An Indirect state-of-health estimation method based on improved genetic and back propagation for online lithium-ion battery used in electric vehicles

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***Abstract*—Lithium-ion battery state of health (SOH) estimation technology is an important part of the design of a battery monitoring system (BMS) for electric vehicles. People often use battery capacity and internal resistance as SOH estimation indicators. However, due to actual working conditions, it is difficult for electric vehicles to achieve complete charge and discharge, so the battery capacity and internal resistance cannot be monitored online. In view of the above questions, this article proposes an indirect SOH estimation method for online EV lithium-ion batteries based on arctangent function adaptive genetic algorithm combination with back propagation neural network (ATAGA-BP). Firstly, constant current drop time (CCDT), constant current drop capacity (CCDC) and maximum constant current drop rate (MCCDR) in constant voltage charging stage are used as health indicator (HI) to evaluate battery SOH in order to indirectly quantify the degradation process of lithium-ion batteries. Error point optimization and correlation verification are also carried out. Secondly, an ATAGA-BP algorithm is proposed to establish the relationship between HI and available battery capacity, and SOH estimate is made for lithium-ion batteries according to the proposed algorithm. Finally, simulation results with NASA data show the correlation between the proposed HI and lithium-ion battery capacity is above 85%, the error of SOH estimation method proposed is 3.7%, and the iteration efficiency is increased by 17.8%.**

***Index Terms*—Lithium-ion battery, Electric vehicles, State of health estimation, Health indicator, Artan function adaptive genetic algorithm**

I. Introduction

LITHIUM-ion batteries with high energy density, low self-discharge rate, and no memory effect are often used in power batteries for electric vehicles (EV) [1,2]. However, improper operation such as excessive charging/discharging and overheating of lithium-ion batteries can cause premature degradation of the battery, thereby affecting the life of instruments and equipment. The state of health (SOH) estimation can monitor the battery health in real time and replace the problem battery so that the battery pack is always in optimal working condition, increasing the service life of the entire battery pack and reduces the use of electric vehicles Costs [3-5].

Generally, there are three types of SOH estimation methods for lithium-ion batteries: experimental estimation methods, data-driven methods, and fusion methods. The experimental estimation method is an estimation method that requires a large number of experiments in the laboratory and analyzes the aging behavior of the battery [6-8]. The data-driven method refers to the establishment of some general approximate models based on the collected data to match the relationship between observation results and hidden indicators [9-11]. Fusion methods involve the combination of two or more models to enhance prediction and estimation performance [12-15]. At present, the fusion estimation method has become the main research direction of SOH estimation of lithium-ion batteries.

Many valuable SOH fusion estimation models and algorithms have appeared [16-20]. Literature [21] proposed a lithium-ion battery SOH estimation method with a Gauss-Hermit particle filter (GHPF) to improve the precision of the estimation, at the same time, a multi-scale extended Kalman filter was utilized to reduce the computational complexity. Literature [22] proposed a battery SOH estimation model based on support vector regression, using battery capacity as output, voltage and current as input, and combining particle filters to suppress voltage and current noise. Literature [23] requires a neural network as the observation equation based on the particle filter algorithm, which has better accuracy and robustness. Literature [24] proposed a fusion model of autoregressive moving average and Elman neural network to obtain an accurate prediction of the SOH of lithium-ion batteries. Literature [25] proposed a model to predict the remaining life of lithium-ion batteries, which is based on the support of vector regression and differential evolution.

It is useful to noting that the lithium-ion batteries SOH estimation method mentioned above cannot be directly applied to EV lithium-ion batteries online monitoring. Since the measurement and monitor of the EV batteries are difficult and expensive due to the incomplete charging and discharging state [26]. Therefore, there is an urgent need for a method that can indirectly quantify the degradation process of lithium-ion

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batteries, rather than directly monitoring the battery capacity and internal resistance.

Some scholars extracted health indicator (HI) from charging and discharging behavior and cycle times to establish the mapping relationship between HI and SOH for lithium-ion batteries real-time online SOH estimation [26-30]. Literature [26,27] proposed an online SOH evaluation method based on the Unscented Kalman Filter (UPF) algorithm, using a constant current discharge time as HI, establishing the mapping relationship between HI and SOH, and applying it to the state space equation. Literature [28,29] proposed a method for estimating the SOH of lithium batteries with a partial constant current charging voltage-time curve as HI. Literature [30] analyzed the battery open circuit voltage test to establish HI, and the relationship between HI and battery capacity was established by using the support vector machine algorithm, so as to obtain SOH.

For EV lithium-ion batteries, the above SOH online estimation methods are not appropriate since the charging and discharging behavior and cycle times are different in actual operation. In fact, the discharge process of EV lithium-ion batteries is random, but the charging process is regular. In charging process, the constant voltage charging information is completely retained. Its initial state and the termination state are the same, and incomplete discharge will not affect its initial state. Literature [31,32] uses constant voltage charging time and constant voltage charging capacity as health indicators to estimate the SOH of lithium-ion batteries. However, the starting time of constant voltage charging is controversial, the standard of constant voltage starting is difficult to determine, and the end time of constant voltage charging may be wrong due to measurement errors.

