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The greenhouse gas emissions of automotive Lithium-ion batteries: a statistical review of life cycle assessment studies.

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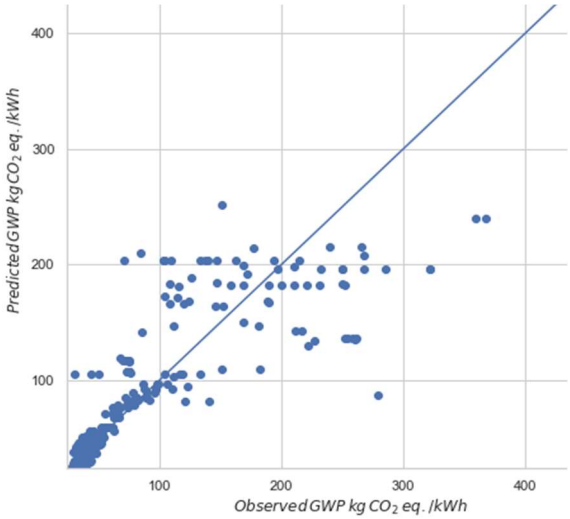
Abstract

Worldwide sales of battery electric vehicles (BEVs) have been steadily increasing for several years and now account for several million vehicles, resulting in a high use of lithium-ion batteries (LIBs). It is then required to assess the real environmental impact of these LIBs and to avoid environmental impacts' transfers. Life cycle assessment (LCA) methodology seems the most appropriate framework as it is a multi-stages and environmental multi-criteria ISO methodology. However, many studies exist on this subject and it appeared that no consensus is emerging on a common environmental value of LIB's production and that the perimeters of the studies differ a lot. To fill this gap and to properly assess the environmental consequences of a massive electrification deployment, this study performs a qualitative and a quantitative review of more than 500 LCA studies referring to LIBs' production for BEVs. 377 Observations for seven selected variables among more than 80 surveyed variables are presented and meta-analysis (MA) methodology is used to compare the final 32 selected studies having not the same perimeter. After many statistical tests and 8 finalists selected, we find that the global warming potential (GWP) impact of mobile LIBs' production can be explained by a reduced parametrized model containing four information: the geographical location of the corresponding author, the cell design of the battery, the battery specific energy, and the manufacturing energy. This allows a generic and systematic approach to assess GWP impacts of LIBs production. We also propose recommendations for LCA practitioners to harmonize LIBs' environmental assessments and save time for further analysis.



Highlights

- A qualitative and quantitative meta-analysis review across more than 500 life cycle assessment studies from 3 search engines on automotive Lithium-ion batteries (LIBs).
- 32 selected studies and 377 observations assessed throughout 7 selected characteristics, equivalent to 21 variables.
- Very high disparity and variability for LIBs' Global Warming Potential (GWP) results.
- A reduced model with only 4 explanatory characteristics: geographical affiliation of the corresponding author, cell design, battery specific energy, and manufacturing energy, can assess GWP for mobile LIBs.

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Keywords

Lithium-ion batteries ; Life cycle assessment ; Meta-analysis ; Literature review ; Reduced parametrized model ; Global warming potential impact.

1. Introduction

By the end of 2019, the global personal vehicle fleet comprises 7.2 million of electrified vehicles, battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs), representing about 1% of the light duty vehicle (LDV) fleet worldwide (International Energy Agency, 2020). Most of countries set ambitious targets for a massive electrification development supported by subsidies called production's subsidy in the United States (US) for example, autonomy's subsidy in China, bonus purchase in Europe, etc. These different directives result into legislative incentives for vehicles with limited tailpipe emissions, or rather like constraints on vehicles running with fossil fuels for instance. European Commission even edited a press release dealing with the sustainability of batteries production in accordance with the European Green Deal (European Commission, 2020) as a 14 fold increase of the global demand for batteries is projected by 2030. This popularity for BEVs led battery manufacturers to develop and increase their offer, both in terms of battery types: lithium-ion batteries (LIBs), nickel metal hydrate batteries (NiMH), lithium metal polymer (LMP), etc.; and also, in terms of battery performances: autonomy range, charging time, and weight. Thus, a plethora of mobile application batteries flooded the markets and environmental questions about the battery carbon footprint have been raised. Though the use of the BEVs improves urban air quality by eliminating tailpipe emissions, numerous studies highlighted that environmental performances of BEVs depend on the battery production process and its related end-of-life. The electricity mix used for charging the battery remains of course at stake regarding the environmental performances of BEVs (Bouter et al., 2020). This raises the question of the environmental footprint of BEV themselves. Today many studies deal with the potential environmental impacts of batteries (Almeida et al., 2019; Dunn et al., 2015; Ellingsen et al., 2015; Peters et al., 2017; Zubi et al., 2018). Though these studies mainly use the standardized methodology of life cycle assessment (LCA) based on ISO norms (14040:2006, 2006; 14044:2006, 2006) to quantify the potential environmental impacts of the studied batteries, the definition of a value range for greenhouse gas (GHG) emissions of mobile application batteries remains an arduous task. The literature related to environmental topics is vast and grows especially quickly when it deals with LCA. Despite the ISO norms, the environmental assessment of one identical product can lead to several publications resulting in different results (Brandão et al., 2012). LCA results can then differ significantly from one study to another and exhibit a high range of uncertainties. This has been shown by some reviewing attempts, either already quite old (Hawkins et al., 2012) given the technological advances and changes in mobile LIBs technologies, or essentially dealing with literature review (Aichberger and Jungmeier, 2020; Peters et al., 2017) and not providing original inventory data. The present work is thus motivated by tackling these two issues: i) to conduct a literature review on an as exhaustive as possible up–to-date bibliographic corpus dealing with potential environmental impacts of mobile LIBs; ii) to attempt to synthetize this literature review into a common perimeter, both in terms of technology and LCA methodology related choices.

To perform the second objective, meta-analysis (MA) methodology (Field and Gillett, 2010) is chosen as it allows to quantify the environmental potential impacts of one single technology based on a common chosen perimeter, as well as to be able to compare existing studies in a statistical sense. MA methodology can also be used to assess predictive potential environmental impacts of the studied

technology for a same common perimeter. The technology studied in this work is LIB for automotive application. The environmental impact assessed is the global warming potential (GWP) indicator expressed in kilograms of CO_2 equivalent per kWh of battery energy capacity. GWP provides the comparison basis between all the relevant studies selected after the literature review process. The second objective of MA is sub-divided into two parts. The first one aiming at identifying the variables that seem to influence the most the GWP result. The second one attempts to quantify the identified variables in a more statistical sense, allowing us to produce an innovative parameterized model using a limited number of common identified variables and aiming at predicting the potential GWP impacts for hypothetical LIBs' production and facilitating LCAs for this product as well as providing recommendations for future LCAs studies.

This article is structured into 4 parts. The first one presents the methodology and the step-by-step construction of a reliable database to fulfill key assumptions and parameters of the selected studies. The second part describes the information contained in the database to identify the explanatory variables that will be retained for the statistical study presented in the third part. The last part deals about the statistical results from an LCA perspective and the regulatory developments.

2. Methods

2.1. Literature search methodological framework

The literature search has been conducted in a systematic way to be exhaustive to identify all available studies of the English-language literature devoted to LCA methodology, applied to on-board vehicles' LIBs' production focusing on personal BEVs. GWP indicator is chosen as the most robust and consensual environmental indicator recommended in UNEP SETAC LCI, 2018. Furthermore and based on Dolan and Heath, 2012; Menten et al., 2013; Whitaker et al., 2012, the characterization method for GWP has an insignificant influence on LCA results. Thus, no harmonization has been performed between the accounted observations. Also, GWP show very low uncertainties in comparison to all other impact categories (Chen et al., 2021).

