Research on Remaining Useful Life Prognostics Based on Fuzzy Evaluation-Gaussian Process Regression Method

WEIJIE KANG, JIYANG XIAO, MINGQING XIAO, YANGGUANG HU, HAIZHEN ZHU, AND JIANFENG LI
School of Aeronautics Engineering, Air Force Engineering University, Xi'an 710051, China
Corresponding author: Jiyang Xiao (741319920@qq.com)

This work was supported in part by the National Natural Science Foundation of China under Grant 61601505, and in part by the Shaanxi Province Innovative Talent Promotion Program under Grant 2018KJXX-002.

ABSTRACT To achieve efficient and accurate remaining life prediction and effectively express the uncertainty of prediction results, this paper proposes a remaining life prediction method based on fuzzy evaluation-Gaussian process regression (FE-GPR). First, the prediction of the remaining useful life (RUL) is affected by unknown variables, such as the environment, and it is difficult to achieve accurate predictions. It is necessary to effectively express the uncertainty of such prediction results. In this paper, we have put forward a RUL prediction method based on GPR, which can realize the RUL prediction with a confidence interval. Second, combined with the characteristics of the GPR method, an observation data preprocessing method based on fuzzy evaluation is proposed. The initial fuzzy evaluation method is established based on expert knowledge. Then, the classification nodes are optimized by the gravitational search algorithm (GSA) and historical data. This method, which uses fuzzy logic combined with expert knowledge, can avoid over-fitting in the case of limited data, and effectively improves the prediction accuracy of the GPR model. Finally, we use NASA PCoE lithium battery data for a case study. The results show that the FE-GPR method achieves a more accurate RUL prediction and effectively reflects the uncertainty of the prediction results.

INDEX TERMS Fuzzy evaluation, gaussian process regression, remaining life prediction, gravitational search algorithm.

I. INTRODUCTION

With the development of science and technology, the remaining useful life (RUL) prediction of complex systems has increasingly received attention. The existing remaining life prediction methods can be divided into three categories [16]: the reliability model, physical model and data driven. On the one hand, with increasing device complexity, the internal structure is difficult to describe by quantitative physical model; on the other hand, due to the environment and state of each device being different, the reliability model is not universally applicable. Therefore, it is difficult to make an accurate RUL prediction, especially in high-tech and high-energy fields such as aerospace [18]. The data-driven method based on observation data has a bright application prospect. The data-driven remaining life prediction method can be transformed into a time series data feature mining and prediction problem [12]. In this type of method, the RUL prediction process can be divided into four parts: observation data feature extraction, health index construction, degradation trend prediction, and RUL conversion. Researchers around the world have also proposed various prediction methods. However, achieving an accurate RUL prediction and reflecting the uncertainty of the results, with a limited amount of data, has both theoretical research and engineering practice significance. Two aspects of research in this paper have been carried out, which achieve a unified measurement of limited but diverse observation data, and effectively reflect the uncertainty of the remaining life prediction results. To carry out related research better, one must first analyze the research status of these two parts.

The existing RUL prediction models, such as the auto regressive (AR) [4] approach, are time-order data processing methods that predict the subsequent changes in the data by
the pre-order variation in the same data, and assume that it is a linear change. The support vector machine (SVM) [5] is a data classification and prediction method for the binary classification and prediction of data through supervised learning. The artificial neural network (ANN) [7] is a nonlinear prediction model, which is modeled after the human brain working mode, and possesses a strong nonlinear input and output mapping ability. These above methods use the historical data to learn the characteristics of the observation data of the target system, and do not rely on expert knowledge and specific physical models. They are suitable for suitable for life prediction research [2], [14].

