Proceedings of the 35th European Safety and Reliability & the 33rd Society for Risk Analysis Europe Conference
Edited by Eirik Bjorheim Abrahamsen, Terje Aven, Frederic Bouder, Roger Flage, Marja Ylönen

doi: 10.3850/978-981-94-3281-3_ESREL-SRA-E2025-P4331-cd

Reliability and Environmental Sustainability Relationships: A Stochastic Analysis of Product Lifespan and Global Warming Potential

Dshamil Efinger

Institute of Machine Components, University of Stuttgart, Germany.
E-mail: dshamil.efinger@ima.uni-stuttgart.de

Martin Dazer

Institute of Machine Components, University of Stuttgart, Germany.
E-mail: martin.dazer@ima.uni-stuttgart.de

This paper introduces the so-called Sustainability-Usage Ratio (SUR), relating the Global Warming Potential (GWP) of a product to the duration of its use and it introduces an approach for evaluating the SUR. To this end, two principal methods are presented: one based on the arithmetic mean usage and another integrating over the product's GWP curve and its usage distribution to derive a mean SUR value. By accounting for reliability data, user behavior, and potential early discarding, more sophisticated assessment of environmental sustainability is enabled.
The paper illustrates these concepts with an example comparing two electric kettles, which differ in their lifetime distributions and GWP contributions from manufacturing and disposal. Results highlight that the arithmetic mean-based method can overly reward products with long nominal lifespans, particularly when user preferences or premature failures reduce actual usage. In contrast, integrating the failure distribution produces a more conservative yet realistic estimation of overall sustainability performance.
These findings underscore the importance of selecting an appropriate metric based on the decision context. The framework presented here aids stakeholders – from product designers to consumers – in making more informed choices about product sustainability, while also providing insights into optimizing product design and usage strategies to reduce greenhouse gas emissions.

Keywords: Reliability Analysis, Environmental Sustainability, Product Lifespan, Global Warming Potential (GWP), Sustainability-Usage Ratio (SUR), Stochastic Effects.

1. Motivation

Global climate change has garnered widespread attention due to the rise in anthropogenic greenhouse gas (GHG) emissions and their detrimental effects on the environment (Stocker et al. (2013)). Recognizing the urgency of the situation, both policy makers and researchers advocate for identifying more sustainable pathways in production and consumption (Albrecht et al. (2021); Uni (2022)). One widely acknowledged metric for quantifying the climate impact of a product or process is the *Global Warming Potential (GWP)*, which compares the energy absorbed by the emissions of a particular gas to the energy absorbed by carbon dioxide over a fixed timescale (Deu (2019)).

The prolongation of product lifetimes is frequently proposed as a pivotal strategy to enhance sustainability (Lyndhurst (2011); Dehoust et al. (2016); Oehme et al. (2016)). This approach is predicated on the assumption that extending the period of usage can distribute the GWP burden over a more extended timescale. However, increasing a product's lifetime can also require more material and energy, thus raising the GWP if it merely leads to a more resource-intensive design. Consequently, it is vital to determine under which circumstances a longer lifetime genuinely improves environmental performance. Furthermore, the mere existence of a technically longer lifetime does not guarantee real-world benefits if user preferences lead to early disposal (Oehme et al. (2016). Hence, the behavior of both products and users – who might replace items before the end of their technical – lifetime must be considered.

Against this backdrop, the present paper investigates which metrics are suitable for evaluating the ecological performance of products in terms of their GWP, and how stochastic lifetime behavior and user preferences influence these metrics. By focusing on methodologies that link the GWP to the usage duration, we aim to provide a foundation for more sophisticated sustainability assessments.

2. Mean Values

The arithmetic mean is a central measure for describing the location of a probability distribution and represents the expected value of a random variable μ_a. In the case of continuous random variables, it can be expressed as an integral, as shown in Eq. (1), where $f(t)$ is the probability density function of the distribution under consideration (Papoulis (1965)). Calculating the arithmetic mean is essential for reliability analysis, as it is used, for example, to determine the mean lifetime of technical systems (Meeker et al. (2022)).