The timeframe ranges from 2015 to 2019. Elder studies identified as references given their number of citations in recent studies have been handily added: Dunn et al., 2012; Ellingsen et al., 2014; Li et al., 2014; Majeau-Bettez et al., 2011; Notter et al., 2010; U.S. EPA, 2013; Zackrisson et al., 2010. The search has been performed with Scopus, Web of Science, and Springer browsers which cover a large perimeter of scientific publications. Some other search engines could have been used instead the three above mentioned but we are confident in the complementarity of the three browsers used based on experts' discussions. The research strategy is iterative and is based on the combination of keywords and logical operators as detailed in Table 1. Regarding the Scopus results, a first broad research LCA oriented and focusing on LIB provided 368 results. The same search has been executed with Web of Science (108 articles) and Springer (88 articles) (Table 1).

To ensure the homogeneity of the bibliographic corpus and to meet the MA requirements, (i) only primary results are included and literature reviews are excluded: Ellingsen et al., 2017; Marmiroli et al., 2018; Meshram et al., 2020; Nordelöf et al., 2019. Nevertheless, a reference cross checking is realized for literature reviews to take into consideration the potential missing entries of their bibliographic references. (ii) Studies shall follow LCA methodology according to ISO norms 14040-44

(14040:2006, 2006; 14044:2006, 2006). (iii) Stationary batteries are excluded, and only "conventional" technologies are considered: no solid state for example nor prospective batteries' technologies. (iv) The common quantitative variable GWP expressed in kg CO_2 eq./kWh of battery energy capacity must be reported, either from the study, or easily calculable based on the hypothesis provided in the material and method description of the related publication. Some calculations have been necessary to convert the observation in a standard measure. For example, the functional unit (FU)[†] chosen in the LCA studies can differ, and thus results must be converted into the common unit chosen: 1 kWh of battery energy capacity for this analysis. This leads to a final database of 44 useable publications giving rise to 441 observations, where one publication can contain one or several observations depending on the study and the sensitivity analyses conducted.

Table 1: Research strategy applied, and search engines used for the literature review

Search engine	Search strategy	Search results
Scopus	((TITLE-ABS-KEY (lca OR "life cycle analysis" OR "life-cycle analysis" OR "life-cycle-analysis") OR TITLE-ABS-KEY ("life cycle assessment" OR "life-cycle assessment" OR "life-cycle-assessment" OR "life cycle impact assessment" OR "environmental assessment" OR "environmental impact") OR TITLE-ABS-KEY ((carbon PRE/2 footprint))) AND PUBYEAR > 2014) AND (((TITLE-ABS-KEY ((battery OR batteries)) AND TITLE-ABS-KEY (((lithium OR li) W/1 ion) OR "li-ion" OR "li ion" OR "li/ion" OR "lithium-ion" OR "lithium ion" OR "lithium/ion")) AND PUBYEAR > 2014) OR (TITLE-ABS-KEY ((battery OR batteries) W/5 (libs OR lib OR lithium)) AND PUBYEAR > 2014))	368 results
Web of Science	TOPIC: (electric* NEAR/1 (vehicle$ or car$ or automo*)) AND TOPIC: ((lca or "life cycle analysis" or "life-cycle analysis" or "life-cycle-analysis")) OR TOPIC: (("life cycle assessment" or "life-cycle assessment" or "life-cycle-assessment" or "life cycle impact assessment")) OR TOPIC: ((environmental NEAR/1 (assessment or impact))) OR TOPIC: ((carbon NEAR/2 footprint)) AND (TOPIC: ((battery or batteries) NEAR/5 (libs or lib)) OR TOPIC: ((battery or batteries)) AND TOPIC: ((lithium NEAR/1 ion) or "li-ion" or "li ion") Indexes=SCI-EXPANDED, CPCI-S, CPCI-SSH, CCR-EXPANDED, IC Timespan=2015-2019)	108 results
Springer	"lithium-ion" AND "life cycle analysis" AND (battery OR batteries)' PY>=2015	88 results

2.2. Database building

Several characteristics must be fulfilled to get a rapid scan of the several literature entries. Basically, they fall into three characterization categories: "Typology of the study", "Technical data", and "Methodological choices" as described in Table 2. 21 characteristics are gathered and compose the database. They are themselves divided into sub-characteristics later named variables as described in Table 3.

[†] A FU quantifies the performance of a product system intended to be used as a reference unit in a

Table 2: The 21 characteristics of the three characterization categories

Typology of the study	Technical data	Methodological choices
Type of study	Cathode chemistry	Type of LCA approach
Year of publication	Anode type	Battery application
Geographical location of corresponding author	Electrolyte	System boundaries
	Solvent	Method for considering uncertainties
	Separator	Number and type of environmental indicator assessed in the study
	Cell design	
	Battery lifetime	
	Battery technical performance	
	Battery size	
	Process technical data	
	Quantity of manufacturing energy	
	Quality of electricity mix used	
	End-of-life treatment	

The fulfillment of the database enables us to explain the differences regarding the results for the common variable: impact on climate change per kWh of battery capacity, based on the investigated variables (Table 3). Not all variables are described as only exploitable results are further presented.

The first cut-off applied among all the variables depends on the number of their related observations. It is set up at 250 observations. This leads to the removal of: the number of cells per module (41 observations), the number of cells per battery pack (45 observations), the weight of one cell (50 observations), the battery lifetime expressed in years (51 observations), the charge/discharge efficiency (52 observations), the mass of the cathode and anode (54 observations), the energy capacity of one cell (54 observations), the number of modules per battery pack (67 observations), the battery specific power (76 observations), the depth of discharge (84 observations), the number of cycles (90 observations), the state of charge (98 observations), the details regarding the mass composition of the separator (113 observations), the details regarding the nature of the electrolyte (166 observations), the weight of battery pack (191 observations) and the battery nominal capacity (205 observations).

Studies and observations focusing on plug-in hybrid vehicles (PHEVs) have been removed (Cusenza et al., 2019a; Cusenza et al., 2019b; Hendrickson et al., 2015; Oliveira et al., 2015; Philippot et al., 2019a; Zackrisson et al., 2010).

Table 3 presents the remaining selected variables after the cut-off processes to depict the observations identified in the publications' database.

Table 3: Remaining variables (in *italic*) based on Table 2, after the cut-off process

Typology of the study		Technical data		Methodological choices	
Type of study	*Peer-reviewed*	Cathode chemistry	*NMC*[‡]	System boundaries	*Cradle to Gate*
			NCA[§]		
	Non-peer-reviewed		*LFP*[**]		*Cradle to Grave*
			LMO[††]		
Year of publication		Cell design	*Cylindrical*		
			Prismatic		
			Pouch		
Geographical location of corresponding author	*Europe*	*Battery specific energy*			
	China				
	North America				
		Quantity of manufacturing energy			
		Quality of electricity mix used	*Europe*		
			China		
			USA		
			Other/Several/Not defined locations[‡‡]		

Based on the selected variables from Table 3,Table 4 presents the 32 selected studies representing 377 observations after the several cut-off selections.

Table 4: The selected studies after cut-off iterations' processes

Study	Number of observations	Year of publication	Geographical location of the authors
Ambrose and Kendall, 2016	5	2016	North America
Berg and Zackrisson, 2019	2	2019	Europe
Burchart-Korol et al., 2018	1	2018	Europe
Ciez and Whitacre, 2019	216	2019	North America
Cox et al., 2020	4	2020	Europe
Dai et al., 2019	1	2019	North America
Deng et al., 2017a	4	2017	China
Deng et al., 2017b	2	2017	China
Deng et al., 2019	4	2019	China
Dunn et al., 2012	4	2012	North America
Ellingsen et al., 2014	3	2014	Europe
Erik Emilsson, 2019	6	2019	Europe
Hao et al., 2017	3	2017	China
Jiang et al., 2020	2	2020	China
Kallitsis et al., 2020	5	2020	Europe
Kelly et al., 2019	7	2019	North America

[‡] Lithium nickel-cobalt-manganese oxide (NMC = $LiNi_xCo_yMn_zO_2$)
[§] Lithium nickel-cobalt-aluminum oxide (NCA = $LiNiCoAlO_2$)
[**] Lithium iron phosphate (LFP = $LiFePO_4$)
[††] Lithium manganese oxide (LMO = $LiMn_2O_4$)
[‡‡] Other location refers to Japan , Korea Jiang et al. (2020); Kelly et al. (2019); Philippot et al. (2019a) and Norway Cusenza et al. (2019a); Erik Emilsson (2019); Philippot et al. (2019b) Several locations refer to observations for which cell manufacturing takes place elsewhere than the battery cell assembly for example Cox et al. (2020); Dunn et al. (2012); Ellingsen et al. (2014); Erik Emilsson (2019); Tagliaferri et al. (2016); U.S. EPA (2013).

