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## Calculation of Condition-based Maintenance Inspection Period for the Girder of Crane

Yang Qiang, Zhi-Li Sun, Bian Ji and Zhao Xin

School of Mechanical Engineering and Automation, Northeastern University, 110819, Shenyang, China

**Abstract:** Lacking of failure samples, the estimation of MTBF of the crane is imprecise. Half of the MTBF is regarded as inspection period in classical condition-based maintenance analysis. Because of ignoring reliability life changing of the product, maintenance with fixed period usually leads to more or less of inspection and replacement. Prior information of reliability estimation can be calculated according to laboratory failure data during the course of designing and precious records of similar products, reliability estimation modal combining with small samples from on-site test is built based on Bayes theorem and reliability forecast is realized. Furthermore, first-time inspection period and repeated inspection period models of condition-based maintenance analysis are set up, on the basis of maintenance cost and availability strategy, the calculation methods of optimal inspection periods are given. This research provides a reference for prediction of reliable life and inspection strategy establishing for condition-based maintenance of mechanical-electrical special equipment which lack failure data of factory and laboratory.

**Key words:** Crane, reliability evaluation, RCM, condition-based maintenance, bayes theorem, small sample

### INTRODUCTION

Crane machinery is one of the special equipments with the most dangerous factors, the maximum likelihood of the accidents and the most serious consequences of the failures, crane accidents result in many serious injuries and fatalities each year in china and abroad. Reliability Centered Maintenance (RCM) is an international systematic engineering used to determine the preventive maintenance work and optimize the maintenance system (Moubray, 1997). At present, RCM technology has been widely used in the defense industry, nuclear industry and railway transport industry (Crocker and Kumar, 2000; Chen *et al.*, 2011). Reasonable maintenance period depends on the reliable life of the product. Lacking of failure samples from on-site test, the key technology is the assessment and prediction of reliable life under the small sample conditions for cranes. Bayes reliability estimation takes full advantage of the information during the course of designing and testing and from similar products. Bayes regards this information as the prior information of reliability estimation and gets the results of reliability estimation combining with small samples from field test (Zou and Yao, 2012; Ming *et al.*, 2010; Paokanta *et al.*, 2012). Condition-based maintenance which also called the state detection of a particular failure mode is to determine whether state parameters of product is in the prescribed limit through the maintenance with fixed period and takes some measures to avoid accident.

Condition-based maintenance is a RCM preventive maintenance work (Niu *et al.*, 2010) and widely used in aerospace industry, electricity industry and military industry (Liu *et al.*, 2006; Lin *et al.*, 2004). Currently, on how to determine the detection interval, the majority of engineering and technical personnel take half of the product MTBF as the testing cycle based on their experience. Fixed detection cycle, however, do not conform to the law of life of the product, which will inevitably results in over-detection or causes accidents due to the lag detection and is contrary to the original intention of the condition maintenance. It is meaningful and has engineering needs to predict the reliability life changing and optimize the inspection cycle.

### CONDITION-BASED MAINTENANCE

The task of condition-based maintenance is to detect potential failure so that accident will be avoided. Measurable potential failure like wear amount of crane's brake pad and deflection values of girder needs to determine the critical value of equipment changing  $x_p$  (potential failure condition) and the limit value of equipment changing  $x_f$  (function failure condition), which is shown in Fig. 1. If mechanical product has measurable degradation processes and  $x_f$  can be obtained from the design process, one of the modeling tasks for this kind of problem is: How to determine optimal the first inspection interval  $T_1$  and duplicate inspection interval  $T$  based on

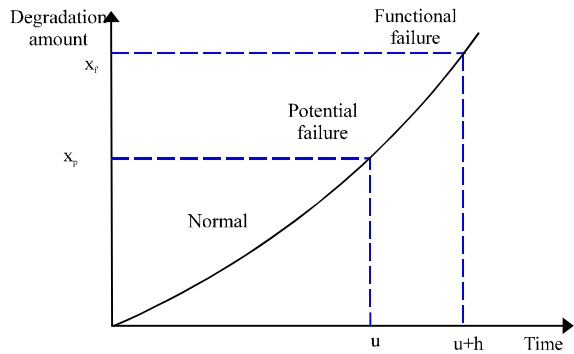


Fig. 1: Condition-based maintenance

product performance degradation and then protect the economy and the availability of machinery products combined with the specific maintenance means according to inspection results.

