

PRODUCT RELIABILITY ANALYSIS METHOD AND SYSTEM

TECHNICAL FIELD

The present invention relates to the product service life analysis field, and in particular, to a product reliability analysis method and system.

BACKGROUND

Many products in modern industry have high reliability and long service life. At present, there are two types of reliability analysis technologies for products. One technology is a classic technology based on life data. This technology has a disadvantage that a large amount of life data is required. For many characteristics such as high reliability and long service life in modern industry, it is usually difficult to obtain sufficient service life data due to constraints of test time and costs. It is difficult to implement product reliability analysis by using a conventional reliability theoretical method.

The other technology is a technology based on performance degradation data, which is one of research hotspots at present. In a reliability analysis method based on performance degradation data, a performance degradation process model is usually first established by using performance degradation data, and then reliability statistical inference is performed based on the performance degradation process model. Product performance parameter measurement can usually be divided into two types: (1) product performance measurement, which does not affect continued work of a product and is referred to as non-destructive measurement; (2) product performance measurement, which is referred to as destructive measurement, where a product is damaged after the product performance measurement and cannot continue to be tested. In non-destructive measurement, measurement may be performed on a product in a test for many times, so as to obtain a relatively large amount of performance degradation data. In an operation process of the product, remaining service life of the product can be predicted according to a performance measured value of the product. In destructive measurement, measurement may be performed on a product only once, and the product is withdrawn from the test after the measurement is performed. Therefore, a relatively small amount of performance degradation data is obtained, and in an operation process of the product, a performance parameter of the product cannot be measured. As a result, it is difficult to predict remaining service life of the product.

Therefore, a current research mainly focuses on the non-destructive measurement and is not applicable to a product in destructive measurement, and reliability analysis of the product in destructive measurement cannot be implemented.

SUMMARY

An objective of the present invention is to provide a product reliability analysis method and

system, so as to implement reliability analysis of a performance degradation product in destructive measurement.

To achieve the above purpose, the present invention provides the following technical solutions.

A product reliability analysis method includes:

obtaining a measured value of a performance parameter-related identification parameter of a product, where measurement of the identification parameter is non-destructive measurement;

determining coefficients μ_y , σ_y , μ_{y_k} , and σ_{y_k} of a reliability analysis model of the product according to the measured value of the identification parameter, where the reliability analysis model includes a service life probability distribution model and a remaining service life prediction model; μ_y and σ_y are parameters in a product performance parameter degeneration process, the performance parameter degeneration process is a unitary Wiener process, μ_y is a drift parameter, and σ_y is a diffusion parameter; and μ_{y_k} and σ_{y_k} are distribution parameters of product performance parameter probability distribution at a moment t_k , the product performance parameter probability distribution obeys normal distribution, μ_{y_k} is a mean of the normal distribution, and σ_{y_k} is a standard deviation of the normal distribution;

determining the service life probability distribution model according to the coefficients, and analyzing service life distribution of the product, where the service life probability distribution model is $F(t) = \Phi\left(\frac{\mu_y t - l}{\sigma_y \sqrt{t}}\right) + \exp\left(\frac{2\mu_y l}{\sigma_y^2}\right) \Phi\left(\frac{-l - \mu_y t}{\sigma_y \sqrt{t}}\right)$, where $\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-\frac{t^2}{2}} dt$, and l is a failure threshold of the product; and

determining the remaining service life prediction model according to the coefficients, and predicting remaining service life of the product, where the remaining service life distribution model is

$$f(t) = \frac{1}{2\pi\sqrt{\sigma_{y_k}^2 \sigma_y^2 t^3}} \cdot \int_{-\infty}^l (l - y_k) \exp\left[-\frac{(l - y_k - \mu_y t)^2}{2\sigma_y^2 t} - \frac{(y_k - \mu_{y_k})^2}{2\sigma_{y_k}^2}\right] dy_k,$$

where y_k is a performance parameter of the product.

Optionally, before the determining coefficients μ_y , σ_y , μ_{y_k} , and σ_{y_k} of a reliability analysis model of the product according to the measured value of the identification parameter, the method further includes:

performing destructive measurement on performance parameters of multiple other similar products of a same type as the product to obtain measured values of multiple performance parameters, where a measured value of a performance parameter of an i^{th} similar product is $Y(t_{im})$; and

performing non-destructive measurement on performance parameter-related identification parameters of the multiple similar products to obtain multiple groups of measured values of the performance parameter-related identification parameters, where a measured value set of an identification parameter of the i^{th} similar product is $X(t) = [X(t_{i1}), X(t_{i2}), \dots, X(t_{ij}), \dots, X(t_{im})]$, where $j = 1, 2, \dots, m$; and $X(t_{ij})$ is a measured value of an identification parameter of the i^{th} similar product at a moment t_{ij} .

Optionally, the determining coefficients μ_y , σ_y , μ_{y_k} , and σ_{y_k} of a reliability analysis model of the product according to the measured value of the identification parameter specifically includes:

determining a joint probability distribution model of measured data of the i^{th} similar product, where the joint probability distribution model is $\mathbf{B}_i \sim N(\boldsymbol{\mu}_{iB}, \boldsymbol{\Sigma}_{iB})$; $\mathbf{B}_i = (X(t_{i1}) \ X(t_{i2}) \ \dots \ X(t_{im_i}) \ Y(t_{im_i}))'$;

$$\boldsymbol{\mu}_{iB} = (\mu_x t_{i1} \ \mu_x t_{i2} \ \dots \ \mu_x t_{im_i} \ \mu_y t_{im_i})';$$

$$\boldsymbol{\Sigma}_{iB} = \mathbf{D} \times \boldsymbol{\Sigma}_{iA} \times \mathbf{D}' = \begin{pmatrix} \boldsymbol{\Sigma}_{iB11} & \boldsymbol{\Sigma}_{iB12} \\ \boldsymbol{\Sigma}_{iB21} & \boldsymbol{\Sigma}_{iB22} \end{pmatrix}; \quad \mathbf{D} = \begin{pmatrix} 1 & 0 & \dots & 0 \\ 1 & 1 & \dots & 0 \\ \dots & & & \mathbf{0} \\ 1 & 1 & \dots & 1 \\ \mathbf{0} & & 1 & 1 & \dots & 1 \end{pmatrix};$$

$$\boldsymbol{\Sigma}_{iB11} = \sigma_x^2 \begin{pmatrix} t_{i1} & t_{i1} & t_{i1} & \dots & t_{i1} \\ t_{i1} & t_{i2} & t_{i2} & \dots & t_{i2} \\ t_{i1} & t_{i2} & t_{i3} & \dots & t_{i3} \\ \dots & & & & \\ t_{i1} & t_{i2} & t_{i3} & \dots & t_{im} \end{pmatrix}; \quad \boldsymbol{\Sigma}_{iB22} = \sigma_y^2 t_{im_i}; \quad \boldsymbol{\Sigma}_{iB21} = \sigma_{xy} (t_{i1} \ t_{i2} \ \dots \ t_{im}); \text{ and}$$

$$\boldsymbol{\Sigma}_{iB12} = \boldsymbol{\Sigma}'_{B21};$$

determining values of the coefficients μ_x and σ_x according to the measured value data of the identification parameter by using a maximum likelihood method; and

determining values of the coefficients μ_y , σ_y , μ_{y_k} , and σ_{y_k} according to measured

value data of the identification parameter and a performance parameter and the coefficients μ_x and σ_x by using the maximum likelihood method.

Optionally, after the determining the service life probability distribution model according to the coefficients, and analyzing service life distribution of the product, the method further includes:

determining a service life probability density distribution model according to the coefficients, and analyzing service life distribution of the product, where the service life probability density distribution model is $G(t) = \sqrt{\frac{l^2}{2\pi\sigma_y^2 t^3}} \exp\left[-\frac{(l - \mu_y t)^2}{2\sigma_y^2 t}\right]$.

