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OPTIMIZATION OF STRUCTURAL COMPUTATIONAL MODELS USING NEURAL NETWORKS: A SYSTEMATIC REVIEW OF CURRENT APPROACHES AND PROSPECTS

Modern computational analysis and optimization of complex engineering structures using the finite element method (FEM) are often limited by high computational costs. This paper presents a systematic review of current research on the application of artificial neural networks (ANNs) for creating fast surrogate models of FEM computations to overcome these limitations. The review provides a detailed analysis of various ANN architectures (including MLP, CNN, GNN, RNN, PINN), their training methodologies, and their effectiveness in accelerating the analysis of stress-strain states, dynamic behavior, nonlinear processes, and solving structural optimization problems (sizing, shape, topology). The literature analysis confirms the capability of ANN surrogates to significantly reduce computation time compared to traditional FEM, thereby opening new possibilities for engineering design. Concurrently, key challenges have been identified, related to the need for large datasets for training, ensuring model generalization capabilities, and the interpretability of their results. The paper concludes with a discussion of unresolved problems and the identification of promising future research directions in this dynamic field.

Keywords: structural mechanics; finite element method; surrogate modeling; artificial neural networks; machine learning; computation acceleration; structural optimization; topology optimization; physics-informed neural networks; PINN; graph neural networks; GNN; literature review; engineering design.

1. Introduction

Modern design and analysis of engineering structures face increasing complexity in engineering tasks, driven by the need to account for nonlinear material behavior, geometric nonlinearity, dynamic influences, and soil-structure interaction. The **finite element method (FEM)** is the standard tool for analyzing such models, providing high accuracy of results [12, 31]. However, despite its power, FEM has a significant drawback – **high computational cost** [7, 12, 14, 31, 38]. This is particularly critical for tasks requiring multiple calculations, such as parametric studies, multi-objective optimization, uncertainty analysis, and modeling complex nonlinear processes [3, 6, 12, 15, 31, 33, 34]. These computational limitations substantially hinder engineers in their search for optimal and innovative design solutions.

In recent years, the rapid development of **artificial intelligence (AI)** methods, particularly **machine learning (ML)** and **artificial neural networks (ANNs)** [12, 20, 31], has opened new prospects for addressing this problem. One of the most promising directions is the creation of **surrogate models (metamodels)** [1, 12, 20, 31] that approximate computationally expensive FEM models. ANN surrogates, trained on data generated by FEM, can predict calculation results orders of magnitude faster [7, 14, 36], making it possible to efficiently solve resource-intensive tasks.

The **aim of this paper** is to conduct a comprehensive review and critical analysis of the current state of research on the application of artificial neural networks for accelerating engineering calculations, analysis, and optimization of computational models for engineering structures. To achieve this aim, the following **objectives** are set:

- To systematize the main approaches to using ANNs as surrogate models in structural mechanics.
- To analyze key ANN architectures (MLP, CNN, GNN, RNN, PINN) and the specifics of their application for various engineering tasks.
- To review successful examples of using ANN surrogates for the analysis of stress-strain states, dynamics, nonlinear behavior, and structural optimization.
- To highlight the potential, advantages, and limitations of physics-informed neural networks (PINNs).
- To discuss the application of decomposition methods and ensemble approaches.
- To analyze methods for evaluating the effectiveness of ANN surrogates.
- To identify key unresolved problems, challenges, and determine promising directions for future research in this field.

This review covers publications dedicated to the development and application of ANN surrogates and is structured as follows: Section 2 is devoted to the concept of surrogate modeling. Section 3 details various ANN architectures. Sections 4, 5, and 6 focus on the application of ANNs for stress-strain state (SSS) analysis and dynamics, structural optimization, and the use of PINNs, respectively. Section 7 discusses decomposition methods and ensemble approaches. Criteria for evaluating ANN effectiveness are considered in Section 8. Section 9 provides a critical analysis of the current state of research, discussing major problems and future research directions. The paper concludes with general conclusions (Section 10).

2. The Concept of Surrogate Modeling for Accelerating FEM Computations

The idea of replacing complex computational models with simpler approximations is not new. However, it was the development of machine learning and, in particular, deep neural networks that provided a powerful impetus to the advancement of surrogate modeling in engineering. A **surrogate model (metamodel)** is defined as a simplified model that mimics the behavior of a more complex, high-fidelity model (in our case, an FEM model) with significantly lower computational costs [1, 12, 20, 31].

The process of creating an ANN-based surrogate model typically includes the following stages [12, 31]:

1. **Data Generation:** Performing a series of computations using the original FEM model with varying values of input parameters (e.g., geometric dimensions, material properties, applied loads, boundary conditions). These parameters define the "design space" or the domain in which the surrogate model is intended to operate. The results of these computations (displacements, stresses, strains, natural frequencies, etc.) form the training dataset.
2. **ANN Architecture Selection:** Defining the type and structure of the neural network (number of layers, neurons, types of activation functions) that will be used to approximate the input-output relationship of the FEM model.
3. **ANN Training:** Adjusting the weight coefficients of the neural network using optimization algorithms (e.g., backpropagation and gradient descent) to minimize the discrepancy between the ANN's predictions and the data from the training dataset.
4. **Validation and Testing:** Evaluating the accuracy of the trained ANN on data not used during training (the test dataset) to verify its generalization capability.

A diagram illustrating the creation and use of an ANN surrogate for an FEM model is presented in Fig. 1. The primary driving force for using surrogate models is the acceleration of computations [7, 12, 14, 31, 38]. After training, an ANN surrogate can perform predictions (inference) extremely fast, often in near real-time. Reported speedups range from hundreds to thousands of times compared to the original FEM computation [14, 36]. This is particularly important for tasks that require a large number of model evaluations, such as optimization, sensitivity analysis, and uncertainty quantification.

A crucial aspect is the **trade-off between accuracy and speed**. Although ANN surrogates are fast, their accuracy depends on the quality and quantity of

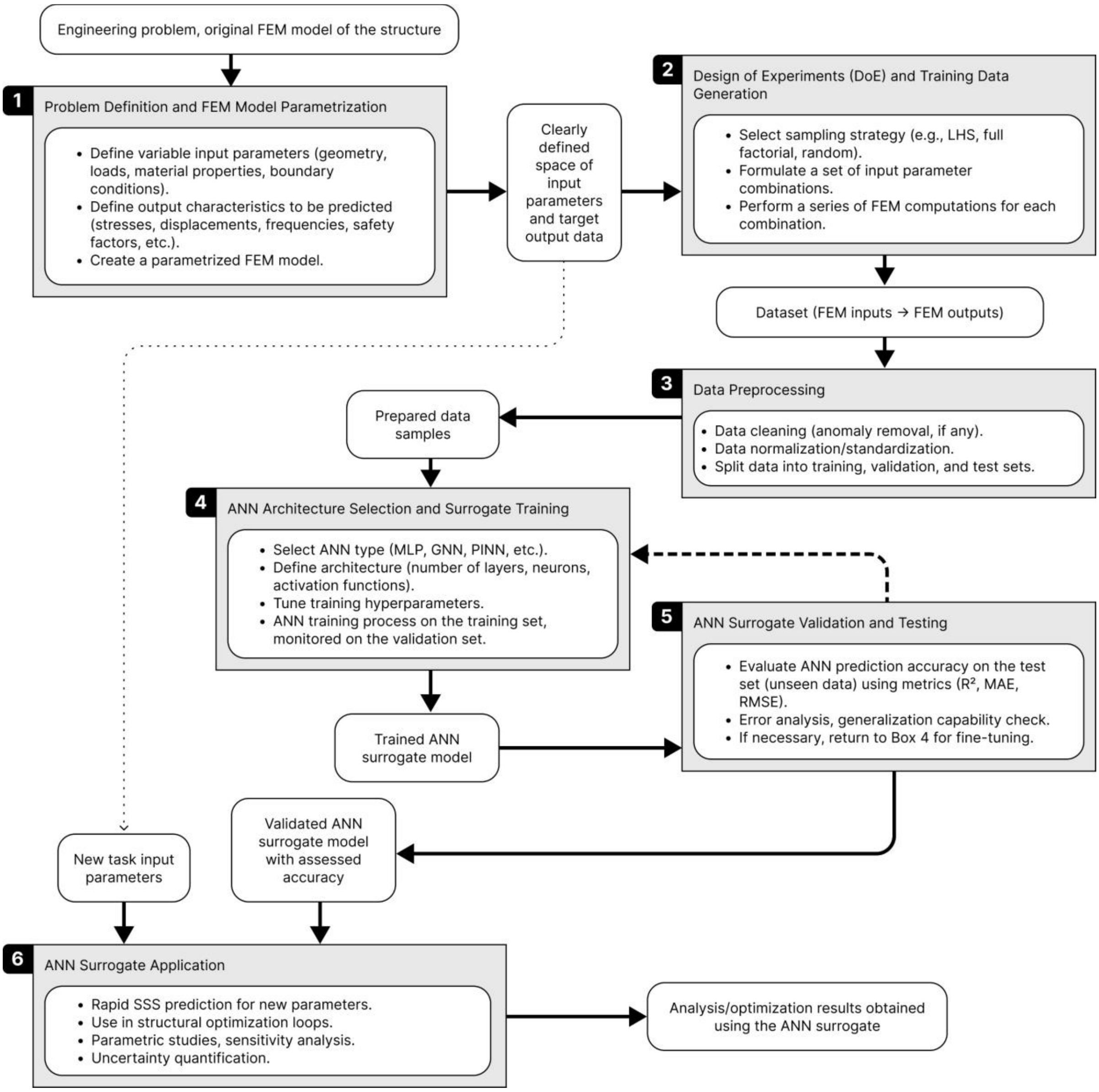

Fig. 1. General process of creating and using an ANN surrogate for FEM models

training data, the chosen ANN architecture, and the complexity of the approximated relationship. Rigorous accuracy validation is a prerequisite for the reliable use of surrogate models in engineering practice [1, 12, 31]. Furthermore, the ANN training process itself, especially for complex models and large datasets, can be computationally intensive.

