Chapter

Probabilistic Methods for Cognitive Solving of Some Problems in Artificial Intelligence Systems

Andrey Kostogryzov and Victor Korolev

Abstract

As a result of the analysis of dispatcher intelligence centers and aerial, land, underground, underwater, universal, and functionally focused artificial intelligence robotics systems, the problems of rational control, due to be performed under specific conditions of uncertainties, are chosen for probabilistic study. The choice covers the problems of planning the possibilities of functions performance on the base of monitored information about events and conditions and the problem of robot route optimization under limitations on risk of "failure" in conditions of uncertainties. These problems are resolved with a use of the proposed probabilistic approach. The proposed methods are based on selected probabilistic models (for "black box" and complex systems), which are implemented effectively in wide application areas. The cognitive solving of problems consists in improvements, accumulation, analysis, and use of appearing knowledge. The described analytical solutions are demonstrated by practical examples.

Keywords: artificial intelligence system, method, probability, risk, uncertainty

1. Introduction

Today, artificial intelligence (AI) has confidently entered our lives. The first mention of it belongs to the mid-50s of the last century. Under AI, we usually understand it as the branch of computer science devoted to develop data processing systems that perform functions normally associated with human intelligence, such as reasoning, learning, and self-improvement (ISO/IEC 2382-1:1993 Information technology–Vocabulary–Part 1). According to this, over the decades, AI has found its application in expert systems supporting decision-making, in heuristic classification, computer vision, pattern recognition, understanding natural language, etc. [1–14]. Here, under AI systems (AIS), we understand systems that include data processing systems that perform functions by AI, in particular by modeling and logic reasoning.

Note. System is a combination of interacting elements organized to achieve one or more stated purposes (according to ISO/IEC/IEEE 15288 "Systems and software engineering–System life cycle processes").

If the modern human brain already possesses skills of adaptation to conditions of various uncertainties in the world around, artificial intelligence systems require creation of effective methods for cognitive solving actual practical problems. "Cognitive solving" means relating to or involving the processes of thinking and reasoning (Cambridge English Dictionary). The applicable mathematical methods are focused mainly on conditions of actions in the logician "if ..., that ..." according to the gathered information, and on an estimation of traced situations by a man-operator. At increase and expansion of uncertainty conditions, quite often, there are failures and errors because of complexity. It means that search of new methods for advanced solving of AIS practical problems today is very important.

In the present chapter, various AIS for supporting decision-making in intellectual manufacture and robotics systems are analyzed. According to robotics, it is supposed that AIS may be used for solving multiple aerial, land, underground, underwater, universal, and special problems of creation and operation. At the same time, we would like to emphasize that the main efforts of this chapter are not focused on illustrating the capabilities of AIS, but on demonstrating the applicability of author's probabilistic models and methods to improve some of the existing capabilities of AIS.

For this goal, the problem of planning the possibilities of functions performance on the base of monitored information and the problem of robot route optimization under uncertainties limitations are chosen. The choice of these problems in AIS applications is caused on the one hand by increase of quantity and a variety of specific uncertainties conditions, and on the other hand by an urgency and width of areas for their practical use. However, some relevant problems (such as the problems of robotics orientation, localization and mapping, information gathering, the perception and analysis of commands, movement and tactile, realizations of manipulations, and also rational control) for which different probabilistic methods are also applicable have been left out of the scope of work.

For cognitive solving and improvements by the use of probabilistic methods, the chosen problems are transformed more specifically to:

- problem 1 of planning the possibilities of functions performance on the base of monitored information about events and conditions, and

- problem 2 of robot route optimization under limitations on risk of "failure" in conditions of uncertainties.

The proposed methods for cognitive solving AIS problems are based on theoretical and practical author's researches [15–37] and need to be used either in combination or in addition to existing methods. There, where often it is required prognostic analysis or where the used approaches are not effective, the proposed methods can be used as rational basis or alternative.

The proposed and referred author's methods and models can be used in AIS life cycle to form system requirements, compare different processes, rationale technical decisions, and estimate reliability, quality, and risks. The decisions, scientifically proved by the offered models and software tools, can provide purposeful essential improvement of quality and mitigation of risks and decrease expenses for created and operating systems. The spectrum of the explored systems by these methods includes systems (not only AIS) operated by government agencies, manufacturing structures (including power generation, coal enterprises, oil and gas systems), food storage, space industry, emergency services, municipal economy, etc. [15–19, 22–37]. The supporting software tools are original Russian creations registered by Rospatent [38–44]. They have been presented at seminars,

symposiums, conferences, ISO/IEC working groups, and other forums since 2000 in Russia, Australia, Canada, China, Finland, France, Germany, Italy, Kuwait, Luxembourg, Poland, Serbia, the USA, etc. The software tools were awarded by the Golden Medal of the International Innovation and Investment Salon and the International Exhibition "Intellectual Robots," acknowledged on the World's fair of information technologies CeBIT in Germany, noted by diplomas of the Hanover Industrial Exhibition and the Russian exhibitions of software.

Note. The proposed methods below do not replace existing methods for robots actions (for example, the methods of solving the systems of differential equations, the methods of refreshed linear and geometric algebra, geometry, Lie groups, linearization, solving Jacobians and Hessians, Kalman filters, Lyapunov analysis, the methods of biomechanics, graph theory, Laplas transforming for large-scale dynamic systems, etc.) [1–14].

The structure of the chapter research is shown in **Figure 1**. It provides an explanation of the essence of cognitive solving of problems on the base of probabilistic modeling, selection of some author's probabilistic models applicable for cognitive solving problems 1 and 2, the practical steps to solve these problems, and five practical examples demonstrating system planning the possibilities of functions performance by using robot-manipulators (in space), by AIS for a coal company and by AIS used for a security service of floating oil and gas platform, example of forming input for probabilistic modeling from monitored data and example of robot route optimization under limitations on risk of "failure" in conditions of uncertainties. Various areas of the examples' applications have been chosen purposely to demonstrate universality and analytical usefulness of the proposed methods and models. Appendices includes the proof for the proposed model of a quite general technology of periodical diagnostics of system integrity and some short models results to estimate quality of used information.

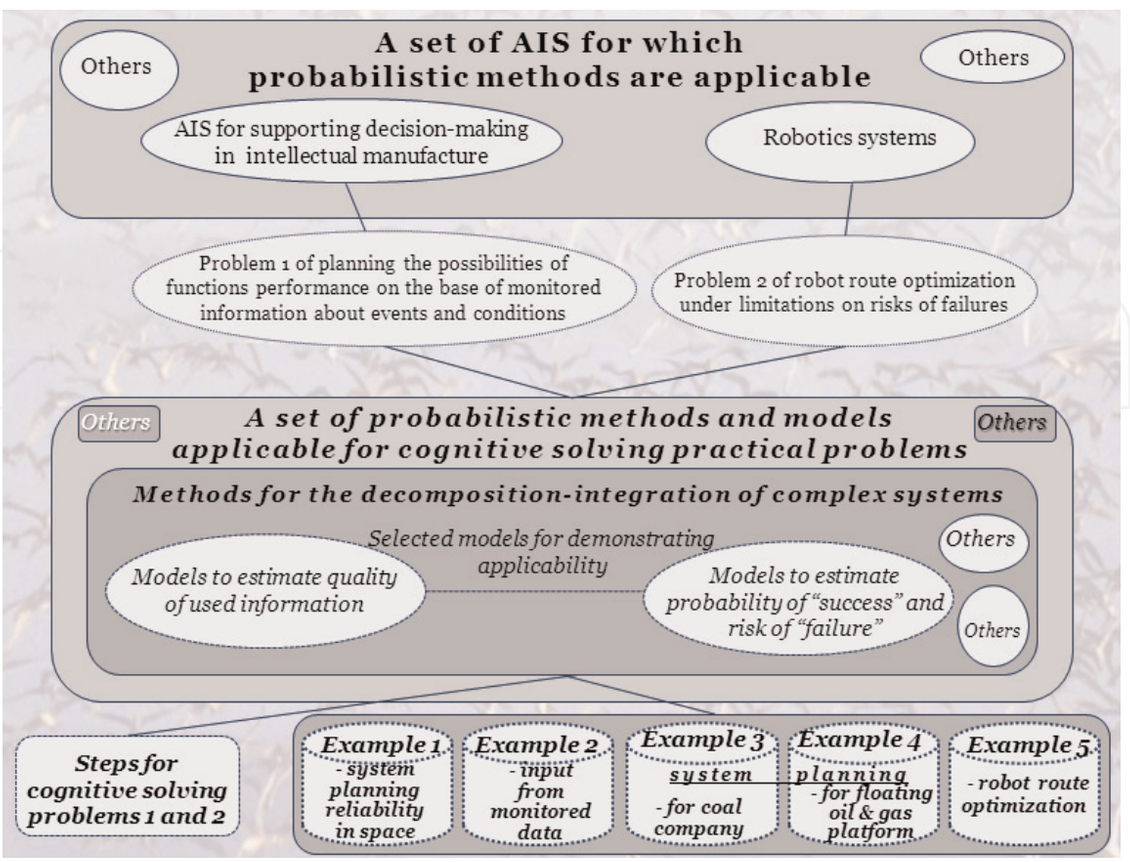

Figure 1.
The structure of the research.

2. The essence of cognitive solving of problems on the base of probabilistic modeling

This section explains the definitions and interpretations which can help to understand the proposed models and results of modeling complex systems in different application areas.

AIS itself can be considered as an interested system (for example, dispatching intellectual center) or as a part of other, more comprehensive interested system (for example, functionally focused robots in safety systems). The current information is processed in real time for performing the set or expected functions of interested system. To meet system requirements, the solutions of considered problems 1 (of planning the possibilities of functions performance) and 2 (of robot route optimization) are initiated along with the solutions of other problems.

The cognitive solving of problems include improvements, accumulation, analysis, and a use of appearing knowledge, see **Figure 2**. Possible uncertainties for the given period (from initial time point t_1 to future moment t_x) may be considered by using proposed probabilistic modeling, prediction, and optimization.

The solutions for problems 1 and 2 are estimated by probability of "success" and/or "failure" (risk of "failure") during given prognostic time period. Thus, prognostic period should be defined so to be in time to recover capabilities (which can be lost), or to carry out preventive action (with which the initiation of solving the problem is connected). Such behavior means operation in real time.

In each real case of modeling the term "success" should be defined in terms of admissible condition of interested system to operate for the purpose. The term "failure" means "unsuccess." Generally, a "success" of interested system operation during the given time period means an admissible degree of integrity. Accordingly, "failure" for interested system during given time period means inadmissible degree of integrity at least once within this period. System (or system element) integrity is defined as such system (system element) state when system (system element) purposes are achieved with the required quality and/or safety. The risk of "failure"

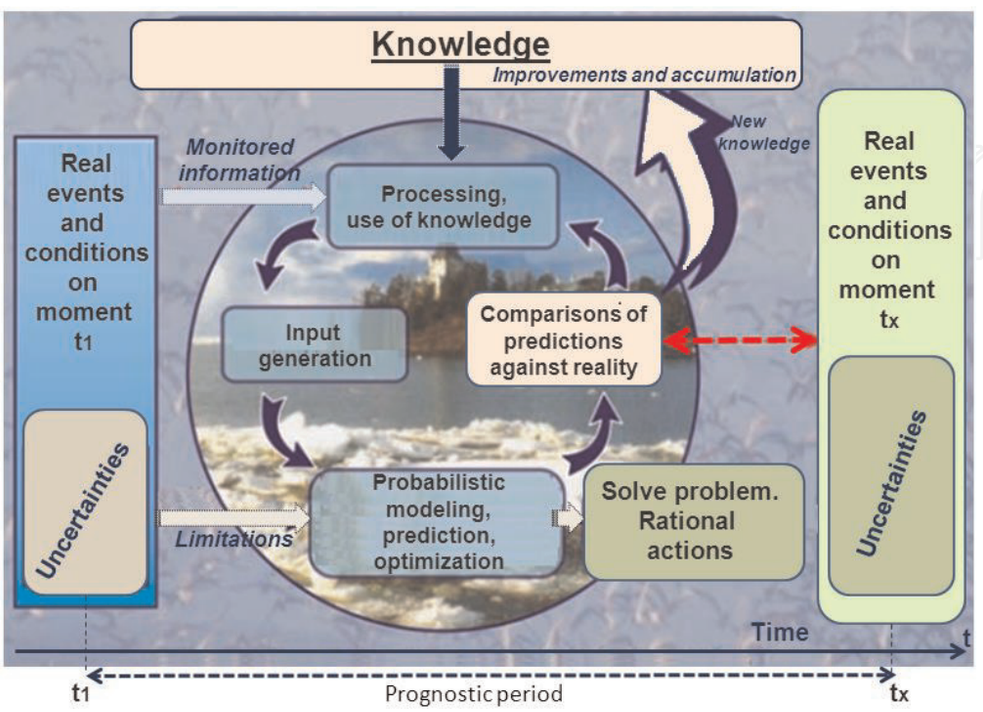

Figure 2.
The essence of cognitive of solving of problems.

is understood as a probabilistic measure of "failure" considering consequences (according to ISO Guide 73).

