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Case studies on the passenger vehicle fleet and stationary storage applications

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To my parents.

Abstract

Lithium-ion batteries (LIBs) are expected to play a key role in the decarbonization of the transport and energy sectors as they are considered to be a commercially available, low-emission energy storage technology. LIBs are needed to replace fuel in vehicles and to provide short-term storage to the electricity grid. However, the electrification of the more than 1.5 billion passenger vehicles on the road today in addition to the LIBs expected to be used for grid storage will require an unprecedented amount of raw materials. This increase has the potential to heavily influence global material cycles and disrupt supply chains. Such outcome would limit the production electric vehicles (EVs) and hinder the integration of renewable energy technologies in the electricity grid. Hence, the reliable access to energy to meet everyone's basic needs and comfort (energy security), such as transport and electricity supply, depends to a large extent on the security of raw material supply for lithium-ion batteries. We term this reliable access to raw materials "material security" in analogy to energy security. Achieving energy and material security thus needs to be investigated from a nexus perspective, in which one cannot be attained without the other.

In this thesis, the demand for LIBs and their materials were investigated at Norwegian, European, and global levels for the passenger vehicle fleet and for grid services in the European case. Using dynamic material flow analysis, we modelled the effects of different parameters on material demand and investigated strategies to mitigate risks of supply chain bottlenecks by reducing demand. To do so, the product-component framework was developed to better understand the consequences of strategies such as reuse and replacement of components. Moreover, we evaluated the potential of vehicle-to-grid, and second-life batteries to replace new stationary batteries for the grid, thereby increasing the resource efficiency of the overall LIB system. We used a novel inflow-driven, stock-constrained methodology that introduces dynamically informed parameters to link the transport and energy industries more intricately.

We showed that while technological changes can be expected to play an important role in the reducing resource use for LIBs, social and behavioral challenges will play similarly important roles. Using smaller EVs with smaller batteries; deciding to drive less if public transport or bicycles are an option; and connecting the EV frequently to participate in the vehicle-to-grid market can be important factors that have positive systemic consequences in reducing raw material demand. Furthermore, the reuse and replacement of batteries within vehicles can also play a pivotal role in reducing resource use. Legislation that focuses on the use of LIBs in EVs explicitly, instead of only targeting EV use, can lead to more efficient strategies to reduce resource use. We demonstrated that the replacement of electric vehicle batteries without reusing retired ones that are still functional can lead to the early obsolescence of the replacement battery and hence increase battery raw material demand. We further demonstrated that while reuse - either in vehicles or as second-life batteries - reduces primary material demand, it can be expected to lower the recycled content of batteries. Regulations around the recycled content of batteries favor recycling over reuse. Relying on this indicator for resource efficiency and sustainability can thus lead to counter-productive conclusions.

The risk of material supply chain disruptions can be mitigated either by increasing supply or by reducing demand. As the industry is increasingly put under stress to satisfy a rapidly increasing demand with a highly uncertain future development, managing the demand side is an ever more important lever society must take into consideration. Policies are often focused on regulating and incentivizing the supply-side of material systems, while neglecting the demand-side. In this thesis, we focus on demand-side intervention options for material and energy security by analyzing the stock dynamics of batteries in vehicles and grid systems.

Acknowledgements

This work has truly only been possible thanks to a number of people who supported me one way or the other and gave me the means to pull through these past four years. I would like to start by thanking my supervisor **Daniel Müller** for his guidance and support throughout my PhD and for providing me with the intellectual freedom to pursue different ideas along the way. Your leadership and devotion to the persons in your team set an example for my professional and personal life.

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The research process would never have been nearly as enjoyable and productive without the contributions of my co-authors. I owe **Romain Billy** immense gratitude for your incredible creativity that you were always ready to use to support me during stressful periods. Your rapidly greying hair is a testament to your patience with me. Special thanks are also due to **Dirk Lauinger** for the interesting discussions, your dedication to high quality research, and for having supported me since my very beginning in the world of electric mobility. I would also like to thank **Francois Vuille, Amund Løvik, Rebecca Thorne, Erik Figenbaum, and Lasse Fridstrøm** for the fruitful collaborations and discussions we had.

The risks of motivation supply bottlenecks due to the cold Norwegian winters were always mitigated by a great atmosphere at the office. Thanks to **Marthe, Kajwan, Lorenzo, Miguel, Johanna, Baptiste, Ahmed, Lola and Manjong** at the distractions, ehm, *sunny* office who were always there when I needed to have a laugh. One day we will fill our research gaps, Chenzo. Also, thanks to my legal representative **Kim Rainer** for making sure the distractions office remained indeed distracted even when I was away. I believe apologies are due to Lola who always pretended she wasn't bothered by our nonsense – except by those few times we did get politely invited to continue our conversations outside. Thanks are also due to **Chipo and Marta** for the good times we had in our office and especially **Diogo,** who was aways ready to lend a helpful hand. Whenever you didn't mysteriously disappear for weeks on end, that is. I will miss hearing **Kamila** laughing at her own jokes (which often came at **Fabio's** expense) in the kitchen – thanks for all the good memories and insightful discussions. I will make sure to visit in Europe's Guatemala and of course, Milano. Finally, I would also like to thank **Martin, Dafna, Cristina, JiaJia, Maren, all the Jans, Avi, Elisa, Philip, Meng, Max, Alex, Homa, Ruslan, Sahin, and Daniel** and the many other colleagues that made my stay at IndEcol so enjoyable.

In addition to my colleagues, I had the privilege to work with many talented students who greatly contributed to add context and relevance to my work. Thanks to **Eric, Elijah, Thomas, Anna, Brent, Kristin, Marceau, Nils, Giulia, Sofia, Tima, Loïs, and Francis** for your efforts. I learned more from you than I could ever teach you. Particularly thanks to my student assistants, whose support allowed me to progress with my research even in intensive teaching periods.

I was also lucky to count on the support of **Fabi, Olivia, Siri, Jannik, and Hannes** in Sweden who opened the doors to their home in the most uncertain of times and became my COVID family. Danke auch an **Dieter und Dagmar**, die immer bereit waren uns zu unterstützen.

To conclude, I would like to express my gratitude and acknowledge the support of my family. Thanks to my **brothers and parents** who have always supported and advised every decision I took along the way – even if it meant having to visit me at the edge of the world in Trondheim. Finally, I would like to thank **my wife, Jill**. This work would have never been remotely possible without your unconditional support, advice, and patience.

Table of Contents

I. Overview of Research Articles

#	Title and authors	Contribution
1	*A product-component framework for modeling stock dynamics and its application for electric vehicles and lithium-ion batteries* *Aguilar Lopez, F.; Billy, R.G.; Müller, D.B. (2022)* *Journal of Industrial Ecology, 26(5), 1605-1615* *https://doi.org/10.1111/JIEC.13316*	Research design, framework development, literature review, visualizations, and writing.
2	*Evaluating strategies for managing resource use in lithium-ion batteries for electric vehicles using the global MATILDA model* *Aguilar Lopez, F.; Billy, R.G.; Müller, D.B. (2023)* *Resources, Conservation & Recycling, 193, 106951* *https://doi.org/10.1016/J.RESCONREC.2023.106951*	Research design, literature review, data collection, modelling, analysis, visualizations, and writing.
3	*On the potential of vehicle-to-grid and second-life batteries to provide energy and material security for the EU* *Aguilar Lopez, F.; Lauinger, D.; Vuille, F.; Müller, D.B. (under review)* *Nature Communications*	Research design, literature review, data collection, modelling, analysis, visualizations, and writing.
4	*Estimating stocks and flows of electric passenger vehicle batteries in the Norwegian fleet from 2011 to 2030* *Thorne, R.; Aguilar Lopez, F.; Figenbaum E.; Fridstrøm, L.; Müller, D.B. (2021)* *Journal of Industrial Ecology* *https://doi.org/10.1111/jiec.13186*	Visualizations, analysis, and writing.

II. Structure of the thesis

The thesis consists of a general introduction (chapter 1) motivating the various topics that were addressed in this work and providing context on the state-of-the- art. Chapter 2 presents the research questions encompassed in the papers which are to be found in subsequently. Figure 1 provides an overview of the topics addressed in chapter 3 for each paper and their scope is visualized in the adjacent icons. Finally, chapter 4 provides a general discussion to directly addressed the research questions based on the findings of the papers. A summarizing conclusion can be found at the end of the document.

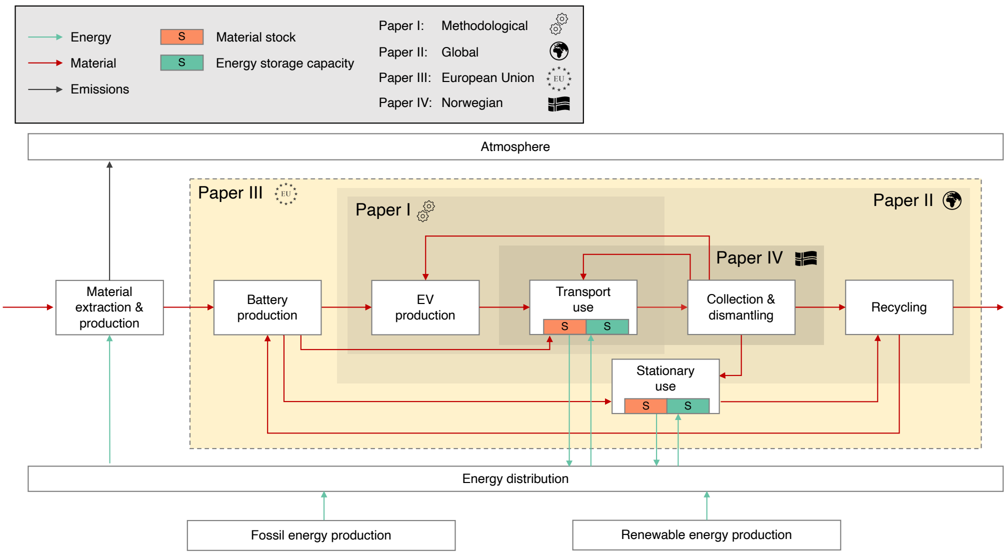

Figure 1: Summary of papers included in this thesis and the scope investigated. The material flows were modelled explicitly, while energy flows represent a driver for the need of battery storage.

1. Introduction

To limit global warming to 1.5 °C and avoid irreversible impacts on the biosphere, greenhouse gas emissions need to be reduced to net zero by 2050 (Darkwah et al., 2018; Fanning et al., 2022; IPCC, 2022; R. L. Peters & Darling, 1985; Raval & Ramanathan, 1989). The decarbonization of energy systems through clean energy technologies is expected to play a key role in enabling a prosperous society that can remain within planetary boundaries (O'Neill et al., 2018; Rockström et al., 2009). Short-term energy storage solutions, such as batteries, will be required for the expected electrification of the transport sector and as stationary storage for renewable energy integration (Rogelj et al., 2019).

Lithium-ion batteries (LIBs) are regarded as a main part of the solution in most global scenarios, since they are considered a low-emission technology that is already widely available in the market (IEA, 2021; IPCC, 2022; Rajaeifar et al., 2022). A shift to this technology would constitute a change from combustion of petroleum products to the production of battery materials (Andersson & Råde, 2001; Busch et al., 2014; Olivetti et al., 2017). By changing the propulsion technology, the entire vehicle supply chain is being fundamentally re-shaped and battery material cycles are being heavily influenced as a result (Matos et al., 2022; Ziemann et al., 2018).

A shift to battery electric vehicles (BEVs) to replace the over 1,5 billion passenger vehicles registered today would require an unprecedented amount of battery materials and massive increases in production infrastructure (International Organization for Motor Vehicles Manufacturers, 33 C.E.; Usai et al., 2022). Furthermore, the constant development of the battery technology itself, and the differences in battery sizes used in BEVs, has led to high uncertainties about which and how many materials will be required (Dunn et al., 2021; Moreau et al., 2019; Xu et al., 2020). This uncertainty has created hesitation by the mining and refining industry to invest in large capacity infrastructure, as it is unclear whether the demand for the specific battery materials will persist over a sustained period of time (Petavratzi & Gunn, 2022). As a result, the historical lack of investment poses great threats to the supply of raw materials and could lead to global material supply shortages (Sanchez et al., 2022; Usai et al., 2022).

It is therefore pressingly relevant to systemically investigate the parameters driving LIB demand and how they affect the need for raw material production. We use dynamic material flow analysis to model strategies for mitigating risks of supply chain disruptions and investigate how the development of different parameters affect raw material demand.

1.2. Battery chemistries and their raw materials: Current and future trends

Within lithium-ion batteries, there exist a wide range of possible chemistries that rely on different raw materials. While they all use lithium-ions for the transfer of electrons, the electrodes can consist of different materials and hence have diverging performance and costs.

Most of the current battery chemistries use a graphitic anode, a form of crystalline carbon either synthesized or naturally occurring, with desirable electrochemical properties (Hebestreit, 2021). Natural graphite tends to have inferior electrochemical performance compared to its synthesized counterpart, since the structure of the synthetic graphite can be tailor-made during the production process (Helbig et al., 2018). However, this tends to be an energy-intensive process which renders synthetic graphite more expensive than the directly mined alternative. Thus, there is a tradeoff between performance and cost and most battery chemistries use a mix of natural and synthetic graphite in their anodes to create a suitable compromise. As a rule of thumb, high-performance batteries tend to use more synthetic graphite, while low-cost batteries lean towards more natural graphite in their mixes.

The choice of cathode materials corresponds to the anode specifications, as high-performance cathodes can be more costly. Indeed, the nickel-manganese-cobalt (NMC) mixes for the battery cathode have been widely adopted for their high energy densities (Thorne et al., 2021). In this case, it is the nickel that provides the desirable electrochemical properties while the cobalt and manganese act as stabilizing agents (Alves Dias et al., 2018). Therefore, in terms of battery performance it would be desirable to have a high-nickel cathode with a synthetic graphite anode, potentially with Si additives to provide increased energy density. Using silicon can theoretically offer significant improvements to the battery performance, but its thermal expansion remains a challenge to stabilize. Existing battery roadmaps aim to achieve this high-nickel NMC batteries stepwise, starting from the initial NMC111, with equal parts of each material, towards NMC532, NMC622, NMC811, and ultimately NMC911 with each number stating the corresponding share of each material in the batteries (Speirs et al., 2014). Some manufacturers, such as Panasonic, have opted for nickel-cobalt-aluminium (NCA) cathodes, which are high-performance, high-cost batteries that use aluminium instead of manganese in different proportions.

Until recently, the lower-cost alternative lithium-iron-phosphate (LFP) batteries had not been considered central to the mobility industry, as their energy density was considered to be too low for transportation (Kushnir, 2015). However, after China's patent on the technology expired in 2021, many players switched almost abruptly towards this option (Lunde, 2022). Manufacturers such as BYD have made significant advances in their fabrication process by introducing the blade batteries; large cells in blade-like shapes that allow the manufacturers to significantly increase the volumetric energy density of LFP battery packs. They also claim that this chemistry and format are safer and longer lasting than other alternatives. Recycling of this type of batteries can be a challenge due to the high reactivity of lithium and phosphorus, but also because of the low value of the materials compared to their nickel and cobalt containing counterparts (Elwert et al., 2019; Gangaja et al., 2021). A smaller number of producers is also exploring lithium-nickel-manganese-oxide (LNMO) and lithium-manganese-oxide (LMO) batteries, but their performance seems to be currently inferior to the other options and are thus not widely used.

Future trends aim to move away from many of the currently used materials by replacing them with lithium-metal electrodes. Such options include lithium-Air (Li-Air) and lithium-Sulphur (Li-S) batteries. While they have a higher energy density than existing chemistries and use less materials overall, the lithium content per kWh of battery is higher than in any other alternative. Other options beyond LIBs are being explored and important advances have recently been reported, primarily in the field of sodium-ion (Na-ion) batteries and hydrogen fuel-cells.

In every battery chemistry within LIBs, there will always be a need for other materials beyond the ones listed above. Copper is used within cells, for cables, and for other components. Steel or plastics are found in certain parts, and Si and others in the battery management system. In this work, we focus mainly on the materials within the electrodes, the battery management system (BMS), and the casing of the battery pack.

1.3. Global battery material cycles and risks of supply chain disruptions

The shift in the energy and transport sectors replaces the need for fuel for propulsion to technology metals for energy storage. These metals need to be extracted and refined at unprecedented rates to build up the stock of clean energy technologies needed to replace the current combustion-based power plants and vehicle engines. Ensuring resilient supply chains for these materials has become a challenge due to environmental implications, resource availability, long lead times in building infrastructure, and the necessary supply chain adjustments involved in such activities.

Lithium is a geologically abundant material that can be found in most parts of the world. It primarily occurs in two types of deposit: brines and minerals (Boswell et al., 2021). The main known lithium brine deposits are considered to be in the “lithium triangle” formed by Argentina, Chile, and Bolivia, although some major operations exist elsewhere (Sanchez et al., 2022). Australia currently has the highest extraction rates of lithium minerals, but the majority of it is refined in China and then sold as a chemical to the LIB industry. As Mudd (2021) pointed out, most of the increase in lithium demand caused by LIBs has been met by increases in production by Australian mines since the inception of LIBs. However, ore grade degradation and need for further extraction capacity remain a challenge for the future. As of 2019 the LIB industry already constituted about half of the global lithium consumption (McNeil, 2022).

Given its geological abundance, lithium reserves are not expected to be a limiting factor in lithium production in the future (Sverdrup, 2016; Vikström et al., 2013). In fact, it has been demonstrated that the reserves of lithium have been rising over time, since the increasing price of the mineral makes new deposits economically viable and thus increases the reserves (Lèbre et al., 2020). The limitations in the future production of lithium are rather of environmental, social, and governance (ESG) nature (Petavratzi & Gunn, 2022; Petavratzi & Josso, 2021). Indeed, these studies have shown that the process of opening new mines can take up to three decades, as it needs to overcome major environmental licensing, building efforts, and social opposition. This for good reasons: lithium brine extraction is a very water-intensive process, as the mineral is pumped out of the ground using pressurized water. The output is a suspension of lithium-enriched water that is concentrated through evaporation in the sun for up to two years until lithium carbonate forms and is sold as a chemical to the LIB industry (see Figure 2) (Kelly et al., 2021). Since the evaporation rate needs to be higher than the precipitation rate, this process often takes place in desertic areas such as Salar de Atacama in Chile, where lithium extraction already consumes more than 60% of the local groundwater. Many efforts to develop lithium mines, from minerals and brines, have failed due to social opposition and environmental concerns. New technologies such as direct lithium extraction are being heavily investigated to extract the lithium at a faster pace. However, no large-scale projects exist yet and the regulatory and social barriers may still pose a threat to the supply of lithium. This would constitute a systematic risk to the overall supply of LIBs, as all chemistries depend on lithium supply.

Figure 2: Left: Pools of lithium-enriched water drying in the sun. Right: Lithium carbonate salt after the drying process has been completed. Taken from: (Barranco, 2022; New Technique Could Reduce Lithium-from-Brine Extraction Time to Just Hours.*)*

Nickel is similarly found in two main types of deposits: lateritic and sulphidic; each of which has different refining needs and production pathways. As for lithium, the geological availability of nickel is not expected to be a limiting factor in LIBs production, but the infrastructure needed for it may well be (Mudd & Jowitt, 2014). Young (2021) demonstrated that the technologies that are fastest to come online for battery grade nickel production are also the ones with the highest greenhouse gas emissions (GHG) per ton of material produced. Hence, a rapidly increasing demand for nickel production bears the risk of increasing overall emissions in the nickel cycle. Moreover, since nickel is only used in a limited set of LIB chemistries, the future demand or even need for it is highly uncertain. This creates deterrence to the industry to make large investments that take several years to pay-off given the considerable risk in building capacity for a demand that does not materialize. The lack of investments in large, clean, production capacity exacerbates the risks of small, CO_2 intensive technologies such as nickel-pig-iron processes to take over the new production market.

Graphite is a naturally occurring form of high purity, crystalline carbon that can also be synthesized through industrial processes (European Carbon and Graphite Association, 2020; Manjong et al., 2021). The feedstock for synthetic graphite production is a byproduct of petrol refining and coal mining and is not produced on its own due to its low value (Reuter et al., 2014). Hence, as countries intensify their efforts to move away from petrol and coal, the availability of pitch and needle coke may be reduced. This would require adjustments to the refining processes to generate more pitch and needle coke in order to ensure that their supply can be consistent with the demand of raw materials for LIB anodes. However, Barre (2023, unpublished) showed that the sulfur content in the petrol deposit can be a limiting factor in the production of suitable needle coke for graphite synthesis. Natural graphite mining on the other hand, can take long lead times to increase production capacity and its supply chain is mostly controlled by China (Jara et al., 2019).

Phosphorus is a heavily geographically concentrated material with around 70% of the world's reserves in areas controlled by Morocco (Ore et al., 2021). Most of the current production is used for fertilizer, as phosphorus is an essential nutrient for growing food (Cordell & White, 2014; Hamilton et al., 2020). While the high-purity phosphoric acid needed for batteries is refined in a different way, it depends on the same feedstock of phosphoric rock as the fertilizer industry. As the LIB industry increasingly adopts phosphorus-containing LFP batteries, it could cause a competition with agriculture for phosphorus resources if the production cannot keep up with the pace at which the demand increases (Lunde, 2022). In addition, to manufacture this high-purity acid, the Wöhler process is needed, which is a highly energy-intensive process that only exists in China, the USA, Russia, Kazakhstan, and Vietnam. This highly concentrated supply chain exposes phosphorus supply to high idiosyncratic risks where local events can have global consequences. The current war against Ukraine for instance, which led to several economic measures against Russia, drove fertilizer prices up to an all-time high as can be seen in Figure 3. The rise in prices has affected both the food and the LIB industries.

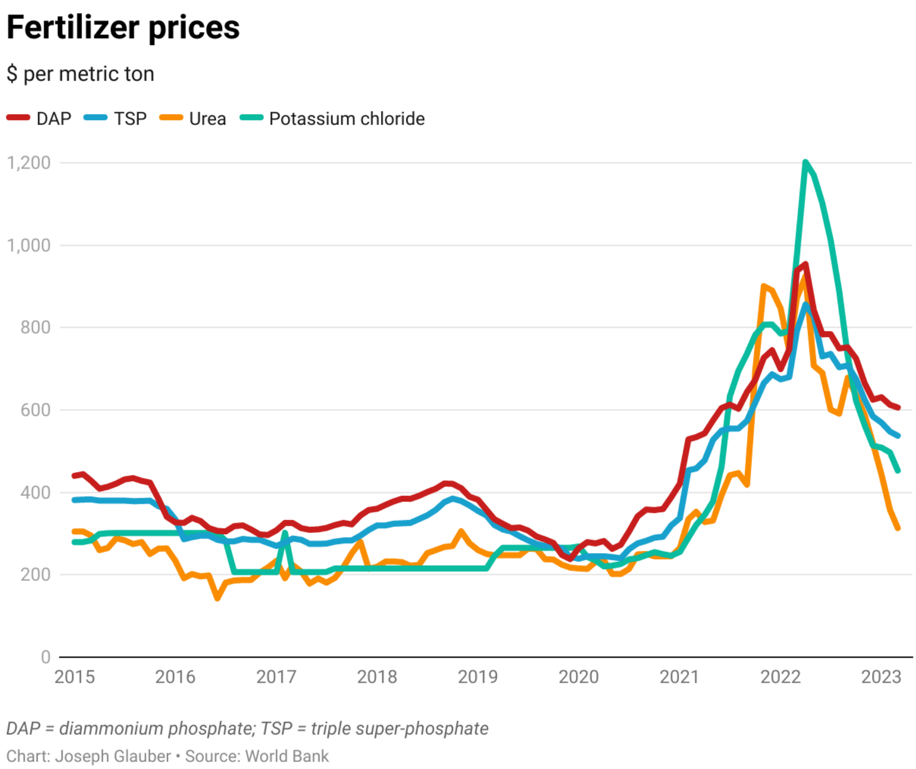

Figure 3: Fertilizer prices over time. The steep increases start with the Russian invasion of Ukraine. Taken from: (The Russia-Ukraine War after a Year: Impacts on Fertilizer Production, Prices, and Trade Flows | IFPRI : International Food Policy Research Institute)

Cobalt is largely a by-product material which is obtained often in copper and nickel mines (Olivetti et al., 2017). More than two thirds of global mine cobalt production came from the Democratic Republic of Congo (DRC) and 67% of refining occurred in China (Zeng et al., 2022). Given the social and environmental concerns around the DRC, industry and governments have expressed their interest in reducing their reliance on this metal as much as possible in the coming years as any political disruption in DRC could lead to supply chain disruptions (Matos et al., 2022).

Aluminium is a metal that has been heavily studied and has become attractive for many industries thanks to its high conductivity and light weight (Elshkaki & Graedel, 2013). Aluminium bauxite deposits are globally abundant but the process of refining the ore into alumina is a highly energy-intensive process that works through electrolysis (Chen et al., 2010). Billy & Müller (2023) showed that if the current trends of aluminium consumption persist, and it is increasingly used for batteries and light weighing of vehicles, the emissions related to its production may consume more than 5% of the remaining carbon budget to limit global warming to 1,5°C.

Copper, manganese, and silicon have similarly concentrated supply chains and their demand is expected to increase within LIBs and other products (J. F. Peters & Weil, 2016; Ryter et al., 2022; Struyf et al., 2009). To limit the risks of supply chain disruptions and environmental damages, reducing the demand for raw materials is a strategic imperative.

1.4. Geopolitical considerations

In addition to the issues outlined above, the struggle to source battery raw materials has sparked new geopolitical tensions and concerns to control their supply (Alves Dias et al., 2018; Lebedeva et al., 2016). As with many products in the past, regions such as the EU have largely outsourced their material production to China and remained reluctant to increase domestic activities that are perceived as environmentally harmful and risky (Graedel et al., 2015; Sun et al., 2018). Those activities include increasing mining and refining infrastructure. The trend towards new-, raw material-intensive technologies such as LIBs has left the EU at a competitive disadvantage compared to China, since it controls a most of the clean technology supply chains (Ericsson et al., 2020). The EU's automotive industry hence increasingly relies on Chinese imports on all levels of their value chain to produce EVs and LIBs. Indeed, China has managed to increase their own electric mobility industry downstream as well. BYD, a Chinese vehicle manufacturer, is today valued more highly than Mercedes Benz, BMW and Volkswagen (*Largest Automakers by Market Capitalization, 2023*).

As a reaction to this, proactive political interventions have been initiated towards fomenting local battery industries in a new approach to governance dubbed "strategic capitalism" (Babić et al., 2022; D'Aveni, 2012; Fjäder & Hartwig, 2022; Torjesen, 2022). In this framework, the motivation underpinning the interventions conducted in the battery industry are linked to securing favourable economic performance relative to other states, rather than increasing welfare. The Inflation Reduction Act in the USA, the European Commission's battery regulation proposal, and the Critical Raw Materials act can be considered examples of such new wave of policymaking (Birkeland & Trondal, 2022; European Commission, 2019, 2020a, 2023; *The Inflation Reduction Act | US EPA*, 2022). The Critical Raw Materials Act explicitly states that its aim is to have a "Comprehensive set of actions to ensure the EU's access to a secure, diversified, affordable and sustainable supply of critical raw materials". It recognizes the fact that Europe's energy and material supply heavily relies on imports and that certain materials are strategically critical for its resilience. The first list of critical raw materials (CRMs) was published in 2011 and contained 14 materials and was subject to be updated every 3 years. This list more than doubled to 30 raw materials by 2017 (European Commission).

1.5. Material criticality and the need for forward-looking models

As a way to measure the security of material supply and the risk of shortages, regions such as the EU and the USA have introduced material criticality assessments and indicators. Methodologically, the EU's criticality assessment accounts for dependance on imports, historical use of the given material, the feasibility to substitute it by other materials, and their recyclability to evaluate their risk of supply (European Commission, 2020b). This is then plotted against its economic importance, measured in the economic relevance of the industry that material is used for and not the value of the material itself (see Figure 4).

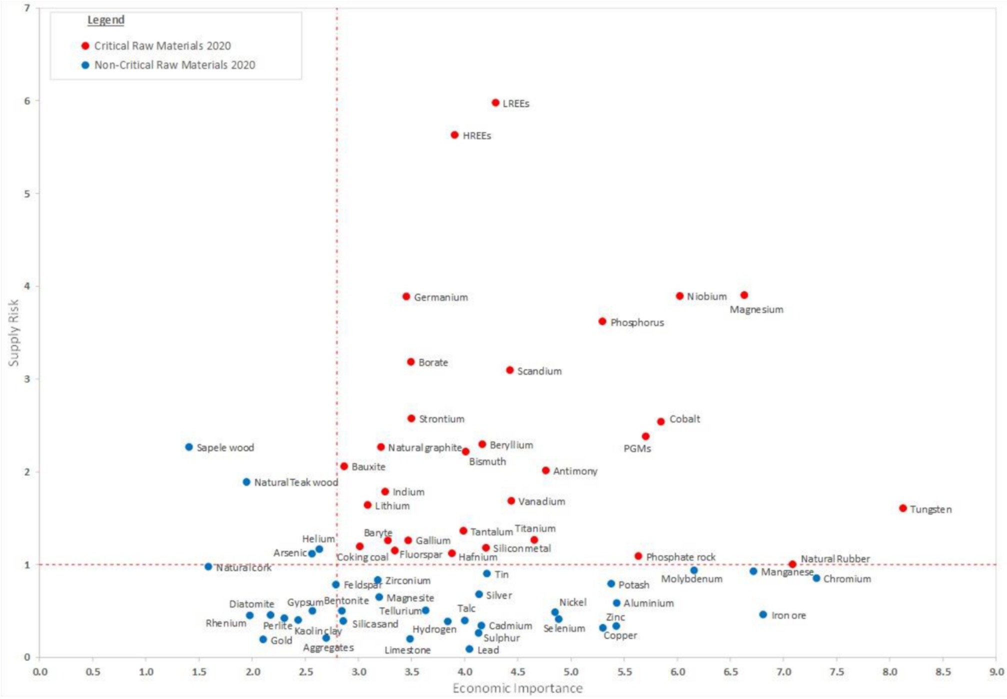

Figure 4: Material criticality assessment of the European Commission. Taken from (European Commission, 2020b).

Thus, the entire supply system of CRMs is reduced to two historically informed dimensions. A material would only be considered as critical once it *already* is at high risk of supply chain disruption and of high economic relevance. Many battery raw materials, including lithium, phosphorus, and graphite fall in the list of materials initially not considered critical only to become so in later assessments once the industry already heavily relied on them. Others, such as nickel, are still not considered critical even though they are expected to play an increasingly important part in LIB technology if the industry moves to high nickel-containing technologies for higher energy density.

The lack of foresight has influenced the EU's and other regions' lag in establishing supply chains for future technologies and now need very quick ramp-up capacity to achieve their electrification goals. Forward-looking models can help to understand the materials that can be expected to play a key role in the future and to prepare the necessary infrastructure *before* the material's supply chains have become disrupted.

