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Sustainable Asset Management: Introducing a Framework for Lifetime Extension

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Abstract: Extending asset lifetime is increasingly recognized as a fundamental sustainability expectation, contributing to the conservation of material and energy resources. The growing business interest in sustainability is driving momentum in this area, supported by emerging experiences, innovative technologies, evolving definitions, new standards, and regulations. This paper aims at proposing a framework that enhances the consistency of this approach. The framework will be illustrated through case studies involving real electrical products used in safety applications.

Keywords: Asset Management, Useful Life, Digital Twin, Sustainability, Artificial Intelligence, Expert Views, Standardization, Ex-Ante, Ex-Post, Salvage Value, Predictive Maintenance, Electrical Power Industry

1.Introduction

Sustainability is increasingly crucial for the health of our planet. Extending the lifetime of products plays a significant role in this endeavor, as it reduces manufacturing carbon emissions, prevents abiotic resources depletion, and minimizes waste compared to purchasing new products. This renewed focus on sustainability has been further fueled by the rapid advancement of the Internet of Things (IoT) and developments in Artificial Intelligence. In this paper, we will show an application on power products such as connected circuit breakers.

Sustainability transcends various domains, necessitating a systemic and verifiable approach. This growing need for consistency has sparked significant efforts to standardize definitions and concepts, and further progresses are still needed. For instance, the term "lifetime extension" remains open to interpretation—which baseline should be considered for an extension, and which extension to account for? In this paper, we will reference the standards set forth by the International Electrotechnical Commission (IEC). As illustrated in Figure 1, derived from the IEC 15686-4 standard on Buildings, the perception of an asset's lifetime—and thus its associated baseline—evolves throughout its life. It is noteworthy that, while distinct, human life expectancy also changes over time.

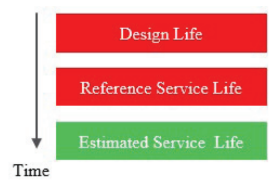

Figure 1: Evolution of lifetime perception over time, derived from IEC 16586-4. From Ex-Ante (red) to Ex-Post (green)

The lifecycle can be divided into two distinct phases: the initial phase, where estimations are made prior to actual use phase, based on simplified mission profile assumptions (design life, which is independent of any specific asset supplier, Reference Service Life (RSL), mapping product with supplier data), and the use phase, which utilizes data reflecting real-world operation, maintenance, and environmental conditions. In economics and finance, these phases are referred to as Ex-Ante (red in the

Figure 1 diagram) and Ex-Post (green in the Figure 1 diagram): this wording will be used in the paper. During the Ex-Ante phase, accelerated testing may be employed to assess product lifetime. At the end of this phase, Environmental Product Declarations (EPD) are developed, relying on a RSL as shown in Figure 1 (Energy management Research Center, 2023). RSL is often a numeric estimate for lifetime estimation that is agreed upon and used as an industry standard on simplified mission profile assumptions.
Conversely, the Ex-Post phase benefits from actual data related to the specific product's operating environment and maintenance history, as well as field observations from installed base of similar products. This allows new estimations and a revised baseline to be established. It is important to note that current off-the-shelf design simulators often face limitations in accurately simulating aging, due to the complexities of multi-physics interactions among product components during the Ex-Ante phase. Ex-Post analytics serve as a valuable method to address these challenges.

This paper is organized as follows: Section 2 provides an overview of sustainability elements for the lifetime extension discussion, Section 3 introduces key technologies, and Section 4 initiates a framework for advancing the initial concepts presented in (Hossenlopp and Chevalier, 2024). This framework discusses lifetime estimation for both the Ex-Ante and Ex-Post phases, explores strategies for extending product lifetimes, and addresses decision-making options that balances sustainability and financial considerations. Examples from the electrical energy sector are illustrating these concepts.

2. Sustainability and the renewed interest on lifetime extension

2.1. Saving resources valuation

Resource savings are crucial from both sustainability and financial perspectives, the latter being vital for driving sustainable initiatives. Extending the lifespan of a product allows to postpone the need for new manufacturing: this not only conserves energy that would have been consumed in production (translated into reduced carbon emissions, considering the carbon footprint associated with the energy mix used in the manufacturing process), but also preserves abiotic resources (Schneider Electric, 2022).
From a financial standpoint, prolonging a product's lifetime positively impacts amortization, cash flow requirements, and the product's salvage value. Note that the second-hand market for the product category considered in this paper is still in its early stages.