Note. For example, an interested system is a dangerous manufacturing object. The object structure includes an AIS, which monitors events and conditions in and/or around its manufacture. Equipment parameters (temperature, pressure, and so forth) which should be in norm limits are traced. The "failure" of interested system operation may mean an incident or accident on object.

Generally, from the point of view of formalization for each estimated variants (for problem 1 or 2), the interested system is logically decomposed to compound subsystems; see **Figures 3** and **4**. Each subsystem is a set of components (elements and/or other subsystems): for problem 1, this set covers the components participating in functions performance; and for problem 2, the set covers compound parts of a possible route of the robot in space. Complete set of these components formally characterizes a variant of decomposed system for solving problem 1 or 2. The analysis and optimization are carried out on complete set of all compared possible variants.

Interpretation of such decomposition is the following:

The subsystem from serial connected elements provides functions performance with admissible level of integrity (quality and/or safety) at given time, if:

- "AND" 1st component, …, "AND" last element provide admissible level of integrity (quality and/or safety) at given time (for problem 1);

- "AND" 1st compound part of the route, …, "AND" last compound part of the route are overcame successfully by the robot at given time (for problem 2).

The subsystem from parallel connected elements provides functions performance with admissible level of integrity (quality and/or safety) at given time, if:

- "OR" 1st component, …, "OR" last component in the subsystem provide admissible level of integrity (quality and/or safety) at given time (for problem 1);

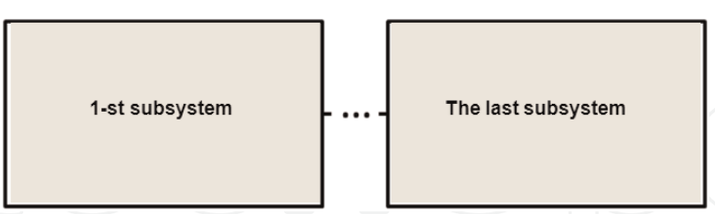

Figure 3.
Variant of system decomposition.

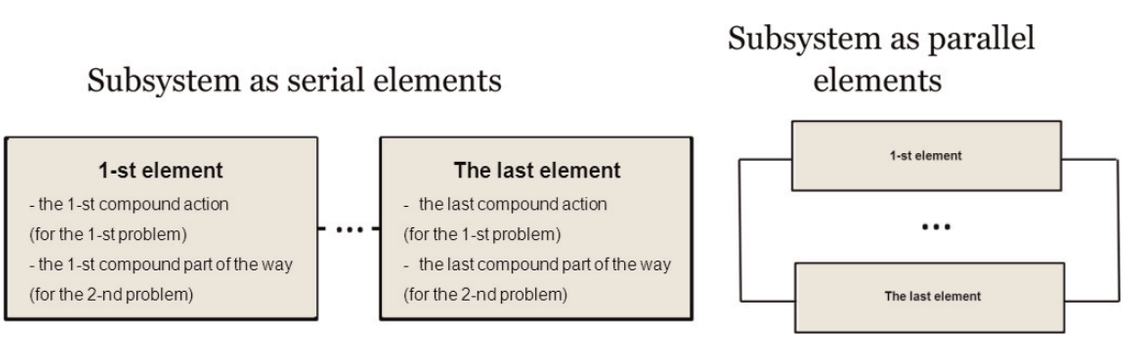

Figure 4.
Variant of subsystem decomposition.

- "OR" 1st compound part of the route, …, "OR" last compound part of the route are overcame successfully by the robot at given time (for problem 2).

Each component after system decomposition is presented as a "black box." For each "black box," various probabilistic models can be applied for calculations and for building required probabilistic distribution function (PDF) of time between the next deviations from an established norm. A norm is connected with definitions of "success" and "failure," it may be connected with the precondition to "failure" (to prevent "failure"—see Example 2). Focus on processes' description allows to use only time characteristics (mean time or frequency of events), the dimensionless or cost characteristics peculiar for various applications.

Appropriate calculated probabilities of "success" and/or "failure" (risk of "failure") in comparisons to real events during the prediction periods represent the knowledge of admissibility borders for probabilities of "success" and acceptability borders for risks of "failure." The process of cognitive solving of problems 1 and 2 means not only the formation and use of this knowledge for interested system, but also the estimated quality of monitored and used information (including definition of input for continuous modeling).

3. Selection of the models

The proposed probabilistic methods for cognitive solving of problems 1 and 2 are based on selected probabilistic models which are implemented effectively in wide application areas. The main principle at a selection of models consists that useful knowledge should be result of their application in conditions of various uncertainties. Knowledge is understood as the form of existence and ordering of results of cognitive activity of human. In the applications to solv**e** problems 1 and 2**,** useful knowledge (received as a result of probabilistic modeling in time) is an output information of admissible quality or cognitive conclusion that allows to solve **a** specific applied problem. As the results of selection**,** the author's models to estimate the probabilistic measures of a quality of used information and the probabilities of "success" and risks of "failure" for "black box" and for complex structures are proposed for AIS. The models are widely tested and approved in practice [15–19, 22–37].

3.1 Selection for "black box"

Selected models for every system element, presented as "black box," allow to estimate probabilities of "success" and/or "failure" during given prognostic period. A probabilistic space (Ω, B, P) for estimation of system operation processes is traditional [15–21], where Ω is a limited space of elementary events; B is a class of all subspace of Ω-space, satisfied to the properties of σ-algebra; and P is a probability measure on a space of elementary events Ω. Such space (Ω, B, P) is built and proposed for using [22–37].

Not considering uncertainty specificities, in general case, intellectual operation of AIS component aims to provide reliable and timely producing complete, valid and/or, if needed, confidential information; see **Figure 5**. The gathered information is used for its proper specificity. And, the proposed models [18–19] allow to estimate the intellectual operation processes on a level of used information quality, which is important for every AIS (information may be used by technical devices, "smart" elements, robotics, users, etc.).

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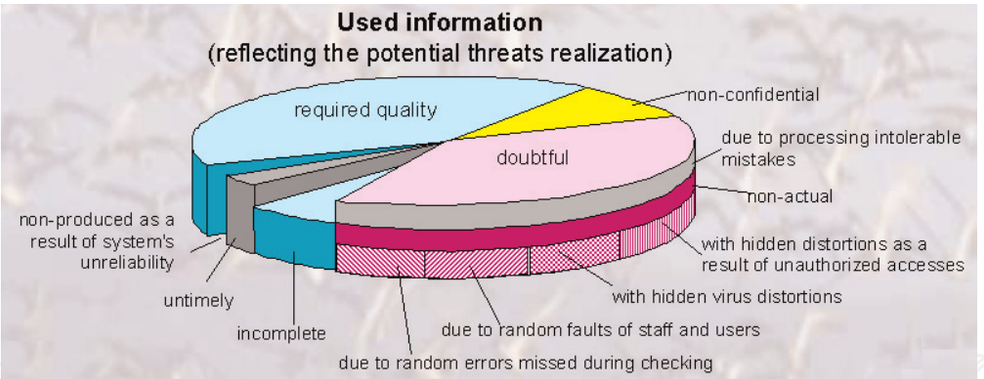

Figure 5.
Quality of used information (abstraction).

The proposed analytical models ("The model of functions performance by a complex system in conditions of unreliability of its components," "The models complex of calls processing for the different dispatcher technologies," "The model of entering into system current data concerning new objects of application domain," "The model of information gathering," "The model of information analysis," "The models complex of dangerous influences on a protected system," and "The models complex of an authorized access to system resources") allow to estimate the probability of "success" and risks to lose quality of intellectual operation during given prognostic period considering consequences; see **Table 1**. Required limits on probability measures are recommended as produced knowledge for the best AIS practice (estimated on dozens practical estimations for various application areas).

The next probabilistic model is devoted to estimate a probability of "success" and risk of "failure" on high meta level. This is based on studying the general AIS technology of periodical diagnostics of system integrity. Some general technologies were researched for "The models complex of dangerous influences on a protected system," see **Table 1**. Here, the general case for AIS is presented.

For system element allowing prediction of risks to lose its integrity during given prognostic period, there is studied the next general AIS technology of providing system integrity.

Technology is based on the periodical diagnostics of system integrity (without the continuous monitoring between diagnostics). Diagnostics are carried out to detect danger sources occurrence from threats into a system or consequences of negative influences (for example, these may be destabilizing factors on dangerous enterprise). The lost system integrity can be detected only as a result of diagnostics, after which system recovery is started. Dangerous influence on system is acted step-by step: at first, a danger source occurs into a system, and then after its activation may be a loss of integrity; see **Figure 6**. Occurrence time is a random value that can be distributed by PDF of time between neighboring occurrences of danger $\Omega_{occur}(t) = P(\tau_{occurrence} \leq t) = 1 - \exp(t/T_{occur})$, T_{occur} is mean time, frequency $\sigma = 1/T_{occur}$. Activation time is also random value which can be distributed by PDF of activation time of occurred danger $\Omega_{activ}(t) = P(\tau_{activation} \leq t) = 1 - \exp(t/T_{activ})$, T_{activ} is mean time. System integrity cannot be lost before an occurred danger source is activated. A threat is considered to be realized only after a danger source has activated and influenced on system.

It is supposed that used diagnostics tools allow to provide system integrity recovery after revealing danger sources occurrence or the consequences of influences. Thus, the probability (P) of providing system integrity within the given

Threats to AIS operation quality	Evaluated measure (required limits as produced knowledge for the best practice)	Model tittle
Information is not produced as a result of system unreliability	Probability of providing reliable functions performance during given time (no less than 0.99). Mean time between failures. System availability (no less than 0.9995)	The model of functions performance by a complex system in conditions of unreliability of its components
Delayed information producing (i.e., not in real time)	Probability of well-timed processing during the required term (no less than 0.95). Mean response time. Relative portion of all well-timed processed calls. Relative portion of well-timed processed calls of those types for which the customer requirements are met (no less than 95%)	The models complex of calls processing for the different dispatcher technologies
Producing of incomplete information	Probability that system contains information about states of all real object and coincides (no less than 0.9)	The model of entering into system current data concerning new objects of application domain
Information validity deterioration caused by: • non-actual input information; • errors missed or made during information verification; • incorrectness of processing	Probability of information actuality on the moment of its use (no less than 0.9). Probability of errors absence after checking (no less than 0.97). Fraction of errors in information after checking. Probability of correct analysis results obtaining (no less than 0.95)	The model of information gathering. The model of information analysis
Violation of information confidentiality	Probability of system protection against unauthorized access during objective period (no less than 0.999)	The models complex of an authorized access to system resources
Violation of secure system operation including • random faults of staff and users; • dangerous influences (revealing of software and technical defects, virus influences, violators' influences, terrorist attacks in information environment, psychological influence etc.); • unauthorized access	Probability of faultless (correct) operation during given time (no less than 0.95). Mean time between errors. Probability of system protection against unauthorized access (no less than 0.99)	The models complex of dangerous influences on a protected system. The models complex of an authorized access to system resources

Table 1.
The proposed analytical models to estimate AIS operation quality [18, 19].

prognostic period T_{given} (i.e., probability of "success") may be estimated as a result of the use of the next probabilistic model. Risk to lose integrity (R) addition to 1 for probability of providing system integrity $R = 1 - P$.

