Information Technology for Performance Assessment of Complex Multilevel Systems in Managing Technogenic Objects

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Abstract. The paper presents the information technology for performance assessment of complex multilevel systems in managing technogenic objects, which complements the theory and methods for solving tasks of ensuring system reliability and survivability, based on the interaction of a set of operability and human factor indicators in control and decision-making at each of its hierarchical levels. Risk conditions of the influence on system performance are determined and the classification and evaluation of the impact degree of the factors on decision-makers in the system's three-level hierarchical structure under fuzzy risk are carried out. A review, systematization, and generalization of publications on the issues of analysis and assessment of the systems for managing technogenic objects were carried out, based on which it was established that, in addition to the parameters of the system, and the influence of the external and industrial environment on the human factor, the efficiency indicator also depends on its hierarchical structure, the nature of the connections between the components, and on the regularities of the system's functioning, being poorly amenable to formalized description and evaluation. To assess the performance of the system, a Bayesian network was built, through which, based on the knowledge of experts, the probability of its performance at each hierarchical level was assessed, taking into account the influence of external and internal workplace factors on the cognitive component of a decision-maker under the fuzzy risk of taking irrelevant decisions. For practical substantiation of the obtained results, an experiment was conducted, the results of which confirmed the practical value of the information technology, which can be used to assess the performance of complex multilevel systems in managing technogenic objects.

Keywords: complex multilevel systems, complex organizational and technical objects, decision-maker, functional sustainability, human factor, relevant decisions, fuzzy risk of decision-making, Bayesian network.

1 Introduction

Currently, in the creation and operation of complex multilevel systems (CMS) for managing complex technogenic objects (CTO), the main task is to increase efficiency, which is associated with increasing their technical and software complexity. As a result, the requirements for both the sustainability of the components that make up the system, and the reliability and performance of the decision-maker are increasing. To solve this problem, it is necessary to be able to assess the levels of reliability of all components and their contribution to the level of performance of the entire system.□

Modern CMSs for managing CTO are developed, as a rule, based on computer networks, which in combination with software and users are designed to increase efficiency, especially that of human management. Currently, the issue of assessing the performance of CMS is given insufficient attention; there is no single conceptual approach to the study of such systems. The reliability of the operator and the performance of software packages have also been insufficiently studied. Elements of a modern CMS can adapt to the operating conditions, i.e. they are adaptive. For such a system, it is difficult to formulate the concept of failure [1].

The issues of the performance assessment related to the emergence of risk situations in the implementation of management decisions at each hierarchical level of the system due to the imperfection of the used mathematical, statistical, and intellectual tools are understudied.

In this regard, solving the above problems is relevant.

2 Related Works

The solution to this problem is reflected in the results of the following scientific studies.

The papers [2, 3] discuss the situation in the analysis of the reliability of human operators. Such an analysis normally includes a human reliability assessment (HRA) in man-machine systems (MMS) and contains a description of the available patterns of human behavior. In this context, man-machine systems represent a real interaction between a human operator and a technical system. The authors present the systems where the human factor plays a significant role, and human failure can lead to a security hazard. Currently, the quantification of human reliability is based on a full probabilistic safety analysis (PSA) of the entire MMS.

In [4], it is noted that the reliability of man-machine systems cannot be considered as of system's hardware or software due to its cognitive abilities, as well as the interaction between man and machine. To understand the ability of human cognition and the interaction between a man and a machine, the work presents a reliability analysis method based on the IDA model, which provides a cognitive model of the operator and a classification of performance influencing factors (PIF) following the human cognitive process.

In [5], human reliability analysis (HRA) models are considered with cognitive psychology models and their internal structures in human information processing. The paper surveys how macro-cognition can arise from the micro-cognition and proposes the training of parameters of a specific cognitive architecture (ACT-R) with the scenarios of human activities in the external world to provide human error probabilities that arise from the proper architecture and are time-dependent and other Performance Shaping Factors (PSFs), related to cognitive stressors.

In [6], the importance of the human factor in modern complex dynamic systems (CDS), under accidents and catastrophes, is noted. It is emphasized that little attention is paid to the problems of risks associated with information and cognitive aspects of man-machine interaction. It is recommended to take into account the risks arising in unpredictable conditions, as well as the special requirements for human psychophysiological state and the admission to perform particularly important work when designing and operating CDS. It is also noted that the information and cognitive aspects of human factors engineering play a key role in the safety, reliability, and efficiency of CDS.

