UDC 621.039:004.94

PREDICTION OF FLOW ACCELERATED CORROSION OF NPP PIPELINE ELEMENTS BY NETWORK SIMULATION METHOD

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Based on a comprehensive approach that uses the computer simulation of the process of destroying structural materials and technology of self-learning neural networks, a methodology has been developed for predicting the rate of flow accelerated corrosion (FAC) of pipeline elements with a single-phase medium of the second circuit of nuclear power plants (NPPs). The neural network model has been implemented in the Delphi Integrated Development Environment. The neural network consists of an input layer containing seven elements and an output layer with two elements. As the input variables of the neural network, the parameters that have the greatest influence on FAC process are chosen. These are the medium temperature, the pipeline internal diameter, the oxygen content in the medium, the coolant flow velocity, the hydrogen index, the time of monitoring (or the start of operation), and the time for which the prediction is performed. For each of the network input parameters, intervals of possible values were chosen. At that, the factors that affect FAC rate, but not included in the feasible model (chromium, copper and molybdenum content in the pipeline material, amine type) are assumed to be permanent. As the output parameters of the neural network, FAC rate and the variation of the pipeline element wall thickness within the predicted time interval have been selected. As the activation function of the neural network the sigmoid function is used. As a method of training the neural network, the error back propagation method has been chosen, which assumes both a forward and reverse passage through the network layers. As the learning algorithm of the neural network, the one with a teacher has been chosen. As a test sample for the neural network, it is proposed, along with operational control data, to use the results of calculations based on a statistical model created in the framework of a special calculation-experimental method. The application of the developed methodology makes it possible to improve the prediction accuracy of FAC rate without determining all the dependencies between the many factors that influence FAC process. The low errors of the constructed models make it possible to use the results of calculations both to determine the resource characteristics of NPP pipelines and optimize operational control.

Keywords: *neural networks, computer simulation, flow accelerated corrosion.*

Introduction

Practically all NPP secondary circuit pipelines and equipment elements, made of pearlitic and slightly alloyed steels, are subject to FAC. FAC of the elements of NPP pipelines is manifested in the form of thinning, which ultimately leads to their destruction. A great variety of mechanisms for destroying NPP pipeline metallic areas is connected with the difference in geometry, thermohydrodynamic characteristics, water and chemical parameters of the working medium, etc. Therefore, in order to optimize the amount of control and prevent critical situations, the task of predicting FAC rate in NPP pipeline elements is topical.

The calculation of FAC rate from the operational control data contains many uncertainties associated with a wide spread of the results of measuring the wall thicknesses of pipeline elements due to FAC nonuniformity. This is often caused by different loading conditions of different pipeline areas, as well as the stochastic properties of FAC process itself. Thus, for example, for the most common computer code CHECKWORKS, the discrepancy between the operational control data and calculated data is ±50% [1]. Due to the lack of reliable data on the factors included in the computer codes on NPP power units, the discrepancy is considered to be satisfactory even with a value between -50 and +250% [2].

Recently, among the variety of different prediction techniques, intellectual information technologies are becoming increasingly popular, in which artificial neural networks are used. A large number of parameters that determine the intensity of FAC process in the elements of NPP pipelines exert a complex effect on each other. The ability of an artificial neural network to generalize can improve the prediction with regard to the magnitude of FAC without determining all the dependencies between the many factors that cause FAC process. The purpose of this paper is to optimize the scope and frequency of monitoring the technical condition of NPP second circuit pipeline elements by developing a method for predicting FAC process intensity based on the process statistical model and technology of self-learning neural networks.

1. FAC process computer simulation

The known models for predicting the development of FAC process in NPP pipelines, as a rule, use both analytical and empirical approaches. The analytical models based on a theoretical description of physical processes are used to study individual FAC mechanisms. The empirical models are built on the basis of operational control data and are divided into statistical and physicochemical.