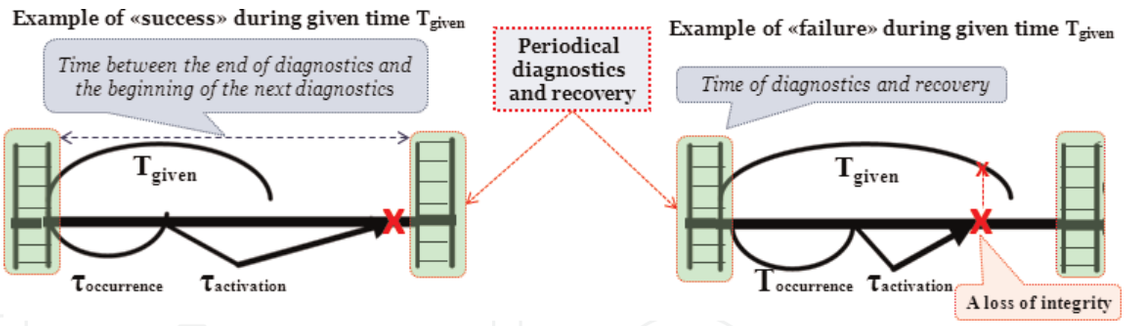

Figure 6.
Some random events for technology: left—correct operation to provide system integrity; right—a loss of integrity during prognostic period T_{given}.

There are possible the next variants:

variant 1—given prognostic period T_{given} is less than the established period between neighboring diagnostics ($T_{given} < T_{betw.} + T_{diag}$);
variant 2—given prognostic period T_{given} is more than or equal to the established period between neighboring diagnostics ($T_{given} \geq T_{betw.} + T_{diag}$).

Here, $T_{betw.}$ is the time between the end of diagnostics and the beginning of the next diagnostics and T_{diag} is the diagnostics time.

For the given period T_{given}, the next statements are proposed for use, see in detail [18, 19, 35–37].

Under the condition of independence of considered characteristics, the probability of providing system integrity (probability of "success") is equal to

1. for variant 1

$$P_{(1)}\left(T_{given}\right) = 1 - \Omega_{occur} * \Omega_{activ}\left(T_{given}\right), \tag{1}$$

2. for variant 2

measure (a)

$$P_{(2)}\left(T_{given}\right) = N\left(\left(T_{betw} + T_{diag}\right)/T_{given}\right) P_{(1)}{}^{N}\left(T_{betw} + T_{diag}\right) + \left(T_{rmn}/T_{given}\right) P_{(1)}\left(T_{rmn}\right), \tag{2}$$

where $N = [T_{given}/(T_{betw.} + T_{diag.})]$ is the integer part, $T_{rmn} = T_{given} - N(T_{betw} + T_{diag})$;

measure (b)

$$P_{(2)}\left(T_{given}\right) = P_{(1)}{}^{N}\left(T_{betw} + T_{diag}\right) P_{(1)}\left(T_{rmn}\right) \tag{3}$$

The probability of success within given prognostic period $P_{(1)}(T_{given})$ is defined by (1).

The modification of this model allows to use different values of diagnostics and recovery time [35–37]; for formulas (1)–(3), recovery time is equal to diagnostics time.

All these models, supported by various versions of software tools, registered by Rospatent, may be applied and improved for solving quality and safety problems, connected with intellectual system presented as "black box" [18, 19, 38–44].

Summaries for the last model are as follows:

- The input for modeling include: frequency of the occurrences of potential threats (or mean time between the moments of the occurrences of potential threats which equals to 1/frequency); mean activation time of threats; mean recovery time; time between the end of diagnostics and the beginning of the next diagnostics; diagnostics time; and given prognostic period.

- The calculated results of modeling include: the probability of providing system integrity within given prognostic period (i.e., probability of "success"); and risk to lose integrity (i.e., probability of "failure") as addition to 1 for probability of "success."

3.2 Integration for complex structures on the level of probability distribution functions

If probability of providing system integrity within given prognostic period for all points T_{given} from 0 to ∞ are computed, it means a trajectory of the PDF depending on characteristics of threats, periodic diagnostics, and recovery. And, the building of PDF is the real base to predict probabilistic metrics for given time T_{given}. In analogy with reliability, it is important to know a mean time between neighboring losses of integrity (MTBLI) like mean time between failures in reliability (MTBF), but in application to concepts of quality, safety, etc.

For complex systems with serial or parallel structure, new models with known PDF can be developed by the next method [17–21]. Let us consider the elementary structure from two independent parallel or serial elements (**Figures 3** and **4**). Let the PDF of time between losses of i-th element integrity be $B_i(t)$, i.e., $B_i(t) = P(\tau_i \le t)$, then:

1. time between losses of integrity for system combined from serial connected-independent elements is equal to minimum from two times τ_i: failure of first or second elements (it means the system goes into a state of lost integrity when either first, or second element integrity is lost). For this case, the PDF of time between losses of system integrity is defined by the expression

$$B(t) = P(\min(\tau_1, \tau_2) \le t) = 1 - P(\min(\tau_1, \tau_2) > t) = 1 - P(\tau_1 > t)P(\tau_2 > t) = 1 - [1 - B_1(t)][1 - B_2(t)] \quad (4)$$

2. time between losses of integrity for system combined from parallel connected independent elements (hot reservation) is equal to a maximum from two times τ_i: failure of first and second elements (it means the system goes into a state of lost integrity when both first and second elements have lost integrity). For this case, the PDF of time between losses of system integrity is defined by the expression

$$B(t) = P(\max(\tau_1, \tau_2) \le t) = P(\tau_1 \le t)P(\tau_2 \le t) = B_1(t)B_2(t) \quad (5)$$

By applying recurrently expressions (4) and (5), it is possible to build PDF of time between losses of integrity for any complex system with parallel and/or serial structure.

As summary, the calculated results of modeling are: PDF of time between losses of integrity for system and each compound subsystems and elements; mean time

between losses of integrity for system and each compound subsystems and elements (MTBLI as analog of MTBF).

For example, integrated complex system, combined from intellectual structures for modeling interested system including AIS (**Figure 7**), can be analyzed by formulas (1)–(5) and probabilistic models described above and allowing to form PDF by (4) and (5). The correct operation of this complex system during the given period means: during this period both first and second subsystems (left and right) should operate correctly according their destinations, i.e., integrity of complex system is provided if "AND" integrity of first system left "AND" integrity of second system right are provided.

All these ideas of analytical modeling operation processes are supported by the software tools [18, 19, 21, 23, 38–44].

What about new knowledge by using the proposed methods and models for cognitive solving of problems 1 and 2 of the chapter? A use of these methods and models on different stages of AIS life cycle (concept, development, utilization, support stages) allows to produce cognitive answers for the following questions:

- What about different risks to lose integrity in operation?
- What about the justified norms for values of monitored parameters?
- What requirements should be specified to MTBLI and to repair time for different possible scenarios of operation?
- Which information operation processes should be duplicated and how?

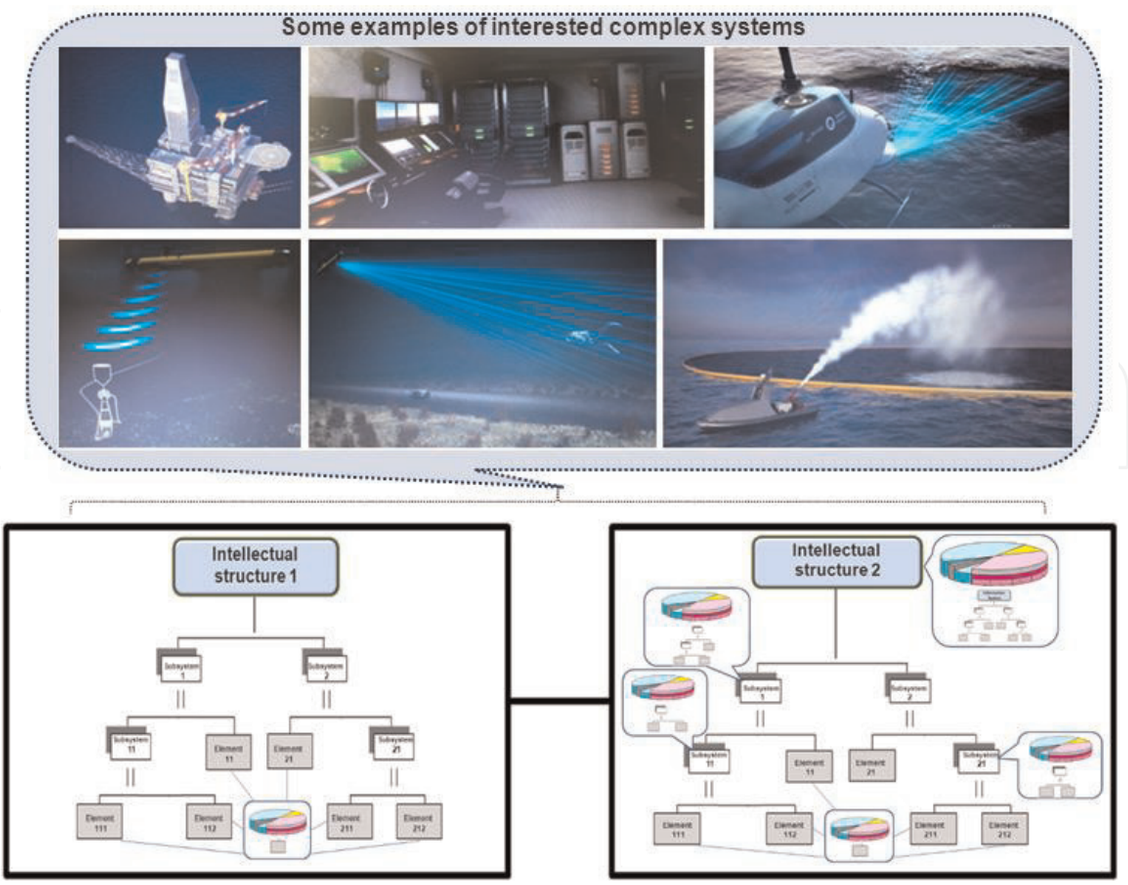

Figure 7.
An integrated complex system of two serial subsystems (abstraction).

- What processing devices and technologies should be used to achieve the necessary level of system integrity (quality, safety, etc.)?
- What is the system tolerance to data flows changing?
- What data flows and functional tasks may be the main causes of "bottlenecks"?
- What data gathering technologies and engineering solutions can guarantee the completeness and actuality of used information?
- What information verification and validation control should be used?
- What qualification requirements should be for the users of AIS (from the AIS effectiveness and efficiency points of view)?
- How dangerous are scenarios of environment influences and what protective technologies will provide the required security?
- How the use of integrity diagnostics and security monitoring will worsen time-probabilistic characteristics of system?
- What protection system effectiveness should be to prevent an unauthorized access?
- What are the information security risks? etc.

The rationale answers allow to improve and accumulate knowledge concerning AIS.

The proposed methods and models provide the next approach for cognitive solving problems 1 and 2.

4. Problem 1 of planning the possibilities of functions performance on the base of monitored information about events and conditions

It is supposed that the terms "success" and accordingly "failure" are defined in terms of admissible condition of interested system to operate for the purpose.

