SOH prediction of lithium-ion battery using a combined GPR-ELM algorithm based on EV fast charging protocol

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ABSTRACT

Accurate prediction of the State of Health (SOH) is necessary to ensure the durability and dependable operation of battery systems in various applications, especially in electric vehicles as fast charging technologies are being adopted by users more willingly. For accurate SOH estimates, this work suggests a novel method that combines the advantages of Gaussian Progression Regression (GPR) and Extreme Learning Machine (ELM) methods. The capacity of GPR to represent non-linear interactions and the speed at which ELM can learn are used to improve the precision and effectiveness of SOH prediction in battery systems. Through extensive testing and validation, the suggested hybrid model shows encouraging outcomes, highlighting its potential for real-world application in SOH monitoring and management.

1. Introduction

Lithium-ion batteries are regarded as one of the most promising battery technologies in the automotive industry where high power and energy are needed for electric vehicles (EVs) and hybrid electric vehicles (HEVs) [1]. However, it may degrade differently for several reasons, such as the battery pack's uneven temperature distribution, resulting in varied capacities and internal resistances which can be caused due to different charge protocols employed. The increase in the number of charge and discharge cycles also leads to the capacity fade and resistance increase [2][3]. Electric vehicle (EV) users are progressively embracing rated chargers equipped with fast-charging protocols due to their ability to significantly extend the vehicle's range. However, fast charging can induce accelerated degradation in batteries, impacting their State of Health (SOH) over time. Therefore, estimating SOH in batteries subjected to fast charging involves several considerations and needs maximum attention. SOH is a crucial measure for determining a battery's remaining usable life and estimating when it should be replaced. Recently, the data-driven approach has gained traction for SOH estimation, with the key components being adaptive state estimation techniques, neural networks, support vector machines (SVM), the Bayesian approach, and others [4]. Elisa et al.[5] Introduce a data-driven battery SOH estimate technique based on a brand-new integrated Gaussian process regression (GPR) model. A battery prognostics and health management (PHM) maximum absolute error of 110 cycles was used [6] to estimate the RUL of battery cells with various aging patterns. The SOH and RUL estimation methods for impedance rising and capacity fading during a battery's lifetime were addressed and contrasted in [7].

This study presents a hybrid version of the novel fusion of Gaussian Progression Regression (GPR) and Extreme Learning Machine (ELM) algorithms aimed at enhancing the precision of SOH estimation in battery systems based on different charging protocols. Multistage constant current (MCC) and Pulse charging protocols are designed and experimented to test the effectiveness of the proposed method which differentiated this work from other previous works that a normal 1C-rate charging protocol. The proposed model offers enhanced accuracy and efficiency in predicting SOH across different charging protocols which is useful in EV regardless of the charger employed.

2. Methodology

An experiment was conducted in a controlled environment of 40°C based on an NCM 18650 3Ah battery cell and various charging profiles (MCC, Pulse) were applied. The discharge phase consisted of 0.5C-rate discharge for 120 cycles. At intervals of every 20 cycles, tests were conducted to evaluate the Capacity and Open Circuit Voltage (OCV) trends indicative of the aging process. SOH for both charging protocols (MCC, PC) was estimated using Eq. 1 where Qp and Qn are the present and nominal capacities respectively. Calculated SOH for both MCC and PC charging protocols are shown in Fig. 1.

This study introduces a hybrid method that combines the intricate, non-linear relationship-capturing power of the GPR algorithm with the quick learning speed of ELM, as depicted in Fig. 2. To start, GPR builds a model to represent the underlying non-linear patterns and trends in the deterioration behavior of the battery. The GPR outputs are then used as inputs by the ELM algorithm, which uses its effective learning and generalization capabilities to further improve the SOH estimation. The Gaussian process model properties are determined by Eq. (2) where m(x) and kf(x,x') are the mean and covariance functions respectively. Eq. (3)-(4) shows the MAE and RMSE deviations of the real and predicted value for ELM.

$$SOH = \frac{Q_p}{Q_n} \quad (1)$$

$$K_f(x,x') = E[(f(x)-m(x))(f(x')-m(x'))] \quad (2)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}[y_i - \overline{y_i^*}] \quad (3)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}[y_i - \overline{y_i^*}]^2} \quad (4)$$

