the middle, with the only outlier being IR, with Sweden having the highest emissions. From these, TETP has the lowest spread of results and FEUP has the highest. It is worth noting that the Swedish energy grid undercuts both the average and Chinese energy grids to the degree where eight out of the twelve parameters show the lowest results as less than 20% of the highest value, five of which show the lowest at under 10% of the highest value. The emissions parameters will be shown by impact category, followed by a holistic analysis and sensitivity assessment.

GWP

From the batteries included in the sample, LFP is the one with the overall least emissions, followed by NMC 811, NCA and NaNMMT. However, the uncertainty ranges of some newer battery chemistries land around LFP's data point, mainly NaNFM, NaNMMT and SSB NMC; this points towards these batteries as suitable alternatives to current chemistries, as their emissions could decrease with further development. It is worth noting that even though most of these data points have a range of less than 30%, two chemistries present a data range over 50%, SSB NMC and NaNVPF, and two over 35%, NaPBA and NaNMMT. These ranges are somewhat expected, as these chemistries are still in development and the source articles may present optimized and non-optimized scenarios. From these chemistries, it is worth noting that SSB NMC has a wide range as the sources used to obtain its data test different materials for battery construction, in contrast to all of the other batteries which have somewhat standardized material lists. Overall, these results show that newer chemistries could prove to be more effective replacements for current battery chemistries, however, these still need more development

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Table 4 Shows the assumptions made in the main study and the sensitivity values corresponding to each assumption.

Assumption	Regular scenario	Sensitivity analysis	
	Avg vehicle	Small vehicle	Large vehicle
Battery capacity	81.2 kWh	48.8 kWh	105.5 kWh
Vehicle energy efficiency	0.150 kWh/km	0.125 kWh/km	0.187 kWh/km
Vehicle usage	200,000 km	50,000-150,000 km (smaller milestone markers)	500,000 km

Table 5 Showcases the number of data sources per data point

Chemistry / Parameter	Battery chemistries (Production)										Energy production sources (Use)							
	NMC 811	NMC 532	NMC 622	LFP	NCA	NaNFM	NaNMMT	NaNVPF	NaPBA	SSB-NMC	Coal	Gas (natural gas)	Oil	Nuclear	Hydropower	Wind	Solar	Bioenergy
GWP / Climate Change	5	3	3	6	3	2	3	3	3	4	2	3	1	2	3	2	3	4
AC / Acidification	2	2	2	2	1	2	1	1	1	2	2	3	1	1	3	2	3	4
FEUP / Eutrophication – Freshwater	2	2	2	2	1	2	1	1	1	2	2	3	1	1	3	2	3	4
FETP / Ecotoxicity – Freshwater	2	2	2	2	1	2	1	1	1	2	2	3	1	1	3	2	3	4
MEUP / Eutrophication – Marine	2	2	2	2	1	2	1	1	1	2	2	3	1	1	3	2	3	4
HTPc / Human Toxicity – Cancer	2	2	2	2	1	2	1	1	1	2	2	3	1	1	3	2	3	4
PM / Particulate Matter	2	2	2	2	1	2	1	1	1	2	2	3	1	1	3	2	3	4
POF / Photochemical. Ozone Formation	2	2	2	2	1	2	1	1	1	2	2	3	1	1	3	2	3	4
HTPnc / Human Toxicity – Non-Cancer	2	2	2	2	1	2	1	1	1	2	2	3	1	1	3	2	3	4
IR / Ionizing Radiation	2	2	2	2	1	2	1	1	1	2	2	3	1	1	3	2	3	4
METP / Ecotoxicity – Marine	2	2	2	2	1	2	1	1	1	2	2	3	1	1	3	2	3	4
TETP / Ecotoxicity – Terrestrial	2	2	2	2	1	2	1	1	1	2	2	3	1	1	3	2	3	4

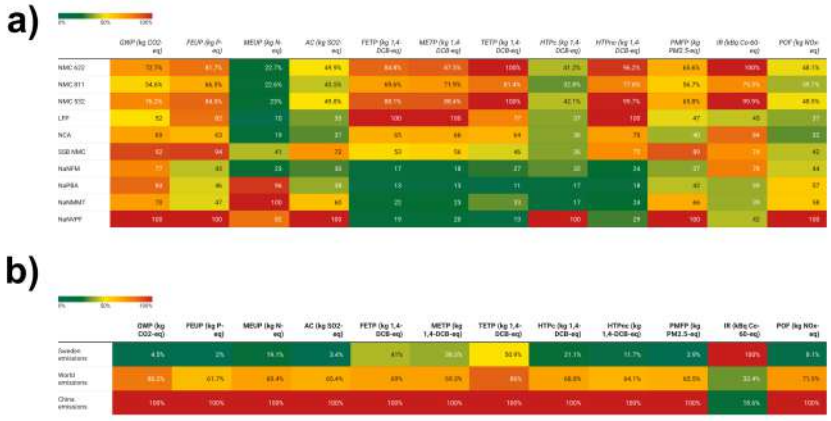

Figure. 2 Shows the relative share of emissions produced per rubric, 100% being the highest data point per parameter. "a" focuses on production emissions and "b" focuses on use emissions.