Moreover, while it is relevant to reduce criticality to a common indicator that allows comparability across different materials, each material cycle has specific challenges in ramping up supply (Eckelman et al., 2012; J. F. Peters & Weil, 2016; Takiguchi & Morita, 2009; Ziemann et al., 2013). Hence, without investigating the effects of increasing material supply related to the penetration of a given technology, the risks and difficulties of producing materials at scale cannot be captured. Systemic approaches that can investigate the effects of increasing demand on a material's global system can thus support the knowledge base on possible future bottlenecks and inform decision makers.

1.6. Modelling product-component systems

Circular economy strategies often focus on extending the time that goods remain in the in-use stock, herein defined as *in-use time,* through reuse and replacement of components as a way to reduce the need for new products and thus reduce material demand (Dunant et al., 2021). That is, instead of disposing the entire product when a component fails, one can replace that component with a reused or new one and continue using the product for a longer period of time. These strategies result in in-use products with different in-use times than components depending on the conditions for reuse and replacements.

Traditional approaches to MFA, however, assume that the in-use time of the components are equal to that of the product and describe the probability of obsolescence with a single *lifetime* function. This function reflects the statistical probability of outflow of given goods on a given year based on its age. In this case, since the product-component system is being described as one entity, the in-use time is equal to the lifetime. However, aggregating over all causes for obsolescence in this way does not differentiate the cause for obsolescence and hence does not allow to investigate the effects of reuse and replacements on product and component in-use time. To model these product-component interactions, one needs to understand the share of functional products that could use a replacement component to extend their in-use time and the share of functional components in obsolete products that could be available for reuse. Introducing an additional lifetime function that allows to track component obsolescence is therefore necessary. The in-use time of products and components hence becomes a composite function of the lifetime of the product, the lifetime of the component, and the conditions for reuse and replacements. In this approach the lifetime reflects the expected time goods would remain in use for if their dynamics where independent of product-component interactions, and the in-use time reflects the actual time they remain in use for.

Common approaches used to model replacement and reuse define rates as fractions of the inflow, stock, or outflow. This methodology omits the component cohort as it is not tracked explicitly in the single-lifetime approach. The approximation that the product and component cohorts are equal can only be correct in a steady state system or where the material composition of the component and inflows remain constant over the entire investigated period. If the stock is changing over time or the component cohorts differ in their material composition, new approaches are needed.

Since the stock of new technologies is usually growing rapidly over time and constantly being developed and improved, existing methodologies are unsuitable to model their dynamics and to understand the resource use in such technologies. Moreover, the lifetime function definition is often based on empirical observations, which are lacking for new technologies. To overcome this, modellers can rely on technical specifications of components to define the expected component lifetime and on estimations of the product lifetime based on comparable existing products to calculate the resulting in-use time. Based on these values, it is possible to investigate the consequences of component reuse and replacement on the in-use time of the products and components in question.

In the case of EV-LIB systems, it is the vehicle that is providing the service of transport (the product), but its dynamics are inextricably linked to the dynamics of their batteries (the component) (Bobba et al., 2019; Song et al., 2019; Thorne et al., 2021; Xu et al., 2020).

It becomes evident that the cause of vehicle obsolescence is strongly linked to 1) the obsolescence of the vehicle itself for technical reasons as well as social preferences; and 2) the obsolescence of the battery. Since the technology is relatively new and developing quickly, empirical data are scarce. As an alternative, modellers can derive the product lifetime based on observations of conventional vehicles, and the component lifetime based on technical data of the battery life expectancy. This would support the understanding of how product-component, i.e. EV-LIB, interactions affect resource use which is pivotal in fostering a more resource efficient transport sector.

1.7. Battery and electric vehicle lifetimes

When EVs were first introduced, concerns were raised about the durability of LIBs and how they may limit their lifetime. Automobile manufacturers offer a warranty of 8-10 years which is significantly lower than the lifetime of internal combustion engine vehicles (ICEVs) (Hossain et al., 2019; IEA, 2020; Tsiropoulos et al., 2018; Vikström et al., 2013). However, these concerns seem to have been unwarranted, as batteries have been shown to last longer than initially expected and estimates of 14-18 years are now more commonly used instead (Dunant et al., 2021; IEA, 2021; Jung et al., 2018; Oguchi & Fuse, 2015; Uddin et al., 2019).

Battery aging mechanisms can be summarized in three phenomena: 1) calendar aging; 2) cycle count; and 3) dis-/charging power (*BU-1003a: Battery Aging in an Electric Vehicle (EV) - Battery University*, n.d.). Calendar aging is the natural decay of capacity over time that depends mainly on the temperature at which the battery is stored and its state of charge (SOC). The higher the temperature, dis-charge power, or the state of charge of the battery, the higher permanent degradation of battery capacity. Hence, smart management of battery charging patterns and conditions plays an important role in the battery's longevity. Charging at low power levels and maintaining a SOC between 20-80% of the available battery capacity are therefore considered good practices (Uddin et al., 2019). For this reason, several reports have demonstrated that technologies such as vehicle-to-grid have no or marginal impact on the battery lifetime, as it ensures that the load on a vehicle remains at around 7-10kW (normal charging) and avoids maintaining high SOC levels for long periods of time (Pinto et al., 2013; Shiau et al., 2009). Hence, while the cycle count may increase due to vehicle-to-grid, dis-/charging power and calendar aging due to more moderate average SOC may be reduced (Doru et al., 2022; Uddin et al., 2019).

1.8. Energy and material security: The role of vehicle-to-grid and second-life batteries

Electric vehicles are expected to reduce emissions in the transport sector, but their effectiveness in doing so depends on the energy used for charging during their lifetime (Ellingsen et al., 2017; Hawkins et al., 2013). Therefore, clean energy production is a central part in decarbonizing passenger transport. Hydropower electricity generation is limited by the topology of regions and thus intermittent renewable energy sources such as wind and solar are expected to be needed at large scale. Their intermittent nature means that production will not necessarily match electricity consumption, and therefore short-term energy storage will be needed. In addition, the absence of turbines in combustion power plants, which usually compensate for fluctuations in the frequency of electricity transmission, also leads to a need for fast-reaction storage technologies such as LIBs for frequency regulation and other ancillary services to the electricity grid. It follows that to achieve clean energy security, i.e. the affordable and stable supply of energy to satisfy humanities basic needs and wants, material security for energy storge to allow the integration of renewable energy is a precondition.

This suggests that a threat to battery raw material supply may translate to a threat to energy security. It is therefore of key relevance to understand how new technologies such as second-life batteries (SLBs) and vehicle-to-grid (V2G) can help mitigate the need for battery raw materials and therefore increase energy security while supporting the integration of renewable energy. The former recognizes that while batteries may no longer be suitable to provide the service of transportation in EVs, they might be still useful for stationary storage applications (Bobba et al., 2019; Zhu et al., 2021). The latter takes advantage of the large amount of time vehicles sit idle by making their batteries available for grid storage while plugged in (Kempton & Letendre, 1997; Lauinger, 2022).

Both strategies would increase the time batteries are effectively used for and thus maximize the services that existing stocks can provide and reduce the need for dedicated new batteries for grid storage.

Thus, the resource implications of V2G and SLBs need to be assessed from a systemic perspective that includes the new stationary batteries (NSBs) that would be needed in the absence of other solutions. Current studies mainly consider SLBs from an inflow-driven perspective, in which their potential capacity is equal to the retired capacity from EVs times a given transfer coefficient (Bobba et al., 2019; Dunn et al., 2021; Thorne et al., 2021; Xu et al., 2023). This leads to the conclusion that reuse is a less resource efficient strategy than recycling directly, since it delays the availability of secondary materials. However, this conclusion ignores the fact that in absence of reused batteries, NSBs would need to be manufactured and installed, requiring more resources themselves. To understand the overall raw material implications of SLBs, new methodologies that link the need for NSBs to the availability of SLBs and V2G are needed.

2. Research questions

1. **To what extent do social and technological developments in the lithium-ion battery system affect raw material demand?**
   What are potential bottlenecks in the supply of battery raw materials and how can they be avoided or reduced? What trade-offs and problem shifts can arise and how can they be addressed?

2. **What role does the replacement and reuse of components play in reducing raw material demand?**
   How can product-component interactions be modelled? How do the lifetime of products and their components influence each other's obsolescence? How can such product-component interactions be relevant in the context of electric vehicles and batteries?

3. **What is the potential of vehicle-to-grid, second-life batteries, and recycling to increase energy and raw material supply security?**
   Which of the strategies has the largest potential to reduce overall resource consumption and how can they be combined most effectively? Under what conditions would either technology be preferable? How do these technologies affect the recycling of materials and overall resource use?

3. Papers

3.1. A product–component framework for modeling stock dynamics and its application for electric vehicles and lithium-ion batteries

DOI: 10.1111/jiec.13316

METHODS ARTICLE

JOURNAL OF INDUSTRIAL ECOLOGY WILEY

A product–component framework for modeling stock dynamics and its application for electric vehicles and lithium-ion batteries

Fernando Aguilar Lopez | **Romain G. Billy** | **Daniel B. Müller**

Department of Energy and Process Engineering, Norwegian University of Science and Technology, Trondheim, Norway

Correspondence
Fernando Aguilar Lopez, Department of Energy and Process Engineering, Norwegian University of Science and Technology, Trondheim, Norway.
Email: fernando.a.lopez@ntnu.no

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Abstract

Models that study the socio-economic metabolism often apply a lifetime approach to capture the stock dynamics of products. The lifetime is usually obtained empirically from statistical information and is assumed to describe the dynamics of the product and its components. However, for new types of products for which historic outflow data is limited, or in cases where a critical component plays a significant role in determining product end-of-life, a more refined understanding of the dynamics of product–component systems is needed. Here, we provide a new framework for product–component systems and 12 different approaches to model their stock dynamics. Then, we discuss which approaches are best suited in different contexts. We illustrate the use of the framework with a case study on electric vehicles and their batteries, highlighting the potential of battery replacement and reuse for reducing material demand. Improving the understanding of these complex systems is relevant for the study of the socio-economic metabolism because (i) accounting for component dynamics can support identifying unintended consequences of product-specific policies; (ii) component replacement and reuse can be a key circular economy strategy to foster efficient resource use; and (iii) accounting for these complex dynamics can lead to more accurate estimates for resource demand and waste-generation expectations, creating more resilient information streams. This article met the requirements for a Gold-Gold *JIE* data openness badge described at https://jie.click/badges.

KEYWORDS
circular economy, dynamic modeling, electric vehicles, industrial ecology, material flow analysis, toolbox

1 INTRODUCTION

Material flow analysis (MFA) has become a prominent modeling tool for understanding how material flows and stocks evolve in metabolic processes in the built environment (Hendriks et al., 2000; Müller et al., 2004). The insights generated using this approach provide an important basis for policy and industry stakeholders in anticipating future anthropogenic activities (Baccini & Brunner, 1991). More specifically, dynamic MFA models seek to build knowledge and foresight about the way different stocks and flows of goods, materials, and energy are used in the socio-economic metabolism and how this changes over time. MFA practitioners often apply a lifetime approach to capture the main driving forces of the stock dynamics as introduced by Baccini and Bader (1996). In-use stocks are composed of products that usually consist of several components, which are assumed to have the same dynamics as the product. This is often not the case in reality; for example, when a component is removed from the product for replacement. Furthermore, this approach can also be limited in cases where critical components in products are an important factor for obsolescence since it does not allow investigating the potential for reuse and replacements to evaluate lifetime extension strategies in sufficient detail.

Several approaches have been put forward in order to deal with such product–component systems. Müller et al. (2004) used different lifetime functions for wood products in buildings and for the buildings themselves to calculate the total wood demand. A similar approach was proposed by Ardente and Mathieux (2014), where two lifetimes are used to test the effect of the durability of two different products, and by Busch et al. (2014), who built an enhanced hierarchical nested description of technologies and their components in which multiple lifetime functions were used to track component outflows in addition to the product dynamics. Furthermore, Sandberg et al. (2014) proposed to consider renovation profiles in buildings to account for changes in the energy intensity of the existing stock, by introducing renovation cycles coupled with the survival curve of the stock-type-cohort matrix. Džubur & Laner (2018) addresses the role of renovation, which can be understood as a critical component of buildings, by adding the demolition and renovation rates in a leaching compared to a lifetime approach. This was further developed by Roca-Puigròs et al. (2020), who proposed a combined lifetime and leaching approach to model the effect of early demolition and renovation strategies for old buildings. To model the dynamics of multiple products containing a common material of interest, Dunant et al. (2021) proposed the use of a transfer function that combines the lifetime functions of different products. However, while these approaches allow to independently track the dynamics of multiple products and components, the combined dynamics and the role of the component in limiting or extending the product's useful time are not considered. Furthermore, the lifetime is usually modeled using the survival function, linking outflows and inflows by tracking the remaining fraction of a given cohort over time (Lauinger et al., 2021). Nevertheless, the life expectancy at birth of an individual does not directly determine the probability of dying in a given year. Similarly, survival functions are not directly linking stocks and outflows.

To address these limitations, we propose a general framework to model the stock dynamics of product–component systems under different conditions. We assume that the lifetime of the product–component system is determined by end-of-life (EOL) of either the product or the component, together with the conditions for product and component reuse and replacement. We introduce a stock matrix by time, product cohort, and component cohort to address these dynamics. We also propose the use of a hazard function to simplify the modeling and establish a direct link between the stocks and the outflows. The interactions of the product–component system can thus be investigated in a detailed way, which allows the evaluation of key circular economy strategies such as reuse and replacement of components.

We present 12 different modeling options, discuss their logics and general relevance for modeling various situations, and provide a specific example with a case study investigating reuse and replacement strategies for batteries in electric vehicles. The Python code for the generic framework is provided and made available for practitioners to use with an open license, building on the foundation laid by Pauliuk et al. (2019) in their work with the dynamic_stock_model library.

2 FRAMEWORK

This section introduces the different options to model the dynamics of product–component systems. The main differences, applications, and assumptions are discussed from a theoretical point of view. We define products as goods providing a required service, and the components as items within products that are critical to their functionality. The models described in this section are introduced in the Python package product_component_model.py and can be found with its respective documentation here: https://doi.org/10.5281/zenodo.6363382

Following the assumption that the products are providing the required service, and that it is the provision of the service that is driving the demand for the product (Müller, 2006), we use a stock-driven model that allows us to investigate the system dynamics under different modeling assumptions (Lauinger et al., 2021). Figure 1 shows a generic system definition of products and components that allows investigating the dynamics of product reuse and repair by replacing failed components. The spare parts can be assumed to be a new component or a reused component from a failed product. The approach that can be used for a given system may differ depending on the purpose of model and will be discussed in the next section. The proposed methodology is valid for inflow-driven models as well.

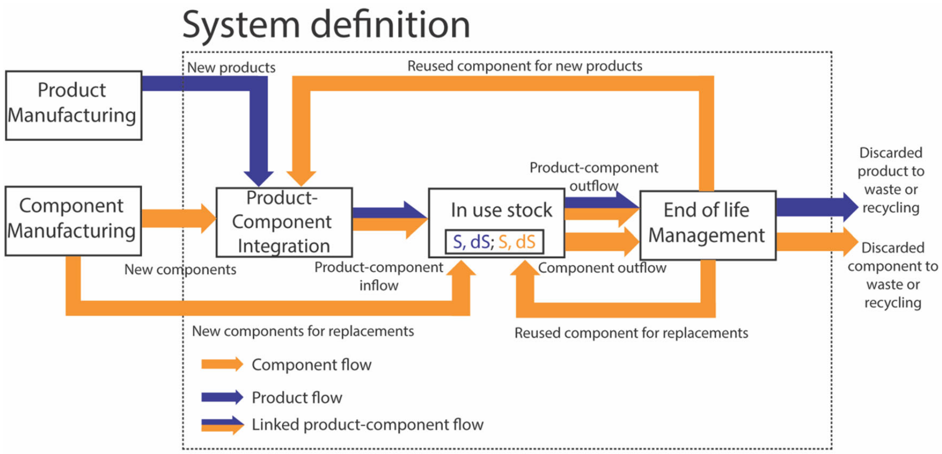

FIGURE 1 System definition of a generic product–component system

2.1 | Considerations about the in-use time and use of hazard functions

Which metric should be used to determine the lifetime of goods? In dynamic MFA studies, the lifetime reflects the statistical probability that a product that entered use at a given time exits use with a specific delay. Therefore, the lifetime does not describe the cause for leaving use, but represents the time interval between when a product enters a balance volume (e.g., use) and when it leaves it to reach EOL. The values used for the lifetime are usually empirically measured, based on sales and waste-generation statistics, or directly measured, and might therefore include periods, when the product is no longer in use but has not reached an EOL reporter yet, known as hibernating stocks. The dynamics of the product and component are assumed to be equal. Therefore, the dynamics of products or technologies where (i) outflow observations are not yet available, (ii) the lifetime of the product and the component is not determined by the same metric, or (iii) where the component dynamics are of relevance to the system should not be characterized in the same way. By considering technical aspects for products, such as kilometers driven by a car, and components, such as number of cycles in a battery, in addition to considerations about other possible causes for obsolescence, we can approximate the useful time of products and components by making use of independent functions.

Component obsolescence can be modeled through a component hazard function, while all other causes for product EOL (including nontechnical failures, such as lifestyle obsolescence) are modeled by a product hazard function. We define the product and component hazard functions as independent functions that describe the theoretical probability of reaching EOL during a given period of time. Despite not having been widely used for dynamic MFA, hazard functions offer significant advantages for the modeling and interpretation of the results and can be derived from statistical lifetime distributions, similarly to the more common survival and probability density functions (see Section 1 in the Supporting Information S1 for a detailed description). Hazard functions determine the time in which the product–component system remains in actual use (providing a service), herein defined as the *in-use time*. Hence, the in-use time varies from the conventional lifetime definition by not including hibernating and obsolete stocks, leading to potentially more accurate inflow but less accurate waste-generation expectations. This relationship holds true in the absence of an additional logic for the hibernating stocks (see Section 2 in the Supporting Information S1). Additionally, given the cohort composition, hazard functions can be used to model the expected outflow of a stock based on its age without requiring previous knowledge of the initial number of inflows, as is the case with the survival function. Thus, the hazard function can establish a direct link between the stock and the outflows (see Section 1 in Supporting Information S1).

2.2 | Modeling options for product–component systems

When evaluating the most suitable approach for a given product–component system, modelers should establish the boundary conditions and limitations around how the component can interact with the product under given circumstances (e.g., whether the component can be replaced or reused). These considerations will not only determine the approach that will be taken, but also the values that should be chosen for the product and component hazard functions.

Figure 2 provides an overview and guide for choosing the most suitable modeling approach to be used dependent on the purpose (and data available). The first consideration is the type of model that is suitable for the problem at hand. This is represented in the uppermost boxes where

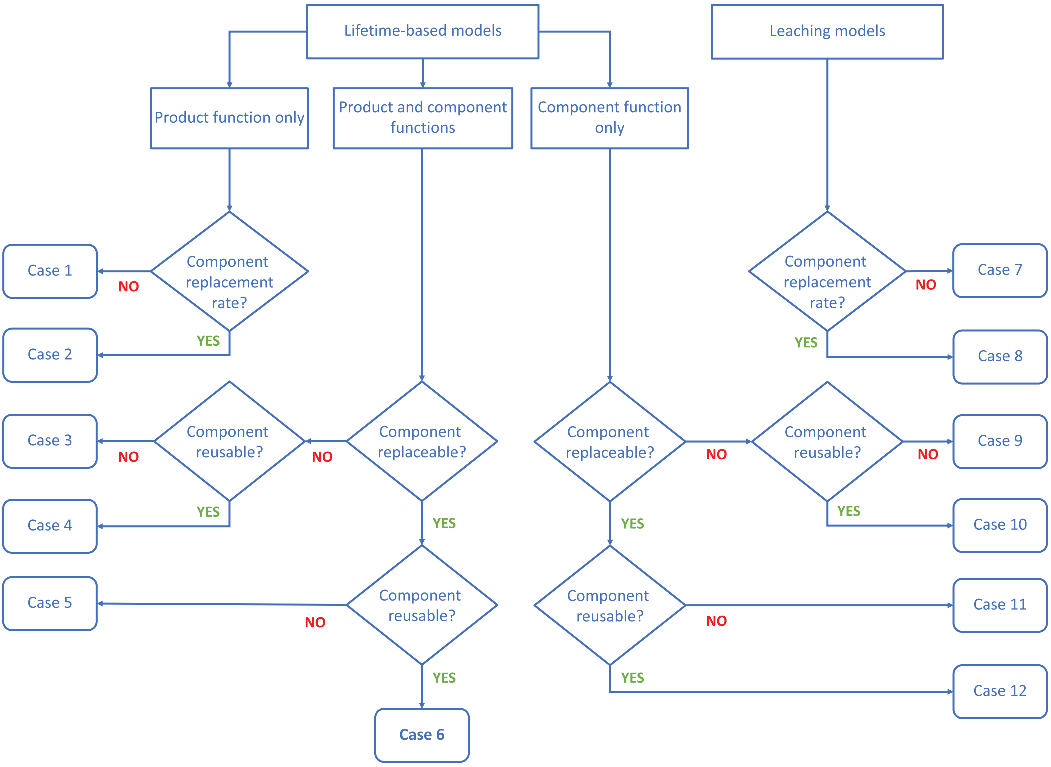

FIGURE 2 Different assumptions for modeling options

lifetime-based models are distinguished from leaching models. Within the lifetime-based models, three main categories are introduced, with several options for reuse and component replacements and will be discussed in detail in the following sections.

2.2.1 | Using a product hazard function

If there is evidence that the relationship between the in- and outflows of goods follows a robust statistical pattern and the dynamics of product–component interactions are not considered or assumed to be equal, a single lifetime approach may be suitable (Melo, 1999). This case can be understood to be equivalent to using only a product hazard function under this framework. The probability distribution of the hazard function is usually calibrated against historical data of inflows or through observations of the size of cohorts over time (survival curve). Examples can be found in products where spare parts are widely available, and components are easy to replace such as lead-acid batteries in vehicles or batteries in consumer electronics.

Case 1: This case depicts the most common approach to dynamic modeling, wherein a single empirical function is used to simulate all outflows. The outflows in this case are calculated based on a probability distribution function of goods flowing out of use given their age. The product and the component are considered inseparable and therefore their system flows are equal. In this case, the product hazard function is equivalent to the lifetime that is traditionally used in dynamic models.

Case 2: In contrast to case 1, here it is assumed that each product uses more than one component through replacements, but it is unknown or irrelevant when the component replacement will be needed. It is therefore assumed that the replacement component enters use at the same time as the product and the first component, and that both components leave use together with the product, leading to a total inflow of components that is always higher than product inflows by an amount equal to the replacement rate. This assumption holds true for constant stocks but leads to an overestimation of the in- and outflows in growing stocks (see Sections 3 and 4 in Supporting Information S1).

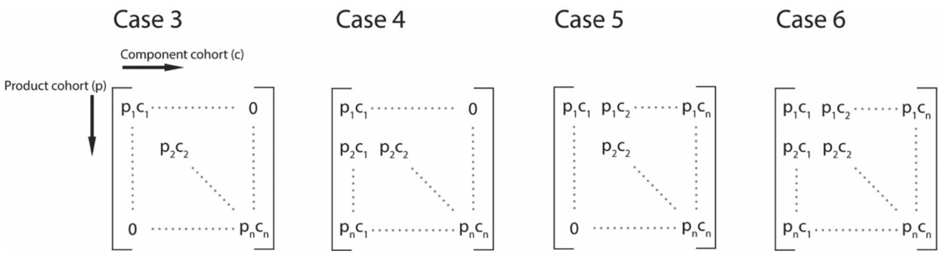

FIGURE 3 Cohort composition of the product–component system for a given time $t = n$ for the different modeling approaches

2.2.2 | Using independent product and component hazard functions

Components may in some cases be a main cause for product obsolescence or contain relevant raw materials, which makes having a refined understanding of their dynamics a pertinent issue. Cases 3, 4, 5, and 6 provide suitable frameworks for this, where the choice of the component hazard function relates closely to the technical aspects limiting its durability, while the product hazard function must also include externalities such as lifestyle choices and accidents relating to the product. This approach allows identifying the outflow of products relating to component and product independently, making it possible to identify strategies for product in-use time extensions and enabling frameworks to avoid planned obsolescence. The strategies for in-use time extension can be tested using the different models under various conditions for component reuse and replacement, which is relevant since for most products there is a market for spare parts, such as tires for vehicles or furniture for buildings. Furthermore, the right to repair is an increasing trend and is an important part of the recently released EU green deal (European Commission, 2019).

Case 3: Here, we introduce the use of component and product hazard functions to estimate the flows of both products and components, as they are considered non-replaceable or reusable. It is assumed that the failure of the component will lead to the obsolescence of the product and vice versa. The in-use time in this case is a composite function resulting from the product and the component hazard functions. The detailed mathematical approach for modeling dual hazard functions and avoiding double-counting issues is described in the documentation of the algorithm. The in-use time of the product and the component, and hence their respective in- and outflows, are equal.

Case 4: Some components might in fact have longer lifetimes than their products and can be reused to build new products once the original one has become obsolete. The separation of product and component flows through the use of independent hazard functions allows the modeler to identify the share of outflows attributed to discarded products that still contain potentially useful components. In a first approximation, we introduce the assumption that a given share of those components is still suitable for further use and can be re-introduced into another new product.

Case 5: This case allows investigating the dynamics of replacing an obsolete component with a new one. Only products that have failed components are considered for a replacement, that is, the outflows related to the component hazard function, so as to not replace the component in an obsolete product. The share of functioning products with failed components that receives a replacement is determined using a component replacement rate.

Case 6: Independent product and component hazard functions are used. Component reuse in addition to component replacements in products already in use is included in this approach. To achieve this, we combine the logics used in cases 4 and 5 to model on the one hand the number of components that can be reused and the number of products that need component replacements. In the case where reused components are not enough to satisfy the demand for replacements, new components are used instead. If too many components are available, then the newest ones will be prioritized, since they are assumed to be in a better state of health.

Figure 3 illustrates the cohort composition of a product–component system for a given time t, where $t = n$ for t in $[t_0, n]$. It can be seen that in case 3, the product and component cohorts are identical, while in case 4 new products may contain older components due to the introduction of replacements with used components. Case 5 shows that older products may contain new components due to replacements, and case 6 combines all these options into a square matrix where a product may contain newer components and where older components may be contained in new products.

2.2.3 | Using inflow/outflow (birth/death) rates

Some goods that exhibit no statistical relationship between their age and the time of outflow or where a share of the total amount is discarded/added every time step independently of age may be better described using rates as drivers. It can be done by introducing product inflow or outflow rates (case 7) and component replacements can be included by using case 8. An important additional shortcoming when using rates instead of lifetimes is the lack of consideration of the cohort composition of the stock and the outflows, as they are calculated as a given share of the total stock. Rates might therefore be better suited for goods that do not have a changing composition over time or for species population investigations where the cohorts are irrelevant.

Since the inflow/outflow rates are linked to the component, in the absence of an additional correction factor, this would assume that no outflows relate to potential product failures, such as accidents. Therefore, the addition of a death rate for the product is considered to address this point.

Case 7: The lifetime approach is fully substituted by calculating the inflows and outflows with birth or death rates, the latter often being referred to as leaching approach (Lauinger et al., 2021). We introduce two cases denominated 7a where a death rate is used as a driver and 7b where a birth rate is used.

Case 8: As an extension to case 7, here we consider no lifetimes and base the flows on either birth or death rates and allow for the component to be replaced at a given rate, which is defined in analogy to case 2.

2.2.4 | Using a component hazard function

In some cases, the dynamics of the components can be considered to be the main limiting factor for the product, e.g. electronical equipment in satellites. Such cases can be approached using cases 9 to 12.

Case 9: Some products might become obsolete if their component fails. Assuming then that the in-use time of the product is mostly determined by the component function, in case 9 the component function is the main driver for the product-component system.

Case 10: Adding complexity to case 9, case 10 depicts a similar situation with the component function being the main cause for outflows but allows for component reuse. Since the component outflows generated by the component's function are by definition obsolete, we assume that none of these components can be reused. However, since the death rate is related to product failures, we define a component reuse rate which determines the share of components that can be reused from failed products.

Case 11: This case illustrates the dynamics of a product whose' component can endlessly be replaced by a new one until the product itself becomes obsolete by a death rate. This could be useful for applications where the component is not critical for the product's in-use time and the product is not the main subject of study, since the cohorts of the same cannot be tracked. Potential examples could be e.g. windows in buildings where the windows are modeled with a given component function and the buildings' dynamics are dictated by a demolition rate. The building would get new windows every time they become obsolete until the building is ultimately demolished.

Case 12: Finally, case 12 can be used as a combined lifetime and leaching approach as described above in analogy to case 11 with further conditions that component reuse and replacements are accounted for using rates.

2.3 | Applicability of the framework

The proposed framework provides greater flexibility in modeling product–component interactions and provides an overview of the modeling considerations that should be taken for product–component systems. The use of independent product and component functions to model their combined dynamics allows a detailed investigation of the consequences of component reuse and replacement strategies. Furthermore, by isolating the cases where obsolescence of the product is caused by the component, different types of data, such as technical specifications, can be used to approximate the hazard functions of new product–component systems where empirical data are unavailable. This might lead to an inflated focus on technical facts, at the expense of more abstract issues, such as consumer behavior and the economics of EOL (Binder, 2007). Therefore, model results should be carefully interpreted and factors external to the measurable causes of obsolescence should be given thorough consideration. The product–component interactions for one component can be addressed using the proposed framework. When several different components are considered, more complex cases can arise, which would require more complex models.

The product_component_model.py library is available to modelers to compute the dynamics of a system for all 12 cases and documentation is provided to facilitate the use.

3 | CASE STUDY: ELECTRIC VEHICLES AND LITHIUM-ION BATTERIES

3.1 | Introduction

The transition toward electric mobility has been a topic of intensive research in recent years due to the quickly growing electric vehicle (EV) production and ever more ambitious national and international targets for electrification (Craglia & Cullen, 2020; IEA, 2021; Xu et al., 2021). This

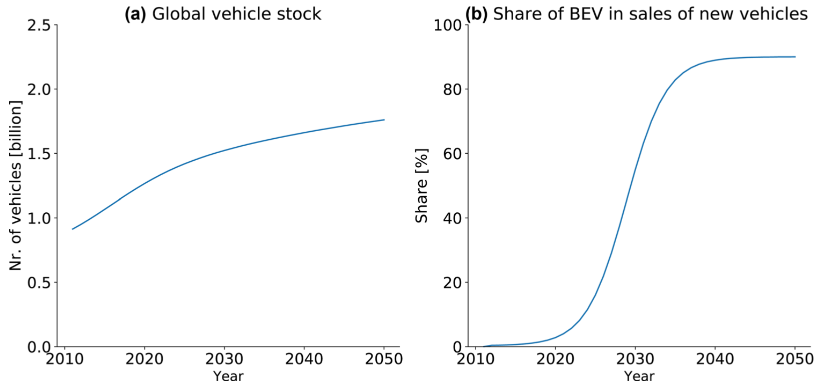

FIGURE 4 Main drivers of the model. Left: The global vehicle stock according to the baseline logistic growth scenario. Right: BEV penetration in the sales according to IEA Net Zero scenario. Underlying data for this figure can be found in Supporting Information S2, file tab "data_for_figure_4_in_manuscript"

shift toward electrification using predominantly lithium-ion batteries (LIBs) results in fundamental changes in the energy demand, resource use, and infrastructure needs globally. From technology metals and rare earths in the LIBs to aluminum for light weighing in the EVs, it is crucial to understand the material needs for both EVs and LIBs as well as options for reuse and recycling (Olivetti et al., 2017).

