Real-Time Performance Reliability Assessment Method Based on Dynamic Probability Model

Cheng Hua[1], Qing Zhang[2], Guanghua Xu[2], and Jun Xie[1]

[1] School of Mechanical Engineering, Xi'an Jiaotong University, Xi'an, P.R. China
[2] State Key Laboratory for Manufacturing Systems Engineering, Xi'an Jiaotong University, Xi'an, P.R. China
huapresent@gmail.com, zhangq@mail.xjtu.edu.cn, xugh@mail.xjtu.edu.cn, jun.xie@stu.xjtu.edu.cn

Abstract. Most previous reliability estimation methods are researched on the assumption of empirical information or prior distribution which is difficult to be acquired in practice. To solve this problem, a real-time reliability assessment method based on Dynamic Probability Model is proposed. The primary step is to establish a Dynamic Probability Model on the basis of nonparametric Parzen window estimating method, and the sliding time-window technique is used to pick statistical samples respectively, then conditional probability density of performance degradation data is estimated. A sequential probability density curve is used to trace the performance degradation process, and probability distribution function on performance degradation data which exceeds the failure threshold is regarded as reliability indicator. Meanwhile, the failure rate is calculated. By analyzing the data from high pressure water descaling pump in the process of failure, it is verified that this method contributes individual equipment to estimate reliability with inadequate empirical information.

Keywords: Dynamic probability model; Reliability estimation; Performance degradation.

1 Introduction

Traditional reliability estimation methods primarily focus on acquiring the failure data of products through a large number of experiments under the same circumstances. Then, the parametric estimation method is utilized based on the selected statistical distribution models according to which the reliability of the products could be predicted. However, these methods lose their scope of application in the event there will be few or no failure for high reliability products in life tests and the acquisition of adequate failure data is impossible in relatively short periods.

In order to eliminate the drawbacks in the traditional reliability estimation methods, a new reliability assessment method which studies the internal relationship between reliability decline and performance degradation is suggested [1-2]. This method enables the track and identification of the degree of reliability decline by establishing a degradation path model of performance variable. Both methods mentioned above focus on the population characteristic of products which is not applied by actual performance

F.L. Wang et al. (Eds.): AICI 2010, Part I, LNAI 6319, pp. 88–96, 2010.

degradation process of individual components due to differences in environmental and operational conditions. In 1992, Kin and Kolarik [3] introduced the concept of "real-time reliability" and made attempt to predict the reliability of individual components using real-time performance degradation data. Some real-time reliability assessment methods available today include regression analysis [4-5] and time series analysis [6-7]. Most previous researches are done based on empirical information or prior distribution hypothesis which have imposed restrictions on the promotion and application of the real-time reliability methods, and do not apply to new equipments.

This paper proposes a real-time reliability assessment method based on Dynamic Probability Model. Using this method, a Dynamic Probability Model is constructed to make a real-time estimation of conditional probability distribution of performance degradation data, a sequential probability curve is used to trace the performance degradation process, and probability distribution function which exceeds the failure threshold are regarded as reliability indicator. This method helps to convert performance degradation data into reliability assessment indicator.

The organization of the remainder of this paper is given as follows: real-time reliability estimation method based on time series is introduced in Section 2. In section 3, the dynamic probability model is constructed and illustrated. In section 4, real-time performance reliability assessment method based on Dynamic Probability Model is discussed in detail. In section 5, an actual application case is given to prove this method feasible. Finally, the conclusions are given in Section 6.

2 Overview of Real-Time Reliability Estimation Based on Time Series

The term reliability refers to the ability of a product to perform its required functions under stated conditions for a specified period of time. And whether a product is able to perform specified functions is inferred from whether its performance variable changes within a certain range. In practice, the performance variable which reflects the performance degradation is called degradation variable, and its measured value and true value may be different due to the inevitable measurement error. This measurement can be presented as [8]:

$$z(t) = x(t) + \varepsilon \tag{1}$$

where $x(t)$ is the true value of degradation variable, $z(t)$ is the measured value, ε is the measurement error and $\varepsilon \sim N(0, \sigma^2)$.

