Uncertainty-Aware Prediction of Remaining Useful Life in Complex Systems

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Abstract

Accurate prediction of the remaining useful life (RUL) of industrial systems is critical to ensuring smooth operation and safety. Various prognostic methods have been developed, but significant challenges remain for field applications. While many methods may achieve high accuracy, they often fall short in quantifying the uncertainty of their predictions. Without uncertainty quantification, it is difficult to assess the confidence level of the prognostic results. Therefore, it is essential to transparently present the uncertainty levels in the predicted results. This Ph.D. project aims to develop novel uncertainty-aware methods for RUL prediction of complex systems. The project will address the following situations where it is more and more uncertain: (a) propose a general framework for data-driven RUL methods to quantify uncertainty and generate adaptive confidence intervals under a single fault mode and a single operating condition; (b) consider both epistemic and aleatoric uncertainties in scenarios with multiple fault modes and multiple operating conditions and then calibrate uncertainty to enhance their accuracy; (c) explore how to predict RUL and quantify uncertainty when there are no run-to-failure data and RUL labels in practice; (d) handle uncertainty propagation from the component level to the system level. Through this research, the project will provide more reliable and comprehensive solutions for RUL prediction in complex systems.

1. Problem Statement

The methods for predicting Remaining Useful Life (RUL) can generally be divided into two main categories: model-based approaches and data-driven approaches (Gebraeel et al., 2023). Model-based methods rely on a deep understanding of degradation mechanisms and the governing principles of the degradation process. However, practical challenges arise due to the complexity of failure mechanisms and operating environments, making it difficult to establish accurate models, especially when there is uncertainty in system behavior.

In contrast, data-driven methods are flexible and not confined to a specific model structure, depending instead on the quantity and quality of the available data. By employing machine learning algorithms and statistical techniques, these methods can identify patterns and relationships without needing explicit knowledge of the underlying degradation mechanisms, making them adaptable to various systems. By learning directly from the data, they can capture complex relationships and patterns, thereby addressing the limitations of traditional model-based approaches. However, most data-driven methods generate single-point RUL estimates and often lack robustness in uncertainty quantification (Zio, 2022).

Deep learning, a prominent data-driven approach, is known for its ability to handle complex nonlinear data structures, achieving high RUL prediction accuracy. However, it often struggles in quantifying prediction uncertainty (Khan & Yairi, 2018), especially in real-world scenarios with multiple fault modes and multiple operating conditions, lack of run-to-failure data and RUL labels, leading to heightened uncertainty levels.

In RUL prediction, there are two primary types of uncertainties: aleatoric uncertainty and epistemic uncertainty (Li, Yang, Lee, Wang, & Rong, 2020). Quantifying these uncertainties in various scenarios poses a significant challenge. Due to inaccuracies stemming from model misspecification and approximate inference, it's imperative to calibrate obtained uncertainties for accurate quantification (Kuleshov, Fenner, & Ermon, 2018). For example, a 95% posteriori confidence interval will typically not cover 95% of the true results. Calibration is therefore essential to accurately quantify uncertainty.

While many existing data-driven approaches focus on prognostics for individual components, predicting RUL and associated uncertainties for entire systems is crucial for devising effective maintenance strategies. In the realm of big data, systems are often treated as black boxes, overlooking component interactions that unveil complexity. Handling uncertainty propagation in RUL prediction from the component level to the system level, while considering diverse structures and interactions between components, remains a significant challenge (Nguyen, Medjaher, & Gogu, 2022).

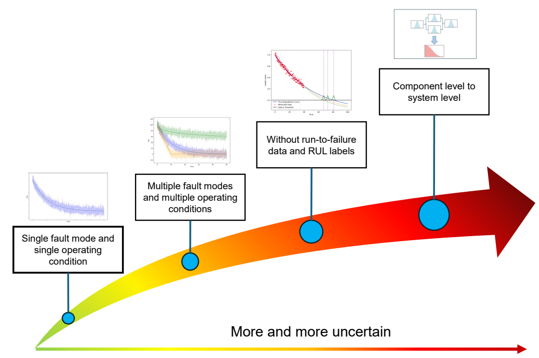

Figure 1. Research objectives of the Ph.D. project.

