Theoretical and Applied Basis of Constructing the Intelligent Control System for Protection of Spacecrafts from Anthropogenic (Technogenic) Particles Impact

Valery K. Kemaykin[1], Boris V. Palyukh[1] and Artur A. Belov[2]

[1] Tver State Technical University, 22, emb. of A. Nikitin, 170026, Tver, Russian Federation
[2] Central Research Institute of the Aerospace Forces, 22, emb. of A. Nikitin, 170026, Tver, Russian Federation

Abstract
The article discusses the problem of increasing the survivability of spacecraft (SC) with long-term orbital operation and areas of autonomous operation under conditions of possible impacts of anthropogenic (technogenic) particles (AP). Algorithms have been developed for predicting the conditions and results of AP strikes, assessing and choosing a protective SC barrier taking into account the current conditions and predicting possible SC damage based on the integrated use of artificial intelligence methods. The principles of construction and functioning of intelligent control systems for SC protection are formulated.

Keywords
Intelligent system, spacecraft, machine learning, knowledge base

1. Introduction

The main disadvantages of the existing SC control system, including protection against AP strikes, are determined by the established rigid principles of building such structures. Thus, the autonomous control of the SC technical state is implemented on the on-board operational control basis. The control parameters processed according to logical equations allow determining the trouble cause and running one of the emergency programs. The list of typical troubles is known, and emergency programs ensure SC recovery by means of system redundancy, reducing the level of energy consumption, changing the position of external structures, etc. This approach does not allow to successfully resist accidental external influences (including AP impacts), the determination of the threat from which is based on risk assessment, and cannot be carried out by means of parametric control. Consequently, to control the protection of the SC from AC strikes, it is necessary to use an exclusively proactive strategy. The basis of this strategy should be the ability to adapt to changes in the conditions of SC functioning caused by possible impacts of anthropogenic (technogenic) cosmic particles. Analysis of the results of work in the artificial intelligence (AI) field in combination with the main provisions of the automatic control theory allows us to expect positive results in the reasonable intellectualization of automatic control systems based on the use of modern methods and technologies of knowledge processing [6]. As part of the creation of this theory, it is necessary to comprehensively solve a number of fundamental scientific problems aimed at researching and developing new theoretical models and methods for creating on their basis a new generation of intelligent control systems for the protection of SC:

- development of models of external mechanical threats. Here it is necessary to distinguish classes of controlled or uncontrolled external threats of collision with AP, the movement of which is carried out along ballistic and non-ballistic trajectories relative to different attracting centers;

Russian Advances in Fuzzy Systems and Soft Computing: Selected Contributions to the 10th International Conference «Integrated Models and Soft Computing in Artificial Intelligence» (IMSC-2021), May 17–20, 2021, Kolomna, Russian Federation
EMAIL: vk-kem@mail.ru (A. 1); pboris@tstu.tver.ru (A. 2); nicpvotver@mil.ru (A. 3)
ORCID: 0000-0001-8619-4712 (A. 1); 0000-0001-8064-2852 (A. 2); 0000-0001-6848-1224 (A. 3)

- creation of a mathematical theory of forecasting, identification of the results of AP possible strikes , assessment and selection of SC effective protective barriers;
- creation of a methodology for constructing the structure of intelligent control systems for the SC protection from AP strikes;
- creation of a methodology for constructing decision support systems for controlling the SC protection from AP strikes.

The solution of the indicated fundamental scientific problems will make it possible to create promising intelligent control systems for SC protection, the main advantage of which will be the ability to detect, prevent and compensate for the threats of possible AP strikes under conditions of initial external uncertainty.

Taking into account the theme of the Conference, the presented material is devoted to the new results of solving the problem of foundation for the construction of an intelligent control system for the SC protection.