2.2. IEC 60050-193 definition

As standards continue to evolve, the on-going IEC 60050-193 development (IEC, 2024), which defines concepts related to circular economy and material efficiency, presents an insightful lifetime diagram, simplified in Figure 2.

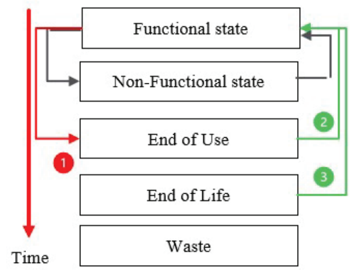

Figure 2: Evolution of a product state over time (derived from IEC 60050-193)

The initial feedback loop between the functional and non-functional states pertains to repairs until they are no longer feasible, which may include factors such as the availability of spare parts or software patches. A product may reach its end of use (arrow 1) while still operational due to being no longer needed, failing to meet performance, or standard or regulation compliance. However, it might still be reused by the same owner in a different location (arrow 2), sold in the second-hand market to a different owner, or upgraded to meet new requirements. Eventually, when the product is no longer reusable, it reaches its end of life, but some components may still be salvaged as spare parts (arrow 3) instead of immediately being sent to waste.
In this diagram, the ability to estimate the aging of the product and its components is crucial for anticipating non-functional states. It plays a significant role as well in determining which spare parts can be reused from a product at the end of its life.

2.3. Portfolio and spare part management

As mentioned in a previous section, the lifetime baseline is often equated with the Reference Service Life (RSL). However, this approach is unlikely to accurately reflect real-world conditions. Modeling when a product will no longer be needed or whether it can be reused by the same owner is complex because of the multiple usages possibly in a site or within multiple sites for instance. This situation is a typical candidate for AI engineering.

The prior section emphasizes the importance of conducting Ex-Post evaluations using real-life data, which reveals two key elements:

- The end of useful life is not sufficient for defining lifetime baseline: there may be multiple lifetimes for a given product.
- Beyond the product itself, the embodied components that can be reused as spare parts should be analyzed to maximize reuse.

To effectively manage this, it is essential to implement asset portfolio management strategies that determine when and where to reuse an asset with a given performance level. Additionally, a smart spare parts management system is needed to facilitate the reuse of spare parts that have a certain age.

3. New technologies enablement

3.1. Iot

Modern architecture is made of three main layers, as shown on Figure 3:

- Smart products. In the picture, this is a low voltage circuit breaker.
- Analytics. In this paper's context, this is about lifetime extension analysis and decision support.
- Service layer. Specialized people ("managed services") are interpreting and complementing the software results, for instance computing financial and carbon benefits related to lifetime extension.

Figure 3: Modern IoT Architecture considered in this paper.

A concrete example of lifetime extension opportunity was identified at one of our customers' last year, where the improper operation of the air-conditioner has led to an accelerated corrosion on one part of the circuit breaker. The software was not connected to the air conditioner, so managed service team had to identify additional data to make a recommendation.

3.2 Artificial Intelligence

Recent advancements in Artificial Intelligence (AI), particularly in Machine Learning (ML) and deep learning, have significantly advanced industrial system health monitoring and predictive maintenance. The ability of AI algorithms to analyze vast quantities of complex sensor data, identify subtle patterns, and learn from historical trends, has enabled new capabilities. This includes the early detection of anomalies and the prediction of impending failures with unprecedented accuracy, minimizing downtime, optimizing maintenance schedules, and improving overall system reliability. The most employed AI techniques for such tasks are ML, and mainly:

- Supervised Learning, which involves training algorithms on labeled datasets to predict future outcomes. Common techniques include regression for predicting a continuous value, such as Remaining Useful Life (RUL), and classification when the aim is to categorize system health into different classes (e.g., healthy, degraded, faulty).
- Unsupervised Learning, which involves finding patterns and structures in unlabeled data. Common techniques include clustering for grouping similar operating modes or fault types, and anomaly detection when the goal is to identify unusual behavior, which could indicate a latent fault, meaning a deviation

from normal operating conditions that not yet cause noticeable symptoms, but may eventually lead to failure.

4. Framework

4.1 Introduction

The proposed framework described in this section is made of three parts, each of them made of three blocks, see Figure 4.

