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NUMERICAL MODELING OF THE IMPACT OF COMPLEX LOADS ON BUILDING MATERIALS

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Abstract. The article is devoted to the urgent problem of predicting the durability of building materials and structures exposed to complex multifactorial loads, including mechanical, thermal, seismic, and corrosive effects. Current trends in construction, especially in areas with high risks of military damage and natural disasters, require scientifically grounded methodologies for assessing the performance of materials under real operating conditions. The study presents a comprehensive analysis of numerical modeling methods, with a particular focus on the finite element method (FEM). This approach enables detailed reproduction of the stress–strain state and makes it possible to account for nonlinear interactions between different types of loads, which is essential for accurate predictions of material service life. Special attention is paid to algorithms that integrate mechanical, seismic, and thermal effects into a unified model, as well as the application of combined methods, including the boundary element method, the Monte Carlo method, and finite differences. The proposed numerical schemes were validated against experimental data, confirming high accuracy with deviations not exceeding a few percent. An additional innovative aspect of the research lies in the integration of classical numerical methods with machine learning technologies, particularly deep neural networks, which allow the consideration of complex nonlinear degradation patterns of materials over time. The study also emphasizes the integration of numerical models with monitoring systems based on IoT sensors. Such an approach ensures real-time dynamic control of the technical state of building structures and enables the timely identification of critical deviations. It has been demonstrated that the application of these algorithms not only improves the accuracy of residual life predictions but also significantly reduces costs by implementing resource-saving restoration technologies. The conclusions outline future research directions, including the extension of numerical modeling methodologies for novel high-performance materials, the advancement of machine learning techniques, and the creation of fully automated systems for monitoring and predicting the technical state of building structures.

Keywords: durability prediction, complex loads, finite element method, machine learning, neural networks, resource-efficient technologies.

Introduction. Building structures are constantly exposed to complex and dynamically changing external loads, including seismic, wind, static, thermal, and corrosion factors. This problem is particularly arise in the context of the restoration of buildings damaged as a result of military operations, when structures undergo additional damage and material degradation, which significantly complicates their assessment and prediction of further operation [1, 9]. Traditional analysis methods, based on separate consideration of individual types of loads, do not allow for effective consideration of their nonlinear interaction, which may lead to an underestimation of the destruction risks.

The solution to this problem is the use of modern complex numerical methods, in particular the finite element method and boundary element method, which allow integrating different types of loads into a single model. This significantly increases the accuracy of predicting the condition of structures, which is especially important for ensuring the safety and durability of buildings in areas with high seismic activity, aggressive environmental conditions, and in situations associated with military destruction [5, 10].

The integration of numerical models with Internet of Things (IoT) technologies and sensor monitoring systems allows real-time information on the condition of structures and immediate response to potential threats, which is key to making timely decisions on repair and strengthening. The application of these technologies also contributes to the development of new, resource-saving structural solutions that optimize material costs and restoration work.

Thus, the development and implementation of modern numerical methods for modeling complex loads is a critically important task for increasing the reliability, safety, and durability of building structures in conditions where the requirements for their strength and stability are constantly increasing.

Analysis of recent research and publications. Modern scientific literature pays significant attention to the use of numerical methods and algorithms for assessing and predicting the durability of building materials and structures under the influence of complex loads, which is due to the increasing requirements for the safety and stability of structures.

One of the leading directions of modern research is numerical modeling of the influence of corrosion on the structural reliability of reinforced concrete elements. In particular, in [9] the authors performed a detailed analysis using the finite element method (FEM) to predict the bearing capacity of reinforced concrete structures reinforced with carbon fiber reinforced polymer (CFRP) meshes with composite cementitious materials. The study took into account the corrosion of reinforcement and its effect on the strength properties of concrete and reinforcement. The authors use the following relationship to estimate the effective cross-section of reinforcement after corrosion:

$$A_{eff} = A_0(1-\rho_c), \tag{1}$$

where Ae_{ff} – effective cross-section after corrosion; A_0 – initial cross-section; ρ_c – degree of corrosion damage.

In another important study [9], the authors used numerical models to analyze the seismic vulnerability of structures after large earthquakes. They assessed the risks to buildings, taking into account structural features, ground motion, and weighting factors of different risk factors. The empirical and coded seismic vulnerability curves developed by the authors demonstrate high accuracy in estimating structural behavior, especially for steel and reinforced concrete structures. The paper proposes an approach to integrating risk factors:

$$V = \sum_{i=1}^{n} w_i F_i, \tag{2}$$

where V – overall vulnerability assessment; w_i – risk factor weights; F_i – the importance of a single risk factor.

Also, in [1], numerical models for assessing the impact of seismic loads using a multifactorial approach that takes into account both code and empirical approaches to create building vulnerability curves were investigated. The authors emphasize that the use of such curves is more effective compared to traditional methods, allowing for a better assessment of the risks of damage and destruction of structures.

