Remaining Useful Life Prediction of Lithium-ion Batteries Based on Stacked AutoEncoder and Gaussian Mixture Regression

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ABSTRACT Lithium-ion batteries have been widely used for energy storage systems and electric vehicles (EVs), the remaining useful life (RUL) prediction is one of the important technologies for prognostics and health management. However, high accuracy RUL predication with reliability is the biggest bottleneck. To improve RUL predication and adaptively extract indirect health indicators (HIs), the RUL prediction framework based on the stacked autoencoder and Gaussian mixture regression (SAE-GMR) is proposed. Firstly, the indirect HIs are extracted from charging and discharging data, and the grey relation analysis (GRA) is used to analyze the relation with capacity. In this paper, the SAE neural network is used to reduce the dimensions and noise of battery and obtain a syncretic HI. Then, the GMR model is proposed not only to improve accuracy of RUL predication, but also describe the reliability. Finally, the proposed method is compared with traditional principal component analysis (PCA) and esixting methods. The results show that the proposed model has high accuracy predication.

INDEX TERMS energy storage systems; lithium-ion batteries; remaining useful life; stacked autoencoder; Gaussian mixture regression

I. INTRODUCTION

With the increasingly serious environmental pollution and energy shortage, and the energy storage industries have developed rapidly[1]. Lithium-ion batteries are widely used in the field of energy storage systems and electric vehicles (EVs) owing to the dvantages of high energy density, superior cycle life, and no memory effect [2]. Due to the complex internal reaction andextermal disturbances, lthium-ion batteries endure performance degradation with the capacity fade [3-4]. This problem not only affects the driving range of EVs, but also causes safety problems[5]. Therefore, a growing number of researches have focused on health predication of the battery system.

Currently, the RUL prediction methods of lithium-ion batteries are mainly divided into two categories: the model-driven method and the data-driven method[6, 7]. The model-driven method excavates the correspondence between observable quantities and health indicators (HIs) by establishing a physical model [8]. It mainly includes the empirical model method and the Kalman filter method. The empirical model method focused on finding the inherent mathematical relation of the capacity degradation trajectory of lithium-ion batteries, including exponential model, linear model, polynomial model, and Verhulst model[9-11]. The mathematical expression based on the input of the number of cycles and output of capacity is established through the data fitting to describe the aged batteries[12]. The empirical model can not only accurately obtain the remaining battery life, but also predict the future life trajectory. However, due to the sensitivity of data fitting and sample fluctuations, RUL prediction results may be biased [13]. The Kalman filter method is based on the state estimation, including, the extended Kalman filter, unscented Kalman filter, particle Kalman filter, and spherical volume Kalman filter[14]. This method updates and corrects the model in real time through observation data, which effectively solves the nonlinear problem in prediction. Although the Kalman filter method improves the convergence of the empirical model method and enhances the prediction accuracy of RUL prediction, the accuracy of the model is easily affected by current, temperature, and external disturbances. Therefore, it is difficult to accurately establish a model-driven.

The data-driven method overcomes the research on the mechanism and internal chemical reaction through analyzing monitoring data and excavating battery degradation information[15]. This method is the core method of RUL predication including, artificial neural networks (ANNs)[16, 17], support vector machines (SVM)[18], and Gaussian process regression (GPR)[19]. ANNs are widely used in data-driven methods [20]. However, it is easy to fall into a local minimum when optimizing parameters. SVM is based on the VC dimensional space theory and trains the model through the Structural risk minimization principle. Although this method has good prediction performance with small sample, nonlinear and high-dimensional problems, it is not suitable for big data processing[21]. At present, the method of GPR has gained widespread attention. The Gaussian process has strong adaptive functions for dealing with nonlinear and small sample problems[22, 23].

However, the capacity fade of lithium-ion batteries is a dynamic and nonlinear problem. The trend of capacity fade is generally decreasing with multiple fluctuations. These fluctuations are due to the capacity regeneration and external disturbances. The phenomenon of capacity regeneration is a false and transient phenomenon, which is also the main reason for the fluctuation of degradation information. The classical GPR uses a single Gaussian distribution, which is difficult to accurately describe the estimation results [24]. To cover this weakness, the Gaussian mixture model (GMM) is established. The GMM uses multiple Gaussian density functions to fit the density distribution. Therefore, a RUL prediction method based on Gaussian Mixture Regression (GMR) is proposed for the nonlinear and unstable battery system. Firstly, the K-means algorithm is used to cluster the test data. Then the expectation-maximization (EM) algorithm is adopted to optimize the optimal parameters of the Gaussian mixture mode, and Gaussian mixture regression (GMR) is established to accurately predict RUL.

The RUL prediction accuracy of the data-driven method is susceptible to the influence of health indicators, therefore the selection of appropriate health indicator is critical to predict the RUL of lithium-ion batteries.Generally, the capacity and internal resistance, as direct health indictors, can better describe the degradation of the battery, however owing to the high precision and expensive measuring instruments, it is difficult to apply in online measurement [25]. Therefore, the parameters of lithium-ion batteries should be measured directly, for example, charge and discharge voltage, current, and temperature, et al. Extracting indirect health indictors that contains battery degradation information can reflect the health of lithium-ion batteries [26].Currently, the indirect health indicators with more practical significance have gained attention of researchers, for example, the voltage cut-off interval, the peak temperature interval, or using the current, voltage, and temperature together as health indictors to estimate the capacity degradation of lithium-ion batteries. However, although the above studies have selected easily measurable health indictors, they lack correlation analysis among health indictors, the redundancy and deficiency of health indictors are dangerous for the prediction accuracy. To address this problem, Grey relational analysis (GRA) and stacked autoencoders (SAE) are introduced into the process of establishing health factors for lithium-ion batteries [27].The SAE is an effective unsupervised feature extraction method through the self-learning to generate the abstract complex functions. Compared with traditional feature extraction, the SAE method has fewer parameters and lower complexity, which overcomes the excessive dependence of traditional methods. Therefore, it is very suitable for the online extraction of lithium-ion battery health factors.

