DOI: 10.1111/jiec.13316

METHODS, TOOLS, DATA, AND SOFTWARE

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

Editor Managing Review: Lynette Cheah

Funding information
Norwegian Research Council (BATMAN Project, 299334); SFI Metal Production (Centre for Research-Based Innovation, 237738)

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.

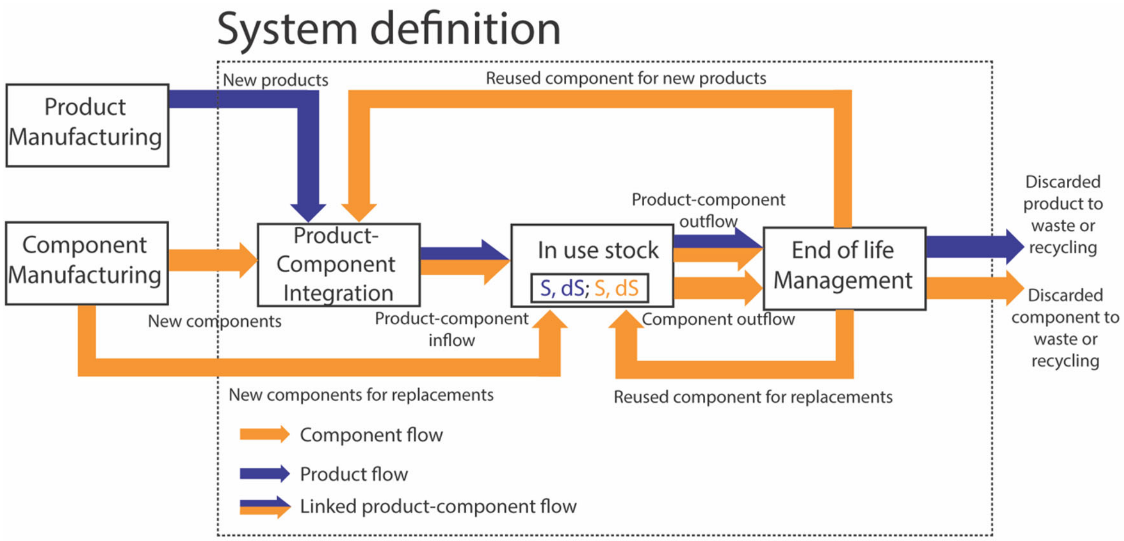

