



SOH Prediction in Li-ion Battery Energy Storage System in Power Energy Network

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Abstract. The prediction of the State of Health (SOH) of Li-ion batteries is crucial for the system safety and stability of the entire energy network. In this paper, we analyse the role of Li-ion batteries as balancing batteries in the communication-energy-transportation network, which are key nodes for energy exchange. These batteries have different states of health and are constantly in a state of bi-directional energy transfer through charging and discharging. They also require coordinated charging and discharging in the network. Due to these differences, the degradation rates of the different balancing batteries vary, making it necessary to monitor the SOH of each battery in real time. To address the problem of numerous nodes and large computational requirements in the network, we propose a method based on the Transformer architecture for accurate and fast estimation, which can alleviate the communication pressure of the energy network layer. In this method, we select the voltage change rate as the only key health indicator and perform correlation analysis while the battery is in a constant current CC charging mode. According to the test results on NASA public battery data set, we continuously collect 3, 5, 10 and 20 voltage change rate values as inputs to the model and validate 1–4 layer transformer models. The model with 20 voltage change rate values as inputs and 4 layers has the best prediction performance, with a Mean Absolute Error (MAE) as low as 4.85%, while the Root Mean Square Error (RMSE) is 6.02%. In addition, the proposed method can process the time series data of multiple network nodes in real time and in parallel, with high prediction accuracy and stable performance, which makes it suitable for widespread use in power energy networks.

Keywords: Voltage change rate · Transformer-based · Battery energy storage system · State of health prediction · Energy network

1 Introduction

As intelligent transportation systems, 5G communication technologies, smart grid technologies, and energy storage technologies further improved, a new trend of network intersections and fusion is gradually forming, involving vehicles, communication base stations, energy supply stations. As the vehicle in the intelligent transportation system, Vehicle-to-Everything (V2X) and Vehicle-to-Grid (V2G) have emerged as key technologies [8]. These technologies facilitate not only the extraction of energy from the power grid, but also the return of stored energy to the grid, thereby enabling bidirectional energy interaction [19]. Around the grid network, smart grid technology has developed. Moreover, with energy storage technologies as the core, the Energy Management System (EMS) incorporates photovoltaic, energy storage, and charging capabilities.

The widespread use of mobile charging terminals (such as electric bicycles, electric cars, etc.) increases the difficulty of planning and ensuring the safety of the entire power system due to the randomness of the charging time, the network node where the charging takes place, and the high power consumption during charging [18]. Pure electric vehicles are the most common type of mobile charging terminal. Battery types in the on-board energy storage system include lead-acid batteries, nickel-hydrogen batteries, Li-ion batteries, super-capacitors, fuel cells, etc. Among these, Li-ion batteries have become the main storage medium. As the power battery of the vehicle, the life of the Li-ion battery determines the life of the electric vehicle. During the use of the power battery, a series of electrochemical reactions occur inside the battery due to the accumulation of time, changes in ambient temperature, and the increase in charging and discharging cycles, which cause the performance of the Li-ion battery to deteriorate, such as the reduction of lithium ions, loss of active materials, and electrode wear. Battery performance is usually represented by available capacity, and the percentage of available capacity to initial capacity is used to indicate the health of the battery [12]. A gradual decline in battery performance will result in abnormal performance, which may even threaten road safety. Battery safety is key to the design of electric vehicles. Predicting battery life and managing battery health can enable timely replacement or maintenance of batteries based on their SOH and Remaining Useful Life (RUL), ensuring safe availability and stable reliability of battery operation. When the capacity of a Li-ion battery is reduced to 80% of its initial capacity, the battery has reached its End of Life (EOL) and is no longer suitable for on-board use. Indicators for measuring the RUL of on-board batteries include when the SOH drops below 80% or when the internal resistance doubles compared to the original value, which indicates that the on-board Li-ion battery has reached the end of its life.

