Data-Driven Battery Health Prognosis Using Scalable Deep Recurrent Structure and Partial Fast-Charging Profiles

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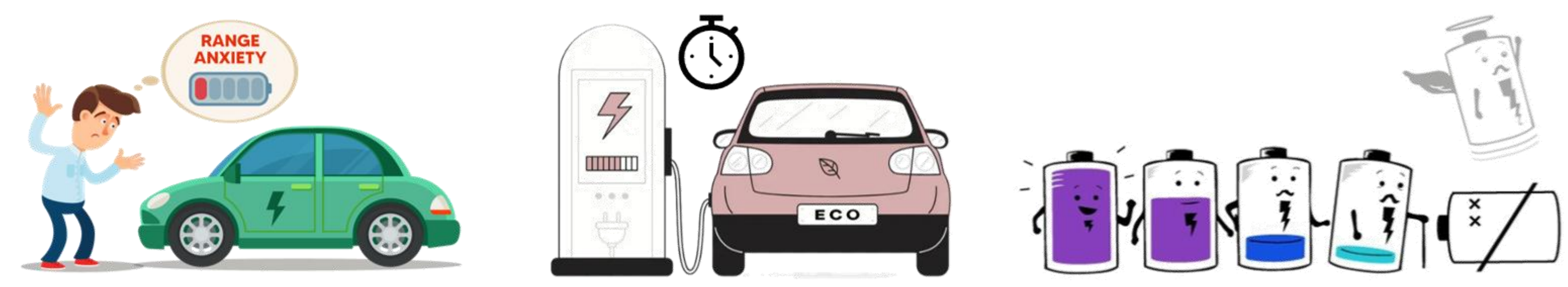
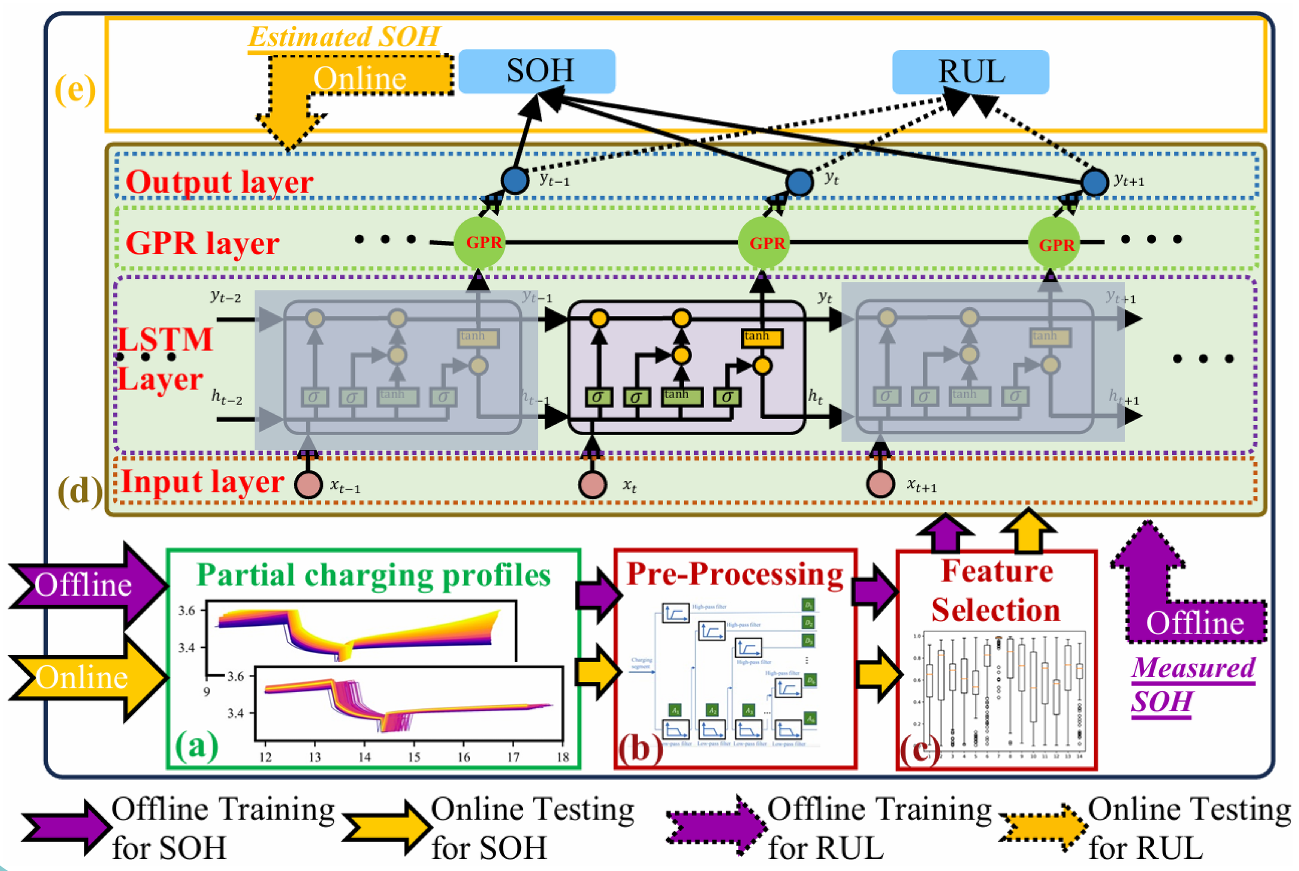
Introduction