Given that there are valuable raw materials in both EVs and LIBs and considering that the limitations within the batteries might affect the longevity of the vehicles, EV–LIB dynamics presents a relevant case of product–component interactions where understanding the coupled dynamics is of policy, environmental, and industrial relevance. Moreover, the lack of empirical data on the obsolescence of those goods outlines the need for novel approaches to investigate the dynamics of this system.

We apply the product–component framework presented above to explore the effects of different EOL conditions and strategies on resource use.

3.2 | Methodology

The total stock is calibrated using historical data of registered passenger vehicles from OICA and UN population statistics (International Organization for Motor Vehicles Manufacturers, 201533AD; United Nations Department of Economic and Social Affairs, 2019). From these values, the historical vehicle ownership per capita is derived, which is used to create baseline projections following current trends. The vehicle ownership per capita is multiplied with the baseline UN population projections for 2010–2050 to obtain the total vehicle fleet for that period (see Section 5 in Supporting Information S1).

The global EV fleet (Figure 4a) is calculated using a logistic regression for the share of BEV in sales of new vehicles (Figure 4b) based on the International Energy Agency Net Zero by 2050 report (IEA, 2021). Using cases 3, 5, and 6 as presented above, we calculate the related inflows and outflows under different EOL conditions by defining several scenarios.

Scenario 1 describes a baseline under the current conditions where battery reuse and replacements are not common practice using the modeling approach described in case 3. LIBs are covered by a warranty of 8–10 years (IEA, 2020; Hossain et al., 2019; Tsiropoulos et al., 2018; Vikström et al., 2013); we assume that this is a conservative estimation for the lifetime because manufacturers try reducing liability. We therefore define the component hazard function using a normally distributed curve with a mean of 12 years and a standard deviation of 4 years. Given that EVs have significantly fewer moving parts than conventional vehicles and lack the main part causing ICE EOL—the engine—we assume a comparatively longer lifetime of 18 years with a standard deviation of 4 years (Jung et al., 2018; Oguchi & Fuse, 2015; IEA, 2019). This value is intended to reflect technical aspects as well as accidents and lifestyle choices of the vehicle owners.

Scenario 2 is defined to investigate the role of battery replacements strategies. We use the modeling approach described in case 5. This allows us to model the EV and LIBs flows if a share of faulty batteries can be replaced by new batteries, thus avoiding the early obsolescence of the vehicle. Furthermore, with this approach we show the change in EV and LIB demand depending on how widespread the practice of battery replacement becomes. To illustrate this, we compare the results of introducing a 30% replacement rate to an 80% replacement rate.

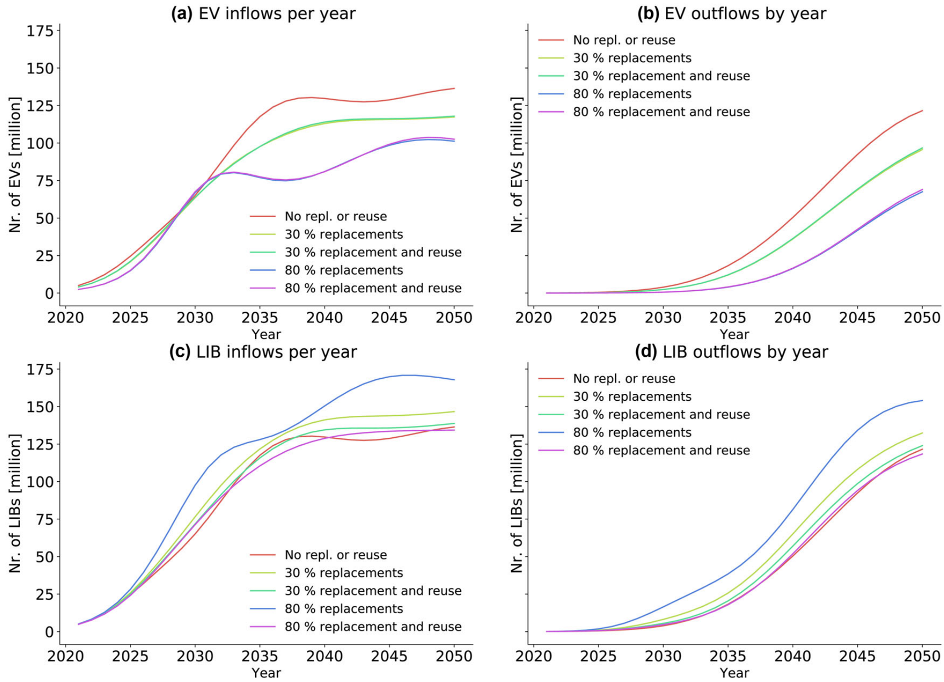

FIGURE 5 (a) EV inflows for the various scenarios, (b) EV outflows for the various scenarios, (c) LIB inflows for the different scenarios, (d) LIB outflows for the different scenarios. Underlying data for this figure can be found in Supporting Information S2, file tab "data_for_figure_5_in_manuscript"

Scenario 3 addresses another intervention that could re-shape the use of LIBs: The reuse of batteries from vehicles that were decommissioned due to car failures such as crashes, but that are still in a good state of health. These batteries could be used for battery replacements in vehicles that are already in the fleet, provided they are in good state of health. We use the methods described in case 6 to calculate the mass flows with a 30% reuse and replacement rate and an 80% reuse and replacement rate.

3.3 | Results

Figures 5a and 5c show the demand for EVs and LIBs for the different modeling assumptions, respectively. It can be seen that the highest EV demand corresponds to scenario 1 in which no replacements or reuse are considered and is simultaneously the case with one of the lowest LIB demands.

After introducing battery replacements, the demand for EVs and LIBs shows that while the LIB demand is increased compared to findings without replacements, the EV demand is reduced. This highlights the fact that the batteries can severely limit the vehicle lifetime, which in turn has significant consequences for resource use. This effect is stronger, the higher the replacement rates (see yellow and blue curves).

Finally, introducing reuse in combination with replacements shows that while this strategy does not seem to have a significant impact on the demand for EVs as compared to the scenario with only replacements, the demand for LIBs is significantly reduced to levels comparable to the findings without replacements. This highlights the synergistic effects that a combined replacement and reuse strategy has on minimizing the resource use of both EVs and LIBs. If the replacement and reuse practices are increased from 30% to 80%, the LIB demand is not affected in a significant way, but the EV demand is further reduced as can be seen in Figure 5a. The non-sensitivity of the LIB flows to these parameters is caused by the large difference between product and component lifetimes, where one EV can in most cases accommodate the use of two new LIBs throughout its lifetime and therefore the outflowing LIBs are in poor state of health and unsuitable for reuse in the fleet. Figure 5b,d shows the corresponding outflows to each modeling case and the survival curves of the first cohort for each case can be found in Section 5 in Supporting Information S1.

3.4 | Discussion

Using the novel methodologies proposed in this paper, an improved understanding of product–component interactions has been presented. Electric vehicles are new products for which empirical data on obsolescence is limited. However, the use of product and component hazard functions allows estimating the in-use time of EVs and LIBs using technical data under different EOL conditions. This results in more robust estimations on resource use and allows the investigation of key circular economy strategies such as repair and reuse of components.

3.4.1 | The role of battery replacement

Since EVs have significantly fewer moving parts, their technical lifetime could be expected to exceed that of an internal combustion engine vehicle, LIB limitations aside. The results show that implementing widespread battery replacements can trigger an effective in-use time extension for the vehicles, which leads to a significant reduction in vehicle, and thus raw material, demand. However, if this strategy is not combined with a widespread battery reuse strategy, it might result in an increased demand for batteries.

Extending the requirements for the duration of battery warranty may be an incentive for manufacturers to extend battery lifetime or to facilitate replacements and repairs. Additionally, informing customers about expected lifetime and repair options could orient purchasing decisions toward more durable goods, and eventually improve the design standards of the industry.[1] Standardization of parts can help the ease of repair and reduce costs, although it might be challenging to achieve given the high competitiveness and quick development of the industry. Furthermore, the risk of planned obsolescence of vehicles by means of limiting battery lifetime and replacements can be reduced by these practices.

Research suggests that durability is preferred in leasing business models (Pangburn & Stavrulaki, 2014), but only if take-back costs of the battery are sufficiently low (Zhu et al., 2021). Therefore, stringent regulations or customer demand for battery replacements may encourage manufacturers to develop new business models such as leasing, where they retain ownership of the batteries and sell a service instead of a product.

3.4.2 | Cost of battery replacement vs. residual value of the vehicle

At present, new battery costs are prohibitively high for battery replacements to be widely adopted, apart from cases where they are covered by warranty. Therefore, as has been shown in scenario 1, consumers might be incentivized to discard their vehicles once the battery fails, even if the vehicle itself would in theory still be in good. This could be addressed by policymakers through the introduction of subsidies or incentives targeted to the batteries themselves instead of only incentivizing EVs. For instance, in Norway, EVs benefit from VAT exemptions, but LIBs do not (Thorne et al., 2021), often rendering the residual value of the vehicle to be lower than the cost of a new battery. This results in an early outflow of the vehicle and can be relatively easily avoided by encouraging car owners to replace their batteries rather than discarding both vehicles and batteries, as presented in scenarios 2 and 3.

3.4.3 | The role of battery reuse

Scenario 3 showed that a widespread adoption of battery reuse could lead to a beneficial synergy with the battery replacement practice that helps reduce the demand for both EVs and batteries. The demand for batteries when reuse is implemented is lowered significantly compared to when only replacements are introduced, and even more compared to when none of these practices are used, as shown in scenario 1. Some challenges may arise regarding the responsibility in case of failure of second-hand batteries in EVs, due to the limited transparency about the state of health of second-hand batteries and the lack of standardized processes for manufacturers and insurance companies. A reliable assessment of the state of health of the battery, clear responsibility guidelines, and a resilient reverse logistics system need to be designed to enable replacements with used batteries.

4 | CONCLUSION

In the transition to a sustainable society, key circular economy strategies include reuse and lifetime extension of products and components. In order to understand the intended and unintended consequences of such strategies, it is essential to adequately represent the dynamics of product–component interactions in MFA models. This is relevant for both policymakers to better understand the impact of interventions and for industry stakeholders to plan their infrastructure to not only meet the demand but also to deal with EOL goods.

The product–component framework proposed in this manuscript expands on current practices for dynamic modeling by differentiating alternative approaches to mode product–component relationships. It provides an overview of alternative approaches and a guide for the user in selecting the approach best suitable for the specific conditions. The product–component framework is made fully available to researchers in generic code that can be further refined for specific cases. Building on these methods, researchers can contribute to deepen the knowledge base for policymakers and industry stakeholders by investigating key circular economy strategies, such as repair and reuse, using more refined and sound approaches that consider the interlinked dynamics of product–component systems.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Data openly available in a public repository that issues datasets with DOIs; see https://github.com/fernaag/product_component_model.

ORCID

Fernando Aguilar Lopez https://orcid.org/0000-0002-4759-6708
Romain G. Billy https://orcid.org/0000-0002-4693-2722
Daniel B. Müller https://orcid.org/0000-0001-7747-9011

[1] The UN has recently expressed the importance of this aspect; the statement can be found in the downloads here: https://unece.org/transport/documents/2021/03/working-documents/iwg-eve-proposal-new-un-gtr-vehicle-battery

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SUPPORTING INFORMATION

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

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3.2. Evaluating strategies for managing resource use in lithium-ion batteries for electric vehicles using the global MATILDA model

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Evaluating strategies for managing resource use in lithium-ion batteries for electric vehicles using the global MATILDA model

Fernando Aguilar Lopez *, Romain G. Billy, Daniel B. Müller

Department of Energy and Process Engineering, Norwegian University of Science and Technology, Trondheim, Norway

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ABSTRACT

The exponential increase in lithium-ion battery (LIB) demand for electric vehicles (EVs) has sparked material supply concerns, which makes the understanding of the LIB system and its drivers a pertinent issue. To understand the uncertainty and sensitivity around these drivers, we introduce the MATerIaL Demand and Availability (MATILDA) model. We investigate resource use within the global LIB cycle in the context of EVs and the potential secondary material supply generated by alternative scenarios. Using this dynamic, multi-layer material flow analysis model, we conducted a detailed, time-explicit sensitivity analysis to broaden our understanding of the critical factors affecting resource supply. We identified potential problem shifts between Co, P, Ni, and Li and evaluated alternative strategies to mitigate their criticality over time. We show that social paradigm shifts such as using fewer, smaller vehicles as well as technological developments can play an important role in enabling a sustainable transition.

1. Introduction

Global warming has increasingly become a topic of research, policy, and societal relevance as nations intensify their efforts to reduce their greenhouse gas (GHG) emissions (Bárcena et al., 2018; IPCC, 2020). The transport sector currently accounts for about 15 % of GHG emissions, from which more than 70 % come from road transport, and is also a significant source of air pollution (Cepeda et al., 2017; IPCC, 2022; Lamb et al., 2021). Therefore, efforts to decarbonize this sector are of key relevance to the sustainable development of society.

Most global scenarios and governmental targets for the decarbonization of the transport sector consider battery electric vehicles (BEVs) as the main part of the solution (IEA, 2021; International Energy Agency, 2019; IPCC, 2022). These developments in the transport sector deeply change material use; from petrol for propulsion to technology metals for energy storage. This can imply a number of consequences, including shifting CO2 emissions to the material production sector (Andersson and Råde, 2001; Bonsu, 2020; Busch et al., 2014; Coffin and Horowitz, 2018; Olivetti et al., 2017) and a need for rapid expansion for material production capacity, particularly of primary materials (Xu et al., 2020). The wide array of battery chemistries used in lithium-ion batteries (LIBs) introduces a high uncertainty related to the materials needed. This results in high risks for large investments into mining and processing facilities (Usai et al., 2022), exacerbating the challenge of potentially insufficient capacity expansion.

To mitigate potential material supply bottlenecks, it is crucial to understand the demand for individual minerals, as well as the potential for recycling, new supply routes, and material substitution options. The circularity of various battery materials under several EV penetration scenarios was estimated by Dunn et al. (2021), but their inflow-driven model is not considering the size of the in-use stock needed to satisfy future transport needs, which limits its robustness for long-term analysis. Other studies have been focusing on selected materials: for instance, Usai et al. (2022) linked the future demand for Co, Li, and graphite to the different Shared Socioeconomic Pathways (O'Neill et al., 2014). Schmidt et al. (2016) described the supply routes of Co and Ni in detail, while Baars et al. (2020) and Zeng et al. (2022) demonstrated how circular economy strategies like technological substitution, more efficient recycling, and battery technology development are useful to reduce the reliance on these two metals. More generally, Pauliuk et al. (2021) have shown that material efficiency meassures like vehicle downsizing, lifetime extension, and car-sharing can help reducing the material demand further. Xu et al. (2020) provided an estimation for the order of magnitude of the quantity of materials needed for the EV transition using a stock-driven material flow analysis (MFA), based on scenarios for the EV penetration, battery chemistry development, and

* Corresponding author.
E-mail address: fernando.a.lopez@ntnu.no (F. Aguilar Lopez).

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recycling technology. However, they did not investigate how the sensitivity of the material demand to a change in these drivers evolve over time and did not include other potentially important parameters, such as total vehicle stocks, vehicle lifetime, and reuse and replacement conditions. Furthermore, the potential substitution options of different battery materials and the subsequent reallocation of supply risks to other material value chains were not evaluated. Indeed, while previous studies have already considered the influence of a wide range of parameters on the future demand of selected materials, the number of combinations analysed remains limited and models often lack clear storylines that provide qualitative context to relevant factors leading to different outcomes.

The MATILDA model allows us to quantify the short- and long-term sensitivities to 9 parameters for the primary demand of 9 materials: lithium (Li), graphite (C), aluminium (Al), silicon (Si), phosphorus (P), manganese (Mn), cobalt (Co), nickel (Ni), and copper (Cu). Using dynamic stock-driven MFA (Baccini, 1996; Müller, 2006), we investigate potential problem shifts between materials and trade-offs of different strategies over time by assessing 3645 possible combinations. By exploring this solution space, we define 5 consistent qualitative storylines that provide a robust basis to explore their consequences of increased material demand on individual material cycles.

2. Methodology

2.1. System definition

Fig. 1 shows the system definition (upper box), quantified layers (lower box), and drivers (hexagons) used for this study. In this model we consider the global passenger vehicle fleet from 1950 to 2050, including options for battery reuse in stationary applications. The material demand associated with the electrification of the fleet is computed with a yearly resolution.. The simplicity of the system definition, leaving out manufacturing losses, scrap imports from other sectors, and so forth, is an intentional component of the design of this study that aims to provide robust high-level assumptions while retaining flexibility for further refinement according to the needs of individual studies.

The vehicle system is quantified for four layers, where the vehicle layer includes four different drive trains (see Fig. 1). We differentiate internal combustion engine vehicles (ICEs), battery electric vehicles (BEVs), plug-in-hybrid electric vehicles (PHEV), and other non-li-containing technologies such as fuel cell electric vehicles.

For BEVs and PHEV, three battery sizes of 33kWh, 66kWh, and 100kWh and 8kWh, 12kWh, 17khW respectively, and are defined for each battery chemistry as introduced by Xu et al. (2021). For each battery size, the weight distribution of three main components, modules, battery management system (BMS), and battery case are characterized.

Finally, the material composition of each part is used to calculate the total material requirements. The materials are tracked throughout the system and are assumed to be part of the batteries until the dismantling process before recycling (process 5 in Fig. 1). At this point, the materials are assumed to go through a recycling process, with material specific efficiencies. The recycled fraction is assumed to be fully reusable for new batteries: this implies that no degradation of the battery material takes place as a result of recycling and that no materials are exported to other industries. It is further assumed that all recovered materials are used to

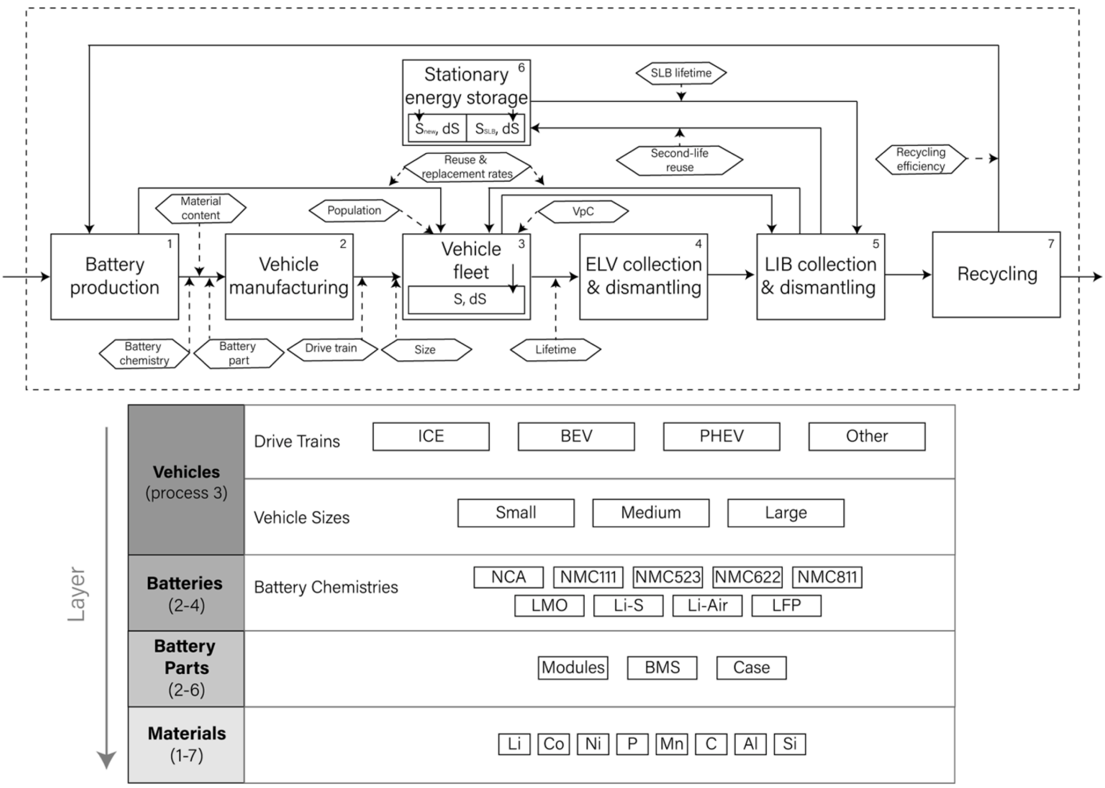

Fig. 1. System definition and parameters for the global LIB system. The hexagonal boxes represent the parameters used in the model. The numbers in parentheses for each layer reflect the processes for which the respective layer can be fully quantified and balanced for the same goods.

manufacture new batteries and that all batteries are collected for recycling after reaching end-of-life (EOL). This simplification is intentional to investigate the maximum possible potential that recycled materials have in the LIB industry.

To evaluate the maximum amount of materials that can be recovered from the battery industry, exchanges of scrap to and from other sectors are not considered as this would require the modelling of other industries and their trade flows. The results in this model thus reflect the material demand and recycling potential for the LIB industry alone.

2.2. Model development and calibration

Assuming that the demand for vehicles is driven by the societal need for transportation, we defined a stock-driven model as introduced by Müller et al. based on the population and vehicle ownership per capita (VpC) (Lauinger et al., 2021; Müller, 2006), see Appendix A.1 for details. The inflows and outflows of the system were calculated based on the lifetime definitions and the conditions for reuse and replacement of EVs and batteries (see Appendix A.2 for a mathematical description). The drive train split was further applied as a share of sales, from which the stock composition was derived. To account for the fact that the vehicle and battery lifetimes may differ, we used a double-lifetime approach, which considers both the vehicle and the battery lifetimes to compute the system dynamics of EVs as described by Lopez et al. (2022).

For the stock dynamics calculations, we assumed a normally distributed lifetime of 16 years with 4 years standard deviation for the vehicles and a 12 year LIB lifetime with 5 years standard deviation based on available lifetime estimations and warranties (Bobba et al., 2019; Hao et al., 2019). Internal combustion engine vehicle and other drive train dynamics are only determined by the vehicle lifetime since the battery is not a limitation for them. For the options with battery reuse and replacement, a battery reuse rate and a replacement rate of 80% was considered as an explorative scenario. Using an adaptation of case 6 of the product-component framework (Lopez et al. (2022), Appendix A2), the potential for battery reuse and vehicles needing a replacement are identified based on their probability of failure, which allows to differentiate the outflows due to battery or vehicle failure separately. If more vehicles need a replacement battery than there are batteries available for reuse, a new battery is installed in those vehicles. Furthermore, the cohort of vehicles and batteries are matched as closely as possible, so that the newest vehicles receive the newest batteries and vice-versa.

The drive train split between BEV, PHEV, and other electric vehicles of the inflows is quantified by using the stated policies, Sustainable Development, and Zero Emissions scenarios from the International Energy Agency (IEA) (IEA, 2021; International Energy Agency, 2019) (see Appendix A.3). We used the vehicle and battery size definitions as presented by Xu et al. (2021). They reflect three different battery sizes as described above and represent vehicles of low-, mid-, and long range (see Appendix A.4). The share of the battery size alternatives are assumed to be constant shares over the entire period as a baseline.

Since the battery technology used is highly relevant to the materials required, we considered five options for the battery chemistry development (see Appendix A.5). They include the NCX and LFP scenarios presented in Xu et al. as well as scenarios by BNEF, and self-defined scenarios that combine literature work with possible future developments (Alves Dias et al., 2018; BNEF, 2021; Xu et al., 2021).

We computed the total materials in the system using data for the weight of the battery modules, pack, and battery management system (BMS) and their material composition from the BatPac model (Ahmed et al., 2016). This material composition data were complemented with data from Elwert et al. (2019) and Reuter et al. (2014) to estimate the phosphorus content in the LFP battery cathode (see Appendix A.6 and A.7).

We defined three reuse alternatives in which non-, all-, and only LFP batteries are reused: LFP batteries are widely considered to have a longer useful life for stationary applications and do not use any Co or Ni (see Appendix A.8), which makes them less attractive for recycling (Klimko et al., 2020; Träger et al., 2015). Furthermore, given that batteries are dismantled before reuse in stationary applications, we assumed that the BMS and the battery case are recycled even if the modules are reused (Harper et al., 2019; Hossain et al., 2019). The batteries are ultimately recycled in one of three alternative processes: pyrometallurgical, hydrometallurgical, and direct recycling with material specific efficiencies (see Appendix A.9).

2.3. Sensitivity analysis by parameter variation

We defined a baseline projection that was used as a benchmark for the sensitivity analysis. Comparing the impact of a change in one parameter on the demand for each material respective to the baseline is crucial to gain a deeper understanding of the effect each driver has on material use and to identify potential problem shifts.

Baseline projection: Moderate level of ambition towards electric mobility and moderate technological advancements. Many of the aspects around mobility and recycling remain at baseline values, resulting in a moderate vehicle fleet increase. Current trends towards Ni-oriented battery technology continue as projected by BNEF, and only LFP batteries are reused in order to recover the valuable metals such as Ni, Co, and Cu using pyrometallurgical technologies, which is the most widespread technology at the moment.

The change in material demand following a change in one specific parameter is investigated for the following parameters and assumptions summarized in Table 1.

Table 1
Parameter changes and corresponding descriptions used for the sensitivity analysis. (Two column fitting image).

Change in parameter	Description
Shift to LFP	Describes an increase from 15% LFP in the baseline to 60% by 2030, remaining at this value until 2050. The remaining chemistries are NCM batteries with different Ni, Co, and Mn concentrations (see Fig. 8 in Appendix A.5).
Shift to high Ni chemistries	Represents a gradual but significant change in NCM chemistries to high -Ni containing chemistries, where NCM955 and NCM811 account for 50% of the battery sales by 2050, NCA for 30%, and the rest is covered by other variations of NCM and LFP batteries (see Fig. 8 in Appendix A.5).
Shift to Li-Air and Li-S	Starting in 2030 new technologies are introduced to the LIB market and Li-Air and Li-Sulfur reach a share of 30% respectively by 2040. The rest is covered by a mix of NCM, NCA, and to a smaller degree LFP according to the baseline BNEF scenario (see Fig. 8 in Appendix A.5).
Fleet growth reduction	Indicates a slower increase in vehicle ownership, leading to about 25% less vehicles in the total fleet by 2050 compared to the baseline stock (see Fig. 5 in Appendix A.1).
Faster electrification	Represents a change from the moderate (SD) EV penetration scenario to a more ambitious, fast (Net Zero) scenario where the total share of BEVs reaches 90% instead of 60% share of sales by 2050 (see Fig. 6 in Appendix A.3).
Smaller batteries	From 2030 onwards, there is a logistically increasing share of vehicles with 33kWh batteries, reaching 70% by 2050 compared to the constant 18% in the baseline (see Fig. 7 in Appendix A.4).
Longer LIB lifetime	Instead of 12 years, this alternative considers a 16 years lifetime for the batteries, which is equal to the vehicle lifetime.
Replacements	This case considers a battery reuse rate and replacement rate of 80% throughout the entire period (used as described in Appendix A.2).
Efficient recycling	Presents a shift from pyrometallurgical recycling technologies to direct recycling, where most of the materials can be recovered with >90% efficiency (see Appendix A.9).

2.4. Material requirement scenarios

Leveraging the findings in the sensitivity analysis, we propose a set of integrated scenarios that aim to characterize the range of uncertainty in material requirements for the electric vehicle transition.

Below we present the proposed qualitative narrative of the following Material Requirement Scenarios (MRS) derived from the MATILDA model. The storylines describe the broad context of each scenario and aim to be internally consistent to reflect the quantitative effects such pathway would have on the respective model parameters. Table 2 presents a summary of the parameter values chosen for each alternative storyline and its temporal development can be found in the appendix sections A1-A9.

EV-MRS 1, Slow transition: Raw material prices increase due to battery demand while the technology development and policy incentives remain slow. Battery manufacturers move towards LFP as a low-cost alternative to other chemistries and favour recycling over reuse in order to obtain recycled materials as soon as possible. Overall, there is a low ambition level towards accelerating the transition which leads to a slow EV penetration rate and no efforts to either reduce the fleet growth or battery size.

EV-MRS 2, Slow transition - technology oriented: Here we present a performance-driven EV penetration where EVs remain a niche product due to high raw material prices. High energy density technologies around Ni are preferred in affluent regions and there is a focus on recovering the related materials as soon as possible while extracting maximum value from LFP batteries by reusing them in a second life.

EV-MRS 3, Moderate transition - baseline: As described above.

EV-MRS 4, Fast transition – focus on electrification: This scenario illustrates the high demand bounds for material use in the case where a high EV penetration is pursued, without further systemic interventions. Vehicle ownership is assumed to keep increasing over time and a higher emphasis is given to more efficient recycling technologies to support the transition using hydrometallurgical processes. Additionally, there are significant investments in developing the battery technology towards Li-S and Li-Air chemistries after 2030. To extract maximum value out of the batteries, batteries from all chemistries are reused in a second life.

EV-MRS 5, Fast transition – diversified portfolio with resource efficiency: This scenario can be considered a resource efficient and fast transition, where policy emphasis is given to fast electrification of the fleet while considering other systemic factors. Slower total vehicle fleet growth, highly efficient recycling, smaller batteries, and lifetime extension strategies such as reuse and replacement in vehicles are a priority. However, in order to enable a fast EV penetration in less-affluent regions, there is still a considerable share of LFP batteries needed. As technology evolves, next generation technologies are expected to penetrate other markets.

3. Results

3.1. Sensitivity analysis (part 1): effect of main drivers on cumulative primary material demand

The first three columns of Table 3 show the change in material demand depending on the battery chemistry development. A shift to LFP batteries causes P, Cu, graphite, and Al demand to increase by 154%, 24%, 11%, and 24% respectively while Ni and Co demand is heavily alleviated by 50% and 34% accordingly. A direct trade-off can be observed between these groups of materials, as the primary demand for Ni, Co and especially Mn (+129%) would significantly increase with a shift to high Ni chemistries such as NMC and NCA. The higher Mn primary demand is due to the nature of the pyrometallurgical recycling process, where Ni and Co can be recovered at 75% efficiency, while Mn is assumed to be completely lost, leading to higher reliance of primary Mn (Pinegar et al., 1234b, 1234a). P, Cu, and Al demand is significantly reduced in this case (up to 90% for P), while graphite demand is only reduced by 3% as it is needed as an additive in the cathode to produce high-Ni containing chemistries. Graphite demand can only be reduced by moving into next generation technologies which result in a lower demand for all materials with the noteworthy exception of Li, which shows the highest sensitivity at +15% - an increase more than double higher than the one caused by using high Ni chemistries.

Valuable materials such as Co, Ni, and Cu are less sensitive to recycling efficiency improvements since they are already recovered at high efficiencies with a pyrometallurgical process (see appendix A.9.). Respectively, materials for which the recycling efficiency is heavily improved by direct recycling show the highest sensitivity to this parameter. Li, graphite, P, and Mn show a reduction of 16-41% while Ni, Co, and Cu are only reduced by 7-9%.