In this paper, the SAE are used and GMR is proposed for accurate RUL predication with reliability. Analyzing the charging and discharging data of battery, the six indirect HIs are proposed based on the data of voltage, current, and temperature. Then, GRA is used to analyze the relation with capacity, and SAE is introduced to address the problem of redundancy and deficiency of indicat HIs. In addition, GMR is proposed to reduce the impact of capacity regeneration and external disturbances. The data is clustered through the K-means algorithm, and the GMM is established for different clustering characteristics. After, the EM algorithm is used to find the optimal parameters. Finally, GMR is proposed to predict the RUL. To verify SAE has a better syncretic HI that contains the battery degradation characters compared with traditional Principal Component Analysis (PCA). At the same time, the proposed model is compared with the traditional back propagation neural network based on particle swarm optimization (BPNN-PSO), the least-squares support vector machine (LS-SVM) and Gaussian process regression (GPR). The structure of this paper is as follows: Section II introduces the construction of indirect HIs based on GRA and SAE. Section III includes the GMR model. The results and discussion is described in Section IV and Section V introduces the conclusion.

II. EXTRACTION OF INDIRECT HEALTH INDICATORS

In this paper, the data of lithium-ion batteries from NASA Ames Prognostics Center of Excellence (PCoE) is used[28]. At room temperature (24°C), the charging and discharging data of 18650 lithium-ion batteries including four batteries (NOs.5, 6, 7, and 18) are selected. The rated capacity of lithium-ion batteries is 2.1Ah and the battery's failure threshold is 1.38Ah. The standard charging method was used to charge the battery, and then 2A discharge current was used to discharge the battery at constant current. The Nos.5, 7, 8 were used to analyze owing to the fragmentary data of battery 18. The curves of capacity fade of each battery is shown in Fig1.

The factors of degradation include internal factors and external factors such as overcharge or over discharge, self-discharge, and temperature variations. Generally, capacity and internal resistance as direct HIs is used for RUL predication. However, the measurement of direct HIs is difficult to online measure. Therefore, it is necessary to obtain indirect HIs such as voltage, current, and temperature by analyzing the direct measurement of lithium-ion batteries. As shown in the Fig2, six indirect HIs are proposed by comparing and analyzing the charging and discharging voltage, current, and temperature under different cycle conditions, including charge voltage saturation interval (CVSI), discharge voltage cut-off interval (DVCI), charge peak temperature interval (CPTI), discharge peak temperature interval(DPTI), constant current charge interval(CCCI), and discharge constant current interval(DCCI).

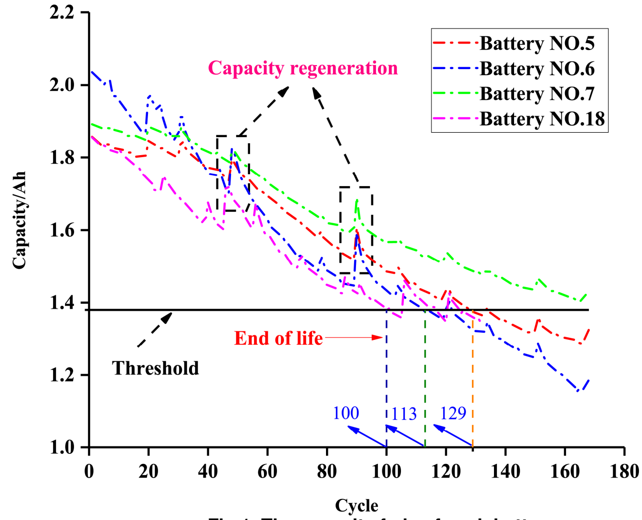
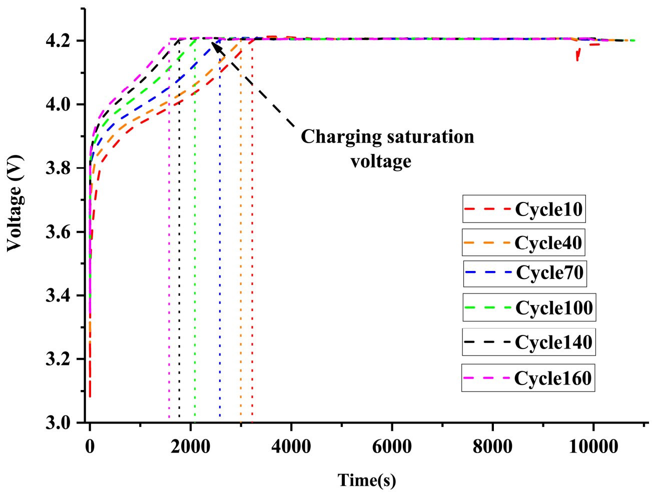


Fig.1. The capacity fade of each battery



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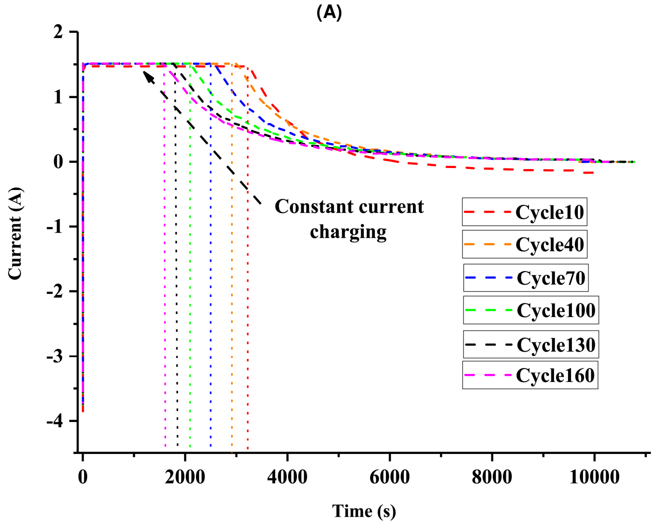

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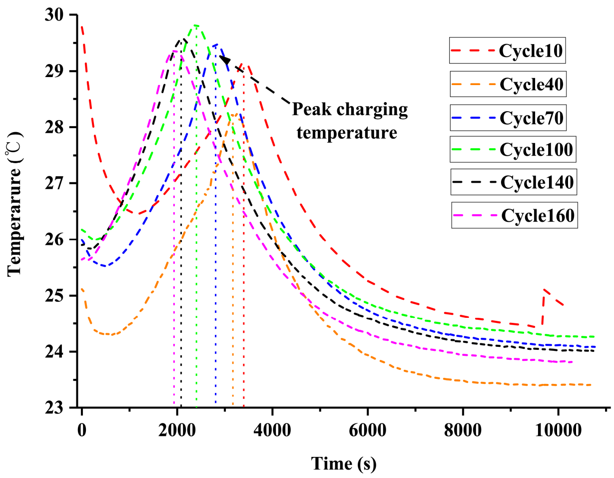


(C)

Fig.2. Charging curves of No. 5, (A) Voltage with different cycles, (B) Current with different cycles, (C) Temperature with different cycles

A. GREY RELATIONAL ANALYSIS

Gray relational analysis, as the evaluation of correlation among factors according to the difference of factors, is used quantitative analysis to show the relation between capacity and six indicat HIs. The extracted HIs represent the degeneration of the RUL. The method of GRA is presented, as shown in step1-5[29].

