Research on Prediction Method of Life Cycle of Nuclear Power Equipment Based on Fuzzy Clustering

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***Abstract*—With the advancement of technology, mechanical equipment has entered a new stage of integration of machine and electricity, and nuclear power integrated equipment has been more and more widely used in production and life. Nuclear power plants provide a large source of electrical energy and become a strong source of radiation due to the accumulation of a large number of radioactive fission products. The safety level instrument control equipment shoulders the major responsibility of the safe and stable operation of the nuclear power plant and the protection of public safety. The quality appraisal of the equipment is the guarantee of its quality. Based on the degradation model of the service life design of nuclear power plant equipment, the degradation characterization index is calculated by fuzzy clustering, and the parameter correlation is eliminated, and the data of the service life of the nuclear power plant is finally obtained.**

Keywords-Nuclear Power Equipment; Fuzzy Clustering; Life Cycle Prediction

I. INTRODUCTION

Equipment identification, on the one hand, is an important cornerstone of the “defense in depth” thinking, which provides high-confidence guarantees for safety standards such as single fault, multiplicity and independence; on the other hand, equipment identification is also mandatory under nuclear safety regulations. However, due to the high reliability of nuclear power equipment, it is difficult to collect enough failure data for the prediction of remaining life even in the short-term accelerated life test. Secondly, due to the wide variety of internal zero-devices in nuclear power equipment and the complex relationship between zero-component devices, the life-cycle evolution of single-zero-devices cannot be used for life prediction of the entire device. Therefore, a wiener degradation process model based on characterization parameter fusion in the paper is proposed, which uses fuzzy clustering analysis methods to combine clustering parameters, eliminates correlation between parameters, and then uses fuzzy clustering parameters to establish a degradation model based on the wiener process[1-2].

II. CHARACTERIZATION PARAMETER FUSION

A. Characterization parameter selection

Large-scale equipment is powerful and complex in structure, and there are many types of sensors connected to it, and the amount of data obtained by monitoring is large. Therefore, the first task is to select data that can characterize the degradation process of the device. Since the degradation process of the device is irreversible, the parameters that can characterize device degradation must change over time and are monotonic. Therefore, the Spear-son correlation coefficient between each parameter and time is calculated by using equation (1), and the parameter with strong time correlation is selected as the device degradation characterization parameter.

$$\lambda i=\frac{\left|(x_i-\bar{x}_i)(t-\bar{t})\right|}{\sqrt{\sum(x-\bar{x}_i)^2\sum(t-\bar{t})^2}} \tag{1}$$

Where $\bar{x}_i$ is the mean of the i-th parameter sample; $\bar{t}$ is the time mean. When the λ_i is closer to 1, it means that the parameter is more correlated with time; on the contrary, when the λ_i is closer to 0, it means that the correlation with time is weaker. When λ_i $\geq$ 0.5, the representative parameter has a strong correlation with time. Therefore, the parameter with λ_i $\geq$ 0.5 is selected as the characterization parameter[3].

B. Clustering parameter weight calculation

If the single clustering parameter (k=1) can well reflect the statistical information of the original characterization parameters, the value of the clustering parameter can be directly used to model the degradation process. If a single clustering parameter cannot fully reflect the statistical information of the original characterization parameters, then multiple clustering parameters (k>1) need to be selected. Multi-clustering parameters can improve the accuracy of large-scale device degradation state characterization, which make system modeling and data processing complicated. In order to carry out degradation modeling, fusion of clustering parameters is also required. Therefore, the concept of clustering parameter weights is introduced to fuse the clustering parameters and the idea of the contribution rate of the clustering parameters is used to calculate the weights of each clustering parameter[4-5].

$$w_j=A_j=\frac{\theta_j}{\sum_{j=1}\theta_j},\qquad j=1,2,\cdots,k \tag{2}$$

Where w_j represents the weight of the j-th clustering parameter. The merged cluster parameter $y=(y_1,y_2,\cdots,y_m)=\sum_{j=1}^{k}w_jY_j$ is obtained.

