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Fault Prediction and Health Assessment of New Energy Lithium-Ion Batteries

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Abstract. As the new energy vehicle sector advances at an accelerated pace, lithium-ion batteries have grown far more prevalent across electric vehicles, energy storage systems, and portable electronic devices. The State of Health (SOH) of lithium batteries bears direct implications for their safety, performance stability, and operational lifespan. For this reason, Prognostics and Health Management (PHM) technology tailored to lithium batteries has steadily become a key area of focus in both academic inquiries and industrial applications. This paper systematically reviews the research progress of lithium battery PHM technology in recent years, mainly covering key methods such as battery thermal state characterization indicators, Physics-Informed Neural Network (PINN), and Integrated Sparse Gaussian Process Regression (SGPR). This paper not only summarized the core principles and applications of each technology, but also analyzed its shortcomings and proposes several improvement directions. This paper provided a reference for future research on SOH prediction and health management of lithium-ion batteries.

Keywords: Lithiun-ion Batteries, Failure Prediction, PHM Technique, SOH

1. Introduction

The rapid expansion of the new energy vehicle industry has led to the ubiquitous application of lithium-ion batteries in fields such as electric vehicles, energy storage systems, and portable electronic devices. The condition of SoH of lithium batteries directly impacts on the battery safety, stable performance and life.Due to this, Li-ion battery PHM technology has gradually become one of the key research points in the academic community, and a key application direction in the industrial field [1]. SOH can not only as an important criterion to represent the health state of the battery at present, but also an indispensable parameter for battery fault and service prediction. In real application, the thermal condition of the battery and operating temperature as well as environment will play a vital role on battery performance. For example, the thermal runaway incident [2-3]. And battery loss of power and energy density under low temperature environment will constrain lithium battery application reliability in large-scale application [4-5]. Hence, it is of great theoretical and practical value for researchers to study the battery SOH and the prediction technology, especially in the environment with diversified conditions. Recently, with the research and development of the data science and machine learning, many kinds of the battery PHM (Predictive Health Monitoring) technologies have been proposed to predict the battery State of Health (SOH) and the remaining

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useful life (RUL).Because physical model is difficult to establish the precise model, it's hard to obtain full discharge capacity information, data driven method has become research mainstream because of lower cost. Generally using voltage, current and temperature information on charging and discharging process to predict battery SOH based on the machine learning. General data-driven approaches are linear regression [6], support vector machines [7] and Gausssian Process Regression (GPR) [8], etc. By extracting features from Incremental capacity (IC) curve or differential voltage (DV) curve, researchers can efficiently predict degradation trends of the battery [9].

Data-driven methods do not require in-depth investigation into complex mechanisms, compared with the methods based on electrochemical models, so they are more flexible and scalable in building a model. This kind of method usually extracts some key characteristics of the battery's charge and discharge, and then feeds into machine learning models as inputs for its learning to obtain the prediction of the SOH and RUL. It is shown that the data driven methods can reflect the electrochemical phase transformation of batteries intuitively and describe battery health status in terms of IC curve characteristics. However, in some special cases (e.g. in rush charging or incomplete charging and discharging state conditions), there are some health features that are hard to extract, so the relationship between Differential Thermal Voltammetry(DTV) [10] and SOH still needs further confirmation. On the other hand, due to increasing new application scenarios of new energy vehicle, non-linear, non-certain load working conditions of battery, non-certain environmental temperature, non-certain charge/discharge strategy make the traditional rule-based prediction method lose more and more available. The hybrid modeling method based on physically based data-driven method has become a promising research direction to study for many scholars in recent years.

2. Measurement of SOH and RUL

SOH (State of Health) and RUL (Remaining Useful Life) accurately measuring is the foundation of lithium-ion battery PHM (Prognostics and Health Management). Both of them are not only technical jargons, but the basic factors characterizing the current state of a lithium-ion battery and remaining serviceable hours. SOH focuses on the near term: it answers the question about whether your phone battery that previously would last a full day now dies at 3 p.m., or your laptop battery that used to last two hours now holds a charge for only 1½ hours during a two-hour meeting. RUL focuses on the future by answering a specific question: For example, "How many more charge cycles does this electric vehicle battery have before its capacity drops to 80%?" This threshold is generally the point at which most EV manufacturers recommend replacing the battery.

