Hybrid Prognosis Method for Remaining Useful Lifetime Estimation Considering Uncertainties

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Abstract

Predictive Maintenance, a desirable maintenance strategy in industrial applications, relies on appropriate condition monitoring solutions to reduce costs and risks of the monitored technical systems. In general, model-based or data-driven methods to diagnose the current state or predict future states of monitored technical systems are utilized in these solutions. Since both methods have advantages and disadvantages, a combination of both methods can be used for appropriate uncertainty management and improved accuracy. In this work, two hybrid approaches are developed. In the first approach, a data-driven diagnosis is used to validate a model-based prognosis, while in the second approach, a data-driven prediction of new measurements is integrated into a model-based prognosis method. In the developed hybrid approaches, a particle filtering method is combined with a machine learning method. To consider uncertainties within the system, a differentiation is made between different system behaviors in the diverse phases of degradation. The developed methods are evaluated based on the use-case of rubber-metal-elements. These elements, which are used to isolate vibrations in several systems, such as railways, trucks and wind turbines, show various uncertainties in their behavior. Moreover, another difficulty is that little run-to-failure data of these elements is available. Finally, the performance of the developed hybrid approaches is compared with a model-based method for estimating the remaining useful lifetime of the same elements.

1. Introduction

Condition monitoring solutions provide the basis for condition-based or predictive maintenance, depending on the aim of the condition monitoring system (CMS): diagnosing the current state or predicting future states of the monitored system. Thereby, condition monitoring enables a higher dependability, a larger utilization of the monitored system and reduced costs. Motivated by these possible achievements, multiple condition monitoring solutions for different technical systems are developed, e.g. for bearings or micro gripper (Javed, Gouriveau, & Zerhouni, 2017), batteries (Laayouj & Jamouli, 2017) and wind turbines (Yucesan & Viana, 2020). Furthermore, with the increase in digitalization, digital twins experience a growing attention. As digital twins are aimed to perform during various lifecycles of a product beginning in the design phase, the combination with a CMS during the application of the product is favorable (Kaul, Bender, & Sextro, 2019; Rosen, Wichert, Lo, & Bettenhausen, 2015). The advantages of a digital twin, e.g. acquire and save measured data, process and provide data and communicate with the corresponding entity, can be extended if the digital twin is combined with a condition monitoring solution. Moreover, more sustainable maintenance concepts are enabled based on simulations of product behavior considering product degradation (Stark, Thoben, Gerhard, Hick, & Kirchner, 2020). However, one mayor challenge in condition monitoring tasks as well as in digital twin design is related to uncertainties (Goebel et al., 2017; Grieves & Vickers, 2017; Javed et al., 2017; Schleich, Anwer, Mathieu, & Wartzack, 2017).

Today monitored systems and the methods of a CMS are affected by various uncertainties. To achieve an accurate CMS, these uncertainties have to be analyzed, evaluated and reduced if possible (Koenen, 2016). In literature, the different sources of uncertainty can be divided in aleatory and epistemic (Baraldi, Popescu, & Zio, 2012; Koenen, 2016). While aleatory sources are based on physical variability, epistemic sources are related to a lack of knowledge. There is no general agreement, whether such a division is meaningful for prognostics tasks (Baraldi et al., 2012; Goebel et al., 2017). Therefore, in this paper different types of uncertainty are considered independent of a classification in aleatory and epistemic (Atamuradov, Medjaher, Dersin, Lamoureux, and Zerhouni 2017; Baraldi, Mangili, and Zio 2013; Goebel et al. 2012; Javed et al. 2017; Su, Wang, Pecht, Zhao, and Ye 2017; Valeti and Pakzad, 2018):

- Uncertainty of the current state,
- Uncertainty of the future,
- Modeling uncertainty and
- Uncertainty of the prognosis method.

The uncertainty of the current state can be caused by the applied sensors and the measurement technology, the choice of the sample rate, measurement noise or uncertainties of the monitored material. The uncertainty of the future considers the future operating and environmental conditions or their uncertainty as well as the uncertainty of the degradation process. Modeling uncertainty comprises the measurement model including its form and its parameters as well as the failure threshold. In the end, the uncertainty of the prognosis method considers sampling errors and model assumptions.

To consider uncertainties, a suitable approach for condition monitoring has to be selected. In general, these approaches can be divided in model-based, data-driven and hybrid approaches (Atamuradov et al., 2017; Baraldi, Di Maio, & Zio, 2014; Javed et al., 2017). Model-based approaches achieve a high accuracy depending on the suitability of the often-intuitive model. Different boundary conditions are easily implemented. Nevertheless, creating such a model can be time consuming and complex depending on the system to be modeled and on the model's type. Since physics-based as well as empirical models can be implemented in model-based approaches (Goebel et al., 2012; Vachtsevanos, 2006). While data-driven methods are easy and fast to implement, they need a certain amount of significant data. Moreover, they often rely on black-box modeling and therefore they do not build understandable models (Kan, Tan, & Mathew, 2015; Vachtsevanos, 2006). That is a disadvantage of these methods because an engineer wants to know why to recommend which maintenance task. Available synergies can be used by a suitable combination of both approaches. Thereby, a hybrid approach can improve accuracy by reducing uncertainty(Goebel et al., 2012; Javed et al., 2017; Kan et al., 2015). Therefore, in this paper hybrid methods are focused.