In the power network, the power grid cannot store electrical energy by itself, and energy storage batteries are utilized as the electrical storage and buffering unit in the system, with Li-ion batteries being the most commonly used [6]. As the primary energy network, the Li-ion batteries in different network nodes often possess dissimilar SOH, which results in variations in their capacity, specifications, power output, and other related characteristics. This, in turn, can cause

inefficient energy bidirectional interaction. The battery module with the lowest SOH in the grid restricts the energy transmission efficiency of the entire network. Adopting diverse SOH-balancing Li-ion batteries and batteries mounted on vehicles can help alleviate this issue. Pure electric vehicles can be used to buffer energy in the grid. However, connecting them directly for bidirectional charging and discharging at high currents and powers may lead to a decrease in safety performance of the energy network terminal. It can even cause fires [24, 25]. The usage, discharge patterns, and operating conditions of Li-ion batteries in power energy network nodes differ from those of electric vehicle Li-ion batteries. The degradation rate of this battery type can be complex and challenging to anticipate. Furthermore, with numerous network nodes in the grid, computing the State of Health (SOH) of each battery singly necessitates significant computation and interaction information transfer with low timeliness. Consequently, there is a need to enhance and complement methods and models for approximating the SOH of these batteries throughout the bidirectional energy exchange system.

The above researchers have proposed many estimation methods for Li-ion batteries. However, in the future, it is expected that Li-ion battery estimation methods can accurately, reliably and quickly estimate the state of health (SOH) of Li-ion batteries based on fewer data types and sample sizes. The purpose of this paper is to use the rate of voltage change during Li-ion battery charging as a single influencing factor to predict the SOH of Li-ion batteries. This application involves comparing the characteristics of existing Li-ion battery SOH prediction methods, including two main directions: (1) model-based SOH prediction and (2) data-driven SOH prediction. Details are given in Sect. 2. It's analysed the challenges of estimating the SOH of Li-ion batteries in the networks, which includes three types of heterogeneous networks: power network, communication network and transportation network in Sect. 3. The Li-ion battery is used as a buffer battery in this network, and Sect. 4 focuses on the challenges of estimating the SOH of Li-ion batteries in the energy network mentioned in the third part. It selects the rate of voltage change as the only influencing factor and adopts a transformer-based model to analyse the NASA public battery datasets. Section 5 presents and discusses the verification results. The paper is concluded in Sect. 6.

2 Related Work

In power grids, the capacity degradation of backup Li-ion batteries is a long-term gradual process and the health of the battery is affected by various factors such as temperature, current rate, cut-off voltage, etc. The available capacity can be used to characterise the performance of the battery and the SOH is the percentage of available capacity compared to the initial capacity. The available capacity can be used to characterise the performance of the battery and the SOH is represented by the percentage of available capacity to the initial capacity.

$$SOH = \frac{Q_t}{Q_{new}} \times 100\% \quad (1)$$

Q_t represents the current battery capacity, and Q_{new} represents the new battery capacity. It quantitatively describes the performance status of the current battery as a percentage from the beginning to the end of its life cycle. The state of health of Li-ion batteries cannot be measured directly. At present, the SOH assessment of lithium batteries can be divided into two main categories.

2.1 Model-Based SOH Prediction

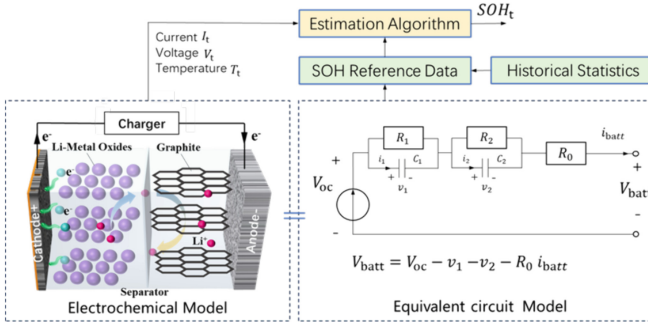


Fig. 1. Electrochemical Model of Lithium Batteries.

There are currently many mainstream types of Li-ion batteries, including lithium cobalt oxide (LiCoO₂) batteries, lithium iron phosphate (LiFePO₄) batteries, lithium manganese oxide (LiMn₂O₄) batteries, nickel cobalt manganese (NCM) batteries, nickel cobalt aluminium (NCA) batteries and lithium manganese oxide (LMO) batteries, among others. Although different Li-ion batteries have different discharge characteristics, their electrochemical charging and discharging principles are almost the same. When analysing the electrochemical model of Li-ion batteries, it is necessary to establish a corresponding complex mathematical model or equivalent circuit model [2]. For example, Bayesian statistical models [10], Kalman filters [16], particle filters [5] and other estimation algorithms can be used. By establishing a dynamic model based on electrochemical principles, technical parameters (reaction rate, etc.) are determined using experimental battery data. A filter algorithm is used to compare the real-time battery status (real-time current I_t , voltage V_t , and temperature T_t) with the standard data in the model to estimate the SOH value of the current battery (see Fig. 1). The accuracy of model-based SOH prediction is often limited by the accuracy of the model and requires more prior knowledge and complex calculations.

