A Fault Prediction Method Based on IAALO-SVM and Similarity Measure

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***Abstract*—As an important part of electronic products, analog circuits are widely used in various fields. However, the fault prediction technology of analog circuit is still in its infancy because of its nonlinear characteristics such as nonlinearity and tolerance. According to the characteristics of small sample nonlinear data in analog circuits, the farther the prediction time distance of IAALO-SVM algorithm is from the initial training sample, the greater the prediction error is. Therefore, this article through the use of analog circuit fault parameters offline database, introduced the choice of time series similarity measure method is similar to database, according to the size of the similarity for failure prediction result, combining the measured data and offline data is put forward based on IAALO - SVM and similarity measure the failure prediction of new scheme to predict the residual service life of main amplifier circuit. The example shows that the new scheme can obtain high prediction accuracy in a long time and has practical application value.**

Keywords-Analog circuit,IAALO-SVM, Similarity measure, Fault prediction

I. INTRODUCTION

Analog circuits are important components commonly used in various types of electronic systems such as home appliances, automotive electronics, wireless sensor networks, and industrial electronics. Statistics show that 80% of electronic circuit faults come from analog circuits [1].

Prognostic and Health Management (PHM) technology has turned the faulty passive maintenance into an early response. The core of the strategy no longer focuses on finding faults and dealing with faults, but moving the focus to predicting when and where faults will occur. This happens, which can effectively reduce the cost of maintenance and the damage caused by the failure. However, as the functions of modern electronic products become more and more abundant and the structure becomes more and more large, the mechanism of analog circuit failure becomes more and more complicated, and the degraded signals are more and more difficult to monitor, and the losses caused by faults are becoming more and more serious. Compared with the PHM technology of mechanical products, the structure and fault mechanism of analog circuits are more complicated. The PHM technology for analog circuits is still in its infancy, and there are still many problems that are difficult to solve. Such as uncertainty in residual life prediction, prediction of intermittent failure, in-situ monitoring of circuit life cycle data, threshold for determining system performance, etc. At the same time, with the popularization of electronic products, the use environment of analog circuits is more and more abundant. The life and reliability of analog circuits in different working environments and different working conditions will be very different.

Electronic product fault prediction technology can be divided into two catagories: model-based method and data-driven method. The model-based prediction technology which mainly used for device-level life prediction based on the physics of failure (PoF) model [2]. Physics model-based approaches describe degradation processes through building mathematical models on the basis of the failure mechanisms or the first principle of damage. The parameters of the physics models are correlated to the material properties and stress levels, which are generally identified by using specific experiments, finite element analysis or other suitable techniques.

The data-driven fault prediction method can detect the change of state parameters in real time, first estimate the existing cumulative damage based on the monitoring data, analyze the data trend, and predict the future fault state. Data-driven methods are widely studied and used because of their simple model and operability. Data-based methods include: Bayesian estimation, Auto-Regressive Moving-Average (ARMA) model [3], Artificial Neural Networks (ANN)[4], Ant Colony Optimization (ACO)[5], Support Vector Machines (SVM)[6,7] , Relevant Vector Machine (RVM)[8], Grey Model (GM)[9], Genetic Algorithms (GA)[10], Particle Filter (PF)[11]. Compared to other intelligent algorithms, SVM has great advantages. SVM can transform the solution optimization problem into quadratic programming optimization problem. For the nonlinear problem of analog circuit, SVM introduces the concept of kernel function and transforms the nonlinear problem into high-dimensional linear problem. At the same time, the SVM application structure risk minimization principle, based on the original empirical risk minimization principle, increases the confidence risk, thus avoiding the error

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caused by "over-learning" and making it have better generalization performance.

Based on these prediction algorithms, many optimization algorithms are proposed to improve the performance of fault prediction. For example, in view of the lack of fault information of electronic equipment and high failure rate, the fault prediction of electronic equipment is analyzed, and a fault prediction method based on least squares support vector machine (LSSVM) is proposed[12]; combined with LSSVR model and The AR model establishes an autoregressive-support vector machine (AR-LS SVR) prediction model[13]; the feedforward neural network (FNN)[14] is incorporated into the prediction framework based on EMD (empirical model decomposition), and a weighted reorganization strategy is proposed.