In [7-9], the issues of creating information technologies for assessing the condition of the decision-maker (DM) in making relevant decisions are considered, where the main attention is paid to the formation of alternatives to decision support (ADS). The algorithms for formalizing the relationship between external factors and the psychological and functional characteristics of the DM to optimize decision-making are developed. However, all this does not allow to describe with maximum accuracy the factors not having known exact patterns and providing for the necessity to associate between qualitative and quantitative assessments of factors influencing the decision-making process under fuzzy conditions and risk, the efficiency of a complex multilevel system in managing technogenic objects being dependent on.

In this regard, for the development of the theory of evaluation of the efficiency of distributed man-machine systems and based on the above analysis of the literature, the information technology to assess the performance of complex multilevel systems in managing technogenic objects is proposed in this paper.

3 Formal problem statement

Review, systematization, and generalization of the publications on analysis, assessment, and management in CMS show that in addition to the parameters of the system, the impact of the external and industrial environment on the human factor, the performance indicator also depends on the system architecture (its hierarchical structure, the nature of the connections between components), as well as on the regularities of the system functioning, poorly amenable to formalized description and assessment.

The functioning of CMS is characterized mainly by the following hierarchical levels:

- the level of local control and automation of technological sections of a complex organizational and technical object (COTO), based on digital control, the tasks of controlling individual units, and technology departments are performed. The purpose of the system functioning at this level is to conduct the technological process to the upper control levels in real-time;

– the level of dispatch control, automatic collection of real-time data, calculation of complex indicators, as well as the upbuilding of the object history;
– analytics level, based on an analytical server, performing tasks on analyzing production data and the efficiency of technological processes.

