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Learning linearized degradation of health indicators using deep Koopman operator approach

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In this study, we showcase the successful application of the Deep Koopman operator approach to model the dynamics of industrial systems at multiple time scales. Specifically, we demonstrate its effectiveness in modeling the rapidly changing operating conditions as well as the slowly evolving degradation of the systems. Furthermore, we propose a novel approach inspired by Koopman theory to model the degradation of controlled dynamical systems. The proposed algorithm allows to predict the degradation trend with a limited number of full run-to-failure trajectories.

Keywords: Deep Koopman operator, remaining useful lifetime, predictive maintenance.

1. Introduction

Recent studies show that incorporating prior physical knowledge and utilizing inductive bias can lead to a significant improvement in the performance of deep learning algorithms Hao et al. (2022). It has been demonstrated by the Deep Koopman operator approach (DKO) Lusch et al. (2017) that it is capable of modelling dynamical systems. The objective of this study is to demonstrate the effectiveness of utilizing DKO for accurately predicting the remaining useful life (RUL) of industrial systems. Furthermore, we propose a novel architecture that allows to separate the degradation of the system state representation and imposed control.

2. Methodology

The Koopman theory offers a means to discover intrinsic coordinate systems where nonlinear dynamics can be expressed in a linear form. Acquiring linear representations of highly nonlinear systems is particularly useful for controlling and predicting their dynamic behaviour. Recently, Lusch et al. (2017) proposed a data-driven approach to learn the Koopman operator. Our proposed approach involves utilizing the Deep Koopman (DK) approach to model the dynamics of degrading industrial systems, which inherently exhibit the combination of two distinct time dynamics.

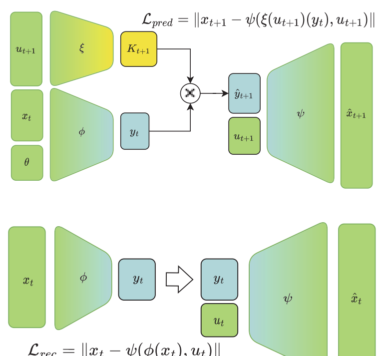

Fig. 1. The Koopman Inspired Degradation Model.

Accurately modeling the dynamics of a system in many industrial applications often requires the incorporation of control variables. Despite the distinct time scale of degradation in comparison to the operating dynamics, prior Koopman-based architectures did not possess the capability to capture the degradation of hidden health indicators of the system through construction. This paper introduces the Koopman Inspired Degradation Model

(KIDM) algorithm. The architecture of KIDM, illustrated in Fig. 1., involves the utilization of the control vector in two distinct ways. Firstly, it is used to enforce the degradation of the latent representation of the system state. Secondly, it is utilized to decode the latent state back to initial state space.

3. Results

We test the DKO on two case studies - a CNC milling machine Li (2021) and Li-ion battery simulation Teubert et al. (2022), both of which incorporate both degradation and dynamics of operating conditions. The first dataset Li (2021) contains high-frequency time series data of real CNC milling machines. The dataset consists of three run-to-failure trajectories of machines with different initial conditions. The second dataset invovles Li-ion battery degradation trajectories simulated suing the simulator proposed in Teubert et al. (2022) under a constant current load. Our objective is to predict the remaining useful life (RUL) based on the learned state representations.

The CNC milling machine data was preprocessed using the Learnable Denoising Sparse Wavelet Network (DeSpaWN) Michau et al. (2022) with 7 levels of decomopsition. The DKO reaches achieves a mean squarred error (MSE) of 0.016 on the RUL prediction task. The feed-forward network (FNN) achieves 0.07 MSE on the same task with DeSpaWN features. Additionally, we applied DKO to model the dynamics of a Li-ion battery under a constant current load, resulting in an MSE of 0.15 for RUL prediction. The principal component analysis (PCA) of the latent representations indicates a correlation coefficient of 0.97 and 0.37 with the two distinct unobserved battery health indicators (qmax and R) that were not presented to the algorithm during training.

To evaluate the performance of the proposed KIDM algorithm, we simulated a Li-ion battery under varying current loads. The current load was used as a control variable. The KIDM achieved an MSE of 0.02 on the voltage prediction task. Principal component analysis shows 0.79 and 0.33 correlation coefficients of 2 principal components and 2 distinct unobserved battery health indicators. The KIDM haven't fully disentangled health indicators. Despite this the latent representation of observables has shown to be informative enough to predict the trend of degradation of health indicators. To compensate the remaining non-linearity in the latent representation we applied a simple random forest (RF) algorithm to predict the RUL based on the latent representation, which was trained on 5 run-to-failure trajectories. We compared these predictions with FNN trained on a feature set of the KIDM encoder. The RF algorithm trained on the prepared latent representation outperforms the FNN, which failed to determine the degradation trend due to lack of training data.

Model	MAE	MAPE	MSE
FNN	0.40	2.56	0.23
KIDM+RF 2	0.27	1.21	0.09

4. Conclusion

The successful application of DKO in modelling real-life dynamical systems and its informative latent space for predicting the RUL inspired us to propose the KIDM, KIDM extends the DKO by modelling the degradation of controlled dynamical systems. Our studies show that KIDM inherited the benefits of the DKO latent space and successfully models system degradation, making it a promising approach for predicting RUL.

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