The adaptive ant lion optimization support vector machine single-step loop iterative (IAALO-SVM)[15] prediction method is to optimize the principle of the support vector machine (SVM) and the ant-lion optimization algorithms and adding a single-step loop iteration method, instead of the initial value of the time before and the new forecast as the training sample in each cycle, and sample updated in real time, reduce the cumulative error, minimizing the error value of each prediction. However, although the IAALO-SVM method can predict a more accurate prediction in a longer time, the prediction error is still large due to the distance between the prediction time and the initial training sample, and the remaining service life is calculated accordingly. Therefore, this paper introduces the method of time series similarity measurement, combines the measured data with offline data, and proposes a new fault prediction scheme based on IAALO-SVM and similarity measurement. According to the similarity, the fault prediction results are fused to predict the residual life of analog circuits. In this paper, the dynamic time warping (DTW) method is used to measure the time series of real-time monitoring and the time series in the database to predict the remaining life of the analog circuit.

This paper is arranged in the following order: Section Π introduces some basic theories including SVM, IAALO-SVM algorithm and DTW method. In the section III, fault prediction scheme based on IAALO-SVM and similarity measure is mentioned. The main channel amplifying circuit is taken as an example to predict the fault in the section IV. It is verified that the method can obtain higher prediction accuracy in a long time and has practical application value. Finally, summary and future work prospects are provided in Section V.

II. Basic Theory

A. SVM for Regression

The basic principle of SVM for regression analysis is to map data X of input space into high-dimensional feature space G through a nonlinear mapping, and realize linear regression in this space. Given k data samples $\{x_i, y_i\}$, $i=1,2,\cdots,k,\ \left(x_i \in R^n, y_i \in R\right)$. y_i is expected value. SVM simplifies regression problem by introducing insensitive coefficient ε, which is called ε-SVR. As standard algorithm of SVR, the aim is to estimate sample data. The output of function f(x) is predicted output y with error limit ε. The estimated function is:

$$y = f(x) = (w, \phi(x)) + b \tag{1}$$

where b is the offset.

Take extreme values of objective function when optimizing the estimation function:

$$\min J = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{k}(\xi_i^* + \xi_i) \tag{2}$$

where C is the penalty coefficient, which is used to achieve the compromise between empirical risk and confidence risk. The larger the value of C is, the higher the fitting ability to data is; ξ_i^* and ξ_i are relaxation factors, which are used to control the linear inseparable boundary. Quadratic programming problems are formalized into Lagrange formula as follows:

$$\begin{aligned} L(w,b,\alpha,\varepsilon,\xi) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{k}(\xi_i + \xi_i^*) - \\ \sum_{i=1}^{k}\alpha_i(\varepsilon + \xi_i - y_i + (w,\phi(x)) + b) - \\ \sum_{i=1}^{k}\alpha_i^*(\varepsilon + \xi_i^* + y_i - (w,\phi(x)) \\ -b) - \sum_{i=1}^{k}(\eta_i\xi_i + \eta_i^*\xi_i^*) \end{aligned} \tag{3}$$

where $\alpha_i \geq 0$, i=1,2,….k represents the Lagrange multipliers. L represents the primal problem. Minimizing L over w, b, ξi* and ξi are defined, respectively, and the dual optimization formula is obtained as follows:

$$\begin{aligned} \max\ J(\alpha) = \max\left\{-\frac{1}{2}\sum_{i,j=1}^{k}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)k(x_i, x_j)\right. \\ \left. -\varepsilon\sum_{i=1}^{k}(\alpha_i + \alpha_i^*) + \sum_{i=1}^{k}y_i(\alpha_i - \alpha_i^*)\right\} \end{aligned} \tag{4}$$