2.2 Data-Driven SOH Prediction

Data-driven methods start from experimental data of the actual charging and discharging process of Li-ion batteries, rely on direct analysis of experimental data, extract specific features for estimating battery SOH, and have higher

accuracy and prediction precision. There are many types of data-driven methods, such as decision tree regression [23], random forest regression, ExtraTree extreme random tree regression [7], and various methods based on deep learning [26], including BP (Back Propagation), ENN (Elman Neural Network) [27], ELM (Extreme Learning Machine) [30], CNN (Convolutional Neural Network) [24], and long short-term memory (LSTM) [28].

By collecting historical data of Li-ion battery charging and discharging (including voltage, current, temperature and other variables), feature factors affecting SOH are extracted to train neural networks. Test data is used to evaluate the model and calculate its accuracy, error and other indicators to obtain a well-trained neural network. According to the current battery status (such as current, voltage, temperature, etc.), this information is converted into a feature vector that is input into the trained neural network-based prediction model, and the model outputs the predicted SOH value (see Fig. 2).

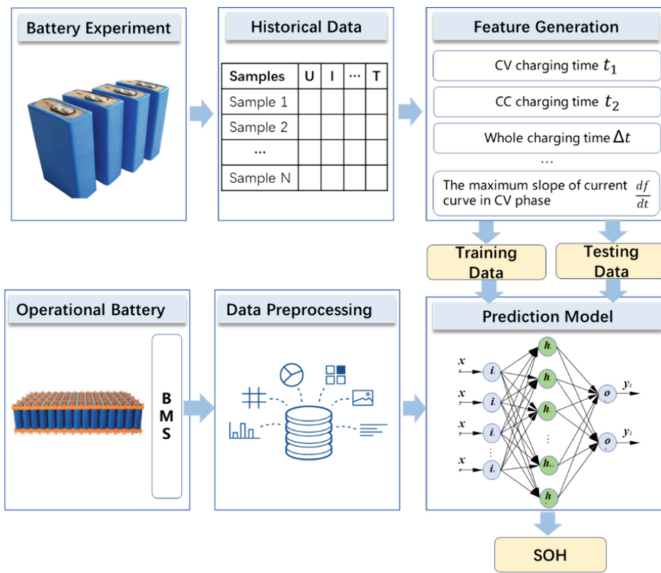


Fig. 2. Data Driven SOH Prediction Process.

Data-driven methods avoid the need for a deep understanding of the electrochemical reaction mechanisms in Li-ion batteries [29]. By using historical data and appropriate neural network algorithms, it is possible to predict State of Health (SOH). This approach is characterised by easy operation, quick modelling, and fast calculations. It is suitable for a range of battery types, including those with complex chemical compositions and structural differences. Based on past data for prediction, it is crucial to have adequate and high-quality historical data. Inadequate or imprecise historical data can have an impact on the

accuracy of the prediction results. It is important to avoid relying too heavily on the completeness of the collected historical data set, especially if the data set is limited, as this can significantly affect the accuracy of the prediction [3]. It is important to avoid relying too heavily on the completeness of the collected historical data set, especially if the data set is limited, as this can significantly affect the accuracy of the prediction.