Accurately evaluating battery state-of-health and lifetime prognostics with uncertainty quantification is important to guarantee the reliability, safety, and efficiency of batteries' deployment. Fast-charging profiles provide a promising way to improve usage efficiency by shortening lengthy charging time. However, the random and highly dynamic fast-charging profiles will affect the availability and generality of existing health indicators and may thus make the existing methods fail to work.



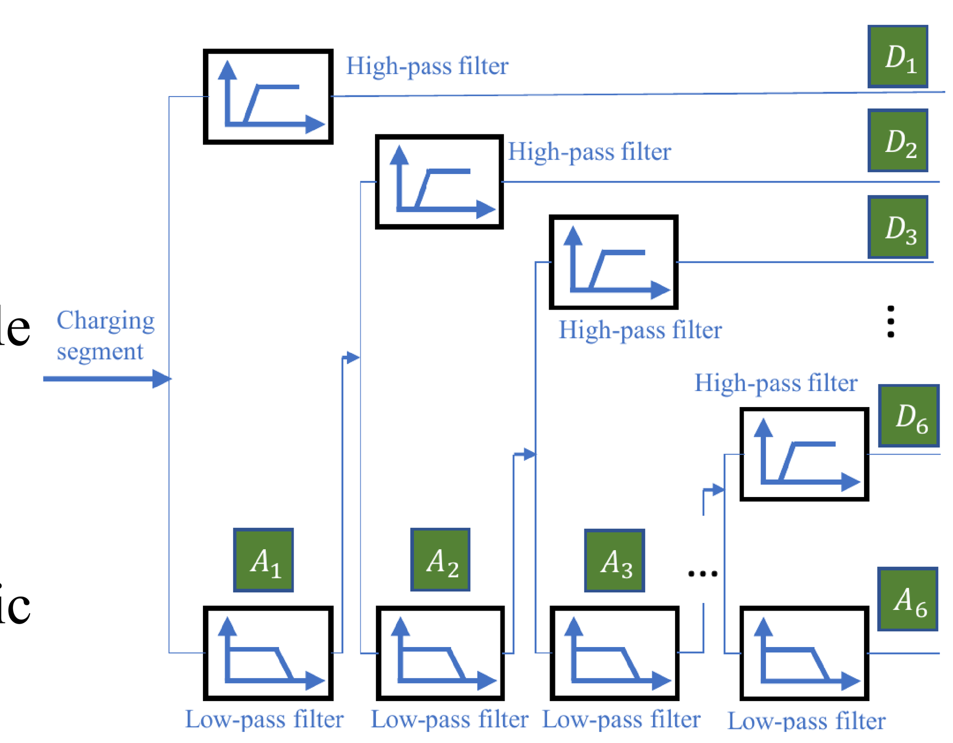
Range Anxiety **Long Charging Time** **Battery Health**



