METHODS AND TOOLS OF INTELLIGENT SUPPORT FOR FORECASTING THE TECHNICAL CONDITION OF CRITICAL SYSTEMS

Oleg Abramov, Dmitry Nazarov

•

Institute of Automation and Control Processes,
Far Eastern Branch of Russian Academy of Sciences, Russia
abramov@iacp.dvo.ru, nazardim@iacp.dvo.ru

Abstract

A variant of an expert-statistical approach to solving the problem of forecasting parametric deviations of critical systems condition is proposed. Issues of development of specialized software (case-based reasonong approach) with the necessary problem orientation (forecasting degradation of technical condition) and allowing to improve the quality of forecast are discussed. An approach to case describing using an ontological model of degradation processes with allowing to take into account both external influences, and internal processes characteristic of specific types of element, is proposed.

Keywords: technical condition, critical system, forecasting, reliability, decision support intelligent system, case-based reasoning

1. Introduction

Forecasting the state of technical devices and systems plays a crucial role in planning their operation and managing technological risks. The ability to predict possible failure moments is especially important for mission-critical objects, the failure of which is associated with significant material losses or catastrophic consequences. In most cases, these are complex systems manufactured in small numbers, operated in varying conditions, and implementing extreme technologies. The operation strategy for such systems should be individualized and preventive (anticipating failures) in nature.

Individualized operational planning is possible provided that current information about the actual condition of each object is obtained. Implementing an individualized operation strategy requires continuous or discrete monitoring and analysis of the technical condition of the object. It is assumed that the real technical condition of the object can be assessed based on the results of monitoring (measurements) of its parameters, and forecasting their changes allows the object to be operated until signs of a dangerous reliability decrease appear, thereby avoiding premature dismantling of units and assemblies, as well as performing other labor-intensive tasks, often of questionable usefulness for operational reliability.

The main difficulties in solving the forecasting problem for synthesis of operational strategies based on the condition are associated with the need to forecast for each object individually, with small volumes of initial information (based on a small set of monitoring results), and in the presence of noise (measurement errors), the statistical properties of which are not reliably known. In these conditions, classical methods of mathematical statistics and the theory of random processes lose their attractive properties, and their use for forecasting leads to significant errors and low forecast reliability.

There are some approaches to solving the problem of individual forecasting and operational planning with a deficit and incomplete reliability of initial information, allowing for sufficiently reliable results in these conditions. Among them is the method of individual guaranteed forecasting [1, 2]. Its main idea is that from the set of possible realizations of the degradation process of the properties (states) of the studied technical object, consistent with the monitoring results (not contradicting them), the "worst" ones are selected. By "worst" realizations, we mean those that can go beyond the operability range before others. Such realizations can be called extreme [2].

Unfortunately, to use the guaranteed forecasting method, it is necessary to have information about the form (model) of the process of changing the parameters of the technical condition of the studied object. Usually, a specific model of the parameter change process is assumed (as a hypothesis), based on which the forecasting problem is solved. In many cases, there is insufficient prior information to substantiate the choice of the preferred model hypothesis, and the sample of posterior data (monitoring results) is too small for any statistical inferences.

If the observation sample is limited and contains too little information for reliable estimation and forecasting, it is advisable to combine all available information, both objective (statistics, measurement results) and subjective (expert), in other words, to use an expert-statistical approach. Within the expert-statistical approach to forecasting, it is natural to use the same action scheme to refine forecasts as what is usually called actions by analogy and based on the cases that constitute the content of the accumulated practical experience of experts.

The essence of the approach to forecasting based on the method of analogs is to combine the capabilities of modern information theory with the apparatus of methods of system theory with artificial intelligence (which in this case are various computer implementations of action schemes by analogy) [3, 4].

The method of analogs is based on the assumption that in forecasting in a number of subject areas, experts try to make forecasts based on their representations of objects or processes, the history of which is well known to them, experts.

It should be noted that the method of analogs is not universal, and the possibility of its application is associated with certain limitations. For the method of analogs to be applicable, the corresponding subject area must have the property that there is always a large number of objects represented by a substantial volume of statistical and expert information describing them. The first step in the forecasting procedure is to choose a class of models describing the phenomenon being forecast. The next step is the process of collecting expert judgments. It is assumed that subject experts can provide estimates of the upper and lower bounds of possible values of the forecasted process (time series), express judgments about the monotonic decrease or increase in the values of the series over time, extract preliminary estimates of the moments of reaching minimum or maximum values of the series from their practical experience, and so on.

As a result, the forecasting problem is reformulated as follows: to find a sequence of future values most consistent with the monitoring results of the forecasted process and expert opinions. Since the length of the forecast base period is insufficient for reliable statistical conclusions, solving the corresponding forecasting problem imposes an additional – but now prioritized – requirement for the model to match fixed expert opinions and only then considering these opinions – observation results.