Step1. Reference sequence capacity $y_i(t)$, comparison sequence indirect HIs $x_j(k)$

Step2. Normalization of Reference sequence capacity $y_i(t)$ and comparison sequence indirect HIs $x_j(k)$

Step3. Calculation the absolute value of $y_i(t)$ and $x_j(k)$ as well as maximum and minimum values

$$\begin{cases} \delta_{ij}(k) = \left| y_i(k) - x_j(k) \right| \\ \alpha = \min \delta_{ij}(k) \\ \beta = \max \delta_{ij}(k) \end{cases} \quad (1)$$

Step4. Calculation grey correlation coefficient

$$\xi_{ij}(k) = \frac{\alpha + \varphi\beta}{\delta_{ij}(k) + \varphi\beta} \quad (2)$$

Where, φ is discrimination coefficient and φ=0.5 .

Step5. Calculation grey relation degree

$$r_{ij} = \sum_{k=1}^{n} \xi_{ij}(k) \quad (3)$$

According to the GRA, the relation between the capacity and extracted HIs is shown in table 1.

TABLE I
RELATION BETWEEN CAPACITY AND EXTRACTED SIX HIS

GRA	CVSI	CPTI	CVSI	DVCI	DPTI	DCCI
NO.5	0.808	0.802	0.725	0.889	0.898	0.888
NO.6	0.663	0.669	0.818	0.913	0.917	0.925
NO.7	0.848	0.852	0.888	0.958	0.924	0.948

B. STACKED AUTOENCODER

Autoencoder (AE) is a typical neural network that can be used to reduce dimensionality and feature extraction of data. However, a single-layer encoder cannot effectively extract complex data features for complex data. To cover this weakness, multiple AEs are stacked into SAE to address complex data and extract dimensions[30]. According to gray relational analysis, the proposed six HIs have a significant relation with the capacity of batteries. Therefore, the proposed six HIs are processed by SAE for reducing dimension and noise.SAE is mainly trained by layer-by-layer unsupervised pre-training and supervised fine-tuning. The structure of the stacked autoencoder is shown in Fig3.

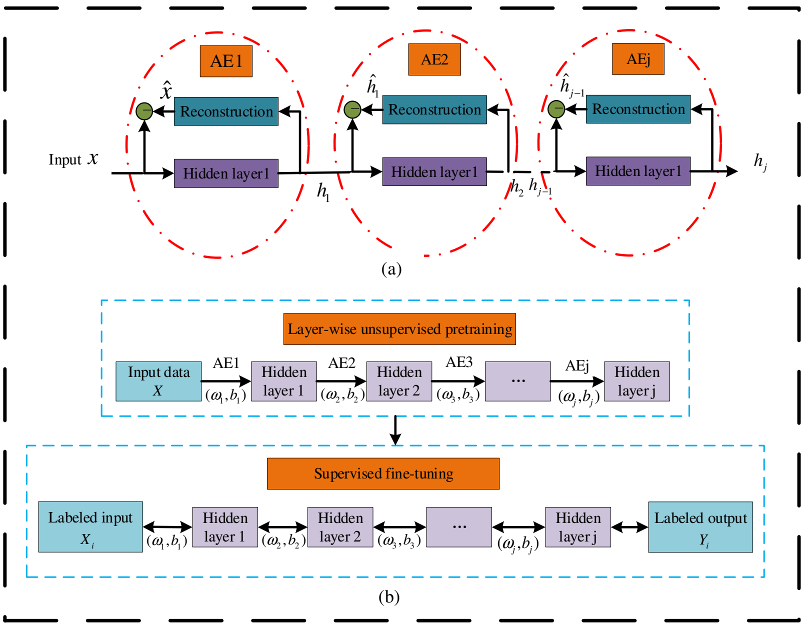


Fig. 3. Schematic diagram of the stacked autoencoder

III. METHOD OF RUL PREDICATION

A. GAUSSIAN MIXTURE MODEL

After fusion information of the proposed six indicat HIs based on SAE, this information is used as observation values of battery data. Each sample of the Gaussian mixture model can be represented by a Gaussian distribution. Number of single Gaussian density functions are used to establish the Gaussian mixture model[31]. Therefore, the probability density function is shown in equation 4.

$$P(x) = \sum_{k=1}^{k} \alpha_k N(\mu_k, \Sigma_k) \qquad (4)$$

Where, μ_k is the value of mean, Σ_k is the value of covariance, k is the number of signal Gaussian process, α_k is the value of weight. Therefore, the hyper-parameters for GMM are shown in equation 5.

$$Q = \{\{\alpha_1, \mu_1, \Sigma_1\}, \{\alpha_2, \mu_2, \Sigma_2\}, \ldots, \{\alpha_n, \mu_n, \Sigma_n\}\} \qquad (5)$$

The EM algorithm is used to find the hyper-parameters in the GMM, which is divided into E-step and M-step.

E-step：

$$P^{(\mathrm{m})}\left(\mathrm{i}|x_n,Q\right)=\frac{\alpha_{\mathrm{i}}^{(\mathrm{m})}\mathrm{N}\left(x_n|\mu_{\mathrm{i}}^{(\mathrm{m})},\Sigma_{\mathrm{i}}^{(\mathrm{m})}\right)}{\sum_{\mathrm{k}=1}^{\mathrm{M}}\alpha_{\mathrm{k}}^{(\mathrm{m})}\mathrm{N}\left(x_n|\mu_{\mathrm{k}}^{(\mathrm{m})},\Sigma_{\mathrm{k}}^{(\mathrm{m})}\right)} \tag{6}$$