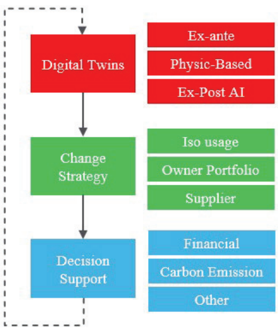

Figure 4: High level framework

It starts by the digital twin aiming at estimating the remaining useful life of a product or its component usable as spare parts. The "Change Strategy" block analyses the way to extend the asset life, compared to purchasing a new product. Finally, decision support is about valuing the scenario of keeping or replacing. The feedback loop is regularly checking that the expected benefits are realized if decision to change is made, contributing to their permanent improvements.

4.2 Digital twins (lifetime estimation)

During the Ex-Ante and Ex-Post phases, our efforts are consistently aligned with the mission profile anticipated at the conclusion of the process. We make necessary adjustments based on the insights we gather throughout this journey, collaborating closely with relevant Subject Matter Experts across various technologies, including electronics, mechanics, lubricants, plastics, electrotechnics, magnetism, and plasma physics for current interruption. This collaborative approach enables us to effectively monitor our progress in relation to the product's expected lifetime (see Figure 5, where we can see the expected life under certain conditions, for subparts A, B… varying from 0 year in the center, to 50 years on the outside of the circle), (Chevalier, 2022).

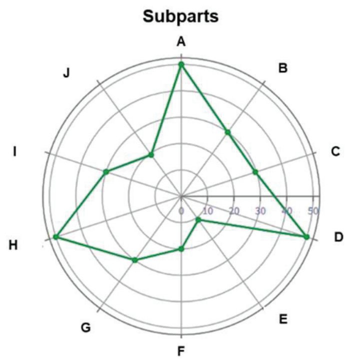

Figure 5: Illustration of the lifetime expectancy by subpart, at a given stage of the product lifecycle.

4.2.1 Ex-Ante – Design

In the Ex-Ante phase, our focus is on establishing a baseline for estimating the lifespan that the design and manufacturing phases can confer to the asset. This estimation primarily relies on insights gained from previous similar assets (or components) and on the anticipated lifespan improvements stemming from the innovative design of critical components within the asset. Additionally, this analysis can be enhanced through Design-of-Experiments and accelerated life tests conducted on specific parts requiring lifespan evaluation. The resulting metric will be termed the Reference Service Life, which will be refined further once the asset is operational under real-world conditions (see next section).

4.2.2 Physics-based model, from Ex-Ante to Ex-Post

In the Ex-Post phase, our objective is to refine the baseline life estimation established during the Ex-Ante phase. This refinement will be primarily based on the mission profiles under which the asset operates.

Fostering the assumptions made during the Ex-Ante phase, along with insights from physical laws found in literature, laboratory test results, and field data, we can estimate the duration until the asset has "consumed" its allocated lifespan. This estimation considers the environmental conditions, usage patterns, and maintenance practices relevant to the asset's operation (Chevalier M. et al, 2021).

However, a limitation of this phase is that two similar products, manufactured simultaneously and operated under identical environmental, usage, and maintenance conditions, will yield the same lifetime estimation. To address this limitation, we must account for specific, minor differences that may arise for example during the manufacturing process. Although Statistical Process Control enables high reproducibility in asset manufacturing, variations in lifetime can still occur due to subtle differences in manufacturing constraints, such as materials, operating modes, and environmental factors. Also, physics-based models, while valuable, cannot encompass the full complexity of all degradation mechanisms. This is particularly true for mechanisms with inherent complexity and randomness, such as electrical arcing in breakers, where the induced degradation is difficult to model with precision.

To enhance our analysis, we have integrated specific sensors into our assets, allowing measurements of combinations of individualized components, such as contact depression or opening speed for circuit breakers. This phase serves to further refine the Ex-Post analysis and will be elaborated upon in the following section.

4.2.3 Ex-Post AI

To further refine the Ex-Post analysis and overcome its main limitation described in previous section, AI-driven approaches are employed. Those approaches do not only leverage AI: they also leverage IoT sensors, and particularly sensors that monitor degradation phenomena as close as possible to their sources.