Hybrid methods for diagnosis and prognosis strive for a combination of data-driven and model-based approaches in such a manner that their potentials are suitable used. In literature, different combinations are given. One general procedure that underlines the differences within the steps of the three types of approaches is shown in Figure 1. While the model-based approach relies on a physical or empirical model that is developed by humans, a data-driven approach learns the relationships between its in- and outputs. In this figure, one possible hybrid approach is given that combines the developed physical or empirical model with the learned model. In this case, a popular distinction between the two models is made. One approach models the dynamic behavior of the monitored system and the other approach models the degradation (Liao & Kottig, 2014; Medjaher & Zerhouni, 2013). Another possible hybrid method bases on single models for different sub-

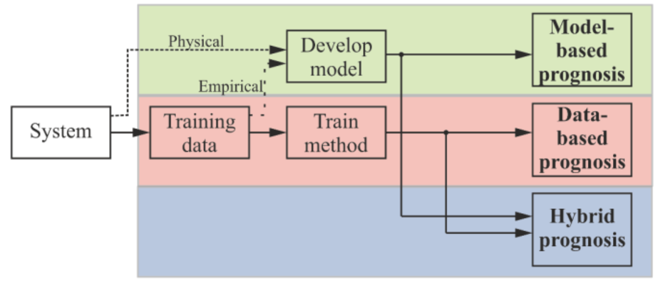

Figure 1. Types of prognosis approaches (Bender, 2021).

systems of one system and their individual degradation (Yucesan & Viana, 2020). Moreover, a physical model is used to represent the general degradation of the system, while a data-based model enables an update of the current degradation level (Tang, Flynn, Brown, Valentin, & Zhao, 2019). To summarize, various possibilities to combine model-based and data-driven approaches can be realized for the purpose of diagnosis or prognosis.

A categorization of four different approaches to combine data-driven and model-based approaches is given in Liao and Kottig (2014). As model-based methods rely on a state and measurement model, in the first approach, the measurement model is realized by a data-driven approach. In the second approach, the state model is learned by a data-driven approach. In the third approach the uncertainty of future measurements is considered by estimating future measurements based on data-driven solutions. While these three approaches combine data-driven and model-based approaches in series, the forth approach is a parallel solution of a data-driven and a model-based diagnosis or prediction by an ensemble. The four named approaches are given in Table 1 for reasons of overview.

To develop a suitable CMS for a particular application that is related to uncertainties a suitable hybrid method is needed. How to choose a suitable hybrid approach? If additionally, only few data are available, an accurate prediction by a hybrid approach is not easy to realize. One reason for that is given by the data-driven approach that depends on the quality and partly on the quantity of the data.

Table 1. Combinations of data-driven and model-based approaches (Liao & Kottig, 2014)

Hybrid approaches
1) Data-driven measurement model within a model-based approach
2) Data-driven state model within a model-based approach
3) Estimated future measurements based on a data-driven model to reduce the uncertainty in the model-based approach
4) Ensemble of a data-driven and a model-based approach

In this work, two hybrid approaches considering potential uncertainties are developed and compared. Due to the boundary conditions related to the small amount of data, the fourth solution of Liao and Kottig (2014) is not recommended as it bases on a separate data-driven prediction. The first approach on a data-driven measurement-model was evaluated in (Kulling & (Betreuerin) Bender, 2019) and does not improve the accuracy of the predicted remaining useful lifetime (RUL). While the second approach is related to the main part of the model-based prediction, the state model, the third approach aims to improve the prediction of the state model. Because a model-based prediction with a suitable state model is implemented in Bender (2021), in this paper the focus is on the third approach of Liao and Kottig (2014). The aim is defined by improving the available prognosis method using the same state model. Therefore, a data-driven estimation of new measurements is integrated within the model-based method. To consider uncertainties within the system, a differentiation between different system behavior is realized throughout diverse phases of degradation. The other hybrid approach combines a data-driven diagnosis and the named model-based prediction. Thereby, the model-based predictions should be validated by a particular classification.

Both developed hybrid prognosis approaches base on a particle filtering method combined with a machine learning method, to estimate the RUL of technical systems. Particle filtering, a Monte Carlo simulation technique, is suitable to map and propagate uncertainties. Moreover, it is a state-of-the-art model-based method for predicting RUL of technical systems (Jouin, Gouriveau, Hissel, Péra, & Zerhouni, 2016). To integrate uncertainties, a Multi-Model-Particle Filter developed in Bender (2021) is employed.

