Antool

NMC vs LFP battery lifecycle GHG emissions estimation based on a battery degradation model

DOCUMENTATION

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Summary

Lithium-ion batteries are a critical component of the current energy transition towards global net zero. As such, their usage needs to be carefully considered from multiple perspectives. Otherwise, they could cause more harm than good with the scale of their uptake. Similarly, different types of lithium-ion batteries may be better suited for different kinds of applications as their performance or sustainability specifications may vary widely. This tool is set to aid in such decision making by comparing performance-sustainability trade-offs between two types of lithium-ion batteries.

A simple spreadsheet model was developed to estimate degradation of NMC and LFP batteries under specific usage conditions. The degradation model, which considers calendar and cycle aging, was based on existing published literature. This model is used in the spreadsheet to calculate lifecycle GHG emissions of a vehicle based on the battery chemistry it uses.

A case study was performed for a Chinese sedan BYD Han used as a taxi in London. Its development is described in Section 3. LFP battery was found to last over 3000 equivalent full cycles, nearly four times longer than an NMC battery. This resulted in overall lower per kilometre GHG emissions for such high intensity use case, despite higher energy consumption due to higher battery mass. BYD Han with LFP or NMC batteries would emit 61 or 96 grams CO2eq/km respectively.

The degradation model results were compared with existing literature. The preliminary findings show similar patterns, however, there is a significant variation not captured by the model. The overall R^2 was found to be 0.65 for tests within the input range of the model, while it was significantly lower for LFP only tests.

The tool can also be applied to non-automotive batteries. However, this requires detailed understanding of the model and working with inputs irrelevant to the use case. For example, even a stationery battery would need input of driven km per year in order to set the right annual usage in full equivalent cycles.

Contents

Nomenclature

Abbrv.	Meaning	Description
LIB	Lithium-Ion Battery	General name of the battery type
NMC	LIB with NiMnCoO2 cathode	Specific LIB type, most common in EVs
LFP	LIB with LiFePO4 cathode	Specific LIB type, common in e-buses
SOC	State of Charge	% of the full charge capacity at given time left in the battery
DoD	Depth of Discharge	Highest SOC – Lowest SOC during cycle
mSOC	Mean SOC	Lowest SOC + (DoD/2) during cycle
LCA	Life Cycle Assesment	
GHG	Greenhouse gas	
CO2eq	GHG equivalent to Carbon Dioxide	
AGW	Anthropogenic Global Warming	
BoL	Beginning of Life	
EoL	End of Life	
SOH	State of Health	What % of initial capacity battery still has
FEC	Full Equivalent Cycle	Equivalent throughput as 0-100% charge-discharge cycle at BoL

1 Overview

Antool (short for Antonin's tool) Excel spreadsheet tool enables its user to calculate:

- lifecycle GHG emissions in [kg CO2eq]

of an

- Electric vehicle (EV)

during its

- Manufacturing
- Use

phases, based on its:

A) specifications
- Vehicle mass
- Battery parameters
- Battery production emission intensity

B) battery chemistry type
- NMC622
- LFP

C) usage conditions
- Annual driven distance
- Typical DoD
- Typical C-rate charging
- Typical C-rate discharging
- Typical SOC mean
- Typical Temperature of operation
- Typical SOC during storage
- Typical Temperature during storage

, which are used to estimate its battery lifetime in a combined cycle & calendar capacity degradation model.

This tool is aimed to be used together with the EverBatt Excel tool by ANL [1], however, the inputs can be taken from different sources, if desired.

