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APPLICATION OF SURROGATE MODELS BASED ON NEURAL NETWORKS FOR FAST OPTIMIZATION OF REINFORCED CONCRETE FRAME STRUCTURES

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This paper presents the development and validation of a complete software pipeline for creating and applying a high-fidelity neural network-based surrogate model to solve the problem of building structure optimization. The design optimization of reinforced concrete structures is a computationally complex task due to the high cost of finite element (FE) analysis, which often makes multi-variant exploration for optimal solutions impractical. The methodology involved creating a parametric FE model of a spatial cell of a reinforced concrete frame, automated generation of a dataset with 12000 unique designs, and their subsequent post-processing. A key stage of the post-processing was the calculation of the required reinforcement area using an iterative algorithm that implements the nonlinear deformation model in accordance with the current Ukrainian State Standard DSTU B V.2.6-156:2010 (harmonized with Eurocode 2: EN 1992-1-1). A Multi-Layer Perceptron (MLP) model was trained on this data.The results demonstrated that the trained surrogate model achieved high predictive capability with a coefficient of determination R^2 = 0.9946 on the test set. When applied to the practical optimization problem with a minimum cost criterion, the model was able to analyze 10 million candidate designs in approximately one minute – a task that would require an estimated 8 years using direct FE analysis. Verification of the top 10 optimal solutions found showed a high correlation between predicted and actual values, with the prediction error for the objective function (cost) not exceeding 2.1%. It is demonstrated that the proposed approach allows for the creation of reliable predictive tools that accelerate the search for optimal structural solutions by orders of magnitude, opening new possibilities for efficient and economically justified design.

Keywords: structural optimization, finite element method, building structures, reinforced concrete frame, surrogate model, neural network, machine learning, ANSYS.

1. Introduction

The optimization of structures in civil engineering, particularly of spatial reinforced concrete frames, represents one of the key and most complex computational challenges in modern design. The goal of optimization is to find a set of design parameters (e.g., the dimensions of beams and columns in frame buildings) that minimizes an objective function (typically cost or material volume) while satisfying a complex set of regulatory requirements for strength and serviceability [1, 16]. The primary tool for verifying these requirements is the Finite Element Method (FEM), which provides high accuracy in predicting structural behavior. However, this accuracy is achieved at the cost of significant, and often prohibitive, computational expense.

When a high-fidelity FE analysis is integrated into an optimization loop, which may require thousands of iterations, the total computation time can extend to weeks or even months [1]. This makes solving multi-variant optimization problems through direct enumeration practically impossible within realistic design timelines. This fundamental computational barrier has spurred the search for alternative strategies, leading to the development of surrogate modeling as a key enabling technology [2, 3].

A surrogate model (or metamodel) is a computationally "lightweight" approximation of a complex FE simulation, allowing the slow calculation to be replaced with a near-instantaneous prediction. Among various machine learning methods, neural networks have become the dominant choice for creating surrogate models due to their ability to approximate highly complex, nonlinear dependencies characteristic of the behavior of reinforced concrete structures [10, 12]. The purpose of this work is to demonstrate the effectiveness and practical viability of applying surrogate models to solve complex optimization problems in structural mechanics. To achieve this goal, the task was set to develop and validate a complete, end-to-end software pipeline: from the generation of training data to the creation and application of a high-fidelity neural network model.

As a proof of concept, a representative yet non-trivial case is considered: the optimization of a spatial cell of a reinforced concrete frame. This choice not only allows for the demonstration of the methodology on a representative engineering object but also helps to identify potential weaknesses and practical nuances of implementing such an approach. Thus, this paper focuses not so much on the optimization results of a specific structure, but on the very process of creating and validating a tool that makes solving similar problems fundamentally possible and efficient.

2. Materials and Methods

This section describes the object of study, the methodology for its finite element analysis, and the architecture of the software suite developed to automate the calculations and create the surrogate model. The general workflow of the developed software pipeline is shown in Fig. 1.

