A Novel Degradation Prediction for Analog Circuits using Particle Filter

Yang Yu
School of Instrument Science and Technology
Harbin Institute of Technology
Harbin, China
yuyanghit@hit.edu.cn

Yueming Jiang
School of Instrument Science and Technology
Harbin Institute of Technology
Harbin, China
14B901009@hit.edu.cn

Junyan Liu
School of Instrument Science and Technology
Harbin Institute of Technology
Harbin, China
line 5: email address

Zhiming Yang
School of Instrument Science and Technology
Harbin Institute of Technology
Harbin, China
yangzm@hit.edu.cn

Xiyuan Peng
School of Instrument Science and Technology
Harbin Institute of Technology
Harbin, China
pxy@hit.edu.cn

***Abstract*—With the increasing demand of high reliability and safety of modern electric devices, failure prediction becomes more and more important since it is efficient to increase reliability and reduce downtime cost. A novel prediction method for analog circuits is proposed in this paper. Firstly, output waveforms in time domain of the initial state and the degradation states are extracted, then particle filter algorithm is implemented to estimate the changes of the waveforms according to the principles of noise estimation based on Grey Theory to obtain more reasonable fault indicators from more complete information. Thereafter, a novel degradation prediction model for analog circuits is constructed according to the newly obtained fault indicators. To validate the proposed degradation prediction method, the experiments are implemented on high-voltage power circuit board. The experimental results show that the method can predict the degradation trend and the information will be useful for the reliability design of the analog circuits.**

Keywords—analog circuit, degradation prediction, grey theory, particle filter

I. INTRODUCTION

At present, analog circuits are widely used in electric devices, it is important to ensure the high reliability of the circuits. One of the significant factors that influences the performance of the analog circuit is the degradation of the components in the circuits[1]. In initial stage, the effect of the degradation on the circuit is weak even incipient, then with the increasing operation time the degradation develops and deteriorates, the reliability of the circuit will be impaired until the catastrophe breakdown happening, which can cause huge economic loss. Therefore, it is necessary to focus on the degradation prediction and failure prognosis to secure system reliability [2].

Degradation prediction models are divided into two main perspectives: physics-based methods and data-driven methods. Physics-based method sets up the topology of the analog circuit, and focuses on the degradation phenomena based on the actual physical circuits, which can give out the probability prediction results for the actual circuits. Yu et al. [3] applied the physics-based hidden Markov model (HMM) to the prediction of the degradation model of the electric vehicle battery. Zhang et al. [4] applied the prediction of residual life of gyroscope based on Copula Function method. Zhou et al. [5] proposed a novel prediction approach for proton exchange membrane fuel cell performance degradation based on a multi-physical aging model with particle filter approach. Data-driven method uses the output samples of the analog circuit as the training data, and can complete the long term degradation prediction without the structure of the actual circuit and regression mechanisms. Li et al. [6] used the correcting coefficient to improve the grey model, and completed the long term prediction of the circuit. Wang et al. [7] proposed a method based on characteristic parameter data and Particle Swarm Optimization RBF(Radial Basis Function) Neural Network for the fault prediction of power electronic circuits. For fusion method, Lyu Tiao et al. fused the GM model, AR model and Kalman filtering model for mining subsidence dynamic prediction [8], Wang Yi et al. [9] proposed the fusion algorithm of fuzzy error neuron network model and local neighbor revision method. For the above researches, it summarizes that physics-based method requires large computation and the actual physical circuit structure, and the long-term prediction results are disappointing. Data-driven method does not have the ability to express prediction probability. Based on these problems, the fusion prediction method is proposed, it has the advantages including the long-term degradation prediction and the probability prediction. Therefore, this paper proposes a fusion model of the degradation prediction for analog circuit using particle filter and grey theory with relatively few data.

This paper is organized as follows. Section II presents the principle of the fusion prediction model combined Grey Model with Particle Filter. Section III describes the simulation experiment circuit used in this paper. Section IV shows the experiment results with the fusion prediction model. Finally Section V concludes this paper.

II. Fusion Degradation Prediction Method

The essence of the physics-based method is time sequence prediction. Although particle filter (PF) model can show the probability prediction results for the actual applications, this method relies on the circuit model, which is hard to be obtained from the actual circuit. The grey model (GM) is a data-driven method, which depends only on the degradation data of the analog circuit. It can obtain the high long-term accuracy, however, it cannot provide the probability.

Therefore, in order to make the prediction model having the accurate long-term prediction accuracy and the expression of prediction probability, the paper proposes a fusion prediction method. Firstly, the regression equation is used to show the state transformation equation, which produces the particle distribution for particle filter algorithm; then the grey model is adopted to construct the observation equation, which provides the observation value required by the particle filter algorithm. Finally, the fusion method is constituted by PF model combined with GM.

A. Grey Model

Grey model is a classic data-driven model, which can be applied to analyze the uncertain problem with a small size of samples or lacking sample information. Compared with the statistical methods, there is no need to regard the statistical distribution of data when using grey model. Thus, grey model (GM) has been extensively used in many applications for the degradation [10].

1) GM(1,1) prediction model: The GM (1, 1) model is one common grey prediction model. This model is obtained by the smooth exponential curve fitting. The essence of the model is searching the regularities from the original data to predict the future data. Compared with other prediction models, the GM (1, 1) model has the advantages of less original data, higher prediction accuracy, faster computation speed and simpler operation [11,12]. Therefore, the GM (1, 1) model is widely used for the prediction of long-term degradation prediction using a small size of samples [13].

The GM (1, 1) model is constructed with the following procedure: firstly, the original data samples are added to obtain the accumulative sequence; then, the GM (1, 1) model is fitted by the least square method; finally, the simulation prediction samples are obtained by the sequence reduction.