C. Determination of clustering threshold

During the operation of the equipment, once the characterization parameters exceed a limit, it will have a serious impact on the performance of the equipment, and even cannot be used, then the equipment is said to have failed. This limit value is called the degradation threshold of the device and is usually represented by the letter ω. Thresholds are usually obtained by engineers' practical experience or through a large number of experiments. The threshold $\varpi'=(\varpi_1',\varpi_2',\cdots,\varpi_n')$ of each of the multi-characterized parameters must be different. A processing method similar to characterization parameters is adopted; first, it is necessary to select whether to standardize the threshold according to the data characteristics; then, the processed threshold $\varpi'=(\varpi_1',\varpi_2',\cdots,\varpi_n')$ is processed by the method in Section 1.1 to process the degradation threshold of each characteristic parameter to obtain a clustering threshold $\varpi=(\varpi_1,\varpi_2,\cdots,\varpi_n)=\varpi' a$ of each clustering parameter; finally, if multiple clustering parameters (k>1) are selected, the obtained clustering weights are also used to calculate the weighted clustering parameter threshold $\varpi=\sum_{j=1}^{k}w_j\varpi_j$.

III. Wiener Process Degradation Model

A. Degradation modeling

When the random process Y(t) satisfies the following three properties:

1) *Y(0)=0;*
2) *Y(t) has a smooth independent increment.*

3) For any t>0, there is Δt such that $\mathrm{Y(t+\Delta t)\text{-}Y(t)} \cong \mathrm{N}(\mu\Delta t, \lambda\Delta t)$ *, that is, the increment obeys the normal distribution, then Y(t) is called the Wiener process. The Wiener process degradation model can be expressed as*

$$\mathrm{Y(t)} = \mathrm{Y(0)} + \lambda \mathrm{t} + \theta \mathrm{B(t)} \tag{3}$$

Where, Y(t) represents the clustering degradation value at time t; Y(0) represents the amount of degradation at the initial moment; B(t) is the standard Brownian motion; θ represents the drift coefficient; λ is the diffusion coefficient and represents the drift rate of the particles in Brownian motion, and is no practical physical meaning here. Y(t) is also known as Brownian motion with linear drift.

B. Parameter estimation

There are two unknown parameters in the model, which are the drift coefficient θ and the diffusion coefficient σ, respectively. The drift coefficient represents the difference between different individuals of the same type of equipment. Some literature researchers generally consider the parameter θ as a random variable when modeling the overall degradation of the device population. The discussion in the paper is only for a single individual, so the parameter θ is considered constant and the diffusion coefficient λ is also constant. Parameter estimation of the degenerate model requires the use of historical degradation data of the device and uses the idea of maximum likelihood to estimate by constructing a likelihood function. For the sake of convenience, the initial degradation amount Y(0)=0 of the device is assumed in the following derivation. It is assumed that the measurement of the amount of degradation is performed on a single device at random m times, and the amount of degradation of the device increases with time. First, ΔY1=Y(t1) represents the degradation increment at the initial time, and YYY is the degradation increment of the degradation amount at time t_{j-1} to t_j. Then, according to the smooth independent increment of the wiener process, the j-th degradation increment ΔY_j obeys the normal distribution with the mean $\theta_j \Delta t_j$ and the variance of $\mu_j^2 \Delta t_j$, which is $\Delta Y_j \sim N(\lambda_j \Delta t_j, \mu_j^2 \Delta t_j)$, and its probability density function is

$$f_{\Delta yj}(\Delta y_j) = (2\pi\mu_j^2\Delta t_j)^{-1/2} \bullet \exp\left[\frac{-(\Delta Y_j - \varpi_j \Delta t_j)^2}{(2\mu_j^2 \Delta t_j)}\right] \tag{4}$$

The likelihood function is

$$L(\lambda, \mu^2) = \prod_{j=1}^{m} (2\pi\mu_j^2\Delta t_j)^{-1/2} \bullet \exp\left[\frac{-(\Delta y_j - \lambda_j \Delta t_j)^2}{(2\mu_j^2 \Delta t_j)}\right] \tag{5}$$

The logarithm of equation (5) is taken, and the logarithmic likelihood function is

$$L(\lambda, \mu^2) = -\frac{m}{2}\ln(2\pi) - \frac{1}{2}\sum_{j=1}^{m}\ln(\mu_j^2\Delta t_j) - \sum_{j=1}^{m}\frac{(\Delta y_j - \mu_j \Delta t_j)^2}{2\mu_j^2\Delta t_j} \tag{6}$$

For the equation (6), the partial derivative of the two parameters is obtained, respectively, and its value 0 is made. The maximum likelihood estimation value $(\bar{\lambda}, \bar{\mu}^2)$ of the parameter (λ, μ^2) can be obtained as follows:

$$\hat{\mu}_j = \frac{Y_j}{t_j} \tag{7}$$

$$\hat{\mu}_j^2 = \frac{1}{j}\left[\sum_{j=1}^{m}\frac{\Delta Y_j^2}{\Delta t_j} - \frac{(Y_j)^2}{t_j}\right] \tag{8}$$

The device's historical degradation data can then be used to calculate unknown parameters in the degradation model, so as to estimate the remaining life of the equipment.