The remaining paper is structured as follows. In section 2, methods to predict the RUL of systems related to uncertainty are developed. A model-based prediction based on a Multi-Model-Particle Filter is introduced. Related to that approach two hybrid approaches are developed. The first one is based on a combination of a diagnosis and a prognosis, while the second approach is a hybrid prognosis. A discussion on the advantages and disadvantages follows. In section 3, the use-case of rubber-metal-elements is introduced and the uncertainties within the degradation phases are described. In section 4 the evaluation of the methods based on the use-case is presented. In section 5 a conclusion highlights the main points of the developed hybrid prognosis method.

2. Developing Prediction methods Considering Uncertainties

The variation of methods to predict RUL is enormous. In this section, the focus is set on such methods that consider uncertainties. At first, a Multi-Model-Particle Filter is presented that has been proven to consider different uncertainties (Bender, 2021). Based on this method hybrid approaches are developed with the aim to improve the accuracy of the named Multi-Model-Particle Filter. The first approach is built upon a diagnosis, while the second approach bases on the third category of hybrid approaches of Liao and Kottig (2014). In the last part of this section, the approaches are compared theoretically.

2.1. Model-based Prediction of Remaining Useful Lifetime

Model-based prognosis methods rely on developed models of the monitored systems. These models simulate the behavior or the degradation of the particular system. By building upon such a model, model-based approaches are capable of predicting the future degradation of the system or the RUL. The aim of such an approach is an accurate, comprehensive and relative cheap prediction in terms of time and costs. Typical approaches are the Kalman and the Particle Filter as well as further derivatives of both filters. Especially, Particle Filters are able to consider different kind of uncertainties as they base on Bayesian probabilities. Therefore, using Particle Filters for condition monitoring tasks is recommended by different authors (Javed et al. 2017; Sankararaman and Goebel, 2015; Orchard, Kacprzynski, Goebel, Saha, and Vachtsevanos 2008).

In Bender (2021) a Multi-Model-Particle Filter is developed that considers even more uncertainties than the general Particle Filter. By including different state models in parallel, it enables the estimated states to follow different degradation paths. Moreover, this Multi-Model-Particle Filter is able to react on different working or environmental conditions by the choice of predefined groups of state models. Therefore, the working conditions have to be known and the particular state models need to be developed prior to the prediction. Then the Particle Filter predicts the future states based on the corresponding group of state models for the present conditions. Furthermore, the Multi-Model-Particle Filter is extended by an approach to estimate an adaptive failure threshold. Thereby, a further uncertainty is considered, the uncertainty of the failure threshold. For simplicity, in this paper only one working condition is considered and the thresholds are assumed to be known. In further developments these extensions can be considered as well.

2.2. Hybrid Approach Combining Diagnosis and Prognosis

The Multi-Model-Particle Filter is able to consider different uncertainties, but there is still potential for improvement. To improve the accuracy of the predictions, available uncertainties should be considered to a higher level.

To achieve this aim, different degradation phases have to be identified in the degradation of the particular system. A machine learning method is used to learn this classification problem based on labeled data. Based on such a classification the predictions of the Multi-Model-Particle Filter are validated in this hybrid approach.

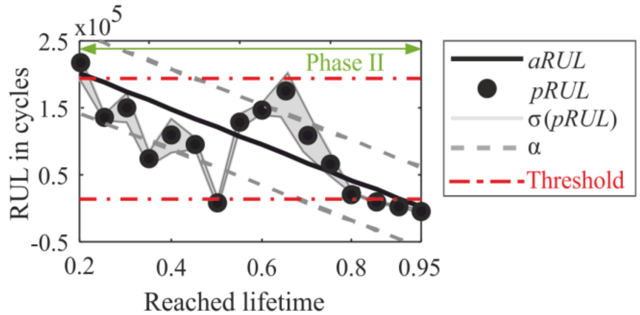

Figure 2. Validation of model-based predictions by a data-driven diagnosis in defined phases and the correlated thresholds of these phases.

A validation is realized as shown in Figure 2. The predicted RULs (*pRUL*), given by black dots, are compared to the actual RULs (*aRUL*), given by a black line, for predictions at different points in time. Furthermore, the standard deviation of the predicted RULs is given in grey to underline the scattering in each prediction. By the error band α a first evaluation of the predictions is possible. A further validation is given by the diagnosis. In Figure 2, it is assumed that for all prediction time points, the monitored system is diagnosed to be in degradation phase II. For this example, three phases of the system are identified. Based on the analyzed data of similar systems it is known that systems in phase II have a minimum RUL and a maximum RUL. Two thresholds, one for the minimum RUL and one for the maximum RUL, mark the area in which predicted RULs of phase II are likely. Furthermore, predictions in phase I are expected to be larger than the higher threshold, while predictions in phase III are expected to be smaller than the lower threshold. Therefore, all predicted RULs that are too large, as the first prediction in Figure **2**, are probably in phase I. All predicted RULs that are smaller than the lower threshold are probably too small if the accuracy of the data-driven classification model is trustworthy. In this case, a further evaluation of the system may be recommended to decide when to maintain the system.

This approach enables a data-driven validation of the model-based predicted RULs. If the diagnosis suggests that the predictions are not compatible with the expected RUL area, the predictions have to be questioned and adapted, e.g. by expert knowledge.