M-step:

$$\alpha_{\mathrm{i}}^{'}=\frac{\sum_{\mathrm{n}=1}^{\mathrm{N}}P^{(\mathrm{m})}\left(\mathrm{i}|x_n,Q\right)}{\mathrm{N}} \tag{7}$$

$$\mu_{\mathrm{i}}^{'}=\frac{\sum_{\mathrm{n}=1}^{\mathrm{N}}P^{(\mathrm{m})}\left(\mathrm{i}|x_n,Q\right)x_n}{\sum_{\mathrm{n}=1}^{\mathrm{N}}P^{(\mathrm{m})}\left(\mathrm{i}|x_n,Q\right)} \tag{8}$$

$$\Sigma_{\mathrm{i}}^{'}=\frac{\sum_{\mathrm{n}=1}^{\mathrm{N}}P^{(\mathrm{m})}\left(\mathrm{i}|x_n,Q\right)x_{\mathrm{n}}^2}{\sum_{\mathrm{n}=1}^{\mathrm{N}}P^{(\mathrm{m})}\left(\mathrm{i}|x_n,Q\right)}-\mu_{\mathrm{i}}^{'2} \tag{9}$$

The hyper-parameters μ_k , Σ_k , and α_k are obtained by using the EM algorithm. The data of lithium-ion batteries includes input data and output data. The new HIs by SAE is set as training data, and the expected output is the capacity. Then, Gaussian mixture model is shown in equation 10.

$$f_{XY}\left(x,y\right)=\sum_{j=1}^{k}\alpha_{\mathrm{j}}\phi\left(x,y,\mu_j,\Sigma_j\right) \tag{10}$$

$$\mu_i=\begin{bmatrix}\mu_{jx}\\ \mu_{jy}\end{bmatrix}\Sigma_j=\begin{bmatrix}\Sigma_{jxx} & \Sigma_{jxy}\\ \Sigma_{jyx} & \Sigma_{jyy}\end{bmatrix} \tag{11}$$

Where, the mean and variance of the conditional distribution are shown in equation 12, 13.

$$\mu_{j(x)}=\mu_{jy}+\Sigma_{jyx}\ \Sigma_{jxx}^{\ \ -1}(x-\mu_{jx}) \tag{12}$$

$$\Sigma_{j(x)}=\Sigma_{jyy}-\Sigma_{jyx}\ \Sigma_{jxx}^{\ \ -1}\Sigma_{jxy} \tag{13}$$

Therefore, Gaussian mixture regression is obtained.

$$\mu_{(x)}=\sum_{j=1}^{k}\alpha_{j(x)}\mu_{j(x)} \tag{14}$$

$$v_{(x)}=\sum_{j=1}^{k}\alpha_{j(x)}\left(\mu_{j(x)}^{\ \ 2}+\Sigma_j^{\ 2}\right)-\left(\sum_{j=1}^{k}\alpha_{j(x)}\mu_{j(x)}\right)^2 \tag{15}$$

Due to the difficulty of online measurement capacity, a new method based on SAE is proposed for extracting HIs by analyzing the battery data from NASA PCoE. Six indicat HIs are extracted, and GRA is used to analyze the relation with capacity. Then, the fusion HIs is proposed to predict RUL. Since the prediction accuracy of the battery is easily affected by the redundancy or deficiency of HIs, the SAE neural network is used to reduce noise and dimensions, which is obtained the fusion information of degeneration. Finally, GMR is established for RUL prediction, which focused on capacity regeneration and external disturbances. This model is composed of multiple single Gaussian density functions to solve the low predication of Gaussian process regression. The Schematic diagram of the proposed GMR and SAE method for RUL prediction is shown in Fig4.

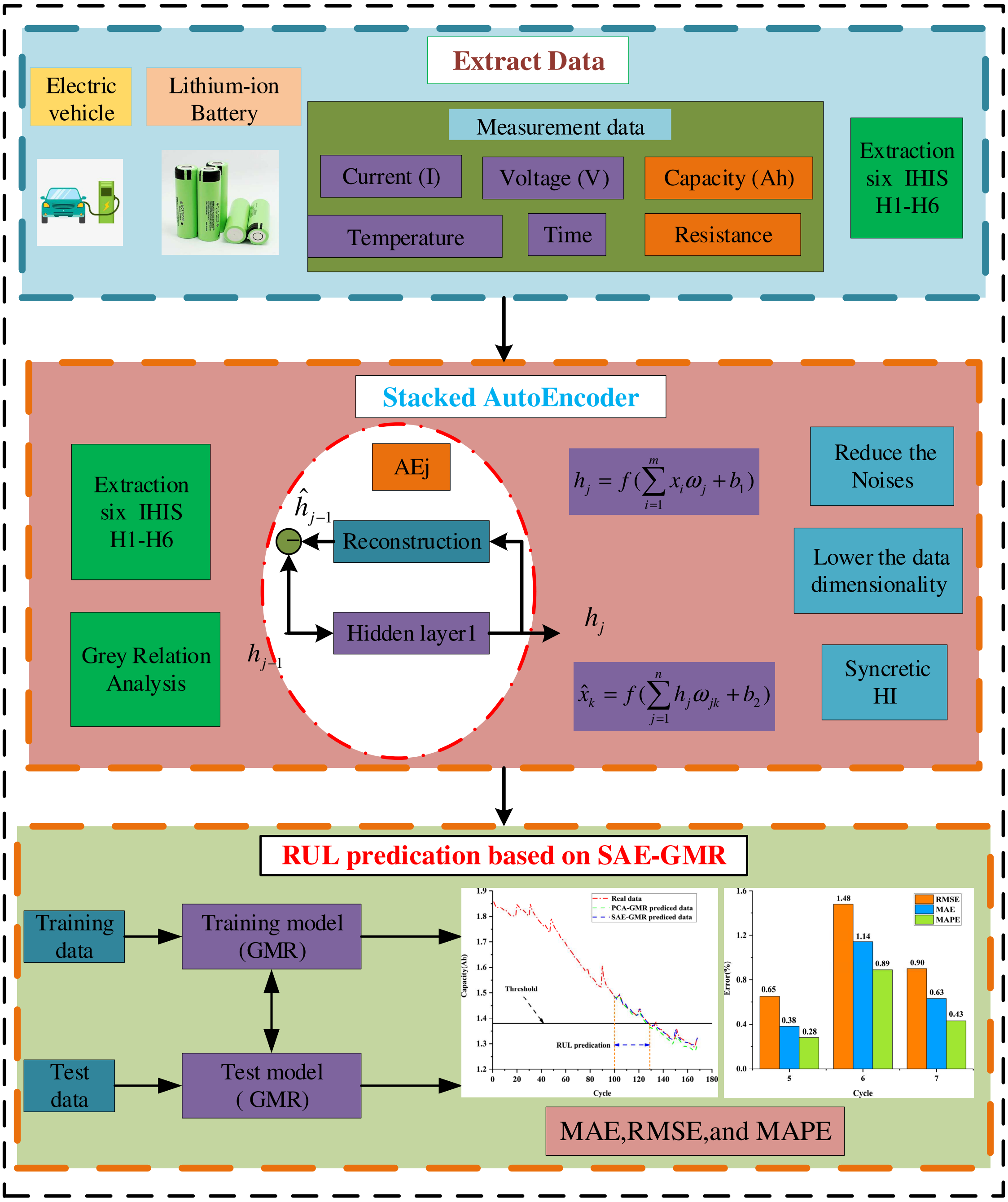
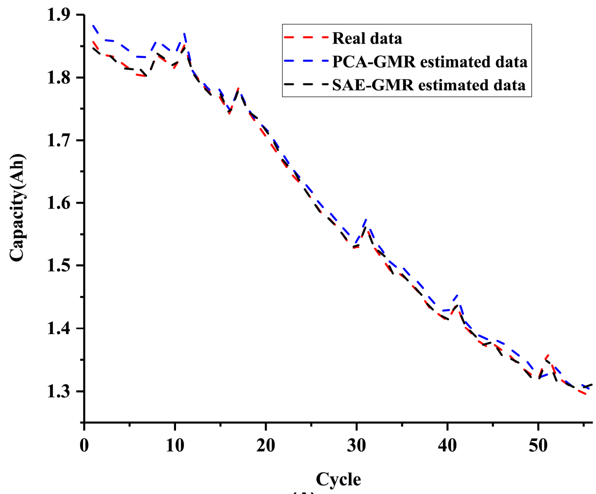


