FAILURE PREVENTION BASED ON PARAMETERS ESTIMATION AND PREDICTION

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Abstract: A problem of the state prediction and condition-based maintenance of complex engineering systems is considered. An approach to solving this problem is based on the construction of the special minimax and robust algorithms, which can be used in the case when inspection data are incomplete and insufficient. The method for individual robust prediction based on the extremal properties of Karlin polynomials and the ideas of minimax estimation is proposed.

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1.INTRODUCTION

For complex engineering systems under heavy-duty service the failure of which leads to heavy losses or disastrous consequences the main problem of system monitoring and diagnostics becomes not the identification and isolation of failure, but prevention of them. The solution of this task can be based on individual maintenance. Predicting and estimating the state of an engineering system forms an information base for individual (condition-based) maintenance.
The difficulty in solving the problem of individual status prediction is largely caused by the lack or shortage of statistic information on field variation of system parameters. In this case the application of classical methods of mathematical statistics to the solution of status estimation and prediction problem may cause serious errors.

The paper states and solves a problem of adopting optimal estimation and prediction strategies when the stochastic properties of measurement errors and errors of status model are unavailable. We use a technique of individual robust prediction which is based on the extremely properties of Karlin polynomials (Karlin and Studden, 1966) and the ideas of minimax estimation. This technique makes a prediction even if the number of test measurements is small. It does not need any stochastic properties of measurement errors and other noises (it is only necessary to know their limits), obtains not only a simple average, but also secures bounds in which an actual value of measurement parameter would lie in future. This technique has adaptive properties improving the prediction accuracy in an instable situation.

2. PREDICTION TECHNIQUE

Let the availability of an engineering system be determined by the value of a certain performance parameter $x(t)$, with the availability condition given in the form

$$A(t) \le \quad x(t) \ \ge B(t)$$

where $A(t)$ and $B(t)$ are lower and upper bounds on the variable parameter, respectively. A parameter variation is considered to be a realization of the random function of the following form

$$X(t) = \sum_{k=0}^{m} x_k\, u_k(t) \tag{1}$$

where x_k is a random variable, $\{u_k(t)\}_{k=0}^{m}$ are deterministic functions of time.

The engineering system serves at the time interval $[0, T]$ during which the parameter may be inspected or adjusted. Measurement errors (as well as errors of process identification, mistakes caused by fluctuation, etc.) are regarded as noise $\Psi(t)$ added to a particular realization of the stochastic process (1). We only know about the noise that

$$\left|\Psi(t)\right| \le \delta, \qquad t \in [0,T], \tag{2}$$

where δ is the extreme error.

The problem consists in specifying such instants of inspection that the parameter x, for certain, lies in the allowed bounds $A(t)$ and $B(t)$ for a time period T. Suppose that we would obtain a section of process realization $\theta(t)$ on the interval $[t_0, t_\mu]$. Then

$$\theta(t) - \delta \le \quad x(t) \ \le \theta(t) + \delta, \qquad t \in [t_0, t_\mu].$$

The actual realization $x(t)$ on interval $[t_0,t_\mu]$ is enclosed in a "tube", bounded by the functions $f(t)=\theta(t)-\delta$ and $g(t)=\theta(t)+\delta$ (Fig.1). In the tube there are many realizations in the form $\sum x_k u_k(t)$ which are referred to as tolerable. In predicting the behavior of the process for $t>t_\mu$ we take the "worst" realizations, i.e. the realizations that at $t \in (t_\mu, T]$ go above or below the rest. We have proved that on imposing certain restrictions on the set of functions $\{u_k(t)\}_{k=0}^{m}$, Karlin polynomials $L^-(t)$ and $L^+(t)$ are the worst realizations (Abramov and Rozenbaum,1990).

The following theorems establish for continuous function (realization of the random process) the existence of two special polynomials processing certain extremal properties.