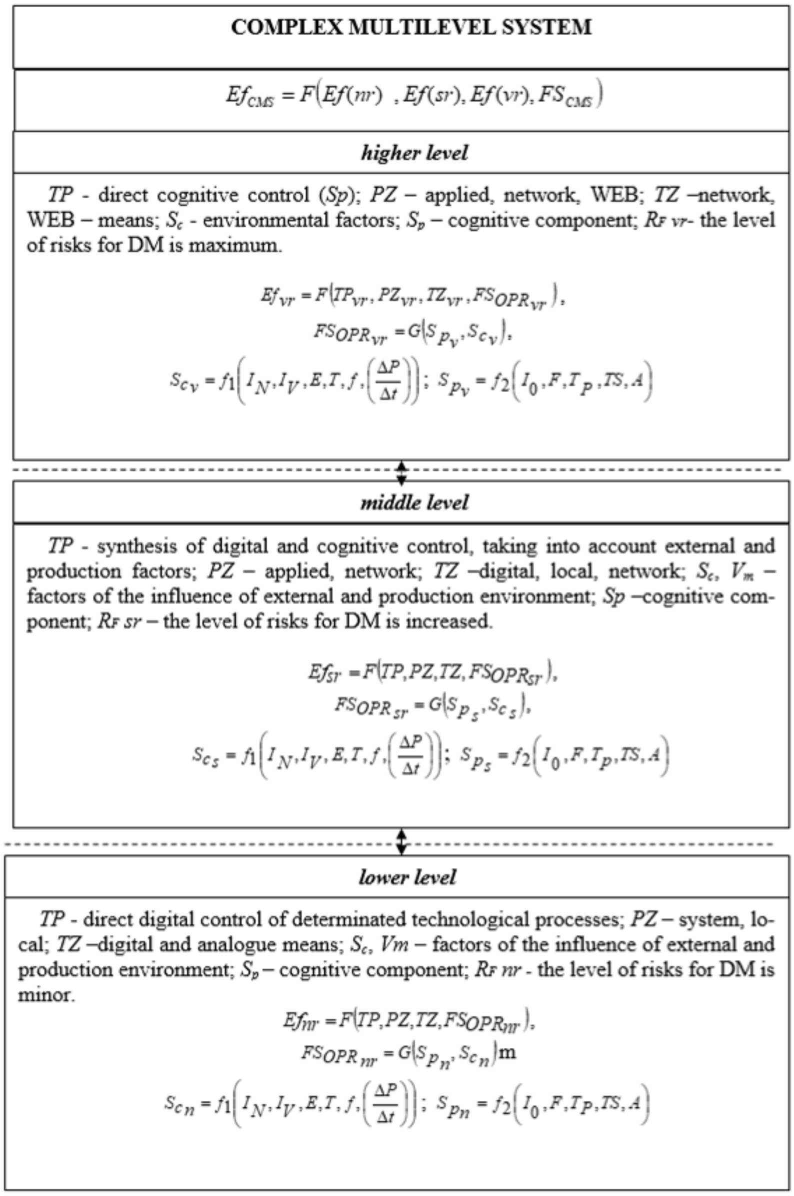

Fig. 1. Conceptual model of the complex multilevel system (CMS)

The efficient performance of CMS at each level is characterized by the following components: the level of the technological process status - *TP*; software status level - *PZ*; hardware status level - *TZ*; the level of the state of functional sustainability of decision-maker, which characterizes risk conditions of decision-making – FS_{OPR}; the level of the state of functional sustainability of CMS - FS_{CMS}; the level of monitoring and adaptation of the system - *MAC*; the level of the operational formation state of adapted alternatives to decision-making support – *FA PPR* (Fig. 1).

If the functioning of CMS occurs under uncertainty and fuzzy risk, the effectiveness of management is ensured by the quality of the performance of decision-makers performance, its psychological state, the cognitive component, and working conditions, which can be characterized as functional sustainability (FS) of decision-maker, which impacts the degree of risk in critical project management.

As shown in [8], the functional sustainability of decision-making under conditions of fuzzy risk depends on the corresponding factors (Fig. 2).

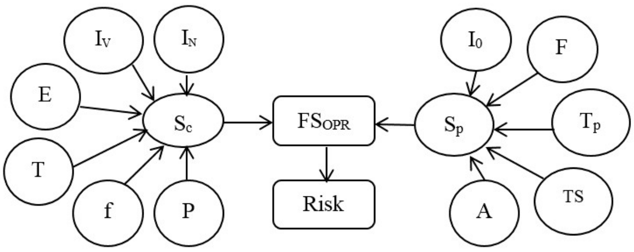

Fig. 2. Graph of factors influencing the determining of fuzzy risk of DM's decision-making

The degree of risk R_F of making irrelevant decisions by the DM depends on his functional sustainability, which in turn depends on the relevant factors, i.e. $\mathrm{R}_{\mathrm{F}} = \varphi\left(FS_{OPR_{vr}}\right)$. Considering that $FS_{OPRvr} = F\left(S_{p_v}, S_{cv}\right)$ it follows that $\mathrm{R}_{\mathrm{F}} = f\left(S_{p_v}, S_{cv}\right)$.

In [2, 3, 5, 7] according to the results of the classification and evaluation of factors influencing decision-maker in the three-level hierarchical system of critical application, it is noted that its productivity is most significantly influenced by the following groups of factors (Fig. 2):

1. factors related to the impact of the user's production environment;
2. factors related to the user's current psychological and cognitive state.

The first group of factors influencing decision-maker includes: a) noise intensity and level I_N; b) intensity and level of electromagnetic field I_V; c) illumination of the workplace *E*; d) premise temperature *T*; e) premise humidity *f*; f) atmospheric pressure $\Delta P / \Delta t$.

The group of influencing factors related to the user's current psychological and cognitive state includes a) the level and frequency of information load I_0; b) the degree of user's fatigue *F*; d) the efficiency of real-time decision-making *Tp*; e) the degree of psychological tension *TS*; f) concentration *A*.

The first group of factors determines the level of the external and production environment condition - S_c, the second group of factors determines the level of the psychological and cognitive state of decision-maker - S_p. Formally, this means that

$$S_c = f_1\left(I_N, I_V, E, T, f, \left(\frac{\Delta P}{\Delta t} \right) \right) \tag{1}$$

$$S_p = f_2\left(I_0, F, T_p, TS, A\right) \tag{2}$$

$$FS_{OPRvr} = G\left(S_{p_V}, S_{cV}\right) \tag{3}$$

The magnitude of risk (risk) R_F of making irrelevant decisions depends on the functional sustainability of the decision-maker, which in turn depends on the relevant factors following (3). Then, given (1-3), it can be written that

$$\begin{aligned} R_F &= \varphi\left(G\left(S_{p_V}, S_{cV}\right)\right) = \psi\left(S_{p_V}, S_{cV}\right) = \\ &= \psi\left(I_N, I_V, E, T, f, \left(\frac{\Delta P}{\Delta t} \right), I_0, F, T_p, TS, A \right) \end{aligned} \tag{4}$$

Even though in the literature there are significantly different interpretations of the concept of "risk", they have in common that risk includes uncertainty whether an undesirable event will occur that can lead to adverse consequences [Mushik, Muller].