A product reliability analysis system includes:

a measured value obtaining module, configured to obtain a measured value of a performance parameter-related identification parameter of a product, where measurement of the identification parameter is non-destructive measurement;

a coefficient determining module, configured to determine coefficients μ_y , σ_y , μ_{yk} , and σ_{yk} of a reliability analysis model of the product according to the measured value of the identification parameter, where the reliability analysis model includes a service life probability distribution model and a remaining service life prediction model; μ_y and σ_y are parameters in a product performance parameter degeneration process, the performance parameter degeneration process is a unitary Wiener process, μ_y is a drift parameter, and σ_y is a diffusion parameter; and μ_{yk} and σ_{yk} are distribution parameters of product performance parameter probability distribution at a moment t_k , the product performance parameter probability distribution obeys normal distribution, μ_{yk} is a mean of the normal distribution, and σ_{yk} is a standard deviation of the normal distribution;

a service life distribution analysis module, configured to determine the service life probability distribution model according to the coefficients, and analyze service life distribution of the product, where the service life probability distribution model is $F(t) = \Phi\left(\frac{\mu_y t - l}{\sigma_y \sqrt{t}}\right) + \exp\left(\frac{2\mu_y l}{\sigma_y^2}\right) \Phi\left(\frac{-l - \mu_y t}{\sigma_y \sqrt{t}}\right)$, where $\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-\frac{t^2}{2}} dt$, and l is a failure threshold of the product;

a remaining service life prediction module, configured to determine the remaining service life prediction model according to the coefficients, and predict remaining service life of the product, where the remaining service life distribution model is

$$f(t) = \frac{1}{2\pi\sqrt{\sigma_{y_k}^2 \sigma_y^2 t^3}} \cdot \int_{-\infty}^l (l - y_k) \exp \left[-\frac{(l - y_k - \mu_y t)^2}{2\sigma_y^2 t} - \frac{(y_k - \mu_{y_k})^2}{2\sigma_{y_k}^2} \right] dy_k ;$$

where y_k is a performance parameter of the product.

Optionally, the system further includes:

a performance parameter measurement module, configured to: before the coefficients μ_y , σ_y , μ_{y_k} , and σ_{y_k} of the reliability analysis model of the product are determined according to the measured value of the identification parameter, perform destructive measurement on performance parameters of multiple other similar products of a same type as the product to obtain measured values of multiple performance parameters, where a measured value of a performance parameter of an i^{th} similar product is $Y(t_{im})$; and

an identification parameter measurement module, configured to perform non-destructive measurement on performance parameter-related identification parameters of the multiple similar products to obtain multiple groups of measured values of the performance parameter-related identification parameters, where a measured value set of an identification parameter of the i^{th} similar product is $X(t) = [X(t_{i1}), X(t_{i2}), \dots, X(t_{ij}), \dots, X(t_{im})]$, where $j = 1, 2, \dots, m$; and $X(t_{ij})$ is a measured value of an identification parameter of the i^{th} similar product at a moment t_{ij} .

Optionally, the coefficient determining module specifically includes:

a joint probability distribution model determining unit, configured to determine a joint probability distribution model of measured data of the i^{th} similar product, where the joint probability distribution model is $\mathbf{B}_i \sim N(\boldsymbol{\mu}_{iB}, \boldsymbol{\Sigma}_{iB})$;

$$\mathbf{B}_i = (X(t_{i1}) \ X(t_{i2}) \ \cdots \ X(t_{im_i}) \ Y(t_{im_i}))';$$

$$\boldsymbol{\mu}_{iB} = (\mu_{x,t_{i1}} \ \mu_{x,t_{i2}} \ \cdots \ \mu_{x,t_{im_i}} \ \mu_{y,t_{im_i}})';$$

$$\Sigma_{iB} = D \times \Sigma_{iA} \times D' = \begin{pmatrix} \Sigma_{iB11} & \Sigma_{iB12} \\ \Sigma_{iB21} & \Sigma_{iB22} \end{pmatrix}; D = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ 1 & 1 & \cdots & 0 \\ \cdots & & & 0 \\ 1 & 1 & \cdots & 1 \\ 0 & & 1 & 1 & \cdots & 1 \end{pmatrix};$$

$$\Sigma_{iB11} = \sigma_x^2 \begin{pmatrix} t_{i1} & t_{i1} & t_{i1} & \cdots & t_{i1} \\ t_{i1} & t_{i2} & t_{i2} & \cdots & t_{i2} \\ t_{i1} & t_{i2} & t_{i3} & \cdots & t_{i3} \\ \cdots & & & & \\ t_{i1} & t_{i2} & t_{i3} & \cdots & t_{im} \end{pmatrix}; \Sigma_{iB22} = \sigma_y^2 t_{im_i}; \Sigma_{iB21} = \sigma_{xy} (t_{i1} \ t_{i2} \ \cdots \ t_{im}); \text{ and}$$

$$\Sigma_{iB12} = \Sigma'_{B21};$$

a first coefficient determining unit, configured to determine values of the coefficients μ_x and σ_x according to the measured value data of the identification parameter by using a maximum likelihood method; and

a second coefficient determining unit, configured to determine values of the coefficients μ_y , σ_y , μ_{yk} , and σ_{yk} according to measured value data of the identification parameter and a performance parameter and the coefficients μ_x and σ_x by using the maximum likelihood method.

Optionally, the service life distribution analysis module is further configured to determine a service life probability density distribution model according to the coefficients, and analyze service life distribution of the product, where the service life probability density distribution

model is $G(t) = \sqrt{\frac{l^2}{2\pi\sigma_y^2 t^3}} \exp\left[-\frac{(l - \mu_y t)^2}{2\sigma_y^2 t}\right]$.

According to specific embodiments provided in the present invention, the present invention discloses the following technical effects:

For a performance degradation product in destructive measurement, according to technical solutions of the present invention, on one hand, accuracy of reliability analysis is improved, thus reducing a number of test samples and test costs; on the other hand, remaining service life of a product in use can be predicted, thus providing a basis for maintenance, replacement, and spare part decision for the product.

BRIEF DESCRIPTION OF THE DRAWINGS

To describe the technical solutions in the embodiments of the present invention or in the prior art more clearly, the following briefly introduces the accompanying drawings required for describing the embodiments. Apparently, the accompanying drawings in the following description show merely some embodiments of the present invention, and a person of ordinary skill in the art may still derive other drawings from these accompanying drawings without creative efforts.

FIG. 1 is a schematic flowchart of a product reliability analysis method according to the present invention;

FIG. 2 is a schematic flowchart of a product reliability analysis system according to the present invention;

FIG. 3 is a schematic diagram of an obtained measured value of an identification parameter in a specific implementation of the present invention; and

FIG. 4 is a schematic diagram of obtaining a remaining service life prediction result in a specific implementation of the present invention.

DETAILED DESCRIPTION

The following clearly and completely describes the technical solutions in the embodiments of the present invention with reference to the accompanying drawings in the embodiments of the present invention. Apparently, the described embodiments are merely a part rather than all of the embodiments of the present invention. All other embodiments obtained by a person of ordinary skill in the art based on the embodiments of the present invention without creative efforts shall fall within the protection scope of the present invention.

To make objectives, features, and advantages of the present invention more comprehensible, the following describes the present invention in more detail with reference to accompanying drawings and specific implementations.

FIG. 1 is a schematic flowchart of a product reliability analysis method according to the present invention. As shown in FIG. 1, the method includes the following steps:

Step 100. Obtain a measured value of a performance parameter-related identification parameter of a product. Measurement of the identification parameter is non-destructive measurement. For some performance-degraded products, some parameters related to their performance parameters may be measured during their operation or test processes, and are usually referred to as identification parameters (marker). Because performance parameters are related to the identification parameters, marker measurement data also includes reliability information of the products. The identification parameter is a parameter that can implement non-destructive measurement. For example, an iron pollution percentage and a horizontal deformation size of an electrolytic cell are regarded as markers, and reliability evaluation is

performed on the electrolytic cell by using life information and marker information at a corresponding time point.

