SELECTION OF MODEL APPROACHES AND MODELLING METHODS FOR LIFETIME PROGNOSIS

Bauer, Robin Steve;
Inkermann, David

Technische Universität Clausthal

ABSTRACT

Lifetime prognoses are fundamentally important to improve products regarding safety, costs, availability and sustainability. To modelling the lifetime of a system or its components and subsystems different methods and model approaches are available, which are not compatible in any case. Depending on the system, use case and available data, the existing model approaches and modelling methods are differently suitable for a precise lifetime prediction. In this contribution a procedure was developed to help in the selection of suitable approach-method combinations. For this purpose, the compatibility of method types with the different model approaches was assessed and criteria for the pre-selection of suitable approaches and methods for lifetime modelling were defined. The selection procedure was applied to the example of entities for electric powertrains of aircraft in early design stages. Finally, the results were summarized and evaluated. The insights gained in this paper can help to enhance lifetime models of products in early design phases.

Keywords: Product Lifecycle Management (PLM), Product modelling / models, Optimisation, Lifetime Heterogeneity, Aircraft

Contact:
Bauer, Robin Steve
Technische Universität Clausthal
Germany
bauer@imw.tu-clausthal.de

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1 INTRODUCTION

Lifetime prognosis of systems is increasingly important to reduce operational and production costs, plan adjusted maintenance cycles and improve safety, reliability and availability (Wang, 2010). Moreover, there are increasing requirements concerning sustainability, that result in the demand to minimize the environmental impact of products during their life cycle. To address different life cycle options like reuse, recycling, upgrade or maintenance, it is mandatory to develop suitable system architectures in early design stages (Inkermann, 2022). Therefore, models for lifetime prognosis of systems are needed (Umeda et al., 2007), however, in early design stages and in the case of new technologies, there is a high uncertainty of lifetime prognoses. A lifetime model adapted to the system must be developed to predict lifetime as precise as possible. If a lifetime model is suitable for the considered system depends on properties and available data. The main research question of this contribution is: *What are fundamental criteria for the pre-selection of suitable lifetime models of defined systems?* The goal is to develop a procedure for the selection of lifetime models and to improve lifetime prognoses for systems in early design stages to optimise system architectures regarding costs, performance, safety and sustainability.

1.1 Challenges of lifetime prognosis due to lifetime heterogeneity

High-tech systems in particular consist of numerous subsystems (e.g. electric motors) and their components (e.g. motor coil, rotor, stator etc.), which are referred to as system entities in this paper. An example are electric powertrains for aircraft, which should be used for short-haul flights in the future (Karpuk and Elham, 2021). A simplified electric powertrain is shown in Figure 1. It consists of a battery and a battery management system (BMS) for power supply, switches and insulated-gate bipolar transistors (IGBT) to increase safety in case of failures, a high voltage bus (HV bus) to manage the power supply of different entities and a converter to control and adjust the current for the electric motor.

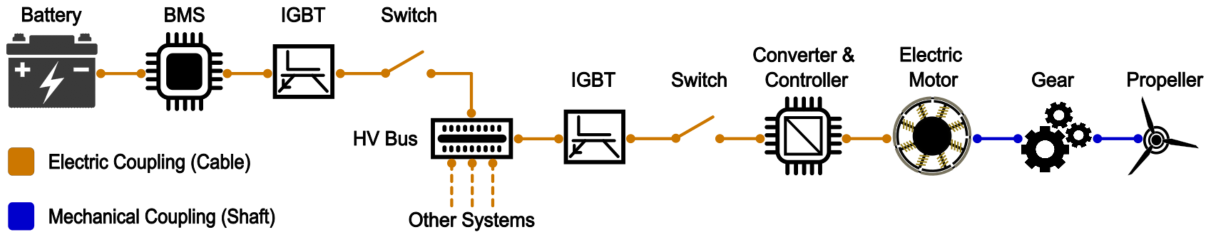

Figure 1. Simplified topology of an electric aircraft powertrain (according to Stückl (2016))

Thereby, the numerous entities of the powertrain are subject to different damage mechanisms, interactions and requirements. These influence factors lead to different lifetimes of entities and consequently to lifetime heterogeneity on system level (Umeda et al., 2007). Each entity lifetime has to be estimated as exact as possible considering different use cases with diverging influence factors like temperature, material behaviour or mechanical loads. In addition, there is a lifetime heterogeneity on entity level due to different lifetime properties like physical properties, customer acceptance or legal regulations, see Figure 2.