**Real-time reliability assessment and prediction model**

**Distribution type and distribution parameter estimation of potential failure:** Combined with experimental data and experts' experience, they are estimated to meet the normal distribution at the same time. According to Bayes method, the unknown parameters in the normal distribution are estimated, the reliability of each moment is calculated and finally the real-time reliability assessment and prediction model of the crane's girder is established. Suppose that there are totally m samples in the history test, at a given time t<sub>j</sub> (j = 1, 2, ..., M), the measured degradation data is x<sub>ij</sub> (1 ≤ i ≤ m, 1 ≤ j ≤ M). Where x<sub>ij</sub> is the product performance data of the I-th product obtained at the t<sub>j</sub> moment. Under the actual operating conditions, the degradation of data of the girder detected at a given moment is y<sub>j</sub> (j = 1, 2, ..., n).

**Determine the distribution of performance parameters to meet:** Assume one of the failure modes of crane's girder is degradation failure and regard degradation amount as the performance parameters of girder. At any time t<sub>j</sub>, the degradation amount of girder follows a normal distribution, ie., y<sub>j</sub> ~ N(μ<sub>j</sub>, σ<sub>j</sub><sup>2</sup>).

**Determine the prior distribution of the unknown parameters:** Based on Bayes, according to the prior information x<sub>ij</sub> at t<sub>j</sub> moment, the prior probability density function of μ<sub>j</sub> is estimated as: π(μ<sub>j</sub>) ~ N(a, b), in which the prior distribution parameters are as follows:

$$a = \frac{1}{m} \sum_{i=1}^m x_{ij}, b = \frac{1}{m} \sigma_j^2 \tag{1}$$

Take D<sub>j</sub> = σ<sub>j</sub><sup>2</sup>, so the prior probability density function for D<sub>j</sub> is the inverse Gamma function, ie., π(D<sub>j</sub>) ~ g(D<sub>j</sub>|α, β). Using the moment matching method, Eq. 2 can get the prior distribution parameter values α, β:

$$\begin{cases} \frac{\alpha}{\beta - 1} = \mu_{D_j} \\ \frac{\alpha^2}{(\beta - 1)^2(\beta - 2)} = \sigma_{D_j}^2 \end{cases} \tag{2}$$

The conjugate method is used to determine the joint prior distribution of (μ<sub>j</sub>, D<sub>j</sub>), which is normal-Inverse Gamma distribution, i.e., the prior distribution density function is:

$$\pi(\mu_j, D_j) = \frac{1}{\sqrt{2\pi b}} e^{-\frac{(\mu_j - a)^2}{2b}} \frac{\alpha^\beta}{\Gamma(\beta)} D_j^{-(\beta+1)} e^{-\alpha/D_j} \tag{3}$$

**Determine the posterior distribution of the unknown parameters:** By detecting, the degradation amount of crane's girder in the actual conditions is Y = (y<sub>1</sub>, y<sub>2</sub>, ..., y<sub>n</sub>) at the given time t<sub>j</sub>. Based on the Bayes, the posterior distribution is:

$$\pi(\mu_j, D_j | Y) = \frac{\pi(\mu_j, D_j) f(Y | \mu_j, D_j)}{\int_0^\infty \int_{-\infty}^\infty \pi(\mu_j, D_j) f(Y | \mu_j, D_j) d\mu_j dD_j} \tag{4}$$

Because:

$$f(Y | \mu_j, D_j) = \prod_{i=1}^n f(y_i | \mu_j, D_j)$$

and:

$$f(x | \mu_j, D_j) = \frac{1}{\sqrt{2\pi D_j}} \exp\left[-\frac{(x - \mu_j)^2}{2D_j}\right]$$

by numerical integration, the posterior distribution of degradation amount of the girder can be got:

$$\pi(\mu_j, D_j | Y) = \frac{D_j^{-\frac{1}{2}} e^{-\frac{1}{2D_j(m+n)}(\mu_j - c)^2} D_j^{-(d+1)} e^{-r/D_j}}{\sqrt{2\pi/(m+n)} \Gamma(d)/r^d} \tag{5}$$

where:

$$r = \alpha - \frac{1}{2(m+n)} \left( am + \sum_{i=1}^n x_i \right)^2 + \frac{1}{2} \left( ma^2 + \sum_{i=1}^n x_i^2 \right)$$

$$c = \frac{(am + \sum_{i=1}^n x_i)}{(m+n)}$$

Due to the posterior distribution of  $(\mu_j, D_j)$  is normal-inverse Gamma distribution, the prior distribution and posterior distribution is conjugate, so the posterior marginal density function of  $\mu_j, D_j$  can be calculated as:

$$\pi(\mu_j | Y) = \int_0^{+\infty} \pi(\mu_j, D_j | Y) dD_j$$

$$= \frac{\Gamma(d + 0.5) \cdot r^d}{\sqrt{2\pi} \cdot (m + n) \Gamma(d)} \left[ \frac{m + n}{2} (\mu_j - c)^2 + r \right]^{-(d+0.5)} \quad (6)$$

$$\pi(D_j | Y) = \int_{-\infty}^{+\infty} \pi(\mu_j, D_j | Y) d\mu_j = \frac{1}{\Gamma(d)/r^d} D_j^{-(d+1)} e^{-\gamma/D_j} \quad (7)$$

$$\begin{cases} \hat{\mu}_j = E(\pi(\mu_j | Y)) = \int_{-\infty}^{+\infty} \mu_j \pi(\mu_j | Y) d\mu_j \\ \hat{D}_j = E(\pi(D_j | Y)) = \int_0^{+\infty} D_j \pi(D_j | Y) dD_j \end{cases} \quad (8)$$

Using the expected values as estimated values of the parameters, the point estimated value of  $\mu_j$  and  $D_j$  is shown in expression (8).

Take  $p = \hat{\mu}_j, q^2 = \hat{D}_j$  so performance parameters can meet  $y_j \sim N(p, q^2)$ , using the limit failure value 1 of the performance parameters, the reliability  $R_j(j = 1, 2, \dots, n)$  of product at time  $t_j$  can be obtained:

$$R_j = P(x(t_j) \leq 1) = \Phi \left[ \frac{(1-p)}{q} \right] \quad (9)$$

where,  $x(t_j)$  is predictive value of performance parameters at  $t_j$  time. At this time, reliability  $R_j$  fusions prior information and on-site information of the product and comprehensively reflects the reliability characteristics of the current product.

**Reliability assessment of products from putting into use to the occurrence of potential failure:** Weibull distribution is one of the most common life distributions. Take the two-parameter Weibull distribution as the failure distribution of a device from putting into use to the occurrence of potential failure, its reliability function is:

$$R(t) = \exp \left[ - \left( \frac{t}{\alpha} \right)^\beta \right] \quad (10)$$

Estimate the life of product based on the previous data  $(t_j, R_j)$  ( $j = 1, 2, \dots, n$ ), change the reliable function of product into linear form of unknown parameters:

$$\ln[-\ln(R(t))] = \beta \ln t - \beta \ln \alpha \quad (11)$$

Take  $y = \ln[-\ln(R(t))], x = \ln t, b = -\beta \ln \alpha$ , calculate the value of  $a, b$  and  $\beta$  and finally get the life reliable function of product.

**Reliability assessment of products from potential failure to functional failure:** It is impossible to get the data of time from potential failure to functional failure for cranes during the course of designing and testing. It's generally considered that failure delay time is meet the Weibull distribution and distribution parameter is hard to find. Non information prior distribution is usually used according to Bayes theorem and shape parameter is considered as  $\beta \in [\beta_1, \beta_2]$ . The union non information prior density function of Weibull distribution is:

$$\pi(\alpha, \beta) \propto \frac{1}{\alpha \beta} \quad (12)$$

Under the situation of censored,  $n$  products is expecting to have reliability life tests until  $r$  products failure. The failure time data of products is  $X = \{x_1, x_2, \dots, x_n\}$  and the union density function is:

$$\begin{aligned} f(X | \alpha, \beta) &= \prod_{i=1}^r \left[ \frac{\beta}{\alpha^\beta} x_i^{\beta-1} \exp \left[ - \left( \frac{x_i}{\alpha} \right)^\beta \right] \right] \\ &= \frac{\beta^r}{\alpha^{\beta r}} u^{\beta-1} \exp \left[ - \left( \frac{t}{\alpha} \right)^\beta \right] \end{aligned} \quad (13)$$

where:

$$u = \prod_{i=1}^r x_i, t^\beta = \sum_{i=1}^r x_i^\beta$$

According to Bayes theorem, the union posterior distribution of  $\alpha, \beta$  is:

$$\pi(\alpha, \beta | X) = \frac{f(X | \alpha, \beta) \pi(\alpha, \beta)}{\iint_{\alpha} f(X | \alpha, \beta) \pi(\alpha, \beta) d\alpha d\beta} \quad (14)$$