2. EXPECTED CONTRIBUTIONS

To address the aforementioned challenges, this Ph.D. project has four research objectives:

1. Uncertainty quantification and calibration of RUL prediction when it is single fault mode and single operating condition: explore methods that can quantify and calibrate uncertainty providing deterministic predictions with associated confidence intervals.
2. Uncertainty quantification and calibration of RUL prediction when it is multiple fault modes and multiple operating conditions: develop methods that are suitable for real-world conditions, such as multiple fault modes and multiple operating conditions, which present higher levels of uncertainty.
3. Predict RUL and quantify uncertainty when there are no run-to-failure data and RUL labels: available data is used to generate RUL labels for data-driven methods, Bayesian deep learning and stochastic process provide feasible solutions to provide uncertainty in conjunction with deterministic predictions.
4. Manage Uncertainty Propagation: address the propagation of uncertainty in RUL prediction from the component level to the system level, taking into account different structures and the interactions between components.

Figure 1 presents the four research objectives of the Ph.D. project.

3. PROPOSED RESEARCH PLAN

Research Objective 1: Predicting RUL using data-driven methods can be approached as a regression problem for time series data. Conformal Prediction (CP) offers a technique to create regression prediction intervals that encompass the target value with a specified confidence level. In Split Conformal Prediction (SCP), the training data is divided into subsets: one for training the regression model and the other for calibrating the prediction intervals during testing. The training subset is used to develop the regression model, while the calibration subset is employed to assess and quantify prediction uncertainty. SCP thus provides a robust framework for uncertainty quantification in data-driven RUL prediction methods. Moreover, incorporating prediction difficulty and time order offers a more practical approach to calibrating RUL uncertainty.

Research Objective 2: To address epistemic and aleatoric uncertainties, Bayesian deep learning is leveraged to quantify uncertainty in more uncertain scenarios, such as multiple fault modes and multiple operating condtions. Specifically, the Bayesian posterior over the weights captures epistemic uncertainty, represented by a probabilistic distribution. Aleatoric uncertainty is manifested through a probabilistic output following a Gaussian distribution parameterized by two neurons in the output layer. The network is trained using Bayes by Backprop, a variational inference method. The ensemble method is adopted to integrate epistemic and aleatoric uncertainties. To effectively calibrate both types of uncertainties, scaling method is used.

Research Objective 3: Available data is firstly used to generate RUL labels for training. Bayesian deep learning and stochastic processes offer viable solutions for integrating uncertainty with deterministic predictions.

Research Objective 4: By integrating the probabilistic model's capacity to capture and quantify uncertainties with the deep neural network's capability to discern intricate patterns and dependencies within the data, the predictive model achieves a holistic understanding of the degradation process. This synergy of methodologies not only enhances the accuracy and reliability of RUL predictions for individual components but also enables a broader perspective on the health and longevity of the overall system.

3.1. Work Performed

Research Objective 1: We introduce a novel framework designed to overcome the constraints of conventional conformal prediction techniques. Figure 2 illustrates the comprehensive data-driven framework for RUL estimation with uncertainty quantification, employing SCP. Our framework pri-

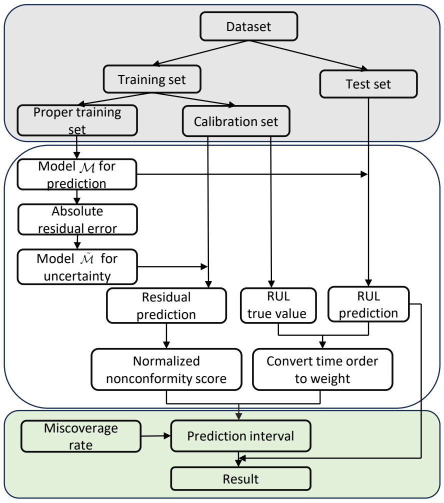

Figure 2. The general data-driven framework for RUL estimation with uncertainty quantification using split conformal prediction.

