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Neural Network Modeling of the Strength of Normal Sections of Prefabricated Reinforced Concrete Ribbed Slabs

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Abstract

Introduction. Precast reinforced concrete ribbed slabs are broadly used as floors and coverings for industrial, residential and public buildings. Their use in this capacity is due to the high technological efficiency of manufacturing, efficient use of concrete and the possibility of automating factory production. One of the critical tasks in designing such structures is to calculate the bearing capacity of normal cross sections. Traditional calculation methods are reliable, but they are outdated. Machine learning methods are increasingly being employed in engineering, where researchers are opting for artificial neural networks (ANNs). The use of traditional methods in processing structured data such as tables and databases has its limitations. Neural networks are capable of analyzing unstructured data such as text, images, and videos, which opens up new prospects for analyzing and comprehending information. The article sets forth an approach to neural network modeling of the bearing capacity of normal sections of prefabricated reinforced concrete ribbed slabs.

Materials and Methods. A structured and processed data array (dataset) includes 20 samples for which a computational model based on a multilayer perceptron has been developed and verified. The input parameters are the geometric as well as physical and mechanical characteristics of the slabs and the applied load, the output parameter is the limiting bending moment calculated using the limit state method.

Research Results. Training on a limited sample did not lead to retraining of the model due to the correct division of data into test, training and control batches and the use of the quasi-Newton optimization method. The model has displayed a high level accuracy and reliability. Artificial neural networks are capable of identifying nonlinear dependencies between the parameters with no a priori assumptions.

Discussion and Conclusion. The suggested model is not a substitute for the existing calculations, but it serves as an efficient digital tool for quick verification of design solutions, optimization of reinforcement and improvement of structural reliability. Its implementation into BIM systems and digital construction platforms is in compliance with the requirements of Industry 4.0 and creates new opportunities for designing prefabricated reinforced concrete structures.

Keywords: ribbed reinforced concrete floor slab, bendable elements, artificial neural networks, machine learning

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Нейросетевое моделирование прочности нормальных сечений сборных железобетонных ребристых плит

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Аннотация

Введение. Сборные железобетонные ребристые плиты получили широкое применение в качестве перекрытий и покрытий зданий промышленного, жилого и общественного назначения. Их использование в данном качестве обусловлено высокой технологичностью изготовления, эффективным использованием бетона и возможностью автоматизации производства на заводах. Одной из важных задач при проектировании таких конструкций является расчет несущей способности нормальных сечений. Традиционные методы расчёта являются надежными, но морально устарели. Сейчас в инженерной практике всё чаще применяются методы машинного обучения, где исследователи делают выбор в пользу искусственных нейронных сетей (ИНС). Использование традиционных методов при обработке структурированных данных, таких как таблицы и базы данных, имеет свои ограничения. Нейросети способны анализировать неструктурированные данные, такие как текст, изображения и видео, что открывает новые возможности для анализа и понимания информации. В статье предложен подход к нейросетевому моделированию несущей способности нормальных сечений сборных железобетонных ребристых плит.

Материалы и методы. Структурированный и обработанный массив данных (датасет) включает 20 образцов, для которых разработана и верифицирована расчётная модель на основе многослойного персептрона. Входными параметрами служат геометрические и физико-механические характеристики плит и величины приложенных нагрузок, выходной параметр — предельный изгибающий момент, вычисленный по методу предельных состояний.

Результаты исследования. Обучение на ограниченной выборке не привело к переобучению модели благодаря корректному разделению данных на тестовую, обучающую и контрольную партии и использованию квазиньютоновского метода оптимизации. Модель продемонстрировала высокую точность и надёжность. Искусственные нейронные сети успешно выявляют нелинейные зависимости между параметрами без априорных допущений.

Обсуждение и заключение. Предложенная модель не заменяет существующие расчёты, но служит эффективным цифровым инструментом для быстрой проверки проектных решений, оптимизации армирования и повышения надёжности конструкций. Её внедрение в системы BIM и цифровые платформы строительства соответствует требованиям Индустрии 4.0 и создает новые возможности для проектирования сборных железобетонных конструкций.