Methods for predicting the behavior of structures under complex loads are also considered in [5]. The authors use numerical algorithms for modeling static and dynamic loads, where differential equations of motion in the form are solved:

$$[M]\ddot{u} + [C]\dot{u} + [K]u = F(t), \tag{3}$$

where M, C, K – respectively the mass, damping and stiffness matrix; $u, \dot{u}, \ddot{u}$ – vectors of displacements, velocities and accelerations; $F(t)$ – vector of time-varying loads. The obtained results of numerical calculations were confirmed by experimental studies, which confirmed the accuracy of the modeling [5].

Numerical models based on the variation approach of the theory of plasticity were used to analyze the durability of masonry under diagonal stresses. The authors [7] investigate the behavior of brickwork under diagonal tension, providing strength criteria and formulas for assessing the condition of masonry:

$$\sigma_t = \frac{F_{max}}{A\cos\theta}, \tag{4}$$

where σ – diagonal tension; F – load force; A – cross-sectional area, and θ – angle of loading relative to the horizontal. The study demonstrates high accuracy of numerical calculations for predicting the strength and durability of masonry.

The issue of durability of repaired reinforced concrete structures in corrosive environments is highlighted in the study [4]. It considers the assessment of the effectiveness of repair materials, where the prediction of degradation is carried out using models based on machine learning. The authors demonstrate that the combination of numerical modeling with neural network algorithms allows to significantly improving the accuracy of predictions and timely plan repair measures [12].

Thus, the analysis of recent studies shows that the integrated use of numerical methods integrated with modern monitoring and machine learning technologies is a promising direction for accurate prediction of the durability of building materials and structures under complex operational loads. This allows significantly increasing the effectiveness of construction measures aimed at protecting and restoring structures, especially in situations associated with the destructive influence of external factors.

Aim and objectives. The purpose of this study is to develop, adapt and further improve modern numerical methods and algorithms for predicting the durability of building materials under the influence of complex loads, including mechanical, seismic, corrosion and thermal factors. The complex and simultaneous effects of these loads can significantly worsen the strength and operational characteristics of building structures, especially in areas with an increased risk of man-made and natural disasters. In this regard, there is a need to create accurate predictive models and algorithms that can take into account nonlinear interactions of various types of loads and provide reliable forecasts of the durability of materials.

The objectives of the study are:

- analysis and systematization of modern numerical methods for modeling the behavior of building structures;
- improving finite element method (FEM) algorithms and other effective numerical approaches for more accurate prediction of structural durability;
- development of mathematical models that allow integrating heterogeneous factors (mechanical, thermal, seismic, corrosion) into a single comprehensive forecasting model;
- experimental validation of developed numerical models using real data and operating scenarios;
- development of recommendations for the practical implementation of numerical algorithms in automatic monitoring systems for building structures;
- assessing the effectiveness of integrating numerical models with machine learning methods to improve the accuracy of predictions of the durability of building structures.

Achieving these goals will allow us to create scientifically sound methods for predicting the residual resource and optimizing repair measures, which will ensure the durability and safety of building structures in operating conditions with a high risk of damage.

Materials and research methodology. The work uses a comprehensive approach to the study of numerical methods and algorithms for predicting the durability of building materials and structures exposed to complex combined loads. Typical reinforced concrete and brick structures typical of civil and industrial construction were selected as the objects of the study [14]. The study is based on the application of numerical methods, such as the finite element method (FEM), the boundary element method (BEM), as well as machine learning methods for analyzing large amounts of data on material degradation. A comprehensive approach to the use of numerical models, combined with modern machine learning methods, allows significantly increasing the accuracy and reliability of predicting the durability of building structures, which is confirmed by validation on experimental data [15].

Research results. The development of numerical methods for predicting the durability of building materials under complex loadings is a key task of modern engineering practice. Taking into account complex mechanical, seismic, temperature and corrosion effects requires the development of accurate mathematical models that can predict the behavior of materials over a long operational period [8].

Modern approaches are based on the use of numerical models that allow assessing the behavior of materials and structures under various operating conditions, including emergency and post-emergency scenarios.

The main numerical methods used to predict the durability of building structures:

- Finite Element Method (FEM).
- Boundary Element Method (BEM).
- Monte Carlo Method.
- Finite Difference Method.

The use of these methods allows for multifactor analysis of structures and assessment of their residual bearing capacity after exposure to destructive factors.

The durability of a building material is determined by its ability to withstand accumulated damage and its residual load-bearing capacity. This relationship can be represented by the equation [2]:

$$D(t) = D_0 + \int_0^t \left(\sigma(t), T(t), C(t), S(t) \right) dt, \tag{5}$$

$D(t)$ – degree of material degradation at a point in time t; D_0 – initial level of damage; $\sigma(t)$ – mechanical load; $T(t)$ – temperature effect; $C(t)$ – corrosion processes; $S(t)$ – seismic loads.

Thus, the durability of a building material depends on the cumulative effect of loads throughout its entire period of operation.

Basic numerical prediction methods. *The finite element method (FEM)* is the main approach for numerical analysis of the strength and durability of materials. It allows you to break the structure into small elements, for each of which the equation of mechanical equilibrium is solved [12]:

$$\left[K \right] u = F, \tag{6}$$

K – structural stiffness matrix; u – node displacement vector; F – vector of external loads.