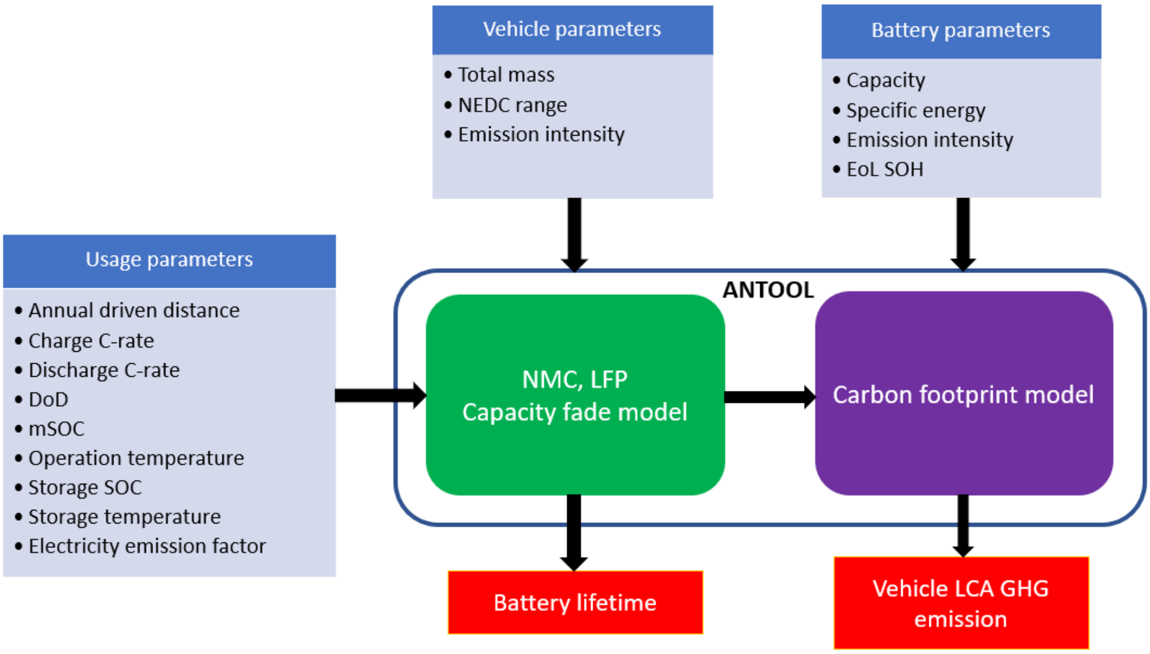


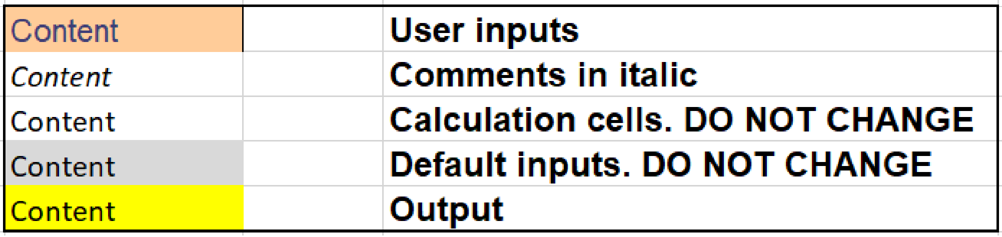
Figure 1: Diagram of the ANTOOL spreadsheet model

1.1 Versioning

V1 - simple structure, input, output
V2 - output working, main graph, improved functionality & started capacity fade model
V3 - added cycling capacity fade model based on #15 paper
V4 - added calendar capacity fade model based on #22 and #21 papers
V5 - added benchmarking of the cycle+calendar fade model against multiple existing studies, a basic statistical analysis of the results
V6 - cleaning up, taking the factor of calendar aging during cycling into account (thus, this is excluded in the few ‘combined’ test results in the ModelValidation tab)
V7 - finalised documentation
V8 - updated and shared publicly

1.2 Usage

The spreadsheet can be simply tailored to user's needs. The cells are colour-coded based on their purpose:



Content		**User inputs**
Content		**Comments in italic**
Content		**Calculation cells. DO NOT CHANGE**
Content		**Default inputs. DO NOT CHANGE**
Content		**Output**

Figure 2: Legend of spreadsheet cell styles

Explanations of the calculations in given row may be in the Comments column.

This tool is intended to be used only after review of its functionality as it may contain errors or ilogicalities. But it should not.

2 Function description

The spreadsheet is divided into sections by its sheet tabs:

2.1 Manufacturing

Parameters of the vehicle itself.
This section has following inputs:

- Pack capacity - assumed to be the same for different chemistries
- Pack specific energy for each of the chemistries
- Vehicle mass - only for one vehicle, the other has it calculated using the difference in battery mass
    - This can be changed by the user, if desired
- Battery emission intensity

And one default value, which can be edited as well:

- Vehicle production emission intensity [#11]

All other cells are calculated directly from the inputs. The key outputs are production emissions and relative vehicle masses.

2.2 Use

This tab aims to calculate the total lifecycle range of the vehicles and the emissions from their fuel with their battery lifetime taken from the Model tab.
Inputs:

- Official BoL range for the vehicle with one battery type (NEDC)
- EoL SOH of the battery (used for both chemistries)
- Annual driven distance of the vehicle

Official BoL range and pack capacity are then translated into the theoretical electricity consumption. However, NEDC consumption is often significantly lower than the real-life one. Thus, this consumption value is then adjusted to a more real-life value by using typical values from users' experiences with other EVs. Website EV Database [2] lists various EVs with their official NEDC, WLTP and estimated 'real-life' ranges. Multiple larger vehicles' data were used to calculate the average difference between these values in the Use tab from the cell T3. It was found that on average, NEDC range is 48% higher than the typical one in reality. This does not specifically account for any additional appliances, but in general, part of the difference are auxiliary devices, HVAC system or non-eco driving style.

- The average value was used to obtain a 'real-life' power consumption of the LFP vehicle
- To find the consumption of the lighter, NMC, vehicle, an additional mass factor was accounted for using data from source #17. There was stated:

Table 4. Results of percent change in energy per percent change in vehicle mass.

Percent Energy Consumption/Percent Mass Change Ratio			
Driving type	**Highway**	**Aggressive**	**City**
Fusion V6	0.21	0.38	0.34
Fusion Hybrid	0.08	0.30	0.24
Nissan Leaf	0.03	0.34	0.42

Figure 3: Variation between mass of an identical vehicle and its energy consumption [#17]

Taking average for Nissan Leaf:

(0.03+0.34+0.42)/3=0.2633

0.263% change in energy consumption / 1% change in mass

The real consumption and real-life ranges are then calculated in I9, J9 and C5, D5, respectively.

To find the relationship between the Cycle and Calendar aging, the annual driven distance is used in the Model tab. Lifecycle range can then be calculated from the number of Full Equivalent Cycles (FECs) the batteries can deliver until the required minimum SOH - this is calculated in the section 2.3.
Lifecycle range only multiplies the FEC initial capacity's range with the lifecycle number of FECs, assuming no changes to efficiency in the drivetrain or resistance increase.

Emission intensity is used to calculate emissions per km of driving. This depends on the location and time of use. No additional losses have been included. Emission intensity is assumed to be constant.
Charging efficiency is taken from an IEEE report [3] as the overall average efficiency of different Level 1 and 2 chargers, as 85.7%.
No maintenance related emissions are included in the model.