Material demand is highly sensitive to the speed of electrification. A shift from the Sustainable Development scenario to the Net Zero scenario, which are assumed to reach 60% and 90% LIB-based EV sales by 2050 respectively (see Appendix A.3.), results in an increase of 64-69% in raw material demand over the entire period.

Using fewer and smaller vehicles show important potential to reduce overall material demand. Lifetime extension strategies through behavioral changes, such as replacing faulty batteries, and reusing healthy ones in other vehicles can reduce the need for all primary materials. Similarly, lifetime extension through technological improvements show further opportunities for material demand reduction, with a marginal increase in demand for metals recovered at high efficiencies. Less efficiency in recycling is translated in a higher relevance of lifetime extension through reuse and replacements to reduce material demand.

3.2. Sensitivity analysis (part 2): effect of main drivers over time

Each subplot in Fig. 2 relates the change in material demand as a response to a change in a given parameter. Figs. 2a, b, and c, reflect a change in battery chemistry in different scenarios. The discontinuities observed around the year 2030 are related to the changes in battery chemistry, which stabilize somewhat abruptly at this time (compare Fig. 8 in the Appendix A.5). As suggested by Table 1, problem shifts occur across different materials depending on the dominant battery chemistry. A shift to LFP (Fig. 2a) could have an immediate and gradual effect on reducing Mn, Ni, and Co demand, while increasing particularly P demand. As expected, a trend towards high Ni-containing chemistries has the opposite effect, increasing particularly Mn to close to a yearly 160% of baseline projections by 2030.

Figs. 2d and 2g show that the size of the vehicle fleet and batteries respectively have important potential to reduce primary material demand. This intervention is shown here to become relevant around 2035, but in theory, this point could come immediately if smaller vehicles gain

Table 2
Overview of the parameter choice for each scenario. (Two column fitting image).

Scenario	Vehicle stock	EV penetration	Chemistry development	Second-life	Reuse & repl.	Vehicle size	Recycling
MRS1	Medium	Slow (STEP)	High LFP	No	No	Baseline	Pyromet.
MRS2	Medium	Slow (STEP)	High Ni	LFP only	No	Shift to large	Pyromet.
MRS3	Medium	Medium (SD)	BNEF	LFP only	No	Baseline	Pyromet.
MRS4	High	Fast (Net Zero)	BNEF and Li-S, Li-Air	All	No	Baseline	Hydromet.
MRS5	Low	Fast (Net Zero)	BNEF with more LFP and Li-S, Li-Air	LFP only	Yes	Shift to small	Direct

Table 3
Change in primary material demand compared to the baseline for each material aggregated from 2010 to 2050. A negative value indicates a reduction compared to the baseline and a positive value indicates an increase.

Element	Shift to LFP	Shift to high Ni chemistries	Shift to Li-Air and Li-S	Fleet growth reduction	Faster electrification	Smaller batteries	Longer LIB lifetime	Replacements and reuse	Efficient recycling
Li	-1%	6%	15%	-26%	68%	-19%	-7%	-17%	-32%
Graphite	11%	-3%	-48%	-26%	68%	-19%	-7%	-18%	-30%
Al	24%	-12%	6%	-26%	64%	-17%	-7%	-18%	-31%
Si	4%	-5%	-23%	-26%	66%	-18%	-7%	-17%	-36%
P	154%	-90%	-48%	-26%	69%	-20%	-7%	-17%	-16%
Mn	-3%	129%	-45%	-25%	65%	-18%	-7%	-16%	-41%
Co	-34%	60%	-55%	-28%	68%	-25%	2%	-6%	-9%
Ni	-50%	22%	-48%	-28%	69%	-25%	2%	-6%	-9%
Cu	24%	-12%	-27%	-28%	66%	-23%	1%	-8%	-7%

momentum.

From Fig. 2e, it becomes clear that more efficient recycling does not play a significant role in reducing primary material demand in the next decade. This is in line with recent findings by Zheng et al. (Zeng et al., 2022) and Nurdiawati and Agrawal (2022) who found that no significant flows of EOL batteries can be expected in the near future. However, around 2035 recycling starts to become gradually more important in reducing reliance on primary raw materials in the long term. Materials which have the potential to be recovered more efficiently show a higher sensitivity over time here too, pointing towards the importance of recycling of all materials beyond the economically more viable such as Ni, Co, and Cu .

An increase in the pace of electrification (Fig. 2f) will invariably increase pressure on all primary raw materials within the next decade, potentially more than doubling annual demand until 2035. The sharp, early peak in material demand results in many spent batteries becoming available after 2035. Combined with the saturation of the EV penetration in the sales, this leads to a sharp reduction in primary material demand towards 2040 compared to the peak.

Finally, an increase in vehicle lifetime (Fig. 2j) could have a reduction effect in material demand of around 10% for all materials which are predominantly lost in current recycling processes. The benefits of lifetime extension (Fig. 2h) are also only significantly perceived after around 2030 due to the long lifetime of vehicles. The benefits of useful life extension through reuse and recycling seem to be greater (up to 25% in 2050) than what can be achieved by extending the battery lifetime without improving the end-of-life management strategies. This can be explained by the fact that without reuse, many batteries that are technically fit for reuse in vehicles are scrapped because the vehicles they reside in have been discarded.

3.3. *Scenario analysis*

Fig. 3 shows the primary material demand for all combinations of the model parameters. The clustering according to EV penetration scenario (colour) in the early years suggests that this parameter plays the determining role in material demand until 2030. After that, other parameters start playing a more important role, as reflected by the crossing of the initial EV penetration scenario colour clusters. The density of the line can be interpreted to be an indication of the likelihood or frequency for a given material demand.

The thick lines relate to the storylines defined above and their colours indicate their relation to the EV penetration scenario. For most materials, the range of the demand is captured by the storylines, with the exception of Ni, Co, Mn, and to a lesser extent P. To reach the upper bounds of the demand for these materials, a set of pessimistic assumptions that are not considered to be realistic would need to be explored. The estimations on current production represented by the black star are taken from [1] US Geological Survey (2022) and [2] British Geological Survey (2020). Fig. 9 in the Appendix A.10. shows the corresponding recovered materials for each combination and the five scenarios analysed.

The grey boxes reflect the statistical distribution of all scenarios and show that while the spread of scenarios is rather wide, most of them are concentrated in a significantly smaller area. Values presented in previous literature are in line with the findings and often fall within the interquartile range shown in Fig. 3 (Dunn et al., 2021; Pauliuk et al., 2021; Usai et al., 2022; Xu et al., 2020).

4. Discussion

4.1. *Reflections on the system drivers and the way forward*

The choice of battery chemistry has been shown to have the largest impact on demand of certain materials, while increasing pressure on others. Notable exceptions are Li and Al, which are present in all chemistries. For all other materials, an approach that relies on a wider portfolio of technologies to diversify the supply risk amongst different materials could contribute to mitigating a supply bottleneck (see MRS5). Such an approach would require co-ordinated long-term planning by the industry and should possibly include non-LIB alternatives. This is particularly relevant considering that the technology that seems to have the lowest risk of supply disruption at time t might become critical later on if the industry collectively shifts towards it. In 2021, many manufacturers including VW, Volvo, and Tesla stated their intentions of adopting LFP as a low-cost alternative to cobalt. The resulting pressure shift to phosphorus might be an indication of such collective shift; there is no silver bullet for the battery chemistry to mitigate supply bottlenecks.

A fast electrification of the fleet puts pressure on raw materials in the next 15 years, meaning that policies to incentivize EV adoption should be accompanied with strategies to ensure the equivalent increase in primary material production. Recycling as a tool to reduce primary raw material demand only becomes significant from 2035 to 2050. Improving the recyclability of P, C, Li, Si, Al, is particularly relevant as their recovery is currently not considered to be financially viable but may reduce the risk of supply shortages in the longer term. We showed that a slower EV penetration can delay and reduce the reliance on

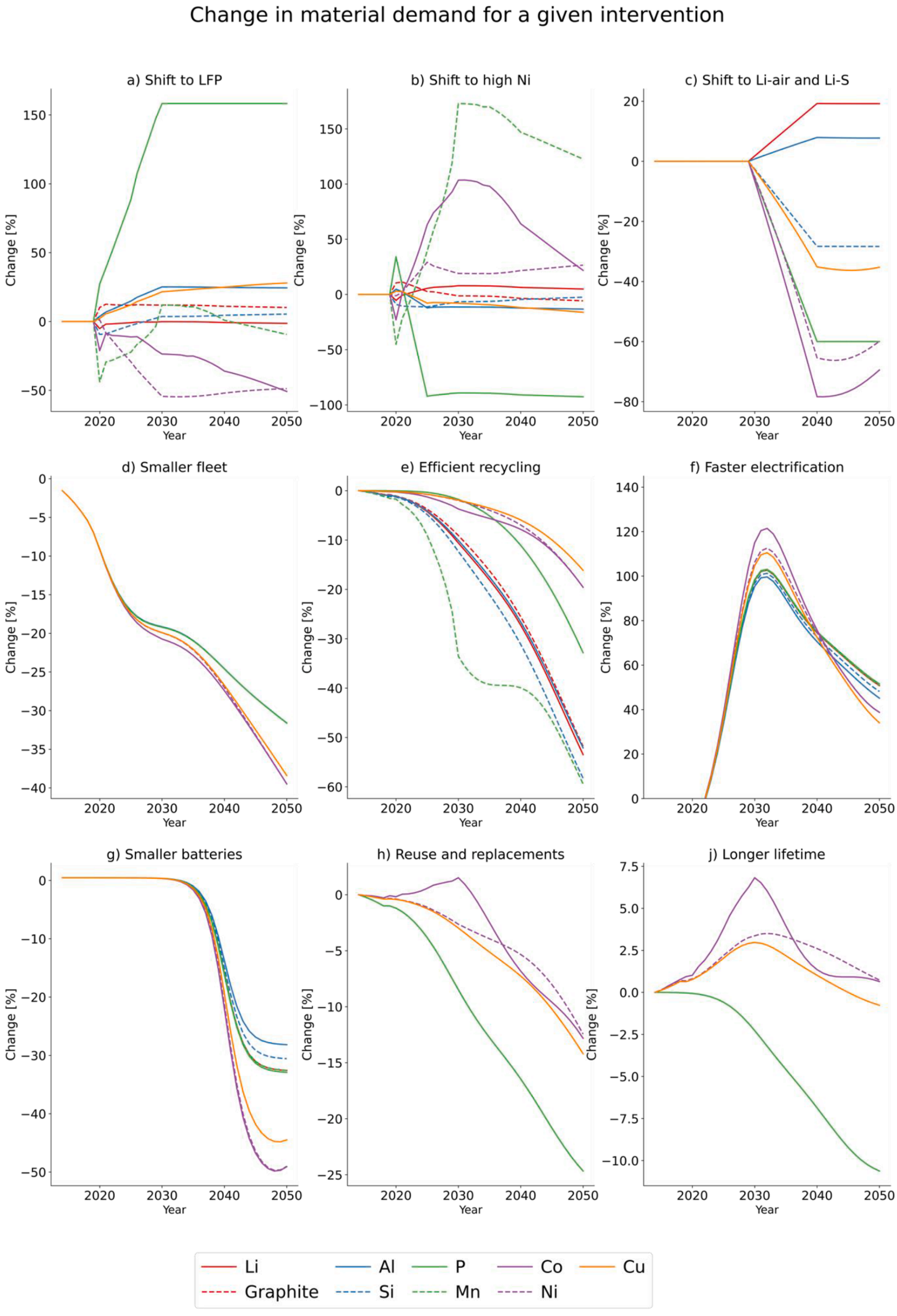

Fig. 2. Percentage change in material demand for different interventions compared to the baseline for all materials over time.

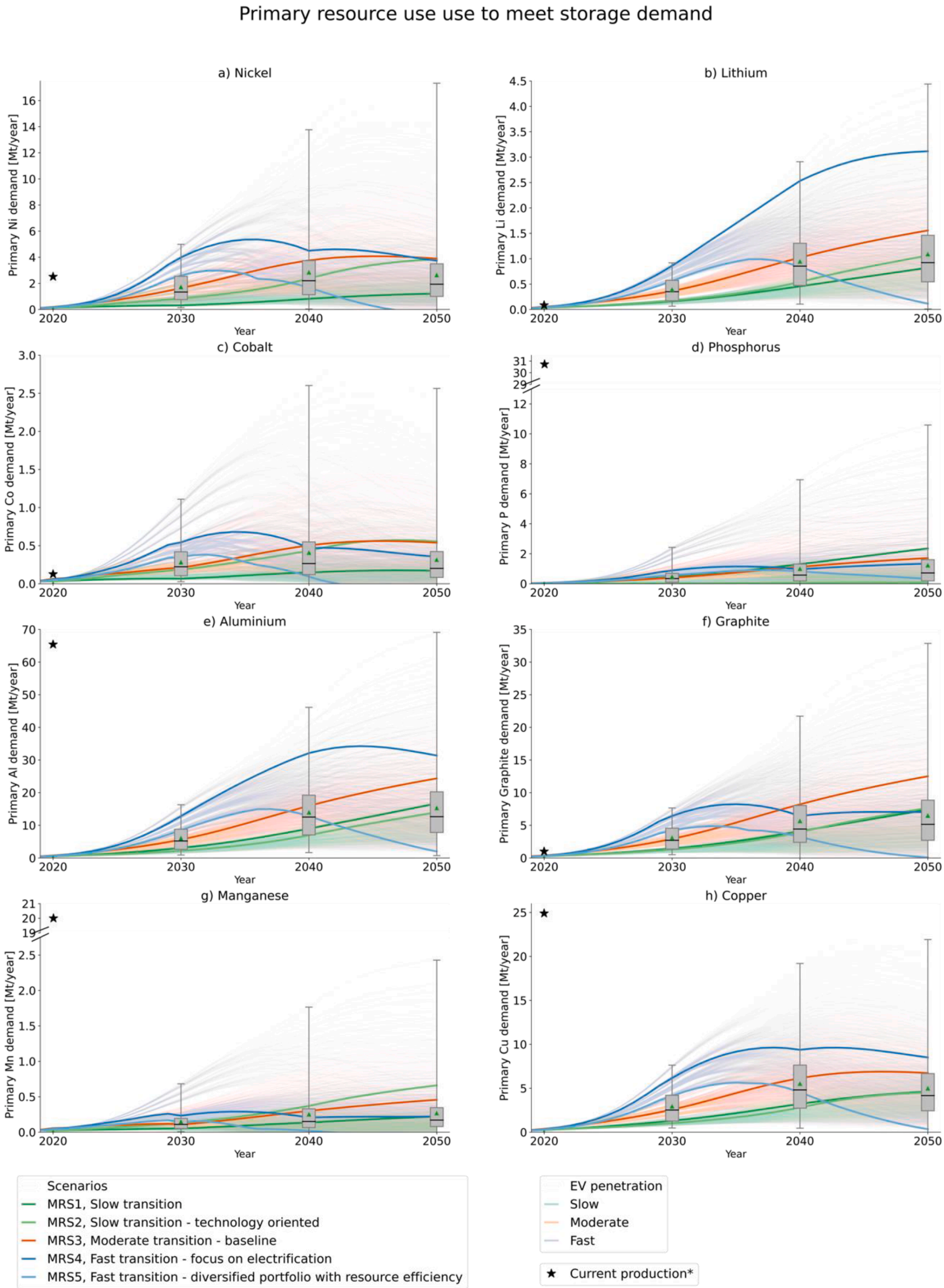

Fig. 3. Analysis of all combinations. The thick lines represent the scenarios presented above and the thin lines represent all possible combinations of the parameter values. The grey boxes show the statistical distribution of all scenarios, the mean (green triangle), median (black line), and inter quartile range.

primary raw materials but would lead to longer periods of time where primary materials are needed, as recycled materials do not become available in sufficient quantities until after 2050. Moreover, such a pathway would rely on oil for vehicle propulsion or on alternative technologies to achieve higher electrification rates such as sodium-ion batteries or fuel-cell vehicles. The material supply risks are even more pressing if the electrification of other sectors such as heavy-duty transport and stationary storage are considered, and further investigation is therefore needed. Furthermore, in this model a perfect substitution of primary materials by recycled materials is assumed, which has been shown to not always be the case if price dynamics are considered (Ryter et al., 2022).

The sensitivity analysis showed that social and policy changes can generate synergistic results that reduce the overall material demand. Policies that minimize the need for vehicles or promote the use of smaller batteries could generate significant reductions in material demand, but the resulting limitations in car ownership, vehicle size, or driving range may require re-thinking the societal services currently expected from vehicles. Conversely, focusing on extending the useful lifetime of cars and batteries has a high potential to reduce primary material demand without requiring strong behavioural changes.

The average battery lifetime can be increased through technological improvements or by facilitating repairs and access to spare parts. Furthermore, efficient management of end-of-life batteries to enable their replacement and/or reuse within vehicles can help to avoid an early obsolescence of the vehicle-battery system and maximize the use of already produced resources (Aguilar Lopez et al., 2022). However, widespread adoption of replacements and reuse is made challenging by current regulations and practices regarding insurance and producers' responsibility: building a suitable legal framework for these circular economy strategies should be a priority to reduce the material supply risks associated with the EV transition.

The MRS5 shows that a diversified portfolio towards electrification and leveraging resource efficiency strategies can lead to a fast decarbonization of the transport sector consuming considerably less materials than without relevant interventions (as in MRS4). Such scenario even becomes almost independent from primary materials by 2050 but relies on an array of policy and technological advancements while still requiring a significant amount of primary materials in the next 15 years. The MRS2 and MRS3 also show that without long-term, systemic interventions, a slower EVs penetration (60% by 2050) could consume more primary materials after 2040 than a fully electrified fleet. However, these two trajectories and the MRS1 would have a more gradual increase in material requirements that mitigates the risk of material supply bottlenecks in the short term. These scenarios can serve as a basis for industry stakeholders, policymakers, and researchers to conduct further investigations in the infrastructure and potential challenges that could appear as a result of the increase in material demand.

4.2. Considerations for a sustainable material supply

The model results show that if a transition to electric mobility is to be achieved by making use of LIBs, an enormous increase in battery raw material demand can be expected. Li is the basis for this technology and the analysis shows that its demand is not very sensitive to the choice of battery chemistry since it is present in all types of LIBs. In fact, it was shown that the current ambitions towards next generation chemistries such as Li-Air and Li-S would not only fail to address concerns for Li supply shortages, but also put an increased pressure on Li, as it is required in higher quantities per kWh. Given the socio-environmental issues related to Li extraction and refining, an increasing concern that the production of Li is unable to meet the demand emerges (Lèbre et al., 2020; Petavratzi and Gunn, 2022). Further research into the limitations of Li supply is needed to evaluate the extent of this potential shortage.

Similarly, graphite is an omnipresent material in current battery technologies which could only be replaced by Li-Air or Li-S batteries, or non-Li based technologies. While it can be produced from natural and synthetic sources, the scalability of its production can be limited due to the lack of infrastructure. Moreover, synthetic graphite production relies on green coke and pitch as an input material, which are byproducts of oil refineries and have a potentially higher carbon footprint. As industries seek to decarbonize by reducing their reliance on oil, the availability of these inputs can be further constrained.

Aluminum was found to be the material with highest increase in demand from a gravimetric point of view of all materials considered, even without including the Al needed for the rest of the vehicle to reduce weight. The significant increase in Al demand for cars, especially for wrought alloys, also has the potential to trigger a deep transformation of the global Al cycle, the current cascading recycling system being likely to lead a mixed scrap surplus and increased carbon footprint (Billy and Müller, 2023).

Presently, there are significant efforts to reduce the reliance on Co due to geopolitical issues involving the Democratic Republic of Congo and LFP batteries are often presented as the go-to alternative (Zeng et al., 2022b). However, P reserves are geographically heavily concentrated and refining capacity is controlled by five countries (Cordell and White, 2014). It is also an essential resource for food production as a fertilizer which could be susceptible to price shocks due to the increase in demand, potentially affecting small farmers in developing countries and threatening food prices. Further research into this material in the context of LIBs is perilously needed.

Ni, Co, and Cu are metals which society already makes widespread use of. However, in the near future, the LIB industry can be expected to drive their demand to record levels. Given the lag that infrastructure buildup has for mining and refining capacity, foresight is needed to prepare a resilient supply of those metals (Petavratzi and Gunn, 2022). Notwithstanding, the western industry has been slow to make the necessary long-term investments due to the high uncertainty involved in future demand. Indeed, the sensitivity analysis showed that the battery chemistry can dramatically affect the final demand for these materials. Having future-ready infrastructure that e.g. can refine scrap in addition to primary material could be a way to mitigate risk in the refining industry, but the material mining remains a challenge.

The large uncertainties in the system parameters and wide array of battery materials that can be used require systemic investigation to better grasp the impact of different interventions. The MATILDA model informs the industries and policymakers' knowledge base as a comprehensive review of all material challenges. Moreover, it can be used to conduct more specific studies to better understand the impact of the transition to EVs for the individual material cycles.

The model results and underlying data are made fully available to the public in the following repository: https://doi.org/10.5281/zenodo.7252047. We also include an interactive visualization tool and user guide for a quick interpretation of the results, which can be found in the same repository.

Credit author statement

All authors were involved in the design of the study; F.A.L. collected the data, developed the model and generated the figures; F.A.L. and R.G. B. developed the scenarios; the writing of the paper was led by F.A.L., with assistance from all co-authors; all authors interpreted the results, reviewed the paper, and approved the final version of the manuscript.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data is fully accessible in the following repository: https://doi.org/10.5281/zenodo.7252047

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.resconrec.2023.106951.

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3.3. On the potential of vehicle-to-grid and second-life batteries to provide energy and material security for the EU

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3.4. Estimating stocks and flows of electric passenger vehicle batteries in the Norwegian fleet from 2011 to 2030

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RESEARCH AND ANALYSIS

Estimating stocks and flows of electric passenger vehicle batteries in the Norwegian fleet from 2011 to 2030

Rebecca Thorne[1] | Fernando Aguilar Lopez[2] | Erik Figenbaum[1] | Lasse Fridstrøm[1] | Daniel Beat Müller[2]

[1] Department of Technology, Institute of Transport Economics (TØI), Oslo, Norway

[2] Department of energy and process engineering, Norwegian University of Science and Technology (NTNU), Trondheim, Norway

Correspondence
Rebecca Thorne, Institute of Transport Economics (TØI), Department of Technology, Gaustadalléen 21, 0349 Oslo, Norway.
Email: Rebecca.Thorne@toi.no

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Abstract

Retired passenger battery electric vehicles (BEVs) are expected to generate significant volumes of lithium-ion batteries (LIBs), opening business opportunities for second life and recycling. In order to evaluate these, robust estimates of the future quantity and composition of LIBs are imperative. Here, we analyzed BEV fate in the Norwegian passenger vehicle fleet and estimated the corresponding battery capacity in retired vehicles from 2011 to 2030, using a stock-flow vehicle cohort model linked to analysis of the battery types and sizes contained in different BEVs. Results based on this combination of modeled and highly disaggregated technical data show that (i) the LIB energy capacity available for second use or recycling from end-of-life vehicles is expected to reach 0.6 GWh in 2025 and 2.1 GWh in 2030 (not accounting for any losses); (ii) most LIBs are currently contained within the weight segment 1500–1599 kg followed by 2000+ kg; (iii) highest sales currently exist for BEVs containing lithium nickel manganese cobalt oxide (NMC) batteries; and (iv) lithium nickel cobalt aluminum oxide batteries initially constitute the largest overall capacity in retired vehicles, but will later be surpassed by NMCs. The results demonstrate rapidly growing opportunities for businesses to make use of retired batteries and a necessity to adapt to changing battery types and sizes.

KEYWORDS
batteries, dynamic modeling, electric vehicles, industrial ecology, recycling, reuse

1 | INTRODUCTION

Users need vehicles that can solve transport tasks efficiently, reliably, and comfortably. To address this, a vehicle and transport culture has been developed based on internal combustion engines (ICEs) that largely relies on fossil fuels. As part of the current shift to a greener society, zero exhaust emission vehicles, hereafter referred to as zero emission vehicles, are now replacing those powered by ICE to reduce local air pollution and greenhouse gas emissions.

Norway is a leading nation in the drive to zero emission transport with ambitious targets set in the Norwegian National Transport Plan (NTP), including that all new passenger vehicles should be zero emission by 2025 (Norwegian Ministry of Transport, 2017). Battery electric technology is currently the most mature zero emission technology in use, relying primarily on lithium-ion batteries (LIBs). Between 2011 and 2019, Norwegian passenger battery electric vehicle (BEV) sales rose from approximately 2000 to 60,345, with BEVs representing about 42% of the passenger vehicle market in 2019 (OFV, 2019). This represents one of the highest market shares worldwide (IRENA, 2017). Consequently, Norway is expected to be one of the first countries with a significant number of retired batteries (Casals et al., 2017), giving rise to major opportunities that include recycling with material recovery (Velazquez-Martinez et al., 2019) or second use as stationary energy storage applications (Ahmadi et al., 2017; Cusenza et al., 2019).

Recycling and second use of BEV batteries is already ongoing, albeit with a relatively low number of end-of-life BEV inflows. Information from "Batteriretur," a Norwegian company responsible for collection and treatment of used batteries, reveals that Norwegian BEV LIBs are generally collected and dismantled to module level in Norway before export to the European Union (EU) for recycling (Svendsen, T. H., personal communication, September 14, 2020). The recycling process is mainly focused on thermal pretreatment before crushing, or batteries may be refurbished/repaired and re-used in vehicles or for other second uses. However, this is dependent on levels of degradation and other faults. Since end-of-life volumes of BEV LIB are currently small, most batteries currently collected derive from accidents and take-back campaigns, but volumes are expected to increase rapidly in the next decade as the market share increases, sales rise, and vehicles retire (Hao et al., 2015; Palencia et al., 2012; Richa et al., 2014; Sato & Nakata, 2020). Quantitative information about the expected future development of retired batteries and an understanding of their drivers is needed to grasp these opportunities, for example, for planning investments in recycling or reuse infrastructures.

Dynamic stock modeling, including material flow analysis, has been used to assess the development of future electric vehicle fleets and forecast end-of-life vehicle and battery flows (Hao et al., 2015; Palencia et al., 2012; Richa et al., 2014; Sato & Nakata, 2020). These models can be based on cohorts where each cohort is assigned an expected lifetime and the cohort's use phase ends when its lifetime elapses. Using sales scenarios and a discrete lifetime distribution for batteries, Bobba et al. (2019) estimated that a total of around 450,000 battery units will leave the European fleet in 2030, and that under two scenarios with low and high second use the actual battery capacity available for second use will be 1.99 and 8.75 GWh (70,400 and 311,500 units), respectively. Other studies based on sales scenarios combined with typical vehicle exit curves or average battery lifetimes, respectively, conclude more conservatively that a total of 125,000 electric vehicles (EV) and the batteries they contain will be scrapped in 2030 in Europe (Element Energy, 2019), or less conservatively that a total of 1.2 million EV batteries (47 GWh) will reach end-of-life in Europe in 2030 (Drabik & Rizos, 2018). Of the former, the authors expect that 15% of battery units may be sent to recycling due to deterioration, and 2.25 GWh (representing 105,000 batteries) may be available for second life. At the combined Nordic level, Dahllöf et al. (2019) estimated from historical vehicle sales and battery lifetime data that around 50,000 and 20,000 battery units would be available together in 2030 for second life and recycling, respectively, but this only accounts for batteries already placed on the Nordic market in 2018. The wide variation in results reflect variation in scope, system boundaries, and inherent uncertainties.

Even though reuse and recycling opportunities are likely to arise first in Norway, no studies to the authors' knowledge have yet fully quantified the Norwegian battery volumes arising to 2030. In addition, no studies estimating battery capacity in retired vehicles in Europe could be found that are fully based on the historical differentiation of vehicles arriving into the market and the individual technical battery characteristics linked to each vehicle make/model and sales year. Here, in addition to providing new analysis of the state of the art of battery use in Norway, we estimate the quantity of LIBs entering and leaving the Norwegian passenger vehicle fleet annually until 2030. The target is to investigate short- to medium-term potentials for recycling opportunities for Norwegian industries, so a dynamic stock model is consequently used to build realistic scenarios for the battery capacity becoming available for recycling in future years. The strength of our approach is the combination of modeled data with a large amount of real, technical data at a vehicle model level, based on individual battery characteristics of each BEV sold in Norway. The result is a battery capacity stock and flow model specific to Norway, although the approach could further be applied to other regions to explore their own potential for recycling.

2 | METHODOLOGY

Results of a vehicle stocks and flows cohort model based on the Norwegian market were linked together with supplementary battery analysis based on BEV historical data and anticipated battery development. An overview of the model and analysis linkage is shown in Figure 1.

2.1 | Application of the stocks and flows cohort model

Passenger BEV stocks and flows were projected to 2030 using a previously developed cohort model that accounts for all initial BEV stocks introduced since 1981 when the first registered electric vehicle sales in Norway occurred (L. Fridstrøm, 2019; L. Fridstrøm et al., 2016). The model splits the fleet by vehicle age and projects new vehicle sales (vehicle age < 1 year) and stock change of older BEV stocks (vehicle age > 1 year) in the Norwegian fleet by year of first registration and weight segment until 2030. Segments defined for the model include 0–999, 1000–1199, 1200–1299, 1300–1399, 1400–1499, 1500–1599, 1600–1799, 1800–1999 and >2000 kg. These segments relate to the vehicle curb weights, the vehicle

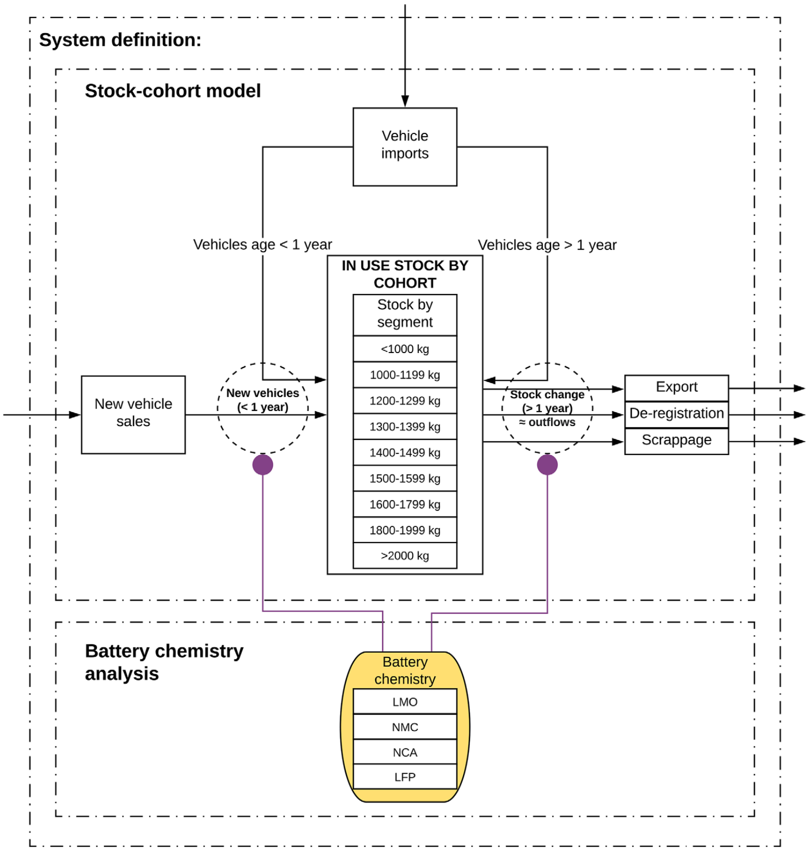

FIGURE 1 System definition of the vehicle fleet model and its link to the battery chemistry analysis. New vehicles (age < 1 year) entering use, in-use stock, and the stock change of vehicles older than one year (age > 1 year) that is assumed to approximate the outflow from the stock. The arrows represent flows, while the dots illustrate parameters that were retro-actively applied to the model results
Note: Although the weight segment <1000 kg is included in the vehicle model, this category was excluded from the LIBs analysis since it was assumed that vehicles in this category are registered as four-wheel motorcycles and not passenger vehicles

weight with all equipment, and also include a 75 kg driver. The model estimates in-use stocks as a balance of new vehicle sales and net stock change values over time.