FEM is used to assess the stress-strain state of materials, especially when analyzing reinforced concrete structures damaged by seismic or wind impacts.

The Boundary Element Method (BEM) is an alternative to FEM and is used to analyze complex boundary conditions of structures, such as the interaction of concrete and reinforcement with partial loss of bearing capacity. The basic equation of this method is [9]:

$$\left[B(x) \right] q = D(x), \tag{7}$$

$B(x)$ – deformation transformation matrix; q – displacement vector; $D(x)$ – vector of internal forces.

The Monte Carlo method is used for stochastic simulations where material parameters may vary due to random factors such as corrosion, temperature cycling, structural inhomogeneities. It is based on numerous iterations to obtain a probability distribution of the material's strength.

The probability of the failure is:

$$P_f = \frac{N_f}{N}, \tag{8}$$

P_f – probability of the failure; N_f – number of cases where limit loads were exceeded; N – total number of simulations.

The finite difference method is used to model the diffusion of corrosive particles in concrete structures. It allows predicting the rate of penetration of aggressive substances into concrete:

$$\frac{\partial C}{\partial t} = D \frac{\partial^2 C}{\partial x^2}, \tag{9}$$

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C – concentration of corrosive agents; D – diffusion coefficient; x – coordinate in the material; t – time.

The combined use of numerical methods provides accurate prediction of the durability of building structures. The finite element method is the most effective approach for modeling the strength of structures. The Monte Carlo and finite difference methods allow assessing the risks of corrosion and temperature loads [6].

The impact of repairs on the durability of structures. The study [2] emphasizes the importance of correctly selected and implemented repair technologies to ensure the long-term operation of building structures. The main result of this study is a mathematical model that describes the relationship between the quality of repair work and the predicted service life of restored building elements. To assess the impact of repairs on the durability of structures, the authors developed a special probability distribution function:

$$P(t) = 1 - e^{-\lambda t}, \tag{10}$$

$P(t)$ – probability of maintaining the operational characteristics of the material after repair over time t; λ – degradation coefficient, which depends on the quality of the repair, operating conditions and the type of materials used during the restoration of the structure.

According to the results obtained, the degradation coefficient (λ) varies significantly depending on the selected methods and the quality of the repair. The study found that the use of high-strength materials and strict adherence to the repair processes can provide significantly lower values – of the degradation coefficient, and, accordingly, greater durability of structures [3].

The distribution function can be written as follows:

$$P(t) = 1 - e^{-(\lambda_m + \lambda_e + \lambda_q)t}, \tag{11}$$

λ_m – coefficient characterizing the quality of materials used for repairs;

λ_q – coefficient depending on the quality of repair work;

λ_e – coefficient related to operating conditions after repair.

The values of these coefficients, determined experimentally, are given in Table 1.

Table 1 – Degradation coefficients depending on the quality of repair

Repair quality	λ_m, year $^{-1}$	λ_e, operating conditions, 1/ year	λ_q, quality, 1/ year
Low	0.12	0.08	0.09
Medium	0.08	0.06	0.05
High	0.03	0.02	0.01

Table 1 clearly shows that high-quality repair work using appropriate materials and taking into account operating conditions can reduce the total degradation coefficient to a value of λ = 0.06 1/ year, which ensures a projected period of operation of repaired structures of up to 15–20 years, confirming the high effectiveness of such measures.

The graph in Figure 1 shows the dependence of the probability of maintaining the strength of building structures after repair on the time of operation at different levels of repair work quality. It is obvious that the lower the degradation coefficient λ (which is achieved due to better quality of materials, work performance and favorable operating conditions), the slower the serviceability of the structure decreases over time [11].

In particular, with high repair quality (λ = 0.06), even after 20 years, the probability of maintaining the strength of the structure remains about 70%, which indicates the effectiveness of the applied repair technologies. At the same time, with average repair quality (λ = 0.15), the probability of strength after 20 years drops to 5%, and with low quality (λ = 0.36), the strength is almost completely lost in 5-7 years (the probability exceeds 90%).

