Review of machine learning method for safety management of lithium-ion battery energy storage

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Abstract. With the broad implementation of electrochemical energy storage technology, the noteworthy issue of ensuring safe operation and maintenance of battery energy storage power plants has become more and more prominent. The conventional battery management system solely acquires data on the voltage, current, and temperature of individual battery cells. Constrained by hardware processing capabilities, limitations in data transmission bandwidth, and latency issues, effectively monitoring the health and safety of large-scale battery energy storage systems has become a critical technological challenge. The implementation of machine learning techniques in predicting the operating conditions of lithium-ion batteries has provided opportunities for enhancing the safety management of energy storage systems. To address the safety management requirements of lithium-ion batteries, this paper firstly introduces research related to the risk mechanism of abusive use and thermal runaway of such batteries. Next, the architecture and application characteristics of the lithium-ion battery management system will be discussed. The implementation of machine learning techniques for analyzing the health and safety status of lithium-ion batteries is extensively discussed. Finally, a safety assessment of lithium-ion batteries for energy storage power stations is anticipated.

1. Introduction

Among all types of electrochemical energy storage, lithium-ion battery account for 90% of the market share. However, Li-ion battery system safety accidents characterized by thermal runaway often occur, which seriously threaten the safety of life and property. Therefore, the high safety of energy storage batteries under the condition of high energy density is the primary guarantee for the commercialization and application. The technical solution of the existing power storage battery management system is obviously not suitable for the safe operation and maintenance requirements of large-scale power storage power stations. There are problems such as large monitoring data, complex information types and urgent safety assessment. At the same time, due to thermal runaway characteristics, it is difficult to control lithium-ion batteries in case of accidents, which may evolve into major safety accidents such as combustion and explosion of energy storage system.

2. Thermal runaway warning and safety management

2.1 Thermal runaway mechanism of battery

In practical applications, if battery abuse occurs, battery material will be damaged and abnormal heating will occur. Heat accumulation intensifies the internal exothermic chemical reaction process, forming positive feedback, and eventually causing thermal runaway. Mechanical abuse, electrical abuse and thermal abuse are the main causes of reversible or irreversible damage to lithium-ion batteries. Literature [1] studies have shown that the decomposition of battery SEI film is the main source of exothermic reaction. Continued increase in temperature will lead to the reaction of negative metal lithium with electrolyte decomposition (about 120°C), membrane melting (130°C-140°C), positive electrode decomposition (150°C-211°C), and cause runaway overcharge heat.

2.2 Characteristic parameters and early warning

Lithium-ion batteries release a lot of heat and flammable gases. When the concentration of flammable gas reaches its explosion limit, an explosion will occur under the action of external high temperature. This will seriously affect energy storage power stations [2]. For electric energy storage systems, thermal runaway is usually caused by electrical abuse. Such as inappropriate overcharge and overdischarge conditions can cause a variety of side effects inside the battery. And that triggers thermal runaway. The external short circuit is the extreme speed discharge of battery in the abnormal state. In

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addition, battery decay and aging are also one of the reasons for thermal runaway accidents.

In view of the reaction mechanism and evolution process of lithium, the existing early warning is mainly aimed at the critical condition. In the process of thermal runaway, its voltage, current, internal resistance, internal pressure, temperature, etc. will change significantly, and characteristic gases will be produced. By monitoring one or several characteristic parameters and characteristic gases, it can be effectively forewarned.

2.3 Battery management system

BMS controls and manages the charging and discharging process of the battery by monitoring, estimating and predicting the battery status parameters. It can keep battery running safely and reliably in different environments and operating conditions. This reduces battery failure, prolongs battery life.

Battery management system is a system combining hardware and software, which integrates monitoring, prediction, control and communication functions. Battery management unit (BMU) is the basic unit of BMS, which can monitor data in real time and calculate and predict battery state. Finally, it communicates with host computer through CAN bus. Under abnormal conditions, battery system can be controlled by BMS to carry out necessary reactions, such as disconnecting, isolating abnormal batteries, etc..

3. Machine learning approach in battery safety management

3.1 Machine learning methods for battery state estimation

As mentioned above, the performance of BMS determines the operating cost and safe operation efficiency [3]. However, the research related to the safety condition monitoring for the risk of thermal runaway of batteries in BMS is still in the development stage. At present, no standard state description parameters such as health status, life expectancy, and thermal runaway risk have been formed.

Data-driven state identification and evaluation of lithium-ion battery is a new battery management technology. It is mainly a kind of method to build a certain mathematical model, and use the battery operation information (voltage, current, temperature, etc.) collected by BMS and environmental monitoring system as the model input and measure the battery degradation state, life expectancy, health state and other related parameters. Data-driven model can provide operational prediction based on historical and current operational status for the safety management of Li-ion batteries. It has a positive effect on dealing with the aging and deterioration of batteries and preventing thermal runaway under battery abuse. Therefore, in recent years, data-driven machine learning method has made great progress, and its effectiveness has been widely verified.

