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REFINEMENT AND ACCURACY CONTROL OF THE SOLUTION METHOD FOR THE DURABILITY PROBLEM OF A CORRODING STRUCTURE USING NEURAL NETWORK

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ABSTRACT

Context. The prediction of the time until failure of corroding hinge-rod structures is a crucial component in risk management across various industrial sectors. An accurate solution to the durability problem of corroding structures allows for the prevention of undesired consequences that may arise in the event of an emergency situation. Alongside this, the question of the effectiveness of existing methods for solving this problem and ways to enhance them arises.

Objective. The objective is to refine the method of solving the durability problem of a corroding structure using an artificial neural network and establish accuracy control.

Method. To refine the original method, alternative sets of input data for the artificial neural network which increase information about the change in axial forces over time are considered. For each set of input data a set of models is trained. Based on target metric values distribution among the obtained sets, a set is selected where the minimum value of the mathematical expectation of the target metric is achieved. For the set of models corresponding to the identified best set, accuracy control of the method is determined by establishing the relationship between the mathematical expectation of the target metric and the parameters of the numerical solution.

Results. The conditions under which a lower value of the mathematical expectation of the target metric is obtained compared to the original method are determined. The results of numerical experiments, depending on the considered case, show, in average, an improvement on 43.54% and 9.67% in the refined method compared to the original. Additionally, the proposed refinement reduces the computational costs required to find a solution by omitting certain steps of the original method. An accuracy control rule of the method is established, which allows to obtain on average a given error value without performing extra computations.

Conclusions. The obtained results indicate the feasibility of applying the proposed refinement. A higher accuracy in predicting the time until failure of corroding hinge-rod structures allows to reduce the risks of an emergency situation. Additionally, accuracy control enables finding a balance between computational costs and the accuracy of solving the problem.

KEYWORDS: artificial neural networks, accuracy control, distribution, mathematical expectation, approximation, numerical methods, durability corroding structure.

ABBREVIATIONS

AE is an aggressive environment;

ANN is an artificial neural network;

CPU is a central process unit;

DE is a differential equation;

FEM is a finite elements method;

GPU is a graphical process unit;

MSE is a mean square error;

HRS is a hinge-rod structure;

PDCS is the problem of durability of a corroding structure;

RMSE is a root mean square error;

RPROP is a resilient propagation;

SDE is a system of differential equations.

NOMENCLATURE

A_0 is an initial area of the section;

A^i is a cross-sectional area of the i-th structural element;

a is a coefficient of a polynomial of degree 3 approximating the dependence of axial forces Q_j in structural elements on time t;

B is a bias unit;

b is a coefficient of a polynomial of degree 3 approximating the dependence of axial forces Q_j in structural elements on time t;

c is a coefficient of a polynomial of degree 3 approximating the dependence of axial forces Q_j in structural elements on time t;

D is a differentiation matrix;

d is a number of neurons in the ANN input layer;

E is an elasticity matrix;

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i is an index of HRS element;

i_0 is an index of HRS element that first fails;

j is a number of nodes of the finite-difference grid;

K is a stiffness matrix;

k is a coefficient of influence of stress on the rate of the corrosion process;

N is a number of structural elements;

n is both training and test dataset size;

n_{test} is a number of samples in the test dataset;

P_0 is an initial perimeter of the section;

Q^i is a value of the axial force in the i-th structural element;

Q_j is values of axial forces at nodal points of the approximate solution $\widetilde{t}$;

$\overline{R}$ is a vector of nodal loads;

s is a number of neurons in the ANN hidden layer;

T_j is a time values at j nodal points of the approximate solution $\widetilde{t}$;

t is a time;

t^* is a reference numerical solution of the PDCS, obtained at a large number of nodal points;

$\widetilde{t}$ is a approximate numerical solution of the PDCS, obtained with lower computational costs than for the reference;

t_i^* is a reference solution of the PDCS for the i-th sample;

$t_i^*(u)$ is an approximate solutions of the PDCS for the i-th sample;

$\overline{u}$ is vector of displacements;

v_0 is a corrosion rate in the absence of stress;

Z is a number of weight coefficients;

α is a shape parameter of the two-parameter inverse gamma distribution;

β is a scale parameter of the two-parameter inverse gamma distribution;

$\Gamma(\cdot)$ is a gamma function.