3 Communication-Energy-Transportation Network

3.1 Topological Structure

In this extensive electricity network, its primary role is to carry the transmission of electrical power. Electricity generation primarily originates from power stations, comprising thermal power stations, nuclear power stations, wind farms, and solar power farms. The resulting electrical power is transported through power lines to the point of consumption of electrical energy. To increase the efficacy of electrical power utilization and promptly fulfil sporadic power needs such as electric vehicle charging, Li-ion batteries have gained significant traction as proficient energy buffer systems with growing application demands [13]. The Communication-Energy-Transportation Network is comprised of three layers: the communication network layer, which is based on the Internet architecture, the energy network layer, which is based on the power grid architecture, and the transportation network layer, which is based on the traffic structure (see Fig. 3). The energy network layer holds a critical role, encompassing the generation, transmission, and dispatch of electrical energy. The dispatch and allocation are dependent on the electricity gateway, which must acquire details of the electric vehicles' charging and discharging requirements from the transportation network layer. When operating in V2G mode, electric vehicles can supply energy back to the power grid and act as portable energy storage stations. When the demand for power falls below the scheduled amount, surplus energy will either be stored in the buffer Li-ion battery (balancing battery) [14] or the onboard Li-ion battery, or a negligible quantity of energy will be absorbed by Pumped Storage. When electricity demand exceeds the scheduled power, the stored energy in the buffer Li-ion battery or the on-board Li-ion battery will discharge into the power grid, supplementing the insufficient power. The energy dispatch and allocation centre, or electricity gateway, is responsible for this function. The gateway transmits scheduling data to the communication network gateway and stores the data in the Data Cloud Server database. The transmission of information regarding vehicles, charging stations, power transmission, and dispatching allocation is facilitated through the communication network layer. This layer operates independently from subjective evaluations, allowing for objectivity and value-neutral communication.

In this complex network, Li-ion batteries are located at the key node position for energy dispatching and allocation, which directly affects the stability and security of the entire energy network [9]. Each buffer battery in the network node has different geographical locations, types, and capacities, and the SOH of

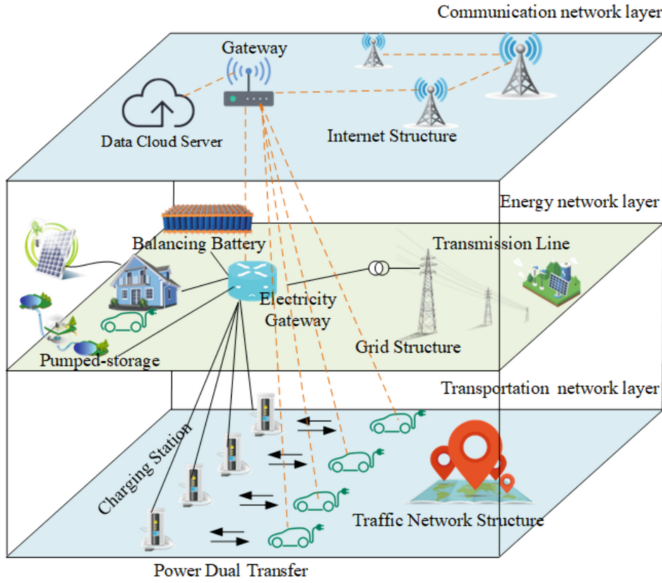


Fig. 3. Integrated Framework for Energy, Communication, and Transportation Networks

each buffer battery determines the optimal charging and discharging strategy. If the SOH judgment of the buffer battery is incorrect, excessive current often leads to overheating of Li-ion batteries, and even internal short circuits, fires, and other issues, threatening the reliability of the entire power system. In the network nodes, a battery management system (BMS) is installed for each buffer battery to monitor the energy flow, power, and temperature changes, especially the SOH of Li-ion batteries [22].

3.2 Stability, Reliability and Safety Requirements in Network

Stability, reliability and safety are crucial measures for evaluating the energy grid. The energy grid possesses traits of bidirectional energy transmission, vast energy distribution and dispatch, as well as substantial volumes of communication data. Buffer batteries are situated in many nodes of the energy grid, and each network node has varying energy storage and supply capabilities. Mobile buffer energy storage systems can determine SOH of the Li-ion batteries onboard by utilising the battery management system (BMS) installed in the vehicle, which can communicate directly with the communication base station [11]. Buffer batteries often draw and release energy from the power network, particularly during emergencies requiring deep or high-power discharge. These batteries prioritize sacrificing the value of Li-ion battery life to maintain grid stability. Nevertheless, the rapid depletion of buffer Li-ion battery life or thermal runaway can reduce the safety and reliability of the energy network. The efficiency of the power

energy network in supplying energy at a specific location and time is somewhat reliant on the precise assessment of the SOH of buffer batteries. The diverse categories, technical features and abilities of buffer batteries within the energy network points, lead to a considerable variation in SOH. This is especially so for buffer batteries utilizing Li-ion batteries for composite utilization, with a power ranging from 40% to 80% of the original capacity. After estimating the SOH in real-time, the data is transmitted to the communication network layer. This layer then processes and sends the data to the energy network gateway for balancing and dispatch of supply and demand. Traditional SOH estimation methods and models are inadequate for the large volume of sequential data from buffer batteries. They require continuous collection, transmission, and processing of large amounts of data and cannot handle large amounts of data in parallel. Serial calculations for individual Li-ion batteries result in low efficiency and fail to meet the requirements for simultaneous bi-directional energy transmission across multiple nodes.