In this context the power of AI techniques resides in their ability to learn from past observations, coming from labs or from the field, analyze vast quantities of data (often time series) and automate the process of building a model dedicated to a specific task. In the field of health assessment and failure prediction, those tasks are typically:

- State Classification: accurately classifying the current state of a system (e.g., healthy, degraded, faulty).
- Anomaly Detection: identifying unusual patterns or deviations from normal behavior can provide early warnings of potential problems, allowing for proactive maintenance before failures occur.
- Failure Prediction: accurate and real time estimation of the Remaining Useful Life (RUL) of a system or component.

These tasks are interconnected and often built upon each other. For example, anomaly detection and state classification are often first steps before running failure prediction models. Indeed, anomalies not only trigger alarms but may also disable the capability to run a failure prediction model if such behavior has never been seen in the data the ML was trained on. Regarding the state of the system, it may condition the failure prediction as each system state may have its own failure prediction model (because of different degradation and failure modes).

However, these approaches face challenges. Firstly, they require large, high-quality datasets for training, representing good operations, failures, and ideally anomalies. Secondly, the reliability of these approaches is inherently linked to the quality and reliability of the sensor data itself. Sensors can degrade, malfunction, or be subject to noise and interference, potentially leading to false alarms or missed detections. This highlights the need for robust sensor validation techniques and the development of AI algorithms that are resilient to sensor imperfections. Thirdly, the complexity of AI models can make their interpretation and explainability difficult.

Rather than relying solely on AI-driven techniques, we believe in hybrid approach which combines AI models with subject matter expertise. This knowledge can include physics-based models, expected behavior, influential factors and their importance, limits of inferred parameters, results from endurance tests, and typical signatures for detecting specific anomalies.

These emerging techniques offer a compelling solution to several challenges in prognostics. Firstly, they mitigate the reliance on large datasets, which are often scarce in real-world applications. Secondly, by integrating physics-based models with sensor data, they enhance robustness and reduce dependence on potentially noisy or incomplete sensor information. Finally, the incorporation of expert knowledge facilitates a more transparent and interpretable assessment of RUL. The widespread adoption of AI-driven health monitoring and failure prediction solutions is still in its early stages due to ongoing challenges. However, promising results, such as those demonstrated for health estimation of distribution transformers (A Cathignol, 2024), highlight the large potential of these techniques.

4.2.4 Smart combination of both approaches

Physics-based and AI-based models offer complementary approaches to system-level prognostics. This synergy is particularly valuable in complex assets where comprehensive sensing may be limited by factors such as:

- Sensor availability: suitable sensors for specific aging mechanisms may not exist (for instance: fatigue crack initiation and propagation, lubricant degradation, or polymer degradation).
- Integration constraints: physical limitations or design considerations can hinder sensor integration.
- Harsh environments: extreme operating conditions may preclude sensor deployment.
- Cost: the expense of sensors, data acquisition, and transmission can be prohibitive.

By employing physics-based models to estimate the age of unmonitored components and AI-driven or hybrid AI-driven approaches to predict failures using sensor data from monitored components, a more holistic and accurate assessment of the asset's RUL can be achieved. In the next section, a practical example on a Medium Voltage (MV) breaker is provided.

4.2.5 Application on MV breaker

Extensive digital sensors have been implemented recently in a new, more robust, and smart Vacuum Circuit Breaker, presented in (V. Kraynov 2022),. Those sensors tackle:

• the mechanism speed sensor, through rotative speed measurement.

• the vacuum interrupter erosion gap sensor.

• the tripping coils current sensor.

• the charging motor current sensor.

A detailed description of these sensors can be found in [11]. Thanks to those sensors, the development of AI-driven failure prediction could be started. As described in 4.2.3, ML algorithms require datasets for training, and these datasets must include examples of failures. Algorithms are trained to predict failures and can only do so if they are trained on failure data. This was made possible through accelerated aging campaigns conducted until failures occurred (El Khouri et al. 2023). The development was first focused on the erosion gap sensor that effectively captures several ageing mechanisms occurring in the contacts and the mobile poles. The algorithm that was developed aims at predicting the remaining number of operations before reaching a critical level of the erosion gap. This algorithm achieved an accuracy of over 90% in predicting the remaining number of operations. Details about this methodology and its results are presented in (El Khouri et al. 2025).

This RUL covers the ageing mechanisms that occur in the contacts and mobile poles. However, other ageing mechanisms from other subparts are not covered by this sensor, nor by the other embedded sensors: they are addressed by physics-based models (see Figure 6).