While neural networks have been the most common tool for creating surrogate models in recent years, other machine learning methods are also employed, such as decision trees (and their ensembles – random forests, gradient boosting), support vector machines (SVM), and Gaussian processes (GPR) [1, 12, 31]. The choice of a specific method depends on the specifics of the task and the characteristics of the data.

3. Neural Network Architectures in Structural Mechanics Problems

The choice of a neural network architecture is crucial for the successful creation of a surrogate model, as different architectures have varying capabilities for data processing and dependency detection. In the context of structural mechanics and FEM modeling, a variety of ANN architectures are employed:

- **Multi-Layer Perceptrons (MLPs)** [1, 12, 31]: These are classic fully connected feedforward neural networks. They consist of an input layer, one or more hidden layers, and an output layer. MLPs are widely used for regression tasks where the input data is a vector of parameters (e.g., geometric dimensions, loads, material properties), and the output is a vector or scalar values (e.g., maximum stresses, displacements, safety factors). Their advantage is the relative simplicity of implementation and training. However, they can be inefficient when working with data that has a spatial or temporal structure (e.g., stress fields on a mesh, dynamic processes) because they do not account for local correlations or sequences.
- **Convolutional Neural Networks (CNNs)** [2, 6, 37]: These networks are specifically designed for processing data with a grid-like structure, such as images. In structural mechanics, CNNs are used for:
  - Analyzing material microstructures and predicting their effective properties based on microstructure images.
  - Predicting stress or strain fields represented as “images” on a regular grid.
  - Identifying damage (e.g., cracks) in images of structures or analyzing vibration monitoring data presented as spectrograms.
  - Topology optimization, where the material density in each element is considered a pixel in an image. However, the direct application of CNNs to unstructured FEM meshes can be inefficient due to the need to map mesh nodes to a regular grid, which leads to data sparsity and loss of information about connection topology.
- **Graph Neural Networks (GNNs)** [5, 13]: This class of networks is designed to work directly with data represented as graphs (nodes and edges). Since an FEM mesh is naturally represented as a graph (nodes are mesh nodes, edges are elements or connections between nodes), GNNs are a very promising architecture for surrogate modeling in mechanics. They can consider both node properties (coordinates, boundary conditions) and mesh topology. GNNs are used to predict displacement or stress fields directly on mesh nodes, avoiding inefficient conversion to a regular grid. They are applied in structural analysis and optimization, for example, to accelerate the size optimization of trusses.
- **Recurrent Neural Networks (RNNs),** particularly **Long Short-Term Memory (LSTM)** and **Gated Recurrent Unit (GRU)** [30]: These networks have internal “memory,” allowing them to process sequences of data and consider dependencies on previous states. This makes them suitable for:

- Modeling the dynamic response of structures, where the response at the current time step depends on the previous history of loading and motion.
- Modeling the history-dependent behavior of materials, particularly elasto-plasticity, where stresses depend not only on current strains but also on the loading path and accumulated plastic strains.
- Structural Health Monitoring (SHM) tasks, where time-series data from sensors are analyzed to detect anomalies or damage.

- **Physics-Informed Neural Networks (PINNs)** [4, 9, 15, 17, 22, 23, 24, 34]: These represent an innovative approach where the physical laws governing the system (usually in the form of partial differential equations) are directly integrated into the neural network's loss function during training. This allows for improved accuracy and generalization capability, especially with limited training data, and ensures the physical consistency of predictions. The potential and specific applications of PINNs in structural mechanics will be discussed in more detail in Section 6.
- **Ensemble Neural Networks** [18]: This methodology involves the joint use of several separately trained neural networks, whose predictions are combined (e.g., by averaging) to obtain the final result. Such an approach often allows for higher accuracy, stability, and reliability of predictions compared to a single model, and also provides an opportunity to assess the uncertainty of the obtained results. The specifics of using ensemble approaches, particularly in conjunction with decomposition methods, will be discussed in more detail in Section 7.

A comparative overview of these discussed architectures, detailing their typical input data, common applications in structural mechanics, primary strengths, and key weaknesses or challenges, is presented in **Table 1**.

The choice of architecture depends on many factors: the type of input and output data, the presence of spatial or temporal dependencies, the need to account for physical laws, the volume of available data, and the desired trade-off between accuracy, speed, and model complexity. There is a trend towards using architectures that better match the data structure (GNNs for meshes) or integrate physical knowledge (PINNs), reflecting the aspiration to create more effective and reliable surrogate models.

4. Application of ANNs for Analysis of Stress-Strain State and Dynamics of Structures

One of the key tasks in structural mechanics is determining the **stress-strain state (SSS)** of a structure under loads. Neural networks are actively used to create surrogate models that predict various aspects of SSS and dynamic behavior.

Table 1. Comparative Analysis of Neural Network Architectures for Surrogate Modeling of FEM in Structural Mechanics

Architecture	*Typical Input Data*	*Applications*	*Strengths*	*Weaknesses / Challenges*
MLP (Multi-Layer Perceptron)	Parameter vectors	Parameter-property mapping, simple regression tasks	Simplicity of implementation and training	Loss of spatial/temporal information, scalability
CNN (Convolutional NN)	Images, regular grids	High accuracy for images/grids. Microstructure analysis, SSS fields as images, SHM (vibrations/images), TO.	Efficient extraction of spatial features	Inefficiency for unstructured meshes, requires a regular grid
GNN (Graph NN)	Graphs, FEM meshes	Mesh-based analysis, truss optimization, SSS prediction. Promising for FEM data.	Naturally handles unstructured meshes, considers topology	Newer technology, potentially more complex to train
RNN (Recurrent NN: LSTM, GRU)	Sequences, time series	Necessary for history-dependent tasks. Dynamic analysis, plasticity (load history), SHM (time series).	Modeling of temporal/path dependency	Vanishing/exploding gradients problem, training time
PINN (Physics-Informed NN)	Coordinates, parameters (+ equations)	Improved accuracy with less data. Solving PDEs, inverse problems, modeling with limited data.	Physical consistency, data efficiency, generalization	Training complexity (loss balancing), precise satisfaction of BCs
Ensemble NNs	Predictions of multiple models	Improved performance compared to individual models. Enhanced accuracy/reliability, uncertainty estimation, damage identification.	Better accuracy and stability, UQ estimation	Increased training and prediction costs

Prediction of stress, strain, and displacement fields [7, 11, 16]**:** This is a fundamental task where ANNs are trained to map input parameters (geometry, material, loads) to output fields or SSS values. Research demonstrates the successful application of ANNs for predicting:

- Stress distribution (e.g., von Mises) and peak values in biomechanical objects (aorta) with high accuracy (errors less than 1%).
- Stress and strain fields in plates with holes and other components.
- SSS of various types of beams under different loading conditions.
- Forces and displacements in truss structures.

- Effective mechanical properties and internal fields in composite materials. Various architectures are used, including MLPs, CNNs (if fields are treated as images), and GNNs (for direct work with meshes).

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Analysis of dynamic response [8, 17, 29]**:** ANNs are applied to accelerate the computation of the dynamic behavior of structures under time-varying loads. This includes predicting time histories of displacements, velocities, accelerations, as well as modal parameters (natural frequencies and mode shapes). Studies cover various types of structures, from simple mechanical systems to bridges and complex components like turbine bladed disks. Ensemble methods based on decision trees (XGBoost, Random Forest) or recurrent networks (LSTM, GRU) are often used to account for time dependency.

Modeling of elasto-plastic behavior [15, 33, 34, 35]**:** The analysis of structures beyond the elastic limit is computationally complex due to nonlinearity and load history dependence. ANNs offer an alternative to traditional incremental FEM procedures. Recurrent architectures (GRU, LSTM) are naturally suited for modeling the path dependency of plasticity. Physics-informed neural networks (PINNs) that incorporate plastic flow equations or principles of strain decomposition show potential for improving data efficiency and extrapolation capabilities. Such models are being developed for various materials, including metals, soils (sands), and composites.