Among the statistical models is the model of FAC process development prediction elaborated within the framework of a special calculation-experimental method (CEM), which allows, in addition to determining FAC, determining the resource characteristics (residual service life) of NPP pipeline elements with a single-phase medium.

The special CEM model [3, 4] is based on the computer simulation of the process of destroying materials and construction elements. To solve the problem of predicting FAC rate, the thicknesses corresponding to the pipeline nominal diameter, are chosen as the nominal thickness values. The calculation of FAC rate and service life of the elements of NPP pipeline systems is based on the use of data from the operational control of pipeline wall thicknesses, and since the pipeline FAC process is associated with the thinning of its walls, only information on the thinnings is used. When determining the permissible depth of FAC damage, the technique is based on the strength standards of NPP equipment and pipelines [5].

The main parameters necessary for calculations, in addition to geometric (element type, diameter, wall thickness) and operational parameters (ambient temperature, operating pressure), include the date of inspection and the result of thickness measurement, as well as the time point for which the value of thinning is predicted.

As a result of computer simulation of FAC process, a sequence of corrosion defects with specified distribution parameters (mean depth and dispersion) is generated in the elements of NPP pipelines and the average destruction depth of the surfaces of the pipe-pipeline elements is predicted for a specified period of its operation. To assess the probability of destruction (when corrosion damage achieves the maximum permissible value), the dependence of the coefficient of variation (dispersion) of the destruction depth on the service life is determined. As a result of the calculation, at any loading stage, an output file is generated containing information on the change in the mean depth and dispersion of FAC damage in time.

The advantage of the developed model is the ability to obtain the distribution of wall thickness values of the pipeline element at any time, in contrast to the operational control data. The statistical model allows predicting FAC rate for straight portions, outlets, bends, and heat affected zones of NPP pipelines. The disadvantages of the model include the inability to evaluate the effect of metal physical and chemical properties (chromium, copper, and molybdenum content); working medium heat-hydraulic characteristics (temperature, velocity); water chemistry regime indicators, etc. on FAC rate.

The above disadvantage is absent in the approach to predicting FAC, based on the use of the mathematical apparatus of the theory of neural networks, which allow reproducing complex dependencies of input data from output ones. Neural networks have proven well in the field of simulation systems and processes, whose internal connections are either poorly understood, or implement complex interactions [6]. FAC of the elements of NPP pipelines relate to such processes. The use of a neural network to solve the problem of predicting FAC can allow assessing the mutual influence of all factors and improve prediction accuracy.

2. Models based on the use of neural networks

The models based on the use of neural networks can be considered as a promising alternative and addition to the traditional methods of estimating FAC of NPP second circuit equipment, including the above statistical model based on computer simulation.

The main characteristics of a neural network are the structure, number of layers, type of neuron, input and output values, and the learning algorithm. The choice of the input parameters of a neural network is determined by the volume and quality of the experimental data available for training.

To solve the problem of predicting FAC rate, it is proposed to implement a neural network model containing seven input parameters and two output ones. The input signals are selected taking into account their relative influence on FAC process. These are the medium temperature, pipeline internal diameter, oxygen content in the medium, coolant flow rate, hydrogen pH, time needed for the control (or start of operation), and the point of time for which the prediction is made.

The values of the input parameters necessary for the network operation are either monitored during operation or indicated in the design and working documentation. The factors affecting FAC rate, but not included in the model being implemented (chromium, copper and, molybdenum content in the pipeline metal, amine type) are assumed to be constant. The values of the input parameters in the developed neural network model were within the following ranges [2]:

– working medium temperature –142 to 300 °C;
– pipeline diameter – 89 to 630 mm;
– oxygen concentration – 0 to 40 mkg/kg;
– working medium velocity – 0.1 to 10 m/s;
– pH – value is 7 to 10.2.

As the neural network output parameters characterizing FAC intensity, the rate and value of the pipeline element wall thinning (the change in the wall thickness divided by the nominal wall thickness) for the predicted time interval were chosen.

