Efficient Structural Design with ANNs

Subjects: Computer Science, Artificial Intelligence | Construction & Building Technology
Contributor: Paloma Pineda, Jorge Navarro Rubio

Artificial Neural Networks (ANNs) are showing their potential as structural design tools. ANNs are applied to design a dry precast concrete connection. They can be easily and effectively adapted to different connection parameters, being possible to use them in both precast or cast in situ concrete connection design.

Keywords: efficient structural design ; artificial neural networks ; dry precast concrete connection ; artificial intelligence ; sustainable built environment

1. Introduction

In different engineering fields, the use of Artificial Neural Networks (ANNs) is gaining a noticeable position in the material design and selection stages. These computational models are powerful tools that allow for not only reducing computing times, but also designing adequate shapes and reducing the amount of raw materials used. As a consequence, ANNs have the potential to significantly reduce both economic cost and environmental impact.

Artificial Neural Networks (ANNs) are biologically inspired computational models that are based on the interconnection mechanisms of the human brain’s neurons. These mathematical models are able to solve complex multivariable linear or nonlinear problems and to obtain relationships between different patterns. ANNs have been traditionally applied to different fields, such as financial analysis, image processing (e.g., target recognition and image completion), medical test diagnosis, robot control, and speech recognition. In addition to performing complex computations, they allow for recognizing patterns that can be applied in the learning computation process. ANNs are especially appropriate if the problem has a difficult or non-defined solving procedure [1].

The main advantage of using neural networks is their ability to learn from experience, generalizing from previous situations to new cases and differentiating essential information from that which is irrelevant. ANNs are able to represent and learn both linear and non-linear relationships directly from the data [2].

Since 1986, the use of ANNs was spread due to the feasibility of developing an error back-propagation training algorithm, which was based on a gradient-descent optimization technique [3]. In addition, ANNs have gained a relevant position in solving industrial design problems. It is worth mentioning that the identification of the optimum design within an industrial process is not always possible due the size of the problem and lack of knowledge, as the design stage is essential [2]. However, ANNs are able to perform constraint checks, requiring less computing time to provide adequate results.

Focusing on civil engineering, it is worth mentioning that although ANNs were developed in the seventies [4], their applications in civil and structural engineering date from 1989 [5]. In 2001, Hojjat published a review on Neural Networks in Civil Engineering [5], where the use of ANN from 1989 to 2001 in civil, structural, and building engineering fields was analyzed. Gupta et al [6] analyzed the feasibility of using ANNs in structural analysis and building design from 1990 to 2011. Amezquita-Sanchez et al. [7] published a review paper analyzing the ANNs’ applications in civil infrastructures. That research focused on structural system identification, structural health monitoring, structural vibration control, structural design and optimization, prediction applications, construction engineering, and geotechnical engineering.

In civil engineering, ANNs have been successfully used in automation and optimization [2][5][8], in material formulation [9], and in system identification and monitoring [10][11]. In structural analysis and design, the following applications could be highlighted [2][6][12]: structural analysis of systems with large degrees of freedom, size optimization of structural members, joint location, shape optimization of structural types (e.g., truss geometry), topology optimization (based on deletion of ineffective structural members), and maximum stress identification and location. Focusing on the application to specific structural problems, Intelligent Finite Element Analysis (IFEA), which combines the Finite Element Method (FEM) together with an ANN, has been used for simulating or predicting constitutive models [13][14][15]. Waszczyszyn and Ziemianski [16] applied a hybrid ANN to analyze elastoplastic beams together with the Finite Difference and Finite Element methods. Neural Networks have been also applied in structural analysis pattern recognition [17][18]. Regarding prediction applications of ANNs, Lee [19] and De-Cheng et al. [20] analyzed their use for predicting the concrete strength; Yan Cao et al. (2020) analyzed their application in the behavior of beam-to-column connections; Van Dao et al. [21] applied these computational models in the compressive strength prediction of concrete mixed with geopolymer; and Abambres et al. [22] predicted the fatigue strength of concrete. Stoffel et al. [23] proposed an ANN to predict deformations in non-linear metal plates, while Kamgar et al. [24] designed a feed-forward back-propagation neural network (FFBPNN) to be used to propose a new formulation for predicting the compressive strength of fiber-reinforced polymer (FRP)-confined concrete cylinders, and Komleh and Maghsoudi [25] applied an Adaptative Neuro-Fuzzy Inference System (ANFIS) and multiple regression analysis in the prediction of the curvature ductility factor of FRP-strengthened reinforced high-strength concrete beams. Focusing on the use of metaheuristic optimization algorithms to optimize structures, the works by Kaleh et al. [26] and by Kaleh and Dadras [27] are remarkable. Focusing on economic issues, Kamgar et al. [8] proposed a fuzzy inference system to evaluate the building design codes from an economic point of view.

