Battery life prediction method based on DE-GWO-LSTM

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Abstract. Aiming at the problem of inaccurate prediction results of lithium-ion battery life, a lithium-ion battery life prediction model based on hybrid algorithm is designed. The position of grey wolf algorithm is updated by differential evolution algorithm, which improves the population diversity and avoids premature stagnation of the algorithm. The GWO-LSTM model and DE-GWO-LSTM model are compared and analyzed by using NASA data. The proposed DE-GWO-LSTM can well conduct global search and local search, and improve the prediction performance to a certain extent.

1. Introduction

During the long-term use of lithium-ion batteries, a series of irreversible chemical reactions, a series of irreversible chemical reactions will occur inside the battery, resulting in an increase in the internal resistance of the battery and a decline in performance [1-2]. Therefore, reliable life prediction can not only use the battery more effectively, but also reduce the of accidents [3]. Remaining useful life (RUL) of lithium-ion battery is the number of charge and discharge cycles experienced by the battery from the new start to the end of life (EOL) under certain working conditions, and the general capacity attenuation is 20 % to EOL.

The lithium battery RUL prediction is mainly based on the model and data-driven method [4]. The model-based method relies on a wide range of prior knowledge to establish the degradation model of lithium batteries. Due to the strong nonlinearity and uncertainty of lithium batteries, it is difficult to accurately and comprehensively describe the degradation of lithium batteries. The data-driven method needs to monitor the early life trend of lithium batteries, so as to predict the late life trend. Therefore, extracting the key parameters that can characterize the system degradation from the state monitoring data is the key to achieving and seeing prediction. In reference [5], the constant voltage drop discharge time and battery temperature during discharge are extracted as health factors, and the SVR algorithm is used to construct the RUL prediction model. In reference [6], a prediction model based on improved incremental capacity analysis ICA long-term and short-term memory neural network LSTM fusion is proposed, and the estimation error is less than 4 %.

The number of hidden layer nodes, training times and initial learning rate of LSTM model have a great influence on the fitting ability of the model. The selection of parameters is often related to the characteristics of data, and either large or small parameters may not obtain good prediction results. In order to find a more reasonable and effective initial hyper-parameters of LSTM, this paper selects the grey wolf optimization algorithm to optimize the hyper-parameters of LSTM, and introduces the difference algorithm to optimize the grey wolf algorithm, so as to avoid the phenomenon that the grey wolf algorithm falls into local optimum and converges too slowly in the, so as to obtain better prediction results.
2. Differential evolution to optimize the gray wolf algorithm

2.1. Differential evolution algorithm
Grey Wolf optimization algorithm is a swarm intelligence optimization algorithm proposed by Mirjalili et al. [7] in 2014, which is inspired by grey Wolf prey activities. It simulates the social hierarchy mechanism and predation behavior of grey wolf population in nature, and has good global search ability, less parameters and fast convergence. Widely used in various fields. Grey wolf is a group of animals. Generally, there are 5-12 wolf in a wolf group, and there is also a strict social hierarchy between the wolf groups. As a new swarm intelligence optimization algorithm, grey wolf algorithm, like other intelligent optimization algorithms, has the disadvantages of easily falling into local optimum and slow convergence speed in the later stage. So differential evolution algorithm is introduced to optimize grey wolf algorithm.

Differential evolution algorithm (DE) is a random search algorithm proposed by storn and price in 1995, which has the characteristics of fast convergence, less control parameters, simple setting and robustness of optimization results. The core idea is to generate mutation individuals by mutating the target individuals, increase the population diversity, and then compare the fitness value with the parent individuals to select the optimal individuals [8–9]. Different from the traditional optimization algorithm, differential evolution algorithm uses two random variables in the population to select different individuals, and the traditional method is determined by the probability distribution function.

2.1.1 Population initialization
The population is initialized. The population size is \( N \), the spatial dimension is \( D \), the evolution algebra is \( t \), and the current population is \( x(t) = \{x_1(t), x_2(t), \ldots, x_D(t)\} \). Then the \( i \)th individual in the population can be expressed as \( x_i(t) = \{x_{i1}(t), x_{i2}(t), \ldots, x_{id}(t)\} \), and the boundary condition of the population is set as \( x_{ij}^{\text{low}} < x_{ij} < x_{ij}^{\text{up}} \). The \( j \) parameter of the initialized \( i \) individual can be expressed as a formula (1), where \( j = \{1, 2, \ldots, D\} \) denotes the parameter index.

\[
x_{ij}(0) = x_{ij}^{\text{low}} + \text{rand}[0,1] \cdot (x_{ij}^{\text{up}} - x_{ij}^{\text{low}})
\]

In: \( \text{rand}[0,1] \) denotes the random number between 0 and 1.

