Degradation Trend Prediction of Linear Regulator Based on SVR Under Nuclear Radiation Stress

Hongwei Qiao
Nuclear Power Institute of China
Chengdu, China
Qiaohongwei99@163.com

Li Zhan
Nuclear Power Institute of China
Chengdu, China
78517996@qq.com

Jie Liu
Nuclear Power Institute of China
Chengdu, China
liujie_cult@163.com

Lin Zhang
Nuclear Power Institute of China
Chengdu, China
castalzhang@126.com

ZhangChun Tang*
University of Electronic Science and Technology of China
Chengdu, China
tangzhangchun@uestc.edu.cn

Jia Xie
University of Electronic Science and Technology of China
Chengdu, China
maggiexie0814@163.com

***Abstract*—Due to the development of science and technology, many electronic products still need a long time to degrade and fail under the condition of accelerated life test, especially under the harsh test conditions such as nuclear radiation, and it brings great challenges to research on the reliability of electronic products. In order to obtain the performance index of electronic product degradation failure, this paper proposes to use support vector regression(SVR) method to predict the performance degradation index of AP1117E series linear voltage stabilizer under nuclear radiation stress, and use the degradation data obtained from the test and the predicted degradation data to complete the reliability evaluation of the device. The prediction method proposed in this paper is used in the actual reliability assessment engineering project, and it has played a certain suggestive role for future reliability assessment work.**

Keywords—nuclear radiation; support vector regression; regression prediction; reliability assessment

I. INTRODUCTION

With the development of various high and new technologies, the reliability of electronic products has been significantly improved, and the conditions for degradation and failure of electronic products through accelerated life test have become increasingly harsh. Due to the limitation of test conditions, the accelerated life test usually cannot be continued before failure threshold, and it brings some difficulties to the reliability evaluation of electronic products. This is the case for the degradation test of the AP1117E series of linear voltage stabilizer components under the nuclear radiation stress studied in this paper. In order to study the reliability of electronic products under this condition, this paper proposes a method for predicting the degradation trend of AP1117 series linear voltage stabilizer components based on support vector regression (SVR) under nuclear radiation stress.

For the product degradation prediction method, scholars have proposed various prediction methods, which can be roughly divided into the following categories. The first method is based on statistical theory [1], the second is about the prediction model, such as neural network [2], Auto-Regressive and Moving Average (ARMA) model [3], Auto Regressive (AR) model [4], they can perform one or more steps of equipment performance evaluation and prediction, and the third one is a prediction of performance degradation based on information fusion [5]. In addition, degenerate variables can be extracted by feature extraction, feature vectors can be predicted, and the predicted results can be evaluated [6].It is easy to find that the prediction of degradation trend of products under conventional stress has been widely studied, but the prediction of degradation trend of products under nuclear radiation stress is relatively rare. Lee. Changyong [7] put forward a prediction method of real-time prediction residual life of solder joints, using support vector machine (SVM) to trend analysis of these early response, and the results of impedance measurement are compared with those of solder joint residual life prediction, it also shows that the method can be used as a real-time health management of the effective means to electronic products, and it can be applied to the system where the performance variable changes gradually before the end of life. Lu.Yanfei [8] proposed a prediction model of bearing vibration signal noise elimination based on wavelet decomposition. The model was tested by experimental data of bearing degradation trend. For the root mean square value of bearing vibration signal, the ARMA algorithm is implemented by recursive least squares (RLS) algorithm.

978-1-7281-0860-5/19/$31.00 ©2019 IEEE

Guo.Shu [9] et al. adopts the method of transient current and cellular automata model, and combines with finite element analysis, evaluating the effect of uniaxial load on pitting corrosion under different passive layer degradation degree and hydrogen ion diffusion coefficient quantitatively. This paper aims to propose a prediction method for product degradation trend of AP1117 series linear regulator device under nuclear radiation environment stress, and use the experimental data and prediction data to evaluate the reliability of the device [10].

The main structure of this paper is as follows: the second part introduces the background method and principle, the third part focuses on the prediction method of degradation trend using support vector machine (SVR), the fourth part introduces the process of nuclear radiation test and shows the prediction result of degradation trend, and the conclusion is in the fifth part.

