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Prognostics of Remaining Useful Life for Aviation Structures Considering Imperfect Repairs

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Abstract

Maintenance plays an important role in fulfilling the goals of the Prognostics and Health Management (PHM) field. As of now, no publication has addressed the impact of imperfect repair actions from the prognostics perspective. Imperfect repairs introduce complexities, altering system degradation processes and increasing prediction uncertainties, thereby impacting the accuracy of Remaining Useful Life (RUL) predictions. To fill this gap in the literature, the study proposes developing a robust prognostic model adaptable to post-repair operations. The prognostic model that will be developed is stochastic since stochastic models have already proven their adaptability to unseen test data. However, further development of such models is needed to deal with data on repaired systems. In addition to that, the implementation of a Bayesian Extension allows uncertainty interpretability to be considered to account for the uncertainty coming from the repair action itself but also from the different sources of uncertainties that have not been studied in the field of prognostics.

1. Problem statement and state-of-the-art

Prognostics and Health Management (PHM) is a field that provides users with a thorough analysis of the health condition of a system which allows users to maximize the operational availability, reduce maintenance costs, and improve the system's reliability and safety (Tsui et al., 2015). PHM includes the following modules: data acquisition, diagnosis, prognosis, and decision-making (Moradi & Groth, 2020). Prognosis takes the information of the data coming from data acquisition alone or both the information of diagnosis and data acquisition. The output of prognosis is then the prediction of the Remaining Useful Life (RUL) of the system, which is the time left before the system reaches failure.

Prognostics plays a vital role in decision-making processes, guiding actions like system retirement or maintenance scheduling. Maintenance strategies vary from perfect maintenance (replacement) to imperfect maintenance (repair), with the latter being favored for its cost-effectiveness (Do Van et al., 2013). (Bougacha et al., 2020) conducted a review on post-prognostic decision-making, particularly focusing on aerospace applications. Existing approaches in this review typically consider current degradation levels or use prognostics assuming the system is as good as new to inform maintenance decisions. (Nguyen & Medjaher, 2019) developed a Deep Learning-based framework that covers the entire process from data-driven prognostics to maintenance decisions. However, the framework's limitation lies in its consideration of only perfect maintenance. To the best of the author's knowledge, (Welz et al., 2017) is the only work that has addressed repair actions in prognostics, emphasizing the importance of including data from repaired systems to enhance prediction accuracy. Yet, this study lacks reporting on RUL prediction and corresponding confidence intervals, providing only an average error of failure time.

Therefore, a significant research gap exists in the current literature regarding how to perform prognostic when the engineering system has been subjected to imperfect maintenance. In other words, there is a need to develop prognostic models that perform accurately when trained on data from systems with no repair but tested on systems repaired one or more times. This gap is notable given PHM's predictive maintenance and cost reduction goal.

Understanding the effects of repair actions on prognostic models is crucial, as repairs can alter the degradation process of a system. As a consequence, it will negatively affect the performance of the prognostic model by the decrease in the accuracy of RUL predictions, and an increase in the uncertainty of the predictions. Thus, it will reduce the reliability and robustness of prognostics, which will raise concerns about the eligibility of prognostics for decision-making. Therefore, many questions arise to deal with such a scenario. Should prognostic models consider dependencies between pre and post-repair operations? How can the prognostic model acknowledge the health recovery of the system? And how can uncertainty arising from repair actions be managed effectively?

To address the consideration of imperfect repairs in prognostics, it is necessary to develop a robust prognostic model that allows for interpretable uncertainty given the increased uncertainty expected from the repair actions. Understanding the concepts of robustness and uncertainty management, along with the challenges they present, is essential.