Battery capacity and internal resistance are the two most common SOH measurement indicators found in labs and the real world. There's a straightforward pattern of research results over the last decades: the lower the capacity, the higher the internal resistance, usually. This is not a trivial rise in resistance—it's immediately painful, because it immediately hurts the performance of the battery to "give out" available energy to your tools. So, for instance, when you charge up a higher-resistance battery, it'll charge more slowly; more, when you charge faster, the battery can get hot, and less, when you try to get it to charge you drill though the entire project. Now here's the catch: experimentally, internal resistance is actually hard to measure directly. You'd need a picky and expensive measurement device to detect the minuscule changes in voltage, plus little anomalies—like a sudden jump in voltage that occurs when a fast-charging battery runs out of juice and drops into trickle charging—can distort the results. For those reasons, most people interested in SOH stick to a direct measurement of capacity, since it's easier to accurately measure the change in capacity (using low-fi testing gear as well).

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The prediction of Remaining Useful Life (RUL) is about providing a measure to how many more years (days, weeks, hours) the battery has left before it fails, and this information is extremely important in decision making about, for instance, maintenance activities to mitigate an unplanned failure of the batteries, as for the example of a hospital's back-up battery system: if we know the RUL of such batteries, we can replace them in some planned activities, and we don't have to wait to see them out when there is an emergency power outage. Note that our challenge is to provide a faithful model of the dynamics of SOH to be able to predict RUL. You can predict the future behavior of the battery through observations of the previous history—for instance if SOH decreases from 100% to 91% in 5 months—that will enable you to take prevention measures: to replace the battery if RUL is smaller than the one assumed or modify the way the battery is exploited (for example charge the vehicle in a more gradual manner) to extend its life.

But RUL prediction isn't as simple as plugging old charging data into a formula. You have to account for all the messy real-world factors that affect a battery. There's the environment: a battery left in a hot car all summer will age way faster than one kept in a climate-controlled room. Temperature swings matter too—if a battery goes from a cold garage to a warm house every day, that back-and-forth stress speeds up degradation. Then there's cycle depth: a battery that's only discharged to 50% before recharging (shallow cycles) will last longer than one drained to 10% every time (deep cycles). Miss any of these, and your RUL guess can be way off—like thinking a battery will last two more years when it dies in nine months. That's why right now, a big part of lithium battery health research is building RUL models that can handle all this multi-dimensional info, not just old charge logs.

What's more, in use, SOH estimation and RUL prediction are team effort, not adversaries. SOH is your current health check: it says where the battery stands right now (e.g., "This battery is at 86% SOH— still OK, but starting to go away"). RUL then takes your checkup, and makes it into a forecast: "At this pace, it'll hit 80% SOH in 16 months.") This pair is the silver bullet for the maintenance team: use SOH to flag batteries that require attention (the ones with sudden dips) and RUL to forecast budget and replace time.

3. Application of PINN in SOH prediction

PINN, a data-driven modeling approach integrating the physics information into neural network, is to minimize the reliance on large amount data of conventional data-driven models, which is one of the key merits.It even works under the ill-condition of data scarcity by constraining model training process via pre-existing physical laws through which model's prediction accuracy and stability can be well preserved, necessary in engineering situations that data collection cost or difficulty is high.