This paper proposes an indirect SOH online estimation method for EV lithium-ion batteries based on arctangent (AT) function adaptive genetic algorithm (AGA) combined with back propagation (BP) neural network algorithm (ATAGA-BP). The contributions of this paper are as follows

- Utilising the measurable parameters of the actual charging process of an electric vehicle, the constant current drop time (CCDT), constant current drop capacity (CCDC) and maximum constant current drop rate (MCCDR) in the constant voltage charging stage as the lithium-ion battery capacity health indicator (HI), Compared with the whole stage of constant voltage charging, it is easy to extract, increases the data dimension and reduces the data volume, and improves the robustness and efficiency of the prediction model.
- The proposed HI is optimized and verified using PauTa criterion [33,34] and Pearson Product-Moment Correlation Coefficient (PPMCC) [35], which improves the accuracy of HI and verifies the feasibility of HI for SOH estimation.
- An ATAGA-BP algorithm is proposed to establish the relationship between HI and available battery capacity, and an indirect SOH estimation for electric vehicle lithium-ion batteries is performed based on the above method.

In addition, simulations are carried out with the public data of NASA Ames Prognostics Center of Excellence (PCOE) to demonstrate the effectiveness and robustness of the proposed method.

The remaining sections of this paper are organized as follows: Section 2 introduces the framework of this paper and the ATAGA-BP algorithm. Section 3 describes the proposed HI extraction, optimization and validation. Section 4 introduces the novel HI and ATAGA-BP fusion methods for EV lithium-ion batteries SOH estimation, and the effectiveness and robustness of the proposed method are verified through comparison and analysis of various methods. Finally, we discuss the results and summarize this paper in Section 5.

II. Online EV lithium-ion batteries SOH estimation based on ATAGA-BP algorithm

The constant current drop time (CCDT), constant current drop capacity (CCDC) and maximum constant current drop rate (MCCDR) in constant voltage charging stage are used as the health indicator (HI) to indirectly monitor the electric vehicle under actual working conditions. Considering the non-linear and complex characteristics of lithium-ion batteries, an ATAGA-BP algorithm is proposed for the establishment of the relationship between HI and lithium-ion battery capacity. The framework of online EV lithium-ion batteries SOH estimation with HI and ATAGA-BP algorithm is presented in **Fig. 1**. The proposed Ataga-BP algorithm for lithium ion battery estimation method is in section 2, and the proposed health indicators and optimization method is in section 3.

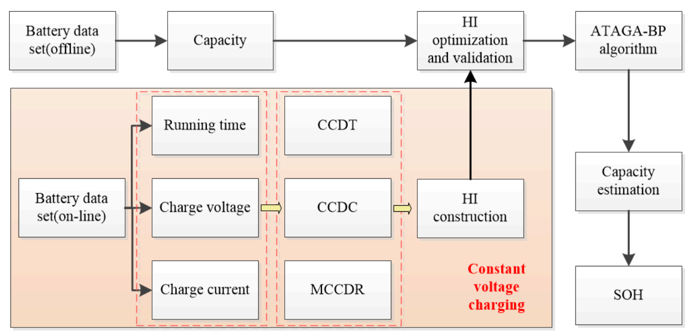

Fig. 1. Online SOH estimation framework for EV Lithium-ion batteries.

A. BP neural network algorithm

BP neural network usually refers to a multi-layer forward neural network based on error back propagation algorithm [34,35]. The training steps are as following.

Step 1. Network initialization. The network input layer node n is the system input X dimension, and the network output node number m is the system output Y dimension. Determine the amount of hidden layer nodes l. Randomly initialize the weights between the input layer and the hidden layer ω_{ij}, the weights between the hidden layer and the output layer ω_{jk}, the hidden layer threshold a, and the output layer threshold b, Finally identify the learning rate η and activation function.

Step 2. Hidden layer output calculation. According to the X, ω_{ij}, a and sigmoid activation functions, the hidden layer output H is calculated as follows.

$$H_j = f\left(\sum_{i=1}^{n} \omega_{ij} x_i - a_j\right) \qquad j = 1, 2, \ldots, l \tag{1}$$

Step 3.Output layer output calculation. According to H, ω_{jk}, and b. the network output O is calculated.

$$O_k=\sum_{j=1}^{i} H_j\omega_{jk}-b_k \qquad k=1,2,\ldots,m \tag{2}$$

Step 4. Error calculation. According to the predicted output O and the actual output Y, the prediction error e is calculated.

$$e_k=Y_k-O_k \qquad k=1,2,\ldots,m \tag{3}$$

Step 5. Update weights and thresholds. According to the prediction error e, the network weights ω_{ij} and ω_{jk} are updated, and the thresholds a and b are updated.

$$\begin{cases} \omega_{ij}=\omega_{ij}+\eta H_j(1-H_j)x(i) \\ \omega_{jk}=\omega_{jk}+\eta H_j e_k \\ a_j=a_j+\eta H_j(1-H_j)x(i)\sum\limits_{k=1}^{m}\omega_{jk}e_k \\ b_k=b_k+e_k \end{cases} \tag{4}$$

Step 6. Determine whether the prediction error or the number of iterations meets the conditions. If not, return to step 2.