2. Methods and algorithms for constructing an intelligent control system for the SC protection from AP strikes

Prediction of the results of AP exposure is implemented in the form of a fuzzy inference tree hierarchical structure. Logical-linguistic approximation makes it possible to visualize the input parameters and their interconnection on the basis of logically consistent and interpretable statements about the influence of factors on the forecast result. Hybrid technology, supplemented by the formalism of neural networks, allows not only to build a model, but also provides its tuning by machine learning methods [4]. The algorithm for predicting and identifying the results of possible AP strikes is implemented in a neural fuzzy network (NFN). NFN is a signal feed-forward network, which is built on the basis of a multilayer architecture using AND, OR neurons. The structure of NFN is shown in Fig. 1.

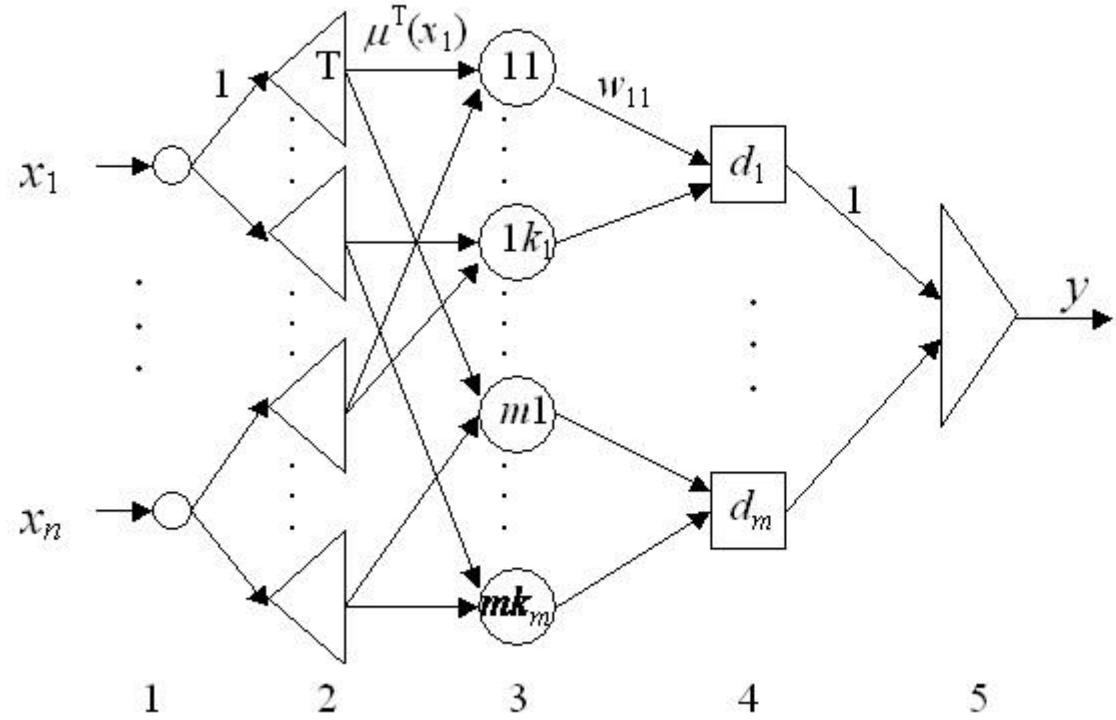

Figure 1: The structure of NFN

Number of nodes in NFN:

- the 1st layer: the number of nodes is equal to the number of prediction input parameters;

- the 2nd layer: the number of nodes is equal to the number of fuzzy terms for parameters in the knowledge base;
- the 3rd layer: the number of nodes is equal to the number of rules (conjunction lines) in the knowledge base;
- the 4th layer: the number of nodes is equal to the number of damage criteria selected for prediction;
- the 5th layer is the level that forms the forecast error.

