Deep Koopman Operator-based degradation modelling

Chair of Intelligent Maintenance & Operations Systems (IMOS)

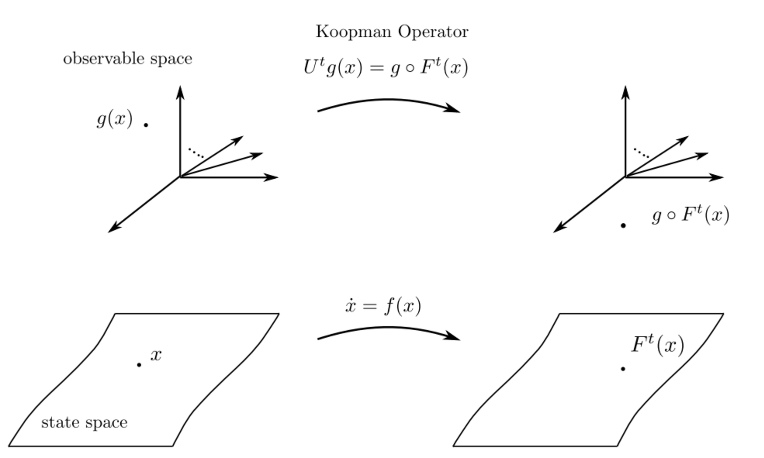
Sergei Garmaev, Olga Fink

Intelligent Maintenance and Operations Systems Lab, EPFL

Motivation

- A crucial criterion for reliable health indicators is their capability to discern a degradation trend
- Koopman theory provides a means to find coordinates where dynamics becomes linear
- Based on this theory, there was previously proposed the Deep Koopman Operator (DKO) approach that learns linear dynamics operator in the latent space of an autoencoder
- In this work, **our objective** is to evaluate if DKO and proposed in this work ***Koopman-inspired Degradation Model*** (KIDM) are able to construct reliable health representation of industrial dynamical systems and develop an approach that is able to capture the hidden degradation dynamics for the trendable degradation predictions
- We learn the dynamics of the process by DKO and KIDM and evaluate the learned representations in the Remaining Useful Life (RUL) prediction

Koopman Operator

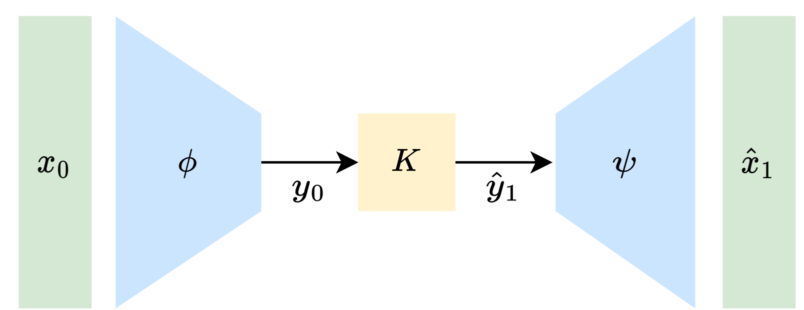


✓ Finite-dimensional
❑ Nonlinear

❑ Infinite-dimensional
✓ Linear

- There exist infinite-dimensional space where the system dynamics becomes linear
- In applications, one usually looks for finite-dimensional approximation of such space

Deep Koopman Operator (DKO)



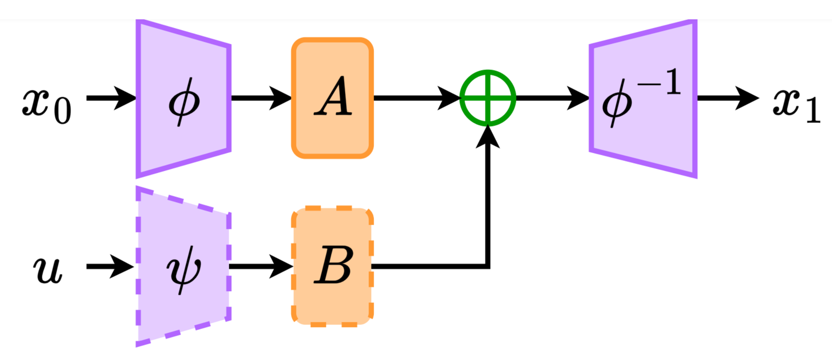
$$\mathcal{L}_{rec} = \|x_t - \psi(\phi(x_t))\|$$