Theorem 1. Let $\{u_k(t)\}_0^m$ be a Tchebycheff system (T-system) and f and g two continuous functions on $[a, b]$ such that there exists a polynomial $\nu(t)$ being between f and g i. e., $f(t) < \nu(t) < g(t)$, $t \in [a,b]$.

a) There exists a unique polynomial $L^-(t)$ satisfying the properties:

$(i)\ \ f(t) \le L^-(t) \le g(t),\ \ t \in [a,b],$

and

(ii) there exist m+1 points $(a \le) t_1 < t_2 ... < t_{m+1} (\le b)$ such that

$$(*)\ \ L^-(t_{m+1-i}) = \begin{cases} g(t_{m+1-i}), & i = 0,2,4,... \\ f(t_{m+1-i}), & i = 1,3,5,.... \end{cases}$$

b) Let condition (ii) be replaced by $(ii)'$ from (*) by interchanging the functions f and g. Then there exists a unique polynomial $L^+(t)$ satisfying (i) and $(ii)'$.

Theorem 2. Let $\{u_k(t)\}_{k=0}^m$ be a T-system on $[M,N]$ and in accordance with Theorem 1 for continuos functions *f(t), g(t)* we constructed two polynomials $L^+(t), L^-(t)$ on [*a*, *b*], where *M*<*a*<*b*<*N*. Then for an arbitrary polynomial *u(t)* satisfies conditions

$$f(t) \le u(t) \le g(t),$$

we have

$$\min\{L^-(t), L^+(t)\} < u(t) < \max\{L^-(t), L^+(t)\},\ \forall t \in [M,a) \cup (b,N].$$

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The curves of $L^-(t)$ and $L^+(t)$ define so called *"prediction cone"* (Fig. 1) in the sense that the actual realization of the process under study is for certain within the cone at $t \in (t_\mu, T]$.

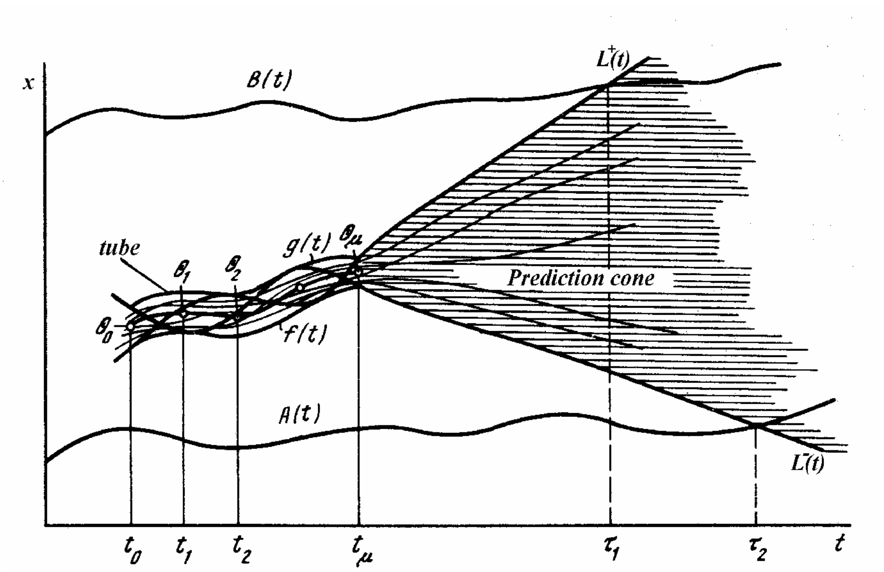

Fig.1. Tube of admissible realizations and prediction cone

We have synthesized algorithms for finding extreme realizations and investigated their properties.
Usually, we have the discrete measurement results of system state parameters. In the case of discrete inspection measurements form a sequence $\{\theta_j\}^{\mu}_{j=0}$, at $t_0 < t_1 < \ldots < t_j \ldots < t_\mu$. Measurement errors satisfy conditions $|\Psi j| \leq \delta$.

Then the actual realization $x(t)$ at $t=t_j$ is enclosed in the "*windows*" $[\theta_j - \delta, \theta_j + \delta]$,. $j=1,\ldots,\mu$.. The set of realizations which belong at $t_0, t_1,\ \ ,t_\mu$ to all windows is the set of admissible (tolerable) realizations.

It is not difficult to shown that in the case of discrete inspections the solution for $L^-(t)$ and $L^+(t)$ is reduced to the solution of the two problems of linear programming

1. $\max\limits_{x_k} \sum\limits_{k=0}^{N} x_k u_k(t^*)$
2. $\min\limits_{x_k} \sum\limits_{k=0}^{N} x_k u_k(t^*), \quad t^* > t_\mu$

subject to $\theta_j - \delta \leq \sum\limits_{k=0}^{N} x_k u_k(t^*) \leq \theta_j + \delta$, $j=0,1,\ldots,m$,

where t^* - arbitrary selected time from $(t_{\mu,}, T]$.