When a decision is made by the DM in conditions of uncertainty, under the influence of such factors as ambiguity, inaccuracy, and fuzziness [10], the risk of making irrelevant decisions is considered fuzzy.

Therefore, in this paper, the fuzzy risk R_F (or risk level) is understood as the probability of making an irrelevant decision by the DM under the influence of the above-mentioned factors, i.e. $R_F=P_r$.

Therefore, the main objectives of the work performed are to determine the functional dependence of the efficiency of the 3-level CMS performance on production factors and the fuzzy risk of making irrelevant decisions by the DM, as well as the dependence of fuzzy risk on external and cognitive factors.

Herewith, it is not possible to obtain analytical formulas for the above functional dependencies.

Most managerial decisions at each level of CMS are made under fuzzy risk, which is determined by the lack of complete information, the presence of opposing trends, elements of randomness, when possible outcomes can be described using a certain probability distribution, for the construction of which it is necessary to have statistical data or expert evaluations [2-6].

The solution of the task under uncertainty, when the initial information is incomplete, inaccurate, non-quantitative, and a type of the formal display is either too complicated or not known, then in such cases, the expert knowledge is involved. For its representation and processing, various methods of applied decision-making theory and artificial intelligence methods are used.

This paper considers the solution to the above problems using the mathematical apparatus of the Bayesian network (BN).

BNs are graphical models of events and processes based on combining some inferences of probability theory and graph theory [11], which are based on pairs $< G, B >$, where the first component G is a directed acyclic graph corresponding to random variables, and the second B represents numerous parameters that determine the system.

The total probability of BN is calculated by the following formula:

$$P_B(X^{(1)},...,X^{(N)}) = \prod_{i=1}^{N} P_B(X^{(i)} \big| P_A(X^{(i)})) \tag{5}$$

where: $A-$ is a set of environment states; $N = (x_1,...,x_N)-$ vector of parameters of their distributions.

The conditional probability of an event is determined by the following ratio:

$$p(E \big| H_k) = \frac{p(E \cap H_k)}{p(H_k)} \tag{6}$$

where: E and H_k $-$are interrelated variables. This dependence allows determining what the probability of the event E will be if a particular event H_k occurs.

Mutually exclusive events form an exhaustive set if

$$\bigcup_{i=1}^{n} E_i = \Omega \tag{7}$$

Two variables do not intersect if they do not have equal values. Bayesian network theory is based on the assumption that events are exhaustive and do not intersect. In this case, the probability of the event E can be calculated using conditional probabilities:

$$p(E) = \sum_{i=1}^{n} p(E \cap H_i) = \sum_{i=1}^{n} p(E \mid H_i) \cdot p(H_i) \tag{8}$$

Using the formula (6), the probability of the intersection of the events E and H can be expressed as follows:

$$p(E \cap H_k) = p(E \mid H_k) \cdot p(H_k) = p(H_k \mid E) \cdot p(E) \tag{9}$$

whence it follows that:

$$p(H_k \mid E) = \frac{p(E \mid H_k) \cdot p(H_k)}{p(E)} \quad (10)$$

Considering the formula (7) and (10), it can be represented as follows:

$$p(H_k \mid E) = \frac{p(E \mid H_k) \cdot p(H_k)}{\sum_{i=1}^{n} p(E \mid H_i) \cdot p(H_i)} \quad (11)$$

BN (Fig. 3) was used to assess the CMS efficiency, where for considering the influence on its performance efficiency (node "Efficiency") of such factors as the technological process, software, hardware, functional sustainability of CMS, the support of the system monitoring and adaptation, the operative formation of the adapted alternatives to decision-making support the nodes *TP*, *PZ*, *TZ*, *FC*, *MAC*, *FA PPR* respectively are introduced. They are nodes of the "Decision" type and can take three values: "normal", "workable" and "critical" depending on the states that the above factors take.