Here, the following is to be noted. When software for calculating FAC is developed abroad, it is assumed that service life does not affect FAC rate and change in wall thickness (thinning). This assumption can be realized if the factors accelerating FAC and those slowing it down are balanced by each other. However, for the operating conditions of NPP pipelines, the linear dependence of the amount of thinning on time and the constancy of FAC rate are not typical. Thus, for example, the analysis of measurements of the wall thickness of the feed water pipelines of NPPs with VVER-1000 shows that the average FAC rate in the first five years of operation is 0.84 mm/year, and in the next five years it is 0.38 mm/year, i.e. it is reduced by a factor of 2.2 approximately times [7]. Therefore, the use of the moment of control and the moment of time for which the prediction is performed as the network input parameters should make it possible to take into account the non-linear dependence of the pipeline wall thickness on time and, accordingly, improve prediction quality.

The most commonly used neural network activation function is the sigmoid function $f(x)$

$$f(x) = \frac{1}{1+e^{-\alpha x}},$$

where α is the parameter characterizing the slope of the activation function graph; x is the input parameter; $f(x)$ is the value of the neuron output.

The sigmoid function is strictly monotonically increasing, continuous and differentiable. The main advantage of this function is that it can be differentiated along the whole axis of abscissas and has a simple derivative

$$\frac{\partial f}{\partial x} = \alpha f(x)(1 - f(x)),$$

which makes it possible to significantly reduce the computational complexity of the neural network training method, which uses the error back propagation method [8].

The initial data are converted to the form in which they can be fed to the network inputs. Normalization is performed when data of different dimensions are fed to different inputs. The data are normalized to the interval (0, 1) – the sigmoid function range of output values. The conversion of x into s is performed in accordance with the formula

$$s = [x - \min(x_1 \ldots x_n)]/[\max(x_1 \ldots x_n) - \min(x_1 \ldots x_n)],$$

where n is the number of x values.

The inverse conversion from s to x is performed as follows:

$$x = \min(x_1 \ldots x_n) + s[\max(x_1 \ldots x_n) - \min(x_1 \ldots x_n)].$$

As a method of training a neural network, the back propagation method is used, which assumes a forward and reverse passes through the layers of the network. During the forward pass, the input vector is fed to the input layer of the neural network, and then propagates through the network. As a result, a set of output signals is generated, which is the actual response of the network to this input image. During the forward pass, all the weights of the network are fixed. During the reverse pass, all the weights are adjusted according to the error correction rule, namely: the actual network output is subtracted from the desired one, resulting in an error signal. This signal later propagates through the network in the opposite direction. The network weights are adjusted in order to maximally approximate the network output signal to the desired one.

The back propagation algorithm looks as follows.

1. A training pair is selected from a training set, and the input vector is fed to the network input.

2. The output of the network is calculated by the formula

$$y = f(S) = \frac{1}{1+e^{-\alpha S}},$$

where $S = \sum_{i=1}^{n}(x_i w_i)$; n is the number of input parameters; x_i is the value of the i-th input; w_i is the weight of the i-th input.

The values of the weights are selected in the course of network training, which consists in approximating the output parameters to the expected values. Unfortunately, there is no universal method for selecting weights that would guarantee finding the best starting point for any problem being solved [8]. For this reason, in most practical implementations, a random selection of weights with a uniform distribution of values in a given interval (in our case in the interval (-0.5, 0.5)) is most often used. The very approach to training a neural network implies starting from the wrong position in the search for the right one.

3. The difference between the network output and the required output (the target vector of the training pair) is determined

$$\Delta_i = y_i - d_i.$$

4. Weight change is determined by the formula

$$\Delta w_i = \eta \Delta_i y_i (1 - y_i) x_i,$$

where η is the parameter that determines the speed of training.

5. For each vector of the training set, steps 2 through 4 are repeated until the error on the entire set has reached an acceptable level.