Fig. 4. Schematic diagram of the GMR based on SAE model for RUL prediction

IV. RESULTS AND DISCUSSION

A. SYNACRETIC HI BASED ON SAE

In order to verify the advantages of SAE compared with traditional feature extraction method of Principal Component Analysis (PCA) for syncretic HI. As shown in Figure 5, the three battery packs are respectively based on the syncretic HI based on SAE and PCA, and the GMR model is used for health estimation. The indirect health indicators and capacity for lithium-ion batteries are used to as training data and test data. The training data includes 112 samples of real-time data and the test data includes 56 samples. In these figures, the HI extracted based on SAE are basically fitted the same as the capacity curve. This method not only accurately fits the capacity degeneration of battery, but also accurately reflects the phenomenon of capacity regeneration. Therefore, syncretic HI based on SAE can accurately express the degradation characteristics of battery. However, the fluctuation of HI based on PCA is larger. To further verify the advantages of the SAE method, GMR are used to predict the RUL under the SAE and PCA. The 99th cycles are used as training data to predict the RUL in the later period. As shown in Fig.6, the RUL prediction based on SAE feature extraction under different models is higher than the PCA fusion under the same model. The results shown that syncretic HI based on the SAE has the strongest ability to express battery degradation information.



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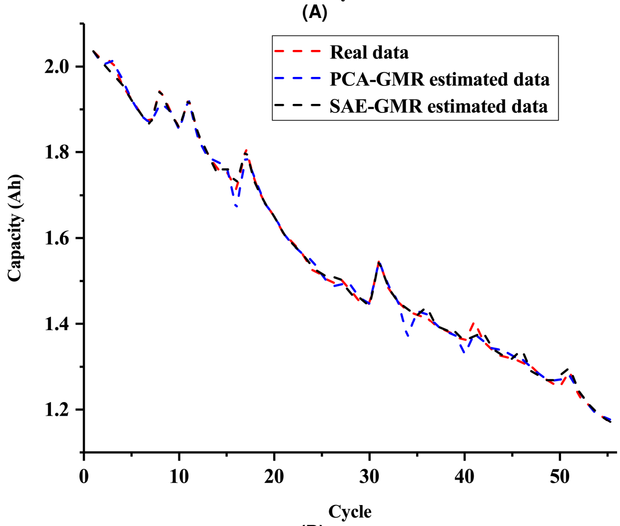

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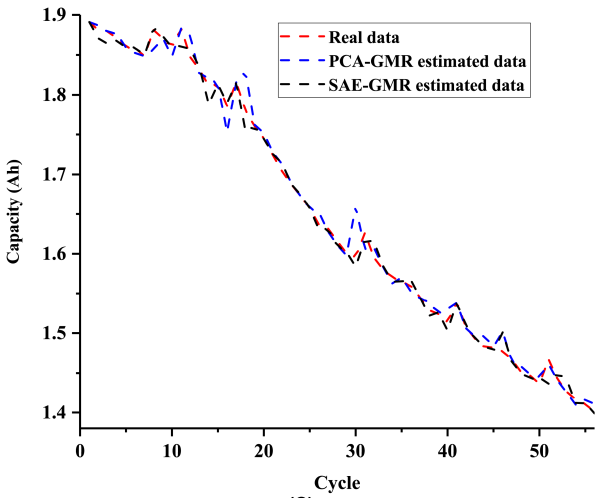

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Fig.5. **Syncretic HI based on SAE and PCA, (A) No. 5, (B) No. 6, (C) No. 7**