4 Transformer-Based SOH Prediction Method

4.1 Feature Extraction and Selection

After a period of usage, the capacity of Li-ion batteries diminishes and their internal resistance increases. This is caused by the loss of active materials and the thickening of the Solid Electrolyte Interface (SEI) membrane, among other factors [1,20]. The depletion of active materials in Li-ion batteries is primarily caused by metal ions dissolving from the positive electrode material into the electrolyte. Simultaneously, a film of SEI gradually develops on the negative electrode surface, progressively impacting the lithium ion supply and inducing an uptick in internal resistance. Electrochemical reaction processes are responsible for the internal alterations of Li-ion batteries, which present quantitative monitoring challenges. From the external characteristics of Li-ion batteries, the mentioned internal changes result in increased internal resistance, reduced capacity Q , and a stronger inclination towards heat generation. Different SOH Li-ion batteries have charging characteristics as shown (see Fig. 4).

When charging Li-ion batteries by connecting to the power grid, a constant current charging mode is typically utilised. Additionally, factual and unambiguous titles should be used, along with conventional academic sections. Lastly, objective and value-neutral language should be employed, avoiding biased or emotional language and intricate terminology. In such a mode, the charging curve for batteries with different SOH levels demonstrates that with an increase in the cycle times of Li-ion batteries, the battery reaches its cut-off voltage more rapidly. It is essential to explain the abbreviations of technical terms when they are first used in the text. When applying a constant current mode to charge a Li-ion battery, the rate at which its voltage rises varies. Among them, with a constant current charging mode of 0.5 C as an example, the charging rate is faster when the SOH of the battery is worse, making it easier to fully charge. We take the parameter x .

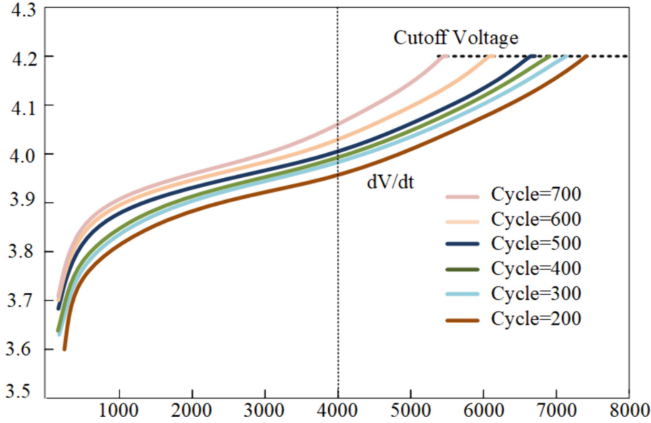


Fig. 4. The Voltage Change Curve of Li-ion Batteries Charged in CC Mode After Different Cycles.

$$x = \frac{dV(t)}{dt} \tag{2}$$

$V(t)$ represents the real-time voltage that changes with time t . Although batteries with lower SOH have faster charging rates, that is, the x value will be larger. In data-driven SOH prediction methods, if the selected features have a higher correlation with SOH changes, the prediction accuracy will be higher [17]. Pearson correlation is calculated as:

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \tag{3}$$

Here, n is the cycle number of the battery, and r takes a value between -1 and $+1$. x_i represents the x value taken at time i , and y_i represents the SOH value at time i . For the state data during continuous charging of the battery, due to the large randomness of individual x values, we take 3, 5, 10, and 20 consecutive x values at time i , $x_i = [x_i^3, x_i^5, x_i^{10}, x_i^{20}]$. We perform correlation analysis on them separately to obtain the result $r = 0.959$ (when $x_i = x_i^{20}$), where $r = 0.915$ (when $x_i = x_i^3$), $r = 0.924$ (when $x_i = x_i^5$), $r = 0.932$ (when $x_i = x_i^{10}$), that all are higher than other indicators (e.g. temperature, current rate, cut-off voltage, etc.).