The original random sequence $X^{(0)}$ is denoted as (1).

$$X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), ..., x^{(0)}(n)\} \tag{1}$$

where, n is the length of the original random data sequence. After the accumulated generation operation, the obtained sequence $X^{(1)}$ is defined as:

$$X^{(1)} = \{x^{(1)}(1), x^{(1)}(2), x^{(1)}(3), ..., x^{(1)}(n)\} \tag{2}$$

where

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), k = 1, 2, 3, ..., n \tag{3}$$

The relationship of between $X^{(0)}$ and $X^{(1)}$ is followed as (4).

$$x^{(0)}(k) + a x^{(1)}(k) = u \tag{4}$$

Equation (4) is the differential equation of GM (1,1). It is assumed that $x(k)$ and $x(k\text{-}1)$ are one pair of the adjacent values, and defined $z^{(1)}(k)$ as (5).

$$z^{(1)}(k) = \frac{1}{2}[(k-1) + x^{(1)}(k)], k = 2, 3, 4, ..., n \tag{5}$$

Then the basic model of GM (1, 1) is obtained and shown as (6).

$$x^{(0)}(k) + a z^{(1)}(k) = u \tag{6}$$

where, a is the development coefficient, u manifests the grey action. The least square method is applied to (6), then it is described as (7).

$$A = \begin{bmatrix} a \\ u \end{bmatrix} = (B^T B)^{-1} B^T Y \tag{7}$$

Where, $B = \begin{bmatrix} -\frac{1}{2}(x^{(1)}(1) + x^{(1)}(2)) & 1 \\ -\frac{1}{2}(x^{(1)}(2) + x^{(1)}(3)) & 1 \\ \vdots & \vdots \\ -\frac{1}{2}(x^{(1)}(n-1) + x^{(1)}(n) & 1 \end{bmatrix}$,

$Y = \left(x^{(0)}(2), x^{(0)}(3), x^{(0)}(4), ..., x^{(0)}(n)\right)^T$.

The GM (1, 1) model of $X^{(1)}$ obeys to one first order differential equation (8).

$$\mathrm{d}x^{(1)}(k) / \mathrm{d}k + a x^{(1)}(k) = u \tag{8}$$

According to the initial condition $x^{(1)}(1) = x^{(0)}(1)$, the solution of (8) is shown as (9).

$$\tilde{x}^{(1)}(k) = (x^{(0)}(1) - \frac{u}{a}) e^{-a(k-1)}, k = 2, 3, 4, ..., n \tag{9}$$

Then,

$$\tilde{x}^{(1)}(k)=\sum_{i=1}^{k}\tilde{x}^{(0)}(i)$$
$$=\sum_{i=1}^{k-1}\tilde{x}^{(0)}(i)+\tilde{x}^{(0)}(k)=\tilde{x}^{(1)}(k-1)+\tilde{x}^{(0)}(k) \quad (10)$$

After the sequence reduction, the fitting sequence $\tilde{X}^{(0)}$ of $X^{(0)}$ is obtained:

$$\tilde{x}^{(0)}(k)=\tilde{x}^{(1)}(k)-\tilde{x}^{(1)}(k-1), k=2,3,4,...,n \quad (11)$$

This equation contains two situations: when $k \le n$, $\tilde{x}^{(0)}$ means the fitting values of the original random sequence. When $k \ge n$, $\tilde{x}^{(0)}$ means the prediction values.

2) Precision Test of the Grey Model: Residual test is a point-by-point precision test method, denote the absolute error as the $e^{(0)}(k)$, $\varepsilon^{(0)}(k)$ is the relative error, $\bar{\varepsilon}$ is the average relative error, and p^0 is the precision, the corresponding equations are followed as:

$$e^{(0)}(k)=X^{(0)}(k)-\tilde{X}^{(0)}(k), k=1,2,3,...,n \quad (12)$$

$$\varepsilon^{(0)}(k)=\frac{X^{(0)}(k)-\tilde{X}^{(0)}(k)}{X^{(0)}(k)}\times 100\%, k=1,2,3,...,n \quad (13)$$

$$\bar{\varepsilon}=\frac{1}{n-1}\sum_{k=2}^{n}\left|\varepsilon^{(0)}(k)\right| \quad (14)$$

$$p^{(0)}=(1-\bar{\varepsilon})\times 100\% \quad (15)$$

Posterior difference test requires the mean value and mean deviation square value of $X^{(0)}$, the calculation equations are shown as (16) and (17).

$$\bar{X}=\frac{1}{n}\sum_{k=1}^{n}X^{(0)}(k) \quad (16)$$

$$S_1^2=\frac{1}{n-1}\sum_{k=1}^{n}\left(X^{(0)}(k)-\bar{X}\right)^2 \quad (17)$$

The mean value and mean deviation square value of residual sequence $E^{(0)}$ are defined as (18) and (19):

$$\bar{e}=\frac{1}{n}\sum_{k=1}^{n}\left|e^{(0)}(k)\right| \quad (18)$$

$$S_2^2=\frac{1}{n-1}\sum_{k=1}^{n}\left(\left|e^{(0)}(k)\right|-\bar{e}\right)^2 \quad (19)$$

The small probability error is:

$$P=P\left\{\left|\left|e^{(0)}(k)\right|-\bar{e}\right|<0.6745S_1\right\} \quad (20)$$

The posterior error ratio is :

$$C=S_2/S_1 \quad (21)$$

Based on the two tests, the model precision is dependent on $\bar{\varepsilon}$, P, p^0, and C, according to the values of these parameters, there are four common grades.

TABLE I. GM MODEL PRECISION TEST

	Relative Error $\left\|\varepsilon^{(0)}(k)\right\|$	**Precision** p^0	**Posterior Error Ratio** C	**Little Probability Error** P
Grade I	1%	99%	0.35	0.95
Grade II	5%	95%	0.50	0.80
Grade III	10%	90%	0.65	0.70
Grade IV	20%	80%	0.80	0.60

B. Particle Filtering Model

Particle filtering (PF) model is one filtering model based on Monte Carlo Method, which can be used to solve non-Gaussian and non-linear distributions problems [14]. PF model provides the complete representation of the posterior distribution of the states, as one uncertainty model, and any statistical estimates can be easily computed [15].