2.3. Hybrid Prognosis Approach

The aim of the hybrid prognosis approach is improving the accuracy of the prediction by a data-driven classification and the approximation of new measurements depending on the classification.

The used Particle Filter relies on the scheme of sampling-importance-resampling (SIR). In general, resampling as a part of the particle filtering approach has the potential to lead to an accurate prediction as it prevents the degeneracy of particles (Arulampalam, Maskell, Gordon, & Clapp, 2002). Therefore, the predicted states described by particles are weighted based on their importance compared to a new measurement. Based on these weights the particles are resampled. However, in the case where no future measurements are available, no new weights can be estimated. Thus, resampling may increase the uncertainty of the prediction. Therefore, no resampling is conducted if no future measurements are available. One possibility to reduce the degeneracy of the particles is seen in estimating new measurements and realizing SIR until the failure threshold is reached. In this approach, the uncertainties are reduced within a data-driven approach that is connected to the developed Multi-Model-Particle Filter. Hence, both parts of the hybrid approach strive to account for and reduce uncertainties. The hybrid prognosis procedure is depicted in Figure 3. The acquired measurements are preprocessed and suitable features are extracted and selected. However, even if the aim of the approach is a prediction, at first a diagnosis is realized. Thereby, the current degradation phase is estimated. Only for previously defined phases, a prediction is realized. In all other cases the degradation process has not yet started. Therefore, it is too early to predict an accurate RUL. If the diagnosed phase allows for a prediction, the next state is predicted by a model-based prognosis method. In this

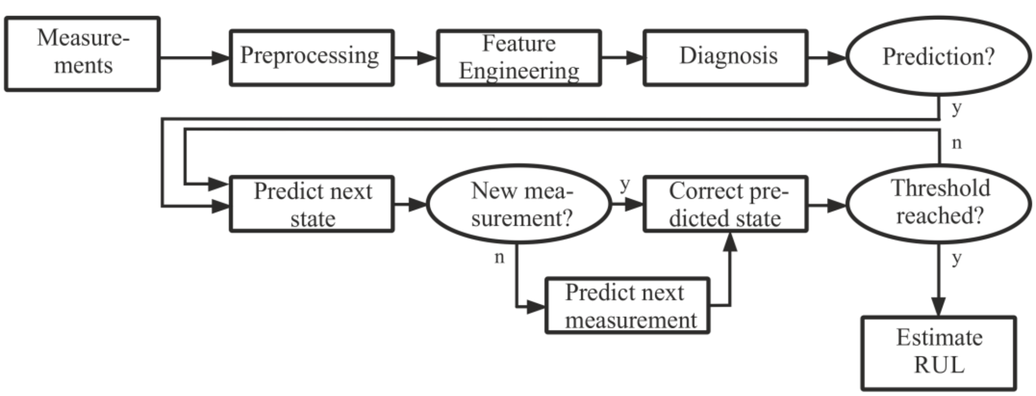

Figure 3. Procedure of the hybrid prognosis approach.

method the predicted state is corrected by a new measurement if available. If no new measurement is available, a coresponding approximation of a new measurement is conducted. Due to the amount of data, a statistical solution based on a functional relation is chosen. If the amount of data allows for a data-driven prediction, such a calculation can be integrated as well. Thereby, it is differentiated which degradation phase is classified. For each phase an individual relation is stored in the hybrid approach. Subsequently, the next measurement is approximated. Thus, in every case the predicted state is corrected. Afterwards, it is examined whether the failure threshold is reached by the estimated and corrected state. If it is reached, the RUL is predicted. If the threshold is not yet reached, the next state is predicted. This slope runs iteratively until the threshold is reached.

2.3.1. Comparison of the Approaches

In this subsection, the three presented approaches are compared. While the Multi-Model-Particle Filter is already approved, the two hybrid approaches have to be evaluated in the next section.

The Multi-Model-Particle Filter enables condition monitoring of technical systems related to a higher level of uncertainty. The approach is more complex than a general Particle Filter, but is able to consider uncertainties to a larger extend. Even for few data that contains a high level of uncertainty, this approach is able to predict the RUL. This is shown in a CMS for rubber-metal-elements in Bender (2021). Comparing a preventive and a predictive maintenance strategy for these elements, this CMS allows a larger utilization of the rubber-metal-elements when they are maintained predictively based on the predicted RULs. Thus, this CMS is a base for a future predictive maintenance concept of rubber-metal-elements. Nevertheless, the Multi-Model-Particle Filter still allows for a certain level of uncertainty.

The two hybrid approaches try to improve this model-based approach by either diagnosis or approximation of new measurements.

The combined hybrid approach based on a diagnosis and a prognosis is faster to implement and extends the former approach. Thereby, it enables the opportunity to validate the predicted RULs of the Multi-Model-Particle Filter. The two methods do not interact. However, machine learning can be challenging if only few data are available. Therefore, a certain uncertainty is contained within the classification. All in all, the prediction cannot be improved by this approach, but he predictions are validated and the uncertainty of the prediction may be reduced due to a second statement.