Ключевые слова: ребристая железобетонная плита перекрытия, изгибаемые элементы, искусственные нейронные сети, машинное обучение

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Introduction. In modern industrial and civil engineering, prefabricated reinforced concrete ribbed slabs are still one of the most sought-after solutions for building floors and coverings due to a combination of cost-effectiveness, reliability and adaptability they offer. Their use is justified by a high degree of factory readiness, ease of mass serial production, and the optimal cross-sectional shape that minimizes concrete consumption while providing the necessary bearing capacity and deformability.

The calculation of the strength of normal sections of ribbed slabs is an essential part of the calculations for the 1st group of limit states. Traditional calculation methods provided in SP (СП) 63.13330.2018 "Concrete and Reinforced Concrete Structures. Main Provisions" are reliable and reputable, but over the past two decades, machine learning methods have been increasingly used in engineering. Researchers most often opt for artificial neural networks (ANNs). The advantage of ANNs is their capacity to identify hidden non-linear relationships between a set of input parameters and a target variable. Unlike analytical models, ANNs do not call for a priori specification of functional dependencies making them of a particular value, especially for identifying the bearing capacity of building structures. The issues of

information modeling in calculating building structures and using artificial intelligence in this field have been elaborated in Russian [1–8] and overseas [9–16] technical literature.

The aim of the study is to develop and verify a neural network model for predicting the bearing capacity of normal sections of prefabricated reinforced concrete ribbed slabs.

Materials and Methods. The objects of the study were 20 ribbed slabs with a cross-section width from 1460 to 1150 mm, a working height from 370 to 240 mm and a span from 4550 to 8100 mm. For more information about the dataset, see Table 1.

Table 1

Characteristics of ribbed reinforced concrete slabs

No.	b_f' , mm	h_0 , mm	b , mm	l_0 , mm	q , kN/m	R_b , MPa	R_s , MPa	A_{sp} , cm ²	M_{ult} , kNm
1	1460	370	150	6250	16.95	17	695	4.40	124.15
2	1160	370	185	7080	19.60	17	870	6.08	147.39
3	1160	344	185	7900	11.93	22	1215	2.49	111.70
4	1150	270	150	5675	18.15	17	520	5.88	87.70
5	1360	344	185	8100	18.66	22	1300	4.51	214.25
6	1360	344	185	8100	17.40	17	1300	2.27	94.54
7	1450	240	150	5400	16.90	17	1250	2.88	92.40
8	1450	270	150	7050	16.89	17	1390	3.23	157.42
9	1450	270	150	4700	11.31	17	1390	1.15	46.84
10	1360	260	185	4690	17.54	22	1130	2.12	67.52
11	1460	370	150	6200	17.05	17	690	4.50	128.20
12	1160	370	185	7050	19.30	17	880	5.98	145.10
13	1160	344	185	7850	11.53	22	1190	2.53	115.10
14	1150	270	150	5700	18.25	17	530	6.05	90.30
15	1360	344	185	8000	18.82	22	1300	4.61	220.10
16	1360	350	185	8050	17.00	17	1250	2.05	93.38
17	1450	240	150	5350	16.50	17	1250	2.72	90.50
18	1450	270	150	7000	16.68	17	1390	3.18	156.10
19	1450	270	150	4750	11.33	17	1390	1.19	49.92
20	1360	260	185	4550	17.24	22	1130	1.95	65.23

The following parameters are provided for each plate: the reduced shelf width b_f' (x_1), working height h_0 (x_2), reduced rib width b (x_3), estimated span l_0 (x_4), applied evenly distributed load q (x_5), prismatic concrete strength R_b (x_6), yield strength of steel reinforcement R_s (x_7), cross-sectional area of the prestressed reinforcement A_{sp} (x_8) and the limit bending moment M_{ult} (y). The latter will be the result of the prediction of the neural network model in the future. The limit bending moments are calculated using the limiting state method.