and optimization in order to definitively phase them out. Regarding use emissions, Sweden's energy grid produces drastically less emissions when compared to the world average and China. Even then, China's emissions still surpass the global average by a considerable margin, providing no overlap between their uncertainties even though they both use a similar amount of fossil fuels. The main reason for this gap is China's reliance on coal for electricity production, as it is

Table 6 Shows the criteria and scores for all sources used in the study.

Article / Rubric	LCI inventory transparency	System-boundary clarity	LCI data recency	Background database & version	Total Score
Arshad et al.	5	5	5	5	20
Chen et al.	5	5	5	5	20
Lai et al.	5	5	5	5	20
Xu et al.	5	5	5	5	20
San Miguel (2024)	5	5	5	5	20
Yousefi et al. (2023)	5	5	4	5	19
Le Varlet et al.	5	5	3	5	18
Liu et al.	4	5	4	5	18
Zhang et al.	4	5	4	5	18
Mohsen / Hosseini et al. (2022)	4	5	3	5	17
Degen et al.	3	5	2	5	15
Accardo et al.	4	3	2	4	13
Nibelius et al.	3	3	3	4	13
Rietdorf et al.	3	4	3	3	13
Diemer et al. (2024)	1	5	3	3	12

by far the most polluting energy source and makes up over half of China's electricity grid. In contrast, the world average electricity grid uses more natural gas, the least polluting non-renewable energy source, than China. This change allows world emissions to reduce GWP emissions while still using mostly non-renewable energy sources, however, cutting down a grid's reliance on these energy sources is the more definitive solution to this problem. When comparing both phases, certain patterns emerge when analysing emissions, mainly that the importance of production emission tends to decrease with mileage. This rule holds true with the world average and Chinese energy grids, as these rely mostly on non-renewable energy sources. Nevertheless, Sweden's energy grid is the exception to this rule, as it produces way less emissions than every chemistry even at higher usage.

Regional impact indicators (FEUP, MEUP, AC)

When comparing battery performance in regional emissions indicators, NaNFM is the least harmful chemistry, followed by NCA, LFP and NMC 811. From these, NaNFM is the most consistent, being the chemistry with the lowest FEUP and AC emissions. Overall, NaNFM was the only developing chemistry to consistently outperform established chemistries, while the rest tend to underperform in these categories. This is especially true with SSB NMC and NaNVPF, which underperform in all three regional emission indicators. As for NaPBA and NaNMMT, these have a few good results, mainly FEUP and AC for NaPBA. Regarding uncertainties, conventional battery chemistries tend to show tighter ranges when compared to SSB NMC and NaNFM, which have more sporadic data sources. NaPBA, NaNVPF and NaNMMT only have one data point for each of these indicators, so these data points are not as well-grounded as the rest of the sample. Use emissions follow a similar pattern between regional indicators, as Sweden's energy mix has little to no AC or FEUP impact. The outlier in this case is MEUP, since Sweden's grid produces around 20% of China's MEUP emissions, compared to under 5% for the other two indicators. The cross comparison of both phases yields three different results. FEUP emissions almost completely rely on the use stage of the vehicle, even when it is driven only 50,000 km using the most polluting chemistries. In contrast, marine eutrophication mostly depends on battery production, even at 200,000 km, with the only exception being LFP, which is surpassed at around 100,000km in China's energy grid and 150,000km in the world average energy grid. Meanwhile, acidification relies on both phases depending on the mileage of the car, since battery emissions become less important at higher mileages, especially in coal dependent energy grids.

Ecotoxicity (FETP, METP, TETP)

All three indicators follow similar trends, since all in-development battery chemistries show lower emissions than currently available options. This is especially noticeable in sodium-based batteries, as these present substantially lower emissions than their lithium-based counterparts, producing under half of LIB's emissions. It is worth noting that SSB NMC does reduce ecotoxicity emissions in all cases when compared to liquid lithium batteries although not at the same level as SIBs. The uncertainties of these measurements tend to show similar patterns to previous cases, with some exceptions, such as LFP's large range of values for TETP and SSB's range of over 190%. Use emissions paint a similar picture to previous indicators with a significant change: Sweden's energy grid presents emissions which are close to both China's and the world average, unlike other scenarios where these appeared almost flat. This is due in part to the high FETP and METP emissions of wind and solar energy, which are common in Sweden's energy grid, as these are even higher than the ecotoxicity emission of natural gas. When analysing the bigger picture and comparing both phases, two main scenarios appear: LIB emissions and SIB emissions. In all cases, LIBs have higher ecotoxicity emissions than even China at 200,000km, usually by a wide margin for liquid electrolyte LIBs. In contrast, SIBs have a fraction of these emissions and can, in some cases, be lower than use ecotoxicity emissions in coal-heavy grids. An example of this is NaPBA and NaNVPF, which have lower production emissions than a vehicle driven for 200,000 km in an average energy grid. Nevertheless, production emissions are generally the main priority to