II. BACKGROUND PRINCIPLE

A. Support Vector Regression

Support vector regression [11] means that the support vector machine is used as a regression model, and the basic mathematical theory of the regression model will be briefly deduced and explained below. First, the dimensional training sample set $S=\{(x_1,y_1),(x_2,y_2),\ldots,(x_m,y_m)\}, x_i, y_i \in R$ is given, where x_i and y_i are the corresponding inputs and outputs in the R -dimensional space, and m represents the number of training samples. Support vector regression is based on the probability distribution function obtained from the training samples to estimate the output value corresponding to the new input sample, as shown in equation (1).

$$f(x)=\boldsymbol{w}\cdot\boldsymbol{x}+b \quad (\boldsymbol{w},\boldsymbol{x}\in R) \tag{1}$$

Here, $\boldsymbol{w}$ is the normal vector of the regression hyperplane and b is the offset of the origin. The goal of this method is to find a function for each pair of x_i and y_i, and this function should minimize the value of $\boldsymbol{w}$ and each set of training data (x_i,y_i) can be fitted with this function under the precision ε. When looking for the minimum value of $\boldsymbol{w}$, it will involve the optimization problem shown in equation (2).

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

The constraint condition of the above formula is shown in equation (3).

$$\begin{cases} y_i-w\cdot x_i-b\le\varepsilon+\xi_i \\ w\cdot x_i+b-y_i\le\varepsilon+\xi_i^* \\ \xi_i,\xi_i^*\ge 0 \end{cases} \tag{3}$$

Here ε is the precision value of the output estimation, ξ_i and ξ_i^* represent the positive and negative errors of non-negative relaxation variables respectively, and their absolute values are all greater than ε. The constant $C>0$ is used to balance the number of deviations greater than the ε sample point and the flatness of the regression function f. In other words, the SVR only minimizes errors that greater than ε. The two formulas above are all based on the following insensitive loss function, and it is expressed as follows:

$$|\xi|_\varepsilon=\begin{cases} 0, & |\xi|\le\varepsilon \\ |\xi|\text{-}\varepsilon, & |\xi|>\varepsilon \end{cases} \tag{4}$$

Here data points outside the ε range have non-zero slack variables, and the slack variables of the data points within the range are zero. Therefore, the optimization problem of the formula (2) can be expressed by the formula (5).

$$\begin{aligned} L=&\frac{1}{2}\|w\|^2+C\sum_{i=1}^{m}(\xi_i+\xi_i^*) \\ &+\sum_i\lambda_i(y_i-\langle w,x_i\rangle-b-\varepsilon-\xi_i) \\ &+\sum_i\lambda_i^*(\langle w,x_i\rangle+b-y_i-\varepsilon-\xi_i^*) \\ &-\sum_i\mu_i\xi_i-\sum_i\mu_i^*\xi_i^* \end{aligned} \tag{5}$$

Among them, λ_i, λ_i^*, μ_i, μ_i^* are Lagrangian multipliers related to constraints. Equation (5) strives for the partial derivatives of the parameters w, b, ξ_i and ξ_i^*, and then makes it equal to zero, finally the minimum value of the optimization problem in equation (5) can be obtained.

$$\begin{aligned} &w=\sum_i(\lambda_i-\lambda_i^*)x_i \\ &\sum_i\lambda=\sum_i\lambda_i^* \\ &\lambda_i+\mu_j=C \\ &\lambda_j^*+\mu_j^*=C \end{aligned} \tag{6}$$

Substituting the value in (6) into (5), and replacing the dot product $\langle x_i,x_j\rangle$ with $K\langle x_i,x_j\rangle$, the following dual optimization problem is obtained：

$$\begin{aligned} \max\{&-\frac{1}{2}\sum_{i,j}(\lambda_i-\lambda_i^*)(\lambda_j-\lambda_j^*)K(x_i,x_j) \\ &+\sum_i(\lambda_i-\lambda_i^*)y_i-\varepsilon\sum(\lambda_i+\lambda_i^*) \\ &+\sum_i(\lambda_i-\lambda_i^*)y_i-\varepsilon\sum(\lambda_i+\lambda_i^*)\} \end{aligned} \tag{7}$$

The constraint condition of equation (7) is as follows.

$$\begin{cases} \sum_i\lambda=\sum_i\lambda_i^* \\ 0\le\lambda_j\le C \\ 0\le\lambda_j^*\le C \end{cases} \tag{8}$$

The dual optimization problem is solved by finding the Lagrangian multiplier to get the value of w. Note that the support vector here is a data point where the Lagrangian multiplier is greater than zero and less than C. The Lagrangian multiplier of the data points in the $\pm\varepsilon$ range is zero, so this is not part of the solution. Finally, the b value can be obtained by applying the Karo-Kun-Tucker (KKT) condition [12]. The

KKT condition means that the product of the multiplier and the constraint must be zero, as shown in equation (9):

$$\begin{cases} \lambda_i\left(y_i - \langle w, x_i\rangle - b - \varepsilon - \xi_i\right) = 0 \\ \lambda_i^*\left(\langle w, x_i\rangle + b - y_i - \varepsilon - \xi_i^*\right) = 0 \end{cases} \tag{9}$$

B. Monte carlo method

Monte carlo method [13], also known as statistical simulation method and random sampling technique, is a random simulation method.

