Remaining Useful Life Prediction of Capacitor Based on Genetic Algorithm and Particle Filter

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Abstract: The failure rate of capacitors is high in the circuit system, and in the system with high requirement for capacitance reliability, it is very important to predict the remaining useful life accurately. In this paper, a particle filter method based on genetic algorithm is proposed to predict the remaining useful life of capacitors. Using the capacitance data set published by NASA, an exponential degradation model is established, and the resampling procedure in traditional particle filter method is optimized by crossover, mutation and optimization in genetic algorithm to increase the particle diversity, and to propel particles move to the high likelihood region. Therefore, the particle depletion problem caused by the resampling step in the traditional particle filter is improved to some extent. The simulation results show that the particle filter method based on genetic algorithm can be used to achieve more accurate prediction of remaining life of electrolyte capacitor.

Key Words: Capacitor; prognostic; remaining useful life; particle filter; genetic algorithm

1 Introduction

Capacitors have lower reliability than other power supply components, so it is necessary to analyze the degradation trend and remaining useful life (RUL) prediction of capacitors in high reliability areas, such as aviation, the utility model can effectively avoid the avionics equipment failure caused by the capacitor failure and the serious accident caused by the capacitor failure.

The RUL prediction methods can be commonly classified into the data-driven methods and the physical model-based methods[1,2]. The physical model-based methods are suitable for the objects with clear fault mechanism. However, in practice, the physical model-based methods are not suitable for most complex systems because of the complexity of degradation process, and the data-driven methods are widely used, including artificial neural networks[3, 4], Support vector machine[5], Gauss process regression[6], Bayesian filter[7], etc. .

Among the data-driven methods, the Bayesian filter method is commonly used, including the Kalman filter, the extended Kalman filter (EKF) and the particle filter (PF) and so on. Celaya J R et al.[9] use Kalman filter to predict the RUL of capacitors, Xian W et al.[10] use particle filter to estimate the state and predict the RUL of lithium-ion battery, and Miao Q et al.[11] use the unscented particle filter to predict the degradation trajectory of lithium-ion battery. Particle filter method is designed for nonlinear and non-Gaussian systems, so particle filter is widely used to solve the state estimation problem of nonlinear and non-Gaussian dynamical system.

The sequential importance sampling and resampling strategy are used in particle filter, which uses a group of particles propagating in the state space as an approximation of the posterior probability density of the system state, therefore, it is possible to estimate the uncertainty of the prediction result and provide more prediction information for the actual prediction problem[12, 13]. However, there are two problems in particle filter method: first, the importance density function of particle filter method does not take into account the latest observed value, therefore, there may be a big difference between the state distribution represented by the sampled particles and the real state posterior distribution, which makes the precision of state estimation worse. Secondly, because of the resampling in particle filter, the problem of particle impoverishment is unavoidable. After several iterations, the diversity of particles decreases, which leads to the decrease of prediction accuracy. To solve these two problems, the genetic algorithm-based particle filter method is proposed and applied to RUL prediction of capacitors. The experimental results show that compared with the traditional particle filter method, the genetic algorithm-based particle filter method can effectively reduce the confidence interval of RUL prediction, and get more accurate life prediction estimation.

2 Genetic Algorithm-Based Particle Filter

2.1 Particle Filter

Particle filter is a statistical filtering method based on Monte Carlo and recursive Bayes. The basic idea is: first, a set of random samples, called particles, are obtained from the prior distribution of the system state, and then the current particle weights are updated according to the measurements of the system state at this time, the particle calibrated by the measured value is taken as the updated state of the system.

The steps of the traditional particle filter algorithm are as follows:

(1) Particle set initialization. N particles are samples from the prior distribution $p(x_0)$, and the initial particle set is obtained as $\{\mathrm{x}_0^i\}_{i=1}^N$.

(2) Importance sampling. For cycle k, N particles $\{\tilde{x}_k^i\}_{i=1}^N$ are samples from the prior distribution $p(x_k|\mathrm{x}_{k-\Delta k})$.

(3) Calculate the weight of each particle. The weight of the particles sampled in the previous step are calculated as $\tilde{w}_k^i = p(y_k \mid x_k^i)$, and the weight is normalized as $\tilde{w}_k^i = \tilde{w}_k^i / \sum_{i=1}^{N} \tilde{w}_k^i$.

(4) Resampling. For particle set $\{\tilde{\mathrm{x}}_k^i, \tilde{\mathrm{w}}_k^i\}$, the particles are resampled according to their normalized weights, and the resampled particle set is obtained as $\{\mathrm{x}_k^i, \frac{1}{N}\}$. Now the weight of all particles is $1/N$.