Li et al., 2014	2	2014	North America
Majeau-Bettez et al., 2011	20	2011	Europe
Marques et al., 2019	8	2019	Europe
Notter et al., 2010	1	2010	Europe
Peters and Weil, 2018	7	2018	Europe
Philippot et al., 2019a	1	2019	Europe
Philippot et al., 2019b	10	2019	Europe
Sanfélix et al., 2016	1	2016	Europe
Sanfélix et al., 2015	4	2015	Europe
Tagliaferri et al., 2016	2	2016	Europe
U.S. EPA, 2013	6	2013	North America
Wang et al., 2018	1	2018	China
Wang et al., 2019	2	2019	North America
Wu and Kong, 2018	9	2018	China
Xiong et al., 2019	2	2019	China
Zhao and You, 2019	32	2019	North America

2.3. Meta-analysis methodology

Meta-analysis (MA) is a quantitative research methodology aiming to compare in a statistical way the results of several individual quantitative studies with common characteristics (Brandão et al., 2012; Lipsey and Wilson, 2001). Each result from the individual studies can be grouped into a database and defined according to differentiating characteristics which represent their potential explicative variables (Menten et al., 2013). In a MA framework, the observations are a function of these explicative variables. MA enables to statistically identify and quantify the effect of the most influent characteristics. Besides, a MA allows to produce an estimation of the mean results weighted by the systematic influence of its main drivers. Once statistically estimated, the meta-function can be used to deduce original values of the results by specifying new values for the main drivers identified.

3. Literature review results: datasets observation and discussion

The variables related to the type of the study, depicted as peer-reviewed or not, are discarded from the sample as 355 observations over the 377 are sourced from peer-reviewed publications.

The variable “year of publication” is also removed from the analysis as a vast majority of the studies are dated from 2019 with 290 related observations.

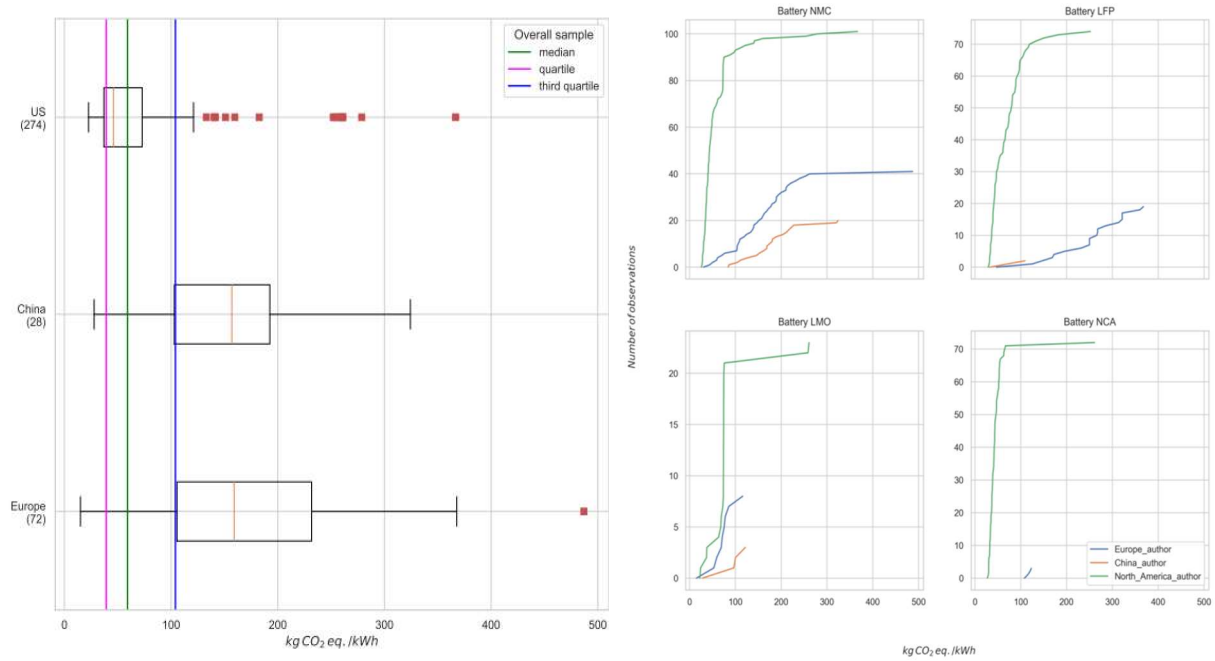
Section 3 presents the main observations obtained from the sample of the remaining selected characteristics of Table 3.

3.1. Observation per geographical location of corresponding authors

Figure 1(a) depicts the results according to the three geographical locations of corresponding authors retained as variables. Of a total of 377 observations, 274 observations are associated with an American corresponding author, 75 with a European one, and 28 with a Chinese one.

The decomposition of the GHG emissions factor distribution reveals some clear differences depending on the geographical location of the corresponding author. The median assessment of the GHG emissions factor within the studies with a corresponding author from the US is 45.9 kg CO_2 eq./kWh. It is 157.9 kg CO_2 eq./kWh with a corresponding author from Europe, and 156.9 kg CO_2 eq./kWh with a

corresponding author from China. GHG emissions for LIBs production published by American corresponding authors exhibit lower values and are less scattered than those published by either European or Chinese authors. This is difficult to explain as the fourth cathodes' chemistries are represented.



(a) **(b)**

Figure 1: (a) Dispersion of LCA GHG emissions results by geographical location of corresponding author; The solid green line represents the median of the overall sample; the pink and blue lines represent the quartile and third quartile of the overall sample respectively ; **(b)** according to the cathode chemistry

Figure 1(b) describes the results from two characteristics' perspectives: the geographical location of the corresponding author and the cathode chemistry. It is noticeable that NCA cathode chemistry seems to be a North American subject of study, as well as the LFP chemistry. American studies are more occurring through this literature review with 274 observations versus European ones (75 observations). GHG emissions results obtained by North American corresponding authors seem to be systematically lower than those coming from a European study for an equivalent cathode chemistry: NMC, LMO, and LFP. No explanation emerged at this stage as the fourth batteries' chemistries are represented but it is noticeable that the curve's shape, in green on Figure 1(b), is similar and with few variabilities among the four cathodes' type.

It is also noticeable and surprising that very few Asian authors appear in the literature review whereas they are well represented on the electric vehicles' market (Tsiropoulos et al., 2018).

3.2. Observation per cathode chemistry

Figure 2 presents the LCA GHG emissions results depending on the cathode chemistry. The number of observations by cathode chemistry is presented below the cathode chemistry in brackets. The green line represents the median value among all the 377 observations, the pink one corresponds to the first

quartile, and the blue one to the third quartile. Results are represented with box plots diagrams with whiskers with maximum 1.5 interquartile range[§§]. All other observed points are plotted as outliers.

Results range from 15.0 kg CO_2 eq./kWh for LMO cathode chemistry (Sanfélix et al., 2015) to 487.0 kg CO_2 eq./kWh for NMC cathode chemistry (Ellingsen et al., 2014). It highlights the high disparity among LIB's GHG emissions' results and the difficulty for politics and norms to rule on a default value for LIBs' production. The median value among all the 377 publications is 59.2 kg CO_2 eq./kWh, where the median for NMC observations is 72.5 kg CO_2 eq./kWh, 73.5 kg CO_2 eq./kWh for LFP, and 74.1 kg CO_2 eq./kWh for LMO cathode chemistries. This is the median value for NCA cathode chemistry which is significantly lower than the other median values at 41.7 kg CO_2 eq./kWh which lowered the global median value. However, NCA chemistry for mobile LIB's use is a specific market for automotive industry and the NCA results represent especially one industrial.