$\overline{\delta}$ is a vector of values of the depth of corrosion damage of each structural element;

$\delta^i(t)$ is a value of the depth of corrosion damage in the i-th structural element (damage parameter);

$\overline{\varepsilon}$ is a vector of deformations;

ε_i is a value of the target function for the i-th sample;

$\varepsilon_i(u)$ is an output value of the model from M_u for the i-th sample;

σ^i is a current stress in the i-th structural element;

σ_0 is an initial stress;

$\overline{\sigma}$ is a vector of stresses;

$[\sigma]$ is an yield stress.

INTRODUCTION

In many strategic industrial sectors including nuclear and thermal energy, chemical and petrochemical industries, the use of metal structures in aggressive environments leading to corrosion is involved. Corrosion is a primary factor contributing to the catastrophic failure of equipment, which can be accompanied by significant financial losses and severe environmental consequences [1]. Ensuring the ability to respond promptly to the mentioned risks raises the relevant issue of determining the duration during which a structure will perform its functions – the durability of the structure. This matter is typically addressed through computer modeling. Moreover, the latter is complicated by the fact that the rate of the corrosion process is influenced by mechanical stresses in the structural elements. Existing models of corrosion-induced deformation consist of systems of differential equations and systems of mechanics equations, the solution of which requires significant computational costs. To solve the problem of reducing computing costs in 2021, Zelenstov D.G., Korotka L.I. and Denysiuk O.R. proposed (see [2]) a method for solving the PDCS using ANN (hereinafter Method). However, the authors do not consider the problem of establishing accuracy control of Method. Also, in [2] and related approaches (see, for example, [3, 4]), the dependence of the output of the neural network model on the set of initial values of the weight coefficients of the neural network is not taken into account. These coefficients represent the realization of a certain random variable, meaning that depending on a particular realization, the output of the neural network, in general, will be different. Therefore, it is appropriate to consider not just the individual result in the form of the output of the neural network, but rather certain characteristics of the distribution of the results, such as mathematical expectation.

The paper investigates the refinement of the method proposed in [2] and establishes accuracy control. At the same time, the presence of the aforementioned dependence of the ANN's output on a set of random initial values of weight coefficients is taken into account.

The **object of the study** is the problem of accuracy-controlled numerical analysis of the problem of solving PDCS.

The **subject of the study** is artificial neural networks as a means of enhancing the efficiency of numerical methods while simultaneously ensuring a specified level of result accuracy.

The purpose of the study is to refine the method of solving PDCS using ANN and establish accuracy control rule.

1 PROBLEM STATEMENT

Let's consider the model of corrosive deformation of HRS operating in aggressive environments based on the FEM (for more details, see [2, 5]):

$$\begin{aligned} &\frac{d\delta^i(t)}{dt} = v_0 \cdot \left(1 + k \cdot \sigma_i\left(A^i(\delta^i(t)), Q^i(\overline{\delta})\right)\right), \\ &\delta^i(t)\big|_{t=0} = 0; \quad i = \overline{1, N}. \end{aligned} \tag{1}$$

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Assuming Q = const, by knowing the solutions $\delta_i(t)$ of the differential equations (1) and the limit values of the corrosion damage depths δ_i^* one can find the time values $t_i = t_i^*$, at which the δ_i^* values are reached. The value $t_{i_0}^* = \min t_i^*, i = \overline{1,N}$ is referred to as the durability of the structure. To calculate σ_i in the right-hand side of (1) deformable solid mechanics equation are utilized, which in the form of the FEM system of equations are represented as:

$$\begin{cases} \overline{R} = K^{-1} \cdot \overline{u}, \\ \overline{\varepsilon} = D \cdot \overline{u}, \\ \overline{\sigma} = E \cdot \overline{\varepsilon}. \end{cases} \quad (2)$$

As the cross-sectional areas of elements change during the process of corrosive wear, the elements of the structural stiffness matrix K, as well as the stresses σ_i in the elements, vary over time. Thus, in the numerical solution of (1), it is necessary to compute (2) at each node of the finite difference grid. This significantly increases computational costs.