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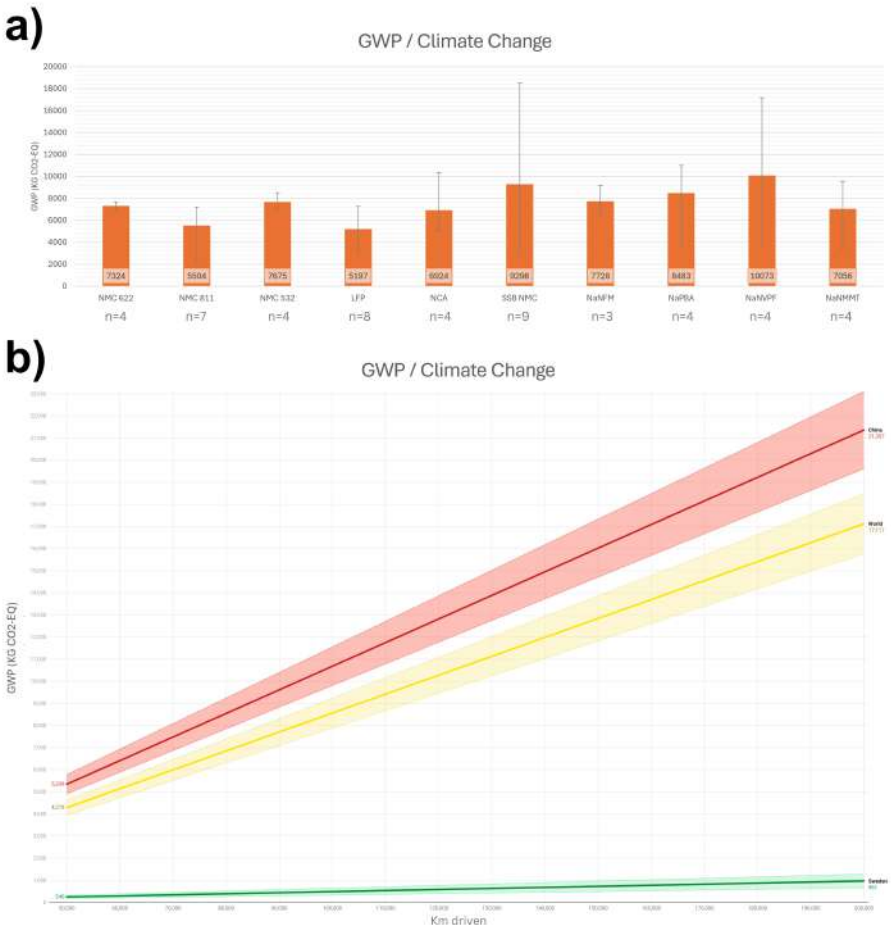

Figure. 3 Shows GWP emissions of both phases, with n = the number of data points per battery chemistry. The use phase used all sources to calculate the three scenarios. "a" focuses on production emissions and "b" focuses on use emissions.

lower emissions in this category.

Human health (HTPc, HTPnc, PMFP)

In General, HTPc and HTPnc exhibit similarities in the way batteries are ranked by emissions with one conspicuous outlier: NaNVPF exhibits cancer toxicity levels over twice that of the next worst chemistry. Even though there is only one source for this data point, it is still worth noting this massive difference when compared to the rest of the sample. Otherwise, both parameters show a division between SIB and LIB emissions with large gaps between the two groups. PMFP shows a more unique trend than the other indicators, as most values are roughly equal, with the lowest being NaNFM, NaPBA and NCA. The outliers in this case, although not as noticeable as with HTPc are still visible as SSB NMC and NaNVPF, which both feature abnormally high levels of particulate matter formation when compared against current chemistries. The min-max ranges of each battery chemistry follow usual patterns up to a certain extent, since these ranges tend to be wider than the ranges for other parameters. This effect is extended to chemistries with usually large min-max ranges, such as SSB NMC. The use stage energy grids show similar trends as other parameters, since Sweden's energy mix consistently undercuts both the global and Chinese energy grids to different extents, the most extreme example of this being PMFP, where Sweden's PMFP emissions at 200,000 km are under 25% of the global average PMFP emissions at 50,000 km. When comparing both phases, PMFP and HTPc show similar trends, as production emissions make up a noticeably smaller percentage of emissions with higher mileage, since both phases have a similar share of emissions up until the 200,000 km mark of average emissions for most battery chemistries. However, HTPnc emissions show a completely different trend, as production emissions from most batteries are higher than even the Chinese energy grid at 200,000 km. The notable excep-

