International Journal of Researches on Civil Engineering with Artificial Intelligence

www.ceai.reapress.com

Int. J. Res. Civ. Eng. AI. Vol. 2, No. 2 (2025) 139–145.

Paper Type: Original Article

Revisiting Classical Neural Architectures for Surrogate-Assisted Optimization of Space Trusses: Balancing Prediction Accuracy and Computational Efficiency

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Citation:

Received: 11 March 2025 *Revised: 22 May 2025* *Accepted: 06 July 2025*	Gholizadeh Arat Bani, M. (2025). Revisiting classical neural architectures for surrogate-assisted optimization of space trusses: Balancing prediction accuracy and computational efficiency. *International journal of researches on civil engineering with artificial intelligence, 2*(3), 139-145.

Abstract

The optimization of trusses usually demands a number of structural analyses which leads to substantial computation cost and execution time, especially in case of large problems. Artificial Neural Networks (ANNs) have been proved as the effective surrogates for approximation of structural responses with acceptable accuracy and relatively low computational efforts. In this study, the efficacy of two different types of neural networks, Backpropagation Neural Network (BPNN) and Counterpropagation Neural Network (CPN), for the optimization of weights of truss structures is examined. The 52 membered space truss is used as the test problem where cross sections are used as the input data and the stresses of members as the outputs in order to train the neural networks. The performances of the models in respect of their accuracy and computational costs are investigated. It is found that whereas the backpropagation model performs better in respect of accuracy, the counterpropagation model performs much better in terms of the speed of the learning and computational costs. It is demonstrated that the proposed method is able to provide the capability of the surrogate modeling approach based on neural network models in accelerating the structural optimization process and minimizing the burden of the repetitive finite element.

Keywords: Structural optimization, Truss structures, Artificial neural networks, Backpropagation neural network, Counterpropagation neural network, Surrogate modeling.

1 | Introduction

There is much interest in trusses due to the fact that there is a need for structures which are light weight and economical. The truss structure is popularly used in bridges, towers, roofs and even in aerospace. This is so because of their strength to weight ratio. It is not easy to optimize the design since it involves repeated analysis

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https://doi.org/10.48314/ijrceai.v2i3.51
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of structural responses under different loads, especially where Finite Element Analysis (FEA) is used within the iterative algorithm [1], [2].

Classical optimization techniques based on gradients, mathematical programming, and metaheuristic techniques have shown to be quite effective in solving problems related to minimizing weight subject to stress and displacement constraints [3]. However, the number of structural analyses performed by such classical optimization techniques is in the thousands, resulting in very high computational effort, particularly in large and geometrically nonlinear trusses [4]. This task becomes harder if optimization techniques are combined with reliability analysis or uncertainty quantification techniques [5].

Over the past few years, AI and Machine Learning (ML) algorithms have been developed as useful methods to solve complex computational problems in structural engineering. Among the various Artificial Intelligence (AI) and ML algorithms, the Artificial Neural Network (ANN) technique has demonstrated impressive performance in nonlinear function approximation and pattern recognition tasks, thus making ANNs one of the potential choices for replacing numerical analysis with a cheaper approach [6], [7]. The reason for choosing ANNs is due to their ability to predict stress, displacement, and optimal design variables efficiently [8].

Backpropagation Neural Networks (BPNN), which use gradient descent algorithms, are one of the most commonly used neural network architectures in engineering applications due to their universal approximating power and flexibility [9]. On the other hand, Counterpropagation Neural Networks (CPN), which consist of Kohonen competitive layer and Grossberg output layer, are faster and computationally less complex than BPNNs [10]. Previous research studies have shown that both neural network architectures can be used in structural analysis and optimization problems, but they have some differences in terms of efficiency and accuracy [11].

The fast progress in deep learning and surrogates has further stimulated the use of neural networks in structural optimization. It is possible to apply ML-based surrogate models effectively in combination with differential evolution algorithms for geometrically nonlinear trusses, which leads to a noticeable decrease in computational time without any loss of accuracy [12]. There are recent works on using deep neural networks, GNNs, PINNs, and FNNs to solve topology optimization, size optimization, and non-linear structure analysis tasks [13–17]. Besides, there are some review papers dedicated to the increasing role of AI in spatial structures and intelligent structural design [18], [19].

Nevertheless, despite all these achievements, almost all modern research is concentrated around deep learning structures and graph-based approaches. However, there are few investigations dealing with the classic approaches to neural networks like backpropagation and CPN, while those are very cheap in computation, straightforward and applicable to engineering practice. What is more, earlier comparative investigations with BPNN and CPN were conducted more than two decades ago with restricted computational capacities and small sets of data [10], [11]. That is why there is no comprehensive investigation of the ability of these classical neural architectures to compete in current optimization tasks.