New vehicle sales per year and weight segment are defined in the model as the number of vehicles sold with age < 1 year ($I_{t<1}$), which includes both vehicles sold first in Norway and "nearly new" vehicles first registered elsewhere before being imported secondhand to Norway and re-registered the same year. To estimate annual new vehicle sales, the model accounts for market uptake of electric vehicles using the assumptions in the National Budget 2019 (Royal Ministry of Finance, 2019). Based on this, Fridstrøm (2019) constructed a long-term scenario which was used for the calculations here; in this scenario BEV sales reach 70 % in 2025 and 74.3 % in 2030, meaning that fleet BEVs equate to approximately 800,000 and 1,354,000 in 2025 and 2030, respectively. This is a slower market uptake of electric vehicles than is suggested by Norwegian National targets, but a conservative outlook is favored for this study. The model was also calibrated around historical sales data with a vehicle model-by-model level of disaggregation.

The net stock change of older BEV stocks follow from transition rates calculated on empirical stock data taken from the national motor vehicle register for the years 2012 to 2017, and are defined per year and weight segment as the sum of the number of vehicles imported and registered in Norway with age > 1 year ($I_{t>1}$), minus those exported, deregistered and scrapped (O). Deregistered BEVs are considered negligible. New vehicle sales are thus excluded from this sum and a negative value equates to a decrease in vehicle numbers. Only net flows are calculated by the model, but it is assumed that among younger vehicles, secondhand import is the dominant gross flow, while among older BEVs, scrapping would dwarf all other gross flows.

In essence, survival rates are calculated by observing the change in the stock of a given cohort of vehicles from one year to the next. There is currently limited data available to calculate the survival rates of passenger BEVs older than 6–8 years, but since there is rapid technological development that means that models soon become outdated, BEV survival rates for each weight segment were set in the model similar but somewhat lower to those of correspondingly sized petrol-driven vehicles. The limited evidence so far suggests that BEV batteries last the life of the vehicles, which is consequently assumed here. Survival curves for different BEV weight segments used in the model, as well as a discussion of assumptions, are shown in Supporting Information S1. Knowing the survival rate of each vehicle segment to the next year, and accounting for secondhand sales of imports, allowed us to estimate annual fleet stock changes for all vehicles older than 1 year. In this way, estimates were made of the change in the number of vehicles from different first registration years and for different weight segments.

Equation (1) shows the relationship between the defined annual stock change of these vehicles $dS_{t>1}$ and the outflows O which aggregates exports, deregistration, and scrappage. This suggests that for small numbers of vehicle imports older than 1 year (which we assume here), the stock change can be set equal to the outflows. Total stock change for the whole fleet (dS_{total}) can be thereafter calculated by summing up the inflow of vehicle sales and imports of vehicles less than 1 year old ($I_{t<1}$) with the stock change of older vehicles (Equation 2). dS_{total} was not needed for this study, so Equation (2) serves only to demonstrate the difference between dS_{total} and $dS_{t>1}$. Finally, Equation (3) shows how the vehicle outflows are calculated using a survival function $sf(s)_{t,c}$ specific for each vehicle segment s, which is applied to the stock S. This function determines the share of vehicles of a given cohort that remain in the fleet at any given time.

$$d\,S_{t>1} = I_{t>1} - O, \tag{1}$$

$$d\,S_{\text{total}} = I_{t<1} + dS_{t>1}, \tag{2}$$

$$O = sf(s)_{t,c} \cdot S_{t,c}. \tag{3}$$

The stocks and flows cohort model itself does not make any assumptions about battery characteristics of the vehicles, but this analysis relating to battery quantities was retro-actively performed using the output (see Sections 2.2 and 2.3). Although the weight segment <1000 kg is included in the model as standard, this category was excluded from subsequent analysis since it was assumed that these vehicles in this category are registered as four-wheel motorcycles and not passenger vehicles. Note that "age" in the model is defined as the number of years completed by December 31 from initial registration, rounded upward to the nearest integer. For example, vehicles aged "3 years" in 2021 are those first registered in 2019. Although the model includes electric vehicles produced from the year 1981, significant LIB BEV annual sales did not occur until after 2010/2011.

2.2 | Assessment of electric vehicle battery characteristics

Analysis to estimate LIB capacity from the cohort model results was performed based on historical and statistical data of Norwegian vehicle sales (at a vehicle model level), their associated battery characteristics and expected future battery development.

Historical data on all electric vehicle make/model characteristics (including nominal battery capacity, kWh) that have been available on the market was first obtained from the Electric Vehicle Database (EV Database, 2019). This was supplemented with information about the battery type for each vehicle make/model sourced from Kelleher Environmental (2019), Wagner et al. (2019) and other open sources. Battery types in use in passenger BEVs include lithium manganese oxide (LMO), lithium nickel manganese cobalt oxide (NMC), lithium nickel cobalt aluminum oxide (NCA), and combinations thereof. Lithium iron phosphate (LFP) has also been used for the <1000 kg segment. In this analysis only overarching battery material types are considered (i.e., NMC is not categorized according to NMC111, NMC622 or NMC811, etc.), due to a lack of reliable and consistent data. Where no data about battery chemistries was available, vehicle battery types were set to "unknown Li-ion type."

Historical sales data of Norwegian passenger BEVs between the years 2011 to 2018 was obtained from Opplysningsrådet for Veitrafikken AS (OFV, 2019). Vehicles <1000 kg were excluded as before. It was also assumed that electric vehicles sold prior to 2011 when the modern BEV was launched were either not of LIB type, or were registered as four-wheel motorcycles, and were excluded. The sales data was thereafter combined with the background data of battery type and size for different vehicle makes/models to assign a battery capacity and type to each vehicle sold. Examples of data for the five most popular passenger BEV models, reflecting around 70% of all vehicles sold in Norway between 2011 and 2018, are shown in Table S2 in Supporting Information S1. The combined historical sales and background battery data was used to estimate the amount of type of batteries introduced into the Norwegian passenger vehicle fleet between 2011 and 2018.

In preparation for combination with the stocks-flows cohort model results, the sales of passenger BEVs and associated battery characteristics were grouped into the same weight segments as for the cohort model by using associated vehicle curb weights in the EV database (and accounting for a 75 kg driver). The data was also transformed to calculate the sales weighted average battery capacity and type for Norwegian passenger BEVs purchased in each weight segment and for each vehicle sale year. Where several battery types were used for vehicles sold within one weight segment (and for one vehicle sale year), a weighting factor was determined to estimate the distribution of vehicles actually sold according to battery type. Any gaps in weight segments/years were filled with data from an adjacent weight segment, and data for the year 2019 was assumed the same as 2018.

The estimated battery characteristics were extended to 2030. Although the Electric Vehicle Database also contains the available information about known models arriving to the market in future years (to 2022), few models beyond 2021 have been announced and there is thus little concrete information available about the growth in battery capacity to 2030. Within each segment there is a band of battery capacities; we therefore assumed for this analysis that the maximum capacity in each segment will continue to increase and that the sales weighted average battery capacity will converge toward the upper end of these bands in all segments by 2030, with the phasing out of older vehicle models and the demand for long-range driving. We also assume that large and luxury vehicles will develop an even larger battery capacity, in the region of 90–120 kWh. Resulting assumptions of battery capacity growth used in the analysis here to 2022—and beyond to 2030—are shown in Table S1 in Supporting Information S1, with linear approximation used to extend current capacity values from today. Due to a lack of reliable data on the battery types of future models, battery types for years 2020–2030 were set to unknown Li-ion.

2.3 | Estimation of new batteries and stock change annually until 2030

The number and capacity of batteries of different types entering the electric passenger vehicle fleet, as well as the stock change, were estimated for years 2011–2030 by combining results from the stock-flow cohort model with the assumptions of battery type and size for each weight segment and cohort year in the battery analysis. Uncertainties in the final results stem mainly from (1) model uncertainties in the estimated stocks and flows of vehicle numbers toward 2030, and (2) uncertainties in the assumptions of the battery capacity of vehicle models toward 2030.

Model uncertainties (1) originate from the fact that only one scenario of BEV penetration was investigated, and that the modeled stock change of vehicles older than 1 year (i.e., excluding new vehicle sales) was assumed to equate to scrappage. In reality the stock change of these vehicles is also affected by imports and exports, as well as other contributions from deregistration, but these individual flows are not estimated by the model. To establish how the import/export flows may affect total vehicle outflows estimated by the stocks-flows model, these flows were investigated further using data from the year as an example (SSB, 2020a).

Uncertainties in battery capacity development (2) also affect results, reflecting underlying complex dynamics beyond the scope of this study. For example, as technology advances and batteries become more efficient, several trends can unfold. First, the efficiency gains can be used to further increase battery capacity and driving range. However, this may be limited in the medium, compact, and smaller vehicles compared to larger vehicles due to costs (potentially exacerbated by constraints in raw material and battery supply) and improvements in charging infrastructure. Second, efficiency gains can be used to reduce the battery size. This option would reduce battery and vehicle weight and consequently also increase the range while keeping costs low, but could lead to the stagnation of the maximum battery capacity.

3 | RESULTS AND DISCUSSION

3.1 | Application of the stocks and flows cohort model

The total Norwegian fleet of passenger BEVs to 2030 based on the Norwegian National budget, estimated by the stocks and flows cohort model, is shown in Figure 2. Up to and including 2018, actual data on the number of vehicles of different technologies that have been registered each year has been used, based on data from the national vehicle register.

Annual results from the model of total new passenger BEV sales, and stock change of older vehicles (age > 1 year), are shown in Figure 3. According to the model, new BEV sales in 2018 summed for all weight segments >1000 kg (Figure 3a) amounted to around 57,000, rising to 116,000 in 2025 and 163,000 in 2030. Figures related to a single cohort should be interpreted with caution, since survival rates for vehicles older than 3–4 years rely on a relatively small number of cases.

Model estimates for new BEV sales for the years 2011 to 2018 were compared to historical passenger BEV sales data. Modeled new vehicles are approximately 10–25% higher than new vehicle sales registered by OFV, but when the number of new registrations from secondhand imports registered by OFV is also considered (as also implemented in the cohort model), than the difference is <4%. See Table S3 in Supporting Information S1 for more details. Many of these latter vehicles have already been registered abroad once before during the same year and have been imported secondhand due to the high demand for some popular models in Norway that have not been available in sufficient volumes. The fact that BEVs are

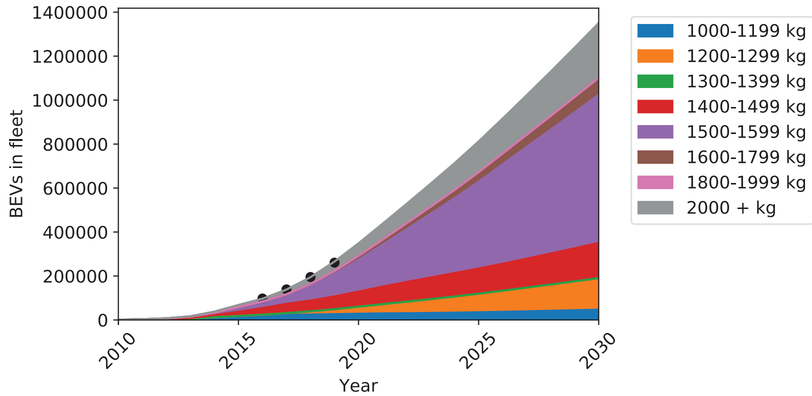

FIGURE 2 The estimated number of electric passenger vehicles in the Norwegian fleet until 2030, broken down by weight segment. Historical data, as of December 31 for each year, is shown by black circles for comparison (SSB, 2020b). Data underlying this figure are available in Supporting Information S2

subsidized in many countries, but not directly in Norway, gives rise to business opportunities particularly within secondhand import. In some cases, vehicles have been registered in an EU country for just a day to be counted toward the EU CO_2 requirement before being exported to Norway. This translates to a double benefit for Norwegian BEV owners, who take advantage of both the purchase subsidies in the EU and the exemption from taxes and other incentives of the like when registering the vehicle in Norway.

When considering the model output for outflows from the Norwegian passenger BEV fleet for weight segments >1000 kg (Figure 3b), the model estimates around (–) 1200 vehicles in 2018, rising to (–) 17,000 in 2025 and (–) 51,000 in 2030. The numbers here represent the stock change per year of passenger BEVs older than 1 year, that is, the net stock change of the older vehicles that were already in the fleet each year, excluding new vehicle sales that year. Since we assume here that imports of older vehicles are negligible, this equates to fleet outflows due to scrappage, deregistration or export. The numbers also directly equate to the number of battery packs in these vehicles (i.e., one per vehicle).

For this article, the assumption is that vehicles in the outflows are mostly scrapped in Norway rather than exported. Historically this has been the case due to the high taxes on passenger vehicles compared to other countries, which make old used vehicles more valuable in Norway than in other countries. Since BEVs do not have purchase taxes in Norway, they could potentially be exported to other countries. However, the user demand for BEVs has been much higher in Norway than elsewhere, which makes it reasonable to assume these flows to be negligible. For battery electric trucks and buses the situation may be different. For verification, comparisons were made of the total net vehicle stock change estimated by the model for all vehicle types and ages with historical scrappage data from years 2010 to 2018 (SSB, 2019). Results, shown in Figure 3c, are comparable. Whilst inferring that other flows contributing to the stock change for these older vehicles are small in comparison to scrappage, the data reflects the situation for the entire vehicle fleet and not specifically for BEVs. This is since scrappage data specifically of passenger BEVs in Norway is not publicly available for detailed comparisons.

3.2 | Effects of imports and exports on estimated outflows

It was assumed for this work that imports of older vehicles than 1 year, and exports of all ages, are negligible, which makes the stock change (vehicle age > 1 year) equate to outflows (cf. Equation 1). These assumptions are investigated here in more detail. Figure 4 shows estimated outflows from the stocks and flows cohort model broken down by vehicle age. For 2015 and 2020 a significant fraction of the outflow is constituted by vehicles younger than 7 years. This is expected, since the majority of EVs have not yet reached end-of-life and therefore the main cause of outflows are accidents, callbacks, or malfunctions of any nature. For 2025 and 2030 these outflows make up for a smaller share and the main outflow of BEVs is around 10 years old. Although these vehicles are still short of their full lifetime, the reason for this trend lies in the relative differences in cohort abundance: BEVs aged 10 years are still the most scrapped in 2030 because they are more numerous than older vehicles. Correspondingly, even if their scrappage rate is low, the absolute number of those scrapped is higher than for older vehicles. Differences in the spread of vehicle ages can also be seen in the figures. In 2015 many older vehicles (dating back to 1981) were phased out due to the rapid market development. Between 2020 and 2030, the spread of vehicle outflow age is anticipated to widen as time increases from 2011 when the rapid BEV introduction began, and the vehicles are able to progress along their survival curves.

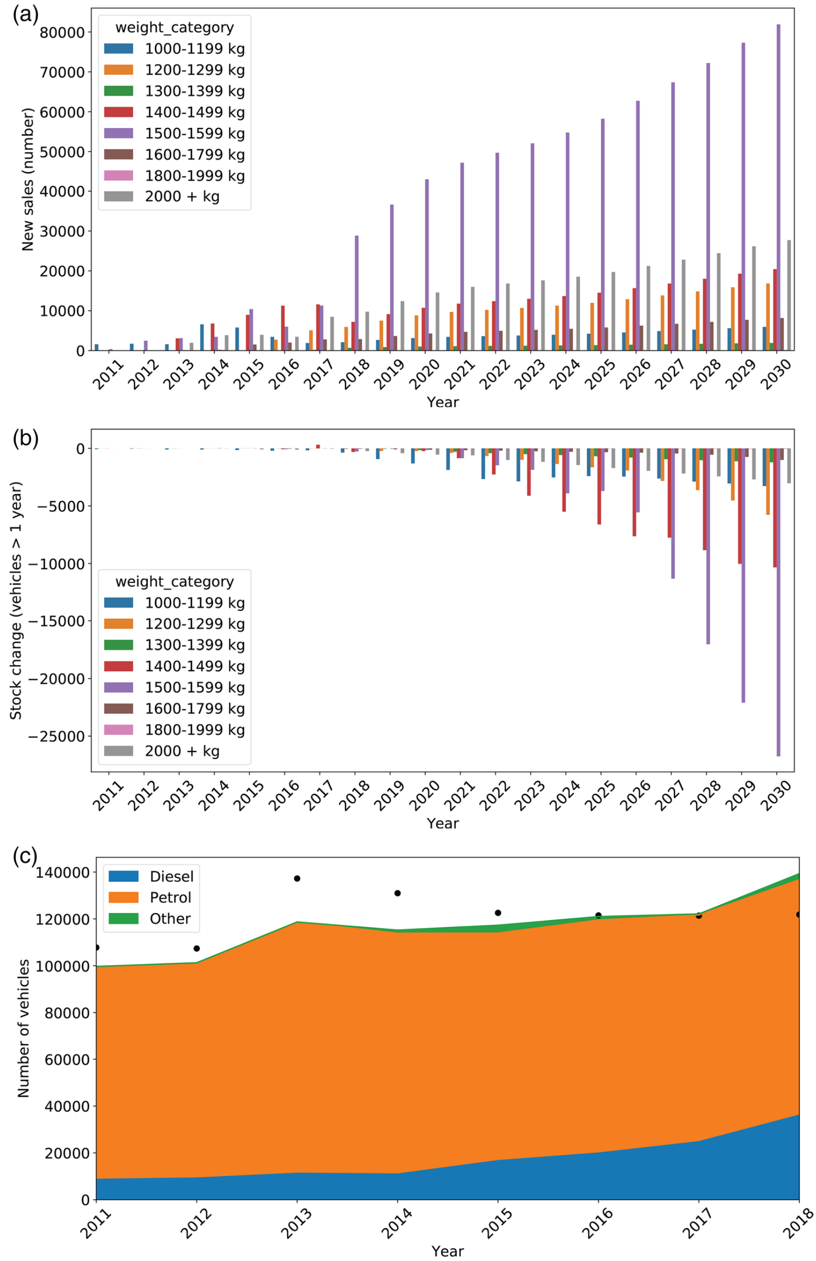

FIGURE 3 The estimated number of (a) total new electric passenger vehicle sales, and (b) stock change from the Norwegian electric passenger vehicle fleet (for vehicles older than 1 year), annually until 2030. (c) The modeled net vehicle stock change data for vehicles older than 1 year of all vehicles in the Norwegian passenger vehicle fleet, compared with actual fleet scrappage numbers for years 2010–2018 (black, open circles). Data underlying this figure are available in Supporting Information S2

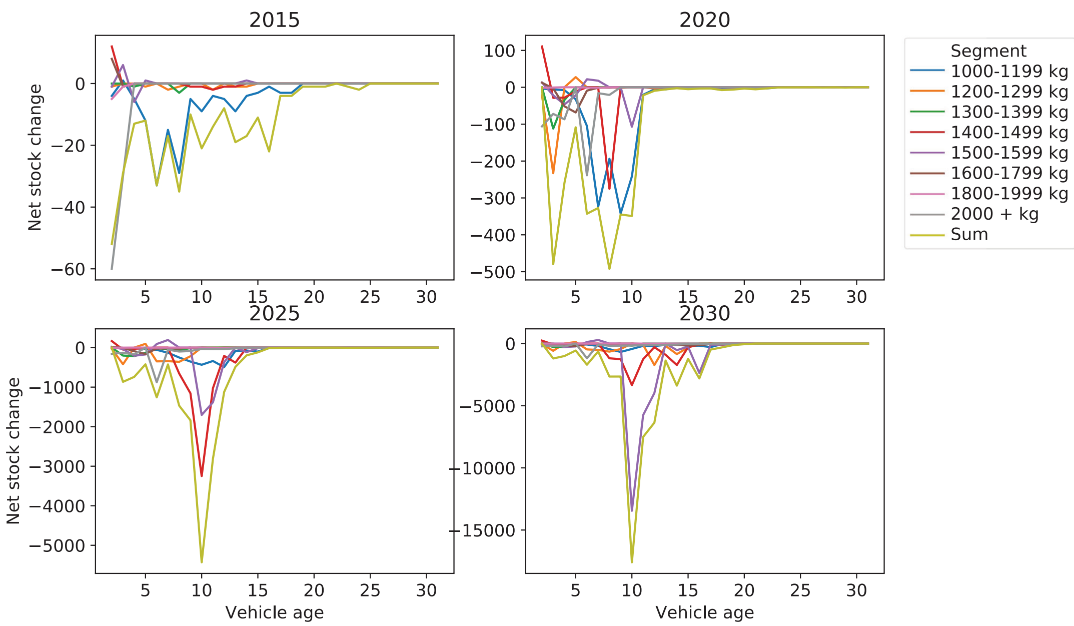

FIGURE 4 Net stock change (number) of vehicles older than 1 year, by vehicle age. Vehicle age is age at year end, rounded upward to nearest integer. Years 2015, 2020, 2025, and 2030 are selected and shown for comparison. Note that the curves oscillate widely between years since they are calibrated in part on historical data (thus large trends only should be focused upon). Data underlying this figure are available in Supporting Information S2

The majority of imported/exported vehicles can be assumed to be relatively young, for example, less than 5 years old, and hence they are unlikely to significantly affect the main outflows shown in Figure 3b. However, to establish how import/export flows may affect total vehicle outflows, these flows were investigated further using the year 2018 as an example. For this year, total recorded imports of new and used vehicles to Norway equaled 50,840 and 11,913, respectively, whilst exports of new and used vehicles from Norway were much lower at 10 and 46, respectively (SSB, 2020a). This imbalance is not unexpected and is due to the subsidies paid out in many countries that make it profitable to import BEVs into Norway coupled with high demand in Norway compared to other countries.

Since export flows of BEVs are almost negligible and imports dominate, the calculations for BEV scrappage, and associated estimates of the batteries they contain, may be underestimated. However, most imported vehicles to Norway are likely to be nearly new (age < 1 year) and were therefore accounted together with new BEV sales in the model. Recorded data shows that for the year 2018, there were 11,899 first time registrations of imported vehicles in Norway (OFV, 2020). Although these do not necessarily derive from the total pool of 11,913 used vehicles imported during 2018 (vehicles can also derive from previous year imports), the difference is small. Since vehicles of age > 1 year are directly counted along with new sales in the stocks-flow cohort model as "new vehicles," it is unlikely that used imports have a large impact on the estimates of vehicle scrappage in this study.

3.3 | Assessment of electric vehicle battery characteristics

Data of the development in battery capacity for all vehicles available on the market, including BEVs known to be arriving on the market in the next years, is shown in Figure 5. Both the average and maximum battery capacity of BEVs available on the market per year has in general shown an upward growth trend since BEV introduction, although the growth can in most cases be described as stepwise. Little is known about models arriving on the market after 2021, aside from several examples in the 1400–1499 kg and >2000 kg segments. For the latter, the large increase in maximum capacity relates to the announcement of the new Tesla Roadster, anticipated in 2022, with 200 kWh battery capacity per vehicle. However, this is unlikely to be representative of the whole segment.

Estimates of the types of batteries entering the fleet based on historical sales data combined directly with known battery characteristics for these vehicle models are shown in Figure 6. According to these results, NMC and NCA are battery types currently used in greatest amounts, with around 0.9 and 0.7 GWh entering the fleet in new passenger BEV sales in 2018, respectively (Figure 6a). There is also a division of battery types by

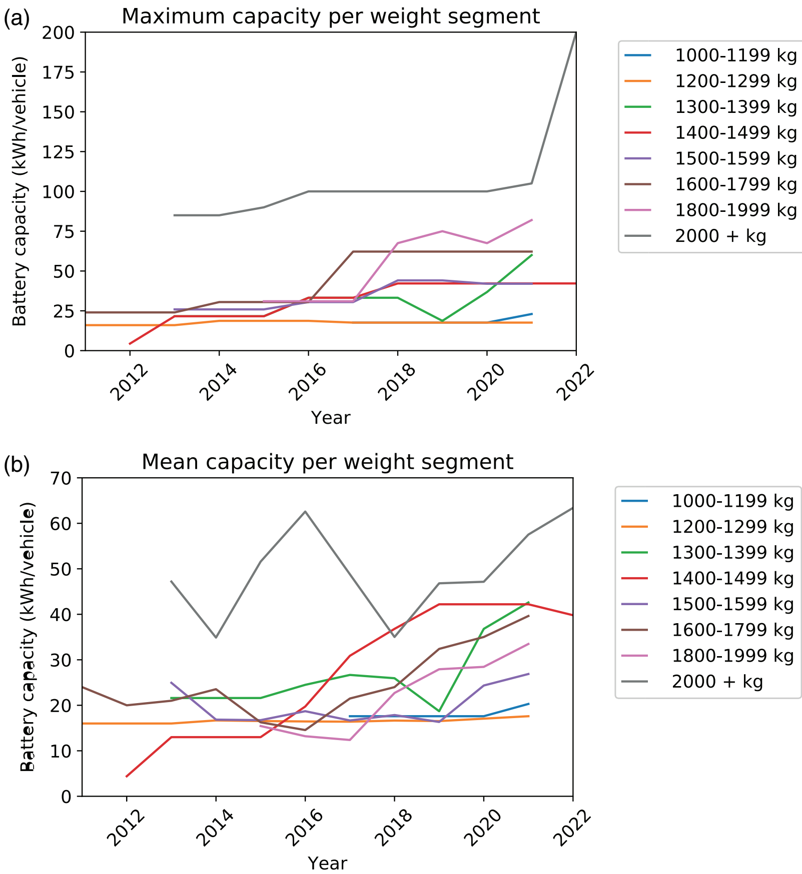

FIGURE 5 Change in (a) maximum and (b) average (mean) battery capacity per BEV with time, when assessing data from all vehicle makes/models/variants known to be available on the market between 2011 and 2022. Data derives from EV Database (2019). Data underlying this figure are available in Supporting Information S2

weight segment evident, with NCA in use for heavier weight segments and NMC in use for lighter weight segments. Although a small amount of LFP has been used in vehicles <1000 kg, these vehicles are excluded here since they are assumed to be registered as four-wheeled motorcycles.

The stark increase in available battery capacity can open possibilities for the vehicle fleet to participate in the ancillary services market for the grid through technologies such as vehicle-to-grid or reuse of batteries in stationary applications. In terms of the number of battery packs (Figure 6b), around 25,000 NCA battery packs were introduced into the Norwegian fleet in 2018 alone. Between 2011 and 2018 combined, over 50,000 battery packs were introduced in the 1500–1599 kg segment, and around 30,000 in the >2000 kg segment. These mostly correspond to sales of Nissan Leaf that contains NMC batteries and lies in the 1500–1599 kg segment, and Tesla models X and S that contain NCA batteries and lie in the >2000 kg segment. Together, these vehicles have accounted for around 41% of market sales between 2011 and 2018. The average energy density of battery packs in new vehicle sales has increased between 2011 and 2018 for all battery chemistries (Figure 6c), with the largest battery capacities evident in the largest vehicle segments. The growth in battery capacity entering the fleet can therefore be explained by growth in the number of battery packs entering the fleet coupled with an increase in battery size. As technology improves it can be expected that lighter batteries will be able to deliver the same energy capacity, resulting in a positive rebound effect in which fewer materials are required to provide the same service. The range of modern BEVs is already approaching that of ICE vehicles, suggesting that further developments will soon focus on reducing battery sizes and therewith EV prices.