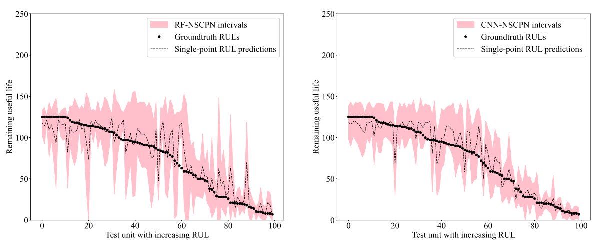

Figure 3. Sorted RUL single-point estimation with predicted intervals from NSCPN by RF and CNN.

oritizes the generation of prediction intervals for single-point estimators, thus facilitating robust uncertainty quantification. This approach addresses the limitations of interval adaptivity and surpasses the assumption of data exchangeability inherent in previous methodologies. To assess the efficacy of our framework, we conducted experiments using the extensively utilized Commercial Modular Aero-Propulsion System Simulation (CMAPSS) datasets.

We conformalize six estimators using Nonexchangeable Split Conformal Prediction with a normalized nonconformity measure (NSCPN). The NSCPN framework can provide prediction intervals for both conventional machine learning estimators and modern deep learning estimators, establishing it as a general data-driven RUL estimation framework with uncertainty quantification. Figure 3 shows single-point estimation with predicted intervals from proposed framework by Random Forest (RF) and Convolutional Neural Networks (CNN). Furthermore, we apply the NSCPN framework to each estimator and compare it with Split Conformal Prediction (SCP) and Nonexchangeable Split Conformal Prediction (NSCP). Across all six estimators, we observe a consistent pattern:

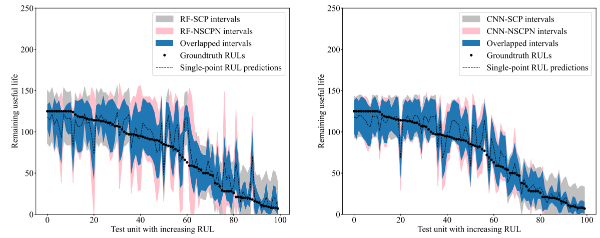

Figure 4. RF and CNN applied with SCP an NSCPN.

both score normalization and nonexchangeability improve the split conformal prediction. They give more adaptive and flexible prediction intervals that can better capture the varying levels of prediction difficulty or uncertainty in different regions of the data space. As data points approach failure times, single-point predictions of RUL become more accurate, particularly when RUL is near zero. This observation indicates that data points closer to failure times are relatively easier to predict compared to those with larger actual RUL values. Therefore, we anticipate narrower prediction intervals for these data points, which means we have strong confidence in the prediction results. It is evident that for those areas where the prediction results are not accurate, especially those peaks which are far away from real values, NSCPN gives a wider prediction interval, proving that we have weak confidence in the prediction results. It is thus demonstrated that NSCPN is more adaptive, a crucial performance characteristic for decision-making in safety-critical scenarios. The validation of our framework underscores its potential for practical application in uncertain prediction tasks.

Research Objective 2: We propose a Bayesian Deep Learning framework for RUL prediction that considers both aleatoric and epistemic uncertainties across multiple operating conditions and fault modes, which is presented in Figure 5. In such high-level uncertain scenarios, our framework demonstrates a significant ability for uncertainty quantification. Not only does our proposed framework provide prediction intervals when compared with frequentist deep learning, but it also exhibits superior capability for uncertainty quantification compared to traditional Monte Carlo Dropout-based Deep Learning methods. Deterministic predictions with confidence intervals are presented in Figure 6.