2.3 Model

Cycle and Calendar degradation model of generic NMC and LFP batteries

- Assumptions:
    - No degradation changes due to sequential order of use phases is accounted for
    - Parameters of the usage are assumed to influence the degradation separately, not in combination
    - No sudden degradation after 80% SOH assumed, although it may occur [#23]
    - Similarly, no initial increase in capacity is accounted for [#15]
    - The vehicle would be driven most of the time according to the input parameters
    - The batteries would not be cycled at very low temperatures, nor at constant very low or high mean SOC
- Inputs are divided into the Operational (Cycling) and Storage (Calendar aging):
    - C-rate charging = The typical C-rate, at which the batteries would be charged, depends on the charger power and battery capacity
    - C-rate discharging = The average power output of the vehicle during driving in corresponding C-rate
    - DoD, Depth-of-discharge = Typical for the usecase (i.e. average daily driven distance equivalent)
    - mSOC, or SOCmean = the typical SOC value around which the battery would be cycled. This cannot be outside of the 15-85% limits as beyond them, the model does not estimate the degradation well.
    - Operation Temperature = The typical temperature of the battery cells during cycling, can be significantly higher than the ambient temperature.
    - Storage Temperature = The typical temperature of the battery cells when they are not cycled. This can be close to the typical ambient temperature, but it might be raised somewhat by residual temperature from previous cycling, or by Battery thermal management system.
    - Storage SOC = The typical SOC at which it stays. Can differ from the mSOC, depending on charging patterns, for example.
- The tab is intended to estimate the number of FECs until specific SOH for the batteries.
- As it is a generic model, it does not accurately describe any specific real-life or experimental result. However, it is benchmarked against existing results in the ModelValidation tab (2.7).

Model function
The degradation is calculated separately for Cycle and Calendar aging and then summed up for each month of operation.
Cycle aging model
This was developed directly based on paper #15, which used multiple experimental results for NMC and LFP cycle degradation to produce an empirical model describing their capacity loss. This has a form of the function below [#15] with specific parameters for each of the chemistries.

$$SOH = 100 - \beta \cdot exp\left(k_T \cdot \frac{T - T_{ref}}{T} + k_{DOD} \cdot DOD + k_{Cch} \cdot C_{ch} + k_{Cdch} \cdot C_{dch} \right) \cdot \left[1 + b_{mSOC} \cdot mSOC \cdot \left(1 - \frac{mSOC}{2 \cdot mSOC_{ref}} \right) \right] \cdot FEC^{\alpha_{opt}} \quad (19)$$

Figure 4: Equation for cycle aging from #15

These parameters are listed below the input table in the sheet.
Calculations between rows 30 and 40 are included only for reference.
The degradation is modelled from the row 48 for the two chemistries separately. For NMC, the column H uses the equation shown above to calculate each month's cycle degradation. This is then used in column I to get the total degradation at the time. Cell I45 displays the month at which the NMC battery reaches its desired EoL SOH.
This model has limitations arising from the original paper. It does not account for lithium plating and some of the stress factor patterns for LFP battery seem to contradict the typical findings for LIBs.

Calendar aging model
This model is not as straightforward as the Cycle one.
In the Model tab, it follows a pattern found in a study #21, which looked at multiple calendar aging experiments of different chemistries. It found that it typically follows a power function with a month^(1/2) dependency, which is multiplied by a degradation factor. This factor is calculated in the Calendar tab and shown in the column C for the NMC battery. Calendar degradation is then calculated in the column D, however, to account for the time the vehicle does cycle, and so the calendar degradation is accounted for in the cycle one, in column E, the calendar aging is lowered by the share of this time (shown in cell B46). These long degradation tables run to ~75 years of time, and thus should always cover the EoL.

Graphs showing the two aging mechanisms are produced for both chemistries.

2.4 Calendar

The only data incoming to this tab are the SOC and temperature during storage, inputs in the Model tab. The only output is the degradation factor, which is then used as described in section above.

This tab is based on experimental results obtained in the paper #22. The same procedure was followed for both chemistries. Data points' values from Figure 2 of the paper were estimated and inputted to columns B to E for NMC. Example of the graph [#22] is shown below.

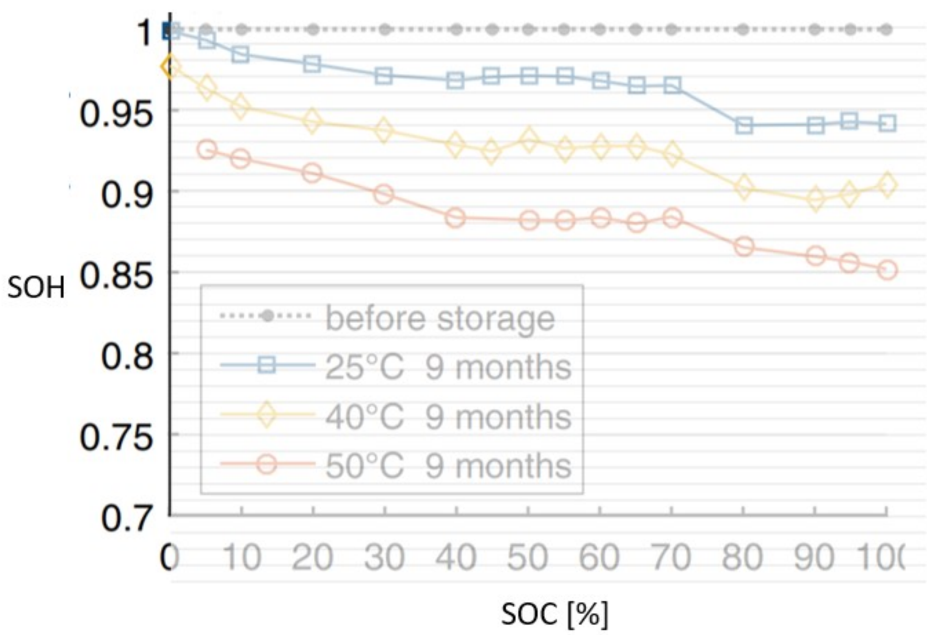


Figure 5: Calendar degradation test results for LFP cells, modified [#22]

Relationship between the degradation and storage temperature at given SOC was then estimated to be following an exponential curve. These were fitted to the experimental results for each of the SOC that was tested, as shown on the following figure.

