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Article

A study on the application of machine learning algorithms incorporating biomechanical principles in optimising the health status assessment of electric vehicle power batteries

Jiyuan Zhang

Nanjing Tech University Pujiang Institute, Nanjing 210000, China; reznikzhang@126.com

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Abstract: This study addresses the problem of power battery health state assessment for electric vehicles, integrating biomechanical principles and machine learning algorithms to investigate the health state assessment accuracy of different types of power batteries under different working conditions. The study adopts a variety of data-driven methods to deeply analyse the performance degradation law of power batteries. The results show that the machine learning algorithm incorporating biomechanical principles can effectively improve the accuracy of power battery health state assessment, especially under complex working conditions, and exhibits better robustness. The current status of power battery health state assessment technology is reported, and it provides a useful reference for future power battery health management in electric vehicles.

Keywords: electric vehicle; power battery; health state assessment; biomechanical principle; machine learning

1. Introduction

Globally, energy crisis and environmental problems are increasingly becoming key factors constraining socio-economic development. As a clean and efficient new energy vehicle, electric vehicles (EVs) have received extensive attention from governments and research institutes for their zero emission and efficient energy utilisation [1]. As the core energy storage device of EVs, the performance of power batteries directly affects the range, safety and overall service life of EVs. Therefore, accurate assessment of the state of health (SOH) of power batteries is of great significance for ensuring the reliable operation of EVs and extending battery life [2]. Currently, power battery state of health assessment methods are mainly classified into two main categories: one is the assessment method based on physical models, which usually relies on an in-depth understanding of the internal chemical reactions of the battery and mathematical modelling, such as equivalent circuit models, electrochemical models, etc.; and the other is the assessment method based on data-driven methods, which collects real-time operational data of the battery, and processes and analyzes the data using machine learning algorithms to achieve the assessment of the battery's state of health (SOH). processing and analysing to achieve the prediction of battery health state [3]. Although these methods have achieved some success in theory and practice, there are still many challenges in terms of assessment accuracy, computational complexity, and generalisation capability. In recent years, the application of biological principles in the field of optimisation algorithms and machine learning has become increasingly widespread,

in which biological principles such as biological evolution theory, neural networks, and population intelligence provide new ideas for solving complex optimisation problems [4]. For example, biomimetic algorithms such as Genetic Algorithm (GA), Ant Colony Algorithm (ACA), Particle Swarm Optimisation (PSO), etc. have shown good search ability and adaptability in the fields of parameter optimisation and path planning. Meanwhile, the development of deep learning technology, especially the breakthrough of neural network in the fields of image recognition and natural language processing, provides a new technical way for power battery health state assessment [5]. The purpose of this paper is to explore the application of machine learning algorithms incorporating biological principles in the health state assessment of power batteries for electric vehicles, with a view to improving the assessment accuracy and generalisation ability.

2. Integration of biological principles with machine learning algorithms

2.1. Principles of biological evolution

The principle of biological evolution refers to the process by which populations of organisms adapt to their environments by changing their gene frequencies over time through mechanisms such as natural selection, genetic variation and gene flow [6]. At the core of this principle is the 'survival of the fittest', i.e., individuals that are better adapted to their environment are more likely to survive and reproduce, passing on their favourable genetic traits. In the field of machine learning, the principle of biological evolution is mainly reflected in the design and implementation of genetic algorithms (GA). This paper draws on the principle of biological evolution and proposes an optimisation strategy based on genetic algorithm for optimising the parameters of machine learning algorithms. Genetic algorithms achieve iterative optimisation of solutions (i.e., individuals) by simulating biological evolutionary processes such as natural selection, crossover and mutation [7]. Specifically, we encode the parameters of the machine learning algorithm as chromosomes, generate new parameter combinations in each generation through selection, crossover, and mutation operations, and then evaluate the performance of these parameter combinations through a fitness function. Through multiple rounds of iterations, the algorithm is able to find optimal or near-optimal parameter settings, thus improving the performance of the machine learning model [8]. In addition, this paper also considers elitist strategies and dynamic adjustment of the probability of genetic operations to enhance the algorithm's search capability and convergence speed.