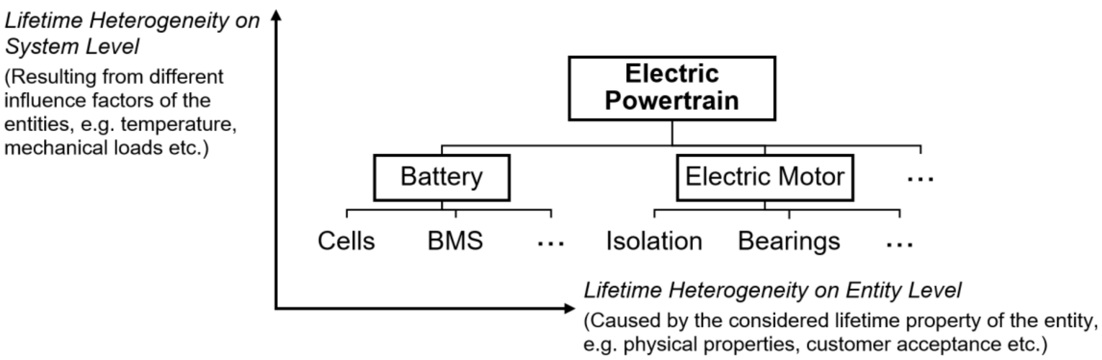

Figure 2. Concept of lifetime heterogeneity on system and entity level

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Moreover, availability of data is often different for single entities in early design stages, where the considered system only exists virtually and no final design is defined. For components and subsystems used in similar design for other applications (e.g. IGBT, propeller) more information about lifetime or damage behaviour are available as for entities modified for completely new applications (e.g. electric motors in aircraft). To consider the damage behaviour of entities and the availability of measurement data for lifetime prognosis, a new concept by dividing lifetime models into underlying model approaches and modelling methods was used. In this contribution model approaches for lifetime prognosis define concepts to determine end of lifetime (e.g. degradation) and illustrate influence factors on lifetime. Properties must be defined to calculate end of lifetime (e.g. a specific failure rate). Model approaches have to be implemented by modelling methods, which are mathematical principles to describe the properties determining lifetime. Equations or algorithms to model these factors are based on theoretical considerations like fracture mechanics or tribology and system data.

1.2 Research focus to improve lifetime prognoses

To develop precise lifetime models in early design stages, when no final product design and only virtual concepts of the system exist, methods and approaches are needed which are suitable for the considered system or entity. Therefore, overviews of fundamental properties, examples, advantages and disadvantages of existing methods and approaches for lifetime modelling will be presented. Existing reviews on lifetime modelling are studied to provide comprehensive information with no focus on specific lifetime models. The derived overviews consider the similarities of existing elaborations and are based on a larger number of publications than the results of a new review. The gained information are used to develop a procedure for the pre-selection of suitable methods and approaches for lifetime evaluation in early design stages. At first, the compatibility of individual model approaches with various modelling methods will be analysed. Based on this, criteria for the selection of model approaches and modelling methods will be formulated with the help of previous work. These criteria take into account properties of the regarded entity as well as availability of measurement data. In the last step, the developed criteria are applied to pre-select approaches and methods for lifetime modelling of entities from electric aircraft powertrain.

By analysing methods and approaches of lifetime models, preparing overviews of properties, advantages and disadvantages of modelling methods and model approaches, the evaluation of their compatibility and the definition of pre-selection criteria in consideration of available measurement data and damage mechanisms, assistance is given to improve lifetime prognosis of components and subsystems. The selection assistance for lifetime models developed in this contribution is an addition to previous studies, were just overviews of lifetime models were presented, and will support further research to forecast the lifetime heterogeneity of electric powertrains for aircraft.