C. Remaining life-prediction analysis

There are two definitions of the life of nuclear power equipment:

1) The device loses a certain function and cannot be used normally. It needs to be repaired or replaced.

2) A critical parameter of the equipment meets or exceeds the degradation threshold for the first time, but the equipment has not experienced a major fault.

In the study of residual life prediction based on degraded data, a second life definition is generally selected. Therefore, the prediction of the life of the device translates to the time at which the characterization parameter first arrives or exceeds the degradation threshold. This time is called the first time.

$$\mathrm{T}=\inf\{\mathrm{t}:\mathrm{Y}(\mathrm{t})\geq\varpi \mid \mathrm{Y}(0)<\varpi\} \tag{9}$$

From equation (10), the lifetime T is a random variable. The probability density function and the reliability function, respectively, are

$$f_T(t)=\sqrt{\frac{\varpi^2}{2\pi t^3\mu_j^3}}\exp\left[-\frac{(\varpi-\lambda_t)^2}{2t\mu_j^2}\right] \tag{10}$$

$$R_T(t)=\Phi\left(\varpi-\frac{\lambda_t}{\sqrt{\mu_j^2 t}}\right)-\exp\left(\frac{2\lambda\varpi}{\mu_j^2}\right)\phi\left(-\varpi-\frac{\lambda_t}{\sqrt{\mu_j^2 t}}\right) \tag{11}$$

IV. DEGRADATION MODELING AND PREDICTION

Degradation modeling is made by using data. The parameters of 0 ～ 420d are used as the calculation samples for parameter calculation. The data of the 450～480d samples are used as test samples to verify the accuracy of the model. The obtained value $\left(\hat{\mu}_j,\hat{\varpi}_j^2\right)$ is shown in Table 1.

TABLE I. PARAMETER ESTIMATE VALUES

t/d	60	120	180	240	300	360	420
$\hat{\mu}_j/(10^{-4})$	28	30	33	34	35	42	42
$\hat{\varpi}_{ij}^2/(10^{-5})$	0	0.7	6	6.5	5.1	12.5	9.5

When t=450d, the degradation measurements of the original degradation parameters are (26.52, 7.30, 8.00, 8.88), and the cluster degradation obtained after centralization and principal component analysis is 1.95.

$$\mathrm{y}_{450}=\lambda_{450}\mathrm{t}\pm\mu_{450}^2\mathrm{t}=0.0042\times 450\pm 9.5\times 10^{?}\times 450=1.89\pm 0.04$$

When t=480d, the cluster degradation amount is 2.

$$\mathrm{y}_{480}=\lambda_{480}\mathrm{t}\pm\mu_{480}^2\mathrm{t}=0.0042\times 480\pm 10.6\times 10^{?}\times 480=2.016\pm 0.05$$

It is found from the calculation results that the predicted result is consistent with the true value, which proves the validity of the proposed method. The computer numerical control machine tools have experienced multiple failures during the 400-500d period, and the equipment degradation phenomenon is remarkable. The life density function, the reliability function and the remaining life density function of the computer numerical control machine tools can be calculated by using equation (10). It can be concluded that the average life of the computer numerical control machine tools is 480d, and its reliability is greatly reduced at 450d and enters the stage of high accident occurrence. It shows the accuracy of the method proposed in the paper for the remaining life of computer numerical control machine tools

V. CONCLUSION

In the paper, a life prediction method for complex nuclear power equipment based on clustering data fusion is proposed. By means of weighted principal component analysis, the multi-source characterization parameters are fused, and then the wiener degradation process of complex nuclear power equipment based on clustering data fusion is established, so the prediction of the remaining life of complex nuclear power equipment is realized. The verification results show that the prediction accuracy of the method is higher than that of the residual life prediction method of single characterization parameters. Due to the certain volatility of the device degradation data, the monotonicity of the corresponding function relationship of the degraded data affects the effectiveness of the clustering parameter fusion. Therefore, based on the research in the paper, how to analyze the monotonicity of the corresponding function relationship of equipment degradation data is the next problem to be solved.

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