Storage Life Prediction Method of the Aerospace Electromagnetic Relays Based on Physics of Failure and Data-Driven Fusion

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ABSTRACT The storage life prediction of the aerospace electromagnetic relays(AEMRs) has become an engineering challenge due to the nonlinearity of AEMRs’ complex degradation process. As the widely used life prediction approaches, data-driven methods also failed to address this issue effectively. The main reason is their inherent flaw: the inability to effectively quantify the direct correlation between top-level failures and underlying physical or chemical changes. Therefore, based on the fusion of the physics of failure(PoF) and data-driven, a storage life prediction method for AEMR has been proposed in this manuscript. Firstly, according to the characteristics of the AEMR during storage, the degradation performance parameters were analyzed, and the accurate expression of the degradation model was established based on the failed physical process. Then, the degradation process of AEMR was modelled by fusion of the PoF and data-driven, while the model parameters were updated by an improved particle filter based on degradation data. Finally, the storage life of AEMR was predicted by the updated model. Compared with typical methods and machine-learning-based methods, on the one hand, the results show that the proposed method can restrain the fluctuation of nonlinear degradation data to some extent and make the fluctuation range of prediction error more stable, thus making the life prediction result more accurate. On the other hand, even when there is only a small sample size of observation data, it also gives a good prediction effect. Moreover, it establishes the relationship between life and underlying physical and chemical processes, which will be conducive to the optimization design of AEMR, to further improve the reliability of weapons and equipment.

INDEX TERMS Aerospace electromagnetic relay, storage life prediction, physics of failure, data-driven.

I. INTRODUCTION

Due to its high reliability, long life, solid on-off performance and other positive features, in the vital position of weapon equipment systems widely using AEMR to undertake the system power supply and distribution and timing logic control. So once one fails, the whole system will collapse. At the same time, the reliability of AEMR is the worst among many military electronic devices, so it is reasonable to consider that the reliability of AEMR determines the reliability of weapon equipment systems. It might argue that the reliability of AEMR is of considerable importance to guarantee the effective use of weapon systems and even national defense security [1], [2]. In peacetime, weapons and equipment such as missiles and torpedoes often experience a storage period of more than a decade from production to use. During storage, even in a relatively stable storage environment, external stress will inevitably affect them, ultimately resulting in internal degradation of AEMR and failure. However, through the life prediction of AEMR, according to the predicted state, replacing that with severe degradation will effectively extend the storage life of the entire weapon system and the service reliability after the storage period. Therefore, it is necessary to research AEMR’s storage life prediction technology.

Nowadays, with the development of big data technology, data-driven-based is becoming widely applied for life
prediction methods. The fundamental idea of their methods is that through the feature extraction of equipment historical and maintenance data, choose an appropriate mathematical model, based on the real-time gathering of operational data, through the model to realize life prediction. Some researchers have conducted studies that used their methods. For instance, Deng et al. [3] used a method of filter that is a double adaptive extended Kalman filter algorithm to estimate model parameters and charged state. In this method, they used a least-squares support vector machine to predict battery capacity, coupling state estimation and capacity prediction to indirectly predict life. Unlike filtering methods, Li et al. [4] presented a data-driven method based on similarity theory matching failed reference data with developed products, which effectively predicted the remaining useful life of the relay by calculating point-state similarity and fuzzy similarity. In addition, a new data-driven method can be found in [5], combining long and short-term memory neural networks and the adversarial domain network. They verified the method’s feasibility with the data provided by NASA. While the data-driven method can obtain comparatively accurate life prediction results without describing the failed physical process of the research object specified, it only reflects the fitting relationship between degradation characterization and life. It fails to accurately describe the quantitative relationship between the changes in underlying physical and chemical parameters and product life.

There are still some limitations when further considering the application of data-driven methods to the research objects in this paper. On the one hand, many factors are coupling influencing the storage degradation process of AEMR, and the current classical model cannot accurately describe its degradation trajectory. On the other hand, data-driven approaches often need to build on vast data to achieve accurate predictions. Nevertheless, the application object of AEMR generally has the trait of “long-term storage and one-shoot.” Suppose the degradation data is obtained by frequently power-on tests on AEMR, which will lead its storage life to be substantially affected, making it harder to reflect the reliability of the results when using data for life prediction. Therefore, applying the data-driven method in the life prediction of AEMR has some restrictions.