The hybrid prognosis approach enables a data-driven possibility to correct the predicted state of the Multi-Model-Particle Filter. Normally such a correction is not realized if no future measurements are available. A combination of a diagnosis and a depending approximation of the next measurement seems to be suitable as features to represent the general degradation often change with regard to different degradation phases (Kimotho, 2016). A suitable approximation of the next measurement has to be developed for the particular application. If only few data are available, a functional relation is preferred. If sufficient data is available, a data-driven model can be trained to learn the relation. The uncertainty of this approach is assumed to be higher than the previous approach as the approach bases on a data-driven classification and an approximation of the next measurement. Nevertheless, if the uncertainty is reduced in these parts, the approach may be able to improve the predictions of the Multi-Model-Particle Filter.

3. Use-case: Rubber-Metal-Elements

Rubber-metal-elements are employed as a use-case to evaluate the developed approaches. The characteristics of rubber-metal-elements, which are used to isolate vibrations in various systems, such as railways, trucks and wind turbines, are given by their viscoelasticity and their adaptability to different application (Domininghaus, Elsner, Eyerer, & Hirth, 2012). However, these advantages are coupled to various uncertainties in their behavior and their degradation. Those uncertainties are caused by diverse inner and outer factors, such as manufacturing influences and operating conditions (Johlitz, 2015; Molls, 2013). By expert knowledge the influences are described, analyzed and reduced if possible. Thus, the remaining uncertainties have to be considered within the hybrid prognosis method.

In Figure 4 a focused rubber-metal-element is depicted. It is built up of three main parts: an outer steel tube, an inner steel tube and a rubber part that connects the two steel tubes. Moreover, the outer steel tube is slotted to allow for a longer lifetime. Therefore, the element is preloaded in the application by a hollow cylinder around the outer tube and a bolt through the inner tube.

In lifetime tests, the element's inner tube is fixed by the bolt that is connected to a heavy bracket. The test rig is shown in

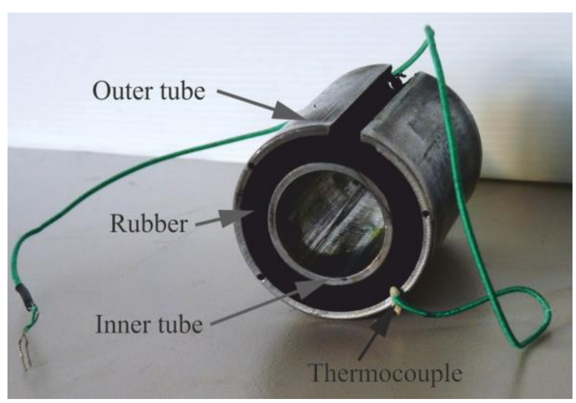

Figure 4. Structure of the rubber-metal-element (Bender, 2019).

Figure 5. To see the structure of the test rig, the second block to fix the bolt is removed in this figure. The outer tube is stimulated by a hydraulic cylinder in a force-controlled, sinusoidal movement. Thereby, small movements are enabled by the rubber. The critical part of the rubber-metal-element, the part that will lead to system failure, is given by the softest component, the rubber. It degrades under load over time. Therefore, the rubber is monitored during the lifetime tests.

Relative temperature is selected to monitor and describe the element's degradation. In lifetime tests, it is measured as the difference between the element's temperature and the ambient temperature. Thereby, one uncertainty of the future, the influence of the ambient temperature on the element's temperature is considered. These elements show three typical phases of degradation that are identified within the temperature measurements. In Figure 6 these three phases of degradation are marked in the curve of the focused measurement quantity. In the beginning (blue, dashed line) the relative temperature increases degressively due to the settling process of the rubber. The main part (green, solid line) describes a phase of a nearly stable temperature. The low points of temperature are caused by pauses during the lifetime tests. Since these systems experience pauses during real applications as well, e.g. in railways, they are considered in these experiments. The final degradation state (red, dotted line) characterizes the degradation of the element and is a sign for the contemporary end of life. For the classification, the labeling of the three phases is based on rate of change of the relative temperature.

However, due to material uncertainties and uncertainties of the environmental conditions these temperature curves show relevant deviations. For the focused five elements the mean standard deviation during the three phases of degradation is estimated based on the relative temperature:

- Phase I: 0.8 °C
- Phase II: 1.0 °C
- Phase III: 1.2 °C

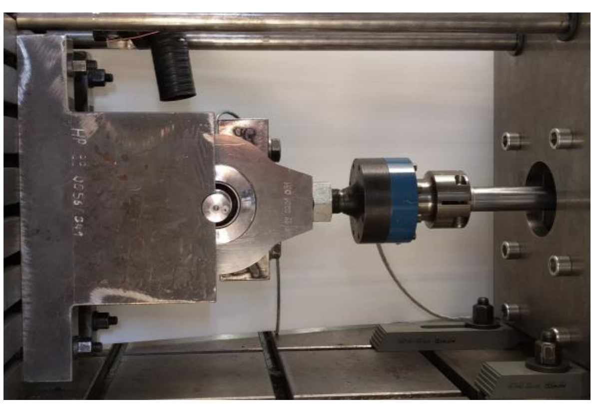

Figure 5. Structure of lifetime test rig (Bender, 2021).