Step 200. Determine a coefficient of a reliability analysis model of the product according to the measured value of the identification parameter. The reliability analysis model includes a service life probability distribution model and a remaining service life prediction model, and coefficient include μ_y , σ_y , μ_{y_k} , and σ_{y_k} . μ_y and σ_y are parameters in a product performance parameter degradation process. The performance parameter degradation process is a unitary Wiener (wiener) process. μ_y is a drift parameter, and σ_y is a diffusion parameter. μ_{y_k} and σ_{y_k} are distribution parameters of product performance parameter probability distribution of the product at a moment t_k , the product performance parameter probability distribution obeys normal distribution, that is, $y_k \sim N(\mu_{y_k}, \sigma_{y_k}^2)$. μ_{y_k} is an mean of the normal distribution, and σ_{y_k} is a standard deviation of the normal distribution. Before the parameters are determined, destructive measurement needs to be performed on performance parameters of multiple other similar products of a same type as the product to obtain measured values of multiple performance parameters, where a measured value of a performance parameter of an i^{th} similar product is $Y(t_{im})$ (one product can be measured only once). is also necessary to perform non-destructive measurement further needs to be performed on performance parameter-related identification parameters of the multiple similar products (one product is measured for multiple times) to obtain multiple groups of measured values of the performance parameter-related identification parameters, where a measured value set of an identification parameter of the i^{th} similar product is $X(t) = [X(t_{i1}), X(t_{i2}), \dots, X(t_{ij}), \dots, X(t_{im})]$, where $j = 1, 2, \dots, m$; and $X(t_{ij})$ is a measured value of an identification parameter of the i^{th} similar product at a moment t_{ij} .

A specific value of a coefficient is obtained according to the obtained measured data, and the process is as follows:

Step 1. Determine a joint probability distribution model of measured data of the i^{th} similar product, where the joint probability distribution model is $\mathbf{B}_i \sim N(\mu_{iB}, \Sigma_{iB})$; $\mathbf{B}_i = (X(t_{i1}) \ X(t_{i2}) \ \dots \ X(t_{im_i}) \ Y(t_{im_i}))'$;

$$\mu_{iB} = (\mu_x t_{i1} \ \mu_x t_{i2} \ \dots \ \mu_x t_{im_i} \ \mu_y t_{im_i})';$$

$$\Sigma_{iB} = D \times \Sigma_{iA} \times D' = \begin{pmatrix} \Sigma_{iB11} & \Sigma_{iB12} \\ \Sigma_{iB21} & \Sigma_{iB22} \end{pmatrix}; \quad D = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ 1 & 1 & \cdots & 0 \\ \cdots & & & \\ 1 & 1 & \cdots & 1 \\ \mathbf{0} & & 1 & 1 & \cdots & 1 \end{pmatrix};$$

$$\Sigma_{iB11} = \sigma_x^2 \begin{pmatrix} t_{i1} & t_{i1} & t_{i1} & \cdots & t_{i1} \\ t_{i1} & t_{i2} & t_{i2} & \cdots & t_{i2} \\ t_{i1} & t_{i2} & t_{i3} & \cdots & t_{i3} \\ \cdots & & & & \\ t_{i1} & t_{i2} & t_{i3} & \cdots & t_{im} \end{pmatrix}; \quad \Sigma_{iB22} = \sigma_y^2 t_{im_i}, \quad \Sigma_{iB21} = \sigma_{xy} (t_{i1} \ t_{i2} \ \cdots \ t_{im}); \text{ and}$$

$\Sigma_{iB12} = \Sigma'_{B21}$. B_i is a random vector herein, and an observed value of B_i can be obtained in each test.

For each similar product, $(X(t) \ Y(t))'$ is a binary Wiener process, and at an initial moment, $X(0)=0, Y(0)=0$. At a moment t , $(X(t) \ Y(t))' \sim N(t\mu, t\Sigma)$, where

$$\mu' = (\mu_x \ \mu_y), \quad \Sigma = \begin{pmatrix} \sigma_x^2 & \sigma_{xy} \\ \sigma_{xy} & \sigma_y^2 \end{pmatrix}, \quad \sigma_{xy} = \rho \sigma_x \sigma_y, \text{ and } \rho \text{ is a correlation coefficient. Because}$$

of destructive measurement, only a performance parameter value at an end moment of the test can be obtained. In addition, during the test and operation, multiple times of non-destructive measurement may be performed on a marker of the product, so that one piece of performance degradation data and multiple pieces of marker data may be obtained for one product in one test.

For a product i , in a performance degradation test process, m times of measurement of a marker of the product are performed at moments $t_{i1}, t_{i2}, \dots, t_{im}$, respectively. However, because measurement of a performance parameter is destructive, one time of measurement is performed on the performance parameter of the product i only at a moment t_{im} , and then the product is damaged and is withdrawn from the test. A time interval between two times of marker measurement is recorded as $\Delta t_{ij} = t_{ij} - t_{i(j-1)}$, a variable quantity of a marker is $\Delta X(t_{ij}) = X(t_{ij}) - X(t_{i(j-1)})$, and a variable quantity of product performance is $\Delta Y(t_{ij}) = Y(t_{ij}) - Y(t_{i(j-1)})$, where $j=1, 2, \dots, m_i$. Degeneration quantity measured values of markers and performance parameters of all products at a moment 0 are 0, that is, $t_{i0} = 0, X(t_{i0}) = Y(t_{i0}) = 0$, and therefore $\Delta X(t_{i1}) = X(t_{i1}), \Delta Y(t_{i1}) = Y(t_{i1})$.

It can be learned from an independent increment feature of the binary Wiener process, that $(\Delta X(t_{i1}) \ \Delta Y(t_{i1}))', \dots$ and $(\Delta X(t_{im}) \ \Delta Y(t_{im}))'$ are mutually independent and obey binary normal distribution: $(\Delta X(t_{i1}) \ \Delta Y(t_{i1}))' \sim N(\Delta t_{i1} \boldsymbol{\mu}, \Delta t_{i1} \boldsymbol{\Sigma})$, ..., and $(\Delta X(t_{im}) \ \Delta Y(t_{im}))' \sim N(\Delta t_{im} \boldsymbol{\mu}, \Delta t_{im} \boldsymbol{\Sigma})$, which is recorded as $\mathbf{C} = (\Delta X(t_{i1}) \ \Delta Y(t_{i1}) \ \Delta X(t_{i2}) \ \Delta Y(t_{i2}) \cdots \Delta X(t_{im}) \ \Delta Y(t_{im}))'$, and therefore $\mathbf{C}$ obeys normal distribution with a dimension of $2m$, that is, $\mathbf{C} \sim N(\boldsymbol{\mu}_C, \boldsymbol{\Sigma}_C)$, where $\boldsymbol{\mu}_C = (\Delta t_{i1} \mu_x \ \Delta t_{i1} \mu_y \ \Delta t_{i2} \mu_x \ \Delta t_{i2} \mu_y \cdots \Delta t_{im} \mu_x \ \Delta t_{im} \mu_y)'$, and

$$\boldsymbol{\Sigma}_C = \begin{pmatrix} \Delta t_{i1} \boldsymbol{\Sigma} & 0 & 0 & \cdots & 0 \\ 0 & \Delta t_{i2} \boldsymbol{\Sigma} & 0 & \cdots & 0 \\ \cdots & & & & \\ 0 & 0 & 0 & \cdots & \Delta t_{im} \boldsymbol{\Sigma} \end{pmatrix}.$$

A sequence of $\mathbf{C}$ is adjusted. Assuming that $\mathbf{A} = (\Delta X(t_{i1}) \ \Delta X(t_{i2}) \cdots \Delta X(t_{im}) \ \Delta Y(t_{i1}) \ \Delta Y(t_{i2}) \cdots \Delta Y(t_{im}))'$, $\mathbf{A}$ also obeys normal distribution with a dimension of $2m$, that is, $\mathbf{A} \sim N(\boldsymbol{\mu}_A, \boldsymbol{\Sigma}_A)$.