(5) Outputs the mean of the current set of particles as the estimate value of the system state at cycle k.

(6) $k = k + \Delta k$. If $k < k_{th}$, return to step (2), otherwise, terminate the procedure.

There are two weaknesses in traditional particle filter: the one is the selection of the important density function does not take into account the new measurement, and the other one is particle impoverishment caused by the resampling step. In the importance sampling step, the prior distribution is chosen as the importance distribution by the traditional particle filter, and the information of the latest observed value in the importance distribution is ignored. In the resampling step, the particles with small weights are eliminated and the particles with large weights are duplicated. The resampling process is iterative at each cycle, so as the resampling algorithm is iterated, the continuous resampling will lead to an extreme case, that is, the diversity of particles will be greatly reduced, and only a few heavy particles are left, creating the problem of particle impoverishment. The suboptimal selection of the importance distribution and the particle impoverishment will lead to the decrease of the prediction accuracy. Therefore, an improved particle filter algorithm based on genetic algorithm is proposed to solve these two problems simultaneously.

2.2 Genetic Algorithm

Genetic algorithm (GA)[15] is a randomized search method, which defines a population to represent the set of possible solutions of the problem to be solved. Each individual in the population is a possible solution, an individual's phenotype is determined by a gene-coded chromosome, the mapping from chromosome to gene is a coding process, otherwise it is called the decoding process. Genetic algorithms generate new populations through individual gene selection, crossover and mutation, and use a fitness function to evaluate the fitness of individuals, thus making the new population better than the previous population, it's an evolutionary algorithm.

2.3 Genetic Algorithm-Based Particle Filter

Aiming at the defects of traditional particle filter in importance sampling and resampling, this paper introduces genetic algorithm after resampling step to move particles to high likelihood area and improve the problem of particle impoverishment, so the precision of state estimation and RUL prediction can be improved.

In the genetic algorithm step, all particles obtained after the importance sampling at this cycle are used as the primary population, and the resampling step is equivalent to the selection step in GA, therefore, only crossover and mutation are included in the GA steps in this paper, and real number coding is used. The fitness function is defined as:

$$fit(x_k^i, y_k) = p(y_k \mid x_k^i) \qquad (1)$$

Where x_k^i is the i th particle after resampling at cycle k, and it is also the i th individual of a certain generation of population at cycle k. The fitness function is consistent with the formula for calculating particle weight and it is the likelihood function of the particle. The genetic algorithm steps in this paper are as follows:

(1) Population Initialization. The particle set obtained after resampling is regarded as the first generation population after the selection operation, define $M = 0$.

(2) Crossover.

① $p = 0$, define the probability of crossover P_c, the number of individuals (i. e. , the number of particles) in a population is N.

② Two individuals $\{\mathrm{x}_k^m, \mathrm{x}_k^n\}$ are randomly selected from the population as the parents of the current generation, and the following crossover operation is performed

$$\tilde{x}_k^m = \alpha x_k^m + (1-\alpha)x_k^n + \eta \qquad (2)$$

$$\tilde{x}_k^n = \alpha x_k^n + (1-\alpha)x_k^m + \eta \qquad (3)$$

Where η is a zero-mean Gaussian random variable, α is a standard Gaussian random variable. The criteria for selecting offspring is: if $fit(\tilde{x}_k^m, y_k) > \max(fit(x_k^m, y_k), fit(x_k^n, y_k))$, accept the crossed particle as the descendant, otherwise accept the particle whose fitness function is $\max(fit(x_k^m, y_k), fit(x_k^n, y_k))$ as the descendant; For the particle $\tilde{x}_k^n$, perform the same operation.

③ $p = p + 2$, if $p < N \cdot P_c$, return to setp ②,otherwise, perform step (3).

(3) Mutation.

① $p = 0$, define the probability of mutation P_s.

② Select an individual x_k^j randomly from the population as the parent, and perform the following mutation operation

$$\tilde{x}_k^j = x_k^j + \eta \qquad (4)$$

The criteria for selecting offspring is: if $fit(\tilde{x}_k^j, y_k) > fit(x_k^j, y_k)$, accept the mutated particle as the descendant, otherwise still accept x_k^j as the descendant.

③ $p = p+1$, if $p < N \cdot P_s$, return to step ②, otherwise, perform step (4).

(4) $M = M+1$. If $M < M_{th}$, return to step (2), otherwise, terminate the procedure.