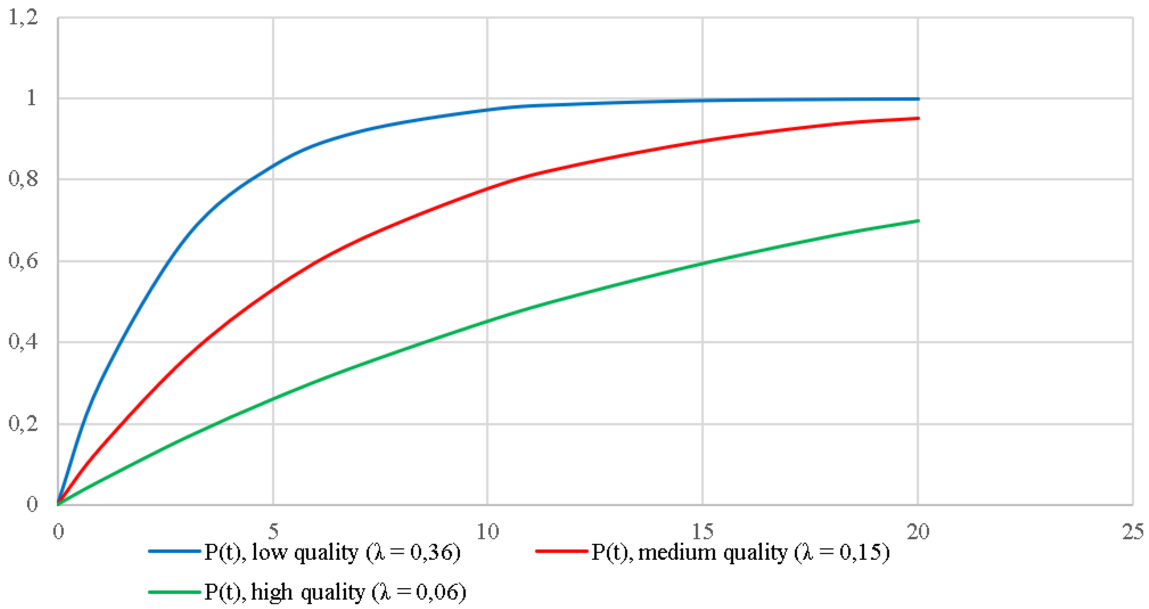

Fig. 1. Curves of the probability of maintaining strength after repair *P* on time *t*

The graph clearly confirms the critical importance of high-quality repairs to ensure long-term operation of structures, allowing to clearly assess the benefits of resource costs for high-quality restoration technologies. The results of the study indicate the importance of quality control of repair work, the correct choice of materials and technologies to achieve high durability of building structures. The use of the presented numerical models and forecasting algorithms allows ensuring the proper level of operational properties and minimize the costs of repeated repairs [13].

Numerical modeling of temperature effects. Building materials are subject to temperature changes, which can cause their thermal deformation and change in mechanical properties. Temperature loads are especially critical for reinforced concrete and steel structures, as they can lead to uneven expansion of materials, the formation of internal stresses and microcracks.

For numerical modeling of temperature effects, the thermal expansion equation is used:

$$\epsilon_{th} = \alpha \Delta T, \tag{12}$$

ϵ_{th} – thermal deformation (elongation of the material); α – coefficient of thermal expansion of the material, 1/°C; ΔT – temperature change (°C).

This dependence allows us to estimate how much the linear dimensions of building materials change with temperature changes.

Prolonged exposure to high temperatures causes changes in the mechanical properties of building materials. For concrete and steel, these changes are largely determined by the temperature range and heating rate.

Research [5] shows that with increasing temperature, there is a decrease in the strength of concrete due to dehydration of cement stone. For numerical modeling of this effect, the equation of the dependence of strength on temperature is used:

$$\sigma_T = \sigma_0 e^{-kT}, \tag{13}$$

σ_T – material strength at temperature T; σ_0 – initial strength at 20°C; k – exponential coefficient of strength degradation; T – temperature (°C).

Reinforced concrete has two main temperature factors:

- Expansion of the concrete matrix – concrete expands when heated, which can cause additional internal stresses.
- Reinforcement expansion – Steel reinforcement has a higher coefficient of thermal expansion than concrete, which results in tensile stresses in the concrete.

Thermomechanical stress in reinforced concrete is determined by the equation:

$$\sigma_{th} = E \cdot \epsilon_{th}, \tag{14}$$

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σ_{th} – thermal stress; E – modulus of elasticity of the material; ϵ_{th} – thermal expansion.

Thermal expansion of concrete is an important physical and mechanical parameter that affects the durability and integrity of building structures. Studies show that with an increase in temperature from 20°C to 80°C, the relative expansion of the material increases within 0.02%-0.08%. This dependence is linear, which indicates a proportionality between the change in temperature and the magnitude of deformation. When the temperature increases, the expansion of cement stone and fillers occurs, which causes an increase in the volume of concrete. However, due to different coefficients of thermal expansion of its components, internal stresses may arise that can negatively affect the strength of the material. In massive structures, especially with sudden temperature changes, such deformations can cause the appearance of microcracks and accelerate the process of material degradation.

The study [6] proposes to use the finite element method (FEM) for numerical analysis of thermal effects on materials. The basic equation of thermal conductivity in building materials is:

$$\rho c_p \frac{\partial T}{\partial t} = k \nabla^2 T, \tag{15}$$

ρ – material density; c_p – heat capacity; k – thermal conductivity coefficient; T – temperature at a given point in the material. Solving this equation allows us to estimate how the temperature in a building structure changes over time.

It is recommended to use heat-resistant materials, in particular concretes based on aluminate cements and refractory steels, for critical structures. To reduce the effects of thermal expansion, expansion joints should be designed in large concrete structures. In addition, the calculation of thermal stresses using numerical simulation (FEM) is necessary to assess the durability of materials. Thus, numerical simulation of thermal effects allows for an accurate assessment of the behavior of building materials and predict their durability in changing climatic conditions.