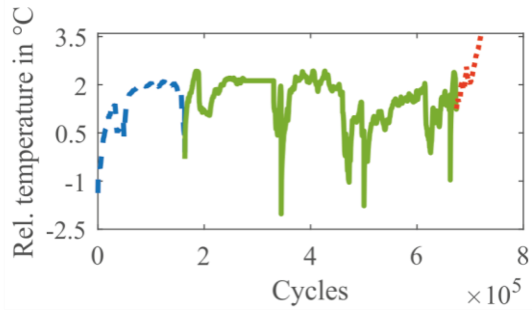

Figure 6. Three phases of degradation of a rubber-metal-element apparent in its relative temperature.

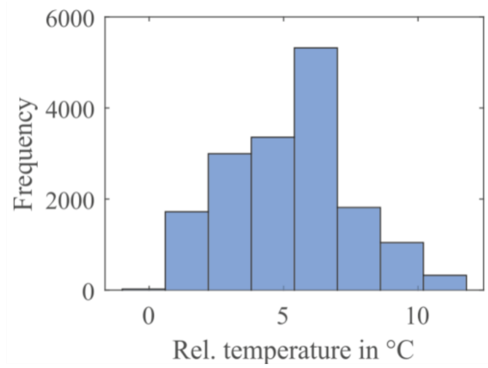

Figure 7. Distribution of relative temperatures during phase III for all focused elements.

Analyzing the whole data set, results in higher standard deviations for the phases II and III:

- Phase I: 1.2°C
- Phase II: 1.9 °C
- Phase III: 2.2 °C

All distributions resemble normal distributions as Figure 7 shows exemplary for degradations phase III of the whole data set.

It is concluded that the uncertainty increases with the degradation of the monitored system. Therefore, the particular phases are analyzed separately.

4. Evaluation of the Approaches Based on the Use-Case of Rubber-Metal-Elements

In this section, the in section 2 presented approaches are evaluated based on data of five rubber-metal-elements introduced in section 3. At first the ability of the combined hybrid approach to generate an added value to the predictions of the Multi-Model-Particle Filter is evaluated. Subsequently the hybrid prognosis approach that adds an approximation of new measurements to the same Particle Filter is evaluated based on the performance indices mean absolute percentage error (*MAPE*), rate of negative errors and prognostic horizon (*PH*).

4.1. Hybrid Approach Combining Diagnosis and Prognosis

Methodically a Random Forest is used to learn a classification model for each of the five focused elements based on the data of the other elements. Twenty different statistical features, such as root mean square, kurtosis and entropy of the relative and the ambient temperature are selected for this purpose. The mean classification error over all is 7.9%. The predictions of the Multi-Model-Particle Filter developed in Bender (2021) are evaluated at defined points in time during the lifetime of the elements. To ensure a greater comparability, for each element predictions are realized from 0.2 to 0.95 of their normalized reached lifetimes in steps of 0.05.

Exemplary, the curve of the relative temperature over the load cycles of element 8 is given in Figure 8. The black vertical lines symbolize the ends of the particular phases I, II and III. The dashed green lines mark the time span, during which the classification and the predictions are realized. At all points in time between 0.2 and 0.95 of the end time (t_e) phase II is classified. The learned model misclassifies the last time points due to the uncertainty in the training data. Comparing Figure 6 and Figure 8, a few differences become apparent, e.g. the absolute relative temperatures or the different slopes in the particular phases.

For all five elements the classification rate for these 16 time points is given in Table 2. Despite element 7, the classification shows an accuracy of more than 75%. Element 7 has an exceptional temperature curve that differs more from the others. The relative temperature decreases nearly continuously during phase II. Therefore, the classification of this element is error prone. Moreover, the mean accuracy and the mean precision per phase over the five elements is given in Table 3. Due to the chosen prediction time points, no time points of phase I are evaluated. Again element 7 has an impact on both performance indices.

Over all diagnoses, most often phase II is identified as expected because phase II is the longest phase of each lifetime test and the most of the learned points belong to that phase. However, especially early and late predictions during an element's lifetime are misclassified. While misclassified early predictions are not critical, as the RUL is long enough at this point in time, misclassified late predictions are critical for maintenance decisions. One reason might be the imbalanced training dataset. Due to the already small amount of training data, no data points of phase II were ignored. However, in the future the effects of a balanced dataset compared to the chosen dataset should be investigated. Based on the analyzed data of all elements a threshold for the minimum RUL in phase II is set to 4 x 10^4 cycles. Additionally, an upper threshold of phase II is set to 13 x 10^5 cycles. For element 8 the results of the model-based prediction and the diagnosed phases are visualized in Figure 9. The thresholds are included within the figure to mark the extreme RULs. Five predictions after 0.65 reached lifetime are close to the lower threshold and the predicted RUL at 0.96 reached lifetime has crossed this threshold. Therefore, it is concluded that the last predicted RUL belongs to phase III and a maintenance action should be planned. Regarding the previous predicted RULs that are close to the threshold, it has to be evaluated by an expert whether the system is close to its end of life or whether the results are explained by the remaining uncertainty of the classification.