$$\mathcal{L}_{lin} = \|\phi(x_{t+m}) - \mathbf{K}^m \phi(x_t)\|$$

$$\mathcal{L}_{pred} = \|x_{t+m} - \psi(\mathbf{K}^m \phi(x_k))\|$$

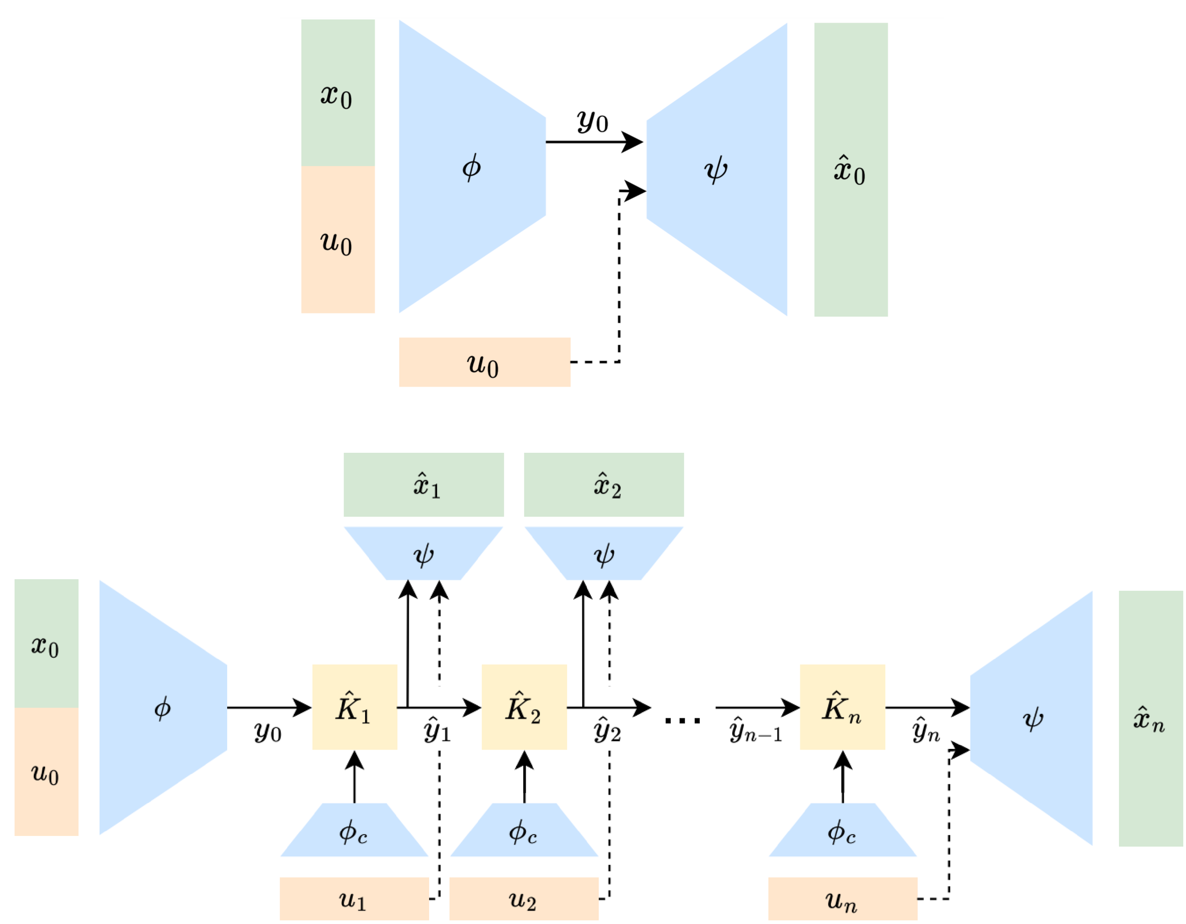
- Based on autoencoder architecture
- Learns invertible mapping of system state to latent space
- Further, learns linear dynamics in the latent space and in the initial system state space over multiple timesteps

