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Indirect Prediction Method for Remaining Useful Life of Lithium-ion Battery based on Gray Wolf Optimized Extreme Learning Machine

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Abstract: In this paper, a novel indirect method for predicting the remaining useful life (RUL) of lithium-ion battery is proposed, not requiring the direct measurement of capacity. Firstly, a variety of indirect health indicators (HI) that can characterize the degradation state of lithium-ion battery are extracted from the charging and discharging process curves of lithium-ion battery. To reduce the redundancy among indirect HIs Principal Component Analysis (PCA) is used to fuse all these HIs into one indirect HI that can represent the degradation characteristics. Then, in order to avoid the interference of noise on the prediction accuracy of the model, we use the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) to decompose and denoise the fused indirect HI. Finally, the Gray Wolf Optimized Extreme Learning Machine (GWO-ELM) model is applied to make the RUL prediction and compare its prediction results with the prediction results of other models. Finally, simulations are conducted and the results show that the proposed indirect prediction method can predict lithium-ion battery RUL more accurately.

Key Words: lithium-ion battery，RUL prediction, PCA，CEEMDAN，GWO-ELM

1 Introduction

As a environmentally-friendly products, lithium-ion battery have the advantages of strong sustainability, long lifespan, high energy density, energy-saving, and environmental protection. Thus, it has been extensively used in mobile communications and other fields[1]. With an increase in the number of charge and discharge cycles, lithium-ion battery undergo a decrease in both their capacity and safety, which can result in various safety issues. Accurately predicting the remaining lifespan of lithium-ion battery is crucial in enhancing the safety of these batteries and optimizing their management systems[2].

There are two primary approaches for predicting the lifespan of lithium-ion battery: model-based methods and data-driven methods. Model-based methods involve creating a mathematical model that is based on the battery's dynamics in order to characterize its aging process. Wang et al. proposed an observation framework of lithium battery RUL based on untracked particle filtering by establishing an equivalent circuit model considering hysteresis[3]. Mastali et al. proposed an electrochemical model to describe the diffusion and migration of lithium-ion within the battery[4]. Although the prediction accuracy of model-based methods is high, they still have certain limitations in practical applications, such as poor applicability, time-consuming and so on[5].

The data-driven approach for lithium-ion battery life prediction does not require an understanding of the intricate electrochemical reactions that occur within the battery, it is only necessary to gather the historical operational data of a lithium-ion battery's performance. By analyzing parameters such as the charge-discharge curve, internal resistance, and temperature of lithium-ion battery, it is possible to calculate the RUL of the battery using various intelligent algorithms. Currently, the prevalent research methods based on data analysis include: Auto Regressive model[6], Neural Network[7], Gaussian Process Regression[8], Support Vector Machine[9].

Note that there are still some disadvantages of the established data-based methods for remaining life prediction. (1) The capacity is a commonly used direct health indicator (HI) to describe the degradation trend of lithium-ion battery when evaluating RUL of the battery. However, obtaining real-time capacity data of lithium-ion battery during practical operation may present a challenge, so selecting measurable parameters as indirect HI to predict the remaining life has become a research hotspot[10]. Chen et al. used the equal voltage drop discharge time as a health factor to monitor battery life[11]. But a single health factor may not be enough to detect system abnormalities in time. (2) Studies have shown that multiple HIs can better reflect the degradation status of a battery than a single HI. To assess the health condition of lithium-ion battery, Zhang et al. identified a few HIs associated with capacity degradation by analyzing the discharging procedure of the batteries[12]. But multiple HIs are likely to cause information redundancy.

In this paper, a novel prediction method based on data for the remaining useful life (RUL) of lithium-ion battery is proposed. Four indirect HIs reflecting capacity degradation of lithium-ion battery are firstly extracted. Principal Component Analysis (PCA) is then used to a obtain fusion indirect HI that can represent the degenerative characteristics and reduce the redundancy of input data. To reduce the influence of noise on the prediction results, Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) technique is utilized to denoise the data and the Gray Wolf Optimized Extreme Learning Machine (GWO-ELM) model is applied to predict the RUL of lithium-ion battery. Finally, simulations and comparisons with other methods are conducted to show the effectiveness of the proposed method.