2 LIFETIME MODELLING

To analyse existing approaches and methods for lifetime modelling, available reviews of this field were studied. Therefore, the tool *"Harzing's Publish or Perish"* (Harzing, 2007) and the search string *"review AND life OR lifetime AND model OR modelling OR estimation OR prognostic"* were used for a title search in the online library Google Scholar, citation records were ignored. Since scientific fields and topics like medicine or demography were not excluded, 205 articles were detected in the first step. After analysing paper titles and scanning the content eight reviews remained, which are discussed in Chapter 2.2. The knowledge gained by studying the reviews is the foundation of this paper and was complemented by expanded researches on single topics.

2.1 Approaches for lifetime models

With the findings from research three fundamental concepts for lifetime prognosis were derived. In the following they will be explained in detail.

2.1.1 Degradation

Degradation is the negative and continuous change of physical properties over time, with malfunctions and loss of performance as possible results (McPherson, 2010). Degradation can be defined as a function d of time t, internal entity properties $\vec{\mathrm{x}}_{\mathrm{int}}$, external impacts of the environment $\vec{\mathrm{x}}_{\mathrm{ext}}$ and operational conditions $\vec{\mathrm{x}}_{\mathrm{op}}$.

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$$d = f(t, \vec{x}_{int}, \vec{x}_{ext}, \vec{x}_{op}). \tag{1}$$

The function d is defined as one or more properties which are relevant for the functional performance of the product, e.g. the capacity loss of a battery or the maximum crack length in materials. Additionally, a critical value of the degradation function d_{crit} is defined whereby the product doesn't meet the requirements anymore and thus end of lifetime t_L is reached, see Figure 3, left (Petit et al., 2016).

2.1.2 Probability measure and failure rate

The lifetime of a product with in a defined use case can be described with the probability measure of failure. The probability measure is a function F(t), which indicates the probability of a system or entity failure over time based on determined boundary conditions. The time derivative of F(t) is the probability density function δ(t). With F(t), δ(t) the failure rate λ(t) can be calculated based on equation (2), which is the probability of failure in an infinitesimal time span, if the system or entity is functioning until the defined time point (Härtler, 2016).

$$\lambda(t) = \frac{\delta(t)}{1-F(t)}. \tag{2}$$

Often the failure rate is a function similar to the middle graph shown in Figure 3. At the beginning early failures, e.g. due to manufacturing faults, lead to high failure rates. Than the failure rate declines, stays nearly constant and increases because of continuing damage processes (Finkelstein, 2008).

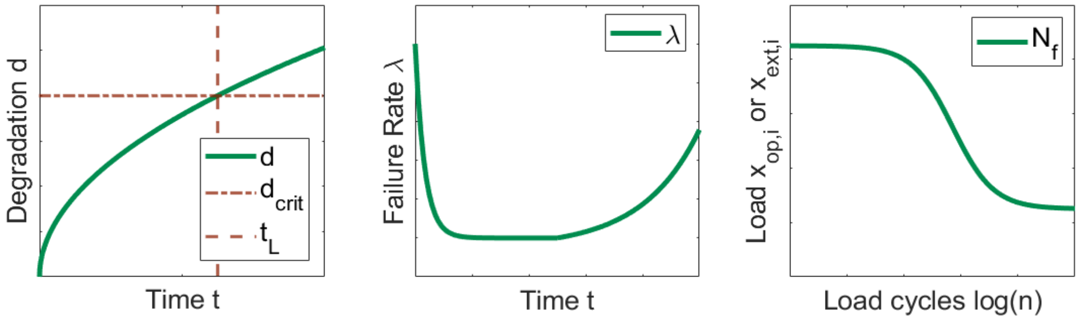

Figure 3. Degradation (left), failure rate (middle) and load cycles (right) as basic model approaches for lifetime prognosis

2.1.3 Load cycles

If a product is exposed to cyclic loads the number of cycles to failure can be recorded. By measurements under different load amplitudes models can be derived which are functions of the number of cycles n and the specific load. Thereby, environmental conditions and influences have to be as similar as possible for the different measurements (Weißbach, 2015). Under variation of operational and external conditions and with additional measurements it is possible to model the function of load cycles to failure N_f depending on further influence factors (Stroe, 2014). An example for N_f is shown in Figure 3, right.

$$N_f = f(n, \vec{x}_{ext}, \vec{x}_{op}). \tag{3}$$

In contrast to degradation, N_f is a model of a failure criteria and not of continuous functionally relevant properties. Either the chronological sequence of cyclic loads has to be consistent or the damage behaviour of the considered system has to be time independent (Weißbach, 2015).