FIGURE 1 System definition of a generic product–component system

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

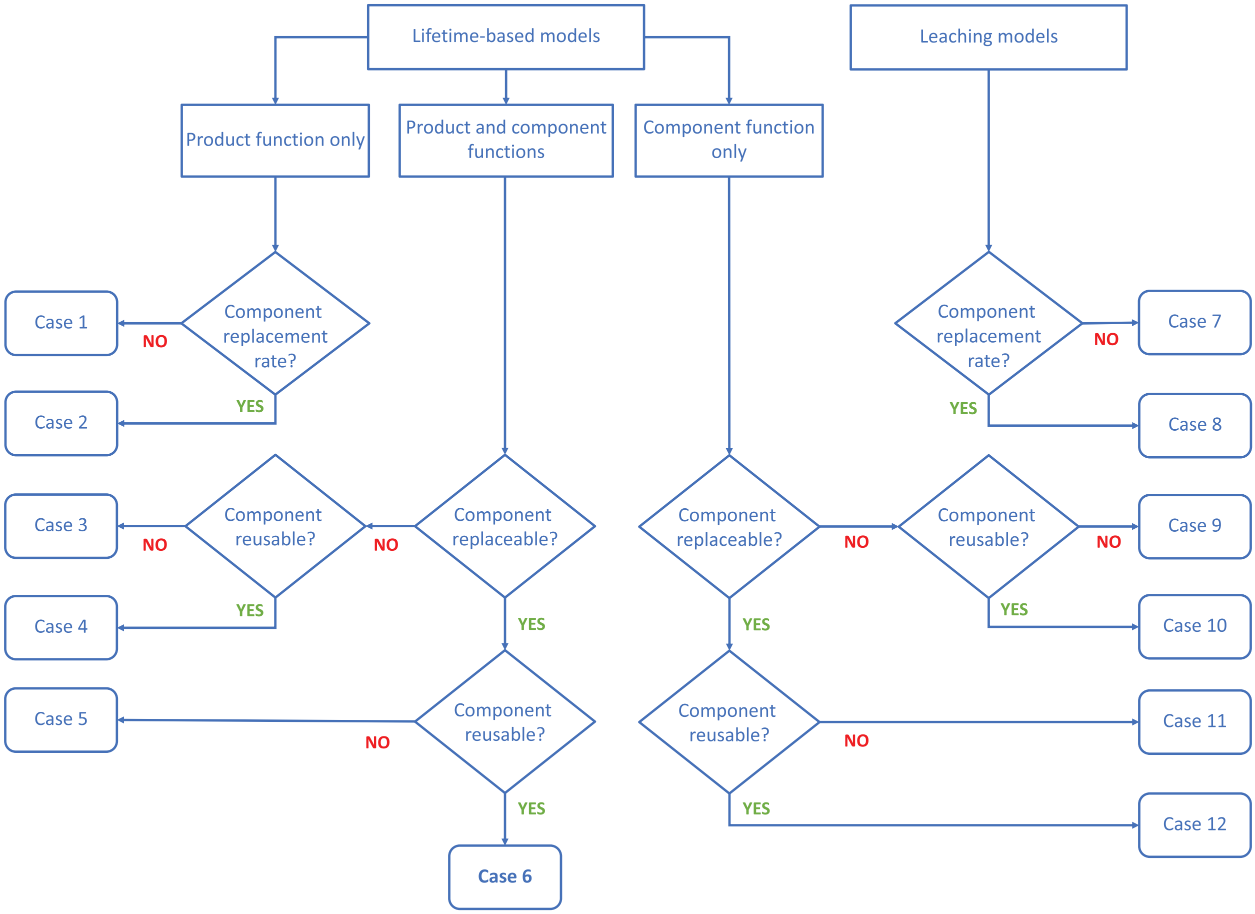

FIGURE 2 Different assumptions for modeling options

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).

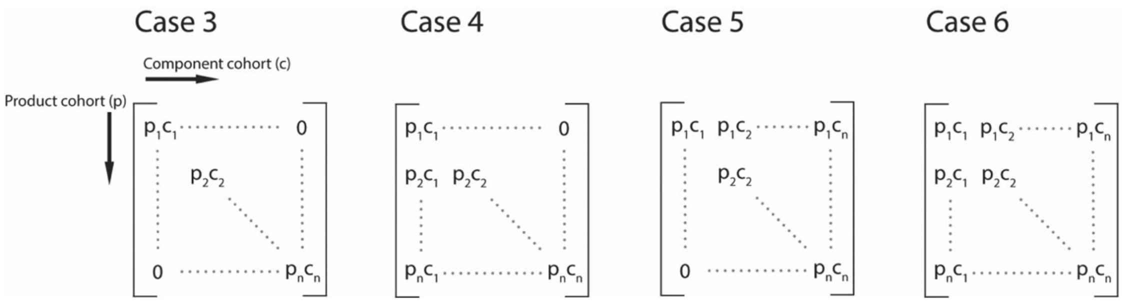

FIGURE 3 Cohort composition of the product–component system for a given time $t = n$ for the different modeling approaches