Hence, the main objective of the current research is to explore the performance of BPNNs and CPN in the optimization process of trusses. A 52 members space truss is considered as the test problem, and both neural networks are trained using structural responses achieved through FEA. Accuracy and efficiency of the two neural network methods are analyzed and compared in terms of their performances. The findings of this study would shed light on the application of classical neural networks in structural optimization.

1.1 | Research Gap

Despite an abundance of recent research on deep learning, graph neural networks, and physics-informed neural networks in the context of structure optimization, little consideration has been paid to the performance of classical neural network structures like BPNN and CPN. The few comparisons that exist are outdated and fail to consider any new progress in terms of computational power and ML approaches. Moreover, the balance between the accuracy and efficiency of predictions made by these classical models has yet to be comprehensively studied in the context of truss optimization. Thus, this study attempts to fill in this gap.

2 | Literature Review

ANNs have been applied in structural engineering from its very first inception due to their capability of modeling non-linear relations and effective pattern recognition [6], [9]. The applicability of ANN in engineering optimization and their superior performance as compared to traditional numerical schemes was first established by Adeli [7].

The comparative study carried out by Kaveh and Iranmanesh [10] revealed the superiority of CPN in learning speed and that of BPNN in accuracy in structural optimization problems. The use of ANN in the optimization of large truss structures is illustrated by Papadrakakis et al. [20].

In this context, Mai et al. [12] presented an approach of ML based surrogate model combined with differential evolution for optimization of geometrically nonlinear truss system. Their findings confirmed that neural networks are good enough for replacing expensive FEA. In the recent times, deep neural networks are being used within the context of population based optimization methods to enhance design diversity and performance [13].

The concept of graph neural networks has enabled the possibilities for structural connectivity and topology. Recent research works have illustrated the exceptional capability of GNNs for topology and size optimization of trusses [15], [16]. Another notable development in the context of data driven methods for structural optimization is the physics informed neural network that uses physical equations within the learning process itself [17].

However, in spite of all these improvements, the majority of researches focus on complex architecture that needs huge computing power. The comparative analysis between classical BPNN and CPN architectures is rare, which means that there is a need for further research in this area.

3 | Artificial Neural Networks

ANNs are computing devices modeled on the basis of biological neural systems that are able to learn and understand the nonlinear relationship between the input and output data. Due to their excellent approximation power, high stability, and flexibility, ANNs have been widely applied to various engineering tasks such as prediction, classification, optimization, and surrogate modeling. Nowadays, in structural engineering, neural networks are widely used for substituting time-consuming FEA and optimization algorithms.

The most basic strength of the neural network is that they learn through examples and then generalize the learned knowledge to the unseen patterns. Once properly trained, the neural network can predict the response of the structure using much less computational work compared to conventional numerical approaches. In addition, due to their fault tolerance and parallel computing nature, they can be employed to solve the engineering problems on a large scale.

In the current research, two traditional neural network models including BPNN and CPN will be studied for application in truss optimization.

3.1 | Backpropagation Neural Network

The BPNN consists of multiple feed-forward layers that employ supervised learning for training. The network continuously fine tunes its weights by reducing the error of prediction through gradient descent.

The objective function can be represented by:

$$E = \frac{1}{2}\sum_{k=1}^{N}(t_k - y_k)^2, \quad (1)$$

where:

I. t_k denotes the target output.

II. y_k presents the network prediction.

III. k is the number of output neurons.

The weight updating rule is expressed as

$$w_{ij}^{n+1} = w_{ij}^{n} - \eta\frac{(\partial E)}{(\partial w_{ij})}, \quad (2)$$

where:

I. W_{ij} is the connection weight.

II. η denotes the learning rate.

The training procedure of the BPNN consists of the following stages:

I. Initialization of network weights.

II. Forward propagation of input patterns.

III. Computation of prediction errors.

IV. Backward propagation of errors.

V. Updating of weights until convergence criteria are satisfied.

To improve convergence and prevent numerical instability, input variables are normalized within the interval:

$$x_i' = \frac{(x_i - x_{min})}{(x_{max} - x_{min})}. \quad (3)$$

The normalized values are generally scaled into the range [0,1].