The regression function can be expressed as:

$$f(x) = \sum_{i=1}^{k}(\beta_i + \beta_i^*)k(x_i, x_j) + b \tag{5}$$

where: β_i, $\beta_i^* \geq 0$; i=1,2,⋯,k is a Lagrangian multiplier, b is the bias term, which can be calculated according to the KKT condition. At present, there are three commonly used kernel functions: linear kernel functions, polynomial kernel functions, and radial basis functions. RBF (radial basis functions) has advantages of not too much complexity for multivariate input, radial symmetry, smoothness, and convenience for theoretical analysis. Additionally, it has been proved by practice that the RBF kernel function has a good predictive effect even when the sample size is large or small, and the spatial dimension is low or high. It also has more wide usability and better accuracy than other kernel functions. so RBF is selected in this paper.

$$k(x,y)=\exp(-\|x-y\|^2/\sigma^2) \quad (6)$$

In SVM, the penalty parameter C, the insensitive error function ε and the kernel function parameters σ have a great impact on prediction performance and generalization ability of SVM.

B. IAALO-SVM algorithm

IAALO-SVM algorithm includes parameters optimization and iteration prediction phases. In the parameters optimization phase, AALO is adopted to obtain the better parameters values of ε，C，σ for SVM, which make a great influence on the prediction performance and complexity of SVM. And in iteration prediction phase, using single-step iteration strategy to update the sample in real time to obtain the predicted values of multiple moments. The operation flow chart is shown in Fig.1.

The specific steps are:

Step.1: Initialize AALO parameters. In addition to the number of populations and the maximum iteration numbers that AALO needs to set, AALO uses the training set to train SVM model to provide SVM regression machine values of C, σ, ε, so it is also necessary to set the upper limits Cmax and lower limits Cmin of penalty parameter C, upper limits σmax and lower limits σmin of kernel parameter, upper limits εmax and lower limits εmin of insensitive function, and vector dimension Dim;

Step.2: Train SVM regression model. The data set is preprocessed into train set and test set, as the data set for fault prediction is a time series data set, so the data at the time before some moment is considered as train set, and data of the future time is test set. SVM regression model is trained by using parameters C, σ, ε obtained in the previous step and train set updated in real time based on single-step iteration strategy.

Step 3: Judge the stopping criteria. If termination criterion is met, output SVM optimization parameters; if criterion is not met, AALO is used to generate a new solution, that is, update position of the ant and the antlion for the next iteration.

Step 4: Fault prediction. When the parameters C, σ, ε are determined, the complete SVM model has been constructed, the test set are input into the model, the predicted values of future fault moments are obtained.

C. Dynamic time warping(DTW)

DTW uses time series as a reference template to construct a regularization function, calculates the correspondence between similar points of unknown time series, minimizes the distance between the two sequences after matching, and obtains a regularization function. DTW uses the idea of dynamic programming to calculate the similarity of time series. The principle of DTW is to build a grid with length n and width m. Each intersection point in the grid represents the position of time series Q and C representing the distance measurement $d(q_i,c_j)$ of the two time series (the similarity of each point of Q to each point in the sequence C, the more the distance Small, the higher the similarity), where $d(q_i,c_j)=(q_i,c_j)^2$. The purpose of this method is to find a path through several grid points in the grid. The grid points through which the path passes are the alignment points for calculating the two sequences.

This path is defined as a regular path, represented by W, and the KTH element of W is defined as $W_k=(i,j)_k$, $W=\{w_1,w_2,\cdots w_k,\cdots w_K\}$, $\max(m,n)\le K<m+n-1$. The path needs to meet the following constraints:

(1) Boundary conditions: The selected path must start from the lower left corner and end in the upper right corner.

$$w_1=(1,1), w_K=(m,n) \quad (7)$$

(2) Continuity: If $w_{k-1}=(a',b')$, then the next point of the path $w_{k-1}=(a',b')$ needs to be satisfied

$$(a-a')\le 1, (b-b')\le 1 \quad (8)$$

(3) Monotonic: If $w_{k-1}=(a',b')$, then the next point of the path $w_{k-1}=(a',b')$ needs to be satisfied

$$0\le(a-a'), 0\le(b-b') \quad (9)$$

The minimum path is:

$$DTW=(Q,C)=\min\{\sqrt{\sum_{k=1}^{K} w_k}/k\} \quad (10)$$

The accumulated distance f(i,j) can be expressed as:

$$f(i,j)=d(q_i,c_j)+\min\{r(i-1,j-1),r(i-1,j),r(i,j-1)\} \quad (11)$$

The similarity can be calculated by comparing the distance values of the paths.