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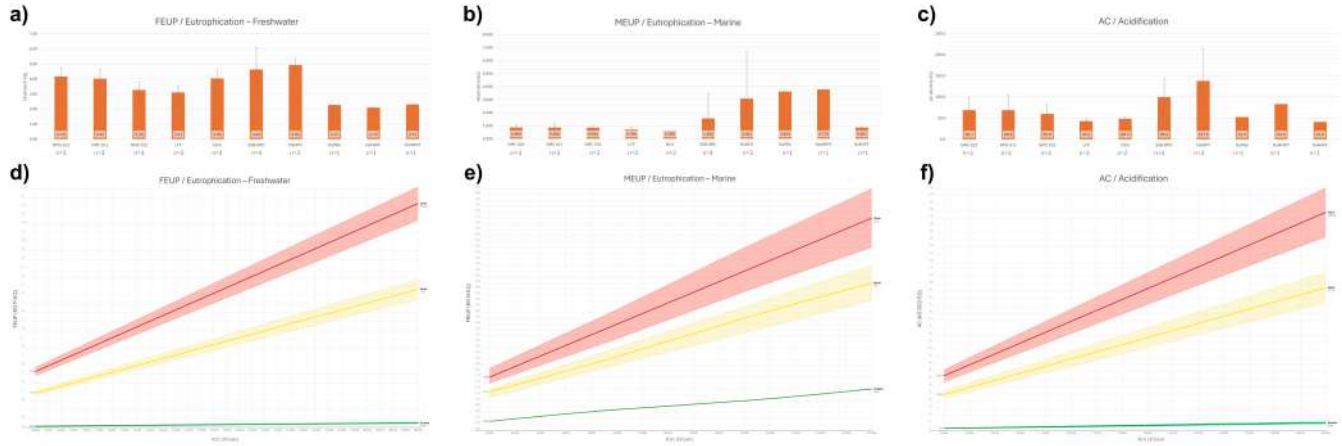

Figure. 4 Shows FEUP ("a" & "d"), MEUP ("b" & "e"), and AC ("c" & "f") emissions of both phases, with n= being the number of sources per battery chemistry. The use phase used all sources to calculate the three scenarios. "a", "b" & "c" focus on production emissions and "d", "e" & "f" focus on use emissions.

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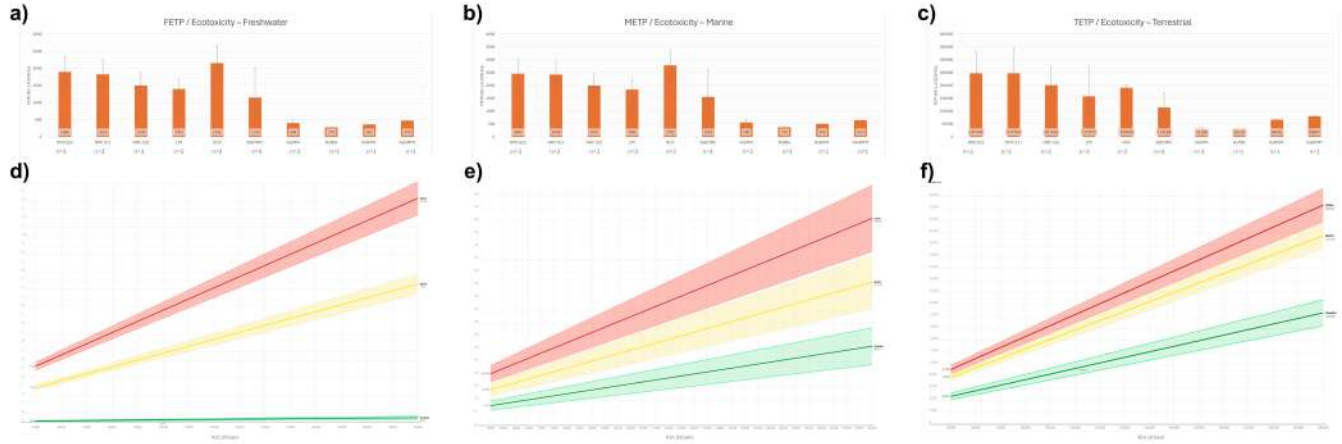

Figure. 5 Shows FETP ("a" & "d"), METP ("b" & "e"), and TETP ("c" & "f") emissions of both phases, with n= being the number of sources per battery chemistry. The use phase used all sources to calculate the three scenarios. "a", "b" & "c" focus on production emissions and "d", "e" & "f" focus on use emissions.

tions to this rule are SIBs, as the HTPnc emissions of these batteries tend to be lower than either the global average scenario at 100,000 km or at 150,000 km.