Machine learning studies and builds special algorithms that allow computers to make predictions by learning from data on their own. In general, machine learning falls into three main categories. It can be seen that supervised learning is applicable to the evaluation and trend prediction of battery health factors, while unsupervised learning is applicable to the determination and differentiation of abnormal battery states.

3.2 Typical application of machine learning in battery safety assessment

3.2.1 State space statistical filter. State space method uses electrochemical model or equivalent circuit model to establish the nonlinear dynamic relationship between state of charge, load current and terminal voltage of lithium-ion battery, constructs state space equation, and uses statistical filter to estimate battery characteristic parameters.

Commonly used algorithms include Kalman filter (KF) and its extension method, particle filter and its extension method, etc. KF method supports unbiased minimum error variance optimal estimation for linear systems. Because KF can handle sensor noise, it fits closely with the monitoring requirements of lithium-ion batteries. Taylor approximation method is used to linearize the lithium-ion battery model in nonlinear problems. Common ones include extended Kalman filter (EKF) [4], untracked Kalman filter (UKF) [5], variable-variance Kalman filter (VVKF) and adaptive extended Kalman particle filter (AEKPF) [6].

3.2.2 Artificial neural network. ANN is an important technology in machine learning. It typically consists of three layers: input, hidden, and output, each with their own distinct structures.

Neural network algorithm is widely used in the field of battery state prediction. In terms of state of charge prediction, literature uses BP neural network (BPNN). The three parameters of battery voltage, current and temperature are used as the input of the network. SOC calculated by the ampere measurement method is used as the network output, and the network with good interpolation data generalization is trained. In terms of health state prediction, literature [7] uses deep convolutional network (DCNN) to establish a health state estimation model for lithium-ion batteries. In terms of battery life prediction, neural network methods are also feasible, such as hybrid convolutional neural network (CNN) [8], recursive neural network (RNN) [9] and dilated convolutional neural network (dilated CNN) [10].

3.2.3 Support vector machine. SVM uses structural risk minimization as the optimal criterion to obtain the global optimal solution. SVM overcomes the problems of local extremum, slow convergence rate, difficult determination of network structure and large samples for training of ANN. The computational complexity is significantly lower than that of ANN method. The principle is shown in Figure 1.

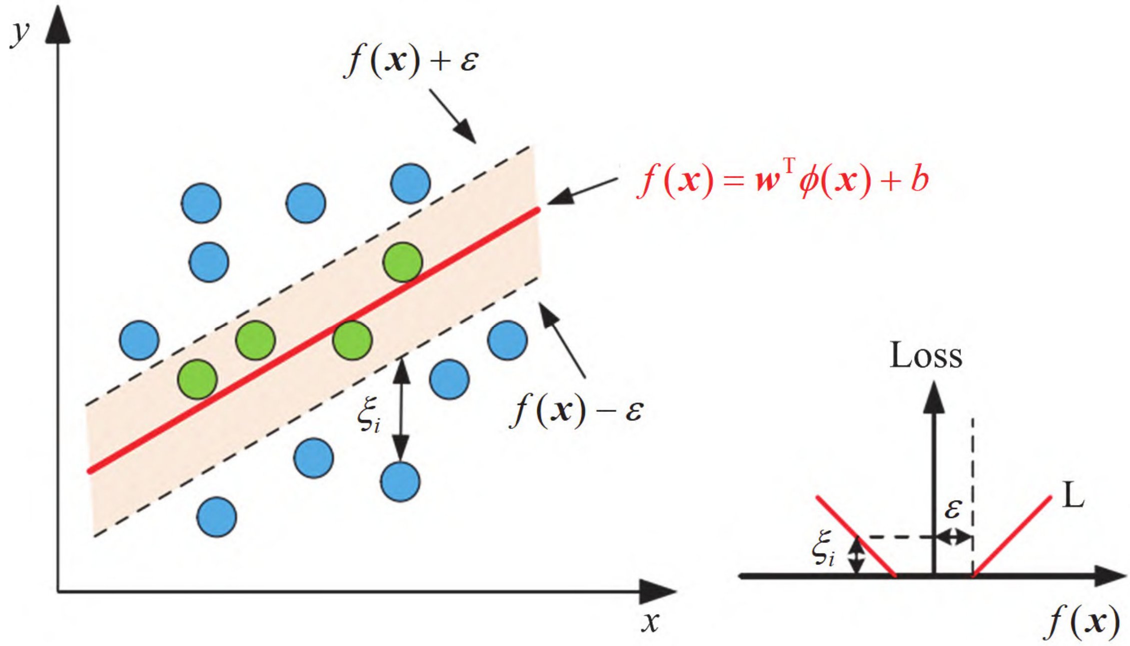

Figure 1. The basic Principle

SVM is often used to predict the status and life. For the prediction of state of charge, literature [10] introduces particle swarm optimization algorithm (PSO) into the least square support vector machine (LS-SVM) algorithm to improve training efficiency and model accuracy. For the prediction of health state, LS-SVM is used as the measurement equation of noise variance variable Kalman filter (VVKF) in literature [10], and a SOH estimation algorithm is proposed by integrating KF and LS-SVM.