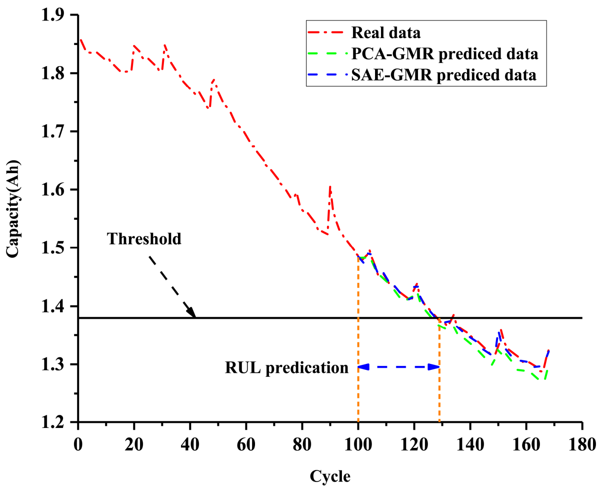


Fig.6. **Syncretic HI based on SAE for RUL prediction of No. 5**

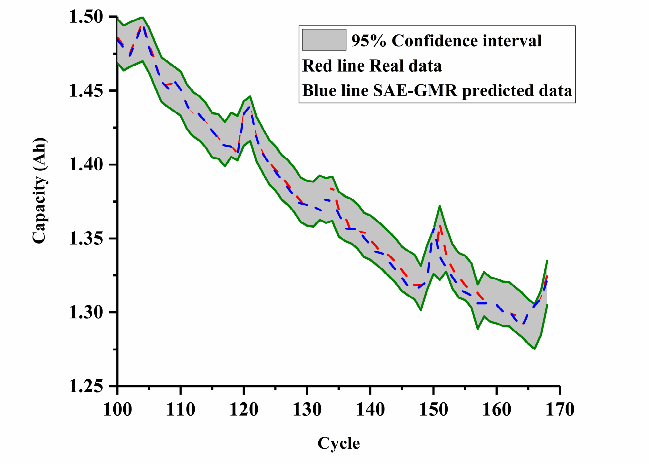
The predication prefermance of root mean square error (RMSE), mean absolute percentage error (MAPE), and mean absolute error (MAE) are used to evaluate methods. Three indicators are used to evaluate the estimation performance of SAE and PCA. According to Table II, the estimated performance indicators of syncretic HI based on the SAE are all lower than traditional PCA.

TABLE II
ESTIMATION PERFORMANCE OF THESE METHODS

Methods	Numbers	RMSE(%)	MAPE (%)	MAE(%)
	NO.5	1.55	0.85	1.34
PCA-GMR	NO.6	1.49	0.60	0.90
	NO.7	1.46	0.52	0.85
	NO.5	0.77	0.20	0.29
SAE-GMR	NO.6	1.05	0.42	0.62
	NO.7	0.96	0.37	0.61

B. RUL PREDICTION RESULTS

The NO.5, NO.6, and NO.7 data sets are used for RUL prediction, the 99th cycles as training data, and the prediction starting point is the 100th cycle. Due to uncertainty of the battery model, point estimation of traditional neural network becomes difficult. To accurately predict the RUL with reliability of lithium-ion batteries, this paper presents Gaussian mixture model to obtain the mean and variance of the output distribution. The mean value is used as the RUL prediction value and the variance is used to establish the 95% confidence interval. Therefore, the RUL prediction result with uncertainty can be obtained.As shown in Fig.7, it can be seen that the proposed SAE-GMR model for lithium-ion battery RUL prediction has reached a satisfactory effect.



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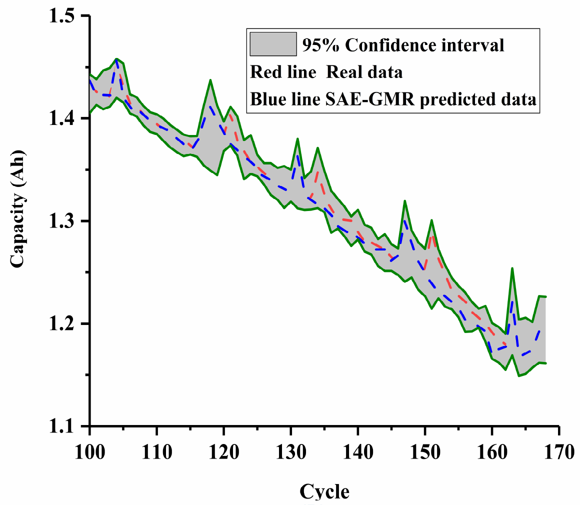

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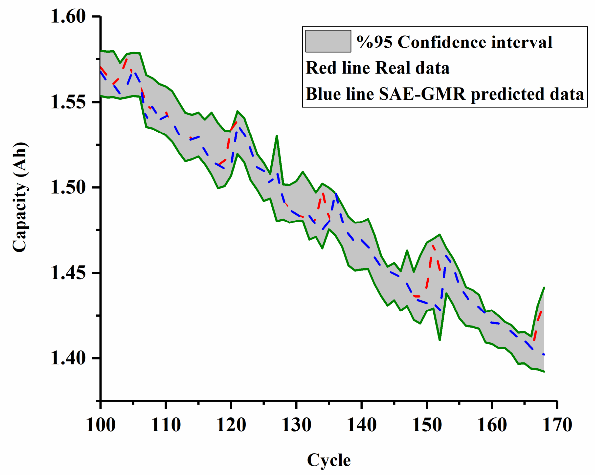


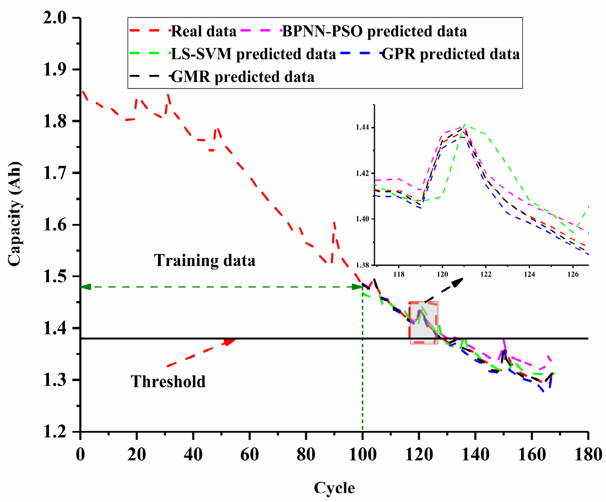
(C)

Fig.7. RUL prediction based on SAE-GMR. (A) No. 5, (B) No. 6, (C) No. 7

C. VERIFICATION WITH EXISTING METHODS

The SAE-GMR model is compared with the classical BPNN-PSO, LL-SVM, and GPR to further verify the effectiveness of the proposed model. The prediction results shown in Fig.8. The errors of predication performance are shown in Fig.9. Due to capacity regeneration and external disturbances, the real rate of capacity presents a dynamic and nonlinear degeneration. Although the standard BPNN-PSO and LL-SVM have a good RUL predication for lithium-ion batteries, the prediction error is large for the slope of the capacity degeneration, and the lithium-ion batteries RUL prediction fluctuates greatly. The standard GPR and proposed GMR based on SAE models can accurately predict the RUL of the batteries compared with traditional BPNN-PSO and LL-SVM. The proposed GMR based on SAE model not only effectively address the improves the prediction accuracy but also describes the reliability of RUL predication.

