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ORIGINAL ARTICLE

Reliability analysis of man–machine systems using fuzzy cognitive mapping with genetic tuning

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Abstract

This article offers a method for analyzing the reliability of a man–machine system (MMS) and ranking of influencing factors based on a fuzzy cognitive map (FCM). The ranking of influencing factors is analogous to the ranking of system elements the probabilistic theory of reliability. To approximate the dependence of "influencing factors—reliability," the relationship of variable increments is used, which ensures the sensitivity of the reliability level to variations in the levels of influencing factors. The novelty of the method lies in the fact that the expert values of the weights of the FCM graph edges (arcs) are adjusted based on the results of observations using a genetic algorithm. The algorithm's chromosomes are generated from the intervals of acceptable values of edge weights, and the selection criterion is the sum of squares of deviations of the reliability simulation results from observations. The method is illustrated by the example of a multifactor analysis of the reliability of the "driver–car–road" system. It is shown that the FCM adjustment reduces the discrepancy between the reliability forecast and observations almost in half. Possible applications of the method can be complex systems with vaguely defined structures whose reliability depends very much on interrelated factors measured expertly.

KEYWORDS
Birnbaum importance index, fuzzy cognitive map, influencing factors, man–machine system, ranking of factors, reliability, tuning

1 | INTRODUCTION

The research in the field of reliability of systems with humans is one of the most important areas in the science of reliability (Zio, 2009). A man–machine system (MMS) is a system in which people interact with tools (technical means) in order to obtain the required product of labor (Lomov, 1966; Montmollin, 1973). Depending on the product of labor that appears at the output of the MMS operation process, these systems can be of various types: production, transport, information, medical, educational ones, etc. The reliability of the MMS and its security is an important quantitative criterion used to make decisions when designing a system. The development of methods for evaluating the reliability of MMS began in the 1960s and continues today. In the development of these methods, there is a tendency to move from modeling the reliability of a system based on the structure of its components to modeling based on the structure of factors that affect reliability: individual, technological, organizational, environmental ones, etc. The complexity of modeling is connected with the fact that these factors not only affect the reliability of the system, but also interact with each other, that is, they affect each other. In order to solve successfully the modeling problems, you must have a mathematical tool allowing you:

- to describe the interaction of an arbitrary number of factors affecting the reliability of the system,
- to quantify the influence of factors on each other and on the reliability of the system as a whole under conditions of uncertainty,
- to add and remove easily the influencing factors during the modeling.

These requirements are met by fuzzy cognitive maps (FCM), a modeling apparatus that has been widely used in the last two decades. The application of FCM in the field of reliability is described in a relatively small number of works that have a common drawback: they use expert assessment of the strength of factor influence and do not allow for the adjustment of the model based on the results of observations. Without the adjustment, you cannot guarantee that the simulation results are close to the actual reliability values which are observed in practice.

This article proposes a method for analyzing the reliability of MMS where FCM is used for the approximation of the "influencing factors—reliability" dependency, and a genetic algorithm is used to adjust FCM.

2 | EVOLUTION OF METHODS

2.1 | The structuring: First-generation methods

The first models of MMS reliability were based on the general theory of reliability (Barlow & Proschan, 1975), which was already known at that time. According to Barlow and Proschan (1975), the initial stage of modeling the reliability of any system is its *structuring*, that is, decomposition into components (blocks, nodes, elements), for which the failure probabilities are known. To do this, we use the concept of a *structural (Boolean) function* (Barlow & Proschan, 1975), which connects the logical condition of the system's operability (1: no failure, 0: there is a failure) with similar conditions for its elements. The formal apparatus for the transition from a structural function to a probabilistic reliability model is the probabilistic logic calculus (Ryabinin, 1976).

The structural function contains information that is used in the interrelated fundamental methods of reliability engineering.

- *Fault tree analysis*: (FTA) (Eckberg, 1964) allows you to predict the probability of system failure based on the probability of failure of its elements.
- *Birnbaum importance index* (Birnbaum, 1969) allows you to rank elements by the importance of their impact on system reliability, which is necessary for resource distribution to ensure the system reliability.
- *Failure mode and effect analysis* (FMEA) (Tashjian, 1975) is used for determining the effect of component failures on the system operation.

Structuring and FTA are the basis for the so-called *first generation* of Human Reliability Analysis (HRA) methods (Di Pasquale et al., 2013; Havlikova et al., 2015) among which the most popular is THERP (technique for human error rate prediction) (Swain & Guttmann, 1983). A task performed by a human is divided into separate actions for which the error probabilities are known. These probabilities can be modified taking into account such factors as available time, level of stress, task type, and level of experience. To calculate the reliability, the logic of events that lead to incorrect task execution is used.