The union posterior density function is:

$$\pi(\alpha, \beta | D) \propto \beta^{r-1} \alpha^{-\beta r-1} u^{\beta-1} \exp \left[ - \left( \frac{t}{\alpha} \right)^\beta \right] \quad (15)$$

The posterior density function of scale parameter  $\alpha$  is:

$$\pi(\alpha | D) = \frac{\int_{\beta_1}^{\beta_2} \beta^{r-1} \alpha^{-\beta r-1} u^{\beta-1} \exp \left[ - \left( \frac{t}{\alpha} \right)^\beta \right] d\beta}{\Gamma(r) \int_{\beta_1}^{\beta_2} \beta^{r-2} u^{\beta-1} t^{-\beta} d\beta} \quad (16)$$

The estimate value of scale parameter  $\alpha$  is:

$$\hat{\alpha} = E(\alpha | D) = \int_0^{+\infty} \alpha \pi(\alpha | D) d\alpha \quad (17)$$

The posterior density function of scale parameter  $\beta$  is:

$$\pi(\beta|D) = \frac{\beta^{r-2} u^{\beta-1} t^{-\beta}}{\int_{\beta_1}^{\beta_2} \beta^{r-2} u^{\beta-1} t^{-\beta} d\beta} \quad (18)$$

The estimate value of scale parameter  $\beta$  is:

$$\hat{\beta} = E(\beta|D) = \int_{\beta_1}^{\beta_2} \beta \pi(\beta|D) d\beta \quad (19)$$

**INSPECTION CYCLE CALCULATION MODEL FOR CONDITION-BASED MAINTENANCE**

**First-time inspection cycle model for condition-based maintenance:** First-time inspection means the first time equipment detection planned in accordance with a predetermined first inspection interval cycle from the beginning of operating. The failure of the equipment should be immediately repaired in this process and the time consumed in the maintenance process belongs to the maintenance intervals, which is shown in Fig. 2.

The principle to determine the best first-time inspection interval is to minimum expected maintenance costs per unit time and maximum equipment availability in the inspection period. Cost (economic) model of the equipment is as follows in equation:

$$C(T) = \frac{\text{Expectations of the maintenance costs in the initial inspection interval}}{\text{Expectations of the initial inspection interval}} = \frac{(T_1 + T_r)L + C_1 + C_f}{T} = \frac{\left(T_p \int_0^T \lambda(t) dt + T_r\right)L + C_p \int_0^T \lambda(t) dt + C_f}{T} \quad (20)$$

where, Maintenance costs include the failure repairing costs, detecting costs, production losses during the course of detecting and replacing;  $C_f$  is the cost for the first-time inspection;  $T_f$  is the interval of first-time inspection;  $L$  is the loss of production per unit time; repairing time after the equipment failure is:

$$T_1 = T_p \int_0^T \lambda(t) dt,$$

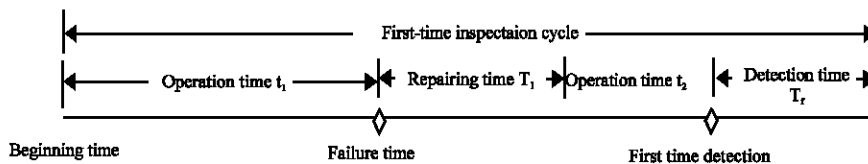


Fig. 2: First detection interval plans for condition-based maintenance

$\lambda(t)$  is the failure rate function from the beginning to the development of potential failure,  $T_p$  is repairing time for each failure; maintenance costs after the failure is:

$$C_1 = C_p \int_0^T \lambda(t) dt$$

where,  $C_p$  is maintenance costs for each failure. Availability model of equipment is:

$$A(T) = \frac{\text{Expected value of the equipment working Time in the initial inspection interval}}{\text{Expectations of the initial inspection interval}} = \frac{T - (T_1 + T_r)}{T} = \frac{T - \left(T_p \int_0^T \lambda(t) dt + T_r\right)}{T} \quad (21)$$

Expectation of the operating time during the course of first-time inspection cycle refers to an inspection period of the equipment removing the maintenance time and inspection time.