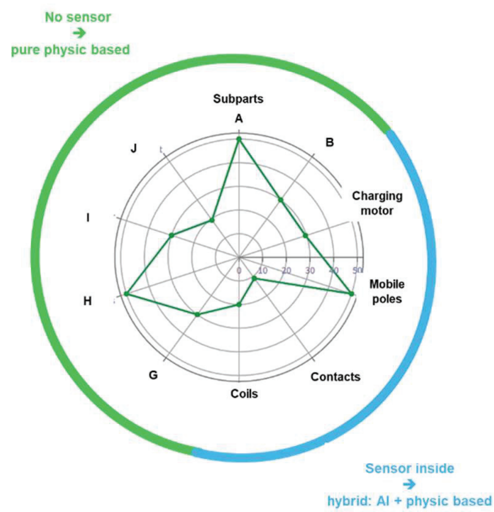

Figure 6: Combined physics-based and AI-driven approach for assessing age and estimating Remaining Useful Life respectively. Illustration of a possible state at a given stage of the asset lifetime.

4.3. Change Strategy

This section introduces options for extending the product life.

The first use case focuses on maintaining the product for its current mission, possibly upgrading it. Decisions regarding changes, supported by the IoT architecture, include:

- Updating the maintenance policy: transitioning to preventive maintenance strategies, for instance (Arnaud Rival, 2020)
- Adapting to evolving environmental conditions: typically, prioritizing factors such as humidity and temperature.
- Modifying operating conditions: usually coordinated at the system level.
- Upgrading for performance improvement: enhancing performance while reusing existing hardware components of the product.

Transitioning to the owner portfolio introduces additional options:

- Asset reallocation: balancing asset performance with risk tolerance.
- Spare part management: reusing spare parts from assets approaching the end of their life cycle.

Some activities require close collaboration with suppliers and users:

- Extending spare part availability: this may involve offering compatible upgrades.
- Facilitating circular economy practices: promoting the reuse of products and spare parts while maximizing salvage value, then recycling.

4.4. Decision support

This part aims at comparing multiple scenarios (extending vs. replacing, as defined in the previous section) using a multi-criteria approach that evaluates financial, carbon, and risk factors to prioritize actionable recommendations.

Several key dimensions must be considered:

- Asset equivalence: assess the potential equivalence of the current asset with other assets for replacement. From our experience (typically on aging three-phases Uninterruptible Power Supply), this is also the right time to possibly resize an asset according to its historical usage, and optimize its future energy consumption; or to optimize at the system level, new assets possibly replacing multiple ones.
- Carbon accounting: implement a carbon accounting template that has been audited (to prevent greenwashing). This template must integrate the system view: in the example given earlier, the full carbon impact of the air-conditioner reducing humidity.
- Financial accounting template: develop a financial accounting template likely to be customized to meet specific needs. This should encompass total cost of ownership, Net Present Value (NPV), depreciation, and tax impact.
- Risks criteria: consider other factors such as reliability vs criticality, anticipated future changes, flexibility to accommodate process evolution and user acceptance.

The decision-making process will leverage a combination of software tools and expert advice to ensure comprehensive analysis and recommendations.

5. Conclusion

Lifetime extension plays a crucial role in sustainability by promoting resource conservation and influencing the increasingly significant Green House Gas (GHG) scope 3 calculations (Green House gaz Procol, 2020). This paper highlights the necessity of refining a framework to better characterize and increase lifetime. Accurate real-world measurements are essential to enhance these estimations, and it is vital to reconcile sustainability and financial considerations.

From a sustainability standpoint, emerging rebound effects (David Font Vivancia et. al, 2016) may also impact product lifetime, underscoring the value of a dynamic analytical approach. For instance, in the case of circuit breakers, high-frequency signals resulting from the widespread integration of renewable generation and power electronics, while contributing to sustainability, have traditionally been unmodeled but are expected to impact product longevity.

We propose several recommendations to enhance product design and lifetime services, introducing new trade-offs to consider. The suggested analytic solutions emphasize an "iso-design" approach for connected products, extending their traditional resource aspects. Further analyses are anticipated on topics briefly mentioned, including portfolio management, smart spare parts management, upward compatibility, and partial reuse. Additionally, simplifying these concepts for non-connected products presents another avenue for future research.

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