As a teaching algorithm of the neural network developed, the teaching algorithm with a teacher is chosen. With this training, the set of input data is divided into two parts – the actual training sample and the test data. The training data are sent to the network for training, and the test data are used to calculate the network error.

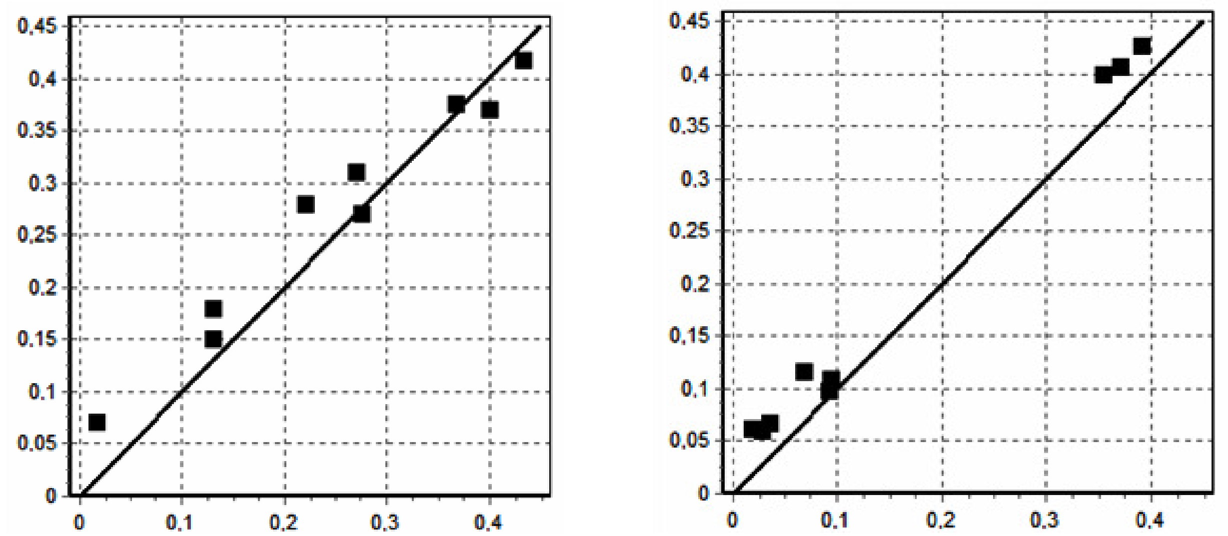
Despite the fact that a large number of operational control data have been currently accumulated, only a small part of this data is processed. In addition, the analysis of monitoring data is difficult to perform due to the objective complexities associated with the presentation of measurement data and their accuracy. Therefore, in this work, test samples are generated on the basis of both the operational control data and computer simulation results.

3. Results of applying the developed methodology

A separate network must be built for each geometric type of pipeline elements (straight portion, bend, outlet, etc.), which will greatly simplify the neural network structure and improve the model accuracy. The developed methodology assisted in predicting FAC rate for pipeline straight portions with NPP second circuit single-phase medium.

Usually, in predicting, both an estimate of the expected variable value (in our case, FAC rate or pipeline wall thicknesses) and that of the time interval (at which the probability of finding the variable predicted values is preserved) are made. In some cases, predicting the specific values of the predicted variable is not so important as predicting significant changes in its magnitude, in particular, the pipeline element wall thickness reduction below the maximum permissible one. In this case, there are also used the results of calculations based on a computer-simulated statistical model.