In order to design the neural network model, the STATISTICA 14.0 software package was used with the Neural Networks module providing the implementation of the architecture as a multi-layer perceptron with reverse error propagation. Designing the neural network as a multi-layer perceptron is due to the special features of the task at hand. The artificial neural network includes three layers. The input layer consisted of the above 8 independent variables. The number of neurons in the hidden layer ranged from 1 to 20. After passing through the hidden layer, the signal, trans-

formed at each stage with the corresponding activation functions, entered the output layer containing a single dependent variable, M_{ult} (y). Each of the neurons of the hidden and output layers is connected to all of the neurons in the previous layer.

The dataset size allowed us to obtain the optimal ratio of the training, test, and control samples in percentage rates of 70, 15, and 15, respectively. The number of epochs (training cycles) is 1000 (Fig. 1). All the activation functions were tested at each stage to process the incoming signals (Fig. 2).

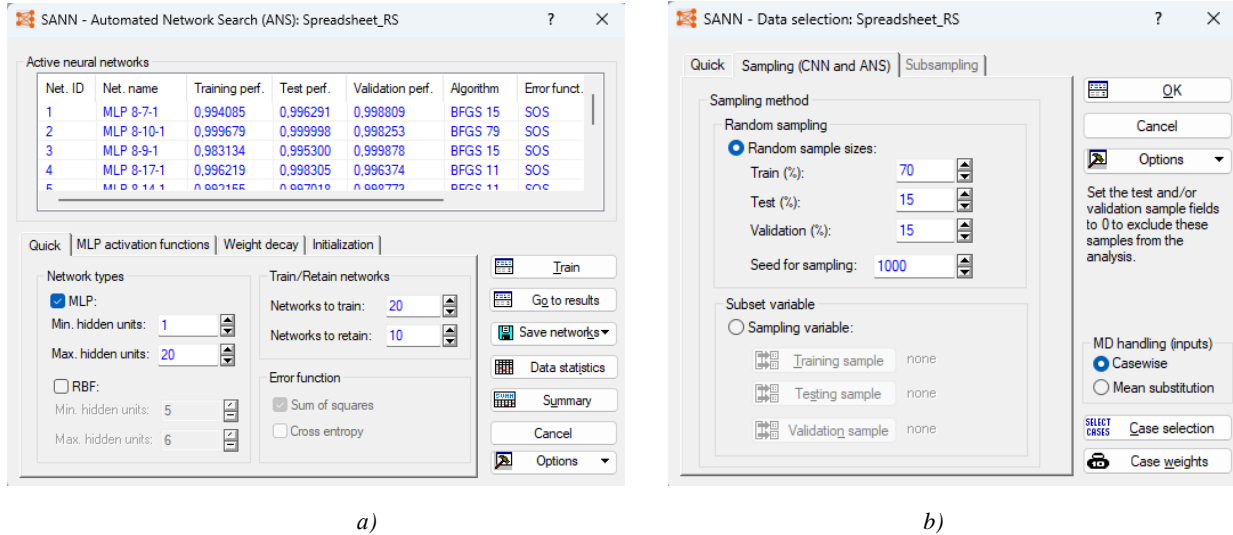


Fig. 1. Characteristics of the neural network model: a — for a random selection; b — for the hidden layer and the ANN training

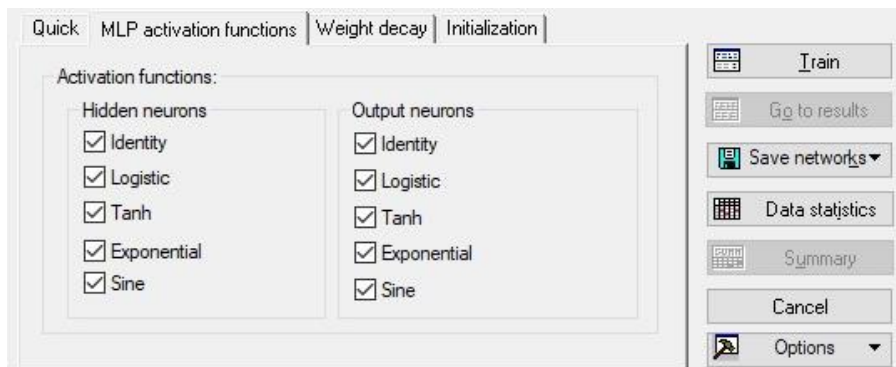


Fig. 2. Selected activation functions of the hidden and output layer of the neurons

