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Lifecycle Option Selection in Early Design Stages Based on Degradation Model Evaluation

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Abstract

Components of modern systems are characterised by differing lifetimes. The resulting lifetime heterogeneity (LTH) is a core criteria to determine life cycle options (LCO) for more sustainable products, e.g. by upgrading or reuse. Estimating the lifetimes is challenged by a lack of suitable degradation models (DM) describing the detrimental change performance of components during the use phase. This paper expands the state of the art in LCO selection by a method to evaluate fitness and sensitivity of DM based on the similarity of use cases, environments and operation profiles of the system.

Keywords: life cycle, sustainability, product architecture, design for x (DfX), model-based systems engineering (MBSE)

1. Introduction

Behaviour and performance of technical products are affected by degradation. From a technical viewpoint *degradation is the detrimental change in physical condition, caused by time, use or external influences*. Ultimately degradation results in the inability of a component or whole product to perform its function - generally indicated as a failure. A sound understanding of the degradation of subsystems and components is an essential criteria for the engineering of more sustainable products. Knowledge about the specific degradation mechanisms is needed to improve the ratio of the deployed material and energy and the provided value of the product by enhancing the operating lifetime or implement resource circulation paths. Current systems, however, are characterized by numerous and strongly interacting subsystems that stem from different engineering domains and are based on heterogeneous and emerging technologies. In consequence degradation mechanisms differ for each subsystems. For long-lasting systems like aircraft systems, strategies are established to handle the resulting heterogeneity of the lifetimes of subsystems by maintenance, refurbishment, replacement or upgrading, e.g. Ahmadi *et al.*, 2010. These strategies, also referred to as lifecycle options (LCO) (Umeda, 2001), are driven by economic and more often sustainability criteria. The LCO have to be implemented by suitable product architectures (PA), enabling for instance simple exchange of subsystems or components during the use phase. The interaction between established LCO and PA get challenged, when new technologies are integrated and architectures of systems are changing fundamentally. This is applies for most products that transform form predominantly mechanical systems into mechatronic systems involving an increasing amount of solution elements form software and electronic domain. At the same time an increasing mix of technologies, e.g. applied in power train systems of vehicles, is challenging established LCO for subsystems like batteries. A major challenge is to estimate the lifetimes of subsystems and components used in new fields of application, since there are limited information on the specific degradation mechanisms. For instance there are very limited information on the degradation of

Li-Ion cells used in power systems of aircrafts. To support identification of LCO in early design stages, this paper introduces a method to evaluate the uncertainty of degradation models (DM) based on the similarity of use cases, environments and operation profiles of the system under development. This method is an important element to investigate the lifetime heterogeneity (LTH) induced by new technologies and recent operation profiles and conditions. This LTH resulting on system level provides a sound basis to define LCO to increase sustainability of products.

1.1. Lifecycle Selection based on Lifetime Assessment

Lifecycle planning is a core task of lifecycle development, aiming to specify the product and its lifecycle and establishing eco-design concepts (Kobayashi, 2005). Focusing on environmental impacts, resource circulation paths, referred to as lifecycle options (LCO), have to be defined for subsystems and components. In general these LCO can be classified into *ownership transfer*, *use continuation*, and *design modifications strategies* (Umeda, 2001), that are implemented for instance by upgrade or maintenance, product and component reuse or material recycling. The different LCO require specific product architectures (PA) enabling for instance efficient replacement or reuse of single components. Table 1 provides an overview of basic LCO and references for the definition of modules for PA development. This overview indicates basic strategies for PA development and essential weighting attributes used to select a LCO. Like indicated in Table 1, the expected lifetime of a component is an important criteria to be considered in order to define resource efficient LCO.

Table 1. Lifecycle Options, Weighting Attributes & Design Strategies, c.f. Umeda *et al.* (2008).

