

Research Article

Prognostics and Health Management System for Electric Vehicles with a Hierarchy Fusion Framework: Concepts, Architectures, and Methods

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The prognostics and health management (PHM) of electric vehicles is an important guarantee for their safety and long-term development. At present, there are few studies researching about life cycle PHM system of electric vehicles. In this paper, we first summarize the research progress and key methods of PHM. Then, we propose a three-level PHM system with a hierarchy fusion architecture for electric vehicles based on the structure, data source of them. In the PHM system, we introduce a database consisting of the factory data, real-time data, and detection data. The electric vehicle's factory parameters are used for determining the life curve of the electric vehicle and its components, the real-time data are used for predicting the remaining useful lifetime (RUL) of the electric vehicle and its components, and the detection data are used for fault diagnosis. This health management database is established to help make condition-based maintenance decisions for electric vehicles. In this way, a complete electric vehicle PHM system is formed, which can realize the whole-life-cycle life prediction and fault diagnosis of electric vehicles.

1. Introduction

The development of new-energy-related technologies and the advancement of environmental awareness have promoted the rise of new energy vehicle [1, 2], and electric vehicle is one of the important branches. Electric vehicles have become the development trend in the automotive field since their energy-saving nature.

Compared with traditional automobiles, electric vehicles are different in electric drive and control systems due to different energy consumption types. Meanwhile, the fault and accident types of electric vehicles are also different from traditional vehicles. In terms of the fault type, electric vehicles may fail in the battery system (such as inconsistency of cells and degradation of battery), while traditional vehicles may fail in their fuel engine (such as the failure of the cooling system). In terms of the accident type, fire accidents are

more likely to occur in electric vehicles than traditional ones. In recent years, many electric vehicle accidents have occurred in different countries. Take China as an example; 59 accidents such as fire accidents occurred in electric vehicles in China between 2016 and 2018. The causes of the accidents are related to many factors of the battery system such as battery aging and overcharging. The health management mode of traditional fuel vehicles cannot be directly used. Therefore, it is urgent to establish a prognostics and health management (PHM) system specifically for the essential characteristics of electric vehicles, comprehensively monitor the health state of electric vehicles, and improve the safety level of electric vehicles. The contribution of this study is that we show a comprehensive PHM system for electric vehicles.

This paper summarizes the research progress of health management and the demand of electric vehicle health management and then proposes a comprehensive three-level

PHM system with a hierarchy fusion architecture for electric vehicles. The remainder of this paper is organized as follows. Section 2 introduces the content of PHM. Section 3 describes the architectures and key methods of the PHM method. Section 4 proposes a three-level PHM system with a hierarchy fusion architecture for electric vehicles. Finally, we conclude the work of this paper.

2. Prognostics and Health Management

2.1. What Is PHM? The content of PHM includes two aspects, namely, prognostics and health management. Prognostics is to predict the future status based on the current and historical status of the system, including the health state, remaining useful lifetime, and faults of the system and components. Health management is to make decisions on maintenance based on fault prediction information, maintenance resources, and application requirements. Prognostics is the core aspect of health management. PHM systems usually have functions such as fault detection, fault isolation, fault diagnosis, fault prediction, health management, and life tracking. For complex equipment and systems, PHM can achieve comprehensive diagnosis and fault prediction at different levels.

In the 20th century, the US military first proposed the concept of health management. Health management aims to monitor equipment working conditions, predict its remaining useful lifetime, potential failures, and health issues, and provide repair and maintenance recommendations. Advanced sensor technology, data transmission technology, and data processing technology are often used as the technical methods. In recent years, health management technology has received extensive attention, research, and application and has now developed into prognostics and health management technology [3–5]. Lee [6] proposed a “5S”-based health management system and process for the mechanical system. Brahimi et al. [7] summarized the health management system of railway infrastructure. Pecht [8] analyzed the health management and technical methods of electronic systems. Johnson et al. [9] described the health management system and application of the space system. In addition to military field, health management technology plays an important role in the mechanical system [6, 10], battery health management system [11, 12], aerospace [13], and other fields. For example, the PHM technology is widely used in the aircraft system in the UK, the US, and Canada, as well as other complex engineering equipment such as automobiles. Vehicle health management (VHM) system has been utilized to realize the automated decisions in the last decades. For instance, the OnStar system of General Motors company sets a good example for the use of VHM. This system is capable of prognostics and information transmission from subsystem to a central processing system. This centralized architecture and data processing technology can be applied to the electric vehicle PHM system design.