Assume statistically independent random variables are as follows:

$$X_i (i = 1,2,3,\ldots,\ k) \tag{10}$$

The corresponding probability density functions are respectively are as follows:

$$f(x)_1,\ f(x)_2,\ldots,\ f(x)_k \tag{11}$$

Suppose the functional function of the structure is as follows:

$$Z = \mathrm{g}(\boldsymbol{x}) = g(x_1, x_2, \cdots, x_n) \tag{12}$$

N groups of random numbers are generated according to the corresponding distribution of each random variable $\boldsymbol{x} = (x_1, x_2, \cdots, x_n)^T$.

The limit state function divides the basic variable space of the structure into failure region and reliable region, and the failure probability can be defined as:

$$P_f = \int\cdots\int_{g(x)\le 0} f_x(x_1, x_2, \cdots x_n)dx_1 dx_2 \cdots dx_n \tag{13}$$

Here, $f_x(x_1, x_2, \cdots x_n)$ is the joint probability density function.

The failure probability is expressed as the integral of the joint probability density function in the failure domain, so the failure probability can also be expressed as the mathematical expectation by the indicator function, shown as follows:

$$\begin{aligned} P_f &= \int\cdots\int_{g(x)\le 0} f_x(x_1, x_2, \cdots x_n)dx_1 dx_2 \cdots dx_n \\ &= \int\cdots\int_{R^n} I_F(\boldsymbol{x}) f_x(x_1, x_2, \cdots x_n)dx_1 dx_2 \cdots dx_n \\ &= E[I_F(\boldsymbol{x})] \end{aligned} \tag{14}$$

Here, R^n represents the dimensional variable space, $I_F(\boldsymbol{x}) = \begin{cases} 1, \boldsymbol{x} \in F \\ 0, \boldsymbol{x} \notin F \end{cases}$ represents the indicator function, and $E[\bullet]$ represents the expectation factor.

If the method is integrated, the estimated failure probability can be expressed as follows:

$$\hat{P}_f \approx \frac{1}{N}\sum_{j=1}^{N} I_F(\boldsymbol{x}_j) = \frac{N_f}{N} \tag{15}$$

Here, $\boldsymbol{x}_j$ is the number j pseudo-random sampling point generated by the pseudo-random generator, and N_f is the number of fault samples.

As can be seen from the idea of Monte Carlo Method, this method avoids the mathematical difficulties in structural reliability analysis. Whether the state variable is nonlinear, or the random variable is non-normal, as long as the number of simulation is sufficient, a relatively accurate failure probability and reliability index can be obtained.

III. DEGRADATION TREND PREDICTION BASED ON SVR

For progressive failure components, due to the limitation of experimental conditions, the irradiation intensity may not reach the failure threshold of the component at the end of the test. This will make subsequent failure analysis work difficult, so this paper proposes to use SVR to predict the degradation trend of progressive failure components. Since there are only a small number of m-group test data limited by the test conditions in this paper, In order to reduce accidental errors and obtain more accurate prediction results, this paper will average the m-group test data for predictive analysis. The specific prediction steps are as follows, which can be summarized as shown in fig.1.

Step1: Firstly, the degenerate average values of the three sets of degradation test data are obtained. According to the measurement error of the instrument, the pseudo-random generator is used to generate N groups of uniformly distributed random variables within the measurement error range.

Step2: The irradiation intensity was used as the abscissa and the output voltage as the ordinate, and the irradiation intensity and output voltage values were trained by using the support vector regression theory, and the output voltage values at specific irradiation intensity were predicted by using the trained model.

Step3: In each of the set of degraded data in Step 2, a predicted output voltage value can be obtained, and N sets of predicted values are generated according to the N sets of random variables in Step 1. Kernel density prediction is performed on the predicted values using the ksdensity function in MATLAB.

Step 4: After obtaining the probability density function in Step 3, the confidence interval of the predicted value can be obtained and the reliability is obtained.