3 RUL Prediction of Capacitors

In this paper, a genetic algorithm-based particle filter method is used to predict the RUL of the capacitors based on the published capacitance data set of NASA. First of all, the accelerated aging test process needed to get the capacitor degradation data is briefly described, then the exponential function is used as the degradation model of the capacitor data, the first five groups of capacitor data are used as the training set, and the sixth group is used as the testing set, finally, the parameters of the degradation model are obtained, and the state estimation and RUL prediction are carried out.

3.1 Accelerated Aging Test

In the field of RUL prediction, the degradation data are usually obtained by accelerated aging test. In this experiment, the effect of high voltage on the degradation of capacitor is obtained by accelerating superstress experiment, and the degradation data of capacitor is obtained.

The experiment is accomplished by applying a square wave stress to the capacitors. the Function generator generates a square wave stress, which is then applied to the device under test, causing the capacitors to be charged and discharged in a continuous cycle under high stress, and the capacitor begins to degrade[9]. In the accelerated aging test, electrochemical impedance spectroscopy (EIS) is used to characterize the frequency response of capacitor impedance. In this test, six capacitors whose maximum rated voltage are 10V and maximum rated current are 1A are selected, the degradation data are obtained by measuring EIS of the six selected capacitors every 8 to 10 hours.

3.2 Degradation Model

In this paper, the degradation data of capacitors published by NASA are used to do RUL prediction. The exponential degradation model is used to characterize the degradation trend of these six capacitors. The degradation function is as follows:

$$y = f(x) = \exp(a * x) + b \qquad (5)$$

Where a and b are model parameters, y is the percentage loss of the capacitance. In this paper, the degradation data of the first 5 capacitors are used as the training set, and the degradation data of the 6th capacitor C6 is used as the testing set. Matlab curve fitting toolbox is used to fit the training set capacitors data with degradation model (5), and the fitting parameters are obtained.

Table 1 fitting parameters of training set capacitors

Capacitor ID	a	b	R-square	MSE
C1	0.01549	-0.8736	0.9701	.143
C2	0.01651	-0.3778	0.9678	.459
C3	0.01638	-0.4266	0.9676	.428
C4	0.01664	-0.5021	0.9731	.362
C5	0.01624	-0.6314	0.9761	.184
mean	0.01625	-0.5623		

Table 1 shows the fitting parameters of the five groups of capacitance data. C1 ~ C5 represents degradation data of five groups of capacitors in the training set, a and b are the fitting model parameters, and R-square and RMSE are two indexes evaluate the fitting model, which are called decision coefficient and root mean square error respectively. The more R-square approaches 1, the more the RMSE approaches 0, the better the fitting of the model. As can be seen from Table 1, degradation model (5) can fit the capacitance data well. the model parameters of capacitor C6 is determined as follows:

$$a_0 = 0.016252 \quad b_0 = -0.5623 \tag{6}$$

The degradation data has a small number of data points and is not the result of equal interval measurement. In this paper, the degradation data is smoothed by cubic spline interpolation and uniformly sampled to obtain the degradation data with 10-hour sampling interval, which is used to predict the RUL of the capacitors.

3.3 RUL Prediction

Firstly, the state transition equation and measurement equation are established according to the degradation model (5). The derivation of the degradation equation (5) gives:

$$\dot{C}=\frac{dC(t)}{dt}=a*C(t)-ab \tag{7}$$

The derivative is approximated by finite difference operation:

$$\frac{C(t)-C(t-\Delta t)}{\Delta t}=a*C(t-\Delta t)-ab \tag{8}$$

$$C(t)=(1+a\Delta t)*C(t-\Delta t)-ab\Delta t \tag{9}$$

Let $t_k = t$, $t_{k-1} = t-\Delta t$, and the state degradation model is obtained as

$$C(t_k)=(1+a*\Delta k)*C(t_{k-1})-ab*\Delta k \tag{10}$$

So the state transition equation and measurement equation are obtained as

$$x_k = A_k x_{k-1} + B_k + v \tag{11}$$

$$y_k = x_k + w \tag{12}$$

Where
$$\begin{aligned} A_k &= (1+\Delta k) \\ B_k &= -a*b*\Delta k \\ v &\sim N(0,\sigma_v) \\ w &\sim N(0,\sigma_w) \end{aligned}$$