B. BP neural network Algorithm optimized by ATAGA

Since BP neural network algorithm uses gradient descent algorithm to easily fall to the local optimum, people often use swarm intelligence algorithm to optimize hyperparameters in BP neural network algorithm to improve the ability to find the global optimum. The genetic algorithm (GA) is a major branch of the swarm intelligence algorithm. Traditional standard GA uses fixed control parameters, resulting in poor global search ability and immature convergence. To solve the problem, an adaptive genetic algorithm (AGA) and an improved adaptive genetic algorithm (IAGA) suggest in [36] and [37], respectively. The idea is that both the probability of crossing p_c and the probability of mutation p_m increase when the fitness of the population is concentrated. On the contrary, p_c and p_m decrease when the fitness of the population is distributed. However, the above methods can have local convergence problems. This article proposes an adaptive genetic algorithm based on the arctangent function (ATAGA). The adaptive selection formula for the values of the crossover probability p_c and the mutation probability p_m is calculated as follows.

$$p_c=\begin{cases} k_1-(k_1-k_2)\cdot\arctan(\frac{f'-f_{avg}}{f_{\max}-f_{avg}}\times\frac{\pi}{2}) & f'\geq f_{avg} \\ k_1 & f'<f_{avg} \end{cases} \tag{5}$$

$$p_m=\begin{cases} k_3-(k_3-k_4)\cdot\arctan(\frac{f-f_{avg}}{f_{\max}-f_{avg}}\times\frac{\pi}{2})\;) & f\geq f_{avg} \\ k_3 & f<f_{avg} \end{cases} \tag{6}$$

Where, k_1 is the maximum value of crossover probability, k_2 is the minimum value of crossover probability, k_3 is the maximum value of change probability, and k_4 is the minimum value of change probability. f' is the fitness value of the larger two individuals that need to be crossed, f_{max} is the maximum fitness of the population, f_{avg} is the average fitness of the population, and f is the fitness of the mutant.

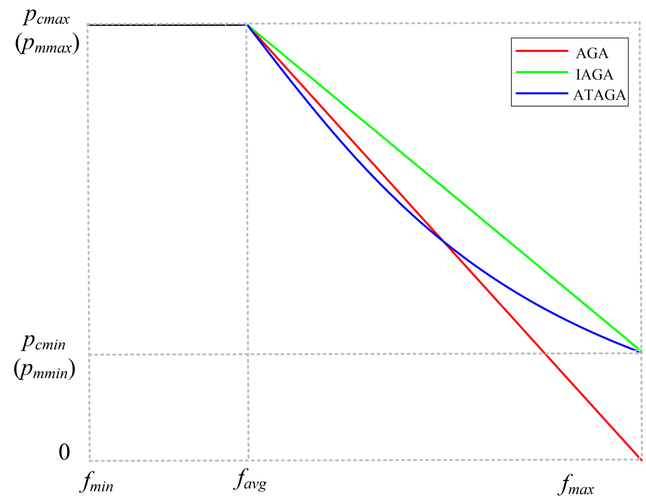

Fig. 2. Adaptive adjustment curve contrast graph of three algorithms..

The adaptive adjustment curve contrast of AGA, IAGA and ATAGA is shown in **Fig. 2**. When the individual fitness value of the AGA algorithm is close to f_{max}, its p_c and p_m are approximately equal to 0, so this method is easy to converge, and it is not easy to find the global optimum. Both AGA and IAGA algorithms linearly modify p_c and p_m. If most individuals are close to f_{avg}, the probability of crossover and mutation is very high. This situation is not easy to converge; if most individuals are close to f_{max}, the probability of crossover and mutation is very low. It is easy to converge, but it will fall into a local optimum.

The ATAGA method proposed in this paper can ensure stable changes in crossover probability and mutation probability. Since the range of the arctangent function is (-1, 1), the crossover/mutation probability close to f_{avg} and f_{max} will not be too large or too small, which avoids the situation that it is not easy to converge and fall into the local optimum. The flow chart of the ATAGA-BP algorithm used in online SOH estimation is presented in **Fig. 3**.