**REPEATED INSPECTION CYCLE MODEL FOR CONDITION-BASED MAINTENANCE**

The repeated inspection of delay time mode is implemented according to predetermined time  $kT$ , which is showed in Fig. 3. Maintenance costs  $C(T)$  per unit time and availability  $A(T)$  during the maintenance cycle are calculated according basic renewal theory in the repeated inspection modal.

$$C(T) = \frac{\text{The expected value of total costs per unit cycle}}{\text{Inspection cycle length}} = \frac{EC(T) + C_f}{T + T_r} \quad (22)$$

$$A(T) = \frac{\text{Expected value of available per unit cycle}}{\text{Inspection cycle length}} = \frac{T - D(T)}{T + T_r} \quad (23)$$

Where, the total costs of inspection cycle include the expected value  $EC(T)$  of maintenance costs after the failure for each cycle and the costs  $C_f$  of an inspection.  $A$

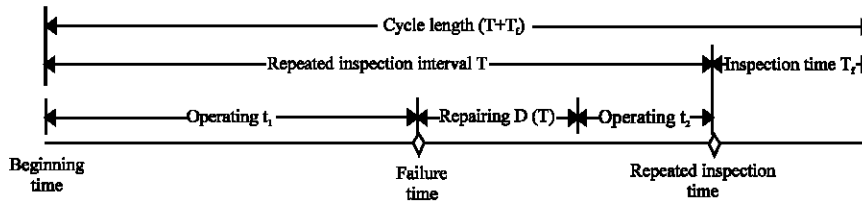


Fig. 3: Repeated inspection for condition-based maintenance

cycle length includes inspection cycle  $T$  and an inspection time  $T_f$ . The expected value of maintenance time after the failure is  $D(T)$ .  $EC(T)$  and  $D(T)$  is calculated by the Eq. 24:

$$\begin{cases} EC(T) = C_p EN_b(T) \\ D(T) = T_p EN_b(T) \end{cases} \quad (24)$$

where,  $C_p$  is the total costs of every failure including maintenance costs and productive losses of failure. The maintenance time of every failure is  $T_p$  and the expected time of failure in  $[0, T]$  is  $EN_b(T)$ .  $EN_b(T)$  is a renewal process according to failure distribute function, which is showed in Eq. 25.

$$EN_b(T) = \begin{cases} \int_0^T [1 + EN_b(T - T_f - x)] dF(x) & T > T_f \\ 0 & T \leq T_f \end{cases} \quad (25)$$

The costs and available per unit time in an inspection cycle are calculated according to Eq. 22 and 23. Finally the optimal repeated inspection interval is selected.

**RELIABLE MODAL**

The life of the product meets the failure modes distribution of Weibull and thus can determine the reliability of the products in the detection interval of  $T$  is the lowest. Therefore, from the first-time inspection and the repeated inspection for the condition-based maintenance, a reliability model can be built in the inspection interval of  $T$  is as follows:

$$R(T) = 1 - F(T) = 1 - \int_0^T f(t) dt \quad (26)$$

**An example:** Taking the girder in a certain type of gantry crane from a certain factory for example, the best detection cycle for the first time and the repeated detection cycle ( $T_1, T$ ) are calculated. The main failure model of the girder is excessive down deflection, of which the degradation amount is determined by the value of mid-span deformation of the girder. The span of the girder is  $S = 10.5$  m. Supervision and Inspection Regulations for Hoisting Machinery provides that, under rated load, when

the value of mid-span deformation of the girder reaches to  $S/700$  below horizontal line, the girder should be scrapped if it's not repairable. Therefore, the degradation amount  $l = 15.0$  mm is regarded as the failure threshold of function fault point and the degradation amount  $l = 9.5$  mm as the failure threshold of potential fault point.

**Determination of the first-time inspection interval  $T_1$ :**

- Calculating the distribution form of the girder's developing to potential failure. As shown in Table1, degradation quantity of 2 products in design phase are tested and recorded in columns  $V_1$  and  $V_2$  and degradation quantity of 8 sets of the same type and similar products are inspected and recorded in columns  $V_3$ - $V_{10}$ . Taking small sample physical tests on 2 cranes, under actual working conditions, field data are measured and shown in last two columns

According to traditional reliability analysis method, reliability of the main beam at time  $t_j$  is calculated, using the historical experimental data and field data separately and shown in Table 2; combining the historical data with field data, the values of point-estimating for parameters  $\mu_j$  and  $D_j$  at the moment of  $t_j$ , is also shown in Table 2, using Eq. 8 on the basis of Bayes method; the reliability of the main beam at moment  $t_j$  computed by Eq. 9 is shown in Table 2; values of parameters  $\alpha$  and  $\beta$  in life reliability model, which is estimated by eq. 1, is shown in Table 3. Curves are drawn in Fig. 4 based on historical test data, actual operating data and actual-historical test data. As the unknown parameters  $\alpha$  and  $\beta$  in Weibull distribution are calculated, the distribution function of the time that girders develop from starting work to potential failure can be computed. Furthermore, the corresponding cumulative distribution function, reliability distribution function and failure rate distribution function will also be found out.