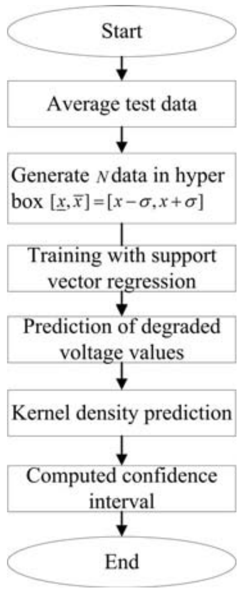

Fig.1. proposed method flow chart

IV. CASE ANALYSIS

In this paper, the degradation trend of AP1117 series chiplinear regulator device under nuclear radiation stress is predicted. The irradiation test is carried out in the cobalt source chamber of Peking University School of Chemistry. The cobalt source is cobalt 60 (Co), the radioisotope of metal element cobalt [14]. It can emit gamma rays and thus has ionizing radiation, and it is generally used as a radioactive source in engineering [15]. The linear power board is connected to the test board, placed in the irradiation room. After the irradiation starts, the computer records the monitored voltage value in real time. Through experiments, three groups of experimental degradation trends can be obtained, as shown in Fig. 2. Due to the different production batches of different devices, there are manufacturing differences between chip devices of the same model. The failure threshold of the linear voltage regulator device can be obtained by using the power supply condition of the linear regulated power supply as shown in Table Ⅰ.

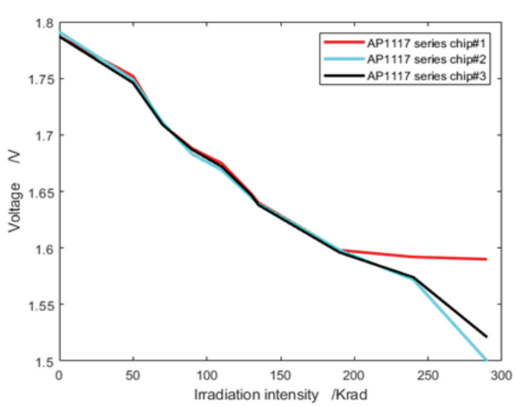

Fig. 2 Test degradation tendency

TABLE Ⅰ Failure threshold for linear regulators

Type	**AP1117** series chip **(#1)**	**AP1117** series chip **(#2)**	**AP1117** series chip **(#3)**
Failure threshold	1.46V	1.41V	1.42V

According to the prediction steps above, the linear voltage stabilizing device AP1117 series chip is predicted in this paper. This part will predict the degraded voltage values when the irradiation intensity is 450Krad, 500Krad and 550Krad.

The prediction result is shown in Fig.3. The blue points represent experimental data, and the remaining three voltage values are predicted at three irradiation dose points, and the least squares method is used to fit the curve in the figure.

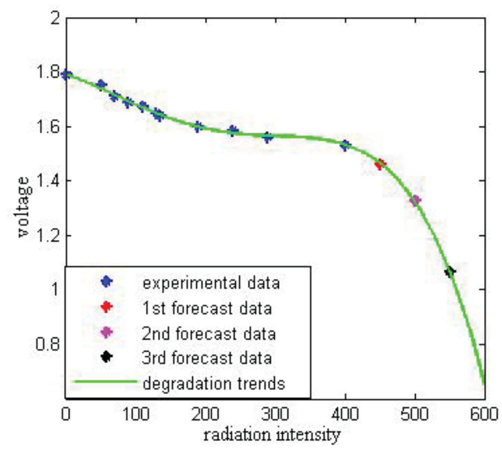

Fig.3. Regression trend prediction chart

Due to measurement error, insufficient accuracy, measurement sample difference and other factors, it is difficult to accurately determine the voltage value range. Therefore, the voltage value here should be a random variable obeying a certain distribution, and the uniform distribution $U\in\left[U^{-},U^{+}\right]$ is often used in engineering. In the nuclear radiation environment, the voltage trend of electronic components has obvious degradation phenomenon. In this paper, the pseudo-random generator is used to generate the voltage random variable corresponding to the dose points at each point, and the kernel density estimation method is used to obtain the probability density curve at each prediction point, as shown in Fig.4. The reliability of each prediction point is obtained by Monte Carlo method, and the specific prediction data are shown in Table Ⅱ.