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The following is the organization of this paper. Section II is the research motivation of this work. Section III introduces the proposed forecasting methods. Section IV analyzes the prediction results. The conclusion is drawn in Section V.

2 Research motivation

Prior research on predicting the RUL of lithium-ion battery typically employs the battery's capacity as the direct HI to describe its degradation trend. Measuring the capacity of lithium-ion battery directly in practical applications is challenging. As a result, measurable parameters such as voltage, current, and temperature are often selected as indirect HIs to forecast the battery's RUL. Based on the charge and discharge curves of lithium-ion battery, this paper selects four indirect health indicators to predict the RUL of the battery. These HIs exhibit a strong correlation with the battery capacity and thus provide a more accurate reflection of the battery's degradation state. However, if multiple HIs are brought into the GWO-ELM model as input, it will not only cause data redundancy but also lead to long computational time consumption, which decreases the prediction accuracy. Therefore, we adopt the dimensionality reduction methods to deal with multiple indirect HIs. The primary objective of PCA is to preserve the intrinsic information of the data while reducing its dimensionality. This approach meets the requirements of reducing data redundancy and computation cost, while simultaneously maximizing the useful characteristics of the data[13]. Therefore, in this work, PCA will be adopted to fuse the multiple indirect HIs.

Under the influence of complex environmental factors such as physics and chemistry, the degradation curve of lithium battery may exhibit noise and capacity rebound phenomena. There are several denoising methods available for mitigating noise in the degradation curve of a lithium-ion battery. These methods include Kalman Filter (KF), Particle Filter (PF), Empirical Mode Decomposition (EMD), Ensemble Empirical Mode Decomposition (EEMD) and so on. These denoising methods are not easy to reveal the trend of fluctuations when dealing with low-frequency components. The CEEDMAN algorithm is a refined approach that builds upon the EEMD and EMD techniques. It is main aim is to overcome the problem of mode mixing encountered in the EMD algorithm, while also addressing the incomplete decomposition and high reconstruction errors inherent in the EEMD algorithm[14]. This paper employs CEEMDAN to preprocess the lithium-ion battery data. CEEMDAN effectively eliminates the irregular fluctuations in the original data while preserving its essential characteristics.

How to find the optimal set of key parameters to complete the incremental processing of new data also becomes a challenge. Various optimization algorithms, including Differential Evolution (DE), Gray Wolf Optimization (GWO), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA), have been commonly employed to find the optimal key parameters for addressing this problem. Compared with other optimization algorithms, as a new heuristic algorithm, GWO has good optimization ability and simple parameters to set and implement[15]. ELM is a Feedforward Neural Network-based machine learning approach that does not require multiple iterations to update the parameters of the hidden layer[16]. In contrast to traditional neural network algorithms, the ELM method exhibits fast learning speed and robust non-linear approximation capabilities. Therefore, it is highly suitable for assessing the capacity degradation of lithium-ion battery. In this paper, GWO and ELM will be combined to establish the prediction and optimization model of RUL. In practice, data are always generated continuously, and all the data need to be retrained whenever a new data sample is added.

3 Proposed Prediction Method

This article proposes an indirect prediction method for estimating the remaining life of lithium-ion battery. As shown in Fig. 1, the method mainly consists of two parts: data pre-processing and construction of the prediction model.