However, the traditional GPR method also has shortcomings such as a poor performance in large data learning and a large computational overhead. When the GPR model is applied to the RUL prediction, it is necessary to effectively preprocess the observation data according to their characteristics. Existing methods, such as the principal component analysis (PCA) method [11], converts the variables that may be coupled in the system into linear irrelevance through an orthogonal transformation; similar methods include independent component analysis (ICA) [22] and linear discriminant analysis (LDA) [10]. These methods primarily identify and extract linear features from the data. Among the processing methods of nonlinear observation data, singular value decomposition (SVD) [9] is a feature decomposition method for arbitrary matrices. The empirical mode decomposition (EMD) method [8] is suitable for the analysis and processing of nonlinear and nonstationary signals. The minimum noise fraction (MNF) [19] analysis separates noise data and reduces the complexity of the calculation process. The above methods use the kernel transformation to reduce the dimensionality of the observed data. However, due to the increasing complexity of the device, these feature extraction methods require abundant historical data. In signal processing, the classic time-frequency representation (Fourier transform) can no longer meet such requirements, so a nonlinear time-frequency representation is needed, such as the MFCC [6]. When extracting feature parameters in the time and frequency domains, the process needs to be improved based on traditional methods such as Euclidean distance and angle [20]. Once the amount of data is insufficient, these methods become difficult to apply. The fuzzy evaluation method shows a certain advantage in the normalization of observation data [17], [23]. Although the problem of uncertainty variables cannot be completely overcome, in the case of the amount of data being insufficient, combining certain expert knowledge with fuzzy evaluation method can achieve a more effective feature extraction. Based on the above discussion, combined with the characteristics of the GPR method, an observation data processing method based on fuzzy evaluation is proposed. First, the initial fuzzy evaluation calculation method based on expert knowledge is proposed. The expert knowledge can effectively improve the initial computational efficiency of the method. Based on the GSA and historical data, the classification node parameters are optimized. The new data can be used to update the parameters and improve the practicality of the algorithm. The method proposed in this paper effectively combines the advantages of expert knowledge and parameter learning methods and can improve the prediction accuracy of the GPR method, especially when the data set is not large enough.

Therefore, this paper proposes a RUL prediction model based on fuzzy evaluation-Gaussian process regression (FE-GPR) to realize the RUL prediction with confidence interval. This method uses the fuzzy evaluation to normalize the observation data, combines the GPR model to achieve a more accurate RUL prediction, and effectively reflects the uncertainty expressed in the result of the remaining life prediction.

The implementation process of the method proposed in this paper is shown in Figure 1.

II. GPR-BASED RUL PREDICTION

Gaussian process regression (GPR) is a kind of Bayesian nonparametric model. It is a Bayesian model defined in an infinite dimensional parameter space. The model exhibits a good adaptability to an input data set, and it is not necessary to specify the input dimensions and the number of parameters. The output set of this method has an indeterminate expressive ability and is adapted to characterize the RUL.

Given a training data set \((x_i, y_i)\), setting \(G\) as the conversion relationship between input and output, the GPR model is defined, as in

\[
\begin{align*}
y_i &= G(x_i) + \epsilon \\
G &= GP(m, \sigma)
\end{align*}
\]

(1)

where \(\epsilon\) is a noise function, \(m\) is satisfied as a mean function and \(\sigma\) is a covariance function. Since the Gaussian process is a stochastic process, each component satisfies the multivariate Gaussian distribution. Set the training data input matrix consisting of \(x_i\) to \(X\), the training output vector to \(y\), and \(g\) to its theoretical vector value. Then, the corresponding test data input matrix is \(X_s\), and its theoretical vector value is \(g_s\); therefore, \(y\) and \(g_s\) satisfy the joint Gaussian distribution. This Gaussian process regression is defined, as in

\[
g_s | X, y, X_s \sim GP(m(X_s), cov(g_s))
\]

(2)

Let \(\sigma(X, X)\) be the covariance matrix formed by the training data. Similarly, we can obtain \(\sigma(X, X_s)\) and \(\sigma(X_s, X)^T\), and the calculation method for \(m(X_s)\) and \(cov(g_s)\) are defined,
as in

\[
\begin{align*}
    m(X_s) &= \sigma + \sigma(X, X_s)\sigma(X, X)^{-1}(y - m) \\
    \text{cov}(g_s) &= \sigma(X, X_s)\sigma(X, X)^{-1}\sigma(X, X_s)
\end{align*}
\]  

(3)