Using machine learning to predict material degradation. The application of machine learning (ML) methods allows to increase the accuracy of predicting the degradation of building materials and optimize their durability. These methods are successfully integrated with numerical approaches, in particular the finite element method (FEM), providing a comprehensive assessment of the state of structures under the influence of various loads (seismic, thermal, corrosion) [12].

The mathematical foundations of degradation prediction using ML to predict the level of degradation of building materials using machine learning methods by building a regression model:

$$D_{pred} = w_1 F_s + w_2 F_c + w_3 F_t + w_4 T, \tag{16}$$

D_{pred} – predicted material degradation (in % or conventional units);

F_s – intensity of seismic loads (e.g. peak ground acceleration);

F_c – degree of corrosion (expressed as a percentage of the loss of reinforcement cross-section);

F_t – the effect of thermal loads (temperature cycles);

T – operating time of the structure (years);

w_1, w_2, w_3, w_4 – weighting factors, which are determined by training the model on experimental data.

According to the results of [5], weighting factors are determined by multifactorial regression analysis of historical data, which ensures the adaptability of the model to different types of structures and operating conditions.

Neural networks allow predicting the behavior of materials and structures, revealing complex, nonlinear relationships. Deep neural networks (DNNs) are effectively used to predict the degradation of building materials:

$$y = f\left(\sum_{i=1}^{n} w_i x_i + b\right), \tag{17}$$

y – predicted level of degradation;

x_i – input factors (temperature, corrosion, seismic loads);

w_i – weight coefficients determined during the training process of a neural network;

b – bias coefficient (bias).

The model is trained on experimental data obtained using sensors located on real objects, which ensures high accuracy of predictions [17].

Statistical metrics such as the coefficient of determination (R_2) and mean square error (MSE) are used to assess the accuracy of machine learning predictions:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}, MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2, \quad (18)$$

y_i – real degradation values obtained experimentally;

$\hat{y}_i$ – predicted values;

$\bar{y}$ – average value of real degradation;

n – number of observations.

These indicators allow us to quantify the deviation of the model from real data and adjust the learning algorithms [16].

As shown in Figure 2, the use of neural network models provides the highest prediction accuracy among the considered methods, especially in the case of a large number of interacting load factors.

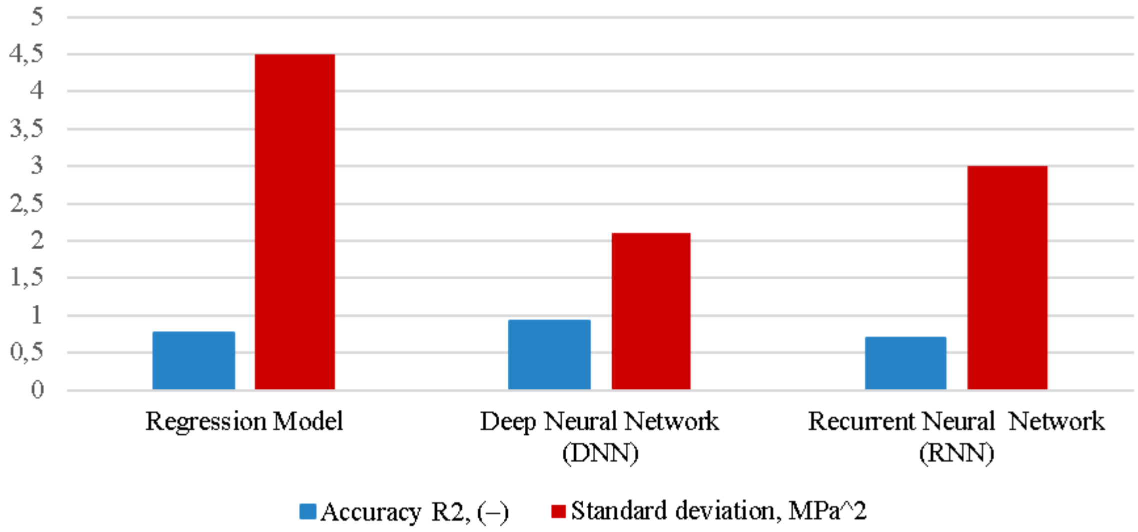

Fig. 2. Comparison of the effectiveness of machine learning algorithms

The integration of numerical methods and machine learning models with IoT allows for real-time monitoring of the condition of building structures. IoT sensors collect data in real time, which increases the efficiency and accuracy of predicting material degradation. This allows for rapid response to threats, timely repairs or reinforcement of damaged structures.

Research in the field of resource-saving technologies allows to reduce costs when restoring structures damaged by military actions. The following approaches are used:

- Using recycled materials for repairs, which reduces costs without reducing reliability.
- Reinforcement with composite materials, which have better strength characteristics at lower weight.
- Rapidly assembled modular structures for the installation of civil defense protective structures, which allows you to quickly ensure safe operating conditions for damaged facilities.