The figure below shows the results of estimating the accuracy of approximating the results of the neural network operation (line – regression line, points – output values) for two test samples. The average quadratic error of the prediction calculated by the neural network for the case of using operational control data as a test sample is 0.035; for a test sample based on the calculations using a statistical model that uses CEM it is 0.037. The network target values are 0.31; 0.18; 0.15; 0.07; 0.27; 0.28; 0.375; 0.37; 0.417; output data are – 0.271; 0.13; 0.13; 0.016; 0.275; 0.22; 0.367; 0.4; 0.433.



a b

Graphs of linear regression between the network output and the standard. Test samples are based on:
a – control data; b – results of computer simulation

Almost the same error in predicting FAC rate in the case of using two different test samples indicates the possibility of applying the results obtained by the calculation and experimental method for test samples in the absence of the required amount of exploitation control data, verification of the neural network being developed for each type of NPP pipeline elements, refinement of calculation results and predictions.

With the help of the developed neural network, the inverse problem can also be solved, when the value of one of the unknown initial parameters (temperature, medium velocity, oxygen concentration, etc.) can be calculated from the known value of FAC rate.

Conclusions

The principal possibility of using the technology of self-learning neural networks for predicting FAC rate in the pipeline elements of NPP second circuit has been established.

The joint use of the two components (the developed methodology based on CEM and neural network) may be useful in assessing the possibility of reliable and safe operation of NPP pipeline elements subject to FAC.

The main advantage of the developed approach is the possibility of carrying out predictive calculations of FAC rate and the optimizing operational control.

With the help of the developed neural network, it is possible to solve both direct problems, in which the input values determine the output value (FAC rate) of the model used, and inverse ones, in which the known output values are used for searching the input data leading to the appearance of the available output ones. Thus, the developed methodology can be used to assess the effectiveness of water chemistry regimes, to study the effect of both geometry and regime parameters on FAC intensity of NPP pipeline elements.

References

1. Naftal, M. M., Baranenko, V. I., & Gulina O. M. (2004). Use of software tools for calculating flow accelerated corrosion of nuclear power plant equipment and pipelines. *Thermal Eng.,* vol. 61, no. 6, pp. 456–463.
2. Baranenko, V. I., Yanchenko, Yu. A., Gulina, O. M., & Dokukin, D. A. (2010). *O raschete skorosti erozionno-korrozionnogo iznosa i ostatochnogo resursa truboprovodov AES* [Calculation of the rate of erosion-corrosion wear and residual life of NPP pipelines]. *Izv. Vuzov. Yader. Energetika – Izvestia Vysshikh Uchebnykh Zavedeniy. Yadernaya Energetika,* no. 2, pp. 55–63 [in Russian].
3. Mileshkin, M. B., & Biblik, I. V. (2006). *Primeneniye spetsialnogo raschetno-eksperimentalnogo metoda dlya otsenki ostatochnogo resursa elementov konstruktsiy po fakticheskomu sostoyaniyu materiala* [Application of a special calculation and experimental method for estimating the residual life of structural elements based on the actual state of the material]. *Nadezhnost i Dolgovechnost Mashin i Sooruzheniy – Reliability and Life of Machines and Installations,* iss. 27, pp. 304–310 [in Russian].