Methods that address the issue of reducing computational costs may require both the absence of accuracy loss and the ability to control this accuracy. Therefore, following the Method in [2], we will explore the problem of its refinement and accuracy control. By accuracy of the method, will mean the value of the mathematical expectation of the target metric – E(RMSE); by refinement of the method – identification of conditions that allow reducing the value of E(RMSE) compared to the corresponding value of the inherited method without, at least, increasing computational costs; and by accuracy control – determination of the dependence between the values of E(RMSE) and the parameters of the approximate solution.

2 REVIEW OF THE LITERATURE

The use of Artificial Neural Networks (ANNs) in the algorithm for controlling the accuracy of numerical solution of the differential equation of the form (1) was proposed in [3]. The authors considered a trained ANN, which determined the parameter of numerical integration to achieve the specified solution error. This method was further developed in [4], where instead of training separate ANNs for different error values, a unified ANN with the error value as an input parameter was suggested. A common feature of these algorithms is the ignoring of changes in axial forces in elements of corroding structures during the formation of training samples for ANNs. As a result, the predicted error value did not always meet the specified level.

In [2], a method of correction functions was proposed, in which the solution of the PDCS was approximated with minimal computational costs and refined using a correction function. The corrective function included an ANN that approximated the dependency between the error of the approximate solution and certain input parameters of the PDCS, including the coefficients of a polynomial used to describe the variation in time of axial forces in the HRS elements. The coefficients of this polynomial were determined at the stage of finding the approximate solution of the PDCS. This approach reduced computational costs and solved the problem of taking into account changes in axial forces over time, but the problem of accuracy control of the algorithm remained open.

3 MATERIALS AND METHODS

First, let's outline the general scheme of refining the Method, after which we will proceed to a more detailed exposition. The general refinement scheme of the Method consists of the following steps:

1) by varying the input parameters sets of the ANN, the Method will be using to solve the PDCS. In other words, models will be training according to the Method on different input parameters sets, including the proposed Method set;

2) let's create a set V, which includes L different sets of initial values of weight coefficients $\{w_p\}_{p=1}^{P}, w_p \in [0,1]$, where P – the number of weight coefficients. The procedure from the previous step for each input parameters set and for each element of set V will performed. As a result, for each input parameters set, we will have a distribution of target metric values; the distribution parameters will be estimated using the maximum likelihood method [6];

3) for each distribution calculate the mathematical expectation and compare the obtained values;

4) the input parameters set on which the smallest value of the mathematical expectation is achieved is the sought-after condition that refines the Method, if at least it does not increase computational costs at the stage of applying the obtained refinement. Remark: we ignore changes in computational costs arising from a certain increase in the number of input parameters of the ANN, because the application stage of the Method requires the existence of a previously trained ANN.

Let's now consider in more detail the outlined scheme, using also [2].

Dataset forming. A sample of volume n with training samples is generated, containing construction parameters $A_0, P_0, [\sigma]$, environmental parameters (v_0, k), value t^* of the reference solution of the PDCS, time values and axial forces (T_j, Q_j) at j = 4 nodal points $T_j = \{t_1, t_2, \ldots, t_j\}$ and $Q_j = \{q_1, q_2, \ldots, q_j\}$, where $t_j = \tilde{t}$, coefficients (a, b, c) of a polynomial of degree 3 that approximates the dependence $Q(t)$ at points (T_j, Q_j). The target function is defined as the error $\varepsilon = \frac{t^*}{\tilde{t}}$ between the reference and approximate solutions of the PDCS.