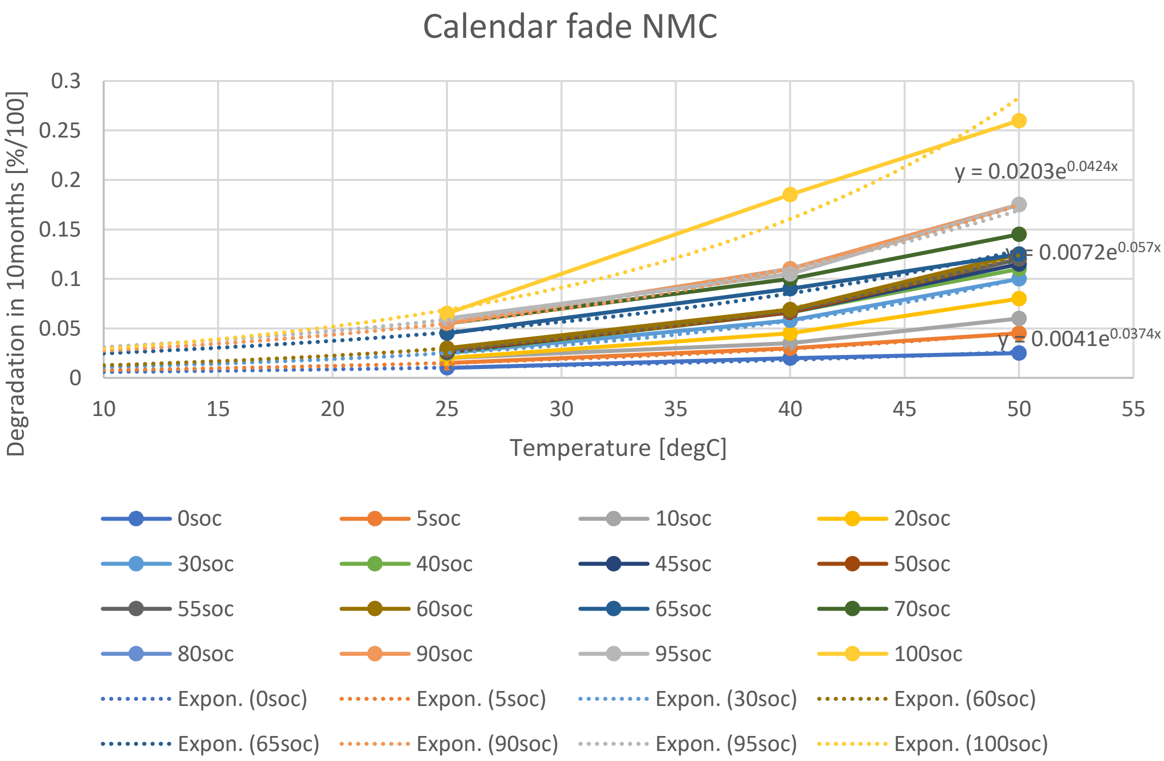


Figure 6: Graph of NMC calendar degradation for 3 different storage temperatures and different constant SOC. Includes best fit exponential lines.

For this reason, the Model tab input for Storage SOC can only be from the list of these SOC levels. The Storage temperature is then used to find the expected degradation in 10 months using these functions. By adopting the power function with the exponent of 0.5, the degradation factor for the input SOC and temperature is then calculated, shown in column M.

This process has a major limitation in the vulnerability to the experimental errors arising from the direct relationship with results of a single experiment.

2.5 EoL

Modelling of the impacts of the batteries' End of life phase was outside of the scope of this project due to the complexity of recycling environmental impacts. Possible extensions to this model could include:

- Second life uses, such as grid storage
- Valuation of the residual capacity of the battery after the engineering lifetime of the vehicle is over
- Different recycling techniques

2.6 Output

This tab shows only the results of the calculations from previous sections. Cumulative lifecycle emissions are presented here. Then they are recalculated per driven kilometre, which results in the main output, kg CO2e/km of lifecycle GHG emissions. No battery or glider replacement is assumed.
Graphs are produced to help visualise the results.

2.7 ModelValidation

This tab is used to benchmark the capacity fade model developed against existing literature. Thus, various studies are presented here with their name, author and year published. Then for individual tests, their inputs, type of experiment, source from within the paper and results obtained are shown in each column. The same parameters were inputted into the developed model and the outputs are compared in rows 19 and 20.

Main considerations:

- For some experiments, not all inputs were given and thus they were estimated. In such cases, it is mentioned in the comments below the results.
- Care must be taken when using this table as errors in understanding or reading the referenced studies could have happened. User is referred to the studies for review of the parameters and output values.
- This tab is largely static and does not reflect any changes made to the model beyond Version V5.

Row 21 then shows the relative difference between the results of the referenced study and the one outputted by the Antool model. If a range of values was obtained for either of them, the value closer to the other one was selected for this calculation and thus, the calculation of the differences in this tab is somewhat optimistic.

Statistical analysis

The 66 individual tests were then subject to a simple statistical analysis. 3 outliers were identified, all resulted in over 10% [SOH] difference between the model and the study values, however, each of them also used input values outside of the input range of the model (low operational temperature and low and high mSOC). Thus, these were excluded from the key statistical calculations.

Results and plots can be seen on the sheet below the row 27. Graph of the variation between the model and study SOH value for each of the test, including the outliers, is shown on Figure 7.

