Data-Driven Prognostic Techniques for Estimation of the Remaining Useful Life of Lithium-ion Batteries

EECOMOBILITY (ORF) & HEVPD&D CREATE

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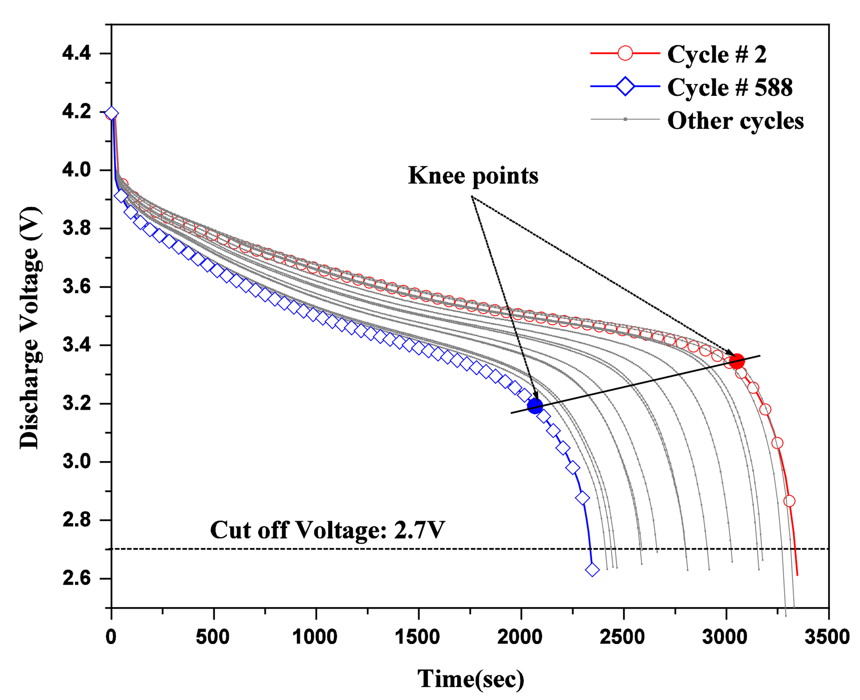
RUL Estimation – Li-ion Battery

The lithium-ion batteries are a vital element for many machines, computers and electrical vehicles. This work aims to study the use of various data-driven techniques for estimating the remaining useful life (RUL) of the Li-ion batteries. These data-driven techniques include neural networks, group method of data handling, neuro-fuzzy networks, and random forests as an ensemble-based system. These prognostic techniques make use of the past and current data to predict the upcoming values of the capacity to estimate the remaining useful life of the battery. This work presents a comparative study of these data-driven prognostic techniques on constant load experimental data collected from Li-ion batteries. Experimental results show that these data-driven prognostic techniques can effectively estimate the remaining useful life of the Li-ion batteries. However, the random forests and neuro-fuzzy techniques outperform other competitors in terms of the RUL prediction error and root mean square error (RMSE), respectively.

Battery Life Aging

This work aims to study the degradation of Li-ion batteries and predict their remaining useful life. The data of a set of Li-ion batteries is used for estimating their remaining useful life in terms of capacity. These data are tested at the Idaho National Lab and can be obtained through the NASA Prognostic Center of Excellence Data Repository. In this study, three datasets are considered that are related to three Li-ion batteries (B5, B6 and B7), each set is recorded through three different operational conditions.



These datasets represent accelerated aging of batteries through repetitive charge and discharge cycles. It is considered that these batteries are completely discharged once the voltage reaches to 2.7V, 2.5V and 2.2V for batteries B5, B6 and B7, respectively.
The battery performance degradation as a result of operational usage has an impact on the end of discharge (EoD) time. This has been illustrated in Figure, which presents various discharge profiles for the battery B5 under constant discharge loading. Considering battery B5 for illustration, which contains 168 discharge cycles, the variations of discharge voltage for only 17 discharge cycles are presented in the Figure for the ease of visualization. Figure shows that EoD time where the battery voltage reaches to the threshold (e.g., 2.7V for battery B5) is significantly decreased for the subsequent discharge cycles due to operational usage of battery life. Figure also shows that the location of knee point (i.e., sharp drop-off in the voltage profile) for each discharge cycle is changed which can represent the performance degradation in terms of cycle. However, these knee points are difficult to obtain due to decreased curvature as battery ages. One of the most common indexes to estimate the remaining useful life of batteries is capacity C (Ahr). In this work, capacity is used for the RUL estimation and only discharge cycles are considered into account. The capacities of all 168 discharge cycles are extracted to form the necessary inputs for predictors.