Other (POF and IR)

When comparing IR battery emissions, newer chemistries tend to obtain better results compared to current options, especially when comparing NaPBA, NaNVPF and NaNMMT to the rest of chemistries, as these have dramatically lower emissions than the rest. Nevertheless, these battery chemistries are the three most polluting chemistries when analysing POF emissions. Even when excluding these batteries from the comparison, results tend to be quite similar across both traditional and experimental battery chemistries. Use phase results for POF paint a similar picture as previous emissions parameters, as Sweden's energy grid produces under 10% of China's energy grid POF emissions, with the world average close by to China's emissions. However, this standard is, for the only time in this comparison, inverted in favour of both China's and the world average energy grid, as Sweden's IR emissions surpass both China and the world average by a sizeable margin, to the point that to reach Sweden's 50,000 km IR emissions, over 200,000 km would have to be driven using the Chinese energy grid and around 150,000 km would have to be driven using the world average energy grid. This is due to Sweden's extensive

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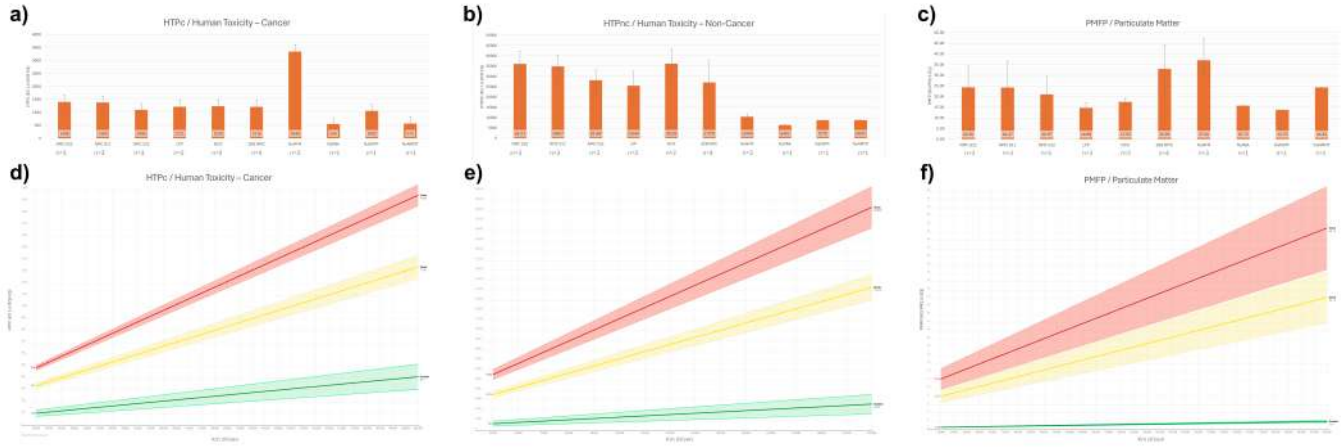

Figure. 6 Shows HTPc ("a" & "d"), HTPnc ("b" & "e"), and PMFP ("c" & "f") emissions of both phases, with n = the number of data points per battery chemistry. The use phase used all sources to calculate the three scenarios. "a", "b" & "c" focus on production emissions and "d", "e" & "f" focus on use emissions.

use of nuclear energy, which is by far the highest IR source in energy production. Overall, POF emissions follow a similar pattern to GWP emissions, where mileage is king when determining the main source of emissions, since 100,000 km driven in the world average energy produce as many POF emissions as most batteries at this stage, not to mention the 75,000 km required to reach this point in the Chinese energy grid. In contrast, IR production results are usually entirely dependent on use emissions, especially in nuclear-heavy energy grids. Even still, battery production IR emissions for most batteries are surpassed by the average energy grid at 100,000 km.

Cross parameter trends

Between battery chemistries, the ones with the least impact across all categories are NaNFM, NaPBA, NCA, NaNMMT and NMC 811. From these, NaNFM and NaPBA consistently show lower emissions than the rest of the batteries, both of them often being one of the three lowest emissions sources for eight of the twelve parameters tested and usually producing under 40% of the highest data point's emissions. Regarding the other chemistries, NaNMMT also performs above average, as it is comparable to the previously mentioned SIBs and is only partially surpassed by NCA, while NaNVPF and SSB NMC do not score as highly as LFP or NCA in most categories but show potential as they tend to make around 65% of the worst performing battery's emissions compared to 60% for LFP and NMC 811. Of note is SSB NMC, as this battery chemistry tends to be around the middle of the ranking in most parameters, as it is between the 4th and 6th spots in seven out of the twelve categories, and most importantly, never being the worst option in any parameter. In contrast, chemistries like LFP rank higher on average but have more sporadic results. Furthermore, SSB NMC often shows the widest range of values of any other chemistry, often exceeding 50% in either direction due to different sources' bill of materials for battery production. Most developing battery chemistries show promising results which could be fixed over time, especially SIBs due to their generally consistent performance in most categories, especially toxicity.