1) State Space Modeling: The state space model of the system consists of a state equation and an observation equation. The state equation shows that the state of the system changes with the time, the observation equation exhibits the relationship between the inputs and outputs at a certain time point. The state equation is:

$$x_k=f\left(x_{k-1},w_k\right) \quad (22)$$

The observation equation is:

$$y_k=h\left(x_k,e_k\right) \quad (23)$$

where, f(*) and h(*) are the deterministic process and observation function, respectively, w_k means the systematic noise, e_k is the observation noise, x_k manifests the state variable at time point k, y_k is the observation value of x_k. The relationship of y_k and x_k is illustrated in Fig.1.

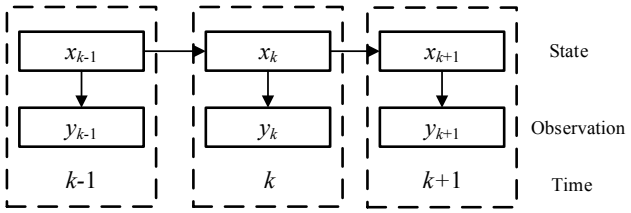

Fig. 1. State Space Model.

2) Bayesian Theory: Bayesian theory offers one probability for the actual unknown non-random value of a quantity [16]. The main object of Bayesian theory is acquiring the probability density function $P(x_k|y_{1:k})$, and the actual observation data y_k are used to correct the prior knowledge of the system state x_k.

Obtaining $P(x_k|y_{1:k})$ is based on observing the values of x_k at time point k. It is assumed that the initial probability density function $P(x_k|y_{1:k})$ is known, then $P(x_k|y_{1:k})$ can be obtained by (24) and (25):

$$P\left(x_k \left| y_{1:k-1}\right.\right)=\int P(x_k \left| x_{k-1}\right.) \cdot P(x_{k-1} \left| y_{1:k-1}\right.) dx_{k-1} \tag{24}$$

$$P\left(x_k \left| y_{1:k}\right.\right) = P(y_k \left| x_k\right.) \cdot P(x_k \left| y_{1:k\text{-}1}\right.) \cdot P(y_k \left| y_{1:k\text{-}1}\right.) \tag{25}$$

where, (24) is the prediction equation and (25) is the renewal equation. Firstly, the probability density $P(x_k|x_{k\text{-}1})$ at time point k is predicted by using the posteriori filtering probability density $P(x_{k\text{-}1}|y_{1:k\text{-}1})$ at time point $k-1$ and the system model, the priori filtering probability density $P(x_k|y_{1:k\text{-}1})$ of x_k at time point k is acquired. Then, the observation value y_k at time point k is used to adjust $P(x_k|y_{1:k\text{-}1})$, which is a normalization constant. Finally, the posteriori filtering probability density $P(x_k|y_{1:k})$ is obtained, the relationship between $P(x_k|y_{1:k\text{-}1})$ and $P(x_k|y_{1:k})$ is shown as (26).

$$P(y_k \left| y_{1:k-1}\right.) = \int P(y_k \left| x_k\right.) \cdot P(x_k \left| y_{1:k-1}\right.) dx_k \tag{26}$$

3) Monte Carlo Integral: Monte Carlo (MC) method can solve the problems on the integral of high dimensional variables. The particle filter used in this paper is based on MC method to sample the data.

MC method extracts N samples from the posteriori probability density distribution of the state space. These samples are mutually independent, so the approximate posteriori probability density of the state space is shown as (27):

$$P(x_{0:k} \left| y_{1:k}\right.) = \frac{1}{N}\sum_{i=1}^{N} \partial x_{0:k}^{(i)}(dx_0;k) \tag{27}$$

where, $\partial(*)$ is Dirac function. According to (27), the expectation of $g(x_{0:k})$ is:

$$E\left[g(x_{0:k})\right] = \int g(x_{0:k}) P(x_{0:k} \left| y_{1:k}\right.) dx_{0:k} \tag{28}$$

It is known that $g(x_{0:k})$ is a distribution obeying to the probability density function $P(x_{0:k}|y_{1:k})$, the expectation of $g(x_{0:k})$ equals approximately to the values obtained by MC integral. The mean value of the acquired N samples can approximately represent the integral value, then (28) is converted into (29):

$$E\left[g(x_{0:k})\right] = \frac{1}{N}\sum_{i=1}^{N} g(x_{0:k}^{(i)}) \tag{29}$$

4) Sequential Importance Sampling: MC method needs all observation samples to estimate the data, and massive computation is required to determine the sequential importance weigh values when renewing data. So the sequential importance sampling (SIS) is proposed.

SIS realizes the weight calculation by the recursive method [17]. Which consists of two procedures, namely the prediction and renewal; the details are below:

- Prediction: According to $x_k(i)$:$q(x_k|x_{0:k\text{-}1},y_{1:k})$ (i = 1,2,3,..,N), the renewal samples of the system state is $x_{0:k}(i) = \{x_k(i), x_{0:k\text{-}1}(i)\}$.
- Renewal: The weight values $w^*_k(i)$ of the renewal samples are acquired by (30):

$$w_k^*(i) = w_{k-1}^*(i) \frac{p(y_k \left| x_k\right.) p(x_k \left| x_{k-1}\right.)}{q(x_k \left| x_{0:k-1}, y_{1:k}\right.)} \tag{30}$$

Then, the normalized weight values of the samples are calculated by (31):

$$w_k(i) = \frac{w_k^*(i)}{\sum_{i=1}^{N} w_k^*(i)} \tag{31}$$

The obtained weighted samples are $\{x_k(i), w_k(i)\}$ (1,2,..,N). The probability density is shown as (32)

$$P\left(x_k \left| y_{1:k}\right.\right) = \sum_{i=1}^{N} w_k(i) d\left(x_k - x_{k-1}(i)\right) \tag{32}$$

For the prediction procedure, firstly, use the probability distribution of $x_{k\text{-}1}(i)$ to acquire the particle, which is the distribution of the particle in the state space. Then, predict all particles according to the state transition equation. Finally, in the renewal procedure, assess all particles according to the observation equation and observation values y_k.