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

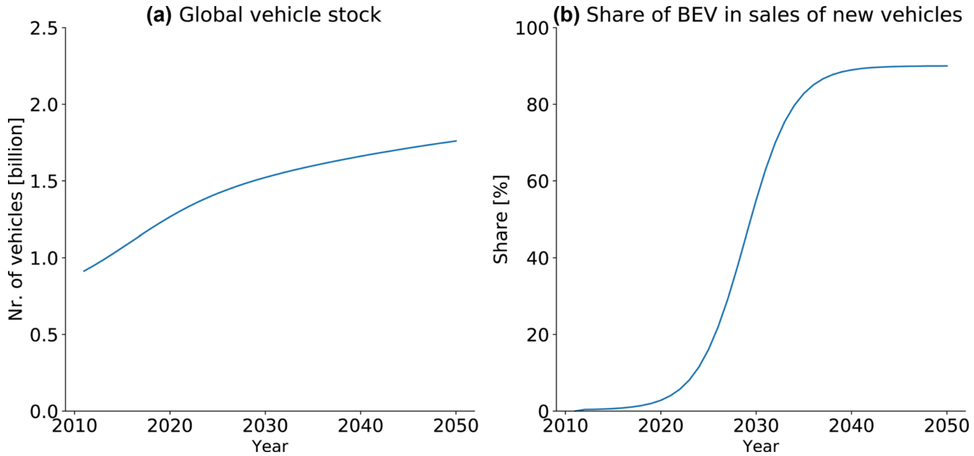

FIGURE 4 Main drivers of the model. Left: The global vehicle stock according to the baseline logistic growth scenario. Right: BEV penetration in the sales according to IEA Net Zero scenario. Underlying data for this figure can be found in Supporting Information S2, file tab "data_for_figure_4_in_manuscript"

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.

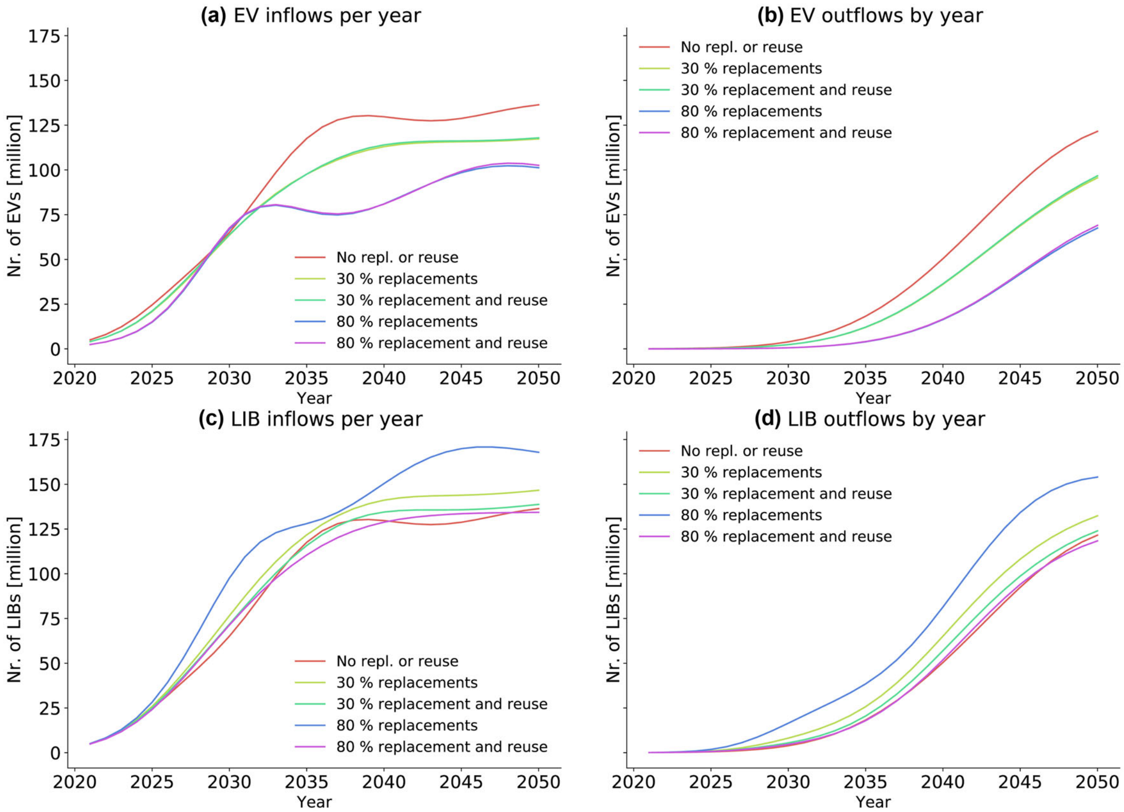

FIGURE 5 (a) EV inflows for the various scenarios, (b) EV outflows for the various scenarios, (c) LIB inflows for the different scenarios, (d) LIB outflows for the different scenarios. Underlying data for this figure can be found in Supporting Information S2, file tab "data_for_figure_5_in_manuscript"

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.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the financial support from the Research Council of Norway and the partners of the SFI Metal Production. We would like to thank Kamila Krych for her useful comments that helped improve the structure of this paper.