2.1.2 Variation operation
The mutation operation can generate a new individual through the difference strategy of three different individuals in the population. The operation process can be expressed as Formulas (2), and the generated mutation individuals are expressed as \( v_{ij}(t) = \{v_{i1}(t), v_{i2}(t), \ldots, v_{ijd}(t)\} \).

\[
v_{ij}(t+1) = x_{ij}(t) + F \cdot (x_{ij}(t) - x_{ij}(t))
\]

In the formula: \( x_{i1}(t), x_{i2}(t), \ldots, x_{id}(t) \) is three randomly selected individuals, and not the same. \( F \) is the mutation operator, which controls the amplification of the deviation variable and is generally valued as \([0, 2]\).

2.1.3 Interlace operation
In order to increase the diversity of the population, the new variable after mutation is used to cross with the original variable to obtain better individuals. The new variable can be expressed as \( u_i(t) = \{u_{i1}(t), u_{i2}(t), \ldots, u_{id}(t)\} \).

\[
u_{ij}(t+1) = \begin{cases} v_{ij}(t+1) & \text{if } \text{rand} (0,1) \leq C_R \text{ or } j = j_{\text{rand}} \\ x_{ij}(t) & \text{if } \text{rand} (0,1) > C_R \text{ and } j \neq j_{\text{rand}} \end{cases}
\]
In: \( rand(0,1) \) represents a random value between 0 and 1. \( C_g \) represents a crossover operator with a specific value. When the value is between 0 and 1, the larger the \( C_g \) value is, the greater the probability of the \( v_{ij}(t+1) \) value is, that is, the greater the possibility of crossover is. When the \( C_g \) value is smaller, it is conducive to maintaining population diversity and global pheromone search. \( j_{rand} \) represents a random selection dimension.

2.1.4 Selecting operation
Differential evolution algorithm compares the new vector \( u_i(t+1) \) generated by crossover with the original individual vector \( x_i(t) \) according to the greedy criterion, and takes the individuals with smaller fitness value as members of the next generation population.

\[
x_i(t+1) = \begin{cases} 
  u_i(t+1) & \text{if } f(u_i(t+1)) \leq f(x_i(t)) \\
  x_i(t) & \text{if } f(u_i(t+1)) > f(x_i(t))
\end{cases}
\]  

(4)

In the formula: \( f \) is the fitness function.

2.2. Differential evolution algorithm to optimize the process of gray Wolf algorithm
The basic idea of the grey wolf algorithm based on differential evolution algorithm optimization proposed in this paper is that the population first conducts surround, hunting and attack according to the GWO algorithm. Then, the differential evolution algorithm is used to update the optimal wolf position. Then according to the Wolf group update mechanism of strong survival mechanism, the position of the whole population is updated [10]. The hybrid optimization algorithm combining DE and GWO can make GWO jump out of local optimum. In addition, DE-GWAO algorithm can also improve the convergence speed of GWO algorithm. General hybrid algorithm performs GWO algorithm search and DE algorithm variation in turn, which is a two-layer serial structure. The process of DE-GWO hybrid algorithm is as follows:

Step1: Initialize three populations of the same size: parent population \( x(t) \), variant population \( v(t) \), offspring population \( u(t+1) \). Set wolf group size \( N \), maximum iteration number \( t_{max} \), search space dimension \( D \), search boundary conditions \( D \), mutation operator \( F \), crossover operator \( R_C \).

Step2: Calculate the individual fitness value of the parent population \( x(t) \), sort the fitness value of each individual, and select the three individuals with the smallest fitness value. The individual position is denoted \( x_\alpha, x_\beta, x_\delta \).

Step3: According to the formula \( x_{ij}(t+1) = \frac{1}{3} \sum_{k=1}^{3} (x_{ij}(t) + x_k(t) + x_\delta(t)) \), calculate the distance between the other individuals and the optimal three individual vectors, and get the updated new generation of parent population position vector, then calculate the individual fitness value.

Step 4: According to Formulas (2), the mutation population \( v(t) \) is obtained by mutation operation, and the offspring population \( u(t) \) is obtained by crossover operation according to Formulas (3). The fitness values of parent population and offspring population are compared, and the individuals with the smallest fitness value are selected as the next generation of parent population.

Step 5: Update the \( A, a, c \) parameters of the grey wolf algorithm, and determine the three individual wolf \( a \), wolf \( \beta \) and wolf \( \delta \) with the smallest fitness value in the new generation of parent population. Update \( x_\alpha, x_\beta, x_\delta \).