The coefficient of trueness for the damage criterion dj (Kd) was chosen as an indicator for forecasting the AP impact. It is calculated in layer 4:

$$K_d = \max_{j=\overline{1,m}}\{\mu^{d_j}(x_1,x_2,\dots,x_n\} = \max_{j=\overline{1,m}}\left\{\max_{p=\overline{1,k_j}}\left\{w^{jp}\min_{i=\overline{1,n}}(\mu^{a_i^{jp}}(x_i)\right\}\right\}, i=\overline{1,n}, j=\overline{1,m} \quad (1)$$

where $x_i, w^{jp},. \mu^{d_j}, \mu^{a_i^{jp}}$ are the values of the input parameters, the weights of the rules and the parameters of the membership functions for the input parameter value and the damage criterion

The indicator is calculated based on the Zadeh's compositional rule: when predicting the result of exposure, the definition of the linguistic term of the damage criterion by the maximum of the membership function is used, and the generalization of this idea to the entire knowledge base. For the membership function of the parameters x, a two-parameter form is chosen that is convenient for further tuning:

$$\mu^j(x) = \frac{1}{1+\left(\frac{x-b_j}{c_j}\right)^2} \quad (2)$$

where b_j and c_j are the parameters of the membership function: maximum coordinate and concentration coefficient.

The NFN training is carried out by the error backpropagation method using a dual network [5], which is shown in Figure 2.

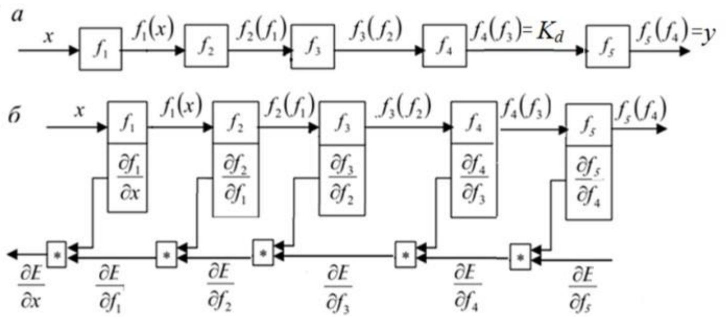

Figure 2: The structure and operating modes for the dual network: a - direct functioning of the network, b - direct loaded and reverse functioning of the network

Functional dependence at the output of the NFN, which is involved in the formation of the error value, is used to adjust:

$$E_t = \frac{1}{2}(\hat{y}_t - y_t)^2$$

where: $\hat{y}_t$ and y_t are theoretical and experimental network outputs at the t-th learning step.

A distinctive feature of the algorithm is that the backpropagation method for training the NFN is consistently applied in two stages.

The 1st stage is training NFN synaptic map:

$$\sum_{p=1}^{M}\left[\mu^y(X_p, W, B, C) - \mu_p^y\right] = \min_{W,B,C}$$

The 2nd stage is training parameters at the NFN input:

$$\sum_{p=1}^{M}\left[\mu^y(X_p, W, B, C) - \mu_p^y\right] = \min_{x}$$

The use of the learning algorithm made it possible to automatically adjust the knowledge base (KB) for changes in the subject area of protection against AP and improve the quality of predicting the results of AP strikes (see Table 1).

Table 1
The quality of forecasting the results of the AP impact obtained in the development environment of the knowledge base

Damage criteria	Probability of error-free prediction before training KB	Probability of error-free prediction after training KB
Aberration, scratch, dent (d1)	0,60	0,90
Blind channel (crater) (d2)	0,71	0,92
Through channel, (breakout) (d3)	0,58	0,83
Destruction of an element, (d4)	0,51	0,88
Average score	0,60	0,88

Assessment and selection of the protective barrier is a multi-criteria task. The structure of this task contains a set of protective barriers $S = \{s_v\}$ created on the SC, a set of criteria for their assessment $C = \{c_l\}$ and importance coefficients for each criterion $F = \{f_l\}$. Evaluation and selection of S^* is carried out upon detection of each AP dangerous blow in automatic mode.

The algorithm for assessing and choosing a security barrier is implemented in the form of a semantic fuzzy network (SFN).

Semantic fuzzy network is the carrier of the statement: "An effective barrier must be effective, operational and economical." The assessment is carried out on the basis of logical inference using criteria (values of barrier parameters) and importance factors, presented in the form of fuzzy sets.