$\boldsymbol{\mu}_A = (\Delta t_{i1} \mu_x \ \Delta t_{i2} \mu_x \cdots \Delta t_{im} \mu_x \ \Delta t_{i1} \mu_y \ \Delta t_{i2} \mu_y \cdots \Delta t_{im} \mu_y)'$, and

$$\boldsymbol{\Sigma}_A = \begin{pmatrix} \Delta t_{i1} \sigma_x^2 & 0 & 0 & \cdots & 0 & \Delta t_{i1} \sigma_{xy} & 0 & 0 & \cdots & 0 \\ 0 & \Delta t_{i2} \sigma_x^2 & 0 & \cdots & 0 & 0 & \Delta t_{i2} \sigma_{xy} & 0 & \cdots & 0 \\ \cdots & & & & & \cdots & & & & \\ 0 & 0 & 0 & \cdots & \Delta t_{im} \sigma_x^2 & 0 & 0 & 0 & \cdots & \Delta t_{im} \sigma_{xy} \\ \Delta t_{i1} \sigma_{xy} & 0 & 0 & \cdots & 0 & \Delta t_{i1} \sigma_y^2 & 0 & 0 & \cdots & 0 \\ 0 & \Delta t_{i2} \sigma_{xy} & 0 & \cdots & 0 & 0 & \Delta t_{i2} \sigma_y^2 & 0 & \cdots & 0 \\ \cdots & & & & & \cdots & & & & \\ 0 & 0 & 0 & \cdots & \Delta t_{im} \sigma_{xy} & 0 & 0 & 0 & \cdots & \Delta t_{im} \sigma_y^2 \end{pmatrix}; \text{ and}$$

assuming that $\mathbf{B}_i = (X(t_{i1}) \ X(t_{i2}) \cdots X(t_{im}) \ Y(t_{im}))'$, $\mathbf{B}_i = \mathbf{D} \times \mathbf{A}$, where $\mathbf{D}$ is a matrix

$$(m+1) \times 2m, \text{ and } \mathbf{D} = \begin{pmatrix} 1 & 0 & \cdots & 0 & & \\ 1 & 1 & \cdots & 0 & & \\ \cdots & & & & \mathbf{0} & \\ 1 & 1 & \cdots & 1 & & \\ & \mathbf{0} & & 1 & 1 & \cdots & 1 \end{pmatrix}.$$

Step 2. Determine values of the coefficients μ_x and σ_x according to the measured value data of the identification parameter by using a maximum likelihood method.

It can be learned from the foregoing model, that when only a marker is considered, $X(t)$ is a unitary Wiener process. $\Delta X(t_{ij}) \sim N(\mu_x \Delta t_{ij}, \sigma_x^2 \Delta t_{ij})$ can be obtained according to a feature of the Wiener process, where μ_x and σ_x are parameters of an identification parameter (marker) degradation process (unitary Wiener process) of the product, μ_y is a drift parameter, and σ_y is a diffusion parameter.

According to the foregoing formula, the maximum likelihood method may be used to estimate parameters μ_x, σ_x^2 .

$$\hat{\mu}_x = \frac{\sum_{i=1}^n x_{im}}{nt_m}, \text{ and } \hat{\sigma}_x^2 = \frac{1}{nm} \left[\sum_{i=1}^n \sum_{j=1}^m \frac{(\Delta x_{ij})^2}{\Delta t_j} - \frac{\left(\sum_{i=1}^n x_{im} \right)^2}{nt_m} \right].$$

Measured data of the

product i is $X(t_{i1}) = x_{i1}, X(t_{i2}) = x_{i2}, \dots$, and $X(t_{im_i}) = x_{im}$. Therefore, estimated values are determined as values of the coefficients μ_x and σ_x .

Step 3: Determine values of the coefficients $\mu_y, \sigma_y, \mu_{Yk},$ and σ_{Yk} according to measured value data of the identification parameter and a performance parameter and the coefficients μ_x and σ_x by using the maximum likelihood method. μ_y and σ_y are parameters of the performance parameter degradation process (unitary Wiener process) of the product, where μ_y is a drift parameter, and σ_y is a diffusion parameter. μ_{Yk} and σ_{Yk} are distribution parameters of the product performance parameter probability distribution (normal distribution) at a moment t_k , where μ_{Yk} is a mean, and σ_{Yk} is a standard deviation.

Marker measurement times of all similar products are the same, and measurement is performed at a same moment, or in other words, for any i , $t_{i1} = t_1, t_{i2} = t_2, \dots, t_{im} = t_m$, and therefore $\Delta t_{i1} = t_1, \Delta t_{i2} = t_2, \dots, \Delta t_{im} = t_m$. If a sequence of elements in B_i is exchanged which is recorded as $W = (Y(t_{im}) \ X(t_{i1}) \ X(t_{i2}) \ \cdots \ X(t_{im}))'$, it can be learned that W obeys $m+1$ dimension normal distribution and $W \sim N(\mu_w, \Sigma_w)$, where

$$\mu_w = (\mu_y t_m \ \mu_x t_1 \ \mu_x t_2 \ \cdots \ \mu_x t_m)', \quad \Sigma_w = \begin{pmatrix} \Sigma_{w11} & \Sigma_{w12} \\ \Sigma_{w21} & \Sigma_{w22} \end{pmatrix}, \quad \Sigma_{w11} = \sigma_y^2 t_m,$$

$$\Sigma_{w12} = \sigma_{xy} (t_1 \ t_2 \ \cdots \ t_m), \Sigma_{w21} = \Sigma'_{w12}, \text{ and } \Sigma_{w22} = \sigma_x^2 \begin{pmatrix} t_1 & t_1 & t_1 & \cdots & t_1 \\ t_1 & t_2 & t_2 & \cdots & t_2 \\ t_1 & t_2 & t_3 & \cdots & t_3 \\ \cdots & & & & \\ t_1 & t_2 & t_3 & \cdots & t_m \end{pmatrix}.$$

During measurement, a marker measured value $\mathbf{x}_i = (x_{i1} \ x_{i2} \ \cdots \ x_{im})'$ of the product i is recorded as $\boldsymbol{\mu}_1 = \hat{\boldsymbol{\mu}}_x (t_1 \ t_2 \ \cdots \ t_m)'$. It can be learned from a characteristic of conditional distribution of normal distribution that when , a performance degradation quantity Y_{im} of the product obeys unitary normal distribution when $\mathbf{x}_i$ is given:

$$Y_{im} |_{x_{i1}, x_{i2}, \dots, x_{im}} \sim N(\mu_{Y_{im}}, \sigma_{Y_{im}}^2), \text{ where } \begin{cases} \mu_{Y_{im}} = \mu_y t_m + \Sigma_{w12} \Sigma_{w22}^{-1} (\mathbf{x}_i - \boldsymbol{\mu}_1) \\ \sigma_{Y_{im}}^2 = \sigma_y^2 t_m - \Sigma_{w12} \Sigma_{w22}^{-1} \Sigma_{w21} \end{cases}.$$

Expressions of constants C_i and D_i are as follows:

$$C_i = (t_1 \ t_2 \ \cdots \ t_m) \times \frac{1}{\hat{\sigma}_x^2} \begin{pmatrix} t_1 & t_1 & t_1 & \cdots & t_1 \\ t_1 & t_2 & t_2 & \cdots & t_2 \\ t_1 & t_2 & t_3 & \cdots & t_3 \\ \cdots & & & & \\ t_1 & t_2 & t_3 & \cdots & t_m \end{pmatrix}^{-1} \times (\mathbf{x}_i - \boldsymbol{\mu}_1)$$

$$D_i = (t_1 \ t_2 \ \cdots \ t_m) \times \begin{pmatrix} t_1 & t_1 & t_1 & \cdots & t_1 \\ t_1 & t_2 & t_2 & \cdots & t_2 \\ t_1 & t_2 & t_3 & \cdots & t_3 \\ \cdots & & & & \\ t_1 & t_2 & t_3 & \cdots & t_m \end{pmatrix}^{-1} \times \begin{pmatrix} t_1 \\ t_2 \\ \vdots \\ t_m \end{pmatrix}$$

A log-likelihood function is as follows:

$$\ln L(\mu_y, \sigma_{xy}, \sigma_y^2) = -\frac{n}{2} \ln(2\pi) - \frac{n}{2} \ln(\sigma_y^2 t_m - \sigma_{xy}^2 D_i) - \frac{1}{2(\sigma_y^2 t_m - \sigma_{xy}^2 D_i)} \cdot \sum_{i=1}^n (y_{im} - \mu_y t_m - \sigma_{xy} C_i)^2.$$