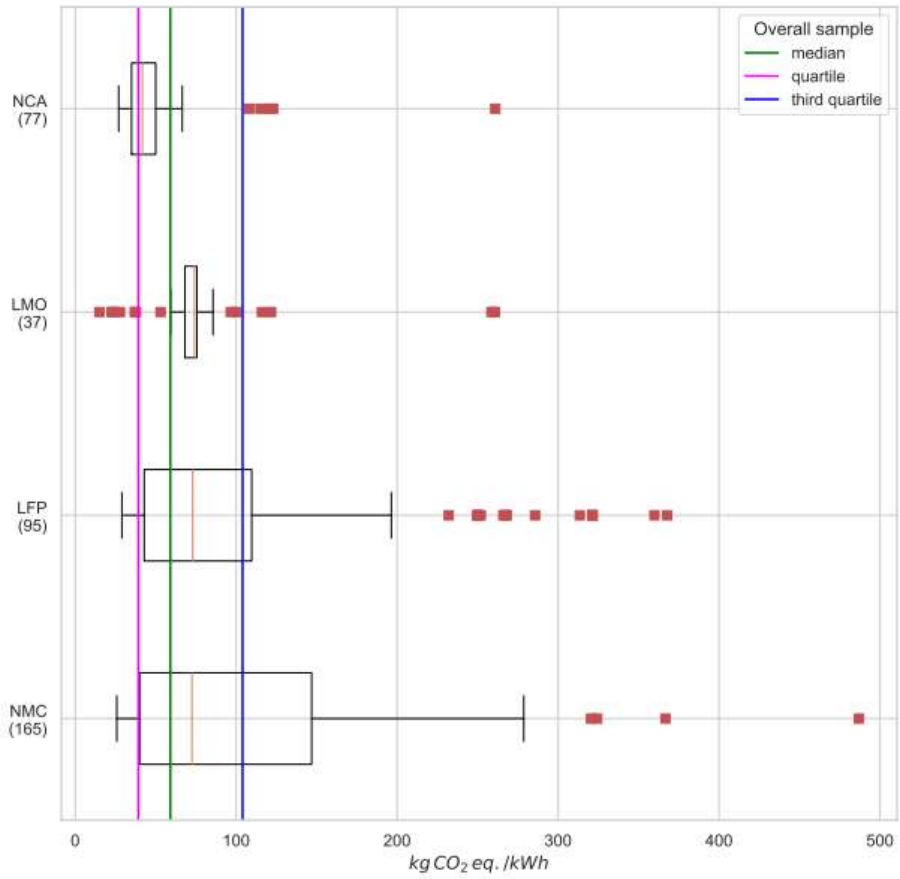


Figure 2: Dispersion of LCA GHG emission results for the different types of LIB cathodes (32 studies, 377 observations); The solid green line represents the median of the overall sample; the pink and blue lines represent the quartile and third quartile of the overall sample respectively.

3.3. Observation per cell design

Besides cathode chemistry, cell design seems to be another differentiating characteristic. The prismatic and cylindrical designs represent the inner cell structure where the pouch design combines both the

[§§] Interquartile range is the distance between the upper and lower quartiles.

prismatic inner cell structure and the shape of the LIB. Pouch design has several advantages in terms of energy and packing densities as well as of manufacturing costs (Dufner et al., 2020) and is over-represented as depicted on Figure 3. Pouch design also allows an easy access to cells during the battery's life for maintenance and reparability as well during the battery's dismantling at the end-of-life stage.

The decomposition of the distribution of the GHG emissions factor reveals some clear differences depending on the cell design. The median assessment of the GHG emissions factor within the studies with a pouch cell design (227 observations) is 52.5 kg CO_2 eq./kWh. It results in 51.7 kg CO_2 eq./kWh for cylindrical cell design (111 observations), and 114.4 kg CO_2 eq./kWh for prismatic cell design (38 observations).

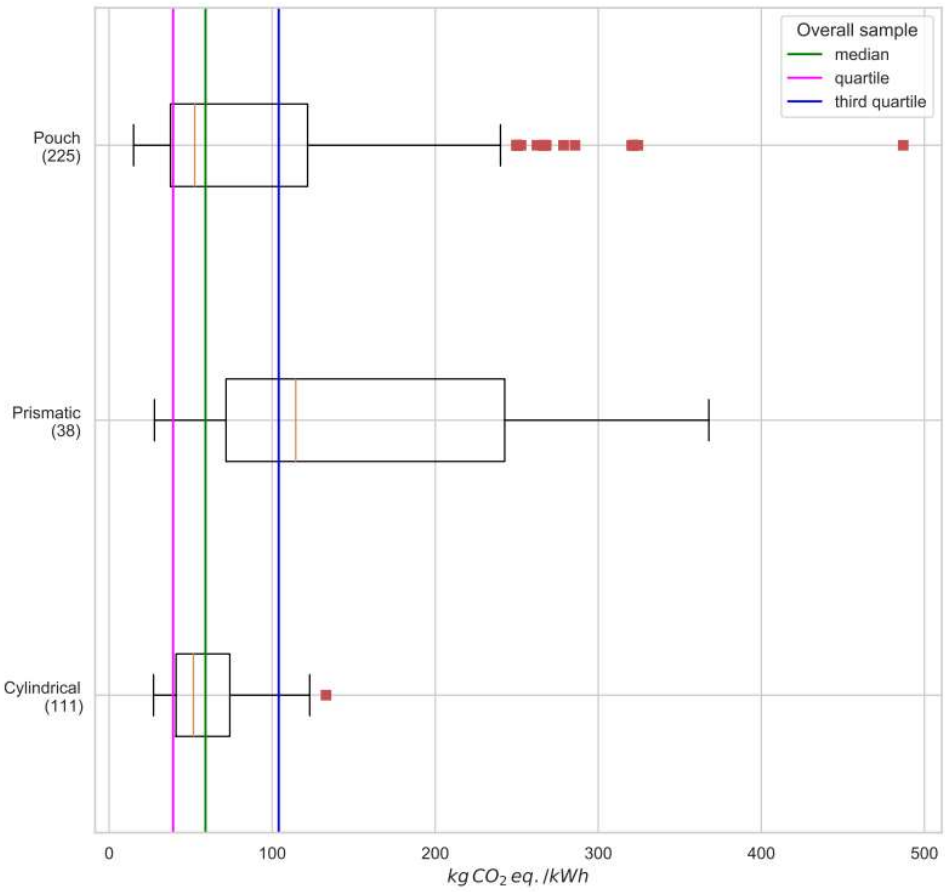


Figure 3: Dispersion of LCA GHG emission results per cell design's batteries; The solid green line represents the median of the overall sample; the pink and blue lines represent the quartile and third quartile of the overall sample respectively

The sample for prismatic cell's design contains few observations with high variability and it is noticeable that their production emits around twice more GHG than the cylindric and the pouch cell design.

3.4. Observation per battery specific energy

Figure 4 displays the ratio of GHG emissions to the battery specific energy in Wh[***] as a function of a battery specific energy (Wh per kg) for the different cathode chemistries. The distribution of the number of observations according to the cathode chemistry is given both for battery specific energy (in Wh/kg) on the horizontal axis and for GHG emissions (in kg CO_2 eq./kWh) on the vertical axis.

LFP cathode chemistry seems to be associated with a low battery specific energy (less than about 100 Wh/kg) and low GHG emissions. The NCA cathode chemistry exhibits a high specific energy with very low associated GHG emissions. As for the NMC cathode chemistry, the specific energy values are more dispersed, even if the majority of GHG emissions remains low. Finally, the LMO cathode chemistry, which is the less represented chemistry, is associated with both low specific energy and low GHG emissions.