4.2 Transformer-Based Model

To enhance parallel computing and the accuracy of time series data processing, this study adopts the Transformer framework [4, 15, 21]. The framework, illustrated in the figure, comprises essential input, output, and data preprocessing modules. The key component of the Transformer Encoder is the multi-layered Multi-head self-attention, which utilises various sets of attention mechanisms (see Fig. 5).

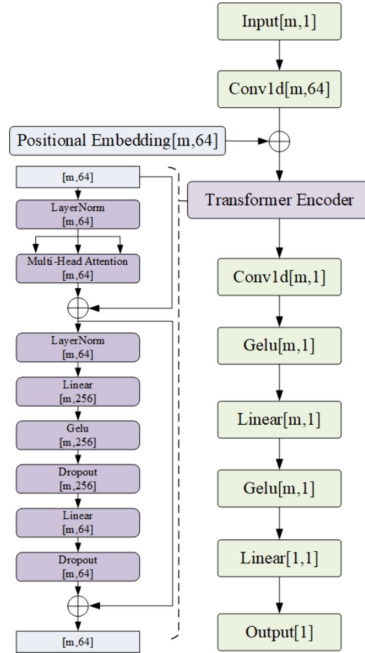


Fig. 5. Data Processing Diagram Based on Transformer.

5 Test Result and Analysis

To accurately simulate a random buffer battery within an energy network node and estimate its State of Health (SOH) for comparison with the actual value, thus demonstrating the accuracy of our model predictions, we utilised a standard charge-discharge test dataset in this paper. For Experiment I, we randomly selected deteriorated lithium batteries ($SOH = 0.837$) from NASA’s publicly available 18650 Li-ion battery dataset. The lithium batteries selected were subjected to constant current charging using a current of $I = 1.5\text{ A}$ and cut-off voltage of 4.2 V . A total of m consecutive data x were obtained randomly from the initial charging process and fed into the prediction model for calculation. To ensure improved verification of the impact of consistently collecting various parameters on the ultimate prediction accuracy. We selected $m = 3, 5, 10,$ and 20 to compare the predicted SOH with the actual SOH, and the corresponding graphs are shown respectively (see Fig. 6, Fig. 7, Fig. 8, Fig. 9).

In an operational energy network, it is imperative to carry out real-time calculations of the SOH of buffer lithium batteries in a network node. When the SOH of these buffer lithium batteries drops to 80%, they are removed from the network. The buffer lithium batteries are assumed to be built using the highest-quality new batteries with uniform quality. It is paramount to validate

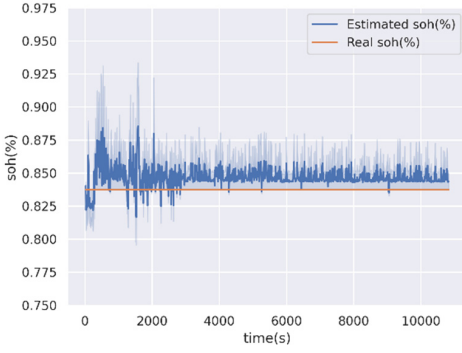


Fig. 6. Estimationd SOH Values ($m = 3$)

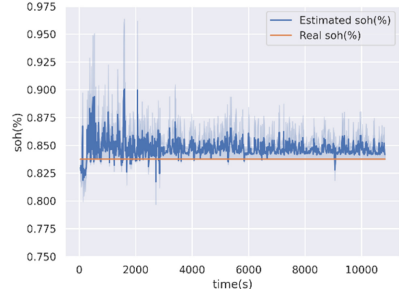


Fig. 7. Estimationd SOH Values ($m = 5$)

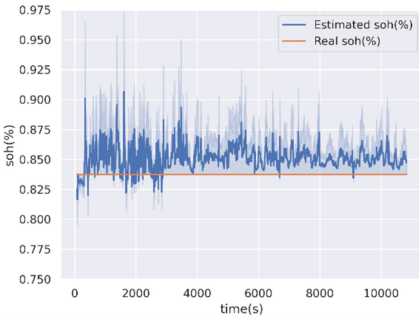


Fig. 8. Estimationd SOH Values ($m = 10$)

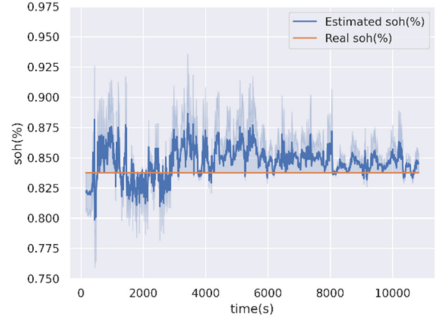


Fig. 9. Estimationd SOH Values ($m = 20$)

the accuracy of the Transformer prediction method in predicting slow decay of lithium batteries throughout their lifecycle.