According to the maximum likelihood method, partial derivatives of $\mu_y, \sigma_{xy}, \sigma_y^2$ are calculated, and assuming that the partial derivatives of $\mu_y, \sigma_{xy}, \sigma_y^2$ are 0, the following equations are obtained:

$$\left\{ \begin{array}{l} \frac{\partial}{\partial \mu_y} \ln L(\mu_y, \sigma_{xy}, \sigma_y^2) = \frac{t_m}{\sigma_y^2 t_m - \sigma_{xy}^2 D_i} \sum_{i=1}^n (y_{im} - \mu_y t_m - \sigma_{xy} C_i) = 0 \\ \frac{\partial}{\partial \sigma_{xy}} \ln L(\mu_y, \sigma_{xy}, \sigma_y^2) = \frac{n D_i \sigma_{xy}}{\sigma_y^2 t_m - \sigma_{xy}^2 D_i} - \frac{D_i \sigma_{xy}}{(\sigma_y^2 t_m - \sigma_{xy}^2 D_i)^2} \sum_{i=1}^n (y_{im} - \mu_y t_m - \sigma_{xy} C_i)^2 \\ \quad + \frac{1}{(\sigma_y^2 t_m - \sigma_{xy}^2 D_i)} \sum_{i=1}^n C_i (y_{im} - \mu_y t_m - \sigma_{xy} C_i) = 0 \\ \frac{\partial}{\partial \sigma_y^2} \ln L(\mu_y, \sigma_{xy}, \sigma_y^2) = -\frac{n t_m}{2(\sigma_y^2 t_m - \sigma_{xy}^2 D_i)} + \\ \quad \frac{t_m}{2(\sigma_y^2 t_m - \sigma_{xy}^2 D_i)^2} \sum_{i=1}^n (y_{im} - \mu_y t_m - \sigma_{xy} C_i)^2 = 0 \end{array} \right.$$

The following formulas can be obtained by resolving the foregoing equations:

$$\begin{aligned} \hat{\sigma}_{xy} &= \frac{n \sum_{i=1}^n C_i y_{im} - \sum_{i=1}^n y_{im} \sum_{i=1}^n C_i}{n \sum_{i=1}^n C_i^2 - \left(\sum_{i=1}^n C_i \right)^2} \\ \hat{\mu}_y &= \frac{1}{n t_m} \left(\sum_{i=1}^n y_{im} - \hat{\sigma}_{xy} \sum_{i=1}^n C_i \right) \\ \hat{\sigma}_y^2 &= \frac{D_i}{t_m} \hat{\sigma}_{xy}^2 + \frac{1}{n t_m} \sum_{i=1}^n (y_{im} - \hat{\mu}_y t_m - \hat{\sigma}_{xy} C_i)^2 \end{aligned}$$

Estimated values of μ_y , σ_y , μ_{Y_k} , and σ_{Y_k} are determined as values of the coefficients μ_y and σ_y .

$\mu_{Y_{im}} = \mu_y t_m + \sigma_{xy} C_i$, $\sigma_{Y_i}^2 = \sigma_y^2 t_m - \sigma_{xy}^2 D_i$ can be obtained according to the foregoing formulas. In this case, according to a measured value of an identification parameter-related performance parameter of a to-be-analyzed product, a measurement time t_k is substituted into the foregoing formula, and a coefficient $\mu_{Y_k} = \mu_y t_k + \sigma_{xy} C_i$, $\sigma_{Y_k}^2 = \sigma_y^2 t_k - \sigma_{xy}^2 D_i$ can be determined.

Step 300. Determine the service life probability distribution model according to the coefficients, and analyze service life distribution of the product. The service life probability

distribution model is $F(t) = \Phi\left(\frac{\mu_y t - l}{\sigma_y \sqrt{t}}\right) + \exp\left(\frac{2\mu_y l}{\sigma_y^2}\right) \Phi\left(\frac{-l - \mu_y t}{\sigma_y \sqrt{t}}\right)$, where

$$\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-\frac{t^2}{2}} dt, \text{ and } l \text{ is a failure threshold of the product.}$$

Service life distribution of the product is probability distribution, may be analyzed by using the foregoing probability distribution model, or may be analyzed by using a service life probability density distribution model: $G(t) = \sqrt{\frac{l^2}{2\pi\sigma_y^2 t^3}} \exp\left[-\frac{(l - \mu_y t)^2}{2\sigma_y^2 t}\right]$. A derivative of the probability distribution model is the probability density distribution model.

Step 400. Determine the remaining service life prediction model according to the coefficients, and predict remaining service life of the product.

During operation, markers of the product that are measured at moments $t_1, t_2, \dots, t_k$ are $X(t_1) = x_1, X(t_2) = x_2, \dots, X(t_k) = x_k$. A performance parameter degeneration quantity of the product at a moment t_k obeys unitary normal distribution: $Y_k |_{x_1, x_2, \dots, x_k} \sim N(\mu_{Y_k}, \sigma_{Y_k}^2)$.

According to a feature of the unitary Wiener process, remaining service life of the product is $f(t) = \sqrt{\frac{(l - y_k)^2}{2\pi\sigma_y^2 t^3}} \exp\left[-\frac{(l - y_k - \mu_y t)^2}{2\sigma_y^2 t}\right]$, where y_k obeys normal distribution:

$y_k \sim N(\mu_{Y_k}, \sigma_{Y_k}^2)$, and

$$\begin{aligned} f(t) &= \int_{-\infty}^l \sqrt{\frac{(l - y_k)^2}{2\pi\sigma_y^2 t^3}} \exp\left[-\frac{(l - y_k - \mu_y t)^2}{2\sigma_y^2 t}\right] \cdot \frac{1}{\sqrt{2\pi\sigma_{Y_k}^2}} \exp\left[-\frac{(y_k - \mu_{Y_k})^2}{2\sigma_{Y_k}^2}\right] dy_k \\ &= \frac{1}{2\pi\sqrt{\sigma_{Y_k}^2 \sigma_y^2 t^3}} \cdot \int_{-\infty}^l (l - y_k) \exp\left[-\frac{(l - y_k - \mu_y t)^2}{2\sigma_y^2 t} - \frac{(y_k - \mu_{Y_k})^2}{2\sigma_{Y_k}^2}\right] dy_k. \end{aligned}$$

Therefore, the remaining service life prediction model is as follows:

$$f(t) = \frac{1}{2\pi\sqrt{\sigma_{Y_k}^2 \sigma_y^2 t^3}} \cdot \int_{-\infty}^l (l - y_k) \exp\left[-\frac{(l - y_k - \mu_y t)^2}{2\sigma_y^2 t} - \frac{(y_k - \mu_{Y_k})^2}{2\sigma_{Y_k}^2}\right] dy_k, \text{ where}$$

y_k is a performance parameter of the product.

FIG. 2 is a schematic structural diagram of a product reliability analysis system according to

the present invention. As shown in FIG. 2, the system includes:

a measured value obtaining module 201, configured to obtain a measured value of a performance parameter–related identification parameter of a product, where measurement of the identification parameter is non-destructive measurement;

a coefficient determining module 202, configured to determine coefficients μ_y , σ_y , μ_{y_k} , and σ_{y_k} of a reliability analysis model of the product according to the measured value of the identification parameter, where the reliability analysis model includes a service life probability distribution model and a remaining service life prediction model;

a service life distribution analysis module 203, configured to determine the service life probability distribution model according to the coefficients, and analyze service life distribution of the product, where the service life probability distribution model is $F(t) = \Phi\left(\frac{\mu_y t - l}{\sigma_y \sqrt{t}}\right) + \exp\left(\frac{2\mu_y l}{\sigma_y^2}\right) \Phi\left(\frac{-l - \mu_y t}{\sigma_y \sqrt{t}}\right)$, where $\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-\frac{t^2}{2}} dt$, and l is a failure threshold of the product; and

a remaining service life prediction module 204, configured to determine the remaining service life prediction model according to the coefficients, and predict remaining service life of the product, where the remaining service life distribution model is

$$f(t) = \frac{1}{2\pi\sqrt{\sigma_{y_k}^2 \sigma_y^2 t^3}} \cdot \int_{-\infty}^l (l - y_k) \exp\left[-\frac{(l - y_k - \mu_y t)^2}{2\sigma_y^2 t} - \frac{(y_k - \mu_{y_k})^2}{2\sigma_{y_k}^2}\right] dy_k;$$

where y_k is a performance parameter of the product.