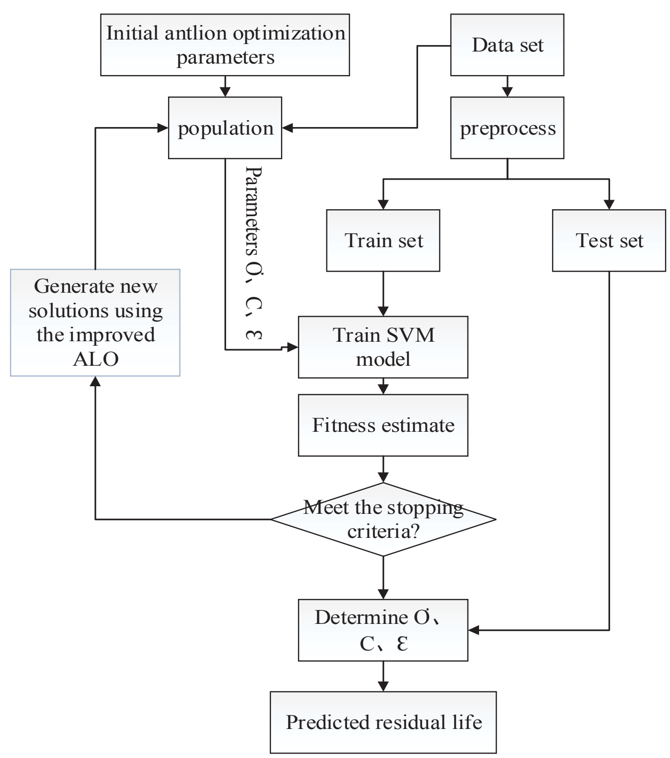

Figure 1. The operation flow chart of IAALO-SVM.

III. FAULT PREDICTION SCHEME BASED ON IAALO-SVM AND SIMILARITY MEASURE

In this section, the fault prediction scheme design based on IAALO-SVM and similarity measure is proposed as shown in Fig.2.

The specific steps are:

Step 1: Create an offline database. Comprehensively utilize the large amount of data information containing reliability generated during the design, production and testing of electronic products to establish an offline database, including test data for reliability testing of products, performance test data for various products in various environments, Simulation data for computer software aided design.

Step 2: Feature extraction. The fault parameters of the analog circuit are analyzed, and the fault parameters that can characterize the degradation trend of the circuit system are selected. The parameters are processed and extracted as the fault characteristics of the electronic product.

Step 3: Train the prediction model to get n complete degenerate trajectories. Based on the SVM for modeling, the offline fault features are input into the SVM respectively, and the SVM parameters are optimized by the IAALO to train the prediction model.

Step 4: Determine weights and perform fault prediction based on similarity measure. On the one hand, the real-time monitored data is input into the support vector machine model established by the offline data to obtain a series of life prediction results. At the same time, the real-time monitored data and the fault data in the database are determined by the similarity measure, and a series of life prediction results are combined to obtain the final remaining life.