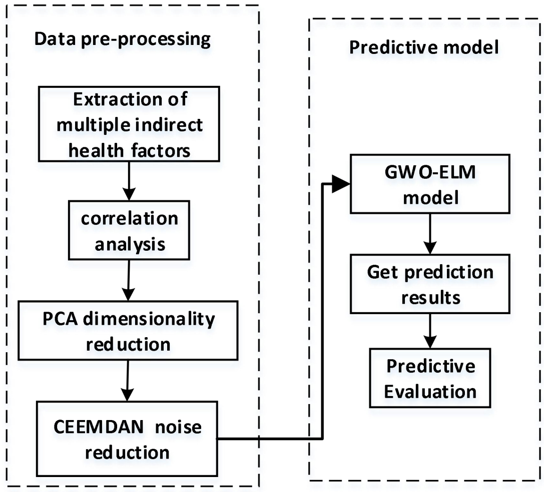


Fig. 1: lithium-ion battery RUL prediction flow chart

The data pre-processing stage comprises several steps. Firstly, we extract four types of indirect HIs from the charge and discharge curves of lithium-ion battery. Next, we conduct a correlation analysis to demonstrate the strong correlation between these indirect HIs and battery capacity. In order to enhance the model's efficiency and eliminate redundancy among indirect HIs, the PCA method is employed to reduce the dimensionality[17]. Lastly, to mitigate the influence of noise on the prediction outcomes, the reduced HIs are decomposed and denoised via CEEMDAN[18].

The modal components with high correlation after CEEMDAN decomposition are selected as the training input of the GWO-ELM model, and the capacity as the training output. The principle of the GWO-ELM is as follows:

ELM is a specific type of feedforward neural network with a single hidden layer, which is characterized by unique features. Assuming that there are n neurons in the input layer, m neurons in the output layer, and l neurons in the hidden layer. The output Y of ELM can be expressed as $H \bullet \beta = Y$. H is the output of the implied layer, which can be expressed by the following equation[19].

$$H = \begin{bmatrix} G(\omega_1 \bullet x_1 + b_1) & \cdots & G(\omega_L \bullet x_1 + b_L) \\ \vdots & \ddots & \vdots \\ G(\omega_1 \bullet x_n + b_1) & \cdots & G(\omega_L \bullet x_n + b_L) \end{bmatrix} \quad (1)$$

$$\omega = \begin{bmatrix} \omega_{11} & \cdots & \omega_{1L} \\ \vdots & \ddots & \vdots \\ \omega_{1n} & \cdots & \omega_{nL} \end{bmatrix}_{n\times L} \quad (2)$$

$$b = \begin{bmatrix} b_1 & b_2 & \cdots & b_L \end{bmatrix}_{1\times L} \quad (3)$$

Where ω represents the connection weight between the input layer and the hidden layer; b represents the the bias of the hidden layer; β represents the connection weight between the output layer and the hidden layer; $G(\bullet)$ represents an activation function. Both ω and b are generated by random initialization. β can be calculated using the following equation: $\beta = H^{+}Y$.

ELM randomly generates model parameters ω and b, resulting in the reduction of the prediction accuracy. Therefore, we employ the GWO algorithm to optimize the parameters of the ELM model and construct the GWO-ELM model to improve the estimation accuracy of the RUL, which is called GWO-ELM model. The optimization process is performed with a maximum of 1000 iterations and a population size of 20 wolves. The process of GWO optimization of ELM is shown in Fig. 2.