Lifecycle Option	Weighting Attribute	Basic Strategy for Module Definition
Recycling	Constituent materials	Grouping components of which materials can be recycled without separation
Maintenance	Physical Lifetime	Grouping components with short physical lifetime for easy replacement
Reuse	Physical/Value Lifetime	Grouping components with long physical/ value lifetime
Upgrading	Value Lifetime	Grouping components with short value lifetime

Existing methods to select LCO focus either on the whole lifecycle, e.g. (Umeda *et al.*, 2007) or single lifecycle phases like end of life, e.g. (Herrmann *et al.*, 2008) or single LCO like reconfiguration, e.g. (Umeda *et al.*, 2005), or upgradeability e.g. (Inkermann *et al.*, 2018) and changeability (Rose *et al.*, 2001). Kobayashi (2005) focusses of the identification of design targets and supports the selection of LCO by a QFD from development perspective by integrating customer and environmental requirements and lifecycle analysis results of a baseline product. LCO are prioritized based on the ratio of the useful lifetime and value lifetime of a product or component. Umeda *et al.* (2007) propose a methodology to select LCO based on a disposal cause analysis. Again, here, the ratio of two lifetime perspectives, referred to as value and physical lifetime, are used to define the LCO for components. Based on the identified LCO, modular product structures can be developed that aggregate components with similar lifecycle properties and take into account geometrical feasibility (Umeda *et al.*, 2008), functionalities or communality for reuse (Kimura *et al.*, 2001). The methods proposed by Kobayashi and Umeda *et al.* point out the expected lifetime as a main criteria for LCO selection. However, they provide low assistance to determine the lifetimes of components, rather the evaluation is based on the direct comparison of value and physical/ useful lifetime derived from previous applications. This paper focusses on the evaluation of degradation models (DM) taking into account new technologies and the recent operation profiles and conditions of subsystems in early design stages. Here the focus is on the physical degradation and resulting physical lifetime, c.f. section 2.1.

1.2. Objective, Methods and Structure of the Paper

The purpose of this paper is to show, how uncertainty of degradation models (DM) can be handled to support LCO in early design stages. It is highlighted how basic influences on the degradation can be evaluated and transferred to changed operation profiles and environmental conditions expected for the

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system under development. Therefore, the informational value of existing DM is assessed based on the analysis of changed use cases and their operational and environmental requirements. The proposed method assists to evaluate the degradation to be expected for single components. This paper expands the state of art in LCO selection for more sustainable products by the following contributions:

- A refined definition of lifetime dimensions and basic degradation mechanisms to be considered for LCO selection;
- An aligned classification of DM to be used in LCO selection;
- A new method to evaluate uncertainties of DM and impacts on the LCO selection process.

Further parts of tis paper are organized as follows: Section 2 introduced the fundamentals of degradation modelling and basic lifetime dimensions relevant for LCO selection for more sustainable products. In Section 3 a method to evaluate uncertainties of DM when applied to new field of applications is introduced. Section 4 highlights the procedure using the example of a Li-Ion battery for the power system of an all-electric aircraft. In Section 5 a summary is given and future research is outlined.

2. Degradation Modelling

Generally spoken degradation is the process in which the quality of something is destroyed or spoiled. Degradation models (DM) describe the relationship between the influencing factors and the detrimental change of specific system properties. Formulation of DM requires both, a description of how degradation affects the ability of the system to perform its function and the definition how degradation is influenced by the way the system operates (Zagorowska *et al.*, 2020). Kang *et al.* (2020) distinguish between degradation law modelling, describing the tendency of the degradation level, and stochastic process modelling, representing both the trend and fluctuation of degradation. While there is a number of degradation law models, representing the functional relationship between degradation time or degradation quantity and the degradation cause like the fracture mechanism theory, the main uncertainty for degradation prognosis results from the environmental and working conditions as well as the cognitive uncertainty due to a lack of information. This section introduced basic degradation mechanisms to be considered for LCO selection and provides a classification of physical degradation models to be used for lifetime assessment in early design stages.

2.1. Basic Degradation Mechanisms and Lifetime Dimensions for LCO Selection

A major objective of lifecycle planning is to produce enduringly valuable systems (Browning and Honour, 2008). The value a system provides during its lifecycle called lifecycle value (LCV). However, this LCV is not constant but changes over time as a result of degradation. Degradation mechanisms relevant for LCO selection can be classified based on the principles of accumulation and evolution. Accumulation is the concept suitable to describe the basic law of physical degradation of systems. It represents the loss of required properties as a result of damage and wearing caused by working and environmental conditions. Evolution is suitable to represent the loss of performance and quality form the viewpoint of users and operators. This value degradation is a consequence of the proceeding difference between the value desired by stakeholders and the value provided by the system without taking into account the physical degradation. Based on the definition of a minimal acceptable system performance and specific failure threshold the lifetime of a subsystem or component can be determined, c.f. Table 2. Since main functions and the performance of systems appear or change depending on other systems, it is not valid to describe the degradation of a system without take into account the systems' context. Therefore, an extension of lifetime dimensions for LCO selection is proposed. Table 2 presents the proposed lifetime dimensions and underlying basic degradation mechanisms. The distinction between *context* and *physical lifetime* allows to consider external effects and neighbouring systems, needed to realize the systems functions more rigorous. The single lifetime dimensions and underlying degradation laws can be applied to single-unit systems or systems considered as a whole. However, to support LCO selection for more sustainable products the three degradation mechanisms have to be evaluated for the single subsystems and components. Although it is obvious, that in practice there are competitive degradations (Kang *et al.*, 2020), caused by coupling effects resulting from the structure of