$$\mu_a = \int_0^{\infty} t \cdot f(t)\, dt \tag{1}$$

Another measure of central tendency is the harmonic mean. It is particularly useful when averaging ratios or rates. For continuous random variables, it is defined by Eq. (2), where the harmonic mean μ_h is calculated as the reciprocal of the expected value of the reciprocals of the random variable t, with $f(t)$ denoting the probability density function (Mood (1950); Benesch (2012)). The harmonic mean is utilized in reliability engineering for analyzing aging processes and system failures, particularly in modeling failure times and defining new aging functions, such as in the study of harmonic hazard rates and inactivity time analysis (Bhattacharjee et al. (2024); Izadkhah and Kayid (2013)).

$$\mu_h = \frac{1}{\int_0^{\infty} \frac{1}{t} \cdot f(t)\, dt} \tag{2}$$

3. Reliability and Sustainability

A commonly used approach to assess the ecological sustainability of products is to relate the Global Warming Potential (GWP) to a reference time (Albrecht et al. (2013); Efinger et al. (2022)). This allows for the comparison of products belonging to the same category in terms of ecological sustainability, even if they differ in their GWP and/or reference time. The principle behind this method is to place the effort (GWP) in relation to the benefit (reference time). The resulting ratio, which expresses ecological sustainability in terms of GWP relative to usage, is hereafter referred to as the *Sustainability-Usage Ratio (SUR)*. However, this approach raises the question of which reference time should be applied. One possibility is to use the product's lifetime. Yet the commonly cited "lifetime" as a single value is, in reality, a stochastic variable following a probability distribution. Moreover, a product's inherent lifetime does not necessarily imply that customers will use it until failure. Many products are removed from operation for other reasons (Dehoust et al. (2016); Rudenauer and Prakash (2020)). Furthermore, not every customer behaves identically at any given point in time. Customer behavior can also be captured statistically, both for the entire customer base and for individual users at each point in time.

In the following, the ratio GWP/t is used as a metric for the *Sustainability-Usage Ratio (SUR)*. A lower GWP is associated with higher ecological sustainability. Longer usage increases the overall value gained for the incurred CO_2-equivalent. Consequently, a lower GWP/t is interpreted as a higher SUR. The ratio GWP/t can be plotted against time t, thereby illustrating the SUR as a function of useful life. This approach follows the same principles as the time-dependent average availability $A_{Av}(t)$ derived from the point availability $A(t)$ (Bertsche and Dazer (2022)). The behavior of GWP/t is influenced by five fundamental effects, which are depicted qualitatively in Figure 1.

- First (Figure 1 (a)), the initial demand, i.e., the initial GWP GWP_{init}, must be considered. It includes the GWP expenses for manufacturing, possibly distribution, and the product's disposal. Viewed over the entire useful life, this forms a hyperbola.
- In addition (Figure 1 (b)), there may be constant

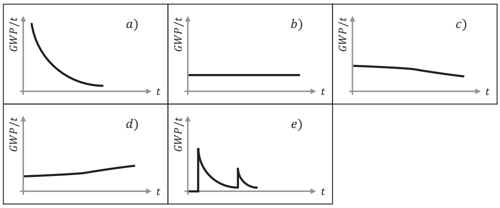

Fig. 1. Qualitative representation of the GWP/t curves over time t, based on five fundamental effects.

demands during use, for example for operating energy. These represent a constant shift of GWP/t on the y-axis.

- Over time, however, demand reductions can occur. Such reductions can be constant or abrupt. In Figure 1 (c), an example of such a demand reduction is depicted, which could result, for instance, from changes in the electricity mix.
- In contrast to demand reduction, there may also be additional demands. These can arise from increasing friction losses due to wear or aging, for example. Figure 1 (d) shows an increase in demand over time.
- Finally, maintenance demands may occur. They can manifest as sudden increases in GWP/t, followed by a hyperbolic-like decline. Figure 1 (e) illustrates such a case in which two GWP relevant maintenance measures are performed.

The individual curves can be combined to form an overall product curve. Such a curve can represent either a single entity or a typical representative from a larger population of entities. For the sake of clarity, only the case with an initial GWP demand is considered in the following.