Fracture mechanics and damage analysis [10, 19, 21, 22]**:** ANNs are used to predict damage evolution, determine stress intensity factors (SIFs) near cracks, model delamination in composites, and other aspects of fracture. These methods also form the basis for structural health monitoring (SHM) systems, where ANNs analyze sensor data to detect, locate, and classify damage.

Contact mechanics [14, 36]**:** The computation of contact interaction between structural elements is another computationally expensive task. ANN surrogates are successfully applied to approximate contact forces and moments, for example, in biomechanical simulations of joints, achieving significant speedups (up to 1000 times) while maintaining acceptable accuracy.

Overall, neural networks demonstrate great versatility in modeling various phenomena in structural mechanics. However, the complexity of applying ANNs increases with the complexity of the process physics. While approaches for linear elastic static problems are relatively well-established, dynamics, plasticity, or contact require more complex architectures (RNN, GNN, PINN) and specialized training methods, reflecting the need to adapt ML tools to the specifics of physical phenomena.

5. Use of ANN Surrogates in Structural Optimization Problems

Structural optimization – the search for the best design solution according to specified criteria and constraints – is one of the most computationally demanding tasks in engineering [3, 6, 12, 31, 38]. Traditional optimization methods combined with FEM often prove impractical due to the vast number of required computations. ANN surrogates offer a revolutionary approach by replacing or accelerating FEM analysis within the optimization loop.

Main areas of application:

- **Sizing Optimization:** Determining the optimal cross-sectional areas of bar elements (trusses, frames) [5, 28, 38]. ANNs are trained to predict the SSS (stresses, displacements) for given cross-sections, allowing for rapid verification of strength and stiffness constraints in optimization algorithms (e.g., genetic algorithms, differential evolution, particle swarm optimization). Both DNNs and GNNs are used.
- **Shape Optimization** [6]**:** Finding the optimal configuration of external and internal boundaries of a structure (e.g., coordinates of truss nodes). ANNs can predict structural characteristics for different shapes or directly replace FEM in the iterations of a shape optimization algorithm.
- **Topology Optimization (TO)** [6, 26, 27, 32, 37, 39, 40]**:** Determining the optimal material distribution within a given design domain to achieve maximum stiffness, minimum mass, or other objectives. This is one of the most complex optimization tasks, requiring thousands of FEM computations. ANNs and deep learning (DL) methods are applied here in several aspects:
    - **Accelerating iterations:** ANNs predict FEM results or sensitivity fields during intermediate TO iterations.
    - **Non-iterative TO:** ANNs are trained to directly map input conditions (domain, loads, boundary conditions) to the final optimal topology.
    - **Metamodeling:** ANNs act as surrogates for the objective function or constraints.
    - **Dimensionality reduction:** ANNs help reduce the number of design variables.
    - **Post-processing:** ANNs are used for smoothing or interpreting TO results. CNNs are a common architecture due to the similarity of density fields to images. However, creating universal and accurate ANNs for TO is a challenging task due to the high dimensionality of the problem and sensitivity to input conditions.
- **Other optimization tasks:** ANN surrogates are also applied in more specific tasks, such as optimizing the durability of reinforced concrete structures considering corrosion processes [3], optimizing the placement of shear walls in buildings for wind load resistance [29], and optimizing the acoustic characteristics of structures [40].

Integration with optimizers [5, 28, 38]**:** ANN surrogates are successfully integrated with various classes of optimization algorithms: evolutionary (GA, DE), swarm-based (PSO, ABC), multi-objective (NSGA-II), and potentially with gradient-based methods if the ANN ensures differentiability.

The use of ANN surrogates fundamentally changes the approach to structural optimization. Removing the computational barrier of FEM allows optimizers to explore a significantly larger number of variants in the same amount of time. This makes it possible to solve more complex problems (e.g., TO, multi-objective optimization), consider a larger number of design variables and constraints, and consequently, obtain more efficient, economical, and innovative structural solutions. Optimization ceases to be a final stage of checking a few variants and becomes an interactive tool for exploring the design space.

6. Physics-Informed Neural Networks (PINNs) and Their Potential

Standard ANN surrogates learn exclusively from data, ignoring the fundamental physical laws that govern the system's behavior [4, 9, 15]. This can lead to several problems: the need for large volumes of training data, obtaining physically incorrect predictions (especially during extrapolation), and a limited ability to generalize to new, unseen conditions. **Physics-Informed Neural Networks (PINNs)** were proposed as an approach to overcome these shortcomings by integrating physical knowledge into the training process [4, 9, 15, 17, 22, 23, 24, 34].

The core idea of PINNs: To incorporate information about the physical laws describing the system (usually in the form of partial differential equations – PDEs), as well as boundary and initial conditions, directly into the neural network's loss function [4, 9, 15]. The ANN learns not only to minimize the discrepancy with available data (if any) but also to minimize the residual of the physical equations at certain points in the domain (collocation points). To compute the derivatives included in the PDEs, the technique of automatic differentiation is used, which is standard in many deep learning frameworks.

Advantages of PINNs [4, 9, 15, 17, 22, 23, 24, 34]**:**

- **Data efficiency:** PINNs can potentially achieve high accuracy with significantly less training data compared to standard ANNs, as physical constraints act as a regularizer, guiding the learning towards physically plausible solutions.
- **Physical consistency:** Predictions from PINNs are more likely to be consistent with fundamental physical principles.
- **Improved generalization and extrapolation:** The inclusion of physics can enhance the model's ability to predict system behavior under conditions that extend beyond the training dataset.
- **Solving inverse problems:** PINNs are naturally suited for inverse problems, where unknown model parameters (e.g., material properties) need to be determined based on partial observations of the system's behavior.

Application of PINNs in mechanics: PINNs are actively being researched for a wide range of problems in continuum mechanics, including:

- Solving forward problems (predicting displacement and stress fields) for linear elasticity [9, 24], nonlinear elasticity, and elasto-plasticity [15, 34].
- Modeling structural dynamics [17].

- Analyzing plates and shells [9, 22].
- Structural Health Monitoring (SHM) [22].
- Creating surrogate models for optimization [4].

Challenges and limitations of PINNs [23, 24]**:** Despite their significant potential, the practical application of PINNs faces several difficulties:

- **Training complexity:** The PINN loss function is a combination of several terms (data error, PDE residual, boundary condition errors), and their proper weighting and balancing is a non-trivial task that significantly affects training convergence and accuracy.
- **Accuracy in satisfying boundary conditions:** Ensuring the exact enforcement of boundary conditions (especially Dirichlet type) can be challenging when using "soft" constraints via the loss function. Methods for "hard" enforcement of BCs through ANN architecture modification are being developed.
- **Computational cost of training:** Although PINNs can be data-efficient, their training can be more computationally expensive than training standard ANNs due to the need to compute derivatives and PDE residuals at many collocation points.
- **Scalability and complex geometries:** Applying PINNs to complex three-dimensional problems and domains with irregular boundaries is still an active area of research. To overcome these limitations, advanced architectures using domain decomposition, such as XPINN [42], FBPINN [43], IDPINN [44], or hybrid approaches combining FEM and neural operators with domain decomposition [45], are being developed. Standard PINNs generate solutions in an infinite Euclidean domain, which does not correspond to the finite boundaries of real structures. This motivates the development of new architectures, such as Finite-PINN [23], which attempt to overcome these limitations by separating the approximation of stress and displacement fields and using a combined Euclidean-topological solution space.

PINNs represent an important step towards creating hybrid models that combine the power of data-driven approaches with the reliability of physics-based methods. They are not a universal replacement but rather a complement to existing methods, particularly valuable in situations with limited data or where physical consistency is critically important. Further development of PINNs, especially the creation of architectures adapted to the specifics of solid mechanics problems, is a key research direction.

7. Decomposition Methods and Ensemble Approaches

The complexity of real engineering structures often makes the direct application of global surrogate models ineffective or inaccurate. Two approaches that help manage this complexity are **decomposition methods** and **ensemble methods**.

Decomposition and substructuring: The idea is to divide a complex system into simpler subsystems (substructures, components, nodes), analyze these subsystems, and then combine the results to obtain the behavior of the entire system [25, 26]. This is a classic technique in FEM (e.g., the super-element method, modal synthesis method). In the context of machine learning and surrogate modeling, decomposition can be used for:

- **Training local models:** Instead of one large ANN for the entire structure, smaller, specialized ANNs can be trained for individual types of components or substructures [25]. For example, dynamic substructuring techniques can be used to generate data and train ANNs that identify the dynamic properties of joints between components.
- **Multi-scale modeling and optimization:** In hierarchical structures (e.g., lattices), both the microstructure (individual lattice elements) and the macrostructure can be modeled. Substructuring allows the behavior of the microstructure to be "condensed" into equivalent properties of a "super-element" at the macro level, for which a surrogate model can then be built (e.g., using spline interpolation or ANNs) [26]. ML can also be used to link different scales or resolution levels in topology optimization.
- Another important direction for using decomposition in conjunction with ANNs is **domain decomposition methods**, which are primarily used for solving partial differential equations. In this context, physics-informed neural networks (PINNs) have been extended to work with subdomains. Approaches such as XPINN [42], FBPINN [43], and IDPINN [44] divide a complex computational domain into smaller subdomains, train separate ANNs for each, and then ensure the continuity and consistency of the solution at the subdomain interfaces using modified loss functions or architectural solutions. Similar ideas of hybridizing traditional numerical methods (FEM) and neural operators using domain decomposition are also being actively researched [45].