2.2. Why PHM for Electric Vehicles? The market of electric vehicles has been expanding a lot for the last decade and the number of electric vehicles is increasing sharply. The

monitoring of the safety level and identifying of possible faults about the vehicle in use are of great significance. Electric vehicle is a complex system composed of the battery system, motor system, and electronic control system, and the safety performance is closely related to each system. However, nowadays the health management is mainly concentrated on battery systems [14–16]. A mature electric vehicle health management system framework has not yet been formed. Therefore, it is necessary to establish a health management system for electric vehicles, which will directly affect the long-term development of electric vehicles. The PHM system has been successfully applied to some complex system such as the aircraft system. And, it has advantages over the whole-life cycle health management. Therefore, introducing the idea of PHM to the electric vehicle field is a promising idea.

3. PHM Architectures and Key Methods

In this section, we will give an overview about the PHM architectures, especially three different classifications. Next, two important technologies used in the PHM system will be introduced, namely, the life prediction and fault diagnosis. Fault diagnosis is used to realize the prognosis, and life prediction is an important branch of health management. Thus, we mainly carry on the elaboration in these two aspects.

3.1. PHM Architectures. PHM architectures are divided into three categories: centralized architecture, distributed architecture, and hierarchy fusion architecture. In the centralized PHM architecture, the information is processed within a central management controller which integrates the function of information collection, transformation, and processing. In a distributed architecture, each subsystem can realize the information processing process and then achieve the function of fault diagnosis and prediction. After the processing of the subsystem, the health status of the subsystem can be directly transmitted to the integrated display and control unit. The hierarchical fusion architecture combines the centralized and distributed architecture. Each subsystem has basic PHM functions, while the higher-level system has more powerful integration capability. And the high-level system can comprehensively process and control all diagnosis and prediction results.

3.2. Life Prediction Methods. There exist three kinds of methods to make the life prediction: physical model-based method, data-driven method, and fusion method.

The physical model-based method establishes a physical failure model to investigate the internal cause of the system failure and then predicts the remaining useful lifetime (RUL) of the system [17]. Son et al. [18] proposed a RUL prediction method based on the gamma process. A nonstationary gamma process model was used to establish a system degradation model to predict the RUL. Wang [19] proposed a second-order remaining life prediction model based on semirandom, semilinear, and non-Gaussian filtering techniques based on degradation data. Lin [20] studied the two-

stage modelling method of failure based on Bayesian change point estimation, mainly considering the existence of change points in the system failure rate function. Yuan and Yuo [21] also considered the existence of change points in the failure rate function. The physical model-based method can accurately predict the remaining life of the equipment, but it is often difficult to obtain the model parameters. Meanwhile, it is difficult to establish a physical model for the failure of complex systems.

Data-driven methods can overcome those aforementioned difficulties. These kinds of methods use system detection data to establish the state models of the characteristic index and the remaining life of the system. Data-driven methods include neural networks, support vector machines, Bayesian networks, and stochastic processes. Wang and Vachtsevanos [22] realized the life prediction of the automobile-bearing system through the dynamic wavelet neural network model. You et al. [23] proposed a method for predicting the real-time state of electric vehicle power batteries based on neural network models and proved the accuracy of the method through battery tests. Khelif et al. [24] used support vector machines to build a model between the remaining life and sensor parameters. In addition, according to different degradation models, researchers have also established RUL prediction methods based on the Gamma process [25] and Wiener process [26, 27]. Data-driven methods require large-scale and high-quality datasets. At the same time, the algorithm needs to make a balance between the accuracy and complexity so that the efficiency of the algorithm is acceptable.

The fusion method combines the advantages of the physical model-based method and the data-driven method. Liao Kottig [28] proposed a hybrid method combining a data-driven method and a physical model method. The validity of the method was proved by the prediction of the remaining life of the lithium battery. The fusion method can combine the advantages of the first two methods, but the algorithm is more complicated.

3.3. Fault Diagnosis Methods. A fault is a deviation from expectations of the parameters or states in a normally operating system. Fault diagnosis technologies mainly include model-based fault diagnosis and data-based fault diagnosis.

The model-based method compares the model output information with the actual monitoring information of the system to determine whether the system has failed. Common methods include observer-based methods [29, 30] and parameter identification-based methods [31]. Observer-based methods are flexible and easy to apply, such as Kalman filter (EKF) [32], adaptive EKF (AEKF) [33], sliding model observer (SMO) [34], or proportional integral observer (PIO) [30]. The parameter identification-based methods detect abnormalities through online parameter estimation to diagnose faults. However, the application of model-based method is limited since it is difficult to obtain an accurate system model for a complex system.