3.1. *Reliability and sustainability separately*

The conventional approach to computing GWP/t, as employed by Albrecht et al. (2013) and Efinger et al. (2022), is divided into three distinct steps. First, the reference time is determined. Then, the GWP is calculated. Finally, GWP/t is calculated. This method uses the arithmetic mean of the lifetime, denoted t_{m_a}. For this average lifetime, GWP_{t_m} is calculated by adding the initial GWP GWP_{init} to the average GWP demand $\overline{GWP_{use,t_m}}$ (up to time t_m), and then dividing this sum by the arithmetic mean lifetime t_{m_a}. The initial GWP corresponds to case (a) in Figure 1, while the average GWP demand encompasses cases (b)–(e). Equation (3) shows the relationship:

$$\mathrm{GWP}_{t_m} = \frac{\mathrm{GWP}_{\mathrm{init}} + \overline{\mathrm{GWP}_{\mathrm{use},t_m}}}{t_{m_a}} \tag{3}$$

We calculate the arithmetic mean of the lifetime t_{m_a} for a two-parameter Weibull distribution, for example. The starting point is the failure density function $f(t)$ given in Eq. (4). By integrating, substituting and using the gamma function, we finally obtain Eq. (5).

$$f(t) = \frac{b}{T} \cdot \left(\frac{t}{T}\right)^{b-1} \cdot e^{-\left(\frac{t}{T}\right)^b} \tag{4}$$

$$t_{\mathrm{m_a}} = T \cdot \Gamma\left(1 + \frac{1}{b}\right) \tag{5}$$

The SUR calculated in this manner describes the GWP/t at the average lifetime t_{m_a}. This allows the determination of the average SUR for a population that follows a given distribution. Such an approach is particularly relevant when an evaluation is required for a large set of entities in the population. For instance, if these entities are used simultaneously. Alternatively, if a fixed time span t_x must be covered by sequentially using multiple units of the same product. Nevertheless, when using the average lifetime to form the mean, it is necessary that all entities be used until the end of their lifetime, since shortening the reference time for long-lived units impacts the calculation considerably.

However, this type of calculation offers only limited insight into the actual utility value (SUR) associated with a single decision to select a product. Imagine a situation. A customer has the choice between two identical products, except for the technical lifespan. 99% of the parts of one product last exactly 1 year and 1% of the parts last 110 years. For the other product, the technical lifespan of 100% of the parts is exactly 2 years. Here the question arises as to which product the customer should choose in the event of a case-by-case decision. Furthermore, substantial deviations may arise based on the actual useful life, as GWP requirements during the usage period can vary considerably. This approach also runs short on information about the value of continued use or the implementation of maintenance measures.

3.2. *Reliability and sustainability combined*

In this method, the reference time, the determination of GWP, and the calculation of GWP/t are considered simultaneously. The procedure begins by plotting GWP/t over the time t, which describes the Sustainability-Usage Ratio (SUR) as a function of the usage duration for a single entity. This plot is then extended into the third dimension, representing the entire population of entities. Assuming that the initial GWP is the same for all entities and that the usage-related demand does not differ among them, the GWP/t curve over t can simply be extruded into the third dimension.

Regardless of whether a single curve has been extruded into a surface or each entity has its own curve, the plot now depicts GWP/t over t for every portion of the entire population. The reference time can then be used to truncate the curve for larger times, effectively cropping the curve at an arbitrary time t_{ref}. These reference times t_{ref} can, for instance, be arranged in ascending order along the third dimension.

If the reference time is defined solely by the product's technical lifetime, the third dimension can be aligned with the cumulative failure probability. This approach produces a plot as shown in Figure 2. In the illustration, we use case (a) from Figure 1 with an initial GWP of $500\,\text{kg CO}_2\text{eq}$, and we apply a two-parameter Weibull distribution with a shape parameter $b = 2.5$ and a scale parameter $T = 5.6353\,\text{years}$.

Along the intersection of the GWP/t surface over time t with the lifetime distribution, the SUR is determined for each portion of the population. By integrating along this intersection, the mean SUR for the entire population can be obtained. This mean SUR is hereafter denoted GWP_m, which can be calculated according to Eq. (6).