Models training. To refine the Method, we will consider sets of input parameters that enhance the information about the variation of axial forces over time compared to those proposed in the Method. Let's define the set V and on the next sets of input parameters for the

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ANN: $u_{a,b,c} = (A_0, P_0, \sigma_0, a, b, c)$, $u_{a,b,c,T_j} = (A_0, P_0, \sigma_0, a, b, c, T_j)$, $u_{Q_j} = (A_0, P_0, \sigma_0, Q_j)$, $u_{Q_j,T_j} = (A_0, P_0, \sigma_0, Q_j, T_j)$ will be trained L models accordingly. These sets of L models will be denoted as $M_{(a, b, c)}$, $M_{((a, b, c),T)}$, $M_{(Q)}$, $M_{(Q,T)}$, or simply M_u, when referring to the set of models corresponding to a specific u as defined above. Note that $u_{a,b,c}$ is the set which is used in the Method itself; hence, this set will be referred to as the base set, and the set of models $M_{(a,b,c)}$ – will be called the set of base models. As the metric to be minimized during the training of the ANN, we will consider $\text{MSE} = \frac{1}{n_{\text{test}}} \sum_{i=1}^{n_{\text{test}}} (\varepsilon_i - \varepsilon_i(u))^2$. The refined solution of the PDCS will have the form $t^*(u) = \tilde{t} \cdot \varepsilon(u)$, which means $t^* \approx t^*(u)$.

Distributions constructing. To each model from M_u will assign the value of the target metric $\text{RMSE} = \sqrt{\left(\frac{1}{n_{\text{test}}} \sum_{i=1}^{n_{\text{test}}} \left(t_i^* - t_i^*(u) \right)^2 \right)}$. As mentioned earlier, the value of the MSE metric depends, among other things, on the set of initial weight coefficients of the ANN $\{w_z\}_{z=1}^{Z}, w_z \in [0,1]$, which is an realization of a random variable W, (in practice, it can be, for example, $W \sim U([0,1])$). Thus, under the defined conditions, MSE, and consequently RMSE, are functions of the random variable W. Having obtained the set M_u comprising L models, where the latter differ only in the initial sets $\{w_z^l\}$, $z = \overline{1,Z}$, $l = \overline{1,L}$, can be constructed the distribution of the target metric RMSE for each set M_u find estimates of its parameters, and calculate the mathematical expectation E(RMSE).

Refinement of the Method. The set u_0, which corresponds to the smallest value of mathematical expectation (or the best set), is the sought-after condition that refines the Method.

Accuracy control rule. Let $J = \{2,3,...j'\}$. For the identified best set, will be constructed several sets $M_{u_0}(j)$ each of size L', where $j \in J$. For each of these sets, values of E(RMSE(j)) will be calculated. By approximating the points (j, E(RMSE(j))), $j \in J$, will be built the dependency $y = g(x)$, $x \in [2, \infty)$, $y \in (0, \infty)$. The function $h(y) = [g^{-1}(y)]^{\sim}$, $h(y) \in \{2, 3, \ldots, j', \ldots\}$, where $[\cdot]^{\sim}$ denotes rounding to the nearest integer value, represents the sought dependence between the values of E(RMSE) and the number of required nodes j, which are parameters of the approximate solution.

4 EXPERIMENTS

For further research, two cases were considered based on the nature of the variation of axial forces Q over time t in the elements of the corroding structure, differing in the number of monotonicity intervals. The number of monotonicity intervals in this case affects the quality of approximation of these dependencies by a polynomial of degree 3. In case A there is one monotonicity interval, while in case B there are two monotonicity intervals. The graphs illustrating the variation of axial forces over time and their approximation by a polynomial of degree 3 at 4 nodes are presented in Fig. 1 and Fig. 2 for case A and case B, respectively.