From the above analysis, after training the model with the training data set, and then inputting the test data set, the Gaussian distribution of \( g_s \sim GP(m(X_s), \text{cov}(g_s)) \) can be obtained, where \( m(X_s) \) is the mean value, and \( \text{cov}(g_s) \) is the covariance. Using the above method, a prediction interval value with a 95% confidence level is output, as in

\[
[m(X_s) - 2\sqrt{\text{cov}(g_s)}, m(X_s) + 2\sqrt{\text{cov}(g_s)}]
\]  

(4)

In the GPR method, it is first necessary to select the corresponding mean function and covariance function according to the characteristics of the applied object. Second, by adding noise terms, the inaccurate data acquisition effect in reality is simulated. Third, the initialization of the hyperparameters and the training of the GPR model are performed. Fourth, hyperparameters are optimized, and the observed data is inputted. Finally, the predicted value is given along with its corresponding confidence interval, and the simplified implementation process is shown in Figure 2.

In the actual application process, the input training data in the GPR model needs to be normalized, and the average value is zero. In the method proposed in this paper, all the data are processed by the fuzzy evaluation mechanism, and the classification node parameters are optimized to make it suitable for the GPR method.

### III. FE-GPR METHOD

#### A. FE METHOD BASED ON EXPERT KNOWLEDGE

In the process of predicting the RUL of an actual device, the magnitudes and dimensions of each observation datum are quite different, and even the value range of the same parameter may be large. Traditional health index extraction methods, such as ratios, distances, and angles, often fail to explain the meaning intuitively. Furthermore, the range of the calculation results is large, which is not suitable for further prediction models, and cannot be effectively used to compare with that of others. The normalized evaluation of known feature quantities using expert knowledge can effectively improve the readability of the data, and the entire feature quantity is included as the same magnitude for analysis; this treatment is convenient for the processing of the later prediction model, especially when the data set is not sufficiently large. However, how to effectively avoid the subjective nature of expert knowledge that can produce errors in the model has become an important part of this method.

On the one hand, through the Delphi method, multiple experts comprehensively evaluate the multidimensional observation data then synthesize the results, effectively avoiding the impact of a single expert on the evaluation results. On the other hand, through the key node optimization method presented in the next section, combined with historical data, the fuzzy evaluation method proposed in this paper is further optimized.

To achieve consistency with the following GPR method, the fuzzy evaluation method proposed in this paper satisfies the basic Gaussian distribution characteristics, and its mean value approaches zero. The initial value of each classification node is given by expert knowledge, and the fuzzy evaluation...
The observation data set $T_k = \{T_{k1}, \ldots, T_{ki}, \ldots, T_{ks}\}$ is subjected to a fuzzy evaluation. Let $f$ be the 5-segment membership function of the fuzzy evaluation. When the $T_{ki}$ value falls in the interval $(T_{dj}, T_{dj+1})$, where $j = 1, \ldots, 5$, then the fuzzy evaluation is defined, as in

$$x_{ki} = f(x_{ki}) = \frac{T_{ki} - T_{dj}}{T_{dj+1} - T_{dj}} \ast [f(T_{dj+1}) - f(T_{dj})] + f(T_{dj})$$  

(5)

**B. OPTIMIZATION METHOD BASED ON GSA**

The fuzzy evaluation method proposed above can be achieved by a relatively simple and efficient calculation. However, the value of its classification node $T_{dj}$ is highly dependent on expert knowledge and fails to effectively utilize the observation data accumulated by the test system. Therefore, it is necessary to optimize the classification node $T_{dj}$. Thus, this paper proposes a classification node optimization method based on information entropy and GSA, which can effectively optimize the classification effect.

