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Engineering Systems Maintenance by Optimal Decision Making Strategies under Uncertainty Conditions

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***Abstract**: This article summarizes the optimal strategies approaches for decision making under uncertainty conditions in case of engineering systems maintenance. The characteristics of uncertainty information and approaches to decision making based on optimization models are described. A generalized problem for the optimization predictive model for the diagnostic goals of engineering systems is shown.*

***Keywords:** Engineering systems maintenance, decision making, uncertainty, optimal strategies.*

1. Introduction

The machine reliability improving is the major industry focus to gain the maximum machinery working life while minimizing the maintenance and operating costs. Therefore it is necessary to establish maintenance monitoring strategies to predict the engineering system life efficiency. Any engineering system is subject to deterioration over time. This natural process of deterioration of the technological parameters during operation can be accelerated by uncertain factors or can be decelerated by monitoring, diagnostics and the corresponding relevant activities.

For this propose appropriate strategies for decisions making under uncertainty conditions and incomplete information about the system must be developed. The strategies can involve the predictive life assessment system [1]. This could be realized by a proper system for control and management of the investigated object (engineering system). The structure of such a system consists of four main components [2].

Fig. 1. Control and management structure

The goal of the subsystem "Information" is to prepare the database for the objects state data collected by the subsystem "Monitoring". There are different methods that can be employed for machine condition monitoring to support maintenance decisions [3]. "Security" is a subsystem, which determines the degree of access to the collected information. The subsystem "Management" is designed to assist decision making according to a predefined situations set. The monitoring subsystem is one of the most important in the control and management structure because it provides data for diagnosis and decision making. The choice of monitoring strategy depends on the requirements and knowledge about the object (the engineering system). If the knowledge of the object is incomplete, the life cycle forecast using an adaptive model is useless because the model input parameters are more or less unknown. In such cases monitoring can be used to observe the threshold values of certain essential object parameters. To overcome such situations some innovative methods [4, 5] for monitoring and diagnosis, and effective allocation of resources to maintain the deteriorating parameters of the object could be used. That is why the ISO 13381-1: 2004 Standard prescribes to start with monitoring, followed by diagnostic, prediction and posterior actions (Fig. 2) [6].

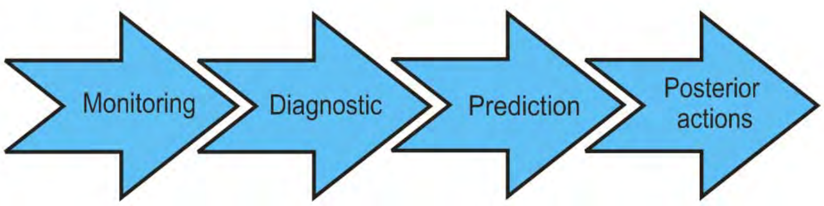

Fig. 2. Stages of ISO 13381-1: 2004 Standard

The object life cycle cost analysis facilitates the cost effective alternative solutions comparison. The condition monitoring has become a recognized tool for assessment of the operational state of industrial equipment. Maintenance decisions, such as when to undertake an action and what type of an action to realize, can be made based on the analysis of condition monitoring information. The ultimate goal is to improve the condition, safety and long-term performance of the system while reducing the lifecycle cost. The predictive maintenance strategies are very efficient in mechanical-failure modes, when the failure probability increases with time, and one or more condition-monitoring techniques can predict the failure before breakage [7]. Predictive maintenance seeks for a much more cost-effective analysis than preventive maintenance. The intersection point between the value of each parameter or feature and its corresponding alarm threshold leads to what is known as remaining useful life of the system (Fig. 3) [8].

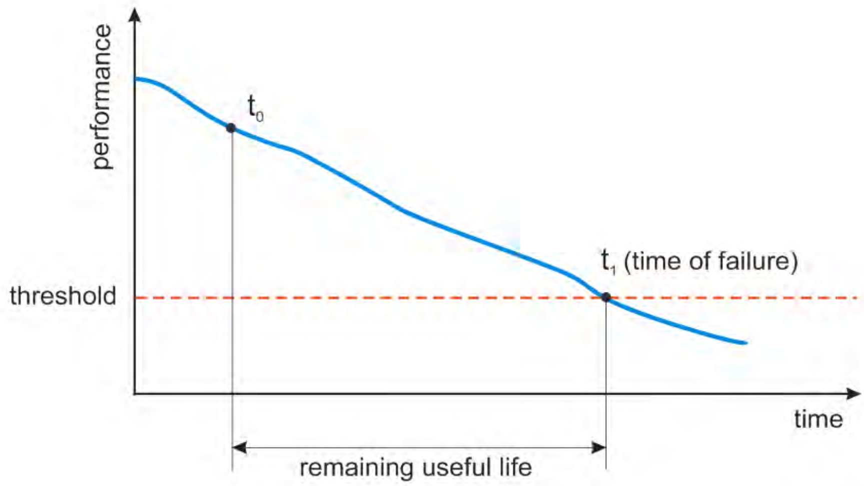

Fig. 3. Estimation of the remaining useful life

Depending on the estimated remaining useful life, appropriate maintenance actions can be taken. These actions may aim at eliminating the origin of a failure which can lead the system to evolve to any critical failure mode, delaying the instant of a failure by some maintenance actions or simply stopping the system if this is considered necessary.