Although SIS algorithm improves the weight calculation, it exists the sample degradation problem. To solve this situation, Gordon proposed the resampling model [18]. Resampling model can increase the number of particles with larger weight and reduce those with smaller weight. The effective number N_{eff} of particles is used to measure the degradation degree of particles, which is calculated as (33).

$$N_{eff} = round\left[1 \Big/ \sum_{i=1}^{N} \left(w_k(i)\right)^2\right] \tag{33}$$

Where *round* (·) represents the round operation to the nearest integral; the smaller N_{eff} represents the more serious degradation. When N_{eff} is smaller than the threshold value N_{th}, the resampling is required to improve filter performance.

5) The Basic Algorithm of Particle Filter: Standard PF algorithm has four steps: particle production, particle weight calculation, resampling, and state estimation.

Step 1: Particle production: generate the particle sets from the transition probability density of the system state: $x_k(i)$: $q(x_k|x_{k-1})$ (i = 1, 2, 3, …, N).

Step 2: Particle weight calculation: particle importance sampling $x_k(i)$~$p(x_k|x_{k-1}(i))$, it is assumed that the weight means that the probability of the observed values is y when the real state x_k takes the ith particle. Renew the particle weight $w_k^*(i)$, and $w_k^*(i)$ is normalized to get $w_k(i)$.

Step 3: Resampling: if $N_{eff}<N_{th}$, resample $x(i)$ to generate a new particle set $x_k^*(i)$, and set the weight values of all particles as $w_k(i) = 1/N$.

Step 4: State Estimation: the state estimation function is:

$$x(i) = \sum_{i=1}^{N} w_k(i) x_k(i) \tag{34}$$

where, a sequence of weighted samples $\{x_k(i), w_k(i)\}$ (i = 1, 2, 3, …, N) is obtained.

C. Fusion Method

PF method can provide a satisfied prediction result of the circuit state, but it must require the state transition equation, which is not always available in actual applications, and sometimes the tracking trajectory of the circuit state can only be obtained, where PF method are not suitable for the degradation prediction. In addition, the prediction results based on particle filter are heavily dependent on the empirical models, which results in the weak adaptability for different data. Therefore, this paper adopts the trend equation of the historical data constructed by the regression curve fitting method instead of the state transition equation to produce the particles. The fusion method consists of three aspects. The framework is presented in Fig.2.

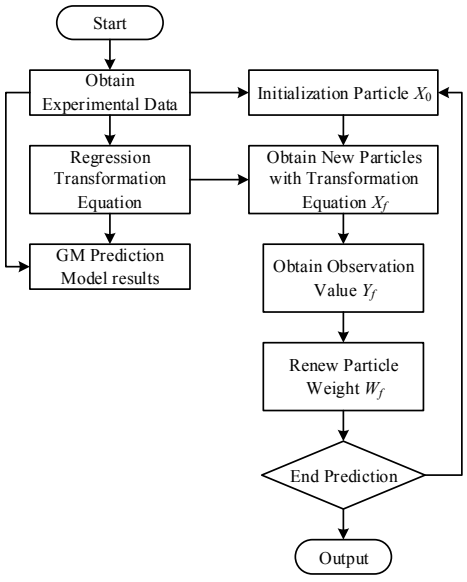

Fig. 2. The Framework of the Fusion Method

Step 1: Obtain experimental data y^* and preprocess the experimental data y^*.

Step 2: Set up the moment T as the starting point of the prediction, namely, select the experimental data before the moment T as the known historical data, and execute the prediction algorithm after the moment T.

Step 3: Establish the regression equation for the experimental data before the moment T, and obtain the state space model of the system x_k.

Step 4: Obtain the long term prediction output sequence of the data based on GM model. The prediction values are considered as the observation values y_k of the observation equation in the PF method.

Step 5 Initialize PF method. Set the parameters of the prediction process: the number of particles N, the covariance R of the system noise w_k, the covariance Q of the observation noise e_k, and the initial state value x_0.

Step 6: Start the prediction from the moment T, execute the PF method.

Step 7: Estimate whether the prediction quantity reaches the requirement, if it does, terminate the circulation, and the final prediction values are obtained. The prediction results are compared with the simulation results, and the prediction error is calculated

III. Simulation Experiment Circuit

In this paper, the high-voltage power board (HPB) based on UC1846 is used as the experiment circuit. The HPB can produce three high voltage DC signals of the KV level.

A. High-voltage Power Board

The HPB is divided into five modules, the circuit diagram is shown as Fig. 3.

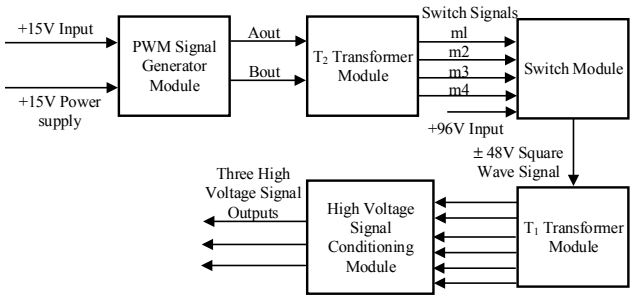

Fig. 3. The Circuit of the High-Tension Power Board.

