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REAL-WORLD LIFETIME ASSESSMENT OF ENGINEERING ASSETS: CROSS-MARKET DATA FOR CIRCULAR LCA ACCURACY

Thesis for the Degree of Master of Science in Engineering - Product and Process Development 30.0 credits

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08/06/2026

Abstract

Product lifetime is a central yet weakly validated parameter in Life Cycle Assessment (LCA), where it functions as a scaling mechanism for allocating environmental impacts. In the context of heavy construction equipment, lifetime is commonly assumed rather than empirically established, often fixed at standardized values despite evidence of significant variation in real-world use. This study addresses this gap by empirically examining the operational lifetime of construction equipment and comparing observed patterns with the assumptions used in LCA models. The research adopts a qualitative case study approach, combining literature review with semi-structured interviews involving OEM representatives and service actors, supported by insights from secondary market observations. The findings indicate that product lifetime is not primarily determined by technical limits, but by economic decisions, service infrastructure, and cross-market redistribution, with equipment frequently remaining in operation beyond its initially assumed lifetime. This creates a structural mismatch between model assumptions and actual system behaviour, with direct implications for environmental impact allocation and circular economy strategies. The study contributes by highlighting the need for empirically grounded lifetime modelling and by demonstrating how multi-owner and cross-market dynamics reshape the understanding of product lifetime in sustainability assessments.

Keywords: lifetime assessment, life cycle assessment (LCA), construction equipment, circular economy, product lifetime, empirical validation, secondary markets

Sammanfattning

Produktlivslängd utgör en central men empiriskt otillräckligt etablerad parameter inom livscykelanalys (LCA), där den fungerar som en avgörande skalningsfaktor för fördelning av miljöpåverkan. Inom tunga entreprenadmaskiner baseras livslängd i stor utsträckning på standardiserade antaganden, trots att faktisk användning sträcker sig över flera ägarled, marknader och driftförhållanden. Denna studie analyserar den operativa livslängden för entreprenadmaskiner och jämför observerade livslängdsmönster med de antaganden som används i LCA-modeller, samt identifierar de faktorer som driver variation i livslängd. Studien genomförs som en kvalitativ fallstudie baserad på litteraturgenomgång och semistrukturerade intervjuer med tillverkare och serviceaktörer, kompletterat med observationer från andrahandsmarknader. Resultaten visar att produktlivslängd i praktiken formas av ekonomiska beslut, serviceinfrastruktur och marknadsdynamik snarare än enbart tekniska begränsningar, där utrustning regelmässigt används långt bortom de livslängder som antas i modeller. Detta innebär att etablerade LCA-antaganden systematiskt felrepresenterar fördelningen av miljöpåverkan över tid, vilket påverkar både resultatens tillförlitlighet och utvärderingen av cirkulära strategier. Studien bidrar med ett empiriskt förankrat perspektiv på livslängd och visar hur flerägarskap och globala flöden behöver integreras för att möjliggöra mer träffsäkra hållbarhetsbedömningar.

Acknowledgments

We would like to thank everyone who supported this thesis and contributed with guidance, time, and valuable feedback throughout the process.

Especially our examiner and supervisor for their support, encouragement, and constructive feedback throughout the project. We would also like to thank the companies that participated in this study and generously shared their experiences and perspectives.

Finally, we are grateful to all interview participants who took the time to contribute to this research. Without your willingness to participate and share your insights, this thesis would not have been possible.

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Eskilstuna, June 2026

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ABBREVIATIONS

ALCA	Attributional Life Cycle Assessment
CE	Circular Economy
CLCA	Consequential Life Cycle Assessment
CO_2	Carbon Dioxide
CO_2e	Carbon Dioxide Equivalent
CSRD	Corporate Sustainability Reporting Directive
EoL	End-of-Life
EPR	Extended Producer Responsibility
EU	European Union
FU	Functional Unit
GWP	Global Warming Potential
IEC	International Electrotechnical Commission
ISO	International Organization for Standardization
JRC	Joint Research Centre
LCA	Life Cycle Assessment
LCC	Life Cycle Costing
LCI	Life Cycle Inventory
OEM	Original Equipment Manufacturer
PSS	Product-Service System

1. INTRODUCTION

The following chapter brings a short background to the research area along with a problem statement leading to the aim and research questions of this thesis. Finally, some project limitations will be presented.

1.1 Background

Heavy construction equipment remains one of the least understood sectors in terms of real-world lifecycles, reuse potential, and end-of-life processes. Unlike passenger cars or road vehicles, where registration systems and regulatory end-of-life (EoL) frameworks are well established off-road machinery often circulates across multiple owners, countries, and market conditions without consistent traceability or reporting according to United Nations Environment Programme (2024).

This creates a serious gap for manufacturers, policymakers, and Life Cycle Assessment (LCA) practitioners. Many industrial LCA models rely on standardized product lifetime assumptions, commonly fixed at 10 years regardless of actual usage variation. These simplifications, while useful for consistency, risk distorting environmental assessments and steering circular design strategies in misaligned directions. Emerging reports confirm this mismatch. European Automobile Manufacturers' Association (2025) highlights the wide variations in the age of scrapping and export flows of heavy trucks in European markets, while United Nations Environment Programme (2024) reveals critical inconsistencies in lifetime treatment and recyclability in developing economies. Similar discrepancies are expected in the off-road sector, yet reliable empirical data is lacking.

At the same time, there has been a push for circular business models, including remanufacturing and refurbishment. Research shows that extending product lifetimes can significantly reduce emissions and material demand Bocken et al. (2016) and Maldini et al. (2025). However, many of these studies are based on theoretical frameworks or aggregated market assumptions, rather than on machine-level lifetime data across actual secondary markets.

This lack of validated lifetime data has become a bottleneck. With new reporting obligations under the EU Taxonomy and Corporate Sustainability Reporting Directive (CSRD), industries must now demonstrate verifiable evidence of circularity, including durability, reuse rates, and traceable end-of-life flows.

Without better data, assumptions remain speculative and circularity targets unmeasurable. Previous research has shown that product lifetime depends on both company strategies and consumer behaviour. At the same time, several studies present a lack of empirical understanding, such as the exploration between consumer behaviour and the extension of product lifetime Rivera and Lallmahomed (2016). This implies that there is a conceptual knowledge regarding factual principles around product lifetime, but a need of empirical studies meshing actual product lifetime results, behaviour and market strategies.

Furthermore, Nishijima and Oguchi (2023) similarly express a need to explore strategies and policies that influence product lifetime expectations among consumers. Previous research has also acknowledged that product lifetime in LCA calculations is often based on assumptions, database defaults, or engineering estimates rather than operational data gathered from real-world systems. Heijungs and Suh (2002), Ciroth et al. (2016), and Jerome and Ljunggren (2025) all identify this limitation. The literature also highlights the limited visibility of secondary-market flows and real-world product trajectories across ownership cycles, as discussed by Müller (2006) and Pauliuk et al. (2017).

To include even additional research demand, Amatuni et al. (2023) agreed with the lack of empirical evidence of lifetime models and real-world tracking data to validate the same models. Lastly, the same authors suggest a demand of better understanding of second-hand product usage and consumer behaviour. Previous research has shown that LCA literature reveals several research gaps.ISO-based LCA International Organization for Standardization (2006a) and International Organization for Standardization (2006b)product lifetime is used as a scaling parameter to the functional unit. Heijungs and Suh (2002) product lifetime influence intensities impact through how production-related challenges are allocated over delivered service. Therefore, small variations in assumed lifetime could alter environmental results because of how the model is structured. Even though this structural sensitivity exists, there is no description of how product lifetime should be established empirically in the ISO standards. Generally, assumptions about lifetime are made by generic database defaults, estimates done by engineers or industry agreements, rather than real-life operational data Ciroth et al. (2016) and Müller (2006).

By analysing 349 machines across seven markets and comparing real-world operational lifetime patterns together with LCA assumptions used in the case company, this study contributes through empirical observation. It also contributes by highlighting the importance of using operational hours rather than years when assessing lifetime in construction equipment and also illustrating how product lifetime extends over own-

ership and secondary market. Lastly, the findings provide future recommendations for improving lifetime representation, visibility in LCA practice in secondary markets and suggestion strategies within circular economy.

1.2 Problem Statement & Research gap

When attempting to seek articles containing empirical data on product lifetime investigation and assessment, very few studies fulfill the requirements. Most of the articles found researching theoretical literature for this study contained simulated or estimated product lifetimes rather than actual data collected from companies or other traders. Similarly, companies participating in this study have exclaimed that they do not have any real-world data on actual product lifetime, nor from past, recent or current production. Instead, they use an estimated lifetime for the products. They have also stated that they lack traceability in the second-hand market and therefore cannot observe and determine the actual product lifetime.

The combination of theoretical and industrial practices shows the research gap that product lifetime assumptions are central in calculations and strategies when it comes to sustainability. Yet there is limited information about empirical validation across ownership cycles and secondary markets. Previous studies and participant companies support the purpose of this study to be performed, as both theoretical and empirical findings indicate the same research gap and need for actual product lifetime investigation. This thesis addresses this gap by investigating the real-world operational lifetimes of construction equipment and analyzing how such deviations affect the validity of circular LCA models.

If this research gap is not addressed, both LCA and CE risk will be based on incorrect and unverified assumptions. This could lead to misleading environmental results, ineffective strategies and a missed opportunity to find and extend the product lifetime of construction equipment.

1.3 Aim & Research questions

This study aims to empirically examine the product lifetime of construction equipment, compare them with theoretical assumptions commonly used in LCA models, as well as identify factors influencing product lifetime and how these can be addressed.

RQ1 *How accurately do lifetime assumptions used in LCA calculations reflect the observed lifetime of construction equipment?*

RQ2 *What factors explain the variation between the actual lifetime of construction equipment and the lifetime assumptions used in LCA calculations?*

1.4 Project limitations

This study analyses and investigates a specific assembly of construction equipment from OEM. This may imply that the results found in this study might be applicable and generalized for all manufacturers, machine types and geographical markets. It also indicates that the results should be interpreted as a framework for the investigative case, if not factors such as product usage, maintenance strategies and product lifetime are equivalent as in the case study. No other empirical information or investigation except for that assembly will be collected or concluded.

Furthermore, the quality of data collected in secondary markets is seen as inferior due to the lack of traceability across ownership and the geographical aspects of the market. The information collected regarding actual usage, work hours and the equipment's remaining lifetime was often limited after export to less structured or non structured markets. This also means that the study cannot, with certainty, conclude exactly when or how the equipment has reached its EoL. Instead, the results are based on indications from available real-world market data. Lastly, there is a need for caution regarding the CO2-calculations since they cannot be applied using global average values, such as usage conditions, the mix of energy and emissions connected to transport. This is because these values can vary between countries and regions. Therefore, the calculations need to be modified according to regional and national conditions.

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

This chapter develops the theoretical framework underpinning the study by synthesising literature on product lifetime, Life Cycle Assessment, and Circular Economy, and by identifying the empirical lifetime gap that motivates the research.

2.1 Constructing Product Lifetime

In LCA, product lifetime is commonly introduced through the functional unit or a related reference flow, the elements through which Heijungs and Suh (2002) formalise how production-stage burdens are scaled to delivered service. This does not mean the parameter is absent from LCA practice; a study can and often does estimate its own lifetime value. But the computational structure itself does not generate that value: it has to be supplied from elsewhere Jerome and Ljunggren (2025). Its typical origins lie in engineering reliability planning International Organization for Standardization (2011), accounting regulation International Accounting Standards Board (2003), and service infrastructures Tukker (2004), each examined in turn below.

Design life, accounting useful life, and economic life each fulfil specific functions within their respective domains. International Organization for Standardization (2011) addresses engineering planning, International Accounting Standards Board (2003) financial reporting, and Ladopoulos et al. (2020) economic replacement. This does not challenge the legitimacy of those institutional logics. The issue is structural rather than normative. These time horizons, whether expressed as ten years, five years, or 12,000 operating hours, are constructed to manage technical risk International Organization for Standardization (2011), capital allocation International Accounting Standards Board (2003), and replacement decisions Ladopoulos et al. (2020), rather than to represent the real-world operational lifetime of the asset.

2.1.1 Engineering Logics and Design Life

Engineering planning depends on a defined temporal boundary within which performance and cost criteria can be evaluated under stated operating conditions. International Organization for Standardization (2011) formalises this boundary through the concept of design life: a specified planning horizon under assumed environmental

exposure and maintenance conditions, established primarily to structure engineering decisions. Realised service life depends instead on the conditions actually experienced during use, which means that the design horizon is conditional by construction. It expresses expected performance under stated assumptions rather than the real-world operational lifetime patterns reconstructed across heterogeneous use contexts International Organization for Standardization (2011).

A related but distinct boundary appears in life-cycle costing. International Electrotechnical Commission (2017) structures the evaluation of costs incurred across an item's life cycle: acquisition, operation, maintenance, downtime, and disposal. The selected life-cycle period sets the frame within which these costs and any resulting replacement decision are evaluated. The former framework addresses technical performance, whereas the latter addresses cost. Lifetime, in this second context, enables economic calculation rather than describing how long the equipment remained in service International Electrotechnical Commission (2017).

A comparable dependence on assumed rather than observed lifetime appears at system level in industrial ecology, where the concern shifts from a single asset to the development of material stocks over time. Müller (2006) demonstrates this in a dynamic stock-flow model of the Dutch housing sector: varying the assumed service lifetime shifts projected material stock accumulation and the timing of outflows. Although the study does not examine construction equipment directly, its modelling principle carries over to the present case: assumed rather than observed lifetime shapes system-level outcomes Müller (2006).

Pauliuk et al. (2017) extend the analysis across geographic regions and multiple product life cycles by tracing steel through international trade and recycling processes. Their scenario analysis shows that product lifetimes, recovery rates, and trade patterns jointly influence the distribution and losses of steel over time. Taken together, these models illustrate that lifetime enters industrial ecology modelling as an assumed input rather than as a value reconstructed from the observed continued use of individual assets.

For analytical clarity, this study distinguishes three temporally related but conceptually different constructs:

- *Design life*: the engineered planning horizon defined under specified technical and environmental assumptions International Organization for Standardization (2011).
- *Service life*: the realised operational duration under actual use conditions, which may differ from the original design horizon International Organization for Stan-

dardization (2011).

- *Economic life*: the period during which continued ownership and operation remain financially preferable to replacement Ladopoulos et al. (2020), following a replacement logic first formalised through dynamic programming by Bellman (1955).

These horizons may coincide numerically, but they originate from different logics: technical planning, realised operational performance, and owner-specific capital optimisation. Ladopoulos et al. (2020) examine economic life as a replacement decision based on ownership and operating costs for construction equipment specifically. Economic replacement timing should therefore not automatically be interpreted as the asset's total real-world operational lifetime, because economic life is derived from cost-based replacement criteria rather than from observed continued use Ladopoulos et al. (2020).

The same distinction matters for LCA. Jerome and Ljunggren (2025) review 67 LCA studies of lifetime extension and find that product lifetime is commonly represented using a single value, whereas population-level lifetime distributions remain rare. The lifetime assumed in an environmental model may therefore differ from real-world operational lifetime patterns reconstructed across successive owners and markets Jerome and Ljunggren (2025).

2.1.2 Accounting Useful Life and Economic Life

Design life and accounting useful life do not, by themselves, determine how long equipment remains in real-world operation. Gransberg and O'Connor (2015) show that decisions to repair, retain, or replace major equipment are based on ownership and operating costs across the equipment's economic life. Liu et al. (2020) add a more detailed perspective by using historical ownership and maintenance-cost data to distinguish maintenance stages across the equipment life cycle. Together, the cost-based replacement logic described by Gransberg and O'Connor (2015) and the maintenance-stage analysis developed by Liu et al. (2020) show that continued operation is shaped not only by technical condition but also by whether maintenance and repair remain economically viable. This distinguishes equipment that remains technically repairable from equipment that is still economically rational to keep in service.

Servitization research addresses a related mechanism at the level of business models. Tukker (2004) distinguish between product-, use-, and result-oriented product-service systems. In several of these arrangements, the provider retains responsibility for maintenance, repair, control, or the continued availability of the delivered function. Baines

et al. (2009) review the broader transition towards service-based manufacturing, in which maintenance and support activities become integrated into the value proposition. Taken together, the product-service system categories described by Tukker (2004) and the servitization literature reviewed by Baines et al. (2009) indicate that providers may have stronger incentives to preserve equipment functionality when value creation depends on continued product performance rather than on the initial sale alone.

A separate issue concerns the visibility of products after they move beyond their original ownership and service contexts. Pauliuk et al. (2017) trace how steel is distributed across regions and product groups through international trade, recycling, and multiple product life cycles, although their study does not examine ownership records or service histories directly. Amatuni et al. (2023) address the ownership dimension more explicitly. In their stochastic model, incorporating second-hand use and successive ownership periods increased the estimated average total product lifetime by 34% relative to single-use behaviour. A related measurement problem appears in LCA. Across the 67 studies reviewed by Jerome and Ljunggren (2025), 63% used unclear lifetime definitions and 26% did not report the source of the lifetime data applied.

Taken together, the findings reported by Pauliuk et al. (2017), Amatuni et al. (2023), and Jerome and Ljunggren (2025) suggest that continued use may extend beyond the records available to institutions and LCA practitioners. For capital equipment, this literature therefore provides the theoretical basis for examining whether lifetime values used in environmental modelling reflect institutional planning horizons more closely than real-world operational lifetime patterns across successive owners and markets.

2.1.3 Service Strategy and Operational Continuity

Engineering durability and accounting useful life do not, in themselves, determine actual operational duration. Continued operation depends on the service ecosystem within which equipment is present. Gransberg and O'Connor (2015) show that life-cycle cost analysis for major equipment is structured around usage-based cost evolution, while Liu et al. (2020) demonstrate that maintenance phases in heavy equipment can be identified from operating-hour data. Taken together, these findings indicate that maintenance requirements and life-cycle costs evolve with accumulated use rather than solely with calendar time. Operating hours are therefore relevant for understanding when maintenance needs intensify and when replacement becomes economically preferable. When maintenance and repair are no longer economically viable, technically repairable equipment may become functionally obsolete. Conversely, sustained maintenance capacity and technical competence can extend operational duration be-

yond initial planning assumptions.

Servitization research further clarifies this mechanism. Tukker (2004) and Baines et al. (2009) show that performance-based and availability-based contracts align manufacturer incentives with uptime rather than sales volume. Under such arrangements, incentives shift towards maintenance and condition monitoring, which can support longer service duration by linking manufacturer revenue to continued product performance rather than to unit sales.