The system further includes:

a performance parameter measurement module, configured to: before the coefficients μ_y , σ_y , μ_{y_k} , and σ_{y_k} of the reliability analysis model of the product are determined according to the measured value of the identification parameter, perform destructive measurement on performance parameters of multiple other similar products of a same type as the product to obtain measured values of multiple performance parameters, where a measured value of a performance parameter of an i^{th} similar product is $Y(t_{im})$; and

an identification parameter measurement module, configured to perform non-destructive measurement on performance parameter–related identification parameters of the multiple similar

products to obtain multiple groups of measured values of the performance parameter-related identification parameters, where a measured value set of an identification parameter of the i^{th} similar product is $X(t) = [X(t_{i1}), X(t_{i2}), \dots, X(t_{ij}), \dots, X(t_{im})]$, where $j = 1, 2, \dots, m$; and $X(t_{ij})$ is a measured value of an identification parameter of the i^{th} similar product at a moment t_{ij} .

The coefficient determining module 202 specifically includes:

a joint probability distribution model determining unit, configured to determine a joint probability distribution model of measured data of the i^{th} similar product, where the joint probability distribution model is $\mathbf{B}_i \sim N(\boldsymbol{\mu}_{iB}, \boldsymbol{\Sigma}_{iB})$;

$$\mathbf{B}_i = (X(t_{i1}) \ X(t_{i2}) \ \cdots \ X(t_{im_i}) \ Y(t_{im_i}))';$$

$$\boldsymbol{\mu}_{iB} = (\mu_x t_{i1} \ \mu_x t_{i2} \ \cdots \ \mu_x t_{im_i} \ \mu_y t_{im_i})';$$

$$\boldsymbol{\Sigma}_{iB} = \mathbf{D} \times \boldsymbol{\Sigma}_{iA} \times \mathbf{D}' = \begin{pmatrix} \boldsymbol{\Sigma}_{iB11} & \boldsymbol{\Sigma}_{iB12} \\ \boldsymbol{\Sigma}_{iB21} & \boldsymbol{\Sigma}_{iB22} \end{pmatrix}; \quad \mathbf{D} = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ 1 & 1 & \cdots & 0 \\ \cdots & & & \mathbf{0} \\ 1 & 1 & \cdots & 1 \\ \mathbf{0} & & 1 & 1 & \cdots & 1 \end{pmatrix};$$

$$\boldsymbol{\Sigma}_{iB11} = \sigma_x^2 \begin{pmatrix} t_{i1} & t_{i1} & t_{i1} & \cdots & t_{i1} \\ t_{i1} & t_{i2} & t_{i2} & \cdots & t_{i2} \\ t_{i1} & t_{i2} & t_{i3} & \cdots & t_{i3} \\ \cdots & & & & \\ t_{i1} & t_{i2} & t_{i3} & \cdots & t_{im} \end{pmatrix}; \quad \boldsymbol{\Sigma}_{iB22} = \sigma_y^2 t_{im_i}, \quad \boldsymbol{\Sigma}_{iB21} = \sigma_{xy} (t_{i1} \ t_{i2} \ \cdots \ t_{im}); \text{ and}$$

$$\boldsymbol{\Sigma}_{iB12} = \boldsymbol{\Sigma}_{iB21}';$$

a first coefficient determining unit, configured to determine values of the coefficients μ_x and σ_x according to the measured value data of the identification parameter by using a maximum likelihood method; and

a second coefficient determining unit, configured to determine values of the coefficients μ_y , σ_y , μ_{yk} , and σ_{yk} according to measured value data of the identification parameter and a performance parameter and the coefficients μ_x and σ_x by using the maximum likelihood method.

The service life distribution analysis module 203 is further configured to determine a service

life probability density distribution model according to the coefficients, and analyze service life distribution of the product, where the service life probability density distribution model is

$$G(t) = \sqrt{\frac{l^2}{2\pi\sigma_y^2 t^3}} \exp\left[-\frac{(l - \mu_y t)^2}{2\sigma_y^2 t}\right].$$

In a specific implementation of the present invention, assuming that the performance parameter and the marker of the product obey a binary Wiener process, parameters $(\mu_x, \mu_y, \sigma_x, \sigma_y, \rho) = (1.0, 0.1, 0.1, 0.4, 0.75)$, and the failure threshold of the product is $l = 3$, average life of the product is $l/\mu_y = 30$. According to an independent increment feature of the binary Wiener process, a time step 0.01 is selected to generate $n = 30$ simulation sample paths. For each sample path, marker values at $t_1 = 1, t_2 = 2, t_3 = 3, t_4 = 4, t_5 = 5$ and performance parameter values at $t_5 = 5$ are selected as simulation test data of the product. Table

1 provides simulation test data. Details are listed in the following table:

Table 1 Simulation test data

X_{i1}	X_{i2}	X_{i3}	X_{i4}	X_{i5}	Y_{i5}
1.0266	1.919	2.9858	4.1635	5.1731	1.3646
0.97128	1.9564	2.8811	3.7638	4.6814	-1.7309
1.0924	2.0504	3.048	4.1284	5.0111	0.32368
1.0621	2.0521	2.9758	4.0212	5.1307	0.99951
0.94891	2.0003	3.0845	3.9611	4.9151	-0.08588
0.90495	2.0044	3.0508	4.1757	5.0275	0.8561
0.97736	1.7897	2.8932	3.8981	4.8679	0.95564
1.0333	1.8993	2.8837	3.9547	4.9962	0.59729
0.96957	1.8876	2.8843	3.7726	4.9173	0.62484
1.1189	2.1407	3.0808	4.2271	5.3749	2.257
1.0591	2.0183	2.9756	3.937	4.9862	0.18516
0.99686	1.8524	2.797	3.7303	4.6605	-0.88799
0.97685	2.0573	3.0099	3.9713	4.968	0.89732
1.1295	2.0278	3.08	4.0823	4.9022	-0.07659
1.0944	2.008	3.0794	4.0738	5.144	0.98363
1.0353	2.0351	2.9995	3.9626	4.8958	0.36931
0.83553	1.8423	2.8621	3.802	4.7036	-0.83054
1.0165	2.1573	3.2652	4.4118	5.3987	1.635
0.99148	1.9381	3.0513	4.0188	4.9399	-0.21816
0.94298	1.9703	3.1209	4.152	5.1772	1.1721
0.8497	1.7903	2.8471	3.8634	4.9511	0.17706
0.97488	1.9517	2.8658	4.0077	5.0052	0.35624
0.9537	1.9726	2.9813	3.9637	4.9254	0.31714
1.0379	2.0618	3.1325	4.2643	5.1675	0.98304
1.0219	1.9635	2.9713	3.8793	4.8474	1.2875
1.1763	2.245	3.234	4.1898	5.1553	1.0042
1.179	2.173	3.2274	4.2042	5.067	1.1943
0.91689	1.8342	2.8697	3.78	4.8489	0.12089
1.0778	2.0781	3.0457	3.9963	4.9978	0.20682

0.96141	1.8929	2.752	3.8722	4.8949	0.86466
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The following result is obtained through estimation by using the foregoing provided method:

$$(\hat{\mu}_x, \hat{\mu}_y, \hat{\sigma}_x, \hat{\sigma}_y, \hat{\rho}) = (0.99665, 0.11043, 0.085523, 0.38498, 0.8683) \cdot$$

The service life probability density distribution model of the product is as follows:

$$G(t) = \frac{3}{\sqrt{0.9312t^3}} \exp \left[-\frac{(3 - 0.85523t)^2}{0.2964t} \right].$$

Actually, when only performance degradation data is considered, and $Y_{im} \sim N(\mu_y, t_m \sigma_y^2)$, only the product performance degradation data is used to estimate the parameters μ_y, σ_y , to obtain the following results:

$$\hat{\mu}_y = \frac{1}{nt_m} \sum_{i=1}^n y_{im}, \hat{\sigma}_y^2 = \frac{1}{(n-1)t_m} \sum_{i=1}^n (y_{im} - t_m \hat{\mu}_y)^2.$$

The two estimation methods are compared herein. The foregoing simulation is repeated for 1000 times, and the parameters μ_y, σ_y are estimated by each of the two methods, to obtain Bootstrap interval estimation [13] of the parameters. Table 2 provides estimation results of the two methods.

