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Assessment Concept for Transfer Learning Methods in Context of Lifetime Prognosis of Systems

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Abstract

Transfer Learning uses information from comparative problems for modeling and is therefore a promising method for lifetime prognosis under a lack of data. A literature review is conducted to provide an overview of existing Transfer Learning methods and their requirements and properties. On this basis, a procedure is developed with which the suitability of collected Transfer Learning methods can be assessed stepwise, considering the requirements and the available data for the implementation of a lifetime prognosis. The developed procedure takes particular account of different approaches of lifetime modeling and the similarity evaluation of systems.

Keywords: lifetime prognosis; lifecycle planning; Transfer Learning; lack of data; uncertainty

1. Introduction

Planning of lifecycle options, like reuse, upgrade or maintenance to improve sustainability of products requires precise prognosis of degradation and resulting lifetime of systems and components [1]. Degradation describes the detrimental change in physical properties over time, resulting in the failure of functions and a reduction in the performance of the product [2]. Performing lifetime prognosis (LP) in early design stages allows effective adaptions of product architectures and selection of suitable components [3]. A common method for LP is empirical modeling. Test operations or laboratory studies under defined constraints are used to investigate relevant damage mechanisms and generate data to derive model functions, e.g. by data regression using suitable initial functions [4]. However, in early design stages only limited data is available to perform LP. Thus, information from reference systems and associated lifetime models must be used [5]. However, this procedure is associated with a high degree of uncertainty, as both the use case and the system structure generally deviate from the reference system. An approach transfer existing information to similar but not identical problems is Transfer Learning (TL). It involves Machine Learning (ML) methods that have already been applied in image classification, speech recognition or error analysis of software problems. The basis of TL are comparison models and their underlying data [6]. For the degradation modeling of new products, sufficient similarity between systems of the comparison models is needed. Therefore, the feature space of the system and its use cases have to be as identical as possible [7]. Domains with high similarity are formed, see Table 1.

Table 1. Formation of domains to perform TL

Domain	System	Use Case
Domain 1	System A	Use Case 1
Domain 2	System B	Use Case 1
Domain 3	System A	Use Case 2
Domain 4	System B	Use Case 2

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TL is used to create new models from the data of the considered domains, which are derived from properties that are as generally valid as possible [8]. This is done by recognizing common properties or patterns in the data and models of the single domains, see Figure 1. Properties that are not found in several domains are ignored during modeling or have less influence. The model generated this way should provide precise results for all considered domains and sufficient similar domains.

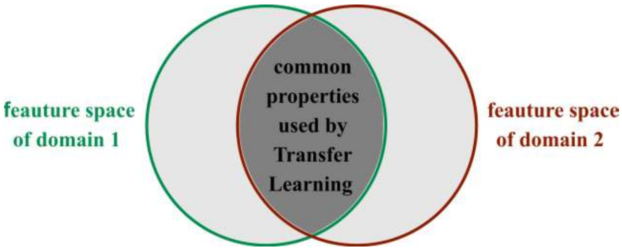

Fig. 1. Concept of TL (according to [6])

The advantages of TL compared with other ML methods are significant lower data requirement, the possibility of improving existing models with additional data from comparative domains, faster and easier model creation as well as the possibility of transferring models to similar domains with a lack of data [6]. TL thus is seen as a promising method to support LP in early design stages.

2. Focus and Objectives of Research

This paper analyses the application of TL methods for lifetime modeling under a lack of data. The underlying hypothesis is that TL can be used to create lifetime models that are transferable to other areas if damage mechanisms and feature spaces are sufficiently similar. Therefore, a literature review is conducted to analyze existing TL methods and their characteristics and requirements. Based on the findings a procedure is proposed to select suitable TL methods and improve LP in early design stages. In particular, the requirements for modeling and similarity evaluation of domains are addressed. Therefore, the following research questions are in focus:

- Which methods exist to create lifetime models by TL?
- Which amounts of data are required to apply TL and to achieve sufficient accuracy?
- How can the required similarity of domains as a precondition for using TL be specified?
- Which approaches for the similarity assessment of domains are suitable for different scenarios of LP?

To answer these questions, the remaining part of the paper is structured as follows. In Section 3 the methodology and results of the systematic literature review are introduced. In Section 4 the procedure to select suitable TL methods for LP in early design stages is described. The conclusion and aims for future work are given in Section 5.