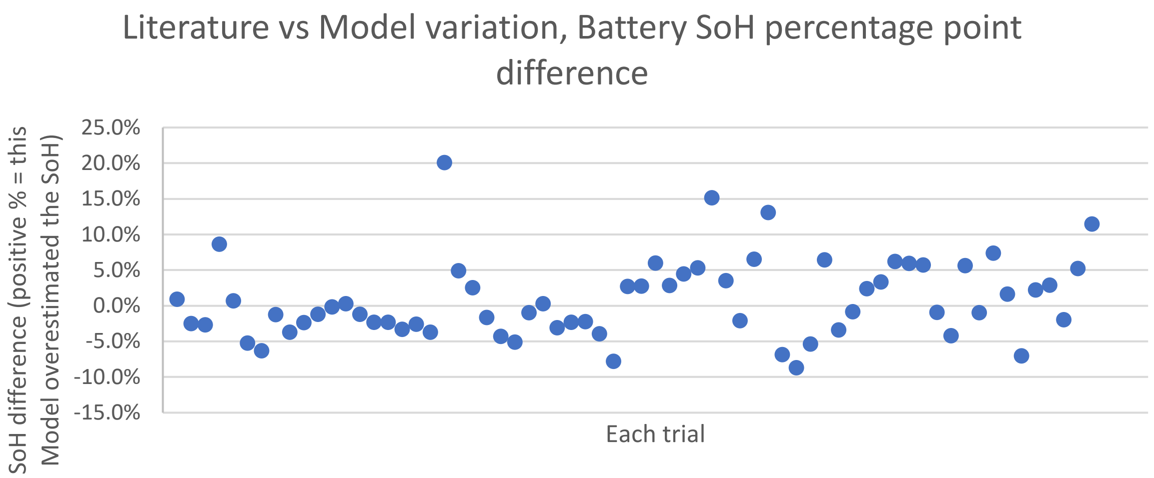


Figure 7: Variation between the model result and the study's value. In case of a range of values, the most optimistic was used. Output values range between 75 and 100% SOH, includes outliers

The overall statistics, excluding outliers, is shown below.

Table 1: Overall statistics of the model validation trials, excludes 3 outliers, whose inputs are outside of the model input range. Can be found on ModelValidation tab below the tests' parameters

Stats table (no outliers):		Variation between study & model			
Chemistry	Test type	Avg. [SOH%]	StDev [SOH%]	R^2	#datapoints
LFP	Calendar (&combined)	-2.58%	2.02%	0.4678	20
LFP	Cycle (&combined)	0.51%	3.46%	0.0032	9
NMC	Calendar (&combined)	1.13%	4.19%	0.6774	28
NMC	Cycle (&combined)	1.89%	3.79%	0.6273	20
NMC&LFP	All	-0.11%	3.91%	0.6468	66
		Average >0% means the model overestimates the SOH			

General findings:

- Studies and the model follow similar trends
- Some variation is very significant and not captured by the model
- Overall, the model predicts the test value better for the NMC chemistry (R^2 values over 0.6)
- On the other hand, LFP Calendar test yielded a near 0 R^2
- On average, the model slightly underestimates the degradation of NMC cells, while it overestimates it in case of LFP cells during calendar test. For LFP cycle tests, no significant trend is seen.
- Not a high number of studies were investigated and thus, variation in methodology of even only one of them can result in significantly increased difference between the model and the studies' results statistics
- Varies in some cases significantly
- The model was found to yield excessive variability for mSOC lower than 15% or higher than 85%, as well as for cycling at temperatures under 20 degrees C and thus, the inputs in Model tab are restricted by these limits

3 Case studies

Case studies were produced to assess the two LIB chemistries in different applications, using this tool together with other resources. They are described below, including changes to the appropriate tools.

3.1 Case study 1: BYD Han 2020

Vehicle: BYD Han 2020 77kWh AWD sedan
Usecase: Taxi in London

Figure 8: Luxury sedan BYD Han 2020 [4]

Battery: LFP (Blade) with 76.8kWh = original

- NMC622 76.8kWh = alternative (equivalent to the battery used in BYD Tang 2019, only scaled down slightly)
- *This is the only difference between the two scenarios and so the batteries are compared in this use case.*

Production: China (influences production emissions)

Blade battery

BYD designed a new cell-to-pack design of LFP batteries, increasing their overall specific energy significantly. NMC chemistry most probably cannot use a similar pack design at this moment. To read more, see [5] *and* [6].

3.1.1 EverBatt

EverBatt 2020 is used to generate emission intensity of the two battery chemistries using their specifications obtained from A2Mac1 database. The battery's masses and specific energy were edited to represent the vehicle's battery better.
The two modified versions of this tool, [F1] [F2], can be provided on request.

- **Blade battery LFP**
  - Edits made to the EverBatt spreadsheet:
    - **Input tab**
      - Selection of LFP production in China, 10000t/y, no recycling
    - **Man Par tab**
      - Cell manufacturing (B5 cell)
        - 1.2 Change mass/cell (to specific energy from A2Mac1 167.7 Wh/kg [4])
          - mass=1.001kg
      - Pack (AB5 cell)
        - 1.2 Pack to have number of cells to equal capacity (457) & number of modules representative (1 as no modules used)
        - 1.3 Module heavier (each part by 4x (from LFP) to account for the same components)
        - 1.4 Pack heavier (each part by 2.53x to be the same mass as in A2mac1)

1.3 Module components mass (g/module)		Default								
	Selected	NMC(111)	NMC(532)	NMC(622)	NMC(811)	LCO	NCA	LMO	LFP	User-defined
Module state-of-charge regulator assembly	448	112	112	112	112	112	112	112	112	448
Module terminals	254	54	53	54	53	51	54	51	63	254
Aluminum heat conductors or thermal enclosures	1697	335	321	309	312	341	303	341	424	1697
Polymer spacers	53	13	13	13	13	13	13	13	13	53
Module enclosure	1360	295	285	280	281	298	276	298	340	1360

1.4 Pack components mass (kg/pack)		Default								
	Selected	NMC(111)	NMC(532)	NMC(622)	NMC(811)	LCO	NCA	LMO	LFP	User-defined
Module inter-connect (g/piece)	193	65	64	64	64	61	65	61	76	192.76
Module compression plates and steel straps	2.85	0.86	0.83	0.80	0.80	0.89	0.78	0.89	1.13	2.85
Battery pack terminals	0.37	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.15	0.37
Battery pack heaters	0.51	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.51
Battery jacket	60.51	21.19	20.60	20.30	20.34	21.48	20.12	21.48	23.92	60.51
Battery coolant	23.89	6.80	6.48	6.53	6.37	7.55	6.54	7.55	9.44	23.89
BMS and disconnects	8.56	3.38	3.38	3.38	3.38	3.38	3.38	3.38	3.38	8.56

Figure 9: Values used for module and pack masses of components in Man par tab Everbatt LFP

- Now the pack and cells have the same specific energy as in A2Mac1
- The pack has ~the same kWh capacity

The masses were increased for each component to equal the total mass of the real one, however, this might not be an accurate representation of the masses and materials of components within the pack and cells!