It was discovered through Experiment I that the prediction accuracy of the proposed Transformer-based technique varies based on the value of m , and the corresponding errors also differ. The accuracy of the prediction results is assessed using MAE (Mean Absolute Error) and RMSE, where MAE stands for Mean Absolute Error.

$$MAE = \frac{1}{K} \sum_{i=1}^K |SOH_i - \overline{SOH}_i| \tag{4}$$

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{K} \sum_{i=1}^K (SOH_i - \overline{SOH}_i)^2} \tag{5}$$

K is the total number of regression samples. SOH_i represents the estimationd SOH value from data science regression models while \overline{SOH}_i stand for the real SOH value.

We conducted Experiment I on different values of m using Transformer models with different layers, and calculated the MAE and RMSE of the SOH prediction results. From the table (see Table 1), we can clearly see that the error rate is lowest ($MAE = 0.0485$, $RMSE = 0.0602$) when m is 20.

Table 1. Errors Corresponding to Different Layers and m values (Experiment I).

Number of layers	Value of m	MAE	RMSE
1 layers	$m = 3$	0.0513	0.0639
	$m = 5$	0.0508	0.0645
	$m = 10$	0.0524	0.0631
	$m = 20$	0.0523	0.0635
2 layers	$m = 3$	0.0509	0.0629
	$m = 5$	0.0488	0.0629
	$m = 10$	0.0491	0.0612
	$m = 20$	0.0492	0.0608
3 layers	$m = 3$	0.0509	0.0629
	$m = 5$	0.0488	0.0629
	$m = 10$	0.0491	0.0612
	$m = 20$	0.0490	0.0604
4 layers	$m = 3$	0.0497	0.0631
	$m = 5$	0.0490	0.0626
	$m = 10$	0.0491	0.0606
	$m = 20$	0.0485	0.0602

Based on the results of Experiment I, we selected the Transformer model with $m=20$ and Layer=4 to repeat Experiment I and compared it with the main algorithm models currently used. The results (see Table 2) clearly indicate that our proposed Transformer-based method has lower error rates ($MAE = 0.0485$, $RMSE = 0.0602$), and therefore, higher prediction accuracy.

Table 2. Compare the Transformer-based (layers = 4, $m = 20$) Results with those of other prediction models (Experiment I).

Value of m	Model	MAE	RMSE
$m = 20$	Decision Tree Regression	0.0752	0.0937
	Linear Regression	0.0503	0.0661
	KNN Regression	0.0549	0.0720
	Random Forest Regression	0.0494	0.0635
	Adaboost Regression	0.0504	0.0631
	GBRT Regression	0.0483	0.0648
	Bagging Regression	0.0511	0.0656
	ExtraTree Extreme Random Tree Regression	0.0762	0.0947
	Transformer (4 layer)	0.0485	0.0602

6 Conclusion

Li-ion batteries as network nodes for storing energy in energy networks, playing a crucial role in achieving bidirectional energy transmission. The stability, reliability, and security of the power grid are highly dependent on reducing the monitoring data sample and accurately predicting the SOH of multiple Li-ion batteries distributed throughout the network in a timely and effective manner. This article presents a novel data-driven approach that utilises a single-factor Transformer-based technique to predict the State of Health (SOH) of a Li-ion battery energy storage system within a power grid. The method involves consistently monitoring voltage change rates of 3, 5, 10, and 20 as vital health indicators when charging Li-ion batteries in the CC charging mode. These data are parallelised in the Transformer-based model to predict SOH accurately. Experiment I examines and analyses the predicted results against the actual SOH.

Due to the diverse types of Li-ion batteries used within the network, some decommissioned batteries are utilized as buffer power sources in the power grid. Thus, the risk of achieving bidirectional energy transmission is amplified within the network. Further enhancements to the model will be made in the future to cater to a broader range of application areas, involving more complex and diverse topological network nodes.

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