Since the CMS efficiency is significantly influenced by the risk of adopting irrelevant decisions by the DM, the probability P_r is taken to assess the degree of influence of the fuzzy risk.

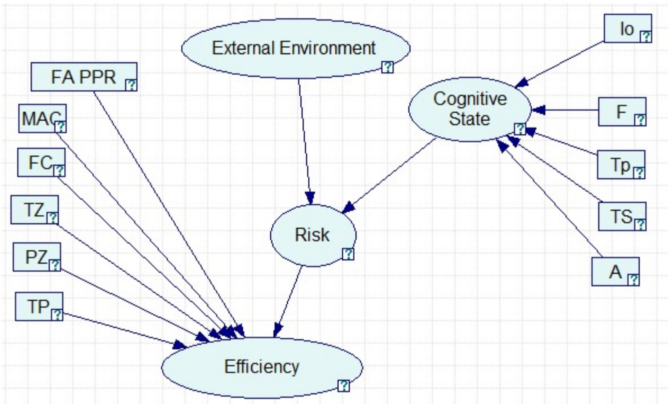

Fig. 3. BN for the assessment of CMS performance efficiency

Thus, the risk is set on the BN by a node Chance - NoisyMax type, which is called “Risk”. Since the DM risk of making a decision depends on the state of the environment and the cognitive state of the decision-maker, the Risk node has two parent nodes “External Environment” and “Cognitive State”.

The “External Environment” is the node of the Chance type and characterizes the degree of influence of the environment on the decision-maker. This influence is determined to a varying degree at each hierarchical level of the system by the factors following Fig. 3. The standard values of these factors are given in Table 1.

Table 1. Normative values of environmental factors

factors	I_N dBA	I_V mm/s	E lx	T °C	f %	$\Delta P / \Delta t$ mm Hg/day
norm	≤ 50	7.6-11.2	250	22-24	40-60	≤ 4

If the values of external factors differ from the normative ones, then a nonzero probability arises that their impact on the decision-maker will be negative. In this paper, it is assumed that the random variable "External Environment" takes two values: "negative" and "positive" depending on whether the influence of external factors on the decision-maker is positive or negative. The question naturally arises: what is the probability P_n that the random variable "External Environment" takes negative value?

Table 2. Results of expert evaluation of the cognitive factor values

Cognitive factor		**Node value**		
		low	**middle**	**high**
I_0 (rank)	**Change limits**	0-5	6-10	11-15
F (rank)		0-5	6-10	11-15
T_p (min)		0-5	5-30	30-60
TS (rank)		0-5	6-10	11-15
A (rank)		0-5	6-10	11-15

Table 3. ″Cognitive State″ node description

Parent	I_0			F		
State	**low**	**middle**	**high**	**high**	**middle**	**low**
negative	0.25	0.05	0	0.65	0.2	0
positive	0.75	0.95	1	0.35	0.8	1
Parent	T_p			TS		
State	**high**	**middle**	**low**	**high**	**middle**	**low**
negative	0.3	0.05	0	0.35	0.1	0
positive	0.7	0.95	1	0.65	0.9	1
Parent	A					
State	**high**	**middle**	**low**			
negative	0,7	0,15	0			
positive	0,3	0,85	1			

To answer this question and to estimate the probability P_n, a system is created for predicting the values of probabilities based on fuzzy inference according to the

Mamdani algorithm, in which the values of the input variables I_N; I_V; E; T; f; $\Delta P / \Delta t$ and the output variable P_n are given by fuzzy sets. For this inference, a fuzzy knowledge base was proposed [9], taking into account that, according to [7], the most noticeable influence on decision-makers is exerted by such factors as noise intensity, workplace illumination, and vibration intensity. To set up a fuzzy model, i.e. determination of the coefficients of the membership functions of the terms of the input and output variables, the method of minimizing the root-mean-square residual error was used. The implementation of the proposed fuzzy inference for assessing the probability P_n was carried out using the *Fuzzy Logic Toolbox* and *Optimization Toolbox* packages.