Pauliuk et al. (2017) show that materials embedded in products can be redistributed across geographic regions and multiple product life cycles through international trade. Amatuni et al. (2023) similarly argue, in the context of consumer products, that second-hand use and ownership transitions are often incompletely captured in conventional lifetime data. Together, these findings indicate that operational persistence and institutional visibility may diverge. Applied to capital equipment, this suggests that equipment may continue operating even when ownership and service records become fragmented. Jerome et al. (2025) further note that product lifetime is frequently introduced in LCA as a predefined modelling input rather than as an empirically reconstructed distribution. Consequently, the lifetime figures incorporated into environmental modelling may reflect stabilised planning horizons produced within engineering and accounting regimes rather than empirically reconstructed multi-owner operational durations.

2.2 Product Lifetime in Life Cycle Assessment

Product lifetime constitutes a central modelling parameter in Life Cycle Assessment (LCA), as lifetime assumptions influence estimated environmental impacts and the interpretation of environmental performance Jerome and Ljunggren (2025). This section examines how product lifetime is conceptualised and applied within LCA and highlights challenges associated with its empirical representation.

2.2.1 Lifetime as Allocation Mechanism in LCA

Life Cycle Assessment is defined in ISO 14040 and ISO 14044 as a structured framework for compiling and evaluating inputs, outputs, and potential environmental impacts associated with a product system throughout its life cycle European Commission and Joint Research Centre (2010). A central element in this framework is the functional unit, which expresses the quantified performance of the studied system. Environmental impacts are therefore attributed not to the product as a physical object, but to

the function it delivers European Commission and Joint Research Centre (2010) and Guinée et al. (2011).

Despite this formalisation, key parameters within the framework are not internally derived but externally assumed, including the temporal horizon over which the functional unit is realised European Commission and Joint Research Centre (2010).

For capital goods, this distinction has direct methodological consequences. The functional unit expresses performance delivered over time. In order to relate production-related impacts to the functional unit, the model therefore requires an assumption regarding how long the product provides service. Service life, operating hours, or total output become necessary parameters in order to complete the allocation. Lifetime is therefore not an optional descriptive variable. It is a necessary scaling parameter without which allocation to the functional unit cannot be completed.

> *This section therefore does not treat lifetime as a descriptive parameter, but as a structurally embedded modelling assumption with direct implications for impact allocation.*

Technology (product) balance.

The standard process-based LCA inventory can be written in compact matrix form as

$$\mathbf{As} = \mathbf{f}, \qquad \mathbf{s} = \mathbf{A}^{-1}\mathbf{f}, \tag{2.1}$$

where $\mathbf{A}$ is the technology matrix, representing products and processes, and $\mathbf{s}$ is the vector of process activity levels required to meet the functional unit $\mathbf{f}$. The life-cycle inventory (LCI) then follows as

$$\mathbf{g} = \mathbf{Bs} = \mathbf{BA}^{-1}\mathbf{f}, \tag{2.2}$$

where $\mathbf{B}$ denotes the intervention, or elementary-flow, matrix and $\mathbf{g}$ is the vector of life-cycle elementary flows Heijungs and Suh (2002).

Within this framework, production impacts are distributed proportionally across the reference flow associated with the functional unit. Dividing embodied emissions by total delivered service, such as years in operation, operating hours, or service units, directly determines impact intensity. Adjusting the assumed lifetime therefore produces a proportional change in the burden allocated to the functional unit.

> *Lifetime controls the denominator through which production-related impacts are distributed, thereby structurally shaping impact intensity.*

This relationship follows from the equations themselves rather than from an additional interpretive choice Heijungs and Suh (2002).

Lifetime-based allocation for capital goods.

Let E_{prod} denote the production-stage burden of the capital good, u the realised utilisation rate, L the realised service life, and q the quantity represented by the functional unit, such as one operating hour. Total delivered service can then be expressed as

$$Q_{\text{tot}} = uL. \tag{2.3}$$

Allocating the production-stage burden to the functional unit yields

$$I_{\text{prod}\to\text{FU}} = E_{\text{prod}} \frac{q}{Q_{\text{tot}}} = E_{\text{prod}} \frac{q}{uL}. \tag{2.4}$$

This formulation makes the inverse relationship between lifetime and the production-related impact allocated to the functional unit explicit. It also links directly to the linear scaling represented by $\mathbf{s} = \mathbf{A}^{-1}\mathbf{f}$ and $\mathbf{g} = \mathbf{B}\mathbf{A}^{-1}\mathbf{f}$.

> *Equation* (2.4) *can be interpreted as a reduced-form representation of the scaling mechanism embedded in Eqs.* (2.1)–(2.2).

Lifetime is therefore not only a scaling parameter, but a structurally decisive modelling variable Heijungs and Suh (2002).

Although this scaling mechanism is inherent in ISO-based LCA, the standards do not prescribe how lifetime values should be empirically established. ISO 14044 requires transparency, consistency, and documentation of assumptions, but leaves parameter selection to practitioner judgement. In practice, lifetime values are typically derived from engineering estimates, industry conventions, or database defaults. The framework ensures procedural consistency, but not necessarily the empirical validation of structurally influential parameters European Commission and Joint Research Centre (2010) and Guinée et al. (2011).

The issue becomes clearer once uncertainty is considered. Reap et al. (2008) show that parameter uncertainty is a recurring methodological problem in LCA, especially when values are assumed rather than empirically established. Lloyd and Ries (2007) further demonstrate that this uncertainty does not remain isolated. It propagates through the computational structure of LCA and can significantly influence final impact results. This corresponds with first-order uncertainty propagation and established practices in global sensitivity analysis for complex models Heijungs and Lenzen (2014) and Saltelli et al. (2008). However, the issue extends beyond statistical dispersion.

It also concerns structural sensitivity. A parameter may be assigned a single deterministic value and still exert a decisive influence over the results because of its position within the model architecture. Lifetime affects how upstream burdens are distributed across use-phase output. It shapes the denominator of the impact equation and thereby influences both the magnitude and certainty of the calculated results Finnveden et al. (2009) and Plevin et al. (2014).

Temporal dynamics in LCA further illustrate the importance of time-related parameters. Studies show that dynamic emission factors and stock-driven modelling approaches can produce materially different results from static models, particularly for long-lived assets. These findings reinforce that parameters such as lifetime are not neutral inputs, but structurally influential elements of impact assessment Finnveden et al. (2009) and Guinée et al. (2011).

Characterisation and global warming potential.

Once the inventory has been obtained, characterisation maps the elementary flows to environmental impact indicators:

$$\text{Impact} = \mathbf{c}^\top \mathbf{g} = \sum_i c_i g_i, \tag{2.5}$$

where $\mathbf{c}$ contains the method-specific characterisation factors.

Climate impact, expressed in CO_2 equivalents, can correspondingly be calculated as

$$\text{GWP}_H = \left(\mathbf{c}^{\text{GWP},H}\right)^\top \mathbf{g} = \sum_i c_i^{\text{GWP},H} g_i, \tag{2.6}$$

where $\mathbf{c}^{\text{GWP},H}$ contains the IPCC-consistent global warming potential factors for the selected time horizon H European Commission and Joint Research Centre (2010).

Capital goods and database implementation.

The treatment of capital goods is not merely a modelling detail; it has direct implications for calculated environmental impacts. Previous analyses show that the inclusion or exclusion of capital goods can materially affect results across sectors, while database documentation demonstrates how such assumptions are operationalised in practice. This directly connects lifetime assumptions, including how long assets are used and at what level of utilisation, to the allocation mechanisms formalised above Frischknecht et al. (2007).

Taken together, these observations establish lifetime not as a neutral input, but as a structurally decisive parameter within LCA modelling.

2.2.2 Static Assumptions and Dynamic Challenges: ALCA, CLCA, and Uncertainty

Product lifetime is treated differently across LCA modelling approaches, particularly between attributional LCA (ALCA) and consequential LCA (CLCA). Clarifying why lifetime assumptions are frequently untested requires understanding this distinction.

ALCA determines the environmental burdens of a product system within specified boundaries. In practice, lifetime is treated as a fixed parameter used to allocate manufacturing impacts across the functional unit Guinée et al. (2011). According to this static modelling logic, a product is assumed to deliver a predefined quantity of service over a predetermined duration, which explains why lifetime typically enters inventory models as a constant rather than an observed variable Guinée et al. (2011).

CLCA, by contrast, seeks to estimate the environmental consequences of decisions—often small changes in supply or demand-where lifetime can, in principle, shift replacement timing and affect market responses Weidema (2018). In this context, lifetime does not only distribute impacts but can influence when and whether new production occurs, thereby affecting which marginal processes are included in the model. Yet, even in consequential applications, lifetime is rarely established through empirical tracking across ownership cycles; it remains an assumed rather than an observed variable.

This distinction matters for decision support. Plevin et al. (2014) show that modelling choices in CLCA can strongly influence outcomes if key assumptions are not grounded in real behaviour. Their argument extends directly to lifetime: if the parameter governing allocation (ALCA) and replacement dynamics (CLCA) is not empirically validated, model results risk reflecting assumptions rather than system behaviour. In both frameworks, lifetime remains structurally central, but differently operationalised Finnveden et al. (2009) and Guinée et al. (2011).

Uncertainty and structural sensitivity.

Uncertainty analysis does not resolve this issue if the underlying parameter remains unobserved. In first-order error propagation, the variance of a result z e.g., an impact score can be approximated as

$$\mathrm{Var}(z) \approx \sum_i \left(\frac{\partial z}{\partial x_i}\right)^2 \mathrm{Var}(x_i) + \sum_{i \neq j} 2 \frac{\partial z}{\partial x_i} \frac{\partial z}{\partial x_j} \mathrm{Cov}(x_i, x_j), \tag{2.7}$$

which can be evaluated analytically or through Monte Carlo simulation in LCA Heijungs and Lenzen (2014). Global sensitivity analysis further identifies parameters with dominant influence across the input space, often highlighting lifetime as a key driver

of output variability Saltelli et al. (2008). However, propagating uncertainty around an assumed lifetime is not equivalent to validating realised service duration.

2.2.3 The Specific Gap: Lack of Empirical Lifetime Validation

LCA research has long treated uncertainty as a structural problem rather than a marginal one. Huijbregts et al. (2003) distinguish three types of uncertainty relevant to this discussion: parameter uncertainty arising from input data, model uncertainty arising from the mathematical structure of the assessment, and scenario uncertainty arising from normative choices. Reap et al. (2008) review unresolved methodological problems across LCA's goal and scope definition and life-cycle inventory phases, including problems related to uncertainty and the representativeness of input data. Lloyd and Ries (2007) review the quantitative methods available for characterising and propagating this uncertainty through an LCA model. Applying Huijbregts et al.'s general finding that variation in key inputs can substantially shift environmental outcomes to the specific case of lifetime, this study reads it as especially consequential when the parameter in question affects allocation: since lifetime forms the denominator in impact intensity calculations, as established in Section 2.2.1, changing the assumed lifetime, holding other parameters constant, changes that denominator directly and can alter comparative conclusions between alternatives.

Although lifetime is rarely treated as a standalone issue in Reap et al.'s review, it falls within the broader problem of representativeness and assumption robustness that they describe. Huijbregts et al. (2003) note that methods such as Monte Carlo simulation and probabilistic modelling have been proposed to manage this type of uncertainty. This study distinguishes, however, between two different things such methods can achieve: formalising a distribution around an assumed lifetime value, and validating that value against observed longitudinal data. The methods reviewed by Huijbregts et al. (2003) and Lloyd and Ries (2007) address the former. Neither study evaluates lifetime against empirically reconstructed operating-hour estimates of the kind developed in this study's methodology.

This distinction matters directly for capital goods that circulate across ownership cycles and secondary markets. Holding other parameters constant, if real-world operational lifetime in secondary markets is systematically longer than the lifetime assumed in a given model, impact intensities per functional unit are overstated; if early retirement dominates in a given context, they are understated. The lifetime-specific gap this implies is documented directly elsewhere in this chapter: Jerome and Ljunggren (2025) find unclear lifetime definitions in 63% of the LCA studies they reviewed,

and Amatuni et al. (2023) show that conventional lifetime estimates can substantially underrepresent total product lifetime once second-hand use and successive ownership periods are taken into account. Formal representation of uncertainty within an LCA model, in other words, does not by itself constitute empirical validation of the lifetime value being represented.

2.3 Product Lifetime in Circular Economy

In Circular Economy (CE), lifetime extension is commonly framed as a strategy for slowing resource loops through maintenance, repair, reuse, refurbishment, and remanufacturing Bocken et al. (2016). Its environmental significance, however, depends on how product lifetime is defined and represented in assessment. In their review of 67 LCA studies of lifetime extension, Jerome and Ljunggren (2025) identify substantial variation in lifetime definitions, modelling approaches, and data sources.

Product lifetime therefore connects circular strategy with environmental assessment: CE treats longer use as a way to reduce material throughput, while LCA determines how the environmental consequences of that longer use are quantified. This section examines that relationship.

2.3.1 Lifetime Extension as Core Circular Strategy

Bocken et al. (2016) distinguish between narrowing, closing, and slowing loops, situating lifetime extension, maintenance, repair, refurbishment, remanufacturing, and reuse within slowing strategies specifically. When other model conditions remain constant, distributing production-stage impacts over a longer service period reduces the calculated impact intensity per functional unit Heijungs and Suh (2002).

Jerome and Ljunggren (2025) complicate this reasoning. Reviewing 67 LCA studies of lifetime extension, they find that lifetime is frequently introduced as a modelling assumption rather than as an empirically reconstructed parameter, with unclear definitions in 63% of cases and undisclosed data sources in 26%. The sensitivity analyses reported in the reviewed studies further show that environmental conclusions can change with the lifetime values and baselines used in the assessment. Applied here, this suggests that the environmental benefit attributed to extension is not a fixed property of extending use, but depends on how lifetime is defined and where the baseline is set Jerome and Ljunggren (2025).

Stahel (2010) offer a complementary account at the level of business models. By tying revenue to performance rather than unit sales, the performance economy redirects

economic incentives towards preserving product functionality over time. Stahel (2016) places these value-preserving activities within the wider Circular Economy. Lifetime extension, in other words, is not environmentally beneficial by default; its assessed magnitude and direction depend on how lifetime is defined and operationalised in the assessment Jerome and Ljunggren (2025).

2.3.2 Secondary Markets and Global Redistribution

Yi et al. (2016) model end-of-life construction machinery within a retailer-oriented closed-loop supply-chain network for remanufacturing. Their study treats used construction machinery as part of remanufacturing and reverse-logistics processes rather than solely as material intended for disposal.

At a broader system level, Müller (2006) use a stock-driven model of the Dutch housing sector to examine how assumed lifetimes influence stock accumulation and the timing of material outflows. Pauliuk et al. (2017) extend this system perspective by examining how international trade, recycling losses, and multiple product life cycles affect the regional distribution of end-of-life steel.

2.3.3 The Measurement Gap in Circular Economy

Product lifetime extension is positioned within Circular Economy as a strategy for slowing resource loops. Bocken et al. (2016) describe maintenance, repair, reuse, refurbishment, and remanufacturing as central approaches for extending product use. However, the assessment of product lifetime remains methodologically inconsistent. In their review of lifetime modelling in LCA studies of Circular Economy strategies, Jerome and Ljunggren (2025) identify substantial variation in the definitions, modelling approaches, and data sources used to represent product lifetime.

A particular challenge concerns products that pass through several ownership periods. Amatuni et al. (2023) describe available data on total product lifetime as limited and develop a modelling approach that explicitly accounts for second-hand use. Their study highlights that total lifetime is difficult to estimate when available information does not cover all successive users.

This measurement gap is relevant to both Circular Economy and LCA. Bocken et al. (2016) position lifetime extension as a means of slowing resource flows, whereas Heijungs and Suh (2002) explain how delivered service forms the basis for allocating environmental burdens in LCA. Jerome and Ljunggren (2025) further show that the way lifetime is defined and modelled can influence the assessment of Circular Economy

strategies. When lifetime is represented through predefined values or incomplete use histories, the modelled duration may therefore fail to capture total use across successive ownership periods, particularly where second-hand use is not fully documented Amatuni et al. (2023).

2.4 The Empirical Lifetime Gap

Despite the importance of product lifetime within both LCA and Circular Economy research, empirical evidence describing actual lifetime patterns remains limited. Lifetime assumptions are frequently derived from standardised values or institutional conventions rather than observed operational behaviour. This section examines the gap between assumed and observed lifetimes and establishes its relevance for the present study.

2.4.1 Institutional Assumptions vs Observed Reality

The preceding sections establish that lifetime does not originate within any single domain but is stabilised separately within engineering, accounting, LCA, and Circular Economy, each for a different coordinating purpose. International Organization for Standardization (2011) formalises design life as a planning horizon under specified technical and environmental conditions. International Accounting Standards Board (2003) defines useful life, in accounting, as the period over which an asset is expected to generate economic benefit for a specific reporting entity. Heijungs and Suh (2002) formalise lifetime, in LCA, as a scaling parameter embedded in the functional unit and allocation structure. Bakker et al. (2014) and Bocken et al. (2016) conceptualise lifetime extension, in Circular Economy, as a strategy for slowing material loops. In engineering, accounting, and LCA, the horizon is commonly specified in advance to serve a coordinating or modelling function rather than reconstructed from observed use, a pattern already established in Sections 2.1 and 2.2.

A remaining challenge is the limited empirical evidence on continued use beyond the first owner Amatuni et al. (2023) and Jerome and Ljunggren (2025). The construction-equipment studies discussed in Section 2.1.2 help explain why this distinction matters. Ladopoulos et al. (2020) and Gransberg and O'Connor (2015) show that repair, retention, and replacement decisions are shaped by ownership and operating costs. Economic replacement may therefore occur before material exhaustion, which means that exit from a first owner's records does not necessarily imply exit from service. At system scale, Müller (2006) and Pauliuk et al. (2017) reinforce this from a different angle:

their stock-flow and material-trade models show that assumed lifetime distributions and cross-regional redistribution shape system-level outcomes without providing validation of any individual asset's continued use. Read together, these findings establish a consistent principle: realised service duration may diverge from institutional lifetime assumptions once assets circulate across owners and markets.

Amatuni et al. (2023) point to a related asymmetry in data visibility: once a product changes ownership, records of its continued use can become difficult to trace, so that institutional lifetime assumptions may remain formally stable even as empirical visibility of the asset fragments.

This study defines the *empirical lifetime gap* as follows:

> *The divergence between institutionally stabilised lifetime assumptions and the real-world operational lifetime patterns indicated by available evidence across owners and markets.*

The definition captures situations in which continued use may extend beyond predefined institutional horizons, while complete ownership histories and exact end-of-life points remain unavailable.