The first part is PWM signal generator module, which is composed of the chip UC1846, the power supply and input signal are both +15V, two PWM signals A_{out} and B_{out} are produced by UC1846. Then, these two signals are converted to four switch signals m1, m2, m3, m4 from the T_2 transformer module. Thereafter, the obtained four signals are used as the controlling signals of MOS transistors in switch module, the ±48V square wave signal is obtained under the +96V input signal. Finally, the square wave signal is converted into three high voltage signals by T_1 transformer module and signal conditioning module.

B. Experimental Data Acquisition

The components of HPB contain resistors, capacitors, MOS transistors and the UC1846 chip. With the increasing operation time, the parameter degradation of the components will occur under the environment stresses, and the voltage outputs are inevitably changed. This paper uses the simulation experiments to obtain the degradation data of the HPB by Pspice, take three months as one time stage, and select 40 time points. Then, calculate the degradation parameters of the components in 40 time points. Finally, 40 degradation parameters of all components are bought into the circuit to get 40 degradation outputs of the circuit. When analyzing the experimental outputs of the HPB, it discovers that the outputs of HPB mainly have two types of the degradation trends, they are shown in Fig.4 and Fig.5.

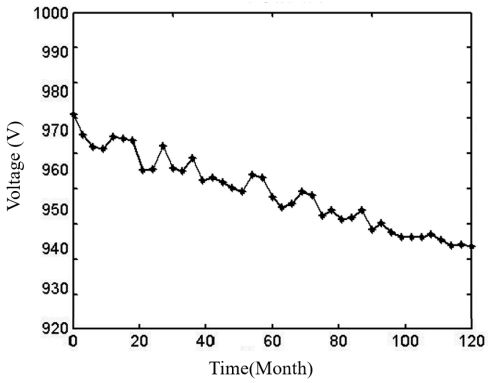

Fig. 4. The voltage amplitude of V1 of HPB.

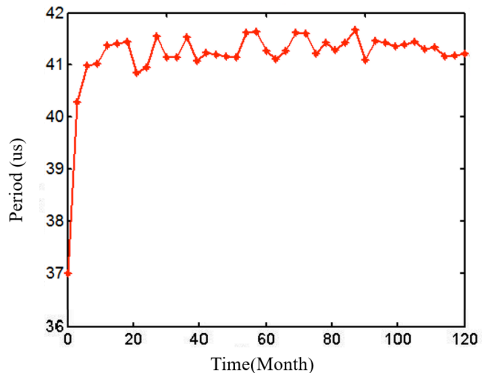

Fig. 5. The period of Aout of HPB.

Denote the experimental data as $X^* = \{x^*(1), x^*(2), \ldots, x^*(n)\}$. According to (35), the new data with the uniform size standard are obtained.

$$x(i) = \frac{x^*(i) - x^*_{\min}}{x^*_{\max} - x^*_{\min}} \tag{35}$$

The difference between two adjacent data points is calculated based on (36) and the residual sequence is $V = \{v(1), v(2), \ldots, v(n)\}$.

$$v(i) = x(i+1) - x(i) \tag{36}$$

The mean value of the sequence is:

$$v = \frac{1}{n}\sum_{i=1}^{n} v(i) \tag{37}$$

The variance of the sequence is:

$$S_1^2 = \frac{1}{n-1}\sum_{i=1}^{n}\left(v(i) - v\right)^2 \tag{38}$$

The variance S_1^2 of the output V_1 and the period A_{out} of HPB are 0.973 and 0.974, respectively. After removing the maximum residual, the updating variance S_2^2 of V_1 and A_{out} are 0.691 and 0.045 respectively. When the value of S_1^2 is more 10 times than that of S_2^2, it suggests that some data points are seriously deviating from other data points, the type of the data is supposed to be the mutation data. When the value S_1^2 equals approximately to S_2^2, the degree of data points deviating from the center are similar, and the type of data belongs to the slow variable data. According to the above evaluation criteria, the degradation amplitude values of V_1 conforms to the characteristics of the slow variable data, and the degradation period values of A_{out} is supposed to be the mutation data.

IV. Degradation Prediction Experiment

The fusion prediction method is applied to these two types of data sets obtained from the HPB in Section III, B. Then compare the prediction results with the actual experiment outputs to calculate the error, which is used to validate the prediction method. In the experiments, set the prediction start time point T as 60. For the obtained 40 data sets, the first 20 data sets are regarded as known to predict the last 20 data sets, which are compared with the obtained last 20 data sets to validate the method.

A. Simulation Experiment of the Slow Variable Data

The slow variable data consists of the degradation amplitude values of V_1 in HPB with 10-year operation time. The paper uses the regression curve fitting method to establish the state equation x_k of PF based on the first 20 data sets of the degenerate amplitude values of V_1 using the fusion method.

1) Curve Fitting Results: The regression curve fitting method is conducted by Curve Fitting tool toolbox of MATLAB. The results and actual output are shown in Fig. 6.

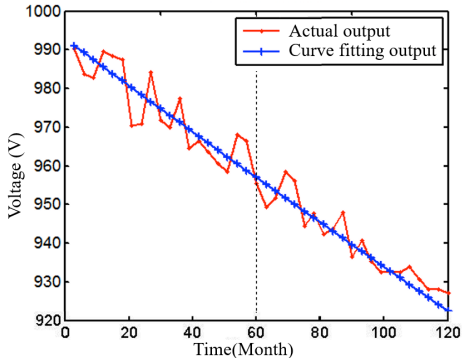

Fig. 6. The actual output and curve fitting output of V1.

2) GM(1, 1) Experiment Results: The known first 20 data are used to predict the next 20 data sets of the degradation amplitude values of V_1 based on GM(1, 1) method. The predicted 20 data sets are considered as the observation values y_k for the PF method. The outputs are shown in Fig. 7.