Ensemble methods [18]**:** This approach involves using not one, but several ANNs to solve a single problem, with the final result obtained by combining their individual predictions. Various strategies exist for creating an ensemble:

- **Bagging (Bootstrap Aggregating):** Training identical models on different data subsamples (e.g., Random Forest for decision trees).
- **Boosting:** Sequentially training models where each subsequent model focuses on the errors of the previous one (e.g., AdaBoost, XGBoost).
- **Stacking:** Training a meta-model that combines the predictions of base models.
- **Simple averaging:** Averaging the predictions of several models trained independently (possibly with different initializations or on slightly different data).

The main advantages of ensembles [18] include:

- **Increased accuracy:** An ensemble often yields a more accurate prediction than any single constituent model.

- **Enhanced reliability and stability:** The risk of obtaining a poor result due to an unfortunate choice of a single model or its overfitting is reduced.
- **Uncertainty estimation:** The discrepancy between the predictions of ensemble members can be used as a measure of prediction uncertainty.

In structural mechanics and engineering analysis tasks, ensemble neural networks are used for several key purposes:

- **Increasing the accuracy and reliability of surrogate model predictions:** Averaging or combining the results of several ANNs, trained independently or on different data/features, often allows for more accurate and stable predictions of structural characteristics (e.g., stress fields, displacements, dynamic response) compared to individual models [12, 31].
- **Uncertainty Quantification (UQ):** Analyzing the discrepancies between the predictions of different models in an ensemble allows for an assessment of the confidence level in the result obtained from the surrogate model, which is important for risk assessment [12, 31].
- **Damage Identification (SHM):** In structural health monitoring systems, ensembles can effectively combine information from various sources (e.g., different sensors or modal characteristics) for more reliable damage detection and classification [18].

Synergy of decomposition and ensembles [18, 25, 26]**:** Combining decomposition strategies with specialized local models and ensemble methods for integrating their predictions appears promising for enhancing the accuracy and reliability of analyzing complex systems. A key scientific challenge in such approaches is the development of effective methods for integrating local predictions. The development of such methods can draw on the experience of both classical substructuring [25, 26] and modern achievements in domain decomposition methods using machine learning [42, 43, 44, 45], as well as on general principles of applying ANNs in mechanics [46-50].

8. Performance Evaluation: Computational Speedup and Prediction Accuracy

For ANN surrogates to be reliably used in engineering practice, their performance must be thoroughly evaluated based on two key criteria: speed and accuracy.

Computational Speedup: This is the primary motivation for using surrogate models. Speedup is usually measured as the ratio of the computation time using the original FEM model to the prediction time using the trained ANN surrogate [7, 12, 14, 31, 38]. The literature reports significant speedup factors, reaching orders of magnitude: from tens and hundreds of times to thousands of times and more [14, 36]. Such acceleration is critically important for optimization tasks, uncertainty analysis, and real-time applications.

Prediction Accuracy: Accuracy determines how well the predictions of an ANN surrogate correspond to the results obtained using the original FEM model (which is considered the “reference” or “ground truth”) [1, 7, 9, 12, 14, 31]. Various regression metrics are used to assess accuracy:

- **Coefficient of determination (R-squared, R^2)** [1, 7, 9, 14]: Shows the proportion of the variance in the output variable that is explained by the model. Values close to 1 indicate high accuracy. Many studies achieve R^2 values > 0.9 or even > 0.98.
- **Mean Absolute Error (MAE)** [1, 7, 9, 14]: The average absolute deviation of predictions from true values.
- **Root Mean Squared Error (RMSE)**: The square root of the average of squared deviations; gives more weight to large errors.
- **Mean Absolute Percentage Error (MAPE)**: Relative error expressed as a percentage. Reported achievements include MAPE < 10%.
- **Normalized errors (NMAE, NRMSE)**: Errors normalized by the range or mean of the variable, allowing for accuracy comparison across different quantities. Errors of less than 1% are achieved.

Validation Strategies: For an objective assessment of accuracy, it is necessary to use data that was not involved in model training. The standard approach is to divide the available dataset into three parts: training (for adjusting ANN weights), validation (for tuning model hyperparameters, e.g., number of layers, neurons, learning rate), and testing (for final evaluation of the trained model’s performance) [12, 31]. It is important that the test set is representative of the tasks the model will solve in practice. Cross-validation can be used to increase the reliability of the assessment.

Challenges in Performance Evaluation [12, 23, 31]**:**

- **Interpolation** vs. **Extrapolation:** Most models perform well within the range of parameters represented in the training data (interpolation), but their accuracy can drop sharply outside this range (extrapolation). Assessing extrapolation capability is important but often overlooked.
- **Generalization:** The ability of a model to perform correctly on data that differs somewhat from the training data (e.g., different geometry, different boundary conditions) is critical for practical application. PINNs and GNNs are often positioned as having better generalization capabilities.
- **Lack of standard benchmarks:** Comparing the effectiveness of different approaches proposed in various publications is complicated by the absence of standardized test problems and datasets.

Therefore, while computational speedup using ANN surrogates is demonstrated quite easily, the key factor for their implementation is ensuring and thoroughly verifying accuracy. It is necessary to clearly define validation conditions (interpolation or extrapolation) and use adequate metrics to build confidence in the results obtained with ANNs within the engineering community.

9. Discussion: Current State, Key Challenges, and Future Research Directions

The conducted literature review demonstrates significant progress and great potential in the application of neural network surrogate models in structural mechanics and optimization. ANNs are successfully used to accelerate SSS calculations, dynamics, nonlinear behavior, as well as in solving complex optimization problems that were previously intractable due to computational limitations. A trend is observed towards the development of increasingly specialized architectures (GNN, PINN) and training methodologies aimed at enhancing the accuracy, reliability, and physical soundness of models.

Despite these successes, the widespread adoption of neural network surrogates in engineering practice is still hindered by a number of interconnected challenges that require in-depth analysis and innovative solutions:

- **Data dependency and quality of training datasets:** Although ANNs can learn from data, the effectiveness of this learning critically depends on the volume, representativeness, and quality of the training datasets [12, 17, 31]. Generating a sufficient number of high-fidelity FEM computations to cover the entire multidimensional space of design parameters is itself a laborious and computationally expensive process. This raises questions about optimal Design of Experiments for data generation and the development of methods effective with limited data.
- **Limited generalization and extrapolation capabilities:** Neural networks, being essentially powerful interpolation tools, often exhibit unpredictable behavior and low accuracy when attempting to extrapolate beyond the domain covered by the training data [12, 23, 31]. This significantly limits their reliability in real-world engineering tasks where structures may experience unforeseen loads or have parameters outside the training range. Ensuring robustness and the ability of models to perform reasoned extrapolation remains a key challenge.
- **Training, tuning, and interpretability issues:** The training process, especially for deep and complex ANN architectures, is often non-trivial, requiring considerable expertise in selecting the architecture, loss function, optimizer, and tuning numerous hyperparameters [12, 31]. Moreover, ANNs often function as "black boxes," which complicates understanding the physical basis of their predictions and causes justified caution among engineers for whom understanding model behavior and the reasons for obtaining particular results is critically important.
- **Difficulties in modeling complex physical behavior:** Although progress has been made in modeling nonlinear processes, the accurate and reliable reproduction of highly nonlinear, history-dependent phenomena (like plasticity [15, 33, 34]) or multi-scale physical phenomena (like fracture or contact interaction [28]) remains a challenging task [30, 35]. This requires the development of specialized ANN architectures, possibly with deeper integration of physical principles than is currently implemented in PINNs.

- **Sensitivity to changes in geometry, mesh topology, and scalability:** Many standard ANN architectures (especially MLPs and CNNs) adapt poorly to changes in structural geometry or FEM mesh topology, requiring retraining or complex data transformation procedures [30]. Although GNNs partially address this issue, the question of effectively scaling developed approaches to very large, real-world engineering systems with millions of degrees of freedom remains open, both in terms of data generation and model training and usage [12, 31].
- **Integration into engineering workflows and uncertainty quantification:** For the practical application of ANN surrogates, their seamless integration into existing CAD/CAE systems and engineering workflows is necessary [12, 31, 36]. Furthermore, it is critically important not only to obtain a point prediction but also to assess its reliability and uncertainty (UQ) [3, 12, 18], which allows for making informed engineering decisions considering potential risks. Existing UQ methods for ANNs are often computationally complex or provide only approximate estimates.