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

REFERENCES

Ardente, F., & Mathieux, F. (2014). Environmental assessment of the durability of energy-using products: Method and application. *Journal of Cleaner Production*, *74*, 62–73. https://doi.org/10.1016/j.jclepro.2014.03.049

Baccini, P., & Bader, H. (1996). Regionaler Stoffhaushalt, Spektrum, Heidelberg.

Baccini, P., & Brunner, P. H. (1991). *Metabolism of the anthroposphere*. https://books.google.se/books/about/Metabolism_of_the_Anthroposphere.html?id=s2kYAQAAMAAJ&redir_esc=y

Binder, C. R. (2007). From material flow analysis to material flow management Part I: Social sciences modeling approaches coupled to MFA. *Journal of Cleaner Production*, *15*(17), 1596–1604. https://doi.org/10.1016/j.jclepro.2006.08.006

Busch, J., Steinberger, J. K., Dawson, D. A., Purnell, P., & Roelich, K. (2014). Managing critical materials with a technology-specific stocks and flows model. *Environmental Science and Technology*, *48*(2), 1298–1305. https://doi.org/10.1021/es404877u

Craglia, M., & Cullen, J. (2020). Modelling transport emissions in an uncertain future: What actions make a difference?. *Transportation Research Part D: Transport and Environment*, *89*, 102614. https://doi.org/10.1016/j.trd.2020.102614

Dunant, C. F., Shah, T., Drewniok, M. P., Craglia, M., & Cullen, J. M. (2021). A new method to estimate the lifetime of long-life product categories. *Journal of Industrial Ecology*, *25*(2), 321–332. https://doi.org/10.1111/jiec.13093

Džubur, N., & Laner, D. (2018). Evaluation of modeling approaches to determine end-of-life flows associated with buildings: A Viennese case study on wood and contaminants. *Journal of Industrial Ecology*, *22*(5), 1156–1169. https://doi.org/10.1111/jiec.12654

European Commission. (2019). The European green deal. *European Commission*, *53*(9), 24. https://doi.org/10.1017/CBO9781107415324.004

Global EV Outlook 2020. (2020). Global EV outlook 2020. https://doi.org/10.1787/d394399e-en

Hendriks, C., Obernosterer, R., Müller, D., Kytzia, S., Baccini, P., & Brunner, P. H. (2000). Material flow analysis: A tool to support environmental policy decision making. Case-studies on the city of Vienna and the Swiss lowlands. *Local Environment*, *5*(3), 311–328. https://doi.org/10.1080/13549830050134257

Hossain, E., Murtaugh, D., Mody, J., Hossain Mansur Resalat, F., Sunny, M. S. H., & Mohammad, N. (2019). *A comprehensive review on second-life batteries: Current state, manufacturing considerations, applications, impacts, barriers & potential solutions, business strategies, and policies*. https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=8718282

IEA. (2021). *Net zero by 2050: A roadmap for the*. 222. https://www.iea.org/reports/net-zero-by-2050

IEA. (2020). Global EV Outlook 2020: Entering the decade of electric drive? OECD Publishing, Paris. https://doi.org/10.1787/d394399e-en

IEA. (2019). Global EV Outlook 2019. IEA, Paris. https://www.iea.org/reports/global-ev-outlook-2019

International Organization for Motor Vehicles Manufacturers. (2015). Vehicles in use. https://www.oica.net/category/vehicles-in-use/

Jung, H., Silva, R., & Han, M. (2018). Scaling trends of electric vehicle performance: Driving range, fuel economy, peak power output, and temperature effect. https://doi.org/10.3390/wevj9040046

Lauinger, D., Billy, R. G., Vásquez, F., & Müller, D. B. (2021). A general framework for stock dynamics of populations and built and natural environments [Gold Contribution Accessibility Gold]. https://doi.org/10.1111/jiec.13117