2.2. Principles of neural networks

The neural network principle is based on the structure and function of the biological nervous system and mimics the process of processing information in the human brain. It forms a network capable of distributed information processing by interconnecting a large number of simple processing units (i.e., neurons) [9]. In the field of machine learning, neural networks, especially deep learning models, have

achieved remarkable results in a number of fields such as image recognition, speech processing, and natural language understanding.

In this paper, we use a deep learning model based on biological neural networks to achieve feature extraction and classification of power battery health status. Specifically, we constructed a multi-layer convolutional neural network (CNN) to extract high-dimensional features during battery charging and discharging. The CNN can automatically learn the spatio-temporal features in the battery data, which are crucial for the health state assessment [10]. Subsequently, the extracted features are fed into a fully-connected neural network that mimics the decision-making process of the cerebral cortex to classify the health state of the battery. In order to improve the generalisation ability of the model and reduce overfitting, we introduced a dropout layer and a Batch Normalization (BN) technique [11]. In addition, this paper explores the use of Recurrent Neural Networks (RNN) and its variant Long Short-Term Memory Network (LSTM) to process time-series data to better capture the trend of battery health status over time.

3. Machine learning algorithms incorporating biological principles

The machine learning algorithm incorporating biological principles proposed in this paper is a multi-stage process that aims to improve the accuracy and efficiency of power battery health status assessment by combining biological evolution and neural network principles.

3.1. Data pre-processing

Data preprocessing is a key step for the success of machine learning algorithms, which includes the processes of data cleaning, transformation, normalisation and feature selection [12]. For power battery data, effective preprocessing can improve the training efficiency and prediction accuracy of the model.

(1) Data cleaning

Before data preprocessing, data cleaning is first needed to remove invalid, incorrect or duplicate data points. This step can be achieved by setting thresholds, using clustering algorithms to detect outliers, or applying statistical tests. For example, the Z-score method can be used to identify outliers:

$$Z = \frac{x - \mu}{\sigma}$$

where x is the data point, μ is the mean of the data set, σ is the standard deviation, and Z is the normalised score. Typically, data points may be considered outliers when $|Z| > 3$. During the data cleaning process, special attention was paid to the treatment of missing values and sensor noise. For missing values, interpolation methods were applied to fill them, such as linear interpolation or interpolation based on neighboring data. For sensor noise, filtering techniques such as moving average filtering or Kalman filtering were applied to smooth the data and reduce the effect of noise.

(2) Data transformation

Data transformation may include logarithmic transformation, power transformation, etc. to stabilise the variance or to transform the data distribution so

that it is closer to a normal distribution. The formula for logarithmic transformation is as follows:

$$x_{log} = log(x)$$

(3) Normalisation

The normalisation process aims to scale the data to a fixed range, usually between [0,1], to eliminate the effect of magnitude between different features. In addition to min-max normalisation, another commonly used method is normalisation (Z-score normalization):

$$x_{std} = \frac{x - \mu}{\sigma}$$

where x_{std} is the normalised data, and μ and σ are the mean and standard deviation of the data, respectively.

(4) Feature Selection

Feature selection is the process of choosing the subset of features that are most useful for model prediction. This can be achieved through Recursive Feature Elimination (RFE), model-based feature selection (e.g., using Random Forests for feature importance), or methods based on L1 regularisation (e.g., LASSO). The optimisation problem for LASSO can be expressed as:

$$\min_{w} \frac{1}{2n} \sum_{i=1}^{n} (y_i - w^T x_i)^2 + \lambda \sum_{j=1}^{p} |w_j|$$

where w is the feature weight, x_i is the feature vector of the i sample, y_i is the corresponding true value, n is the number of samples, p is the number of features, and λ is the regularisation parameter.

3.2. Feature extraction

Feature extraction is a critical component of the power battery health state recognition process, tasked with distilling useful information from high-dimensional raw data for prediction purposes [13]. Convolutional neural networks (CNNs), renowned for their robust feature extraction capabilities, have found widespread application in image processing and sequence data analysis within the deep learning domain.