The structure of the semantic fuzzy network (SFN) for assessing and choosing a security barrier is shown in Fig. 3.

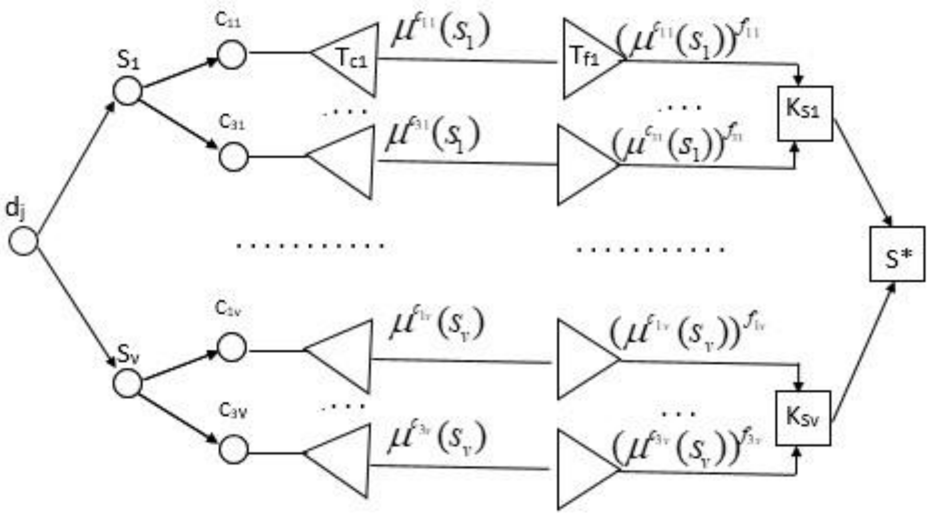

Figure 3: Semantic fuzzy network (SFN) structure assessment and selection of a protective barrier

where: d_j is predicted criteria for SC damage from the AP impact;

s_v is barriers implemented on the SC for each d_j;

c_1-c_3 are criteria (parameters) for assessing the effectiveness of a protective barrier, presented in the form of linguistic variables: “Productivity”, “Responsiveness”, “Economy”;

f_1-f_3 are coefficients of importance of the barrier assessment parameters, determined by the current conditions, presented in the form of fuzzy sets (FS);

S^* - selected protective barrier.

Based on the Bellman-Zadeh’s principle, the best barrier has the highest guaranteed score for the selected performance indicators: c_1 - responsiveness, c_2 - economy, c_3 - productivity (reliability) of the barrier. Efficiency assessment is determined in the form of their intersection. Considering that, the intersection operation corresponds to min in the theory of fuzzy sets, the calculated ratio for the security factor in the early assessment, i.e. equilibrium criteria has the form:

$$k_s = \left\{ \frac{\min\limits_{i=1...3} \mu^l(s_1)}{s_1}, \frac{\min\limits_{i=1...3} \mu^l(s_2)}{s_2}, \dots, \frac{\min\limits_{i=1...3} \mu^l(s_v)}{s_v} \right\}$$

To take into account the conditions of the situation, determined by the time, material and probabilistic characteristics of a possible collision, the coefficients of the importance of the assessment parameters are introduced. The calculation of the coefficients $F = \{f_l\}$ is used in the decision-making system (DSS) of ground command control (GCC) with the participation of a human operator and without participation of one directly on board the spacecraft, in the case of an autonomous operation section. For this, a knowledge base of the importance of the parameters has been developed, with its help, the values of the criteria and the effectiveness of the barrier are specified [7].