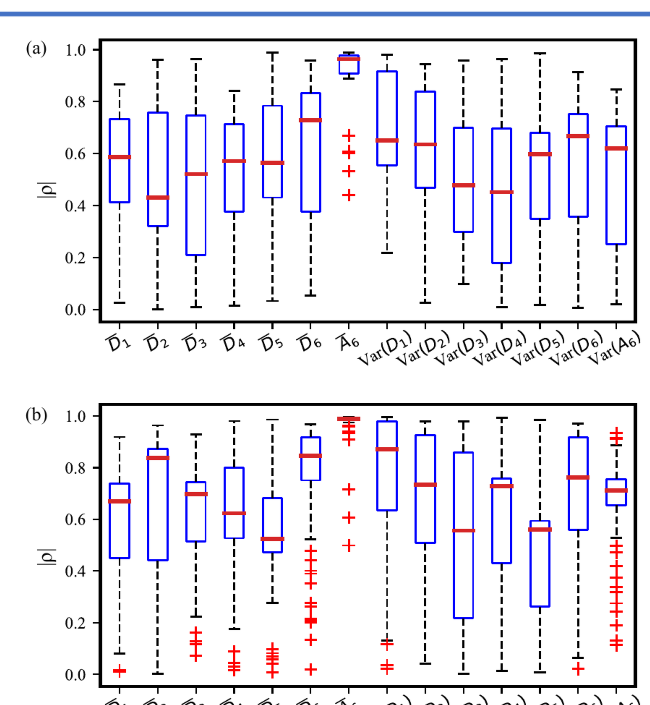
To improve the scalability while retaining desirable health prediction quality under fast-charging scenarios, this paper proposes a scalable deep recurrent structure for battery health prognosis. First, a health indicator is extracted by applying discrete wavelet transform (DWT) on partial fast-charging profiles. Second, a recurrent structure is proposed to establish battery health prognosis models, which encapsulates the series dependency learning of a short-term memory network, while retaining the non-parametric probability advantages of Gaussian process regression. Then, structured sparse approximations and a semi-stochastic gradient procedure are established for scalable training and prediction by optimizing the Gaussian process marginal likelihood. Finally, experimental results conducted on battery aging datasets using different fast-charging profiles demonstrate the state-of-the-art performance on robustness, prediction accuracy, scalability, and predictive uncertainties.

Contribution

- ☐ A robust HI is proposed by applying discrete wavelet transform (DWT) on partial voltage curves of MCC-based fast-charging profiles. The unique characteristics of DWT in extracting time-frequency domain features can be employed for the internal properties of battery nonlinear and nonstationary characteristics. The extracted features are selected as the proposed HI through correlation analysis.
- ☐ The proposed scalable deep recurrent structure encapsulates the structural properties of LSTMs while retaining the nonparametric probabilistic advantages of the Gaussian process. The proposed structure allows for a principled representation with uncertainty quantification and non-parametric flexibility.
- ☐ For the scalability, the learning and inference operations of the standard typically require $\mathcal{O}(n^3)$ computations for n training samples and $\mathcal{O}(n^2)$ for storage. In contrast, this paper exploits the algebraic structure of the kernel functions. The scalability is achieved through structure-exploiting inference and semi-stochastic training, for $\mathcal{O}(n)$ training time and $\mathcal{O}(1)$ test predictions.