3.2.4 Gaussian process regression. GPR can give the non-determinism expression of prediction results, which is a flexible non-parametric type. The RUL forecasting of lithium-ion batteries utilizing GPR does not require integration with the actual battery model. Instead, it employs the Gaussian process as a probabilistic prediction approach to simulate the battery's behavior. In order to improve SOC estimation accuracy, literature [9] proposed an online estimation method based on GPR.

3.3 Characteristic engineering of battery safety assessment

Feature engineering is a key step in machine learning, which is to convert original data into data types that are easier for models to understand, in order to improve the prediction accuracy of machine learning model. It mainly includes three aspects: feature processing, feature selection and feature generation. Battery state parameters can not be directly measured online, so it is necessary to establish a mapping model between measurable parameters and critical state quantities. Taking the SOC estimation task as an example, since the state is closely related to parameters such as voltage, current, and temperature, most literatures choose V, I, and T as input features. The input of model is at each moment, and the output is SOC of current state.

In literature [10], sampled values of voltage interval in incremental capacity analysis (ICA) graph are selected as input features of GPR model, and the mapping between ICA features and SOH is established. The algorithm structure of above method is shown in Figure 2. The outputs are battery SOC (fig. 2(a)), SOH (fig. 2(b)), battery capacity (fig. 2(c)) or RUL (fig. 2(d)), etc. The input is specific electrochemical test characteristics.

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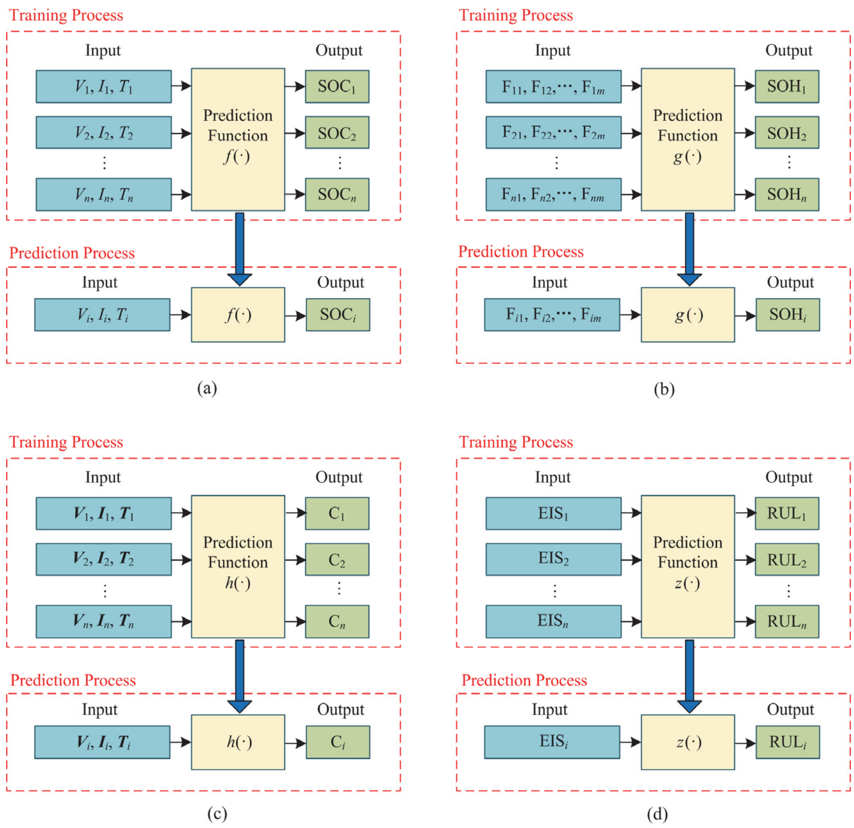

Figure 2. Feature selections of different state estimation for batteries

4. Conclusion

In this paper, the machine learning method in the safety management system of lithium-ion battery is comprehensively analyzed and discussed.

- The core problem of battery safety comes from the thermal runaway process caused by battery abuse. Based on the real-time measurement data of BMS, machine learning can be used to realize the early evaluation and warning of battery safety characteristics.
- Due to the variety of battery types, incomplete operation data and different operating conditions in energy storage system, the existing machine learning methods used for battery safety state assessment still have deficiencies and need to be improved.
- The optimization of BMS function of energy storage power station lies in the combination of prediction and measurement. Moreover, the existing machine learning algorithm is optimized with measured data step by step to track and predict the real-time state of battery.

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