Use emissions show a very consistent pattern: clean energy grids produce far less emissions than other energy grids with higher use of fossil fuels, as Sweden's energy grid outperformed both the world average energy grid and China's energy mix in eleven out of the twelve parameters, eight of which were under 20% of the highest value and five under 10% of the highest value. Still, the main emission source in both the world average and Chinese energy grid is coal, as this is the main energy source which sets both energy mixes apart, since oil and especially gas have lower emission overall. From these, gas is the better alternative, as it is the least polluting non-renewable energy source and can be considered a stepping stone to reduce emissions if clean energy sources are not available. When comparing both phases to each other, the energy mix and battery chemistry combination is essential when determining each phase's importance. For example, Sweden's energy mix produced way less emissions than most battery chemistries, even at 200,000 km. However, world average energy mix emissions tend to be somewhat closer to battery emissions, especially for chemistries with already low emissions or at higher mileages. This trend is amplified in the Chinese energy grid, which tends to surpass battery emissions in most parameters at 200,000 or even 150,000 km. In short: the cleaner the energy grid, the more important production is in overall emissions.

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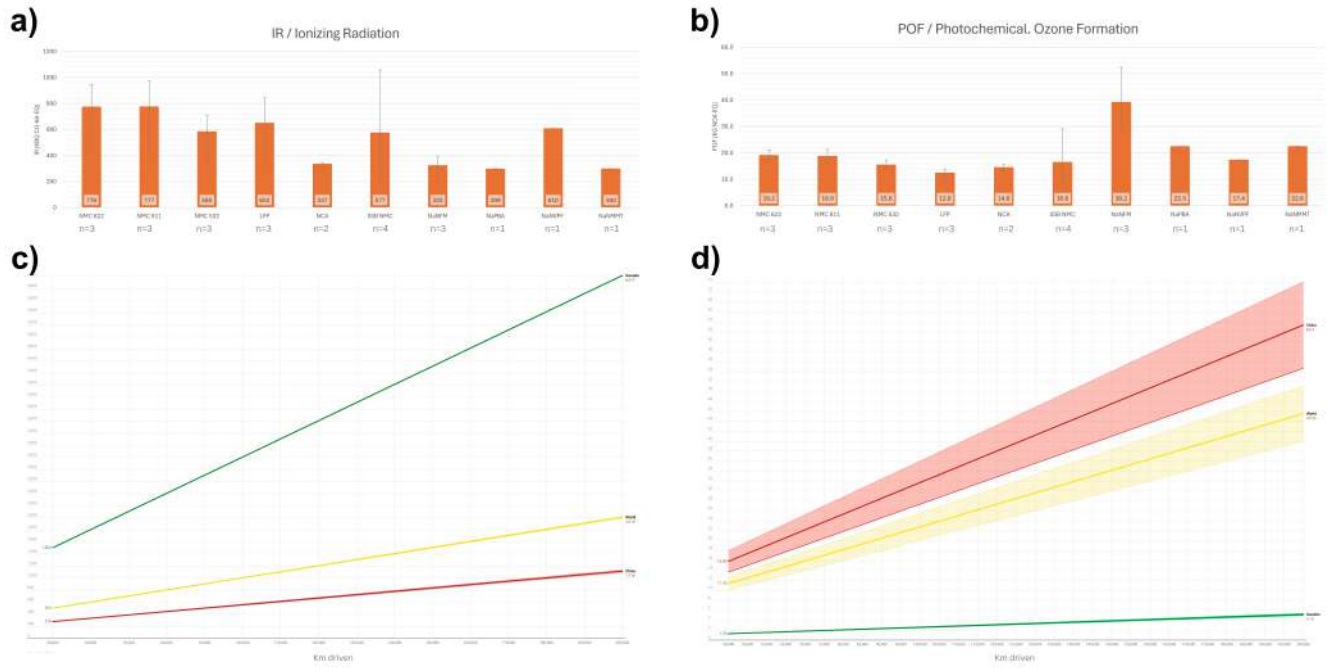

Figure. 7 Shows IR ("a" & "c") and POF ("b" & "d") emissions of both phases, with n= being the number of sources per battery chemistry. The use phase used all sources to calculate the three scenarios. "a" & "b" focus on production emissions and "c" & "d" focus on use emissions.