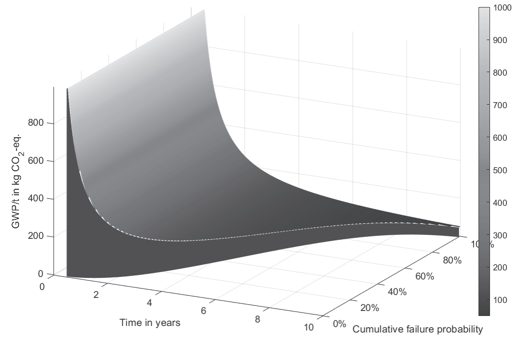

Fig. 2. Three-dimensional representation of the GWP/t surface over time t and the cumulative failure probability, truncated by the cumulative failure probability function.

$$\text{GWP}_m = \int_0^\infty \text{GWP}(t) \cdot f(t)\,dt \qquad (6)$$

The calculation of the SUR GWP_m for a two-parameter Weibull lifetime distribution also begins with the failure density function given by Eq. (4). To keep the subsequent steps straightforward, only the initial GWP GWP_{init} is considered. This yields Eq. (7).

$$\text{GWP}(t) = \frac{\text{GWP}_{\text{init}}}{t} \qquad (7)$$

By substituting Eq. (7) into Eq. (6), we obtain Eq. (8). Using the substitution from Eq. (9), Eq. (10) follows. Applying the Gamma integral from Eq. (11) and substituting x as per Eq. (12) finally leads to Eq. (13).

$$\text{GWP}_m = \text{GWP}_{\text{init}} \cdot \frac{b}{T} \cdot \int_0^\infty \frac{1}{t} \cdot \left(\frac{t}{T}\right)^{b-1} \cdot e^{-\left(\frac{t}{T}\right)^b}\,dt = \text{GWP}_{\text{init}} \cdot \frac{b}{T^b} \cdot \int_0^\infty t^{b-2} \cdot e^{-\left(\frac{t}{T}\right)^b}\,dt \qquad (8)$$

$$u = \left(\frac{t}{T}\right)^b \qquad (9)$$

$$\text{GWP}_m = \text{GWP}_{\text{init}} \cdot \frac{1}{T} \cdot \int_0^\infty u^{\frac{b-2}{b}} \cdot e^{-u}\,du \qquad (10)$$

$$\int_0^\infty u^{x-1} e^{-u}\, du = \Gamma(x) \tag{11}$$

$$x = \frac{b-1}{b} \tag{12}$$

$$\mathrm{GWP}_m = \mathrm{GWP}_{\mathrm{init}} \cdot \frac{1}{T} \cdot \Gamma\left(\frac{b-1}{b}\right) \tag{13}$$

The chosen approach for the simplified case (a) in Figure 1, under the constraint that the reference time equals the product lifetime, amounts to dividing the initial GWP by the harmonic mean of the failure probability function from Eq. (2).

The mean value calculated in this manner describes the average utility (in terms of SUR) across the different entities in the population. It is always at least as large as the one computed in Subsection 3.1. The higher the proportion of short usage times, the larger the discrepancy becomes, effectively assigning a greater weight to short reference times. Well-designed products (with a large shape parameter) therefore perform better than poorly designed products (with a small shape parameter) with lifetimes of the same arithmetic mean value t_{m_a}.

When deciding between multiple different products, this approach incorporates the risk of early failure into the SUR, while also recognizing that the probability of obtaining a long-running unit is relatively low. Moreover, it raises the question of whether a long-lived product's lifetime would actually be fully utilized by the user. If not, that would considerably affect the mean value derived in Subsection 3.1. The following subsection will address this issue of user preference in greater detail.

3.3. *Consideration of user preference*

In practice, a longer technical lifetime does not necessarily imply a better Sustainability-Usage Ratio (SUR). After all, the SUR emerges from two factors: the GWP effort and the duration of use. The latter – which is the focus of this subsection – depends not only on the technical lifetime but also on user preferences. This explains why a significant fraction of discarded products has not actually failed functionally (Dehoust et al. (2016); Rudenauer and Prakash (2020)). There are various drivers behind discarding functional products (see Montalvo et al. (2016) for a detailed discussion). Technological progress is one of the central drivers, indicating that the lifetime of such products cannot be increased arbitrarily to improve the SUR.

User preferences for usage duration can be captured in different ways. On the one hand, they can be modeled for individual users as the probability that a user's desire to continue using the product will persist over time. On the other hand, a distribution of desired usage times can be established for an entire user population, analogous to the approach used for technical lifetimes. The actual usage duration of a particular product entity arises from the interplay of that entity's technical lifetime and the individual user's desire to continue using it. Whichever is shorter determines the actual usage duration. Depending on boundary conditions, there are different ways to combine product entities from the overall population with individual users from the user population; each way allows for different calculation methods. In the present work, we restrict ourselves to the assumption of random assignment, which can be simulated via Monte Carlo methods and statistically approximated.