Jerome and Ljunggren (2025) confirm that this issue extends into current LCA methodology: lifetime is frequently represented through predefined values, while definitions and underlying data sources are not consistently reported.

2.4.2 Why Empirical Lifetime Matters for Both LCA and CE

The empirical lifetime gap matters in LCA because lifetime helps determine the amount of service over which production-related impacts are distributed. Holding the remaining model conditions constant, a longer assumed lifetime reduces the calculated impact per functional unit Heijungs and Suh (2002). The proportional logic is therefore conditional: doubling lifetime only halves the production-related impact per service unit when the other assumptions in the model remain unchanged.

This condition matters because lifetime extension is not assessed in isolation. In the studies reviewed by Jerome and Ljunggren (2025), environmental results change with the initial lifetime, the additional period of use, the resources required to enable that extension, and differences in efficiency between continued use and replacement. Empirical lifetime evidence cannot resolve each of these factors on its own. It can, however, show whether the service duration represented in the model is consistent with real-world operational lifetime patterns rather than only with a predefined horizon.

In Circular Economy, the problem is different. Lifetime extension is treated as a way of slowing resource loops by keeping products in use through repair, reuse, refurbishment, and remanufacturing Bocken et al. (2016). That strategy still requires a credible baseline. Amatuni et al. (2023) show that total product lifetime can include second-hand use and successive ownership periods that are not captured when lifetime is measured only through the first use period. When this later use is missing from the baseline, an assessment may treat continued use as a new extension even when it is already occurring through resale and redistribution.

Empirical lifetime evidence therefore has a dual role. In LCA, it provides a basis for evaluating the lifetime value used to scale environmental burdens Heijungs and Suh (2002). In Circular Economy, it helps determine whether a proposed strategy creates additional use beyond the baseline already realised across successive owners Amatuni et al. (2023). The aim is not to replace every model with one universal lifetime value, but to ensure that the assumed lifetime is transparent and consistent with the product and market context being assessed Jerome and Ljunggren (2025).

2.4.3 Positioning the Present Study

Jerome and Ljunggren (2025) show that lifetime in LCA is often represented through predefined values and that the underlying data sources are not consistently reported. Müller (2006) demonstrate how assumed lifetime distributions affect stock accumulation and the timing of material outflows, while Pauliuk et al. (2017) examine redistribution across regions and repeated product cycles. These studies explain how lifetime assumptions affect system-level outcomes, but they do not reconstruct the operational histories of individual capital assets.

A further challenge is that total product lifetime may extend beyond the first ownership period, while available data do not necessarily cover all subsequent users Amatuni et al. (2023). Against this background, the present study estimates real-world operational lifetime patterns for capital equipment using available machine-age and operating-hour data from different market contexts. The estimates are interpreted in relation to the lifetime-modelling problems identified by Jerome and Ljunggren (2025) and the lifetime-extension strategies described by Bocken et al. (2016). The study therefore addresses the gap between modelled lifetime and continued use across successive owners and markets.

2.5 Defining Product Lifetime and End-of-Life

Product lifetime can be defined in different ways depending on which period of a product's life is measured. Jerome and Ljunggren (2025) distinguish between four concepts: *technical use time*, *use time*, *technical lifetime*, and *service lifetime*.

According to Jerome and Ljunggren (2025), *technical use time* refers to the accumulated period of active use until the product no longer has the physical capacity to function. Periods during which the product is not in use, such as during maintenance or repair, are excluded. *Use time* is similarly defined as the total period during which the product is actively used. However, use time may end before the product's full physical capacity has been exhausted.

Within the classification presented by Jerome and Ljunggren (2025), *technical lifetime* refers to the elapsed period during which the product retains the physical capacity to function. This period ends when the product can no longer perform its intended function because of durability, material degradation, or physical wear. Unlike technical use time, technical lifetime includes periods during which the product is not actively used.

Jerome and Ljunggren (2025) define *service lifetime* as the elapsed period from the beginning to the end of a product's use. This definition includes both periods of active use and periods during which the product is temporarily inactive. Service lifetime ends when the product is taken out of use, even if it remains physically capable of functioning.

Jerome and Ljunggren (2025) further explain that service lifetime and technical lifetime are equal when a product remains in use until its physical capacity is exhausted. When a product is taken out of use while it is still functional, its service lifetime is shorter than its technical lifetime. Correspondingly, use time is shorter than technical use time when active use ends before the product's full technical use capacity has been reached Jerome and Ljunggren (2025).

2.6 Planned obsolescence

Many factors can impact product lifetime, and one of them is product obsolescence. One category of obsolescence is *planned obsolescence*. Rivera and Lallmahomed (2016) define planned obsolescence as a strategy created to shorten a product's lifespan with the purpose of stimulating recurrent acquisition of products.

This is done by producers and can be performed by intentionally constructing design

flaws concerning durability, by lowering performance in devices through software updates, making it hard for consumers to repair the product or changing the style of the product depending on trends Rivera and Lallmahomed (2016), Tadj (2025), and Wieser (2016). At the same time, Wieser (2016) argues that planned obsolescence consists of a network between all market sectors rather than only being defined by marketers and designers. Planned obsolescence is also criticized both in theory and in practice, mainly because of its negative environmental impact. Wieser (2016) argues that there is too much focus on the blatant cases of planned obsolescence instead of a mutual understanding of what normality in product lifespan means. And that a shift in politics, commercial interest and sales strategies is needed to achieve this and to avoid backlash when promoting circular economy.

Continuing on the regulatory perspective, planned obsolescence has been discussed several times. Maitre-Ekern and Dalhammar (2016) discuss, much like Wieser (2016), that product lifetime must be regulated through legal strategies and not only by market incentives. They argue that durability and repairability should be addressed together as a matter of legal governance. At the same time, it is a complex legal situation, where it has historically been limited possibilities to enforce measures for shortened lifetimes Maitre-Ekern and Dalhammar (2016).

A recent EU legislative initiative has attempted to solve this challenge by defining early obsolescence. It states that "a commercial policy involving deliberately planning or designing a product with limited useful life so that it prematurely becomes obsolete or non-functional after a certain period of time" European Commission (2022). The definition aims to strengthen the legal basis for intervention but also enable transparency in the market when it comes to strategies that limit performance, durability and therefore product lifetime extension.

Likewise European Economic and Social Committee (2013) has earlier wanted a ban on products consisting of a built-in design defect that affects product lifetime. It is proposed that there is a need for stronger structural intervention which gathered the idea of a labelling system. The labelling system for products should constitute a minimum product lifetime which should be guaranteed. EESC also argues that manufacturers should make it easier to buy replacement parts and thereby enable consumers to repair their products instead of throwing them away.

Further environmental consequences are elaborated by Malinauskaite and Erdem (2021). They argue that the culture of *"buy new and buy often"* is reinforced by planned obsolescence and therefore undermines circular economy. The same authors argue that the lifetime of electrical and electronic equipment has decreased meanwhile the waste for the same equipment has increased. Seemingly linking shortened product lifetime,

increased resource usage and waste to planned obsolescence's negative environmental impact.

Malinauskaite and Erdem (2021) also enlighten existing legal needs to address planned obsolescence similar to Wieser (2016). They argue that the current instruments aren't sufficient enough and that durability affecting product lifetime should be embedded at all times in product design. A need for focus on reparability, recycling and reuse is emphasized. In Malinauskaite and Erdem (2021), it is implied that at this time, product lifetime extension is a voluntary market outcome rather than an objective that is structurally regulated.

Kuppelwieser et al. (2019) also contribute to recognizing planned obsolescence from innovation strategies. Highlighting the detail that customer behaviour changes as fast as there is an idea of a product being obsolete. Which in turn might mean that mere anticipation of obsolescence could alter perceived product value. This reinforces the thought of product lifetime being formed by different market stakeholders rather than only by technical durability.

2.7 Consumer factors

Connected to product lifetime and product obsolescence is the consumers' impact. The actual product lifetime depends on many factors, more than just technical sustainability and decisions regarding design from the producers. It is influenced by consumer behaviour, the type of expectations there are on the market and market response. In practice several studies have shown that the product's lifetime largely and often lies with the consumer rather than with the producer. Rivera and Lallmahomed (2016) have investigated in their study that product lifetime becomes shorter if consumers choose to replace or throw away a product earlier than what the actual product lifetime is, even though the product itself might function longer.

The same authors also explain that consumer purchase behaviour is influenced by how product lifetime attributes are presented. If the producer presents a shorter product lifetime, consumers often respond by replacing the product more frequently than if the product lifetime were conveyed to be longer. Which in turn affects actual product lifetime Rivera and Lallmahomed (2016). Nishijima and Oguchi (2023) similarly provides insight into how consumer expectations measurably influence product lifetime if the expectations are enhanced. The study shows that if consumers expect the product to function for several years, they tend to use the same product over a longer period of time, matching expectations. Kuppelwieser et al. (2019) reach similar conclusions when it comes to replacement timing and behavioural intentions. Their results indicate

that longer replacement cycles are value-enhancing for producers.

At the same time, there have to be sufficient support systems in place for consumers to extend the life of the product. Such as repair services or product guarantees, not only technical developments and reliable information on the product lifetime Nishijima and Oguchi (2023). Hand in hand, the authors argue that if there is a lack of trustworthy information and policies on product lifetime, consumers tend to discard the product in advance Nishijima and Oguchi (2023). The rapid change in customer needs and preferences is identified by Rivera and Lallmahomed (2016) as one of the reasons consumers would throw away or change their products, as well as market strategies. The market strategies introduce new functions and models to consumers. Combined they create even more transposition and lower the threshold for product exchange Rivera and Lallmahomed (2016).

A type of combination between consumer needs, preferences and market strategies is also analyzed further by Amatuni et al. (2023). The study states that customers' replacement frequency accelerates when exposed to attractive offers, which might affect product lifetime negatively, even though actual product lifetime and usage can be longer. Supporting this notion are Kuppelwieser et al. (2019) through their argument that consumer choices may be influenced by if the devaluation of the product will be substituted sooner rather than later, and not by actual functional improvements of the product. Other than that, the same authors investigate how behaviour regarding disposal and *hibernation time* can affect product lifetime. *Hibernation time* is the time between active usage of the product and final disposal. A big portion of products is stored away without being used, meaning that there is a delay in the recycling process. It covers potential repair, reuse or resale processes. This may result in a longer, misleading product lifetime since the product is not used but still in possession of the consumer Amatuni et al. (2023).

External factors

Other than the consumer factors that were explained above, there are consumer factors that are classified as external factors. That is how consumers or customers treat and use the product. This can also affect the product's lifetime and as mentioned earlier, not only technical criteria. Polizzi di Sorrentino et al. (2016) argue that a big part of product lifetime influence depends on consumer usage behaviour and that there is a need for a great understanding of the actual user behaviour to be able to estimate the actual product lifetime.

The user behaviour can consist of factors such as the intensity of usage or the maintenance schedule, which can lead to quicker reach to technical lifetime. Gnanapragasam

et al. (2017) also calls this a disuse and a mismatch between function, application, as well as product and durability, triggering early obsolescence. Other than that, the same author explains that culture, media influence, norms and individual situations occurring can change the perception of the product. Therefore decreased consumer value can happen even though the product itself remains unchanged and useful for its original purpose. It also declares that society as a whole affects product lifetime and not only through individual means and perceptions Gnanapragasam et al. (2017).

Gnanapragasam et al. (2017) further explains that product lifetime is affected by economic discrepancies. This can happen when the product's cost becomes disproportionate to the company's needs. Maintenance cost and operational cost can influence the economic point of view, as well as whether spare parts are taken out of production from the producer's side or are unavailable due to logistical circumstances. Similarly, Amatuni et al. (2023) argue that companies might not invest in prolonging product lifetime and durability because of the idle time. They attest that the value lost, decreased sales or production, is not compensated for in their business model. It is quickly mentioned that this mainly regards companies that do not practice servitization models.

Another factor, according to Gnanapragasam et al. (2017), that can shorten the lifetime of the product is if it is hard to integrate into new, upgraded infrastructure or systems. If the product is not compatible, consumers might replace the product in advance. Finally, the environmental conditions are found to be an external factor that impacts a product's lifetime. In Płota and Mašek (2020), it has been found that several environmental factors make changes in the primary use properties of the product. After long-term exposure to the factors, destruction of the product will occur influencing product lifetime negatively.

Some of these factors that are mentioned in the study are dynamic stress, heat, oxygen and water vapour. The authors also argue that it is hard to estimate which of the factors that influence product lifetime the most, since many of them can affect the product simultaneously. To have in mind is that the degradation of product lifetime would happen eventually either way, but that the environmental factors speed up the process Płota and Mašek (2020).

Definitions of End-of-Life

End-of-life (EoL) is more appropriately understood as a transition rather than a discrete point in time. Den Hollander et al. demonstrate that circular product design requires a layered understanding of product lifetime, where different forms of value persist beyond initial use Den Hollander et al. (2017).

From an environmental perspective, reuse decisions are typically made before functional exhaustion is reached. Cooper and Gutowski show that the environmental benefit of reuse depends on the remaining functional value of a product, rather than on its absolute technical condition Cooper and Gutowski (2017).

At the material level, value does not disappear when a product ceases operation. Allwood et al. show that material efficiency strategies rely on extending product use, reusing components, and delaying the transition to raw material recovery Allwood et al. (2011). This perspective is consistent with Stahel's conceptualisation of the circular economy, where value retention occurs at multiple levels of use Stahel (2016).

Technical End-of-Life

Technical end-of-life refers to the stage at which a system no longer satisfies functional and reliability requirements without substantial repair. Ardente and Mathieux relate this to measurable degradation and the need for intervention at the component level Ardente and Mathieux (2014). In practice, this condition emerges gradually as maintenance intensity increases and reliability declines Cooper and Gutowski (2017).

Economic End-of-Life

Economic end-of-life occurs earlier, when continued operation is no longer justified in cost terms. Bakker et al. show that product life extension depends on trade-offs between continued use, repair, and replacement Bakker et al. (2014). Den Hollander et al. further conceptualise this as a recovery horizon, where products shift between users and markets before technical exhaustion Den Hollander et al. (2017).

Material End-of-Life

Material end-of-life describes the stage at which the asset is no longer primarily valued as an operating system, but as a source of components or materials. Stahel frames this as a shift from product-level value to material-level value retention Stahel (2016). Sundin and Bras show that remanufacturing can delay this transition by preserving the value embedded in components Sundin and Bras (2005).

Operationalising Life-Cycle Intervals

Operating hours provide a suitable metric for analysing lifetime in construction equipment, as degradation is driven by accumulated use rather than calendar time. Liu et al. (2020) demonstrate that maintenance phases in heavy equipment can be identified using operating-hour data. Similarly, Gransberg and O'Connor (2015) show that life-cycle cost analysis for major equipment is structured around usage-based cost

evolution.

End-of-life construction machinery has also been analysed within closed-loop systems. Yi et al. (2016) model remanufacturing and secondary-market flows as structured components of a circular system rather than as residual processes.

3. RESEARCH METHOD

This chapter presents the research design and methodological choices underlying the study, including the research approach, empirical data collection, data analysis, and research quality considerations.

3.1 Research approach

This study adopts a multi-method, case-based empirical research design to examine the real world operational lifetimes of heavy construction equipment and to understand how observed lifetime variation affects circular Life Cycle Assessment (LCA) modelling. A case-based approach is particularly appropriate when the phenomenon under investigation cannot be meaningfully separated from its real-life context Yin (2018). In the off-road sector, product lifetime is rarely determined by a single factor. Equipment frequently changes ownership, is exported across markets, and enters secondary use phases where maintenance intensity and operational demands differ substantially. These transitions are embedded in organizational practices and market logics, meaning that lifetime outcomes cannot be understood without examining the broader structural context in which they unfold.

The study follows a theory-building logic. Eisenhardt and Graebner emphasize that case-based research is especially valuable when key constructs remain insufficiently specified and when empirical grounding is needed to challenge established assumptions Eisenhardt and Graebner (2007). In LCA methodology, product lifetime operates as a scaling parameter that determines how production-related impacts are distributed over delivered service Heijungs and Suh (2002). Because this parameter directly influences environmental results, even modest deviations in assumed lifetime may alter assessment outcomes. However, lifetime values are often based on standardized defaults or engineering estimates instead of systematically collected operational data Ciroth et al. (2016). By looking at different companies in various markets, the study aims to show how actual lifetime trends differ from what models expect and what these differences mean for evaluating circular performance.

The research takes a practical approach, focusing on creating explanations based on real-world evidence that are both strong in analysis and useful in practice. The study uses qualitative methods like semi-structured interviews, workshops, and internal documents to follow the paths of assets, how they are maintained, and how they are reused, which are often missed. These empirical insights inform an embedded compar-

ative LCA modelling component, where observed lifetime parameters are introduced into environmental calculations to assess structural sensitivity. In this study, empirical observation and modelling are not treated as isolated steps. Instead, findings from the field directly inform modelling parameters, and modelling outcomes are used to reflect back on empirical patterns. Rather than aiming for statistical representativeness, the study seeks analytical generalization, meaning that the ambition is to develop explanations that are theoretically transferable to comparable contexts Yin (2018). As Lincoln and Guba argue, qualitative research builds credibility through contextual depth rather than numerical breadth Lincoln and Guba (1985). In line with contemporary discussions on qualitative rigor, particular attention is therefore given to making transparent how empirical observations are developed into theoretical insights and modelling implications Mees-Buss et al. (2022).

3.2 Literature Review

The literature review was carried out through a structured and documented search process. Searches were conducted in Scopus, Web of Science, and ScienceDirect using keyword combinations related to product lifetime, circular economy, asset utilization, and life-cycle assessment (LCA) modelling (see *Table 3.1* for representative search strings). The search strategy was iterative, with keywords refined throughout the screening process as new relevant terminology emerged. To increase coverage, backward and forward snowballing were used by reviewing selected peer-reviewed journal articles' reference lists and citations Wohlin (2014).

Table 3.1: Showing Keyword and Search Strings

Thematic Cluster	**Search Strings**
Sustainability	Sustainability & construction equipment
Circular Economy	Circular economy & asset lifetime
Business Strategy	Business model & product-service system
Life Cycle Assessment	LCA & machinery lifespan
Product Lifetime	Product lifetime estimation & empirical data
Engineering Practices	Over-engineering OR under-engineering & durability
Asset Utilization	Asset utilization & construction fleet

The inclusion criteria focused on peer-reviewed journal articles, book chapters, and authoritative standards published between 2004 and 2026 that addressed product lifetime estimation, asset management, circular strategies, or modelling implications. Contributions lacking methodological clarity or consisting solely of opinion-based discussion were excluded. Given the relevance of regulatory and industry standards for equipment

lifetime transparency, selected grey literature, such as ISO standards and regulatory documents, was included where directly applicable and documented using the same protocol.