- Calculation of the first-time inspection interval. The failure time of the crane's main beam developing to potential failure meets Weibull distribution, with shape parameter  $\beta = 9.29$ , scale parameter  $\alpha = 225.6219$ , under the condition that

Table 1: Actual data and historical data of the main beam degradation amount

Time (day)	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	Actual data	
15	5.51	6.83	6.47	6.04	6.78	6.06	6.69	6.88	6.87	6.15	6.69	7.24
45	6.12	7.41	7.07	6.45	7.19	6.88	7.10	7.49	7.47	6.46	7.26	7.63
75	6.46	7.94	7.28	6.95	7.88	7.26	7.78	7.99	7.89	7.27	7.68	8.15
105	7.04	8.22	7.87	7.66	8.27	7.57	8.29	8.47	8.27	7.56	8.18	8.53
135	7.43	8.89	8.56	7.95	8.68	7.96	8.67	8.76	8.68	8.08	8.77	8.94
165	8.07	9.17	8.77	8.37	9.16	8.39	9.09	9.25	9.12	8.46	9.08	9.40
195	8.68	9.74	9.45	8.95	9.78	9.06	9.79	9.79	9.86	9.19	9.69	10.25

Table 2: Reliability estimates for the main beam under different circumstances

Time (day)	$t_1 = 15$	$t_2 = 45$	$t_3 = 75$	$t_4 = 105$	$t_5 = 135$	$t_6 = 165$	$t_7 = 195$
Reliability estimation of historical data	0.99	0.99	0.99	0.99	0.99	0.95	0.57
Reliability estimation of actual data	1	1	1	1	1	1	0
Parameter estimation of the mean	6.53	7.05	7.55	8.03	8.47	8.87	9.53
Parameter estimation of the variance	0.30	0.31	0.28	0.24	0.30	0.24	0.28
Reliability estimation of actual-historical data	0.99	0.99	0.99	0.99	0.97	0.90	0.48

Table 3: Distribution parameters under different data

Parameter estimation	$\beta$	$\alpha$
Estimation of historical data	6.61	246.61
Estimation of Bayes method	9.29	225.92

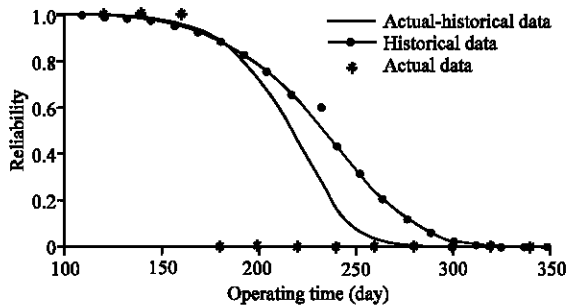


Fig. 4: Failure distribution curve under different circumstances

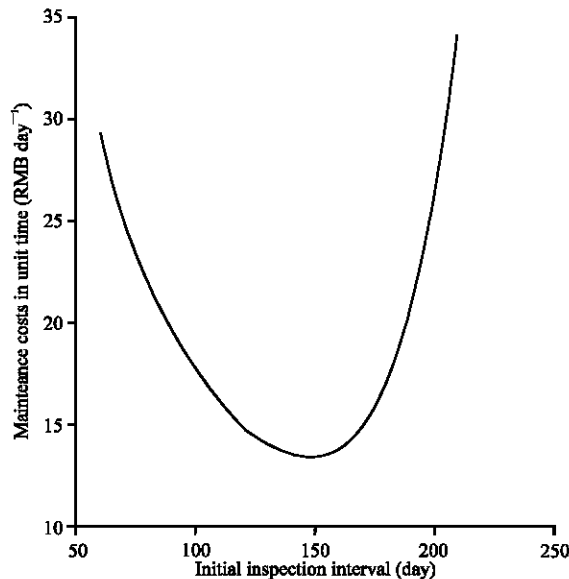


Fig. 5: Maintenance costs in unit time changing with the inspection interval curve