4. Mileshkin, M. B., Biblik, I. V., & Inkulis, V. V. (2009). *Otsenka veroyatnosti bezotkaznoy raboty oborudovaniya AES na osnove modelirovaniya izmeneniya stepeni ekspluatatsionnoy povrezhdennosti* [Evaluation of the probability of failure-free operation of NPP equipment on the basis of modeling the change in the degree of operational damage]. *Nadezhnost i Dolgovechnost Mashin i Sooruzheniy – Reliability and Life of Machines and Installations,* iss. 32, pp. 105–112 [in Russian].
5. RD EO 0571-2006. (2006). *Normy dopustimykh tolshchin elementov truboprovodov iz uglerodistykh staley atomnykh stantsiy* [Norms of admissible thickness of carbon steel pipeline elements of nuclear power plants]. Valid from 2006.11.01. Moscow: OAO 'Kontsern Rosenergoatom', 44 p. [in Russian].
6. Baranenko, V. I., Gulina, O. M., & Dokukin, D. A. (2008). *Metodologicheskaya osnova prognozirovaniya erozionno-korrozionnogo iznosa oborudovaniya AES metodom neyrosetevogo modelirovaniya* [Methodological basis of prediction of erosion-corrosion wear of NPP equipment by the method of neural network modeling]. *Izv. Vuzov. Yader. Energetika – Izvestia Vysshikh Uchebnykh Zavedeniy. Yadernaya Energetika,* no. 1, pp. 3–8 [in Russian].
7. Baranenko, V. I., Getman, A. F., Ovcharov, O. V., & Gusarov, A. Ye. (2006). *Ispolzovaniye programmnykh sredstv dlya rascheta korrozii truboprovodov i oborudovaniya energoblokov AES* [Use of software for calculation of corrosion of pipelines and equipment of NPP power units. Available at: www.gidropress.podolsk.ru/files/proceedings/mntk2017/autorun/article19-ru.htm.
8. Khaykin, S. *Neyronnyye seti: per. s angl.* [Nuron networks (trans. from English)] Moscow: Izdat. dom 'Vilyams', 1104 p. [in Russian].

Received 07 June 2018

Прогнозування ерозійно-корозійного зносу елементів трубопроводів атомних електростанцій методом нейромережевого моделювання

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На основі комплексного підходу, що використовує комп'ютерне моделювання процесу руйнування конструкційних матеріалів і технологію самонавчальних нейронних мереж, розроблено методологію прогнозування швидкості ерозійно-корозійного зносу (ЕКЗ) елементів трубопроводів з однофазним середовищем другого контуру АЕС. Нейромережева модель реалізована в середовищі програмування Delphi. Нейронна мережа складається з вхідного шару, що містить сім елементів, і вихідного шару з двома елементами. Як вхідні змінні нейронної мережі обрані параметри, які чинять найбільший вплив на процес ЕКЗ. Це температура середовища, внутрішній діаметр трубопроводу, вміст кисню в середовищі, швидкість течії теплоносія, водневий показник, час проведення контролю (або початку експлуатації) і час, на який здійснюється прогнозування. Для кожного з вхідних параметрів мережі вибиралися інтервали можливих значень. Проте чинники, що впливають на швидкість ЕКЗ, але не увійшли в реалізовану модель (вміст хрому, міді та молібдену в матеріалі трубопроводу, тип аміну), прийняті постійними. Вихідними параметрами нейронної мережі є швидкість ЕКЗ і зміна товщини стінки елемента трубопроводу за прогнозований часовий інтервал. Як метод навчання нейронної мережі обраний метод зворотного поширення помилки, що передбачає прямий і зворотний прохід. Навчальним алгоритмом нейронної мережі є алгоритм навчання з учителем. Для тестової вибірки пропонується, поряд з даними експлуатаційного контролю, використовувати результати розрахунків за статистичною моделлю, створеною в рамках спеціального розрахунково-експериментального методу. Встановлено принципову можливість використання нейронних мереж для прогнозування швидкості ЕКЗ в елементах трубопроводів другого контуру АЕС. Розроблений підхід дозволяє поліпшити точність прогнозу швидкості ерозійно-корозійного зносу без визначення всіх залежностей між безліччю факторів, що впливають на процес ЕКЗ. Низькі значення помилок побудованих моделей дозволяють використовувати результати розрахунків для визначення ресурсних характеристик трубопроводів з однофазним середовищем другого контуру АЕС і оптимізації експлуатаційного контролю.

***Ключові слова**: нейронні мережі, комп'ютерне моделювання, ерозійно-корозійний знос.*

Література

1. Naftal’ M. M., Baranenko V. I., Gulina O. M. Use of software tools for calculating flow accelerated corrosion of nuclear power plant equipment and pipelines. *Thermal Eng.* 2014. Vol. 61. № 6. P. 456–463.