Table 3.2: Excel Literature Documentation

Field	**Purpose**
Article Title	Unique identification
Author(s)	Attribution and source verification
Year	Temporal mapping of research development
DOI / Link	Traceability of search origin
Primary Keyword Cluster	Traceability of search origin
Relevance Note	Assessment of contribution to WP2
Thematic Tag	Analytical classification

All identified sources were recorded in a structured Excel matrix serving as an audit trail (see *Table 3.2*). The matrix included bibliographic information, search origin, thematic classification, and a concise relevance note. Articles were screened at the title and abstract levels, followed by full-text review as needed. Studies were classified into analytical categories based on thematic tagging and consistent color-coding, such as lifetime estimation methods, empirical data collection approaches, transparency mechanisms, and business model implications. This structured mapping enabled a descriptive overview, thematic comparison, and the identification of research focus areas. The review revealed extensive modelling-oriented research but comparatively limited empirical investigation of real-world lifetime data in construction equipment contexts. This imbalance forms the empirical starting point of the present study. The review process emphasized transparency and traceability. To maintain reproducibility and methodological clarity, search terms, screening choices, and thematic classifications were all documented.

3.2.1 Research Context

The empirical study was conducted within a research project, which investigates real-world lifetime and end-of-use conditions for construction equipment across multiple market contexts. Data collection was carried out in collaboration with industrial partners representing different stages of the construction equipment value chain.

This study forms part of Work Package 2 (WP2), which focuses on empirical assessment of real-world equipment lifetime and reconstruction of lifetime patterns across market contexts.

Participating organizations included actors from manufacturing, aftermarket services,

rental operations, and asset management. This multi-actor setting provided access to different operational perspectives and empirical contexts related to equipment ownership, maintenance practices, service provision, and market circulation.

Including organizations from different positions in the value chain supported the study objective of examining product lifetime beyond a single organizational context and enabled analysis of how lifetime-related decisions and data practices are embedded in operational and strategic processes Yin (2018).

3.2.2 Semi-Structured Interviews

Semi-structured interviews were conducted with key informants from participating organizations. The interviews were conducted either online using Microsoft Teams/Zoom or in person, depending on availability. Each session was attended by both authors of this study, who took turns conducting the interview. This setup allowed one author to lead the discussion while the other documented emerging themes and asked follow-up questions when additional clarification was needed.

A thematic interviewing framework was developed to ensure consistency across all cases while allowing for the flexibility to tailor questions to each informant's area of expertise. The primary topics covered were modeling assumptions, asset utilization, sustainability strategy, and product lifetime practices. However, the format and order of the questions differed based on the role and area of expertise of the respondent. This approach enabled structured yet context-sensitive exploration of organizational practices Kvale and Brinkmann (2015).

Informants were carefully selected based on their involvement in sustainability, asset management, digitalization, manufacturing, or related operational areas relevant to product lifetime and data practices. All interviews were audio-recorded, sometimes even with video, with participant consent and subsequently transcribed for analysis. An overview of the interview cases and respondents is presented in Table 3.3.

Table 3.3: Overview of interview cases and respondents

ID	Organization Type	Respondent Role	Date	Duration
I1	OEM	Head of Resource Sustainability	2026-02-17	59:29
I2	OEM	Head of LCA Program	2026-03-13	64:43
I3	Construction Contractor	District Manager + Category Manager Construction Equipment	2026-02-19	46:06
I4	Dealer	Head of Used Spare Parts	2026-03-16	46:20
I5	Manufacturer	Sustainability Strategist	2026-03-24	62:15
I6	OEM	Head of Virtual Product Development	2026-03-27	64:40
I7	OEM	Head of Product Management	2026-03-27	78:32
I8	Regional Dealer	Business Transformation and Executive Team	2026-05-12	45:32
I9	OEM	SBT Lead – Products in Use	2026-04-17	62:26

Note: Additional interview sessions were conducted when necessary.

3.2.3 Empirical Reconstruction of Operating Lifetime

This section specifies the quantitative reconstruction procedure through which secondary-market listing data was converted into empirical operating-lifetime estimates suitable for comparison with LCA baseline assumptions. The procedure was formalised to ensure reproducibility and to make the relationship between raw market observations and the derived deviation figures in Table 4.8 transparent.

Reconstruction approach. Operating lifetime in heavy construction equipment was not directly observable in the secondary-market data. Listings reported operating hours at a single point in time, namely the moment of listing, rather than at end-of-life. The reconstruction therefore did not estimate true retirement points. Instead, it estimated the minimum accumulated service output already delivered by each machine, conditional on its calendar age cohort and observed operating-hour interval. Each secondary-market observation was treated as evidence that the machine had remained operational up to at least the listed operating-hour level. The resulting estimates were therefore interpreted as conservative lower-bound measures of delivered operating lifetime.

Operating-hour interval aggregation. Operating-hour data in the listings varied in precision. Some listings reported exact hour readings, some reported approximate values or ranges, and others omitted operating hours entirely. To enable systematic comparison across markets and machine categories, observations were aggregated into four standardised operating-hour intervals. These intervals were selected to reflect major lifecycle transitions in construction equipment, including primary use, transition phases, and late-life operation.

Table 3.4: Operating-hour intervals used for empirical lifetime reconstruction

Interval	Operating-hour range	Lifecycle interpretation
I	0–7,999 h	Primary-use phase with high reliability and limited corrective maintenance
II	8,000–11,999 h	Early transition phase where technical functionality is maintained and economic pressure begins to increase
III	12,000–14,999 h	Late transition phase where major component replacement becomes more likely
IV	≥15,000 h	Late-life phase where technical, economic, and material end-of-life boundaries increasingly overlap

Exact observations were assigned directly to the corresponding interval. Range-based observations were assigned using the interval midpoint. Listings with missing operating-hour data were excluded from interval-based calculations but retained as missing-value counts in the market tables to preserve transparency about data completeness.

For each market-category combination, empirical operating lifetime was reconstructed using interval-weighted averaging:

$$Emp_h = \frac{\sum_i x_i f_i}{\sum_i f_i}$$

where x_i denotes the representative operating-hour value assigned to interval i, and f_i denotes the number of observations within interval i.

Baseline reconstruction. The LCA baseline was constructed from the standard 10-year lifetime assumption used for comparison in the study. To translate this calendar-year assumption into an operating-hour equivalent, average annual utilisation was multiplied by the assumed useful life:

$$LCA_h = \bar{u} \cdot L_{LCA}$$

where $\bar{u}$ denotes average annual utilisation in operating hours per year, and L_{LCA} denotes the assumed lifetime in years. In this study, L_{LCA} was set to 10 years. Category-specific baseline values were then used as the reference values against which empirical operating-hour estimates were compared.

Lifetime deviation calculation. Deviation from the LCA baseline was calculated in both absolute and relative terms. The absolute deviation was calculated as:

$$Dev_h = Emp_h - LCA_h$$

The relative deviation was calculated as:

$$Dev_{\%} = \frac{Emp_h - LCA_h}{LCA_h} \times 100$$

Positive values indicate that the reconstructed empirical operating hours exceed the LCA baseline, whereas negative values indicate that the reconstructed empirical operating hours fall below the baseline. The deviation value was used as an indicator of the direction and magnitude of difference between observed market data and the standardised LCA lifetime assumption.

Lifetime emission reconstruction. Where sufficient data were available at machine-category and market level, reconstructed operating lifetime was also used in emission-related calculations. The lifetime emission estimate was calculated as:

$$CO_2 = \frac{\Delta_{IF} \cdot u \cdot FC \cdot EF \cdot 10}{1000 \cdot 1000}$$

where Δ_{IF} denotes the improvement factor relative to the reference configuration, u denotes annual utilisation, FC denotes fuel consumption per operating hour, and EF denotes the emission factor. The denominator converts the result into kilotonnes of CO_2.

Production-phase impact allocation was adjusted by substituting the empirically reconstructed operating-hour estimate into the functional-unit allocation expression:

$$I_{prod \to FU} = \frac{E_{prod} \cdot q}{Emp_h}$$

where E_{prod} denotes the production-phase environmental burden, q denotes the functional unit, and Emp_h denotes the empirically reconstructed operating-hour estimate. This calculation was performed only where the required variables were available at sufficient resolution. Observations with incomplete parameter availability were excluded from emission reconstruction and reported accordingly.

3.3 Data Analysis

The analytical strategy integrates quantitative lifetime analysis with qualitative interpretation to examine both measurable and behavioural dimensions of equipment use across markets. Secondary-market observations, interview evidence, and embedded LCA assumptions are treated as complementary sources of evidence within an explanatory mixed-methods design Creswell and Plano Clark (2017). Quantitative analysis is used to identify patterns in observed lifetime behaviour, while qualitative evidence supports interpretation of the institutional and operational conditions asso-

ciated with those observations.

Quantitative analysis is performed using the operating-lifetime variables reconstructed in Section 3.2.3. Lifetime is analysed jointly through calendar age and accumulated operating hours to distinguish between temporal ageing and utilisation-driven wear. Since secondary-market observations represent machines that remain operational at the point of listing, complete lifetime information is generally unavailable. These observations are therefore treated as right-censored following established reliability methodology, where survival to the observation point is known while completed lifetime remains unobserved Meeker and Escobar (1998). Retaining censored observations reduces systematic underestimation of lifetime distributions and allows observed service continuation to contribute to statistical estimation.

Initial analysis proceeds through descriptive statistics and distributional diagnostics to characterise heterogeneity across machine categories and market tiers. Operating-hour distributions are examined separately by machine category and market context before cross-market comparison is performed in order to preserve structural differences in utilisation intensity and observed lifetime continuation.

Where sample size permits, formal lifetime estimation is conducted using Weibull reliability modelling:

$$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right], \qquad t \geq 0$$

where β denotes the shape parameter and η denotes the scale parameter (characteristic lifetime). Model parameters are estimated using maximum likelihood estimation with censoring adjustment. The Weibull model is applied to examine variation in lifetime behaviour across machine categories and market contexts rather than to impose a predefined failure structure.

Economic lifetime is analysed using replacement-cost logic derived from equipment replacement theory. Empirically observed lifetime continuation is interpreted in relation to theoretical replacement conditions in order to distinguish observed operational persistence from economically optimal replacement timing Abensur et al. (2023) and Bellman (1955).

Determinants of lifetime variation are examined using multivariate regression analysis. Accumulated operating hours at the point of observation constitute the dependent variable, while explanatory variables include machine category, market tier, calendar age cohort, where applicable. Whether these operational differences correspond to statistically distinguishable lifetime outcomes is treated as an empirical question rather

than a modelling assumption.

Interview transcripts are analysed using a structured thematic approach combining predefined analytical categories with inductively emerging themes identified during repeated reading of the material. Coding categories include lifetime definition, data collection practices, traceability mechanisms, end-of-life decision logic, and market transition behaviour. Coding is conducted independently by both authors of this study and consolidated through discussion in accordance with qualitative reliability practice Bryman (2016).

Integration follows an explanatory mixed-methods logic in which quantitative findings identify patterns requiring contextual interpretation and qualitative evidence is used to interpret how organisational practices, maintenance decisions, market structures, and operational routines relate to observed lifetime outcomes. Where quantitative and qualitative findings converge, interpretation confidence increases. Where findings diverge, the discrepancy is retained and interpreted rather than resolved through prioritisation of a single evidence source.

3.3.1 Research Quality

Research quality is strengthened by grounding the study's core constructs technical lifetime, economic lifetime, and circular value retention in established methodological traditions. Reliability research emphasises that technical lifetime must be measured in ways that reflect both temporal ageing and utilisation-driven wear, which is why the study uses both calendar years and operating hours as complementary indicators. This approach follows the logic developed in reliability statistics, where right-censored observations and incomplete lifetime data must be incorporated to avoid biased estimates, rather than removed or imputed Meeker and Escobar (1998). Economic lifetime is defined using cost-minimisation principles from equipment replacement theory, where the optimal replacement point is the age at which average annual cost is lowest. The study implies that its constructs reflect how lifetime is conceptualized in the pertinent scholarly traditions by coordinating measurement with these established definitions Abensur et al. (2023) and Bellman (1955). At the same time, the study recognises that observable proxies such as operating hours or maintenance expenditure cannot fully capture duty-cycle severity or firm-specific risk preferences, and therefore uses transparent variable definitions, standardised measurement rules across markets, and robustness checks to strengthen construct validity.

The study supports internal validity by systematic cross-verification of data sources and explicit treatment of censoring, both of which reliability scholars identify as essen-

tial for unbiased lifetime estimation. Triangulating quantitative outliers with interview evidence reduces the probability that extreme values are the product of data artifacts rather than real operational patterns. Reliability is enhanced through a predefined data model, documented cleaning rules, stable parameter definitions across markets, and coding manuals for qualitative material, consistent with best practice in social research Bryman (2016). Mixed-methods research emphasises that integration quality depends on conceptual alignment rather than simply combining methods, which is why the study uses a shared parameter framework and interprets convergence and divergence analytically Creswell and Plano Clark (2017). External validity is pursued through analytical generalisation rather than statistical representativeness, following case-based research traditions where the goal is to identify mechanisms rather than universal averages. Markets are therefore selected to reflect meaningful variation in equipment usage patterns, and market structure. The remaining limitations of the study, such as uneven data availability across markets and incomplete export tracking, are explicitly acknowledged and set the parameters for its interpretation.

3.4 Use of Generative AI

During the study, Microsoft Copilot, AskYourPDF, Claude, and ChatGPT were used as supporting tools after the relevant literature had been identified through academic databases and publisher platforms, including Scopus, Web of Science, and ScienceDirect. Copilot and AskYourPDF were used to produce short summaries of selected articles and organise the material according to the topics addressed. The resulting notes were documented in an Excel file to provide an overview of the literature. Claude was used to structure longer tables and map preliminary notes.

ChatGPT and Microsoft Copilot were used for language review, reflection, alternative formulations, and improvements to clarity and sentence structure. ChatGPT was also used to identify and correct LaTeX syntax errors.

All AI-assisted material was manually reviewed by the authors. Each passage was read and assessed before inclusion, and only formulations that accurately reflected the authors' intended meaning were retained. Suggestions were revised or rejected where necessary. Generative AI was used solely as a supporting tool rather than as an academic source, while the final wording and academic judgements remained those of the authors.

4. CASE & FINDINGS

This chapter presents the case this study is being a part of, the empirical findings derived from quantitative market observations and qualitative interview evidence.

4.1 The Case

The project is a collaborative research initiative involving the case company, Mälardalen University (MDU), and two additional companies. To preserve the anonymity of the case company, it is referred to throughout this report as OEM. Together, over a three-year period, these companies will examine and gather insights into circular practices in construction equipment. More specifically, they will investigate LCA, product lifetime, and traceability related to ownership patterns, markets, and end-of-life under unknown circumstances. The goal of the project is to combine product flow, real-world product lifetime, technical conditions of the equipment and recycling processes to discover more resource-efficient and circular business models. The project also aims to address economic and environmental aspects through less usage of resources and CO2-emissions, and at the same time, maintain value in products and materials.

To achieve this, OEM and the other companies will provide product, market insights, and expertise within recycling and circular value chains and MDU with research competencies. To get a good structure throughout the project, six work packages have been developed to cover the whole life cycle of the construction equipment. This particular report is part of work package 2 (WP2). WP2 focuses on analysing the actual product lifetime of OEM's excavators and comparing the LCAs commonly used at OEM and similar companies in the industry. In this case, a 10-year period is used when calculating LCAs and WP2 intends to investigate whether this assumption is correct and what factors influence the results of the LCA.

4.2 Observed Machine Data per Market

The secondary-market observations are organised into seven market tiers representing different observable stages of machine circulation across ownership cycles and market contexts. The tiers progress from highly structured markets with strong traceability to later-life and fragmented markets where visibility decreases and operational continuation becomes more difficult to observe.

Sweden (Table 4.1) serves as the reference market and represents the highest-confidence observation context. Germany (Table 4.2) provides a comparable structured European market. The Netherlands and Belgium (Tables 4.3–4.4) represent export-oriented redistribution environments linked to international secondary-market flows. The UAE (Table 4.5) represents a secondary-market hub with concentrated machine circulation patterns. The late-life structured tier (Table 4.6) captures machines remaining observable in organised resale channels, while the end-of-life unstructured tier (Table 4.7) captures fragmented market contexts with reduced metadata availability and supplementary presence observations.

Together, the seven market tiers provide an empirical overview of observable machine continuation across different lifecycle stages and form the basis for the lifetime comparison presented in Section 4.2.1.

Table 4.1: Sweden machine observations, representing the origin market of OEM's construction equipment and a high-transparency context with strong data availability. The dataset reflects machines circulating within a well-documented domestic secondary market and serves as a primary reference case for the study, given its direct connection to the geographical and institutional setting in which the research is conducted. Observations are distributed by period, category, and operating-hour interval. Values are reported as counts with row percentages.

Period	Category	N	$\geq$ 0–$<$ 8k	$\geq$ 8k–$<$ 15k	$\geq$ 15k	Missing	Sellers / Sources
1998–2005	Compact	4	1 (25%)	0 (0%)	1 (25%)	2 (50%)	Blocket; Marcus/Mascus; Machineryline
1998–2005	Medium crawler	6	1 (17%)	3 (50%)	2 (33%)	0 (0%)	Marcus/Mascus; Machineryline; Blocket; Larssons Maskiner; PMT
1998–2005	Medium wheeled	4	2 (50%)	0 (0%)	1 (25%)	1 (25%)	Machineryline; Klaravik; Marcus/Mascus; Blocket
1998–2005	Large crawler	13	0 (0%)	5 (38%)	6 (46%)	2 (15%)	Marcus/Mascus; ATS Sweden; Machineryline
2006–2015	Compact	7	5 (71%)	2 (29%)	0 (0%)	0 (0%)	Machineryline; Blocket; Saxtorp; private
2006–2015	Medium crawler	16	4 (25%)	7 (44%)	5 (31%)	0 (0%)	Machineryline; Marcus/Mascus; Blocket; Klaravik; ATS; PMT
2006–2015	Medium wheeled	7	0 (0%)	6 (86%)	1 (14%)	0 (0%)	Klaravik; Machineryline; Retrade; Blinto; Blocket
2006–2015	Large crawler	21	0 (0%)	9 (43%)	9 (43%)	3 (14%)	Marcus/Mascus; Machineryline; ATS; PS Auction; PMT; Reuterhäll
2016–2026	Compact	11	7 (64%)	3 (27%)	1 (9%)	0 (0%)	Machineryline; Blinto; Blocket; Alsike; Albinsson; Maskinpunkten; PMT
2016–2026	Medium crawler	18	6 (33%)	11 (61%)	1 (6%)	0 (0%)	Marcus/Mascus; Klaravik; Blocket; Blinto; Machineryline; Vårgårda; Maskinpunkten; Braun
2016–2026	Medium wheeled	20	4 (20%)	15 (75%)	1 (5%)	0 (0%)	Klaravik; Machineryline; IronPlanet; Marcus/Mascus; Maskinpunkten; ATS; Braun; Maskinera
2016–2026	Large crawler	14	2 (14%)	11 (79%)	1 (7%)	0 (0%)	Machineryline; Marcus/Mascus; PMT; Maskinpunkten; Braun; Reuterhäll
Total		**141**	**32 (22.7%)**	**72 (51.1%)**	**29 (20.6%)**	**8 (5.7%)**	

Table 4.2: Germany machine observations, representing a mature EU-regulated market comparable to Sweden. The dataset reflects machines circulating within a structured domestic and regional secondary market under common regulatory and operational conditions. Observations are distributed by period, category, and operating-hour interval. Values are reported as counts with row percentages.