The obtained values of f_l are the exponents for the values of the estimates of the barrier parameters and are the coefficients of the concentration for fuzzy sets. Taking into account the importance of the parameters, the efficiency of the spacecraft protection is specified and the protection factor will take the form:

$$k_s = \left\{ \frac{\min\limits_{i=1...3} \mu^l(s_1)^{f_l}}{s_1}, \frac{\min\limits_{i=1...3} \mu^l(s_2)^{f_l}}{s_2}, \dots, \frac{\min\limits_{i=1...3} \mu^l(s_v)^{f_l}}{s_v} \right\}$$

A protective barrier with the highest Ks value is selected.

3. Principles of constructing an intelligent control system for the SC protection from AP strikes

The theoretical foundations of the construction and operation of an intelligent SC protection control system take into account the features of building the knowledge base for an intelligent system [2] and are represented by the following provisions:

1. The principle of existing a built-in forecasting device:

- environmental conditions associated with possible AP impacts;
- the results of such impacts and their identification with the specified criteria for SC damage (defeat);
- evaluating the effectiveness of the available protective barriers for various environmental conditions.

This principle allows you to avoid a situation associated with possible impacts, for which barriers are not provided due to temporary and other restrictions on the operation of mechanisms that form control actions and (or) connect a protective barrier. This principle is especially important for areas of SC autonomous operation in orbit.

2. The ability to predict the conditions and results of AP impacts makes it possible to formulate another principle, the implementation of which will prevent serious damage. This is the principle of the worst result. The principle presupposes modeling of predictable situations, checking them on high-precision model. In accordance with this principle, it is necessary to focus on the most unfavorable conditions.
3. The principle of a variant approach to solving problems of SC protection control, based on the provisions of the theory of situational control.

A distinctive feature of the intelligent control system from the one built according to the "traditional" scheme is the presence of mechanisms for storing and processing knowledge of protection control in uncertain conditions of possible AP impacts.

When a threat of an impact is detected, the accumulated body of knowledge (KB) should ensure the identification of a possible impact result, according to its belonging to the selected classes of criteria for damage to SC and assess the effectiveness of protective barriers, taking into account the current situation.

4. The principle of multi-level hierarchical construction of control systems.

The hierarchy of SC protection control levels is determined based on the set (tree) of goals to be achieved. These goals define:

- planning the appropriate behavior of the SC, taking into account a possible impact and further performance of tasks as intended;
- planning reasonable actions for effective protection against a possible impact in the current conditions;
- planning the implementation of the selected actions (connecting protective barriers) compensating or reducing the threat of damage from particle impact.

5. The principle of operation continuity (possibly with some loss of quality or efficiency) in the event of breaking liaisons and the impossibility of receiving control actions from the higher levels of the system hierarchy.

The principle establishes a partial decrease in the level of intelligence, but not the termination of the functioning of the system as a whole. The control of the SC defense is carried out on the basis of operational threat prediction using up-to-date (trained) knowledge bases, their configuration, work with the bases of events, knowledge and adaptive protection measures, selected using intelligent mechanisms implemented both on the SC and using the GCC. With this approach, the inaccuracy of knowledge about the situation can be compensated for by the presence of the intelligence of the system and the corresponding control algorithms. The presence of an assessment mechanism and a knowledge base for predicting damage and assessing the effectiveness of protective barriers on a SC provides a mode of continuous operation and maximum survivability of the SC as a whole.

6. The principle of the adequacy of the intelligence level for the control system to the uncertainty factors affecting it.

In accordance with this principle, the constructed system must comply with the IPDI (Increasing Precision with Decreasing Intelligence) rule of the theory of intelligent machines and have a degree of intelligence on at least two layers.

The block diagram of the control system is shown in Fig. 4.

The detection and recognition module, which is part of the system, solves the problem of spatial selection, detection, recognition of AP and the estimation of their parameters, including: mass-dimensional characteristics, motion parameters and distance from the SC, estimated time to collision [3].