Previous DKO-based model for control systems



- Previous DKO-based setups for controlled systems mainly have a linear mapping to Koopman observables
- Linear mapping of control may limit the choice of observables
- Control has significant influence on the observables space

Proposed *Koopman-Inspired Degradation Model* (KIDM)



$$\mathcal{L}_{rec} = \|x_t - \psi(\phi(x_t, u_t), u_t)\|$$

$$\mathcal{L}_{lin} = \|\phi(x_{t+m}) - \hat{K}_{t+m}\hat{K}_{t+m-1}...\hat{K}_{t+1}\phi(x_t)\|$$

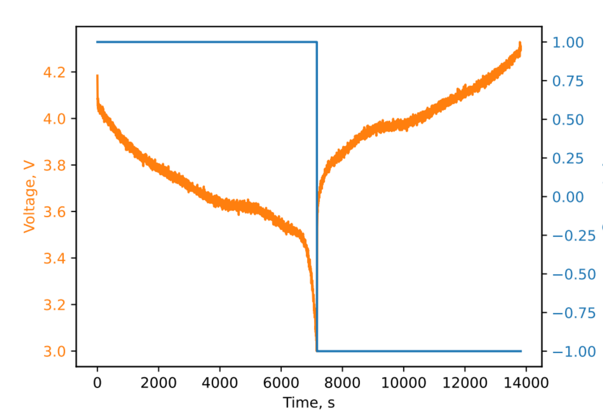
$$\mathcal{L}_{pred} = \|x_{t+m} - \psi(\hat{K}_{t+m}\hat{K}_{t+m-1}...\hat{K}_{t+1}\phi(x_t))\|$$

- Koopman operator is produced by encoding the control vector
- Control vector is applied again, together with the latent representation, to predict the future state
- Reconstruction task without applying Koopman operators in the latent space allows Koopman operator to learns the dynamics of degradation

Case studies

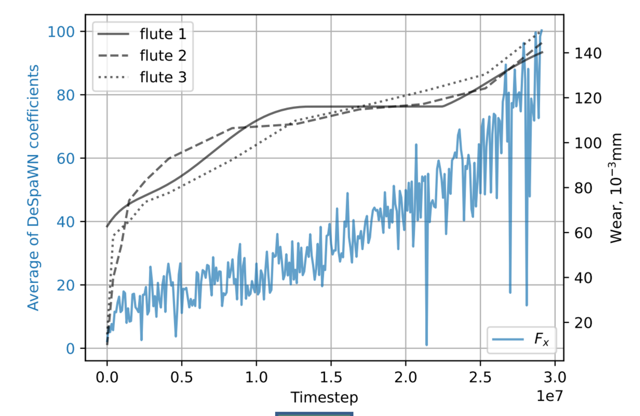
1. Li-ion battery under constant current load

Hidden health parameters:
- Number of available Li-ions
- Internal resistance of battery



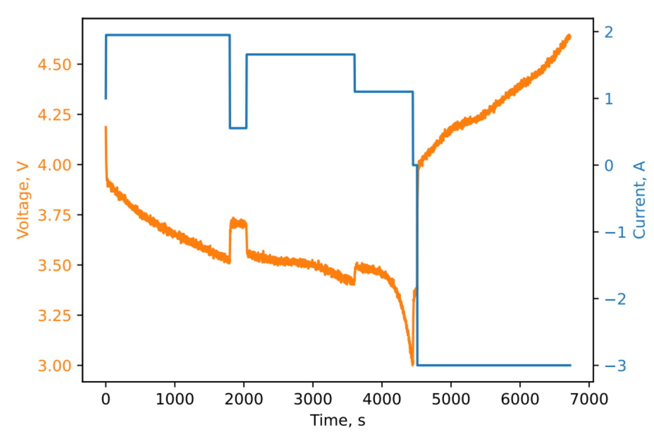
2. CNC milling machine cutters

High frequency time-series. Each cutter has 3 flutes that accumulate wear during the lifetime.
Hidden health parameters:
- Number of available Li-ions
- Internal resistance of battery