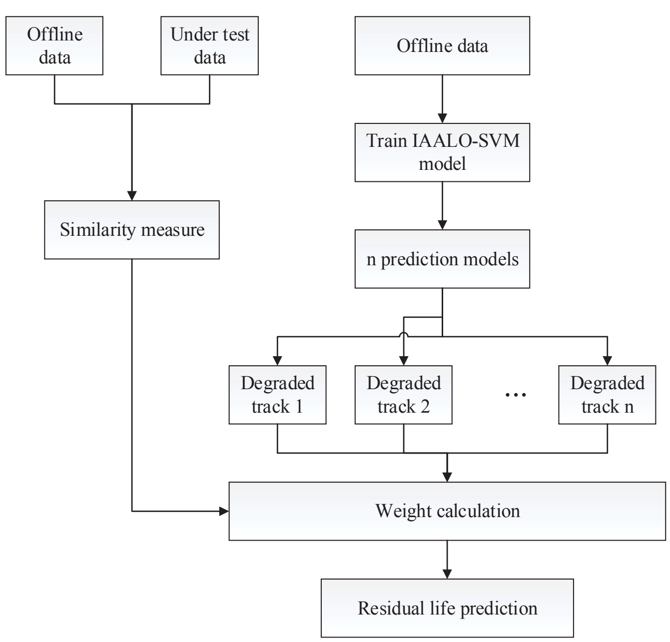

Figure 2. The operation flow chart of IAALO-SVM and similarity measure.

IV. CASE STUDY

In this paper, the main channel amplifying circuit in the rudder loop of an unmanned aircraft autopilot is selected as the experimental object to verify the proposed fault prediction method. By analyzing the circuit schematic diagram, the simulation circuit model of the main channel amplifying circuit is drawn in Pspice, which is shown in Fig. 3. R3 is the metal film resistor and C1 is the solid tantalum electrolytic capacitor.

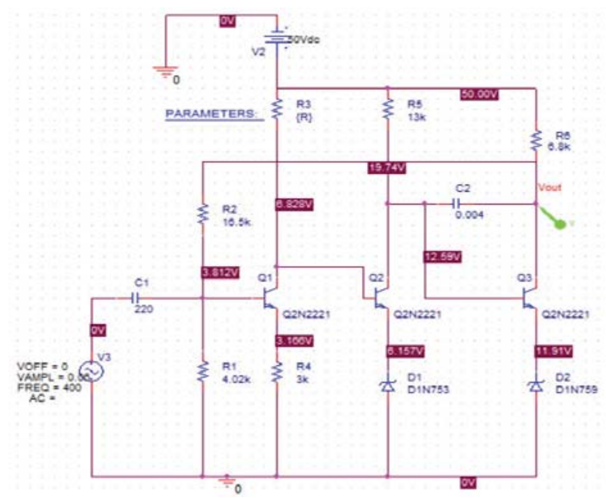

Figure 3. Input signal amplification circuit schematic diagram

A. *Fault feature parameter analysis and extractions*

1) *Select critical failure devices*

The nominal value of C1 of solid tantalum electrolytic capacitor is 220uF, and the variation range of 5% for C1 is taken as 209uF~231uF, with each increase of 2.2uF. The variation of frequency response voltage with capacitance value at 1KHz is shown in Fig.4.

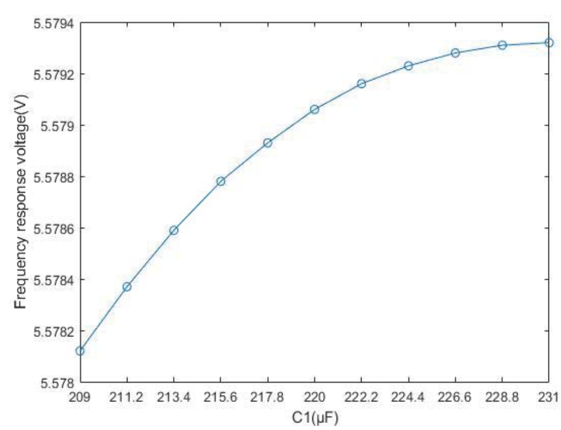

Figure 4. Frequency response voltage at 1KHz varies with C1 capacitance value

In Fig.4, the frequency response voltage increases with the increase of the C1 capacitance value. The metal film resistor R3 is nominally 30kΩ, and the variation range of ±5% for R3, that is, R3 is 28.5 kΩ~31.5 kΩ, each time increasing 300Ω. The frequency response voltage at 1 kHz varies with the resistance value as shown in Fig.5.