At the first layer, the tasks of predicting events, constructing and maintaining the knowledge base in an up-to-date state, automated development of proposals for increasing the survivability and SC operational reliability are solved. At this level, the SC control is carried out via the command radio link with the available time for analysis, preparation and issuance of commands and control programs. To do this, using the module for evaluating the results of experimental studies and modeling interaction, it is carried out a computational-experimental and computer analysis of the stress-strain states of SC materials and structures taking into account mechanical and thermal loads, analysis of the criteria and conditions for the appearance of damage to the SC, as well as an assessment of the durability of materials for the stages of formation and the development of craters and cracks.

The specified analysis using the developed computational-experimental and computer models makes it possible to detail the forecast of events and develop sound proposals for the application of protective measures [1].

In addition, the development and training environment for the knowledge base of the developed system is implemented on the upper layer. Here, logical-linguistic models of knowledge representation are developed and the technology of neural networks is used to customize them. This allows for reliable identification of the presented situations. In this case, the most important feature of neural network structures is high speed, achieved due to the parallel processing of information in their hardware implementation [4].

The distinctive feature of KB learning is the presence of the second stage. It solves the inverse recognition problem by adjusting the values of the input parameters through the gradient of the error function at the input of the network for each of the damage criteria. For this, the generated sets of values of the input parameters are fed to the input of the trained network. Having a given criterion of damage and the result given by the network, the gradient of the error function is calculated by the input parameters of the network and by the technology of the method of loaded dual networks.

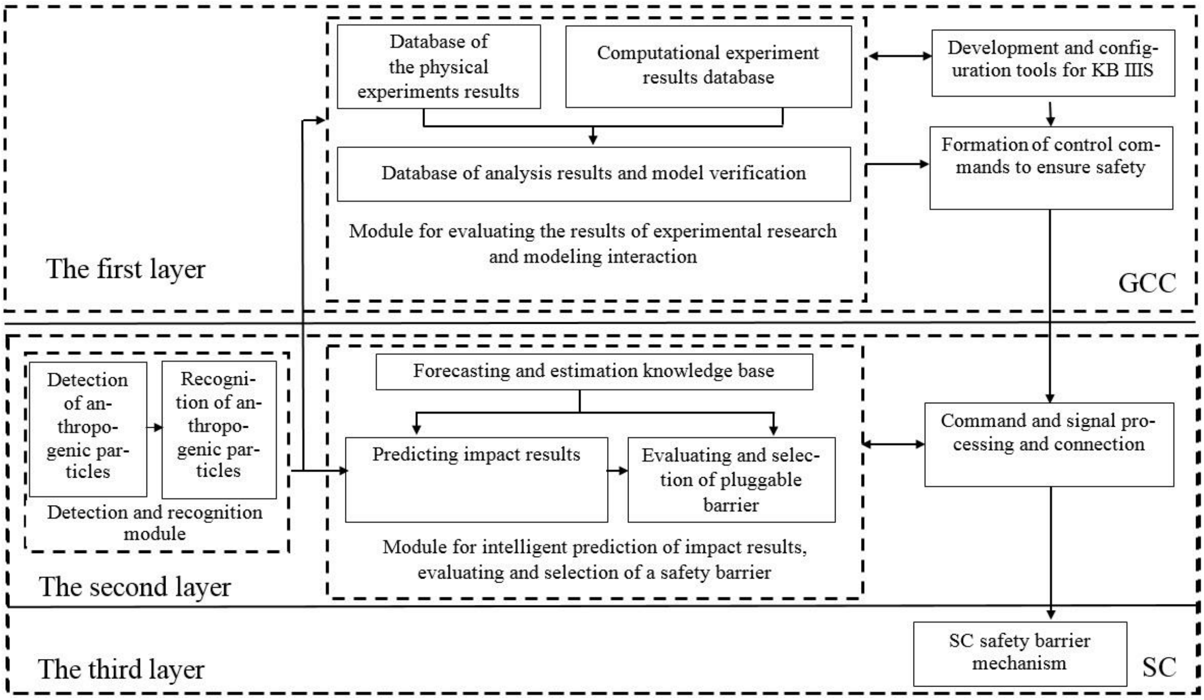

Figure 4: Hierarchical structure of an intelligent control system for the SC protection from AP strikes

In accordance with the values of the gradient elements, the values of the input parameters change in the direction of decreasing the error, which makes it possible to iteratively obtain sets of input vectors that generate the required result. In this case, the synaptic network map configured in the previous step remains unchanged.