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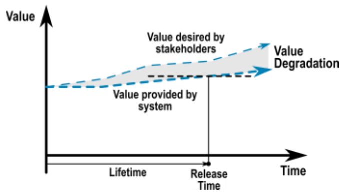
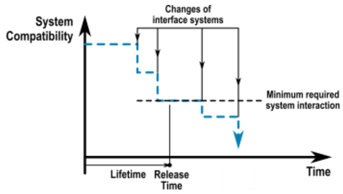
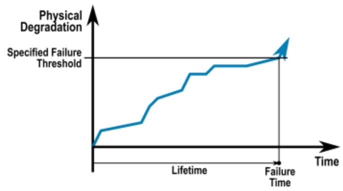
the system and the working and environmental conditions, this contribution focusses is on the physical degradation.

Table 2. Distinction of Lifetime Dimensions and underlying Degradation Mechanisms

	Value Lifetime	Context Lifetime	Physical Lifetime
Explanation	Determines the period until a system is no longer accepted by the users. The value lifetime is defined by the ratio of expected functions and performance of the system (value) and the provided system properties in a specific use case of the system.	Determines the period until a system no longer provides its complete functionalities or performance is limited due to incompatibility to interacting systems. The context lifetime is defined by the limitation or inoperability of functional and physical system interfaces.	Determines the period until a system no longer provides entire functionality or performance due to failure of subsystems/ components or significantly underrunning its performance. Physical lifetime is defined by damage, wear-out mechanisms and failure behaviour.
Degradation Law			
Degradation Mechanism	**Divergence** of system functions/ performance and stakeholder needs caused by increasing and changed stakeholder requirements	**Decline** of compatibility with surrounding systems caused by changes of the operational environment	Loss of systems performance and operational functionality caused by **accumulation** of wear, failure; ageing of system components
Influencing Factors	Technology development and diffusion social trends and conventions	Evolution of infrastructure and legislation Technology evolution of interfaces	Physical and chemical properties load profiles environmental conditions

2.2. Classification of Physical Degradation Models

Degradation models (DM) describe the relationship between influencing factors and the detrimental change of system properties for different types of influencing factors, degradation processes, and applications. Effectiveness and accuracy of a DM increases when it is able to capture the specific environment and operation conditions and their effects of the system property under investigation. Based on the available knowledge about the process and influencing factors, DM that are frequently used for prognostic applications can be classified into physical models, data-driven models and knowledge-based models (Zagorowska *et al.*, 2020). Physical models are based on physics-of-failure approaches (Modarres *et al.*, 2017) and focus on the process of degradation like erosion or wear taking into account influencing factors like physical and chemical properties of material or load profiles. Data-driven models are developed using data learning techniques applied to information of system state and performance collected over time (Meeker *et al.*, 2011). Knowledge-based models are based on cognitive experience of mankind (Kang *et al.*, 2020) and thus provide a knowledge-based description of degradation without physical interpretation. Detailed reviews and classifications of degradation models are for instance provided by Zagorowska *et al.* (2020) focussing on control systems, e.g. Le (2015) focussing on prognostics in general or e.g. Gorjian *et al.* (2010) focussing on reliability analysis. Following the classification proposed by Zagorowska *et al.* (2020), most relevant for the method proposed to evaluate the uncertainty of degradation models in early design stages, are factor-based DM describing the degradation depending on different influencing factors. Table 3 gives an overview of factor-based degradation models and their basic character. Models of physical degradation and reliability-oriented models are case-specific. Constants and influencing factors in these models have to be defined for the application and its operational and environmental boundary conditions at hand.

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Heuristic models are application specific and provide more general but less exact information about degradation for single applications like batteries in electric vehicles (Fang *et al.*, 2017). The examples given in Table 3 indicate the complexity of the degradation models resulting from the number of influencing factors included and demands for parameter definition given by the model parameters.