Table 4. "Risk" node description

Parent	**External Environment**		**Cognitive State**	
State	**negative**	**positive**	**negative**	**positive**
occurs	0.3	0	0.6	0
does not occur	0.7	1	0.4	1

Table 5. "Efficiency" node description

Parent	***TP***			***PZ***		
State	**critical**	**workable**	**normal**	**critical**	**workable**	**normal**
occurs	0.9	0.1	0	0.2	0.05	0
does not occur	0.1	0.9	1	0.8	0.95	1
Parent	***TZ***			***FC***		
State	**critical**	**workable**	**normal**	**critical**	**workable**	**normal**
occurs	0.35	0.05	0	0.85	0.12	0
does not occur	0.65	0.95	1	0.15	0.88	1
Parent	***MAC***			***FA PPR***		
State	**critical**	**workable**	**normal**	**critical**	**workable**	**normal**
does not occur	0.8	0.15	0	0.25	0.05	0
occurs	0.2	0.85	1	0.75	0.95	1
Parent	**Risk**					
State	**occurs**	**does not occur**				
does not occur	0.6	0				
occurs	0.4	1				

The "Cognitive State" node is of the Chance - Noisy Max type and characterizes the degree of influence of cognitive factors on the DM performance: Information throughput I_0; the degree of user's fatigue F; time for decision-making Tp; stress level TS; attention concentration A. These factors on the BN correspond to the nodes of the same name I_0; *F; Tp; TS; A*, which can take on the values "low", "middle" and "high". In this case, the «Cognitive State" node can take two values: "negative" and "positive", depending on whether the influence of cognitive factors on the DM performance is positive or negative.

As a result of expert evaluation, a correspondence is established, presented in Table 2, between the interval of values of cognitive factors and the value (″low″, ″middle″ and high″) of the corresponding BN node.

The assignment of the Chance - Noisy Max type to the nodes "Cognitive State", "Risk", "Efficiency" is conditioned by the following considerations: firstly, these nodes have a large number of parent connections, which greatly complicates the filling of the table of conditional probabilities; secondly, it is much easier for experts to estimate the value of the unconditional probability than the conditional one.

To describe the noisy nodes "Cognitive State" and "Risk", and to describe the node "Efficiency", the experts-specialists and experts-administrators correspondingly were requested to evaluate the conditional probabilities of possible states of the indicated nodes. The results of the expert evaluation are presented in tables 3-5.

4 Experiment and Results

Further, it is assumed that only one factor negatively affects the efficiency of CMS performance to some extent: the technological process - *TP*, i.e. *TP* node takes the value "workable". In this case, the nodes *PZ, TZ, FC, MAC, FA PPR* take the value "normal". The result of calculating the probability P_{ef} of efficient performance of CMS according to the above-considered BN without taking into account the risk ($P_r = 0$) of making an irrelevant decision by the decision-maker is shown in Fig. 4.

The figure shows that the efficiency of the CMS performance, when the risk $P_r = 0$, is 90% ($P_{ef} = 0{,}9$).

To demonstrate how the risk of irrelevant decision making by the DM depends on his cognitive state and environmental factors and how it affects the efficiency of the CMS performance.

The lower level of the system is considered below.

At this level, cognitive factors practically do not have a noticeable effect on decision-makers. Therefore, it is assumed that the nodes *F*; T_p; *TS; A* take on the values "low", and the node Io takes on the value "high". At the same time, environmental factors with the probability $P_n = 0{,}3$ negatively affect decision-makers.

At this case, the calculation according to the above-considered BN shows that the risk at the lower level is minor ($P_r = 0{,}09$), which leads to a decrease in the efficiency of the CMS performance by only 5% ($P_{ef} = 0{,}85$) in comparison with the case when the risk is not taken into account.

At the middle level, cognitive factors have a minor effect on decision-makers. Therefore, it is assumed that *F, TS, and A* nodes take the value "middle", and the nodes T_p and I_0 take the values "low" and "high", respectively. At the same time, environmental factors at the middle level negatively affect decision-makers to a lesser extent than at the lower level. It is assumed that $P_n = 0{,}2$.