In general, the degradation of a product $\{x(t), t \geq 0\}$ can be regarded as a random process, and the distribution of $x(t)$ is presented as:

$$G(x,t) = P(x(t) \leq x) \tag{2}$$

And its probability density function is defined as:

$$g(x,t) = \partial G(x,t) / \partial x \tag{3}$$

The degradation statistical model indicates that a product is considered to be a failure when $x(t)$ reaches the failure threshold L for the first time. Meanwhile, the time when a product fails is presented as:

$$T(l) = \inf\{t : x(t) = l, t \geq 0\} \tag{4}$$

According to the failure time mentioned above, the cumulative failure distribution function of a product can be identified as $F(t \mid L) = P\{T(L) \leq t\}$, which describes the regular pattern of product degradation. Thus it is also known as the model for degradation-failure of a product. The statistical model previous mentioned based on degradation variable and the degradation-failure model indicate an important interrelation between them based on the failure threshold. The statistical inference based on degradation-failure model can be transformed into that based on model of degradation variable [9], which follows the formula:

$$F(t \mid L) = P\{T(L) \leq t\} = P\{x(t) \geq L\} = 1 - G(L,t) \tag{5}$$

Based on this model, reference [6] studies the issue of real-time reliability assessment by analyzing a sequence of performance degradation by time. Now assuming that this sequence of performance degradation is a realization of random process of performance degradation, as shown in Figure 1, at any time t, the performance variable V_t follows normal distribution. Provided that failure threshold V_L is fixed and failure distribution corresponds to the function $F(t,V_L) = P(v(t) > V_L)$, we can get a reliability indicator $R(t) = 1 - F(t,V_L)$, by which the reliability assessment of individual equipment can be accomplished.

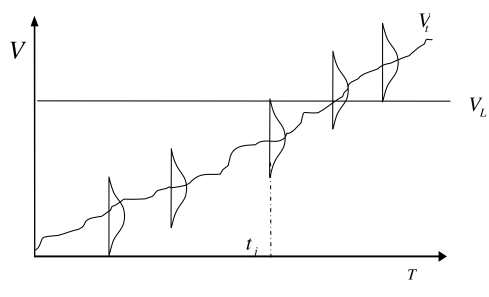


Fig. 1. Reliability assessment curve of performance degradation

The application of reliability assessment based time series is somehow restricted since a large amount of experimental dada or historical information are required to estimate distribution parameter; besides, the application scope of parameter distribution model has some limitations; what is more, the experimental condition is irreproducible. Empirical information of operation equipment is hard to get, and the parameter distribution model does not apply to situations in which operating conditions may be changing. To solve these drawbacks properly, a Dynamic Probability Model (DPM) is introduced into this paper.

3 Dynamic Probability Model

3.1 Principle of Dynamic Probability Model

The model depicted in Figure 2 contains three layers: sampling layer, sample layer and summation layer. Among them the sampling layer consists of equal interval sampling points within the range of observed data, which array orderly. The sample layer contains series of measures data which slide into the network orderly. Summation layer shows the conditional probability density of the set in this situation.

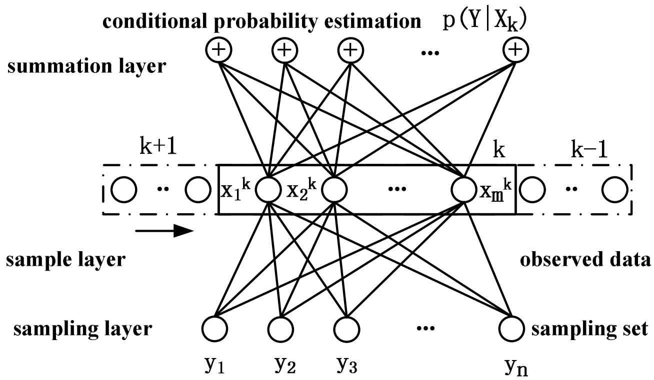


Fig. 2. Dynamic Probability Model

Let X represent a data series. Suppose that the length of the window be m, and the sliding distance be s , whenever the time window slides, $m-s$ observed data are preserved in the window, and the number of newly added data is s. When being computed at the kth time, the samples in the window can be defined as $X_k = \{x_1^k, x_2^k, \cdots, x_m^k)$. Now let it be mapped to sample layer and after the kernel function operations is done, we can obtain conditional probability function:

$$P(y_i \mid X_k) = \frac{1}{m\sigma}\sum_{j=1}^{m} K(x_j^k, y_i) \quad i = 1,2,\cdots,n \tag{6}$$

where σ a smoothing factor ; $K(\cdot)$ is the kernel function and $K(x_j^k, y_i) = \frac{1}{(2m)^{1/2}} e^{-\frac{(x_j^k - y_i)^2}{2\sigma^2}}$ if it is Gaussian function that has been adopted.

When data being observed slide into the time window accordingly, n probability estimation values are got to form a probability distribution curve

$$F(Y) = p(y_i \le Y) = \sum_{\{i:y_i \le Y\}} P(y_i \mid X_k) \tag{7}$$

New probability distribution curve at different time can be get even when new data enters the network by partially updating the estimated probability density value of the previous time.

3.2 The Influences of Parameters in the Mode

There are three parameters in the probability model, namely window length m, sliding distance s and smoothing factor σ , which impact the computation speed and accuracy of the model.

Window length m determines the capacity of the statistical model, sliding distance s determines moving speed of time window. In order to hold consistency of the analysis, m should have a fixed value, and then the same statistical features are granted to every object being analyzed at each moment. S can be adjusted to the condition of objects accordingly to capture the detailed information during the slides. For example, when the condition of the object changes slowly, a relatively longer s can be adopted and vice versa. The selection of the smoothing factor σ is also important: if it is too big, the model will be too smooth to address detailed information in the changing process. If it is too small, the curve will be too sensitive to fake data to tell noise from useful information.

4 Real-Time Reliability Assessment Method

To overcome the limitations which exist in real-time reliability assessment method based on time series, this paper studies two key techniques: the obtaining approach of statistical samples and the dynamic adjustable model of probability distribution.

4.1 Real-Time Acquision of Statistical Samples

Statistical samples used to estimate parameters are hard to obtain without experimental data or historical information. To solve this problem, an approximate method of obtaining statistical samples based on performance degradation data is researched. To reach this goal, the following assumption is proposed:

Assumption: The performance degradation data series is a random time series and the process of performance degradation is nonstationary random process. This process consists of a series of short-time stationary performance degradation data.

Based on the assumption, let a sliding time window ΔT be selected, for the whole degradation period T , $\Delta T / T \to 0$, and the stochastic data series in the window is stationary time series, the statistical feature of which does not change with time, thus the data series in the window can be regarded as statistical sample with identical distribution. At any moment t_k , let data in time window $[t_k - \Delta T, t_k]$ be statistical samples, since $\Delta T / T \to 0$, these samples can also be regarded as the statistical sample at time t_K .

4.2 Dynamic Adjustable Model for Probability Distribution

After the statistical samples are acquired at any moment by using the sliding window technique, the parameter can be estimated according to the assumed parameter distribution model. Due to the fact that the parameter distribution model depends heavily on samples, the application scope of the model is limited. Even sometimes, the estimated model does not correspond to the actual data. To solve this problem, this paper adopts nonparametric Parzen window estimating method [10], also known as kernel estimation method in which no assumption is necessary. This method gets the asymptotic estimation by weighting local functions in the center of sample points. In theory, this method could approximately approach any density functions. Thus when external circumstances or operation conditions change, dynamic adjustment could be made to adapt changes in actual distribution.

4.3 Real-Time Reliability Assessments

Provided that the real-time acquisition of statistical samples is available, the reliability assessment can be done using failure threshold and the probability distribution of performance degradation data which can be estimated by adopting Dynamic Probability Model in real-time. The process is like the following:

1) Acquire the performance degradation data series ;

2) Select model parameters, namely, window length m , sliding distance s , smooth factor σ and the set of sampling points $Y = \{ y_i \mid i = 1,2,\cdots,n\}$;

3) When performance degradation data enter into the network, a time series is picked using window length m as a statistical sample ;

4) At the kth calculation, data inside the window $V_k = \{v_1^k, v_2^k, \cdots, v_m^k\}$ are mapped to the sample layer and Gaussian kernel functional calculation is done. Then in the summation layer, conditional probability distribution is got as the probability distribution of performance degradation at time t_K ;

5) Assuming that failure threshold is V_L , by using equation(2) at t_k , the failure probability distribution and performance reliability can be calculated.