- **Output tab**:
  - AJ7 Changed the specific energy of LFP blade battery (as from Man Par Cell 1.2)
- **Result:**
  - Emission intensity 6% lower in CO2/kWh than LFP with default values = 55.2 kg CO2eq / kWh

- **NMC622 battery**
  - Edits:
    - **Input tab**
      - Selection of NMC622 production in China, 10000t/y, no recycling
    - **Man Par tab**
      - Cell
        - 1.2 Change mass/cell (to specific energy from A2Mac1 215 Wh/kg [7])
          - mass=0.782kg
      - Pack
        - 1.2 Pack to have number of cells (36) to equal the capacity & number of modules representative (14) as in A2Mac1
        - 1.3 Module heavier (each part by 6.5x (from NMC622) to be the same mass as in A2mac1)
        - 1.4 Pack heavier (each part by 1.6x to be the same mass as in A2mac1)

1.3 Module components mass (g/module)		Default								
	Selected	NMC(111)	NMC(532)	NMC(622)	NMC(811)	LCO	NCA	LMO	LFP	User-defined
Module state-of-charge regulator assembly	728	112	112	112	112	112	112	112	112	728
Module terminals	347	54	53	54	53	51	54	51	63	347
Aluminum heat conductors or thermal enclosures	2028	335	321	309	312	341	303	341	424	2028
Polymer spacers	86	13	13	13	13	13	13	13	13	86
Module enclosure	1825	295	285	280	281	298	276	298	340	1825

1.4 Pack components mass (kg/pack)		Default								
	Selected	NMC(111)	NMC(532)	NMC(622)	NMC(811)	LCO	NCA	LMO	LFP	User-defined
Module inter-connect (g/piece)	103	65	64	64	64	61	65	61	76	103.01
Module compression plates and steel straps	1.27	0.86	0.83	0.80	0.80	0.89	0.78	0.89	1.13	1.27
Battery pack terminals	0.20	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.15	0.20
Battery pack heaters	0.32	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.32
Battery jacket	32.48	21.19	20.60	20.30	20.34	21.48	20.12	21.48	23.92	32.48
Battery coolant	10.45	6.80	6.48	6.53	6.37	7.55	6.54	7.55	9.44	10.45
BMS and disconnects	5.41	3.38	3.38	3.38	3.38	3.38	3.38	3.38	3.38	5.41

Figure 10: Values used for module and pack masses of components in Man par tab Everbatt NMC

- Now the pack, cells and modules have the same specific energy as in A2Mac1

- The pack has ~the same kWh capacity

The masses were increased for each component to equal the total mass of the real one, however, this might not be an accurate representation of the masses and materials of components within the pack, modules and cells!

- **Output tab:**
  - AF7 Changed the specific energy of NMC622 (as from Cell 1.2)
- **Result:**
  - Emission intensity 6% increase CO_2/kWh = 80.3 kg CO_2eq/kWh

3.1.2 WLTP tool

This Matlab tool, [F3][F4], was produced by James Eaton to model vehicle power consumption during WLTP driving cycle and was edited to represent BYD Han accordingly:

- Lines 26 – 30:
  - m = 2159; % BYD Han LFP battery car mass + 100kg for driver
  - A = 2.22; % Frontal area of BYD Han, estimate (same as Tesla Model 3, source of error)
  - cd = 0.22; % coefficient of drag of BYD Han [8]
- Renaming the key output, the average non-zero non-negative power output during WLTP cycle to "avg_nonzero_kw"
- **Output:**
  - avg_nonzero_kw = 12.6 kW

3.1.3 Antonin's tool

This tool was used to estimate the lifecycle GHG emissions. Input, orange, fields were edited as well as some of the grey ones, as described:

Manufacturing tab

- Inputs for pack and vehicle data are from A2Mac1 analysis and vehicle specification [4]
  - Total mass for the original vehicle with LFP battery (2059kg)
  - Calculated actual specific energy of the 2 battery packs as total mass / total rated capacity for each of the chemistries [4] [7]
- Emission intensity of battery manufacture is from the EverBatt tool described above in 3.1.1

Use tab

- BoL NEDC official range for this AWD model, 550km [9]
- EoL capacity set at 80% SOH
- Average current electricity emission intensity in the UK used (not a marginal one, not changing with time) [10]
- Annual driven distance is set to be 48 280 km, as the typical annual driven distance of London taxis is 30 000 miles [11]

Model tab

- **C rate charge:**
  - It was assumed to be charged half the time by a DCFC charger, the other half of the time with Level 2 charger
    - DCFC: Han is claimed to be able to charge 30 – 80% in 25min [9], thus 1.2C
    - Level 2 charger is typically around 7 kW, thus approximately 0.1C
  - Averaging them yields **0.65 C-rate**

- **C rate discharge:**
  - Taking the average power output from Section 3.1.2 for WLTP cycle
  - Multiplying by the same factor as by which the real-life consumption was found to typically be higher than the WLTP in Section 2.2.
  - 12.6*1.229=15.485 kW
  - Thus, **0.2 C-rate** was used as 15.485/76.8=0.202
- **DoD**
  - Average daily distance, assuming 256 working days in a year, is 189 km.
  - Average range of Han during its lifetime is 336.5 km
  - Thus, **56% DoD** is used
- **mSOC**
  - This is assumed to be near the highest possible to always enable high range:
  - **65%**
- **Operational Temperature**
  - Was estimated to be typically **45 degrees C** for this high intensity use
- **Storage Temperature**
  - Although average ambient London annual temperature is approximately 11.5 degrees C [12], this was increased slightly to account for the battery being often still heated up after its operation.
  - Thus, set to **15 degrees C**
- **Storage SOC**
  - Set as mSOC above to **65%**
- Degradation graph for these inputs & NMC chemistry shows that after 4 years of use, the battery pack will keep only approximately 85% of its initial capacity.

