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Generating Controlled Physics-Informed Time-to-failure Trajectories for Prognostics in Unseen Operational Conditions

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The performance of deep learning (DL)-based methods for predicting remaining useful life (RUL) may be limited in practice due to the scarcity of representative time-to-failure (TTF) data. To overcome this challenge, generating physically plausible synthetic data is a promising approach. In this study, a novel hybrid framework is proposed that combines a controlled physics-informed data generation approach with a DL-based prediction model for prognostics. The framework introduces a new controlled physics-informed generative adversarial network (CPI-GAN) that generates diverse and physically interpretable synthetic degradation trajectories. The generator includes five basic physics constraints that serve as controllable settings. The regularization term, which is a physics-informed loss function with a penalty, ensures that the synthetic data's changing health state trend complies with the underlying physical laws. The synthetic data is then fed to the DL-based prediction model to estimate RUL. The framework's effectiveness is evaluated using the New Commercial Modular Aero-Propulsion System Simulation (N-CMAPSS), a turbofan engine prognostics dataset with limited TTF trajectories. The experimental results demonstrate that the proposed framework can generate synthetic TTF trajectories that are consistent with underlying degradation trends and significantly improve RUL prediction accuracy.

Keywords: Prognostics, Time-to-failure trajectory generation, Deep learning, Physics-informed generative adversarial networks.

1. Introduction

One of the corner stones of Prognostics & Health Management (PHM) is the prediction of the remaining useful life (RUL) of industrial assets, which enables decision-makers to plan maintenance actions in advance and prevent failures [1]. However, the performance of deep learning (DL)-based approaches for RUL prediction in practice is limited due to the lack of representative TTF data. Inspired by the Time series Generative Adversarial Networks (TimeGAN) [2], this study focuses on the challenging problem of RUL prediction when the available TTF trajectories are not sufficiently representative, specifically when the observed operating conditions (OC) in the training dataset do not match those in the testing dataset. To overcome this issue, the proposed approach introduces a physics-informed generative framework for prognostics that enables controlling the TTF trajectory generation while ensuring that the generated trajectories are realistic, fully interpretable, and consistent with the underlying degradation processes. This framework is referred to as a controlled physics-informed generative adversarial network (CPI-GAN).

2. Methodology

This section presents the proposed approach for generating synthetic data and using a DL-based prognostics model, as shown in Figure 1. The framework comprises three main steps: data preprocessing, synthetic trajectory generation, and prognostics. In the first step, the data is pre-processed through downsampling, normalization by flight class, and statistical analysis (obtaining the physical characteristics of the degradation trajectories under various flight classes as basic physics constraints for synthetic trajectory generation). Since real health parameters are only available during training, a surrogate model (deep neural network with three layers) is developed to replace the

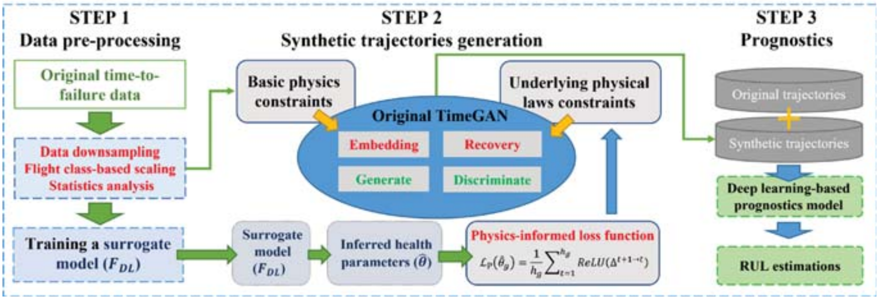

Fig. 1. The framework of the proposed controlled physics-informed data generation for RUL prediction.

traditional physics-based system performance model to obtain the inferred health parameters. In the second step, the basic physics constraints are used to initialize the generator. Then, the generated sequence is fed into the surrogate model to infer the unobservable health parameters. These parameters are used to enforce penalty targets of the physics-informed loss function during generation, ensuring adherence to the engine's underlying degradation characteristics. In the final step, the synthetic degradation trajectories and original degradation trajectories are combined into a training dataset, which is then used as input to the prognostics model to output RUL estimations.

3. Results and Conclusions

The proposed framework was evaluated on the new Commercial Modular Aero-Propulsion System Simulation (N-CMAPSS) dataset. As depicted in Table 1, the hybrid outperforms the purely data-driven approach with the same 1D-CNN architecture by 17.67% in terms of RMSE and 52.08% in the NASA *score* reduction, demonstrating a clear improvement. This performance improvement is primarily attributed to the four synthetic units that belong to unseen OCs. Moreover, the proposed framework handles RUL overestimation more efficiently, as evident by the substantial decrease in the score metric, which penalizes overestimation rather than underestimation, compared to the symmetric RMSE metric.

Table 1. Overview of the results of the hybrid framework and the baseline approach, respectively. The Mean and standard deviation of the prediction results are obtained over five runs.

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Metric	Baseline	Hybrid	rel. Delta
RMSE	4.64±0.14	**3.82±0.11**	-17.67%
score	0.48±0.05	**0.23±0.04**	-52.08%

4. Conclusions

The proposed approach in this study presents a novel solution to overcome the challenges of limited representativeness and missing time-to-failure trajectories by utilizing a controlled data generation technique based on physical information to generate synthetic data for unseen scenarios. Our proposed approach leverages prior knowledge and underlying physical laws to generate time-to-failure data that complies with basic physics constraints and the system's degradation trend under different operating conditions. The generated synthetic data, combined with real data, are used to train a DL-based model to predict the RUL. Extensive evaluations demonstrate that the synthetic data adheres to the physical constraints and the degradation trend of the system, and the inclusion of synthetic data leads to improved RUL prediction accuracy.

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