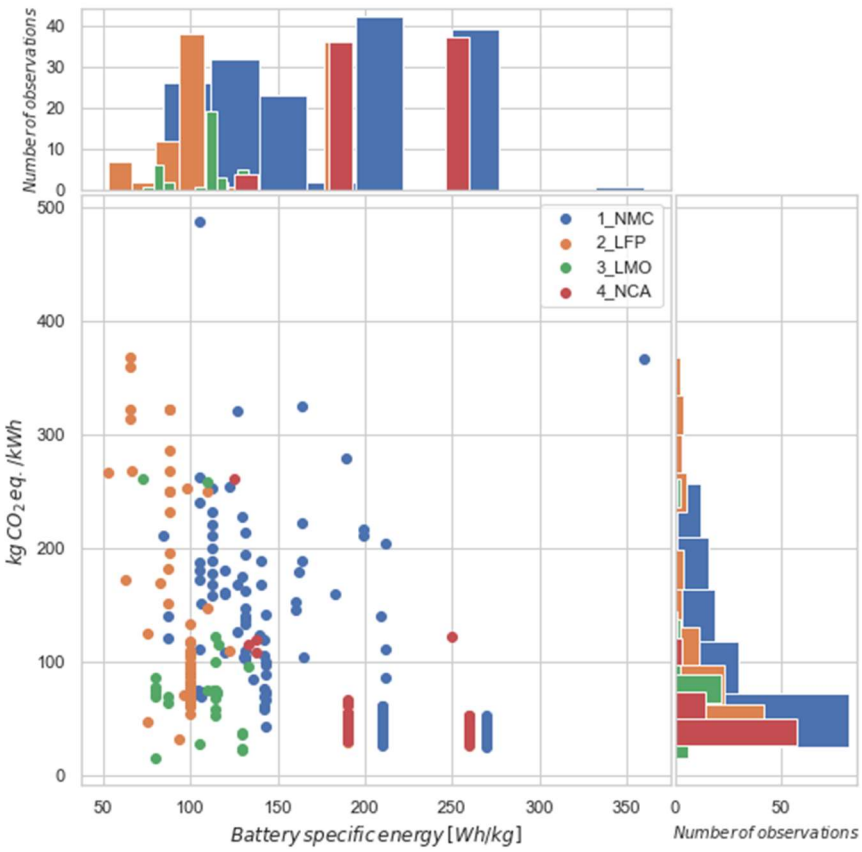


Figure 4: Dispersion of LCA GHG emissions results according to the battery specific energy, for the different cathode's chemistries. Bars (right) represent the number of observations per range of GHG emissions values, and bars (top) represent the number of observations per range of specific energy values

It is noticeable that higher specific energies (> 150 Wh/kg) are only encountered for batteries with NCA and NMC cathode chemistries.

[***] 1 Wh = 3600 Joules

3.5. Observation per energy needed for battery manufacturing

The observations according to the cathode chemistry are plotted as a function of the energy needed to produce the battery, also called manufacturing energy. The distribution of the observations is given for both GHG emissions in kg CO_2 eq./kWh on the right vertical axis, and for the manufacturing energy on the top horizontal axis expressed in kWh per kg of battery pack.

Some values for the manufacturing energy are very low: near 0 kWh/kg, and some other very high: above 100 kWh/kg. Based on Yuan et al., 2017 and our literature review experience, we decided to consider LIB manufacturing energy values accurate enough if they are ranging from 10 kWh/kg to 70 kWh/kg, as presented in Figure 5.

The manufacturing energy values for NMC cathode chemistry covers the entire range. The dispersion is less marked for LFP cathode chemistry as the maximum manufacturing energy value stands around 38 kWh/kg. Few observations are made for LMO cathode chemistry. Values range for NCA cathode chemistry are grouped between 25 kWh/kg and 45 kWh/kg, corresponding to low GHG emissions. A group of observations for LFP cathode chemistry is also noticeable a little bit above the NCA observations regarding GHG emissions.

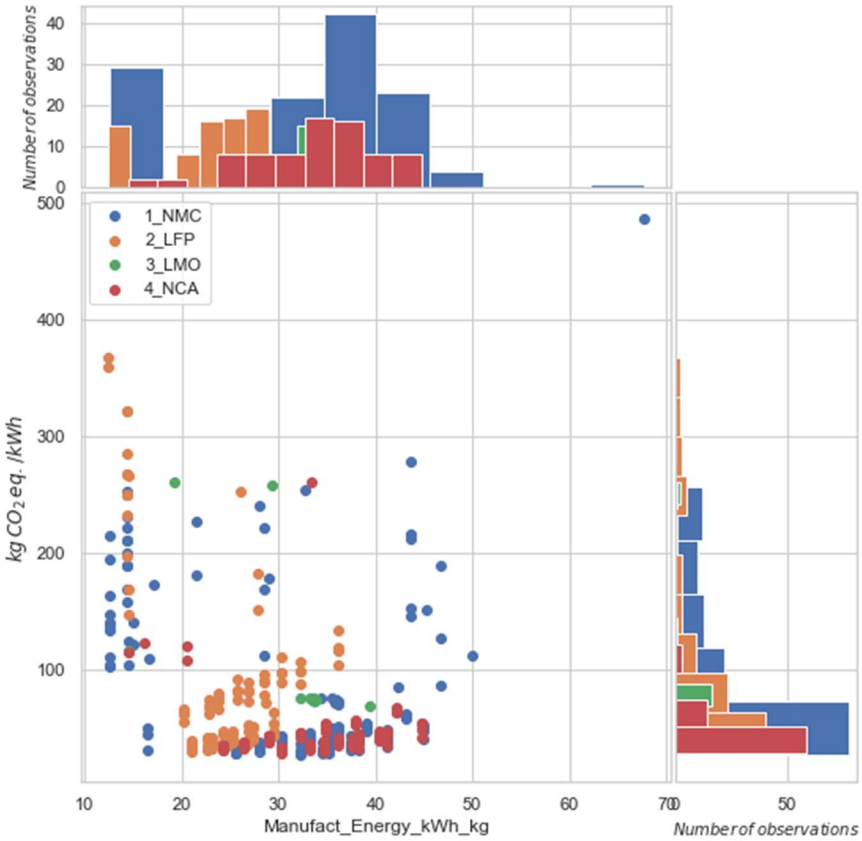


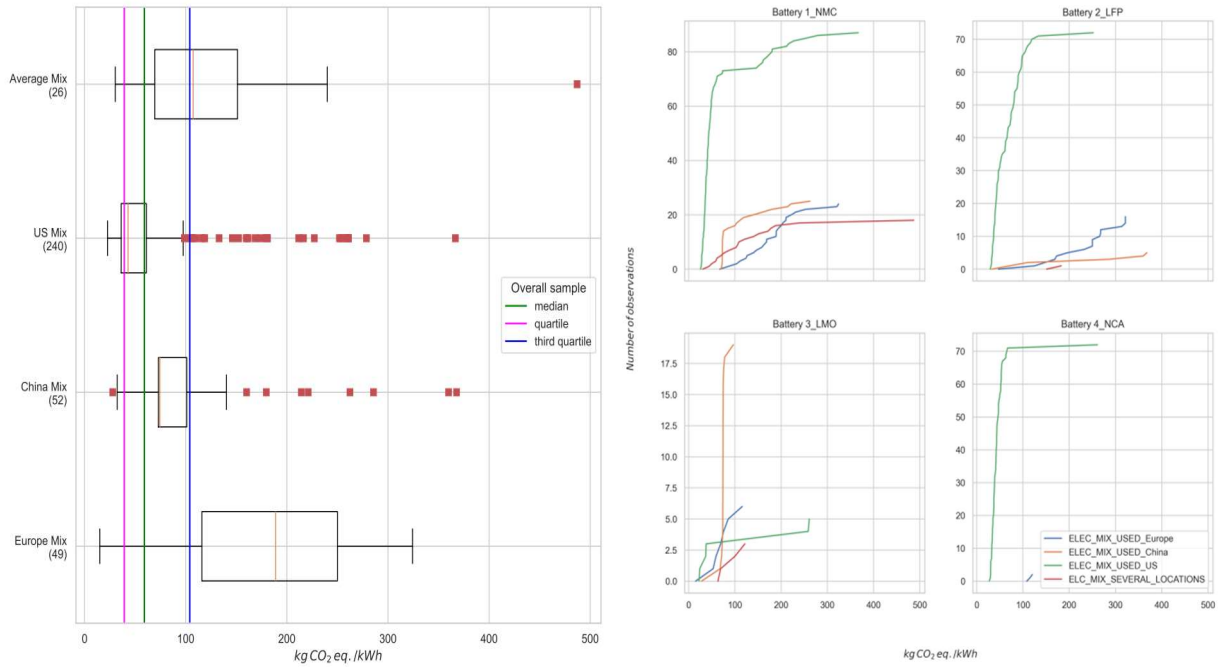
Figure 5: Dispersion of LCA GHG emissions results according to the selected accurate range of manufacturing energy for EV LIBs production (10-70 kWh/kg) for the different cathode chemistries. Bars (right) represent the number of observations per range of GHG emissions values, and bars (top) represent the number of observations per range of specific manufacturing energy values