III. HI EXTRACTION, OPTIMIZATION, AND VALIDATION

In order to improve the robustness of the model, this section selects the constant current drop time (CCDT), constant current drop capacity (CCDC) and maximum constant current drop rate (MCCDR) in the constant voltage charging stage as the lithium-ion battery capacity health indicator (HI). The proposed HI can indirectly quantify the degradation process of lithium-ion batteries, replacing the complicated and expensive online capacity and internal resistance measurement.

A. HI extraction

Due to the random discharge characteristics of EV in actual operation, the existing HI extraction method in constant

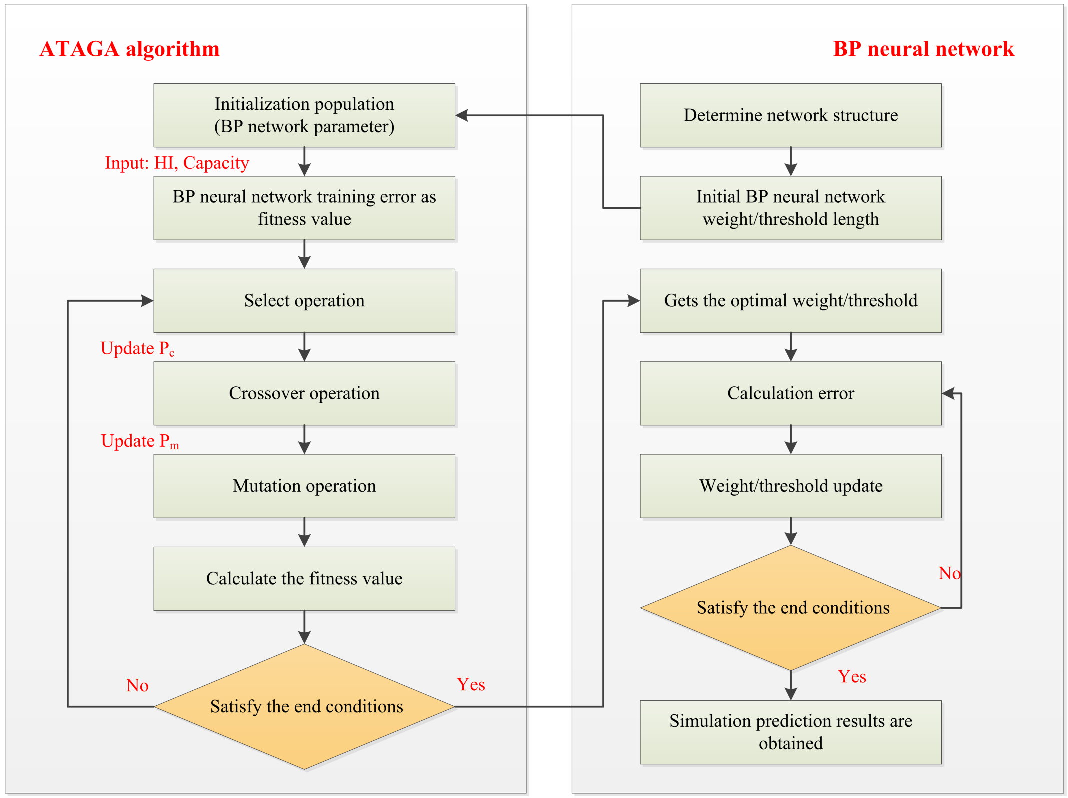

Fig. 3. Flow chart of ATAGA-BP algorithm used in Online SOH estimation.

current discharge mode is not suitable for electric vehicle lithium-ion batteries [26,27]. On the contrary, the charging time of the constant voltage charging stage is longer, the parameters are more obvious, and the start and end states are the same. Therefore, the characteristics of the constant voltage charging stage are used as HI.

In order to ensure that the degradation phenomenon of the constant voltage charging stage more intuitive, this article uses the external measurement data of the battery No.5 in the NASA PCOE data set to visualize the dynamic characteristics of the constant voltage charging stage. In **Fig. 4**, this paper draws the constant voltage charging current curve under different degradation conditions (the number of cycles is 30, 60, 90, 120, and 150, respectively). It can be seen that the constant voltage charging stage curve is very different for different cycle time. As the number of cycles increases, the constant voltage charging time will increase, the charging capacity will also increase, and the maximum current drop rate will decrease. Therefore, SOH of battery is related to CCDT, CCDC and MCCDR, and these three indirect parameters are selected as HI in the following paper.