The data-based method analyzes and diagnoses based on a large amount of historical data without the need for

accurate system models and signal types. The main methods include neural networks, decision trees, and support vector machines. Yam realized the prediction of system failure through the regression neural network model [35]. Wang chose a fuzzy neural network model to predict and determine system failures [36]. Qiu et al. proposed a fault recognition algorithm based on Hidden Markov for fault sign recognition at an early stage [37]. Goebel compared the performance of three data analysis methods, i.e., neural network, decision tree, and support vector machine in fault prediction [38]. Skormi et al. realized prediction of the fault development process based on clustering algorithm [39].

The rise of electric vehicles in recent years has accumulated a small volume of fault data. And, the methods based on big data are not applicable due to the small-scale sample data. There are some studies dealing with the fault diagnosis of small-scale data. Vachtsevanos [40] calculated the probability density of fault by statistical methods such as Bayes. Weibull [41] used the Weibull distribution to expand the sample data. The application of Monte Carlo and Bayesian methods [42] to obtain the probability density of faults is often used.

In summary, the PHM method is mainly oriented to fault prediction and fault diagnosis. There are some differences in the methods and application requirements in different fields. For the PHM for electric vehicles, we should not only focus on battery system health management but also establish a complete PHM system for the entire vehicle.

4. PHM System for Electric Vehicles

4.1. PHM System. PHM system for electric vehicle mainly concerns with the following two problems: prognostics and health management. First health management deals with the life prediction and evaluation for electric vehicle and its components. And, prognostics deals with the fault diagnosis and prediction.

Three kinds of PHM architectures are described before, and now we will introduce a three-level PHM system with a hierarchy fusion architecture for electric vehicles considering the vehicle structure, data source, and health management requirements of them. The PHM system is shown in Figure 1.

The detailed composition of the database is shown in Figure 2. There are four sources of data in this database, namely, the electronic control system, motor system, battery system, and electric vehicle. For each component, factory data, detection data, and real-time data are included to provide a comprehensive view about the vehicle. According to different stages of data source in the health management database, the PHM system is divided into three levels:

Level 1 deals with the life prediction of electric vehicles at the factory stage. In this level, the lifetime of electric vehicles and its subsystems and components are predicted. The main product is the life curves of electric vehicle, battery system, motor system, electronic control system, and components.

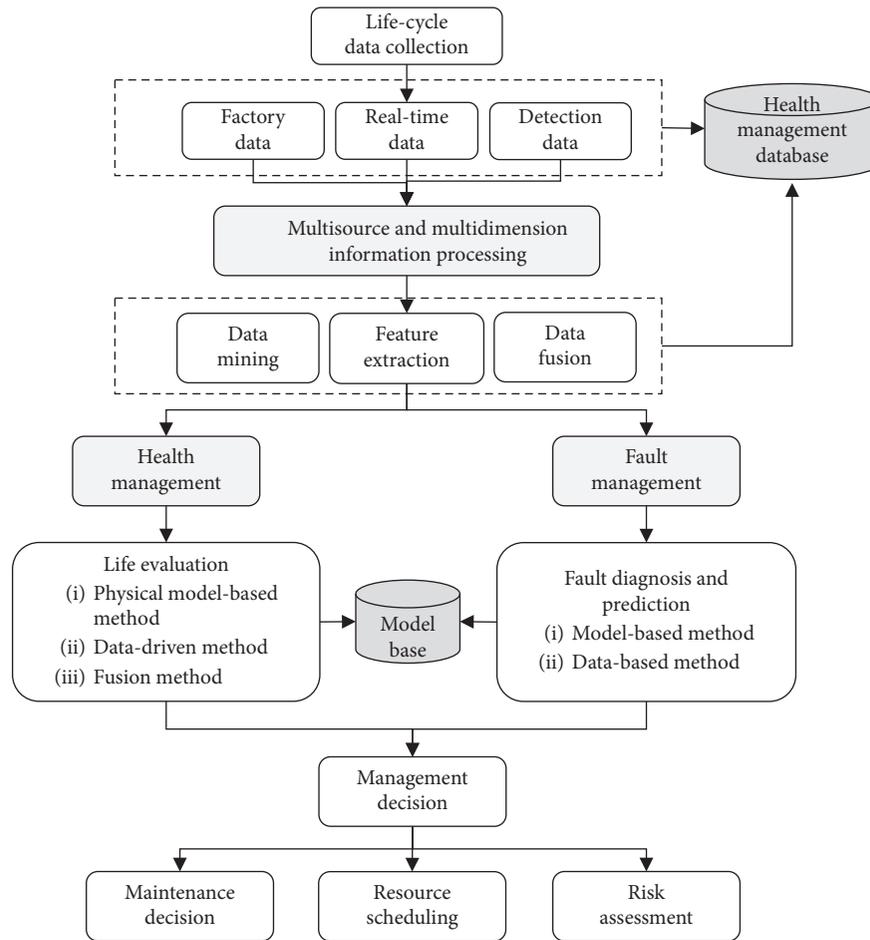


FIGURE 1: PHM system for electric vehicles.