It appears to be a correlation between LFP and NCA cathode's chemistries, both in terms of GHG emissions and energy consumption for battery manufacturing.

3.6. Observation per electricity mix used for battery production

Figure 6(a) displays the results of GHG emissions for LIBs manufacturing according to the geographical location of the electricity mix used for battery manufacturing, and Figure 6(b) includes additional information on cathode chemistry. The decomposition of the GHG emissions factor distribution reveals some clear differences depending on the electricity mix used for battery production. The median assessment for a US electric mix (240 observations) is 43.0 kg CO_2 eq./kWh. It is 74.3 kg CO_2 eq./kWh with a Chinese electric mix (52 observations), and 170.7 kg CO_2 eq./kWh with a European electric mix (52 observations). It is highly surprising that the GHG emissions for LIBs manufactured with the European electricity mix are the highest whereas the European electricity mix is the smallest GHG emitter among the three known electricity mixes studied: Chinese electricity mix (~1'020 g CO_2 eq./kWh), US electricity mix (~563 g CO_2 eq./kWh), and European electricity mix (~420 g CO_2 eq./kWh). Electricity mixes' GHG emissions are calculated from the Ecoinvent v3.3 database (Frischknecht et al., 2005) and the IPCC 2013 methodology (IPCC 2013). One possible explanation could be the difference in the number of observations for the three electricity mixes as the US one accounts for almost five times the number of the European observations.

These counter intuitive results seem to be decorrelated from the geographical affiliation of the authors (see Figure 1(a)) as the results for this variable were similar from a European author to a Chinese one. The only common trend is the low results for both the US electricity mix variable (Figure 6(a)) and the US author affiliation (Figure 1(a)).



(a) **(b)**

Figure 6: **(a)** Dispersion of LCA GHG emissions results according to the geographical origin of the electricity mix used for battery manufacturing. The solid green line represents the median of the overall sample; the pink and blue lines represent the quartile and third quartile of the overall sample respectively; **(b)** breakdown by cathode's chemistry

The results for the NCA cathode chemistry are in line with the results of Figure 2 showing that NCA LIB are produced mainly in the US in our sample. It appears that NMC batteries are rather produced in the US as well, even if Europe and China are also represented. LMO LIB are mainly depicted as produced in China and that those produced in China emit a very consensual amount of GHGs around 72.8 kg CO_2 eq./kWh on average. The same trend can be observed for NCA LIB produced in the US with average emissions around 48.7 kg CO_2 eq./kWh. On a general way, NMC LIB and LFP LIB produced in the US are also associated to a very consensual value for GHG emissions as the shape of the curve is very steep. It seems that less consensual values are linked with a European production as the associated curves (Figure 6(b)) are flatter than those for the other production countries.

3.7. Observation per methodological choices: cradle-to-gate and cradle-to grave

The last characteristics to be studied represent the system boundaries of the studies and is depicted in Figure 7. The observations are well divided into both perimeters. They highlight the fact that the inclusion of the end-of-life stage into the system boundaries seems to decrease the median value of the observations (43.5 kg CO_2 eq./kWh), in comparison to a cradle-to-gate perimeter (74.2 kg CO_2 eq./kWh). Results for cradle-to-grave perimeter present much less variability than the cradle-to-gate perimeter due to the high number of observations for cradle-to-grave perimeter (162 observations) from Ciez and Whitacre, 2019.

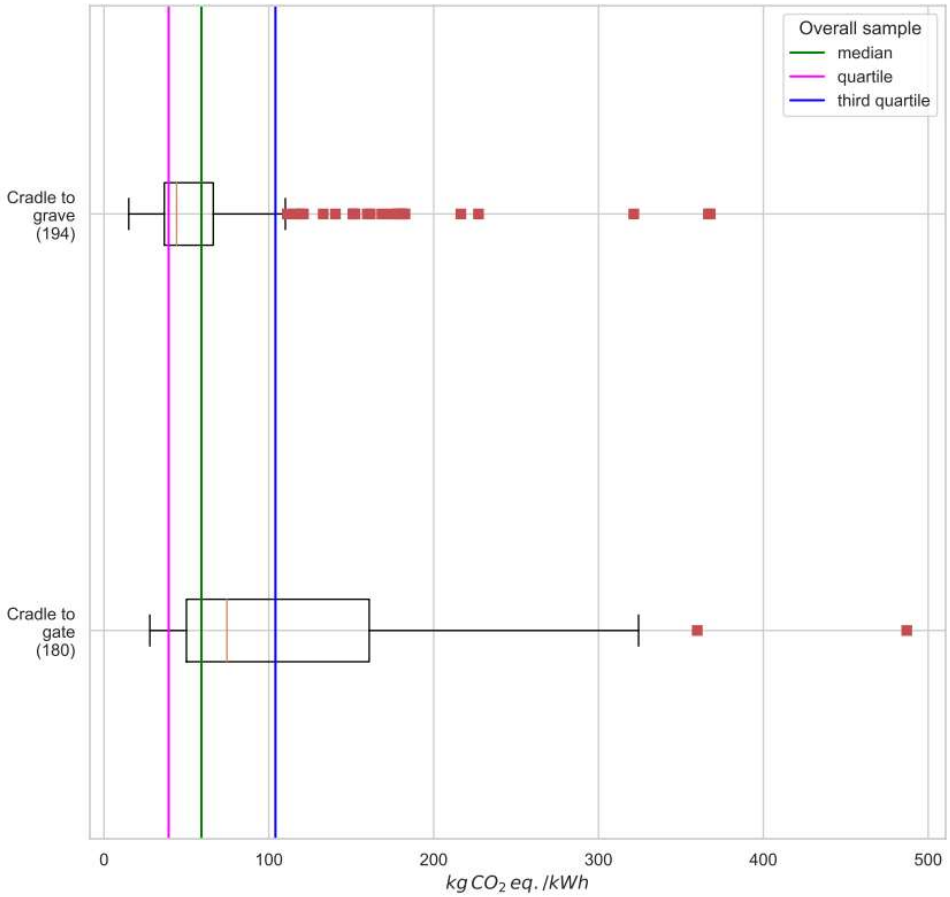


Figure 7: System boundaries represented by the two variables "*cradle-to-gate*" and "*cradle-to-grave*"; The solid green line represents the median of the overall sample; the pink and blue lines represent the quartile and third quartile of the overall sample respectively

4. Statistical analysis

The variability of the GWP indicator has been highlighted in the section 3. This partly reflects the diversity of approaches, definitions, and assumptions that have been adopted in the literature. The objective of this paragraph is: (i) to distinguish the effect of differences in hypotheses and approach from the effect of uncertainty; (ii) to quantify the effect of the adoption of different assumptions on the GWP indicator; (iii) to use all the collected information to predict the GWP indicator associated with a given set of assumptions and study's characteristics.