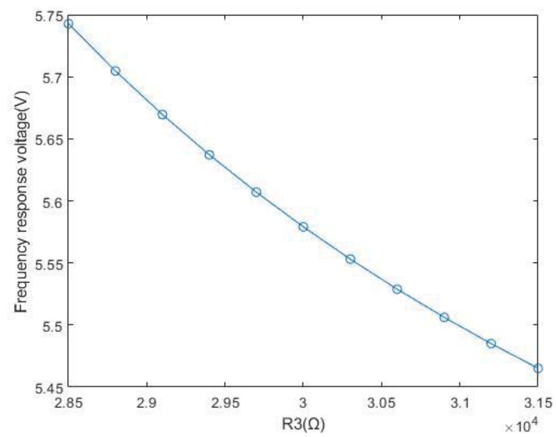

Figure 5. Frequency response voltage at 1KHz varies with R3 capacitance value

In Fig.5, the frequency response voltage decreases as the metal film resistance R3 increases. The solid tantalum electrolytic capacitor C1 is selected, and the metal film resistor R3 is selected as a critical fault device. With the degradation of the two types of devices, the frequency response voltage of the circuit system is reduced. Therefore, the frequency response voltage at 1KHZ frequency is selected as the characteristic parameter. The normal value is 5.58V, and the frequency response voltage fluctuates more than 5%. According to the range of [5.301V, 5.859V], the circuit is considered to be invalid.

2) Extracting circuit system fault characteristic parameters

According to the failure analysis of the metal film resistor R3, the law of resistance degradation is:

$$R_3(t) = 30000 + t \tag{12}$$

According to the failure analysis of the solid tantalum electrolytic capacitor C1, the degradation model of the capacitance value with time is as shown in equation:

$$C(t) = C(0)[1 - \Delta C(t)] = 220 \times [1 - 0.002 \times (e^{6\times10^{-5}t} - 1)] \tag{13}$$

The R3 and C1 values are set in the circuit diagram every 100 hours, and the frequency response voltage value of the corresponding system 1KHZ is obtained through simulation. When the frequency response voltage reaches the threshold value of 5.301V, the circuit fault is recognized, and the whole life cycle is intercepted until the fault occurs. Characteristic parameter value as a degenerate trajectory.

In order to obtain multiple sample data, Monte Carlo simulation was performed within the tolerance range of ±2% of the nominal value of each device. The number of simulations was 9 times, and the previous sample was counted, and a total of 10 degenerate trajectories were obtained.

B. *Fault prediction and life fusion*

Among the 10 degraded trajectories obtained, 7 of them were selected as the training set to train the IAALO-SVM model, and 7 complete models were obtained. The predicted model parameters are shown in TABLE I. The other 3 are used as test sets. To expand the sample size, assume that the current time is i hours (i=1600, 1700, ...2000, 3000, 3100, ..., 3400), and intercept the [i-1100, i] before the current time. The data in the range and the data of the training set are similarly measured based on the dynamic time warping method, and the similarity list of the object to be tested and each training set is obtained.

The smaller the distance d of the two data sets, the higher the similarity between the two sequences, the greater the weight of the prediction results of the corresponding sequence, and the weight of the sequence prediction result is assumed to be $w_i = 1/d_i$ (i=1, 2...7), then the final life prediction fusion result at a certain time is:

$$t = \sum_{i=1}^{7} t_i w_i \Big/ \sum_{i=1}^{7} w_i \tag{14}$$

where t_i is the prediction result input to different models.

The comparison between the prediction error of the main channel amplification circuit based on IAALO-SVM and similarity measure method and the prediction error based on IAALO-SVM method is shown in Fig.6- Fig.8.