The first generation of HRA methods is the *Gubinsky structural method* (Gubinskij, 1982), which was widely used in the former Soviet Union for ergonomic design in shipbuilding (Gubinskij & Evgrafov, 1977), aviation, cosmonautics (Popovich et al., 1984) and other fields. To describe events related to the occurrence, detection and elimination of human errors and equipment failures, the structural method uses the system functioning algorithm, and the probabilistic reliability model is based on the theory of semi-Markov processes (Gubinskij, 1982). Models for optimizing the algorithms of MMS functioning according to the criteria of reliability and time consumption are proposed by Rotshtein and Kuznetcov (1992).

The main difficulties in applying the first generation of HRA methods are the following:

- In the course of the functioning of MMS, it is not always possible to distinguish elementary operations that are independent of each other for which error probabilities are known.
- The difficulties in considering the factors that affect the probability of human errors may cause distrust in reliability calculations (Barnard, 2012). Creation of models "influencing factors—reliability" remains an actual problem of reliability engineering.

2.2 | From components to factors: empirical modeling

The algorithmic description (Gubinskij, 1982) is a natural way of structuring systems with discrete functioning processes, where the presence of clear boundaries between individual operations allows you to collect statistics on error probabilities necessary for modeling. Algorithmization difficulties arise in MMS with the continuous nature of human activity, where tracking and decision-making operations predominate. Examples are the control systems in transport, in the chemical and nuclear industries, and other high-risk systems where human error leads to disastrous consequences.

The lack of clear boundaries between operations does not allow us to assess correctly the probability of their proper execution. Therefore, the entire process of functioning has to be considered as a single operation, whose correctness depends on many heterogenous and interrelated factors: individual, technological, organizational ones, etc. The modeled system turns into a "black box" with an unknown structure, where the output is reliability and the inputs are influencing factors. In this case, the traditional problems for reliability engineering of ranking system components (Birnbaum, 1969) and their combinations (Tashjian, 1975) turn into problems of ranking factors that affect reliability. There is no universal way to choose a set of influencing factors. In solving this problem, the experience of selecting factors that affect the response function from the theory of experiment planning (Montgomery, 2012) and the Ishikawa "fishbone" diagram from quality management methods (Ishikawa, 1991) can be useful.

TABLE 10 Importance indices of the joint influence of concepts

Concepts	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
C_1	0.200	0.143	0.330	0.329	0.229	0.227	0.275	0.191
C_2		0.080	0.267	0.266	0.167	0.164	0.213	0.128
C_3			0.210	0.209	0.110	0.107	0.156	0.071
C_4				0.396	0.296	0.294	0.342	0.258
C_5					0.295	0.293	0.341	0.257
C_6						0.194	0.242	0.157
C_7							0.240	0.155
C_8								0.203

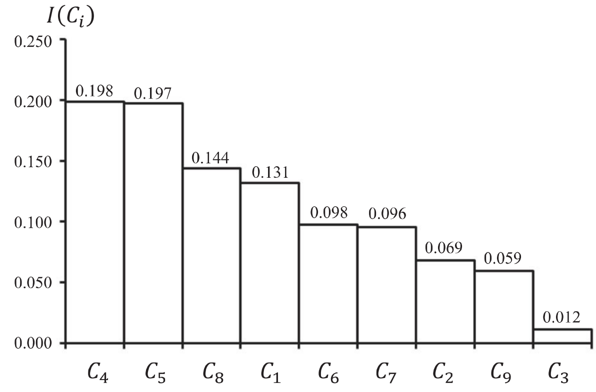

FIGURE 8 Concept importance indexes diagram

9 | CONCLUSION

This article offers a method for analyzing the reliability of MMS and ranking factors that affect reliability, based on a fuzzy cognitive map (FCM). The ranking of influencing factors is considered as an analog of the ranking of system elements according to Birnbaum in the probabilistic theory of reliability. To approximate the dependence "influencing factors—reliability," the relationship of variable increments is used, which ensures the sensitivity of the reliability level to variations in the levels of influencing factors. The weights of the FCM arcs that characterize the strength of influence of variables on each other are set by the expert, and then are adjusted based on the results of observations. For optimal adjustment of arc weights, a genetic algorithm is used, in which chromosomes are generated from intervals of acceptable values, and the selection criterion is the sum of the squares of deviations between the modeling results and observations. The advantage of this method is the ease of extension of influencing factors by introducing additional vertices and arcs of the graph. The method is illustrated by the example of a multi-factor analysis of the reliability of the "car–driver–road" system. It has been shown that the FCM adjustment reduces the discrepancy between the reliability forecast and observations by almost twice.

Possible applications of the method can be complex systems with vaguely defined structures, whose reliability depends on interrelated factors measured by experts.

A promising direction for further development of the proposed method might include using fuzzy numbers for the weights of arcs and levels of concept assessment in the graph of FCM, which will allow for estimating the variation of simulation results.

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