Period	Category	N	0 h	1–2,999 h	3,000–7,999 h	8,000–11,999 h	12,000–14,999 h	≥15,000 h	Missing	Sellers / Sources
1998–2005	Compact	3	0 (0%)	1 (33%)	2 (67%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	Mascus
1998–2005	Medium crawler	0	0	0	0	0	0	0	0	–
1998–2005	Medium wheeled	1	0 (0%)	0 (0%)	1 (100%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	Mascus
1998–2005	Large crawler	2	0 (0%)	0 (0%)	0 (0%)	1 (50%)	1 (50%)	0 (0%)	0 (0%)	Mascus
2006–2015	Compact	3	0 (0%)	0 (0%)	2 (67%)	1 (33%)	0 (0%)	0 (0%)	0 (0%)	Mascus
2006–2015	Medium crawler	3	0 (0%)	0 (0%)	0 (0%)	2 (67%)	1 (33%)	0 (0%)	0 (0%)	Mascus
2006–2015	Medium wheeled	3	0 (0%)	0 (0%)	0 (0%)	1 (33%)	2 (67%)	0 (0%)	0 (0%)	Mascus; BD Machine Sales
2006–2015	Large crawler	3	0 (0%)	0 (0%)	0 (0%)	1 (33%)	1 (33%)	1 (33%)	0 (0%)	Mascus
2016–2026	Compact	3	0 (0%)	2 (67%)	1 (33%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	Mascus
2016–2026	Medium crawler	3	0 (0%)	0 (0%)	1 (33%)	2 (67%)	0 (0%)	0 (0%)	0 (0%)	Mascus
2016–2026	Medium wheeled	3	0 (0%)	0 (0%)	1 (33%)	2 (67%)	0 (0%)	0 (0%)	0 (0%)	Mascus
2016–2026	Large crawler	3	0 (0%)	0 (0%)	0 (0%)	1 (33%)	2 (67%)	0 (0%)	0 (0%)	Mascus
Total	**All categories**	**30**	**0 (0%)**	**3 (10%)**	**8 (27%)**	**12 (40%)**	**6 (20%)**	**1 (3%)**	**0 (0%)**	**Primarily Mascus-based listings**

Table 4.3: The Netherlands machine observations, representing a major international trade and export hub for construction equipment. The dataset reflects machines listed within secondary markets connected to port-based export activity and was selected as one of two export-oriented cases in the study. Observations are distributed by period, category, and operating-hour interval. Values are reported as counts with row percentages.

Period	Category	N	0 h	1–2,999 h	3,000–7,999 h	8,000–11,999 h	12,000–14,999 h	≥15,000 h	Missing	Sellers / Sources
1998–2005	Compact	0	0	0	0	0	0	0	0	–
1998–2005	Medium crawler	1	0 (0%)	0 (0%)	1 (100%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	MachineryLine
1998–2005	Medium wheeled	0	0	0	0	0	0	0	0	–
1998–2005	Large crawler	1	0 (0%)	0 (0%)	0 (0%)	1 (100%)	0 (0%)	0 (0%)	0 (0%)	Delta Machinery
2006–2015	Compact	6	0 (0%)	1 (17%)	3 (50%)	1 (17%)	0 (0%)	0 (0%)	1 (17%)	MachineryLine; Tolhoek; Bontebok; Ritchie Bros
2006–2015	Medium crawler	6	0 (0%)	0 (0%)	0 (0%)	2 (33%)	1 (17%)	3 (50%)	0 (0%)	BAS World; Van Wijk; Tolhoek
2006–2015	Medium wheeled	1	0 (0%)	0 (0%)	0 (0%)	1 (100%)	0 (0%)	0 (0%)	0 (0%)	Schots Machinery
2006–2015	Large crawler	4	0 (0%)	0 (0%)	0 (0%)	2 (50%)	1 (25%)	1 (25%)	0 (0%)	BAS World; K.F.M Trading; Boss Machinery
2016–2026	Compact	7	4 (57%)	1 (14%)	1 (14%)	1 (14%)	0 (0%)	0 (0%)	0 (0%)	Kraakman; Laan Equipment; Tolhoek
2016–2026	Medium crawler	3	1 (33%)	1 (33%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	1 (33%)	Yellowdozer; JORD Equipment
2016–2026	Medium wheeled	4	1 (25%)	0 (0%)	0 (0%)	3 (75%)	0 (0%)	0 (0%)	0 (0%)	JR Trading; SMITMA; Mostert
2016–2026	Large crawler	10	1 (10%)	3 (30%)	2 (20%)	3 (30%)	1 (10%)	0 (0%)	0 (0%)	JR Trading; Yellowdozer; SMT; Boss Machinery
Total	**All categories**	**43**	**6 (14%)**	**6 (14%)**	**7 (16%)**	**14 (33%)**	**3 (7%)**	**4 (9%)**	**3 (7%)**	**Mixed platforms**

Table 4.4: Belgium machine observations, representing an EU-based trade and export node with strong connections to international secondary markets through port-oriented activity. The dataset reflects machines circulating within a mixed domestic and export-oriented secondary market. Observations are distributed by period, category, and operating-hour interval. Values are reported as counts with row percentages.

Period	Category	N	0 h	1–2,999 h	3,000–7,999 h	8,000–11,999 h	12,000–14,999 h	≥15,000 h	Missing	Sellers / Sources
1998–2005	Medium crawler	1	0 (0%)	0 (0%)	0 (0%)	0 (0%)	1 (100%)	0 (0%)	0 (0%)	Mascus
2006–2015	Compact	4	0 (0%)	0 (0%)	2 (50%)	1 (25%)	1 (25%)	0 (0%)	0 (0%)	Areen Truck; Vetrucks; Auction-Port
2006–2015	Medium crawler	6	0 (0%)	0 (0%)	1 (17%)	2 (33%)	2 (33%)	1 (17%)	0 (0%)	De Nijl; Machinery Resale; Aertssen
2006–2015	Medium wheeled	2	0 (0%)	0 (0%)	0 (0%)	2 (100%)	0 (0%)	0 (0%)	0 (0%)	Meurrens; Machinery Resale
2006–2015	Large crawler	1	0 (0%)	0 (0%)	0 (0%)	1 (100%)	0 (0%)	0 (0%)	0 (0%)	Mascus
2016–2026	Compact	3	0 (0%)	1 (33%)	2 (67%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	CMGC; AuctionPort
2016–2026	Medium crawler	7	0 (0%)	0 (0%)	2 (29%)	4 (57%)	1 (14%)	0 (0%)	0 (0%)	Aertssen; Meurrens; Plant & Equipment
2016–2026	Medium wheeled	3	0 (0%)	1 (33%)	0 (0%)	1 (33%)	0 (0%)	0 (0%)	1 (33%)	Meurrens; Million Power Machine
2016–2026	Large crawler	4	0 (0%)	1 (25%)	0 (0%)	2 (50%)	1 (25%)	0 (0%)	0 (0%)	Aertssen; De Nijl; Jacalis
Total	**All categories**	**30**	**0 (0%)**	**2 (6%)**	**7 (23%)**	**13 (42%)**	**6 (19%)**	**1 (3%)**	**1 (3%)**	**Mixed platforms**

Table 4.5: UAE machine observations representing a secondary market hub, compiled from multiple online sources. Observations are distributed by period, category, and operating-hour interval. Values are reported as counts with row percentages.

Period	Category	N	0 h	1–2,999 h	3,000–7,999 h	8,000–11,999 h	12,000–14,999 h	≥15,000 h	Missing	Sellers / Sources
1998–2005	Compact	0	0	0	0	0	0	0	0	–
1998–2005	Medium crawler	0	0	0	0	0	0	0	0	–
1998–2005	Medium wheeled	0	0	0	0	0	0	0	0	–
1998–2005	Large crawler	0	0	0	0	0	0	0	0	–
2006–2015	Compact	0	0	0	0	0	0	0	0	–
2006–2015	Medium crawler	3	0 (0%)	0 (0%)	1 (33%)	0 (0%)	0 (0%)	2 (67%)	0 (0%)	Machinery Planet; MachineryTrader; MHJ Heavy Equipment
2006–2015	Medium wheeled	3	0 (0%)	0 (0%)	0 (0%)	1 (33%)	2 (67%)	0 (0%)	0 (0%)	Makana; MachineryLine; Rolman World
2006–2015	Large crawler	2	0 (0%)	0 (0%)	2 (100%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	MHJ Heavy Equipment; MachineryTrader
2016–2026	Compact	7	0 (0%)	1 (14%)	6 (86%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	Makana
2016–2026	Medium crawler	11	0 (0%)	2 (18%)	0 (0%)	1 (9%)	0 (0%)	7 (64%)	1 (9%)	Machinery Planet; Rolman World; Hexco Global
2016–2026	Medium wheeled	0	0	0	0	0	0	0	0	–
2016–2026	Large crawler	6	0 (0%)	3 (50%)	0 (0%)	1 (17%)	0 (0%)	1 (17%)	1 (17%)	MachineryLine; Makana
Total	**All categories**	**32**	**0 (0%)**	**6 (19%)**	**9 (28%)**	**3 (9%)**	**2 (6%)**	**10 (31%)**	**2 (6%)**	**Mixed platforms**

Table 4.6: Late-life structured machine observations, representing listed OEM's construction equipment from six non-EU secondary-market countries across Africa, Latin America, and Oceania. The case was selected to capture machines that remain in structured resale channels at later lifecycle stages outside the main European baseline markets. Observations are distributed by period, category, country composition, and operating-hour interval. Values are reported as counts with row percentages.

Period	Category	N	Countries represented	0 h	1–2,999 h	3,000–7,999 h	8,000–11,999 h	12,000–14,999 h	≥15,000 h	Missing	Sellers / Sources
1998–2005	Compact	1	Mexico (1)	0 (0%)	0 (0%)	1 (100%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	Maquinaria Wiebe Km 24 Sa
1998–2005	Medium crawler	1	Australia (1)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	1 (100%)	0 (0%)	Private seller
1998–2005	Medium wheeled	0	–	0	0	0	0	0	0	0	–
1998–2005	Large crawler	0	–	0	0	0	0	0	0	0	–
2006–2015	Compact	0	–	0	0	0	0	0	0	0	–
2006–2015	Medium crawler	5	South Africa (3); Brazil (1); country not stated (1)	0 (0%)	0 (0%)	0 (0%)	1 (20%)	1 (20%)	3 (60%)	0 (0%)	Mascus; AM MÁQUINAS; private seller
2006–2015	Medium wheeled	0	–	0	0	0	0	0	0	0	–
2006–2015	Large crawler	9	South Africa (3); Peru (1); Australia (5)	0 (0%)	0 (0%)	2 (22%)	1 (11%)	1 (11%)	5 (56%)	0 (0%)	Mascus; Plant & Equipment; ConstructionSales; dealer listings
2016–2026	Compact	0	–	0	0	0	0	0	0	0	–
2016–2026	Medium crawler	2	Chile/Brazil origin (1); Australia (1)	0 (0%)	2 (100%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	be-market.com; private seller
2016–2026	Medium wheeled	0	–	0	0	0	0	0	0	0	–
2016–2026	Large crawler	26	Chile (15); Peru (7); South Africa (2); Australia (2)	0 (0%)	1 (4%)	20 (77%)	0 (0%)	1 (4%)	1 (4%)	3 (12%)	be-market.com; MachineryLine; Plant & Equipment; China Machinery Trading; Vendel Equipment Sales; Benabilla Auctions; Slattery
Total	**All categories**	**44**	**Mexico (1); Brazil (1); Chile (16); Peru (8); South Africa (8); Australia (9); not stated (1)**	**0 (0%)**	**3 (7%)**	**23 (52%)**	**2 (5%)**	**3 (7%)**	**10 (23%)**	**3 (7%)**	**Mixed structured secondary-market sources**

Table 4.7: End-of-life, unstructured machine observations, representing fragmented and underreported secondary markets across Africa, Latin America, Southeast Asia, and South Asia. Only countries identified in the dataset are included. Observations are distributed by period, category, and operating-hour interval. Values are reported as counts with row percentages. Indicative market presence is included separately based on visual evidence where structured data is unavailable.

Period	Category	N	Region / Countries	Indicative presence	0 h	1–2,999 h	3,000–7,999 h	8,000–11,999 h	12,000–14,999 h	≥15,000 h	Missing	Sellers / Sources
2006–2015	Large crawler	6	Peru	Low (structured listings only)	0 (0%)	0 (0%)	1 (17%)	0 (0%)	1 (17%)	4 (67%)	0 (0%)	Mascus; Plant & Equipment
2016–2026	Medium crawler	6	Nigeria; Tanzania; Brazil; Vietnam	Moderate (fragmented listings)	0 (0%)	1 (17%)	0 (0%)	0 (0%)	1 (17%)	0 (0%)	4 (67%)	Jiji; Mascus; private
2016–2026	Large crawler	16	Ghana; Tanzania; Bolivia; Malaysia; Sri Lanka	High (multi-region, weak metadata)	0 (0%)	2 (13%)	4 (25%)	0 (0%)	2 (13%)	5 (31%)	3 (19%)	MachineryLine; Jiji; Mudah; Mascus
Total	**All categories**	**28**	**Africa (Nigeria, Ghana, Tanzania); Latin America (, Bolivia); Southeast Asia (Vietnam, Malaysia); South Asia (Sri Lanka)**	**Very high (India: 100+ observed; Tanzania: 10+ units per listing)**	**0 (0%)**	**3 (11%)**	**5 (18%)**	**0 (0%)**	**3 (11%)**	**9 (32%)**	**8 (29%)**	**Highly fragmented sources**

4.3 Comparison: Observed Lifetime versus LCA Assumptions

Table 4.8 compares the standardised LCA baseline, assuming a fixed operational lifetime of 10 years, with empirically reconstructed operating-hour estimates derived from observed machine distributions across the seven market tiers.

Deviation values (Dev. %) express the relative difference between empirical operating-hour estimates and the operating-hour output implied by the baseline assumption. Positive values represent empirical operating-hour estimates above the baseline level, whereas negative values represent estimates below the baseline level.

Across the European primary markets, positive deviations dominate. Sweden shows positive deviations across all machine categories, with compact machines reaching +203% and medium crawler categories ranging between +14% and +37%. Germany follows a similar pattern, with compact machines reaching +179% and remaining categories showing positive deviations between +11% and +31%.

The European export-oriented market tier shows greater variation between machine categories. In the Netherlands and Belgium, medium and large crawler categories remain above the baseline, while wheeled categories show smaller negative deviations ranging from approximately −16% to −22%.

In the international secondary-market hub tier, deviations are predominantly negative. UAE observations range from approximately −37% to −65% across categories. Australia displays values close to the baseline for crawler categories and moderate negative deviations for wheeled categories.

The structured late-life market tier shows predominantly negative deviations across observed categories. Large crawler categories display values ranging from approximately −18% to −50% depending on country and observation group.

The end-of-life unstructured market tier displays consistently negative deviations. Observed values include −57% for South African large crawler categories, −45% for Malaysian large crawler categories, and approximately −64% for Vietnamese medium crawler categories.

Across all market tiers, deviation patterns vary between market context, machine category, and observed lifecycle interval. Positive and negative deviations occur simultaneously across the dataset, indicating substantial variation in operating-hour distributions relative to the standardised baseline assumption.

Table 4.8 presents the complete comparison.

Table 4.8: LCA baseline and empirical operating-hour comparison. Left: LCA lifetime assumptions using a 10-year standard. Right: empirically reconstructed operating-hour estimates from secondary-market interval distributions. Market groups are shown as separate section bands to avoid repeated labels in the first column. Age cohort is derived from period distribution: P1 = 21–28 years, P2 = 11–20 years, P3 = 0–10 years.