In the study of battery lithium battery SOH, the primary application of PINN is to establish a high-accuracy degrading battery degradation model by first taking the empirical battery degradation model (extracted from a series of long-term experimental data related to the capacity fade, internal resistance growth, performance degradation behaviors of a battery, etc.), as well as the state-space equation (which is to describe the battery internal state (for example, the state of charge and aging degree) dynamical evolution over time).Using such fusion, the battery degradation dynamics model can be built.On the other hand, targeting the nonlinear property of the battery degradation (e.g., the non-monotonic deterioration rule of battery capacity loss due to the SEI layer growth and electrode material pulverization), PINN employs the excellent nonlinear fitting ability of neural networks to precisely characterize the complicated variation laws of the degradation process, overcompleting the limitation of empirical models cannot characterize the nonlinear behaviors completely.

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In order to improve the practicability of the engineering model, the previous studies adopted a charging process-based feature extracting method according to the mechanism different between battery charging and discharging: different from battery discharging, the charging behavior of users will be more regular than discharging—most users charge the battery until the battery charging is complete, and the charging current, voltage gradient and other parameters of charging is relatively stable. On the contrary, discharging behavior is quite diverse as users are usage scenarios vary (e.g., different electric vehicle power consumption, intermittent portable device usage), and always can not be fully discharged. Thus, researchers extracted features using shorttime window in which battery is close to complete charge stage that can effectively reject interference of irregular discharging data and guarantees that stability and representativeness of input data of the model. This feature extracting strategy realizes the following technical functions: first, it mitigates the influence of the changes of data fluctuation (such as the non-recoverable instantaneous voltage jump while a battery is running out). The excessive fitting for the distorted data leads to overfitting; and, second, it can directly enhance the accuracy of the prediction for SOH, to provide effective decision support to the health monitoring and life cycle management of the batteries.

Because of the incorporation of physical constraints, the model can still finish effective training even when data is not sufficient (i.e., when a study at the early stage is available with only a few test samples) or partial (i.e., when there is missing data due to sensor failure in experiments).Moreover, it is somewhat robust to the perturbation from external environment (e.g., temperature ranges from -20∘C to 60∘C and humidity, etc.) and can achieve stable prediction performance under complex working conditions. Finally, it can implement direct modeling of the battery degradation dynamics which can considerably improve the interpretability of the model against pure data-driven models. Conventional data-driven models (e.g. Though the black-box nature of a typical CNN, LSTM), i.e., inability to track the prediction logics, is often discouraged for the above models, the incorporation of physiochemical mechanisms using PINN makes it possible to connect the prediction performance (i.e., SOH) to underlying electrochemical processes (i.e., for example, lithium diffusion efficiency, depleting active material), which is of potential importance in terms of verifying the models and crossverifying with academic sources. Scientists carried out the long-term degradation experiments of 55 Li batteries to validate the accuracy of the PINN including various charging-discharge strategies (e.g. CC charging vs. CP charging, shallow cycle vs. deep cycle) and environment conditions [3].The experiment results in Section III demonstrate that PINN performs well with low prediction error (error $<3\%$) and long-term stability in all test cases when compared with conventional empirical models and data driven models. Moreover, PINN framework enables us to incorporate electro-chemical features (incremental capacity (IC) curve, differential voltage (DV) curve, etc.) which are very sensitive with battery inner structures' minute changes (e.g. electrode volume)., peak shift of IC curves due to the active loss material loss)—making the nonlinear degradation process model more accurate and offering technical support for in-depth analysis of battery aging mechanism, thus allowing PINN to predict the state of health (SOH), offer important input data for the remaining useful life (RUL) prediction and providing all-around support for the battery health management.

4. Application of integrated Sparse Gaussian Process Regression (SGPR) in SOH prediction

The integrated sparse Gaussian process regression (SGPR) is of considerable potential application in prediction of the state of health (SOH) of Li–ion batteries. Gaussian Process Regression (GPR) is a Bayesian non-parametric statistical modelling method. Its main advantage is that not only the predicted values are output, but also the confidence intervals to quantify the prediction uncertainty

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for further battery management and maintenance decision making. Looking at the function space, from the Gaussian perspective, the Gaussian processes may be conceived as multivariate gaussian random variables set. Based on the input data set, this method is able to model the historical charge and discharge test data, and learn the battery degradation pattern and nonlinear behavior to realize the accurate SOH prediction. As the statistical foundation of GPR can keep high robustness in the presence of noisy data or uncertainty factors, the above two areas are quite essential to consider the complex factors of temperature fluctuations, load changes and operational habit difference in the practical battery operation environment. In this way, GPR is a prediction tool not only, but also an evaluation means to provide quantitative uncertainties for L-I- batteries health management, giving scientific basis of maintenance person to formulate maintenance strategy.