Note. For example, for each parameter of equipment, the ranges of possible values of conditions may be estimated as "Working range inside of norm" and "Out of working range, but inside of norm" ("success") or "Abnormality" ("failure"), interpreted similarly light signals—"green," "yellow," and "red." For this definition, a "failure" of equipment operation characterizes a threat to lose system norm integrity after danger influence (on the logic level this range "Abnormality" may be interpreted analytically as failure, fault, losses of quality, or safety etc.). But the definition may be another: for example, a "failure" may be defined as incident or accident. For this definition, short-time being in the range "Abnormality" is not "failure," because the incident or accident may not happen.

There are four steps proposed for cognitive solving of problem 1 of planning the possibilities of functions performance on the base of monitored information about events and conditions; see **Figure 8**.

Step 1. The complete set of variants for actions, and for each variant—a set of components is defined. Each use case may be characterized by an expected gain in comparable conventional units. If the objective value of gain cannot be defined,

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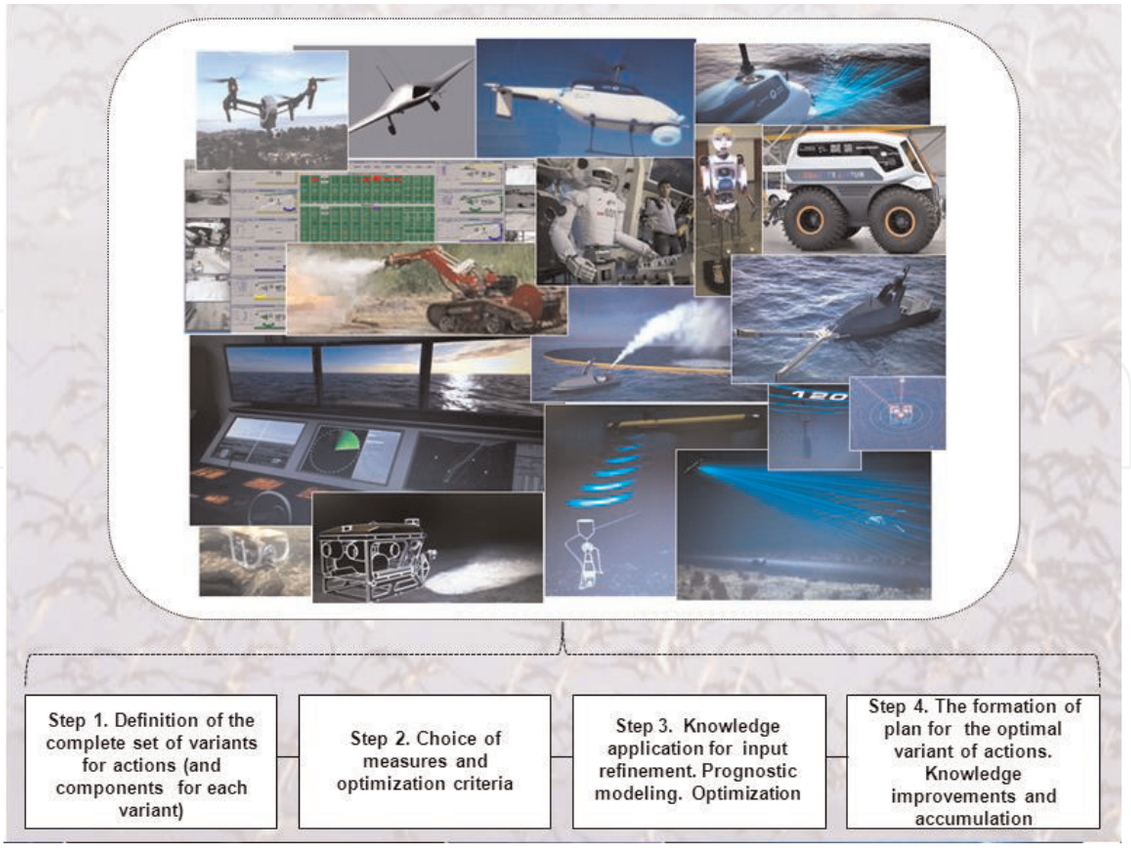

Figure 8.
Steps for cognitive solving of problem 1.

expert value of expected level of "success" for each variant may be established, for example, on a dimensionless scale from 0 to 100 (0—"no gain", i.e., "failure"; 100—"the maximal gain," i.e., complete "success"). After learning by knowledge base, self-improving AIS uses input and the corresponding results of probabilistic modeling in a form of the solution of previously specific encountered problem 1.

Knowledge base (K-base) is defined as a database that contains inference rules and information about human experience and expertise in a domain (ISO/IEC 2382-1:1993).

Step 2. The measures and optimization criteria are chosen. As criteria can be accepted:

- Maximum of gain as a result of the functions performance under the given conditions and limitations on the acceptable risk of failure and/or other limitations

- Maximum probability of "success" or minimum risk of "failure" under limitations

Step 3. The accumulated knowledge is used to refine the input for modeling. A quality of used information is estimated by models above considering limitations from **Table 1**. Using the model for each variant, the probabilistic measures are calculated for given prognostic period (see proposed models above and Step 1). From a set of possible variants, the optimal one is chosen, according to Step 2 criterion.

Note. For example, there are proposed the next general formal statements of problems for system optimization:

1. on the stages of system concept, development, production, and support: system parameters, software, technical, and management measures (Q) are the most rationale for the given period if on them the minimum of expenses ($Z_{dev.}$) for creation of system is reached

$$Z_{dev.}\ (Q_{rational}) = \min_{Q} Z_{dev.}\ (Q), \tag{6}$$

at limitations on probability of an admissible level of quality $P_{quality}\ (Q) \geq P_{adm.}$ and expenses for operation $C_{oper.}\ (Q) \leq C_{adm.}$ and under other development, operation, or maintenance conditions;

2. on utilization stage: system parameters, software, technical, and management measures (Q) are the most rational for the given period of operation if on them the maximum of probability of correct system operation is reached

$$P_{quality}\ (Q_{rational}) = \max_{Q} P_{quality}\ (Q), \tag{7}$$

at limitations on probability of an admissible level of quality $P_{quality}\ (Q) \geq P_{adm.}$ and expenses for operation $C_{oper.}\ (Q) \leq C_{adm.}$ and under other operation or maintenance conditions.

For limitation on $P_{quality}\ (Q)$ K-base is used; for example, see **Table 1**. For calculation probabilistic measures for given prognostic period, the proposed models are used.

These statements (6), (7) may be transformed into the problems of expenses or risk minimization in different limitations. There may be a combination of these formal statements in system's life cycle.

Step 4. A plan for the optimal variant of actions (defined in Step 3) is formed. To support the efficiency and/or effectiveness of the functions, the achievable gain calculated at Step 3 is recorded. New knowledge is improved, accumulated, and systematized in K-base by comparing it with reality (for example, by a specific method considering AIS capabilities for self-improving).

Note. A solution that meets all conditions may not exist. In this case, there is no optimal variant of planning the possibilities of functions performance on the base of monitored information. Additional systems analysis, adjustment of the criteria, or limitations is required (see, for example, ISO/IEC/IEEE 15288).

5. Problem 2 of robot route optimization under limitations on risk of "failure" in conditions of uncertainties

For a robot, the concept of "failure" under uncertainty is defined as the "unsuccess" to achieve the goal within a given time. It is assumed that there are several possible routes to achieve the goal, and uncertainties may include both the conditions for robot operation (including random events in orientation, localization, and mapping in cooperation with drone for gathering actual data). The minimum risk of failure under the existing conditions and limitations is used as a criterion of optimization.

The next four steps are proposed for cognitive solving of problem 2 of robot route optimization under limitations on risk of "failure" in conditions of uncertainties, see **Figure 9**.

Step 1. The complete set of route variants to achieve the goal within the given time, and for each variant—a set of components is defined (redefined). Data characterizing every part of route for each of the variants are gathered (refined) for

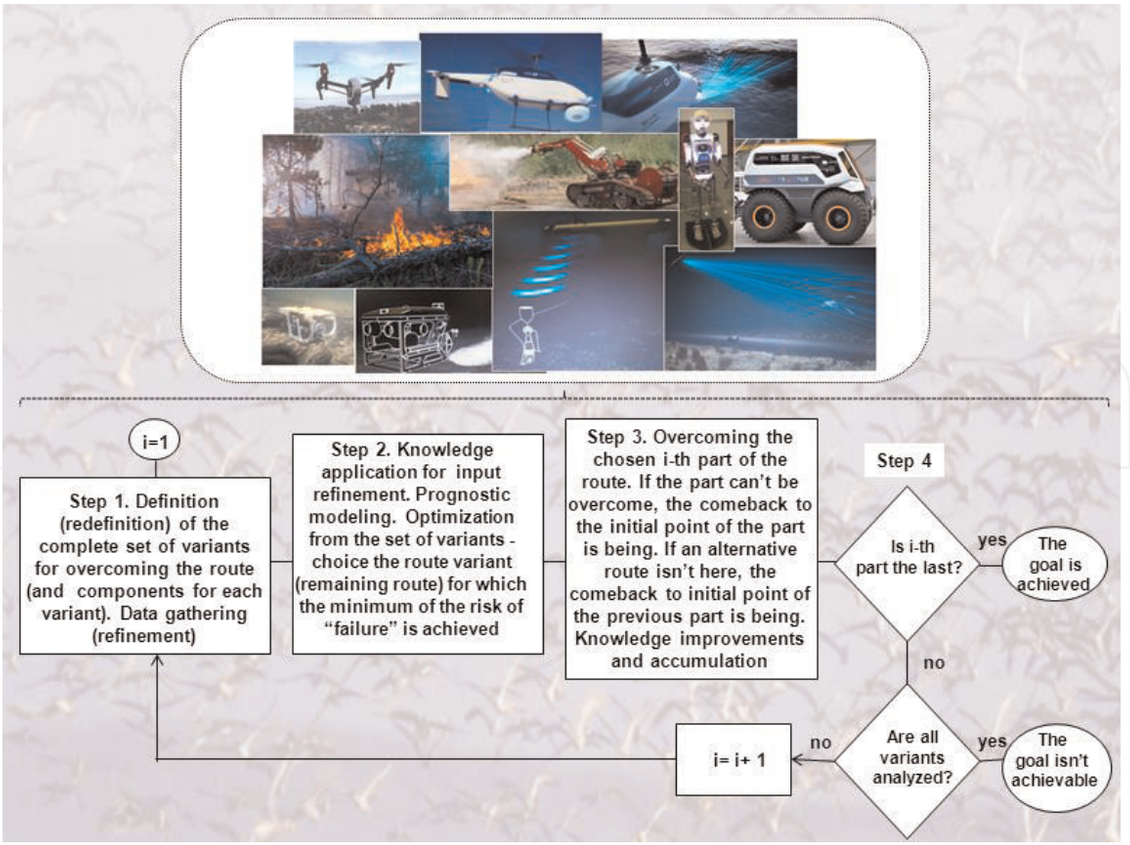

Figure 9.
Steps for cognitive solving of problem 2.

modeling. To do this, the robot can use data from various sources (for example, from air drones, intelligent buoys on the water or sensors under water, etc.). If necessary, possible damages are taken into account. For example, each use case may be characterized by an expected damage in comparable conventional units. If the objective value of a damage cannot be defined, expert value of expected level of "failure" for each variant may be established, for example, on a dimensionless scale from 0 to 100 (0—"no damages", i.e., "success"; 100—"the maximal damage"). After learning by K-base, self-improving AIS also uses input and the corresponding results of probabilistic modeling in a form of the solution of previously specific encountered problem 2.

The index i of the first part of the selected route is set to the initial value i = 1.

Step 2. The accumulated knowledge is used to refine the input for prognostic modeling. A quality of used information is estimated by models above considering limitations from **Table 1**. Using probabilistic model, a calculation of the probability of failure is carried out for each variant. From the set of remaining route variants, the optimal one is chosen (for it is the minimum probability of failure that is achieved).