The expression of HI is as follows:

$$HI = \begin{bmatrix} CCDT \\ CCDC \\ MCCDR \end{bmatrix}^T = \begin{bmatrix} t(end) - t(start) \\ \sum\limits_{k=start}^{end} i(k) \cdot t(k) \\ \frac{i(start+1) - i(start)}{t(start+1) - t(start)} \end{bmatrix}^T \tag{7}$$

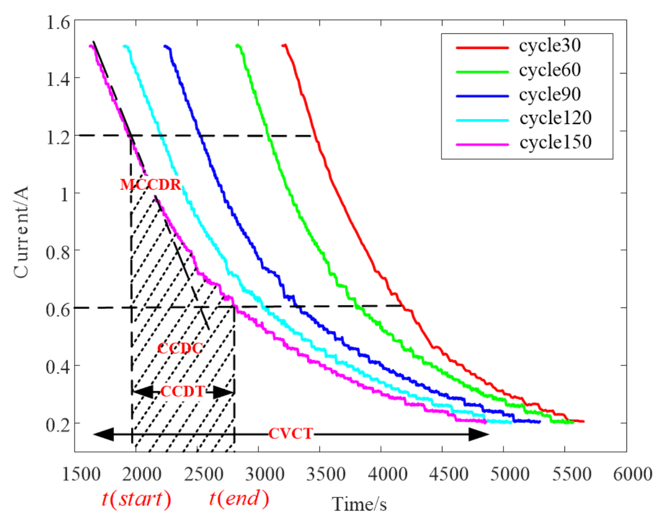

Fig. 4. Current measurement diagram during constant voltage charging.

Where, $t(start)$ is the start time of constant current drop, $t(end)$ is the end time of constant current drop, $i(k)$ is the current at time k, and $t(k)$ is the kth sampling interval. As shown in **Fig. 4**, $t(start)$ and $t(end)$ used in the experiment in this paper are the moment when battery discharge current is 1.2A and 0.6A, respectively.

Compared with the constant voltage charging time (CVCT), CCDT, CCDC and MCCDR require less data volume and easier to extract. The CVCT has a wider range of starting time (the voltage is close to the constant voltage setting value and rises slowly, and it may be lower than the given voltage value), the very small current at the end time may cause measurement errors.

All the constant voltage charging *HI* of lithium-ion batteries are represented by matrix ***HI***.

$$\boldsymbol{HI} = \begin{bmatrix} HI_1 \\ HI_2 \\ \vdots \\ HI_N \end{bmatrix} \tag{8}$$

Where, *N* represents the number of cycles of lithium-ion battery charging.

B. HI optimization

In the actual extraction process, the HI will appear outliers under the influence of measurement error and random noise. In order to improve the accuracy of the prediction, the PauTa criterion method is adopted to modify the data in this research [33,34]. PauTa Criterion is a common method of dealing with bad data, it is the standard deviation σ of three observed values as the criterion for limiting selection. Standard deviation σ is the parameter calculated after a large number of repeated observations, and its formula is:

$$\sigma = \sqrt{\frac{\sum\limits_{n=1}^{N} (HI_n - \overline{HI})^2}{N}} \tag{9}$$

Where, *n* is the number of lithium-ion battery cycles, which should not be less than 20 times in general, and $\overline{HI}$ is the arithmetic mean value of HI_n.

The discrimination basis of PauTa criterion is as follows.

$$R_n = \left| HI_n - \widehat{HI_n} \right| \tag{10}$$

Where R_n is the residual and $\widehat{HI}$ is the HI_n estimate. If the R_n is greater than 3σ, HI_n is a gross error and should be discarded or compensated. If the R_n is less than or equal to 3σ, HI_n is normal data and retained.

C. HI validation

To verify the precision of the HI proposed in this article, Pearson Product Moment Correlation Coefficient (PPMCC) is used to analyze the correlation between HI_i and capacity sequence C_i of EV lithium-ion battery in constant voltage charging process [37]. The correlation coefficient is represented by *r*. In general, the higher the absolute value of *r*, the stronger the correlation. Coefficient *r* of Pearson product moment correlation is as follows.

$$r = \frac{\sum\limits_{n=1}^{N} (HI_n - \overline{HI})(C_n - \overline{C})}{\sqrt{\sum\limits_{n=1}^{N} (HI_n - \overline{HI})^2} \sqrt{\sum\limits_{n=1}^{N} (C_n - \overline{C})^2}} \tag{11}$$

Where, *n* is the cycles of lithium-ion battery, $\overline{HI}$ is the arithmetic mean value of HI_n, and $\overline{C}$ is the average capacity of EV lithium-ion battery.

IV. Simulation analysis

A. Data source

This study analyzed the degradation experimental data of lithium-ion batteries from the NASA Ames Prognostics Center of Excellence (PCOE) [20,26]. One set of 18650 batteries (No. 5, No. 6, No. 7, No. 33, No.45, No. 46, No. 47, No. 48, No. 55, No. 56) as the experimental data for the verification method. All batteries are charged with a constant current of 1.5A. When the voltage reaches 4.2V, it is converted to constant voltage charging until the current drops to 20mA.

B. Error evaluation standard

Maximum absolute error (AE_{MAX}), mean absolute error (*MAE*) and root mean square error (*RMSE*) are used to evaluate the prediction effect of the proposed method.