Table 2 Parameter estimation results of two methods

	μ_y		σ_y	
	Confidence coefficient $1 - \alpha = 0.9$	Confidence coefficient $1 - \alpha = 0.8$	Confidence coefficient $1 - \alpha = 0.9$	Confidence coefficient $1 - \alpha = 0.8$
Method in which only performance degradation data is used	(0.0470, 0.1517)	(0.0576, 0.1399)	(0.3183, 0.4812)	(0.3339, 0.4603)
Method in this specification	(0.0462, 0.1551)	(0.0564, 0.1422)	(0.3357, 0.4636)	(0.3461, 0.4445)

It can be learned from Table 2 that there is a small difference between interval lengths of interval estimation of the parameter μ_y that are obtained by the two methods, while an interval length, obtained by the method in this specification, of interval estimation of the parameter σ_y is shorter, and therefore accuracy of the method in this specification is higher.

In addition, a parameter ρ represents a correlation between a performance parameters and a marker. Assuming that $\rho = 0.55, 0.75, 0.95$, interval estimation of μ_y, σ_y that is obtained by the foregoing methods is given in Table 3.

Table 3 Parameter estimation results when correlation coefficients are different

	μ_y		σ_y	
	Confidence coefficient $1 - \alpha = 0.9$	Confidence coefficient $1 - \alpha = 0.8$	Confidence coefficient $1 - \alpha = 0.9$	Confidence coefficient $1 - \alpha = 0.8$
$\rho = 0.55$	(0.0456, 0.1543)	(0.05745, 0.1434)	(0.3112, 0.4779)	(0.3284, 0.4599)
$\rho = 0.75$	(0.0462, 0.1551)	(0.0564, 0.1422)	(0.3357, 0.4636)	(0.3461, 0.4445)
$\rho = 0.95$	(0.0414, 0.1512)	(0.05414, 0.1406)	(0.3577, 0.4429)	(0.3695, 0.4313)

It can be learned from Table 3 that an interval length of interval estimation of μ_y changes little as a correlation coefficient changes, but when ρ is larger, an interval estimation length is shorter, that is, accuracy is higher.

FIG. 3 is a schematic diagram of an obtained measured value of an identification parameter in a specific implementation of the present invention. FIG. 3 provides another sample path for obtaining $(X(t), Y(t))$ through simulation, which is regarded as measurement of a marker during operation of a product. In this case, a performance degradation quantity y_4 of the product when $t = 4$ obeys normal distribution $y_4 \sim N(\mu_{y_4}, \sigma_{y_4}^2)$, and $\mu_{y_4} = 0.1255, \sigma_{y_4}^2 = 0.1459$ are obtained by using the method of the present invention.

Remaining service life distribution of the product obtained through numerical calculation is shown in FIG. 4. FIG. 4 is a schematic diagram of a remaining service life prediction result obtained in a specific implementation of the present invention. As shown in FIG. 4, mean remaining service life is 34.92, and it is estimated that an interval corresponding to a confidence coefficient $1 - \alpha = 0.9$ is (7.22, 89.89).

In the present invention, performance degradation data and marker data are comprehensively used to perform reliability analysis on a product. First, a relationship between a performance parameter and a marker of the product needs to be determined. If there is a specific functional relationship between the performance parameter and the marker of the product, the marker data can be transformed and transformed data is directly used to perform reliability analysis of the product. The analysis process of the product is the same as general reliability analysis based on performance degradation, and therefore this case is not considered herein. In the present invention, a case in which there is a statistical correlation between performance degradation data and a marker is mainly considered. Because a unitary Wiener process is relatively widely used in product performance degradation analysis, a unitary Wiener process is used as a product performance degradation process. Further, because a binary Wiener process is relatively widely used in describing a relationship between a product performance parameter and a marker of a

product, a case in which the performance parameter and the marker of the product obey the binary Wiener process is mainly considered herein. In the present invention, joint distribution of a performance measured value and a marker measured value is first obtained, and a parameter estimation method and product service life distribution are provided. In addition, on this basis, a remaining service life distribution prediction method based on the marker measured value during operation of the product is provided. Each embodiment of the present specification is described in a progressive manner, each embodiment focuses on the difference from other embodiments, and the same and similar parts between the embodiments may refer to each other. For a system disclosed in the embodiments, since it corresponds to the method disclosed in the embodiments, the description is relatively simple, and reference can be made to the method description.

Several examples are used for illustration of the principles and implementation methods of the present invention. The description of the embodiments is used to help illustrate the method and its core principles of the present invention. In addition, those skilled in the art can make various modifications in terms of specific embodiments and scope of application in accordance with the teachings of the present invention. In conclusion, the content of this specification shall not be construed as a limitation to the invention.

What is claimed is:

1. A product reliability analysis method, wherein the method comprises:

obtaining a measured value of a performance parameter-related identification parameter of a product, wherein measurement of the identification parameter is non-destructive measurement;

determining coefficients μ_y , σ_y , μ_{y_k} , and σ_{y_k} of a reliability analysis model of the product according to the measured value of the identification parameter, wherein the reliability analysis model comprises a service life probability distribution model and a remaining service life prediction model; μ_y and σ_y are parameters in a product performance parameter degeneration process, the performance parameter degeneration process is a unitary Wiener process, μ_y is a drift parameter, and σ_y is a diffusion parameter; and μ_{y_k} and σ_{y_k} are distribution parameters of product performance parameter probability distribution at a moment t_k , the product performance parameter probability distribution obeys normal distribution, μ_{y_k} is a mean of the normal distribution, and σ_{y_k} is a standard deviation of the normal distribution;

determining the service life probability distribution model according to the coefficients, and analyzing service life distribution of the product, wherein the service life probability distribution model is

$$F(t) = \Phi\left(\frac{\mu_y t - l}{\sigma_y \sqrt{t}}\right) + \exp\left(\frac{2\mu_y l}{\sigma_y^2}\right) \Phi\left(\frac{-l - \mu_y t}{\sigma_y \sqrt{t}}\right), \quad \text{wherein}$$

$$\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-\frac{t^2}{2}} dt, \text{ and } l \text{ is a failure threshold of the product; and}$$

determining the remaining service life prediction model according to the coefficients, and predicting remaining service life of the product, wherein the remaining service life distribution model is

$$f(t) = \frac{1}{2\pi \sqrt{\sigma_{y_k}^2 \sigma_y^2 t^3}} \cdot \int_{-\infty}^l (l - y_k) \exp\left[-\frac{(l - y_k - \mu_y t)^2}{2\sigma_y^2 t} - \frac{(y_k - \mu_{y_k})^2}{2\sigma_{y_k}^2}\right] dy_k,$$

wherein y_k is a performance parameter of the product.

2. The method according to claim 1, wherein before the determining coefficients μ_y , σ_y , μ_{y_k} , and σ_{y_k} of a reliability analysis model of the product according to the measured value of the identification parameter, the method further comprises:

performing destructive measurement on performance parameters of multiple other similar

products of a same type as the product to obtain measured values of multiple performance parameters, wherein a measured value of a performance parameter of an i^{th} similar product is $Y(t_{im})$; and

performing non-destructive measurement on performance parameter-related identification parameters of the multiple similar products to obtain multiple groups of measured values of the performance parameter-related identification parameters, wherein a measured value set of an identification parameter of the i^{th} similar product is $X(t) = [X(t_{i1}), X(t_{i2}), \dots, X(t_{ij}), \dots, X(t_{im})]$, wherein $j = 1, 2, \dots, m$; and $X(t_{ij})$ is a measured value of an identification parameter of the i^{th} similar product at a moment t_{ij} .