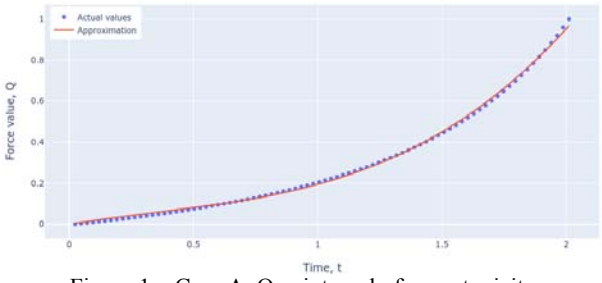

Figure 1 – Case A. One interval of monotonicity

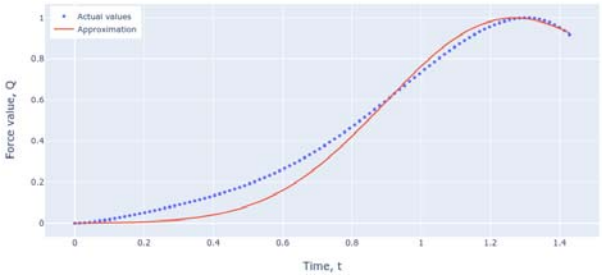

Figure 2 – Case B. Two interval of monotonicity

For numerical experiments, two datasets were generated for case A and case B, each containing n = 20,000 samples. An I-beam profile was chosen as the type of the leading element of the HRS. Initial geometric parameters of the I-beam profile for each sample were randomly selected from the set of standard sizes defined for this type of profile. The datasets were divided into training and testing sets in a ratio of 70% to 30%, meaning the training set consisted of 14,000 samples and the testing set of 6,000 samples.

The architecture of the ANN takes the form of a multilayer perceptron (see Fig. 3) with dimensions $d \times s \times 1$, where d equal to the number of features in the input set, $s = 2 \cdot d + 1$ calculating according to the Hecht-Nielsen theorem [7]. The activation function for the hidden and output layers is Sigmoid [8]. Each model was trained for 1000 epochs using the RPROP learning algorithm [9] in batch mode.

The number of models L for refining the method is equal to 100. The number of models L' for determining the accuracy control is equal to 500. According to the values of L and L', sets V and V' of random seed values are generated from a discrete uniform distribution, which is equivalent to creating sets of initial weight coefficient values.

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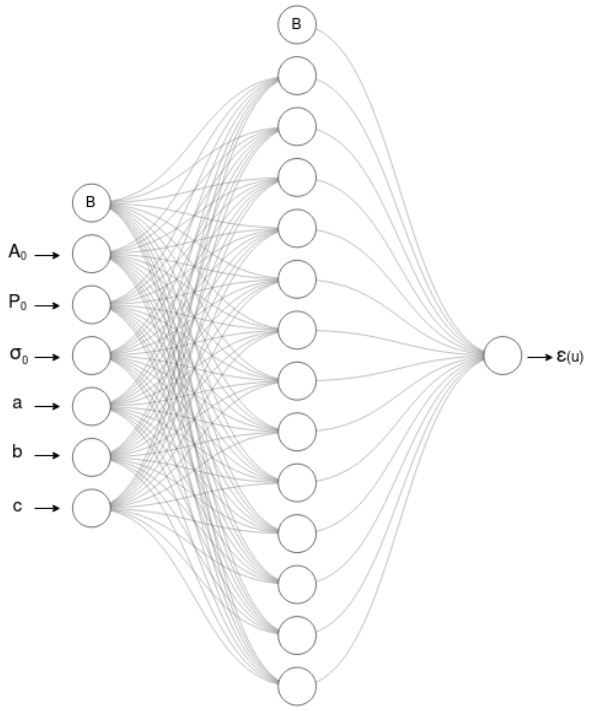

Figure 3 – ANN architecture for the base model

To obtain distributions of RMSE values for models from the sets M_u, $M_{u_0}(j)$, $j \in J = \{2, 3, 4, 6, 8, 12, 16\}$, a two-parameter inverse gamma distribution [10] is considered as a hypothetical distribution, and its probability density function is given by $f(x,\alpha,\beta) = \frac{\beta^\alpha}{\Gamma(\alpha)} \cdot \left(\frac{1}{x}\right)^{\alpha+1} \cdot \exp\left(\frac{-\beta}{x}\right)$, $x > 0$. The distribution parameters α and β are estimated using the maximum likelihood method, and the mathematical expectation of the distribution is calculated as $\frac{\beta}{\alpha - 1}$ for $\alpha > 1$.

The implementation of this approach was carried out in the PyCharm and Jupyter Notebook environments using the Python programming language and the following modules and libraries: Numpy, Pandas, scikit-learn for data preprocessing and manipulation; module stats from SciPy for working with probability distributions; Plotly for data visualization. The PyTorch machine learning framework [11] was chosen for working with ANNs. Computations were performed on a CPU 3.7 GHz AMD Ryzen 9 5900X, a GeForce RTX 3060 GPU, and 32GB of RAM.