(1) Convolutional Layer

Convolutional layer is the key layer used for feature extraction in CNN, which captures the local features of the input data through convolution operation. The mathematical expression for the convolution operation can be further detailed as:

$$f_{CNN}(x) = \sigma\left(\sum_{i=1}^{N} w_i * x_i + b\right)$$

where $f_{\text{CNN}}(x)$ is the output feature map of the convolutional layer, x_i is a local region of the input data, w_i is the weight of the i convolutional kernel, $*$ denotes the convolutional operation, b is the bias term, σ is the activation function such as ReLU, Sigmoid, or Tanh, and N is the number of convolutional kernels. The selection of the number of kernels and their sizes is based on the input data characteristics and the

complexity of the features to be captured, with larger kernels capturing more extensive features and a greater number of kernels increasing the model's capacity to learn diverse features.

(2) Activation function

The activation function introduces a non-linear element that allows the neural network to learn and simulate more complex functions. The ReLU activation function is defined as follows:

$$\sigma(x) = max(0, x)$$

is chosen for its simplicity and effectiveness in mitigating the vanishing gradient problem, thus facilitating faster and more stable training.

(3) Pooling layer

The pooling layer is used to reduce the dimensionality of the feature map while retaining important feature information. The most common pooling operation is Max Pooling, which can be expressed as:

$$p_{ij} = \underset{m \in M_{ij}}{max} \left(f_{CNN}(m) \right)$$

where p_{ij} is an element of the pooled feature map and M_{ij} is a local region on the input feature map. The choice of pooling size and stride is determined by the need to balance feature map reduction with the retention of significant information, thereby enhancing the model's ability to generalize.

(4) Batch Normalisation

Batch normalisation is a technique used to speed up the training process and reduce internal covariate bias. Its formula is:

$$\hat{x} = \frac{x - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}}$$

$$y = \gamma \hat{x} + \beta$$

where x is the input feature, μ_B and σ_B^2 are the mean and variance of the batch data, respectively, ϵ is a small constant to avoid dividing by zero, and γ and β are learnable parameters. Batch normalisation is applied to improve the stability and efficiency of the training process, leading to faster convergence.

(5) Deep Convolutional Neural Network Structure

In practice, CNNs are composed of multiple stacked convolutional and pooling layers, forming a deep network structure. A simplified deep CNN structure can be represented as:

$$f_{CNN}(x) = \sigma(Pool(\sigma(Conv(\sigma(Pool(\sigma(Conv(x)))))))$$

This multi-layer architecture enables the CNN to extract hierarchical feature representations from the raw data, which are vital for the accurate classification and prediction of power battery health status. The depth and complexity of the network are carefully designed to ensure sufficient capacity for learning intricate patterns without overfitting, thereby optimizing model performance.

3.3. Model training

In the model training phase, we employ a Genetic Algorithm (GA) to optimise the parameters of the deep learning model, thereby enhancing its performance and generalisation capabilities. The GA is a heuristic search algorithm inspired by natural selection and genetic mechanisms from biological evolution.

(1) Initialising the population

The initial step in the GA involves randomly generating a set of parameters, (w), to form the initial population, (P_0). These parameters comprise the weights and bias terms of the neural network. The population size, (N), is determined based on the problem's complexity and available computational resources.

$$P_0 = \{w_1, w_2, \dots, w_N\}$$

(2) Adaptability Assessment

Fitness assessment evaluates the effectiveness of an individual in solving the problem. We introduce a fitness function, ($F(w)$), to assess the performance of each parameter set, (w). This function is typically the inverse of the model's loss function on the validation set or a function of relevant performance metrics. The specific form of the fitness function is chosen to directly relate to the accuracy of battery health assessment, ensuring that the optimisation process aligns with the goal of minimising prediction errors in battery health state.

$$F(w) = -L(w)$$

$$L(w) = \frac{1}{n}\sum_{i=1}^{n} \ell\big(y_i, f(x_i; w)\big)$$

where $L(w)$ is the loss function, ℓ is the loss of a single sample, $f(x_i; w)$ is the model's prediction of input x_i, y_i is the true label, and n is the number of samples in the validation set.