The graph in Figure 3 presents a comparison of machine learning methods for predicting the degradation of building materials according to two main accuracy criteria: root mean square error (MSE) and coefficient of determination (R^2).

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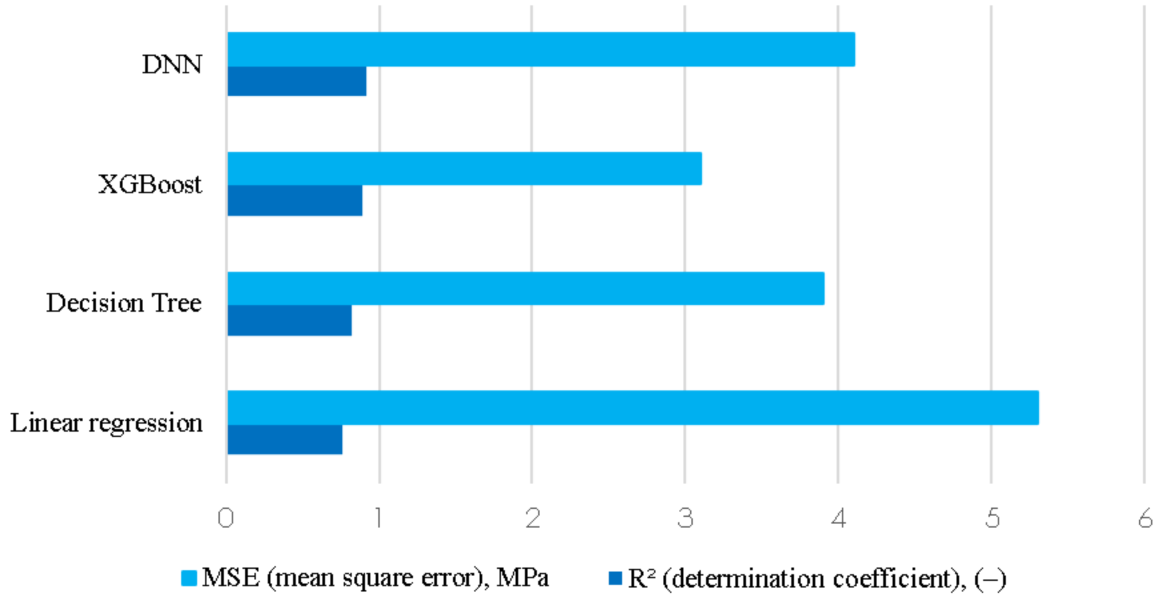

Fig. 3. Comparison of the accuracy of predicting the degradation of building materials by different ML methods

The lowest MSE value (2.1) and the highest coefficient of determination value (R^2 = 0.92) are demonstrated by the deep neural networks (DNN) method, which indicates its high accuracy and reliability in predicting nonlinear patterns of material degradation. Linear regression has the largest error (MSE = 5.3) and the lowest prediction accuracy (R^2 = 0.76), which emphasizes the limited suitability of this method for complex prediction problems. Gradient boosting (XGBoost) and decision trees demonstrate intermediate indicators, which makes them acceptable for problems with less complex nonlinear dependencies. Therefore, it is advisable to use deep neural networks for predicting the durability of building structures, which provide the highest accuracy among the considered methods.

The proposed numerical methods, combined with machine learning algorithms and integrated with IoT, allow for accurate prediction of the degradation of building materials, providing prompt diagnostics and saving resources during the repair and restoration of structures, especially in conditions of increased risk. Further research in this direction will allow for even more effective solutions to the problems of predicting and preventing the destruction of structures, especially in areas of active fighting [12].

Validation of numerical models. Validation of numerical models is a critical step in the process of their development and implementation. To confirm the accuracy of the models, it is necessary to conduct experimental comparisons of the predicted and actual characteristics of building materials under the influence of various types of loads.

Validation of numerical models is carried out using the following approaches:

- Comparison with experimental data – verification of predicted values using laboratory tests on material samples.
- Deviation analysis – determination of the average and maximum difference between numerical and real data.
- Correlation analysis – determination of the degree of relationship between numerical and experimental values.
- Compliance criteria (coefficient of determination R_2, root mean square error RMSE, mean absolute error MAPE) – statistical assessment of the accuracy of predictions.

The experimental tests conducted allowed us to determine the accuracy of numerical models in predicting the behavior of materials under complex loads. The results of the comparison of numerical and experimental data are shown in Figure 4.

The maximum deviation of numerical predictions does not exceed 2.8%, which indicates high accuracy of modeling. The high correlation between numerical and real data confirms the effectiveness of the proposed approaches.