It is worth noting that the use of ANNs in precast concrete elements or connections is an open research field. In fact, neither the prediction of complex nonlinear structural stresses and deformations nor their use in the design stage has been widely analyzed.

2. Apply ANNs in Material Design Stages

The use of ANNs for the efficient design of structural elements is an open research field where successful developments have recently been achieved.

ANNs can be developed to be applied in material design stages and to predict the stress field in structural elements, particularly in the design of dry precast concrete connections.

As ANN input, data from FEM analyses were used in the learning process (i.e., material parameters, nodal stresses, and deformations). The ANNs were designed by means of different parameter combinations in order to enable an efficient learning process. Once the learning process was finished, 10 parameter combinations were used to validate the ANN.

Four ANNs were designed. A multilayer perceptron and a backpropagation algorithm are implemented. Six inputs were applied in the input layer. Two hidden layers with a variable number of neurons, up to 25, were necessary to reach convergence; only one value was obtained in the output layer—the predicted stress.

When the FEM analysis results were compared to those provided by the ANNs, a maximum error of 9.16% was obtained for the stresses, when concrete strength was close to the limit value. The average error value was less than 8.38% in the worst validation scenario. When the concrete stress was less than 20 MPa, the maximum difference remained under 5%. Due to the application of the Codes’ safety factors, such a difference is safe enough to design and calculate structural connections.

The designed networks can solve complex numerical analyses, allowing for prediction of reliable results to be used as decision tools in the early design stages of structural elements. It is also corroborated that the proposed networks reduce the computing time when compared to common numerical methods (e.g., FEM analyses).

The proposed procedure is flexible and adaptable enough to be applied to different materials and configurations, including new parameters, dimensions, shapes, and connections, by using ANNs for predicting stresses of elements. This procedure is reliable enough to be used for optimal configuration of elements in the early design stage of structures.

3. Future Prospects

In future research, the proposed ANN could be combined with optimization algorithms (e.g., metaheuristic) to foster the design of optimal, economical, and sustainable structural precast connections. In addition, the application of the proposed ANN to the design and optimization of different precast elements could be applied and investigated. An especially interesting field could be the application in precast concrete structure connections for industrial buildings, as well as in bus or car canopy connections between beams and column.

References

1. Günaydın, H.M.; Doğan, S.Z. A neural network approach for early cost estimation of structural systems of buildings. Int. J. Proj. Manag. 2004, 22, 595–602.
2. Meon, M.S.; Anuar, M.A.; Ramli, M.H.M.; Kuntjoro, W.; Muhammad, Z. Frame Optimization using Neural Network. Int. J. Adv. Sci. Eng. Inf. Technol. 2012, 2, 28–33.