4. Analysis of an Electric Kettle

The concepts introduced above are now exemplified by comparing two different electric kettles, referred to as "Product A" and "Product B". First, we consider only the technical lifetime, followed by a second step that incorporates user behavior.

4.1. *Considering technical lifetime only*

Table 1 presents the data for the two kettles, adapted from (Wang et al. (2013)). Both devices offer comparable functionalities but differ in their technical design, particularly with respect to the GWP incurred during manufacturing and disposal, as well as their lifetimes. Since the energy consumption during use is identical for both devices, it is omitted from the analysis.

Table 1. Comparison of kettle A and B, baseline data.

	Product A	Product B
Filling capacity	identical	
Energy consumption	identical	
Electrical power	identical	
Heating time	identical	
GWP for production and disposal in CO_2eq	500	700
Average lifetime t_{m_a}	$5years$	$8years$
Failure behavior	Weibull	
Shape parameter b	2.5	1.8

4.1.1. *Separate*

The SUR $\left(GWP_{t_m}\right)$ at the arithmetic mean lifetime t_{m_a} for production and disposal is calculated according to the procedure in Subsection 3.1. For Product A, this yields $100\,\mathrm{CO_2eq/yr}$, and for Product B, $87.5\,\mathrm{CO_2eq/yr}$. Hence, the average SUR of Product B is better than that of Product A.

4.1.2. *Combined*

Using the combined approach outlined in Subsection 3.2 (i.e., integrating along the intersection curve), we obtain the SUR $\left(GWP_m\right)$ for production and disposal. To do so, we apply Eq. (13). For Product A, this results in $132.1\,\mathrm{CO_2eq/yr}$, and for Product B, $155.1\,\mathrm{CO_2eq/yr}$. Under this assessment, Product A performs better than Product B.

4.2. *Considering user behavior*

Subsection 4.1 investigates the SUR purely on the basis of the failure behavior (i.e., the technical lifetimes) of Products A and B. According to Lyndhurst (2011), electric kettles belong to the category of "workhorse products" and thus undergo only minor technological changes. Technological advancements therefore rarely serve as a motive for replacing them. However, as shown in Dehoust et al. (2016), only about 50% of kettles are discarded due to a functional failure – that is, upon reaching the end of their technical lifetime. Consequently, in the next step, we also account for the user's desired usage duration. The user preference regarding usage duration is treated statistically via probability distributions, analogous to the approach for technical lifetimes. We restrict ourselves to the case of random assignment of product entities to user preferences (see Subsection 3.3). The combination of random durations for the technical lifetime and for the desired usage duration is carried out using Monte Carlo simulation. For Products A and B, several scenarios are considered. We begin with a scenario in which each product has its own usage pattern such that 20% of the units are discarded by the user while still fully functional. This proportion is then increased to 50%. In addition, we investigate a scenario in which the user preference is assumed identical for both products, reflecting the assumption that the overall user base is not product-specific. Table 2 summarizes the parameters.

Table 2. Comparison of kettle A and B, parameter overview.

	Product A	Product B
Failure behavior following Weibull distribution		
Shape parameter b	2.5	1.8
Scale parameter T	5.6353	8.9960
Desired usage times following Weibull distribution – 20%		
Shape parameter b	4.0	4.0
Scale parameter T	8.3	14.1
Desired usage times following Weibull distribution – 50%		
Shape parameter b	4.0	4.0
Scale parameter T	5.4	8.2
Desired usage times following same Weibull distribution		
Shape parameter b	4.0	
Scale parameter T	6.5	

4.3. *Discussion of results and findings*

Table 3 presents the results of these studies, combining the findings from Subsection 4.1 and Subsection 4.2.

The analysis shows that the two calculation methods, GWP_{t_m} and GWP_m, respond differently to variations in usage duration. While both values increase as the fraction of units used until the technical end of life decreases, the relative rise in GWP_{t_m} is substantially higher than that of

Table 3. Comparison of kettle A and B, result overview.