The Broyden-Fletcher-Goldfarb-Shanno algorithm (BFGS) is one of the most efficient quasi-Newton optimization methods for training artificial neural networks. The loss function with weights is iteratively minimized. As part of the ongoing study, this algorithm was used in order to adaptively update network parameters based on the approximation of the inverse Hesse matrix allowing us to account for the second derivatives of the error function without explicitly calculating them. The Sum of squares (SOS) given by formula (1) was used as the objective function:

$$E(w_{ij}) = \sum_{i=1}^m (y_i - y'_i)^2, \tag{1}$$

where y_i is the output value of the i -th neuron of the output layer; y'_i is the required value of the i -th neuron of the output layer.

The training was carried out iteratively, i.e., at each stage (epoch), all the observations were the sequential input, and the resulting values were compared with the target ones and the corresponding error was calculated. In the STATISTICA software package, the calculation results are presented in a table. The accuracy of the neural network forecasting results was estimated by comparing the results of the designed model with the experimental values and was calculated using the formula (2):

$$\delta = \frac{y_{\text{инс}} - y_i}{y_i} \cdot 100\%, \tag{2}$$

where $y_{i\text{ANN}}$ is the value of the destructive bending moment obtained during prediction using ANN in the first test; y_i is the actual value of the breaking bending moment in the i th test.

10 MLP architectures with the number of hidden layers from 2 to 19 were tested (Fig. 3 and 4). The best results were shown by a neural network with the MLP 8-9-1 architecture highlighted in a green frame.

Net. name	Training perf.	Test perf.	Validation perf.	Training error	Test error	Validation error	Training algorithm	Error function	Hidden activation	Output activation
MLP 8-7-1	0.994085	0.996291	0.998809	10.62153	16.48046	9.93623	BFGS 15	SOS	Logistic	Identity
MLP 8-10-1	0.999679	0.999998	0.998253	0.69092	0.07326	15.30478	BFGS 79	SOS	Tanh	Tanh
MLP 8-9-1	0.983134	0.995300	0.999878	31.72447	12.67781	58.40971	BFGS 15	SOS	Identity	Tanh
MLP 8-17-1	0.996219	0.998305	0.996374	6.83131	18.37588	20.66575	BFGS 11	SOS	Tanh	Identity
MLP 8-14-1	0.992155	0.997018	0.998773	13.76911	21.46851	20.28928	BFGS 11	SOS	Identity	Identity
MLP 8-13-1	0.984357	0.998660	0.999682	28.98711	6.83088	53.70908	BFGS 21	SOS	Tanh	Tanh
MLP 8-11-1	0.992339	0.997115	0.999887	13.50086	16.44569	11.82677	BFGS 11	SOS	Tanh	Identity
MLP 8-19-1	0.995462	0.996490	0.998304	8.10334	15.24956	9.80945	BFGS 11	SOS	Logistic	Identity
MLP 8-9-1	0.998522	0.997551	0.998666	2.71952	7.02600	9.66670	BFGS 34	SOS	Tanh	Exponential
MLP 8-2-1	0.999066	0.998745	0.998871	1.76863	4.50505	4.40192	BFGS 58	SOS	Logistic	Exponential

Fig. 3. Characteristics of the resulting ANNs

Net. name	Training perf.	Test perf.	Validation perf.	Training error	Test error	Validation error	Training algorithm	Error function	Hidden activation	Output activation
MLP 8-9-1	0.983134	0.995300	0.999878	31.72447	12.67781	58.40971	BFGS 15	SOS	Identity	Tanh

Fig. 4. Characteristics of the best ANN

The values of the limiting bending moment according to the calculation and forecast of the selected ANN are shown in Table 2. It can also be seen whether each case belongs to the training or test series.