failure changing time  $T_p = 5$  days, detection time  $T_r = 0.5$  day, detection cost each time  $C_r = 1000$  yuan, maintenance cost each time  $C_p = 3000$  yuan, a daily production loss due to the failure or detection  $C_d = 1500$  yuan. The best detection intervals for the first time which meet the 97% reliability of the main beam is calculated and the curve of the maintenance cost in unit time for the main beam changing with the first-time inspection interval is shown in Fig. 5; meanwhile the curve that the availability of the main beam changing with the first-time inspection interval is also made and shown in Fig. 6. We can learn from Fig. 5 and 6 that, the best first-time inspection time, based on the principle of economy, should be  $T_1 = 145$  days, while on the principle of availability, should be  $T_2 = 138$  days. Considering the impact of the economic criteria  $u_1$  and availability criteria  $u_2$  on the maintenance cycle, based on fuzzy mathematics and combined with engineering experience and experts suggestions, these two factors' weight are determined to be 0.5556 and 0.4444. So, the best first-time detection interval can be computed as  $T_1 = 0.5556 \times 145 + 0.4444 \times 138 = 142$  days. Finally, the reliability under the case that the maintenance interval is kept as 142 days for the main beam, is calculated using Eq. 26 to be  $R(T) = 98.76\%$ , which meet the requirement of a 97% reliability.

**Determination of the repeated inspection interval T:**

- Calculating distribution form of the main beam's delay time. The maintenance record of the main beam in this type of cranes show that, there are 9 time data that products develop from potential failure to function failure, which are 96.5, 121, 126, 113.5, 118, 121, 104.5, 114 (days). The main beam's delay time meets the two-parameter Weibull distribution, of which shape parameter is estimated to be  $\beta \in [3, 12]$  according to expert's experience. Based on Eq. 15, the union posterior density function of  $\alpha, \beta$  is:

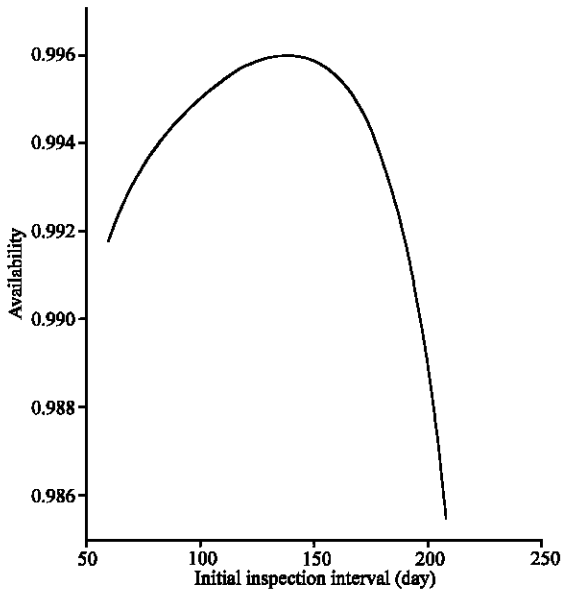


Fig. 6: Availability

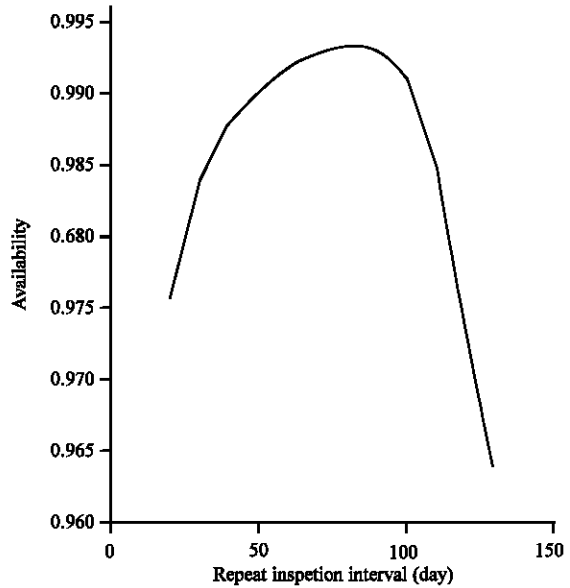


Fig. 8: Availability

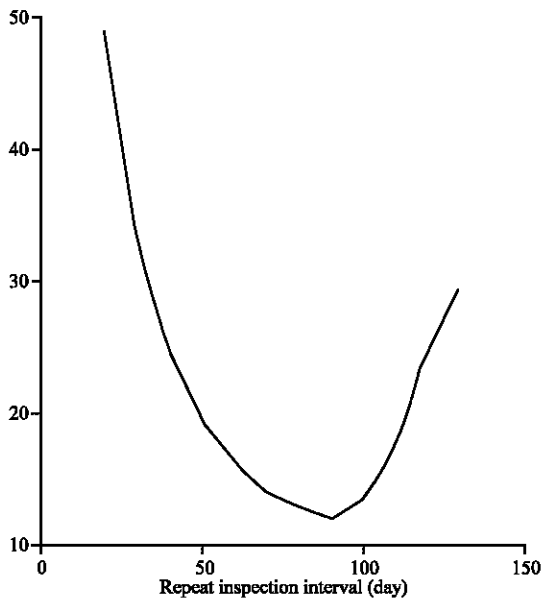


Fig. 7: Maintenance costs in unit time changing with the inspection interval curve