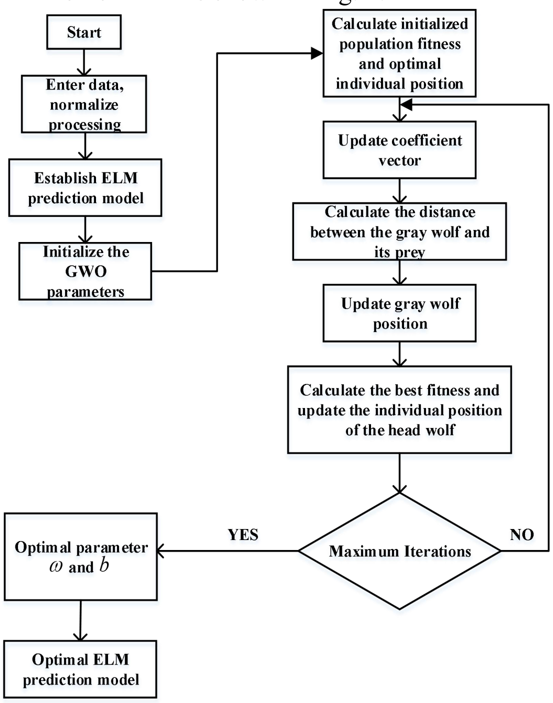


Fig. 2: Structure diagram of GWO-ELM

4 Forecast results and analysis

The datasets used in this paper are from the NASA Ames Center of Excellence[20]. The data set is obtained by cyclic charge and discharge experiments at room temperature for 18650 lithium-ion batteries (B0005, B0006, B0007, and B0018), which are considered to have reached the end of their life when their capacity decays by 30%. Each battery cycle in this study includes two stages, namely charging and discharging. To be specific, the battery is charged at a constant current of 1.5A until its voltage reaches 4.2V, and then charged at a constant voltage until the charging current declines to 20mA. Subsequently, the battery is discharged at a constant current of 2A until its voltage drops to a certain threshold. Fig. 3 illustrates the changes in battery capacity as a function of the number of cycles.

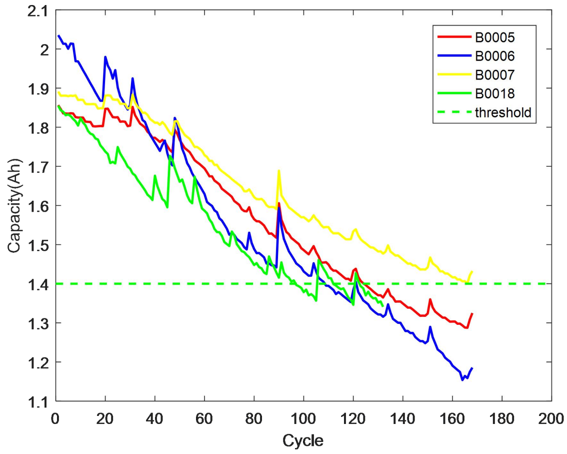


Fig. 3: The degradation curve of Lithium battery capacity.

4.1 The selection of Indirect health factor

Charging and discharging a lithium-ion battery provides insights into its degradation status by reflecting its overall health. This information characterizes the battery's health status. As depicted in Fig. 4, the discharge voltage curve shows that the rate of voltage decline accelerates with an increase in the number of cycles within a given time period, across various discharge curves.

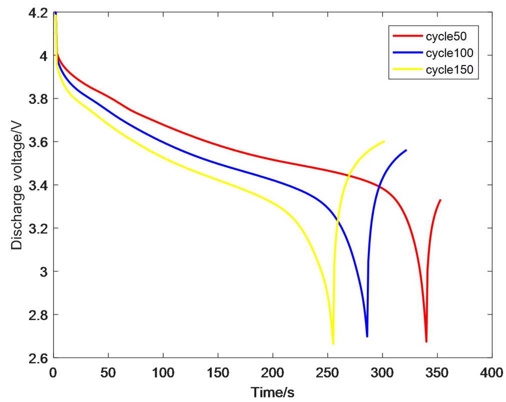


Fig. 4: Charge and Discharge curve

This article extracted four different health factors from the charge-discharge curves of lithium battery to characterize their degradation, as shown in Table 1.

Table 1: Lithium-ion Battery Indirect Factors

Indirect HIs	Calculation formula
Equal voltage drop discharge time Δt_i	$\Delta t_i = \lvert t_{V_L} - t_{V_H} \rvert, (i = 1, 2, \cdots, N)$
Average rate of change of equal voltage v_i	$v_i = \dfrac{\Delta U}{\Delta t_i}, (i = 1, 2, \cdots, N)$
Equal time discharge voltage ΔV_i	$\Delta V_i = \lvert V_{t_1} - V_{t_2} \rvert, (i = 1, 2, \cdots, N)$
Equal voltage rise charge time $\Delta t_i'$	$\Delta t_i' = \lvert t'_{V_L} - t'_{V_H} \rvert, (i = 1, 2, \cdots, N)$

Where t_{V_L} and t_{V_H} indicate the discharge time corresponding to the discharge of the battery to low and high voltages, respectively. V_{t_1} and V_{t_2} denotes the voltage corresponding to the selected moments t_1 and t_2 during the discharge of the battery, respectively. t'_{V_L} and t'_{V_H} are the charging times corresponding to the low and high voltages during battery charging, respectively.