In fact, using the method based on the PoF can develop a theoretical model describing the mechanism of product degradation from the physical and chemical perspectives. At the same time, based on the macroscopic appearance characteristics and microscopic process of product failure, and accurately reflects the theoretical relationship between characterization parameters and life. In this way, the life prediction of production can be achieved by using a modest amount of data and integrating the environmental elements related to equipment with the empirical knowledge of specific production and the defect growth equation [6], [7], [8]. If the life prediction method can be data-driven, merging the PoF model will make up for the data-driven method, making the life prediction results with the underlying degradation failure process reflect the correlation and reducing the demand for the quantity of data. For further, the life prediction results of AEMR can reflect its authenticity.

Life prediction using the fusion method is currently in the exploratory stage, but some academics have successfully applied it in their respective domains. To explain that the fusion method is more advantageous than a single model, Chao et al. [9] presented a fusion method of the PoF and data-driven which achieved effective remaining useful life prediction for turbofan engines under actual flight conditions. A fusion algorithm by merging the electric-thermal coupling model with state monitoring data in [10] realized the online reliability evaluation of IGBT. Chen et al. [11] proposed an adaptive residual life prediction method based on the combination of EM-EKF for airborne electronic equipment and proved the accuracy of the prediction method. Although Chen et al. chose an extended Kalman filter in their paper to broaden the application scope of the Kalman filter to solve nonlinear problems, linearization of nonlinear problems by Taylor expansion and omission of higher-order terms may easily lead to bring larger estimation errors. The particle filter (PF) algorithm, theoretically, has more significant advantages for treating nonlinear system problems [12], [13], [14], [15], but its particle degradation problem also seriously restricts the practical application effect, resulting in an unsatisfactory final prediction result. Therefore, solving the particle degradation problem will significantly enhance prediction accuracy.

In summary, using the data-driven AEMR storage life prediction method must address three problems. The first is that existing models failed to capture the representative relationship between the underlying mechanism and AEMR lifetime. The second is that data-driven methods require excessive data, making it hard for AEMR to provide vast data. The third is particle deterioration in the implementation of the fusion method. Therefore, in this paper, we propose a fusion method of the PoF and a data-driven to predict the storage life of AEMR. Firstly, according to the storage characteristics of AEMR, the physical failure process of storage degradation is analyzed, and establish a model. Then, combining the PoF model with the data-driven method, the modeled degradation model, and using the improved particle filter to update the model. Finally, the updated model predicts the storage failure life according to the failure threshold.

The remainder of this article is organized as follows. Section II, the PoF model of AEMR is established based on stress relaxation. In section III, we proposed an improved particle filter algorithm and conducted particle diversity tests. In section IV, a case study is carried out to verify the storage degradation data of AEMR. Section V concludes this article.

II. A MODEL OF STORAGE DEGRADATION OF AEMR BASED ON STRESS RELAXATION

The internal reeds, coils, bobbins, enameled wires, and magnetic materials of AEMR are susceptible to deterioration during long-term storage, which affects the movement and contact properties of the AEMR itself. That will fail if it
exceeds the acceptable range. In the case of AEMR in storage, the main reason is the stress relaxation of the reeds, which decreases the response force and therefore affects the matching of the reaction force characteristics, resulting in contact failure and malfunction [16].

A. BASEMENT OF STRESS RELAXATION THEORY

Stress relaxation [17] is a phenomenon when a part or material is subjected to deformation, transitions from elastic to plastic strain and stress decrease with time. When the reed material is processed through deformation and failure process treatment, the uneven distribution of the intergranular type II stress and macroscopic stress in the material leads to an increase in the elastic strain energy of system, making the whole system, which is a stable state, destabilized. Then the free energy of a system can be expressed as:

\[ dG = dU - T \cdot dS + dE \]  
(1)

where \( dG \) denote the entropy change in system, \( dU \) is internal energy, \( dG \) is Gibbs free energy, \( T \) is absolute temperature.