LCA BASELINE – 10-year standard assumption					EMPIRICAL COMPARISON – Reconstructed vs. assumed lifetime							
Country	Category	Avg h/yr	LCA h	IPH	LCA CO_2	Emp. h	Dev. h	Dev. %	Emp. CO_2	CO_2 diff	Period dist. P1/P2/P3	Age cohort from P1/P2/P3	Assessment
Market group: Europe primary market | *Region/countries represented: Sweden; Germany*													
Sweden	Compact							**+203%**			P1:16% P2:28% P3:44%	P1:21–28 P2:11–20 P3:0–10	↑ **Greatly exceeds**
Sweden	Med. crawler							**+13%**			P1:38% P2:38% P3:25%	P1:21–28 P2:11–20 P3:0–10	↑ **Exceeds**
Sweden	Med. wheeled							**+15%**			P1:40% P2:40% P3:20%	P1:21–28 P2:11–20 P3:0–10	↑ **Exceeds**
Sweden	Large crawler							**+11%**			P1:27% P2:43% P3:29%	P1:21–28 P2:11–20 P3:0–10	↑ **Exceeds**
Germany	Compact							**+179%**			P1:10% P2:30% P3:30%	P1:21–28 P2:11–20 P3:0–10	↑ **Greatly exceeds**
Germany	Med. crawler							**+30%**			P1:0% P2:20% P3:20%	P2:11–20 P3:0–10	↑ **Exceeds**
Germany	Med. wheeled							**+37%**			P1:10% P2:30% P3:30%	P1:21–28 P2:11–20 P3:0–10	↑ **Exceeds**
Germany	Large crawler							**+28%**			P1:13% P2:25% P3:25%	P1:21–28 P2:11–20 P3:0–10	↑ **Exceeds**
Market group: Europe export hub | *Region/countries represented: Netherlands; Belgium*													
Netherlands	Compact							**+86%**			P1:0% P2:42% P3:39%	P2:11–20 P3:0–10	↑ **Exceeds**
Netherlands	Med. crawler							**+37%**			P1:13% P2:47% P3:40%	P1:21–28 P2:11–20 P3:0–10	↑ **Exceeds**
Netherlands	Med. wheeled							**-16%**			P1:0% P2:17% P3:58%	P2:11–20 P3:0–10	↓ **Below LCA**
Netherlands	Large crawler							**+8%**			P1:13% P2:50% P3:63%	P1:21–28 P2:11–20 P3:0–10	↑ **Exceeds**
Belgium	Compact							**+80%**			P1:0% P2:42% P3:33%	P2:11–20 P3:0–10	↑ **Exceeds**

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LCA BASELINE – 10-year standard assumption						EMPIRICAL COMPARISON – Reconstructed vs. assumed lifetime							
Country	Category	Avg h/yr	LCA h	IPH	LCA CO_2	Emp. h	Dev. h	Dev. %	Emp. CO_2	CO_2 diff	Period dist. P1/P2/P3	Age cohort from P1/P2/P3	Assessment
Belgium	Med. crawler							+37%			P1:5% P2:52% P3:43%	P1:21–28 P2:11–20 P3:0–10	↑ Exceeds
Belgium	Med. wheeled							-22%			P1:0% P2:31% P3:44%	P2:11–20 P3:0–10	↓ Below LCA
Belgium	Large crawler							+27%			P1:0% P2:30% P3:50%	P2:11–20 P3:0–10	↑ Exceeds
Market group: International secondary hub | *Region/countries represented: UAE; Australia*													
UAE	Compact							-63%			P1:0% P2:0% P3:100%	P3:0–10	↓ Far below
UAE	Med. crawler							-37%			P1:0% P2:60% P3:40%	P2:11–20 P3:0–10	↓ Far below
UAE	Med. wheeled							-53%			P1:0% P2:75% P3:0%	P2:11–20	↓ Far below
UAE	Large crawler							-65%			P1:0% P2:27% P3:55%	P2:11–20 P3:0–10	↓ Far below
Australien	Compact							+1%			P1:0% P2:43% P3:43%	P2:11–20 P3:0–10	→ Aligned
Australien	Med. crawler							+5%			P1:0% P2:60% P3:40%	P2:11–20 P3:0–10	↑ Exceeds
Australien	Med. wheeled							-43%			P1:0% P2:0% P3:0%	n/a	↓ Far below
Australien	Large crawler							-3%			P1:8% P2:54% P3:38%	P1:21–28 P2:11–20 P3:0–10	→ Aligned
Market group: Late-life structured | *Region/countries represented: Africa; Latin America; Oceania*													
Brasilien	Compact							+0%			P1:0% P2:60% P3:40%	P2:11–20 P3:0–10	→ Aligned
Brasilien	Med. crawler							-16%			P1:8% P2:50% P3:42%	P1:21–28 P2:11–20 P3:0–10	↓ Below LCA
Brasilien	Large crawler							-32%			P1:13% P2:50% P3:38%	P1:21–28 P2:11–20 P3:0–10	↓ Far below
Mexico	Med. crawler							-21%			P1:0% P2:50% P3:50%	P2:11–20 P3:0–10	↓ Below LCA
Mexico	Large crawler							-18%			P1:0% P2:50% P3:50%	P2:11–20 P3:0–10	↓ Below LCA
Chile	Med. crawler							-26%			P1:0% P2:33% P3:67%	P2:11–20 P3:0–10	↓ Below LCA

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LCA BASELINE – 10-year standard assumption						EMPIRICAL COMPARISON – Reconstructed vs. assumed lifetime							
Country	Category	Avg h/yr	LCA h	IPH	LCA CO_2	Emp. h	Dev. h	Dev. %	Emp. CO_2	CO_2 diff	Period dist. P1/P2/P3	Age cohort from P1/P2/P3	Assessment
Chile	Large crawler							-26%			P1:0% P2:44% P3:56%	P2:11–20 P3:0–10	↓ Below LCA
Chile	Med. wheeled							-58%			P1:0% P2:0% P3:100%	P3:0–10	↓ Far below
Peru	Med. wheeled							-65%			P1:0% P2:0% P3:100%	P3:0–10	↓ Far below
Peru	Med. crawler							-65%			P1:0% P2:0% P3:100%	P3:0–10	↓ Far below
Peru	Large crawler							-50%			P1:0% P2:33% P3:67%	P2:11–20 P3:0–10	↓ Far below
Bolivia	Compact							+4%			P1:0% P2:100% P3:0%	P2:11–20	→ Aligned
Bolivia	Med. crawler							-22%			P1:0% P2:100% P3:0%	P2:11–20	↓ Below LCA
Bolivia	Large crawler							-22%			P1:100% P2:0% P3:0%	P1:21–28	↓ Below LCA
Market group: End-of-life unstructured | *Region/countries represented: Africa; Southeast Asia; South Asia*													
South Africa	Compact							-74%			P1:0% P2:0% P3:100%	P3:0–10	↓ Far below
South Africa	Med. crawler							-37%			P1:0% P2:57% P3:43%	P2:11–20 P3:0–10	↓ Far below
South Africa	Large crawler							-57%			P1:0% P2:22% P3:78%	P2:11–20 P3:0–10	↓ Far below
Nigeria	Compact							-58%			P1:0% P2:0% P3:100%	P3:0–10	↓ Far below
Nigeria	Med. crawler							-33%			P1:0% P2:25% P3:75%	P2:11–20 P3:0–10	↓ Far below
Nigeria	Large crawler							-53%			P1:14% P2:57% P3:29%	P1:21–28 P2:11–20 P3:0–10	↓ Far below
Ghana	Compact							-3%			P1:0% P2:50% P3:50%	P2:11–20 P3:0–10	→ Aligned
Ghana	Med. crawler							-34%			P1:0% P2:33% P3:67%	P2:11–20 P3:0–10	↓ Far below
Ghana	Large crawler							-45%			P1:0% P2:40% P3:60%	P2:11–20 P3:0–10	↓ Far below
Tanzania	Compact							-59%			P1:0% P2:0% P3:100%	P3:0–10	↓ Far below

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LCA BASELINE – 10-year standard assumption						EMPIRICAL COMPARISON – Reconstructed vs. assumed lifetime							
Country	Category	Avg h/yr	LCA h	IPH	LCA CO_2	Emp. h	Dev. h	Dev. %	Emp. CO_2	CO_2 diff	Period dist. P1/P2/P3	Age cohort from P1/P2/P3	Assessment
Tanzania	Large crawler							+5%			P1:0% P2:100% P3:0%	P2:11–20	→ Aligned
Malaysia	Compact							-67%			P1:0% P2:33% P3:67%	P2:11–20 P3:0–10	↓ Far below
Malaysia	Med. crawler							-36%			P1:0% P2:33% P3:67%	P2:11–20 P3:0–10	↓ Far below
Malaysia	Large crawler							-45%			P1:0% P2:44% P3:56%	P2:11–20 P3:0–10	↓ Far below
Vietnam	Compact							-68%			P1:0% P2:0% P3:100%	P3:0–10	↓ Far below
Vietnam	Med. crawler							-64%			P1:0% P2:0% P3:100%	P3:0–10	↓ Far below
Vietnam	Large crawler							-36%			P1:0% P2:43% P3:57%	P2:11–20 P3:0–10	↓ Far below
Sri Lanka	Compact							+3%			P1:0% P2:100% P3:0%	P2:11–20	→ Aligned
Sri Lanka	Med. crawler							+47%			P1:0% P2:100% P3:0%	P2:11–20	↑ Exceeds

Note: P1 = 21–28 years, P2 = 11–20 years, P3 = 0–10 years. ↑ = empirical hours above the LCA assumption, → = broadly aligned, ↓ = empirical hours below the LCA assumption. CO_2 values are reported in tonnes. Empirical hours are interval-based reconstructions, not directly observed end-of-life records. Source: Research Project, WP2.

4.4 Qualitative Insights on Lifetime Assumptions

The empirical findings indicate that several companies face challenges in defining product lifetime due to the absence of systematic real-world data collection. Instead, lifetime assumptions are often based on estimates embedded in LCA models rather than on observed operational evidence.

This is reflected in interview responses, where informants describe a lack of visibility into end-of-life outcomes:

LCA	*"It is not recorded anywhere that that product has reached the end of life. In most cases, the end of life is entirely out of our control." (OEM)*
Product lifetime	*"It is really dependent on how the machine is used and maintained." (OEM)*

These statements illustrate how lifetime is not treated as a fixed parameter in practice, but rather as a context-dependent outcome shaped by usage patterns, maintenance practices, and market dynamics.

4.4.1 Interview Findings: OEM

In the interview with OEM, it is explained that production lifetime is a parameter in the company's calculations in LCA. However, the likelihood of the production lifetime being anchored in actual, empirical data is low. Often a 10-year lifespan in LCA is used as an overall assessment, but that does not mean that every machine uses it. It is noted that product lifetime is more often expressed in work hours than in years. For example, they mention that some machines reach 30,000 or 10,000 working hours within the same time span, depending on operating conditions and the use frequency. A quick mention about presumed product lifetime is that there is a longer life expectancy than 10 years for some machines. According to I1, there are examples of machines from the 1950's still being in use, though there is no evidence collected for the majority of the machines.

The need for empirical evidence and knowledge of product lifetime is motivated by an ambition to strengthen the company's long-term sustainability work. But it is made

clear that the OEM has limited control over its whole lifecycle. After the first sale from the company and by the time any additional purchase of service lease ends, the traceability of the machine vanishes with it. There is no systematic data collection or database inheriting information on the actual end of life. One exceptional case is disclosed, which is if a machine is brought back for dismantling. Other than that, it is up to the end user when and if the machine is dated out of use, which is not registered in the company's system. Since this is the case, lifetime assumptions are made by historical guideline values and from engineering experience.

Other factors that influence product lifetime, both positively and negatively, are the external factors. I1 mentions the area of usage, climate, maintenance process, operator usage patterns and terrain conditions as external factors that affect their machines. For electrical machines, there is also the consideration of how the machines are charged and battery management. When asked about planned obsolescence, the respondent replies that OEM is not consciously working with that kind of strategy. Instead, the respondent argues that customers expect to be able to resell the equipment later and that it is a reputational risk to consciously design products for a shorter product lifetime. However, the respondent believes that some "obsolescence" may arise indirectly through technological development, especially connected to electronics and batteries. That scenario is more likely than a strategy to shorten the lifespan, the respondent argues.

In the interview, spare part provision is also mentioned as a factor that could eventually increase product lifetime, and I1 believes that if the OEM were to provide spare parts for a longer time period than they do now, the lifetime would be enhanced. Even though the company has knowledge of these factors, there is a lack of information about the proportion of each factor influencing the machine's lifetime. Since there is no data about the machine's actual product lifetime, the company does not communicate the expected lifetime in work hours or years to consumers. Instead, they use warranties as a formal timeline, but the company also relies on the brand's reputation and consumers' historical perception and experience of previous purchases.

4.4.2 Second Interview OEM

Another interview was held with OEM, but this time with the company's Head of LCA, called Respondent I2. The respondent starts the interview by explaining that the company's LCA has a big focus on how the company affects the environment. The LCA is based on a standardized methodology where the whole machine is analysed as a unit. It also has a focus on continuously developing a scalable work process that quantifies

climate impact rather than going through general analyses of the environment. Such as calculating carbon footprint, which is motivated by customer demand. The lifetime parameter is used in the LCA as a general feature and is based on assumptions and some available data about the equipment. Such as average usage and telematics from real-world operations. Specifically, an assumed lifetime of 10 years is used in the LCA model and I2 explains that the assumption is not an arbitrary value. It is a result of empirically collected data on how their machines are used globally, but at the same time, it is acknowledged that it's a simplification of reality where individual variations in usage are important. To handle these variations the values that are used are an average of different usage patterns.

Other than the fact that the 10-year lifetime assumption is based on real-world data, the motivation for its use can be found in strategic and organizational goals. Respondent I2 explains that it is a compatible value for the company's science-based targets and is used over several product categories to maintain comparability. At the same time, it is mentioned that the actual lifetime of a machine varies a lot due to usage patterns, which makes it hard to create an exact model. To counter this, the OEM uses a method of average usage time and fuel consumption when calculating, making it easier to handle large numbers of products and create comparable results. It's also mentioned that the lifetime of machines is not described as a constant value over time, but as a value decreasing in usage intensity. Meaning that machines are often used more intensely in the beginning of their life cycle and less in the end. Resulting in an uneven distribution of total work hours over time. This leads to machines living longer than the 10-year assumption, as long as 30 years have been observed.

A big aspect mentioned in the interview is that changes in the lifetime assumption have very little impact on the results of the LCA calculation, especially if the lifetime is expressed in working hours. The sensitivity analyses that have been made by the OEM for the LCA show that prolonging lifetime assumptions from 10 to 30 years has less than 1% difference. This is explained by the high impact of fuel consumption and the user phase on total environmental impact. Other than that, a pilot case tracking an excavator's life at the OEM is discussed. The pilot case showed that out of 8 different factors, usage is the main factor affecting the excavator's lifetime. As shown in Figure 4.1, the usage factor represents 93.8% of the total share affecting product lifetime, while the sum of the remaining 7 factors equals 6.2% of the total share.

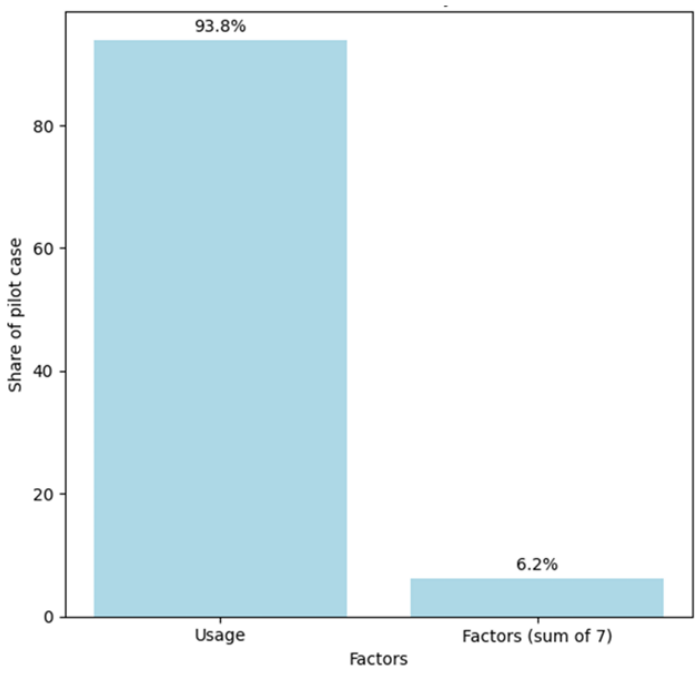

Figure 4.1: Relative contribution of usage compared with other factors affecting product lifetime in the pilot case.

4.4.3 Interview with a Construction Contractor

When conducting the interview, a different perspective emerged, as the respondent represents a large construction contractor (hereafter referred to as "the contractor") acting as both purchaser and operator of construction equipment supplied by OEM. This enabled the collection of empirical insights related to perceived product lifetime, user behaviour, disposal practices, and other parameters relevant to this study.

Warranty terms from suppliers such as OEM typically cover 2–3 years, although this varies depending on country and brand. In some cases, warranties are defined in operating terms, for example up to 5 years or 10,000 operating hours. However, the contractor emphasizes that warranty periods do not coincide with the assumed 8–10 year lifetime, but rather represent a defined risk period. The respondents (I3) further express a lack of access to data regarding actual product lifetime beyond the warranty period.

The interview indicates that operational decisions are primarily driven by economic considerations rather than technical limitations. The typical usage period for the equipment is estimated at 8–10 years, based on internal calculations grounded in depreciation principles and financial evaluation. At the same time, this range is described as a general guideline rather than a fixed lifetime, as actual duration varies depending

on operator behaviour, task type, and project conditions. Even for identical machine models, wear patterns differ significantly across usage environments, indicating that lifetime in practice is situational rather than standardized.

Product lifetime is therefore understood less as a fixed technical boundary and more as an economic threshold, where maintenance and repair costs exceed the profitability of continued operation. Replacement decisions are closely linked to this threshold, and once maintenance costs increase disproportionately relative to generated value, replacement becomes financially justified.

In addition, the contractor highlights that technological development and upgrade potential influence replacement cycles. Improvements in fuel efficiency and cost-saving functionalities play a significant role in decision-making, linking economic and environmental considerations. The organization has set long-term climate targets, which directly affect procurement strategies and lifetime considerations. This creates a tension between optimizing economic lifespan and aligning with emission reduction goals.

When equipment is replaced, it is typically sold through external auction platforms. At this stage, the contractor loses visibility and control over the continued use of the machines. Rather than being scrapped, the equipment often enters secondary markets, where other actors extend its operational life under different economic conditions.

4.4.4 Interview with the Dealer

Unlike the previous interviews with OEM and the contractor, the interview with the dealer provided broader experience-based insights into product lifetime and LCA. Rather than focusing on assumptions, this perspective is grounded in actual usage and practical data. This is because the dealer operates as a construction equipment dealer that repairs and resells equipment or repairs and returns equipment to the owner. The equipment handled is exclusively supplied by OEM.

During the interview, respondent I4 emphasizes a clear distinction between the commonly assumed 10-year product lifetime used in LCA and the variation observed in practice. I4 explains that such assumptions may serve as general guidelines in some cases, but lack information about how long a machine is actually used. It has been observed that machines handled and repaired by the dealer often exceed these assumed lifetimes. It is not uncommon for machines to remain in operation for 20, 30, or even 40 years, largely depending on how they are used and maintained. However, I4 notes that the use of lifetime assumptions is not inherently problematic, but that such assumptions have clear limitations. These limitations are mainly related to variations in usage conditions, including load, environment, and operator behaviour. These fac-

tors make it difficult to define a standardized lifetime that accurately represents all machines in LCA contexts.

Respondent I4 provides an example of machines used in demanding environments such as mining, where continuous overload can significantly shorten lifetime compared to machines used sporadically under controlled conditions. At the same time, it is acknowledged that a general lifetime parameter is necessary for companies to ensure that products meet promised performance expectations. It is also mentioned that setting conservative lifetime limits that can later be exceeded contributes to increased confidence in the equipment. Furthermore, the dealer explains that product lifetime is primarily measured in working hours rather than years. However, working hours alone are not sufficient to determine the actual condition of a machine and are therefore not enough to fully capture its lifetime.