5 RESULTS

For each set M_u, L models were trained with different initial values of weight coefficients. Based on the results of these models, distributions for RMSE values were constructed. Table 1 presents the mean RMSE values and mathematical expectations E(RMSE) for the sets of obtained models.

Table 1 – Results of models training

	$M_{(Q,T)}$	$M_{(Q)}$	$M_{(a,b,c,T)}$	$M_{(a,b,c)}$
Case A, mean(RMSE)	$1.20626 \cdot 10^{-3}$	$1.47549 \cdot 10^{-3}$	$1.91016 \cdot 10^{-3}$	$2.13634 \cdot 10^{-3}$
Case A, E(RMSE)	$1.20624 \cdot 10^{-3}$	$1.47031 \cdot 10^{-3}$	$1.91096 \cdot 10^{-3}$	$2.13673 \cdot 10^{-3}$
Case B, mean(RMSE	$4.311255 \cdot 10^{-2}$	$4.376519 \cdot 10^{-2}$	$4.730537 \cdot 10^{-2}$	$4.762757 \cdot 10^{-2}$
Case B, E(RMSE)	$4.311258 \cdot 10^{-2}$	$4.376514 \cdot 10^{-2}$	$4.730537 \cdot 10^{-2}$	$4.772759 \cdot 10^{-2}$

Thus, in comparison with the baseline set, for case A, the mathematical expectation value corresponding to the best set is less by $\frac{\left(0.0021364 \cdot 10^{-3} - 0.00120626 \cdot 10^{-3}\right)}{0.0021364 \cdot 10^{-3}} \cdot 100\% \approx 43.54\%$;
and for case B, it is less by $\frac{\left(0.04772759 \cdot 10^{-2} - 0.04311258 \cdot 10^{-2}\right)}{0.04772759 \cdot 10^{-2}} \cdot 100\% \approx 9.67\%$.

The constructed distributions for case A and case B are shown in Fig. 4 and Fig. 5, respectively.

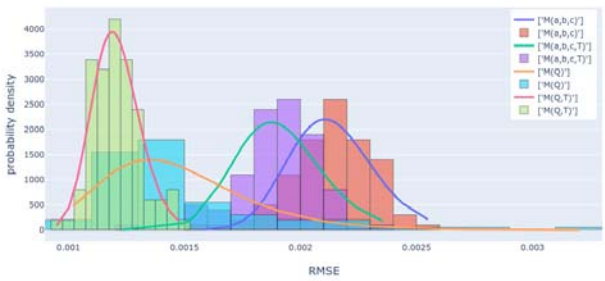

Figure 4 – RMSE distributions of trained models for case A

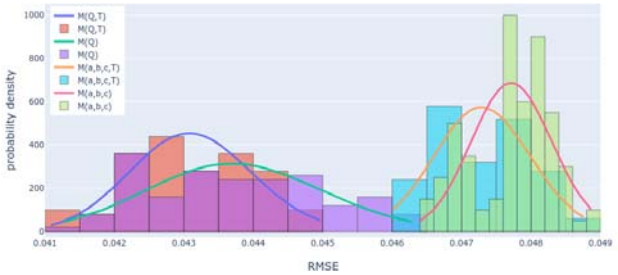

Figure 5 – RMSE distributions of trained models for case B

For the best set u_{Q_j,T_j} L' models were built for each number of nodes j from J. For each set of obtained models, distributions were constructed, and the mathematical expectations E(RMSE) were calculated. Fig. 6 shows the correspondence between E(RMSE) values and number of nodes j, their approximation by the function $y = g(x) = a \cdot (x+c)^b$, which obtained based on points $j \in \{2, 3, 4, 6\}$, and the mean values of RMSE before refining the solution using artificial neural network (the mean value of RMSE at the point $j = 2$ is equal to 0.10217255).