2.2 Methods to modelling lifetime

Some of the selected paper focus on specific types of modelling methods, e.g. curve fitting (Kalayci et al., 2020; Li et al., 2019), stochastic methods (Si et al., 2011) or intelligent methods, which often use machine learning (Li et al., 2019; Fang et al., 2018). Further contributions try to create general overviews of modelling methods (Chen et al., 2011; Lipu et al., 2018; Su and Chen, 2017; Heng et al., 2009), but don't consider all aspects from other examinations. Consequently, an own classification of methods for lifetime modelling was developed to take into account the similarities of existing overviews and to classify modelling method types more comprehensively, see Figure 4.

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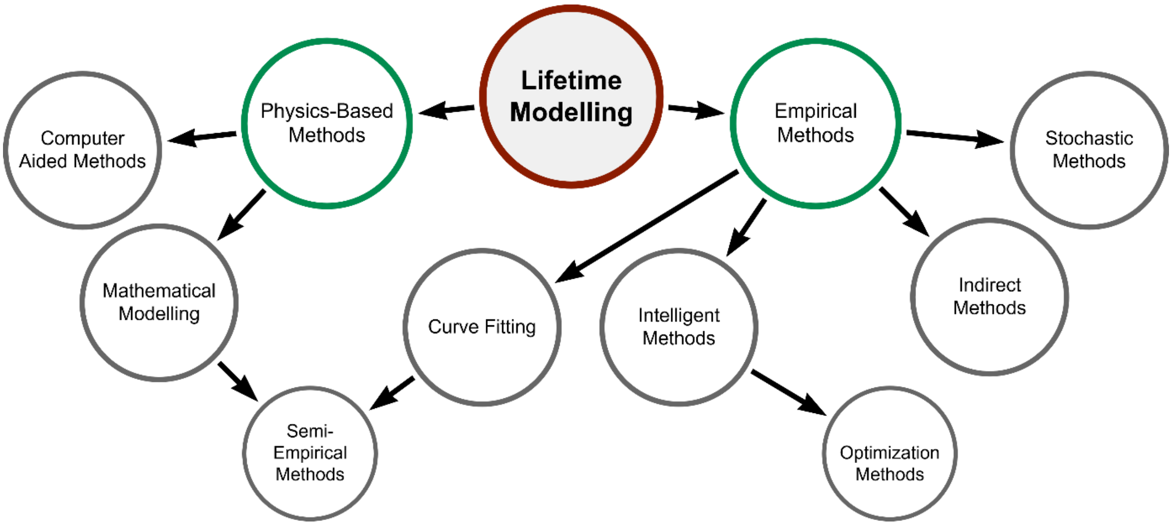

Figure 4. Classification of methods for lifetime prognosis

Physics-based methods are based on mathematical equations derived from theoretical considerations which describe the damage behaviour of a system while empirical methods use measurement data for lifetime prognosis (Zagórowska et al., 2020). The advantages and disadvantages of method types deduced from this categorization and some examples to methods are summarized in Table 1.