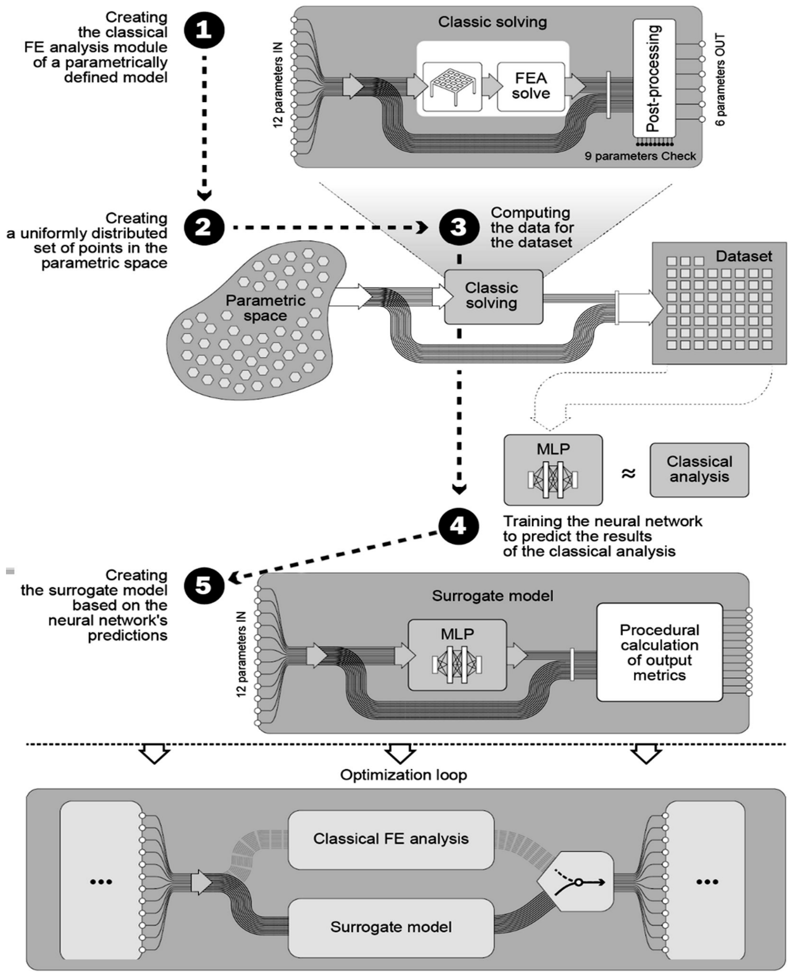

Fig. 1. Conceptual workflow scheme: stages of creating the neural network surrogate model (1-5) and its application to replace direct FE analysis within the optimization loop

The pipeline consists of two main phases: the creation of the surrogate model (stages 1-4) and its practical application (stage 5 and the optimization loop). In the first stage, a parametric FE model is created (1), defining the full range of possible design parameters. Next, a separate tool, utilizing Latin Hypercube Sampling (LHS), is used to generate a "cloud" of uniformly distributed points within this predefined parameter space (2). These points serve as the input data for which the "raw" engineering results are computed via batch FE analysis (3). This data is then processed and enriched, forming the final dataset on which a neural network (MLP) is trained to approximate the behavior of the classical calculation (4). In the second phase, the trained neural network is integrated into a fast surrogate model (5), which replaces the slow FE calculation inside the optimization loop for an efficient search for optimal solutions.

2.1. Object of Study and its Computational Model. As the object of study to test the methodology, a representative element of modern cast-in-situ reinforced concrete buildings was chosen – a spatial cell with a ribbed slab (Fig. 2). The model consists of four columns with a square cross-section, rigidly fixed at the base, four primary beams (girders), and six secondary beams (ribs) that form an orthogonal slab grid. All connections between elements (column-girder, girder-rib, rib-rib) are modeled as perfectly rigid, which corresponds to the actual behavior of a monolithic reinforced concrete structure [6].

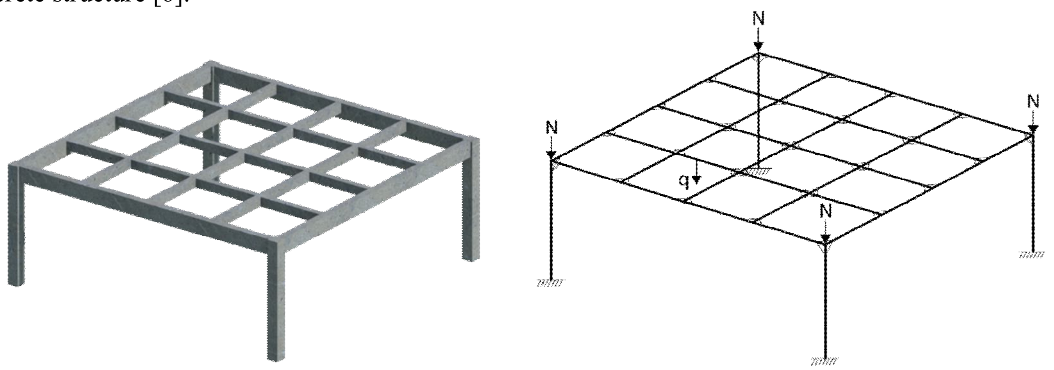

Fig. 2. Isometric view of the structural cell's computational model, showing the elements and the schematic application of loads *q* and *N*

A spatial frame structural scheme is used for the analysis, where each structural element is represented by its central axis. Such idealization is a standard practice in structural mechanics for analyzing frame systems and allows for the accurate determination of the overall stress-strain state of structures.