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3. MAIN PROPERTIES AND APPLICATION

The approach under discussion meets general requirements to any prediction procedure. Estimates found are unique, optimal and unbiased. In addition to measurement errors, the approach allows one to take into account some other mistakes caused by the difference of real processes of parameter variation from a mathematical model adopted. Models of the form (1) sufficiently well describe processes of "irreversible" parameter variation during system aging or wear. Reversible changes caused by fluctuation in supply voltage, loads, ambient temperature, etc. are usually regarded as certain high-frequency noise imposed on the basic trend of parameter variation. The stochastic properties of the noise are usually unknown. A more real situation is that we know restrictions on the values of reversible fluctuations. This corresponds to the application of additional restrictions in the form (2) and, consequently, the reversible fluctuations do not influence, in principle, to the procedure of building a prediction cone. But if the basic model contains an error, then a special-purpose adaptation algorithm is proposed to improve prediction accuracy. The algorithm is based on the ideas used in the technique of moving average or exponential smoothing and consists in weighing measurement data.

By using prediction data we can, in optimal way, solve the problem of specifying the time of next inspection or preventive maintenance.

Crossing the bounds $A(t)$ and $B(t)$ of tolerance range by the extreme realizations $L^-(t)$ and $L^+(t)$ determines two values the minimum of which should advantageously be taken as the time of the next $\mu+1$-*th* inspection

$$t_{\mu+1} = min\,(\tau_1, \tau_2)$$

where τ_1 and τ_2 are solutions o f the equations $L^-(t)=B(t)$ and $L^+(t)=A(t)$, respectively. Evidently, the inspected parameter will, for certain, lie in the tolerance range for the time interval $t_c = t_{\mu+1} - t_\mu$. The $\mu+1$-*th* measurement is used to find the next time interval during which the parameter does not leave the tolerance range. If the time interval (we call it the interval of dependable service) appears to be less than a certain minimum interval $t_c^{\min}$:

$$(t_{\mu+2} - t_{\mu+1}) < t_c^{\min}$$

then we must carry out preventive adjustment of the parameter $x(t)$.

We can easily extend the proposed approach on the case where the working state of an engineering system is described by several parameters.

If a set to which possible measurement errors belong is determined with a certain probability (say, the inequality (2) is fulfilled with probability *Pr*), then the approach allows one to find margins in which a parameter will lie the in future with probability no less than *Pr*.

The approach has been implemented as a program module PROGNOSIS which runs on PC under the MS Widows operating system. Windows application PROGNOSIS is intended to predict the state of observable complex engineering systems and to schedule their condition-based maintenance. The software is most advantageous to be used within computer aided control (measuring) systems of heavy-duty objects, e.g. ship and aircraft engines, power stations. Besides that PROGNOSIS system may also be applied for operational-life accelerated tests of high-reliable equipment.

The techniques applied are oriented onto conditions of initial data shortage and require neither knowing stochastic properties of measurement errors and disturbances nor large amount of the observation results.

An efficiency of the software implementation is proved by failure prevention along with reducing repair and maintenance expenses.

4.CONCLUSION

Condition-based maintenance of engineering systems considerably improves their functionality. Preventing both failure and unnecessary maintaining operations, such a strategy is the most favorable one heavy –duty systems. Scheduling the condition-based maintenance is based on systems state estimation and prediction.

The method for individual secure(robust) prediction based on the extremal properties of Karlin polynomials and the ideas of minimax estimation is proposed.

This technique makes a prediction even if the number of test measurements is small. It does not need any stochastic properties of measurement errors and other noises (it is only necessary to know their limits), obtains not only a simple average, but also secures bounds in which an actual value of

measurement parameter would lie in future. This technique has adaptive properties improving the prediction accuracy in an unstable situation.
It is advantageous to apply the technique to the design of servicing schedules for high-duty complex engineering systems which failure may cause heavy manufacturing losses or grave consequences.

REFERENCES

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