The failure probability distribution is

$$F(t_k, V_L) = p(y_i \le V_L) = \sum_{\{i: y_i \le V_L\}} P(y_i \mid V_k) \tag{8}$$

And the performance liability is

$$R(t_k, V_L) = 1 - F(t_k, V_L) \tag{9}$$

And the instantaneous failure rate $\lambda(t)$ is

$$\lambda(t) = \lim_{\Delta t \to 0} \frac{P(t < T \le t + \Delta t \mid T > t)}{\Delta t} = \frac{F'(t)}{R(t)} \tag{10}$$

Since the observed data are discrete, $\lambda(t)$ is calculated through the following difference equation:

$$\lambda(t_k) = \frac{F'(t_k, V_L)}{R(t_k, V_L)} = \frac{R(t_k, V_L) - R(t_{k+1}, V_L)}{R(t_k, V_L)(t_{k+1} - t_k)} \tag{11}$$

6) When $k \leftarrow k+1$, sliding distance of time window is s, the number of observed data being preserved in the window is $m-s$, and the number of newly added data is s, then step 4 and 5 are redone, getting the failure probability distribution of performance degradation and performance reliability at t_{k+1}. As shown in Figure 3, the value of performance reliability at each sampling moment can be achieved by sliding the time-window.

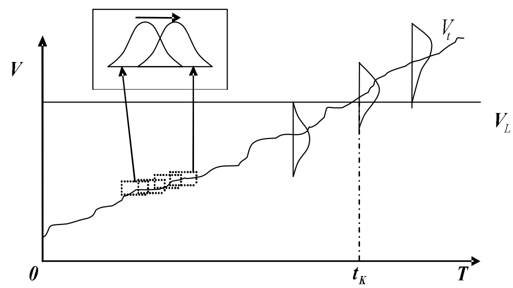
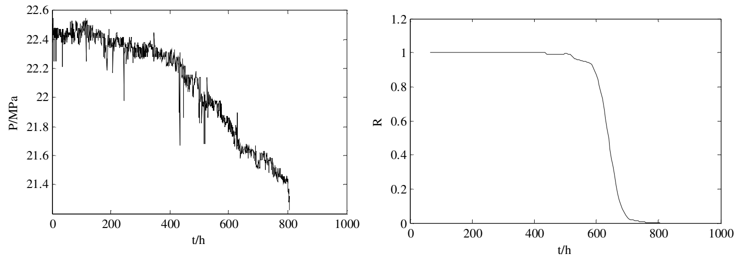


Fig. 3. Tacking curve of performance degradation probability

5 Case Study

The stainless steel plant in Jiuquan Iron and Steel Group Co. (JISCO) uses hydraulic jet descales which are equipped with 11-level centrifugal pump with big flow, which functions to wipe off the oxide scale formed on the surface of stainless steel during the process of steeling rolling. Thus, the pressure at the exist of the pump must meet a certain criteria. That is why pressure sensors are installed at both the entrance and exist of the descaler, and they will record the data in every 30 minutes. For example, the 2# jet descaler in the field was installed in august in 2006, and it has been working since then for 4 months during which 1615 pressure data have been collected. On 13th December, an incident took place on this machine and the cause was later found to be severely worn out of its seal ring. Its worn out process can be regarded as a process of gradual performance degradation, so we can analyze it using the moving neural network. Let the length of sliding window m=120, the distance of sliding s=10 and the smooth factor σ =0.064 ,the number of sampling points n=200, and the failure threshold V_L=21.8MPa (according to the information provided by the manufacturer).

The reliability assessment curve in Figure 4 shows that after being operated for 500 hours, the reliability of the descaler began to decline. And between 600 and 700 hours of operation, its reliability dropped sharply which indicated that its sealing rings were being worn out rapidly. Finally, at 807th hours of operation, an accident happened when the reliability had dropped to 0.