Step 3. The robot overcomes the i-th part of the selected route. If the part cannot be overcome successfully according to probabilistic modeling and/or actual data, the comeback to the initial point of the part is being. If an alternative route is not here, the comeback to initial point of the previous part is being. The input for modeling every part of possible route for each of the variants is updated. New knowledge is improved, accumulated, and systematized in K-base by comparing it with reality (using a specific method considering AIS capabilities for self-improving).

Step 4. If, after overcoming the i-th part, the robot arrived at the intended point of route (i.e., the last part of the route is overcome and the goal is achieved), then the solution of task 2 for optimizing the route is complete. If the robot has not yet arrived at the intended point (i.e., the last part of the route is not overcome), then

the complete set of different route variants for achieving the goal is redefined (similar to step 1). The input for modeling every part of possible route for each of the variants is updated. i = i + 1. Then, Steps 2–4 are repeated until the last part of the route is overcome on the set of possible variants (i.e., it means the goal is achieved and problem 2 is solved).

If the set of possible options is exhausted and the goal is not achieved, it is concluded that the goal is unattainable with the risk of "failure" less than the acceptable risk (i.e., it means an impossibility of solving problem 2 in the defined conditions).

Thus, for optimizing robot route in space (i.e., for the "successful" solution of problem 2) in real time, information gathering, probabilistic predictions for possible route variants, their comparison, the choice of the best variant, the implementation of further actions, the improvement, accumulation, systematization, and use of knowledge are being, see **Figure 9**.

Note. The proposed methods of solving problems 1 and 2 are essentially identical approaches based on the use of the same probabilistic models (Section 3). The only difference is that for the system planning the possibilities of functions performance (problem 1), the concept of "success" is used; and for the robot route optimization under limitations on risk of "failure" (problem 2), the concept of "failure," which is defined as the lack of "success," is used.

6. Examples

6.1 Example 1 of system planning the possibilities of functions performance in space by using robot-manipulators

Here, problem 1 (of planning the possibilities of functions performance) is solved by the proposed approach on the base of information gathered from different similar projects, accumulated and systematized in K-base including history. Applicability of the proposed probabilistic methods and models on development stage is demonstrated to improve some of the existing capabilities of robot-manipulator. It is required to predict the possible period of robot-manipulator use in space. When planning the possibilities of performing the functions of the cosmonaut-operator, two variants were compared: first variant–without a use of AIS; second–by using some AIS for supporting decision-making and monitoring the status of the operator's console, power units, central controller, and control handle for manipulator means.

A robot-manipulator as a system is composed on subsystems: an operator's console, a power unit, a central controller with a handle of control and manipulator means. There are supposed that a frequency of anomalies is in average 1 times a year, mean activation time from anomaly occurrence to failure is about 3 days. Time between the end of diagnostics and the beginning of the next diagnostics is about 2 months, and the recovery time is about 2 days.

System decomposition is presented on **Figure 10**. We do STEPS 1–4 (**Figure 8**) and use formulas (1)–(3) for solving the problem for complex structure composed by elementary variants decompositions presented on **Figures 3** and **4**. Here, probability of "success" (P) covers the following:

- Probability of reliable operation of robot-manipulator as a system
- Probability of reliable operation of every subsystem

Risks of "failure" (R) means addition to 1 for probability of "success."

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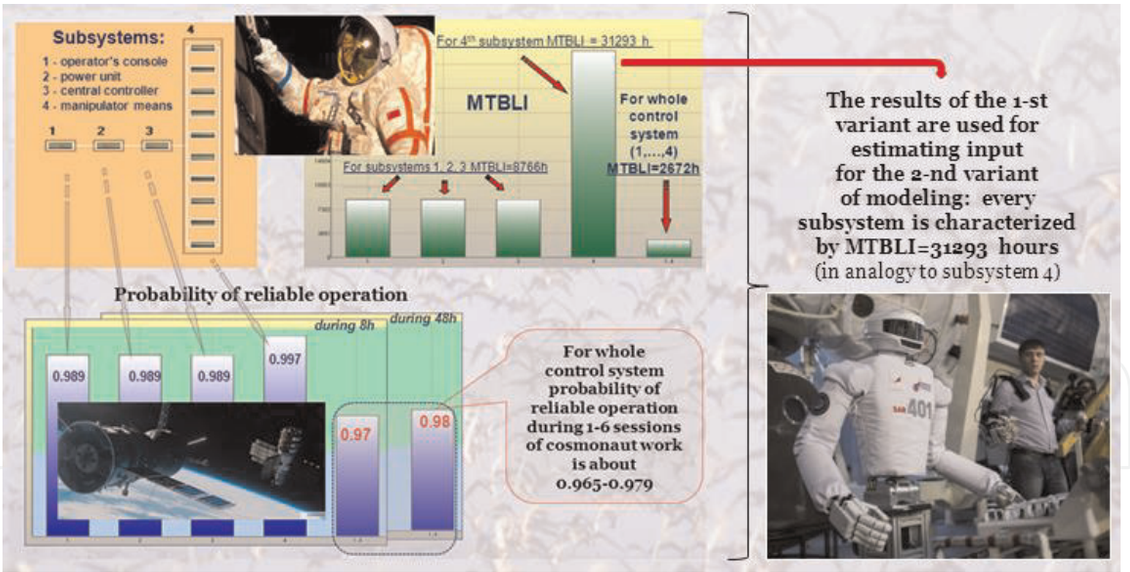

Figure 10.
Results of probabilistic modeling robot-manipulator operation.

Results of modeling the first variant of project have shown the following (**Figure 10**): for operator's console (first subsystem), power unit (second subsystem) and central controller with a handle of control (third subsystem) MTBLI = 8766 h, for manipulator means (including a hinge of roving of key, a hinge of shoulder, a hinge of roving of elbow, a hinge of elbow, a hinge of roving of brush, a hinge of brushes, a hinge of brush rotation, a device for grasping, videocamera—united as subsystem 4, which can operate if one of these means is available) MTBLI = 31,293 h, for all complex 1,...,4 MTBLI = 2672 h; probability of reliable operation of complex 1,...,4 during 8 h is equal to 0.979; probability of reliable operation of complex 1,...,4 during 48 h is equal to 0.965.

The maximum probability of "success" and minimum risk of "failure" under limitations on the successful functions performance are used as a criterion.

The results of first variant are used for estimating input for the second variant of modeling: every subsystem for second variant (for subsystems equipped by AIS) is characterized by MTBLI = 31,293 h in analogy to the subsystem 4 of first variant. Owing to AIS, the frequency of anomalies is about 0.28 year^{-1} (it is equal to 1/MTBLI), but the conditions of anomalies activation time are more strong: the mean time is 30 min. The time between the end of diagnostics and the beginning of the next diagnostics is 1 month, and the recovery time is about 1 day.

What about the risks of "failure" during period from 0.05 to 2 years?

Analysis of modeling results proves: risks are very high despite the use of AIS with the described characteristics, see **Figure 11**.

For a robot-manipulator used in space, new knowledge for accumulating and improving K-base is as follows:

1. The input (used for modeling) characterizes inadmissible conditions for functions performance by robot-manipulator.

2. The probability of "success" on level 0.98 or risk of "failure" on level 0.02 during six sessions of cosmonaut work is inadmissible for reliable robot-manipulator operation more than 1–2 weeks in space.

3. For a robot-manipulator used in space, the level 31,293 h of MTBLI is inadmissible level for every compound subsystem equipped by considered AIS.

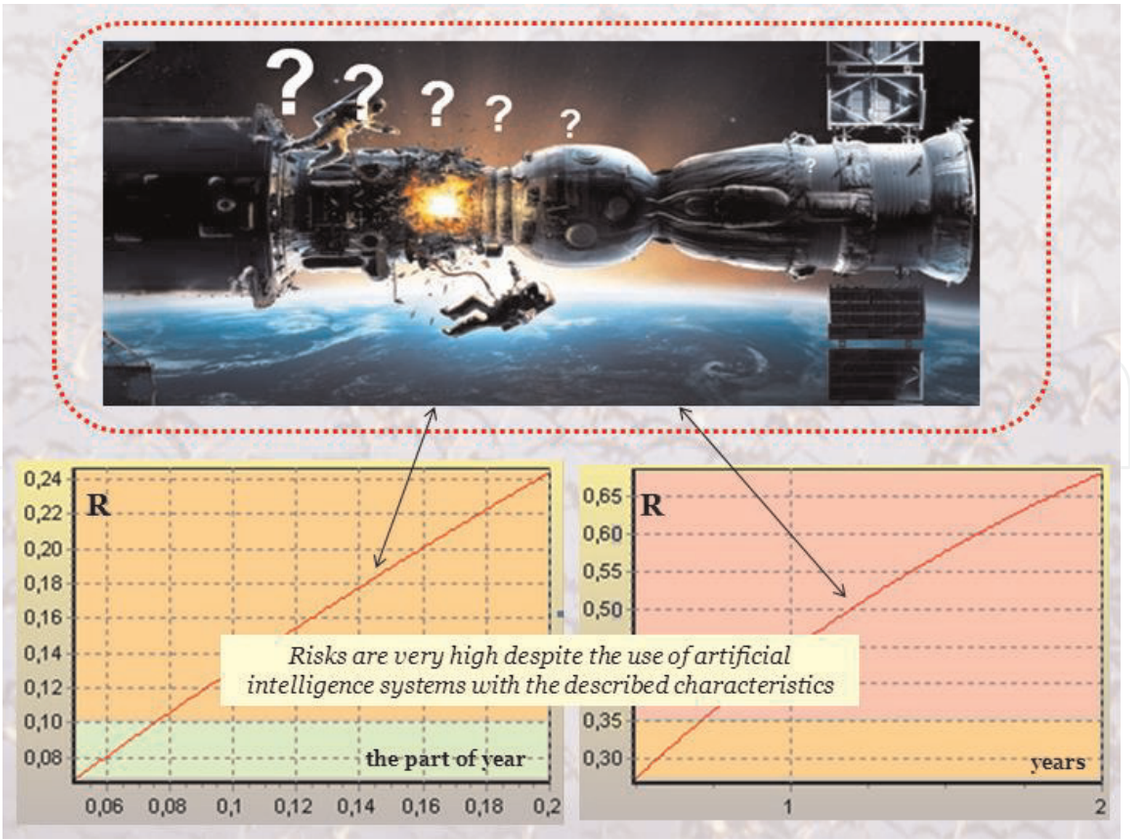

Figure 11.
Risks of "failures" depending on the prognostic period of use (from 0.05 to 2 years).

4. Analyzed project of robot-manipulator operation effectiveness can be added to K-base history as precedent of "unsuccess."

5. For analyzed project, new research for decreasing risks with the proof of its efficiency on the basis of modeling is strongly required after improving characteristics for every subsystem of robot-manipulator.

6.2 Example of forming input for probabilistic modeling from monitored data

In practice, many devices proper to intelligent manufacturing are sources of data monitored. This example explains how monitored data can be tailored in AIS for probabilistic modeling to solve both problems 1 and 2.

The approach to form specific input for modeling is demonstrated on example of mean time T_{occur} for PDF $\Omega_{occur}(t)$ and mean time T_{activ} for PDF $\Omega_{activ}(t)$ from random values $\tau_{occurrence}$ and $\tau_{activation}$ (**Figures 6** and **12**).

The elementary ranges for monitored parameters from quality or safety point of view should be set. For each parameter, the ranges of possible values of conditions are set: "Working range inside of norm," "Out of working range, but inside of norm," and "Abnormality," The condition "Abnormality" characterizes a threat to lose system integrity after danger influence (on the logic level this range "Abnormality" may be interpreted analytically as failure, fault, losses of quality, or safety etc.). The construction on **Figure 12** allows to extract data for probabilistic modeling: time between moments of the occurrences of dangers (potential threats), activation time of occurred dangers, and recovery time.