$$\pi(\alpha, \beta | D) \propto \beta^8 \alpha^{-8\beta-1} \beta^{-1} \exp\left[-\left(\frac{t}{\alpha}\right)^\beta\right]$$

in which:

$$u = \prod_{i=1}^r x_i = 2.4548 \times 10^8$$

$$t^\beta = \sum_{i=1}^r x_i^\beta + (n-r)x_r^\beta = \sum_{i=1}^9 x_i^\beta$$

Furthermore, scale parameter  $\alpha$  can be computed as:  $\beta = 120.6586$ , using Eq. 16 and 17; shape parameter  $\beta$  can be computed as  $\beta$ . At last, the distribution function of the time that this girder develop from potential failure to function failure can be computed, thus the corresponding cumulative distribution function, reliability distribution function and failure rate distribution function will also be found out

- Calculating the repeated inspection interval. The time that the crane's main beam developing from potential failure to function failure meets Weibull distribution, with the shape parameter  $\beta = 11.6875$ , scale parameter  $\alpha = 120.6586$ , under the condition that failure changing time  $T_p = 5$  days, detection time  $T_f = 0.5$  day, detection cost each time  $C_f = 1000$  yuan, maintenance cost each time  $C_p = 3000$  yuan, a daily production loss due to the failure or detection  $C_d = 1500$  yuan. The best repeat detection intervals that meet a 97% reliability requirement for the main beam is calculated. The curve of the maintenance cost in unit time for the main beam changing with the inspection intervals is shown in Fig. 7; meanwhile the curve that the availability of the main beam changing with the inspection intervals is shown in Fig. 8

We can learn from Fig. 7 and 8 that, the best repeat inspection time, based on the principle of economy, should be  $T = 92$  days, while on the principle of availability, should be  $T = 85$  days. Using the same method, the best repeated detection interval can be computed as  $T = 0.5556 \times 92 + 0.4444 \times 85 = 89$  days. Finally,



the reliability under the case that the maintenance interval is kept as 89 days for the main beam, is calculated using Eq. 26 to be  $R(T) = 97.19\%$ , which meet the requirement of a 97% reliability. Traditional condition-based maintenance method takes half of the delay time's MTBF as average maintenance cycle. It can be computed from the density function of the delay time as:  $MTBF = \alpha\Gamma(1+1/\beta) = 115.5105$  (d) According to traditional method, inspection intervals time should be  $T = 0.5MTBF = 57.7552$  (d) Using Eq. 22-25, taking the inspection intervals time computed before, the maintenance cost in unit time is 17.8793 yuan for the main beam and the availability is 0.9910. It can be learned from Fig. 7 and that, when  $T = 89$  days, the maintenance cost is 12.2320 yuan and the availability is 0.9932. When meeting the requirement of reliability, using the method put forward in this essay, the maintenance cost is reduced by 31.59% and the availability of the main beam is increased by 0.22%.

#### CONCLUSION

- The failure time of the main beam in a certain type of crane developing from starting work to potential failure with a degradation amount  $l = 9.5$  mm meets a Weibull distribution with its shape parameter  $\beta = 9.29$ , scale parameter  $\alpha = 225.6219$ . The failure time of the main beam developing from potential failure to functional failure with a degradation amount  $l = 15.0$  mm, meets a Weibull distribution with its  $\beta = 11.6875$ , scale parameter  $\alpha = 120.6586$ . The reliability evaluation method with small sample base on Bayes theory have practical engineering significance
- Considering the main beam in a certain type of crane, the best first-time inspection interval time is 142 days and the repeat inspection interval time is 89 days. The example shows that, since performance degradation of a product is considered, with meeting the requirement of reliability and maintaining the device's availability, using the non-periodic maintenance detection strategy of first-time inspection and repeat inspection, the maintenance cost in unit time is reduced by 31.59%, compared with traditional periodic maintenance.

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