	Electric vehicle	Electronic control system	Motor system	Battery system
Factory data	Initial state data	Initial state data	Initial state data	Initial state data
Detection data	(i) DC/AC withstand voltage data (ii) Insulation resistance (iii) Safety regulation data of charging port	(i) Dashboard data (ii) CAN communication capability (iii) CAN communication function (iv) OBD fault diagnosis	(i) Acceleration performance (ii) Driving ability (iii) Under extreme working condition	(i) Fast/slow charging performance (ii) Charge/discharge performance (iii) Capacity (iv) Temperature
Real-time data	(i) Vehicle state (ii) Charging state (iii) Speed (iv) Vehicle position (v) ...	(i) Collection module (ii) Transmission module (iii) CAN module (iv) ...	(i) Temperature (ii) Vibration (iii) Current (iv) Rotation rate (v) Torque (vi) ...	(i) Temperature (ii) Voltage (iii) Current (iv) SOC (v) ...

FIGURE 2: Composition of health management database.

Level 2 deals with the real-time remaining useful lifetime prediction of electric vehicles. In this level, the remaining useful lifetime is predicted through the real-

time operation data of electric vehicle to realize the real-time monitoring and evaluation of electric vehicle's state.

Level 3 deals with the fault diagnosis of electric vehicle detection process. In this level, we detect the faults of the electric vehicle and diagnose the faulty system or components.

The main functions of the electric vehicle PHM system include information collection, fault detection, fault diagnosis, fault prediction, and health management. The details of each function are listed as follows.

- (1) Information collection: integrate the factory parameters, test data, and real-time driving data of electric vehicles to form a health management database
- (2) Fault detection: determine the performance degradation state of battery, motor, and electronic control system, such as normal state, performance degradation state, or a function failure state
- (3) Fault diagnosis: determine the fault system or parts to be repaired
- (4) Fault prediction: predict the time when the battery, motor, and electronic control system will fail
- (5) Health management: make condition-based maintenance decision on battery, motor, electronic control system, and parts according to the information of fault detection, fault diagnosis, and fault prediction

Next, we will introduce the key methods of the PHM system for electric vehicles. Firstly, we will elaborate the life prediction at factory stage and real-time life prediction of electric vehicle in use (postfactory stage). The life prediction at the factory stage is a necessary input for the real-time life prediction, which provides information for health management. Secondly, we will show the fault diagnosis of electric vehicle.

5. Life Prediction of Electric Vehicles at Factory Stage

The key components of a vehicle will have permanent damage during long-time driving, and its fatigue life has always been the focus of vehicle safety. The life of the components of electric vehicles and the life of battery, motor, and electronic control systems are closely related. For example, the individual battery cells in the battery system constitute the entire battery pack. And the battery system, the motor system, and the electronic control system interact with each other to form the entire vehicle. Thus, the life of electric vehicle is closely related to its components and subsystems. Through the method of nonlinear and linear fusion, the life curve can be obtained from the component to the entire vehicle. Therefore, the life prediction of the electric vehicle at the factory stage includes the life curve of single components, the life curve of the subsystem, and the life curve of the entire vehicle.

5.1. Life Curve of Single Component. The life of electric vehicle components changes with time and shows nonlinear

characteristics. So, the traditional regression algorithm is difficult to predict the life accurately. Taking the battery system as an example, its life prediction methods mainly includes physical model-based method, data-driven method, and fusion method. And, the algorithm based on data-driven has good adaptability, among which the BP neural network is used the most widely. Through the error backpropagation algorithm, the model parameters can be self-updated and the training data can be fitted. The model structure is shown in Figure 3.

Here, we take the battery system as an example. Assume that the parameters of the component are the number of charge and discharge, discharge voltage, and temperature, which is noted as vector $[x_1, x_2, x_3]$. Using this vector as the input data of the neural network, through multiple hidden layers and delinearized softmax layers, the feature of the part can be extracted and the corresponding component life can be predicted.

