Sandia National Laboratories

Data-Driven Battery Modeling using Koopman Operator

*Hyungjin Choi, †Valerio de Angelis, ‡Yuliya Preger
*hchoi@sandia.gov, †vdeange@sandia.gov, ‡ypreger@sandia.gov

Objective

In this work, we propose a data-driven battery modeling framework to construct linear surrogate model of high-fidelity battery models based on Koopman operator and neural network learning using time-series data.

Motivation

Model reduction is commonly used to simplify battery models to facilitate mathematical analysis. A surrogate model by our proposed method has computational advantages compared to existing reduced-order models:

- The constructed model is linear in high-dimensional function space, hence it preserves global accuracy while simplifying the original model.
- It utilizes time-series data to construct a model which does not require domain-specific knowledge and is applicable to any types of high-fidelity battery models.

Koopman Operator

- Given a dynamical system $\dot{x} = f(x)$, the Koopman operator associated to f is a linear operator defined in infinite-dimensional function space:

$$K \circ g(x) \coloneqq g(\phi_{\Delta t}(x)) \qquad (1)$$

where $g \in L_\infty$ is a bounded function, also known as an observable, and $\phi_{\Delta t}(x)$ is a flow map of (1) at time t starting from the point x.

- Koopman operator is a linear operator which equivalently describes the original (nonlinear) dynamical system (1) through functions along the trajectory of the states.

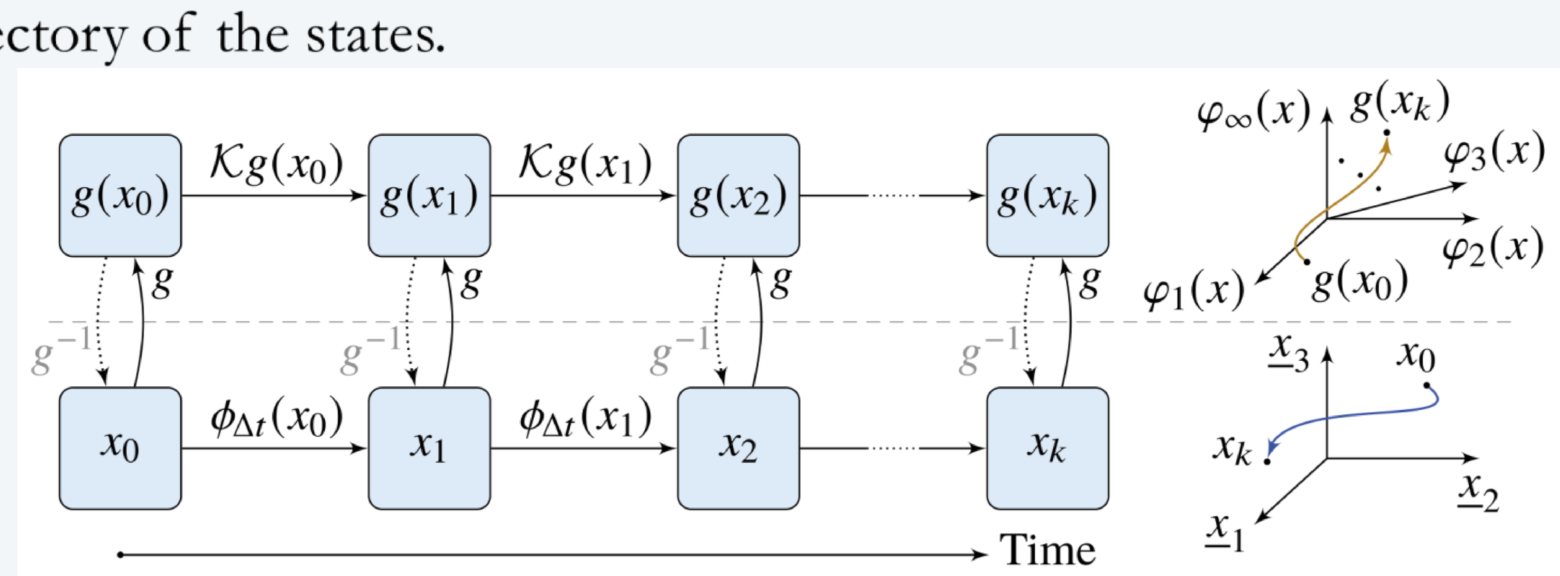


Fig. 1. Koopman operator framework (adopted from [1, Figure 7])