The analysis of these challenges shows that, despite considerable enthusiasm, the path to the ubiquitous use of ANNs in engineering practice requires not only the improvement of machine learning algorithms themselves but also the development of comprehensive methodologies that consider the specifics of engineering tasks, and the requirements for reliability and interpretability of results.

Promising future research directions include:

- Developing hybrid models that effectively combine the strengths of FEM and ANNs, particularly further improving PINNs and their variants for solid mechanics problems, including domain decomposition methods [42, 43, 44, 45].
- In-depth research of graph neural networks (GNNs) for the analysis and optimization of structures with complex geometries and on unstructured meshes.
- Developing transfer and active learning methods to reduce dependence on large data volumes and enhance model adaptability.
- Creating reliable and computationally efficient methods for uncertainty quantification for ANN surrogates.
- Developing approaches that increase the interpretability of ANNs and creating standardized benchmarks for comparing the effectiveness of different methods.
- Particular attention should be given to researching methodologies that combine the decomposition of complex structural systems into typical elements/subproblems with the training of specialized ANN surrogates for these elements and the subsequent integration of their predictions using ensemble or hierarchical approaches. Such an approach could potentially offer greater flexibility, scalability, and accuracy for analyzing heterogeneous systems compared to global surrogates, representing an important

step towards creating effective tools for next-generation engineering design.

10. Conclusions

The application of artificial neural networks for creating surrogate models of FEM computations demonstrates revolutionary potential for overcoming the problem of high computational costs in structural mechanics and engineering design. The conducted literature review indicates significant progress in the development and application of ANN surrogates for substantially accelerating the analysis of stress-strain states, dynamic responses, and nonlinear behavior of structures, as well as for effectively solving problems in size, shape, and topology optimization.

Various ANN architectures have been investigated and successfully applied, from classic MLPs to more complex CNNs, GNNs, RNNs, and physics-informed PINNs, each offering advantages for specific classes of problems. The use of ANNs for multi-variant calculations within optimization loops is particularly promising, allowing for the exploration of a much broader design space and the discovery of more efficient and innovative structural designs.

Despite the obvious advantages, a number of fundamental and practical challenges remain. These include the need for large representative datasets for training, ensuring the models' ability to generalize and extrapolate to new conditions, the complexity of hyperparameter tuning, and the interpretation of "black box" ANN results. Modeling complex physics, dependence on changes in geometry and mesh, as well as scaling to large real-world problems, continue to be active areas of research.

Future development in this field is likely to be associated with the creation of hybrid physics-informed models, the development of more robust and data-efficient ANN architectures, and methods that ensure the interpretability and reliable uncertainty assessment of predictions. The development of comprehensive methodologies that combine the advantages of decomposition, specialized local ANN surrogates, and ensemble approaches is one of the promising paths for creating computationally efficient and accurate tools for the analysis and optimization of complex engineering structures, which will open new horizons for engineering design.

References

1. *Hoffer J. G., Geiger B. C., Ofner P., Kern R. Mesh-Free* Surrogate Models for Structural Mechanic FEM Simulation: A Comparative Study of Approaches. Applied Sciences. 2021. Vol. 11, No. 20, pp. 9411. DOI: 10.3390/app11209411. {in English}

2. *Messner M. C.* Convolutional Neural Network Surrogate Models for the Mechanical Properties of Periodic Structures. ASME. Journal of Mechani-cal Design. 2020. Vol. 142, No. 2, pp. 024503. DOI: 10.1115/1.4045040. {in English}

3. *Freitag S., Edler P., Schoen S., Meschke G.* Artificial neural network surrogate modeling for uncertainty quantification and structural optimization of reinforced concrete structures. Proceedings in Applied Mathematics & Me-chanics. 2023. Vol. 23, e202300286, pp. 1–8. DOI: 10.1002/pamm.202300286. {in English}

4. *Wu H., Wu Y.-C., Zhi P., Wu X., Zhu T.* Structural optimization of single-layer domes using surrogate-based physics-informed neural networks. Heliyon. 2023. Vol. 9, No. 10, e20867. DOI: 10.1016/j.heliyon.2023.e20867. {in English}
5. *Nourian N., El-Badry M., Jamshidi M.* Design Optimization of Truss Structures Using a Graph Neural Network-Based Surrogate Model. Algo-rithms. 2023. Vol. 16, No. 8, pp. 380. DOI: 10.3390/a16080380. {in English}
6. *Shin S., Shin D., Kang N.* Topology optimization via machine learn-ing and deep learning: a review. Journal of Computational Design and Engi-neering. 2023. Vol. 10, No. 4, pp. 1736–1766. DOI: 10.1093/jcde/qwad072. {in English}
7. *Liang L., Liu M., Martin C., Sun W.* A deep learning approach to es-timate stress distribution: a fast and accurate surrogate of finite-element analy-sis. Journal of The Royal Society Interface. 2018. Vol. 15, No. 138, 20170844. DOI: 10.1098/rsif.2017.0844. {in English}
8. *Xie K., Huo Y., Li Z., Wu Z.* ODE-DSN: A surrogate model for dy-namic stiffness in microscopic RVE problems under nonuniform time-step strain inputs. Journal of Computational Design and Engineering. 2025. Vol. 12, No. 2, pp. 49–60. DOI: 10.1093/jcde/qwaf012. {in English}
9. *Han Z., Ou J., Koyamada K.* A Physics-informed neural network-based Surrogate Model for Analyzing Elasticity Problems in Plates with Holes. Journal of Advanced Simulation in Science and Engineering. 2024. Vol. 11, No. 1, pp. 21–31. DOI: 10.15748/jasse.11.21. {in English}
10. *Numan M.* Advancements in structural health monitoring: a review of machine learning approaches for damage detection and assessment. Interna-tional Journal for Computational Civil and Structural Engineering. 2024. Vol. 20, No. 1, pp. 124–142. DOI: 10.22337/2587-9618-2024-20-1-124-142. {in English}
11. *Enabe P. A. F., Provasi R.* A hybrid virtual element method and deep learning approach for solving one-dimensional Euler-Bernoulli beams. arXiv preprint arXiv:2501.06925. 2025. pp. 1–17. DOI: 10.48550/arXiv.2501.06925. {in English}
12. *Samadian D., Muhit I. B., Dawood N.* Application of Data-Driven Surrogate Models in Structural Engineering: A Literature Review. Archives of Computational Methods in Engi-neering. 2024. Vol. 31, No. 2, pp. 735–784. DOI: 10.1007/s11831-024-10152-0. {in English}
13. *Haderbache A., Shirahata K., Tabaru T., Okuda H.* Surrogate Model for Structural Analy-sis Simulation using Graph Convolutional Network. IPSJ SIG Technical Report. 2021. Vol. 2021-HPC-180, No. 10, pp. 1–9. URL: https://www.researchgate.net/publication/360062139_Surrogate_Model_for_Structural_Analysis_Simulation_using_Graph_Convolutional_Network (data zvernennia 03.05.2025). {in English}
14. *Eskinazi I., Fregly B. J.* Surrogate Modeling of Deformable Joint Contact using Artificial Neural Networks. Medical Engineering & Physics. 2015. Vol. 37, No. 9, pp. 885–891. DOI: 10.1016/j.medengphy.2015.06.006. {in English}
15. *Eghbalian M., Pouragha M., Wan R.* A physics-informed deep neu-ral network for surrogate modeling in classical elasto-plasticity. arXiv preprint arXiv:2204.12088. 2022, pp. 1–53. DOI: 10.48550/arXiv.2204.12088. {in English}
16. *Ribeiro B. A. ta in.* SimuStruct: Simulated Structural Plate with Holes Dataset with Machine Learning Applications. OpenReview.net. 2023. URL: https://openreview.net/forum?id=s3tOuyR1vM7 (data zvernennia 03.05.2025). {in English}
17. *Fan Y. ta in.* Physics-Informed Neural Network Surrogate Model for Small-Sample Mistuned Bladed Disk. AIAA Journal. 2024. DOI: 10.2514/1.J064832. (Prymitka: Tom, nomer, storinky ne vkazani u vykhidnykh danykh). {in English}
18. *Hakim S. J., Razak H. A., Ravanfar S. A.* Ensemble neural networks for structural damage identification using modal data. International Journal of Damage Mechanics. 2015. Vol. 25, No. 3. DOI: 10.1177/1056789515598639. {in English}