The model considers three main types of loads, the magnitudes of which are controllable parameters:

- **Slab load**: Modeled as a uniformly distributed load q applied vertically downward to all primary and secondary beams. It simulates the dead load (weight of the slab structures) and the live load on the floor.
- **Load from upper floors**: Modeled as concentrated vertical forces N applied to the top nodes of each of the four columns, simulating the load from the floors above.
- **Self-weight of the structure**: Calculated automatically by applying the Standard Earth Gravity to the entire model, taking into account the dimensions of the elements and material density.

2.2. Mathematical Apparatus of the Finite Element Analysis. The model is analyzed using the Finite Element Method (FEM) in a linear elastic formulation, implemented in the *Ansys Mechanical* software package. The method is based on the discretization of the structure into finite elements and the solution of a system of linear algebraic equations describing its equilibrium.

Each frame member (beam or column) is modeled as a 3D beam element, which has six degrees of freedom at each node (three linear displacements u, v, w, and three rotations θ_x, θ_y, θ_z). The equilibrium equation for a single element in a local coordinate system is:

$$\{F\}_e = [k]_e \{d\}_e ,$$

where $\{F\}_e$ is the vector of nodal forces and moments of the element; $[k]_e$ is the 12×12 element stiffness matrix, which accounts for its geometry (length L, cross-sectional area A, moments of inertia I_y, I_z) and the physical properties of the material (Young's modulus E, Poisson's ratio v); $\{d\}_e$ is the vector of nodal displacements and rotations of the element.

After forming the stiffness matrices for all elements, they are assembled into a single global stiffness matrix [K]. The final system of equations describing the equilibrium of the entire structure is:

$$\{F\} = [K]\ \{D\}$$

where{F} is the global vector of external loads (including self-weight, slab load, and load from upper floors); [K] is the global stiffness matrix of the entire system; {D} is the global vector of unknown nodal displacements and rotations.

By solving this system for {D}, the software calculates the displacements at each node of the structure. Based on these displacements, the strains and internal forces (axial forces N, bending moments M_y, M_z) are computed for each finite element, which serve as the raw output data for our subsequent analysis. It is important to emphasize that while this approach is implemented in *Ansys*, it is fundamental and can be applied in any other FEM package (e.g., LIRA-SAPR, SAP2000, Abaqus), making the proposed methodology for creating a surrogate model universal [2].

2.3. Automated Data Generation Pipeline. Creating the training dataset is the most computationally intensive stage. To automate this, a software suite in PYTHON was developed, which implements the following pipeline:

- **Design of Experiments (DoE) Generation**: The *doe_generator.py* script creates a set of unique combinations of input parameters using the Latin Hypercube Sampling (LHS) method to efficiently cover the design space (the results described below were achieved with a dataset of 12000 samples).
- **Batch Analysis in Ansys**: A specialized orchestration script (*main_loop.py*) manages the batch execution of analyses in Ansys for the entire set of generated parameters, ensuring fault tolerance and error handling.
- **Data Post-Processing and Enrichment**: The *post_processor.py* script reads the raw engineering data (internal forces, moments, and deflections) from ANSYS. Based on this data, it performs data enrichment, which includes:
  - Calculation of the required reinforcement area according to the DSTU B V.2.6-156:2010 standard [16]
  - Validation of each design for compliance with strength and stiffness requirements.
  - Computation of all derived metrics: the exact physical volume of concrete, the mass of reinforcement, and the final cost.

The result of this stage is the final, enriched dataset (*final_dataset.csv*), which contains complete informationfor each experiment and serves as the basis for training the surrogate model.

The key stage of post-processing is the calculation of the required reinforcement area A_s for each structural element. Unlike simplified methods, this work implements an iterative algorithm based on the nonlinear deformation model detailed in sections 4.1 and 4.2 of DSTU B V.2.6-156:2010. The general flowchart of the algorithm is presented in Fig. 3.

As shown in Fig. 3, the algorithm consists of two nested loops. *Component A* illustrates the outer iterative loop, which performs a sequential search for the reinforcement area A_s, starting from the minimum permissible value $A_{s,\min}$ (according to clause 8.2.1.1 of the DSTU). At each iteration, the section's load-bearing capacity is checked. *Component B* details this check, which is based on the nonlinear deformation model. For a given reinforcement area A_s, the algorithm iterates through the strains on the compressed face $\varepsilon_{c(1)}$ to find the neutral axis position x that satisfies the axial force equilibrium equation ($N_{\text{int}} \approx N_{Ed}$). The moment capacity M_{Rd} is determined as the maximum internal moment that the section can resist before reaching ultimate deformations. To determine the stresses (σ_c, σ_s) , bi-linear material state diagrams, shown in the schematic, are used, and the strain distribution (ε_c, ε_s) is assumed to be linear (plane sections remain plane), which is illustrated by the corresponding stress and strain diagrams (analogous to Fig. 4.2 of the DSTU). This approach allows for the high-fidelity modeling of the actual behavior of a reinforced concrete section through all stages up to failure.