To clarify the comparison between the available assessments, we statistically estimate a model where the GWP indicator depends simultaneously on several explanatory variables reflecting the characteristics and hypotheses of the study. This model is referred to as a "meta-model" in which the variable of interest is not derived from observations but is itself the result of simulations of different models. Estimation of the meta-model thus allows us to quantify and isolate the effect of each variable on the GWP factor. We can then interpret the influence of each of the selected variables *ceteris paribus*. In addition, the statistical relationship obtained allows us to predict the GWP factor associated with a given combination of variables. This paragraph briefly describes the estimated meta-model, the estimation strategy used, the explanatory variables selected, and the treatments performed on the sample.

A classic problem faced in a MA is the multi-collinearity between the explanatory variables. In case of strict collinearity, the model is not selected. The quasi-collinearity between different linear combinations of variables does not prevent the estimation but affects the robustness of the estimated coefficients. The risk of collinearity increases with the number of explanatory variables.

Most of our selected variables are dichotomous variables, except the "*Battery specific energy*" and "*Manufacturing energy*" which are ordinal quantitative variables. For dichotomous variables, if their number is less than or equal to 3, we can obviously delete a variable to avoid direct collinearities. It results into 14 remaining variables to be simultaneously tested, representing 9 couples: possible combinations of 2 among 3, for two families.

We performed a step-by-step top-down approach consisting in considering a model with the 15 explanatory variables, and to proceed by successive elimination of variables. A Student's test is performed for each explanatory variable and the least significant one is discarded until all the variables are significant. Then a final step consists in checking the model assumptions by analyzing the residuals, which must display a normal distribution for the errors.

The regression analysis and the test for error normality are performed with the Python StatsModels package (Seabold and Perktold, 2010). The results are presented in Table 5. "***", "**", and "*" respectively indicate 1%, 5%, and 10% significance levels. For every final model, the Variance Inflating factor (VIF) is used to test the presence of multi-collinearity in our regression models (Table 5).

The 9 initial models with 14 explanatory variables lead to 8 models with 6 explanatory variables and one model with 9 explanatory variables. The statistical performance of the 8 models with 6 variables is very comparable but models #1 and #3 can be distinguished because they have the lowest collinearities. The 9-variables model has high collinearity. The coefficients resulting from the ordinary least squares (OLS) regression with the 6 explanatory variables for model #1 and #3 are listed with their standard error and p-value in Table 6. Only the pair of cell design variables differ for models #1 and #3.

Table 5: Presentation of the 9 initial models obtained by the top-down method

		Model #1				Model #2				Model #3				Model #4				Model #5				Model #6				Model #7				Model #8				Model #9			
		Initial Variables	Final Variables	p-student	VIF	Initial Variables	Final Variables	p-student	VIF	Initial Variables	Final Variables	p-student	VIF	Initial Variables	Final Variables	p-student	VIF	Initial Variables	Final Variables	p-student	VIF	Initial Variables	Final Variables	p-student	VIF	Initial Variables	Final Variables	p-student	VIF	Initial Variables	Final Variables	p-student	VIF	Initial Variables	Final Variables	p-student	VIF
Geographical location of corresponding author	American author													y	y	***	2,3	y	y	***	2,4	y	y	***	2,3	y	y	***	2,3	y	y	***	2,3	y	y	***	2,4
	Europe author	y	y	***	2,2	y	y	***	2,3	y	y	***	2,3													y				y				y			
	China author	y	y	***	1,1	y	y	***	1,1	y	y	***	1,1	y				y				y															
Cell Design	Prismatic cell design	y	y	**	1,5					y				y				y	y	**	1,6									y				y	y	**	1,6
	Pouch cell design	y	y	***	1,4	y												y	y	***	1,6	y				y								y	y	***	1,6
	Cylindrical cell design					y	y	***	1,4	y	y	***	1,4	y	y	***	1,4					y	y	***	1,4	y	y	***	1,4	y	y	***	1,4				
Cathode Chemistry	NMC	y				y	y	***	4,8	y	y	***	4,8	y	y	***	4,5	y	y	***	4,8	y	y	***	4,5	y	y	***	4,5	y	y	***	4,5	y	y	***	4,8
	NCA	y				y	y	***	4,5	y	y	***	4,5	y	y	***	4,1	y	y	***	4,4	y	y	***	4,1	y	y	***	4,1	y	y	***	4,1	y	y	***	4,4
	LFP	y				y	y	***	3,2	y	y	***	3,2	y	y	***	3	y	y	***	3,2	y	y	***	3	y	y	***	3	y	y	***	3	y	y	***	3,2
	LMO	y	y	***	1,3	y				y				y				y				y				y				y				y			
Quality of electricity mix used	US Elec. Mix	y				y				y				y				y				y				y				y				y			
	Europe Elec. Mix	y				y				y				y				y				y				y				y				y			
	China Elec. Mix	y				y				y				y				y				y				y				y				y			
Battery specific energy		y	y	***	2,9	y	y	***	3,2	y	y	***	3,2	y	y	***	2,9	y	y	***	3,1	y	y	***	2,9	y	y	***	2,9	y	y	***	2,9	y	y	***	3,1
Quantity of manufacturing energy		y	y	***	1,9	y	y	***	1,8	y	y	***	1,8	y	y	***	1,6	y	y	***	1,6	y	y	***	1,6	y	y	***	1,6	y	y	***	1,6	y	y	***	1,6
Cradle to Grave		y				y				y				y				y				y				y				y				y			
	Total Initial Variables	14				14				14				14				14				14				14				14				14			
	Total Final Variables		7				8				8				7				8				7				7				7				8		
	Adj. R-squared		0,815				0,76				0,76				0,746				0,782				0,746				0,746				0,746				0,782		
	AIC		2975				3193				3193				3316				3213				3316				3316				3316				3213		
	BIC		3005				3228				3228				3347				3248				3347				3347				3347				3248		
	Number of observations		323				337				337				349				343				349				349				349				343		

Table 6: Coefficients resulting from the OLS regression for model #1 and #3

Model	Variable	coef	stderr	t	P>|t|	[0.025	0.975]
#1	Intercept	82.56	11.24	7.35	0.000	60.44	104.67
	Europe author	115.58	8.36	13.83	0.000	99.13	132.02
	China author	61.06	11.34	5.39	0.000	38.75	83.37
	Prismatic cell design	51.38	10.75	4.78	0.000	30.22	72.53
	Pouch cell design	5.54	5.08	3.06	0.002	5.55	25.54
	Battery specific energy (Wh/kg)	-0.55	0.04	-13.51	0.000	-0.63	-0.47
	Manuf. Energy (kWh/kg)	2.15	0.34	6.38	0.000	1.49	2.81
#3	Intercept	98.10	12.16	8.07	0.000	74.18	122.02
	Europe author	115.58	8.36	13.83	0.000	99.13	132.02
	China author	61.06	11.34	5.39	0.000	38.75	83.37
	Cylindrical cell design	-15.54	5.08	-3.06	0.002	-25.54	-5.55
	Prismatic cell design	35.84	10.15	3.53	0.000	15.86	55.81
	Battery specific energy (Wh/kg)	-0.55	0.04	-13.51	0.000	-0.63	-0.47
	Manuf. Energy (kWh/kg)	2.15	0.34	6.38	0.000	1.49	2.81

The value of the intercept at the origin for model #1 (82.55±11.24) is closer to the value of the sample median (83.18±71.18) than the value obtained with model #3 (98.09±12.15) and its uncertainty is somewhat lower. Therefore, we consider model #1 as the best model we have obtained.

The regression obtained with model #1 for 6 variables is represented in Figure 8.