For example, from **Figure 12**:

Mean time between moments of the occurrences of dangers (potential threats)

$T_{occur} = (\tau_{occurrence\ 1} + \tau_{occurrence\ 2})/2$

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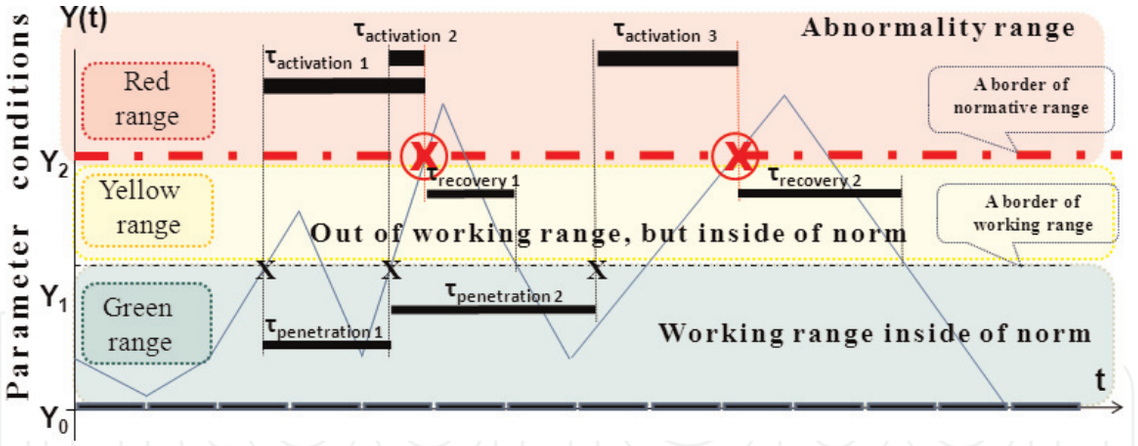

Figure 12.
The universal elementary ranges for monitored parameters.

Mean activation time $T_{activ} = (\tau_{activation\ 1} + \tau_{activation\ 2} + \tau_{activation\ 3})/3$
Mean recovery time for $T_{recovery} = (\tau_{recovery\ 1} + \tau_{recovery\ 2})/2$

This example is auxiliary to understand some sources of input for the proposed models (Sections 3–5) used for the next examples.

6.3 Example of system planning the possibilities of functions performance by AIS for a coal company

Applicability of the proposed probabilistic methods and models is demonstrated to improve some of the existing capabilities of AIS for a coal company. This subsection contains an explanation how problem 1 (of planning the possibilities of functions performance) may be solved for intelligent manufacturing by the proposed approach on the base of data monitored. This demonstrates AIS possibilities for a coal company on its operation stage.

Let a coal company (as system) is decomposed on 9 subsystems for studying efficiency. Of course, every subsystem also may be considered as complex system, for example, see **Figure 7**. Components from 1 to 6 united by multifunctional safety system of the mine, component 7 is associated with the washing factory, component 8 is associated with transport, and component 9 with port, see **Figure 13**: 1—the control system of ventilation and local airing equipment; 2—the system of modular decontamination equipment and compressed air control; 3—the system of air and gas control; 4—the system of air dust content control; 5—the system of dynamic phenomena control and forecasting; 6—the system of fire-prevention protection; 7—the safety system of washing factory; 8—the safety system for transport; and 9—the safety system of port. Information is monitored from different sources, accumulated in a database of dispatcher intelligence center, processed, and systematized (including systematization described in Example 2 to get input for modeling).

For planning possibilities of functions performance by AIS in this example, the probabilistic modeling is being to answer the next two questions:

- How every responsible worker can know a residual time before the next parameters abnormalities?

- What risks to lose system integrity may be for a year, for 10 and 20 years if all subsystems are supported by AISs that transform all system components to the level which is proper to skilled workers (Optimistic view on dangerous coal intelligent manufacturing)?

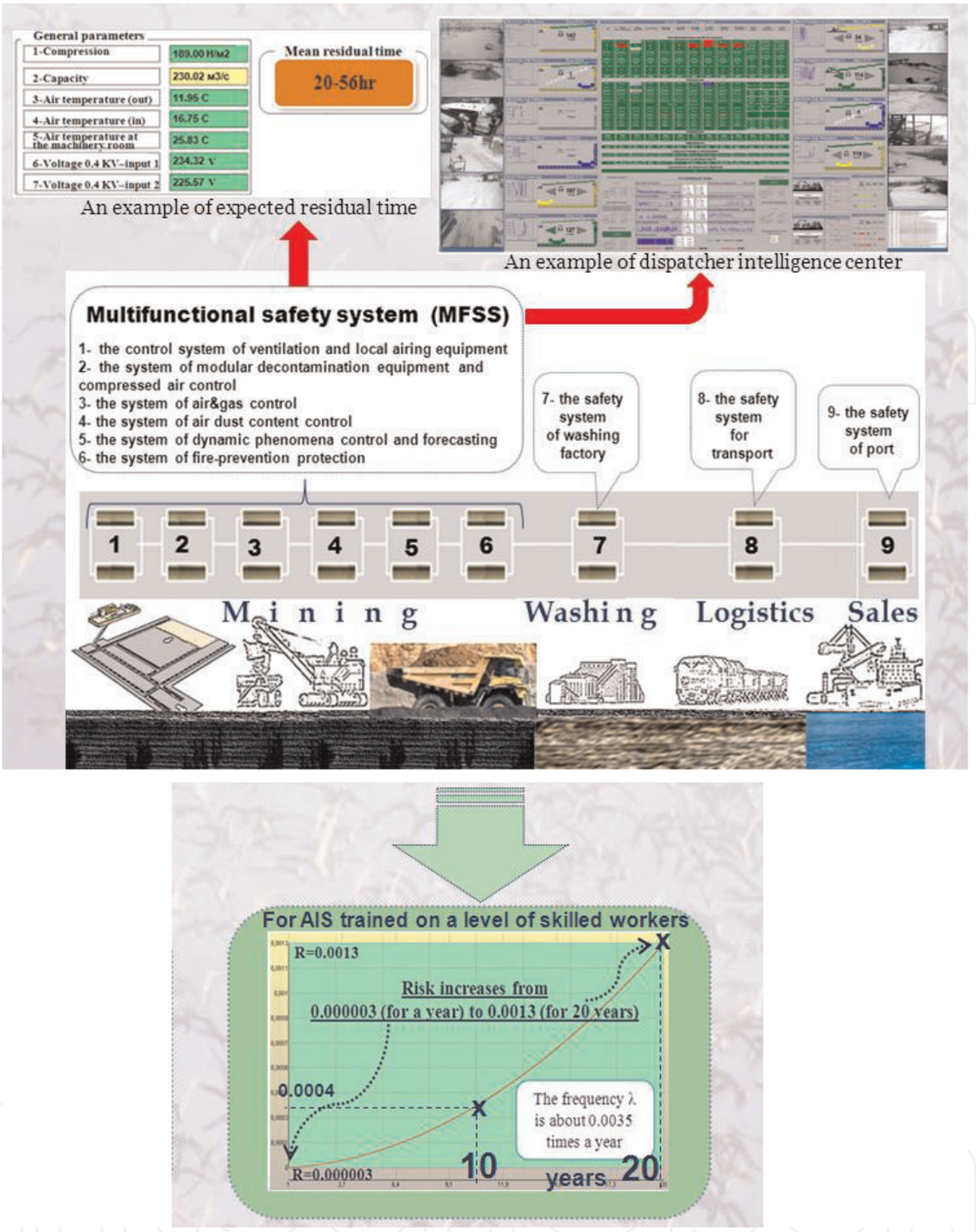

Figure 13.
An example of a coal company with AISs that transformed all system components to the level which is proper to skilled workers.

To answer the first question, the ranges of possible values of conditions are established: "Working range inside of norm," "Out of working range, but inside of norm," and "Abnormality" for each separate critical parameter of equipment. It is interpreted similarly by light signals—"green," "yellow," and "red," as it is reflected on **Figure 12**. Some examples of parameters may include compression, capacity, air temperature (out, in, at machinery room), voltage, etc. The information from Example 6.2 and additional time data of enterprise procedures are used by AIS as input for using formulas (1) and (3) and Steps 1–4 (from **Figure 8**) in real time of company operation activity. Here, risks to lose the system integrity during the given period T_{given} means risks to be at least once in state "Abnormality" within T_{given}. The functions of modeling is performed on special servers (centralized or mapped);

see details in [27, 36]. If virtual risks are computed by formulas (1) and (3) for all points T_{given} from 0 to ∞, the calculated values form a trajectory of the PDF. The mathematical expectation of this PDF means the mean residual time to the next state "Abnormality." It defines MTBLI from this PDF. This output of probabilistic modeling can be transmitted to interested workers. Requirements to AIS operation quality are: quality measures of used information by AIS should meet admissible level recommended in **Table 1**.

Thus, the answer on the first question "How responsible worker can know a residual time before the next parameters abnormalities?" is: the calculated mean residual time to the next state "Abnormality" (MTBLI for "red" range on **Figure 12**) can be transmitted in real time to responsible worker immediately after parameter value cross the border from "Working range inside of norm," "Out of working range, but inside of norm" (from "green" to "yellow" range on **Figures 12** and **13**). It is possible as a result of implementation of the proposed approach—see example of implementation in [27, 36].

To answer the second question, let the next input be formed from data monitored.

Let for every system component, a frequency of occurrence of the latent or obvious threats is equal to once a month and the mean activation time of threats is about 1 day. The system diagnostics are used once for work shift 8 h, a mean duration of the system control is about 10 min, and the mean recovery time of the lost integrity of object equals to 1 day. The workers (they may be robotics, skilled mechanics, technologists, engineers, etc.) are supported by capabilities of an AIS and a remote monitoring systems allowing estimating in real time the mean residual time before the next parameters abnormalities considering the results of probabilistic modeling. Formally they operate as parallel elements with hot reservation (structure on **Figure 4**, right). Owing to AIS support workers are capable to revealing signs of a critical situation after their occurrence. Workers can commit errors on the average not more often once a year (it is proper to skilled workers).

To answer the question we do Steps 1–4 (from **Figure 8**) and use formulas (1)–(3) for solving the problem for complex structure, see **Figure 13**. Here, risks to lose system integrity means risks of "failure" for every subsystem which can be detailed to the level of every separate critical parameter of equipment.

The fragments of built PDF on **Figure 13** show: risk of "failure" increases from 0.000003 for a year to 0.0004 for 10 years and to 0.0013 for 20 years. Thus, the mean time between neighboring losses of integrity (MTBLI) equals to 283 years.

These are some estimations for example assumptions.

Thus, the answer on second question "What risks to lose system integrity may be for a year, for 10 and 20 years if all subsystems are supported by AISs that transform all system components to the level which is proper to skilled workers?" is: risks to lose system integrity may be 0.000003 for a year, 0.0004 for 10 years and 0.0013 for 20 years, herewith (MTBLI) is equal to 283 years. These are the Optimistic estimations for dangerous coal intelligent manufacturing that make sense to take over a desired level of AIS operation effectiveness.

New knowledge for accumulating and improving K-base is as follows:

1. The input (used for modeling) characterizes admissible conditions for functions performance by AIS for a coal company.

2. The probability of "success" on levels 0.99997 for a year, 0.9996 for 10 years and 0.9987 for 20 years or risk of "failure" on levels 0.000003 for a year to 0.0004 for 10 years and 0.0013 for 20 years (with predicted risks levels for discovered "bottlenecks") are admissible.

3. Expected term in average 283 years and more is admissible systemic aim for providing safe company operation.

4. Analyzed project of AISs operation effectiveness (that transform all system components to the level which is proper to skilled workers of coal company) can be added to K-base history as a precedent of "success."