Table 3. Characterization of Factor-based Degradation Models, c.f. Zagorowska *et al.* (2020)

	Physical Degradation Models	Reliability-oriented Models	Heuristic Models
Application	Focussing on early stage of degradation and are based on **physics-of-failure** approaches and knowledge about physical and chemical properties, load profiles, environmental conditions, failure	Focussing on the end of the degradation period **Parametric models** are based on physical relationships (see models of physical degradation) **Non-parametric models** use proportional hazard models	No focus on a specific phase of degradation based on knowledge and experience about process and influencing factors of degradation for specific applications
Character	Provides accurate models of degradation Is complex and requires detailed knowledge about degradation	Captures uncertainty nature of degradation Requires knowledge about past degradations	Is tailored to the application Does not have any interpretation
Use	Case specific	Case specific	Application specific
Example	Physical model of battery aging, capacity loss in % (Suri und Onori, 2016), c.f. Table 4	Arrhenius life relationship $d = A\exp(-BT)$ with constants A, B and influencing factor T (temperature)	Heuristic for battery aging (Fang *et al.*, 2017) $d = V_s - V_b$ with voltage corresponding to the electrode surface V_s and the inner part of electrode V_b

The introduced classification indicates the need of detailed knowledge about the impact of internal and external influencing factors on system state and performance. This information in most cases are derived from past applications (degradation data) of in field products or accelerated degradation tests (Meeker *et al.*, 2011). Focussing on early design stages and conceptual decision-making there is the need to provide consistent but less exact information about the degradation of components and subsystems in the intended applications. Therefore, in the following Section a method to evaluate the uncertainty of DM based on changed operating and environmental conditions is introduced.

3. Evaluation of Degradation Models in Early Design Stages

In this section reasons for uncertainties in early design stages as well as methods to handle these are introduced. This background serves as a basis to develop a method to assess the uncertainty of DM for lifetime estimation and LCO selection in early design stages.

3.1. Reasons and Handling for Uncertainties in Early Design Stages

Uncertainties have to be considered in every stage of development. Taking into account the increasing state of knowledge gain about the product and the processes, Engelhardt *et al.* (2010) propose three categories of uncertainty, namely *stochastic uncertainty*, *estimated uncertainty*, and *unknown uncertainty*. *Unknown uncertainty* occurs in early design stages, when limited information about the future product is known and the product's properties are not determined yet (Eifler *et al.*, 2011). *Estimated uncertainty* is given, when the effects of an uncertain property are known but the probability distribution of the resulting deviation is only partially known (Eifler *et al.*, 2011). Transferred to the assessment of DM, *unknown uncertainty* is given if neither the effect of influencing factors nor the resulting derivations of the degradation path are known. *Estimated uncertainty* in degradation modelling is given, when the effect of influencing factors is known, but the probability distribution of the resulting deviation cannot be described. To cope with uncertainties in engineering design different approaches are proposed in literature including sensitivity evaluation based of model-based assessment, use of

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comparable products and the known behaviour as well as expert assessments (Eifler *et al.*, 2011). Mathias *et al.* (2011) point out that anticipating of planned behaviour and potential disturbances is essential to develop robust product concepts able to cope with uncertainties. To select physical effects he proposes three robustness ratios to measure the number of disturbances that affect the a physical effect in general, indicate the number of disturbances which affect a physical effect within the assumed environment, and to evaluate the sensitivity of an effect when reacting to the disturbances in the supposed environment. These robustness ratios allow to compare the robustness of different physical effects within conceptual design based on knowledge about the physical effect, its formula and potential disturbances occurring in the environment of the product under development. In this contribution the basic idea of robustness evaluation and sensitivity analysis is transferred to DM. Therefore, expected changes of operational and environmental conditions as well as an analysis of the sensitivity of a DM with regard to changed influencing factors are in focus. With regard to the DM described in Section 2.2, only physical degradation indicating the physics-of-failure as well as reference use cases providing knowledge about the lifetime to be expected is considered.