3. Review of TL Methods for LP

A structured review is performed to provide an overview of characteristics and requirements of existing TL methods for LP. The information gained are used the derive a systematic procedure to select TL methods for LP in early design stages.

3.1. Methodology

The review was intended to identify TL methods used in the context of LP. The Harzing's Publish or Perish tool was used to find relevant articles [9] and the internet data base Google Scholar was the source of the detected paper. To find as many publications on TL methods for LP as possible, the search string shown in Figure 2 was created, including different terms related to TL and lifetime of systems.

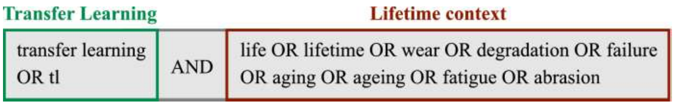

Fig. 2. Search string used for the review

To extract relevant contributions in a first step titles and abstracts were analyzed applying the exclusion criteria listed in Table 2. If necessary, the full texts were also cross-read.

Table 2. Exclusion criteria of detected publications

No.	Exclusion criterion
1.	The context is not degradation/ lifetime modeling of technical systems with TL.
2.	The publication does not deal with TL as defined in Section 1.
3.	The publication has not been peer-reviewed.
4.	The publication can only be viewed for a fee by the author.
5.	TL has not been applied, only concepts are presented.
6.	The paper was not written in English.
7.	The paper is a duplicate or has already been viewed.

The articles identified this way were studied in more detail and the information obtained was collected in a table. The table contains columns on the title and source of the remaining publications, TL methods used, a comprehension of the structure of the respective TL method (used methods for TL, regression and similarity assessment, sequence and combination of methods), considered application examples, data requirements (especially the amount of data sets from reference systems) and existing performance assessments (especially precision of the prognosis) of the TL methods. To ensure the quality of the filtered contributions, snowballing was performed [10] to check given assumptions and information.

Based on the search string, 297 articles were initially found and filtered using the exclusion criteria. 37 remaining articles were analyzed in more detail regarding to TL methods used, application examples, requirements and the prediction results achieved.

3.2. Results of the Review

The information collected from the publications were summarized in a table to create an overview of existing TL methods. Two reviews on LP using TL, which were additionally found using the search string, were also considered [11, 12]. Figure 3 shows the typical architecture of TL models for LP determined from [11 - 49], as well as an overview of the methods used in the reviewed articles to implement individual steps. TL for LP under a lack of data is usually include the following tasks:

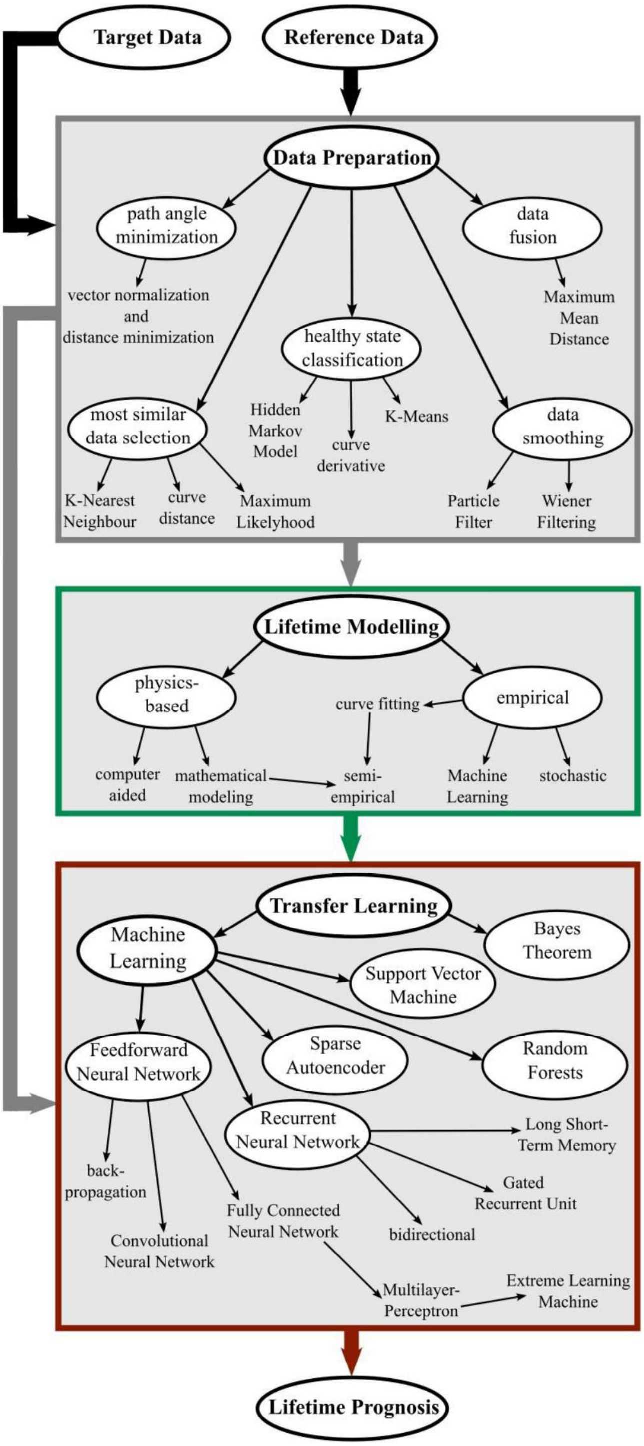

Fig. 3. Procedure and methods of reviewed TL-based LP

1. **Preparation of reference lifetime data** by smoothing or filtering of interfering signals or statistical deviations. Sometimes the data sets, which are most similar to some available lifetime data of the target domain, are selected before further preparation. Then the data is frequently adjusted to determine common properties by using algorithms (e.g. splitting of data sets into sections and subsequent classification, overlapping of data sets/data fusion).
2. **Lifetime modeling** based on the prepared reference data. Various methods can be used for this purpose. A detailed analysis and description of possible modeling methods can be found in [4]. In the reviewed articles, ML methods were often used, e.g. in [13 – 26].
3. **Adaptation of created lifetime models** to the target domain using the TL concept, see Section 1. Additional reference data is used in some cases. In all cases, prepared lifetime data of the target domain is required in the reviewed articles, but the information can be incomplete and only include early degradation phases.

The TL methods reported in [11 - 49] are shown in Figure 3 in classified form using additional information from [11, 12]. Five different ML methods were used, namely Feedforward Neural Networks (FFNN), Recurrent Neural Networks (RNN), Sparse Autoencoder (SAE), Support Vector Machines (SVM) and Random Forests (RF). RNNs were used in modified versions, namely with Long-Short Term Memory (LSTM RNN) or as a Gated Recurrent Unit (GRU), and often with bidirectional information flow. FFNNs were mostly implemented with backpropagation of information. As modifications of FFNNs, Convolutional Neural Networks (CNN) and Fully Connected Neural Networks (FCNN) were created and tested. Specific forms of FCNN, the Multilayer Perceptron (MLP) and Extreme Learning Machines (ELM), were also used. In addition to ML methods, Bayes' theorem was used for TL. Hybrid variants of different TL methods were also frequently applied. Moreover, a distinction between two types of data basis for lifetime modeling must be made:

- *Direct lifetime data*: Data of reference and target domains contain measured values of the base size of the lifetime model or variables to calculate it analytically (e.g. capacity loss of batteries).
- *Indirect lifetime data*: Data of reference and target domains contain measured values that are only used to infer the base size of the lifetime model (e.g. vibration behavior with ball bearings).

When modeling using indirect lifetime data, the uncertainty of a LP is increased, making it more difficult to create precise models. Table 3 summarizes the TL methods used in the reviewed articles, including the type of data basis and associated sources. Furthermore, Table 3 provides an assessment of the required amount of reference data and the precision of the LP of the used TL method and its underlying lifetime models of the reference domains.