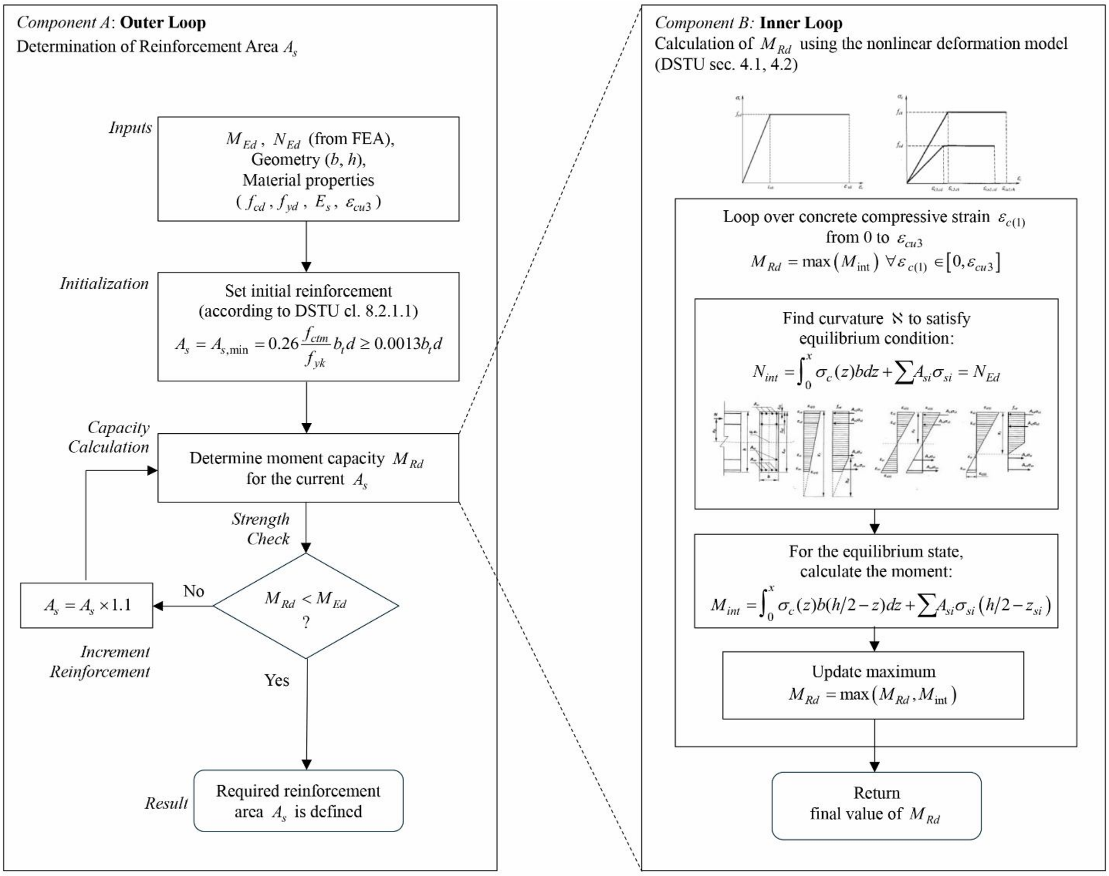

Fig. 3. Flowchart of the algorithm for determining the reinforcement area using the nonlinear deformation model (according to DSTU B V.2.6-156:2010, harmonized with Eurocode 2: EN 1992-1-1)

2.4. Surrogate Model Development

- **Data Preparation**:Before training, the data undergoes mandatory preparation: filtering (using only valid designs), splitting into input (*X*) and target (*Y*) parameters, and scaling of all numerical data (both input and output) using a *Standard Scaler* to stabilize the training process. Categorical parameters (material classes) are encoded using a *One Hot Encoder*.
- **Architecture and Training**:A Multi-Layer Perceptron (MLP) was chosen as the surrogate model, which is a fundamental architecture for such regression tasks [4, 9]. The model, implemented using the *Keras* library (*Tensor Flow*), consists of an input layer, three hidden layers (128, 128, and 64 neurons) with the *ReLU* activation function, and an output layer with a linear activation function for predicting the 6 engineering outputs. The training process is monitored using *Tensor Board*, and an *Early Stopping* mechanism is used to automatically stop at the optimal moment and prevent overfitting.

3. Results and Discussion

This section is dedicated to the validation of the developed surrogate model, its application to solve a practical optimization problem, and the verification of the obtained result by comparing it with a direct finite element analysis.

3.1. Surrogate Model Validation. The key stage of the research was to assess the accuracy and adequacy of the trained surrogate model. The dataset used for training contained 11979 valid computational instances (out of 12000 generated). This sample was split in an approximate ≈80/10/10 ratio, forming a training set (9702 examples), a validation set (1079 examples), and a test set (1198 examples) held out for the final, independent quality assessment.