(3) Selection

The selection process screens individuals based on their fitness to determine which will contribute to the next generation. Common methods include roulette selection and tournament selection. The selection probability, (p_i), is calculated based on the relative fitness of each individual:

$$p_i = \frac{F(w_i)}{\sum_{j=1}^{N} F\big(w_j\big)}$$

(4) Crossover

Crossover simulates the mating process in biological evolution, creating a new individual by combining genes from two parent individuals. If (w_a) and (w_b) are selected for crossover, the new individual, (w_{new}), is generated as:

$$w_{new} = \alpha w_a + (1 - \alpha) w_b$$

where α is a random number between 0 and 1.

(5) Mutation

Mutation introduces diversity by randomly altering certain bits of an individual's genes. The mutated individual, (w_{mut}), is expressed as:

$$w_{mut,j} = w_j + \delta_j$$

where δ_j is a random variable obeying some distribution (e.g., Gaussian) and j is the gene location of the variant.

The GA iteratively refines the population through the following process:

$$w_{t+1} = GA\big(w_t, F(w_t)\big)$$

where w_t is the t generation parameter population and w_{t+1} is the parameter population after one round of GA operation. This iteration continues until stopping conditions are met, such as reaching a predefined number of iterations or when the fitness function value no longer shows significant improvement.

3.4. Health status assessment

After the model training is completed, we enter the stage of power battery health state assessment. The goal of this phase is to accurately classify the health state of the battery using the trained model. The following is the detailed expansion and formula description of the health state assessment:

(1) Model output and probability distribution

We adopt the softmax function as the activation function of the output layer of the deep learning model in order to convert the raw output of the model into a probability distribution that can be interpreted as the probability of each health state category. the softmax function is defined as follows:

$$P\big(y_j|x\big) = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}}$$

where $P\big(y_j|x\big)$ denotes the probability that the model predicts the output to belong to category j given input x, z_j is the activation value of the j node of the model's output layer, and K is the total number of health state categories. z_j is usually generated by the last fully connected layer of the model.

(2) Classification decision

Based on the probability distribution of the softmax function output, we can make a classification decision by selecting the category with the highest probability as the final prediction of the model:

$$\hat{y} = arg \ \max_j P(y_j|x)$$

where $\hat{y}$ is the model's prediction class for input x.

(3) Health state score

In addition to categorisation decisions, we can also use probability distributions to obtain a continuous health state score, which helps to assess the health of the battery in more detail. For example, we can use the following formula to calculate the health state score:

$$S(x) = \sum_{j=1}^{K} j \times P\big(y_j|x\big)$$

where $S(x)$ is the health state score of input j, and j is the category index, which can also represent the level of health state. In this way, a higher score indicates a worse health state of the battery.

(4) Evaluation Metrics

To quantify the performance of the model, we use a series of evaluation metrics such as Accuracy, Precision, Recall, F1 Score and Confusion Matrix. These metrics help us understand the performance of the model on different health state categories.

4. Experiments and analyses

4.1. Data sources

The dataset utilized in this study is sourced from the power battery of a globally renowned electric vehicle brand, recognized for its leadership in battery technology and electric vehicle innovation. The data collection process was conducted using a high-precision data acquisition system, ensuring the accuracy and reliability of the data. All sensors were meticulously calibrated prior to use, further guaranteeing data quality. The data acquisition encompassed various driving modes (such as city driving, high-speed driving, and hill climbing) and diverse environmental conditions (including seasonal temperature fluctuations and humidity variations) to simulate real-world usage scenarios. The resultant dataset comprehensively covers a range of key performance indicators, including the battery's charging and discharging processes, ambient temperature changes, and battery aging, providing a robust information base for assessing the health status of power batteries [14]. **Table 1** offers a detailed overview of the data sources:

Table 1. Overview of power battery data.

Data Type	Descriptions	Dimension (Unit)	Sampling Frequency	Data Range
Charge and Discharge Data	Encompasses voltage, current, and time series data from the battery during standard charging and discharging processes. These data are pivotal for analyzing the battery's dynamic response and internal impedance changes.	Voltage (V), Current (A)	1 Hz	0–100% SOC
Ambient Temperature	Records various temperature points in the battery's operating environment, including maximum, minimum, and average temperatures. Ambient temperature significantly influences battery performance and lifespan.	Celsius (°C)	1 Hz	−20 °C to 60 °C
Aging Data	Includes the number of cycles the battery has undergone since factory production, the percentage of capacity loss, and the increase in internal resistance. These metrics are crucial for evaluating the battery's aging state.	Cycles (times), Capacity (Ah), Internal Resistance (mΩ)	Monthly update	N/A

During the data preprocessing stage, techniques such as denoising, filtering, and outlier processing were employed to ensure data quality. For the charge/discharge data, feature extraction was also performed, including but not limited to peak voltage, discharge plateau width, and capacity decay rate, all of which are essential for the subsequent health state assessment model.