Melo, M. T. (1999). Statistical analysis of metal scrap generation: The case of aluminium in Germany. *Resources, Conservation and Recycling*, *26*(2), 91–113. https://doi.org/10.1016/S0921-3449(98)00077-9

Müller, D. B. (2006). Stock dynamics for forecasting material flows—Case study for housing in the Netherlands. *Ecological Economics*, *59*(1), 142–156. https://doi.org/10.1016/j.ecolecon.2005.09.025

Müller, D. B., Bader, H. P., & Baccini, P. (2004). Long-term coordination of timber production and consumption using a dynamic material and energy flow analysis. *Journal of Industrial Ecology*, *8*(3), 65–88. https://doi.org/10.1162/1088198042442342

Oguchi, M., & Fuse, M. (2015). Regional and longitudinal estimation of product lifespan distribution: A case study for automobiles and a simplified estimation method. *Environmental Science and Technology*, *49*(3), 1738–1743. https://doi.org/10.1021/es505245q

Olivetti, E. A., Ceder, G., Gaustad, G. G., & Fu, X. (2017). Lithium-ion battery supply chain considerations: Analysis of potential bottlenecks in critical metals. *Joule*, *1*(2), 229–243. https://doi.org/10.1016/j.joule.2017.08.019

Pangburn, M. S., & Stavrulaki, E. (2014). Take back costs and product durability. *European Journal of Operational Research*, *238*(1), 175–184. https://doi.org/10.1016/j.ejor.2014.03.008

Pauliuk, S., Heeren, N., Hasan, M. M., & Müller, D. B. (2019). A general data model for socioeconomic metabolism and its implementation in an industrial ecology data commons prototype. *Journal of Industrial Ecology*, *23*(5), 1016–1027. https://doi.org/10.1111/jiec.12890

Roca-Puigròs, M., Billy, R. G., Gerber, A., Wäger, P., & Müller, D. B. (2020). Pathways toward a carbon-neutral Swiss residential building stock. *Buildings and Cities*, *1*(1), 579–593. https://doi.org/10.5334/bc.61

Sandberg, N. H., Sartori, I., & Brattebø, H. (2014). Using a dynamic segmented model to examine future renovation activities in the Norwegian dwelling stock. *Energy and Buildings*, *82*, 287–295. https://doi.org/10.1016/j.enbuild.2014.07.005

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*, https://doi.org/10.1111/jiec.13186

Tsiropoulos, I., Tarvydas, D., & Lebedeva, N. (2018). *Li-ion batteries for mobility and stationary storage applications.* Publications Office of the European Union. https://doi.org/10.2760/87175

United Nations Department of Economic and Social Affairs. (n.d.). World population prospects 2019. https://population.un.org/wpp/Download/Standard/Population/

Vikström, H., Davidsson, S., & Höök, M. (2013). Lithium availability and future production outlooks. *Applied Energy*, *110*, 252–266. https://doi.org/10.1016/j.apenergy.2013.04.005

Xu, C., Dai, Q., Gaines, L., Hu, M., Tukker, A., & Steubing, B. (2021). Future material demand for automotive lithium-based batteries. *Nature Communications Materials*, https://doi.org/10.1038/s43246-020-00095-x

Zhu, J., Mathews, I., Ren, D., Li, W., Cogswell, D., Xing, B., Sedlatschek, T., Kantareddy, S. N. R., Yi, M., Gao, T., Xia, Y., Zhou, T., Wierzbicki, Q., & Bazant, M. Z. (2021). End-of-life or second-life options for retired electric vehicle batteries. *Cell Reports Physical Science*, *2*(8), 100537. https://doi.org/10.1016/j.xcrp.2021.100537

SUPPORTING INFORMATION

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

How to cite this article: Aguilar Lopez, F., Billy, R. G., & Müller, D. B. (2022). A product–component framework for modeling stock dynamics and its application for electric vehicles and lithium-ion batteries. *Journal of Industrial Ecology*, 1–11. https://doi.org/10.1111/jiec.13316