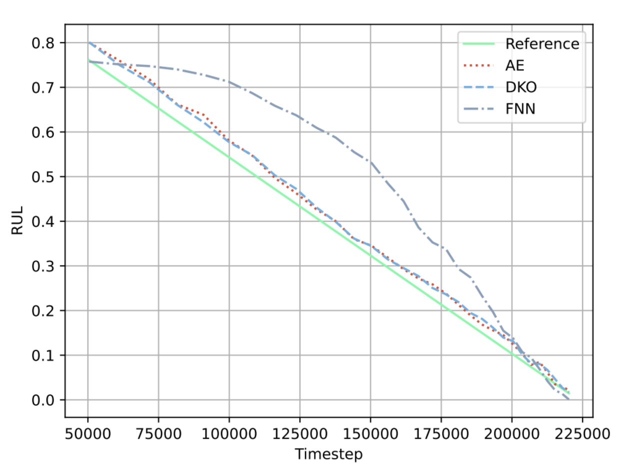
3. Li-ion battery under varying current load

Discharge current is random piece-wise constant function.
Hidden health parameters are similar to the case 1.

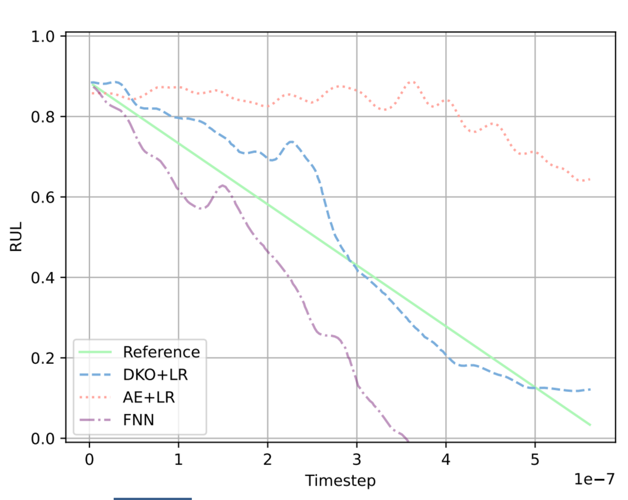


RUL predictions

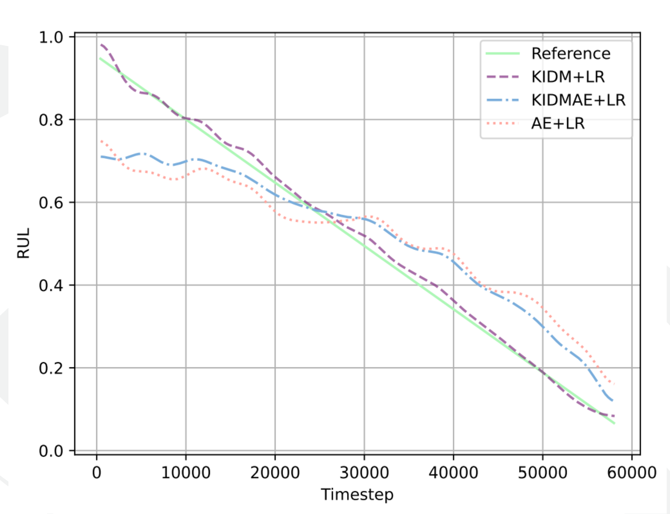
1. Li-ion battery under constant current load



2. CNC milling machine cutters



3. Li-ion battery under varying current load



Conclusions

- DKO can be used to represents the health state of the dynamical system in the unsupervised manner
- Incorporating multiple steps prediction loss helps to build a more robust model
- We roposed KIDM algorithm showed superior performance in early lifetime RUL prediction
- DKO and KIDM approaches are robust in RUL prediction even with one ground truth run-to failure trajectory
- Learned Koopman operators can be further analyzed

References

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***Author** is a Ph.D. student at EDCE, EPFL and a doctorial assistant at Intelligent Maintenance and Operation Systems (IMOS)
Email: sergei.garmaev@epfl.ch