To better understand actual lifetime, functionality is highlighted as a key starting point. The ability of the machine to operate, such as whether it can start, is used as a basic indicator. If a machine is not operational, it is assumed that critical components, such as the engine, are defective in terms of value and utility. Additional factors influencing lifetime include usage patterns and maintenance. Respondent I4 explains that regular servicing, including oil changes and inspections, is essential for extending lifetime and preventing minor issues from developing into major failures. Operator behaviour is also emphasized, as improper use such as overloading can significantly accelerate wear, while proper use within intended limits supports longer lifetime.

Another factor contributing to complexity is that a machine consists of multiple components with different lifespans. It is explained that machines require replacement of several components throughout their lifetime, and that overall machine lifetime does not correspond to the lifespan of individual components. In addition, smaller components or components lacking proper connectivity are often not traceable, which makes it difficult to construct accurate lifetime data for specific equipment. However, certain components, such as engines and transmissions, can be traced through serial numbers. Respondent I4 also notes that, despite efforts to repair equipment, all components have material limits, meaning that at some point they are no longer suitable for continued use regardless of maintenance.

Traceability is identified as both an opportunity and a limitation. For some components, detailed documentation exists regarding origin, operation, and repair history. However, in many cases, such information is incomplete or unavailable. This is partly due to inconsistent recording of maintenance and component replacement, especially when conducted outside authorized systems. As a result, it becomes difficult to establish a complete and reliable history of the machine, limiting the ability to determine

actual product lifetime.

4.4.5 Interview with the Manufacturer

In this interview, respondent I5 is a sustainability strategist at the manufacturer. The interview reveals that the lifetime of equipment is highly simplified and not based on standardized or systematic approaches. Instead, the manufacturer assumes that their equipment have the same lifetime as the equipment of OEM on which they are mounted. Similar to previous observations, lifetime is expressed in working hours, typically around 10,000 hours, rather than years. These values are based on industry practice, stress testing, and customer feedback rather than detailed LCA modelling. At the same time, the respondent explains that such assumptions can be misleading, as some customers have used their equipment for up to 20 years. However, due to a lack of detailed working-hour data for specific units, accurate comparisons are difficult.

The interview further identifies several factors influencing the variation between actual lifetime and LCA assumptions. One key factor is the lack of detailed user data, as the manufacturer has limited insight into product use after the initial sale, particularly after the warranty period. As a result, factors such as usage intensity, maintenance practices, and environmental conditions are not systematically captured. In addition, there is limited traceability regarding repairs and spare parts. The manufacturer currently lacks the ability to link spare parts to specific units, which limits understanding of how maintenance affects product lifetime. There is also a need for better data on repair frequency, long-term component durability, and the environmental impact of their equipment when integrated into machines.

Lastly, the respondent explains that there is a need for a better LCA model at their company due to future EU legislation and demand for value chain responsibility. It is described that the company currently only has control over the product until the EOL until the warranty period, as mentioned above, which may be considered insufficient in the long term. Future regulations will likely require greater tranparancy regarding product use and recycling, the respondent argues.

4.4.6 Third Interview with OEM

In this interview, respondent I6, Head of Virtual Product Development at OEM, explains that product lifetime is primarily measured in working hours rather than years. Lifetime is defined as the time during which the engine is in operation, including idle time, meaning that all operating conditions are considered. The respondent further

explains that lifetime assumptions are generally conservative, as machines and components are often designed to exceed specified requirements. This leads to actual lifetimes often exceeding those assumed in LCA models. However, verifying this in practice is difficult due to limited reliable data, particularly for later life stages such as end-of-life.

The interview highlights usage patterns and intensity as key factors influencing lifetime variation. The same machine type can have significantly different lifetimes in years depending on how quickly working hours accumulate. Factors such as load, driving behaviour, and environment directly affect component wear. For example, operation in rough terrain leads to higher loads and faster degradation, while less demanding conditions can extend service life. Another factor is that machines are often designed for more demanding conditions than those encountered in practice, resulting in longer actual lifetimes. Variation between components is also significant, as different parts have different durability requirements and degradation patterns. The respondent emphasizes the importance of integrating field data into design processes, using failure reports and service data to improve future products. Uncertainty is managed through probabilistic models that allow for a defined level of acceptable failure over time.

4.4.7 Fourth Interview with OEM

In the fourth interview, respondent I7, Head of Product Management at OEM, describes product lifetime as a dynamic process influenced by usage patterns and ownership changes rather than a fixed parameter. The interview indicates that actual lifetimes are often longer than assumed in models, particularly when machines transition from intensive use to less demanding applications over time. Machines used intensively may reach their limits relatively quickly, whereas those used sporadically can remain in operation for several decades.

Lifetime is again described in terms of working hours, with some machines reaching 20,000–25,000 hours before major overhaul is required. Continued use beyond this point is possible with proper maintenance and component replacement. An important insight is that replacement of components does not necessarily mark the end of machine lifetime, but can instead extend it, which has implications for LCA modelling. Additional factors influencing lifetime include the quality of spare parts and economic considerations. The use of low-quality or non-certified parts can reduce lifetime through increased failure risk. At the same time, even if technical repair is possible, economic constraints may lead to earlier replacement, shortening the effective product lifetime despite remaining technical potential.

4.4.8 Interview with the Distributor

In the interview with the respondent I8, describes the company as an established dealer of construction equipment and other products of the OEM's Group. The respondent is part of the executive team and reports directly to the CEO. The first topic during the interview was that the African market differs a lot from country to country and is a heterogeneous market. Both economic development, regulations, and infrastructure influence the market, and each country needs its own solutions and adaptation. A recurring subject during the interview is the misconception that African markets mainly import retired or economically unprofitable construction equipment, such as excavators, from Europe. This is not the reality of the present but rather a lingering conception of history when it comes to market patterns. There was an established secondhand market from Europe to Africa back in time, but according to the respondent, this type of trade has almost vanished.

The respondent describes the reason for this is that European equipment is more sensitive to water, fuel quality and impurities in the fuel, which makes them less suitable for many African countries. Another reason is that Chinese manufacturers have taken a big part of the market due to cheaper machines, which in turn has decreased the demand for European secondhand machines. It is also stated by the respondent that the company sells 99 percent of new machines to their African customers on the market. This is used as a direct counterargument to the view that Africa functions as a final destination for machines near end of life.

During the interview, the respondent defines end of life as the point when the machine is "impossible to repair, completely dead", rather than a predetermined lifespan. Furthermore, it is explained that the lifetime of the machines, such as excavators, changes greatly depending on the usage area and operational conditions. Machines used during mining, where the equipment is used all the time, can reach 10 000 – 15 000 hours quite quickly, he says. At the same time, he highlights that the same machines used in less intense conditions can be used up to 20 years. Other factors that are mentioned during the interview that can influence the lifetime repair options are the level of electronics in the machines and the availability of spare parts. The respondent argues that simpler machines with fewer electronics can be operational for a longer period of time, through local repair shops and the usage of alternative spare parts from informal markets long after retailers have lost control of them.

4.4.9 Fifth Interview with OEM

The last interview held with OEM, was with respondent I9, who works with XX at OEM. The whole interview concerns an Excel file containing data used in this study. Information about the collection and processing of data regarding the equipment's use phase and CO2 emissions on both global, national and regional levels in LCA was discussed. More exactly, the data concerns different sizes of excavators during the years between 2019 and 2025, and is presented in an Excel document. The respondent explains that the data can be used in calculations for countries, globally or regionally, but that the results can vary depending on which area is analysed. This is because different areas have different emissions, use patterns and the mix of energy being used. It is also highlighted that if the data is used incorrectly, the results can be misleading because the calculations are based on the data, which should be seen as individual data points. However, the data in documents is statistically reliable according to the respondent. This is because at least a certain number of machines are required to calculate the statistical average for a specific model of excavator. If the data set for a specific excavator is too small, the data is aggregated to model family or the category of the machine. In addition, a long period of time is used to reduce the effect of market fluctuations.

5. ANALYSIS

This chapter interprets the empirical findings in relation to the research questions and existing theory. The analysis follows a structured progression from observation to interpretation and implication. New empirical results and recommendations are reserved for the chapters that follow.

5.1 RQ1: How accurately do lifetime assumptions used in LCA calculations reflect the observed lifetime of construction equipment?

Observation.

Across 349 machines observed in seven market tiers, the pattern that emerged was consistent across categories and markets. Machines do not appear to exit observed circulation near the 10-year boundary assumed in LCA. In European primary markets, positive deviations from the baseline are present across all categories. Sweden shows deviations ranging from +11 percent for large crawlers to +203 percent for compact machines. Germany follows a similar pattern, with compact machines at +179 percent and large crawlers at +28 percent (Table 4.8). Machines in the oldest age cohort, those manufactured between 1998 and 2005 and now aged 21 to 28 years, remain listed in structured secondary-market channels with documented operating hours across Sweden, Germany, Australia, and South Africa. These observations represent machines that remained visible in active market channels at the time of data collection rather than confirmed completed lifetime trajectories. The pattern recurred across cohorts, categories, and markets in a way that is difficult to attribute solely to data artefacts.

Interpretation.

The findings suggest that the 10-year assumption may function less as an empirical end-of-life boundary and more as a planning horizon aligned with first-owner economic logic. In LCA, lifetime determines how production-phase impact is distributed across delivered service:

$$I_{\text{prod}\to\text{FU}} = \frac{E_{\text{prod}} \times q}{u \times L} \tag{5.1}$$

When L is set to 10 years but a machine continues delivering service across 25 years and

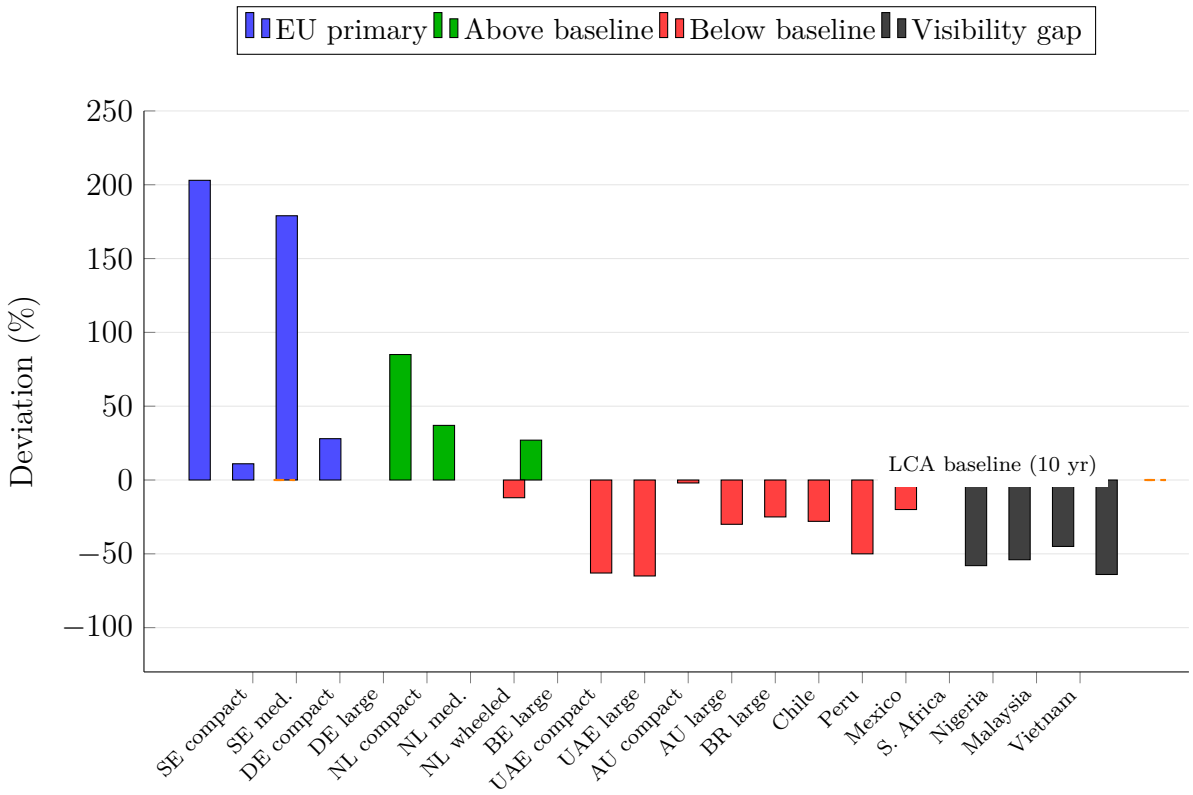

Figure 5.1: Observed operating-hour deviation from the 10-year LCA baseline (%), by market tier and machine category. Positive values indicate observed hours above the assumed baseline. Negative values indicate observed hours below the assumed baseline. Exact values are reported in Table 4.8.

multiple ownership cycles, the model distributes the same production burden across a denominator that is substantially smaller than the observed total. A deviation of +203 percent does not simply mean the machine lasts longer than assumed. It suggests that the actual functional output may be approximately three times what the model credits to the assumed lifetime period.

The interview evidence helps explain why this pattern appears consistently across observations. Respondent I3, representing a large construction contractor, described replacement decisions as primarily financial rather than technical: machines are sold when maintenance costs approach a threshold relative to depreciation value, not when they fail. At the point of sale, the machines are typically still functional. Respondent I4, working as a dealer who repairs and resells equipment, noted that machines operating for 20, 30, or even 40 years are not unusual depending on how they are used and maintained. Respondent I6 added that machines are often engineered to exceed their stated design requirements, which means well-maintained equipment in moderate conditions tend to outlive the assumed horizon by a meaningful margin.

Three end-of-life logics appear to be present in the observations, and none of them corresponds straightforwardly to a 10-year calendar boundary (Table 5.1). This is not to say that the 10-year value is without purpose. It provides a useful modelling convention and supports comparability across product categories. The question is whether it accurately reflects the system it is meant to represent.

Table 5.1: Three end-of-life logics observed in this study and corresponding empirical support.

EoL type	Mechanism	Evidence in this study
Technical EoL	Machine or component can no longer satisfy functional requirements without major repair	I4: Machines become inoperable only after structural or engine failure. P1-cohort machines (21–28 yr) remain visible in secondary-market listings with documented operating hours in Sweden and Germany.
Economic EoL	Continued operation is no longer cost-efficient for the current owner	I3: Replacement is driven by a depreciation-based financial threshold. Machines enter secondary markets rather than immediate scrappage. First-owner exit does not mark end of machine life.
Material EoL	Machine is removed from service and enters material recovery, recycling, dismantling, or disposal pathways	Direct material end-of-life was not observed in the present dataset. Secondary-market observations indicate continued circulation across ownership systems, but final material retirement remains outside the observable system boundary.

Source: Authors of this study, Three end-of-life logics identified in this study, supported by secondary-market observations and interview evidence..

Illustrative interval. Equivalent operating hours within a nominal 10-year lifetime may vary due to differences in machine configuration, application and usage patterns, utilisation intensity, operating conditions, and ownership context.

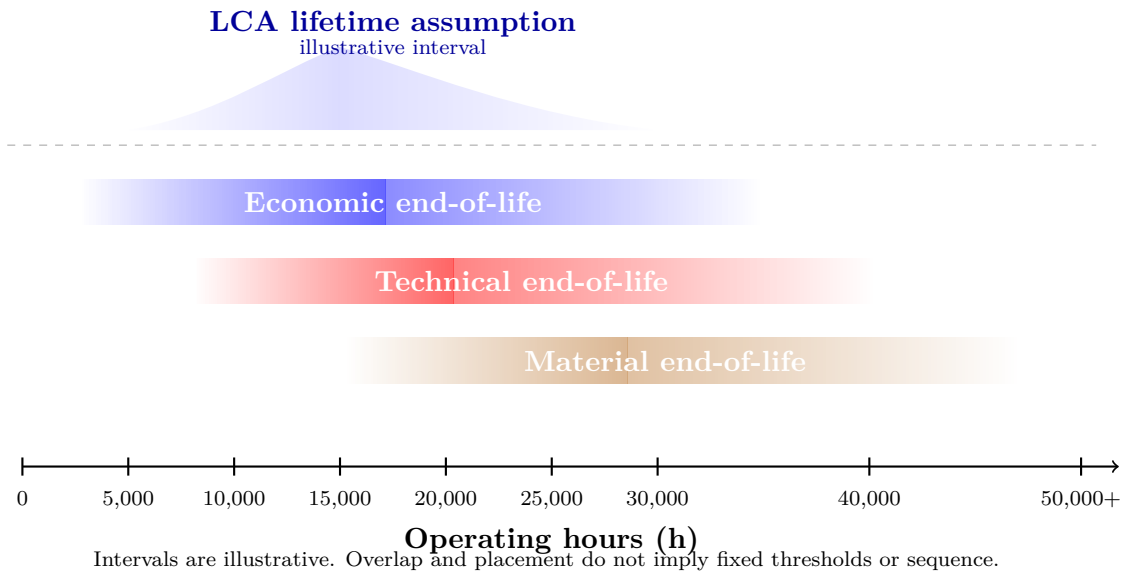

Figure 5.2: Conceptual illustration of end-of-life mechanisms relative to lifetime assumptions used in LCA.

Implication.

The findings suggest that impact allocation in current LCA models may diverge from observed service delivery in a structured rather than purely random way. This is not only a question of choosing a better number. A single fixed boundary may not fully capture a system in which three concurrent end-of-life logics operate across different timescales and through different mechanisms. Updating the assumption from 10 to 15 years would reduce the observed deviation without addressing that underlying structure. A related implication concerns machine category. Larger machines tend to operate at higher annual utilisation than compact machines. Applying the same 10-year calendar assumption across both categories means that the total service output implied by the baseline differs between them, producing inconsistent impact allocation even within a single LCA study covering multiple machine types.

5.2 RQ2: What factors explain the variation between the actual lifetime of construction equipment and the lifetime assumptions used in LCA calculations?

This section outlines the factors that contribute to addressing the second research question

5.2.1 Usage intensity

Observation.

The pilot case conducted by OEM, discussed in interview I2, found that usage intensity accounts for 93.8 percent of the influence on machine lifetime, with the remaining seven factors combined representing 6.2 percent (Figure 4.1).

Interpretation.