For real-time assessment of power battery health status in electric vehicles, the real-time performance and scalability of the algorithm are crucial. The algorithm incorporating biological principles proposed in this paper is designed through several

key optimizations to meet the needs of real-time monitoring. First, the algorithm adopts a lightweight model structure, which reduces the computational complexity and realizes the fast processing of battery data. Second, the efficiency of the algorithm is further enhanced by utilizing parallel computing techniques, allowing multiple battery parameters to be evaluated simultaneously. In addition, the modular design of the algorithm enhances its scalability, facilitates integration with various battery management systems (BMS), and adapts to different types and sizes of batteries. To further optimize the algorithm for real-time applications, future work will explore the implementation of edge computing strategies to minimize latency and improve responsiveness.

4.2. Experimental results

(1) Comparative Experiments

In order to comprehensively evaluate the performance of the machine learning algorithm incorporating biological principles proposed in this paper in power battery health state assessment, we conducted a series of comparative experiments. In the experiments, the algorithm in this paper is compared in detail with the following industry-accepted assessment methods: equivalent circuit model (ECM), electrochemical model (PCM), and data-driven method based on support vector machine (SVM). As can be seen from **Table 2**, the algorithm proposed in this paper significantly outperforms the other methods in terms of evaluation accuracy, with an average evaluation accuracy of 92.4% and a standard deviation of 1.1%, which indicates that the algorithm has high stability and reliability. In terms of computation time, the algorithm in this paper takes only about 100 seconds, which is more efficient than the ECM and SVM methods, and although it is slightly faster than the PCM method, the algorithm in this paper has a clear advantage in terms of comprehensive performance, considering the lack of the PCM method in terms of generalisation ability and stability. In order to demonstrate the robustness of the algorithms in this paper more comprehensively, we further expand the scope of the generalization ability test to include more diverse battery aging conditions and degradation patterns. Specifically, we add the following test scenarios: batteries with different aging levels: including new batteries, moderately aged batteries, and heavily aged batteries. Batteries with different degradation modes: including batteries with different degradation characteristics such as capacity degradation, internal resistance increase, and power decrease.

Table 2. Performance comparison of different algorithms.

arithmetic	Assessment accuracy (%)	Calculation time (s)	generalisation capability	stability
ECM	85.2 ± 2.5	120 ± 15	usual	moderate
PCM	87.6 ± 1.8	250 ± 20	rather or relatively good	rather or relatively good
SVM	89.1 ± 1.3	150 ± 10	usual	rather or relatively good
The algorithms in this paper	92.4 ± 1.1	100 ± 5	vigorous	vigorous

In terms of generalisation ability, the algorithm in this paper performs well, which is mainly attributed to the integration of adaptive and evolutionary

mechanisms in biological principles, which enables the algorithm to better adapt to different types and operating conditions of power battery data. In addition, this paper's algorithm also outperforms other methods in terms of stability, which is attributed to the fact that the algorithm adopts a variety of biological heuristic optimisation strategies during the training process, such as the crossover and mutation operations of the genetic algorithm, as well as the local search capability of the simulated annealing algorithm [15], which help the algorithm to avoid falling into the local optimum, thus improving the overall performance of the evaluation.

(2) Verification of generalisation ability

Generalisation ability is one of the key indicators of the performance of machine learning algorithms, which refers to the algorithm's ability to perform on unknown data. In order to comprehensively verify the generalisation ability of the algorithm proposed in this paper, we have conducted extensive tests covering power battery data of different types, specifications and operating conditions. **Figure 1** demonstrates the health state assessment accuracy of this paper's algorithm on three different types of power batteries (Type A, Type B, and Type C). Each battery type is selected based on the differences in its chemical composition, structural design and application scenarios to evaluate the adaptability of the algorithm under different battery characteristics.