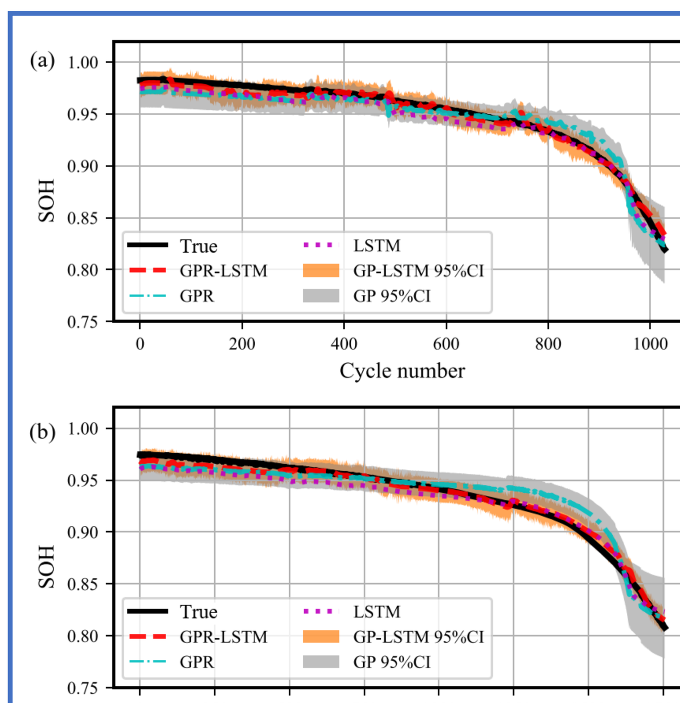


Results & Discussion



Boxplot of absolute Pearson correlation between extracted DWT features and labeled SOH.

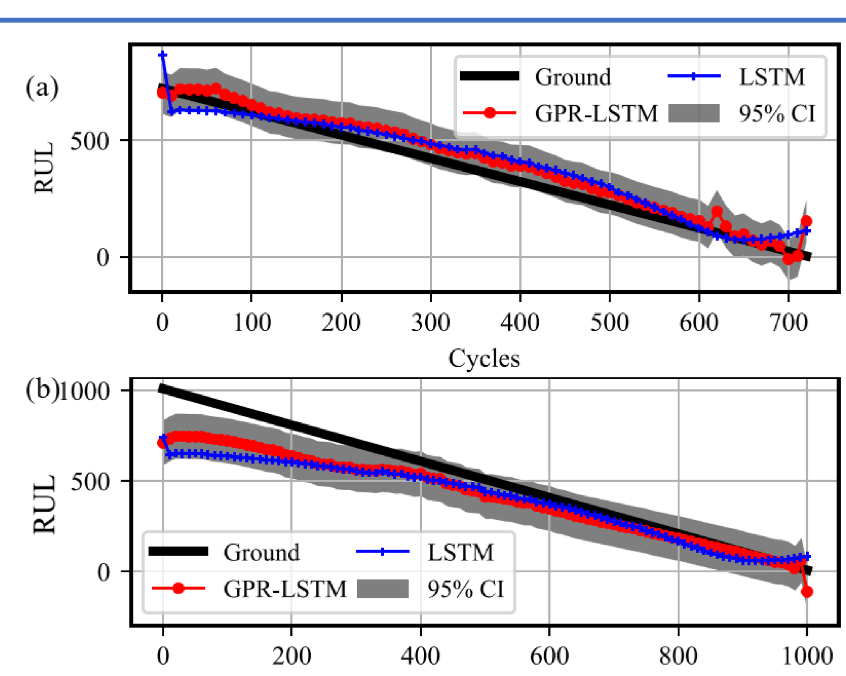
The adaptive time-frequency window enables DWT to extract aging features from fast charging profiles which have different frequency bands. Seven multi-resolution analysis (MRA) signals with different temporal resolutions can be obtained, including one approximate component A_6 and six detailed components at different DWT levels, $D_i, i = 1, \ldots 6$. It can be seen that these signals show different correlations to battery health.



State of health estimation for the proposed GPR-LSTM, GPR, LSTM methods.

To validate the performance of the proposed HI and the proposed deep recurrent structure, aging data from 4 randomly selected battery cells with one-step and two-step MCC profiles are fed into the training algorithm. Moreover, to highlight the state-of-the-art performance of the proposed structure, the LSTM model and GPR model are compared.

To validate the RUL prediction performance of the proposed method, we train the proposed scalable recurrent structure and the comparative LSTM model using measured SOH offline, and test both models with estimated SOH. We observe that the RUL prediction results are less accurate in early cycles of lifespan than the later cycles. The RUL prediction converges to the real value as degradation progresses due to more aging data become accessible.



Remaining useful life prediction results for the proposed GPR-LSTM and LSTM

Conclusion

In this paper, a scalable deep recurrent structure is proposed for lithium-ion battery SOH regression and RUL prediction. Discrete wavelet transform is applied to extract features in the voltage segments under the fast-charging profiles. The SOH estimation over batteries of two fast-charging profiles is discussed and compared with other advanced methods, which confirms the state-of-the-art performance on robustness, prediction accuracy, and predictive.

Link

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