There is large uncertainty regarding future battery chemistries, but an overall trend to move away from cobalt seems to be dominant throughout the industry as can be seen by efforts to move from NMC111 to NMC811 (Alves Dias et al., 2018; Azevedo et al., 2018). Tesla, the main NCA battery user, has also expressed commitment to reducing cobalt use through increased use of nickel and, as has been seen in the Chinese market, moving

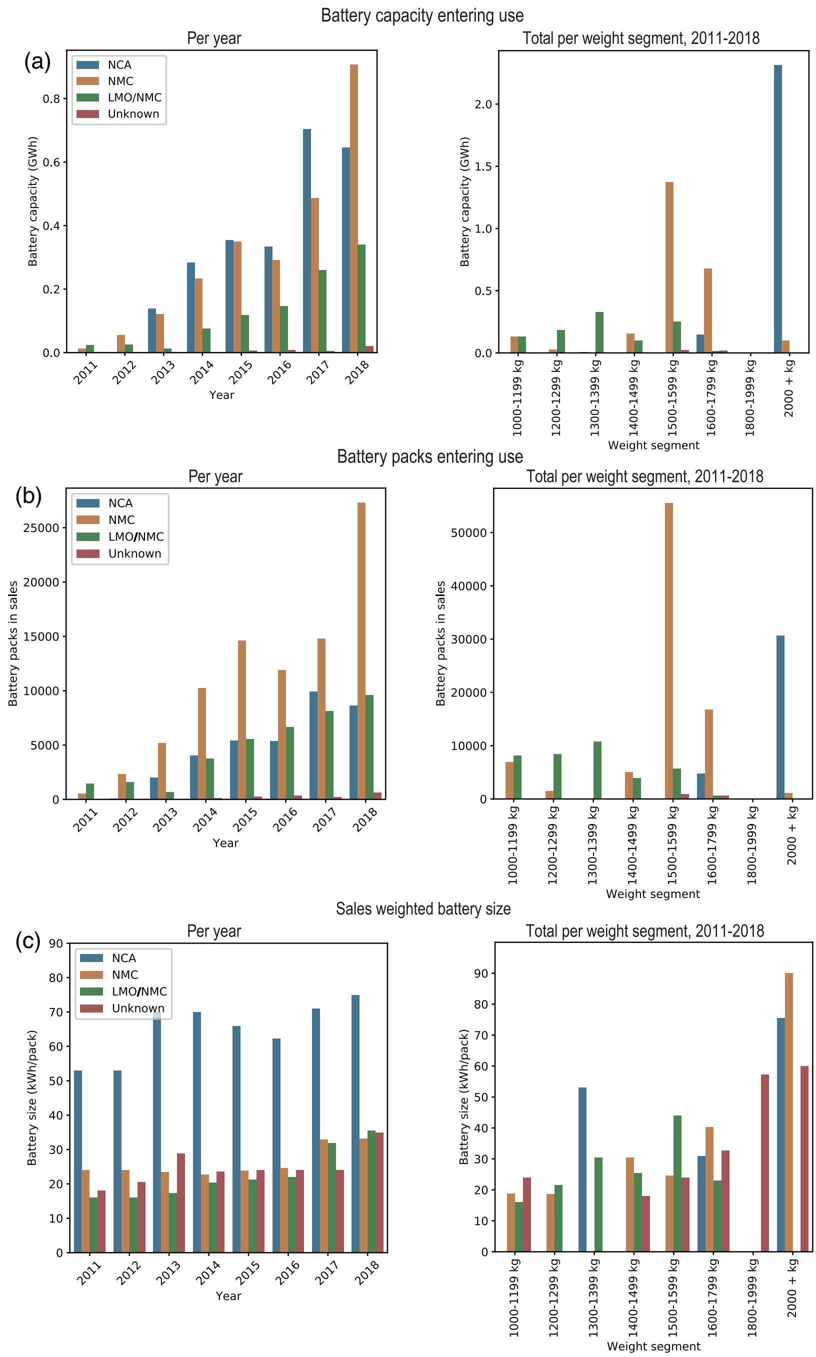

FIGURE 6 The estimated inflow of (a) battery capacity (GWh), (b) number of battery packs, and (c) sales weighted battery size (kWh/pack) introduced to the Norwegian electric passenger vehicle fleet, both annually between 2011 and 2018 and by weight segment (total for all years). Data are based on historical sales data (OFV, 2019b) and background battery characteristics data (Kelleher Environmental, 2019; Wagner et al., 2019; EV Database, 2019). "Unknown" refers to unknown Li-ion type. Data underlying this figure are available in Supporting Information S2

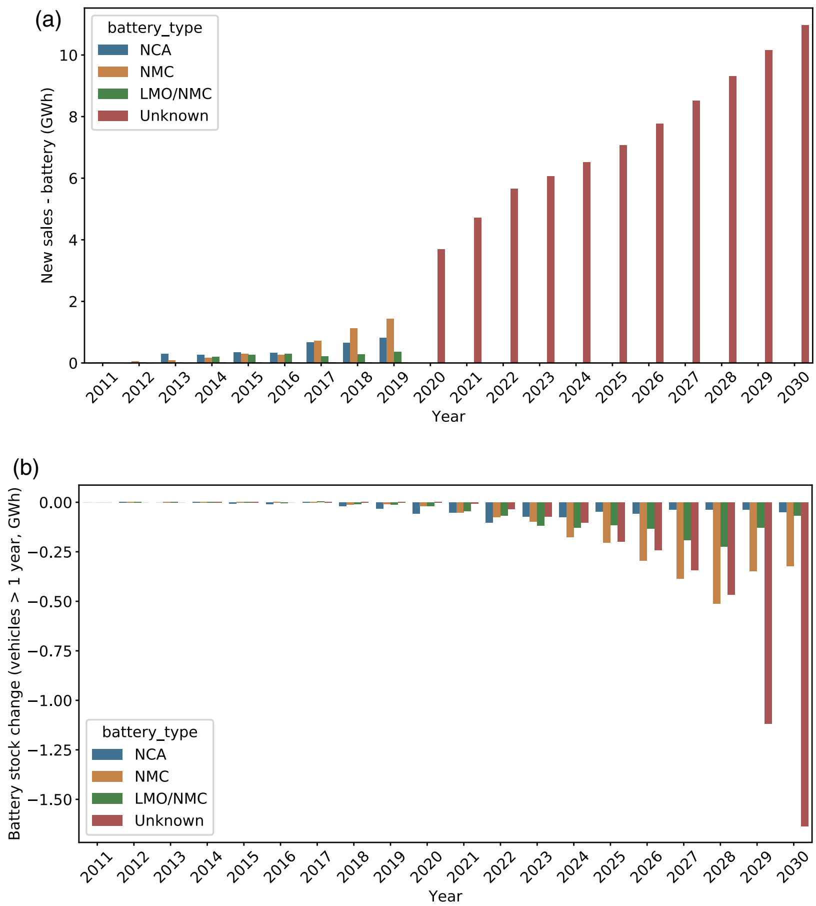

FIGURE 7 The estimated (a) total battery (GWh) introduced to the Norwegian electric vehicle fleet through new electric passenger vehicle sales, and (b) battery stock change (GWh) from the Norwegian electric passenger vehicle fleet (from vehicles older than 1 year), annually until 2030. "Unknown" refers to unknown Li-ion type. Data underlying this figure are available in Supporting Information S2

toward LFP batteries (Holland, 2020). While this trend strengthens raw material supply security, it may result in problem-shifting toward scarcity of nickel supply.

3.4 | Estimation of new batteries and net change annually until 2030

Output from the stocks and flows cohort model was combined with the supplementary battery analysis to estimate the respective battery flows until 2030. Results are shown in Figure 7, with an in-depth summary of annual net stock change for the years 2017–2025 given in Figure S3 in Supporting Information S1 that represents the arising Norwegian "window of opportunity" for end-of-life BEV, for both recycling and second-life purposes. The large increase in battery capacity entering the fleet between 2019 and 2022 is due to the increase in assumed battery sizes in many weight classes to 85% of their 2030 value, as described in Table S1 in Supporting Information S1. According to results, total battery amount used in new vehicle sales across all vehicle segments and battery types is estimated to be around 2.1 GWh in 2018, rising to 11 GWh in the year 2030. The assumed annual end-of-life summed battery quantity from BEVs older than 1 year (i.e., fleet outflows) is estimated to be around 0.6 GWh in 2025, and 2.1 GWh in 2030. Comparisons of these estimates with historical data for years 2011–2019 are not yet possible due to a lack of scrappage data. A summary of the results in terms of inflows, outflows and in-use battery stock for years 2018 and 2030 is given in Figure 8.

Recycling and second-life battery concepts are currently in relative infancy due to low battery volumes, but are gaining in popularity across Europe with developmental work being carried out by key industrial players that include Northvolt and Hydro in Scandinavia (Hossain et al., 2019;

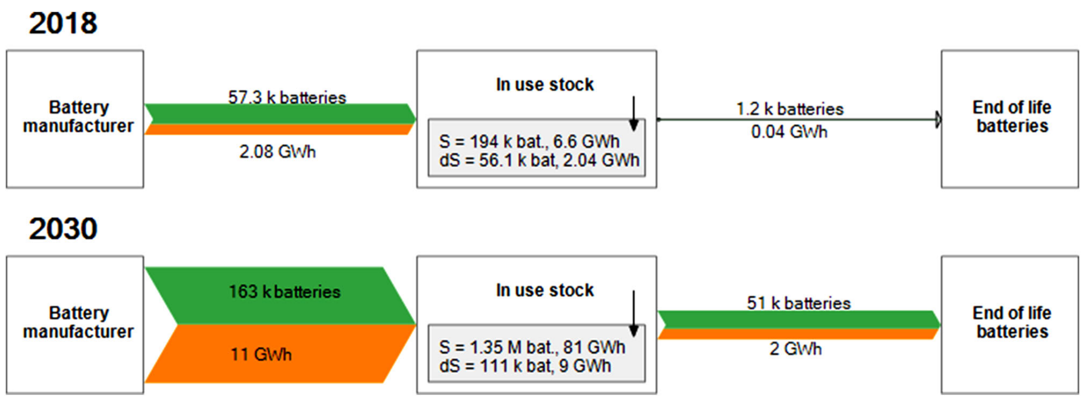

FIGURE 8 Summary of estimated inflows, outflows and in-use battery stock within the Norwegian electric passenger vehicle fleet for years 2018 and 2030. Data underlying this figure are available in Supporting Information S2

Walz, 2018). Together these companies have announced the formation of a joint venture to enable recycling of battery materials and aluminum from electric vehicles by building a pilot battery recycling plant, which will be the first of its kind in Norway (Hydro, 2020). The quantity of assumed end-of-life batteries estimated here represents the potential total available for both recycling and second-life concepts. If the quantity of batteries assumed going mostly to scrap is instead allocated wholly for second-life purposes, these batteries could potentially feed 70,000 and 260,000 typical home/cabin battery energy systems of 8 kWh in 2025 and 2030, respectively (Alternativ Energi AS, 2020). Nevertheless, far from all batteries can be re-used due to degradation or other faults (Svendsen, T. H., personal communication, September 14, 2020). These applications are still in an early phase and the dynamics will depend on a range of factors from policy to business opportunities. Based on the recently released EU proposal for the battery legislation it seems that incentives are targeted toward recycling, while reuse will be rather market regulated. Reuse can be seen as delaying the availability of secondary raw materials for automakers, while potentially also reducing the demand for new batteries for stationary applications. Thus, there is a need to further study these dynamics and better understand the impact of reuse and recycling for material security.

Complicating the picture, differences in recycling and reuse economic viability are relatively unknown at present, and other types of losses will also affect the actual total quantity of batteries available for recycling and second life. It is assumed in many studies that around 10% of vehicles are lost and not collected when scrapped, and there is widespread criteria established in the literature for EV battery retirement that capacity is reduced to 70–80% at first end-of-life (Martinez-Laserna et al., 2018; Saxena et al., 2015; Zhao, 2017). Applying these values means that battery capacity available for second use in 2025 and 2030 without refurbishments or repairs is reduced to 0.4 GWh and 1.5 GWh, respectively. Nevertheless, battery repair via refurbishment involving assembly of used cells/modules in a pack followed by calibrating and balancing can in many cases reincrease the capacity (Svendsen, T. H., personal communication, September 14, 2020).

No calculations have been made here for Europe as a whole. Although findings vary, other studies have previously indicated that between approximately 2 and 8.75 GWh may be available in 2030 for second use from end-of-life EV batteries (Bobba et al., 2019; Element Energy, 2019). Comparisons of Norwegian market data (number of new EV vehicle sales and new vehicle sales corrected for secondhand export/import) with the total EU+EFTA market from Figenbaum et al. (2020) indicate that the battery volumes becoming available for reuse or recycling elsewhere in Europe could be about double the Norwegian volume in 2025 and about quadruple the Norwegian volume in 2030. This picture, along with the results from the other studies, fit relatively well with the model estimates here. After 2030, volumes for reuse/recycling should grow much more rapidly outside of Norway as the market is expected to increase faster in other EU-EFTA (European Free Trade Association) countries from 2020 onward due to the already high domestic Norwegian market BEV saturation.

4 | CONCLUSIONS

Short- to medium-term potentials for recycling opportunities for Norwegian industries were investigated in this study; the total number of battery packs in new passenger BEV sales in Norway was estimated to be 116,000 in 2025 and 163,000 in 2030, and the number in retired vehicles to be approximately 17,000 in 2025 and 51,000 in 2030. In terms of battery capacity, this equates in new sales to 2.1 GWh in 2025 and 11.0 GWh in 2030, and in retired vehicles, 0.6 GWh in 2025 and 2.1 GWh in 2030 (not accounting for losses). Results show that NMC and NCA are battery types currently used in greatest amounts, and that there is also a division by weight segment evident. Most LIBs are currently contained within the weight segment 1500–1599 kg followed by the weight segment 2000+ kg. NCA is in use for heavier weight segments and LMO/NMC in use for lighter weight segments. In terms of LIB types in retired vehicles, NCA batteries initially constitute the largest overall capacity, but we estimate they will be surpassed by NMCs in later years. Not included in calculations are batteries from plug-in hybrid electric vehicles (PHEVs) and batteries from battery electric light commercial vehicles (BE-LCVs). However, these constitute lower fleet vehicle volumes; at end of year 2019 there were 116,042 PHEVs and 7332 BE-LCVs versus 260,292 BEVs (SSB, 2020b), with PHEVs also having smaller battery capacity than BEVs per vehicle.

Since the study builds on multiple modeling processes, various uncertainties are present. Although an overall trend to move away from cobalt seems to be dominant throughout the industry, very little concrete data is publicly available about the specific type of Li-ion batteries future BEV models will utilize. Thus all batteries arriving into the fleet between 2020 and 2030 were assigned in this study as unknown Li-ion type. This simplification allows the forecast uncertainty to be reduced but leaves unanswered questions about the end-of-life materials available. Other key uncertainties relate to the lack of differentiation of import and export flows in the stocks-flow model output, and the non-inclusion of other detailed types of outflows (e.g., vehicle and battery capacity losses), that will also affect the main results. For the former uncertainty, the available data suggest that exports are currently low and the majority of used vehicles imported in recent years are less than 1 year old, which significantly reduces the model uncertainty. Nevertheless, this may change over time.

In summary, this analysis based on a combination of vehicle-specific data and assumptions of BEV market uptake from the Norwegian national budget estimates that the battery capacity and pack number in retired BEVs will increase dramatically toward 2030, indicating great potential for domestic markets to develop around battery recycling and reuse. Further, it provides insights into the materials embedded in the batteries as well as a theoretical framework that can be applied to other regions. The results also indicate that it will be necessary to adapt to changing battery types and sizes of the retired batteries. Making use of business opportunities activities will require a large amount of infrastructure, as well as new regulations, for which the estimates provided here can act as a guide.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from Opplysningsrådet for veitrafikken (OFV) and EV Database. Restrictions apply to the availability of these data, which were used under license for this study. Data are available directly from OFV and EV Database.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

ORCID

Rebecca Thorne https://orcid.org/0000-0003-3399-9116
Erik Figenbaum https://orcid.org/0000-0003-2092-369X

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SUPPORTING INFORMATION

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

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4. Key findings and discussion

4.1. To what extent do social and technological developments in the lithium-ion battery system affect raw material demand?

The electrification of the transport sector and the integration of renewable energy heavily depend on a resilient supply of battery raw materials. However, given the various types of LIB technologies available and fast development of the industry, there is high uncertainty related to the scale at which each individual material will be required. Our simulation results showed that this uncertainty in the demand propagates through the entire battery materials system and could cause material supply bottlenecks if the industry if regions cannot adapt their production swiftly enough. Thus, forward-looking models as the ones proposed in this thesis can play an important role in informing the relevant stakeholders about possible outcomes and effective strategies to mitigate the risk of material supply shortages.

What are potential bottlenecks in the supply of battery raw materials and how can they be avoided or reduced?

On the manufacturing side, we find that a portfolio of technologies would allow industry to diversify the materials used in the LIB production and so reduce the idiosyncratic risk battery manufacturers are exposed to for any given material. Currently available technologies include NMC batteries, which contain nickel, manganese, and cobalt in the cathodes, and LFP batteries that rely on iron and phosphorus instead. A collective reliance on one specific technology involves high risk of a future shortage in material supply and could result in a global shortfall of battery production. Given that manufacturers usually specialize on specific technologies and rely on different material supply chains, such a shift would require time to adjust the production processes. Furthermore, all of the current LIB technologies require similar amounts of lithium and graphite for the anode, making these materials a systemic risk that cannot be reduced through diversification of LIB types.

Hence a portfolio of LFP and NMC batteries would mitigate the risk related to the cathode materials, but not the anode materials and lithium. Intense research is ongoing in efforts to commercialize so-called next-generation LIB technologies, which include mainly Li-Air and Li-S. These chemistries are very promising in reducing the need for current cathode and anode materials but may in fact intensify lithium demand given their use of lithium-metal instead of the current cathode materials outlined above. This highlights the importance and potential criticality of lithium. Non-LIB technologies such as sodium-ion (Na-ion) batteries and hydrogen (H+) fuel-cells could be an important part of the solution by further expanding the material portfolio for energy storage. These technologies, while not fully commercial yet, have shown promise in pilot projects and increasingly approach viability (Brooks, 2002; *V2G Hub | V2G Around the World*). The Chinese automaker BYD announced their intention to produce EVs with Na-ion batteries by the end of 2023 already[1]. Barriers such as inferior energy density compared to LIBs are determined by the physical properties of the materials used, but different market segments and material prices may make such lower-performing technologies acceptable in the future.

The rapid development of battery technologies is also a cause of difficulty for battery recyclers, as the recoverable value depends on the materials within the battery and the recycling process may need to be adjusted to specific chemistries as well. Indeed, large-scale industrial processes are often fine-tuned to treat a specific type of feedstock, meaning that a diversification of risk on the supply side may result in an increased complexity for EOL handlers. Efforts such as the battery passport, in which material specifications of each battery are made available throughout the battery system, may be essential to ensure that the feedstock is treated in an effective way.

As shown in our models, recycling can be expected to play an important role in reducing primary material demand, but it can only become significant in the mid- to long term, when large amounts of battery raw materials become available as scrap. Therefore, important interventions on the demand side are needed to fill the gap. Existing regulations and proposals mainly target the supply side, setting standards for recycled content in LIBs, recycling efficiency of specific materials, and CO2 emissions of material

[1] https://www.electrive.com/2023/04/21/catl-and-byd-to-use-sodium-ion-batteries-in-evs-this-year/

production. However, such regulations presume that any amount of materials can be produced under such standards regardless of the demand. However, we demonstrated how a steep increase in LIB demand during the next decade might make reaching standards such as the recycled content of batteries unfeasible due to limitations of scrap availability. The current lack of a system-based definition of recycled content in batteries might mean that producers may source scrap from other sectors to increase the recycled content of batteries to meet the requirements. This may create problem shifts from the battery industry to other sectors that are not subject to similarly stringent regulations.

Furthermore, recycled content requirements may make the use of the regulated materials such as nickel, cobalt, and copper less attractive. Thus, a recycled content-based approach can contribute in creating a shift to LFP batteries, which use the unregulated phosphorus instead of the regulated metals outlined above. While phosphorus is considered to be widely available worldwide, its geological reserves are heavily concentrated. Moreover, the production capacity of the high-purity phosphoric acid needed for batteries is as of today controlled by only 5 countries (Lunde, 2022). Problem shifts also occur for CO_2 requirements, as demonstrated by Young (2021), where the heavily regulated LIB industry may source the low-CO_2 nickel, while the unregulated stainless steel industry absorbs the high-CO_2 Ni. Overall in the nickel cycle, CO_2 emissions are not reduced, but the battery industry appears more environmentally friendly.

We showed that reducing the need for batteries in the first place has the biggest potential to avoid supply shortages and unintended consequences. These can include, but are not limited to, incentivizing the use of vehicles with smaller batteries by e.g. offering a large infrastructure of charging and fast charging stations; reducing the need for vehicles by e.g. investing in public transport; and requiring OEMs to facilitate the reuse and replacement of batteries within vehicles and stationary applications, e.g. by making the batteries' BMS accessible. The right to repair and lifetime extensions of batteries and vehicles holds an important key in reducing the demand for battery raw materials. Moreover, focusing on maximizing the use of existing battery stocks can create synergistic benefits by reducing material demand while increasing the resilience of the grid. Vehicle-to-grid (V2G) is a technologically viable option that requires several policy and regulatory incentives to be adopted widely, but it also promises to bring the biggest gains in energy and material supply security.

What trade-offs and problem shifts can arise and how can they be addressed?

Demand and use-phase interventions, however, often come with trade-offs and social barriers. Smaller vehicles with smaller batteries would necessitate people to accept more regular charging stop-overs on longer trips and corresponding increases in travelling time and planning. Thus, the incentive to adopt smaller vehicles would need to be large enough for the population to accept changing current habits and behaviours. Beyond that, certain resource-efficiency strategies can conflict with the commercial interest of the automotive industry. Reuse and replacement of batteries as a lifetime extension strategy for vehicles and batteries, for instance, may reduce new vehicle sales. This can be in direct contradiction with an industry that is trying to maximize profits by selling as many vehicles as possible. The loss in sales could potentially be counter-acted by encouraging the industry to enter the energy market as an alternative source of income through e.g. V2G and SLBs. Indeed, this work demonstrated that a) there is a market for stationary storage for grid services that can be satisfied by V2G and SLBs; and b) that the excess capacity available from each technology can support the electrification of other sectors and act as a strategic reserve.

Nevertheless, V2G also requires people to overcome their anxiety of perceived increased battery degradation and would need their commitment to connecting their vehicle as often as possible to the grid so it can provide storage services. Information campaigns and good charging infrastructures can be key in lowering those thresholds. In addition to individual behavioural changes, the aggregators, and a restructuring of the workings of energy market would be needed. On the other hand, SLBs require users to accept purchasing used batteries for stationary applications. As their performance is uncertain, SLB adopters may incur more risks and would thus likely rely on warranties and novel business models to succeed. Offering storage as a service rather than selling the batteries themselves might be one such option.

In the context of regional and country-specific strategies, high collection rates of battery scrap can be crucial to keep the materials within the regional system. In regions like Norway and the EU however, many materials may exit the regional system in second-hand vehicle and used battery exports even with high collection rates of scrap. More than 60% of ELVs were exported from Norway to other regions in 2019 (Lone, 2022). To keep the materials in the regional loop, there is thus a need for more integrated solutions in which the batteries are tracked throughout their lives so they can be collected at their final use point and recycled domestically. Global partnerships to re-source the scrap and good collection infrastructure will be crucial in enabling such strategy.

4.2. What role does the replacement and reuse of components play in reducing raw material demand?

How can product-component interactions be modelled? How do the lifetime of products and their components influence each other's obsolescence? How can such product-component interactions be relevant in the context of electric vehicles and batteries?

Replacement and reuse of LIBs shows an important potential to extend the in-use time of EV-LIB stocks. We showed that replacing batteries in vehicles without reuse can increase the in-use time of EVs but may reduce that of the LIBs. This can have counter-productive outcomes from a resource use perspective, as the demand for LIBs could be inadvertedly or consciously increased (see Figure 5). Such is the case when the lifetime of LIBs is not significantly shorter than the lifetime of EVs (e.g. 12 years for the LIBs and 16 for the EVs). When the battery fails at 12 years, it gets replaced by a new one until the EV reaches end-of-life. By this point the replacement battery will only have been used for 4 years, having another 8 years of theoretically useful time but reaching early obsolescence in the absence of reuse.

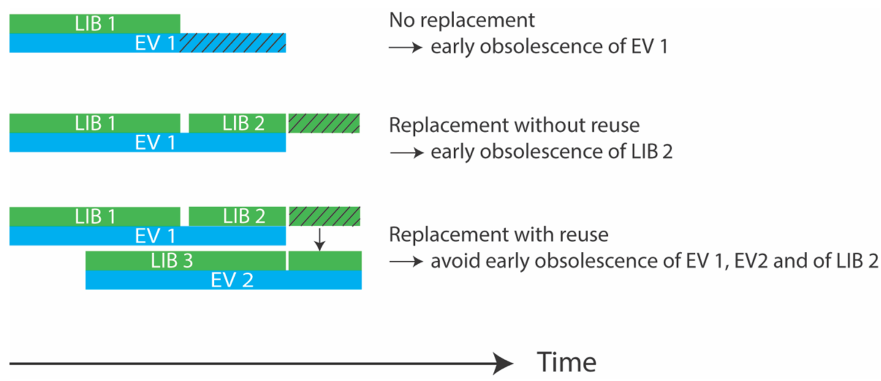

Figure 5: Product-component dynamics under different conditions for reuse and replacement. The length of the bars represent the lifetime of LIBs (green) and EVs (blue).

The product-component framework thus points towards the relevance of not only focusing policy efforts on products, but also paying attention to components. Regulations that target component reuse and replacement can be a powerful tool in moving towards a more circular economy. A current barrier in enabling battery replacements in EV-LIB systems is the significant cost of new batteries. This can lead EV owners to acquire a new EV once the LIB no longer performs at acceptable levels instead of replacing it. Current incentives, such as tax exemptions, have been effective at fostering the adoption of EVs but have not yet addressed the cost reduction of LIBs for replacements or reuse explicitly. Doing so may be an important step in extending the lifetime of EV-LIB systems and thus reduce resource use.

The lifetime of products is a concept needs further attention for modelling several of the circular economy strategies. The lifetime is considered to be the time span a product spends between entering use and being scraped. In MFA studies, this is traditionally reflected as a statistical probability function to simulate when a product that has entered the use phase exits at a given time. Another common assumption is that products and all of their parts (components) reach obsolescence simultaneously, without explicitly modelling the potential differences in lifetimes of different parts. The product-component framework developed here proposes the use of several functions to reflect the lifetime of products and components independently. This provides further insight into the consequences of product-component system obsolescence and ways to extend the service life of products and components. It presumes that the obsolescence of goods can be due to failed components that can be replaced in order to extend the in-use time of the product in question. Moreover, it proposes that while a product may reach obsolescence, its components may continue to be functional and can therefore be reused in other similar products or in other applications. Hence, by differentiating between the potential lifetime that products and components can have, the proposed framework suggests a novel way to model the in-use time of goods as a composite function of the two lifetimes and the conditions for reuse and replacement.

This approach enables practitioners to evaluate the consequences of reuse and replacement of components on resource use, which are fundamental to the circular economy proposition. The product-component framework enables the tracking of component cohorts, which relate directly with technical and material specifications of the components of a given year. In the case of LIBs, the material composition is changing on a yearly basis and so tracking their cohorts accurately is an imperative to understand resource use and scrap availability.

This introduces further complexity to the modelling: Reusing and replacing components means that the product- and the component cohorts can differ, and that the probability of outflow is determined by the lifetime of both goods. Traditional approaches use the probability density function (*pdf*) derived from a statistical distribution as fraction of the initial inflow leaving the stock at a given year. However, since part of that outflow re-enters use as an additional inflow, the historical value no longer reflects the number of goods that are still in use. The remaining expected lifetime of the reused components is not accounted for in the original *pdf*, resulting in stocks that never leave use. We introduce the use of a *hazard function (hf)* to overcome this limitation. Similar to the *pdf*, it is derived from a statistical distribution around given values, but its formulation enables to link the probability of obsolescence based on the age of the goods in question at a given time, rather than the initial size of the historical inflow (see Figure 6).

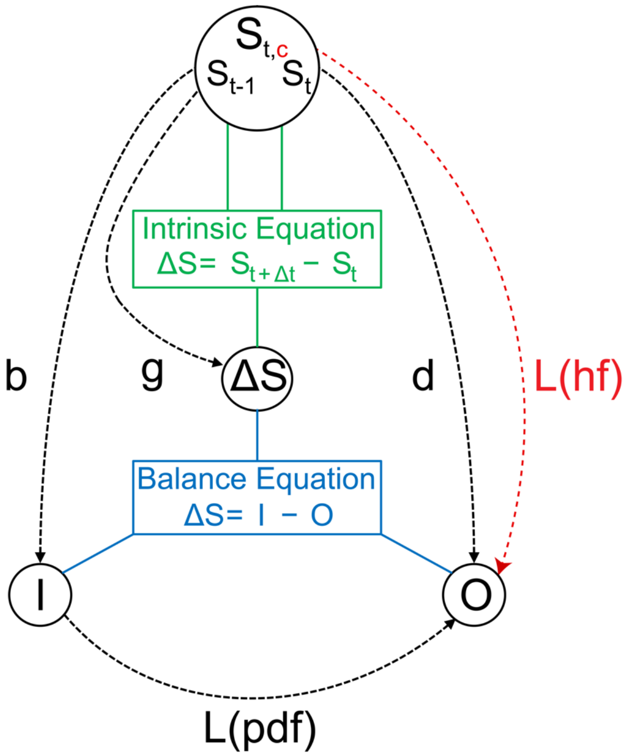

Figure 6: Stock dynamics modelling options for linking the stocks and flows. Previously, the outflows could be calculated either based on historical inflows (I) and a pdf function of the lifetime L(pdf) or based on the total stock S(t) ignoring the cohort and a death rate (d). The lifetime function represented through hazard function L(hf) is a novel formulation that connects the stock by cohort (c) directly to the outflows (red dotted arrow), without requiring information about the historical initial inflows. Adapted from: Lauinger et al., 2021

Hence, modelers need only know the age or cohort composition of an existing stock and the lifetime expectancy of the cohorts to calculate the system flows without the need to know the historical inflows. The knowledge of the size of the initial inflow becomes irrelevant. This has substantial implications: the hazard function can change over time for a given cohort as it ages and as conditions change. The stock dynamics are thus not defined at the inflow time but can dynamically be adjusted over time for each cohort. Moreover, data on the initial stock composition can be scarce which presents a challenge when using the probability density function. The hazard function not only bypasses this issue, but can easily be combined with death rates in a combined lifetime-leaching model to simulate e.g. one-time events such as earthquakes that destroy stocks; or regular events related to specific cohorts that are not captured in the lifetime of goods, such as accidents that render the stock in question obsolete.

4.3. What is the potential of vehicle-to-grid, second-life batteries and recycling to increase energy and raw material supply security?

Which of the strategies has the largest potential to reduce overall resource consumption and how can they be combined most effectively?

Lithium-ion batteries are central to the decarbonization of transport and energy systems and require large amounts of raw materials to be produced. Therefore, they stand at a critical nexus between energy and material security and minimizing the risks of supply chain disruptions by reducing total material demand is a strategic imperative. V2G and SLBs are options that enable the multifunctional use of LIB stocks during the EV lifetime for the former, and as a lifetime extension after automotive use for the later and so increase the potential of storage provided per battery over their lifetime.

We showed that the potential capacity for each V2G and SLB could exceed the demand for grid services, such as frequency regulation, by a factor of 2 in the long term. Therefore, a competition between the technologies can arise for the grid services market. The timing of V2G adoption seems to be one of the defining factors in the technologies' largescale success, as any delay could result in the stationary battery model to establish itself as the standard in the industry. Given the long lifetime of batteries, installing a large stock of NSBs could lead to a technology lock-in effect which prevents the widespread adoption of other options.

The existence of an excess capacity of V2G and SLBs points to the possibility of deploying it for other sectors. Countries such as Switzerland have mandates stipulating the need for excess capacity on their hydropower dams only to be used in case of emergencies. Others such as Germany have large stocks of fossil fuels to be used in cases of supply shortages. While the services of these approaches are not inherently equivalent, using the excess capacity of batteries though V2G can cover some of the demand for reserve capacity and hence reduce the need for idle stocks. The spatial distribution of vehicles compared to centralized power-plants can be considered an additional advantage in crisis situations, as idiosyncratic risks related to specific locations can be mitigated. Additionally, the need for capacity shedding, wherein the industry is asked to reduce their energy consumption in peak demand hours due to shortages in productions, could further be reduced with V2G and SLB stocks. In this case, supply of energy would be increased by discharging batteries instead of reducing the consumption of the industry, which can be very costly.

However, both V2G and SLBs require important restructuring of the energy market and infrastructure to function efficiently. Bi-directional chargers would be widely needed to maximize the time V2G-ready vehicles are available to the grid. In addition to this, the user opt-in thresholds should be minimized, by making participation easy and attractive. Reducing any further barriers in enabling mass participation in the market can be key, as many behavioural and social changes are needed for widespread deployment of V2G. In addition to behavioural changes, participation in the wholesale energy market is currently at 1 MW of minimum available for the EU. Given the decentralized nature of V2G and SLBs alike, there would be a need to either reduce this threshold to allow for individual participation or introduce aggregators that can pool the capacity of several vehicles/SLB installations to reach the minimum 1 MW threshold to participate in the market. This would be the equivalent of around 100 large EVs discharging at 10 kW, but the aggregator would need to have significantly more due to the stochastic availability of vehicles.

> Under what conditions would either technology be preferable? How do these technologies affect the recycling of materials and overall resource use?

We showed that V2G, SLBs, NSBs can be in competition for the grid storage market. Their development will be determined by their physical availability but also by regulatory, economic, and behavioural factors. The potential displacement of NSBs by V2G and SLBs will be discussed below.