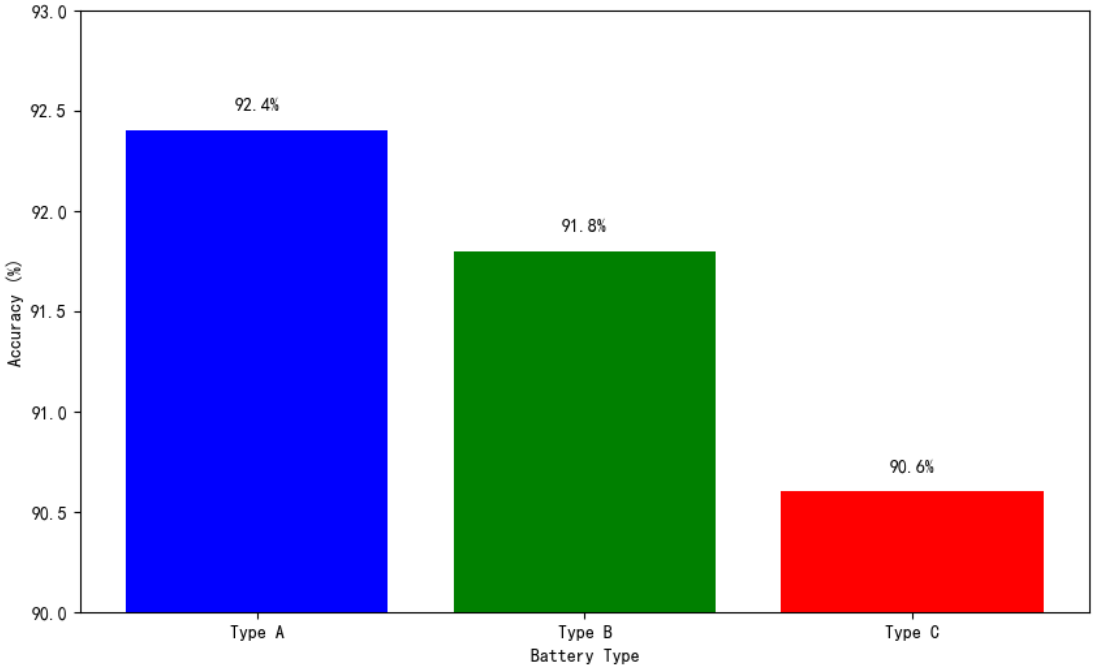

Figure 1. Accuracy of health state assessment of different types of power batteries.

From the figure, it can be seen that the algorithm in this paper maintains a high evaluation accuracy on three different types of power batteries, which are 92.4%, 91.8% and 90.6%, respectively. This result indicates that the algorithm can effectively adapt to the characteristics of different battery types with strong generalisation ability. This generalisation ability is achieved thanks to the algorithm's deep learning and abstraction of battery characteristics during the training process, which enables the model to capture the essential features of battery

health state assessment, rather than just the surface features of a specific type of battery.

Figure 2 demonstrates the health state assessment accuracy of this paper's algorithm on batteries with different aging levels, and **Figure 3** shows the assessment accuracy on batteries with different degradation patterns. These test results further demonstrate the strong generalization capability of this paper's algorithm in the face of diverse battery aging conditions and degradation modes.