2. Means of Intelligent Support for Forecasting Methods

The use of the expert-statistical approach in solving forecasting tasks necessitates the application of information technologies for computer support of decision-makers. One way to provide such support is the creation of specialized software with a specific problem orientation (forecasting the degradation of technical condition) that allows improving the quality of the obtained results. Such software can be developed using an approach based on modeling of case-based reasoning (CBR) [4].

Choosing this approach is justified if, by the time the forecasting degradation problem arises, a certain experience of solving similar problems has already been accumulated, which occurred earlier on similar technical objects (analogues). Representing this experience in the form of precedents and its automated processing using specialized software systems can significantly improve the effectiveness of the results.

Solving the forecasting problem based on precedents is based on recognizing the current problem situation, information about which is presented in the form of a certain pattern (case), and searching for similar pattern contained in the repository of patterns (cases base), followed by their adaptation and use for solving the forecasting task.

Let's highlight the main functions of the intelligent support system that ensure solving the forecasting task using plausible inference based on precedents.

- Formation of a case (analogue).
- Formation of a cases repository based on the forulated model.
- Finding a solution (plausible inference) based on cases.

To implement these functions, the following main modules of the intelligent support system are necessary:

- Module for cases modeling, which provides creation and modification of case models, formulation and updating of cases repositories based on existing models;
- Internal memory, which should provide storage of case models;
- Case inference engine, performing the search for precedents based on a given description;
- Management module, providing interaction between modules and providing an interface for communication with the external environment.

3. Case Structure

Automated systems implementing the case-based approach allow finding solutions to current problems based on past experience of solving similar problems. The success of implementing the case-based approach consists in preliminary analysis of the specificity of the problem being solved and largely depends on the choice of the way to describe the case.

Modeling of reasoning for forecasting the technical condition of a system based on the analysis of parameter drift over time is reduced to analyzing the degradation processes of its elements' properties. Every individual case consists a model of the parameter drift of the element. Each such model takes into account not only fatigue and wear processes, external environmental factors (which can also affect wear), but also more complex processes of mutual influence between elements (electromagnetic fields, heating from neighboring elements, vibrations), also taking into account their spatial arrangement relative to each other. However, in practice, known linear or exponential drift models are usually used [5]. Taking into account various external factors when modeling the drift process of each parameter requires a more complete description of the structure of the studied system.

The ontological approach offers broad possibilities for describing the structure of a technical object, taking into account the interaction of its components when solving tasks related to forecasting the technical condition [6, 7, 8, 10]. An ontology is a conceptual model of the subject area that describes the studied objects, processes, and phenomena in the form of a graph, where the vertices are concepts of the subject area, and the edges are all possible relations between them. For practical tasks, there are models of ontologies of various complexity, but in most cases and within the framework of the considered problem, it is sufficient to use a model in the form of a triplet $O = (X, R, \Phi)$, where X is the set of concepts of the subject area, R is the set of relations between these concepts, and Φ is the set of interpretation functions [6].

The use of ontologies allows describing the structure of a system of any complexity and level of detail with any known types of relationships between its elements and external influences. Such an approach to representing the structure of a technical object, taking into account the interconnections of its elements and factors causing failures, is used in software systems for Prognostic Health Management (PHM). In such systems, the hierarchy of elements with possible causes of their failure is usually described in detail, with quantitative characteristics specified as intervals of admission and their current values [6], or probabilistic properties such as failure distribution density, mean time to failure, etc. [7]. On the basis of this description, it is possible to build a fault tree, identify the causes of failures, and build reasoning about the system's state in the form of productions based on predicate logic expressing the state of individual nodes in the hierarchy of elements, for example, the OntoProg model [6].

The ontological approach can also be used to build a degradation model of a complex system. When describing its structure, experts specify the factors affecting the performance and wear of each element. For example, Figure 1 illustrates an example of ontological representation of the hierarchy of system elements with a description of factors influencing the values of their operating parameters. The structure of the system is formed by set-theoretic relations "a-part-of" (depicted by solid arrows), describing the hierarchy of elements, and their influence on each other is described by relations based on changes in the physical parameters of the element's degradation model (shown by dashed arrows on the figure). Thus, over time, a rotating shaft due to friction can increase the temperature of surrounding elements, which can be accounted for in the used model of resistor and capacitor drift in the electronic circuit. Over time, a rotating shaft can become a source of vibrations, which negatively affects the quality of contacts of electronic components, accelerates the destruction of solder joints, which can be reflected in the corresponding failure model of the electronic board.