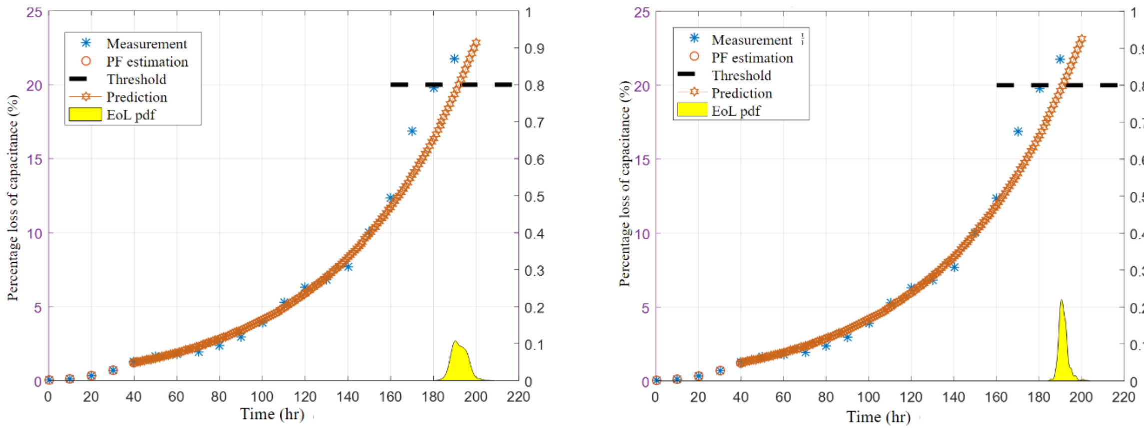
After the state transition equation and measurement equation are obtained, the current percentage loss of capacitance can be estimated and the future percentage loss can be predicted according to the particle filter method based on genetic algorithm. The RUL can be predicted using a failure threshold. When the percentage loss of capacitance comes to 20%, the capacitance is considered to be out of service. The moment is the end of life (EoL) and is recorded as t_{EOL}, t_p is the time at which the prediction begins. The RUL is therefore calculated using the following formula:

$$RUL(t_p) = t_{EoL} - t_p \tag{13}$$

Assuming that the first t_p degradation data are known, the particle filter based on genetic algorithm is used to filter the previous t_p data, and the posteriori probability distribution and the percentage loss of capacitance of the capacitor in first t_p cycle are estimated.

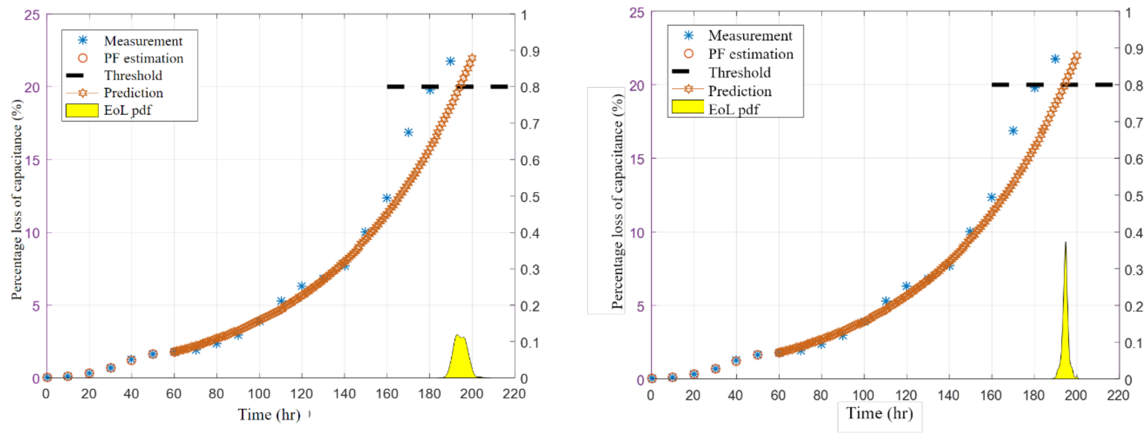
In the prediction stage, the particle filter cannot be used because of the loss of the measurement of the percentage loss of capacitance. The estimated percentage loss of capacitance at time t_p is iterated using the state transition equation. When the percentage loss of capacitance is greater than 20%, the corresponding time is t_{EOL}. Thus, the remaining useful life can be obtained as $RUL(t_p) = t_{EOL} - t_p$. The distribution of the remaining useful life can also be obtained by iterating the posterior probability distribution at time t_p with the state transition equation.