To judge the validity of the selected indirect health factors, Pearson correlation coefficient r [21] and Spearman correlation coefficient ρ [22] are calculated between indirect HIs and the capacity, respectively, according to (10) and (11). The vaules of Pearson correlation coefficient and Spearman correlation coefficient are shown in Table 2.

$$r=\frac{\sum\left(V_i-\bar{V}\right)\left(C_i-\bar{C}\right)}{\sqrt{\sum\left(V_i-\bar{V}\right)^2\left(C_i-\bar{C}\right)^2}} \tag{4}$$

$$\rho=\frac{\sum\left(V_i-\bar{V}\right)\left(C_i-\bar{C}\right)}{\sqrt{\sum\left(V_i-\bar{V}\right)^2\sum\left(C_i-\bar{C}\right)^2}} \tag{5}$$

Where V_i and C_i are two variables, $\bar{V}$ and $\bar{C}$ are the averages of V_i and C_i, respectively.

Table 2: Correlation Coefficients

Battery	r	ρ
B0005	0.9962	0.9929
B0006	-0.9921	0.9787
B0007	-0.9803	0.9925
B0018	0.9483	0.9447

As shown in Table 2, the correlation coefficients between indirect health factors and capacity are all in the range of $\pm(0.9\sim1.0)$, indicating that there is a close relationship between the extracted health factors and capacity, which can indirectly characterize the battery capacity degradation characteristics and describe the battery health status informationmore accurately.

PCA is used to fuse four indirect HIs into a principal component with the highest contribution rate. Table 3 indicates that the principal components of all four batteries have contribution rates exceeding 90%. Therefore, for the other principal components, only one principal component can replace the originally selected four indirect health factors, which greatly reduces their complexity while preserving the original information.

Table 3: Principal Component Contribution Rate

Battery	Contribution rate
B0005	0.9731
B0006	0.9729
B0007	0.9535
B0018	0.9280

Then CEEMDAN is then applied to decompose the indirect health factors after dimensionality reduction by PCA, and the decomposition results are shown in Fig. 5 which represent the main degradation trend of the battery and correlates with capacity up to 0.9929.

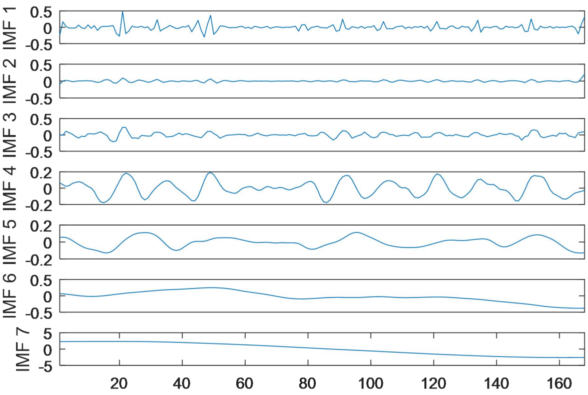


Fig. 5: Modal components after CEEMDAN decomposition of B0005.

4.2 Analysis of results

In this paper, GEO-ELM is used to predict the remaining life of the B0005, B0006, B0007, and B0018 batteries and compared with the standard ELM, standard Back Propagation (BP), and Sparrow Search Algorithm Optimized Back Propagation (SSA-BP) neural networks. Furthermore, to evaluate the prediction models, Absolute Error (AE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) are employed as evaluation metrics. The equations for these metrics are:

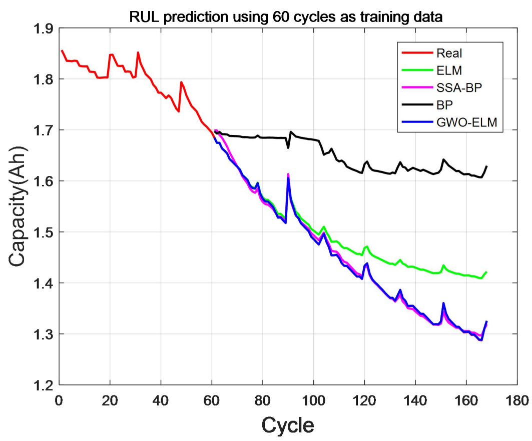
$$AE=\left|T_{RUL}-\hat{T}_{RUL}\right| \tag{6}$$

$$MAE=\frac{1}{\mathrm{n}}\sum_{i=1}^{n}\left|x(i)-\hat{x}(i)\right| \tag{7}$$

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x(i)-\hat{x}(i)\right)^2} \tag{8}$$

Where T_{RUL} and $\hat{T}_{RUL}$ refer to the predicted and actual RUL values, respectively, $x(i)$ and $\hat{x}(i)$ represent the true and predicted capacity values, respectively.