The model can also be applied to life prediction of other components such as motor bearings. By collecting the vibration data of the motor bearing, transforming it to the frequency domain for feature analysis, and extracting indicators related to bearing performance degradation through PCA (Principal Component Analysis), we can obtain the input data. Taking these indicators as the input and the predicted life of the motor bearing as the output, the model is established.

5.2. Life Curve of Subsystem. Electric vehicle is a complex mechanical and electronic system. The life curve of a single component cannot accurately reflect the performance and life of the module or system, not to mention the entire vehicle. The life of the multicomponent system usually depends on the components with the shortest life. Linear and nonlinear fusion of each component life curves can obtain the life curve of the corresponding module or system.

5.2.1. Life Curve of Subsystems Based on Linear Fusion.

The life of each component is given in different weights according to its importance. The system life prediction model can be obtained by the linear weighting method :

$$T = \sum_{i=1}^n \omega_i \cdot t_i, \quad (1)$$

where T represent the life of system, n indicates the number of components that make up the system, t_i is the life of component i , and ω_i is the weight of component i .

This method can be applied to the life prediction of the battery, motor, and electronic control system. Taking battery pack as an example, the life of single battery is predicted by particle filter and data-driven algorithm. Then, the life of the whole battery pack is obtained by weighting the life of all single batteries, in which the weight of each single battery is the same.

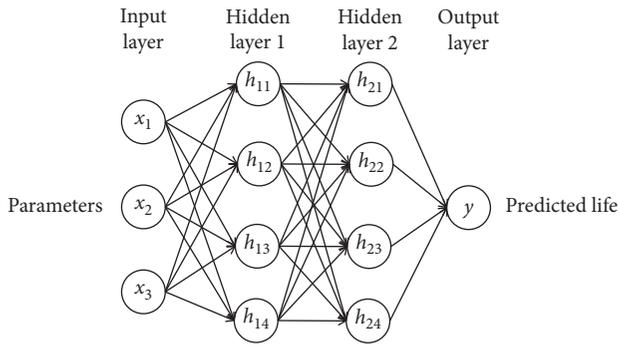


FIGURE 3: The structure of the neural network.

The linear weighting method is simple to realize, but the results of prediction is not good. Due to the nonlinear characteristics of electrical components and complex driving conditions, the linear model with the same weight assigned to subsystem cannot be directly applied to different conditions. Aiming at this problem, the weight is adjusted dynamically to improve the applicability of the model.

5.2.2. Life Curve of Systems Based on Nonlinear Fusion.

The commonly used methods are the waterfall fusion method and feature fusion method. The waterfall fusion method is suitable for modules with strong correlation between various components. This method connects each component in series. The life of the previous component will affect the next component. It is progressively connected in series to finally obtain the life of the entire module. The feature fusion method is a statistical-based method. It collects the life curve and parameters of the same module in multiple samples and digs the statistical rules to obtain the life curve of this module.

This method can be applied to the life prediction of batteries, motors, and electronic control systems. Take the motor system as an example. The system includes bearings, insulation, DC bus capacitors, IGBT (insulated gate bipolar transistor), and other electronic components. The series model is shown in Figure 4. The life of the whole system is composed of all components in series, not a simple linear combination.

5.3. Life Curve of the Entire Electric Vehicle. The relationship between the battery, motor, and electronic control systems of an electric vehicle is shown in Figure 5. The battery system provides power. The motor system drives the vehicle. The electronic control system sends commands to the motor controller to control the motor according to the accelerator pedal and brake pedal signal input by the driver.

The life of the entire vehicle is related to the life of the three subsystems: battery system, motor system, and electronic control system. It can be determined by statistical analysis methods, simulation methods, and data-driven methods.

Statistical analysis methods mainly include series system, parallel system, and series-parallel system reliability analysis. Cheng et al. and Dong et al. [43, 44] studied the reliability analysis and life estimation of a two-component series system. Gu [45] studied the parameter estimation problem of series systems subject to discrete binary geometric distribution. Dong [46] studied the reliability equivalent factor of series systems under the gamma distribution. Zhang and Chang and Sadegh [47, 48] discussed the estimation of the remaining useful lifetime of parallel systems with independent and different distributed structures. Li et al. [49] studied the random comparison of the life of series-parallel systems for a series-parallel system composed of N components with random numbers and N components with nonrandom numbers.

In terms of simulation methods, the Monte Carlo method is widely used for reliability analysis due to its robustness and ability to solve complex failure area problems [50]. However, it is inefficient to solve the problem of large number of random variables and small probability. In addition, the Monte Carlo method cannot calculate the multiple failure function combination equation.