When the reed is subjected to bending stress, we have \( dE = A \cdot f \cdot dp \cdot d \rho \) denote the load micro-element on the reed, \( f \) is deflection of the reed, and \( A \) is constant. At the lower temperature, \( dU = T \cdot dS \), \( dG = dE(dG) \) denotes the driving force of the stress relaxation process. So if \( dG \) is less than 0, then \( dE \) is less than 0, which means that the elastic strain energy decreases gradually during stress relaxation process.

Therefore, the stress relaxation in the macroscopic changes as \( dG = -A \cdot f \cdot dp \) and the reduction of load-bearing capacity. Microscopic changes as experience of merging, grain boundary elimination, individual grain growth, twin band elimination and boundary corner passivation.

B. REEDS REACTION DEGRADATION MODEL BASED ON STRESS RELAXATION

Since during stress relaxation, the total strain \( \varepsilon_t \) is the sum of plastic strain \( \varepsilon_p \) and elastic strain \( \varepsilon_e \):

\[ \varepsilon_t = \varepsilon_p + \varepsilon_e = \frac{\sigma_0}{E_c} + \varepsilon_p \]  
(2)

where \( \sigma_0 \) is initial stress, \( \sigma \) is residual stress, \( E_c \) is elastics modulus. Take the derivative of both sides of (2):

\[ \dot{\varepsilon}_p = \frac{d\sigma}{E_c dt} \]  
(3)

According to Orowan equation [18], the plastic strain rate can be expressed as:

\[ \dot{\varepsilon}_p = \Psi \cdot \rho_m \cdot b \cdot \nu \]  
(4)

where \( \Psi \) is the geometric parameter, \( \rho_m \) is the movable dislocation density, \( b \) is burgers vector and \( \nu \) is the average dislocation rate. According to the Johnston-Gilman formula, the average dislocation rate can be expressed as:

\[ \nu = B(\sigma^*)^{m*} \]  
(5)

where \( B \) and \( m^* \) are the material constants at a given temperature. Simultaneous (3) to (5) are obtained:

\[ \dot{\sigma}^* = -\Psi \cdot E_c \cdot \rho_m \cdot b \cdot (\sigma^*)^{m*} \]  
(6)

Further, it can be obtained:

\[ \sigma^* = (kt + a)^{-n} \]  
(7)

The equation (7) is Li’s equation, where \( \sigma^* \) is the effective stress, \( k = \Psi \cdot (m^* - 1) \cdot b \cdot B \cdot \rho_m \cdot E_c \), \( a = \sigma_0^*(1 - m^*), n = 1/(m^* - 1) \), \( \sigma_0^* \) is initial effective stress.

According to (7), after the stress relaxation of the spring occurs, the reaction force \( F_s \) of the AEMR meets the following relationship:

\[ F_s = c(kt + a)^{-n} \]  
(8)

The relationship between the density of movable dislocations and time is considered in the [19]:

\[ \rho_m(t) = A/(t + a_0) \]  
(9)

Substituted (9) into (6) can be solved:

\[ \sigma^* = (k' \cdot \ln(t + a_0) + D)^{-n} \]  
(10)

The equation (10) can be established under the condition that dislocation density is unevenly distributed. In the equation, \( n = 1/(m^* - 1) \), \( D = \sigma_0^*(1-m^*) - (m^* - 1) \cdot \Psi \cdot E_c \cdot b \cdot B \cdot A \cdot \ln a_0 \), and \( k' = \Psi \cdot (m^* - 1) \cdot b \cdot A \cdot B \cdot E_c \). If the distribution is uniform, the Li equation can be used directly.