Robustness, defined as a system's ability to perform acceptably across various conditions, poses a challenge in prognostics due to the lack of adaptation mechanisms in existing models. Attempts have been made to improve robustness, such as using adaptive batch normalization or domain adversarial neural networks. Still, challenges persist, with high errors in terms of accuracy, along with instability and noise in the predictions

Exceptionally, the Adaptive Non-Homogeneous Hidden Semi-Markov Model (ANHHSMM) demonstrated adaptable capabilities (Eleftheroglou et al., 2020). This stochastic model was trained with 8 composite specimens under fatigue loading, and later on, tested with 3 specimens, also under fatigue loading, and suddenly experienced an unexpected phenomenon. The model provided good results, however, it has not been validated for a case study involving repairs.

Uncertainty management is the second challenge when performing prognostics with data from repaired specimens in the test set. Uncertainty management is defined as the identification of sources of uncertainty and the reduction of uncertainty by leveraging data to better characterize the inherent prognostic uncertainties, thereby reducing their impact on RUL predictions (Sankararaman, 2015).

However, to identify uncertainty it is first necessary to quantify it. Uncertainty quantification (UQ) is already a challenge in data-driven prognostics when using ML models that are deterministic by nature. Such models usually do not report UQ in their RUL predictions, as seen in (Zhu et al., 2020; Ma & Mao, 2020; Ren et al., 2020; Zhang et al., 2023; Cheng et al., 2022). In contrast, some publications address uncertainty quantification when using stochastic models or particle filters, but they provide broad confidence intervals, which results in a lack of valuable information for decision-making (Huang et al., 2017; Cadini, Sbarufatti, Cancelliere, & Giglio, 2019; Cadini, Sbarufatti, Corbetta, et al., 2019; Moghaddass & Zuo, 2014; Liu et al., 2018).

To handle broad ranges of confidence intervals is then necessary to perform uncertainty management. But even though some data-driven prognostic models allow UQ, then it is necessary to identify the sources of uncertainty. The classical categorization divides uncertainty into aleatory and epistemic (Der Kiureghian & Ditlevsen, 2009). However, as the authors themselves have mentioned, such categorization is artificial and it depends mostly on the modeler's choice and the application, which is why it is common to see disagreement on how to disentangle uncertainty by using this categorization.

In (Eleftheroglou et al., 2020), a more relevant categorization for prognostics is proposed, identifying five sources of uncertainty: past uncertainties from manufacturing processes, present uncertainty about the system's health, future uncertainty, model uncertainty, and prediction method uncertainty. This new framework has not been applied to real-life scenarios yet, with existing literature still relying on the classical categorization.

2. Expected Contributions

There is no relevant literature addressing imperfect repair actions from the perspective of prognostics. Therefore, this research will serve as a first attempt to address this issue by developing a robust prognostic model that can be trained with degradation histories of systems that have not been repaired and then tested on degradation histories of repaired systems. Thus, the contribution to the field is a prognostic model that has an adaptation mechanism and can take into account the dependencies between pre and post-repair operation, as well as include the recovery of the system after repair.

Additionally, a Bayesian extension is considered because it allows the estimation of a subjective probability. Unlike the frequentist approach, where the statistics are calculated based on the entire population. This is undesirable since calculating the uncertainty based on the statistics of the entire population when they have been subjected to different conditions has no purpose. Instead, the Bayesian approach works under prior knowledge and available data (Bayarri & Berger, 2004). Even more, the model should include the uncertainty coming from the repair. Identifying this and calculating this source of uncertainty allows for more interpretability in UQ that allows future uncertainty management to have more valuable information for the decision-making process. As mentioned earlier, the classical categorization of uncertainty is not suitable for prognostics. Thus, this research attempts to tackle uncertainty quantification from another perspective that has not been implemented in the literature to date.