6.4 Example of system planning the possibilities of functions performance by AIS used for a security service of floating oil and gas platform

This subsection continues an explanation on how problem 1 (of planning the possibilities of functions performance) may be solved for intelligent manufacturing by the proposed approach on the base of data monitored. This demonstrates the

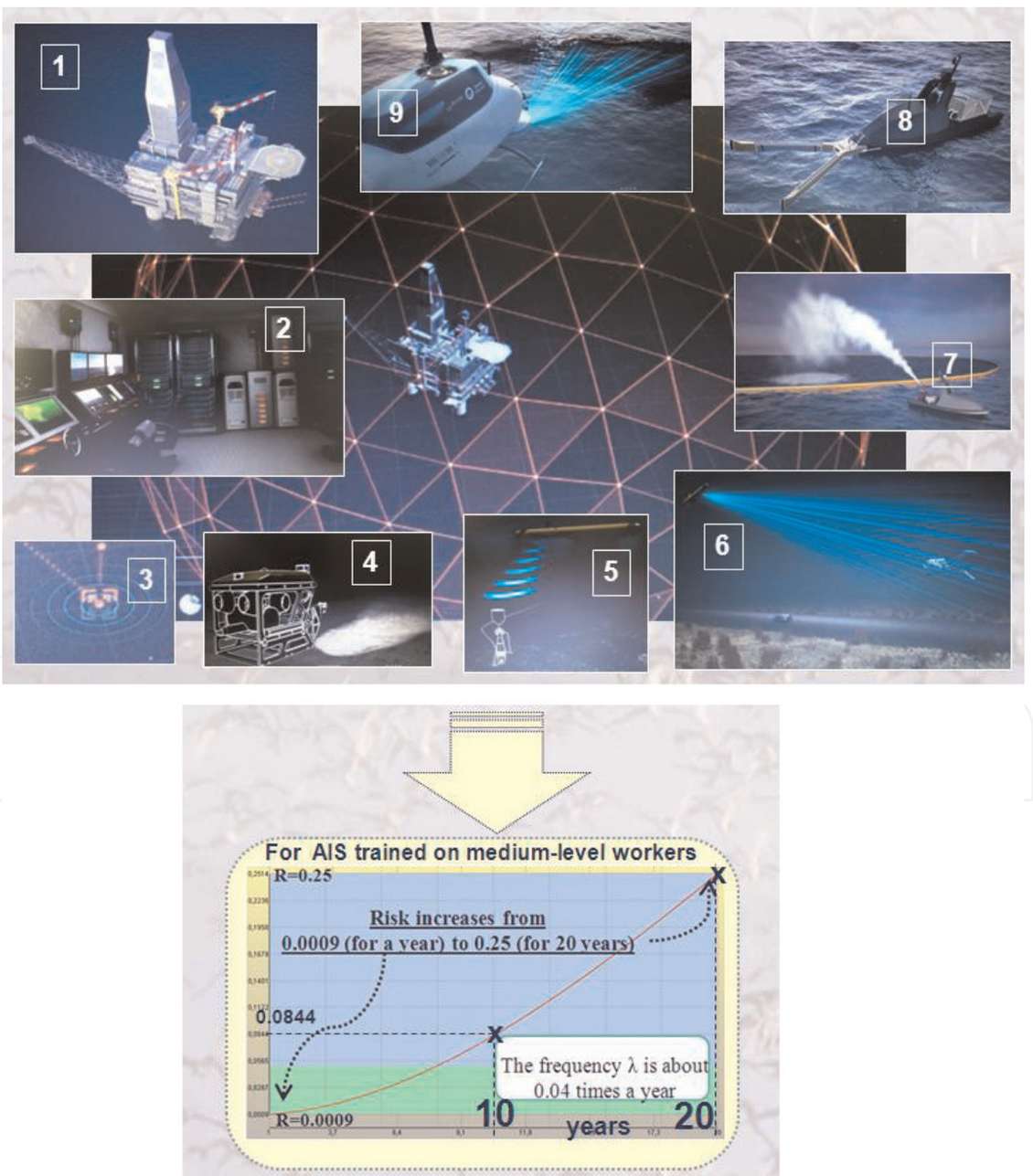

Figure 14.
An example of a floating oil and gas platform with AISs that transform all system components to the level which is proper to medium-level workers.

capabilities of AIS used for a security service of floating oil and gas platform on its operation stage. The difference from previous example is in more degree of uncertainties (because of high complexity) that allows to transform all system components to the level which is proper to medium-level workers of floating oil and gas platform. The same approach, structure, and formulas for probabilistic modeling are used.

Let a floating oil and gas platform is also decomposed on nine subsystems. Every subsystem is enumerated on **Figure 14**, and operates as parallel elements with hot reservation.

Components are: 1—a construction of platform; 2—an AIS on platform for robotics monitoring and control; 3—an underwater communication modem; 4—a remote controlled unmanned underwater robotic vehicle; 5—a sonar beacon; 6—an autonomous unmanned underwater robotic vehicle; 7—non-boarding robotic boat, a spray of the sorbent; 8—non-boarding robotic boat, a pollution collector; and 9—an unmanned aerial vehicle.

And let input for modeling is the same as in Example 6.3. Only one difference is because of complexity characteristics are proper to medium-level workers of floating oil and gas platform. For this example, it means workers and AIS can commit errors more often in comparison with skilled workers, for one element it is equal to 1 time a month instead of once a year.

For planning possibilities of functions performance by AIS in this example, the probabilistic modeling is being to answer the question:

What risks to lose system integrity may be for a year, for 10 and 20 years if all subsystems are supported by AISs that transform all system components to the level which is proper to medium-level workers (realistic view on dangerous oil and gas intelligent manufacturing)?

To answer the question, we do Steps 1–4 (from **Figure 8**) and use formulas (1)–(3) for solving the problem for complex structure, see structure on **Figure 13**. Here, risks to lose the system integrity mean risks of "failure" for every subsystem. The fragments of built PDF on **Figure 14** show: from 0.0009 for a year to 0.0844 for 10 years and 0.25 for 20 years. Thus, MTBLI equals to 24 years. It is 11.4 times less often against the results of Example 6.3.

These are some estimations for example assumptions.

Thus, the answer on question is: risks to lose system integrity may be 0.0009 for a year, 0.0844 for 10 years and 0.25 for 20 years; herewith, mean time between neighboring losses of integrity is equal to 24 years. These are the realistic estimations for dangerous oil and gas intelligent manufacturing.

New knowledge for accumulating and improving K-base is as follows:

1. The input (used for modeling) characterize possible complex conditions for functions performance by AIS used for a security service of floating oil and gas platform.

2. The probability of "success" on levels 0.9991 for a year, 0.9156 for 10 years and 0.75 for 20 years or risk of "failure" on levels 0.0009 for a year, 0.0844 for 10 years and 0.25 for 20 years (with possible consequences) and expected term in average 24 years as estimation of mean time between neighboring losses of integrity are realistic view on dangerous floating oil and gas platform intelligent manufacturing.

3. For analyzed project new research to improve characteristics for the security service of floating oil and gas platform for decreasing risks with the proof of its efficiency on the basis of modeling is required.

4. Analyzed project of AISs operation effectiveness (that transform all system components to the level which is proper to medium-level workers of floating oil and gas platform) can be added to K-base history as precedent.

6.5 Example of robot route optimization under limitations on risk of "failure" in conditions of uncertainties

Applicability of the proposed probabilistic methods and models is demonstrated to improve some of the existing capabilities of rescue robot for route optimization. This subsection contains an explanation on how problem 2 may be cognitively solved. Similar problems of specific robot route optimization from point A (Start) to point F (Finish) can arise on water, under water (**Figure 15**), in burning wood (**Figure 16**), in the conditions of a city or in mountains (**Figure 17**), and in other situations in conditions of uncertainties. Specific cases of uncertainties can be connected additionally with complex conditions of environment and necessity of robotics orientation, localization, and mapping that influences on input for the proposed probabilistic models.

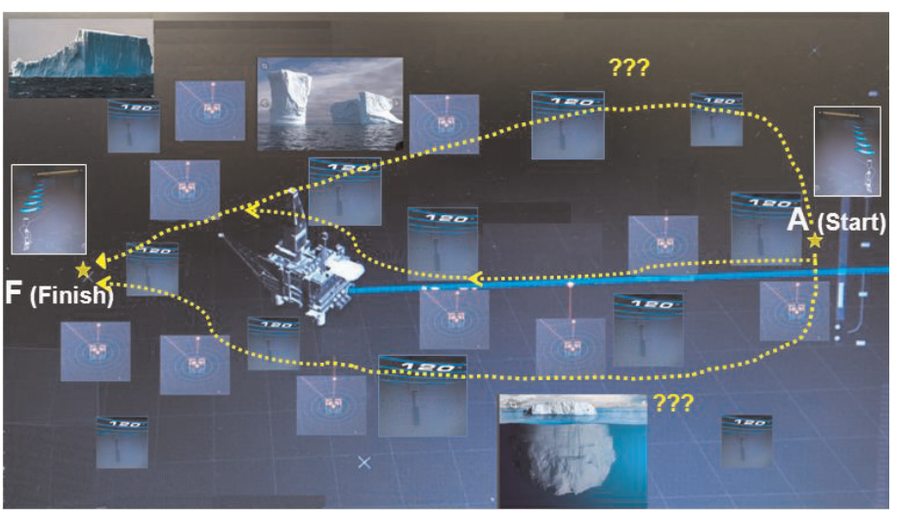

Figure 15.
A system view on situation for robot route from point A (Start) to point F (Finish) on water and under water.

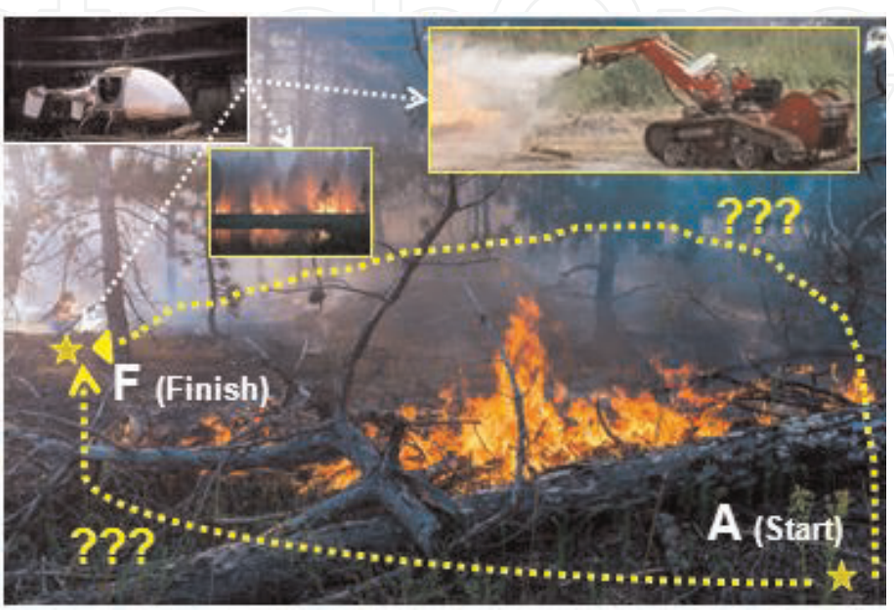

Figure 16.
A system view on situation for robot route from point A (Start) to point F (Finish) in burning wood.