Therefore, according to (10), the degradation formula of the reaction force can be expressed as:

\[ F_s = c(k' \ln(t + a_0) + D)^{-n} \]  
(11)

C. THE STORAGE DEGRADATION MODEL OF RELEASE TIME OF AEMR BASED ON PHYSICS OF FAILURE

By combining the structural features of the AEMR with the storage degradation mechanism analysis, [16] concluded that the increase in the release time during storage is mainly caused by the reduction of the reed reaction force. However, the reed is sealed inside the relay, and it is not easy to directly open and test the stress relaxation state of the reed during actual storage. Therefore, finite element simulation can be used to obtain the relationship between the initial force of the reed and the release time, and the results are shown in Fig. 1. The approximately linear relationship between the release time \( T_{release} \) and the initial force \( F_{initial} \) of the underlying performance parameter as the reaction force of the reed decreases in a certain range. Therefore, this section will express the relationship between the two as a linear function:

\[ T_{release} = a \cdot F_{initial} + b \]  
(12)

where \( a \) and \( b \) represent model parameters related to design and manufacturing process parameters, characterizing individual heterogeneity among AEMRs of the same batch.

From the analysis of mechanism, it can be seen that the basic reason for the reduction of reaction force is caused by
the stress relaxation of the reed during the storage period. Therefore, in this paper, the initial force is taken as the characterization parameter of reaction force, and the release time degradation model of AEMR can be obtained by substituted (11) into (12):

$$T(t)_{\text{release}} = a_1 \cdot (a_2 \ln(t + a_0) + a_3) - a_4 + a_5$$  \hspace{1cm} (13)

To make (13) meaningful at time $t = 0$, let $a_0 = 1$. The remaining $a_1, a_2, a_3, a_4, a_5$ are parameters to be fitted, and $T(t)_{\text{release}}$ is the release time of the AEMR.

III. PARAMETER UPDATING METHOD BASED ON IMPROVED PARTICLE FILTER

A. NORMAL PARTICLE FILTER

Particle filter (PF) is quite effective at dealing with non-Gaussian, nonlinear problems and can approximate any probability density function by generating particles by finding a set of random samples propagating in the state space [20], [21].

Firstly, state transition equation and observation equation are constructed:

$$
\begin{align*}
    x_k &= f(x_{k-1}, q_{k-1}) \\
    y_k &= f(x_k, r_k)
\end{align*}
$$  \hspace{1cm} (14)

where $x_k$ is the predicted value, $y_k$ is the observed value, $q_{k-1}$ is the predicted noise and $r_k$ is the observed noise respectively.

If the initial probability density function (PDF) of the known state is $f(x_0 | y_0) = f(x_0)$, the above nonlinear dynamic system can be regarded as a hidden Markov process, which satisfies the following two equations:

$$
\begin{align*}
    f(x_k | x_{k-1}, y_{0:k-1}) &= f(x_k | x_{k-1}) \\
    f(y_k | x_k, y_{0:k-1}) &= f(y_k | x_k)
\end{align*}
$$  \hspace{1cm} (15)

According to the Bayesian theory, the conditional probability distribution function (CDF) $f(x_k | y_{0:k})$ contains all the information from measured value $y_{0:k}$ to predicted value $x_k$. The values obtained by the estimation criteria can be obtained in this CDF. Therefore, the filtering problem is transformed into the issue of solving the distribution. Under the framework of Bayesian filtering, the CDF can be obtained in two stages: prediction and update. Then the state prediction equation can be written:

$$
    f(x_k | y_{1:k-1}) = \int f(x_k | x_{k-1}) f(x_{k-1} | y_{1:k-1}) dx_{k-1}
$$  \hspace{1cm} (16)

the state update equation can be written:

$$
    f(x_k | y_{1:k}) = \frac{f(x_k | y_k) f(x_k | y_{1:k-1})}{f(y_k | y_{1:k-1})}
$$  \hspace{1cm} (17)

It is evident from the above formula that solving distribution may face dimensional catastrophe, so the particle filter (PF) algorithm is proposed to solve the integral by using particle approximation distribution. Its core idea is based on the sequential Monte Carlo sampling method. However, sampling is usually difficult to sample the target PDF. Therefore, the importance density function, which is easy to sample, is selected for sampling, and samples are given weight to complete the approximation of the target PDF through the weighted samples. Therefore, the PDF can be expressed as:

$$
    f(x_k, y_{1:k}) \approx \frac{M}{\sum_{i=1}^{M} \omega^i} \delta(x_k - x_k^i) \\
    \omega^i = \frac{f(y_k | x_k^i) f(x_k^i | y_{1:k-1})}{H(x_k^i | y_{1:k-1}, y_k)}
$$  \hspace{1cm} (18)

where $\delta(\cdot)$ is Dirac function, $H(\cdot)$ is the importance density function, and $\omega^i$ is the connection weight.