19. *Anjum A. ta in.* Civil Structural Health Monitoring and Machine Learning: A Comprehensive Review. Fracture and Structural Integrity. 2024. Vol. 18, No. 69, pp. 43–59. DOI: 10.3221/IGF-ESIS.69.04. {in English}
20. *Salehi H., Burgueño R.* Machine-Learning Applications in Structural Response Prediction: A Review. Practice Periodical on Structural Design and Construction. 2024. Vol. 29, No. 3. DOI: 10.1061/PPSCFX.SCENG-1292. {in English}
21. *Azimi M., Eslamlou A. D., Pekcan G.* Data-Driven Structural Health Monitoring and Damage Detection through Deep Learning: State-of-the-Art Review. Sensors (Basel). 2020. Vol. 20, No. 10, pp. 2778. DOI: 10.3390/s20102778. {in English}
22. *Al-Adly A. I. F., Kripakaran P.* Physics-informed neural networks for structural health monitoring: a case study for Kirchhoff–Love plates. Data-Centric Engineering. 2024. Vol. 5, e6. DOI: 10.1017/dce.2024.4. {in English}
23. *Li H., Miao Y., Khodaei Z. S., Aliabadi M. H.* Finite-PINN: A Phys-ics-Informed Neural Network Architecture for Solving Solid Mechanics Prob-lems with General Geometries. arXiv preprint arXiv:2412.09453. 2024. DOI: 10.48550/arXiv.2412.09453. {in English}
24. Singh V. ta in. Physics-Informed Neural Network for Solving a One-Dimensional Solid Mechanics Problem. Modelling. 2024. Vol. 5, No. 4, pp. 1532–1549. DOI: 10.3390/modelling5040080. {in English}
25. *Korbar J., Ocepek D., Čepon G., Boltežar M.* Training artificial neu-ral networks using substructuring techniques: Application to joint identifica-tion. Mechanical Systems and Signal Processing. 2023. Vol. 198, 110426. DOI: 10.1016/j.ymssp.2023.110426. {in English}
26. *Wu Z., Fan F., Xiao R., Yu L.* The substructuring-based topology optimization for maximizing the first eigenvalue of hierarchical lattice structure. International Journal for Numerical Methods in Engineering. 2020. Vol. 121, No. 13, pp. 2964–2978. DOI: 10.1002/nme.6342. {in English}
27. *Huang M. ta in.* Problem-independent machine learning (PIML)-based topology optimization – A universal approach. Extreme Mechanics Let-ters. 2022. Vol. 56, 101887. DOI: 10.1016/j.eml.2022.101887. {in English}
28. *Mai H. T., Kang J., Lee J.* A machine learning-based surrogate model for optimization of truss structures with geometrically nonlinear behavior. Fi-nite Elements in Analysis and Design. 2021. Vol. 196, 103572. DOI: 10.1016/j.finel.2021.103572. {in English}
29. *Alanani M., Brown T., Elshaer A.* Multiobjective Structural Layout Optimization of Tall Buildings Subjected to Dynamic Wind Loads. Journal of Structural Engineering. 2024. Vol. 150, No. 7. DOI: 10.1061/JSENDH.STENG-12366. {in English}
30. *Greve L., van de Weg B. P.* Surrogate modeling of parametrized fi-nite element simulations with varying mesh topology using recurrent neural networks. Array. 2022. Vol. 14, 100137. DOI: 10.1016/j.array.2022.100137. {in English}
31. *Thai H.-T.* Machine learning for structural engineering: A state-of-the-art review. Structures. 2022. Vol. 38, pp. 448–491. DOI: 10.1016/j.istruc.2022.02.003. {in English}
32. *Barmada S., Fontana N., Formisano A., Thomopulos D.* A Deep Learning Surrogate Model for Topology Optimization. IEEE Transactions on Magnetics. 2021. Vol. 57, No. 6, pp. 1–5. Art no. 7503305. DOI: 10.1109/TMAG.2021.3063470. {in English}
33. *Vijayaraghavan S. ta in.* A data-driven reduced-order surrogate model for entire elasto-plastic simulations applied to representative volume ele-ments. Scientific Reports. 2023. Vol. 13, 12781. DOI: 10.1038/s41598-023-38104-x. {in English}
34. *Zhou M., Mei G., Xu N.* Enhancing Computational Accuracy in Surrogate Modeling for Elastic–Plastic Problems by Coupling S-FEM and Physics-Informed Deep Learning. Mathematics. 2023. Vol. 11, No. 9, pp. 2016. DOI: 10.3390/math11092016. {in English}
35. *Polydoras V., Tandale S., Stoffel M.* Physics-Based Spiking Neural Network as a Surrogate Model for Viscoplastic Material Law in Impulsively Loaded Beams. PAMM. 2024. Vol. 24, No. 4, e202400066. DOI: 10.1002/pamm.202400066. {in English}

36. *Eskinazi I., Fregly B. J.* An Open-Source Toolbox for Surrogate Modeling of Joint Contact Mechanics. IEEE Transactions on Biomedical En-gineering. 2016. Vol. 63, No. 2, pp. 269–277. DOI: 10.1109/TBME.2015.2455510. {in English}
37. *Chen X. ta in.* Research on structure topology optimization design empowered by deep learning method. Advances in Mechanics. 2024. Vol. 54, No. 2, pp. 213–258. DOI: 10.6052/1000-0992-23-052. {in English}
38. *Nguyen T.-H., Vu A.-T.* Speeding up Composite Differential Evolu-tion for structural optimization using neural networks. Journal of Information and Telecommunication. 2022. Vol. 6, No. 2, pp. 101–120. DOI: 10.1080/24751839.2021.1946740. {in English}
39. *Kong X. ta in.* Novel Artificial Neural Network Aided Structural Topology Optimization. Applied Sciences. 2024. Vol. 14, No. 23, pp. 11416. DOI: 10.3390/app142311416. {in English}
40. Dossett W. C., Kim I. Y. Machine learning-based sound power to-pology optimization for shell structures. Engineering Optimization. 2024. DOI: 10.1080/0305215X.2024.2434188. {in English}
41. *Zhang Z., Liu Q., Wu D.* Predicting stress-strain curves using trans-fer learning: knowledge transfer across fiber reinforced polymer composites. Materials & Design. 2022. Vol. 218. 110700. DOI: 10.1016/j.matdes.2022.110700. {in English}
42. *Jagtap, A. D., & Karniadakis, G. E.* (2020). Extended physics-informed neural networks (XPINNs): A generalized space-time domain de-composition based deep learning framework for nonlinear partial differential equations. Communications in Computational Physics, 28(5), 2002-2041. DOI: 10.4208/cicp.OA-2020-0164. {in English}
43. *Moseley, B., Markham, A., & Nissen-Meyer, T.* (2023). Finite ba-sis physics-informed neural networks (FBPINNs): a scalable domain de-composition approach for solving differential equations. Advances in Com-putational Mathematics. Vol. 49, article number 62. DOI: 10.1007/s10444-023-10065-9. {in English}
44. *Yan, M., Deng, S., & You, H.* (2025). Initialization-enhanced physics-informed neural network with domain decomposition (IDPINN). Journal of Computational Physics, 530, 113914. DOI: 10.1016/j.jcp.2025.113914. {in English}
45. *Abueidda, D. W., Koric, S., Sobh, N. A., & Sehitoglu, H.* (2024). Accelerating Multiscale Modeling with Hybrid Solvers: Coupling FEM and Neural Operators with Domain Decomposition. arXiv preprint arXiv:2504.11383v2. DOI: 10.48550/arXiv.2504.11383. {in English}
46. *Waszczysznk, Z. (Ed.).* (1999). Neural Networks in the Analysis and Design of Structures (CISM International Centre for Mechanical Sciences, 404). Springer Vienna. {in English}
47. *Topping, B. H. V., & Bahreininejad, A.* (1999). Neural Computing for Structural Mechanics. Saxe-Coburg Publications.
48. *Yagawa, G., & Oishi, A.* (2021). Computational Mechanics with Neural Networks. Springer. {in English}
49. *Fritzen, F., & Ryckelynck, D.* (Eds.). (2019). Machine Learning, Low-Rank Approximations and Reduced Order Modeling in Computational Mechanics. MDPI. {in English}
50. *Kollmannsberger, S., DAngella, D., Jokeit, M., & Herrmann, L.* (2021). Deep Learning in Computational Mechanics: An Introductory Course (Studies in Computational Intelligence, 977). Springer. {in English}
51. *Ivanchenko G. m., Koshevyi, O. O., Koshevyi, O. P.* (2024). A numerical study of the multicriteria parametric optimization of the dis-placement and weight of a two-connected conical shell of minimal surface under thermal and power loading. (2023). Strength of Materials and Theory of Structures. No. 111, pp. 102-112. DOI: 10.32347/2410-2547.2023.111.102-112. {in English}
52. *Bazhenov V. A., Sakharov O. S., Huliar O. I., Pyskunov S. O., Maksymiuk Yu. V.* (2014). Osoblyvosti vykorystannia momentnoi skhemy skinchennykh elementiv (MSSE) pry nelini-

inykh rozrakhunkakh obolonok i plastyn. Opir materialiv i teoriia sporud. No. 92, c. 3–16. {in Ukrainian}
53. *Koshevyi O.O., Koshevyi O.P., Hryhorieva L.O.* (2022). Chysel-na realizatsiia bahatokryterialnoi parametrychnoi optymizatsii obolonky minimalnoi poverkhni na priamokutnomu konturi pry termosylovomu na-vantazhenni. Opir materialiv i teoriia sporud. No. 108, c. 309–324. DOI: 10.32347/2410-2547.2022.108.309–324. {in Ukrainian}
54. *Peleshko I. D., Yurchenko V. V.* (2023). Parametric optimization of bar structures with discrete and continuous design variables using im-proved gradient projection method. Opir materialiv i teoriia sporud. No. 110, pp. 178–198. DOI: 10.32347/2410-2547.2023.110.178-198. {in Ukrainian}
55. *Yurchenko V., Peleshko I. D.* (2022). Searching for a compromise solution in cross-section size optimization problems of cold-formed steel structural members. Opir materialiv i teoriia sporud. No. 109. pp. 72–92. DOI: 10.32347/2410-2547.2022.109.72-92. {in Ukrainian}