	Product A	Product B
Entire lifetime of all used		
SUR as GWP_{t_m} in CO_2eq/t	100.0	87.5
SUR as GWP_m in CO_2eq/t	132.1	155.1
Entire lifetime of 80.0% used		
SUR as GWP_{t_m} in CO_2eq/t	107.7	96.8
SUR as GWP_m in CO_2eq/t	138.0	159.5
Entire lifetime of 50.0% used		
SUR as GWP_{t_m} in CO_2eq/t	127.3	122.5
SUR as GWP_m in CO_2eq/t	155.4	178.7
Same desired usage times		
Proportion of failed products	62.7%	36.6%
SUR as GWP_{t_m} in CO_2eq/t	117.3	144.0
SUR as GWP_m in CO_2eq/t	146.3	196.4

GWP_m. This underscores that GWP_{t_m} is more sensitive to reductions in usage duration.

For Product A, GWP_{t_m} increases by 7.7% for 80% of units failing at end of life, by 17.3% for 62.7%, and by 27.3% for 50%. By contrast, GWP_m exhibits smaller increases of 4.5%, 10.7%, and 17.6%, respectively. A similar pattern emerges for Product B, with the highest relative rise in GWP_{t_m} reaching 64.6%, whereas GWP_m increases by at most 26.6%.

Hence, GWP_{t_m} is indeed more sensitive to usage restrictions, whether caused by inaccuracies in the technical lifetime or by ending usage prior to the product's potential technical lifetime. This sensitivity can lead to an initially overly optimistic rating of the SUR. However, if one examines multiple product lifetimes such that every unit is eventually utilized until it fails, GWP_{t_m} represents the long-term expected SUR. By contrast, GWP_m is less sensitive to curtailed usage durations and thus provides a more conservative evaluation. It is therefore better suited when products are unlikely to be used until the end of their lifetime, or if early product failures are of particular concern. In the context of this study:

If every individual device (each entity) is used until the end of its technical lifetime and all entities are considered jointly, GWP_{t_m} provides an appropriate means to evaluate the SUR. In this scenario, Product B outperforms Product A.

From a user's perspective, where the decision is made for a single entity and the actual usage duration is uncertain, or where early failures need to be factored in, GWP_m is more suitable. In this case, Product A proves to be the better choice.

In summary, a complementary application of both methods is advisable: GWP_m can be specifically used to evaluate scenarios involving varying lifetimes and usage preferences, whereas GWP_{t_m} is appropriate for evaluating large populations of product entities or for scenarios where each product is indeed used until the end of its technical lifetime. Accordingly, the choice of calculation method should always reflect the particular objectives of the analysis.

5. Conclusion

This paper has introduced a framework for quantifying the newly defined *Sustainability-Usage Ratio (SUR)* by relating the Global Warming Potential (GWP) of a product to its period of use. Two principal methods of calculating the SUR were compared: GWP_{t_m}, which employs the arithmetic mean lifetime t_{m_a}, and GWP_m, which integrates along the product's failure distribution to derive a mean SUR value.

The analysis reveals that while GWP_{t_m} can serve as a straightforward means of assessing the performance of a large population of products used until the end of their technical lifetimes, it is more sensitive to any reduction in usage duration. This heightened sensitivity means that GWP_{t_m} can yield an overly optimistic assessment in situations where the product may fail prematurely or where users might choose not to exploit its full technical lifetime. By contrast, GWP_m offers a more conservative approach and is particularly advantageous when the actual usage duration is uncertain, or if early failures significantly impact the user's decision-making process.

An empirical comparison of two electric kettles illustrates these differences. Under the assumption that each kettle is utilized until technical failure, GWP_{t_m} indicates that the product with the lower average GWP per year (Product B) achieves a better SUR. However, the combined evaluation method (GWP_m) reveals that, when accounting for stochastic failures and potential early user discard, the other product (Product A) outperforms its competitor. Thus, the choice of metric depends greatly on the context and the objectives of the analysis.

Practical Implications. When forming a purchasing decision from a single-user perspective, factors such as early failure risk and uncertain usage duration should be included, making GWP_m the more suitable metric. On the other hand, for long-term scenarios in which multiple product units are guaranteed to be used until the end of their technical life, GWP_{t_m} can serve as a consistent predictor of long-term performance. Hence, selecting the appropriate metric not only better reflects real-life user behavior and system performance but also fosters more accurate and context-sensitive sustainability assessments.