3.2. A Method to Evaluate Uncertainties of Degradation Models

Objective of the proposed method is to support LCO selection in early design stages based on the evaluation of existing DM. To cope with the given uncertainty in the early design stage, insights for the degradation to be expected are derived from a reference DM and its case-specific form as well as changed influencing factors and their impact of the expected degradation. The method includes 4 steps. Starting point for the uncertainty evaluation of DM is the definition of use cases for the future product as well as a first model of its basic system architecture. Results needed in the different steps of the method are supported by Model-based Systems Engineering (MBSE). In particular information are derived form a use case diagram and an internal block definition diagram, representing the components and their functional interactions (Wymore, 2018). In the last step conclusions can be drawn on the range for the physical lifetime of a component and suitable LCO for components. Steps of the method and required information are introduced in the next subsections.

3.2.1. Definition of Use Cases and Basic System Architecture

In a first step use cases and the basic structure of the system under development have to be defined. This are common tasks in MBSE (Wymore, 2018), providing insights on recurring applications and basic requirements within the use phase of the system. Aside from basic functions to be fulfilled by the system, the use cases are used to specify the environment the system is used in as well as to derive requirements. For instance for a full electric powered vehicle use cases are *charging of traction battery*, *overland travel* or *city tour*. For each use case basic requirements like *required power*, *peak performance* or *maximum/average duration* can be determined. Thus, the use cases and linked requirements provide insights on different load profiles. In addition to the use cases a first model of the system architecture is needed to draw conclusions regarding the functionality of single components in the different use cases. In the use case *charging of traction battery* for instance electric motors of the electric power system are not involved and thus there will not be affected by degradation.

3.2.2. Identification of Reference Applications and Existing Degradation Models

In the second step similar products, components and applications are identified based on the defined use cases and system structure. Essential criteria to select reference applications are similarities in the basic system architecture, similar use cases as well as comparable technologies of the single components. When identifying reference applications a system perspective is appropriate since on this level use cases can be compared effectively. In addition to comparable products it is required to identify existing DM. To enable an informative evaluation of the DM, physical DM in most cases are appropriate since these indicate the effect of single influencing factors on the degradation, c.f. Table 3. At the same time these models have to be tailored for the specific application by determining model parameters. Since these information do not exist in early design stages knowledge about the specific degradation have to be derived from the reference application. For most components and applications there are tailored DM available that can be used to estimate the expected lifetime.

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3.2.3. *Identification of Changed Influencing Factors and Sensitivity Evaluation of DM*

To evaluate the expected degradation behaviour of the component under development, in the third step changes of influencing factors have to be identified and the impact of these changes on the degradation have to be evaluated. As a basis for this evaluation serve the identified DM and the included influencing factors. Changes of the influencing factors can be derived when comparing the use cases of the reference product and the system under development. To indicate changes of the single factors not only a conclusion (is changed/ is not changed) but a trend (increased/ decreased) has to be indicated. In addition to the change of single influencing factors, the sensitivity of the DM for the expected change has to be indicated. Therefore, the sensitivity dependent robustness ratio (R) proposed by Mathias *et al.* (2011) is used. This ratio can be calculated by the following formula:

$$R = \frac{1}{1+\sum S_n} \tag{1}$$

Where S_n is the sensitivity of the DM of each changed influencing factor form 0 (insensitive) to 1 (sensitive). In case a high sensitivity is stated, R becomes < 1 and the informational value of the existing DM for the new application context is limited. To assess the sensitivity of the DM for each changed influencing factor on the one hand the given DM can be used, on the other hand conclusions can be drawn from different applications, e.g. load profiles, of the reference product.

3.2.4. *Drawing Insights for LCO Selection*

Based on the identified changes of influencing factors and the evaluation of the sensitivity of the existing DM in the last step insights for the definition of LCO are drawn. These insights on the one hand address the basic LCO like reuse, recycling or maintenance, c.f. Table 1. On the other hand based on the evaluation of the DM the uncertainty of the expected lifetime is indicated. In order to define the physical lifetime an application specific degree of degradation has to be defined. This definition should be made taking into account the requirements defined in step one of the method and are thus case-specific.
The proposed method was applied for different components of the power system of all-electric aircrafts in order to evaluate the procedure and to gather information for the single steps. The following section highlights the proposed method focussing on the battery system within the power system of an aircraft.