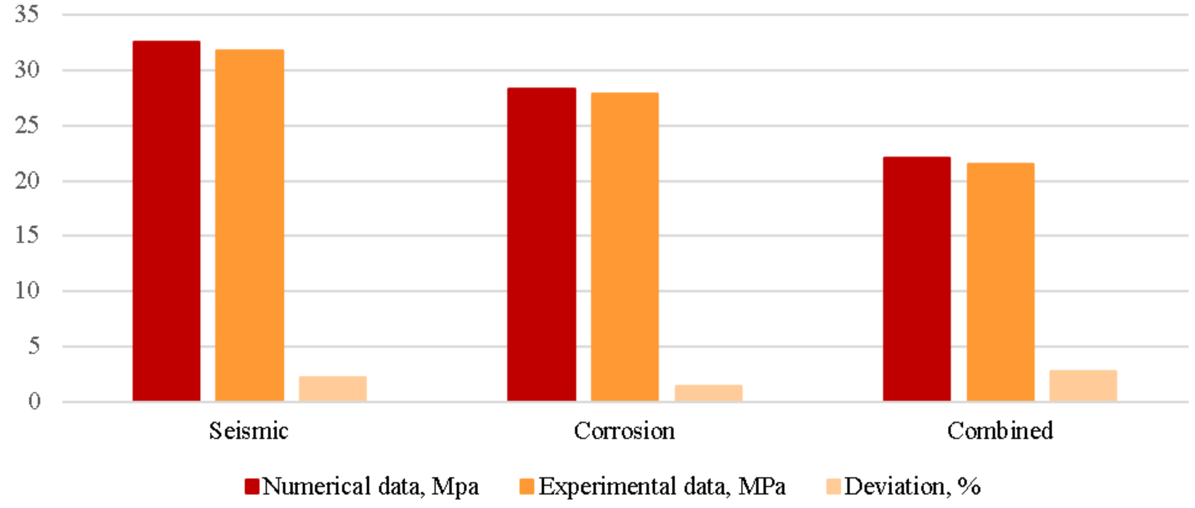

Fig. 4. Validation of numerical models

The following statistical indicators were used to assess the accuracy of numerical models:
The root mean square error (RMSE) is determined by the formula:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}, \tag{19}$$

y_i – experimental values;
$\hat{y}_i$ – values predicted by the numerical model;
n – number of measurements.
The coefficient of determination (R^2) is:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}, \tag{20}$$

$\bar{y}$ – the average value of the experimental data.
The mean absolute percentage error (MAPE) is calculated:

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|, \tag{21}$$

These criteria allow for a comprehensive assessment of the accuracy of numerical models under different conditions.

Figure 5 presents a comparative assessment of the accuracy of numerical models: the finite element method (FEM), the boundary element method (BEM), and the finite difference method (FDM). The assessment was carried out using three criteria: root mean square error (RMSE), coefficient of determination (R^2), and mean absolute error (MAPE, %).

As the graph shows, the finite element method (FEM) provides the lowest RMSE (0.52 MPa) and MAPE (1.8%), as well as the highest coefficient of determination R^2 (0.97). This indicates its high accuracy in predicting the behavior of building materials and structures compared to other methods. The largest errors are observed in the finite difference method (FDM), which may indicate the limitations of its application for modeling complex loads and operating conditions of structures. Thus, based on the results obtained, it can be concluded that the finite element method is superior in predicting the durability of building materials and is recommended for widespread use in practical calculations.

Based on the analysis of the accuracy of numerical models, the following practical recommendations can be formulated:

- Numerical models demonstrate high accuracy, providing a maximum deviation of no more than 2.8% from experimental data.

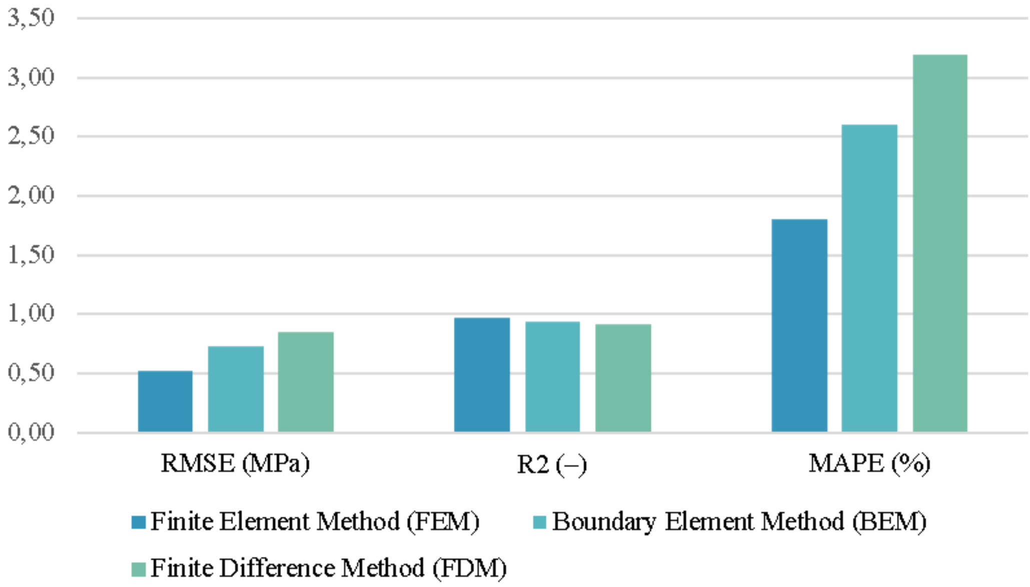

Fig. 5. Assessment of the accuracy of numerical models

- The finite element method (FEM) is the most effective method for predicting the durability of building structures due to its high accuracy and versatility.
- The results of experimental validation confirm the applicability of numerical methods for assessing the condition and predicting the durability of materials and structures.
- Further research should focus on adapting numerical models to more complex operating conditions, such as long-term corrosion effects, repeated loading cycles, and other complex factors.