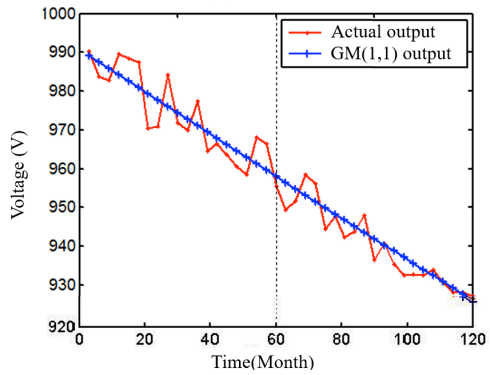

Fig. 7. The actual output and GM(1,1) output of V1.

The prediction data are compared with the actual output data, the parameters of the prediction results are follows. The average relative error $|\varepsilon^{(0)}(k)|$ of is 0.0040, the precision p^0 is 0.9960, the posterior difference ratio C is 0.0132, and the small error probability p is 1. According to the precision evaluation standards of GM model, the parameters including the relative error, the accuracy, the posterior difference ratio, and small error probability are all rated as Grade I. In conclusion, the prediction results are suitable for the medium and long term prediction. The prediction results of GM (1, 1) can be applied to PF prediction method as the observation values.

3) Fusion Method Experiment Results: In the experiment, firstly, initialize the parameters. Set the number of particles N as 1000, set the starting time point T as 60, the covariance R of the process noise w_k is 1, and the covariance Q of the observation noise e_k is 1. Then the algorithm is executed from the time point T, the degenerated amplitude values of V_1 are predicted after each iteration, meanwhile, determine whether T reaching the end point. Finally, the iteration process will terminate when T equals to the end point. The results including the predicted degeneration amplitude values of V_1 and the 95% confidence interval are described as Fig .8.

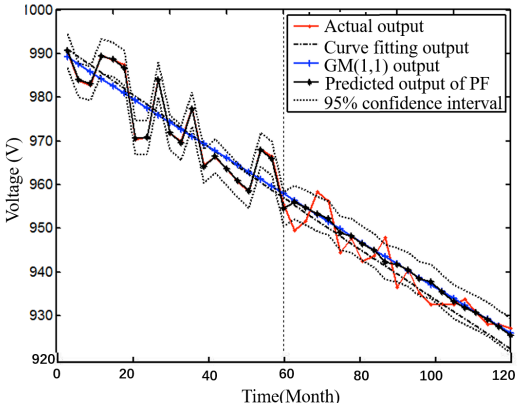

Fig. 8. The actual output and prediction results of V1 based on Fusion Method

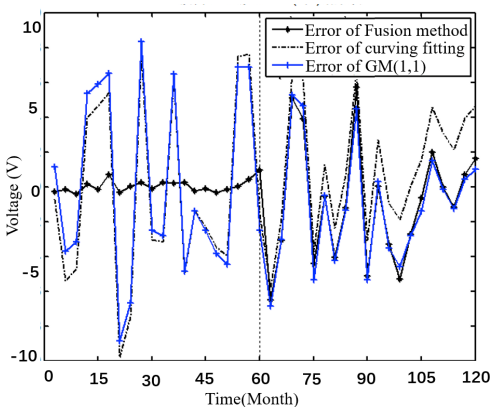

Fig. 9. Prediction Errors of V1 with different prediction Methods

Fig. 8 shows the prediction results of three methods and the actual output. Fig. 9. illustrates the prediction error of three methods. Compared with the actual output, the error mean square values of the curve fitting method, GM (1,1) method and the fusion prediction method are 2.6567, 2.5434, and 2.4707, respectively. The error of the fusion prediction method is about 0.2% of the actual voltage amplitude value, and the actual degradation amplitude values of V_1 all locate in the 95% confidence interval of the prediction values. It shows that the proposed fusion prediction method improves the precision of the long term prediction, and has the ability to express uncertainty.

B. Mutation Data Simulation Experiment

The mutation data consists of the degradation period values of A_{out} in HPB with 10-year operation time. The paper uses the regression curve fitting method to establish the state equation x_k of PF based on the first 20 data sets of the degenerate amplitude values of A_{out} using the fusion method. The output of the degradation period values of A_{out} based on Curve fitting output method is shown as Fig. 10. The fitting output deviates seriously from the actual output. In order to solve this problem, the original data is reconstructed by coordination transformation.

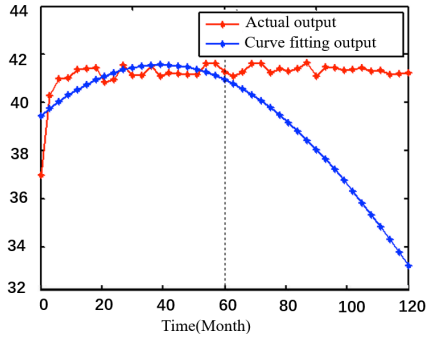

Fig. 10. The actual output and curve fitting output of A_{out}.

1) Results for Coordination Transformation: The principle of coordination transformation is making the degradation period curve conform to the feature of the slow variable data. The paper uses the equation $x^* = \lg(x)$ to transform the coordination. The transformed slow variable data x^* are shown in Fig. 11.

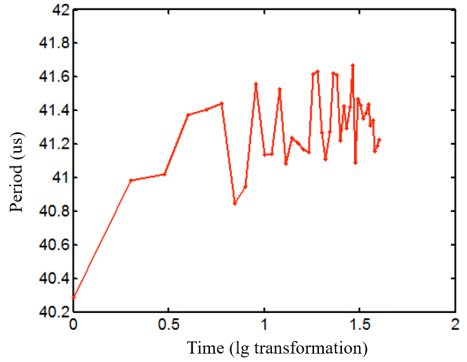

Fig. 11. Results of the data after Coordination Transformation.

Take the new data x^* as the experiment data, and use the Curve fitting output method to carry out the regression curve fitting. The results are illustrated in Fig. 12.