Because the value of the classification node $T_{dj}$ has a complex coupling relationship with the fuzzy evaluation effect, to simplify the problem, the node value is discretized, which converts the problem into a discrete optimization problem. In the process of discretization parameter optimization, a good parameter selection should make the whole system tend to be stable so that the data are more concentrated near the midpoint of the classification interval, which makes the fuzzy evaluation method more effective in characterizing the current observation data distribution. Information entropy is a metric commonly used to select features in this type of problem, and its value can effectively reflect the stability of the current system. Therefore, the difference between the current fuzzy evaluation value and the evaluation value of the median value in the classification interval is defined as a probability function, and the calculation of the information entropy is defined, as in

$$\begin{align*}
F_i &= 1 - \frac{x_{ki}}{f(T_{dj+1} - T_{dj})} \\
H_i &= -\sum_{k=1}^{n} p_i \log_2 p_i
\end{align*}$$  

(6)

Taking the information entropy of the current input set as the objective function, the GSA is used to find the minimum value, and the parameters of each classification node are optimized. The GSA has a strong global search capability and is suitable for the experimental environment established in this paper. Its implementation process is shown in Figure 3.

The implementation process can be described as follows: first, initializing the relevant parameters; second, updating the value of the fitness; third, updating the values of $M$ and $a$; fourth, updating the location; fifth, determining the termination condition; and sixth, outputting the optimized results.

In this algorithm, the calculation method of the particle mass $M_i(t)$ is defined, as in

$$M_i(t) = \frac{\text{fit}(t) - \text{worst}(t)}{\text{best}(t) - \text{worst}(t)}$$  

(7)

where $\text{fit}(t)$ represents the fitness value of the particle, which is represented by the fuzzy evaluation value in this paper; $\text{best}(t)$ represents the optimal solution at time $t$; and $\text{worst}(t)$ represents the worst solution at time $t$, which is calculated as

$$\text{best}(t) = \max_{i \in \{1, 2, \ldots, N\}} \text{fit}(t)$$  

$$\text{worst}(t) = \min_{i \in \{1, 2, \ldots, N\}} \text{fit}(t)$$  

(8)

At time $t$, the gravitational force between the object $j$ and the object $i$ in the $k$th dimension is $F_{ij}^k(t)$, and its calculation method is defined, as in

$$F_{ij}^k(t) = G(t) \frac{M_{pt}^i(t) \times M_{aj}^j(t)}{R_{ij}(t) + \varepsilon} (x_{j}^k - x_{i}^k(t))$$  

(9)

where $\varepsilon$ represents a very small constant, $M_{aj}(t)$ represents the inertial mass of the active object $j$, and $R_{ij}(t)$ represents the Euclidean distance between the particles $X_i$ and $X_j$, from which the sum of the forces received by the particles in the $k$th dimension can be obtained.

During the iterative process of the algorithm, the velocity and position of the particle centroid is calculated from the acceleration. The acceleration is known from the fundamental theorem of physics and will not be described again. The speed
and position update calculation method are defined, as in
\[
\begin{align*}
    v_i^f(t+1) &= \text{rand}_i \times v_i^f(t) + \Delta v_i^f(t) \\
    x_i^f(t+1) &= \text{rand}_i \times x_i^f(t) + v_i^f(t+1)
\end{align*}
\tag{10}
\]

The above method is the standard execution process of the GSA, but the algorithm also has the practical problem that it is easy to be limited to the local optimal solution and the solution precision is not high enough. To solve the above problems, an improved method based on simulated annealing algorithm is proposed.

The simulated annealing algorithm is also a heuristic intelligent algorithm, and its implementation process is relatively simple and presents a strong robustness. The performance of the GSA can be effectively improved by solving multidimensional nonlinear problems.

In the above equation, \(\text{rand}_i\) is adopted to perform the update operation with strong randomness. The random number can be changed to the probability value \(p(t)\), and the calculation method is defined, as in
\[
p(t+1) = \frac{p(t)}{\log(10 + g \times AS)}
\tag{11}
\]
where \(AS\) is the simulated annealing speed, and the introduction of the above operator can effectively improve the global optimization capability of GSA. This improved method is called the GSA-AS algorithm.

When performing the particle speed and position update operation, it is necessary to judge whether the termination conditions are met in real time, and if so, the update operation is not performed, and if not, the iteration is continued. At the same time, the number of iterations and the objective function attenuation value are set as the termination conditions of the algorithm. When the termination condition is satisfied, the algorithm ends iteratively and outputs the parameter result of the algorithm optimization.