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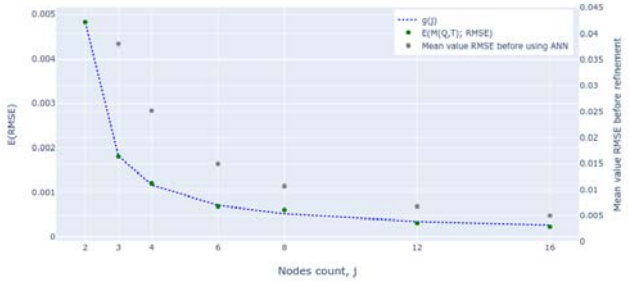

Figure 6 – Graph of the approximate dependence of E(RMSE) on the number of nodes

Table 2 provides consolidated information about dependence between E(RMSE) and number of nodes j based on approximation by points $j \in \{2, 3, 4, 6\}$. Accordingly, at points $j < 6$, the behavior of the obtained approximation is demonstrated on the data to which the approximating function was fitted, and at $j > 6$ on new data.

Table 2 – Dependence of E(RMSE) on the number of nodes j based on approximation

j	E(RMSE)	$g(j)$
2	0.0048214	0.0048209
3	0.0018037	0.0018175
4	0.0012030	0.0011706
6	0.0006873	0.0007089
8	0.0006061	0.0005188
12	0.0003082	0.0003457
16	0.0002238	0.0002631

Using the function $g^{-1}(y)$ a function was constructed:

$$h(y) = \left[g^{-1}(y)\right]^{\sim} = \left[\left(\frac{y}{a}\right)^{\frac{1}{b}} - c\right]^{\sim}, \qquad (3)$$

where $a = 0.00249686$, $b = -0.84226492$, $c = -1.54206767$, which is the sought accuracy control rule for the Method. The graph of the obtained accuracy control rule is shown in Fig. 7.

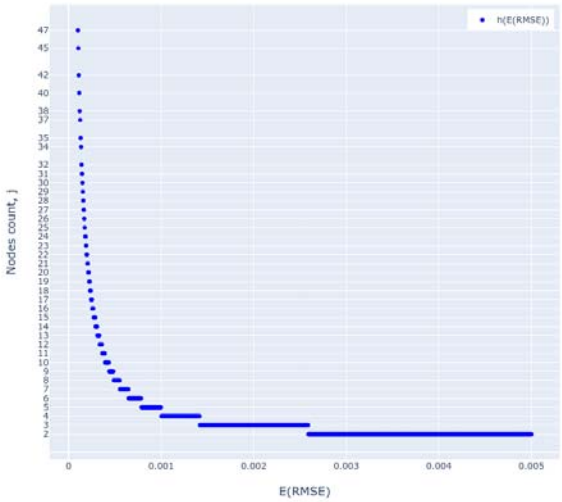

Figure 7 – Graph $h(y)$

6 DISCUSSION

The smallest value of the mathematical expectation of the target metric E(RMSE) for both case A and case B corresponds to the set $u_{Q,T}$. At the same time, the E(RMSE) value of the base set $u_{a,b,c}$ is the largest for both cases. This allows us to conclude that all proposed sets refine the results of the Method. Note that the set $u_{a,b,c}$ contains the least information about the variation of axial forces over time compared to other sets Additionally, the models from the set $M_{(Q,T)}$ do not require a separate approximation of the dependence of axial forces when obtaining input data for ANN. This reduces computational costs in solving PDCS.

The obtained accuracy control rule for the method (3) takes the form of a piecewise-linear function. It allows for determining the necessary number of nodes in a finite-difference grid immediately for a desired value of the mathematical expectation of RMSE. Subsequently, using the obtained value of the number of nodes j as a parameter in the search for an approximate solution $\tilde{t}$, it is possible to construct a set $M_{u_0}(j)$ to which the model corresponding to the desired RMSE value belongs.

Analyzing the graph in Figure 6, it can be observed that with an increase in the number of nodes j the distance between the mean value of RMSE before refining the solution $\tilde{t}$ and the corresponding value of E(RMSE) after refinement decreases. This can be interpreted as follows: the more nodal points we use to find the approximate solution, the closer it becomes to the reference solution. Consequently, there is a reduction in the error value remaining for the refinement of the ANN.