Table 2

Prediction results for the selected ANN

Case name	M_{ult} Target	Mult - Output 3. MLP 8-9-1
1	124,1500	127,8000
2	147,3900	149,7304
3	111,7000	118,3796
4	87,7000	81,9504
6	94,5400	100,3477
7	92,4000	101,5405
9	46,8400	41,1607
10	67,5200	71,4283
12	145,1000	147,2489
13	115,1000	114,5124
14	90,3000	90,6634
15	220,1000	196,9605
16	93,3800	84,6343
20	65,2300	62,0702

The average relative error of MLP 8-10-1 calculated using formula (2) is 5.6%. According to the graph (Fig. 6), the obtained model is highly accurate and is good at the task at hand. It is plain to see that there is only one case that is slightly removed from the diagonal, which is the ideal location of the prediction points. The other values predicted using the model only slightly deviate from the diagonal.

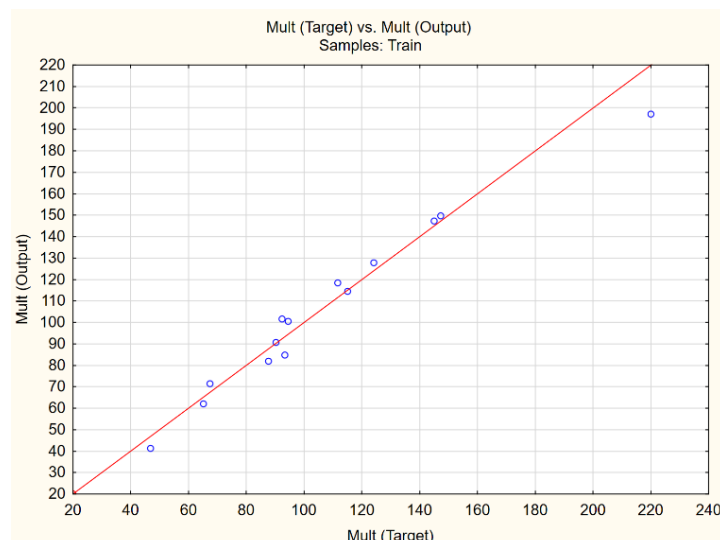


Fig. 6. The actual and prediction values M_{ult} ratio

The selected ANN has been "trained" to account for the existing implicit dependencies between all the parameters. It does not just "memorize" the data, but discovers physically justified patterns. The neural network model does not make use of any assumptions (regarding the shape of the stress plot, etc.), it is only trained on actual data. At the same time, as the size of the dataset increases, a significant rise in the accuracy of the suggested model is to be expected.

It is to be noted separately that it is not only the accuracy of the model that is an advantage, but also the calculation time using all the known methods, including numerical modeling, is inferior to neural networks. This is yet another argument in favor of further implementing ANNs in the design.

Research Results. The results serve to prove that artificial neural networks are a new viable approach to identifying the bearing capacity of bent elements and are an efficient method of the problem solution. The average ratios of actual and calculated destructive bending moments and their variation coefficients turned out to be 0.993 and 0.069, respectively. In spite of its high accuracy, to date ANN has not been able to substitute the other methods of calculating structures, but can be recommended as an additional digital tool for testing design solutions, optimizing reinforced concrete elements and improving structural reliability.

Discussion and Conclusion. The developed model can be integrated into BIM systems, which corresponds to the strategy of Industry 4.0. The successful application of ANNs in construction is a natural stage in the engineering science evolution. A further step might be developing an open API for accessing the model within a digital platform.

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Claimed Contributorship:

VI Rimshin: scientific supervision, research concept, development of the methodology, final conclusions.

SV Usanov: writing the original manuscript, designing and analyzing the models, editing the manuscript.

AN Vydrin: preparation of the manuscript, collection and processing of the data.

AE Kern: collection and processing of the data.

ES Makarova: collection and processing of the data.

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