V2G is a technologically mature option that offers the highest potential capacity in the mid-to long term while having the highest resource efficiency. However, its deployment depends not only on the technological readiness, but also on 1) the percentage of battery capacity that is made available to the grid, 2) the participation rate of people, i.e. the number of people actively making their V2G-ready EV available for grid support, and 3) the charging infrastructure needs in parking spaces. A mandate could increase the V2G technological penetration, but it certainly cannot force people to use the technology and participate in the market. Thus, incentives would be needed, and the entry barrier should be as low as possible to entice a high participation rate. Its cultural invisibility, potentially low cost and wide availability could make V2G the most attractive option for grid storage. However, the regulatory needs to allow V2G to participate in the largescale market as well as the potential for stationary batteries to establish themselves first make timing a central issue for its success.

Indeed, NSBs could remain in use for over a decade and thus installing them carries a lot of inertia, which can limit the penetration of V2G and SLBs in the future. To investigate this, we developed a novel inflow-driven, stock-informed (also called demand-constrained) methodology, in which the installed battery capacity is limited by the need for it. Instead of assuming that all batteries available for reuse would be installed automatically, our model compares this availability to the demand for stationary storage applications. If the demand exceeds or is equal to the supply, all batteries available are installed. Otherwise, only the share needed is installed and the rest is recycled instead. In other words, the transfer coefficient is modified ex-post based on the need for battery storage. The same principle is applied for V2G capacity installations: the pre-defined V2G penetration rates are compared to the need for storage and only the fraction for which there is a demand is equipped with V2G. The rest of the EVs are considered non-V2G ready EVs. In this way, the inflow-driven availability of SLBs and V2G is constrained by the demand for storage stock to ensure that no excess or lack of capacity exists in the stationary storage market. If V2G and SLBs cannot offer enough storge, NSBs are installed and are assumed to remain in use over their expected lifetime – they are not replaced to accommodate more SLB or V2G capacity. For this reason, any delays in V2G availability result in more NSBs being installed and remain in use instead of V2G in the future.

If V2G fails to begin rapidly penetrating the market before around 2025, SLBs could be the next-best option from a resource perspective in the short-term. Given that current recycling processes do not recover many of the materials in batteries including P, Si, Li, Al, and graphite, extending the useful life of batteries trough stationary reuse can reduce primary material demand and the infrastructure needed to manufacture and recycle new batteries. Recycling is still a central strategy to recover the materials that have already been extracted, but its effectiveness compared to lifetime extension though reuse depends on the recovery efficiency. As SLBs can be operated in a similar way as NSBs, the timing issue of their penetration is not as critical as for V2G. They can thus be rather complementary to NSBs in the next decade and allow some time for regions like the EU to build more efficient recycling infrastructure. Recycling becomes more resource efficient using direct-recycling technologies because the losses become marginal (< 10% for all materials). If the recovered materials are used to produce new batteries, they can provide more storage per kg of SLB since they are not degraded, and technology has likely improved. However, benefits such as reducing the need for infrastructure in manufacturing and recycling as well as energy demand could still justify the preference of SLBs over NSBs.

Overall, our models show that a combination of widespread V2G adoption and rapid development of efficient recycling infrastructure could lead to the highest energy and material supply security gains while minimizing the need for batteries overall. Many barriers would need to be overcome to achieve such a high V2G penetration, non the least of which is social acceptance. Given the long lead times needed for V2G and SLBs to become available, NSBs will be needed under most scenarios. Delays in the adoption of V2G and SLBs would lead to more NSBs being installed, which can be expected to exacerbate pressure on LIB raw materials.

Conclusion

In this work, we studied on the implications of using lithium-ion batteries in electric passenger vehicles and stationary applications on resource use at various scales. In doing so, novel methodologies were developed and made openly accessible to the modelling community to enhance the knowledge base around resource use broadly. The latest versions can be found in the following repository: https://github.com/mfa-indecol. The main methodological contributions are specifically:

1. The product-component framework and python script with 12 modelling approaches for product-component systems with a fully open access license. This framework can be highly relevant for several goods with product-component dynamics beyond EV-LIB systems. Such can be the case for roads, where the foundation remains for several decades while the pavement is periodically replaced with new materials; for railways where regular maintenance requires changing certain parts; and for buildings where renovation activities necessitate the exchange of building components.
2. The introduction of inflow-driven, stock-informed MFA models with dynamic transfer coefficients that are informed and adjusted based on specific criteria. This approach is also fully documented and made openly available for practitioners to use.

Additionally, this work supports the dissemination of the results by using interactive scenario visualization tools accessible to a wider audience. The global MATILDA model is calibrated with over 8000 scenarios which can be explored with ease online by choosing any combination of parameters here: http://129.241.153.168:8051/. Practitioners can thus identify the implications of different combinations of parameters on vehicle, battery, and material demand and analyse the effects of different interventions. This helps create awareness about the resource implications of this industry, and it supports the making of complex research findings accessible to policymakers in the decision-making process.

By examining resource use related to batteries from country, regional, and global levels, this thesis proposes insights that address social, geopolitical, and technological challenges in the LIB system. Our models have addressed these issues qualitatively and quantitatively and have provided insights in the face of large uncertainty in the future development of the passenger vehicle fleet. We have shown that while technology will play an important role in enabling the widespread adoption of EVs and integration of RE, societal changes in consumption and behaviour will be a pivotal complement in the transition to a more sustainable civilization. It thus follows that the material criticality issue needs to be tackled from many ends: starting from the demand by encouraging the adoption of smaller vehicles; participation in V2G, and extending the in-use time of battery stocks through reuse; the right to repair, and likely to upgrade EVs and LIBs to avoid their early obsolescence; and complementing with technology by making infrastructure available and having suitable incentives in place.

While this work only focused on demand-side interventions for passenger vehicles and stationary storage needs to address raw material security, there are many other challenges and strategies that need to be further investigated. LIBs are expected to be used in commercial vehicles, heavy-duty vehicles, ferries and a number of other applications, all of which pull on the same resources to satisfy their demand. Thus, the potential material supply bottlenecks investigated here are likely underestimating the total global demand. Evidently, technology development is fast and ongoing and alternatives to LIBs already exist, which can contribute to displacing some LIB material demand in the future. Notwithstanding this, the demand for LIBs will likely be orders of magnitude larger in the future than it is today. Thus, systemically understanding the effects of material demand increases on material supply to inform energy and material security towards a circular economy remains a top priority.

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Appendix

SI Paper I

SUPPORTING INFORMATION FOR:

Aguilar Lopez, F., Billy, RG. & Müller, DB. (2022.) A product-component framework for modelling stock dynamics and its application for electric vehicles and lithium-ion batteries. *Journal of Industrial Ecology.*

Summary

This supporting information provides a detailed mathematical description of the modelling approaches presented in the main body of this manuscript and additional Figures to complement the text.

1. Hazard functions for dynamic MFA modelling

$S(t, c)$ is defined as the remaining stock of cohort c **at the end** of year t (or at the beginning of t-1).

Using the survival function of the chosen lifetime distribution, $sf(t, c)$:

$$S(t, c) = I(c) * sf(t, c)$$
$$S(t-1, c) = I(c) * sf(t-1, c)$$

So if $sf(t, c) \neq 0$ (should be verified in practice, otherwise it is impossible to solve a stock-driven model) , $\forall\, t > 0$:

$$I(c) = \frac{S(t-1, c)}{sf(t-1, c)} \qquad (i)$$

And

$$O(t, c) = S(t, c) - S(t-1, c)$$

So:

$$O(t, c) = I(c) * \left(sf(t, c) - sf(t-1, c)\right) \qquad (ii)$$

By combining equations (i) and (ii):

$$O(t, c) = S(t-1, c) * \frac{sf(t-1, c) - sf(t, c)}{sf(t-1, c)}$$

We define the hazard function $hz(t, c)$ as:

$$hz(t,c) = \frac{sf(t-1,c) - sf(t,c)}{sf(t-1,c)}$$

this hazard function can be used to calculate the outflows of a cohort during a given year from the remaining stock of this cohort at the beginning of the year:

$$O(t,c) = S(t-1,c) * hz(t,c)$$

The relationship between probability density function of the lifetime distribution, $pdf(t,c)$, and the survival function, is given by:

$$sf(t,c) = 1 - \int_{-\infty}^{t} pdf(u,c)\ du = \int_{t}^{\infty} pdf(u,c)\ du$$

Therefore,

$$\begin{aligned} sf(t-1,c) - sf(t,c) &= \int_{t-1}^{\infty} pdf(u,c)\ du - \int_{t}^{\infty} pdf(u,c)\ du \\ &= \int_{t-1}^{t} pdf(u,c)\ du + \int_{t}^{\infty} pdf(u,c)\ du - \int_{t}^{\infty} pdf(u,c)\ du \\ &= \int_{t-1}^{t} pdf(u,c)\ du \end{aligned}$$

So the hazard function could be rewritten:

$$hz(t,c) = \frac{\int_{t-1}^{t} pdf(u,c)\ du}{sf(t-1,c)}$$

This is a discretization of the more commonly used definition of the hazard function, defined as:

$$h(t) = \frac{pdf(t)}{sf(t)}$$

This hazard function h defines the instantaneous force of mortality at time t. Since in MFA, we usually discretize the time, and only measure the stock at given time intervals (every year), the discretized hazard function is more convenient to use.
There are some advantages of using the hazard function instead of the usual survival function in MFA, especially in cases:

- When we only know the initial stock and its cohort composition, but nothing else about the past, or in general when we have missing inflow data but can estimate the lifetime by another way.

- When the size of the stock at time t might have been modified in the past by an external factor not captured by the lifetime distribution of the model (combined leaching-lifetime approach, component failure, reuse, accidents, import/export or immigration/emigration). In these cases, the initial cohort size is no longer representative of the remaining value of the stock, so the formula $S(t,c) = I(c) * sf(t,c)$ can no longer be used.

The hazard function might also facilitate the interpretation of the results in some cases. For instance, for a normal distribution, the hazard function is increasing exponentially indefinitely, which gives a better representation of the actual probability of reaching end-of-life for aged products or individuals. It also allows for a "purer" modelling of stock-driven models, where we only use the stock in the calculations and never involve initial inflow. However, in simple cases, it remains easier to use the survival function, or the matrix relationship $O = IL \Leftrightarrow I = \Delta S\,(\mathbb{I} - L) - 1$

2. Illustration of lifetime and in-use time

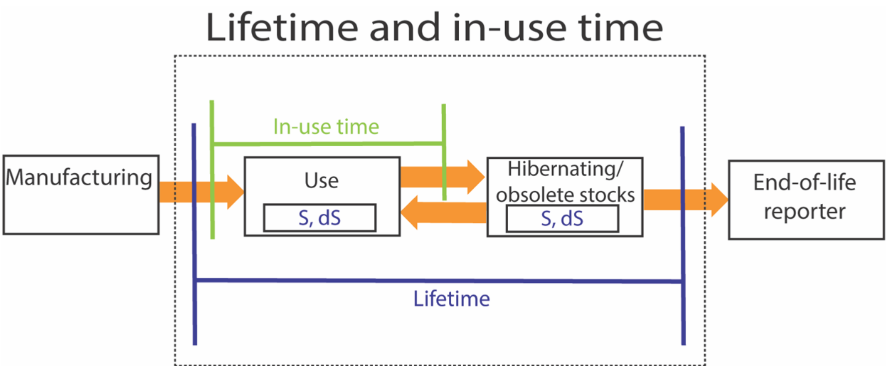

Figure 1: Visualization of the lifetime as opposed to the in-use time in a generic system definition.

Figure 1 illustrate the difference between the definition of the lifetime and the herein introduced in-use time. While the lifetime includes hibernating stocks and only considers outflows once the goods have reached a reporter, the in-use time consider the outflow as soon as the goods have become obsolete. Consequently, the secondary availability of resources is closer to reality when the lifetime approach is used, if no additional logic for the in-use time is introduced. However, the estimations for the inflows are more accurately calculated using the in-use time, since the goods need to be replaced as soon as they have left the use phase and no longer provide the required service.

3. Generic stock used to illustrate cases

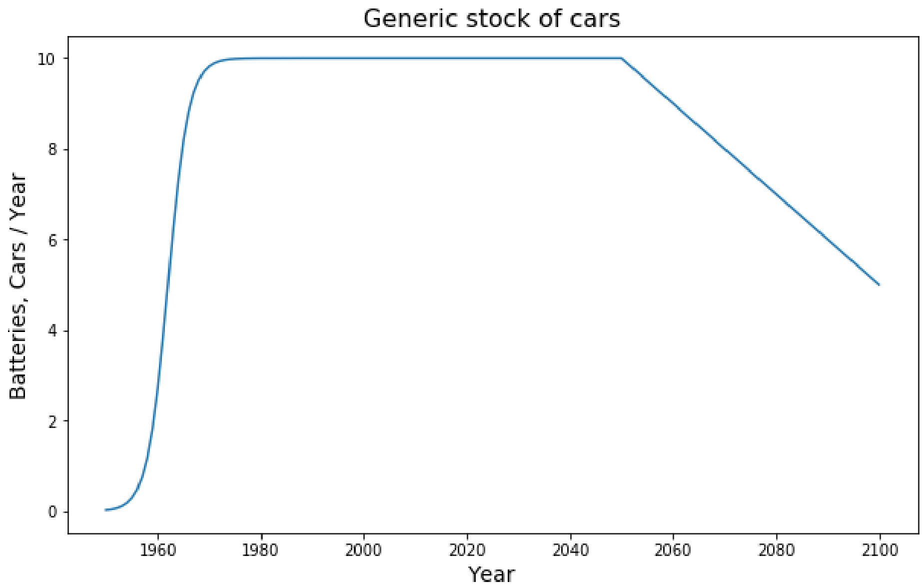

Figure 2: Generic stock used for illustration of the different modelling cases. Underlying data for this Figure can be found in the SI files tab "Supplementary Figure 2"

4. System dynamics calculated using case 2

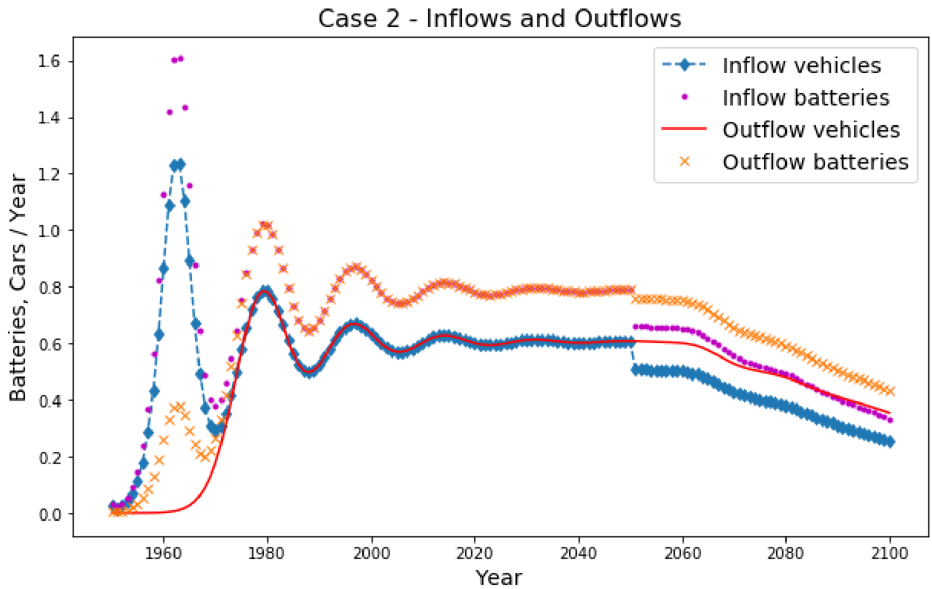

Figure 3: System dynamics of a generic stock (see Figure 2) calculated using case 2. Underlying data for this Figure can be found in the SI files tab “Supplementary Figure 3”

As can be seen in Figure 2, the use of a replacement rate leads to inaccurate estimations of the component, in this case battery, in and outflow. This is particularly evident in the early years where the stock is growing (compare with Figure 1), as an artificial peak in outflows is generated. This can be explained by the fact that the underlying assumption with this modelling approach is that the replacement component goes into use at the same time as the product does. This means that the component inflow is always equal to the product inflow times the replacement rate. Therefore, when the stock is not constant and considering that the total stock of components must be equal to the total stock of products, an artificial outflow is generated to keep mass balance.

5. Calculation of vehicle fleet

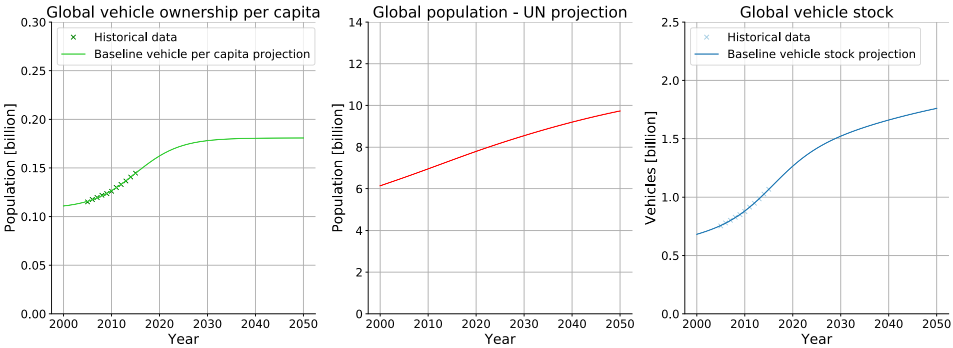

Figure 4: System drivers for the total vehicle stock calculations. Underlying data for this Figure can be found in the SI files tab "Supplementary Figure 4"

The calculation of the total vehicle stock is derived from historical vehicle ownership per capita and population statistics. Baseline projections of the two yield the total vehicle stock until 2050.

6. Survival functions for case study modelling approaches

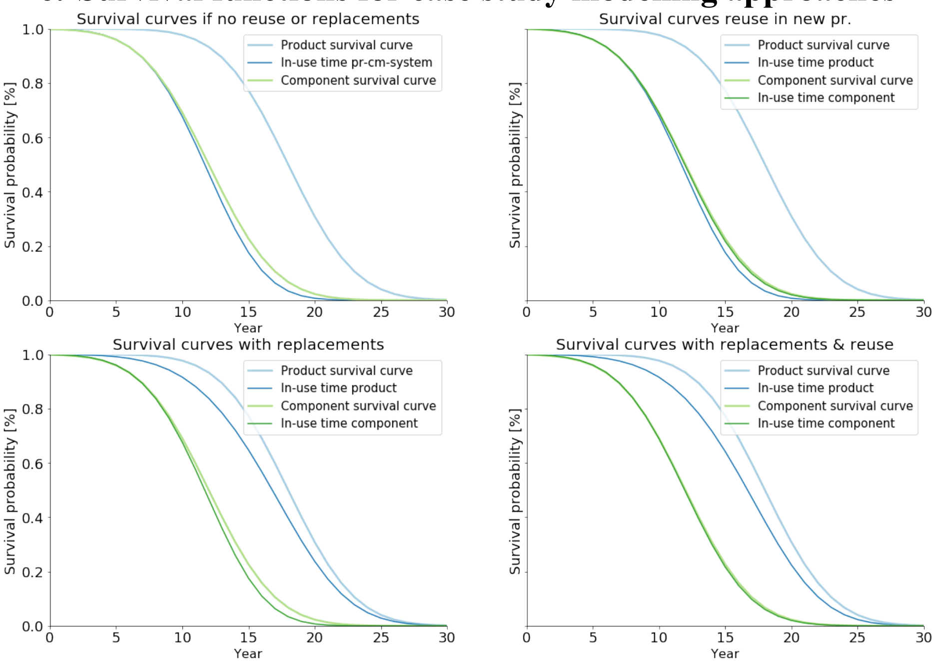

Figure 5: Survival curves of the first EV and LIB cohort as compared to their hazard/lifetime functions. Underlying data for this Figure can be found in the SI files tab "Supplementary Figure 5"

SI Paper II

Supplementary information for the paper: “Evaluating strategies for managing resource use in lithium-ion batteries for electric vehicles using the global MATILDA model”

Fernando Aguilar Lopez[1*], Romain Billy[1], Daniel B. Müller[1]

1. Department of Energy and Process Engineering, Norwegian University of Science and Technology, Trondheim, Norway

*fernando.a.lopez@ntnu.no

A.1. Vehicle stock calculations

The calculation of the total vehicle fleet is assumed to be driven by the increase in population and change in vehicles per capita. The current registered vehicles in the regions South Korea and Japan, US and Canada, ROW, and Europe were taken from OICA for the period of 2005 to 2015 (International Organization for Motor Vehicles Manufacturers, 33AD). The population statistics come from the UN database baseline scenario and are defined within the same geographical scope as the OICA data (United Nations Department of Economic and Social Affairs, n.d.). Figure 1 summarizes the values used for historical calibration. For the vehicles in use, the category Passenger Vehicles was chosen, and special consideration was given to the vehicle fleet in the US, as many vehicles that are reported in other regions as passenger vehicles are not included in the US statistics such as SUVs and pick-up trucks. To adjust for this, all vehicles in the category “light-duty vehicles, short wheeled” and 50% of vehicles in the category “light duty vehicles, long wheeled” were assumed to be passenger vehicles – the rest being commercial.

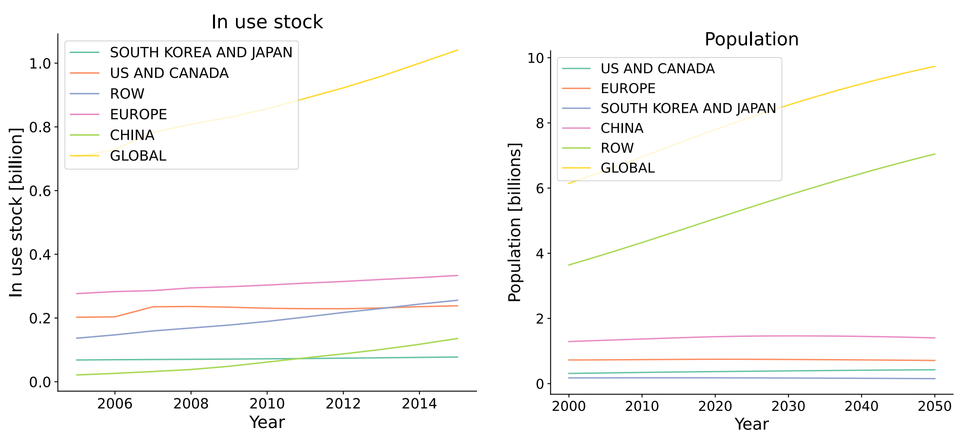

Figure 1: Historical vehicle stock by region (left) and regional population scenarios (right).

From these two parameters, the historical vehicle ownership is calculated by dividing the total stock by the population, yielding the values summarized in Figure 2

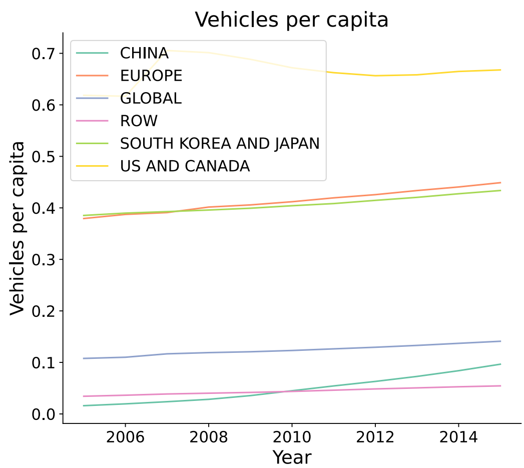

Figure 2: Historical vehicles per capita based on stock and population data

A logistic regression with different targets for three scenarios with low, medium and high ownership levels are calculated for each region. The results of this regression are summarized in Figure 3.

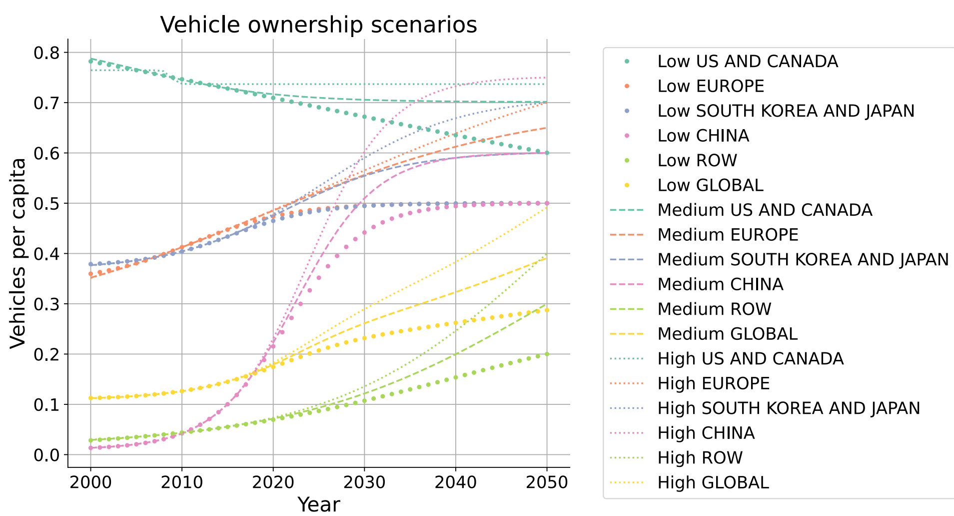

Figure 3: Vehicle per capita scenarios for all regions.

From these, the weighted average is used to calculate the global vehicle ownership. Note that the self-defined scenarios for the Global ownership are not used for the model. By multiplying the vehicle per capita scenarios with the UN population, Figure 4 presents the three global vehicle fleet scenarios used for the model. It can be seen that most of the growth in the future is expected to come from the ROW region, driven by the increase in population, driven by the increase in population.

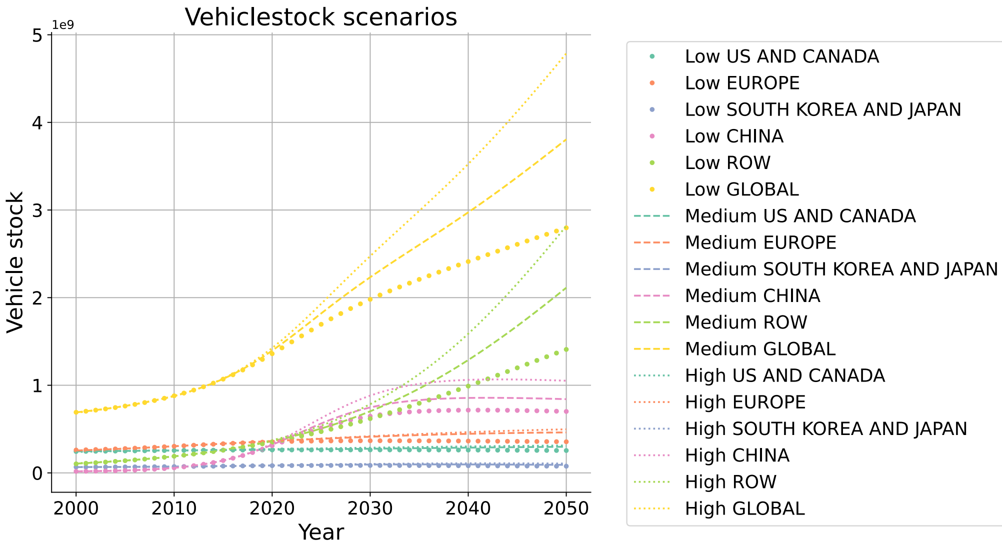

Figure 4: Global and regional vehicle fleet scenarios.

Figure 5 shows the above-introduced scenarios plotted against historical data for validation. The values can be found in the accompanying data supplementary information.

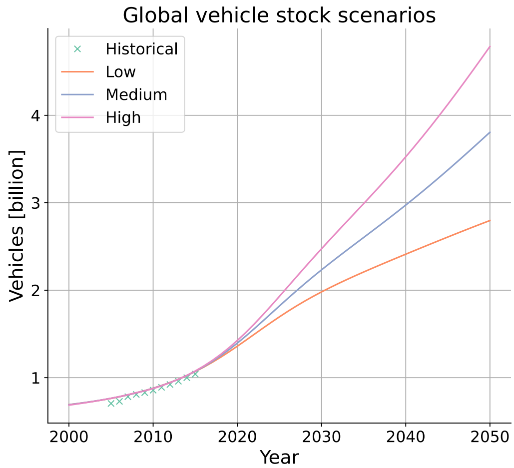

Figure 5: Validation of the global vehicle fleet scenarios.

A. 2. Mathematical description of the model

The MATILDA model is a stock-driven, multi-layer dynamic material flow analysis model.

The total stock of vehicles is calculated by defining the population and vehicle per capita parameters as described above. Multiplying the two yields the total amount of vehicles needed at any time t to satisfy the need for transportation globally. The equation can be written as:

$$Stock(t) = Population(t) \cdot Vehicles\ per\ capita(t)$$

We assumed that the stock is composed four different vehicle types (internal combustion engines (ICEs), plug-in hybrid electric vehicles (PHEV), battery electric vehicles (BEV), and other types of vehicles (OTH)). We estimated the shares of each vehicle type in new vehicle sales (inflows to the stock) over time. The EV penetration is then modelled by the increase of EVs in new sales. A time-product cohort-component cohort matrix *S(t,p,c)* is representing the composition of the stock over time:

- The *time* dimension *t* refers to the year corresponding to a given stock distribution.
- The *product cohort* dimension *p* represents the number of vehicles from different vintage years, defined at the time a vehicle is entering the stock (year of first sale).
- The *component cohort* dimension *c* represents the number of batteries from different vintage years, defined at the time a battery is entering the stock (year of first sale).

In order to initialize the model and populate the stock with a realistic cohort distribution in year 2000, we start the model in 1950 with an initial stock of 0. The stock is then increasing and assumed to be is composed solely of ICEs until 2000.

Inflows and outflows are calculated from the stock and hazard functions representing the lifetimes of vehicles and batteries as described in Aguilar Lopez, Billy, & Müller (2022). The hazard function in year *t* for a cohort *c* can be written as:

$$hf(t,c) = \frac{sf(t-1,c) - sf(t,c)}{sf(t-1,c)}$$

Where *sf* is the survival function. This model is considering different lifetimes for vehicles of the BEV and PHEV types and their batteries, according to the case number 6 from Aguilar Lopez, Billy, & Müller (2022). We assume that these lifetimes are the same for BEVs and PHEVs, which we will refer as EVs in the following part. These two hazard functions are based on a normally distributed lifetime and defined as follows:

$$hf_{Vehicle}(t,p) = \frac{sf_{Vehicle}(t-1,\mathrm{p}) - sf_{Vehicle}(t,p)}{sf_{Vehicle}(t-1,p)}$$

$$hf_{LIB}(t,c) = \frac{sf_{LIB}(t-1,c) - sf_{LIB}(t,c)}{sf_{LIB}(t-1,c)}$$

For other non-LIB containing vehicle types, we modelled the lifetime was a single hazard function for the vehicle only.

The algorithm used to calculate inflows and outflows is described below. This algorithm is run for every year from 1950 to 2050.