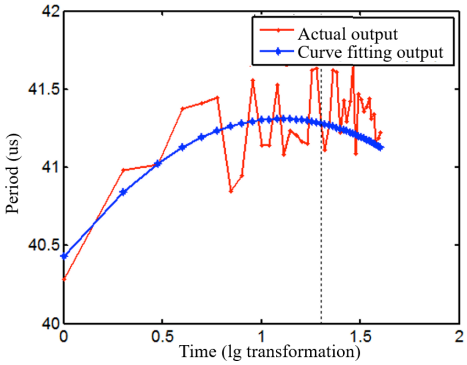

Fig. 12. The actual output and Curve fitting output of Aout.

As shown in Fig.12, the new data x^* conforms to the slow variable data. The curve fitting output can describe the data effectively, which demonstrates that the coordination transformation is valid. The curve fitting output can be used as the state equation for the fusion method.

2) GM(1, 1) Experiment Results: In the GM prediction experiment, the transformation data are interpolated with the equal step, and new experimental data are obtained. The data by different interpolation methods are shown in Fig.13. The results of linear interpolation method are chosen as the experimental data of GM (1, 1). The prediction results are described as Fig. 14.

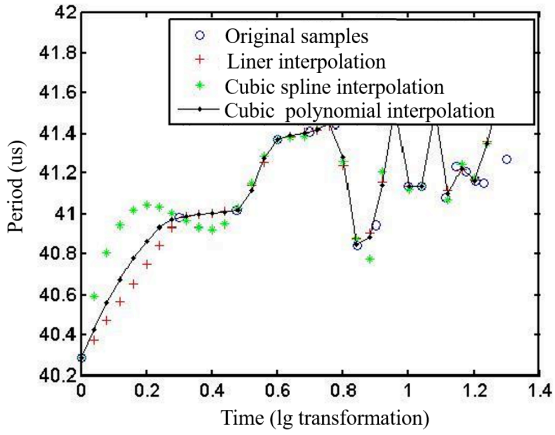

Fig. 13. The results with different interpolation methods.

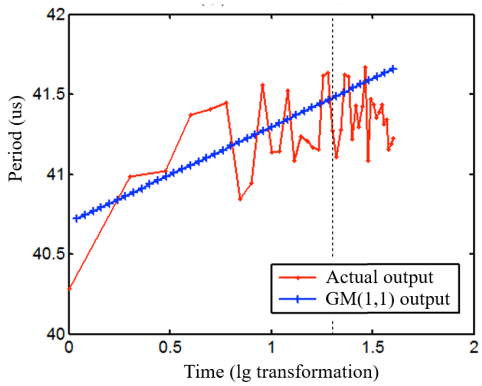

Fig. 14. The actual output and GM(1,1) output of Aout.

The prediction data are compared with the actual output data, the parameters of the prediction results are follows. The average relative error $|\varepsilon^{(0)}(k)|$ of the prediction results is 0.0100, the precision p^0 is 0.9910, the posterior difference ratio C is 0.3114, and the small error probability p is 09756. According to the accuracy evaluation standards of GM prediction, the parameters including the relative error, the accuracy, the posterior difference ratio, and small error probability are all rated as Grade I. In conclusion, the prediction results are suitable for the medium and long term prediction. The prediction results of GM (1, 1) can be applied to PF prediction method as the observation values.

3) Fusion Method Experiment Results: In the experiment, firstly, initialize the parameters. Set the number of particles N as 1000, set the starting time point T as lg20, the covariance R of the process noise w_k is 0.04, and the covariance Q of the observation noise e_k is 0.04. Then the algorithm is executed from the time point T, the degenerated period values of A_{out} are predicted after each iteration. Finally, the iteration process will terminate when T equals to the end point. The results including the predicted degeneration period values of A_{out} and the 95% confidence interval are described as Fig .15. After the experimental results of the coordination transformation are obtained, the abscissa coordination is inversely transformed to get the original coordination, then the degradation period values of A_{out} are shown as Fig. 16.

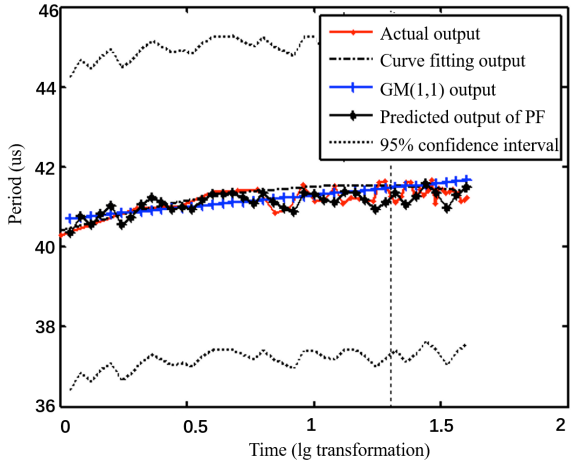

Fig. 15. The actual output and prediction results of A_{out} based on Fusion method with the transformation coordination.

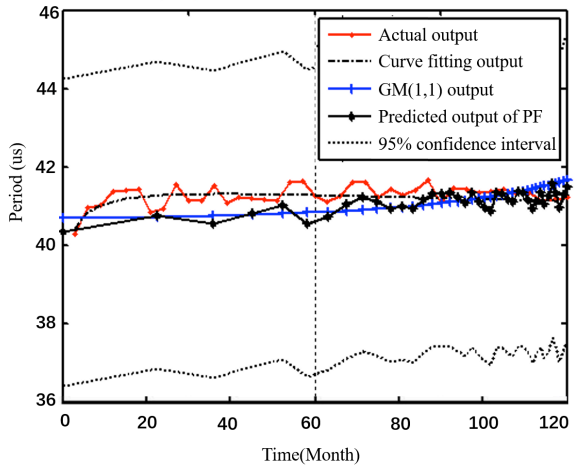

Fig. 16. The actual output and prediction results of A_{out} based on Fusion Method with the original Coordination.