The data (IMF_7) of No. 5 and No. 6 batteries are the input of GWO-ELM, and the capacity is the output. In this simulation, the data of 60, 80 and 100 cycles is respectively taken as training data. The prediction results, depicted in Fig. 6-7, demonstrate that the GWO-ELM algorithm consistently provides the closest approximation to the actual capacity degradation curve, outperforming the standard ELM, standard BP, and SSA-BP neural networks. The prediction error gradually decreases as the number of training cycles increases, thereby improving the prediction performance.



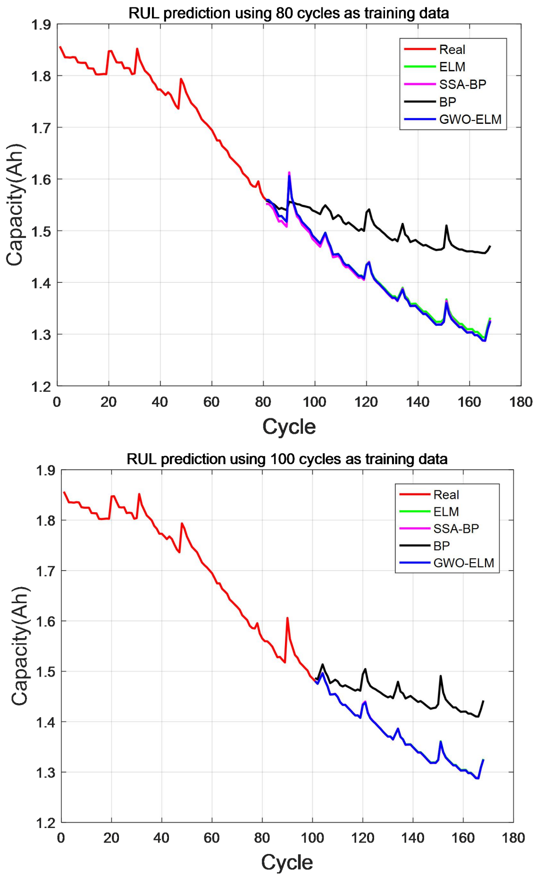
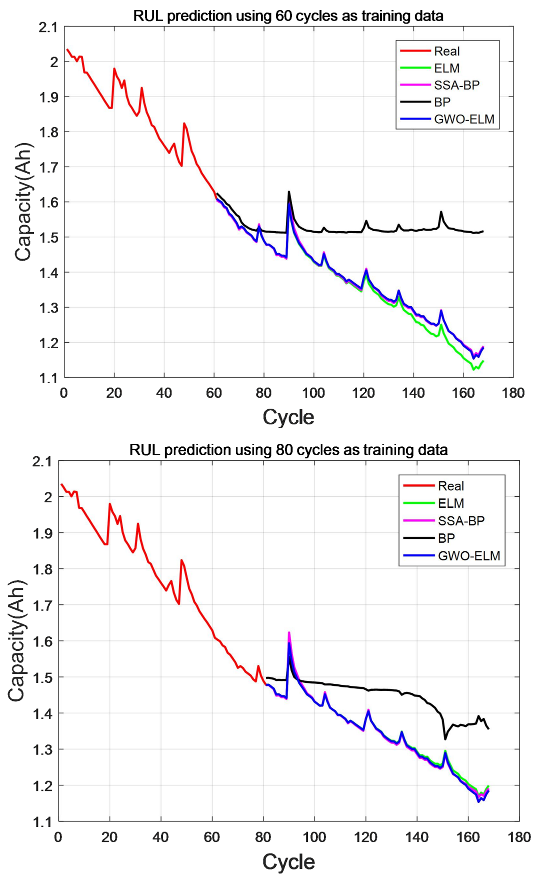


Fig. 6: RUL prediction results of No. 5 battery using different methods when selecting 60, 80 and 100 cycles as training data respectively.