The model's input vector (*features*) consisted of 12 parameters that fully describe the design and loading conditions of the cell: geometric characteristics (plan dimensions of the cell, floor height, cross-sectional dimensions of columns, girders, and ribs), load magnitudes (distributed on the slab and concentrated on the columns), and material strength classes (concrete and reinforcement). Six key engineering indicators, which are the result of FE analysis and subsequent design code calculations and cannot be computed analytically, were selected as the target parameters for prediction (*targets*): the maximum vertical deflection of the slab, as well as five values for the required area of longitudinal reinforcement (for columns, bottom and top zones of girders, and bottom and top zones of ribs).

Prior to training, mandatory data preprocessing was performed, which included scaling all input (*features*) and output (*targets*) numerical parameters using a *Standard Scaler*. This step proved to be critically important for achieving uniform prediction accuracy across all target indicators. To prevent overfitting, an *Early Stopping* mechanism was used, which automatically terminated the training process when the error on the validation set (*validation loss*) ceased to improve, saving the model weights from the best epoch.

The final quality of the model on the test set was evaluated using the coefficient of determination (R^2). With an optimal learning rate of 0.0001, the model consistently achieved an integrated R^2 score greater than 0.994. The coefficient of determination is a statistical metric that indicates the proportion of the variance in the dependent variable that is predictable from the independent variables. It is calculated by the formula:

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

where y_i is the actual value, $\hat{y}_i$ is the value predicted by the model, and $\overline{y}_i$ is the mean of the actual data.

An R^2 value of 0.9946 indicates that the developed model can explain 99.46% of the variability in the data. Such an exceptionally high value is realistic in this context, as the model approximates a deterministic physical system described by the precise laws of structural mechanics, and a large, high-quality dataset devoid of random "noise" was used for its training.

An analysis of the training process graphs, obtained using *Tensor Board* (Fig. 4), demonstrates healthy dynamics. The error curves for the training (*train loss*) and validation (*validation loss*) sets move in sync, which is a clear confirmation that the model has successfully generalized the dependencies in the data and has not overfit.

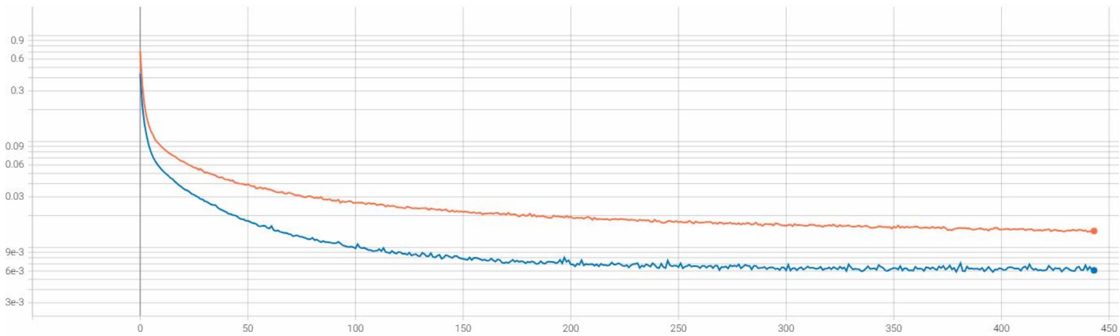

Fig. 4. Loss curves for the training (*train loss*, orange) and validation (*validation loss*, blue) sets.
X-axis — epochs, *Y*-axis — mean squared error (MSE) on a logarithmic scale

For a more in-depth analysis of accuracy, the model's predictions on the test set were evaluated. In addition to the overall R^2 coefficient, a series of additional metrics were calculated for each target indicator, allowing for a detailed assessment of the model's behavior. The summarized results are presented in Table 1.

Analysis of the data presented in Table 1 allows for several important conclusions. Firstly, the model demonstrates high and stable accuracy in predicting the reinforcement areas for beam elements. The Mean Absolute Percentage Error (MAPE) for girders and ribs is in the range of 1-4%, which is an excellent result for practical engineering tasks. The low standard deviation of the error (Std. Dev. MAPE) for these indicators suggests that the predictions are stable across the entire range of input parameters. Secondly, as expected, the most challenging parameters to predict were the systemic, integral characteristics of the structure that are sensitive to the slightest changes in geometry. These include the maximum deflection (d_max, mm) and the column reinforcement area (As_column, mm²), for which the MAPE is ~5.6-5.8%. The high value of the maximum error (Max Error) for column reinforcement, despite a low average error, may indicate the presence of specific “complex” configurations in the design space where the combination of bending moment and significant axial force creates a pronounced nonlinear relationship that is more difficult for the model to approximate. This does not indicate “noise” in the iterative calculation method, as the method itself is deterministic, but rather underscores the complexity of the physics of compressed-bent members, which the model has successfully captured on average, but with occasional larger deviations. Nevertheless, the achieved accuracy is entirely acceptable for use in the early stages of design and in optimization tasks.

