1. Introduction

* Highlights the increasing availability of sensor monitoring data in modern aircraft and its potential for Remaining-Useful-Life (RUL) estimation and predictive maintenance planning.
* Notes that most existing studies either focus on RUL prognostics only or use simple assumptions about degradation trends for maintenance planning.
* Proposes an integrated framework using Convolutional Neural Networks (CNNs) with Monte Carlo dropout for probabilistic RUL prognostics and Deep Reinforcement Learning (DRL) for adaptive maintenance planning.

1. Estimating the distribution of RUL using CNN with Monte Carlo dropout 2.1 Data description and pre-processing

* Uses the C-MAPSS dataset [11] containing simulated degradation data of turbofan engines from 21 sensors under different operating conditions and fault modes.
* Selects 14 non-constant sensor measurements and normalizes them based on operating conditions (Eq. 1).
* Considers additional features like current operating condition, operating condition history, and sensor measurements over a sliding window of nW cycles (Eq. 2).

2.2 Architecture of the multi-channel CNN with Monte Carlo dropout

* Proposes a multi-channel 1D CNN architecture with separate kernels for each sensor measurement (Eq. 3), allowing the network to learn sensor-specific patterns.
* Uses 5 convolutional layers with increasing channels and decreasing kernel sizes, followed by linear layers (Table 2).
* Applies Monte Carlo dropout after each layer during both training (to prevent overfitting) and testing (to estimate RUL uncertainty).

2.3 Probabilistic RUL prognostics for turbofan engines - Validation

* Compares the proposed model's RMSE against other CNN-based approaches (Table 3), showing comparable or superior performance.
* Illustrates the evolution of the estimated RUL distribution over time (Figs. 3-4), demonstrating the benefits of probabilistic prognostics for maintenance decision-making.
* Assesses the calibration of the estimated RUL distributions using calibration plots (Fig. 5), confirming the model's well-calibrated uncertainty estimates.

1. Planning predictive maintenance using DRL and probabilistic RUL prognostics 3.1 Scheduling engine replacements taking into account updated probabilistic RUL prognostics

* Updates RUL prognostics every D flight cycles (decision step) as new sensor measurements become available.
* Aims to minimize total maintenance cost, avoid failures, and minimize wasted useful life by optimally scheduling replacements based on the estimated RUL distribution.

3.2 Predictive maintenance planning as a deep reinforcement learning problem

* Formulates maintenance planning as a DRL problem with states (RUL distribution), actions (replacement decisions), and rewards (costs) (Eqs. 7-10).
* Trains a DRL agent using the Soft Actor-Critic (SAC) algorithm to adaptively make maintenance decisions without relying on fixed degradation thresholds.

3.3 Training the DRL agent for predictive maintenance

* Implements policy, value, and critic networks using deep neural architectures (Fig. 10, Table 4).
* Trains the networks using the SAC algorithm (Algorithm 1) with replay buffer, mini-batch sampling, and loss functions for policy, value, and critic optimization (Eqs. 16-20).

1. Case study: DRL for predictive maintenance of turbofan engines with probabilistic RUL prognostics 4.1 Training the probabilistic RUL prognostics

* Splits the FD002 subset of C-MAPSS into FD002-Prog (for training RUL prognostics) and FD002-DRL (for generating DRL episodes).

4.2 Training the DRL agent

* Generates maintenance episodes using the trained RUL prognostics model and FD002-DRL data.
* Trains the DRL agent for 5000 episodes using the SAC algorithm, with the estimated RUL distribution as the state and replacement decisions as actions.
* Monitors the learning curve (Fig. 11) to assess convergence and stability of the training process.

4.3 Evaluation of the DRL agent: Predictive maintenance using DRL

* Evaluates the trained DRL agent on 1000 new episodes, demonstrating its ability to make adaptive maintenance decisions based on the updated RUL distributions (Figs. 12-13).
* Analyzes the distribution of wasted engine life at the moment of replacement (Fig. 14), showing that the DRL approach effectively minimizes unnecessary early replacements.

1. Predictive maintenance using DRL vs other maintenance strategies

* Compares the proposed DRL approach against three traditional maintenance strategies: predictive maintenance at mean-estimated-RUL, corrective maintenance, and ideal maintenance at true RUL.
* Demonstrates that the DRL approach outperforms the other strategies in terms of total cost, number of unscheduled replacements, and total number of replacements (Table 5, Fig. 15).
* Highlights the benefits of using probabilistic RUL prognostics (RUL distribution) over point estimates (mean-estimated-RUL) for maintenance planning.

1. Conclusions

* Summarizes the main contributions: integrating probabilistic RUL prognostics (using CNN with Monte Carlo dropout) into predictive maintenance planning using DRL.
* Emphasizes the advantages of the proposed approach, including adaptive, threshold-free maintenance decisions and improved cost-reliability trade-offs compared to traditional strategies.
* Discusses potential future work on multi-component maintenance, incorporation of practical constraints, and dynamic operating conditions.

DEFINITIONS:

1. Probabilistic RUL prognostics:
   1. An approach to estimating the probability distribution of RUL, rather than a single point estimate, to quantify the uncertainty associated with the prediction.
2. Convolutional Neural Network (CNN):
   1. A type of deep learning model commonly used for processing grid-like data, such as images or time series. CNNs employ convolutional layers to learn local patterns and pooling layers to summarize information.
3. Monte Carlo dropout:
   1. A technique for estimating the uncertainty of deep learning models by applying dropout (randomly setting a proportion of activations to zero) during both training and inference.
4. Deep Reinforcement Learning (DRL):
   1. A subfield of machine learning that combines deep learning and reinforcement learning to enable agents to learn optimal decision-making policies through interaction with an environment.
5. Soft Actor-Critic (SAC):
   1. An off-policy, model-free DRL algorithm that aims to maximize both the expected reward and the entropy of the policy, promoting exploration and stability during training.
6. Replay buffer:
   1. A data structure used in off-policy DRL algorithms to store past experiences (state, action, reward, next state) for efficient sampling and updates of the neural networks.
7. C-MAPSS dataset:
   1. A publicly available dataset containing simulated degradation data of turbofan engines under different operating conditions and fault modes, commonly used for benchmarking RUL prognostics and predictive maintenance algorithms.
8. Calibration plot:
   1. A graphical tool for assessing the quality of probabilistic predictions by comparing the estimated probabilities against the observed frequencies of events.