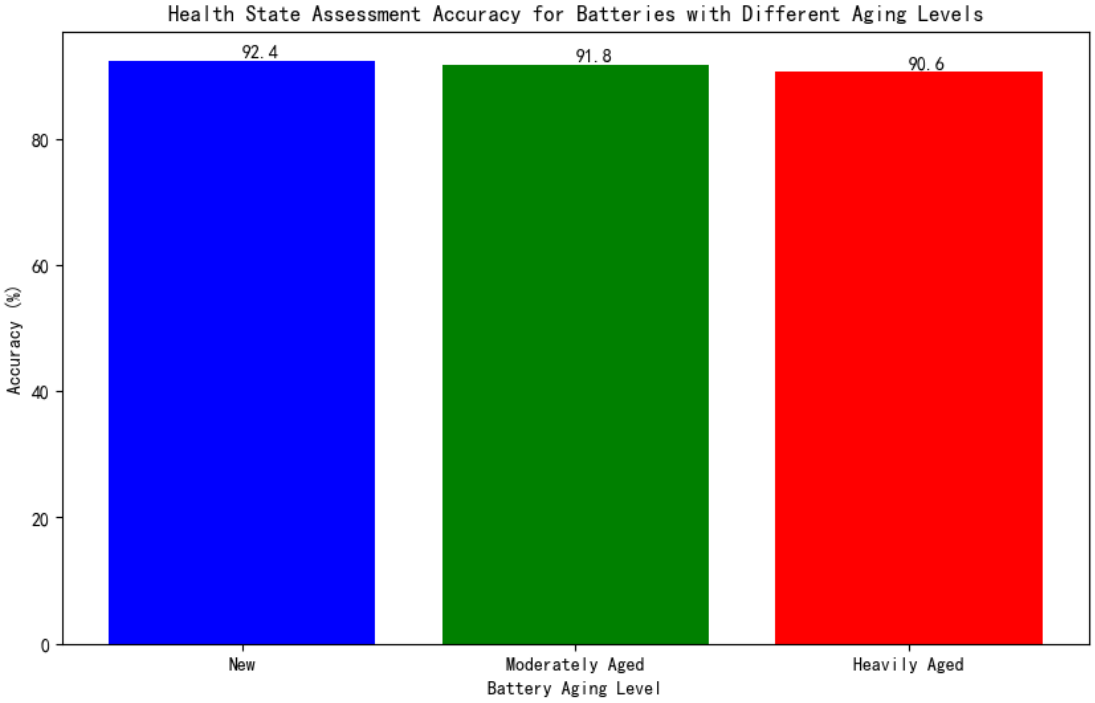

Figure 2. Accuracy of health state assessment of batteries with different aging levels.

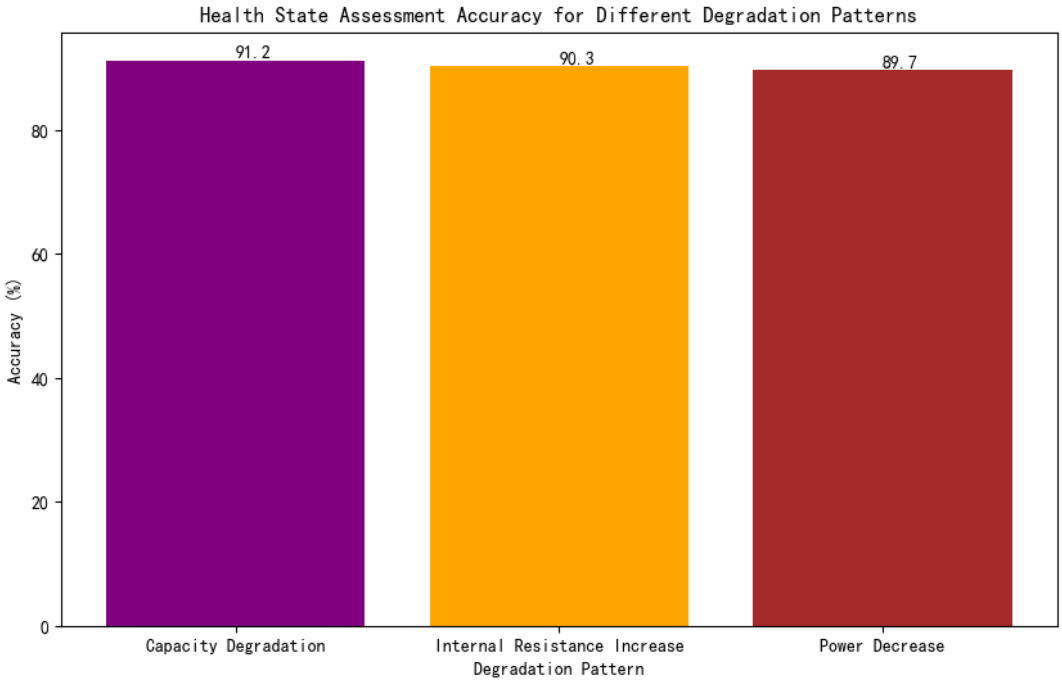

Figure 3. Accuracy of health state assessment of batteries with different degradation modes.