Table 1

Detailed accuracy report for each target indicator

Indicator	MAPE(%)	MAE(units)	Max Error(units)	Std.Dev. MAPE(%)
As_column, mm^2	5.84	27.20	405.83	7.19
As_main_beam_pos, mm^2	2.71	10.34	77.31	2.53
As_main_beam_neg, mm^2	3.36	16.44	82.22	2.70
As_sec_beam_pos, mm^2	1.28	1.95	53.60	1.39
As_sec_beam_neg, mm^2	2.70	6.19	52.66	2.58
d_max, mm	5.58	0.16	1.40	7.26

Overall, the obtained results confirm that the developed surrogate model can approximate the results of a complex finite element analysis and subsequent engineering calculations using a nonlinear deformation model with high accuracy and reliability. This creates a solid foundation for its application as a fast and trustworthy predictive tool.

3.2. Solving an Optimization Problem as a Proof of Concept. The practical value of the developed model was demonstrated by solving a typical engineering problem: finding a structural solution with the minimum cost under given external conditions [1, 4]. It is important to emphasize that this problem is considered as a proof of concept, demonstrating the method’s potential for a much broader range of problems.

Problem Statement:

- **Input Conditions and Constraints**: The user interactively sets fixed parameters, for example:
  - Cell dimensions: $L1$ = 10000mm, $L2$ = 10000 mm, H = 4000 mm;
  - Loads: *Line_Pressure_Q* = –10 N/mm, *Force_on_columns_N* = –500000 N;
  - Constraint: The predicted deflection *d_max*must not exceed the normative value of L/250.
- **Parameters to be Optimized**:Cross-sectional dimensions and material classes (*Class_B*, *Class_A*).
- **Objective Function**: Minimization of *Cost_UAH*.

A key advantage of the developed approach is the separation of engineering prediction and economic calculation. The surrogate model is trained exclusively on physical and geometric dependencies, making it independent of market conditions. Economic parameters, such as the cost of materials, can be dynamically set by the user at the optimization stage without the need to retrain the model. For this calculation, the following prices for concrete and reinforcement were adopted: C20/25 – 4300 UAH/m³, C25/30 – 4500 UAH/m³, C30/37 – 4800 UAH/m³; A400C – 42 UAH/kg, A500C – 45 UAH/kg.

To solve the problem, the method of mass generation and verification of candidate solutions was applied, the practical implementation of which was made possible solely due to the high performance of the developed surrogate model. A search space of 10million unique designs was generated, and its complete analysis (performing 10 million predictions) took approximately one minute. For comparison, performing a similar number of calculations using direct FE analysis (with an achieved average speed of ~25 seconds per design on the test system, including process parallelization) would require an estimated 8 years of continuous computational time.

After filtering the obtained results based on the deflection constraint and sorting them by cost, a ranking of the best solutions was formed (Table 2).

Table 2

Top 5 optimal designs by the minimum cost criterion

Model Prediction and Optimized Parameters									Actual Cost, UAH	Cost Error, %
Cost, UAH	Column, mm	Girder H×W, mm	Rib H×W, mm	Deflection, mm	Rebar Mass, kg	Concrete Vol., m³	Concrete Class	Rebar Class		
62926	308×308	511×254	302×206	13.59	444	9.99	C20/25	A500C	63828	1.41
63497	328×328	504×263	305×204	12.98	431	10.26	C20/25	A500C	64222	1.13
63672	369×369	514×256	304×205	11.86	401	10.60	C20/25	A500C	64728	1.63
63738	355×355	507×270	302×202	12.16	405	10.59	C20/25	A500C	64913	1.81
63751	347×347	549×257	300×204	11.87	396	10.69	C20/25	A500C	63493	0.41

An analysis of the results presented in Table 2 shows a clear and engineering-sound trend: to minimize cost, the optimization system consistently favors the cheapest concrete grade (C20/25), compensating for its lower strength with an optimal selection of geometric dimensions and the use of stronger reinforcement (A500C). It is important that all found solutions have a significant stiffness margin (predicted and actual deflections are 12-14 mm against a normative limit of L/250, which is 40 mm for a 10 m span). This indicates that for the given problem and parameter range, the strength condition was the governing factor, not serviceability.

3.3. Verification of the Optimal Solution. To confirm the accuracy of the predictions and the practical reliability of the developed approach, the top 10 optimal designs were recalculated using a full FE analysis in Ansys, followed by post-processing with the corresponding algorithm. A comparison was made between the key indicators predicted by the model and those obtained from the exact calculation.