(a) (b)

Fig. 4. Real-time reliability assessment of hydraulic jet descaler: (a) Performance degradation data series; (b) Performance reliability

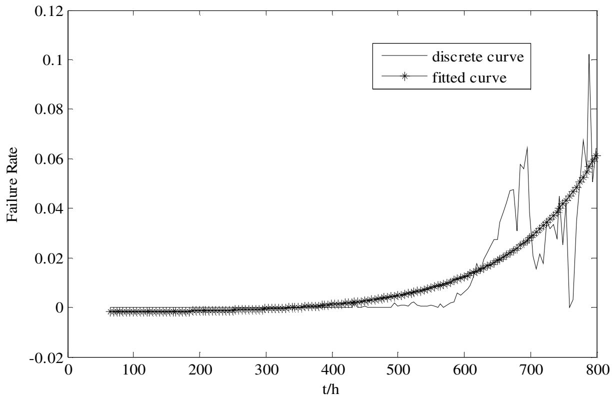


Fig. 5. The failure rates of hydraulic jet descaler

As thown in Figure 5, the dash line is discrete curve of failure rate calculated by function (11). This is an increasing failure rate, known as wear-out failure [11], and the solid line is fitted curve. In this case, the exponential functional form is used to fit discrete failure rate curve by the following formula :

$$\lambda(t) = \alpha + \beta \exp(\phi t) \tag{12}$$

where $\lambda(t)$ denotes failure rate, and α , β , ϕ are constant coefficients of regression model. In this case, the estimation values of regression model parameters are α=-0.0022, β =0.0002, $\phi = 0.0074$.

6 Conclusion

The real-time reliability assessment method proposed based on dynamic probability model in this paper manages to calculate the performance degradation data of equipment without empirical information and distributions being available. The primary step of this work is to establish a dynamic probability model on the basis of nonparametric kernel estimation method, and then sliding time-window technique is used here to pick samples do statistical analysis for the conditional probability distribution. Then the performance degradation data can be converted into reliability assessment indicator by using distribution value of performance degradation data which is more than failure threshold as reliability indicator. Subsequently failure rate is calculated. By analyzing the data from high pressure water descaling pump in the process of failure, this method is proved to be feasible enough to adjust itself to actual running condition and trace the performance degradation process in real-time.

References

1. Carey, M.B., Koenig, R.H.: Reliability assessment based on accelerated degradation: A case study. IEEE Trans. Reliability 40, 499–560 (1991)
2. Lu, C.J., Meeker, W.Q.: Using degradation measures to estimate a time-to-failure distribution. Technometrics 35, 161–174 (1993)
3. Kim, Y.S., Kolarik, W.J.: Real-time conditional reliability prediction from on-line tool performance data. International Journal of Production Research 30, 1831–1844 (1992)
4. Xu, Z., Ji, Y., Zhou, D.: Real-time reliability prediction for a dynamic system based on the hidden degradation process identification. IEEE Transactions on Reliability 57, 230–242 (2008)
5. Gebraeel, N.Z., Lawley, M.A., Li, R., et al.: Residual-life distributions from component degradation signals: a Bayesian approach. IIE Transactions 37, 543–557 (2005)
6. Lu, H., Kolarik, W.J., Lu, S.S.: Real-time performance reliability prediction. IEEE Transactions on Reliability 50, 353–357 (2001)
7. Chan, V., Meeker, W.Q.: Time series modeling of degradation due to outdoor weathering. Communications in Statistics 37, 408–424 (2008)
8. Meeker, W.Q., Escobar, L.A., Lu, C.J.: Accelerated degradation tests modeling and analysis. American Society for Quality 40, 89–99 (1998)
9. Nelson, W.: Analysis of performance-degradation data from accelerated tests. IEEE Trans. Reliability 30, 149–155 (1981)
10. Parzen, E.: On estimation of a probability density function and mode. Annals of Mathematical Statistics, 1065–1076 (1962)
11. Meek, W.Q., Escobar, L.A.: Statitical Methods for Reliability Data. Wiley, New York (1998)