Step6: Determine whether to reach the maximum number of iterations \( t_{max} \), if not reached the maximum number of iterations, then jump step3, if reached the maximum number of iterations, then terminate the iteration, \( x_\alpha \) which represents the optimal solution.
3. Prediction performance verification of GWO-LSTM hybrid model

Using DE-GWO algorithm to optimize LSTM can improve the local optimization ability of LSTM network in later learning and training. In order to verify the effectiveness of DE-GWO-LSTM hybrid algorithm, DE-GWO-LSTM hybrid algorithm is applied to predict the degradation state of lithium-ion battery, and the prediction block diagram is shown in 1.

Fig. 1 DE-GWO-LSTM forecast flow chart

3.1. NASA dataset validation:

The data set is based on the 18650 lithium-ion battery repeated charge and discharge data set published by NASA. The data include the voltage, current, resistance and capacity of lithium-ion battery during charge and discharge. This paper briefly introduces the experimental steps, taking a group of B05, B06, B07, B18 battery as an example, the experimental temperature is 24, the experimental process is as follows:

Charging process: constant current (CC) followed by constant voltage (CV) charging method is used in charging. The charging is carried out in the CC mode of 1.5 A until the charging voltage reaches 4.2 V, and then the charging is continued in the CV mode until the charging current drops to 20 mA, and the sampling frequency is 1 min/time.

Discharge process: Constant current (CC) discharge is used to discharge at 2A until the cut-off voltage of each battery is reached. For example, the cut-off voltages of B05, B06, B07 and B18 batteries in NASA dataset are 2.7 V, 2.5 V, 2.2 V and 2.5 V, respectively, and the sampling frequency is 10 s/time.

Impedance measurement: The corresponding impedance was measured by electrochemical impedance spectroscopy in the frequency range of 0.1 Hz–5 kHz. Impedance measurement can obtain the variation of battery internal resistance with battery degradation.

In order to verify the accuracy of DE-GWO-LSTM prediction algorithm, the same data is used for capacity prediction, and the results are compared with GWO-LSTM algorithm. In the experiment, the B07 battery divides the training set data into 50% of the total data set, the first 84 sets of data, and the test set is the latter 84 sets of data. Due to the low cycle number of B18 battery, the first 60 groups were selected as the training, and the last 72 groups of data were selected as the test set. The capacity prediction results based on GWO-LSTM algorithm and DE-GWO-LSTM algorithm are shown in Figs. 2, and Figs. 3 are the prediction errors of the two algorithms.
From the prediction results and errors in Figs. 3-2 and 3-3, it can be seen that the DE-GWO-LSTM prediction algorithm has further improved the prediction ability of capacity, and its error is about 0.03 Ah. However, it is difficult to see how much the model performance is improved from the figure. In order to more intuitively reflect the prediction effect of DE-GWO-LSTM, the experiment was carried out 10 times, and the average value of the model evaluation index was taken. The prediction results are shown in Table 1.

| Battery | Assessment criteria | GWO-LSTM | DE-GWO-LSTM |
|---------|---------------------|----------|-------------|
| B05     | RMSE/Ah             | 0.0297   | 0.0199      |
|         | MAE/Ah              | 0.0257   | 0.0102      |
|         | MAPE                | 0.0186   | 0.0070      |
|         | R2                  | 0.9641   | 0.9825      |
| B06     | RMSE/Ah             | 0.0531   | 0.0469      |
|         | MAE/Ah              | 0.0398   | 0.0344      |
|         | MAPE                | 0.0303   | 0.0266      |
|         | R2                  | 0.7796   | 0.8489      |
| B07     | RMSE/Ah             | 0.0120   | 0.0119      |
|         | MAE/Ah              | 0.0061   | 0.0060      |
|         | MAPE                | 0.0040   | 0.0037      |
It can be seen from Table 1 that the overall performance of the DE-GWO-LSTM model is better than that of the GWO-LSTM model in the capacity prediction of the four batteries. Among them, the MAPE of B05, B06, B07 and B18 is increased by 1.16%, 0.37%, 0.3% and 2.16% respectively compared with that of the GWO-LSTM, and other performance indexes are also improved to some extent, which is not repeated here. The experimental results show that the proposed DE-GWO-LSTM can well conduct global search and local search, which improves the prediction performance to a certain extent.

### 4. Conclusion

This paper first introduces the differential evolution algorithm, and uses the differential evolution algorithm to update the position of the grey wolf algorithm, which improves the population diversity and avoids premature stagnation of the algorithm. Then, the life prediction model of lithium-ion battery based on the hybrid algorithm is designed. The GWO-LSTM model and DE-GWO-LSTM model are compared and analyzed using NASA data, and it is obtained that the hybrid algorithm has a certain improvement on the performance of the unoptimized model.

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