Data-driven methods mainly include support vector machines, neural networks, and fuzzy logic. Data-driven methods require a large amount of data to support them. Data acquisition and data quality are particularly important in this method.

6. Real-Time Life Prediction of Electric Vehicles in Use

The remaining useful lifetime of electric vehicles can be predicted using the real-time electric vehicle data, which can be used to monitor and evaluate the status of the electric vehicle. The remaining useful lifetime is defined as the time interval from the current moment to the predicted failure according to the current operating conditions [51, 52], also known as the remaining life. A typical life curve is shown in Figure 6, which can be divided into three stages. The first stage is the early failure period, in which the fault shows a tendency of degradation. This stage can be found through detection data. The second stage is the effective life period. There is no early failure of the system. In this stage, the vehicle will stay in a normal working condition. The third stage is the loss failure period, in which the system is under the process of degradation to failure. There is an abnormal time point at the end of the second stage, which is generally called a symptom point.

6.1. Real-Time Operating Data Collection of Electric Vehicles. Real-time operating data is divided into three categories: battery, motor, and electronic control system.

- (1) Data acquisition of the battery system.

Battery system is the power source of the vehicle, and it provides the energy to drive the vehicle. The battery system collects the basic attributes and real-time status of the battery including the number of



FIGURE 4: Series model of the motor system.

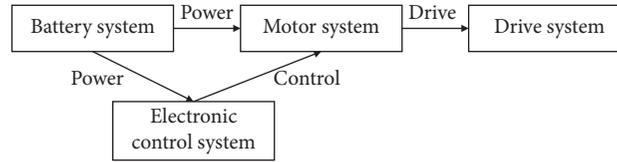


FIGURE 5: Relationships among the subsystems of the electric vehicle.

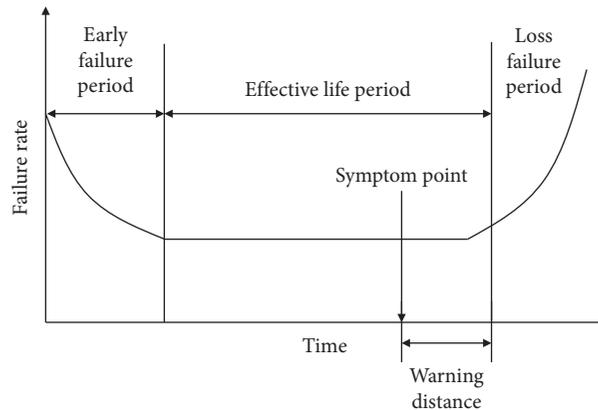


FIGURE 6: Life prediction model.

battery packs, the number of single batteries, the voltage value of the single battery, the battery pack temperature, the state of charge and discharge, the total voltage, the total current, the State of Charge (SOC), the insulation resistance, and the battery failure. The battery pack is also called a battery box, and each battery box contains a fixed number of single batteries.

(2) Data acquisition of the motor system

The motor system is mainly composed of a high-voltage motor that provides torque for the vehicle. In other words, it gives the force to drive the vehicle. The motor system mainly collects information such as the number, temperature, and speed of the driving motors.

(3) Data acquisition of the electronic control system

Although batteries and motors are indispensable, the electronic control system is much more complex. It plays a central role in energy vehicles, and its main function is to collect all kinds of signals from accelerator, brake pedal, steering wheel, and so on and send out corresponding instructions according to the information. The data collected from the electronic system including the output from steering control, power drive control, braking control, CAN management control, and vehicle status monitoring display. For example, vehicle speed gear position,

accelerator pedal position, brake pedal position, and air-conditioner temperature. The electronic control system is a core part of the electric vehicles.

6.2. Prediction of the Remaining Life of Electric Vehicles under Real-Time Operation. By using various data collected from systems, various algorithms, and intelligent models (such as physical models, neural networks, data fusion, fuzzy logic, and expert systems), the state of the system of electric vehicle is monitored, predicted, and managed. The system is always under monitoring so that the faults can be predicted before this system fails. Meanwhile, a series of maintenance advice is condition-based maintenance. The flowchart is shown in Figure 7.