Sensitivity analysis

Between the average vehicle and the hatchback, production emissions are reduced by 40% in all scenarios, while the large vehicle emissions increase by 30% for all battery chemistries. For reference, when analysing GWP emissions, the average-size battery with the smallest emissions (LFP) produces more emissions than eight small battery packs of different chemistries, only being a more suitable alternative to SSB NMC and NaNVPF. In contrast, the large vehicle LFP battery is only worse than two average-sized battery packs. A similar trend is present when analysing vehicle efficiency, however this is at a smaller extent, as the small vehicle scenario reduces overall emissions by 16% and the large vehicle scenario increases emissions by 26%. These changes can be attributed to larger vehicles having larger batteries without a significant increase in range, while smaller EVs have batteries more appropriate to their size without extreme range limitations. When it comes to mileage, the 500,000 km scenario makes use emissions more important across the board, especially in scenarios with the world average and Chinese energy grids. However, this scenario did not affect the results of Sweden's energy grid as much when compared to the emissions of an average battery, since the ratio between energy grid and battery production emissions stayed heavily biased towards battery production even at extended ranges.

Discussion

The findings of this study are somewhat consistent with previous literature regarding battery production emissions. NaNFM, NaPBA and NaNMMT are the three most promising technologies, as they tend to present the lowest emissions across the twelve indicators out of the rest of the sample. However, NCA is the least polluting conventional battery chemistry, followed by NMC 811 and LFP. From all the chemistries, the one that could exhibit the most improvements over time is SSB NMC, as the construction for these types of batteries can be optimized to produce less emissions than most existing chemistries. Regarding use-phase emissions, the results show that the main way to reduce these is the mass adoption of renewable energy sources and nuclear energy, as these perform better than non-renewable energy sources in most cases, for the exception of nuclear energy's IR emissions. If this option is not available, natural gas can be a reasonable alternative to both oil and coal as it is the cleanest non-renewable energy source. On the whole, reducing either parameter individually makes a noticeable impact in overall emissions, however, use emissions have a larger impact than production emissions in most scenarios and only in renewable-heavy energy mixes is this not the case.

The main contribution of this study to the broader field is that, when comparing the importance of battery production

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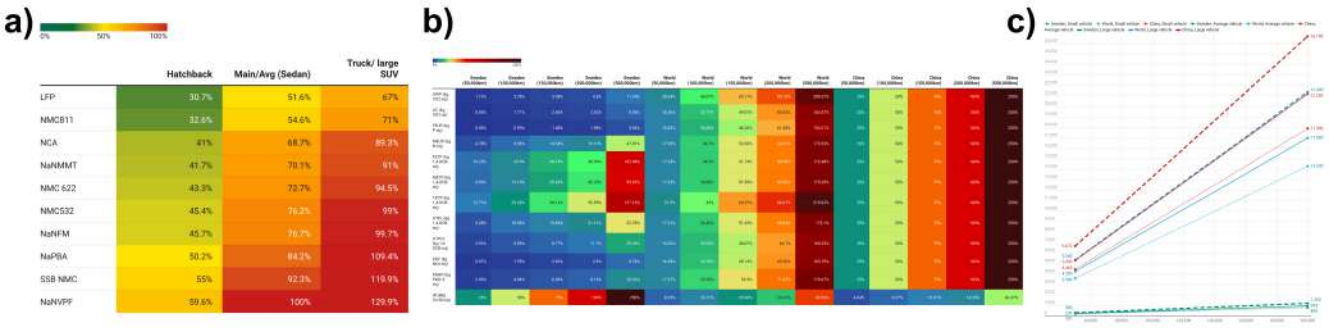

Figure. 8 Shows the results of the sensitivity analysis. Both "a" & "b" show the relative share of emissions produced per rubric, 100% being the highest data point per parameter in the main case. "a" focuses on production emissions for the three different battery models and "b" focuses on use emissions up to 500,000 km. "c" focuses on the total emissions of the three sensitivity scenarios compared to each other up to 200,000 km.

and use in emissions reduction, production is more important than use at lower mileages or in cleaner energy grids, while use is more important at higher mileages or in coal-dependent energy grids. This relationship dictates the main approaches taken to reduce overall EV emissions, since choosing a more sustainable battery is useful when their lifespans are short, especially in countries with clean energy grids. However, this impact is minimized when battery lifespans are longer, and these vehicles are used in countries with an energy grid built on non-renewable energy sources. Since current EV vehicle lifespans are around 200,000 km, their emissions are at a point where current battery production emissions are surpassed by use emissions in some categories when the battery reaches EOL, making both stages roughly equal in contribution to overall emissions in the average energy grid and current chemistries.[30–32] Regarding battery production emissions, the results of this comparison state that even when compared to a wider selection of batteries, both current and in development, SIBs are the better option across the twelve impact indicators, especially NaNFM, NaPBA and NaNMMT. From these, NaNFM has the most sources supporting this claim, making it a suitable alternative for current EV battery technologies. This conclusion is further cemented by the scaling of the emissions up to a vehicle, since emissions reported per kg/kWh are not as directly applicable to an EV. Furthermore, SIBs use sodium instead of lithium in their construction, which allows them to lower both their environmental and social cost. It is worth noting that, even though not as low on emissions as SIBs, NMC SSBs can be a suitable alternative to current battery chemistries as long as more development is done to reduce their ecological impact. Since some sources provided low-emissions and high-emissions scenarios for this battery chemistry, the spread is quite large between the minimum and maximum values, however, the low-emissions scenarios show how this battery could perform better than current battery chemistries in most impact categories.