2. Optimal decision making strategies under uncertainty conditions

Forecasting deterioration of the engineering systems characteristics during the time and proper decision making is associated with considerable uncertainty [9]. The decision maker under uncertainty conditions has an idea about the goals to be achieved, but the information about alternatives and future events is incomplete. Usually, there is no sufficient data to assess the risk of each alternative.

When considering the decision making problem under uncertainty conditions some starting prerequisites should be noted:

- in all cases there exists a decision-maker;
- the optimal solution implies the existence of a function *f*, which should be optimized,

$$x_{\text{opt}} = \max f(x),$$

where x is the set of analyzed alternatives, x_{opt} is the optimal solution.

The decision maker's preference is considered as a function called preference utility function $f(x)$ on the set of possible alternative solutions:

$$x = \{x_1, x_2, ..., x_m\}$$

under the environment state $s = \{s_1, s_2, \dots, s_n\}$.

The choice of solution under uncertainty has to be done in the case of environment and object information lack or shortage. Assuming that the decision maker can assess the usefulness E_{ij} of alternatives x_i (i=1, 2, …, m) in some dimensionless units, he can use the known optimization approaches, using the following criteria:

Wald Criterion. In this case, the decision maker selects the strategy associated with the best possible among the worst outcomes regardless of whether the probabilities are available or not. For each alternative solution x_i (i=1, 2,…, m), the worst output $\min E_{ij}$ (j=1, …, n) is defined. Next, an alternative solution is determined for which $\min E_{ij}$ (j=1, …, n) has a maximum magnitude [10, 11]:

$$x_{\text{opt}} \Rightarrow \max \min E_{ij} \, (i = 1, 2, ..., m; \;\; j = 1, 2, ..., n).$$

Savage Criterion. This criterion looking at small loss of efficiency due to missed opportunities is calculated by the formula

$$R_{ij} = \left| E_{ij} - \max E_{ij} \right|.$$

Based on a "regret matrix" which compares (subtracts) the highest outcomes of each strategy from other outcomes [12]. The Wald's solution rule (maximin/minimax) is applied to this new matrix to gain the minimax regret solution. The optimum would be the minimum losses value R_{ij} among all alternatives:

$$x_{\text{opt}} \Rightarrow \min \max R_{ij} \, (i = 1, 2, ..., m; \;\; j = 1, 2, ..., n).$$

Laplace Criterion. The core of Laplace principle is based on the fact that if there is no information to determine a condition as more likely than another, then the optimal solution can be determined as

$$x_{\text{opt}} \Rightarrow \max_i \left(\sum_{j=1}^{n} \frac{E_{ij}}{n} \right),$$

i.e., all possible states have equal probability when no other information is available.

Hurwicz Criterion. This decision criterion is a simplified version of Laplace principle and involves the identification of the worst and best outcomes for each strategy. Under certain probabilities of particular states, the arithmetic average of the results of the best solutions is taken [13]. The optimal solution can be determined taking into account both the minimum and maximum profit:

$$x_{\text{opt}} \Rightarrow \max\{\alpha \max E_{ij} + (1-\alpha)\min E_{ij}\},$$

where α is optimism coefficient ($0<\alpha<1$). When $\alpha = 0$, Hurwicz solution is the same as the pure Wald solution; when α = 0.5 it corresponds to the equivalent antagonistic and friendly environment and the case α = 1 corresponds to the maximum favourable environment.

3. Problems under uncertainty conditions

Among the many sources of uncertainty the main distinguished incompleteness is the lack of information, fortuitousness, which cannot be predicted. In the decision making process there are various kinds of uncertainty, depending on the reasons for its occurrence. Uncertainty appears in diagnosis problems at different levels, that can be classified as information and/or model flaws. There exist two main characteristics of uncertainty of the available information for solving decision making – fuzziness and stochasticity of the information. The stochastic programming problems consider decision making problems under conditions of random factors needed to be considered into corresponding mathematical models formulation. A typical task for mathematical programming [14] can be written as:

To find such a vector **X**, for which

$$f(\mathbf{X}) \to \min$$

subject to

$$g_i(\mathbf{X}) \le 0,\ i = 1, \dots, m.$$

The stochastic programming problems consider the functions $f(\mathbf{X})$, $g_i(\mathbf{X})$ as dependent on the random parameters ω, where ω is an element of the random parameters space Ω.