The Data Structure: Inputs and Targets

Predictor models are based on nonlinear autoregressive (NAR) structure

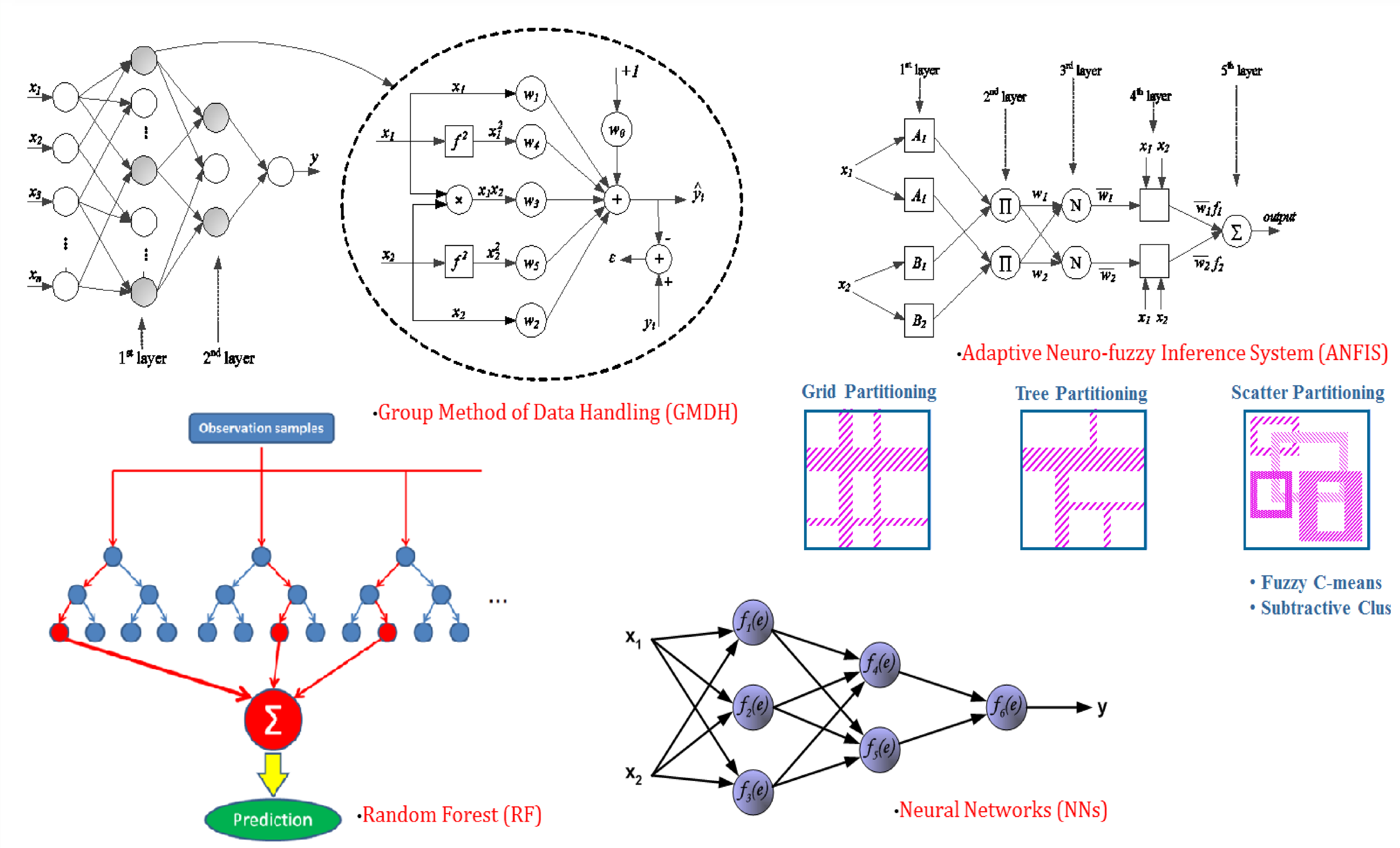
$$C_{t+1} = f(C_t, C_{t-1}, C_{t-2}, \ldots, C_{t-N_d}) + e_{t+1}$$

where C stands for the battery capacity at discharge cycles (Ahr), t is a subscript of cycle number, e stands for the prediction error per cycle, and f is an unknown smooth function which has to be approximated by the predictor during the training session.

Assuming m capacity values $\{C_1, \ldots, C_m\}$, and N_d delay inputs:

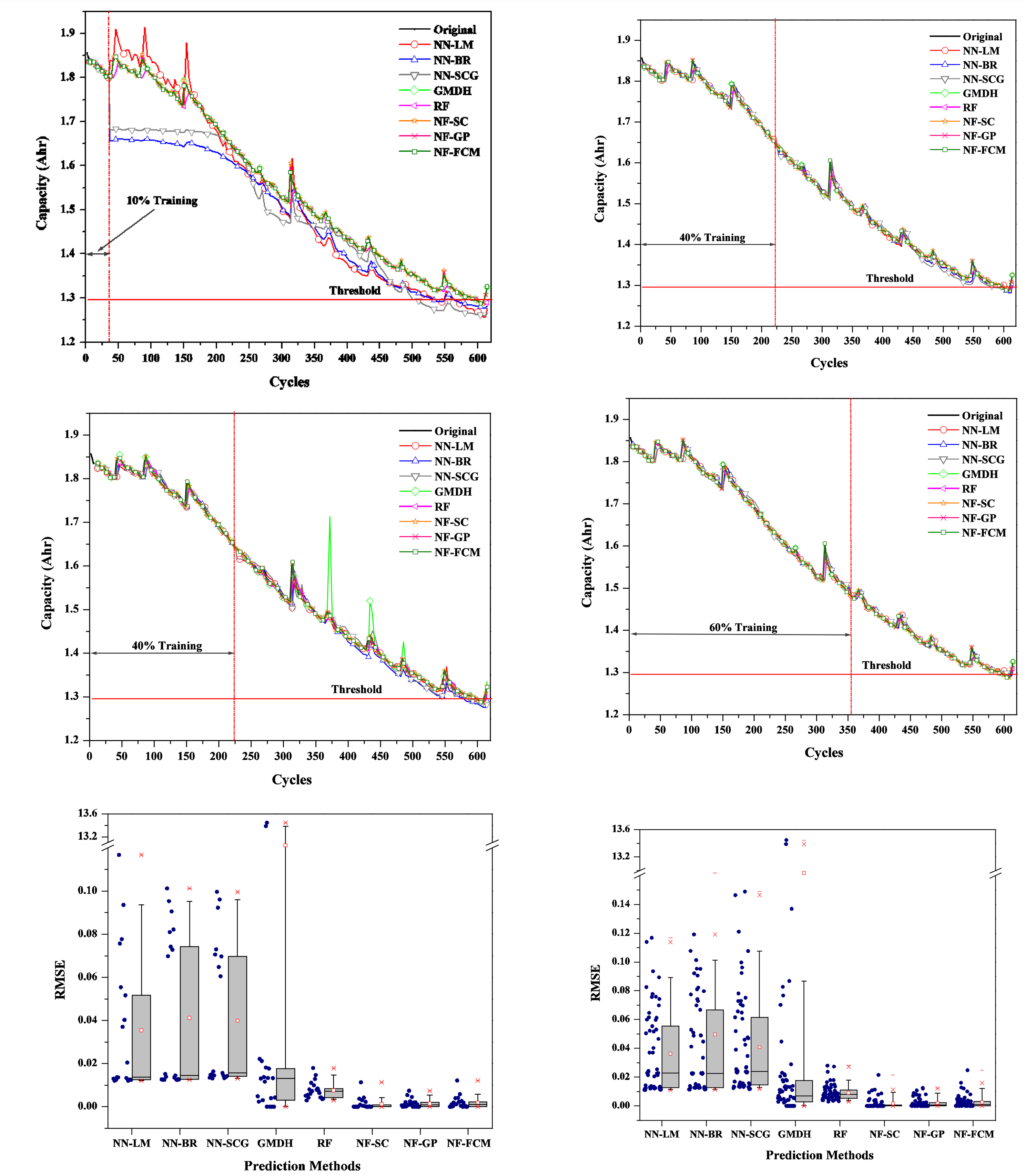
$$\overbrace{\begin{bmatrix} C_t & C_{t-1} & \cdots & C_{t-N_d} \\ C_{t+1} & C_t & \cdots & C_{t+1-N_d} \\ \vdots & \vdots & \cdots & \vdots \\ C_{N_t} & C_{N_t-1} & \cdots & C_{N_t-N_d} \\ \vdots & \vdots & \ddots & \vdots \\ C_m & C_{m-1} & \cdots & C_{m-N_d} \end{bmatrix}}^{\text{Inputs}} \overbrace{\begin{bmatrix} C_{t+1} \\ C_{t+2} \\ \vdots \\ C_{N_t+1} \\ \vdots \\ C_{m+1} \end{bmatrix}}^{\text{Target}} \quad \text{row-wise split}$$

Predictive Models



The predictor models are trained based on nonlinear autoregressive (NAR) structure. These includes Group Method of Data Handling (GMDH), Random Forest (RF), Neural Networks (ANNs), and Adaptive Neuro-fuzzy Inference System (ANFIS).

Experimental Results



(a) Prediction results using two lags and the first 10% of the data for training, i.e., 35 cycles; (b) Prediction results using two lags and the first 40% of the data for training, i.e., 228 cycles; (c) Prediction results using five lags and the first 40% of the data for training, i.e., 228 cycles; (d) Prediction results using two lags and the first 60% of the data for training, i.e., 352 cycles; (e) Box-plots representing the distribution of the $RMSE$ values obtained by each technique for different tests performed on the battery B5 data; (f) Box-plots representing the distribution of the $RMSE$ values obtained by each technique for different tests performed on all three datasets, i.e., B5, B6 and B7.

The experimental results show the effectiveness of the selected techniques in prediction of the RUL of batteries both in terms of $RMSE$ and E_{RUL} prediction errors. A statistical analysis of the attained results shows that the NF-SC and RF predictors outperform other competitors in terms of $RMSE$ and E_{RUL}, respectively.

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