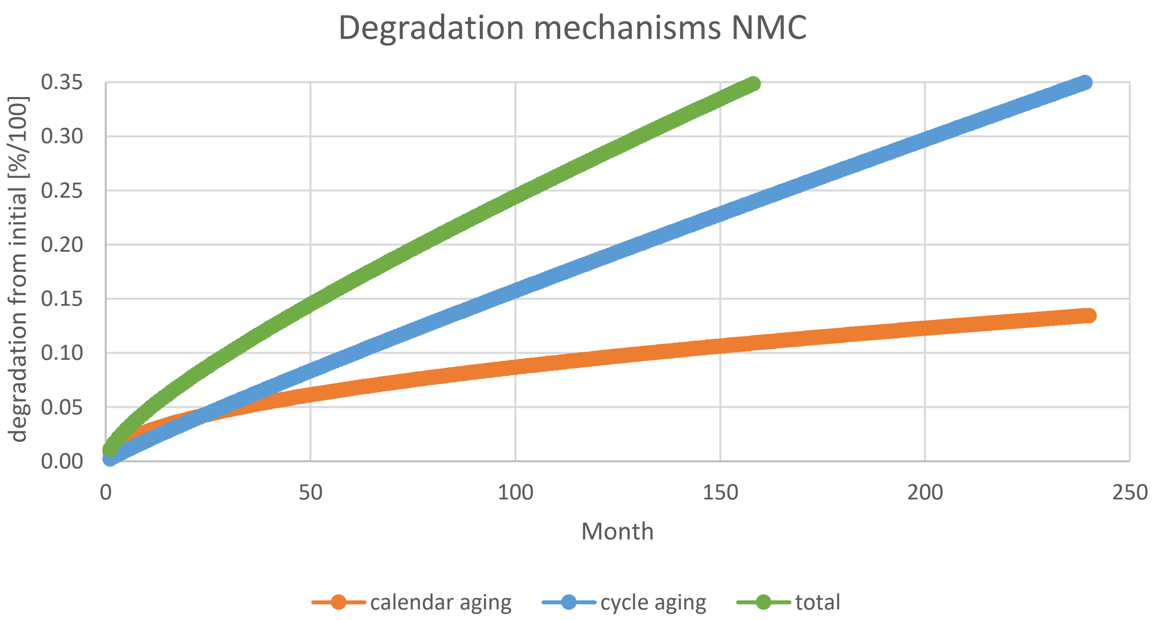


Figure 11: Degradation modes of NMC battery during this case study use, LFP graph can be found on Model tab of the spreadsheet

Output tab

The output tab shows that the total GHG LCA emissions are higher for the LFP battery. However, if recalculated per km driven, assuming the vehicle will keep working as long as the battery does not degrade to the 80% SOH, the emissions for NMC battery are higher. Thus, if the car is needed to be driven for the assumed lifecycle range, LFP battery is better from the environmental point of view. Decreasing electricity emission factor with time would further increase its advantage. However, the impacts can still be higher than those of another alternative mode of transportation, or no transportation at all. Comparison graph of the emission breakdown is shown below.

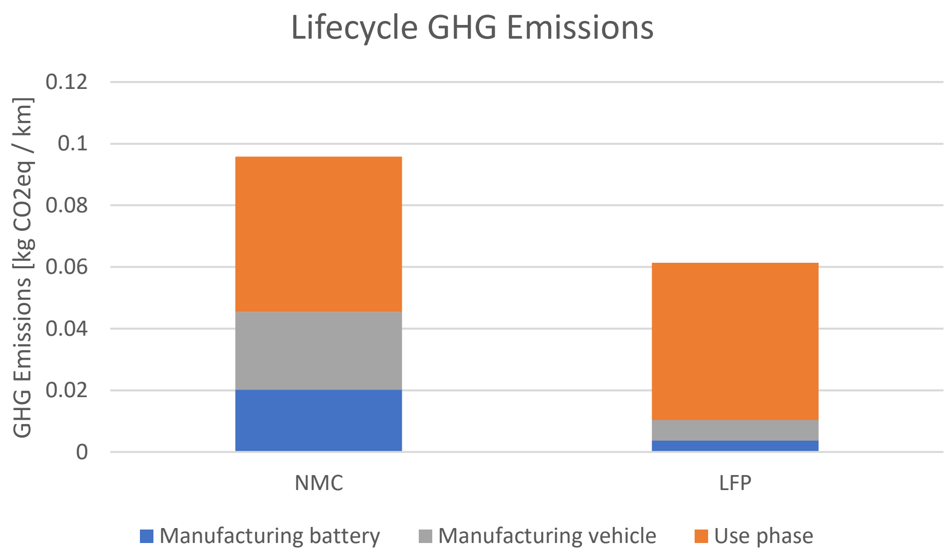


Figure 12: Final comparison between GHG emissions from use of BYD Han in London as a taxi. Assumes electricity emission intensity constant with time.

The lifetime of the NMC and LFP batteries in this case study was calculated to be significantly different as shown on a table below.