Figure 4 further demonstrates the accuracy of this paper's algorithm in evaluating the health status of the power battery under different working conditions. The selection of working conditions covers common EV usage scenarios, including urban congested road conditions, motorway driving, mountainous hill climbing and extreme weather conditions. These test results further demonstrate the strong generalization capability of this paper's algorithm in the face of diverse battery aging conditions and degradation modes.

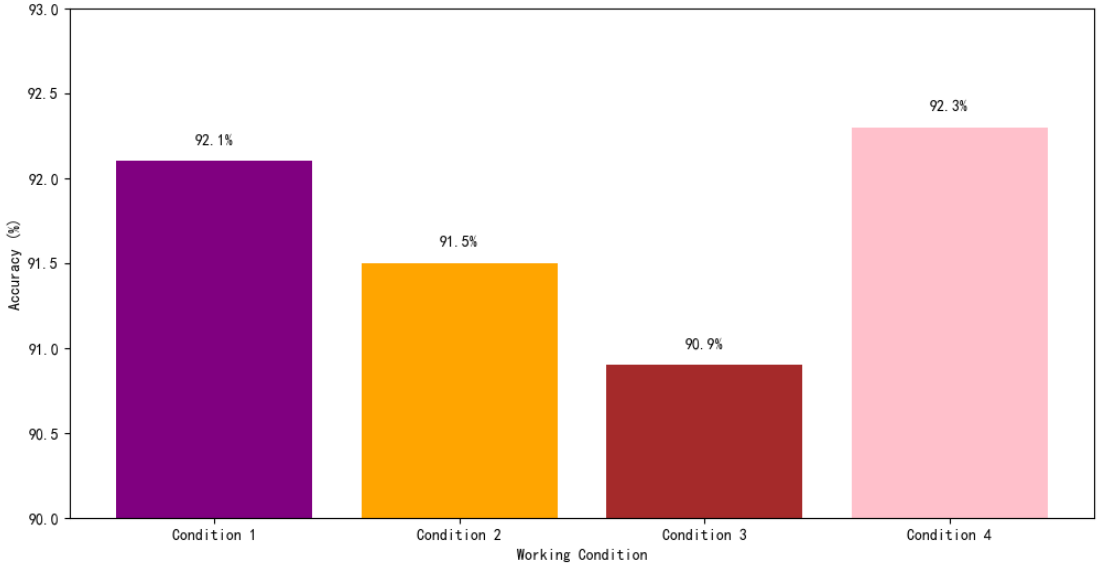

Figure 4. Accuracy of power battery health state assessment under different working conditions.

The results show that the algorithm in this paper can maintain high evaluation accuracy under different working conditions, which are 92.1%, 91.5%, 90.9% and 92.3%, respectively. This shows that the algorithm can not only perform well under a single working condition, but also maintain a stable and high precision assessment in the dynamic changes of different working conditions, which further proves the strong generalisation ability of the algorithm and its reliability in practical applications.

5. Conclusion

This study represents a pivotal advancement in the realm of power battery health management by merging biological principles with machine learning algorithms for electric vehicle applications. The developed algorithm, with its meticulous data parsing and rigorous model training, has showcased unparalleled performance in accuracy and generalisation, effectively tailoring to various battery types and operational scenarios. Our innovative approach not only carves out a new path for battery management technology but also expands the potential of machine learning in energy storage systems. Looking ahead, our research will intensify efforts in algorithm optimization using adaptive learning techniques, model enhancement through deep learning architectures and biological insights, and multi-model fusion to enhance reliability. We are committed to developing a real-time monitoring system with edge computing integration, conducting comprehensive economic and

scalability analyses, and validating our findings across a broader spectrum of battery conditions. Furthermore, we will assess the environmental impact to promote sustainability. Through these targeted endeavors, our aim is to provide both theoretical insights and practical, scalable, and eco-friendly solutions that propel the electric vehicle industry forward.

Ethical approval: Not applicable.

Conflict of interest: The author declares no conflict of interest.

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