Inspired by the original GPR, the sparse Gaussian process regression (SGPR) is introduced to greatly alleviate the computing complexity with the aid of sparse processing, thus the SGPR can be well suitable for big data. The main benefits of SGPR are three folds: First, the SGPR can fit nonlinear and high-dimensional battery characteristics data like capacity, internal resistance, voltage curve features and temperature variation and give an accurate input for the complex battery health condition assessment; Second, the output not only is SOH prediction values, but also have the confidence intervals; Third, there are few simulation configurations are needed to run, simply implemented in the neural networks platform, and other neuron parameters as the filter order N and ARQ parameters are adaptive, the effectiveness in data fitting has nothing to do with them. Used to indicate the prediction uncertainty and aid in develop preventive maintenance and replacement strategy; Finally, by incorporating sparse processing technology, SGPR has the computation efficiency significantly enhanced so that the real-time monitoring and control of the big battery group can be realized. But with SGPR performs well in theory and experiment, its application still has a few problems. In the fast charge condition or irregular charge and discharge condition, characteristic data cannot be collected fully so that the prediction accuracy may reduce. Furthermore, the model needs to be adjusted and optimized specially for different battery models and complex operating environment which ensures its generalization ability and applicability. Hence, in the future work the multi-source data fusion technology can be further integrated to further improve the adaptability of the SGPR in the condition of poor accuracy, the methods combining the physics constraint modeling to achieve good accuracy, more interpretable and efficient estimation of lithium-ion batteries SOH can also be researched.

5. Current issues and strategic recommendations

By using the above-mentioned research ways, researchers can make the prediction of the SOH (State of Health) of the lithium-ion batteries achieve a high accuracy in certain aspects, which makes it possible to provide scientific basis for the maintenance and replacement of lithium-ion batteries. These predictions are crucial for engineers: not only they allow preventive actions to be taken even before an obvious degradation of the batteries' performances occurs, but also optimization of operation strategies can be implemented to lengthen service life and reduce the risk of system unplanned downtime induced by batteries' failures. Using e-mobility or huge storage as an illustration – precise SOH (State of Health) estimation enables the controller to adjust charging/discharging schedules to prevent batteries getting stressed (too much load or temperature) beyond a certain point. Meanwhile, through integrating SOH prediction and RUL(Remaining Useful Life) prediction, researchers and maintenance staff would be equipped to make more reasonable replacement strategies, allocate available resources better, in turn maximize the system's overall economic profit. Nevertheless, with all of the breakthroughs in today's existing research, there are

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still certain barriers in experiment work. The biggest problem is the data collection, where inconsistent charging/discharging pattern and complicated operating conditions in realworld usage lead to difficulty collecting complete sets of key feature data. Second, it should also be noted that the measurement errors of the battery parameters (such as capacity error, measurement error of internal resistance, data deviation due to random fluctuations of surrounding air temperature environment, etc.) will affect the prediction accuracy of the prediction model and lower the confidence of the prediction. Furthermore, when the model scale is large, especially in the case of real-time surveillance of battery group in scale, the problem of low computational efficiency is more prominent. The conventional data-driven model shows the problems of high computational resource requirement and low response time under large-scale data. These issues overall constrains the promotion and application of PHM technology in practical industrial setting, and need optimization and improvement in data acquisition, measuring accuracy and computing time-related issues etc.