Table 1. Advantages and disadvantages of modelling methods

Method and examples	Advantages	Disadvantages	Sources
Computer aided methods e.g. FEM, CFD	No or few measurement data required; Models applicable for different use cases	Good theoretical knowledge necessary; Results can only replace measurement data	Mlikota et al. (2017)
Mathematical modelling e.g. SEI models for batteries	No or few measurement data required; Models applicable for different use cases	Complex formulation, Very good theoretical knowledge necessary; Models often applicable for one defined system only	Zagórowska et al. (2020); Prada et al. (2012)
(Semi-)empirical curve fitting e.g. exponential functions, Coffin-Manson model	Simple modelling; Low calculation effort; Simple implementation	High number of measurement data required; Models applicable for one system only and designed for a specific use case	Li et al. (2019); Heng et al. (2009)
Intelligent methods e.g. neural networks, particle swarm optimization	Can be used for many different problems; No parameters of the system required (e.g. material properties)	Very high number of measurement data required; High calculation effort; Optimization methods often for enhancement of other methods only (e.g. data fit)	Li et al. (2019); Su and Chen (2017); Heng et al. (2009)
Indirect methods e.g. hidden Markov models, Kalman filter	Can be used for many different problems; Several methods can be used despite of incomplete or incorrect data	For recondition of measurement data - for lifetime prognosis further methods are required; For some methods missing relation between results and measurement data	Heng et al. (2009); Peng et al. (2010)
Stochastic methods e.g. Weibull distribution, Wiener process	Calculation of probability measure enables risk analysis; Low calculation effort; Simple implementation	Very high number of measurement data required; Models applicable for one system only and designed for a specific use case	Härtler (2016); Li et al. (2019)

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A detailed explanation of single methods and their examples can be found in the given literature. It has to be noted that distinct modelling principles with different data bases exist for empirical methods (Soualhi et al., 2023), see Table 2. Additionally, there are manifold hybrid modelling methods combining different methods (Su and Chen, 2017).

Table 2. Modelling principles of empirical methods

Model principle	Description
Similarity-based	Prognosis based on measurement data of similar systems, at first no use of measurement data of the considered system but later for model optimization
Recursive	Prognosis based on actual measurement data of the considered system, due to that continuous evaluation parameter necessary
Direct	Use of actual measurement data and existing data of similar systems

3 PROCEDURE FOR THE SELECTION OF APPROACHES AND METHODS

To find suitable approach-method combinations for defined entities the procedure shown in Figure 5 was developed. For this purpose, the compatibility of methods and approaches for lifetime modelling was assessed and an overview was prepared. General criteria for the pre-selection of approaches and methods were derived with the help of previous work.

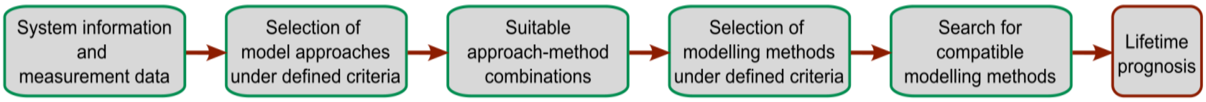

Figure 5. Procedure for the development of a suitable lifetime model

3.1 Compatibility of approaches and methods for lifetime modelling

Not all modelling methods are suitable for every model approach. This is also valid for the different modelling principles of the individual empirical methods (see Table 2). For example, no probability distributions are determined in curve fitting methods (Si et al., 2011; Zagórowska et al., 2020), so they are unsuitable for calculating failure rates. Normally, recursive modelling methods are only appropriate for models of degradation since current and continuous values of the system are required. As a result, there is no possibility of comparison with similar systems (Si et al., 2011; Soualhi et al., 2023). For this reason, most intelligent methods cannot be used with recursive modelling, since they are often based on machine learning using reference data (Su and Chen, 2017). With the help of the literature used so far, an overview was created in which the compatibility of methods and approaches for lifetime modelling is evaluated. For empirical methods, the similarity-based (s), recursive (r) and direct (d) modelling principles were evaluated separately. A + for good compatibility, a Ø for moderate compatibility and a – for poor compatibility were used as symbols in the evaluation, see Table 3.

Table 3. Compatibility of approaches and methods for lifetime modelling

Method	Degradation	Failure rate	Load cycles
Computer aided	Ø	–	+
Mathematical modelling	+	–	Ø
Curve fitting	s: + r: + d: +	s: – r: – d: –	s: + r: – d: Ø
Intelligent	s: + r: – d: +	s: + r: – d: +	s: + r: – d: +
Indirect	s: Ø r: Ø d: Ø	s: + r: + d: +	s: Ø r: Ø d: Ø
Stochastic	s: – r: – d: –	s: + r: – d: +	s: Ø r: – d: Ø

3.2 Criteria for the selection of suitable model approaches

Systems and their entities are subject to various damage mechanisms, which lead to a different evolution of damage over time (Hartzel et al., 2010) and not all model approaches are suitable for a precise lifetime prognosis. Based on their properties determined in Chapter 2.1, criteria for the selection of model approaches based on the damage behavior of entities were derived and their fulfillment by the individual approaches was evaluated. A summary of the results can be seen in Table 4. Again, a + was used for good, a Ø for partial and a – for poor fulfillment of the respective criterion.