3. Rumelhart, D.; Hinton, G.; Williams, R. Learning Internal Representation by Error Propagation, Parallel Distributed Processing; MIT Press: Cambridge, UK, 1986.
4. Chandan, M.; Prasad, B.R.; Amarnath, K. Design of reinforced concrete structures using neural networks. J. Struct. Eng. 2001, 127, 818–828.
5. Adeli, H. Neural Networks in Civil Engineering: 1989–2000. Comput. Civ. Infrastruct. Eng. 2001, 16, 126–142.
6. Gupta, T.; Sharma, R. Structural Analysis and Design of Buildings using neural network: A Review. Int. J. Eng. Manag. Sci. 2011, 2, 216–220.
7. Sanchez, J.A.; Rodriguez, M.V.; Aldwaik, M.; Adeli, H. Neurocomputing in civil infraestructure. Scientia Iranica 2016, 23, 2417–2428.
8. Kamgar, R.; Hatefi, S.M.; Majidi, N. A Fuzzy Inference System in Constructional Engineering Projects to Evaluate the Design Codes for RC Buildings. Civ. Eng. J. 2018, 4, 2155.
9. Ziółkowski, P.; Niedostatkiewicz, M. Machine Learning Techniques in Concrete Mix Design. Materials 2019, 12, 1256.
10. Krishna, B.M.; Reddy, V.G.P.; Shafee, M.; Tadepalli, T. Condition assessment of RC beams using artificial neural networks. Structures 2020, 23, 1–12.
11. De Lautour, O.R.; Omenzetter, P. Prediction of seismic-induced structural damage using artificial neural networks. Eng. Struct. 2009, 31, 600–606.
12. Cao, Y.; Wakil, K.; Alyousef, R.; Jermsittiparsert, K.; Ho, L.S.; Alabduljabbar, H.; Alaskar, A.; Alrshoudi, F.; Mohamed, A.M. Application of extreme learning machine in behavior of beam to column connections. Structures 2020, 25, 861–867.
13. Javadi, A.A.; Mehravar, M.; Faramarzi, A.; Ahangar-Asr, A. An Artificial Intelligence Based Finite Element Method. Comput. Intell. Syst. 2009, 1–7.
14. Ashour, A.F.; Alqedra, M. Concrete breakout strength of single anchors in tension using neural networks. Adv. Eng. Softw. 2005, 36, 87–97.
15. Júnior, S.A.A. Modeling of Concrete Anchors Supporting Non-Structural Components Subjected to Strong Wind and Adverse Environmental Conditions. Ph.D. Thesis, University of Toledo, Toledo, OH, USA, 2019.
16. Waszczyszyn, Z.; Ziemianski, L. Neural networks in mechanics of structures and materials—New resilts and prospects of applications. Comput. Struct. 2001, 79, 2261–2276.
17. Yan, F.; Lin, Z.; Wang, X.; Azarmi, F.; Sobolev, K. Evaluation and prediction of bond strength of GFRP-bar reinforced concrete using artificial neural network optimized with genetic algorithm. Compos. Struct. 2017, 161, 441–452.
18. Kim, T.; Kwon, O.-S.; Song, J. Response prediction of nonlinear hysteretic systems by deep neural networks. Neural Netw. 2019, 111, 1–10.
19. Lee, S.-C. Prediction of concrete strength using artificial neural networks. Eng. Struct. 2003, 25, 849–857.
20. Feng, D.-C.; Liu, Z.-T.; Wang, X.-D.; Chen, Y.; Chang, J.-Q.; Wei, D.-F.; Jiang, Z.-M. Machine learning-based compressive strength prediction for concrete: An adaptive boosting approach. Constr. Build. Mater. 2020, 230, 117000.
21. Van Dao, D.; Ly, H.-B.; Trinh, S.H.; Le, T.-T.; Pham, B.T. Artificial Intelligence Approaches for Prediction of Compressive Strength of Geopolymer Concrete. Materials 2019, 12, 983.
22. Abambres, M.; Lantsoght, E.O. ANN-Based Fatigue Strength of Concrete under Compression. Materials 2019, 12, 3787.
23. Stoffel, M.; Bamer, F.; Markert, B. Artificial neural networks and intelligent finite elements in non-linear structural mechanics. Thin-Walled Struct. 2018, 131, 102–106.
24. Kamgar, R.; Naderpour, H.; Komeleh, H.E.; Jakubczyk-Gałczyńska, A.; Jankowski, R. A Proposed Soft Computing Model for Ultimate Strength Estimation of FRP-Confined Concrete Cylinders. Appl. Sci. 2020, 10, 1769.
25. Ebrahimpour-Komleh, H.; Maghsoudi, A. Prediction of curvature ductility factor for FRP strengthened RHSC beams using ANFIS and regression models. Comput. Concr. 2015, 16, 399–414.
26. Kaveh, A.; Khanzadi, M.; Moghaddam, M.R. Billiards-inspired optimization algorithm; a new meta-heuristic method. Structures 2020, 27, 1722–1739.
27. Kaleh, A.; Eslamlou, A.D. Metaheuristic Optimization Algorithms in Civil Engineering: New Applications; Springer: Warsaw, Poland, 2020.