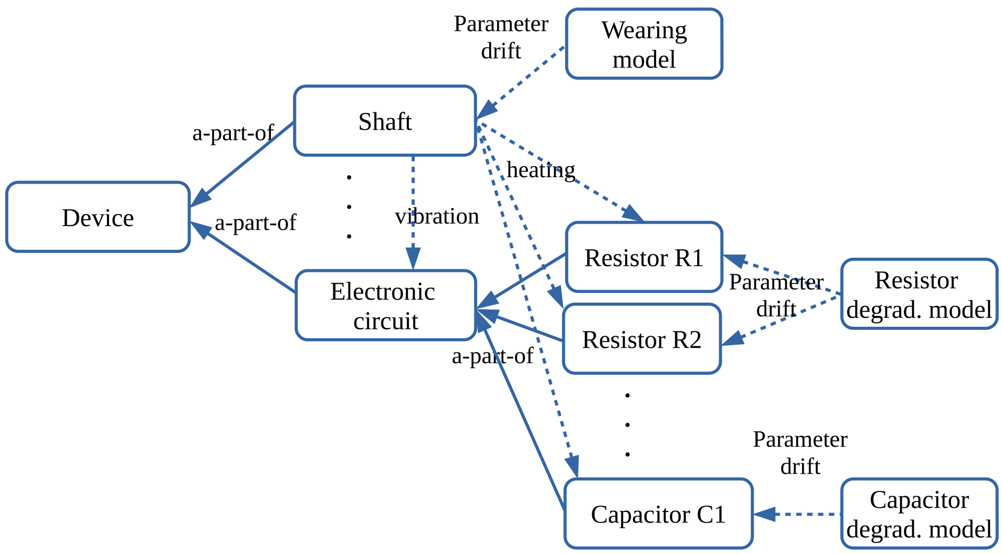

Figure 1: *Example of ontological representation of a technical device including parametric drift models*

Description of a case, considering the mutual influence of system elements and environmental factors, is based on the use of an ontological model and typically is a graph model. Processing graph structures during their storage, loading, and application in specific tasks requires more sophisticated procedures than linear structures of parametric models. A detailed account of all interrelationships influencing the properties of system elements is very labor-intensive and justified when designing expensive or mission-critical systems. On the other hand, overly detailed description of factors affecting parameter degradation may not only hinder expert support but also the reuse of the entire structure, especially for unique systems. Additionally, in similar systems, some components with similar functions may have different implementations (e.g., electrolytic and film capacitors [11]), and their parameter behavior over time and under the influence of the same factors may differ.

Despite the advantages of considering environmental parameters and factors of mutual influence, it is often considered sufficient in practice to use known drift models with a limited set of parameters, based on linear or exponential trends [9]. Thus, the case will include a parameterized drift model for a specific element:

$$C = (x_1, x_2, \ldots, x_{N_p}) \tag{1}$$

where $x_i, i = 1, 2, \ldots, N_p$ are the parameters of the drift model being used, N_p is the number of model parameters. In addition to the parameters of the drift model 1, for its identification (linear, exponential, and polynomial) and correct consideration of its parameters during reuse, the case should contain its conditional name:

$$CASE = (ID, C_p, Descr) \tag{2}$$

where ID is the unique identifier of the drift model type from the known models database, C_p are the parameters of the model 1, $Descr$ is a verbal description, and recommendations for application to the decision-maker. In the case of specifying a unique model not present in the known drift models database, the parameters C_p represent a symbolic description of the model in a specific format, taking into account the rules of the used mathematical expression parser [12].

4. The Module of Case Formation

The formation of a case using a degradation model of parameters is carried out at the stage of designing the technical object by an expert based on their experience and known regularities. The software module for case formation provides unified rules for describing cases based on the parametric model 2 of the case structure, as well as allows interaction with the ontological description of the system structure, in which the parameters of the external environment and the factors influencing other system components are specified.

The case is formed by the expert on the basis of processing and adaptation of the existing structure in the cases repository, or as a completely new one. In different tasks, the same components may or may not use external environmental factors. If a case takes into account any external influencing factor on the degradation process, but its use is not provided in the current task, then such a parameter is usually set to zero or NaN (not a number) when zero values are significant for a certain task.

In the interaction with the user, this software module represents an interactive guide, offering the expert a suitable case as the basis for processing for the current task, or contextual prompts in the form of suitable models for this system and external factors.

The models created by the expert are saved in a single case repository in parametric form. If necessary, ontological information about the system and the relationships between its elements, to which references from the case structure exist, can be saved separately.

5. Case-Based Plausible Inference Module

The search for a suitable case is based on its representation method. The parametric representation of its structure allows the application of cluster search methods, such as the Nearest Neighbor (NN) method [9]. The case inference software module analyzes the current description of the designed system by examining the relationships between its components, considering possible environmental factors, and searches the case database for a suitable model of the degradation process.