There are many parameters of the real-time data collected by electric vehicles, so feature extraction is necessary. Feature extraction is to select important indicators as input to the prediction model. Common feature extraction methods can be classified into three categories: filtering, wrapper, and embedding [53]. The filtering method performs feature extraction on the data first, and then filtered features are used to train the model. The main idea of feature extraction is to assign weights to the features in each dimension and then rank them according to the weight. The main methods are the Pearson correlation coefficient method and mutual information coefficient method. Wrapper method directly integrates feature extraction and

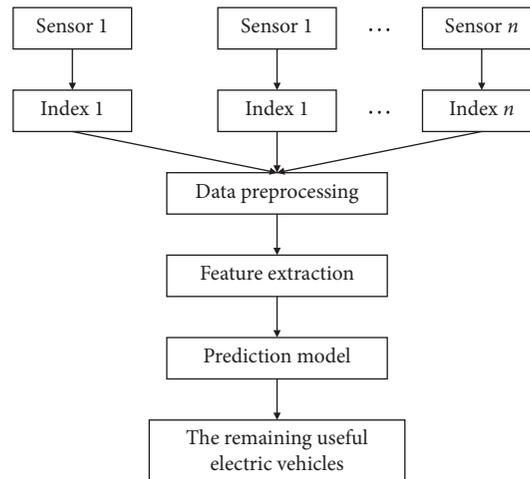


FIGURE 7: Flowchart of electric vehicle life prediction based on detection data.

model training and uses the performance of the model as an evaluation criterion for the feature subset, such as GA algorithm. The embedding algorithm includes a feature extraction process, in which the feature extraction is performed by itself during the training of the learner, such as a decision tree and a random forest.

After the extraction of important indicators, the remaining useful lifetime of electric vehicles can be predicted through inference algorithms and intelligent models. Refer to the life prediction method in the previous section “Life Prediction Methods,” and the remaining useful lifetime prediction methods of the system are divided into physical model methods and data-driven methods [54].

The support vector regression-particle filter is used to predict the remaining useful life of battery [55], and many other machine learning methods are used as well such as neural networks. For each subsystem and component, the prediction models and methods overlapped in many ways except the difference in input data. As for the vehicle remaining useful life prediction, like we introduced before, it needs a model to integrate the information from subsystems to get a final result.

7. Fault Diagnosis of Electric Vehicle Detection Process

When an electric vehicle malfunction occurs, detection is required to determine the malfunctioning system or component for repair and maintenance. As introduced in Section 3.3, fault diagnosis methods can be divided into model-based fault diagnosis and data-based fault diagnosis. In the early stage of the establishment of the electric vehicle fault database, fault diagnosis based on big data is difficult to implement, and the prediction will have a low accuracy rate. A method based on small sample data is needed to achieve the fault diagnosis at this stage. After the accumulation of data, big data analytical methods can be used to find out the fault pattern.

7.1. Fault Diagnosis Based on Quantitative Model. By establishing a mathematical model and comparing the residuals between the model output and the standard output,

we can diagnose the occurrence of faults and the corresponding fault types. Residual generation method can be divided into parameter estimation, state estimation, and synchronization state parameter estimation. Parameter estimation includes methods such as least squares and boundary parameter analysis. Common methods for state estimation include fault detection methods based on Kalman filtering, interval observers, and set theory.

Taking the battery system as an example, the common indicators of the single cell are temperature and voltage. Parameter estimation is the simplest way to identify the temperature and voltage anomaly of single cell. Existing standards require electric vehicles to record and upload the information of minimum single voltage, the maximum cell voltage, the minimum cell temperature, and the maximum cell temperature. Through parameter estimation methods, a quantitative model can be established to perform temperature and voltage consistency analysis and fault detection on the battery.

7.2. Fault Diagnosis Based on Small Sample Data. At present, there are two ways to solve the problem of small-scale sample data analysis: (1) expand the sample data by random algorithms, and then analyze them by traditional data analysis methods; (2) use Bootstrap method, Bayes method, Monte Carlo method, and other analysis methods suitable for small-scale data. However, each method has its limitations. The Bootstrap method neutron sample has a large impact on the estimated parameters, and it is easy to generate parameter faults, causing inaccuracies in the estimation [56]. The accuracy of the Monte Carlo method depends on the mathematical model of the parent. The Bayesian method [57] is more suitable for processing small sample data. When the number of samples is small, the probability of failure can be better estimated, but its prior probability will greatly affect the posterior result. Support vector machine algorithm is also a commonly used machine learning method. It supports fault diagnosis under small sample data and is suitable for fault diagnosis of battery systems.