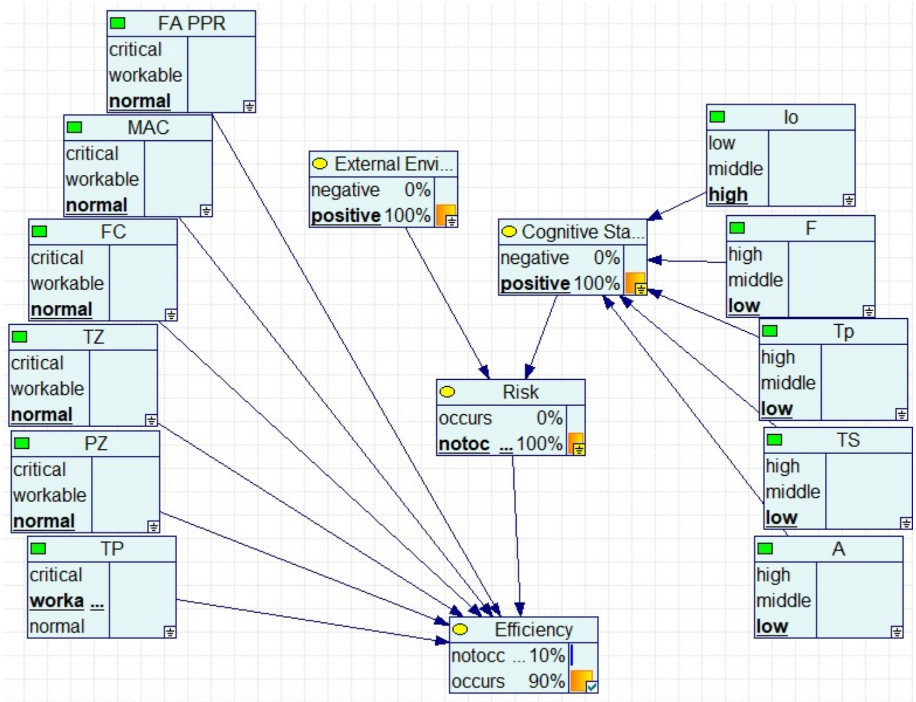

Fig. 4. Probability P_{ef} of the efficient performance of CMS provided that the risk $P_r = 0$

In this case, the calculation according to the above-considered BN shows that the risk at the middle level significantly increases compared to the lower level and amounts to $P_r = 0{,}28$, which leads to a decrease in the efficiency of the CMS performance by 15% ($P_{ef} = 0{,}75$) as compared to the case when the risk is not taken into account.

At the upper level, cognitive factors have a significant impact on decision-makers. Therefore, it is assumed that the nodes *F; TS; A* take on the value "high", and the nodes T_p and I_0 take on the values "low" and "high", respectively. At the same time, environmental factors at the upper level negatively affect decision-makers to an even lesser extent than at the middle level. It is assumed that $P_n = 0{,}1$.

The result of calculating the risk P_r and the probability P_{ef} of the CMS efficient performance at the upper level shows that the risk at the upper level is much greater than the risk at the lower and middle levels $P_r = 0{,}57$, which leads to a significant decrease in the efficiency of the CMS performance to the value $P_{ef} = 0{,}59$.

5 Conclusions

In this work, the information technology for performance assessment of complex multilevel systems under fuzzy risk is developed, which complements the theory and methods of solving issues of ensuring system reliability and survivability, based on the interaction of a set of operability and human factor indicators in control and decision-making at each of its hierarchical levels.

Risk conditions of influence on system performance are determined and the classification and evaluation of the impact degree of the factors on the DM in the system's three-level hierarchical structure under fuzzy risk are carried out. Fuzzy risk is proposed to mean the probability of making an irrelevant decision by the decision-maker.

To determine a quantitative assessment of the dependence of the 3-level CMS efficiency on production factors and the fuzzy risk of making irrelevant decisions by the DM, as well as the dependence of fuzzy risk on external and cognitive factors, taking into account the knowledge of experts, a BN was developed.

For practical substantiation of the obtained results, an experiment was carried out, where, taking into account the characteri6stic values of external and cognitive factors at each of the 3 system's levels, the fuzzy risk of making an irrelevant decision by DM and the CMS efficiency was calculated. It is shown that the magnitude of the risk grows from the lower to the upper level. Herewith, the efficiency of the CMS is correspondingly reduced from an acceptable value at the lower level to a critical value at the upper level. The calculation results are in good agreement with the experimental results of the CMS operation.

The results of the experiment confirmed the practical value of information technology, which can be used to assess the performance of complex multilevel systems under the fuzzy risk of decision-making in managing technogenic objects.

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