The verification results demonstrated the high accuracy and reliability of the surrogate model. The error of the objective function (cost) for the top 10 design variants did not exceed 2.04%, and for the best design found, it was only 1.41%. The prediction error for the total mass of reinforcement was also in a low range of 1-7%. At the same time, the errors in determining the reinforcement areas for individual elements were somewhat higher (reaching 10-15% for some positions), which demonstrates the effect of mutual error compensation when calculating integral indicators such as total cost. The zero error for the volume of concrete is explained by the fact that it is calculated procedurally using the same formulas in both cases.

It is worth noting that the optimal cross-sectional dimensions found are continuous values. In real construction practice, a discrete set of standardized sizes is usually used to unify formwork and simplify technological processes. Thus, the optimization performed in a continuous parameter space is, first and foremost, a demonstration of the potential and high resolution of the method. The developed toolkit can be easily adapted to solve the practical problem of discrete optimization by appropriately constraining the search space to standardized parameter values.

The high convergence between the predicted and actual results definitively confirms the high reliability of the developed surrogate model as a tool for making design decisions at early stages.

3.4. Potential Applications and Future Research Directions. The developed and verified high-fidelity surrogate model opens up opportunities for solving a wide range of multi-criteria optimization problems. This work is only the first step, confirming the viability of the approach. In addition to the problem considered, the model can be used to find solutions that satisfy a wide variety of objective functions, for example:

- **Minimization of steel consumption**: Finding a design with the lowest mass of reinforcement.

- **Maximization of stiffness**: Finding a design with minimal deflection for a given budget.
- **Multi-criteria optimization**: Searching for Pareto-optimal solutions that offer the best compromise between cost and mass [12].
- **Optimization for multi-story buildings**: Finding an optimal set of unified cross-sections for structural elements for a group of floors.

The successful solution of these tasks using the developed toolkit will be the subject of further research.

4. Conclusions

In this study, a comprehensive software pipeline for the creation and application of neural network-based surrogate models for the rapid optimization of reinforced concrete structures in cast-in-situ frame buildings was developed and successfully validated. The research confirmed that the proposed approach is an effective alternative to traditional design methods, which rely on the direct use of computationally expensive finite element analysis.

The main results of the study are as follows:

1. **A robust data pipeline was created.** A fully automated system was developed, encompassing all stages: from the generation of a design of experiments (using LHS) and batch analysis in *Ansys* to engineering post-processing according to DSTU standards and the formation of the final dataset.
2. **A high-fidelity surrogate model was trained.** Based on the generated dataset (12000 points), a Multi-Layer Perceptron (MLP) model was trained, which demonstrated high predictive capability, achieving a coefficient of determination $R^2 > 0.994$. The scaling of not only the input but also the output data played a crucial role in achieving such accuracy.
3. **Practical value was demonstrated.** The trained model was successfully applied to solve a realistic optimization problem. The process of analyzing 10 million candidate designs took a matter of minutes, which would be impossible using traditional FE analysis.
4. **Results were verified.** The best designs found by the optimizer were verified through a full analysis in *Ansys*. A comparative analysis showed a high degree of convergence (average error for key indicators < 7%) between the model's predictions and the "real" results, confirming the reliability of the developed tool.

Thus, the study proves that surrogate modeling is a powerful technology capable of transforming design approaches, making the process of finding optimal solutions significantly faster, more flexible, and more cost-effective.

Future Research Directions

The further development of the project could proceed in the following directions:

- **Expansion of the methodology to other types of structures and implementation of a modular approach.** Creating a library of surrogate models for typical structural elements (girders, columns, joints) of building structures, which could then be combined for the rapid analysis of complex, irregular systems.
- **Expansion of the parameter space.** Generating a new dataset for rectangular plan cells and training a more universal model.
- **Development of a classifier model.** Creating a separate model to predict design validity, trained on a balanced dataset containing both valid and invalid examples.
- **Implementation of advanced optimization algorithms.** Using genetic algorithms or other metaheuristic search methods to solve more complex problems, such as multi-story optimization with the constraint of element unification.
- **Integration with BIM and Digital Twins.** Further developing the system towards integration with BIM platforms to create a fully closed "design-analysis-optimization" loop [5] and using the model as a computational core for digital twins of structures [9, 15].

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ЗАСТОСУВАННЯ СУРОГАТНИХ МОДЕЛЕЙ НА ОСНОВІ НЕЙРОННИХ МЕРЕЖДЛЯ ШВИДКОЇ ОПТИМІЗАЦІЇ ЗАЛІЗОБЕТОННИХ КАРКАСНИХ КОНСТРУКЦІЙ

У статті представлено розробку, імплементацію та валідацію комплексного програмного конвеєра для створення та застосування високоточної нейромережевої сурогатної моделі, призначеної для вирішення багатопараметричної задачі оптимізації конструкцій будівель. Оптимізація проєктування залізобетонних каркасно-монолітних конструкцій є фундаментально складною обчислювальною проблемою. Її складність обумовлена високою вартістю скінченно-елементного (МСЕ) аналізу, який є основним інструментом для перевірки відповідності нормативним вимогам, що робить традиційний багатоваріантний пошук оптимальних рішень за допомогою прямого перебору непрактичним в рамках реалістичних термінів проєктування.