### IV. FORECAST VALUE EVALUATION METHOD

To effectively compare the accuracy of each method in the RUL prediction, this paper utilizes the index \(RA\) as the relative accuracy of the prediction [3]. When there are \(n\) prediction values, \(T_{RL}(k)\) represents the index \(RA\) as the actual value and the \(E_{RL}(k)\) is the \(k\)th predicted expectation value. The calculation method of \(RA\) is defined, as in
\[
RA_k = 1 - \frac{|T_{RL}(k) - E_{RL}(k)|}{T_{RL}(k)}
\tag{12}
\]

However, the commonly used performance evaluation indicators are \(PH\) and \(\alpha - \lambda\). \(PH\) indicates the time difference between when the accuracy requirement is first met and the failure time of the device under test, while \(\alpha - \lambda\) indicates whether the prediction accuracy reaches the accuracy requirement of \(\alpha\). These two indicators are fused using the method in [1] which is defined, as in
\[
PH = T_{FT} - \lambda^*
\tag{13}
\]

where \(T_{FT}\) represents the actual time to failure of the device under test; \(\lambda^*\) indicates that the time that the probability of the predicted value within the \(\pm \alpha\) interval of the true value is greater than \(\beta\) for the first time, and \(T_p\) is the time for prediction; \(\pi(r(\lambda))\) is the sum of the probabilities that the prediction result is within the \(\pm \alpha\) interval of the true value, where the \(\pi\) value can be used to evaluate the prediction accuracy; and \(\lambda^*\) is calculated, as in
\[
\lambda^* = \min \{\lambda | \lambda \in T_p, x \wedge (\pi(r(\lambda)) \pm \alpha) \geq \beta\}
\tag{14}
\]
where \( \alpha \) and \( \beta \) are constant parameters, and generally, \( \beta = 0.5 \). In this paper, \( \pi \) and the RA index are selected as the RUL prediction performance evaluation indicators. The larger the \( \pi \) and RA values are, the higher accuracy of the prediction method performs.

**V. CASE STUDY**

The experimental data in this paper uses the public data set NASA PCoE. The lithium battery data from the NASA “Battery Data Set 1” contains charge and discharge data for \( B_5, B_6, B_7 \) and \( B_{18} \) in 4 groups. The lithium battery has a standard capacity of 2 Ah, and defines a 70% standard capacity as its failure value. By predicting the trend of the remaining capacity value and comparing it with the set failure threshold, the predicted number of remaining charging cycles is obtained, and the remaining life of the lithium battery can be predicted. In the degradation process of each group of batteries, the remaining capacity can directly characterize its health state. The corresponding relationships between the remaining capacity and the number of charge and discharge cycles are shown in Figure 4.

In the prediction of the lithium battery RUL, the charging and discharging times are related to the environment in which the battery is used, and the difference is large. Therefore, this paper uses the number of charging cycles as the remaining life evaluation value, which can more accurately reflect the remaining life of the lithium battery. Thus, the RUL prediction of a lithium battery can be achieved using the FE-GPR method, and the expected capacity value and its confidence interval would be given.

In this experiment, \( B_{18} \) is taken as an example, and the other groups of data can produce similar results. The relevant parameters are set as follows: to shorten the optimization time, the initial fuzzy evaluation classification interval is divided into equal parts, and the basic step size is selected as 0.02. While ensuring a certain experimental precision, the algorithm optimization rate can be effectively improved. In the execution process, the maximum number of iterations is set to 200, \( G_0 \) is 100, and \( a = 20 \). The squared exponential kernel is selected as the kernel function of the GPR model.

In the lithium battery RUL prediction experiment.

First, the classification node parameter optimization experiment is carried out, and the \( B_6 \) battery is selected as the parameter optimization training data set. To achieve the consistency of \( B_{18} \) in the data amount, only the first 130 sets of data are taken, and the obtained results are shown in Table 2, with the information entropy \( H_i \) as the evaluation indicator.

Second, by analyzing the amount of data in each group, the rationality of the classification result can be understood intuitively, and \( B_6 \) is taken as an example to determine the amount of each classification after optimization, as shown in Table 3.