The second layer is designed to predict events, as well as clarify the effectiveness and connect the security barrier in an automatic mode. For this, a module has been developed for intelligent prediction of impact results, assessment and selection of a protective barrier. The key element of the layer is the knowledge base, which is kept up to date by taking into account all changes in the subject area involved in its training. The fuzzy inference mechanism is implemented using the knowledge stored in the knowledge base. The membership function maximum determines the most probable predicted damage criterion.

At the second level, for the selected criterion, estimates of the effectiveness of all barriers that are associated with the identified damage are refined.

Refinement is carried out automatically, taking into account the available and required resources and the reliability of protection

The third layer of the system includes many ready-to-connect protective barriers. Protective barriers implemented on the spacecraft in the form of functions, products, materials, software, etc., are created to prevent, stop or slow down the hazardous situation development. All of them will be executed according to the rigid program and the command to connect them is required [1].

A distinctive feature of the presented protection control system is the provision of SC autonomous operation, in which the tasks of detection, recognition, hazard assessment and prediction of the AP impact results are automatically solved in the cycle of onboard computer operation, as well as the assessment of the effectiveness of protective barriers and the implementation of the selected barrier to protect the SC. This barrier is adaptable to the prevailing environment.

4. Conclusions

The methodology of constructing an intelligent control system for the SC protection from AP strikes has been developed.

The structure and mechanisms are presented that implement intellectual assessment, predicting the results of a hypervelocity impact and the choice of an effective protective barrier when exposed to AP.

The principles of constructing an intelligent system are formulated, which make it possible to implement fast and slow control loops of SC protection against AP impacts.

The intellectual component is implemented in both control loops. At the same time, the fast loop provides an operational (in real time) assessment of the threat level and allows you to form an effective mechanism for protecting the spacecraft without the participation of the operator and the GCC.

If there is a connection with the SC and the balance of time for preparing a solution is fulfilled, the slow loop implements man-machine procedures (including DSS) for controlling SC protection using ground-based high-precision experimental computational and computer models, based on in-depth analysis, forecasting and justification of measures to improve survivability and operational reliability of the SC.

5. Acknowledgements

The research was done within the government task of the Ministry of Education and Science of the Russian Federation. The number for the publication is 2.1777.2017/4.6.

6. References

[1] V. V. Meshkov, Yu. A. Fedosov, N.N. Filatova, An integrated system for modeling hypervelocity interaction of solids. Acta Astronautica. 178 (2021). 606-615. doi:10.1016/j.actaastro.2020.09.047

[2] B.V. Paliukh, V.K. Kemaykin, Y.G. Kozlova, Development principles of knowledge database of intelligent system for estimation of dynamical interaction of orbital systems with space debris. IT in industry, 2.6(2017). 1-6.

[3] B.V. Paliukh, I. I. Zykov, A method for recognizing anthropogenic particles in difficult background conditions, in Proceedings of the Third International Scientifig Conference “Intelligent Information Technologies for Industry”, IITI’19, Czech Republic, Ostava, 2019, pp. 1-6.

[4] N. G. YArushkina, V.V. Voronina, A.V. Miheev, K. V. Svyatov, Theory and practice of machine learning, IPK «Venec», Moscow, Russia, 2017.

[5] R. Kallan, Neural networks: a quick reference, Williams, Moscow, Russia, 2017.

[6] V.B. Trofimov, S.M. Kulakov, Intelligent automated control systems for technological objects, Infra-Inzheneriya,Vologda, Russia, 2020:

[7] V.K. Kemajkin, I.V. Kozhuhin, Formation of a safety barrier on a spacecraft under the threat of space debris by fuzzy logic methods. Software products and systems. 32 (2019). 124-129.