3. The method according to claim 2, the determining coefficients μ_y , σ_y , μ_{yk} , and σ_{yk} of a reliability analysis model of the product according to the measured value of the identification parameter specifically comprises:

determining a joint probability distribution model of measured data of the i^{th} similar product, wherein the joint probability distribution model is $B_i \sim N(\mu_{iB}, \Sigma_{iB})$; $B_i = (X(t_{i1}) \ X(t_{i2}) \ \dots \ X(t_{im_i}) \ Y(t_{im_i}))'$;

$$\mu_{iB} = (\mu_x t_{i1} \ \mu_x t_{i2} \ \dots \ \mu_x t_{im_i} \ \mu_y t_{im_i})';$$

$$\Sigma_{iB} = D \times \Sigma_{iA} \times D' = \begin{pmatrix} \Sigma_{iB11} & \Sigma_{iB12} \\ \Sigma_{iB21} & \Sigma_{iB22} \end{pmatrix}; \quad D = \begin{pmatrix} 1 & 0 & \dots & 0 & & \\ 1 & 1 & \dots & 0 & & \\ \dots & & & & \mathbf{0} & \\ 1 & 1 & \dots & 1 & & \\ & \mathbf{0} & & & 1 & 1 & \dots & 1 \end{pmatrix};$$

$$\Sigma_{iB11} = \sigma_x^2 \begin{pmatrix} t_{i1} & t_{i1} & t_{i1} & \dots & t_{i1} \\ t_{i1} & t_{i2} & t_{i2} & \dots & t_{i2} \\ t_{i1} & t_{i2} & t_{i3} & \dots & t_{i3} \\ \dots & & & & \\ t_{i1} & t_{i2} & t_{i3} & \dots & t_{im} \end{pmatrix}; \quad \Sigma_{iB22} = \sigma_y^2 t_{im_i}; \quad \Sigma_{iB21} = \sigma_{xy} (t_{i1} \ t_{i2} \ \dots \ t_{im}); \text{ and}$$

$$\Sigma_{iB12} = \Sigma'_{B21};$$

determining values of the coefficients μ_x and σ_x according to the measured value data of the identification parameter by using a maximum likelihood method; and

determining values of the coefficients μ_y , σ_y , μ_{yk} , and σ_{yk} according to measured value data of the identification parameter and a performance parameter and the coefficients μ_x

and σ_x by using the maximum likelihood method.

4. The method according to claim 1, wherein after the determining the service life probability distribution model according to the coefficients, and analyzing service life distribution of the product, the method further comprises:

determining a service life probability density distribution model according to the coefficients, and analyzing service life distribution of the product, wherein the service life

probability density distribution model is $G(t) = \sqrt{\frac{l^2}{2\pi\sigma_y^2 t^3}} \exp\left[-\frac{(l - \mu_y t)^2}{2\sigma_y^2 t}\right]$.

5. A product reliability analysis system, wherein the system comprises:

a measured value obtaining module, configured to obtain a measured value of a performance parameter-related identification parameter of a product, wherein measurement of the identification parameter is non-destructive measurement;

a coefficient determining module, configured to determine coefficients μ_y , σ_y , μ_{yk} , and σ_{yk} of a reliability analysis model of the product according to the measured value of the identification parameter, wherein the reliability analysis model comprises a service life probability distribution model and a remaining service life prediction model; μ_y and σ_y are parameters in a product performance parameter degeneration process, the performance parameter degeneration process is a unitary Wiener process, μ_y is a drift parameter, and σ_y is a diffusion parameter; and μ_{yk} and σ_{yk} are distribution parameters of product performance parameter probability distribution at a moment t_k , the product performance parameter probability distribution obeys normal distribution, μ_{yk} is a mean of the normal distribution, and σ_{yk} is a standard deviation of the normal distribution;

a service life distribution analysis module, configured to determine the service life probability distribution model according to the coefficients, and analyze service life distribution of the product, wherein the service life probability distribution model is

$F(t) = \Phi\left(\frac{\mu_y t - l}{\sigma_y \sqrt{t}}\right) + \exp\left(\frac{2\mu_y l}{\sigma_y^2}\right) \Phi\left(\frac{-l - \mu_y t}{\sigma_y \sqrt{t}}\right)$, wherein $\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-\frac{t^2}{2}} dt$, and l

is a failure threshold of the product;

a remaining service life prediction module, configured to determine the remaining service

life prediction model according to the coefficients, and predict remaining service life of the product, wherein the remaining service life distribution model is

$$f(t) = \frac{1}{2\pi\sqrt{\sigma_{Y_k}^2 \sigma_y^2 t^3}} \cdot \int_{-\infty}^l (l - y_k) \exp \left[-\frac{(l - y_k - \mu_y t)^2}{2\sigma_y^2 t} - \frac{(y_k - \mu_{Y_k})^2}{2\sigma_{Y_k}^2} \right] dy_k ;$$

wherein y_k is a performance parameter of the product.

6. The system according to claim 5, wherein the system further comprises:

a performance parameter measurement module, configured to: before the coefficients μ_y , σ_y , μ_{Y_k} , and σ_{Y_k} of the reliability analysis model of the product are determined according to the measured value of the identification parameter, perform destructive measurement on performance parameters of multiple other similar products of a same type as the product to obtain measured values of multiple performance parameters, wherein a measured value of a performance parameter of an i^{th} similar product is $Y(t_{im})$; and

an identification parameter measurement module, configured to perform non-destructive measurement on performance parameter-related identification parameters of the multiple similar products to obtain multiple groups of measured values of the performance parameter-related identification parameters, wherein a measured value set of an identification parameter of the i^{th} similar product is $X(t) = [X(t_{i1}), X(t_{i2}), \dots, X(t_{ij}), \dots, X(t_{im})]$, wherein $j = 1, 2, \dots, m$; and $X(t_{ij})$ is a measured value of an identification parameter of the i^{th} similar product at a moment t_{ij} .

7. The system according to claim 6, wherein the coefficient determining module specifically comprises:

a joint probability distribution model determining unit, configured to determine a joint probability distribution model of measured data of the i^{th} similar product, wherein the joint probability distribution model is $\mathbf{B}_i \sim N(\boldsymbol{\mu}_{iB}, \boldsymbol{\Sigma}_{iB})$;
 $\mathbf{B}_i = (X(t_{i1}) \ X(t_{i2}) \ \dots \ X(t_{im_i}) \ Y(t_{im_i}))'$;

$$\boldsymbol{\mu}_{iB} = (\mu_x t_{i1} \ \mu_x t_{i2} \ \dots \ \mu_x t_{im_i} \ \mu_y t_{im_i})' ;$$

$$\Sigma_{iB} = D \times \Sigma_{iA} \times D' = \begin{pmatrix} \Sigma_{iB11} & \Sigma_{iB12} \\ \Sigma_{iB21} & \Sigma_{iB22} \end{pmatrix}; \quad D = \begin{pmatrix} 1 & 0 & \cdots & 0 & & \\ 1 & 1 & \cdots & 0 & & \\ \cdots & & & & \mathbf{0} & \\ 1 & 1 & \cdots & 1 & & \\ & \mathbf{0} & & & 1 & 1 & \cdots & 1 \end{pmatrix};$$

$$\Sigma_{iB11} = \sigma_x^2 \begin{pmatrix} t_{i1} & t_{i1} & t_{i1} & \cdots & t_{i1} \\ t_{i1} & t_{i2} & t_{i2} & \cdots & t_{i2} \\ t_{i1} & t_{i2} & t_{i3} & \cdots & t_{i3} \\ \cdots & & & & \\ t_{i1} & t_{i2} & t_{i3} & \cdots & t_{im} \end{pmatrix}; \quad \Sigma_{iB22} = \sigma_y^2 t_{im_i}; \quad \Sigma_{iB21} = \sigma_{xy} (t_{i1} \ t_{i2} \ \cdots \ t_{im}); \text{ and}$$

$$\Sigma_{iB12} = \Sigma'_{B21};$$

a first coefficient determining unit, configured to determine values of the coefficients μ_x and σ_x according to the measured value data of the identification parameter by using a maximum likelihood method; and

a second coefficient determining unit, configured to determine values of the coefficients μ_y , σ_y , μ_{yk} , and σ_{yk} according to measured value data of the identification parameter and a performance parameter and the coefficients μ_x and σ_x by using the maximum likelihood method.

8. The system according to claim 5, wherein the service life distribution analysis module is further configured to determine a service life probability density distribution model according to the coefficients, and analyze service life distribution of the product, wherein the service life probability density distribution model is $G(t) = \sqrt{\frac{l^2}{2\pi\sigma_y^2 t^3}} \exp\left[-\frac{(l - \mu_y t)^2}{2\sigma_y^2 t}\right]$.