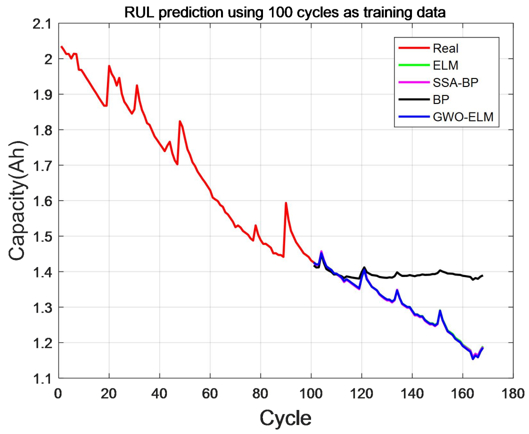


Fig. 7: RUL prediction results of No. 6 battery using different methods when selecting 60, 80 and 100 cycles as training data respectively.

Table 4 and Table 5 present the evaluation metrics, including MAE, AE, and RSME, for the different methods applied to No. 5 and No. 6 batteries. The findings confirm that the proposed approach outperforms other methods in accurately predicting the RUL of lithium-ion battery, as demonstrated by its superior performance across varying training data and number of training cycles. Therefore, the effectiveness of this method has been validated in predicting the lifespan of lithium-ion battery.

Table 4: Comparison For No. 5 Battery Evaluation Indicators

Prediction starting point	Prediction Method	MAE	AE	RSME
60	BP	2.4557	3.9476	2.6734
	SSA-BP	0.0053	0.0246	0.0060
	ELM	0.0450	0.1218	0.0605
	GWO-ELM	0.0015	0.0046	0.0023
80	BP	0.6563	1.1620	0.7392
	SSA-BP	0.0029	0.0102	0.004
	ELM	0.0137	0.0366	0.0185
	GWO-ELM	1.8164e-05	9.0105e-05	2.5568e-05
100	BP	0.4301	0.7052	0.4707
	SSA-BP	3.3477e-04	0.0019	4.897e-04
	ELM	0.0012	0.0034	0.0017
	GWO-ELM	1.2205e-05	4.3909e-05	1.6015e-05

Table 5: Comparison For No. 6 Battery Evaluation Indicators

Prediction starting point	Prediction Method	MAE	AE	RSME
60	BP	0.7266	1.7611	0.8988
	SSA-BP	0.0031	0.0302	0.0046
	ELM	0.0126	0.0394	0.0183
	GWO-ELM	1.4375e-05	5.7042e-05	2.3878e-05
80	BP	0.3827	0.8686	0.4356
	SSA-BP	0.0038	0.02968	0.0057
	ELM	0.0035	0.0159	0.0058
	GWO-ELM	4.8549e-07	2.2443e-06	8.4236e-07

100	BP	0.2902	0.7397	0.3777
	SSA-BP	0.0019	0.0065	0.0023
	ELM	0.0011	0.0049	0.0019

5 Conclusions

A method is proposed in this study for indirectly predicting the RUL of lithium-ion battery. The method extracts indirect health indicators from charge-discharge curves, and then validates the effectiveness of these indicators by calculating the Pearson and Spearman correlation coefficients. To enhance the efficiency of the model training and minimize the feature redundancy, the data undergo preprocessing using PCA reduction and CEEMDAN decomposition noise reduction. The prep-rocessed indirect health factors are used as the input of the GWO-ELM model, and the capacity is used as the output. The effectiveness of the proposed model is assessed using the NASA lithium-ion battery dataset, and the prediction results are compared to those of BP, SSA-BP, and ELM models for verification. The results demonstrate that the proposed indirect prediction method has superior accuracy: the maximum RSME is only 0.03%, the maximum AE is only 0.08%, and the maximum MAE is only 0.02%.

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