3. RESEARCH PLAN

The research plan is divided into three main parts:

- **Experimental Campaign**: since there is no available dataset for prognostics that includes maintenance actions, the first step is to perform an experimental campaign. The experiments consider materials mostly used in aviation structures, such as metals and composites. This phase of the research also involves the analysis of the experimental data, in terms of the effects on the degradation process and a comparison study on how the performance of different prognostic models that are commonly used are affected when dealing with this data.
- **Development of the prognostic model**: As mentioned in Section 1, it is necessary to develop a prognostic model that has an adaptive mechanism. After a literature review, the most suitable model for this application is the ANHHSMM, however, the model needs the addition of variables to take into account the repair of the system as well as the relaxation of some assumptions. Therefore, in this part of the research, the work would consist of developing the mathematical model, including the programming implementation.
- **Bayesian Extension**: Finally, the last part of the research involves the Bayesian extension that allows more interpretable uncertainty in the prognostic model by identifying sources of uncertainty.

As of now, the work that has already been done corresponds to the experimental campaign. The research group performed experiments with open-hole aluminum specimens of material 7075-T6. Each specimen had dimensions $300x45x2$ [mm] and a central hole of 6 [mm] diameter. The aluminum specimens were subjected to constant amplitude fatigue, with a maximum stress of 100 [MPa], frequency of 5 [Hz], and ratio of 0.1. The training data consists of 5 degradation histories of specimens from run to failure. The testing data consists of 5 specimens, also from run to failure. However, the testing specimens were repaired at cycle 14000 with a composite patch to cover the fatigue crack.

Figure 1 shows health indicators derived from experimental data using a neural network developed by the research team. Training trajectories are depicted in blue shades while testing trajectories are in red shades. For visualization, only two trajectories per training and testing set are shown. Notably, a distinct shift in cluster values occurs around cycle 14000 in the testing trajectories, indicating specimen health recovery post-repair. From the plot, it is evident that testing specimens had a longer lifetime, in comparison with the training specimens, due to the repair.

By using this data, a preliminary comparison between prognostic models has been done by the use of SVR and MLP. The results show the poor performance of both of these models

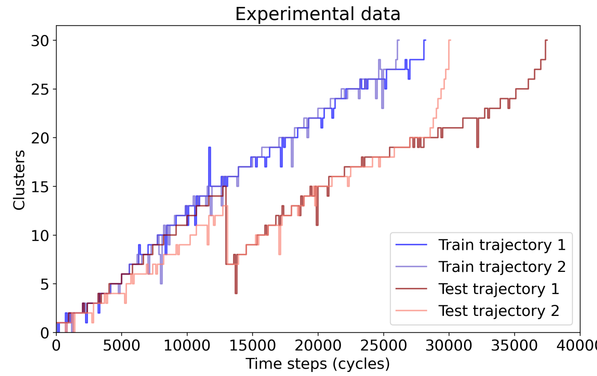

Figure 1. Experimental data of metal specimens for training and testing set.

with an average RMSE value for the test dataset of 131.0119 and 131.4693, respectively. This preliminary comparison shows the lack of adaptability of the models. Future work involves the comparison of more complex prognostic models such as Long Short-Term Memory (LSTM) and the ANHHSMM.

Part of the work in progress, is a literature review on uncertainty quantification in various prognostic models highlights the challenge in data-driven prognostics, particularly with ML models. Despite their high accuracy, ML models struggle with uncertainty quantification due to their deterministic nature. Another limitation is their reliance on the classical categorization of uncertainty into aleatory and epistemic types. The review compares methods for quantifying these uncertainties in ML models and implements a new prognostic measurement for Hidden Markov Models (HMMs) to assess stochastic models' ability to capture relevant uncertainties in prognostics, including past and future sources.

4. CONCLUSIONS

PHM is a field that assesses the health of an engineering system to perform predictive maintenance. Therefore, prognostics are key when predicting the health of the system and give valuable information for decision-making. However, within the prognostic field, a research gap exists when considering maintenance actions, such as repair. Repair is a common procedure that can have an impact on the degradation process of the system, and, therefore, it will negatively impact the performance of a prognostic model if this data is not part of the training set.

This research attempts to develop a robust prognostic model that can be trained with systems that have never been repaired and tested with systems that have been repaired one or several times. Even more, the research will also address UQ challenges such as the quantification of sources of uncertainty under the new categorization allowing more interpretability of uncertainty.

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