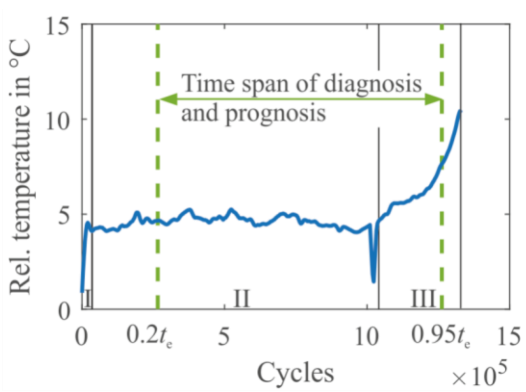

Figure 8. Relevant time points during an element's lifetime.

Over all five elements in 5 out of 85 predictions the additional diagnosis results in a warning because the predicted RUL and

Table 2. Classification results for the focused elements.

Element	4	5	6	7	8
Classification rate	0.88	0.81	0.88	0	0.75

Table 3. Mean accuracy and mean precision per phase

Performance index	Phase I	Phase II	Phase III
Mean accuracy	-	0.66	0.08
Mean precision	-	0.64	0.00

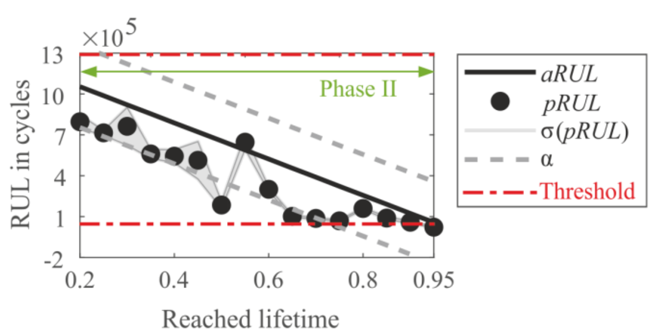

Figure 9. Validation of model-based predictions by a data-driven diagnosis in defined phases and the correlated thresholds of these phases.

the classified phase are not adequate. In these cases, the threshold between phase II and III is reached and an expert has to decide whether an early maintenance action is recommended.

4.2. Hybrid Prognosis Approach

In the hybrid prognosis approach, Random Forrest for the diagnosis part and the developed Multi-Model-Particle Filter developed in Bender (2021) are combined for the prediction task, see Figure 3. The classification error is similar to the previous approach, since the same models are used. However, predictions are performed only when the system is at least in phase II, because phase I is short and non-critical.

Depending on the classified phase, two different approximations of the next measurement are implemented. For phase II, a cubic function is used to approximate the next measurement. To identify suitable cubic functions, the curve fitting toolbox in MATLAB is used. A cubic function is defined for each relative temperature curve, starting at the beginning of phase II. Exemplary one measurement curve and its respective approximated function over the cycles of a tested element are shown in Figure 10. The cubic function (green, dotted line) is able to represent the main slope of the measurement curve (blue line). If the prediction starts in phase III, a linear approximation is implemented based on the mean gradient during this phase of the focused elements.

In the hybrid prognosis method, cubic and linear functions are estimated and stored for all elements. During a prediction, all functions of the diagnosed phase except that one of the tested element are available. At each prediction step of the particle filter, one function is randomly selected to approximate the next measurement.

An exemplary prediction is depicted in Figure 11. The last available measurement (end of black line) is classified to belong to phase II. By the stored cubic functions new measurements are approximated and thereby influence the predictions (grey lines). Moreover, the predictions jump to a higher temperature level at the beginning, which is more similar to the mean temperature in phase II.

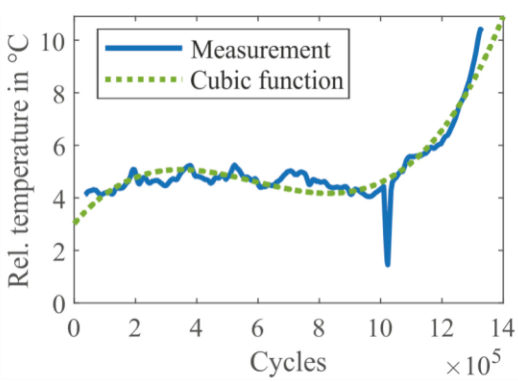

Figure 10. Approximation of next measurement during phase II.