Next, an instance of fault identification will be given. Taking a motor system as an example, we first combine the

Weibull fault distribution model with the Bayesian method to obtain the fault probability density of components and then analyze the probability and category of fault occurrence. The steps are as follows:

- (1) Fit the Weibull distribution through small sample fault data to obtain shape parameters and scale parameters
- (2) Substitute the estimated parameters into the model, obtain bootstrap subsamples by Monte Carlo sampling, and estimate the parameters of each group of subsamples as the prior information of Bayesian
- (3) Obtain the posterior probability density distribution function of system faults through the Bayesian model

The failure probability density of the Weibull distribution is

$$f(t) = mt^{m-1} \frac{\exp[-(t/\eta)^m]}{\eta^m}. \quad (2)$$

The reliability function is

$$R(t) = 1 - F(t) = \exp\left[-\left(\frac{t}{\eta}\right)^m\right]. \quad (3)$$

The failure rate function is

$$\lambda(t) = \frac{mt^{m-1}}{\eta^m}, \quad (4)$$

where t is time, m is the shape parameter, and η is the scale parameter. A set of shape parameters and scale parameters can be determined by regression analysis on a set of fault data and then sampled by the sampling formula [57]:

$$t(n) = \eta(-\ln(e[n]))^{1/m}. \quad (5)$$

Assume that each group of samples obtained by sampling is independent of each other; then, we can perform parameter estimation on them to obtain the parameter estimates of each group. In this way, the reliability function and the failure probability density function are obtained through the Bayesian formula.

7.3. Fault Diagnosis Based on Big Data. With the rapid development of big data and electric vehicles, fault detection and diagnosis of electric vehicles based on big data has a wide application prospect. A commonly used method is Artificial Neural Network (ANN). The basic idea is based on a large number of electric vehicle fault data, with the fault data dimension as the network input layer dimension, and the fault category as the output dimension. Through continuous iterative training, the model weights, thresholds, and other parameters are obtained. Then, we can fit the potential relationship between the sample data and the sample label, realize the fault detection and diagnosis, and constantly update the diagnosis database improvement.

The power battery and motor system of electric vehicles are both nonlinear systems. Traditional neural networks cannot adapt well to nonlinear data. Therefore, neurons need to be

delinearized by adding activation functions. Common activation functions include ReLU function, sigmoid function, and tanh function, and they are shown as follows:

$$f(x) = \max(x, 0), \quad (6)$$

$$f(x) = \frac{1}{(1 + e^{-x})}, \quad (7)$$

$$f(x) = \frac{(1 - e^{-2x})}{(1 + e^{-2x})}. \quad (8)$$

Common faults of power batteries include abnormal temperature, abnormal voltage, and abnormal temperature and voltage consistency. Common faults in motor systems include abnormal output power. The model needs to determine which type of failure has the greatest probability of occurrence among multiple failure types. Now, the softmax function needs to be introduced:

$$\text{soft max}(y_i) = \frac{e^{y_i}}{\sum_{j=1}^n e^{y_j}}. \quad (9)$$

The softmax function converts the output of the neural network into a probability distribution to calculate the cross entropy or directly selects the fault type with the highest probability as the final fault diagnosis result.

8. Conclusion

In this paper, a complete electric vehicle fault prediction and health management system is established based on the system structure of electric vehicles and the sources of data information. The system mainly includes three levels:

- (1) Life prediction of electric vehicles at the factory stage: at the factory stage, a physical model method or a data-driven method is used to obtain the life curve of a single component. Based on this, a linear and nonlinear fusion method is used to obtain the life curve of a system composed of multiple components. The simulation method and the data-driven method are used to obtain the vehicle life prediction curve composed of multiple systems.
- (2) Real-time life prediction of running electric vehicles: the data information to be collected from the three electric vehicle systems under real-time running status is summarized. And the filter information, filter type, wrapper type, and embedded type are used to realize the feature extraction of the data information to predict the remaining life of the electric vehicle.
- (3) Fault diagnosis of electric vehicle detection process: based on the current situation of the fault database of electric vehicles, fault diagnosis method based on quantitative models, small sample data, and big data are proposed.

The electric vehicle PHM system proposed in this article can realize the whole-life-cycle prognostics and health management of electric vehicles since it supports the detection and prediction for vehicles at factory stage and postfactory stage. This will improve the safety level of electric vehicles and provide reference for the design of other product health management systems in the future. Meanwhile the vehicle users, manufactures, and government can also get benefit from it. For users, the PHM system can help them monitor the status of electric vehicles and identify possible faults, so as to improve the safety level of vehicles. For manufacturers, the PHM system is enabled to establish a more complete vehicle management system, especially in the postfactory stage. For the government, the supporting database of the system can promote research innovation and big-data-related services, which is beneficial to the development of the industry.

Data Availability

No data were directly used in this study. However, in the design of this paper, we refer to the dataset which comes from the real-time status data record of Shenzhen electric buses. The dataset has not been made available because this dataset is not open yet.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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