Depending on the accuracy requirements of the method, instead of the mathematical expectation, other distribution characteristics, such as quintile values, etc., may be considered. Additionally, it may be relevant to introduce a penalty for errors leading to an overestimation of the structure's durability in the metric being optimized.

CONCLUSIONS

The scientific novelty: Developed an approach for solving PDCS using ANN. The existing method was refined by revising the input parameters to the ANN and, as a result, abandoned the approach of preliminary approximation of the dependence of axial forces on time. The dependency of the target metric mathematical expectation on the numerical solution parameters was identified, making the method accuracy-controllable. The evaluation of the models took into account the dependence of the ANN output on random initial values of weight coefficients.

The practical significance: According to the results of numerical studies, it was established that, depending on the case under consideration, the refinement allows a reduction in the error by an average on 9.54% and 43.54% compared to the original method. The potential impact of implementing the proposed model lies is to more accurately predict the durability of corroding hinge-rod structures in terms of mathematical expectation, thereby reducing the risk of emergency situations and associated finan-

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cial and environmental consequences. The accuracy control of the method allows solving PDCS with the required accuracy while reducing unnecessary computations.

Prospects for further research are the consideration of the possibility to introduce a penalty for errors that lead to an overestimation of the HRS predicted failure time for the metric being optimized, and the study of the application of the proposed approach in other related problems, for example, for the calculation of the constraint function in the problem of the HRS optimization.

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УТОЧНЕННЯ І КЕРОВАНІСТЬ ЗА ТОЧНІСТЮ МЕТОДУ РОЗВ'ЯЗАННЯ ЗАДАЧІ ДОВГОВІЧНОСТІ КОРОДУЮЧОЇ КОНСТРУКЦІЇ ІЗ ВИКОРИСТАННЯМ НЕЙРОННОЇ МЕРЕЖІ

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АНОТАЦІЯ

Актуальність. Прогнозування часу виходу з ладу кородуючих шарнірно-стрижневих конструкції є важливою складовою управління ризиками багатьох сфер промисловості. Точний розв'язок задачі довговічності кородуючої конструкції дозволяє попередити ряд небажаних наслідків, що виникають у разі настання аварійної ситуації. Разом з цим постає питання ефективності існуючих методів розв'язання даної задачі та способів їх покращення.

Мета роботи полягає в уточненні методу розв'язання задачі довговічності кородуючої конструкції із використанням штучної нейронної мережі і встановлення керованості за точністю.

Метод. Для уточнення оригінального методу розглядаються альтернативні набори вхідних даних для штучної нейронної мережі, що дозволяють збільшити інформацію про зміну осьових зусиль у часі. Для кожного набору вхідних даних навчається множина моделей. На основі розподілів значень цільової метрики моделей із отриманих множин обирається набір, на якому досягається найменше значення математичного сподівання цільової метрики. Для множини моделей, що відповідає знайденому найкращому набору, визначається керованість за точністю методу шляхом встановлення залежності між математичним сподіванням цільової метрики і параметрами чисельного розв'язання.

Результати. Визначено умови, за яких отримано менше значення математичного сподівання цільової метрики порівняно з оригінальним методом. Результати чисельних експериментів, в залежності від розглядуваного випадку, показують в середньому на 43.54% і 9.67% кращі результати уточненого методу порівняно з оригінальним. Окрім цього, запропоноване уточнення зменшує необхідні для знаходження розв'язку обчислювальні витрати за рахунок відмови від деяких кроків оригінального методу. Отримано закон керованості методу за точністю, який дозволяє в середньому отримувати задане значення похибки без виконання зайвих обчислень.

Висновки. Отримані результати свідчать про доцільність застосування запропонованого уточнення. Більш висока точність прогнозування часу виходу з ладу кородуючих шарнірно-стрижневих конструкцій дозволяє зменшити ризики настан-

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ня аварійних ситуацій, а керованість за точністю – знаходити баланс між обчислювальними витратами і точністю розв'язання задачі.

КЛЮЧОВІ СЛОВА: нейронна мережа, керованість за точністю, розподіл, математичне сподівання, апроксимація, чисельні методи, довговічність кородуючої конструкції.

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