Література

1. *Hoffer J. G., Geiger B. C., Ofner P., Kern R.* Mesh-Free Surrogate Models for Structural Mechanic FEM Simulation: A Comparative Study of Approaches. *Applied Sciences*. 2021. Vol. 11, No. 20, pp. 9411. DOI: 10.3390/app11209411.
2. *Messner M. C.* Convolutional Neural Network Surrogate Models for the Mechanical Properties of Periodic Structures. *ASME. Journal of Mechanical Design*. 2020. Vol. 142, No. 2, pp. 024503. DOI: 10.1115/1.4045040.
3. *Freitag S., Edler P., Schoen S., Meschke G.* Artificial neural network surrogate modeling for uncertainty quantification and structural optimization of reinforced concrete structures. *Proceedings in Applied Mathematics & Mechanics*. 2023. Vol. 23, e202300286, pp. 1–8. DOI: 10.1002/pamm.202300286.
4. *Wu H., Wu Y.-C., Zhi P., Wu X., Zhu T.* Structural optimization of single-layer domes using surrogate-based physics-informed neural networks. *Heliyon*. 2023. Vol. 9, No. 10, e20867. DOI: 10.1016/j.heliyon.2023.e20867.
5. *Nourian N., El-Badry M., Jamshidi M.* Design Optimization of Truss Structures Using a Graph Neural Network-Based Surrogate Model. *Algorithms*. 2023. Vol. 16, No. 8, pp. 380. DOI: 10.3390/a16080380.
6. *Shin S., Shin D., Kang N.* Topology optimization via machine learning and deep learning: a review. *Journal of Computational Design and Engineering*. 2023. Vol. 10, No. 4, pp. 1736–1766. DOI: 10.1093/jcde/qwad072.
7. *Liang L., Liu M., Martin C., Sun W.* A deep learning approach to estimate stress distribution: a fast and accurate surrogate of finite-element analysis. *Journal of The Royal Society Interface*. 2018. Vol. 15, No. 138, 20170844. DOI: 10.1098/rsif.2017.0844.
8. *Xie K., Huo Y., Li Z., Wu Z.* ODE-DSN: A surrogate model for dynamic stiffness in microscopic RVE problems under nonuniform time-step strain inputs. *Journal of Computational Design and Engineering*. 2025. Vol. 12, No. 2, pp. 49–60. DOI: 10.1093/jcde/qwaf012.
9. *Han Z., Ou J., Koyamada K.* A Physics-informed neural network-based Surrogate Model for Analyzing Elasticity Problems in Plates with Holes. *Journal of Advanced Simulation in Science and Engineering*. 2024. Vol. 11, No. 1, pp. 21–31. DOI: 10.15748/jasse.11.21.
10. *Numan M.* Advancements in structural health monitoring: a review of machine learning approaches for damage detection and assessment. *International Journal for Computational Civil and Structural Engineering*. 2024. Vol. 20, No. 1, pp. 124–142. DOI: 10.22337/2587-9618-2024-20-1-124-142.
11. *Enabe P. A. F., Provasi R.* A hybrid virtual element method and deep learning approach for solving one-dimensional Euler-Bernoulli beams. *arXiv preprint arXiv:2501.06925*. 2025. pp. 1–17. DOI: 10.48550/arXiv.2501.06925.

12. *Samadian D., Muhit I. B., Dawood N.* Application of Data-Driven Surrogate Models in Structural Engineering: A Literature Review. *Archives of Computational Methods in Engineering*. 2024. Vol. 31, No. 2, pp. 735–784. DOI: 10.1007/s11831-024-10152-0.
13. *Haderbache A., Shirahata K., Tabaru T., Okuda H.* Surrogate Model for Structural Analysis Simulation using Graph Convolutional Network. *IPSJ SIG Technical Report*. 2021. Vol. 2021-HPC-180, No. 10, pp. 1–9. URL: https://www.researchgate.net/publication/360062139_Surrogate_Model_for_Structural_Analysis_Simulation_using_Graph_Convolutional_Network (дата звернення 03.05.2025)
14. *Eskinazi I., Fregly B. J.* Surrogate Modeling of Deformable Joint Contact using Artificial Neural Networks. *Medical Engineering & Physics*. 2015. Vol. 37, No. 9, pp. 885–891. DOI: 10.1016/j.medengphy.2015.06.006.
15. *Eghbalian M., Pouragha M., Wan R.* A physics-informed deep neural network for surrogate modeling in classical elasto-plasticity. *arXiv preprint arXiv:2204.12088*. 2022, pp. 1–53. DOI: 10.48550/arXiv.2204.12088.
16. *Ribeiro B. A.* та ін. SimuStruct: Simulated Structural Plate with Holes Dataset with Machine Learning Applications. *OpenReview.net*. 2023. URL: https://openreview.net/forum?id=s3tOuyR1vM7 (дата звернення 03.05.2025).
17. *Fan Y. та ін.* Physics-Informed Neural Network Surrogate Model for Small-Sample Mistuned Bladed Disk. *AIAA Journal*. 2024. DOI: 10.2514/1.J064832. (Примітка: Том, номер, сторінки не вказані у вихідних даних).
18. *Hakim S. J., Razak H. A., Ravanfar S. A.* Ensemble neural networks for structural damage identification using modal data. *International Journal of Damage Mechanics*. 2015. Vol. 25, No. 3. DOI: 10.1177/1056789515598639.
19. *Anjum A. та ін.* Civil Structural Health Monitoring and Machine Learning: A Comprehensive Review. *Fracture and Structural Integrity*. 2024. Vol. 18, No. 69, pp. 43–59. DOI: 10.3221/IGF-ESIS.69.04.
20. *Salehi H., Burgueño R.* Machine-Learning Applications in Structural Response Prediction: A Review. *Practice Periodical on Structural Design and Construction*. 2024. Vol. 29, No. 3. DOI: 10.1061/PPSCFX.SCENG-1292.
21. *Azimi M., Eslamlou A. D., Pekcan G.* Data-Driven Structural Health Monitoring and Damage Detection through Deep Learning: State-of-the-Art Review. *Sensors (Basel)*. 2020. Vol. 20, No. 10, pp. 2778. DOI: 10.3390/s20102778.
22. *Al-Adly A. I. F., Kripakaran P.* Physics-informed neural networks for structural health monitoring: a case study for Kirchhoff–Love plates. *Data-Centric Engineering*. 2024. Vol. 5, e6. DOI: 10.1017/dce.2024.4.
23. *Li H., Miao Y., Khodaei Z. S., Aliabadi M. H.* Finite-PINN: A Physics-Informed Neural Network Architecture for Solving Solid Mechanics Problems with General Geometries. *arXiv preprint arXiv:2412.09453*. 2024. DOI: 10.48550/arXiv.2412.09453.
24. *Singh V. та ін.* Physics-Informed Neural Network for Solving a One-Dimensional Solid Mechanics Problem. *Modelling*. 2024. Vol. 5, No. 4, pp. 1532–1549. DOI: 10.3390/modelling5040080.
25. *Korbar J., Ocepek D., Čepon G., Boltežar M.* Training artificial neural networks using substructuring techniques: Application to joint identification. *Mechanical Systems and Signal Processing*. 2023. Vol. 198, 110426. DOI: 10.1016/j.ymssp.2023.110426.
26. *Wu Z., Fan F., Xiao R., Yu L.* The substructuring-based topology optimization for maximizing the first eigenvalue of hierarchical lattice structure. *International Journal for Numerical Methods in Engineering*. 2020. Vol. 121, No. 13, pp. 2964–2978. DOI: 10.1002/nme.6342.
27. *Huang M. та ін.* Problem-independent machine learning (PIML)-based topology optimization – A universal approach. *Extreme Mechanics Letters*. 2022. Vol. 56, 101887. DOI: 10.1016/j.eml.2022.101887.