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Table 4. Suitability of model approaches for different damage behaviour criteria

Damage behaviour criteria	Degradation	Failure rate	Load cycles
High scattering of failure	Ø	+	Ø
No monotonic increase of failures over time	–	+	Ø
Damage mechanisms not identified or measurable	–	+	+
Influence factors of damage behaviour unknown	–	Ø	Ø
Chronological sequence of influence factors unknown	Ø	Ø	–
High criticality of damage or failure	Ø	+	–

Since degradation models depict the change of continuously increasing damage parameters (McPherson, 2010), they are particularly suitable for time ranges with monotonically increasing system failures. If the damage mechanisms are unknown, degradation models cannot be created. Especially when modelling the lifetime using load cycles, the simulation of chronological sequence of influencing factors is important (Haibach, 2006). If a system is safety-critical, a lifetime prognosis must also enable a risk analysis (Si et al., 2011). This is only possible by statistically determining the failure rate.

3.3 Criteria for the selection of suitable modelling methods

When a model approach adapted to the damage behavior of the system has been determined, a compatible modelling method for lifetime prognosis can be selected (see Table 3). Which of the possible types of methods are most suitable depends for example on the maximum allowed computational effort (Li et al., 2019) and the present theoretical knowledge (Zagórowska et al., 2020). However, selection criteria that enable an objective evaluation and do not depend on individual properties and requirements of the user refer to the available measurement values and physical properties of the considered system (Härtler, 2016). With the help of the advantages and disadvantages of different types of methods described in Table 1, criteria for the selection of modelling methods were prepared based on the available data. An evaluation of the fulfillment of the criteria by the individual methods was carried out analogously to Chapter 3.2. The results are summarized in Table 5.

Table 5. Suitability of modelling methods for different data criteria

data criteria	Computer aided	Mathe-matical	Curve fitting	Intelligent	Indirect	Stochastic
Data of system properties not available	–	–	Ø	+	+	+
No measurement data of damage mechanisms	+	Ø	–	–	–	–
No lifetime data of similar systems	+	+	Ø	–	+	–
No in situ data of the considered system	+	+	Ø	Ø	+	Ø
Small amount of measurement data	+	+	Ø	–	Ø	–
Low quality of data	Ø	Ø	Ø	Ø	+	–

In the case of no, few or imprecise measurement data, particularly stochastic and intelligent methods are unsuitable. Mathematical modelling and computer-aided methods require sufficient information about the system properties. For curve fitting measurement data of the damage mechanisms and, in the case of semi-empirical variants, system properties are required. Indirect methods are often used to optimize measurement values, which is difficult with small amounts of data (Heng et al., 2009).

3.4 Application of the procedure to an electric powertrain

Based on previous research (Bauer and Inkermann, 2022), the developed procedure was applied to an electric motor and a battery for electric powertrains of aircraft. To do this, the damage behavior was evaluated first using the criteria from Table 4. It should be noted that the electric motor is composed of several entities with different damage behavior, including ball bearings, rotor and coils (Al Badawi and AlMuhaini, 2015). This leads to lifetime heterogeneity and makes an evaluation more difficult.

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The damage behavior is summarized in Table 6. The most important difference between the battery and the electric motor is that damage and failures increase monotonously over time in the battery (Rechkemmer, 2020), but not in the electric motor because of early failures due to manufacturing faults or overloading (Mellah and Hemsas, 2022), which increases scattering of system errors.