In order to verify the validity of the proposed GMR-SAE model，the proposed methods is compared with BPNN-PSO, LS-SVM, GPR for the batteries NO.5, NO.6, NO.7, respectively. Table III presents the GMR-SAE method and existing methods of prediction performance. From the Table III, under the batteries NO.5, the RMSE, MAPE, and MAE of the traditional BPNN-PSO are 1.70%, 0.89%, and 1.18%, respectively. Under the batteries NO.6, the RMSE, MAPE, and MAE are 2.67%, 1.47%, and 1.92%, respectively. The RMSE, MAPE, and MAE are 2.72%, 1.58%, and 2.36%, respectively in the batteries NO.6. Among these existing methods, the classic BPNN-PSO model has the lowest prediction accuracy. The RMSE of LS-SVM under the batteries NO.5, NO.6, NO.7 are 1.32% , 1.98% and 1.22%, MAPE is 0.70%,1.17% and 0.66%, and MAE is 0.96%,1.50% and 0.97%, , respectively. Although the RUL prediction performance of LS-SVM is better than BPNN-PSO, error fluctuations are generally large. In the traditional GPR model, RMSE, MAPE, and MAE are 0.98%, 0.52%, and 0.70%, respectively, under the batteries NO.5. RMSE, MAPE, and MAE are 1.83%, 0.97%, and 1.24%, respectively, under the batteries NO.6. RMSE, MAPE, and MAE are 1.17%, 0.59%, and 0.86%, respectively, under the batteries NO.7. Although traditional GPR has better RUL estimation performance, it cannot accurately predict the capacity regeneration. In the proposed GMR-SAE model, the RMSE is 0.65%, 1.48% and 0.90% under the batteries NO.5, NO.6, NO.7, respectively; MAPE is 0.29%, 0.89%and 0.43%, respectively, and MAE is 0.38%, 1.14% and 0.63%, respectively. The prediction accuracy of the SAE-GMR method is the highest among the three predication indicators, which is lower 1.5%. Compared with standard GPR, RMSE is increased by 34% under the batteries NO.5.



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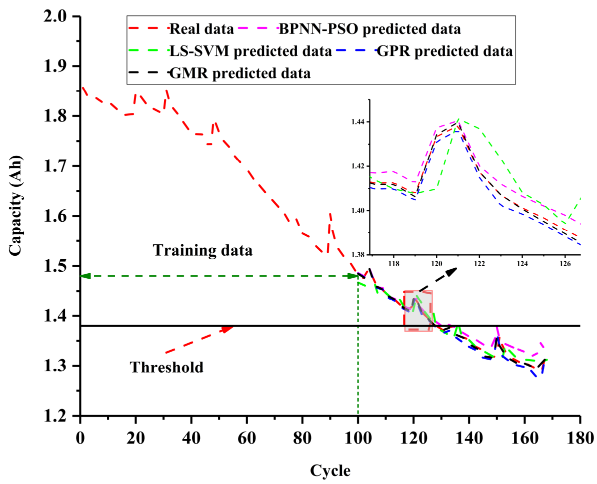

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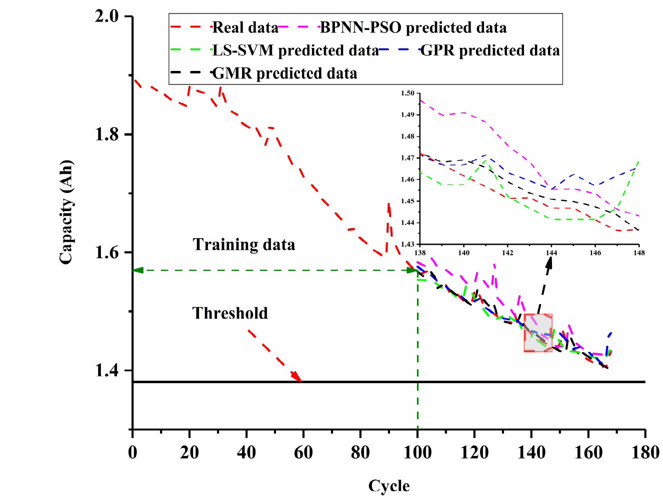
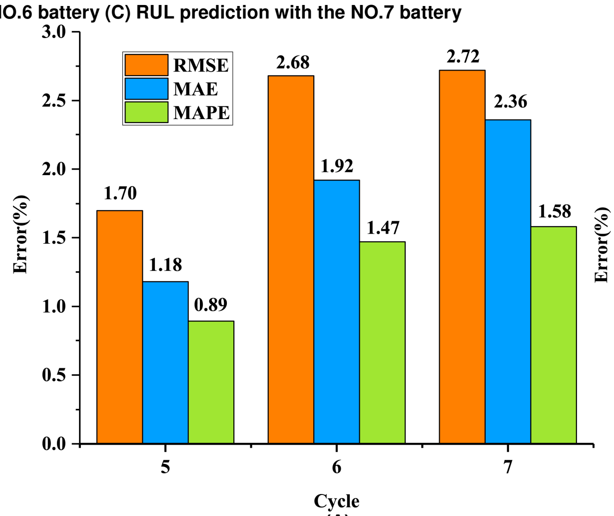


(C)

Fig. 8. Result of lithium-ion batteries for RUL prediction with four different models. (A) RUL prediction with the NO.6 battery (B) RUL prediction error with the NO.6 battery (C) RUL prediction with the NO.7 battery



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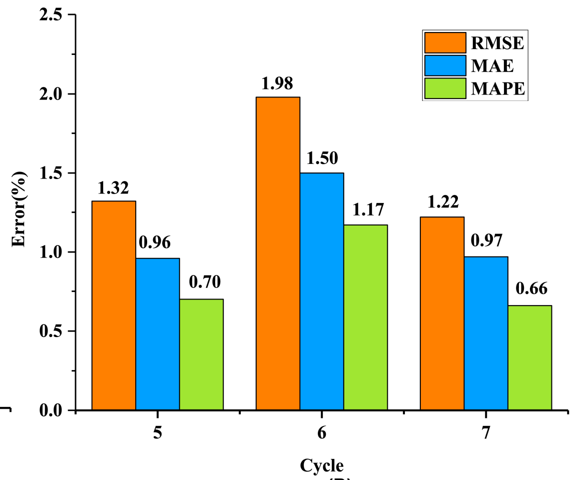