3.4 Prediction Result and Comparison



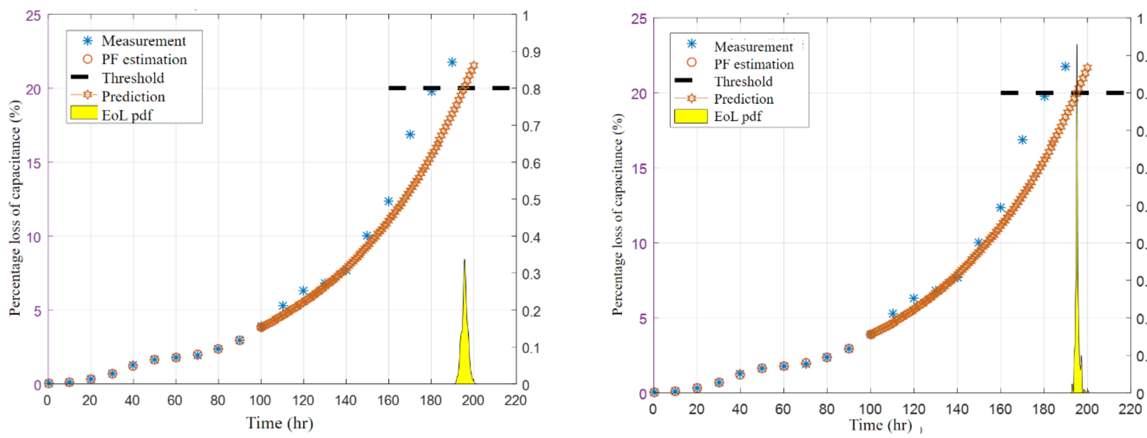
(a) PF　　　　　　　　　　(b) GA-PF

Figure 1. RUL prediction and state estimation at 40 hour. ($t_p = 40$)



(a) PF　　　　　　　　　　(b) GA-PF

Figure 2. RUL prediction and state estimation at 60 hour. ($t_p = 60$)



(a) PF　　　　　　　　　　(b) GA-PF

Figure 3. RUL prediction and state estimation at 100 hour. ($t_p = 100$)

The capacitor C6 is used as the testing set. Figure 1, Figure 2, and Figure 3 shows the predicted curve of percentage loss of capacitance and the predicted probability distribution of the RUL when the prediction begins at t_p=40, t_p=60 and t_p=100. Among them, figure (a) is the prediction result of using traditional particle filter algorithm, figure (b) is the prediction result of using genetic algorithm-based particle filter. The 98% confidence interval (CI) of the probability density of the RUL is calculated and the results are shown in Table 2. Among them, PF represents the traditional particle filter method, GA-PF represents the genetic algorithm-based particle filter.

Tabel 2 Comparison of RUL prediction

	Prediction time point t_p	98% CI of RUL	Width of CI
PF	40	[144,161]	17
GA-PF		[147,157]	10
PF	60	[128,140]	12
GA-PF		[130,138]	8
PF	100	[92,99]	7
GA-PF		[93,97]	4

By comparing Figure 1(a), Figure 2(a) and Figure 3(a) , it can be seen that as the number of known data point increase, the probability density function (pdf) of EoL becomes narrower, so the pdf of RUL becomes narrower too because $RUL(t_p) = t_{EoL} - t_p$. As can be seen in Tabel 2, during t_p change from 40, 60 to 100, the width of 98% confidence interval (CI) is 17, 12, and 7, respectively. The reason for this phenomenon is that the more measured data is known, the more prior knowledge is obtained, and therefore the uncertainty of the RUL prediction is gradually reduced.

At the same time, by comparing figure (a) and figure (b) in Figure 1, Figure 2 and Figure 3 respectively, we can see that the pdf width obtained by the improved particle filter algorithm is obviously reduced compared with the traditional particle filter algorithm. As can be seen from Table 2, when the prediction starts at the 40th hour of capacitor operation, the RUL confidence interval with the traditional particle filter is [144,161], while with the GA-PF method, the RUL confidence interval improves to [147,157], and the width of the confidence interval is reduced from 17 hours to 10 hours. This is because the genetic algorithm makes cross, mutation and fitness function-based selection for the resampled particles, on the one hand, it moves the particles towards the high likelihood region, on the other hand, it increases the diversity of particles, the problem of particle impoverishment is improved to a certain extent, and the prediction accuracy is improved greatly.

4 Conclusion

In this paper, the RUL prediction is carried out by using the NASA open-source capacitor degradation data obtained from accelerated aging tests. Five of the six capacitors are used as training set, and the sixth capacitor is used as testing set. The exponential equation is used as the degradation function, and the state transition equation and measurement equation of the degradation state are established according to the degradation function, the traditional particle filter method and the genetic algorithm-based particle filter method are used to predict the RUL of the sixth capacitor. The experimental results show that the genetic algorithm-based particle filter method can effectively avoid the particle impoverishment caused by resampling in the traditional particle filter method, and drive the particles to move towards the high likelihood region, the predicted pdf of RUL is more concentrated, the confidence interval is reduced, thus the prediction is more accurate and precise.

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