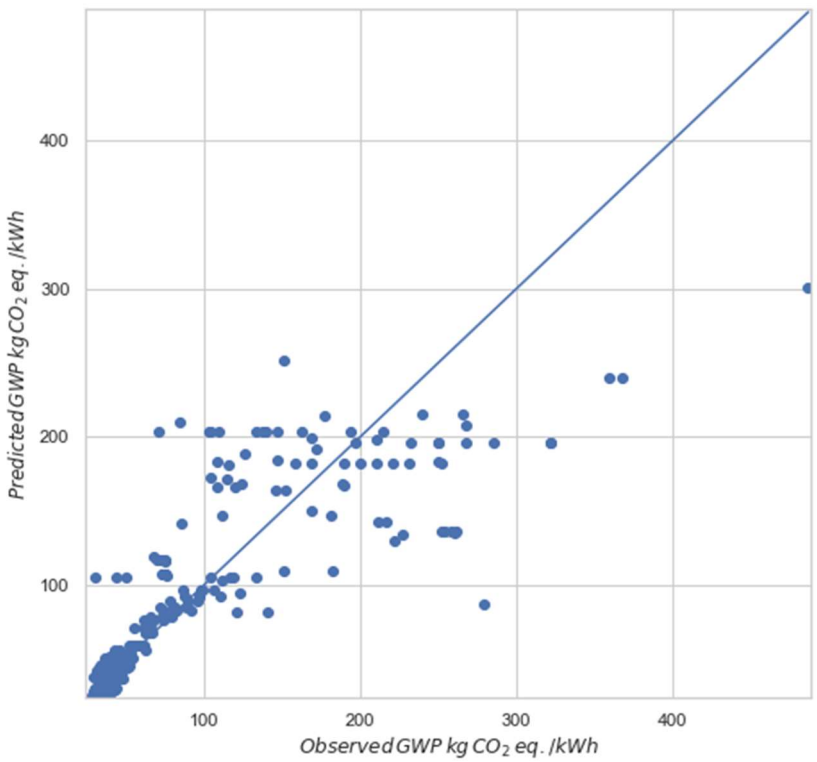


Figure 8: Predicted and collected values for the GHG emissions of LIB production (in kg CO_2 eq./kWh) for model #1

5. Discussion

According to Table 6, the 6 final explanatory variables have a comparable weight on the regression (in absolute value) except for "*Pouch cell design*" whose influence is an order of magnitude less. The "*Battery specific capacity*" varies from 50 to 300 Wh/kg (section 3.4) and its average influence is - 97 kg CO_2 eq./kWh. The same calculation for "*Manufacturing Energy*" leads to the value of + 86 kg CO_2 eq./kWh. Interestingly, cathode chemistry and the definition of the electricity mix used for GWP estimation do not emerge from our analysis whereas the results for the electricity mix used were highly surprising and counter-intuitive, this is not a significant variable for the statistical model. This is not because these variables are not relevant for conducting an LCA of a battery but because in the sample studied these variables are strongly correlated to another one: the geographical location of the corresponding author of the publication here.

Another trend from our statistical results shows up from the characteristic "system boundaries" which were systematically excluded from the results of the models (cf. Table 5). This is surprising as the end-of-life stage for batteries is very highlighted as it plays an important role for resources depletion indicator and circular economy. However, the high number of observations for cradle-to-grave perimeter (162 observations) from Ciez and Whitacre, 2019, will lead to collinearity between perimeter and authors.

Today, EVs are seen as the best alternative for reducing polluting emissions in cities. While the local benefit on emissions is undeniable, particular attention must be paid to the GWP of an EV compared to internal combustion engine vehicles. Studies have shown that the manufacturing stage of the battery explains a large part of the GWP of an electric vehicle (Bouter et al., 2020; Ternel et al., 2021) and that other environmental indicators could be at stake for batteries' production: energetic indicator, resources depletion indicator, toxicity indicators, etc. (Bouter et al., 2021). As mentioned in section 1, the purchase of EV is subsidized in many countries. At the end of 2020, the European Commission stated: "From 1 July 2024, only industrial rechargeable batteries and batteries for electric vehicles for which a carbon footprint declaration has been made may be placed on the market". It is highly interesting how European Commission points out the sole climate change indicator through the carbon footprint and not the entire picture of the other environmental indicators whereas it is known that especially for batteries' sector, the consumption of resources is at stake as well as the exploitation's conditions which are related to through toxicity's indicators: human an eco-toxicity. This should be further addressed in another paper. A very interesting question can be raised: is it possible, based on LCA studies, to define a GWP threshold for an electric vehicle battery so that subsidies can be used to promote the development of the most virtuous batteries?

Today, the batteries' specific energy of the two most sold vehicles in France, a NMC cathode type for a B-Segment[10] vehicle and a NCA cathode type for a D-Segment[11] vehicle, is around 150±15 Wh/kg. Assuming that the pouch cell design will be the trend for future, and according to our statistical model, the GWP of the above mentioned batteries varies from 27 to 271 kg CO_2 eq./kWh (Table 7). It is difficult based on this wide range to set a threshold that must be met by future batteries.

[10] The B-Segment category is the second one for European cars and is described as small cars. In practice these cars have an approximative length of 4 meters.

[11] The D-Segment category is the fourth one for European cars and is described as large cars.

Table 7: GWP calculated with the statistical model #1 described in Table 6, for a battery specific energy of 150 Wh/kg

		GWP [kg CO_2 eq./kWh]		
		North America	China	Europe
Manufacturing Energy [kWh/kg]	10	27	87	142
	30	70	131	185
	70	155	216	271

We are convinced that LCA is the right tool to provide GWP for EVs' batteries. However, reading the academic literature highlights that there is still too much disparity in results to guide the allocation of public subsidies. Based on our results, it seems essential that more details and transparency be provided on the industrial manufacturing processes, so that LCA studies can provide tighter GWP values.

6. Conclusion

This article aims at systematically analyzing the LCA studies dealing with LIBs for automotive application and their environmental potential impact on climate change, from 2015 to 2019. Our bibliographic corpus showed a large variability in the results. This raises the question of the possibility to reach a consensus about GHG emission for LIB production. We decided to analyze this question and to use an unbiased statistical analysis according to meta-analysis' approach. The first part of the assessment brought an extensive overview and allowed us to identify the main drivers inducing GHG emissions' variations: 1) the geographical location of corresponding authors which highlighted that GHG emissions for LIBs production published by American corresponding authors exhibit lower values and are less scattered than those published by either European or Chinese authors; 2) cathode chemistry highlighted the high disparity among LIB's GHG emissions' results from this perspective; 3) cell design shows the environmental benefits of pouch and cylindrical designs as well as their market domination; 4) high battery specific energy are represented through NCA and NMC cathode chemistries; 5) energy for battery manufacturing seems to be related to cathodes' chemistries; 6) electricity mix used for battery production shows surprising results as the European one results into the highest GHG emissions; and 7) methodological choices about the perimeter highlighting that the inclusion of the end-of-life stage into the system boundaries seems to decrease the median value of the observations. The second part of the work statistically confirmed or not the first qualitative and quantitative approach. We provided a reduced parametrized model estimating the GHG emissions related to LIBs' production thanks to four different information: the geographical location of the corresponding author, the cell design, the battery specific energy, and the manufacturing energy. The positive and negative signs of the regression coefficients give an easily understandable relationship between the variables and the GHG emissions as the negative sign related to the battery specific energy highlighting that increasing energy density will decrease the related GHG emissions for example. The absence of some variables, such as the origin of the electricity mix used to produce the battery, and the chemistry of the cathode revealed some very surprising information, not commonly highlighted in the literature. It can be explained by the sample studied whose variables are strongly correlated with the geographical location of the corresponding author of the publication. This last point

could reflect differences in the application of LCA according to geographical location and should be dug into another research work.

Some limitations to the work can be highlighted such as the difficulty to get an up-to-date literature review, meaning that the in-depth analysis needed to fulfill the characteristics of the database is very time-consuming. And due to the high number of publications dealing with this subject, the achievement of a clean database before performing the statistical analysis can be delayed from the first literature review. Another limitation comes from the lack of transparency in accessibility to the primary data used in the scientific studies.

Results of meta-analysis are very encouraging as such a method allows for some harmonization among a huge amount of literature dealing with the same subject but presenting a quite large variability in the results. However, it narrows the perimeter to a very constraint one, given that the selection is based on the least common denominator. This is pointing out a drift among LCA studies which should be more transparent into the description of their assumptions and life cycle inventory data, even when it refers to industrial processes.

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