It can be seen from Table 2 and Table 3 that the fuzzy evaluation method proposed in this paper significantly reduces \( H_i \), effectively improves the classification effect of the data set, and achieves a better classification effect.

The above contents can be used to analyze the classification effect of the proposed fuzzy evaluation method. Next, the efficiency of the proposed GSA-AS algorithm is analyzed. The computational complexity, computational work-load and computational efficiency of the method need to be analyzed. The classical BP neural network algorithm and GSA are meaningful as comparison targets. However, due to the relatively mature research on computational analysis of the above methods, we would not repeat the related work. In engineering applications, the running time of the algorithm is the most intuitive and significant efficiency. In this experiment, the algorithms are implemented on the MATLAB R2019b platform. And the computer used is as follows: i5 processor, frequency 1.80GHz, memory 4GB and win10 system. In addition, the running time and \( H_i \) values of each method are the comparison indicator. In the BP neural network method, the neural network was set as the 11-14-2 hierarchical structure, and the gradient descent method was used to adjust the input weight and offset between layers. The GSA and its improvements use the classic open source code.

| Table 2. Parameter optimization. |
|-----------------|----------------|----------------|----------------|----------------|----------------|----------------|
| \( Td_1 \) | \( Td_2 \) | \( Td_3 \) | \( Td_4 \) | \( Td_5 \) | \( H_i \) |
| Initial | 1.3 | 1.4 | 1.6 | 1.8 | 2.0 | 2.1 | 2.714 |
| Optimal | 1.30 | 1.40 | 1.50 | 1.76 | 1.92 | 2.02 | 2.263 |

| Table 3. The amount of data. |
|----------------|----------------|----------------|----------------|----------------|
| Failure | Low | Mid | High | Full |
| Initial | 23 | 47 | 24 | 31 | 5 |
| Optimal | 23 | 29 | 36 | 25 | 17 |
Since the calculation accuracy ($H_i$) and the calculation speed (Time/s) are a natural contradiction, it is difficult for a single algorithm to achieve a fast solution with a high precision. The experimental results show that the running time of the GSA-AS algorithm is larger than that of the GSA, which is due to the AS factor, but the proposed algorithm is still better than the classic BP method. Moreover, the GSA-AS algorithm shows an excellent classification accuracy and is suitable for the RUL prediction service environment with a low real-time requirement.

However, the accuracy of the FE-GPR method will be discussed in the following part.

Third, the first 40 sets of the $B_{18}$ data are used for modeling and training, and the latter 80 sets of data are used to verify and analyze the model. The failure threshold was 1.4 Ah, so the number of unfailed data sets was 96. To facilitate the analysis, the Bayesian LS-SVR method proposed in [3] is selected, and the GPR method proposed in [15] is compared with the FE-GPR method proposed in this paper. For an intuitive comparison, GPR and FE-GPR only reflect their expected values, and the confidence interval values are analyzed and will be explained later. The experimental results are shown in Figure 6.

From the experimental results, we can conclude that the GPR method can better reflect the degradation trend of the device under testing conditions, but the accuracy is insufficient. The prediction accuracy of LS-SVR method increases with the increase of data amount. The prediction accuracy is the highest after 80 sets of data; however, but the predictive effect is not good, and the practicability needs to be improved. The FE-GPR method can better reflect the degradation trend of the effective life interval, and has a better prediction accuracy. For the prediction of remaining life, when the first 40 sets of data are used, the actual number of remaining charge and discharge cycles is 56, whereas the predicted value of the LS-SVR method is 63. In addition, the predicted value of the GPR method is 42, and the predicted value of the FE-GPR method is 53. It is obvious that the FE-GPR method has a higher prediction accuracy.

Fourth, in order to further analyze the validity of the uncertainty prediction of the FE-GPR method, the upper and lower limits of the confidence interval and the true degradation trajectory are taken as shown in Figure 7.