The tuning parameters of the case search include fundamental properties such as the metric for assessing the proximity of cases and the number of structures used in NN method. However, in the task of investigating unique systems, it is important to consider the uniqueness factor of their individual elements, which may make the use of a case-based approach not entirely appropriate.

The result of this module's operation is a specific degradation model for a system element, which is integrated into the structure of its representation to assess reliability characteristics, operational reserve, and failure risk [13]. This module provides means of explaining the selection made and proposing alternatives in case of identifying disputed decisions. The final decision on the use of the proposed model, its adaptation for correct implementation into the model of the studied system, is made by an expert or the decision-making authority.

6. Conclusion

An expert-statistical approach to forecasting the processes of parametric deviations of the technical condition of critical systems based on the method of analogs has been considered. The essence of the method lies in experts' involvement in solving the forecasting problem, based on their identification of analogs of the predicted process from among previously observed processes.

The development of specialized software (tools for intelligent support implementing a case-based reasonong) with the necessary problem orientation (forecasting the degradation of the technical condition) and capable of improving the quality of the obtained results is discussed. The proposed approach to describing a case is based on an ontological model of knowledge about the degradation processes of system components. The method of using domain-specific ontologies for constructing degradation models taking into account all possible factors of both external influences and internal processes characteristic of specific types of components is considered. The use of such models is most typical for tasks within the framework of the functional-parametric direction in reliability theory.

The research was carried out within the state assignment of IACP FEB RAS (Theme FWFW-2021-0003).

References

[1] Abramov, O., Dimitrov, B. (2017). Reliability design in gradual failures: a functional-parametric approach. *Reliability: TheoryApplication*, Vol.12, 4(47):39–48.

[2] Abramov, O., Nazarov, D. (2016). Condition-based maintenance by minimax criteria. *Applied Mathematics in Engineering and Reliability. Proceedings of the 1st International Conference on Applied Mathematics in Engineering and Reliability (Ho Chi Minh City, Vietnam, 4-6 May 2016). CRC Press*, 91–94. DOI: 10.1201/b21348-16.

[3] Mandel, A.S. (2004). Method of analogs in prediction of short time series: An expert-statistical approach. *Automation and Remote Control*, Vol. 65, 4:634–641.

[4] Aamodt, A., Plaza, E. (1994). Case-based reasoning: foundational issues, methodological variations, and system approaches. *AI Communications*, Vol. 7, 1:39-59.

[5] Jones, J.A. (1999). A toolkit for parametric drift modelling of electronic components. *Reliability Engineering System Safety*, Vol. 63, 1:99–106.

[6] Nunez, D. L., Borsato, M. (2018). OntoProg: an ontology-based model for implementing prognostics health management in mechanical machines. *Advanced Engineering Informatics*, 38:746–759. DOI: 10.1016/j.aei.2018.10.006.

[7] Venceslau, A., Lima, R., Guedes, L.A. and Silva, I. (2014). Ontology for computer-aided fault tree synthesis. *Proceedings of the 2014 IEEE Emerging Technology and Factory Automation (ETFA)*:1–4.

[8] Ebrahimipour, V., Rezaie, K., Shokravi, S. (2009). An ontology approach to support FMEA studies. *Annual Reliability and Maintainability Symposium, Fort Worth, TX, USA, 2009*:407–411. DOI: 10.1109/RAMS.2009.4914711.

[9] Weber, R., Schek, H.-J., Blott, S. (1998). A quantitative analysis and performance study for similarity search methods in high dimensional spaces. *VLDB 98 Proceedings of the 24rd International Conference on Very Large Data Bases*:194–205.

[10] Eremeev, A., Varshavsky, P. (2007). Methods and Tools for Reasoning by Analogy in Intelligent Decision Support Systems. *Proceedings of the International Conference on Dependability of Computer Systems. Szklarska Poreba, Poland, 14-16 June 2007, IEEE*:1–4.

[11] Gupta, A., Yadav, O.P., DeVoto, D., Major, J. (2018). A Review of Degradation Behavior and Modeling of Capacitors. *Proceedings of the ASME 2018 International Technical Conference and Exhibition on Packaging and Integration of Electronic and Photonic Microsystems. ASME 2018*

International Technical Conference and Exhibition on Packaging and Integration of Electronic and Photonic Microsystems. San Francisco, California, USA:1–10.

[12] Lange, C. (2013). Ontologies and languages for representing mathematical knowledge on the Semantic Web. *Semantic Web*, 4, 2:119–158.

[13] Abramov, O.V., Nazarov, D.A. (2022). Functional-parametric direction of risk theory. *Proc. of the 13th Asian Control Conference (ASCC 2022), Korea*:1911–1913. DOI: 10.23919/ASCC56756.2022.9828266.