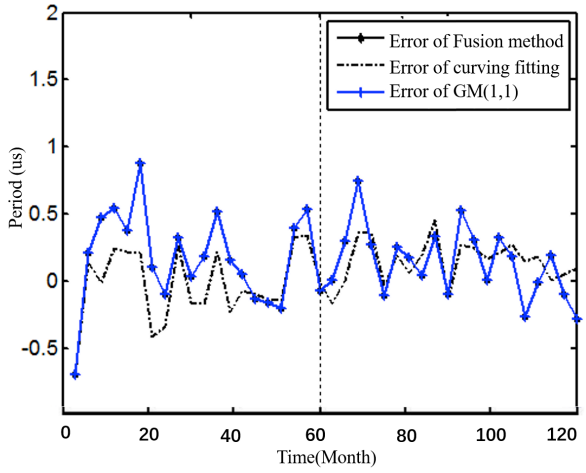

Fig. 17. Prediction Errors of A_{out} with different prediction Methods

Fig. 16 shows the prediction results of the three methods and the actual output. Fig. 17. illustrates the prediction error of three methods. Compared with the actual output, the error mean square values of the curve fitting method, GM (1,1) method and the fusion prediction method are 0.4437, 0.3388, and 0.2388, respectively. The error of the fusion prediction method is about 0.5% of the actual period value, and the actual degradation period values all locate in the 95% confidence interval of the prediction value. It shows that the proposed fusion prediction method improves the precision of the long term prediction, and have the ability to express uncertainty.

V. Conclusion

This paper presented a fusion degradation prediction method having the accurate long-term prediction and the expression of uncertainty. The simulation experiments are applied on the HPB circuit to examine the validity. For two types of data including the slow variable data and the mutation data, all error are less than 0.5%, and all actual degradation values of the circuit locate in 95% confidence interval. That demonstrates the fusion model are suitable for the mid-to-long term prediction for different types of data, and can provide the the prediction probability, the prediction results will be useful for the reliability design of the analog circuits.

References

[1] Kulkarni, Chetan S., Physics based Degradation Modeling and Prognostics of Electrolytic Capacitors under Electrical Overstress Conditions, AIAA Infotech@ Aerospace (I@ A) Conference, 2013.

[2] Huang W, Askin R G. Reliability analysis of electronic devices with multiple competing failure modes involving performance aging degradation[J]. Quality & Reliability Engineering International, 2003, 19(3):241-254.

[3] Yu, Gang, Lu Ying Sheng, and Mi Mi Guo, Degradation Model Prediction for Battery of Electric Vehicle Based on Hidden Markov Model, Applied Mechanics and Materials, vol. 378, Trans Tech Publications, 2013.

[4] Zhang Jianxun, Hu Changhua, Zhou Zhijie, Si Xiao Sheng, Du party wave. Multi Degenerate Variable based on the Copula Function based Residual Life Prediction Method of Gyroscope, 2013,09.

[5] Zhou Daming, Degradation Prediction of PEM Fuel Cell Stack Based on Multiphysical Aging Model With Particle Filter Approach, IEEE Transactions on Industry Applications, vol.53.4, 2017, pp. 4041-4052.

[6] Li X, Zhang P. Medium-Long Power Load Forecasting Based on Improved Grey BP Model[C]// First International Workshop on Education Technology and Computer Science. IEEE, 2009:366-368.

[7] Wang S Y, Chen D J, Ye Y Z. Research on Fault Prediction Method of Power Electronic Circuits Based on Particle Swarm Optimization RBF Neural Network[J]. Applied Mechanics & Materials, 2014, 687-691:3354-3360.

[8] Tiao L, Wang L, Nan L I. Application of Multi-source Heterogeneous Deformation Prediction Model Fusion Method in Dynamic Prediction of Mining Subsidence[J]. Safety in Coal Mines, 2017. pp.140-143+147.

[9] Wang Yi, Xiao Mingqing, Yi W, Xiao M, Fang J. New algorithm for predicting ensemble aggregation fusion based on fuzzy error model and local neighbor revision[J]. Chinese Journal of Scientific Instrument, 2011, 32(10):2283-2289..

[10] Julong, Deng, Introduction to grey system theory, The Journal of grey system 1.1 , 1989, pp.1-24.

[11] Tien, Tzu-Li, A research on the grey prediction model GM (1, n), Applied mathematics and computation 218.9 ,2012, pp.4903-4916.

[12] Zhou, Wei, and Jian-Min He, Generalized GM (1, 1) model and its application in forecasting of fuel production, Applied Mathematical Modelling 37.9, 2013, pp.6234-6243.

[13] Zha Yuqiang, Based on the improved grey GM (1, 1) model, the prediction of gas well production, Reservoir Evaluation and Development, 2015.

[14] Y. Song D. Liu, C. Yang, and Y. Peng "Data-driven hybrid remaining useful life estimation approach for spacecraft lithium-ion battery", Microelectron Reliab, vol. 75, pp. 142-153, Aug. 2017.

[15] Xia B, Sun Z, Zhang R, et al. A Comparative Study of Three Improved Algorithms Based on Particle Filter Algorithms in SOC Estimation of Lithium Ion Batteries[J]. Energies, 2017, 10(8):1149.

[16] Weise, Klaus, and W. Woger, A Bayesian theory of measurement uncertainty, Measurement Science and Technology 4.1, 1993, pp.1.

[17] Olofsson M. Optimal switching problems under partial information : Monte Carlo Methods and Applications[J]. Monte Carlo Methods & Applications, 2015, 21(2):91-120..

[18] Carpenter J, Clifford P. Improved particle filter for nonlinear problems. IEE Proceedings of Rader, Sonar and Navigation, 1999, 1:2-7

..