It can be seen that the degradation trajectory of the battery basically falls within the confidence interval of the FE-GPR method. Therefore, the method proposed in this paper provides a solution to the uncertainty expression of the prediction results. At the same time, since the battery had uncertain charging time intervals, the battery capacity has a significant rebound phenomenon. This brings some difficulties to the remaining life prediction of the battery, but the uncertainty output of the FE-GPR method solves this problem better.

Finally, the influence of the amount of training data on the prediction results is analyzed. The historical data of 40 groups, 60 groups and 80 groups are selected for training. The mean RUL prediction results and corresponding evaluation indicators of each method are shown in Table 4.
From the above results, we can obtain these following conclusions: as the amount of training data increases, the prediction accuracy of each method is improved to some extent. Among them, the LS-SVR method has the best prediction accuracy when the sample size is the largest, and its RA value reaches 0.916. However, although the traditional GPR method can better reflect the degradation trend, the prediction accuracy is always lower than the other two. The FR-GPR method has a good prediction accuracy for small samples. When the training data is 40 sets, the π value reaches 0.256, which is better than other methods, and its prediction accuracy is also being further improved with the increase in training data. On the other hand, the confidence intervals for the predicted remaining lifetimes from the GPR method and the FE-GPR method are given in the table. It can be seen that the real remaining lifetime values all fall in the output confidence interval of the FE-GPR method. Therefore, the FE-GPR method proposed in this paper has a better prediction accuracy and uncertainty of predictive expression.

VI. CONCLUSION

With the continuous development of device technology, the RUL prediction has increasingly attracted attention. However, there are difficulties regarding in feature extraction of the observation data and the inability of the prediction result to effectively reflect the uncertainty of the remaining life. This paper presents related research on the above two aspects and proposes the FE-GPR method.

For one aspect, the observation data is processed by the fuzzy evaluation method. The FE method can effectively combine expert knowledge and historical data, which could effectively improve the accuracy of remaining life predictions. Through experiments, the FE method can effectively improve the accuracy of prediction. The classification accuracy of the GSA-AS method is lower than that of the BP and GSA methods, but it has a good data feature extraction ability. In addition, the average value of the prediction accuracy RA index reaches 0.832, which is 0.119 higher than that of classic GPR method, which achieves a more accurate RUL prediction, especially when the data set is not large enough. Additionally, for the uncertainty characteristics of the remaining life prediction, the life prediction is performed by the GPR method. The GPR method can effectively deal with the data prediction problems of high dimensions and small samples, besides the FE method to effectively improve the applicability and accuracy of this prediction method. Through experiments, the RA value of the small sample (40 sets of training data) reached 0.739, which is better than that of LS-SVR and the GPR methods. In summary, the FE-GPR method proposed in this paper has performed some research to improve the accuracy of the remaining life prediction method.

This method has been verified by NASA lithium battery data and can be generalized to other equipment. Due to space limitations and the insufficient credibility of our own data, this method is no longer verified by other data sets. However, this theoretical method has a certain generality, and with minor changes, it could be applied to other objects. Other than that, just as fuzzy evaluation values are easy to understand, it is convenient for science and technology workers to interpret and understand the observation data more intuitively by this method. Additionally, it could also reduce the personnel skill requirements for device maintenance, which has certain value for engineering applications.

In the future, it is necessary to do certain further research while combining the knowledge reasoning method and more refined prediction model for key components.