The formulation of the problem of stochastic programming is characterized by three features: 1) nature of the decisions; 2) choice of the quality of the decision (criterion); 3) tools of decomposition of the task constraints. The task of stochastic programming could be formulated as:

To minimize $f(\mathbf{X}, \omega)$

subject to $g_i(\mathbf{X}, \omega) \le 0$, $i = 1, \dots, m$.

The formulation of the stochastic programming problem depends on the existence of the possibility in the decision choice to clarify the nature of ω by observations. Two types of tasks could be distinguished – operational stochastic programming and perspective stochastic programming.

In practice the stochastic programming tasks are based on one of the following two forms.

1. To minimize $M_\omega\{f(\mathbf{X}, \omega)\} = F(\mathbf{X})$

subject to $M_\omega\{g_i(\mathbf{X}, \omega)\} = G_i(\mathbf{X}) \le 0$, $i = 1, \dots, m$,

where M_ω is the mathematical expectation.

2. To minimize $P\{f(\mathbf{X}, \omega) \ge a\}$,

subject to $P\{g_i(\mathbf{X}, \omega) \le 0\} \ge P_i$, $i = 1, \dots, m$,

where a, P_i are some numbers; P denotes probability.
Some combinations between these formulations are also possible.

4. General prognostic model for engineering systems

The prognostic model could be essentially considered as an optimization problem. The aim of a prognostic model is to predict the probability of a particular outcome as optimally as possible, and not just to explore the causality of the association between a specific factor and the outcome. The way in which a prognostic model is developed differs therefore from the method for building an explanatory model. When building a prognostic model the focus is on the search for a combination of factors which are as strongly as possible related to the outcome. Accurate prognostic models are based on algorithms that are capable of predicting future component failure rates or performance degradation rates. This prognostic algorithm must collect the data in real time to provide the best estimation about the remaining useful system lifetime. It could be expressed as minimization of the possible costs of overstatement and understatement:

$$\min f(t) = k_{\mathrm{o}}(P_{\mathrm{o}}(t)C_{\mathrm{o}}) + k_{\mathrm{u}}(P_{\mathrm{u}}(t)C_{\mathrm{u}}),$$

where t is the predicted remaining working system lifetime, $f(t)$ is the total estimated cost assessment, $P_{\mathrm{o}}(t)$ is the probability of overestimating and $P_{\mathrm{u}}(t)$ is the probability of underestimating, C_{o} and C_{u} are overestimated and underestimated costs, k_{o} and k_{u} are trustworthy coefficients of overestimating and underestimating.

The development of strategies for assessment prognostic modeling of machinery working life involves various methods including structural system reliability, probabilistic based life cycle assessment and maintenance, optimization of multiple criteria under uncertainty and integration of monitoring in life cycle management. Combining the advantages of these methods could aid the decision maker in decision making process for engineering systems diagnostics under uncertainty or incomplete information conditions.

5. Discussion and conclusion

The increasing competitiveness in the industrial world is motivated by the interest in improvement of asset effectiveness. The application of engineering systems condition monitoring is growing and it is a challenge for researchers to develop appropriate methods. The natural process of deterioration of the technological parameters of the engineering systems in the process of operation can be delayed by appropriate strategies for predictive maintenance. A benefit of such predictive maintenance is the general maintenance level improving of the system that leads to enhanced productivity. Employing this technique on a regular basis will ensure the system reliability improvement by an essential percentage. This is due to the fact that any potential eventualities have been adequately addressed. Such techniques help to reduce the costs usually used for engineering systems replacements. Many components become faulty because the problems are not detected in due time. By identifying the problems in their initial stages, the predictive maintenance system gives notice of impending failure, so repair downtime can be scheduled for the most convenient and inexpensive time. Using a predictive maintenance program, machines are only dismantled when necessary, so the frequency of equipment disassembly is minimized. To achieve these benefits, optimization models and methods can be used. In most cases these optimization techniques are associated with uncertainty – stochastic or fuzzy information. Depending on the specifics of the investigated object, different principles for optimization problems formulation could be applied. The particular optimal strategies for decision making under conditions of uncertainty information for engineering systems maintenance goal depend on the system nature and the individual decision maker's preferences.

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Техническое обслуживание инженерных систем при помощи оптимальных стратегий для принятия решений в условиях неопределенности

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В работе обсуждается применение оптимальной стратегии для принятия решений в условиях неопределенности для диагностики инженерных систем. Описаны характеристики неопределенности информации и подходов к принятию решений на основе оптимизационных моделей. Показаны обобщеная прогнозирующая модель для диагностики, а также и техническое обслуживание инженерных систем.