28. *Mai H. T., Kang J., Lee J.* A machine learning-based surrogate model for optimization of truss structures with geometrically nonlinear behavior. *Finite Elements in Analysis and Design*. 2021. Vol. 196, 103572. DOI: 10.1016/j.finel.2021.103572.
29. *Alanani M., Brown T., Elshaer A.* Multiobjective Structural Layout Optimization of Tall Buildings Subjected to Dynamic Wind Loads. *Journal of Structural Engineering*. 2024. Vol. 150, No. 7. DOI: 10.1061/JSENDH.STENG-12366.
30. *Greve L., van de Weg B. P.* Surrogate modeling of parametrized finite element simulations with varying mesh topology using recurrent neural networks. *Array*. 2022. Vol. 14, 100137. DOI: 10.1016/j.array.2022.100137.
31. *Thai H.-T.* Machine learning for structural engineering: A state-of-the-art review. *Structures*. 2022. Vol. 38, pp. 448–491. DOI: 10.1016/j.istruc.2022.02.003.
32. *Barmada S., Fontana N., Formisano A., Thomopulos D.* A Deep Learning Surrogate Model for Topology Optimization. *IEEE Transactions on Magnetics*. 2021. Vol. 57, No. 6, pp. 1–5. Art no. 7503305. DOI: 10.1109/TMAG.2021.3063470.
33. *Vijayaraghavan S. та ін.* A data-driven reduced-order surrogate model for entire elastoplastic simulations applied to representative volume elements. *Scientific Reports*. 2023. Vol. 13, 12781. DOI: 10.1038/s41598-023-38104-x.
34. *Zhou M., Mei G., Xu N.* Enhancing Computational Accuracy in Surrogate Modeling for Elastic–Plastic Problems by Coupling S-FEM and Physics-Informed Deep Learning. *Mathematics*. 2023. Vol. 11, No. 9, pp. 2016. DOI: 10.3390/math11092016.
35. *Polydoras V., Tandale S., Stoffel M.* Physics-Based Spiking Neural Network as a Surrogate Model for Viscoplastic Material Law in Impulsively Loaded Beams. *PAMM*. 2024. Vol. 24, No. 4, e202400066. DOI: 10.1002/pamm.202400066.
36. *Eskinazi I., Fregly B. J.* An Open-Source Toolbox for Surrogate Modeling of Joint Contact Mechanics. *IEEE Transactions on Biomedical Engineering*. 2016. Vol. 63, No. 2, pp. 269–277. DOI: 10.1109/TBME.2015.2455510.
37. *Chen X. та ін.* Research on structure topology optimization design empowered by deep learning method. *Advances in Mechanics*. 2024. Vol. 54, No. 2, pp. 213–258. DOI: 10.6052/1000-0992-23-052.
38. *Nguyen T.-H., Vu A.-T.* Speeding up Composite Differential Evolution for structural optimization using neural networks. *Journal of Information and Telecommunication*. 2022. Vol. 6, No. 2, pp. 101–120. DOI: 10.1080/24751839.2021.1946740.
39. *Kong X. та ін.* Novel Artificial Neural Network Aided Structural Topology Optimization. *Applied Sciences*. 2024. Vol. 14, No. 23, pp. 11416. DOI: 10.3390/app142311416.
40. *Dossett W. C., Kim I. Y.* Machine learning-based sound power topology optimization for shell structures. *Engineering Optimization*. 2024. DOI: 10.1080/0305215X.2024.2434188.
41. *Zhang Z., Liu Q., Wu D.* Predicting stress-strain curves using transfer learning: knowledge transfer across fiber reinforced polymer composites. *Materials & Design*. 2022. Vol. 218. 110700. DOI: 10.1016/j.matdes.2022.110700.
42. *Jagtap, A. D., & Karniadakis, G. E.* (2020). Extended physics-informed neural networks (XPINNs): A generalized space-time domain decomposition based deep learning framework for nonlinear partial differential equations. *Communications in Computational Physics*, 28(5), 2002-2041. DOI: 10.4208/cicp.OA-2020-0164
43. *Moseley, B., Markham, A., & Nissen-Meyer, T.* (2023). Finite basis physics-informed neural networks (FBPINNs): a scalable domain decomposition approach for solving differential equations. *Advances in Computational Mathematics*. Vol. 49, article number 62. DOI: 10.1007/s10444-023-10065-9
44. *Yan, M., Deng, S., & You, H.* (2025). Initialization-enhanced physics-informed neural network with domain decomposition (IDPINN). *Journal of Computational Physics*, 530, 113914. DOI: 10.1016/j.jcp.2025.113914.

45. *Abueidda, D. W., Koric, S., Sobh, N. A., & Sehitoglu, H.* (2024). Accelerating Multiscale Modeling with Hybrid Solvers: Coupling FEM and Neural Operators with Domain Decomposition. *arXiv preprint arXiv:2504.11383v2*. DOI: 10.48550/arXiv.2504.11383
46. Waszczysznk, Z. (Ed.). (1999). *Neural Networks in the Analysis and Design of Structures* (CISM International Centre for Mechanical Sciences, 404). Springer Vienna.
47. *Topping, B. H. V., & Bahreininejad, A.* (1999). *Neural Computing for Structural Mechanics*. Saxe-Coburg Publications.
48. *Yagawa, G., & Oishi, A.* (2021). *Computational Mechanics with Neural Networks*. Springer.
49. *Fritzen, F., & Ryckelynck, D.* (Eds.). (2019). *Machine Learning, Low-Rank Approximations and Reduced Order Modeling in Computational Mechanics*. MDPI.
50. *Kollmannsberger, S., D'Angella, D., Jokeit, M., & Herrmann, L.* (2021). *Deep Learning in Computational Mechanics: An Introductory Course* (Studies in Computational Intelligence, 977). Springer.
51. *Ivanchenko G. m., Koshevyi, O. O., Koshevyi, O. P.* (2024). A numerical study of the multicriteria parametric optimization of the displacement and weight of a two-connected conical shell of minimal surface under thermal and power loading. (2023). *Strength of Materials and Theory of Structures*. No. 111, pp. 102-112. DOI: 10.32347/2410-2547.2023.111.102-112
52. *Баженов В. А., Сахаров О. С., Гуляр О. І., Пискунов С. О., Максим'юк Ю. В.* (2014). Особливості використання моментної схеми скінченних елементів (МССЕ) при нелінійних розрахунках оболонок і пластин. *Опір матеріалів і теорія споруд*. No. 92, с. 3–16.
53. Кошевий О.О., Кошевий О.П., Григор'єва Л.О. (2022). Чисельна реалізація багатокритеріальної параметричної оптимізації оболонки мінімальної поверхні на прямокутному контурі при термосиловому навантаженні. *Опір матеріалів і теорія споруд*. No. 108, с. 309–324. DOI: 10.32347/2410-2547.2022.108.309–324.
54. *Peleshko I. D., Yurchenko V. V.* (2023). Parametric optimization of bar structures with discrete and continuous design variables using improved gradient projection method. *Опір матеріалів і теорія споруд*. No. 110, pp. 178–198. DOI: 10.32347/2410-2547.2023.110.178-198
55. *Yurchenko V., Peleshko I. D.* (2022). Searching for a compromise solution in cross-section size optimization problems of cold-formed steel structural members. *Опір матеріалів і теорія споруд*. No. 109. pp. 72–92. DOI: 10.32347/2410-2547.2022.109.72-92.

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ОПТИМІЗАЦІЯ РОЗРАХУНКОВИХ МОДЕЛЕЙ СПОРУД З ВИКОРИСТАННЯМ НЕЙРОННИХ МЕРЕЖ: СИСТЕМАТИЧНИЙ ОГЛЯД СУЧАСНИХ ПІДХОДІВ ТА ПЕРСПЕКТИВ

Сучасний розрахунковий аналіз та оптимізація складних будівельних конструкцій за допомогою методу скінченних елементів (МСЕ) часто обмежені високою обчислювальною вартістю. Ця стаття представляє систематичний огляд сучасних досліджень щодо застосування штучних нейронних мереж (НМ) для створення швидких сурогатних моделей МСЕ-розрахунків з метою подолання цих обмежень. В огляді детально аналізуються різноманітні архітектури НМ (зокрема, MLP, CNN, GNN, RNN, PINN), методики їх навчання та ефективність використання для прискорення аналізу напружено-деформованого стану, динамічної поведінки, нелінійних процесів та вирішення задач оптимізації конструкцій (розмірів, форми, топології). Аналіз літератури підтверджує здатність НМ-сурогатів значно скорочувати час розрахунків порівняно з традиційним МСЕ, відкриваючи нові можливості для інженерного проектування. Разом з тим, ідентифіковано ключові виклики, пов'язані з потребою у великих масивах даних для навчання, забезпеченням здатності моделей до узагальнення та інтерпретованістю їхніх результатів. Стаття завершується обговоренням невирішених проблем та визначенням перспективних напрямків майбутніх досліджень у цій динамічній галузі.

Ключові слова: будівельна механіка; метод скінченних елементів; сурогатне моделювання; штучні нейронні мережі; машинне навчання; прискорення розрахунків; оптимізація конструкцій; топологічна оптимізація; фізично-орієнтовані нейронні мережі; PINN; графові нейронні мережі; GNN; огляд літератури; інженерне проектування.