Запропонована методологія включала створення детальної параметричної МСЕ-моделі просторової комірки залізобетонного каркаса в середовищі Ansys, автоматизовану генерацію репрезентативного датасету з 12000 унікальних комбінацій проєктних параметрів та їх подальшу інженерну постобробку. Ключовим етапом постобробки, що забезпечив фізичну коректність навчальних даних, стало обчислення необхідної площі армування для кожного елемента. Цей розрахунок було виконано за допомогою спеціально розробленого ітераційного алгоритму, що повністю реалізує нелінійну деформаційну модель згідно з актуальними нормами України ДСТУ Б В.2.6-156:2010.

На основі цього збагаченого датасету було навчено та валідовано модель багатошарового перцептрона (MLP). Результати фінального тестування на відкладеній вибірці продемонстрували, що навчена сурогатна модель досягла високої прогнозної здатності з коефіцієнтом детермінації R^2 = 0,9946. При застосуванні до практичної задачі оптимізації за критерієм мінімальної вартості, модель змогла проаналізувати 10 мільйонів кандидатських дизайнів приблизно за одну хвилину — завдання, що потребувало б орієнтовно 8 років безперервних обчислень при прямому МСЕ-аналізі. Фінальна верифікація знайдених топ-10 оптимальних рішень шляхом їх повного розрахунку в Ansys показала високу збіжність прогнозних та фактичних значень, з похибкою прогнозування цільової функції (вартості), що не перевищувала 2,1%.

Таким чином, у роботі продемонстровано, що запропонований підхід, який поєднує сучасні інженерні розрахункові моделі та методи машинного навчання, дозволяє створювати надійні предиктивні інструменти, які на порядки прискорюють процес пошуку оптимальних конструктивних рішень, відкриваючи нові можливості для ефективного та економічно обґрунтованого проєктування.

Ключові слова: оптимізація конструкцій, метод скінченних елементів, конструкції будівель, залізобетонний каркас, сурогатна модель, нейронна мережа, машинне навчання, ANSYS.

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APPLICATION OF SURROGATE MODELS BASED ON NEURAL NETWORKS FOR FAST OPTIMIZATION OF REINFORCED CONCRETE FRAME STRUCTURES

This paper presents the development, implementation, and validation of a comprehensive software pipeline for creating and applying a high-fidelity neural network-based surrogate model, designed to solve the multi-parameter optimization problem of building structures. The design optimization of cast-in-situ reinforced concrete frames is a fundamentally complex computational challenge. Its difficulty arises from the high cost of Finite Element (FE) analysis, which is the primary tool for verifying compliance with regulatory requirements, rendering traditional multi-variant searches for optimal solutions via direct enumeration impractical within realistic design timelines.

The proposed methodology involved the creation of a detailed parametric FE model of a spatial cell of a reinforced concrete frame in the Ansys environment, the automated generation of a representative dataset with 12000 unique design parameter combinations, and their subsequent engineering post-processing. A key stage of the post-processing, which ensured the physical correctness of the training data, was the calculation of the required reinforcement area for each element. This calculation was performed using a specially developed iterative algorithm that fully implements the nonlinear deformation model in accordance with the current Ukrainian State Standard DSTU B V.2.6-156:2010 (harmonized with Eurocode 2: EN 1992-1-1).

Based on this enriched dataset, a Multi-Layer Perceptron (MLP) model was trained and validated. The results of the final testing on a hold-out set demonstrated that the trained surrogate model achieved high predictive capability with a coefficient of determination $R^2 = 0.9946$. When applied to a practical optimization problem with a minimum cost criterion, the model was able to analyze 10 million candidate designs in approximately one minute – a task that would require an estimated 8 years of continuous computation using direct FE analysis. The final verification of the top 10 optimal solutions, performed by their full analysis in Ansys, showed a high convergence between predicted and actual values, with the prediction error for the objective function (cost) not exceeding 2.1%.

Thus, this work demonstrates that the proposed approach, which combines modern engineering computational models and machine learning methods, enables the creation of reliable predictive tools that accelerate the process of finding optimal structural solutions by orders of magnitude, opening new possibilities for efficient and economically justified design.

Keywords: Structural optimization, finite element method, building structures, reinforced concrete frame, surrogate model, neural network, machine learning, ANSYS.

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Розроблено та валідовано методику швидкої оптимізації залізобетонних каркасних конструкцій на основі високоточної нейромережевої сурогатної моделі.
Таб. 2. Рис. 4. Бібліогр. 18 назв.

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Tabl. 2. Fig. 4. Refs. 18.

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