In this paper, when using the particle filtering algorithm for life prediction of AEMRs, the nonlinear characteristics presented by the degradation process of aerospace relays lead to a particle degradation problem in the solution process, thereby failing to obtain good approximation results. Therefore, resampling is required. Generally, a random number $u_i \in (0, 1)$ is selected, and when Equation (19) is met, the particles corresponding to $\omega^i$ are selected as resampling samples.

$$
    \sum_{k=1}^{j-1} \omega^k \leq u_i \leq \sum_{k=1}^{j} \omega^k
$$  \hspace{1cm} (19)

However, the traditional re-sampling method only replicates the particles with higher weights and abandons the particles with lower weights. As a result, some high-weight particles may be sampled multiple times, and even worse, in extreme cases, all the sampling operations are carried out around only one high-weight particle, which will seriously lose the diversity of particles, fail to cover the region of the posterior distribution, and seriously affect the subsequent prediction update [22], [23]. Therefore, it is necessary to introduce an effective re-sampling strategy to solve the problem of particle scarcity in the estimation process, given the nonlinear degradation characteristics of the objects studied in the storage process.
B. IMPROVED PARTICLE FILTER RE-SAMPLING STRATEGY

To address the problem of particle degradation in this paper, we proposed a method of combining an intelligent particle filter [24] with an elite retention strategy [25], which can maintain high-weight particle excellence genes without losing particle diversity. Firstly, we sorted the particles according to the weight values and used the effective number of particles to separate the particles with high weights from those with low weights. Then the best high-weight particles are used as elite particles to adopt the retention strategy, and the remaining ordinary particles are crossed and mutated into new particles. The best high-weight particles in the evolved population are compared with the elite particles to decide whether to update. Finally, the combination of elite and new particles was used to approximate the PDF solution. The flow of this re-sampling strategy method is shown in Fig. 2.

Separation: the particles are divided into two groups of high weight and low weight according to their weight size. The high-weight group is reserved for elite particles, and the low-weight group is common for crossover and mutation operation.

\[
x_k^l \in \begin{cases} P_L, & \omega_k^l \leq \sigma \\ P_H, & \omega_k^l > \sigma \end{cases}
\]

where \( P_L \) is the set of particles with low weight, \( P_H \) is the set of particles with high weight, \( x_k^{\text{elite}} \) is elite particle belong to \( P_H \), and \( \sigma \) is the weight used to distinguish particles. By calculating the number of effective particles and sorting the weight \( \omega_j^l \) in descending order, \( \sigma \) is the Neff\textsuperscript{th} value in the particle sequence.

\[
\text{Neff} = \frac{1}{\sum_{i=1}^{n} \omega_k^l} \quad (21)
\]

Crossover: as shown in (22), particles with lower weights after crossover are represented as \( x_{kS}^l \). \( x_{kL} \) is particles randomly taken from \( P_L \).

\[
x_{kS}^l = \alpha x_{kL} + (1 - \alpha) x_{k}^{\text{elite}} \quad (22)
\]

where, \( l = 1, 2, \ldots, L \), \( L \) is the number of particles in \( P_L \). For each \( x_{kS}^l \), it is matched by particle \( x_{kL}^l \) randomly selected from \( P_L \), and \( \alpha \) is the cross coefficient of particles randomly selected from \( [0, 1] \).

Mutation: in order to improve the diversity of particles, the new particle \( x_{kN}^l \) is obtained by mutation operation on the crossed particle \( x_{kS}^l \).

\[
x_{kN}^l = \begin{cases} 2x_{k}^{\text{elite}} - x_{kS}^l, & \xi \leq \beta \\ x_{kS}^l, & \xi > \beta \end{cases} \quad (23)
\]

where \( x_{kN}^l \) is the mutated particle, \( \xi \in [0, 1] \) is the random variation coefficient, \( 1 - (\text{Neff} / N) \) is the adaptive variation probability, and \( N \) is the total number of particles.