Data-driven Koopman Estimation

- We use layered autoencoder [2,3] network to learn finite Koopman operator with additional forcing terms representing input current.
- Loss function to minimize:

$$\min_{\varphi_i,\varphi_o,\varphi_i^{-1},\varphi_o^{-1},K,\Lambda} \sum_{i=1}^{M} \left\| \begin{bmatrix} x_i \\ u_i \end{bmatrix} - \varphi^{-1}\left(\varphi\left(\begin{bmatrix} x_i \\ u_i \end{bmatrix}\right)\right) \right\| \qquad (2)$$

$$+\sum_{i=1}^{M} \left\| \begin{bmatrix} x_i \\ u_i \end{bmatrix} - (\varphi_o^{-1}(y_i') + y_i') \right\| + \sum_{i=1}^{M} \left\| y_i' - \varphi_i^{-1}(\varphi_i(y_i')) \right\| \qquad (3)$$

$$+\sum_{i=1}^{M} \left\| \begin{bmatrix} x_{i+1} \\ u_i \end{bmatrix} - \varphi^{-1}\left(\varphi\left(\begin{bmatrix} x_i \\ u_i \end{bmatrix}\right) K(\lambda)\right) \right\| \qquad (4)$$

$$+\sum_{i=1}^{M} \left\| y_{i+1} - y_i K(\lambda) \right\| \qquad (5)$$

(2)-(3): autoencoder losses, (4): linearity loss, (5): prediction loss.

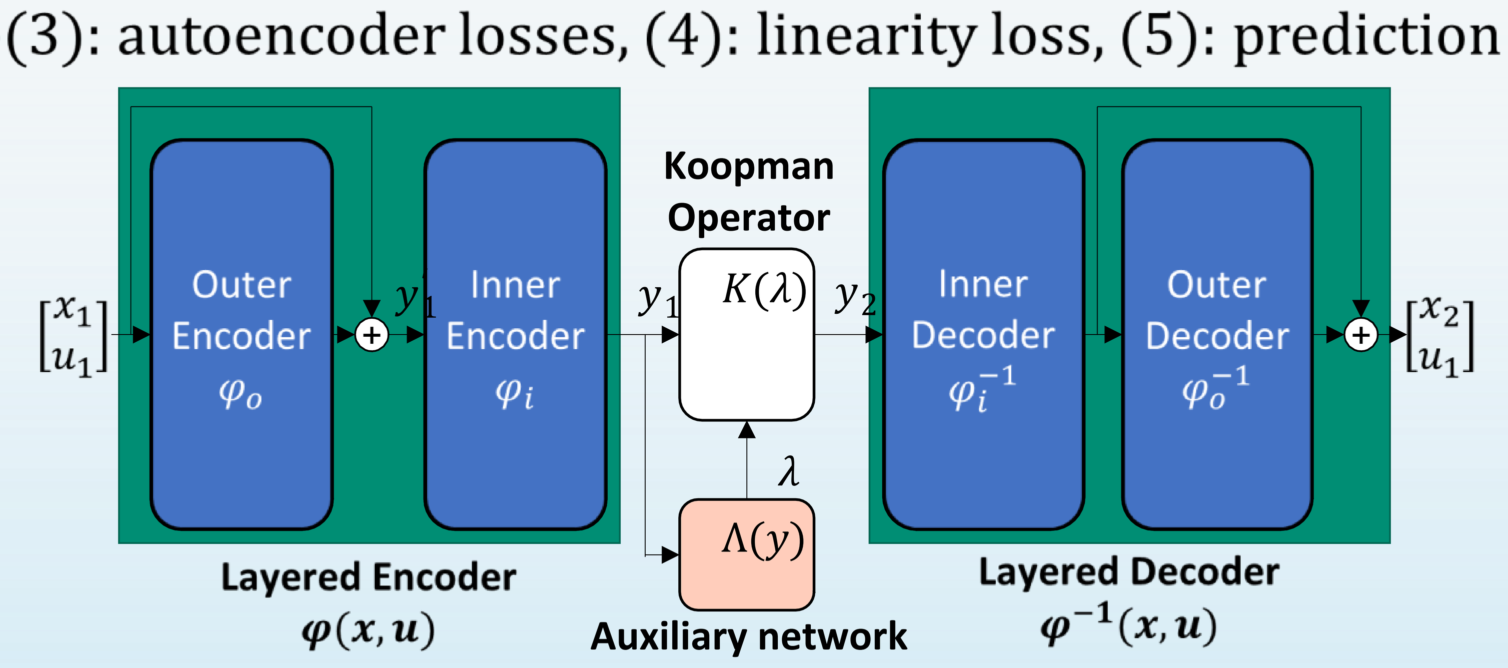
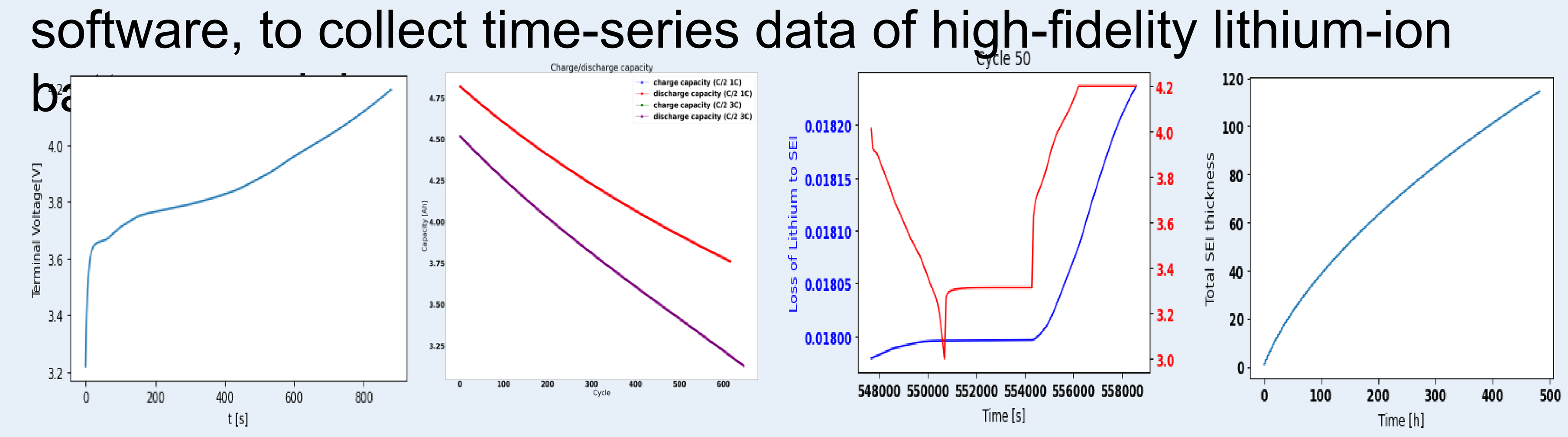