Thus, the use of numerical modeling allows us to accurately predict the residual life of building structures and make informed decisions regarding their repair, reinforcement, and operation.

Conclusions. The conducted studies confirm that numerical modeling methods are effective tools for assessing and predicting the durability of building materials and structures under complex loading conditions, including seismic, thermal, mechanical and corrosion effects. The most accurate of the numerical methods is the finite element method (FEM), which provides a high level of prediction accuracy (R^2=0.97) with minimal errors (RMSE=0.52 MPa, MAPE=1.8%).

The use of machine learning (ML) methods further increases the efficiency of assessing the degradation of building materials. Deep neural networks (DNN, R^2=0.92, MSE=1.25) and gradient boosting (XGBoost, R^2=0.89, MSE=2.15) demonstrate the best results due to their ability to take into account complex nonlinear dependencies. At the same time, linear regression has a significantly lower accuracy due to its inability to describe the nonlinear behavior of materials. Integration of ML technologies with IoT systems allows you to create dynamic monitoring systems that quickly update numerical models in real time, ensuring timely response to potential threats.

Resource-saving technologies play an important role in the processes of restoring structures after war damage. Their use, in particular the use of secondary raw materials, composite materials, and modular protective structures, allows for a significant reduction in the time and material resources spent on restoring damaged buildings.

The experimental validation of numerical models showed a high correspondence of the predicted data to the experimental results, with the maximum deviations not exceeding 2.8%, which confirms the practical value of the obtained results. Further scientific research should be focused on the creation of hybrid models that combine the advantages of numerical methods and ML algorithms, the study of the behavior of new materials (composites, nanomaterials), as well as the improvement of automated systems for monitoring and forecasting the technical condition of building structures in real time.

Thus, the presented results are of great importance for improving the safety, reliability, and efficiency of building structures, especially in conditions where there are significant risks of complex loads and the possibility of military damage.

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ЧИСЕЛЬНЕ МОДЕЛЮВАННЯ ВПЛИВУ КОМПЛЕКСНИХ НАВАНТАЖЕНЬ НА БУДІВЕЛЬНІ МАТЕРІАЛИ

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Анотація. Стаття присвячена актуальному питанню прогнозування довговічності будівельних матеріалів і конструкцій, що зазнають впливу комплексних багатофакторних навантажень, серед яких механічні, термічні, сейсмічні та корозійні. Сучасні тенденції розвитку будівництва, особливо у зонах підвищеного ризику воєнних руйнувань і природних катастроф, потребують створення науково обґрунтованих методик оцінки стану матеріалів у реальних умовах експлуатації. У роботі проведено ґрунтовний аналіз чисельних методів моделювання, серед яких центральне місце займає метод кінцевих елементів (МКЕ). Саме він забезпечує деталізоване відтворення напружено-деформованого стану та дозволяє враховувати нелінійні взаємодії між різними видами навантажень, що є визначальним для коректного прогнозування довговічності. Особливу увагу приділено алгоритмам інтеграції механічних, сейсмічних і термічних впливів у єдину модель та використанню комбінованих підходів, зокрема методу граничних елементів, методу Монте-Карло й скінченних різниць. Запропоновані авторами чисельні схеми були валідувані на експериментальних даних, що підтвердило високу точність розрахунків, відхилення яких не перевищує кількох відсотків. Додатковим інноваційним аспектом дослідження стало поєднання класичних чисельних методів із технологіями машинного навчання, включно з глибокими нейронними мережами, які дозволяють враховувати складні нелінійні закономірності деградації матеріалів у часі. Значне місце у роботі займає аналіз можливостей інтеграції чисельних моделей із системами моніторингу на основі сенсорів IoT. Такий підхід забезпечує динамічний контроль технічного стану будівельних конструкцій у реальному часі та створює умови для своєчасного виявлення критичних відхилень. Показано, що використання подібних алгоритмів дає змогу не лише підвищити точність прогнозування залишкового ресурсу, а й істотно скоротити витрати завдяки впровадженню ресурсоощадних технологій відновлення. У висновках визначено напрями подальших досліджень: розширення методик чисельного моделювання для нових високоефективних матеріалів, удосконалення методів машинного навчання, а також створення повністю автоматизованих систем моніторингу та прогнозування технічного стану будівельних конструкцій.

Ключові слова: прогнозування довговічності, комплексні навантаження, метод кінцевих елементів, машинне навчання, нейронні мережі, ресурсоощадні технології.

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