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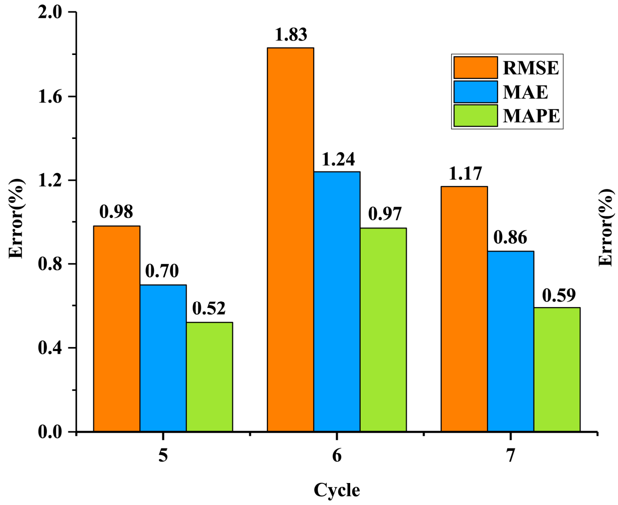

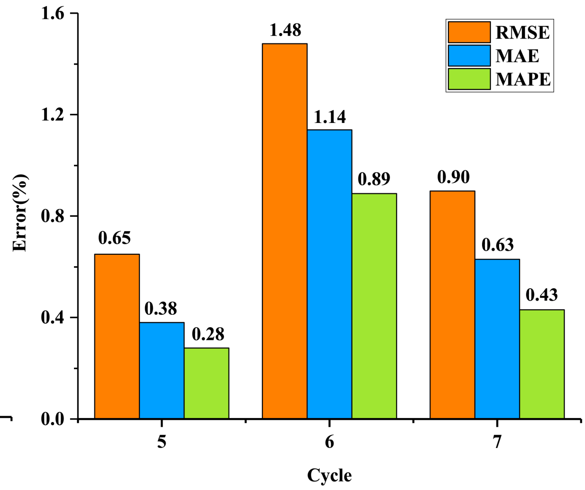

(C) **(D)**

Fig. 9. Errors of lithium-ion batteries for RUL prediction with four different models. (A) Errors with the BPNN-PSO(B) Errors with the LS-SVM (C) Errors with the GPR (D) Errors with the GMR

TABLE III
PREDICTION PERFORMANCE OF TESTED METHODS

Methods	Numbers	RMSE(%)	MAPE (%)	MAE(%)
BPNN-PSO	NO.5	1.70	0.89	1.18
	NO.6	2.68	1.47	1.92
	NO.7	2.72	1.58	2.36
LS-SVM	NO.5	1.32	0.70	0.96
	NO.6	1.98	1.17	1.50
	NO.7	1.22	0.66	0.97
GPR	NO.5	0.98	0.52	0.70
	NO.6	1.83	0.97	1.24
	NO.7	1.17	0.59	0.86
GMR	NO.5	0.65	0.28	0.38
	NO.6	1.48	0.89	1.14
	NO.7	0.90	0.43	0.63

V. CONCLUSION

This paper focuses on high caauracy RUL predication with reliability, a novel RUL prediction framework based on SAE-GMR is proposed. Firstly, the six indirect HIs are proposed based on the data of voltage, current, and temperature to address the phenomenon that the direct HIs cannot be obtained in practical applications. GRA is used to analyze the relation with capacity. Then, the SAE neural network is introduced to reduce dimensions and noise of battery and establish a syncretic HI. Due to the external disturbances and capacity regeneration, the GMR model is proposed to improve RUL predication with reliability. Finally, the SAE-GMR model is compared with PCA, BPNN-PSO, LS-SVM, and GPR.The results shown that the proposed method has strong syncretic degradation information and high accuracy prediction performance.

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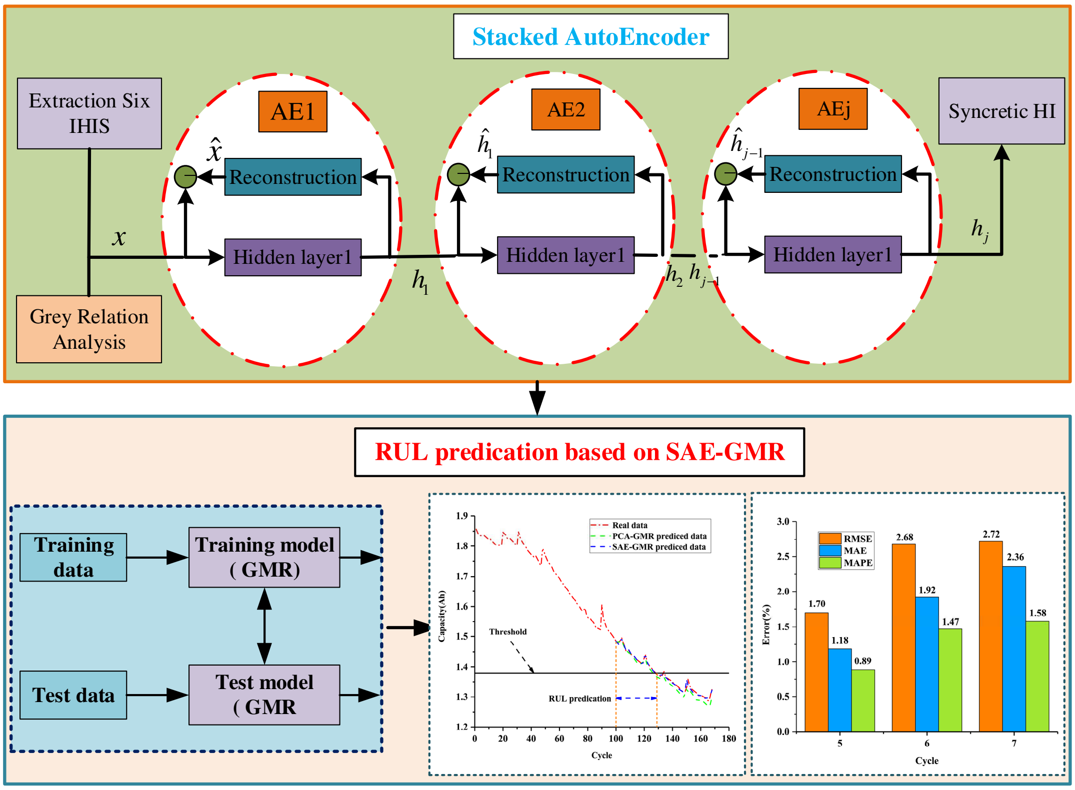
Graphical Abstract



To improve RUL predication and adaptively extract indirect health indicators (HIs), the RUL prediction framework based on the stacked autoencoder and Gaussian mixture regression (SAE-GMR) is proposed. The results show that the proposed model has high accuracy predication.