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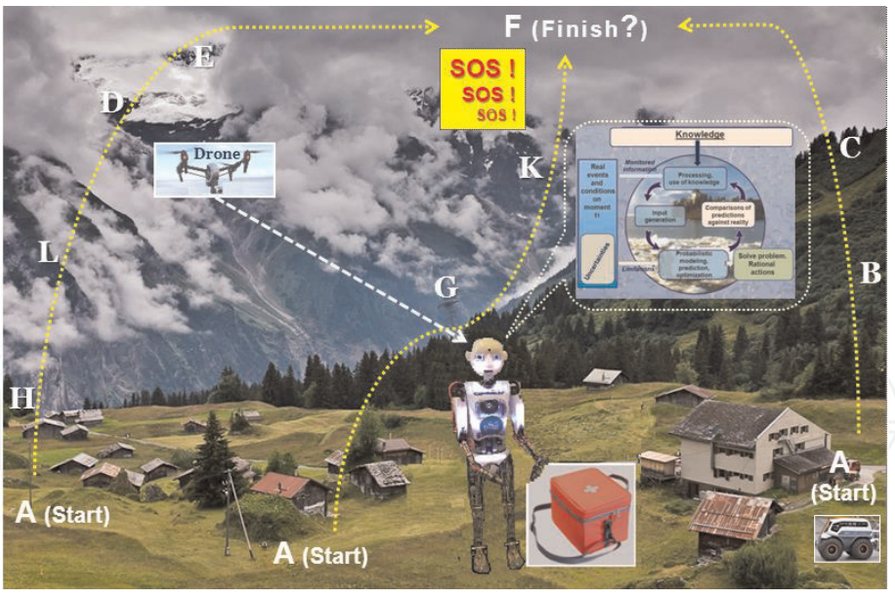

Figure 17.
A system view on situation for robot route from point A (Start) to point F (Finish) in mountains.

Here, we demonstrate the proposed approach by a simplified example of moving a special rescue robot from point A to the final point F of the route (from where the SOS signals from tourists are following). It is required to optimize the route of the robot in space under uncertainty of weather, complex snow conditions in mountains to achieve the goal in 2 h with an acceptable risk of failure less than 0.1 (i.e., a probability of success should be more than 0.9). Interaction with the drone-informant is supposed, see **Figure 17**.

The applications to cognitive solving the problem of robot route optimization are demonstrated by the next steps.

Step 1. The complete set of route variants to achieve the goal within about 2 h: first route is ABCF, second route AGKF, third route if AHLDEF, and fourth variant is a combination of routes 1–3. Points A, B, C, G, K, H, L, D, E, F mean that they may change the route (including return to the previous point). Respectively, it may be a refinement of the further route at these points. Robot speed allows to overcome any route in time.

For each variant, a set of system compared by modeling is defined: there are ABCF, AGKF, AHLDEF, and possible combinations. Inputs characterizing every part of route for each of the variants are formed by K-base and gathered data from drone-informant:

- Frequencies of the occurrences of potential threats are for route ABCF $\sigma = 1$ time at 10 h, AGKF $\sigma = 1.5$ times at 10 h, AHLDEF $\sigma = 2$ times at 10 h (since 8.00 a.m. to 8.00 p.m.)

- Mean activation time of threats $T_{activ} = 30$ min

- Time between the end of diagnostics and the beginning of the next diagnostics of robot availability $T_{betw.} = 2$ min

- Diagnostics time of robot availability $T_{diag} = 30$ s

- Recovery time of robot availability = 10 min (for modified model [42–44])

- Given prognostic period $T_{given} = 2$ h

i = 1.

Step 2 (i = 1). Using probabilistic model, a calculation of the probability of failure is carried out for each variant. From the set of variants ABCF, AGKF, and AHLDEF, the shorter variant ABCF for which risk is equal to 0.034 is chosen (for the route AGKF risk = 0.051, for route AHLDEF risk = 0.067), see **Figure 18**. The relevant data from the drone about the forecasted conditions and the weather on the part CF to 8.30 a.m. are taken into account.

Step 3 (i = 1). The robot overcomes the part AB of route. For the new initial point B, the input for modeling every part of possible route is updated in real time for routes BCF, BGKF, and BGHLDEF.

Step 4 (i = 1). The robot has not yet arrived at the intended point F (i.e., the last part of the route is not overcome).

i = i + 1 = 2.

Step 2 (i = 2 for variants BCF, BGKF, and BGHLDEF). Input for modeling is not changed. Risks are the same. From the route variants BCF, BGKF, and BGHLDEF, the shorter one BCF (with minimal risk) is chosen.

Step 3 (i = 2 for variant BCDEF). The robot overcomes the part BC. For the new initial point C, the input for modeling every part of possible route is updated in real time: bad weather on the CF part does not allow further movement. And weather improvements in the next 2 h are not expected. Part CF is impassable. The come-back to the initial point B of the part is being.

Step 2 (i = 2 for two remaining variants). From variants BGKF and BGHLDEF, the shorter one BGKF (with minimal risk 0.051) is chosen.

Step 3 (i = 2 for variant BGKF). The robot overcomes the part BG. For the new initial point G, the input for modeling every part of possible route is updated in real time: according drone from 9.00 a.m. on parts GK and KF the imminent avalanche are detected. The accumulated knowledge is used to clarify the input for modeling, namely: the frequency threats in the part GKF increases from 1.5 to 2.5 times at 10 h. Using a probabilistic model for each variant, a recalculation of the risk of failure is carried out. Of the variants GKF and GHLDEF, the variant GHLDEF is chosen (risk is equal to 0.067, for the route GKF risk equals 0.083).

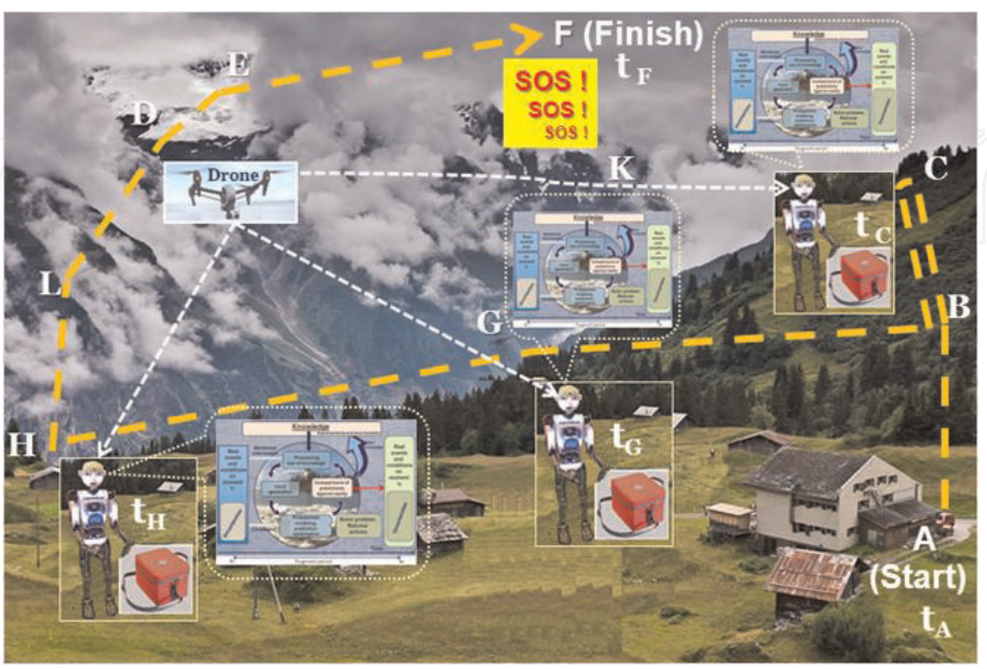

Figure 18.
The risk of "failure" in dependence on prognostic period during the robot route from point A (Start) to point F (Finish).

Step 4. After overcoming the part GHLDEF, the robot arrived at the intended point F of route in time.

Thus, the way ABCBGHLDEF is the result of optimization. The robot purpose was achieved owing to preventive measures which were defined by using risk control on the way (with probability of "success" more than 0.9).

New knowledge for accumulating and improving K-base is as follows:

1. The input (used for modeling) characterizes possible complex conditions for rescue robot route optimization under limitations on risk of "failure" in conditions of uncertainties. In particular, the information updates every 2 min for robot route optimization under limitations on risk of "failure" less than 0.1 is admissible for considered situation.

2. The acceptable risk 0.1 is justified; the predicted risks for all variants of the routes did not exceed 0.1.

3. Analyzed project can be added to K-base history as precedent.

7. Conclusion

The proposed approach to build and implement the probabilistic methods and models is demonstrated by application to cognitive solving:

- The problem of planning the possibilities of functions performance on the base of monitored information about events and conditions

- The problem of robot route optimization under limitations on risk of "failure" in conditions of uncertainties

There is proposed to carry out probabilistic prediction of critical processes in time so that not only to act according to the prediction, but also to compare predictions against their coincidence to the subsequent realities.

The described analytical solutions are demonstrated by practical examples such as:

System planning the possibilities of functions performance in space by using robot-manipulators, by AIS for a coal company and for a floating oil and gas platform

Forming input for probabilistic modeling from monitored data

Robot route optimization under limitations on risk of "failure" in conditions of uncertainties

A cognitive solving of the chosen problems consists in improvements, accumulation, analysis, and use of appearing knowledge.

Appendix

Proofs for formulas (1)–(3)

According to the proof of formula (1): because between diagnostics system is not protected from threats an influence (a loss of integrity) will take place only after danger occurrence and activation during given time before the next diagnostic (**Figure 6**). A risk to lose integrity (i.e., probability of "failure") is equal to

$\Omega_{penetr}{}^{*}\Omega_{activ}(T_{req})$ because these PDF are independent. The found probability of providing system integrity (probability of "success") is equal to addition to 1.

The proof of formula (1) is complete.

For the special case, if $\Omega_{occur}(t) = 1 - \exp(\sigma t)$, $\sigma = 1/T_{occur}$, $\Omega_{activ}(t) = 1 - \exp(t/\beta)$, $\beta = T_{activ}$

$$P_{(1)}(T_{given}) = \begin{cases} (\sigma - \beta^{-1})^{-1}\{\sigma e^{-T_{given}/\beta} - \beta^{-1}e^{-\sigma T_{given}}\}, if\ \sigma \neq \beta^{-1}, \\ e^{-\sigma T_{given}}[1 + \sigma T_{given}], if\ \sigma = \beta^{-1}. \end{cases}$$

Note. This formula (1) is used also for the estimation of system operation without diagnostics. There is supposed that before the beginning of period T_{given} system integrity is provided.

According to the proofs of formulas (2) and (3), we consider independence. Then formula (2) means measure $P_{(2)}(T_{given}) = P_{mdl} + P_{end}$, where P_{mdl} is the probability of correct operation ("success") within the period T_{given} since beginning to the last diagnostics, $P_{mdl} = N((T_{betw} + T_{diag})/T_{req})P_{(1)}{}^{N}(T_{betw} + T_{diag})$, here $P_{(1)}(T_{betw} + T_{diag})$ is defined by formula (1), but one is calculated only for time $T_{betw} + T_{diag}$; P_{end} is the probability of correct operation ("success") within the assigned period T_{given} after the last diagnostics, i.e. in the last remainder $T_{rmn} = T_{req} - [N(T_{betw} + T_{diag})]$, $P_{end} = (T_{rmn}/T_{req})\ P_{(1)}(T_{rmn})$. Here, $P_{(1)}(T_{rmn})$ is defined by formula (1), but one is calculated only for the remainder time T_{rmn}. Really, for this time T_{rmn}, the main condition of the first variant is true: $T_{rmn} < T_{betw} + T_{diag}$.

Formula (3) means measure $P_{(2)}(T_{given}) = P_{(1)}{}^{N}(T_{betw} + T_{diag})P_{(1)}(T_{rmn})$. Interpretation is the next: "success" is on all N periods $(T_{betw} + T_{diag})$ AND on remainder time T_{rmn}.

The proofs for formulas (1)–(3) are complete.

Author details

Andrey Kostogryzov[1*] and Victor Korolev[2]

1 Federal Research Center "Computer Science and Control" of the Russian Academy of Sciences, Gubkin Russian State University of Oil and Gas, Russia

2 Lomonosov Moscow State University (Faculty of Computational Mathematics and Cybernetics, Department of Mathematical Statistics), Federal Research Center "Computer Science and Control" of the Russian Academy of Sciences, Russia

*Address all correspondence to: akostogr@gmail.com

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