Table 2: Final lifetime statistics of LFP and NMC battery use in BYD Han as a typical London taxi

	NMC	LFP	
CYCLE LIFE	812	3116	FECs
LIFECYCLE RANGE	305,773	1,158,720	km
THEORETICAL LIFETIME	6.3	24	years

It is hard to validate this result against real life as electric vehicles of similar sized NMC or LFP batteries have not been available for a long time. The main sedan EV has been the Tesla Model S, which uses an NCA battery pack. Data for Model S show slower average degradation than NMC, at 300 000 km, its capacity would typically be just under 90% [13]. In general, the lifecycle NMC battery range does not seem to be unrealistic.
Data for LFP packs in similar uses are even more scarce. However, the original manufacturer, BYD, claims that these new LFP Blade batteries should clock-up over 1.2 million km and reach 3000 cycles [5]. These values correspond well with the findings.

4 Discussion

4.1 Sensitivity analysis

A proper sensitivity analysis was outside of the scope of this project; however, key potential sources of error and variation are:

- The SOC during storage between 60 and 70% can output vast differences between NMC and LFP, which arises from the experimental data in #22
- LFP cycling model's input paper found higher SoC and higher DoD to result in lower degradation of the battery. An opposite effect on NMC degradation was found in the same study and is more typical for LIBs [#15]. This area probably needs more research and is a major source of potential problem with LFP degradation in this model.
    - There seems to be very limited to nearly no effect of DoD on LFP degradation in some experiments [14]
- Temperature during cycling
    - It affects significantly more NMC than LFP, however, for the same reason, it can be expected that EV battery packs will have better battery thermal management system, resulting in different typical temperatures that different chemistries experience

4.2 Critique

This model has multiple shortcomings. As it tries to work generally for all batteries of each of the chemistries, it cannot precisely estimate the degradation of any specific battery pack. It is only intended to give a first point estimate for the degradation based on usage parameters. These are the main issues affecting the model, which may lead to divergence from real world findings.

- The model does not account for any other differences between the batteries, such as:
    - Battery Management Systems
    - Cooling systems
    - Performance (under specific conditions)
        - i.e. low temperatures for LFP
- The model does not consider variability in usage parameters, such as:
    - Use of multiple different chargers
    - Varied length of trips between charging
    - Different sequences of usage conditions (time between charging and discharging etc)

4.3 Further development

There are multiple improvements that could be made to this tool. A few of them are listed below.

- EoL phase implementation
- Seasonal changes of temperature
- Implementation of resistance increase
- Implementation of the Lithium plating aging effect
- Variability in usage inputs for the two chemistries, mostly the cycling temperature
- Review of the impact of mSOC and DoD on the LFP degradation

- Review of differences between the model and experimental results in order to discover potential biases in the functions
- Variation of the tool that would be able to compare two separate vehicles with individual inputs (not taken as identical vehicle with only different LIB chemistry)
- Limiting the maximal total usage lifetime of a vehicle (i.e. 20 years) and outputting the resulting battery with its SOH
- Adding changing electricity emission intensity

5 References

5.1 General references

[1] "EverBatt Argonne's closed-loop battery life-cycle model.," ANL, [Online]. Available: https://www.anl.gov/egs/everbatt.

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[13] "Tesla battery degradation data," Electrek, 2018. [Online]. Available: https://electrek.co/2018/04/14/tesla-battery-degradation-data/.

[14] Y. Preger, "Degradation of Commercial Lithium-Ion Cells as a Function of Chemistry and Cycling Conditions," *Journal of The Electrochemical Society,* 2020.

5.2 File references

Multiple files were produced in development of the case study, they are referenced below and are available on request on tonda.samal@gmail.com.

ref	File name
F1	Everbatt 2020-NMC622.xlsm
F2	Everbatt 2020-LFP-bladebattery.xlsm
F3	WLTP-tool.m
F4	WLTP data.xlsx

5.3 Literature references from the spreadsheet

References table - #numbers used in the spreadsheet

#ID	Author	Year	Paper name
#11	Kim	2016	Cradle-to-Gate Emissions from a Commercial Electric Vehicle Li-Ion Battery: A Comparative Analysis
#15	Olmos	2021	Modelling the cycling degradation of Li-ion batteries: Chemistry influenced stress factors
#17	Carlson	2013	The Measured Impact of Vehicle Mass on Road Load Forces and Energy Consumption for a BEV, HEV, and ICE Vehicle
#21	Dubarry	2018	Calendar aging of commercial Li-ion cells of different chemistries – A review
#22	Keil	2016	Calendar Aging of Lithium-Ion Batteries
#23	Schimpe	2018	Comprehensive Modeling of Temperature-Dependent Degradation Mechanisms in Lithium Iron Phosphate Batteries
#24	Geisbauer	2021	Comparative Study on the Calendar Aging Behavior of Six Different Lithium-Ion Cell Chemistries in Terms of Parameter Variation
#25	Schimpe	2018	Comprehensive Modeling of Temperature-Dependent Degradation Mechanisms in Lithium Iron Phosphate Batteries
#26	Sui	2021	The Degradation Behavior of LiFePO4/C Batteries during Long-Term Calendar Aging
#27	Schmalstieg	2014	A holistic aging model for Li(NiMnCo)O2 based 18650 lithium-ion batteries
#28	de Hoog	2017	Combined cycling and calendar capacity fade modeling of a Nickel-Manganese-Cobalt Oxide Cell with real-life profile validation
#29	Wang	2011	Cycle-life model for graphite-LiFePO4 cells
#30	Ecker	2014	Calendar and cycle life study of Li(NiMnCo)O2-based 18650 lithiumion batteries

#31	Argue - Geotab	2019	What can 6,000 electric vehicles tell us about EV battery health? https://www.geotab.com/uk/blog/ev-battery-health/