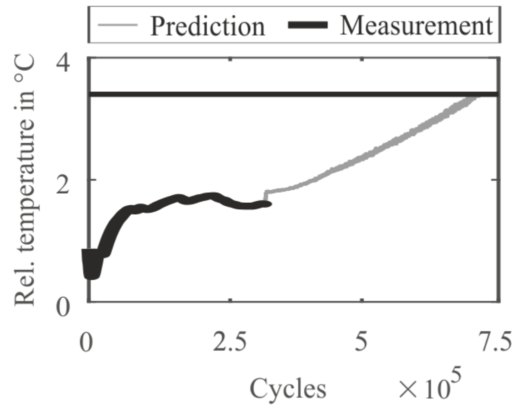

Figure 11. Hybrid prediction.

The estimated predictions are evaluated using three performance indices: mean absolute percentage error (*MAPE*), rate of negative errors and prognostic horizon (*PH*). *MAPE* estimates the absolute mean error between actual and predicted RULs across predictions of an element. The negative error counts undesired, too long predictions that would cause a breakdown of the system. Additionally, the prognostic horizon analyzes the chronological order of the predictions. Thereby, it is checked from which point in time all predictions are within a predefined error band α. (Goebel et al., 2017; Hoenig, Hagmeyer, & Zeiler, 2019; Javed et al., 2017)

Since only one point in time is visualized in Figure 11, an overview of all predicted RULs (*pRULs*, black dots) compared to the actual RULs (*aRULs*, black line) for one element is shown in Figure 12. All but the first four predictions fall within the error band α (grey dashed line). Because these four predictions are the first ones, the prognostic horizon (*PH*) starts at 0.4 of the reached lifetime. Most of the predicted RULs are relatively close to the actual RULs, especially at the end of life. However, the final predictions are too large and result in four negative errors. Therefore, the rate of negative errors for this element is 0.25. The mean absolute percentage error is about 40%.

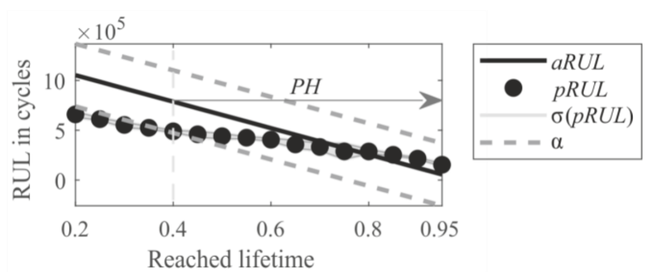

Figure 12. Predictions for element 8, comparing the actual RUL (*aRUL*), the predicted RUL (*pRUL*), the standard deviation of the predictions σ and the error band α.

Predictions are run for four elements. The respective performance indices are presented in Table 4. No predictions are estimated for the fifth element, because element 7 is classified to be in phase I over all points in time. Thus, Figure 12 shows the best result of the four elements. Moreover, the depicted predictions of element 8 are the only predictions that can be improved compared to the prediction of the Multi-Model-Particle Filter. The Multi-Model-Particle Filters results in *MAPEs* from 24% up to 46%, while the hybrid approach partly results in *MAPEs* above 100%, see Table 4. However, the achieved prognostic horizons are comparable. The rate of negative errors is 51% for the Multi-Model-Particle Filter and 69% for the hybrid approach. Therefore, the hybrid approach results in a larger number of too long predicted RULs.

All in all, the prediction of the next measurement does not add any value. Compared to the prediction of the model-based approach in Bender (2021), the results of the hybrid prediction often show no improvement. Sometimes they yield better results and sometimes worse ones. The uncertainty seems to be influential. Thus, the more expensive development of this hybrid approach is not justified. The uncertainty cannot be reduced in this way for this use-case.

Table 4. Performance indices for hybrid prognosis

Element	4	5	6	8
MAPE	81.6	101.4	130.3	40.1
Rate of negative errors	0.59	0.82	0.94	0.24
Prognostic horizon	0.20 – 0.95	0.30 - 0.95	0.20 -0.95	0.40 – 0.95

5. Conclusion

Condition monitoring of systems considering a high level of uncertainty is still a challenge. Since hybrid approaches are promising for these applications, in this paper two hybrid approaches for managing uncertainty are presented. In one approach, a data-driven classification is used to validate a model-based prediction of the RUL. The other approach integrates an approximation of new measurements into a model-based prognosis approach. The two hybrid approaches are evaluated for the use-case of rubber-metal-elements. These elements shown a high level of uncertainty, mainly due to influencing factors such as the production process. Moreover, the data set contains limited data, which is another challenge for the condition monitoring system, especially for the data-driven part. The evaluation of the developed methods based on the use-case underlines that additional classification is able to support an engineer by evaluating the predicted RULs. However, the uncertainties are still present as evidenced by the performance indices. To improve the classification, the choice of a smaller but balanced training dataset will be investigated. The hybrid prognosis approaches are even more sensitive to the existing uncertainties. The aim of improving the model-based prediction could not be achieved. This shows how difficult it is to manage uncertainty, especially when there is little data. If data acquisition is too expensive, a possibility to improve the results is seen in artificial data. However, artificial data adds another uncertainty to the system. The developed hybrid methods should be evaluated by another use-case that considers a high level of uncertainty but provides a larger data set.

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