Maximum Absolute Error

$$AE_{MAX} = \max \left| SOH^k_{estimation} - SOH^k_{true} \right|_{k=1}^{L} \tag{12}$$

Mean Absolute Error

$$MAE = \frac{\sum\limits_{k=1}^{L} \left| SOH^k_{estimation} - SOH^k_{true} \right|}{L} \tag{13}$$

Root Mean Square Error

$$RMSE = \sqrt{\frac{\sum\limits_{k=1}^{L} (SOH^k_{estimation} - SOH^k_{true})^2}{L}} \tag{14}$$

C. Simulation verification of health indicator

Fig. 5 shows the relationship between the HI and battery capacity proposed in this paper before and after optimization. It can be seen that singular values will inevitably appear in the process of extracting health indicators. Singular value correction can improve the accuracy of health indicators and the accuracy of SOH estimation. With the increase of the discharge cycle, the CCDT and CCDC in the constant voltage charging stage are inversely proportional to the capacity, and MCCDR is directly proportional to the capacity. Errors occurred in the three health indicators at the same time during the 30th cycle extraction process, especially the MCCDR calculation uses division. When the denominator is close to 0, the singular value will be particularly large, so it is very necessary to optimize the health indicators.

Table I shows the correlation analysis results of lithium-ion battery capacity before and after HI optimization. The correlation between CCDT and capacity increased by 0.165, the correlation between CCDC and capacity increased by 0.159, and the correlation between MCCDR and capacity increased by 0.329. The absolute values of the optimized correlations are all above 0.8, so the health indicators used in this article can be used to estimate the SOH of lithium-ion batteries.

TABLE I
CORRELATION COEFFICIENT BETWEEN HI AND BATTERY CAPACITY

	CCDT		CCDC		MCCDR	
	before optimization	optimized	before optimization	optimized	before optimization	optimized
No.5	-0.760	-0.968	-0.720	-0.961	0.105	0.965
No.6	-0.885	-0.931	-0.890	-0.930	0.129	0.947
No.7	-0.587	-0.891	-0.549	-0.863	0.107	0.889
No.33	-0.574	-0.848	-0.563	-0.793	0.721	0.859
No.45	-0.842	-0.879	-0.880	-0.880	0.818	0.873
No.46	-0.678	-0.855	-0.696	-0.854	0.695	0.860
No.47	-0.899	-0.925	-0.894	-0.937	0.913	0.922
No.48	-0.618	-0.823	-0.653	-0.898	0.693	0.901
No.55	-0.766	-0.883	-0.756	-0.824	0.871	0.881
No.56	-0.472	-0.732	-0.561	-0.811	0.591	0.835
Average	-0.708	-0.873	-0.716	-0.875	0.564	0.893

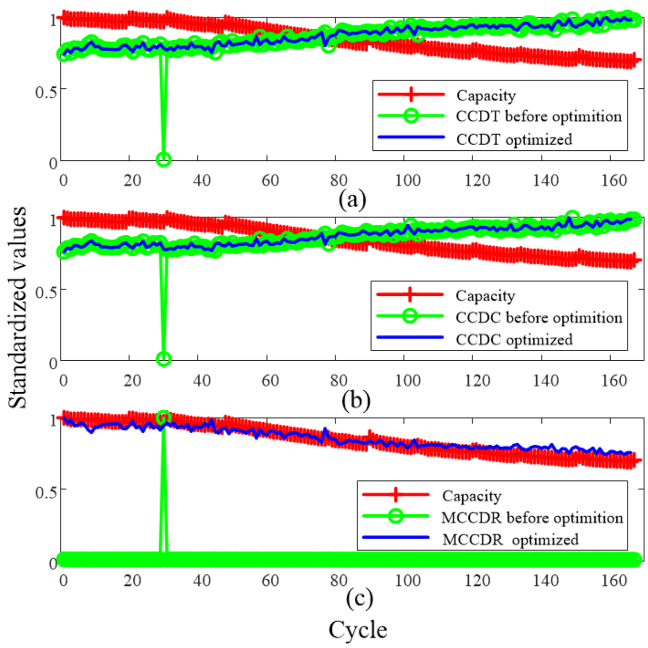

Fig. 5. Relation between HI and lithium-ion battery capacity before and after optimization (No.5 battery) (a) CCDT (b) CCDC (c) MCCDR.

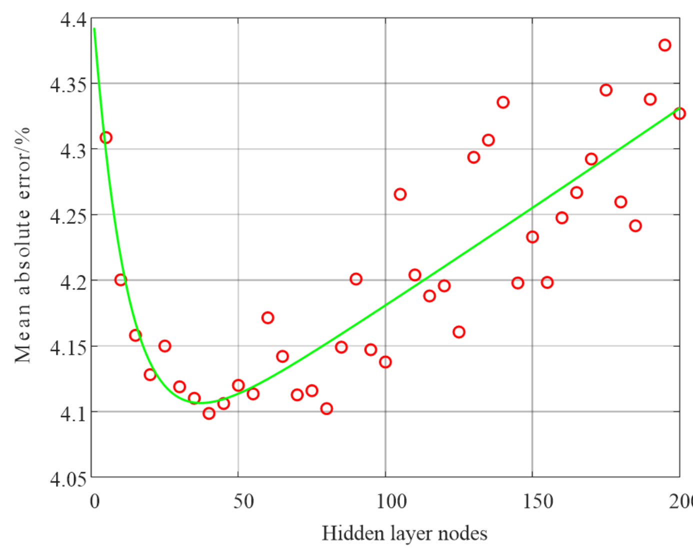

Fig. 6. The MAE results with different number of hidden layer nodes.