To comprehensively address both epistemic and aleatoric uncertainties, our proposed Bayesian deep learning framework represents weights as probability distributions rather than deterministic values. The corresponding mean and standard deviation are estimated from the two-dimensional output layer, enabling the learning of mean and noise observations from input data. In contrast to traditional Monte Carlo Dropout approaches, we utilize Bayes by Backprop to approximate the posterior distribution through variational inference. Finally, the mean and standard deviation of output results are obtained

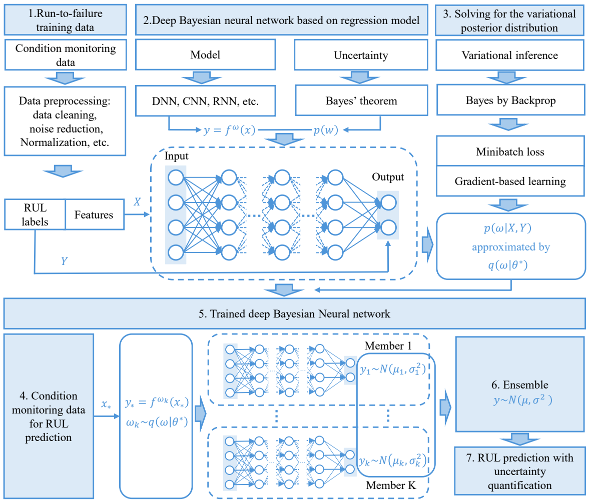

Figure 5. Bayesian Deep Learning framwork for RUL.

by multiple forward passes of the network. RUL predictions with two uncertainties are illustrated in Figure 7.

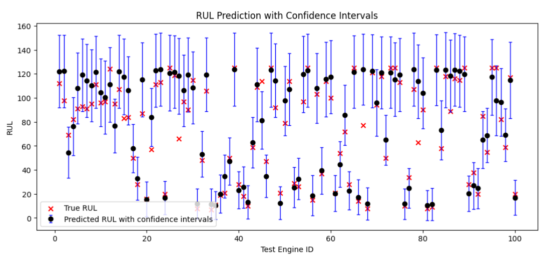

Figure 6. Predicted RUL with confidence interval.

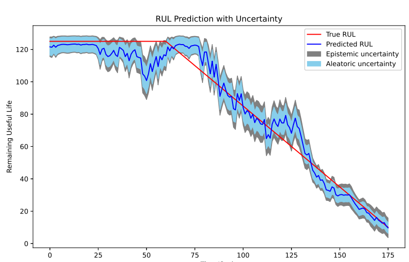

Figure 7. RUL predictions with two uncertainties.

This framework has been validated using the CMAPSS datasets. Particularly in uncertain scenarios involving multiple operating conditions and fault modes, our proposed framework demonstrates significant improvements in prediction accuracy and uncertainty quantification.

3.2. Remaining Work

Research Objective 3: The available data is initially used to generate RUL labels for training. Bayesian deep learning and stochastic processes then provide effective methods for incorporating uncertainty alongside deterministic predictions.

Research Objective 4: The integration of a probabilistic model and deep neural network facilitates the prediction of component-level RUL distributions. Leveraging insights into the system's architecture enables the prediction of system-level RUL, enhancing the overall prognostic capability.

4. CONCLUSION

This research aims to develop uncertainty-aware methods for predicting RUL of complex systems. The first proposed framework is a general approach enabling data-driven methods for RUL estimation with uncertainty quantification, utilizing split conformal prediction. The second proposed framework utilizes Bayesian deep learning to address both aleatoric and epistemic uncertainties across multiple fault modes and working conditions. Future work will explore methods to predict RUL and quantify uncertainty in scenarios where run-to-failure andd RUL labels are unavailable and how uncertainties propagate from component level to system level.

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