Judgment: the weights of the mutated particle are calculated and compared with the \( x_{k}^{\text{elite}} \), and the elite particle is updated if they have a higher value.

C. A TEST OF PARTICLE DIVERSITY

This part is the test of particle diversity. The actual storage degradation data of AEMR is used to verify this method, where the particle number is set to 100. The particle distributions at storage time points \( K = 20, 60 \) and 100 were selected, respectively. The particle distribution is shown in the figure below.

As can be seen from Fig. 3-Fig. 5, since the re-sampling only replicates the particle with high weights in the PF and then performs the state estimation, this leads to the distribution of particles on a few state values, which results in the phenomenon of sample depletion and is not conducive to the
overall state estimation. In this paper, the particle distribution becomes more reasonable after adopting the new re-sampling strategy by improving the particle filtering algorithm. Most of the particles are around the high likelihood region, and a few are distributed in other areas, which keeps the overall diversity of particles and effectively avoids sample depletion.

At the same time, it can be seen from Fig. 6 that IPF has further improved the effective particle number.

D. DETAILED FLOW OF PARAMETER UPDATE METHOD

The specific steps of storage life prediction method based on PoF and data-driven fusion are as follows:

1. Establishment of initial degradation model: The parameters of the PoF model were fitted with the acquired storage degradation data of AEMR, and the initial degradation model was obtained.

2. Model updating: According to the observed degradation data, IPF is used to update the parameters of the established model and obtain the latest degradation model.

3. Prediction of storage life: The failure life was predicted by using the updated degradation model combined with the failure threshold.

   (1) The initial model parameter $\theta_0 = (a_1 \sim a_5)_0$ was obtained by fitting model $T_0(t, \theta_0)$release based on the obtained partial degradation data.

   (2) Model the state space:

   $$
   \begin{align*}
   T_k(t, \theta_k)_{\text{release}} &= T_{k-1}(t, \theta_{k-1})_{\text{release}} + q_k \\
   Y_k &= T_k(t, \theta_k)_{\text{release}} + r_k
   \end{align*}
   $$

   Prediction step:

   (3) Calculate the predicted value at the next moment:

   $$
   f(T_k(t, \theta_k), y_k) \approx \sum_{i=1}^{N} \omega^i_k \delta(x_k - T_k)
   $$

   $$
   \omega^i_k = \frac{\omega^i_{k-1} f(y_k|T_k) f(T_k|T_{k-1})}{H(T_k|T_k, y_k)}
   $$

   (4) $N_{\text{eff}}$ is used to determine whether re-sampling is needed, and if not, go to step 5 to update the output. If necessary, re-sample the particles using the method mentioned above.

   Update step:

   (5) The updated value $\hat{T}_k(t, \hat{\theta}_k)_{\text{release}}$ is obtained, where the latest model parameter is $\hat{\theta}_k = (\hat{a}_1 \sim \hat{a}_5)$.

   (6) By substituted model parameters into (13) and combined with failure threshold, the latest storage life prediction results can be obtained.

IV. CASE STUDY OF AEMR’S STORAGE DEGRADATION DATA

A. ACQUISITION OF DEGRADED DATA

This part will take AEMR as the object to verify the method proposed in this paper. The degradation data acquired from the storage acceleration experiment used the developed time parameter test system. The overall block diagram of the test system is shown in Fig. 7. The testing system comprises a thermostat, relay switching circuit, time parameter testing circuit, lower computer and upper computer software. The relays to be tested are connected to the test circuit by switching circuit for time parameter testing. In addition to controlling the temperature and humidity of the thermostat and the switching state of the switching circuit, the lower computer is also responsible for sending the test data into
the upper computer system software for data analysis and processing.

The electromagnetic and contact spring systems of the AEMR utilized in the experiment are shown in Fig. 8 and Fig. 9, with a coil voltage of 28V DC and a contact load of 5A. The storage degradation test of 10 aerospace relay samples was carried out at 170° for 7448 h. During the storage test, the degradation trend of release time increased in two stages, taking into account the influence of reed stress relaxation. In the early stage, the degradation rate was fast. To better reflect the degradation characteristics, the relay temperature was restored to room temperature every 20 hours in the first stage to measure the release time parameters and every 44 hours in the second stage. The specific degradation data of release time obtained are shown in Fig. 10.