4. Case Study - All Electric Aircraft Power System

There is an increasing demand to reduce environmental impacts of aircraft systems. Thus, current research is aiming to replace fossil-based combustion engines in aircraft systems with impacts on the overall topology as well as architectures of subsystems like the electric power system. Research within the cluster of excellence Sustainable Energy-efficient Aviation covers the single components of the power system including the battery systems, the overall topology of the aircraft as well as the lifecycle assessment focussing on short, mid, and long range aircrafts. To evaluate upcoming architectures and identify LCO for minimal environmental impact, there is a need to understand causes of varying lifetimes on subsystem and component level, taking into account emerging technologies as well as differing operation conditions. The following subsections highlight the proposed method to evaluate uncertainties of DM when applied to new applications. Here, the focus is on the battery system since this on the one hand has a high share of system weight and thus is a critical system for overall architecture design. On the other hand the battery system is expected to be a system with short physical lifetime compared to other systems within the power system of all-electric aircrafts. The reported case study is focussing on a short range aircraft using the requirements and assumptions for mission profile and basic system architecture presented in Karpuk and Elham (2021).

4.1. Use Cases, Basic System Architecture and Reference Products

Based on the mission profile and existing research on power systems for all-electric aircrafts essential used cases and a first system architecture for the electric power system covering the components of the storage subsystem, the distribution system and the electric conversion system can be defined as a baseline for evaluation. Figure 1 presents the use case diagram including first requirements and the system architecture of the electric power system. To specify the different power demands, the use cases

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and structured into the phases of a mission profile including the maximum power needed in each phase. Within the system architecture, basic interactions between the components are indicated using flows and ports in the internal bock definition diagram are presented. The battery system is assumed to comprise four batteries that are Li-Ion high power cells with a gravimetric energy density of $700\ Wh/kg$ (Karpuk and Elham, 2021).

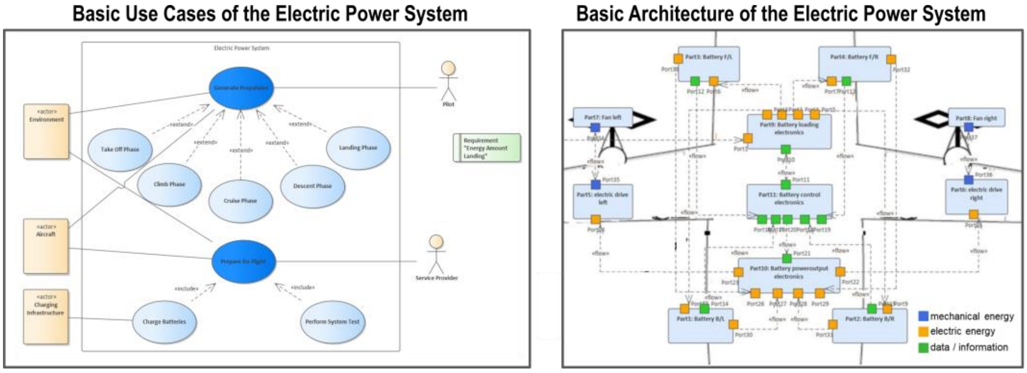
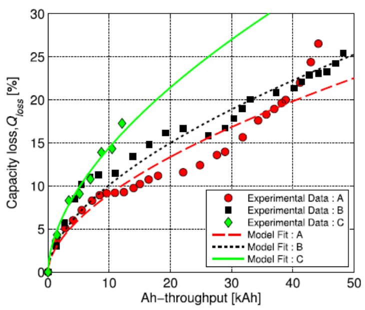


Figure 1. Use Cases and Basic System Architecture of the Electric Power System.

In automotive applications different DM can be found, describing the degradation of traction batteries for different profiles. Suri and Onori (2016) provide a physical model of battery aging describing the capacity loss for Li-Ion cells in hybrid-electric vehicles (HEV). The proposed DM indicates the influence of different profiles defined by the *state of charge*, the *average C-rate* and *average battery temperature*, c.f. Table 4. Although, this model is tailored to the application in HEV it is a sound basis to evaluate the single influencing factors and the sensitivity of changes in those since profiles for three different applications are presented. To identify the changed influence factors and the sensitivity, information about degradation presented in Table 4 are used. The curve fittings resented in the right part of table indicate the specific capacity loss for the application in HEV and therefore serve as a basis to estimate the physical lifetime to be expected in the avionic context as new field of application.

Table 4. Physical Degradation Model and Effects of Different Profiles on Capacity Loss of Li-Ion Traction Batteries in Hybrid Electric Vehicles, based on Suri and Onori (2016).