This proportion is striking. It suggests that how a machine is used, how intensively, in what terrain, for what type of task, may matter far more than the machine's design specifications in determining how long it remains operational. Two machines of the same model and manufacture year can reach fundamentally different total operating hours over the same calendar period. One machine used in continuous mining operations might accumulate 15,000 hours in five years. Another used intermittently in light construction might accumulate the same hours over 20 years. A 10-year calendar assumption assigns these two machines the same modelled service output despite their actual delivered service potentially being equivalent in operating-hour terms but separated by 15 years in calendar time. Respondents I4 and I6 described this concretely. I4 noted that a machine used in demanding environments such as mining, where it operates continuously under overload, will reach wear thresholds far sooner than one used occasionally under controlled conditions. I6 added that load, driving behaviour, and terrain directly affect component wear, and that the same model can show very different wear trajectories depending on where and how it is operated. This aligns with Polizzi di Sorrentino et al. (2016), who argue that actual usage behaviour rather than design specification is the primary determinant of realised lifetime.

Implication.

Operating hours may provide a more appropriate lifetime metric for LCA than calendar years, because they measure actual service delivery rather than elapsed time. This is a well-established principle in equipment lifecycle cost analysis Gransberg and O'Connor (2015) and Liu et al. (2020)that does not yet appear to be consistently applied in

environmental modelling of construction equipment.

5.2.2 Economic replacement logic and the first-owner boundary

Observation.

Respondent I3 described how a large construction contractor makes replacement decisions at roughly 8–10 years, based on depreciation principles and internal financial evaluation. At the point of sale, machines are typically still functional.

Interpretation.

Operating hours may provide a more appropriate lifetime metric for LCA than calendar years, because they measure actual service delivery rather than elapsed time. This is a well-established principle in equipment lifecycle cost analysis Gransberg and O'Connor (2015) and Liu et al. (2020)that does not yet appear to be consistently applied in environmental modelling of construction equipment. Operating hours may provide a more appropriate lifetime metric for LCA than calendar years, because they measure actual service delivery rather than elapsed time. This is a well-established principle in equipment lifecycle cost analysis Gransberg and O'Connor (2015) and Liu et al. (2020)that does not yet appear to be consistently applied in environmental modelling of construction equipment. This suggests that economic end-of-life precedes technical end-of-life in primary European markets, and that the two do not necessarily align. The economic life of an asset, the period during which its average annual cost is minimised, ends before its physical life, a distinction established in equipment replacement theory Ladopoulos et al. (2020). Respondent I3 also noted that advances in fuel efficiency create additional pressure toward early replacement: machines are sometimes replaced not because they are worn out, but because newer models offer cost savings that make continued operation of the older machine financially unattractive.

At first glance, this might seem to support the 10-year LCA assumption. If first owners replace at roughly that horizon, the model may approximate first-owner use reasonably well. The more important observation, however, is what happens next. When a machine is sold at economic end-of-life, it does not disappear from the system. It enters secondary markets, where it continues delivering service under different economic conditions, often for another decade or more. The LCA model boundary closes at first-owner exit; the machine's operational life does not.

Implication.

The 10-year assumption may reflect one owner's cost-optimisation period reasonably

well, while systematically omitting the continued service life of the same machine across subsequent owners. All subsequent service delivery is outside the model boundary by construction, not by evidence of actual retirement.

5.2.3 Market redistribution and traceability loss

Observation.

Machines observed in the late-life structured and end-of-life unstructured tiers spanning Africa, Latin America, Southeast Asia, and South Asia remain in active circulation across P1 and P2 age cohorts (Tables 4.6 and 4.7). The observations were assembled from fragmented listing sources with varying metadata quality, which itself reflects the traceability decline that accompanies market transitions.

Interpretation.

Secondary markets are not residual. They appear to be the mechanism through which machines continue delivering service after institutional visibility has ended. Pauliuk et al. (2017) show through the MaTrace Global model that products and embedded materials re-enter use phases across geographic regions through trade, redistributing service duration well beyond first-owner contexts. The seven market tiers observed in this study are consistent with that logic at machine level.

The interview with respondent I8 introduced a finding that complicates how late-life market observations should be read. A common assumption in European LCA practice, and one that appears to have influenced how secondary-market data in developing regions is interpreted, is that sub-Saharan African markets predominantly absorb end-of-life equipment exported from Europe. According to I8, who represents a regional dealer with direct operating knowledge across multiple African countries, this assumption does not reflect current market conditions. Chinese manufacturers have displaced European secondhand equipment through competitive pricing and better adaptation to local conditions, including fuel quality tolerance and simpler electronics. The dealer's sales are described as almost entirely new equipment, not secondhand imports. This interpretation is plausible, though it is based on a single respondent's market perspective and would benefit from corroboration against transaction-level data.

If I8's account is accurate, a number of the negative operating-hour deviations observed in African market listings may reflect recent new-market purchases rather than late-life retirement trajectories. A machine listed in Nigeria with 4,000 accumulated hours may be two years old, not approaching end-of-life. This would mean that geographic market tier is a less reliable proxy for lifecycle stage than has been assumed, a finding with implications for how future secondary-market studies design their sampling strategies.

Implication.

Machines operating in late-life markets may deliver environmental service, in the form of avoided new production, that current LCA models do not credit, because the model boundary closes before these markets become observable. At the same time, the conditions under which that service is delivered, fuel quality, maintenance standards, and emission environments, may differ meaningfully from primary-market conditions, which introduces uncertainty about the net environmental value of extended operation.

5.2.4 Maintenance quality, component heterogeneity, and spare-part availability

Observation.

Respondents I4 and I7 both described machines reaching 20,000–25,000 operating hours with major component replacement, after which continued operation remains technically feasible with appropriate maintenance and parts.

Interpretation.

A machine is not a single unit with a uniform lifetime. It is an assembly of components with different durability profiles, and the effective system lifetime is shaped by the interaction between component wear trajectories and the economic and logistical feasibility of replacement. Respondent I4 was direct on this point: the most important predictor of whether a machine continues operating is whether it receives regular servicing, oil changes, inspections, timely component replacement. Machines that are well maintained tend to persist; machines that are not tend to fail sooner than their design might suggest.

Respondent I8 added a dimension relevant to informal markets: simpler machines with fewer electronic systems can be maintained through local repair shops using non-OEM spare parts from informal markets, long after OEM parts supply has been discontinued. This informal maintenance ecosystem appears to maintain operational use in ways that generate no formal records. The machine keeps working, but nothing documents it. Jerome and Ljunggren (2025) note that in more than a quarter of reviewed LCA studies, data sources for lifetime values are not transparently disclosed, a finding that may partly reflect this kind of invisible operational continuation.

Implication.

A single machine-level lifetime value may not fully capture the heterogeneous component degradation trajectories that influence actual operational duration. Assigning one lifetime to one machine type treats variation in maintenance quality, usage inten-

sity, and spare-part access as noise, when these may be among the most influential determinants of how long a machine actually operates.

5.2.5 Definitional ambiguity in lifetime concepts

Observation.

Respondents I1, I2, I6, and I7 all described the 10-year value as a simplified parameter rather than a directly measured operational figure. Respondent I2 acknowledged that it represents an average across heterogeneous global usage patterns. The manufacturer (I5) assumes their equipment's lifetime to equal OEM's excavators lifetime by convention, not by measurement.

Interpretation.

Some of the observed variation between assumed and observed lifetime may be partly definitional rather than purely empirical. Jerome and Ljunggren (2025) identify four distinct lifetime concepts, technical use time, use time, technical lifetime, and service lifetime, each covering different intervals and treating idle time, repair periods, and secondary use differently. The 10-year LCA assumption most likely reflects first-owner economic use time. The observations from secondary-market listings reflect service lifetime across all owners, a different quantity. Comparing them as if they measure the same thing introduces apparent deviation that has a definitional component.

This does not make the deviation less real or less important. It does suggest that reducing it requires not only better empirical data, but explicit alignment of which concept of lifetime is being modelled and measured.

Implication.

Future LCA studies would benefit from explicit documentation of which lifetime concept is applied, and from distinguishing between first-owner economic use time and total system service lifetime when making comparisons across studies or between assumptions and observations.

6. DISCUSSION

This chapter discusses the findings in relation to existing literature and reflects on their implications and limitations.

6.1 Relation to Previous Research

The patterns observed in this study are broadly consistent with the theoretical logic developed by Müller (2006) and Pauliuk et al. (2017), but they add something those models alone cannot offer: machine-level empirical evidence.

Using dynamic stock-flow modelling, Müller (2006) demonstrates that assumed lifetime distributions substantially influence stock accumulation and outflow timing, and that relatively modest adjustments to average service life alter projected material availability in meaningful ways.

The present study identifies a comparable difference at machine level. P1-cohort machines aged 21 to 28 years remain in active secondary-market circulation across multiple continents. The principle identified by Müller (2006) at aggregate material level therefore appears to hold at individual machine level as well, although the underlying mechanisms differ. This convergence represents more than theoretical consistency. It suggests that the observed lifetime gap reflects how capital equipment circulates rather than how this particular dataset was constructed.

Reviewing 67 LCA studies, Jerome and Ljunggren (2025) find that lifetime definitions are inconsistent and that data sources are frequently undisclosed. The empirical material presented here provides a concrete illustration of why this inconsistency matters.

The 10-year assumption used at OEM is calibrated to first-owner economic use, whereas the secondary-market observations reflect total system persistence across multiple ownership cycles. Both measures are internally coherent, but they describe different phenomena and therefore cannot be compared directly without explicit alignment of definitions.

This should not be interpreted as criticism of individual studies. Rather, it reflects a methodological gap repeatedly identified in the literature but only rarely demonstrated using machine-level empirical material.

The account from respondent I8 introduces a more challenging implication for existing assumptions. European LCA practice and circular economy discourse have often treated sub-Saharan African markets as destinations for end-of-life European equip-

ment, and some secondary-market studies appear to have inferred lifecycle stage from geographic location.

The interview evidence suggests that this inference may no longer be reliable for the specific segment studied here. This interpretation cannot be fully verified based on a single respondent perspective, and alternative explanations cannot be excluded.

For example, the observed pattern may vary across African regions in ways not captured by I8's experience, or the transition from secondhand import markets to predominantly new-equipment markets may still be ongoing rather than complete.

Nevertheless, the finding is specific and grounded in direct market experience in a way that warrants consideration and highlights a broader challenge in how secondary-market evidence is interpreted in lifecycle studies.

6.2 Implications for LCA and Circular Economy Practice

Two aspects of current practice appear most directly implicated: lifetime representation in LCA and the treatment of secondary markets in circular economy strategy.

For lifetime representation, the issue is less about selecting a better number and more about reconsidering the structure of the assumption itself. Applying a single fixed lifetime uniformly across machine categories, usage contexts, and geographic markets may not fully capture how operational duration varies across those dimensions. A phase-based approach, distinguishing primary use, transition, and late-life phases aligned with operating-hour intervals, could allow models to reflect the changing utilisation intensity and maintenance burden that characterise real machine lifecycles. The operating-hour intervals established in Table 3.4 provide one possible starting structure and could later be evaluated using telematics data if such information becomes available.

For circular economy strategy, one implication emerging from the analysis is that lifetime extension may be conditionally rather than automatically beneficial from an environmental perspective. The proportional argument, that longer lifetime reduces impact intensity per functional unit, depends on performance remaining comparable throughout the extended operating period. A machine operating in a late-life market with lower fuel quality, informal maintenance practices, and gradually declining efficiency delivers a different environmental profile per operating hour than the same machine operating in a regulated primary-market fleet. Cruz Sanchez et al. (2020) note that existing circularity indicators tend to capture design potential rather than realised operational longevity. The findings of this study align with that observation

and add a geographic dimension: the conditions under which lifetime extension occurs may matter as much as the duration itself.

6.3 Limitations and Remaining Uncertainty

Three areas of uncertainty are important enough to state directly rather than leave implicit.The first concerns data coverage. Secondary-market listings document machines that are active at a point in time rather than machines at the end of their lives. The observations therefore provide conservative lower-bound estimates of total operational duration. How much longer machines continue operating after their last secondary-market listing, whether weeks, years, or decades, remains unknown and cannot be estimated from the current data. The true total lifetime of machines operating in late-life and end-of-life markets likely exceeds what the structured dataset captures, but the magnitude of that difference remains an open question.

The second concerns the African market interpretation. The finding from respondent I8, that African markets now sell predominantly new equipment rather than second-hand European imports, is plausible and internally consistent with observable trends in Chinese market entry. However, it is based on one respondent's perspective from one company operating across a selection of African countries. The extent to which this reflects a broader continental transition, rather than conditions specific to the countries and machine types represented by this dealer, cannot be determined from the evidence available here. Alternative explanations therefore remain possible.

The third concerns transferability. The observations cover OEM's construction equipment, premium-segment products with a specific service infrastructure, warranty structure, and geographic distribution. The findings may therefore not transfer directly to lower-price-point equipment, other machine categories, or markets where maintenance cultures and regulatory environments differ substantially from those studied here. The analytical framework, including the three end-of-life logics, operating hours as a lifetime metric, and the secondary-market reconstruction procedure, may generalise more readily than the specific deviation values.fetime metric, and the secondary-market reconstruction procedure, may generalise more readily than the specific deviation values.

7. CONCLUSIONS

This chapter synthesises the findings of the study and outlines their contributions, implications, limitations, and directions for future work.

7.1 Summary of Findings

The findings suggest that the 10-year lifetime assumption used in LCA does not accurately reflect the observed operational lifetime of the equipment studied. In European primary markets, deviations above the baseline range from +11 to +203 percent across machine categories, while machines in the oldest age cohort, manufactured between 1998 and 2005, remain listed in active secondary-market channels across multiple countries. Taken together, these observations suggest that the assumption functions less as an empirical end-of-life boundary and more as a first-owner economic planning horizon. Three concurrent end-of-life logics, technical, economic, and material, were identified in the empirical material, each operating through different mechanisms and across different timescales. As a result, a single fixed lifetime value may not fully capture the structure of observed operational persistence, regardless of whether that value is defined as 10 or 15 years.

7.2 Factors Explaining Lifetime Variation

Five factors appear to contribute to the variation between observed and assumed lifetime.

Usage intensity emerged as the strongest explanatory factor and accounted for 93.8 percent of lifetime influence in the pilot case, suggesting that operating hours may provide a more appropriate basis for lifetime representation in LCA than calendar years.

Economic replacement logic governs first-owner exit independently of technical condition, creating a separation between the model boundary and continued operational use.

Market redistribution extends service delivery across ownership cycles and geographic contexts in ways that current LCA models do not capture.

Maintenance quality and component heterogeneity produce divergent degradation trajectories that cannot be represented adequately through a single machine-level lifetime

value.

Finally, *definitional ambiguity* between first-owner economic use time and total system service lifetime introduces a structural component to the observed deviation that cannot be resolved through improved data alone.

7.3 Contributions of the Study

The empirical material, consisting of 349 machines across seven market tiers and four continents with operating-hour distributions and age-cohort breakdowns, provides what appears to be the first secondary-market reconstruction of construction equipment operational lifetime at this geographic scope. Methodologically, the study demonstrates a replicable procedure for reconstructing lifetime distributions from secondary-market listing data and supports the use of operating hours as the primary lifetime metric in LCA for this equipment category. Theoretically, the three-part end-of-life framework provides a conceptual structure that distinguishes mechanisms that existing LCA and circular economy frameworks often treat as a single event. Practically, the findings point toward changes in data collection practice, LCA modelling conventions, and circular economy reporting that are grounded in observed system behaviour rather than theoretical assumptions alone.

7.4 Implications for Practice

For LCA practice, replacing or supplementing calendar years with operating hours as the basis for lifetime parameterisation would align the model denominator more closely with observed service delivery. Introducing phase-based lifetime representation, distinguishing primary use, transition, and late-life phases, would further allow models to reflect changing utilisation intensity and maintenance requirements across the operational life of machines. Uncertainty associated with secondary-market phases should be acknowledged explicitly in sensitivity analyses and documented in accordance with ISO 14044 transparency requirements. For circular economy strategy, lifetime extension appears conditionally rather than automatically beneficial. Extended use under deteriorating maintenance conditions or in emission environments that differ substantially from primary-market assumptions may not produce the environmental gains implied by current amortisation logic. Secondary-market flows represent genuine circular value in the form of avoided new production and should therefore be incorporated into CSRD reporting frameworks rather than treated as activity outside the model boundary.

7.5 Study Limitations

Secondary-market listings provide conservative lower-bound estimates of operational duration rather than completed lifetime distributions. Data quality and listing density vary across market tiers, with the weakest data often occurring in the markets most relevant to late-life assessment. The study includes one OEM and the projects collaborating companies, meaning that findings may not transfer directly to other brands or equipment categories. Recycling and scrappage actors were not included in the interview sample, leaving material end-of-life empirically underrepresented. Emission calculations were limited to sub-datasets where all required variables were available at machine-category and market level and could not be derived reliably using regional averages.

7.6 Recommendations for Industry

Systematic post-sale data collection should be introduced so that end-of-life and ownership-transition records can be used to calibrate LCA assumptions against observed operational trajectories rather than engineering estimates. Lifetime reporting should prioritise operating hours over calendar years for both technical accuracy and compatibility with usage-based cost and sustainability analysis. End-of-life registration should be integrated into dealer and reseller networks. Secondary-market flows should also be incorporated into circular economy strategy and CSRD reporting. Partnerships with regional dealers, including actors operating in African and Southeast Asian markets, may improve access to provenance and condition data for machines currently outside institutional traceability.

7.7 Suggestions for Future Research

A telematics-based longitudinal study using OEM fleet data would allow operating-hour trajectories to be followed across ownership cycles, replacing secondary-market proxies with direct observation and enabling the full emission calculation framework to be applied using empirically validated inputs. A phase-based LCA model based on operational data should be tested against the conventional single-boundary approach to estimate the practical implications for impact allocation. Component-level lifetime analysis would provide insight into machine-as-system complexity that cannot be represented through a single machine-level value. Comparative studies across other heavy equipment sectors, including mining machinery, forestry equipment, and port

cranes, would help determine whether the observed patterns are specific to construction equipment or reflect a broader feature of capital goods circulating through distributed secondary markets. Taken together, the findings suggest that lifetime in construction equipment systems may be better understood as an emergent outcome of technical condition, economic decisions, and market dynamics across multiple ownership cycles rather than as a fixed parameter established at the point of manufacture. Although uncertainty remains regarding the magnitude of extended service delivery in late-life markets, the direction of the findings is consistent across empirical observations and interview evidence. The observations presented here represent an initial empirical step. The data infrastructure required to follow machines across their full operational trajectory does not yet exist at systematic scale, and developing such infrastructure appears to be a worthwhile priority for both research and industry.

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