REFERENCES

[1] C. K. Arthur, V. A. Temeng, and Y. Y. Ziggah, “Novel approach to predicting blast-induced ground vibration using Gaussian process regression,” Eng. Comput., vol. 36, no. 1, pp. 29–42, Jan. 2020.
[2] X. Bintai, M. Xianglu, T. Anqi, S. Yongjian, C. Libin, and J. Yingjie, “Prediction for state of charge of lead-acid battery by particleswarm optimization with Gaussian process regression,” J. Nanjing Univ. Sci. Technol., 2018.
[3] X. Z. Chen, J. S. Yu, Y. Y. Tang, and X. Y. Wang, “Probabilistic prediction of remaining life of lithium batteries based on Bayesian LS-SVR,” J. Acta Aeronautica Sinica, vol. 34, no. 9, 2013, pp. 2219–2229.
[4] H. C. Dong, S. T. Zhang, Q. H. Li, and C. H. Wang, “A new approach to battery capacity prediction based on hybrid ARMA and ANN model,” Appl. Mech. Mater., vols. 190–191, pp. 241–244, Jul. 2012.
[5] Z. Fangdan, J. Jichun, and C. Kunlong, “Peak power prediction model for batteries based on data statistical characteristic and GS-SVM,” J. Electr. Power Automat. Equip., 2017.
[6] C. Fei, Q. Xin, and Z. Shen, “Method of failure prediction and evaluation based on MFCC feature extraction,” J. Appl. Res. Comput., 2015.
[7] L. Guo, N. Li, F. Jia, Y. Lei, and J. Lin, “A recurrent neural network based health indicator for remaining useful life prediction of bearings,” Neurocomputing, vol. 240, pp. 98–109, May 2017.
[8] S. Hong, Z. Zhou, E. Zio, and K. Hong, “Condition assessment for the performance degradation of bearing based on a combinatorial feature extraction method,” Digit. Signal Process., vol. 27, pp. 159–166, Apr. 2014.

TABLE 4. Experimental result.

| Data | True RL | LS-SVR | GPR | FE-GPR |
|------|---------|--------|------|--------|
|      | Eₚₜ | RA | π | Eₚₜ | RA | π | Eₚₜ | RA | π |
| 40   | 20 | 0.641 | 0.212 | 42 | [35, 49] | 0.574 | 0.172 | 53 | [47, 60] | 0.739 | 0.256 |
| 60   | 25 | 0.824 | 0.377 | 29 | [21, 35] | 0.739 | 0.353 | 41 | [37, 51] | 0.864 | 0.421 |
| 80   | 15 | 0.916 | 0.553 | 11 | [10, 17] | 0.826 | 0.448 | 13 | [12, 18] | 0.893 | 0.574 |
[9] M. Kang and J.-M. Kim, “Singular value decomposition based feature extraction approaches for classifying faults of induction motors,” Mech. Syst. Signal Process., vol. 41, nos. 1–2, pp. 348–356, Dec. 2013.

[10] E. K. Laitinen, “Classification accuracy and correlation: LDA in failure prediction,” Eur. J. Oper. Res., vol. 183, no. 1, pp. 210–225, Nov. 2007.

[11] T. Wang, G. Zhang, J. Zhao, Z. He, J. Wang, and M. J. Perez-Jimenez, “Online state of charge estimation for lithium-ion batteries using Gaussian process regression,” in Proc. 42nd Annu. Conf. IEEE Ind. Electron. Soc., Oct. 2016, pp. 998–1003.

[12] J. Y. Pang, Y. T. Ma, and D. T. Liu, “Indirect prediction method for residual life of lithium ion batteries,” J. Chin. J. Sci. Technol., no. 1, 2014.

[13] P. Baraldi, F. Di Maio, S. Al-Dahidi, E. Zio, and F. Mangili, “Prediction of industrial equipment remaining useful life by fuzzy similarity and belief function theory,” Expert Syst. Appl., vol. 83, pp. 226–241, Oct. 2017, doi: 10.1016/j.eswa.2017.04.035.

[14] G. Ozcan, M. Pajovic, Z. Sahinoglu, Y. Wang, P. V. Orlik, and T. Wada, “Semi-supervised failure prediction for oil production wells,” in Proc. IEEE 11th Int. Conf. Data Mining Workshops (ICDMW), Vancouver, BC, Canada, vol. 11, Dec. 2011, pp. 434–441.

[15] D. Mazurkiewicz, “Maintenance of belt conveyors using an expert system based on fuzzy logic,” Arch. Civ. Mech. Eng., vol. 15, no. 2, pp. 412–418, 2015, doi: 10.1016/j.acme.2014.12.009.

[16] M. Kang and J.-M. Kim, “Singular value decomposition based feature extraction in time and frequency domains of feed motor current,” Int. J. Mach. Tools Manuf., vol. 48, no. 1, pp. 29–39, Jan. 2008.