D. lithium-ion battery SOH estimation simulation results with ATAGA-BP Algorithm

The internal chemical reactions of lithium-ion batteries are different. In order to improve the universality and generalization of the model, the training data randomly uses 70% of each battery's data, and the remaining 30% is used for testing. The number of nodes with hidden layers in the BP neural network influences the predictive accuracy of the training model. Having too many hidden layer nodes leads to excessive learning, poor network adaptability, and large prediction errors. In this research, after much experimentation, it is finally determined that the number of nodes N of the hidden layer is 40, which is the most suitable. As shown in **Fig. 6**, when the hidden layer node is 40, MAE is the smallest and the minimum value is 4.099%.

After determining the number of nodes in the hidden layer of the BP neural network, the ATAGA-BP algorithm proposed in this article is used to optimize the parameters to prevent the BP neural network from falling into the local optimum. In this research, the experimental population size is 50 and the number of iterations is 200, among which the fitness is the reciprocal of the BP network model MAE. The results are shown in **Fig. 7**.

It can be seen from **Fig. 7** that the proposed ATAGA-BP algorithm is superior to the existing method in terms of accuracy. Compared with IAGA-BP, the fitness of ATAGA-BP finally converges to the optimal value 8 times in advance, as a result, its iteration efficiency is increased by 17.8%. As can be seen from **Table II**, compares various SOH estimation methods of lithium ion batteries. The ATAGA-BP algorithm proposed in this paper is superior to the support Vector Regression (SVR) [17], Prior knowledge-based Neural Network (PKNN) [31] and convolutional neural network (CNN) [13].The MAE of SOH estimation using ATAGA-BP algorithm is 3.7%, which is 2% lower than that of IAGA-BP algorithm and 16.1% lower than the error of traditional CNN algorithm.

Table III shows the detailed results of SOH estimation based on ATAGA-BP lithium-ion batteries. The maximum error of all battery estimates is within 0.1, and the MAE is within 4%. Among them, the estimated result of No. 5 is the best, and the estimated result of No. 33 is the worst, so the SOH estimation diagram of these two batteries is drawn.

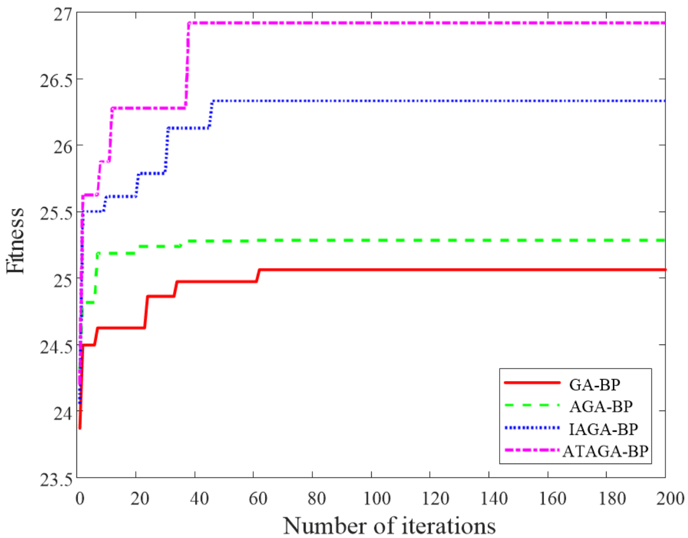

Fig. 7. Results Comparison of various optimized BP algorithms.

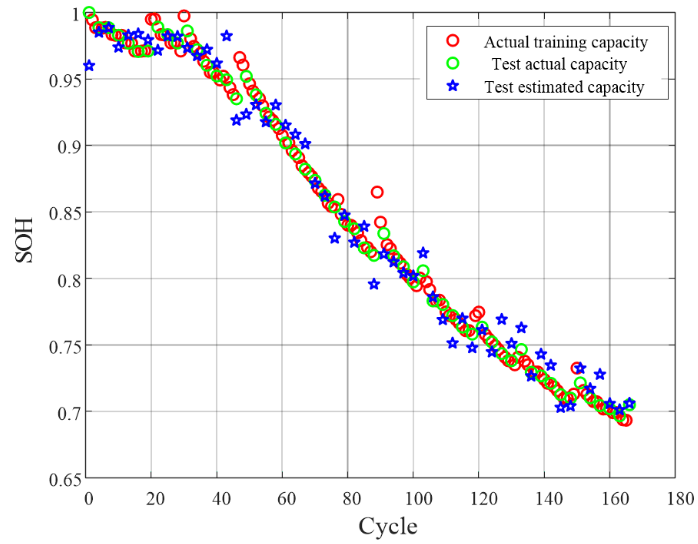

Fig. 8. Multi-cycle SOH estimation and actual comparison of EV lithium-ion batteries(No.5).