Fig. 2. Layered autoencoder structure to learn Koopman operator

Battery Data Collection

- We use PyBaMM, an open-source battery model simulation software, to collect time-series data of high-fidelity lithium-ion ba



Simulation Results

- Surrogate battery model was constructed by the proposed method using time-series data collected from PyBaMM simulations for DFN model with different C rates (1C,2C,3C,4C).

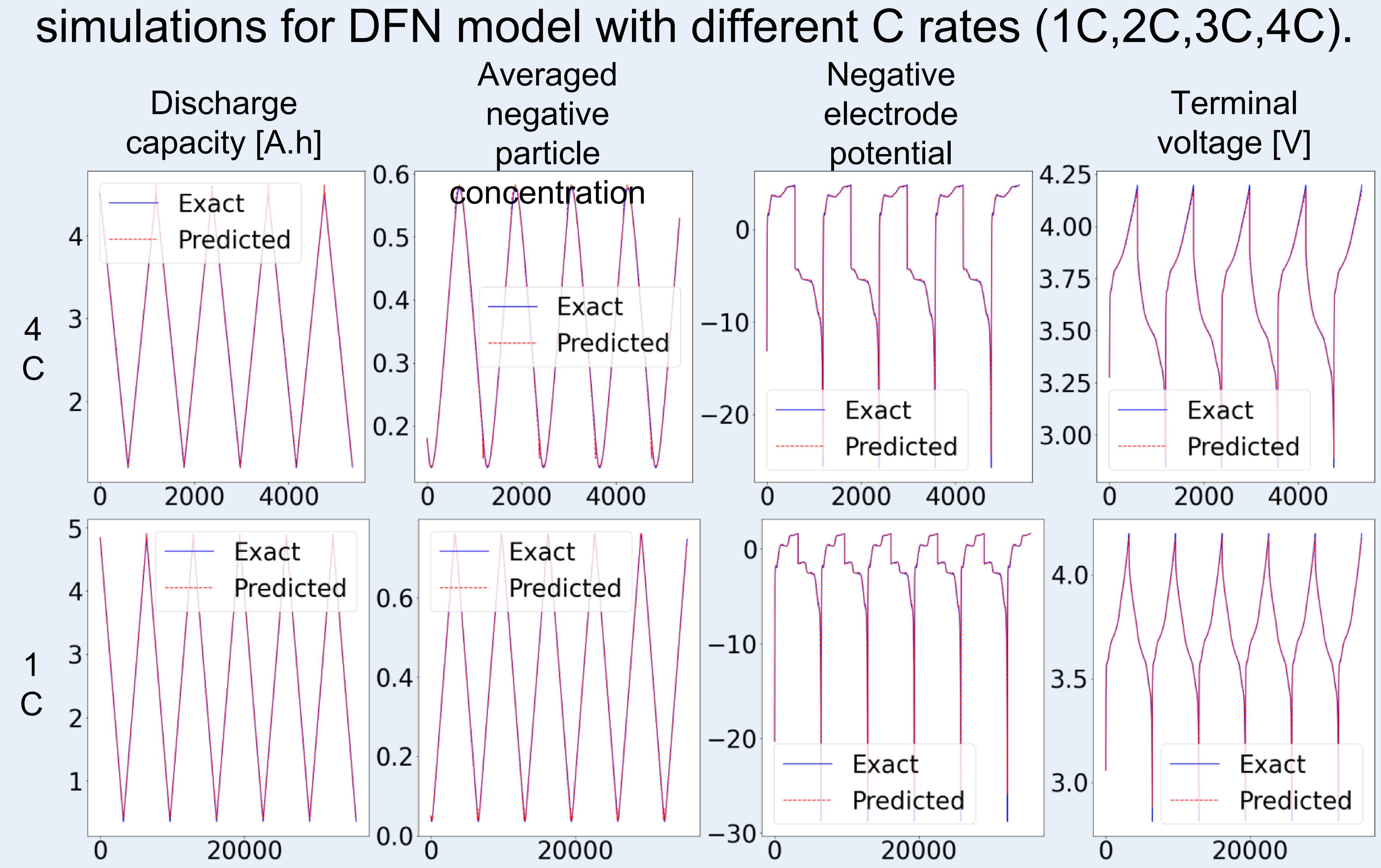


Fig. 3. Prediction vs. exact model for 4C and 1C.

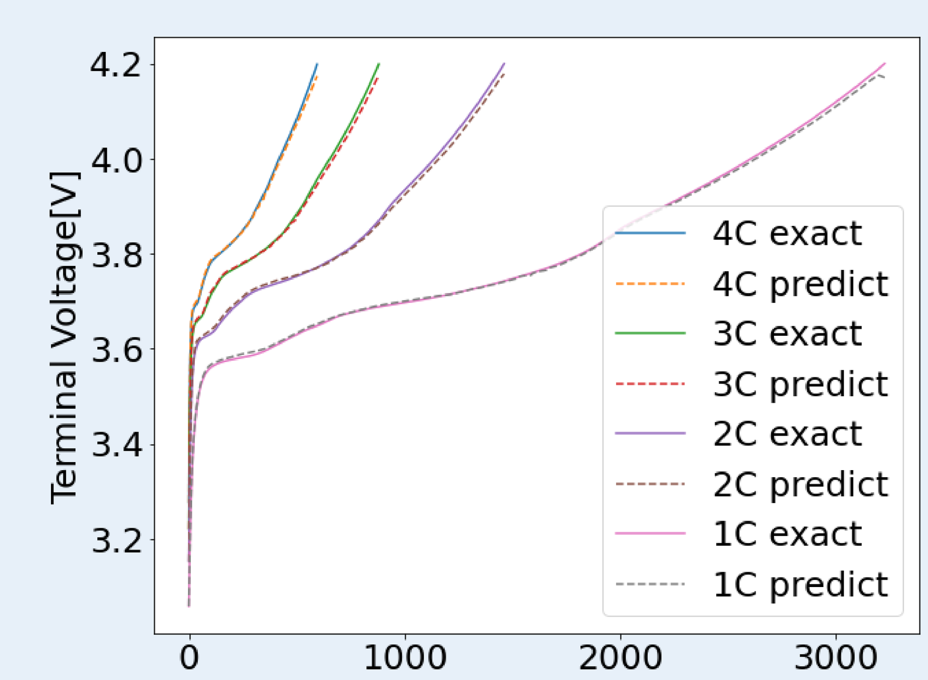


Fig. 4. Predicted voltage profiles for a single discharging cycle.

Acknowledgment

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References

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