Table 6. Damage behaviour of battery and electric motor

Damage behaviour criteria	Battery	Electric motor
High scattering of failure	No	Yes
No monotonic increase of failures over time	No	Yes
Damage mechanisms not identified or measurable	No	No
Influence factors of damage behaviour unknown	No	No
Chronological sequence of influence factors unknown	No	No
High criticality of damage or failure	Failure is critical	Failure is critical

Based on the evaluation of the damage behavior and Table 4 with the criteria for the selection of model approaches for lifetime prognosis, it follows that modelling using load cycles is less suitable for batteries because of the criticality of failures in air traffic. The same applies to electric motors, for which degradation models are also rather unsuitable due to scattering and non-monotony of failures. An exception is the insulation of the motor coils, which is subject to thermal degradation (Zhu et al., 2014).
To determine suitable modelling methods, the compatibility with remaining model approaches should be evaluated first. For the battery, the approaches of degradation and failure rate were assessed as suitable. Both are compatible with almost all types of processes according to Table 3. Therefore, available measurement data are important for the selection of modelling methods. For early system design, the following boundary conditions are assumed with regard to the data criteria listed in Table 5:

- System properties not known exactly, comparison with similar systems necessary
- Measurement data of damage mechanisms available from similar systems for other applications
- No in situ data of the considered system available
- Chronological sequence of influence factors widely known
- few data from very similar systems, many data from systems that are only of the same type
- Good accuracy of measurement data (often from laboratory tests)

Under these conditions, physical modelling methods can only be used by estimating system properties, which can reduce their accuracy. Although indirect methods can be used in principle, but they do not make sense in the case of precise measurements of damage mechanisms from different systems, as they often only serve to further improve the measurement data of a system (Heng et al., 2009). The available data are also less suitable for intelligent and stochastic methods, since many measurements from systems which are as similar as possible required. Existing data can be sufficient for curve fitting, but because of differences between the associated systems, model parameters must be estimated, which can significantly reduce the accuracy of the prognosis (Bauer and Inkermann, 2022). In general, due to the lack of in situ data of the considered system, only similarity-based empirical methods can be used. Overall, the approach-method combinations summarized in Table 7 are assessed as useful for batteries and electric motors. For a final selection of approaches and methods, the exact requirements of the model, the usability of available data for the considered application and limitations such as maximum computational effort are important.

Table 7. Suitable approach-method combinations for battery and electric motor

Subsystem	Model approach	Modelling method
Battery	Degradation	Computer-aided methods Mathematical modelling Curve fitting (similarity-based) Intelligent methods (similarity-based)
Electric motor	Load cycles (only if few data available)	Computer-aided methods Mathematical modelling Curve fitting (similarity-based)
	Failure rate (with enough data of similar systems)	Stochastic methods (similarity-based) Intelligent methods (similarity-based)

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4 CONCLUSION AND DISCUSSION

Lifetime prognoses of systems and their constituting entities are an important prerequisite to ensure security, availability and cost reduction of products, as well as to plan life cycle options in early design stages. In this contribution, a separation of lifetime models to model approaches and modelling methods was developed. Model approaches like degradation or failure rate were explained and an overview of different modelling methods was created to highlight their advantages and disadvantages. Depending on system, damage behaviour and available data, the existing model approaches and modelling methods are differently suitable for a precise lifetime prediction. A procedure was proposed to help to select suitable approach-method combinations for lifetime prognosis. To answer the main research question of this paper, fundamental selection criteria for lifetime models were defined. The compatibility of method types with the different model approaches was assessed and the results were presented. Subsequently, criteria for the damage behavior (e.g. scattering and criticality of failure) of the considered system for the selection of model approaches and criteria for the available data (e.g. data quality, data from similar systems) for the selection of modelling methods were defined. The selection procedure developed was applied to the example of an electric motor and a battery for electric powertrains of aircraft in early design stages. Finally, the model approaches assessed to be suitable and the associated modelling methods were summarized. The proposed selection procedure is only suitable for pre-selecting approaches and methods for lifetime modelling. The final selection depends on the requirements and the individual properties of the system and its use cases. Furthermore, an evaluation of the selection criteria must be carried out partly subjectively by estimating the influence of data properties for entire types of modelling methods with the help of literature. The differing properties of individual examples of methods for lifetime modelling are partially neglected. In addition, no hybrid modelling methods were considered in this article. In further researches, lifetime models for entities of an electrical powertrain for aircraft should be developed. The pre-selection procedure for lifetime models proposed in this article helps to develop lifetime models adapted to the use case and the entities.

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