2. Бараненко В. И., Янченко Ю. А., Гулина О. М., Докукин Д. А. О расчете скорости эрозионно-коррозионного износа и остаточного ресурса трубопроводов АЭС. *Изв. вузов. Ядер. энергетика*. 2010. № 2. С. 55–63.
3. Милешкин М. Б., Библик И. В. Применение специального расчетно-экспериментального метода для оценки остаточного ресурса элементов конструкций по фактическому состоянию материала. *Надежность и долговечность машин и сооружений*. 2006. Вып. 27. С. 304–310.
4. Милешкин М. Б., Библик И. В., Инкулис В. В. Оценка вероятности безотказной работы оборудования АЭС на основе моделирования изменения степени эксплуатационной поврежденности. *Надежность и долговечность машин и сооружений*. 2009. Вып. 32. С. 105–112.
5. РД ЭО 0571-2006. Нормы допустимых толщин элементов трубопроводов из углеродистых сталей атомных станций. – Введ. 2006-11-01. – М.: ОАО «Концерн Росэнергоатом», 2006. 44 с.
6. Бараненко В. И., Гулина О. М., Докукин Д. А. Методологическая основа прогнозирования эрозионно-коррозионного износа оборудования АС методом нейросетевого моделирования. *Изв. вузов. Ядер. энергетика*. 2008. № 1. С. 3–8.
7. Бараненко В. И., Гетман А. Ф., Овчаров О. В., Гусаров А. Е. Использование программных средств для расчета коррозии трубопроводов и оборудования энергоблоков АЭС. [Электронный ресурс]. – Режим доступа: www.gidropress.podolsk.ru/files/proceedings/mntk2017/autorun/article19-ru.htm
8. Хайкин С. Нейронные сети: пер. с англ. – М.: Издат. дом «Вильямс», 2006. 1104 с.

UDC 539.3:629.7

DYNAMIC PROCESSES DURING THE THROUGH-PLASTIC-DAMPER SHOCK INTERACTION OF ROCKET FAIRING SEPARATION SYSTEM COMPONENTS

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This article deals with the actual issues of ensuring the dynamic strength of rocketry components using pyrotechnics. It studies the shock interaction of rocket fairing pyrotechnic separation system components during the second phase of the system operation at so-called capturing. The contacting of the system components occurs through a viscoelastic damper. The damper is installed between a movable part and a fixed one to 'attenuate' impact due to plastic deformation. The damper acts as a one-way connector – it limits compression and does not prevent separation. The whole structure is assumed to be elastic, and plastic deformation is concentrated in the damper. The mechanical model is represented as a combination of elastic elements and a nonlinear damper. The technique of taking into account the nonlinearity of a damper is based on the introduction of variable boundary forces on the damper ends. In the case of plastic compressive deformations, boundary forces increase the deformation, restrained by elastic forces, and when the contact disrupts (separation), they completely compensate the stresses in the damper model, nullifying them. A three-dimensional computational model of the fairing assembly composite design is constructed. The damper is presented in the form of a continuous thin ring. The finite element method is used. The calculation of the structural dynamics with respect to time is carried out by the Wilson finite-difference method. Verification of the technique on the test problem with the known wave solution is carried out. Calculation studies of the dynamic stress state at different impact speeds for damper variants with different plastic stiffness are performed: steel elastic (damper without holes, 'rigid', for comparison); initial (damper with holes, plastic, soft) and rational (damper with a selected characteristic of rigidity). It is shown that the initial damper is inefficient due to insufficient rigidity. The characteristics of plastic stiffness are determined, under which dynamic stresses are significantly reduced in relation to the initial structure. The maximum dynamic stresses in the pyrotechnic separation system of the fairing with rational dampers strongly depend on the impact speed. At significant speeds, they exceed the plasticity limit. A more precise formulation of the 'catch-up' task should be carried out taking into account the plasticity in the entire structure.

Keywords: *fairing, separation system, impact, stress, contact, damper, plasticity.*