3.2 | Counterpropagation Neural Network

CPNs combine unsupervised competitive learning with supervised output mapping. The network consists of two layers:

I. Kohonen competitive layer

II. Grossberg output layer

The competitive layer identifies the neuron whose weight vector is closest to the input vector according to Euclidean distance:

$$D_j = \sqrt{\sum_{i=1}^{n}\left(x_i - w_{ij}\right)^2}, \quad (4)$$

where:

I. (x_i) represents the input vector.

II. (w_{ij}) denotes the weight associated with neuron (j).

The winner neuron is selected according to:

$$j = \arg\min(D_j). \quad (5)$$

The weight adaptation in the Kohonen layer is performed as

$$w_{ij}^{new} = w_{ij}^{old} + \alpha(x_i - w_{ij}^{old}), \quad (6)$$

where α is the learning rate.

In the Grossberg layer, the output weights are modified according to:

$$v_{jk}^{new} = v_{jk}^{old} + \beta(y_k - v_{jk}^{old})z_j, \quad (7)$$

where:

I. (v_{jk}) denotes the output-layer weight.

II. (y_k) is the target response.

III. (z_j) indicates the activation of the winning neuron.

IV. (β) is the learning coefficient.

Compared with BPNNs, counterpropagation networks provide faster convergence and require lower computational effort. However, their prediction accuracy may be slightly inferior to that of backpropagation networks.

4 | Numerical Example and Dataset Generation

For assessing the performance of the designed neural network structures, a space truss made of 52 members is chosen as the test structure. Considering the geometric symmetry of the structure, only a quarter of the structure is taken into account for building the training database.

The cross-sectional area of the truss members serves as the input parameter, while the stress on the members, determined using the exact finite element method, forms the output parameters. The data set is formed using many FEM analyses conducted for various designs.

These data sets are segregated into training and testing data sets to assess the generalization capabilities of the neural networks. The inputs are normalized prior to being fed to the neural network.

5 | Performance Evaluation

The accuracy of the neural networks is evaluated using the Mean Absolute Percentage Error (MAPE):

$$MAPE \frac{(100)}{(N)} \sum_{i=1}^{N} \left| \frac{(\sigma_i^{Exact} - \sigma_i^{Predicted})}{(\sigma_i^{Exact})} \right|, \quad (8)$$

where

I. (σ_i^{Exact}) denotes the exact stress obtained from FEA.

II. ($\sigma_i^{Predicted}$) represents the predicted stress generated by the neural network.

The Root Mean Square Error (RMSE) is defined as

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\sigma_i^{\mathrm{Exact}} - \sigma_i^{\mathrm{Predicted}}\right)^2}. \quad (9)$$

The coefficient of determination R^2 is expressed as

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(\sigma_i^{\mathrm{Exact}} - \sigma_i^{\mathrm{Predicted}}\right)^2}{\sum_{i=1}^{N}\left(\sigma_i^{\mathrm{Exact}} - \overline{\sigma}\right)^2}, \quad (10)$$

where ($\overline{\sigma}$) denotes the mean exact stress.

Training time and computational efficiency are also employed as indicators for comparing the two neural architectures.

6 | Results and Discussion

According to the numerical results, both ANNs can predict the stresses in members accurately and considerably minimize the computation effort for performing FEA repeatedly.

The BPNN is more accurate in prediction due to its strong nonlinear approximation ability. However, the training algorithm needs considerable time for computation.

On the other hand, the CPN enjoys faster convergence and decreased computational expenses. The use of both competitive learning and supervised mapping allows for achieving high levels of accuracy while minimizing time needed to complete the training process.

This comparison shows that the choice of adequate neural architecture depends on the trade-off between prediction accuracy and computational performance. In cases when repetitive analysis and extensive optimization are required, CPN offer an attractive solution because of its speed. In cases where maximum prediction accuracy is crucial, BPNNs should be used instead.

7 | Conclusion

This study investigated the application of BPNNs and CPNs as surrogate models for accelerating truss optimization.

The following conclusions can be drawn:

I. ANNs effectively replace repeated finite element analyses and significantly reduce computational cost.

II. Both neural architectures provide satisfactory prediction accuracy for member stresses in the 52-member space truss.

III. BPNNs exhibit higher accuracy but require longer training times.

IV. CPNs demonstrate faster convergence and lower computational effort.

V. The trade-off between computational efficiency and prediction accuracy suggests that CPNs are suitable for large-scale optimization problems, whereas BPNNs are preferable when high precision is required.

VI. Classical neural architectures remain competitive surrogate models and can still be effectively utilized in modern structural optimization frameworks.

Future studies may integrate these classical neural networks with evolutionary algorithms, deep learning techniques, and graph neural networks to further enhance optimization performance.

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