TABLE I. SVM MODEL PARAMETERS TABLE UNDER EACH TRAINING SET

Training Set	SVM Parameter		
	Penalty parameter C	***Kernel function***	***Insensitive function***
Training set 1	99.99	3.558	0.047
Training set 2	99.99	4.126	6.271
Training set 3	100	3.586	6.570
Training set 4	100	25.221	8.396
Training set 5	99.99	35.326	6.187
Training set 6	99.99	3.841	0.883
Training set 7	99.99	4.184	9.283

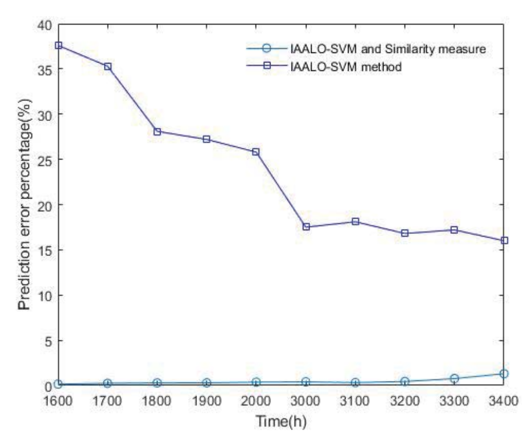

Figure 6. Comparison of life prediction errors based on two methods at each time point of test set 1

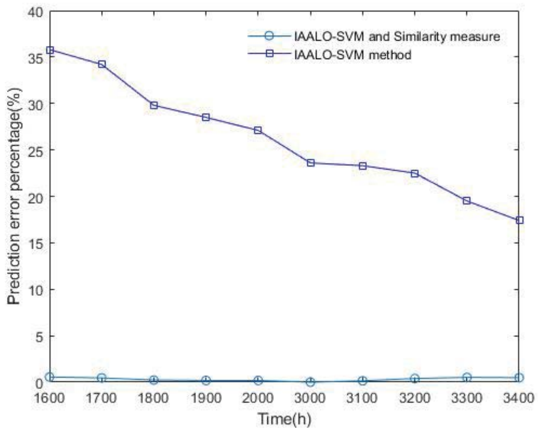

Figure 7. Comparison of life prediction errors based on two methods at each time point of test set 2

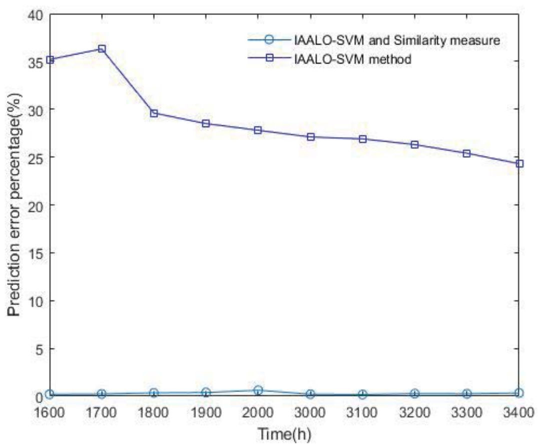

Figure 8. Comparison of life prediction errors based on two methods at each time point of test set 3

From the Fig.6-Fig.8, it can be seen that the prediction error of residual life of main channel amplifier circuit by IAALO-SVM method ranges from 16% to 40%.The fault prediction method based on IAALO-SVM and similarity measure predicts the remaining life of the main channel amplifying circuit, and the corresponding time prediction error is less than 1%, which is far lower than the IAALO-SVM method, indicating that IAALO-SVM and similarity measure are based on the prediction method can combine the measured data with the offline data, fully exploit the useful information in the offline data.

V. Conclusion

In this paper, the offline database of analog circuit fault parameters is used to combine the measured data with the offline data. Then the time series similarity index is deeply studied, and a new idea of fault prediction based on IAALO-SVM and similarity metrics is proposed. On the characteristics of the sequence data, the DTW method is selected to mine the similarity between the object to be tested and the offline data, so as to make full use of the offline data to predict the object to be tested, and finally select the main channel in the rudder ring of the drone autopilot. Circuit. The fault characteristic parameters of the circuit system are extracted by the degradation simulation of key components, and the DTW method for similarity measurement is modeled by the optimized support vector machine method, and then the remaining lifetime of the main lifetime integrated channel amplifier circuit is verified. The proposed fault prediction method based on IAALO-SVM and similarity measure.

Several directions for future research are proposed. First, some public data sets should be tested in the future to validate and extend the proposed algorithm. Secondly, this method needs to be applied to other electronic products to verify the applicability of the proposed method.

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