Acknowledgement

This work was supported by the German Research Foundation (DFG, Deutsche Forschungsgemeinschaft, Project-ID 279064222), as a part of the collaborative research center CRC 1244 (SFB1244) “Adaptive Skins and Structures for the Built Environment of Tomorrow” Projects B03.

References

(2022). *Emissions Gap Report 2019*. Nairobi: United Nations.

(Juni 2019). *DIN EN ISO 14064-1, Treibhausgase. Teil 1, Spezifikation mit Anleitung zur quantitativen Bestimmung und Berichterstattung von Treibhausgasemissionen und Entzug von Treibhausgasen auf Organisationsebene (ISO 14064-1:2018): = Greenhouse gases. Part 1, Specification with guidance at the organization level for quantification and reporting of greenhouse gas emissions and removals (ISO 14064-1:2018)* (Deutsche und englische Fassung EN ISO 14064-1:2018 ed.). Deutsche Norm. Berlin: Beuth Verlag GmbH.

Albrecht, S., P. Brandstetter, T. Beck, P. Fullana-i Palmer, K. Grönman, M. Baitz, S. Deimling, J. Sandilands, and M. Fischer (2013). An extended life cycle analysis of packaging systems for fruit and vegetable transport in europe. *The International Journal of Life Cycle Assessment 18*, 1549–1567.

Albrecht, S., M. Fischer, P. Leistner, and L. Schebek (2021). *Progress in Life Cycle Assessment 2019*. Springer.

Benesch, T. (2012). *Schlüsselkonzepte zur Statistik: die wichtigsten Methoden, Verteilungen, Tests anschaulich erklärt*. Springer-Verlag.

Bertsche, B. and M. Dazer (2022). Berechnung reparierbarer systeme. In *Zuverlässigkeit im Fahrzeug- und Maschinenbau: Ermittlung von Bauteil- und System-Zuverlässigkeiten*, pp. 405–484. Springer.

Bhattacharjee, S., A. Sen, S. Anwar, and A. K. Nanda (2024). Geometric and harmonic aging intensity function and a reliability perspective.

Dehoust, G., M. Gsell, T. Schleicher, and R. Stamminger (2016). Einfluss der nutzungsdauer von produkten auf ihre umweltwirkung: Schaffung einer informationsgrundlage und entwicklung von strategien gegen ”obsoleszenz”. *Öko-Institut eV in Zusammenarbeit mit der Universität Bonn, Institut für Landtechnik*.

Efinger, D., A. Ostertag, M. Dazer, D. Borschewski, S. Albrecht, and B. Bertsche (2022). Reliability as a key driver for a sustainable design of adaptive load-bearing structures. *Sustainability 14*(2).

Izadkhah, S. and M. Kayid (2013, 04). Reliability analysis of the harmonic mean inactivity time order. *IEEE Transactions on Reliability 62*, 329–.

Lyndhurst, B. (2011). Public understanding of product lifetimes and durability. *Department for Environment, Food, and Rural Affairs*.

Meeker, W. Q., L. A. Escobar, and F. G. Pascual (2022). *Statistical methods for reliability data*. John Wiley & Sons.

Montalvo, C., D. Peck, and E. Rietveld (2016). A longer lifetime for products: benefits for consumers and companies.

Mood, A. M. (1950). Introduction to the theory of statistics.

Oehme, I., A. Jacob, L. Cerny, M. Fabian, M. Golde, S. Krause, C. Löwe, and H. Unnersta (2016). Strategien gegen obsoleszenz sicherung einer produktmindestlebensdauer sowie verbesserung der produktnutzungsdauer und der verbraucherinformation.

Papoulis, A. (1965). *Probability, random variables and stochastic processes*. McGraw-Hill series in systems science. New York: McGraw-Hill.

Rudenauer, I. and S. Prakash (2020). Ökonomische und ökologische auswirkungen einer verlängerung der nutzungsdauer von elektrischen und elektronischen geräten.

Stocker, T., D. Qin, G. Plattner, et al. (2013). Intergovernmental panel on climate change ipcc (2013). climate change 2013: the scientific basis [r].

Wang, F., J. Huisman, A. Stevels, and C. P. Baldé (2013). Enhancing e-waste estimates: Improving data quality by multivariate input–output analysis. *Waste management 33*(11), 2397–2407.