B. STORAGE LIFE PREDICTION

This section will use the method proposed in this paper to predict the storage life of AEMR. Firstly, the initial model parameters were obtained as $a_1 = 7.108$, $a_2 = 1.117$, $a_3 = 38.104$, $a_4 = -1.399$, and $a_5 = -0.069$ using the established PoF to fit the degradation data from the first 80 acquisitions. Then, once the new storage degradation data were observed, the model parameters were updated using the IPF for the AEMR. Finally, the latest degradation model was used to predict the storage life of the AEMR. Fig. 11-Fig. 13 respectively shows the degradation model curves of AEMR when 40, 80 and 120 data points are updated, and Fig. 14 shows the life prediction results. It can be seen from the life prediction results that, with the continuous acquisition of new degradation data, the life prediction results can reflect the influence of the change of degradation parameters on the life trend.

C. RESULTS ANALYSIS

To demonstrate the improvement of the proposed AEMR lifetime prediction method that merges PoF and data-driven, the
The method in this paper is compared with the pure data-driven method (M1) and the fusion method of PoF and PF (M2).

M1 adopts the classical logarithmic model to conduct degradation modeling by analyzing the characteristics of degradation data, and the parameter updating method is consistent with the paper. M2 is a fusion method of PoF and ordinary PF. The degradation modeling of this method adopts the PoF model established based on stress relaxation in this paper. Still, the parameter update algorithm adopts an ordinary PF and the traditional approach of copying high-weight particles for resampling. M3 is the method proposed in this paper.

Fig. 19 shows that the early life prediction results of M1 have a significant deviation, mainly because the classical model fails to describe the degradation process well, especially in the early transition stage of rapid and slow degradation. Fig. 15–Fig. 18 shows the fitting curve results of model superiority verification by sampling different AEMR samples. The blue curve is based on the PoF model, and the green curve is the classical logarithmic model. It is evident from the figure that the PoF model can describe the degradation process more accurately. For M2, due to the PoF model adopted, the prediction result of early life is more accurate than M1. However, the overall prediction result differs dramatically from the actual failure life. The main reason is that for severe nonlinear problems if the resampling algorithm of PF is still used, it will cause severe particle degradation, which will directly lead to the accuracy of prediction results.

As for the method in this paper, it can be seen from the mean absolute error (MAE) curve in Fig. 20 that the errors are smaller than M1 and M2, and the MAEs are significantly reduced to 63.4% and 51.6%, respectively. At the same time, the curve changes more gently, which shows that the storage life prediction method in this paper has a better suppression effect on the fluctuation of nonlinear degradation data. However, with the continuous update of data, the MAE curve will also have a certain upward trend in the later period.

D. CONTRAST THE MACHINE LEARNING BASED APPROACHES

Machine learning (ML) is the core of artificial intelligence, and its main function is to enable computers to simulate or implement human learning behavior by acquiring new information and continuously training the model to improve its generalization ability [26]. ML is usually divided into surface and deep learning methods, which have achieved good results when applied to life span prediction. Therefore, to further
verify the effectiveness and superiority of the proposed method, a comparison between this method and the ML-based lifespan prediction method is presented below.

The literature [27] presents a surface learning method, which has previously demonstrated good results for predicting the remaining life of lithium batteries. When this method is used for prediction in this paper, the data before the prediction start point shown in the previous Fig. 11 is first used to train the model for practice, and then when new data is observed, it is fed into the completed training model to predict it, where the model is trained iteratively as the data is observed. A CNN-LSTM-based approach to lifetime prediction, a deep learning approach, is described in literature [28]. In order to adequately train the model, a combination of repetitive segmentation and sliding time windows are used to generate training samples, where the window length is 80, and the step size is 1. The predicted lifetime results are obtained by repetitively generating samples and combining them with a failure threshold based on the first arrival time. The life prediction results and error curves are shown in Fig. 21 and Fig. 22. ML1 and ML2 are the corresponding methods from Ref. 27 and Ref. 28, respectively.