TABLE II
ERROR COMPARISON OF MULTIPLE METHODS

	AE_{MAX}	$MAE(\%)$	$RMSE(\%)$
SVR[17]	0.135	/	3.850
PKNN[31]	/	5.890	7.681
CNN[13]	/	4.430	5.840
BP	0.109	4.099	3.171
GA-BP	0.102	3.955	2.857
AGA-BP	0.099	3.990	2.733
IAGA-BP	0.097	3.798	2.682
ATAGA-BP	0.095	3.715	2.663

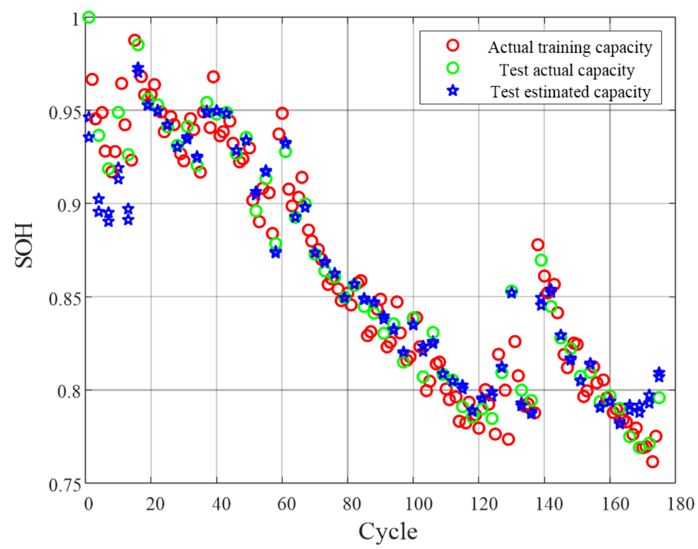

Fig. 9. Multi-cycle SOH estimation and actual comparison of EV lithium-ion batteries(No.33).

Fig. 8 is the SOH estimation diagram of the No. 5 battery, and **Fig. 9** is the SOH estimation diagram of the No.33 battery. In the figure, the training data randomly uses 70% of each battery's data, and the remaining 30% is used for testing. There is a difference between the training and testing data. Therefore, it is proved that the existing data can be used for the establishment of the model. The trend of No.5 is better than that of No.33, so the SOH estimation value of the battery is more accurate.

Fig. 8 and **Fig. 9** is the Multi-cycle SOH estimation and actual comparison of EV lithium-ion batteries, The SOH estimation results are close to the actual results, which can well reflect the SOH trend of electric vehicles and verify the effectiveness of the method presented.

TABLE III
SOH ESTIMATION OF LITHIUM ION BATTERY BASED ON ATAGA-BP ALGORITHM

	AE_{MAX}	$MAE(\%)$	$RMSE(\%)$
No.5	0.067	3.629	2.573
No.6	0.085	3.680	2.535
No.7	0.082	3.749	2.748
No.33	0.095	3.841	2.908
No.45	0.077	3.633	2.561
No.46	0.053	3.764	2.726
No.47	0.083	3.629	2.546
No.48	0.054	3.830	2.846
No.55	0.072	3.802	2.887
No.56	0.060	3.823	2.848

V. CONCLUSION

This article proposes a SOH estimation method based on ATAGA-BP for lithium-ion batteries for electric vehicles. On the one hand, CCDT, CCDC and MCCDR are proposed as the health indicator, which is easy to indirectly quantify the degradation process of lithium-ion battery and realize online lithium-ion SOH estimation of EV. The simulation results show that the correlation between the optimized health indicator and the capacity of the EV lithium-ion battery is greater than 85%. On the other hand, an arctangent function adaptive genetic algorithm combination with back propagation neural network is proposed to optimize the parameters and improve the ability of model precision. The simulation results show that the proposed method improves both the precision and the speed of calculation. The SOH estimation error of lithium-ion battery is only 3.7%, and the iteration efficiency is increased by 17.8%.

It should be noted that the health indicator proposed is extracted under the condition of constant voltage charging of EV, which can be optimized by introducing the constant current charging part of EV. In addition, all the batteries in the experiment are lithium cobalt oxide batteries. In future research, lithium iron phosphate, nickel manganese cobalt, lithium titanate and other batteries will be introduced to optimize the model and establish a model with higher universality.

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