Table 3. Performance analysis of considered TL methods

Used TL Methods	Direct/ indirect	Reference data requirement	Precision	Sources
FFNN or MLP	indirect	medium	low to medium	[13 – 17]
ELM	direct	medium	medium	[18]
CNN	indirect	low to medium	low to medium	[19 – 23]
CNN and FCNN	indirect	medium	low to medium	[24]
CNN and FCNN	direct	high	low to medium	[25, 26]
LSTM RNN	indirect	medium	low to medium	[27, 28]
LSTM RNN	direct	medium to high	high to very high	[29 - 37]
GRU	indirect	medium	low to medium	[38]
GRU	direct	medium	high to very high	[39]
LSTM RNN and FCNN or CNN	indirect	medium	low to medium	[40]
LSTM RNN and FCNN or CNN	direct	medium	high to very high	[41, 42]
GRU and FFNN	indirect	medium	low to medium	[43]
CNN and LSTM	indirect	low	low to medium	[44]
SAE	indirect	high	low to medium	[45]
SAE and LSTM RNN	indirect	medium	medium?	[46]
RF	indirect	medium	medium?	[47]
SVM	indirect	medium	medium?	[48]
BT	direct	medium	high to very high	[49]

As a basis for the assessment of required data, it was defined that a need of lifetime data on a maximum of 20 reference domains can be assessed as “low”. If more than 100 reference domains are required, the data requirement is “high” and otherwise “medium”. If the data requirement is close to the defined limit values, no clear assessment was made and e.g. “low to medium” was selected. For the evaluation of the precision of TL methods, the reliability of prognosis for the target domain is important. If the lifetime model results of the reviewed articles miss the real lifetime data of the target domain sporadically by more than 30%, the accuracy is “low”, as only an uncertain prognosis is then possible. If the results are very close to the real data and rarely deviate by more than 5%, the accuracy is “high” or even “very high”, otherwise “medium”. In many contributions, however, the accuracy of the TL methods varied significantly with variable influencing factors of lifetime, therefore in some cases no clear assessment was made here either. In addition, in some contributions the accuracy of the developed TL methods was not substantiated with sufficient results, so that only a conditional assessment was made (see [46 - 48]).

4. Concept to Select TL-Based Lifetime Models

In the following, a concept for the selection of suitable TL methods is introduced, focusing on the requirements of a LP as well as quantity and properties of available lifetime data. First, suitable approaches for lifetime modeling are selected, concluded by a similarity analysis to compare the target and reference domains. Based on this, a preselection of TL methods considering their properties determined in the review is done.

4.1. Lifetime Model Selection

Three approaches can be distinguished in lifetime modeling, namely degradation, load cycles until failure, and the probability of failure [4]. Which approach should be selected for LP depends on the properties of the available lifetime data and the precision requirements for the prognosis. In [4], criteria for the selection of suitable approaches to model lifetime were defined and have to be considered in the first step of TL method selection as summarized in Table 4. The selection of a modeling approach results in further requirements for the TL method, that must be considered in the presented concept.

Table 4. Evaluation of model approaches with regard to selection criteria [4]

Damage behavior criteria	Degra-dation	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 behavior unknown	–	Ø	Ø
Chronological sequence of influence factors unknown	Ø	Ø	–
High criticality of damage or failure	Ø	+	–
Symbol legend: suitable: +	less suitable: Ø	unsuitable: -	

4.2. Similarity Assessment of Domains

Figure 4 shows the prepared classification of possible similarity assessment methods and some related examples. As explained in Section 1, reference domains must be similar to apply TL to generate a new target domain. For lifetime modeling, the considered systems, use cases and environmental conditions must be sufficiently similar to ensure the same damage mechanisms. In the reviewed articles [11 - 49], data from early degradation phases of the target domain were used for similarity assessment. This comparison between reference and target data is here referred to as empirical similarity assessment. This involves calculating distance measures between different data sets, e.g. used in [13-17], classifying domains based on characteristic features, e.g. applied in [18, 28], or analyzing the cross-correlation of lifetime data, e.g. used in [41]. The lifetime prediction of the target domain is performed by ensuring a high correlation or low distance measures to reference domains evaluated as similar. However, especially in early design stages, no lifetime data of the target domain is available and empirical similarity assessment is not possible. In [50], a possibility is proposed to perform similarity evaluations without lifetime data of the target domain based on physics-based similarity. The precondition is that similar physical processes are given in the considered domains and can be described with common mathematical models. For example, the wear of nozzles can be derived from pipe friction [51]. Parameters for similarity quantification are then calculated for the domains based on all the different influencing factors of the lifetime. These parameters can either be based on basic similarity, i.e. the systems are of the same type (e.g. different lithium-ion batteries) and lifetime-relevant processes can be described by the same model equations. Alternatively, a functional analysis of domains can be performed and equations can be derived to describe similar sub-functions (e.g. transmitting power, storing electrical energy). The similarity for certain damage mechanisms can thus be quantified on the basis of different influencing factors relevant to these functional equations. A detailed description is given in [50].