The aims of the study were all achieved, since the results show that most experimental battery technologies perform better than their current alternatives, with the three best battery technologies all being newer chemistries. The environmental impact of electricity emissions can be equal or higher than the production stage of an EV battery over time, since at lower mileages these make a smaller portion of overall emissions than battery production. The main variable which affects overall emissions is energy mix, since those with almost 100% adoption of renewable energy reduce their environmental impact substantially at all mileages, making battery production the main pollutant throughout a vehicle's lifespan. The results of this review also provided some unexpected results in both stages. NaNVPF, despite being a sodium-based battery, exhibits worse emissions of all experimental chemistries and is the worst battery chemistry in six out of the twelve parameters. However, due to its low source count, it is hard to definitively say whether this battery chemistry is a dead-end in terms of development or if it can be improved like SSB NMC. Another find was the electricity production emissions of natural gas, since these are way lower than those of coal and oil. This difference is the main factor that creates the gap between the average energy mix and the Chinese energy mix, since the world average energy mix uses 19% more gas and 21% less coal relative to the Chinese energy grid, which is the main difference between both energy mixes. This can lead to gas-dependent electricity grids as middle ground between fully renewable and coal-dependent energy mixes.

The main recommendation made to further improve LCA research is providing per-component impact data apart from the LCI when investigating battery production emissions. This data can pinpoint the main emissions sources in per battery, which can allow for more specific solutions when analysing a single chemistry. Furthermore, it can allow for more direct re-

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sults comparisons between studies, especially when they have different boundaries, such as the inclusion of pack overhead, and make review studies more accurate when compiling data from several sources. It is also recommended that both battery production and electricity generation LCAs cross check their results with other sources to either check for improvements or to make sure the results are similar to expected values. This process is done in San Miguel 2024, where the author compares the per-technology emissions of the study with those of other articles from various other locations, which makes these results more reliable as emissions for energy production in the location studied (Spain) and makes the per-technology data on emissions comparable to those of other places. [33]

The main limitation of this study is the selection bias, since only 11 studies were able to be chosen for production, from which only four had per component breakdowns of all impact parameters. This skewed data availability towards GWP and more common battery chemistries, especially those currently available, and may not truly represent all available literature. Even though the use stage also suffers from a low source count, this mostly affects the accuracy of the measurements provided, as the energy production sources are given by Our World in Data. [28] This selection bias is especially important for the chemistries with only one source in all non-GWP parameters, these being NCA, NaPBA, NaNMMT and NaNVPF, as this limits the interpretability of these results. Another area of opportunity in this study is the omission of pack overhead and EOL emissions. Both of these can have an effect in the overall viability of all battery types, specially those in development, since they may have design considerations in their BMS systems which could increase their environmental impact and can increase their importance for overall emissions when compared to use emissions. On the other hand, EOL could alter the viability of SIBs and SSBs, since these batteries use different components than current chemistries and could show different disposal emissions. Furthermore, different EOL scenarios could affect the viability of different chemistries, since a second life or recycling scenario could decrease emissions compared to a battery disposal scenario and therefore affect the feasibility of each battery chemistry's adoption depending on existing infrastructure. Finally, the sensitivity scenarios of a small and large vehicles are entirely dependent on currently available models, which could skew results away from vehicle models which are still on the road but no longer sold. In addition, the vehicles considered in both sensitivity models tend to vary in capacity. The small model is the most consistent of the two, as all of the 78 vehicles included in its sample have battery capacities lower than the average in a range of 64.1 kWh between the smallest and the largest vehicle. In contrast, the large vehicle sample has 21 models with batteries smaller than the average, which are mostly small pickup trucks and basic versions of 3-row crossover SUVs, and a range of over 160 kWh from a large, 223 kWh SUV to a 56-kWh pickup truck with a battery capacity comparable to a car. This variation creates a more varied sample, however it is not as well defined as the small vehicle sample and is more representative of all pickups and 3-row SUVs rather than only large vehicles.

In conclusion, most of the battery chemistries compared in this study show either currently promising results or have potential to be developed into better alternatives to current battery chemistries. Most SIB batteries included in the sample show multiple parameters in which they surpass conventional battery technologies, while SSB NMC's results suggest it can become a more useful and widely used battery type with more development.

Acknowledgements

Special thanks to Dr. Andrea Giusti and Marcin Kedziedra for providing advice and guidance during the creation of this project.

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