To some extent, the physical information neural network (PINN) and the coupled sparse Gaussian process regression (SGPR) will be good solutions for this problem. Compared with pure data-driven method, the benefits of PINN framework include low cost, small amount of data and high stability of model. Its essence is that the neural network training process is to embed the battery degradation mechanism by physical constraints, which can make the battery model have a high degree of prediction precision when it is in short data or noise data. At the same time, PINN can model the nonlinear degradation behavior well and has strong adaptability to various application scenarios and charging and discharging modes. As a complement, SGPR, in addition to provide SOH prediction results, can generate prediction confidence intervals, which can be used to quantify the model uncertainty for further use in the decision-making process of battery maintenance. By taking these two methods as a basis, the research orientation of optimization lithium battery PHM technology can be extended from the following aspects in the future: one is the data measurement optimization, taking high precision and convenient capacity and internal resistance measurement technology into account, reducing experimental error, improving data quality, offering reliable input to the model. Second, the feature extraction optimization, in fast-charging, partialdischarge, and not-ideal use scenarios, to focus on some better feature extraction methods that can improve the generalization ability and robustness of the model in practice application. The algorithm and computing efficiency optimization: Using big data technology, distributed calculation framework and model sparseness method to improve the operation efficiency of the PINN and SGPR for large battery groups.Fouth, system integration and visualization: The SOH estimation function and RUL prediction function are implemented on a unification platform, which can realize data import, processing, analysis and dynamic display results, thus intuitively and scientifically support the decision-making of the battery management. Lastly, future work can also try to bridge the gap between PINN and SGPR for modeling, where the non-linear modeling capability of the former and the confidence interval advantage of the latter is further integrated, to facilitate accurate and reliable SOH/RUL predictions, and offer a more comprehensive and smart solution for the whole life cycle management of lithium battery.

6. Conclusion

The SOH prediction of lithiumion batteries and battery health management are inseparable in new energy vehicles, energy storage and other highperformance energy equipments. This paper reviewed the recent research and studied the key principles and practical application value of battery SOH measurement and RUL methods. It states capacity and the internal resistance as the crucial parameters which are applied to evaluate the battery health status, and these parameters can reflect

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the short-term performance change tendency and long-term degradation trend of the battery directly. Meanwhile, this paper involved using physical information neural network (PINN) and embedded sparse Gaussian process regression (SGPR) into SOH prediction. PINN integrates physical constraints with neural networks to characterize the complex nonlinear degradation process of the batteries and can keep high prediction accuracy under the limitation of scarce data and noise. Compared with PINN, though SGPR could give a precise prediction, meanwhile, can provide uncertainty in form of confidence intervals to make maintenance decisions more quantitatively. Both two schemes fully make good use of the battery capacity and the battery resistance information via extracting feature, training model and modeling system that offer scientific references for battery condition evaluation, maintenance policy design and replacement planning.

Although there has been a great step forward in lithium battery PHM technology, some key problems remain to be solved for lithium battery PHM technology to be applied in practice, such as the difficulty of acquiring experimental data, the excessively large measurement error, the limitations of the feature extraction under non-ideal use conditions and the low computational efficiency of the large-scale models. All these hindered the promotion of PHM technology on the real-time monitoring and the large-scale application. The future research on related work needs to, on one hand, optimize the measuring method to further improve the precision of measuring capacity and internal resistance, and lower the experimental error, on the other hand, upgrade the feature extract method, so that the model is able to apply to real usage state like fast-charging state, low-discharge state and a complex environment, and finally, upgrade the algorithm and computing efficiency by using big-data technology and distributed computing, and realize the online monitoring and maintenance for hundreds of thousands of batteries. And the model sparsity strategies, making that PINN and SGPR work effectively in large-scale battery packs; the 4th, to promote the integration and visualization of SOH prediction and RUL evaluation, realize the integration of data import, analysis and results description. In this way, lithium battery PHM technology can not only ensure the safety and reliability of electric vehicles and energy storage systems, but also improve the battery's life span and lower operation and maintenance cost, with a view to offering strong technical support for further full-life-cycle intelligent management.

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