As can be seen in Fig. 21 and Fig. 22, when comparing the proposed method with the ML-based method, M3 is not inferior to each other in terms of lifetime prediction accuracy, especially in the first half of the degradation process. As more and more observations are available, ML1 and ML2 become more and more effective. It shows that ML has its unique
advantage and excellent fitting ability when the sample of observables is sufficient. However, in the actual service environment of a relay, we do not want to energized test the relay frequently to obtain data. Therefore, to further validate the superiority of the method proposed in this paper, the observed data is sparse, shown in Fig. 23, to simulate the situation where only a small sample of data is available under actual service conditions and compared further with the ML1 and ML2 methods. The prediction results and errors are shown in Fig. 24 and Fig. 25.

The results show that the ML method fails to keep the accuracy when only a small sample size of degraded data is available. As can be seen in Fig. 23, the degraded data show two stages, with the first stage degrading rapidly and the second stage degrading at a significantly slower rate, which makes the model trained from the first stage data to predict the life span of the later stage of degradation not show better results and the accuracy of the prediction is greatly reduced. It can be seen that the proposed method has two advantages over the method based on ML. On the one hand, the method is not affected by the sample size of the degraded data and is significantly better than ML1 and ML2 in terms of prediction accuracy. 56.2% and 49.9% of the MAE are reduced compared to ML1 and ML2, respectively. On the other hand, the ML method only obtains a fitted relationship between the amount of degradation and the lifetime. However, using the paper’s proposed method, by fusing the PoF model, it is possible to establish a link between the underlying physical and chemical processes and the lifetime and to optimize further...
the design of relays based on the lifetime prediction results, providing effective aid to the life-extension work of weapons and equipment, thereby improving their reliability.

V. CONCLUSION
In this paper, a PoF and data-driven fusion solution is proposed to address the difficulty of existing methods in effectively predicting the storage life of AEMR. Firstly, a failure physics model for AEMR is established based on the stress relaxation process of the reed by analyzing the underlying principles of the degradation of the storage life of AEMR. Based on this, a fusion of PoF and data-driven life prediction method is further constructed. In addition, an improved particle resampling strategy is proposed to improve particle diversity. Thus, the fusion method’s prediction accuracy is improved to address the particle degradation problem caused by particle filtering to update the model parameters when using the fusion method for life prediction.

To fully demonstrate the effectiveness and superiority of the method proposed in this paper. The proposed method is compared with a purely data-driven method (M1), a fusion method using ordinary particle filtering (M2) and a machine learning-based method (ML1, ML2). The results show that the proposed method reduces the MAE by 63.4% and 51.6% compared to M1 and M2, demonstrating the effectiveness of an accurate PoF model and improved particle re-sampling strategies in improving lifetime prediction accuracy. The MAE of the proposed method is reduced by 63.4% and 51.6% compared to M1 and ML2, and this shows that the proposed method does not depend on the data sample size compared to the machine-learning-based method and can maintain good accuracy even with small samples of observed data. On the other hand, the fused approach, which constructs a relationship between the underlying physical and chemical changes and the lifetime, allows us to optimize the design of relays based on the prediction results, which will further contribute to the life extension work of weaponry and enable the reliability of weaponry to be improved.

In end, there are two issues needed to be further studied. Firstly, in this paper, only the degradation of the reeds is considered when building the PoF model. However, in the actual storage degradation process, the effect of degradation of other components on the degradation of the AEMR as a whole cannot be ignored. The non-linear characteristics of the entire degradation process are not caused by noise alone but may also result from multi-component degradation and multi-mechanism coupling. Therefore, the results may be improved if we want to improve further the prediction accuracy based on this paper’s research by building a PoF model coupled with multiple degradation mechanisms. Secondly, although using an improved resampling strategy, the particle diversity is improved through separation, mutation and elite retention operations. However, in practice, the whole solution process is relatively slow. Therefore, other intelligent algorithms or further optimization of the resampling strategy can be further considered to improve computational efficiency.

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