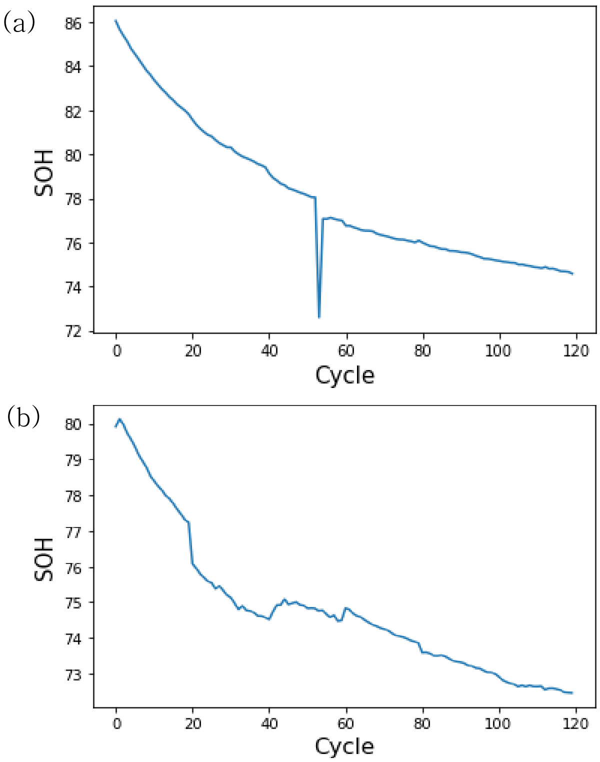

Fig.1. Calculated SOH (a) MCC (b) PC

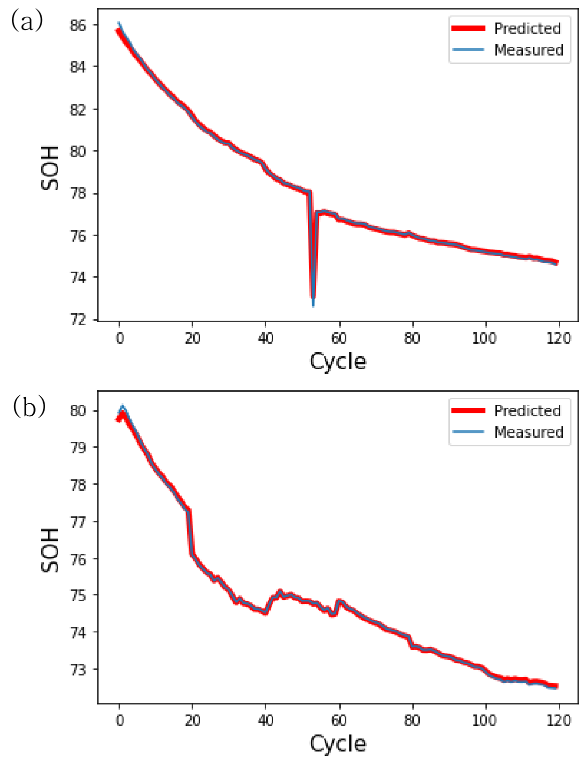

Fig. 3. Predicted SOH estimations (a) MCC (b) PC

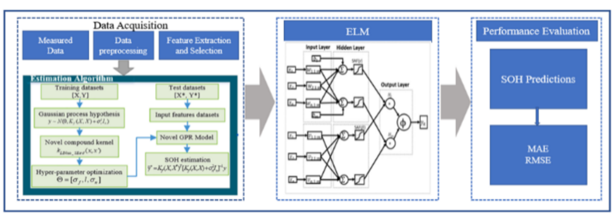

Fig. 2. Flowchart of the proposed GPR-ELM for SOH

3. Results

The mean square error (MSE) and root mean square error (RMSE) obtained for the combined algorithm are 0.000618 and 0.0249 respectively. The low MSE suggests that the average discrepancy between predicted and actual values is extremely small, signifying high precision and accuracy in model performance. The RMSE quantifies the average magnitude of the combined algorithms' prediction errors. With a lower RMSE value obtained, it indicates that, on average, the combined models' predictions deviate by approximately 0.0249 units from the actual SOH values which further confirm the models' accuracy in predicting SOH.

The output metrics showcase the effectiveness and reliability of the combined algorithms for SOH estimation in lithium-ion batteries under a fast-charging protocol. The near-zero errors underscore the models' exceptional predictive capability offering confidence in their utility for accurate and precise SOH estimation in real-world applications.

4. Conclusion

The combined GPR-ELM approach presents a promising solution for precise State of Health (SOH) estimation in battery systems. By synergistically harnessing the strengths of Gaussian Progression Regression and Extreme Learning Machine algorithms, this hybrid model offers enhanced accuracy and efficiency in predicting SOH, thus contributing significantly to the advancement of reliable battery management and monitoring techniques.

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참 고 문 헌

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