Normalized Capacity Loss to Indicate Battery Degradation	Curve Fitting of Aging Model based on Experimental Data for Three Profiles	
$Q_{loss} =$ $(\alpha \cdot SOC + \beta)\exp\left(\frac{-E_a + \eta \cdot I_c}{R_g \cdot (273.15 + \theta)}\right) \cdot Ah^{\bar{z}}$ with SOC State of charge, E_a Activation energy, I_c Current rate normalized to battery charge capacity, R_g Universal gas constant, θ internal temperature, Ah Charge throughput, $\bar{z}$ average power law exponent, and model parameters α, β, η		**Profile A**: $\overline{SOC} = 38{,}5\ \%$; $\bar{I_C} = 2{,}82\ 1/h$; $\bar{\theta} = 36°C$
		Profile B: $\overline{SOC} = 42{,}0\ \%$; $\bar{I_C} = 3{,}00\ 1/h$; $\bar{\theta} = 38°C$
		Profile C: $\overline{SOC} = 68{,}0\ \%$; $\bar{I_C} = 6\ 1/h$; $\bar{\theta} = 45°C$

4.2. Analysis of Influencing Factors and Sensitivity of DM

The use cases for the electric power system and existing DM for the reference application serve as a basis to identify changed influencing factors and evaluate the sensitivity of the given DM (step 3 of the method). The formula given for the capacity loss indicates the essential influencing factors relevant for the operation, that are the *state of charge*, the *C-rate*, and the *charge throughput* as well as the physical and chemical parameters of the specific battery, that are the *activation energy*, *power law exponent*, and the *gas constant*. Based on the use cases defined in Figure 1, changes of these influencing factors (operation) can be derived. These are: the state of charge is expected not be lower than for profiles 1 and 2 for avionic applications since an oversizing of batteries is negative for the overall system (Karpuk

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and Elham, 2021). At the same time the c-rate is expected to be much higher than given in profile C since in particular in the take-off phase there is a high power demand, at the same time charging time is critical for efficient operation of aircrafts, c.f. use case *charge battery*. Since the charge throughput is used to calculate the capacity loss no change is considered here. In addition to the changes of influencing factors, the sensitivity of the DM for each changed factor has to evaluated, using the robustness ratio given in equation 1. To evaluate the sensitivity, the aging model given in Table 4 is relevant. Assuming, that the sensitivity for the c-rate used in the exponent of the equation has a much higher than for the state of charge, the robustness ratio is calculate as $R = 0{,}625$ with ($S_{SOC} = 0{,}2$; $S_{I_c} = 0{,}4$). This clearly indicates the uncertainty to be expected for the lifetime estimation of the battery system that is to be expected significantly lower than those in automotive applications.

4.3. Draw Conclusions for Lifecycle Option Selection

Since in this case study only the battery system is considered as a single component, conclusions for LCO selection are limited. When performing the highlighted for all systems within the power system, two facts are beneficial for the definition of LCO: On the one hand the uncertainty indicated for the DM of each subsystem is a major index for rethinking existing LCO from other applications. On the other hand uncertainties resulting from the evaluation process of the DM are compensated by the assumptions that are true for every model. Moreover, since the definition of LCO is based on the ratio of component lifetime and average lifetime of the power system the effect of uncertainties within the procedure is damped. To draw conclusions for LCO selection the expected physical lifetime for each component or subsystem has to be comparted to the average lifetime of all components. The given ratio indicates the lifetime efficiency as a criteria for LCO definition (Umeda et al., 2007).

5. Conclusion, Discussion and Further Research

Driven by the demand to develop more sustainable products, in this contribution the concept of lifecycle option selection based on the expected lifetime of a component or subsystem was introduced and lifetime dimensions as well as models to describe the degradation were presented. In order to support estimation of the expected lifetime of components in new fields of application where less knowledge about the specific degradation is available, a method to assess the uncertainty of degradation models based on reference applications was proposed. The evaluation of uncertainties is based on the analysis of similarities in use cases and the identification of changed influencing factors. The proposed method and required information where highlighted using the battery system of an all-electric aircraft as an example. However, the method is not validated yet, neither it's applicability for different users nor the validity of the results are evaluated in details. Thus, it has to be understood as a first concept to be detailed with focus on the following aspects. On the one hand a more detailed analysis of degradation models and their general informational value is needed. The aim of this research strand is to build up a knowledge database comparable to know catalogues of physical effects, focussing on the selection of suitable degradation models for different details of knowledge. On the other hand research will focus on the impact of interactions between subsystems and their effects on the degradation process. These works will be performed focussing on systems with high requirements of reliability and upcoming heterogeneity of technologies like electric power systems.

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