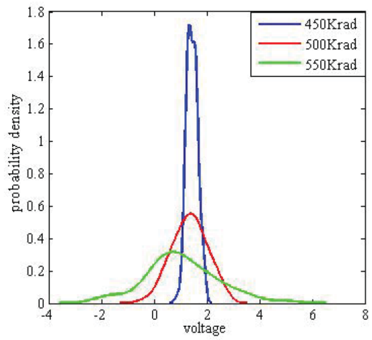

Fig.4. Probability density function

TABLE Ⅱ. Parameter prediction table

Irradiation intensity (Krad)	Predicted voltage value	Confidence interval (confidence 90%)	Reliability
450	1.4627	[1.0509,1.9875]	0.5193
500	1.3840	[0.3233,2.2328]	0.4542
550	1.0869	[-1.4202,3.1126]	0.4236

V. Conclusion

In this paper, the method of support vector regression is used to predict the failure trajectory of components in the case that the degradation data of AP1117 series chip failed devices cannot reach the failure threshold due to limited test conditions. The method used the data predicted by SVR and the data obtained from the experiment to evaluate the reliability of the subjects. It uses the least square method, Monte Carlo and the kernel density estimation method to evaluate the reliability. The method proposed in this paper provides a reference evaluation method for components in engineering applications that are difficult to reach the degradation failure threshold under complex conditions.

Acknowledgment

Comments and suggestions from all reviewers and the Associate Editor are very much appreciated. Meanwhile, authors gratefully thank the support of the National Natural Science Foundation of China (51875087), the Sichuan Science and Technology Program (2018GZ0170), and the Fundamental Research Funds for the Central Universities (ZYGX2018J047).

References

[1] WANG J, LI Z. Degradation model of multi-signals based on a novel feature-selection criterion [J]. Structural Health Monitoring-an International Journal, 2018, 17(6): 1491-1502.

[2] MAO W, HE J, TANG J, et al. Predicting remaining useful life of rolling bearings based on deep feature representation and long short-term memory neural network [J]. Advances in Mechanical Engineering, 2018, 10(12): 1-18

[3] SHENG Z, HU Q, LIU J, et al. Residual life prediction for complex systems with multi-phase degradation by ARMA-filtered hidden Markov model [J]. Quality Technology and Quantitative Management, 2019, 16(1): 19-35.

[4] LU Y, LI Q, LIANG S Y. Physics-based intelligent prognosis for rolling bearing with fault feature extraction [J]. International Journal of Advanced Manufacturing Technology, 2018, 97(1-4): 611-620.

[5] DONG S, SHENG J, LIU Z, et al. Bearing remain life prediction based on weighted complex SVM models [J]. Journal of Vibroengineering, 2016, 18(6): 3636-3653.

[6] LALL P, ZHANG H. Assessment of Lumen Degradation and Remaining Life of Light-Emitting Diodes Using Physics-Based Indicators and Particle Filter [J]. Journal of Electronic Packaging, 2015, 137(2): 1-10

[7] LEE C, KWON D. A similarity based prognostics approach for real time health management of electronics using impedance analysis and SVM regression [J]. Microelectronics Reliability, 2018, 83:77-83.

[8] LU Y, LI Q, LIANG S Y. Adaptive Prognosis of Bearing Degradation Based on Wavelet Decomposition Assisted ARMA Model [M]. 2017.

[9] GUO S, WANG H, HAN E-H. Computational Evaluation of the Influence of Various Uniaxial Load Levels on Pit Growth of Stainless Steel under Mechanoelectrochemical Interactions [J]. Journal of the Electrochemical Society, 2018, 165(9): C515-C23.

[10] LIE J, ZIO E. System dynamic reliability assessment and failure prognostics [J]. Reliability Engineering & System Safety, 2017, 160:21-36.

[11] MIAO F, WU Y, XIE Y, et al. Prediction of landslide displacement with step-like behavior based on multialgorithm optimization and a support vector regression model [J]. Landslides, 2018, 15(3): 475-88.

[12] Wu C , Wang X , Bai D , et al. Fast Incremental Learning Algorithm of SVM on KKT Conditions[C].International Conference on Fuzzy Systems & Knowledge Discovery. IEEE, 2009.

[13] LIU L, ZHOU F, BAI X-R. Method for scatterer trajectory association of sequential ISAR images based on Markov chain Monte Carlo algorithm [J]. Iet Radar Sonar and Navigation, 2018, 12(12): 1535-1542.

[14] SCHWANK J R, SHANEYFELT M R, DODD P E, et al. Correlation between Co-60 and X-ray radiation-induced charge buildup in silicon-on-insulator buried oxides [J]. IEEE Transactions on Nuclear Science, 2000, 47(6): 2175-2182.

[15] LAWAL O M, LIU S, LI Z, et al. Co-60 gamma radiation total ionizing dose combined with conducted electromagnetic interference studies in BJTs [J]. Microelectronics Reliability, 2018, 82:159-164.