For each year, we start by calculating the outflows of EVs for each year and cohort. Since both vehicle (p) and battery (c) cohorts influence the stock dynamics, we model the stock of EVs with a time-product-component matrix $S_{EV}(t,p,c)$ as described in Aguilar Lopez, Billy, & Müller (2022).We apply the hazard function to the respective goods for every year (t) to calculate the probability of simultaneous failure of the vehicle and battery as:

$$O_{EV_{both}}(t,\mathrm{p},c) = S_{EV}(t-1,\mathrm{p},c) * hf_{Vehicle}(t,p) * hf_{Battery}(t,c)$$

We then calculate the probability of outflow due to non-simultaneous battery or vehicle failure:

$$O_{EV_{vehicle}}(t,\mathrm{p},c) = S_{EV}(t-1,\mathrm{p},c) * hf_{Vehicle}(t,p) * (1 - hf_{Battery}(t,c))$$

$$O_{EV_{battery}}(t,\mathrm{p},c) = S_{EV}(t-1,\mathrm{p},c) * hf_{Battery}(t,c) * (1 - hf_{Vehicle}(t,p))$$

The total outflows of EV vehicles are thus given by summing the three values calculated above for each vehicle and battery cohorts:

$$O_{EV}(t,p,c) = O_{EV_{both}}(t,\mathrm{p},c) + O_{EV_{vehicle}}(t,\mathrm{p},c) + O_{EV_{battery}}(t,\mathrm{p},c)$$

The outflows for the ICE and OTH types are only determined by the vehicle hazard function, and can thus be computed as:

$$O_{ICE}(t,\mathrm{p}) = S_{ICE}(t-1,\mathrm{p}) * hf_{Vehicle}(t,p)$$

$$O_{OTH}(t,\mathrm{p}) = S_{OTH}(t-1,\mathrm{p}) * \ hf_{Vehicle}(t,p)$$

And the total outflows:

$$O_{total}(t,\mathrm{p}) = O_{EV}(t,\mathrm{p},c) + O_{ICE}(t,\mathrm{p}) + O_{OTH}(t,\mathrm{p})$$

With this, we can calculate the remaining stocks of each cohort p for each drive train in year t, before we add the new inflow:

$$S_{EV}(t,\mathrm{p},c) = S_{EV}(t-1,\mathrm{p},\mathrm{c}) - O_{EV}(t,\mathrm{p},c)$$

$$S_{ICE}(t,\mathrm{p}) = S_{ICE}(t-1,\mathrm{p}) - O_{ICE}(t,\mathrm{p})$$

$$S_{OTH}(t,\mathrm{p}) = S_{OTH}(t-1,\mathrm{p}) - O_{OTH}(t,\mathrm{p})$$

And the total Stock:

$$S_{total}(t,\mathrm{p},\mathrm{c}) = S_{EV}(t,\mathrm{p},c) + S_{ICE}(t,\mathrm{p},c) + S_{OTH}(t,\mathrm{p},c)$$

And the total Stock Change:

$$dS_{total}(t) = S_{total}(t) - S_{total}(t-1)$$

The total demand for new vehicles in year t, i.e. the total inflows (*I*) to meet the total stock requirements (increase in stock size + replacements) are calculated using the balance equation:

$$I_{total}(t) = dS_{total}(t) + O_{total}(t)$$

With this, we can proceed to compute the inflows by drive train, based on the EV penetration rate

$$I_{EV}(t) = I_{total}(t) * Share_{EV}(t)$$

$$I_{ICE}(t) = I_{total}(t) * Share_{ICE}(t)$$

$$I_{OTH}(t) = I_{total}(t) * Share_{OTH}(t)$$

Using these values, the stock of ICEs and OTH can be computed for year t (where p, c = t), since reuse and replacement dynamics do not play a role here. Hence

$$S_{ICE}(t,t) = I_{ICE}(t)$$

$$S_{OTH}(t,t) = I_{OTH}(t)$$

And the theoretical stock of EVs before replacements are given by mass balance

$$S_{EV}(t) = S_{total}(t) - S_{ICE}(t) - S_{OTH}(t)$$

Next, we need to evaluate the potential for battery reuse and replacement in EVs based on the replacement and reuse rates, since this will affect the inflows (some of the demand will be satisfied by replacements and reuse). Since we know the number of outflows due to battery and vehicle failures separately, we know the potential for battery reuse and potential number of vehicles needing a battery replacement. Therefore, the batteries eligible for reuse are given by

$$Reuse(t, \mathrm{p}, \mathrm{c}) = reuse_{coeff} * O_{Vehicle}(t, p, c)$$

And the vehicles eligible for a battery replacement as

$$Replacement(t, \mathrm{p}, \mathrm{c}) = replacement_{coeff} * O_{Battery}(t, p, c)$$

The number of batteries for reuse is compared to the number of vehicles that need a replacement and the oldest batteries are matched with the oldest vehicles. If there are more vehicles needing battery replacement than reusable batteries available, new batteries used for those vehicles. If there are more reusable batteries than vehicles needing a battery replacement, the excess batteries are installed in new vehicles. The vehicles with replacement batteries are put back into the fleet. Therefore, the stock composition of EVs needs to be updated with the vehicles and batteries that have been reused and replaced.

$$S_{EV}(t, \mathrm{p}, c) = S_{EV}(t, \mathrm{p}, c) + Replacements\ and\ reuse(t, p, c)$$

The need for new cars with new batteries for year t is therefore equal to the theoretical stock needed at time t minus the stock computed after reuse and replacement for all older product and component cohorts:

$$S_{EV}(t, \mathrm{t}, t) = S_{EV}(t) - \sum_{p,c} S_{EV}(t, \mathrm{p}, c)$$

Finally, we calculate the probability of outflow in the first year (i.e. that a vehicle or battery stops working in the same year it was purchased). This is done in analogy to the outflow calculations shown above using the hazard function (probability of outflow) at age zero.

With this, the final values for the inflows of EVs and batteries can be calculated as

$$I_{EV_{Vehicle}}(t) = \sum_{c=0}^{t} \Big(S_{EV}(t, t, c) + O_{EV_{Vehicle}}(t, t, c) \Big)$$

$$I_{EV_{Battery}}(t) = \sum_{p=0}^{t} \Big(S_{EV}(t, p, t) + O_{EV_{Battery}}(t, p, t) \Big)$$

The split of PHEV and BEV within EVs in the stock, inflows, and outflows can be obtained by simply multiplying the values for EVs by the respective shares for each cohort:

$$I_{BEV}(t) = I_{EV}(t) * \frac{share_{BEV}}{share_{BEV} + share_{PHEV}}$$

$$I_{PHEV}(t) = I_{EV}(t) * \frac{share_{PHEV}}{share_{BEV} + share_{PHEV}}$$

$$O_{BEV}(t, p, c) = O_{EV}(t, p, c) * \frac{share_{BEV}}{share_{BEV} + share_{PHEV}}$$

$$O_{PHEV}(t,p,c) = O_{EV}(t,p,c) * \frac{share_{PHEV}}{share_{BEV} + share_{PHEV}}$$

$$S_{BEV}(t,p,c) = S_{EV}(t,p,c) * \frac{share_{BEV}}{share_{BEV} + share_{PHEV}}$$

$$S_{PHEV}(t,p,c) = S_{EV}(t,p,c) * \frac{share_{PHEV}}{share_{BEV} + share_{PHEV}}$$

This simplification is only possible because we assume the same vehicle and battery lifetimes for BEV and PHEVs.

Given the drive train split, the vehicles in each flow (F) are differentiated based on the capacity of the battery (s) they have. This is done using the size split for each cohort (c) and drive train (g) as

$$F(g,s,c) = F(g,c) \cdot Share_{size}(g,s,c)$$

Similarly, they can be broken down into the specific battery chemistry (b) that each vehicle has

$$F(g,s,b,c) = F(g,s,c) \cdot Share_{chemistry}(g,s,b,c)$$

To move to the battery parts and material layers, the batteries are multiplied with specific battery weights given their size and chemistry and the weight (w) is split into three main parts (p). Note that the unit is no longer number of batteries, but weight of the batteries per part.

$$F(g,s,b,p,c) = F(g,s,b,c) \cdot Specific\ weight(g,s,b) \cdot Share_{part}(g,s,b,p)$$

Finally, all flows and stocks can be quantified in terms of elements (e) for the nine materials included in the model by using the specific material content in each battery per chemistry and part.

$$F(g,s,b,p,e,c) = F(g,s,b,p,c) \cdot Share_{material}(g,b,e,c)$$

The model can be thus fully quantified for all layers based on these equations.

A.3. EV penetration scenarios

The EV penetration scenarios follow the IEA targets for three scenarios in 2020 and Net Zero by 2050 report and the Global EV outlook report. The BEV, PHEV, and other drive trains shares are calculated based on those scenarios and the ICE share is calculated from mass balance. Figure 6 shows a summary of the values used which can also be found as a table in the accompanying data.

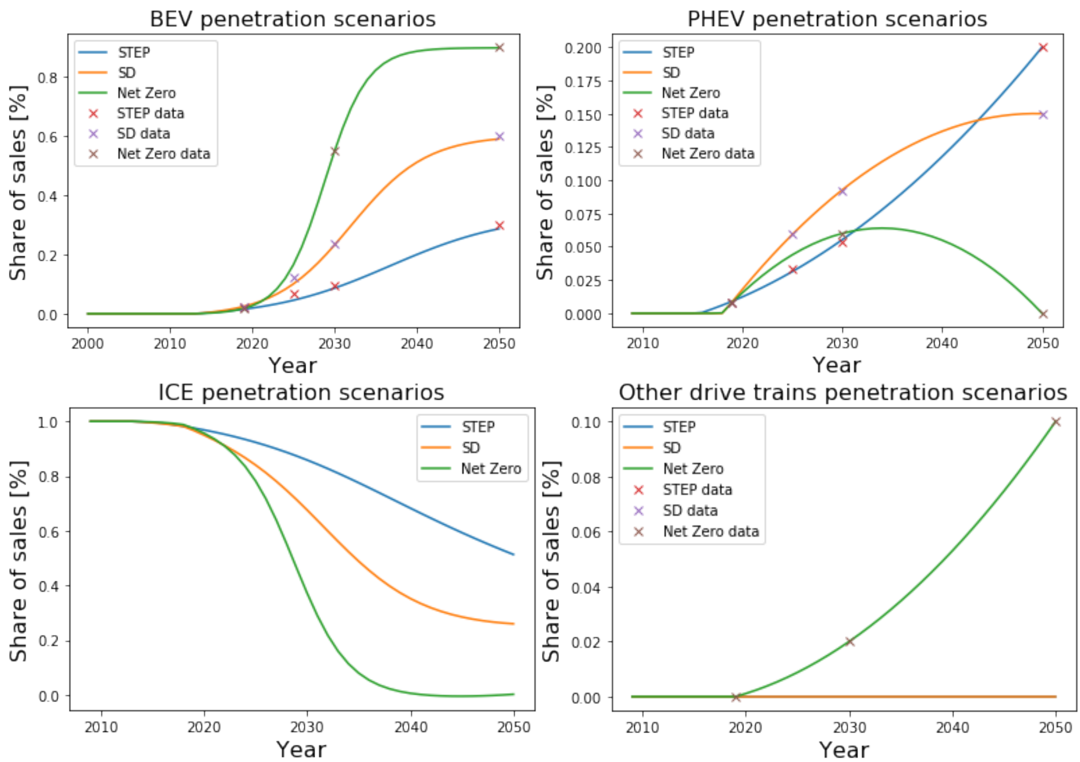

Figure 6: EV penetration scenarios used in the model.

A.4. Vehicle size scenarios

Three vehicle size scenarios were defined to account for potential changes in societal behavior where people's preference for vehicle size and range may stay constant or change over time. Figure 7 shows the vehicle size scenarios used for this model where a shift to small scenario reflects consumers choosing smaller vehicles with less-range batteries with 33kWh capacity, and the shift to large scenario shows the opposite trend towards 100kWh batteries. The size split of BEVs and PHEVs is considered to be the same. The values can be found in the accompanying datasets.

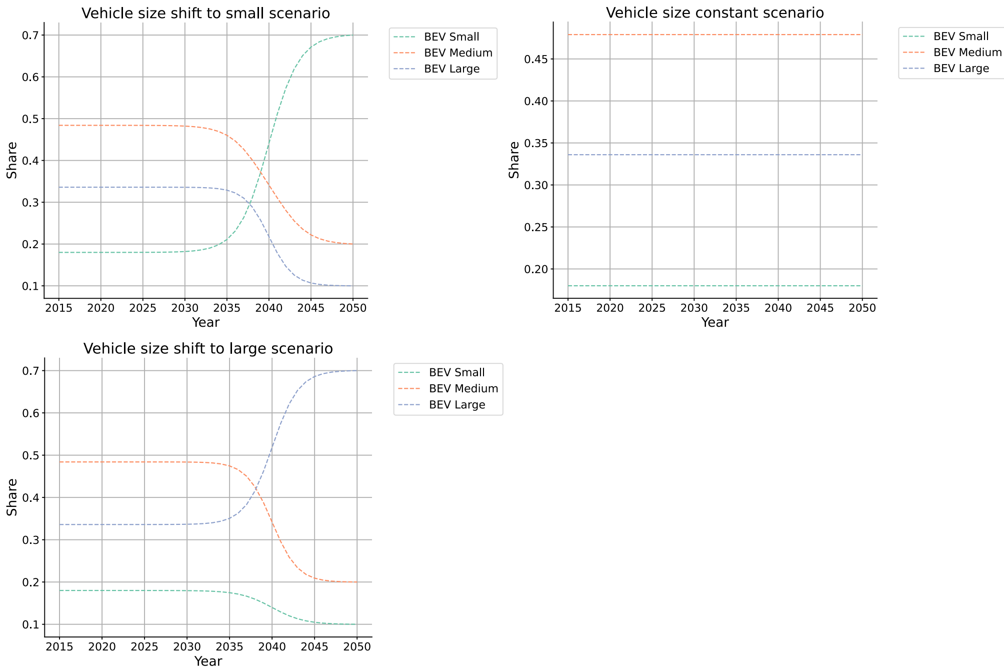

Figure 7: Vehicle and battery size scenarios

A.5. Battery Chemistry Scenarios

Five battery chemistry scenarios where evaluated in this study. The NCX and LFP scenarios are taken from Xu et al., (2021) and the BNEF scenario is taken as a baseline due to the neutral mix of battery techonogies that is presented (BNEF, 2021). The Next_gen_BNEF, and Next_gen_LFP scenarios are self-defined scenarios that aim to explore different pathways towards the introduction of next generation battery chemistries.

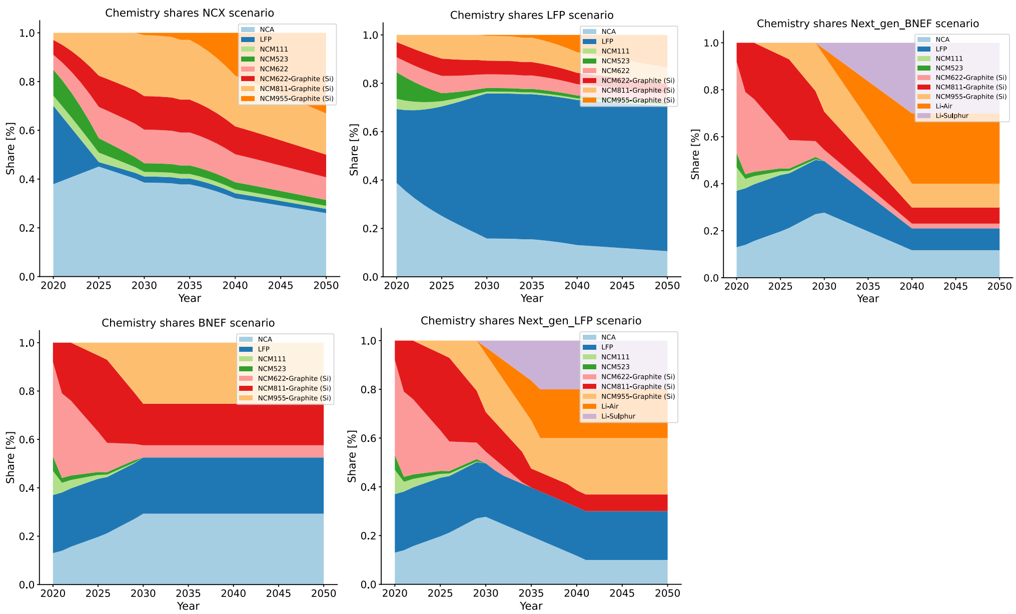

Figure 8: Battery chemistry scenarios used for the model.

A.6. Battery weight

The total number of batteries needed for the fleet are multiplied with their specific weight according to their chemistry. This is used as a way to connect the materials that are going to reuse and the ones that are recycled directly. The specific values can be found in the excel table provided separately.

A.7. Battery parts

The battery parts are calculated as a share of the total battery weight. The weight of the modules is calculated using the BatPack model from as the fraction of module weight divided by total pack weight. BMS, wiring and equipment are assumed to be 10% of the rest of the weight. The case is assumed to be the rest of the weight. For batteries like LFP where the modules are a smaller % of the total weight, the pack becomes more relevant (27% of total weight compared to 16% in other chemistries). We assume that the battery packs are made of Aluminum in 70% of the cases and other materials in the rest. The values can be found in the accompanying datasets.

A.8. Reuse scenarios

Explorative scenarios that include:

- No reuse
- Reuse of LFP batteries only

- Reuse of all batteries

The values can be found in the accompanying datasets.

A.9. Recycling efficiencies

There is rapid development in the recycling efficiency of materials and high uncertainty about the real values that can be achieved. A wide range of processes are proposed in literature that achieve ever more efficient recovery, but it is unclear which ones will make it to the market. Therefore, we define here three explorative scenarios for three broad categories of recycling efficiencies:

Pyrometallurgical: Only Co, Ni, and Cu are recovered at 75%. Taken from "Recycling of End-of-Life Lithium Ion Batteries, Part I: Commercial Processes, recycling of lithium ion batteries from electric vehicles"

Hydrometallurgical: The recovery rates are as follows taken from "Recycling of End-of-Life Lithium Ion Batteries, Part I: Commercial Processes, recycling of lithium ion batteries from electric vehicles:

- Li: 40%
- C: 40%
- Al: 70%
- Si: 70%
- P: 0
- Mn: 50%
- Co: 80%
- Cu: 80%
- Ni: 80%

Direct recycling: Currently at R&D stages, several studies report physical possibilities of achieving close to 100% recovery rates. We therefore assume a close to ideal scenario where 90% of all materials can be recovered (Pražanová, Knap, & Stroe, 2022).

A.10. Sensitivity analysis recycled materials

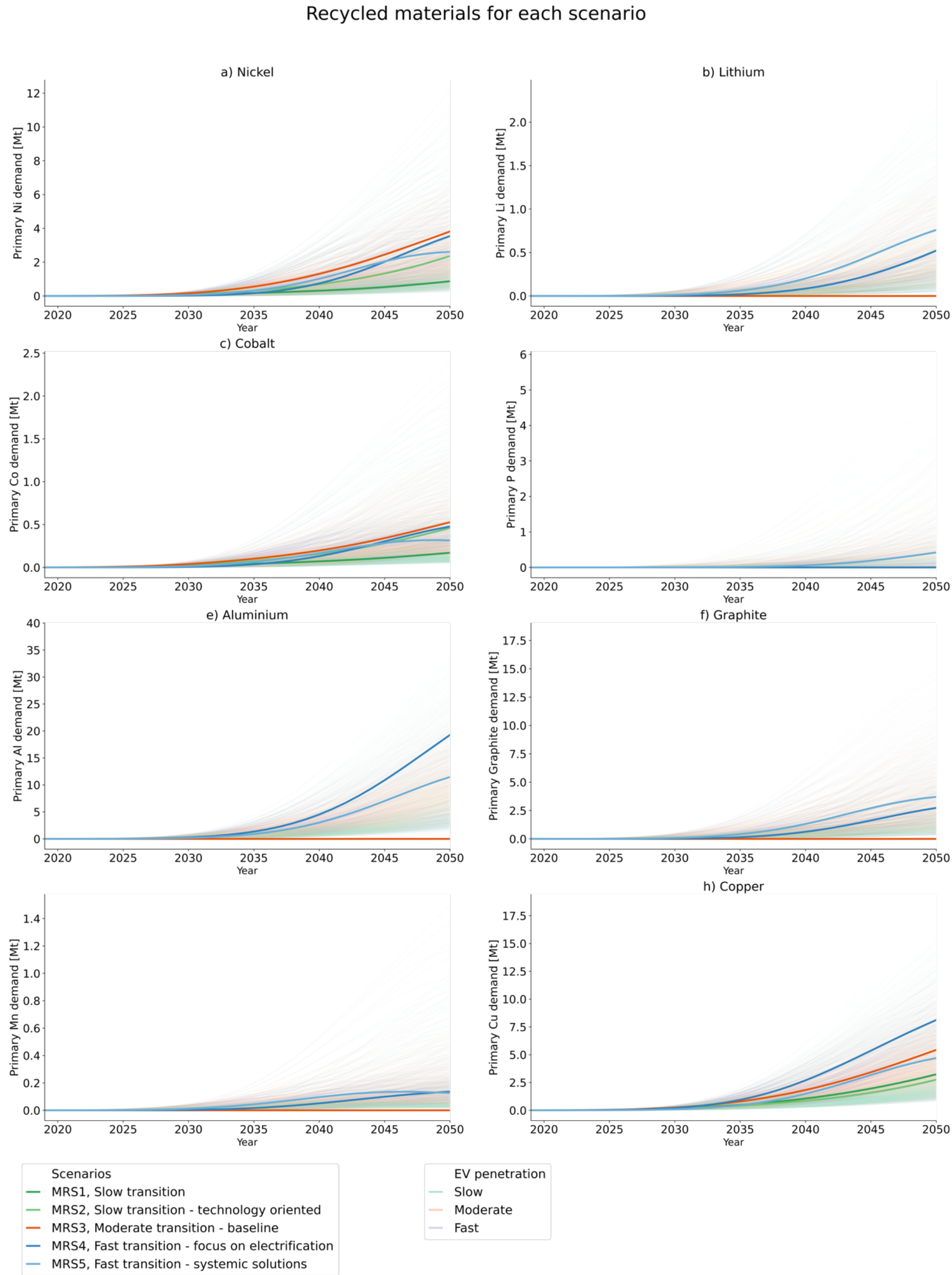

Figure 9: Analysis of all combinations for the recycled materials, in analogy to Figure 3 in the main document.

The values can be found in the accompanying datasets.

SI Paper III

The paper is not yet published
this supplementary information is not included in NTNU Open

SI Paper IV

SUPPORTING INFORMATION FOR:

Thorne, R., Aguilar Lopez, F., Figenbaum, E., Fridstrøm, L. & Müller, D.B. (2021). Estimating stocks and flows of electric passenger vehicle batteries in the Norwegian fleet from 2011 to 2030. *Journal of Industrial Ecology.*

Summary

The supporting information word file provides the method used for calculating the stock change and vehicle outflows which were calculated using age-specific survival curves for each segment. It also includes tables for the assumptions on battery capacity, market share of different battery chemistries, and historical vehicle sales as compared to the modelled sales. A figure with a close-up on the battery stock change in terms of energy is also provided.

The stock-flow cohort model operates with age-specific departure rates that can be summarized in 'survival curves', or cumulative transition rates, which are affected by wrecking, secondhand imports and conversion of vans to passenger vehicles. Figure S1 shows all assumed survival rates for passenger BEVs used in the model, for different weight segments. To demonstrate differences with ICE vehicles, in Figure S2 survival curves for smaller passenger BEVs (<1,500 kg) are compared with smaller passenger vehicles with either petrol or diesel engines.

For electric vehicles > 1,600 kg, the empirical basis for this information is weak, as one currently has observations only for around the first five years of life. The departure rates for six years and up are therefore set equal to the corresponding rates for petrol vehicles, with some adjustments. For electric vehicles between 1,200 and 1,400 kg one has observed rates up to the 10th year of life, then we have copied in rates for petrol vehicles. For the smallest electric vehicles (<1,200 kg) one has observations up to 20-25 years of age. We see that the largest electric vehicles (> 2,000 kg) in the model have a lifespan at least in line with large petrol and diesel vehicles (when we disregard the influx of converted vans). However, for electric vehicles less than 2,000 kg, the service life is somewhat shorter than for similar petrol and diesel vehicles. Among the smallest passenger vehicles, electric vehicles have a shorter service life than vehicles with ICE.

Assumptions of sales weighted battery capacity per vehicle expected in 2022 and 2030 and example background data used in the battery analysis, are shown in Table S1 and Table S2, respectively.

Table S3 gives a comparison of the modeled results with historical data, between 2011 and 2018. Figure S3 shows a summary of the modelled battery stock change from Norwegian passenger BEVs (from vehicles older than 1 year) between 2017 and 2025.

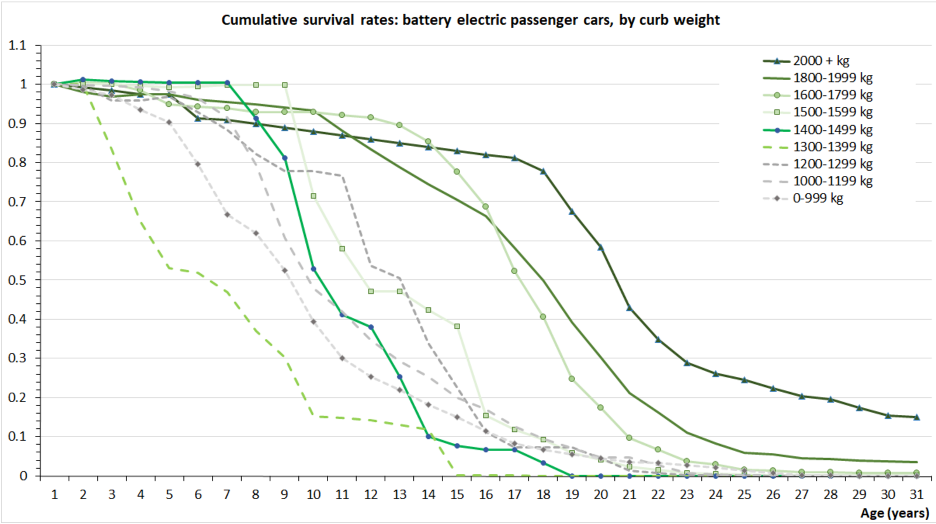

Figure S1. Survival curves for passenger BEVs used in the stock-flow cohort model.

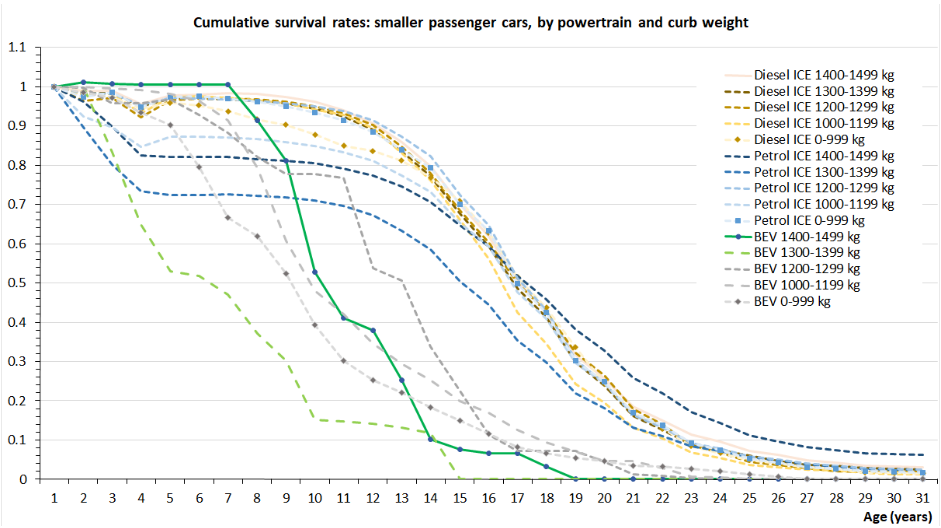

Figure S2. Survival curves for smaller passenger vehicles (<1500 kg) used in the stock-flow cohort model. Survival curves for passenger BEVs are shown alongside those of passenger diesel and petrol vehicles for comparison.

Table S1: Assumptions of sales weighted battery capacity per vehicle expected in 2022 and 2030.

Weight (kg)	Battery capacity in 2022 (kWh/vehicle)	Battery capacity in 2030 (kWh/vehicle)
1,000-1,299	85 % of 2030 value	40
1,300-1,399		50
1,400-1,799		60
1,800-1,999		90
2,000+		120

Table S2: Example background data used in the analysis: market share, vehicle sales numbers, battery type and capacity (all available) for the five most sold vehicle makes/models in Norway between 2011-2018 (OFV, Kelleher Environmental, 2019, Wagner et al., 2019, EV Database, 2019).

Full make/model	Market share 2011-2018 (%)	Number of sales 2011-2018	Nominal battery capacity (kWh)	Battery type
Nissan Leaf (and e+)	22	35,083	24/30/40/62	NMC
Volkswagen e-Golf	18	29,541	24/35.8	NMC
Tesla Model S	12	19,455	60/70/75/85/90/100.0	NCA
BMW i3	12	19,124	22/33/42.2	LMO/NMC
Tesla Model X	7	11,144	60/70/75/90/100	NCA

Table S3: Comparison of the registered and modelled number of firsthand registrations of battery electric passenger vehicles from both new sales and secondhand imports, between 2011 and 2018.

Year	Historical data: New vehicle sales (OFV, 2019)	Historical data: Secondhand imported (OFV, 2020)	Modelled data: New vehicle sales and nearly new secondhand imported	Change (%) modelled vs historical data
2011	2,000	78	1,988	-4
2012	3,951	309	4,231	-1
2013	7,882	2,086	9,884	-1
2014	18,081	3,063	21,055	0
2015	25,777	5,122	30,758	0
2016	24,217	5,281	28,936	0
2017	33,025	8,558	41,423	-2
2018	46,069	11,899	57,555	-1

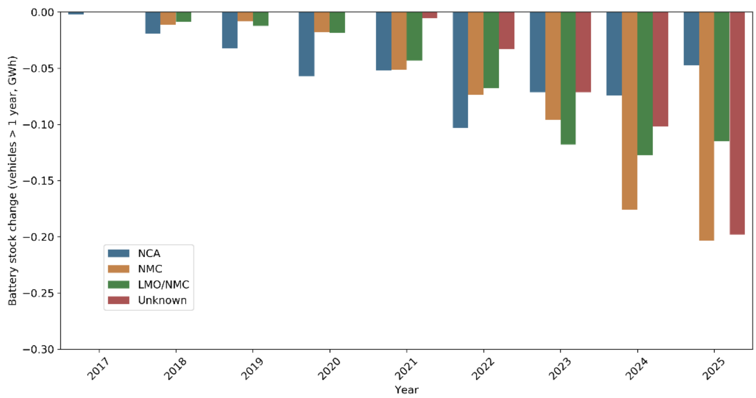

Figure S3: Close-up of the battery stock change (GWh) from the Norwegian electric passenger vehicle fleet (from vehicles older than 1 year), between 2017 and 2025. 'Unknown' refers to unknown Li-ion type.