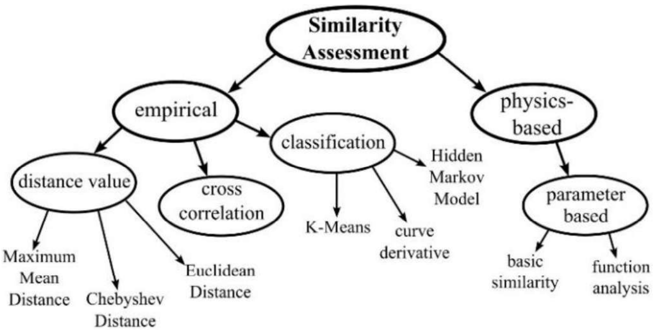

Fig. 4. Classification of methods for similarity assessment

4.3. TL Method Selection

Based on the results of previous sections, influences of data properties on the selection of TL methods were defined. These are summarized in Figure 5. Indirect influences from selected model approaches or similarity assessment methods were also considered and highlighted in reference to Figures 3 and 4.

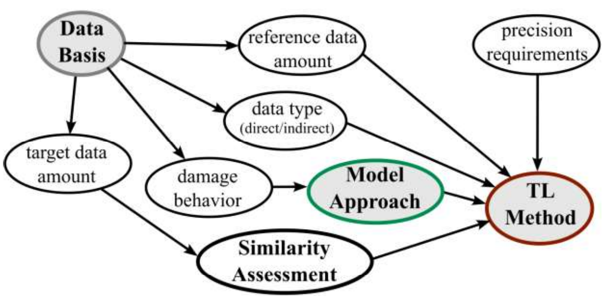

Fig. 5. Influences on TL method selection for lifetime modeling

The stepwise evaluation of the individual influences for the selection of TL methods is explained in more detail below:

- *Target data amount*: If lifetime data of the target domain are available, a deterministic lifetime assessment is useful. Otherwise TL methods must be developed based on physics-based similarity analysis, but there are no studies on this.
- *Damage mechanism*: Depending on the damage mechanism of the considered domains, different approaches of lifetime modeling are suitable, see Table 4. Especially if failure rates are to be modeled, high data amounts are required and TL tends to be unsuitable if there is a lack of data. Due to properties such as monotonicity and clearly defined influencing variables, degradation models appear to be particularly suitable for similarity assessments and TL.
- *Data type, reference data amount and precision requirements*: If only indirect lifetime data is available, the accuracy of TL decreases. In addition, high precision requirements tend to require higher amounts of data without too much variance in the reference domains [11]. In order to identify the most efficient TL methods with the available data, the review results from Table 3 can be used.

5. Conclusion and Future Research

The review provided a comprehensive overview of existing TL methods for lifetime modeling and their characteristics. Significant differences in the accuracy were identified when direct or indirect lifetime data were used for modeling. The requirements on reference data of different TL methods were determined and evaluated, whereby in most cases less than 100 data sets were required. Nevertheless, differences in the efficiency of the methods were identified, whereby LSTM RNN, GRU and BT appear promising here. Furthermore, common methods for similarity assessment were identified, although these mostly require lifetime data of the target domain, which is not always available. Further research led to the identification of similarity assessment methods that do not require data from the target domain but have not yet been used in context of TL. Based on the research results, a procedure was developed that enables a preselection of suitable TL methods, which simplifies the final selection of suitable methods and can increase the performance of the created model.

In further studies, TL methods without the use of target data will be developed, since a research gap has been identified here. In particular, the integration of a suitable similarity assessment must be considered based on application examples and associated lifetime data to derive methods to quantify sufficient similarity. Based on defined similarity criteria, investigations on the possible generalization of degradation models using transfer learning will be performed. Model improvements through integration into digital twins, e.g. with live data from the twin, and resulting additional requirements for the preselection of suitable TL methods will also be investigated.

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